Text in Visualization: Extending the Visualization Design Space
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Text in Visualization

Extending the Visualization Design Space

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Abstract

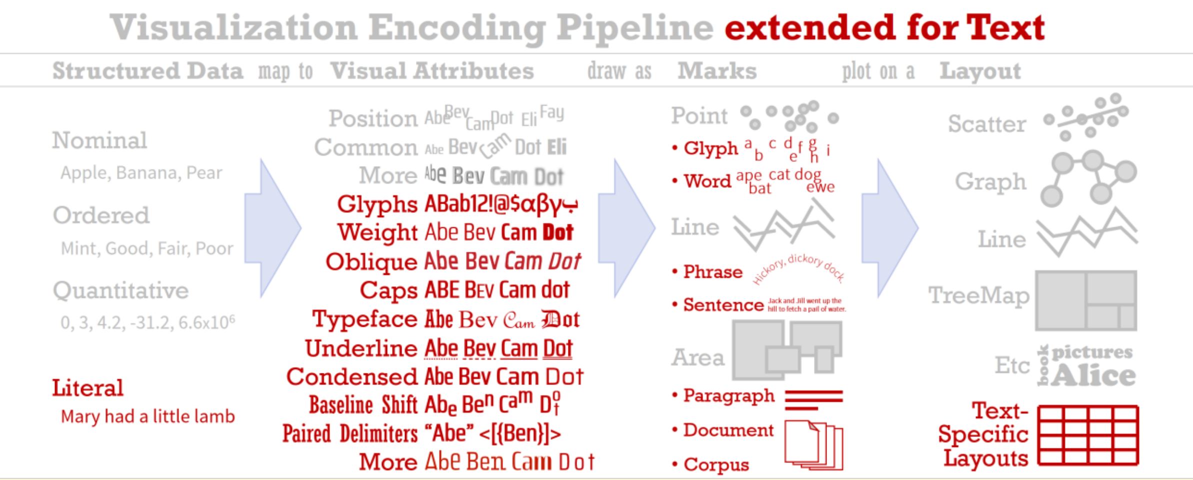
This thesis is a systematic exploration and expansion of the design space of data visualization specifically with regards to text. A critical analysis of text in data visualizations reveals gaps in existing frameworks and the use of text in practice. A cross-disciplinary review across fields such as typography, cartography and technical applications yields typographic techniques to encode data into text and provides the scope for the expanded design space. Mapping new attributes, techniques and considerations back to well understood visualization principles organizes the design space of text in visualization. This design space includes: 1) text as a primary data type literally encoded into alphanumeric glyphs, 2) typographic attributes, such as bold and italic, capable of encoding additional data onto literal text, 3) scope of mark, ranging from individual glyphs, syllables and words; to sentences, paragraphs and documents, and 4) layout of these text elements applicable most known visualization techniques and text specific techniques such as tables. This is the primary contribution of this thesis (Part A and B).

Then, this design space is used to facilitate the design, implementation and evaluation of new types of visualization techniques, ranging from enhancements of existing techniques, such as, extending scatterplots and graphs with literal marks, stem & leaf plots with multivariate glyphs and broader scope, and microtext line charts; to new visualization techniques, such as, multivariate typographic thematic maps; text formatted to facilitate skimming; and proportionally encoding quantitative values in running text – all of which are new contributions to the field (Part C).

Finally, a broad evaluation across the framework and the sample visualizations with cross-discipline expert critiques and a metrics based approach reveals some concerns and many opportunities pointing towards a breadth of future research work now possible with this new framework. (Part D and E).

TEXT IN VISUALIZATION has not been well defined.

The **EXISTING DESIGN SPACE OF VISUALIZATION** (PART A PAGES 1-23) can be described as a pipeline transforming Structured Data into Visual Attributes drawn as Marks and plotted in a Layout (columns in diagram below). In the existing design space (indicated in grey in the diagram below), text is typically preprocessed into structured data such as categories and quantities, represented as simple text words and tends to use simple layouts such as labels and word clouds. Gaps in the framework imply poor definition for text in visualization.



The **DESIGN SPACE FOR TEXT IN VISUALIZATION** (PART B 23-108) is

1. Informed by CROSS-DISCIPLINARY RESEARCH 24, including TYPOGRAPHY 24, CARTOGRAPHY 33, TECHNICAL APPLICATIONS 40, VISUALIZATION 46 and UI GUIDELINES 50.
2. These suggest four UNIQUE TEXT-SPECIFIC EXTENSIONS 52 (red columns in the above pipeline diagram): LITERAL ENCODING 52, TYPE ATTRIBUTES 58, TEXT MARKS 59, and UNIQUE LAYOUTS 61.
3. Text has UNIQUE PERCEPTUAL CONSIDERATIONS 63, including PREATTENTION & GESTALT 63, LEGIBILITY & READABILITY 66, TYPE COLOR 67, ATTENTION 69, TEXT SEMANTICS 69, TYPOGRAPHIC SEMANTICS 70, LANGUAGE 71 and INTERACTION 73.
4. Each TYPOGRAPHIC ATTRIBUTE 75 is characterized: ALPHANUMERICS 75, SYMBOLS 76, WEIGHT 77, ITALICS 80, CASE 82, UNDERLINE 84, TYPEFACE 86, WIDTH 90, BASELINE 92, DELIMITERS 93, LOW-LEVEL DESIGN 94 and NON-TEXT SPECIFIC 99. These are summarized into best encodings →

Group	Font Attribute	Best Encoding	Example
Glyphs	**Alphanumeric Text Glyph**	**L**, **O**	ape bat cat dog 123 456
	Symbols	**C**	:!?#£@†∉☋♤♖♬⚜✂⚲
Font Family Attributes	**Font weight**	**Q** (2-9 levels)	1.0 2.0 3.0 5.0 **8.0**
	Oblique / Italic	**C**, **Q** (via slope angle)	-2.0 -1.0 0.0 *1.0 2.0*
	Case inc small caps	**C**, **O** (2-3 levels)	BIG AVG. Small tiny
	Typeface	**C** (2-6 levels)	Swiss French German *Italian*
	Underline	**C**, **O**, **Q** (via length)	plain dash single double
	Condensed	**Q**, **O** (2-4 levels)	1000 1200 1450 1700
Sequence	**Squished**	**Q**	thinnest thin plain wide fat
	Spacing	**Q**, **O**	tall grand venti
	Baseline shift (e.g. subscript)	**C** (2 levels)	Low Normal High
	Delimiters	**G**	(but) *and* <or>
Font Design	**X-height**	**O**, **Q** (few levels)	ick ick ick
	Contrast / Stress angle	**O** (few levels)	LOW MEDIUM HIGH
	Serif length / Bracket size	**O**, **Q** (too small?)	see prototypo.io and variable fonts

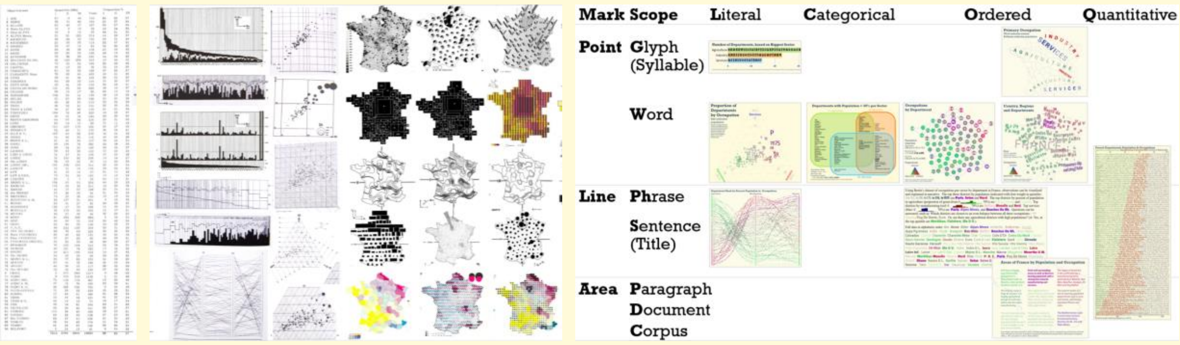
L: literal **C**: categoric **O**: ordered **Q**: quantitative **G**: grouping/relationship

All the above defines the **key contribution of the thesis: the TYPOGRAPHIC VISUALIZATION DESIGN SPACE** 102, summarized by the red extensions in the pipeline diagram 104.

Given a vast design space, Mark scope and Data type (right) can frame potential applications. These are explored in the second half of the thesis.

Mark	Scope	Literal	Categoric	Ordered	Quantitative
Point	Glyph	LG	CG	OG	QG
	Word	LW	CW	OW	QW
Line	Sentence	LS	CS	OS	QS
Area	Paragraph	LP	CP	OP	QP
	Document	LD	CD	OD	QD
	Corpus	LC	CC	OC	QC

This extended design space is **APPLIED TO NEW TYPOGRAPHIC VISUALIZATIONS** (**PART C**[108-205]), and evaluated, in the second half of this thesis. Bertin illustrated the flexibility of his original visualization framework using a sample dataset (left), to design many charts and maps (middle). In turn, using the same dataset, many new typographic visualizations illustrate the flexibility of the extended design space (right).



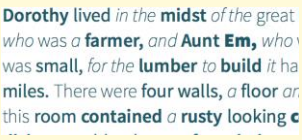
Next, specific new text visualization applications of with different Data encodings and Mark types are created. These address known shortfalls in current visualization techniques and most include a lightweight evaluation:

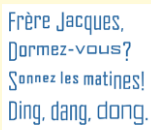
LW: LITERAL LABELS[111] replace legends and interactions on BARS & SCATTERPLOTS aiding faster identification.

LS: MICROTEXT LINE CHARTS[124] facilitate tracking more than ten lines. More experts are able to complete tasks.

LX: TYPOGRAPHIC STEM & LEAF PLOTS[137] extend the technique to glyphs, words and phrases.

CD: CATEGORIC SETS[144] use text with type attributes to show set membership in VENN, MOSAICS, & GRAPHS, with efficient representations of quantities.





OW: TYPOGRAPHIC CARTOGRAMS[164] address shortfalls of choropleth maps and outperform 2.2x.

OP: TEXT SKIMMING[176] is aided by scaling word formats to inverse word frequency. Positive user feedback.

OG: PROSODY & PRONUNCIATION[190] explores glyph and syllable encodings.

QS: QUANTITATIVE SENTENCES[193] indicate magnitude by applying formats to a sentence subset. More items are readable with lower margin of error in size estimation.

A **BROAD EVALUATION across the DESIGN SPACE and APPLICATIONS** (**PART D.** [205-248]) uses:

- CROSS-DISCIPLINARY CRITIQUES[206]: CRITIQUES IN VISUALIZATION[206] are a new contribution. Critiques are applied to the thesis, yielding frequent concerns such as MULTIPLE ENCODINGS[213], LABEL LENGTH BIAS[216], BERTIN'S TYPE ATTRIBUTES[218], NUMBER OF DIMENSIONS[222], and additional DOMAIN SPECIFIC CRITIQUES[225].
- NOVEL METRICS[232]: FIDELITY[234] and LOSSINESS[238] indicate greater information density using text.

The **RESULTS** of this work are (**PART E**. [248-254]) a NEW FRAMEWORK FOR TEXT VISUALIZATION,[248] a BREADTH OF NEW RESEARCH QUESTIONS,[249] and a SHIFT TO MULTI-LAYERED, POST MODERN VISUALIZATION[253].

The **Appendix** [254-269] lists FONTS RECOMMENDATIONS,[254] acknowledges EXPERTS,[254] identifies SOCIAL MEDIA RESPONSE,[256] lists SUPPLEMENTAL MATERIALS (including surveys),[257] and provides a BIBLIOGRAPHY.[269+]

This document overview was inspired by the contents description in Chamber's *Cyclopedia* (1728), Figure 14[25].

Table of Contents

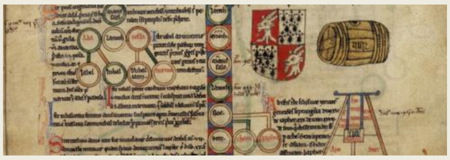
PART A.
Introduction: Extending Visualization Design Spaces

DESCRIPTION OF PART A

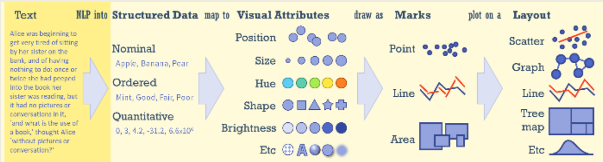
The objective of the overall thesis is to vastly expand the potential opportunities to utilize text in visualization. An initial overview provides the RATIONALE, OUTLINE AND KEY CONTRIBUTIONS of the thesis. PAGE 2

Why text is so poorly utilized in visualization needs to be understood *first*:

- WORD AND IMAGE SEPARATION: 700 year old manuscripts deeply integrate text and visualization – but charts and modern visualizations tend not to mix text and visualization. PAGE 4



- TEXT SEPARATE FROM VISUALIZATION PROCESSING: Many researchers conceptualize the creation of visualization as a pipeline – but text is simply pre-pended to the process to generate data.9



- TEXT IS NOT PREATTENTIVE. Visualization is about easy visual perception of patterns, but text needs to read to be understood – however, text attributes, such as bold, are easily perceived.12

- MANY TEXT VISUALIZATIONS EXIST – but some make errors in encoding data into text for perception.13

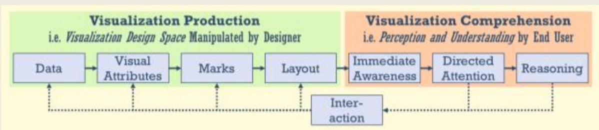
Instead a **design space** of text in visualization is needed:

- **A** DESIGN SPACE is a definition of design parameters used to construction solutions.15

- A METHOD to expand the design space is outlined.16

1. Identify gaps. 2. Research background. 3. Identify unique considerations 4. Identify new applications. 5. Evaluate.

- GAPS exist throughout the visualization pipeline.17



- GAPS IN VISUAL ATTRIBUTES in particular show text is not well defined.18

Text	Text Labels	X	X	X	X	X
	Font Family					X
	Oblique					X

VALUE OF TEXT IN VISUALIZATION is potentially vast, with uses in computer science research, new kinds of applications, new kinds of collaboration, and the potential for billions of dollars of economic value.21

Note: subscripts in this document indicate page numbers, superscripts indicate footnotes. Both are clickable.

A:1. Rationale, Outline and Key Contributions

In data visualization, abstract data elements (such as quantities and categories) are encoded into visual attributes of geometry (such as colors, sizes and shapes) and depicted on an interactive computer screen or paper. This visual representation acts as an external memory aid to the human viewer to facilitate perceptual inferences (such as spotting outliers, estimating trends and comparing sizes) and higher level tasks (such as generating hypotheses and disseminating findings).[1,2,3] However, there is a big gap in current theoretic frameworks that define the *design space of visualization*: the role of text in visualization is undefined. This gap is the focus of this thesis.

The primary contribution of this thesis is a methodological expansion of the design space of visualization specifically with regards to text.

In *PART A. Introduction*, a critical analysis of text in data visualization reveals gaps in existing frameworks and the use of text in practice. This gap may be due to historic limitations (*A:2*), which in turn leads to separation of text analytics from text visualization (*A:3*), to the point where some visualization experts are skeptical about the use of text in visualization (*A:4*). The existing design space of visualization is reviewed (*A:5.1*), a method to probe and expand the design space outlined (*A:5.2*) and text gaps identified based on a review across researchers and use (*A:5.3 and D).* The opportunity for text in visualization is relevant to research (e.g. natural language processing), new kinds of human-computer interaction applications (e.g. search, reading), economic value and collaboration with other communities (*A:6*). The contribution of this section is the framing of the design space and the identification of gaps in text.

PART B. The Design Space of Text in Visualization$_{p52}$ starts with a primary research across multiple disciplines reviewing hundreds of examples of existing text visualizations across 1000 years (*B:1*$_{P24}$). The method is similar to Bertin's analysis of many example visualizations to define and illustrate his framework in *Semiology of Graphics*.[4] This analysis identifies multiple extensions to the existing visualization framework and characterizes them – literal encodings, typographic visual attributes, textual mark types and unique layouts (*B:2*$_{P52}$). Text has unique considerations for visualization, such as readability, type color and semantics (*B:3*$_{P63}$). **The result of all the above defines the design space of text in visualization (*B:5*$_{P104}$), the key contribution of this thesis and summarized by the red text in Figure 110$_{P104}$.**

PART C. Applications of Typographic Visualizations$_{P108}$ uses this design space to facilitate the design, implementation and evaluation of new types of visualization techniques with text. First, similar to Bertin (p.100-138), many different new text-oriented visualizations are created, all using the same dataset as Bertin. This shows the flexibility of the design space to express many different representations of the same data (*0*$_{P109}$). Then,

[1] Robert Kosara, "What is Visualization? A Definition," *EagerEyes.com*, last modified July 24, 2008, https://eagereyes.org/criticism/definition-of-visualization, accessed: April 15, 2016.
[2] Tamara Munzner, *Visualization Analysis and Design,* (Boca Raton, FL: CRC Press, 2015), 1-19.
[3] Min Chen and Luciano Floridi, "An analysis of information visualization", *Synthese,* 190, no. 16 (2013): 3425-3426.
[4] Jacques Bertin, *Semiology of Graphics,* trans. William Berg (Madison, WI: University of Wisconsin Press, 1983).

many new or extended visualizations are presented, typically starting with known limitations of an existing representation, followed with the development of novel text-based approaches, and an evaluation and/or discussion comparing the existing approach to the new approach. The method is similar to the design, development and evaluation of new peer-reviewed visualizations: primary research includes the development of the novel visualization and associated evaluation and/or discussion. The new visualizations include:

- *Literal encodings,* where dots in scatterplots and graphs are extended with labels (*C:1*[P111]); linecharts enhanced with microtext (*C:2*[P124]) and stem & leaf plots extended to broader scopes of text (*C:3*[P137]).
- *Categoric encodings* focus on the use of multiple text attributes to indicate set membership in Euler diagrams, mosaic plots, graphs and maps (*C:4*[P144]).
- *Ordered encodings* introduces typographic cartograms to deal with limitations of choropleth maps (*C:5*[P164]); formatted words paragraphs to facilitate text skimming (*C:6*[P176]); and manipulated glyphs in words to indicate prosody and pronunciation (*C:7*[P190]).
- *Quantitative encodings* introduce positional and proportional encoding techniques whereby a subset of a line or paragraph of text indicates a quantity by its formatting (*C:8*[P193]).

Each of these above novel visualizations is an important contribution to the field of data visualization, as well as the associated lightweight evaluations, including *cognitive modeling*[P119], measurement of *information density*[P200,P232], measurement of *encoding accuracy*[P154]*,* measurement *task performance*[P173]; *user feedback*[P183]; *task observations*[P132]; and *user surveys*[P183,P200] (see also Supplemental Materials[P257] in the Appendix).

PART D. Evaluation of Typographic Visualization Design Space[P205] is a novel approach to evaluate all the above work: the design space and the many new visualizations. A cross-disciplinary critique solicits feedback from experts across visualization, cartography and typography, revealing critical aspects, some of which have been incorporated into the thesis (*D:1*[P206]). Fidelity and lossiness are a new metrics-based evaluation approach (*D:2*[P232]). Both of these evaluation techniques are contributions to the visualization domain.

PART E. Conclusions and Future Work[P248] summarizes the framework, contributions, the wide breadth of future research and finishes with a call to action for a new approach to visualization leveraging text with implied changes in how visualizations are developed, used and interpreted.

This thesis is the result of significant primary research, including:

- The review and analysis of thousands of historic and modern visualizations from many conferences, collections and libraries. See Acknowledgements[P255] in Appendix and Bibliography for list of resources utilized[P269].
- The design and development of eight new or extended visualization approaches and the associated evaluations (Part C[P108]).
- Critiques and discussions with more than two dozen experts from information visualization, typography, cartography and human computer interaction. See Part D[P205] and Acknowledgements[P255] in Appendix.

This research has resulted in the contribution of 13 accepted peer reviewed publications (listed chronologically):

1. "The Design Space of Typeface," at *VisWeek*, 2014 (Paris 2014).
This poster contributes an itemization of typographic attributes to preattentively encode data. *2 pages. Link.*
2. "Using Font Attributes in Knowledge Maps and Information Retrieval," at *First Workshop on Knowledge Maps and Information Retrieval*, 2014 (London 2014).
This paper contributes three new visualization techniques based on typographic attributes relevant to knowledge maps. *8 pages. Link.*
3. "Evaluating Lossiness and Fidelity in Information Visualization" at *SPIE 2015* (San Francisco 2015).
Contribution is a quantitative scoring model for comparing information loss across visualization alternatives. *14 pages. Link.*
4. "Using Text in Visualizations for Micro/Macro Readings" at *TextVis Workshop 2015* (Atlanta 2015).
Contribution is notion of literal encoding as separate from other preattentive encodings enabling micro and macro readings of text visualizations and novel word-based stem-and-leaf plot. *8 pages. Link.*
5. "Using Type to Add Data to Data Visualizations" at *TypeCon 2015,* (Denver 2015).
Contribution is a historic review of the font attribute design space with several applications including one novel glyph-based technique. *4 pages. Link.*
6. "Font Attributes enrich Knowledge Maps and Information Retrieval" in *International Journal on Digital Libraries, 2016*.
This journal article reviews font attributes and applies them to tasks relevant to knowledge maps (document overviews) and information retrieval (search), including text analytic tasks (i.e. natural language processing) such as skimming, opinion analysis, character analysis, topic modeling and sentiment analysis. *20 pages. Link.*
7. "Using Typography to Expand the Design Space of Data Visualization." in *She Ji: The Journal of Design, Economics, and Innovation* vol. 2, no. 1 (Spring 2016): 59–87.
This journal article summarizes the authors' cross-disciplinary research approach engaging visualization researchers, cartographers and typographers to 1) identify the gaps in visualization theory, 2) review adjacent fields to comprehensively assess techniques, 3) extend an common existing visualization framework with separation between type attributes, typographic scope and data type, 4) illustrate many potential applications from this framework, and 5) broad evaluation including critiques across domain. *29 pages. Link. (Note this paper is a template for the entire thesis)*
8. "Typographic Sets: Labelled Set Elements with Font Attributes," at *International Workshop on Set Visualization and Reasoning 2016* (Philadelphia 2016).
This paper shows how many visualization techniques indicating members in sets can be extended using typographic attributes, with unique contributes including identification of membership in up to ten sets and scalability to thousands of elements. *15 pages. Link.*
9. "Evaluation of Visualization by Critiques" at *Beyond Time and Errors: Novel Evaluation Methods for Visualization (BELIV)* (Baltimore 2016).
This position paper extends design critiques as a form of evaluation, different than pre-existing "evaluation by inspection" techniques, uniquely providing broader scope and context. *8 pages. Link.*
10. "Multivariate Label-based Thematic Maps" in *International Journal of Cartography,* 23 Mar 2017.
This journal article focuses on thematic maps where traditionally colored shapes are used to indicate data instead use labels, which can indicate more than one or two variables; and provides solutions to issues of representation of strings of differing lengths and label occlusion. *16 pages. Link*.
11. "Stem & Leaf Plots Extended for Text Visualizations" at *14th International Conference Computer Graphics, Imaging and Visualization* (CGiV) 2017. (Marrakech, 2017).
This short paper extends the visualization technique of "stem and leaf plots" using font attributes and tokens of different scope (single character, word, phrase). *6 pages. Link*.
12. "Microtext Line Charts" at *Information Visualization 2017* (IV2017). (London 2017).
This paper brings together microtext and path dependent cartographic text to embed text directly into lines on line charts, making it easier to identify lines and enabling additional data to be displayed. *8 pages. Link*.
13. "Bertin's Forgotten Typographic Variables and New Typographic Visualization" to be published in *Computer and Geographic Information Systems* (CaGIS) Journal late 2018. *Approximately 21 pages.*
This article, for the 50th anniversary of *Semiology of Graphics*, extends Bertin's initial type work and creates new typographic visualizations using Bertin's data. DOI: 10.1080/15230406.2018.1516572

A:2. Missd Opportunity: 500 years of separation

Typography and data visualization have been closely related for hundreds of years. 700 year old medieval manuscripts show early visualizations such as genealogical trees[5], radial charts[6], and tables[7] of data as shown in Figure 1. Text is tightly integrated, surrounding the diagrams, filling in regions of the diagrams, and enriching specific text labels within the visualizations, for example, with colored labels (in the genealogical tree), illuminated initials (in the radial diagram) or variation in case (in the table). Similar examples can be found in other cultures (e.g. Figure 64P71).

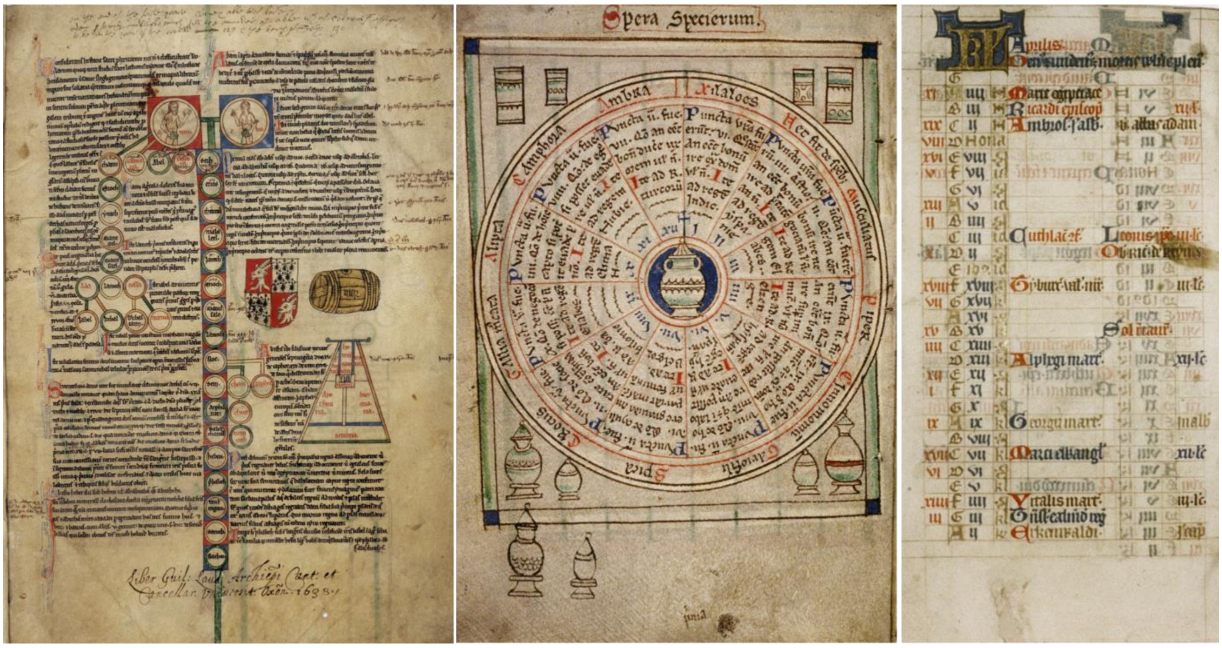


Figure 1. Medieval visualizations. Left: a genealogical tree with nodes varying in type color. Center: a radial diagram with illuminated initials. Right: a table with variation in type color, illuminated initials and case.

In 1439, the introduction of the printing press by Gutenberg changes the technical feasibility of mixing type and imagery. Movable type is not easily combined with woodblock prints: text and image are separated. Although early use of the printing press attempted to retain old techniques such as rubrication (i.e. colored text), a wide variety of ligatures, and illuminated text (text enhanced with imagery), these were difficult to produce and disappeared from common use. Figure 2 left shows facing pages from a text from 1573 with a woodblock print facing text on the opposite page.[8]

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[5] Peter of Poitiers, *Compendium historiae in genealogia Christi*. Mid-13th century. Shelf MS. Laud Misc. 151 fol. 001r. http://bodley30.bodley.ox.ac.uk:8180/luna/servlet/detail/ODLodl~1~1~3554~103738 Accessed August 20, 2016.

[6] Socrates the King, *The Prognostics*. Mid-13th century. Shelf MS. Ashmole 304 fol. 033a verso. http://bodley30.bodley.ox.ac.uk:8180/luna/servlet/s/7l98th Accessed August 20, 2016.

[7] Author unknown, *Breviary of Chertsey Abbey, fragments of the temporale and sanctorale*. Early 14th century. Shelf MS. Lat. liturg. e. 6 fol. 005v http://bodley30.bodley.ox.ac.uk:8180/luna/servlet/detail/ODLodl~1~1~46209~120705 Aug. 20, 2016.

[8] William Bullein, *A dialogue bothe pleasaunte and pietifull, wherein is a goodly regimente against the fever pestilence with a consolacion and comfort against death.* London, 1573. (Bodleian Library, Shakespeare's Dead, 8° E 9(2) Med.)

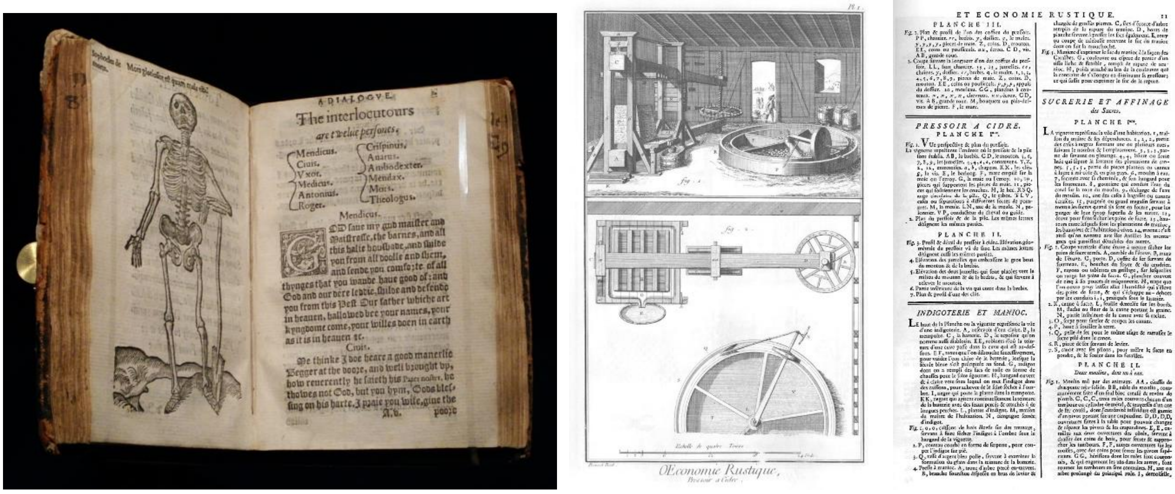

Figure 2. Left: Image separate from text. from William Bullein's *A Dialogue Against the Fever Pestilence* from 1593. Right: Beautiful engravings from Diderot's *Encyclopédie* 1751-1772: images have minimal text requiring the viewer to cross-reference the text. Left: Author photo. Right: http://encyclopedie.uchicago.edu/

By the age of the Enlightenment, high quality engraving and high quality typesetting had completely separated text from image as shown by the pair of pages from Diderot's *Encyclopédie*[9] in Figure 2 right: images have single character labels requiring the viewer to cross-reference the text for explanations. As noted by Albert Biderman, charts and graphics became segregated from text and often produced by a commercial artist who may not have a background in scientific analysis.[10]

By the early 20th century, charts have largely relegated the role of type to simple labels, ticks and titles at the perimeter of the chart, as shown in the examples in Figure 3 left.[11] Note that thesis does not review this marginal use of text around the periphery of visualizations such as legends, axis labels and chart titles as this topic is already addressed in references such as Wallgren et al's *Graphing Statistics and Data,*[12] Wong's *The Wall Street Journal Guide to Information Graphics,*[13] or Brewer's *Designing Better Maps.*[14] This thesis is concerned with larger questions regarding text inside visualizations.

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[9] *Encyclopédie, ou dictionnaire raisonné des sciences, des arts et des métiers, etc.,* eds. Denis Diderot and Jean le Rond d'Alembert. University of Chicago: ARTFL Encyclopédie Project (Spring 2016 Edition), Robert Morrissey and Glenn Roe (eds), http://encyclopedie.uchicago.edu/.

[10] Albert D. Biderman. The graph as a victim of adverse discrimination and segregation, *Information Design Journal*, Volume 1, Issue 4, 1980.

[11] Willard C Brinton. *Graphic Methods for Presenting Facts*. The Engineering Magazine, New York 1919. https://archive.org/details/methodsfo00bringraphicrich Accessed August 26, 2016.

[12] Anders Wallgren et al. *Graphing Statistics & Data: Creating Better Charts*. Sage, 1996.

[13] Dona M. Wong, *The Wall Street Journal Guide to Information Graphics: The Dos and Don'ts of Presenting Data, Facts and Figures.* W.W. Norton & Company, 2010.

[14] Cynthia A. Brewer, *Designing Better Maps: A Guide for GIS Users.* ESRI Press, 2005.

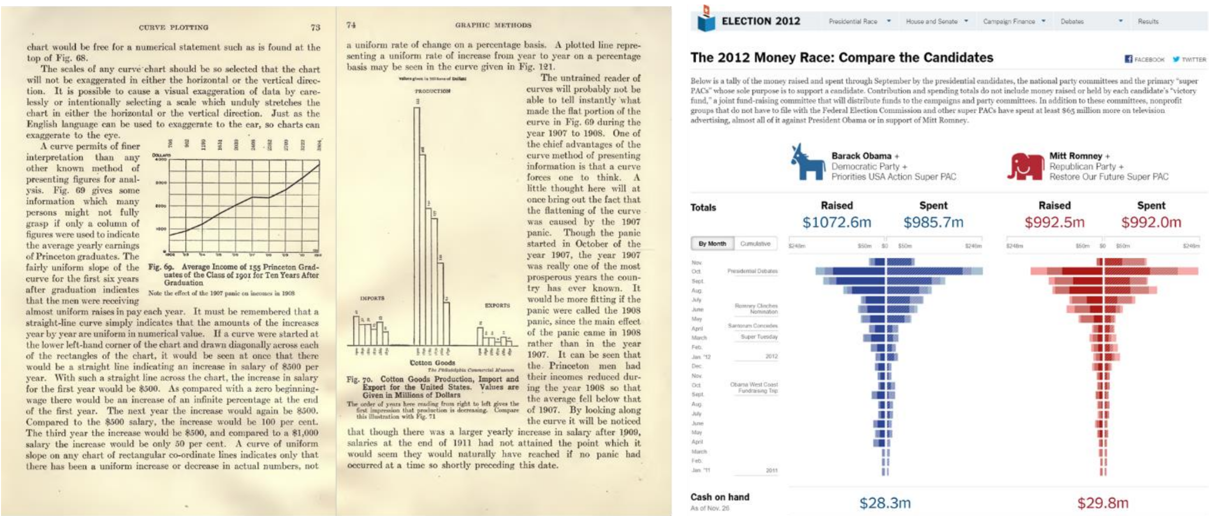

Figure 3. Left: Charts from 1919 – text largely is relegated to the periphery of the chart. Right: Interactive infographic from NY Times: variation in type is used to differential textual components such as titles, paragraphs, call-outs, axis labels, etc.
Left image public domain: Right image © 2012 The New York Times (nytimes.com/elections/2012/campaign-finance.html).

With computer-based visualization, text is no longer technically constrained to the margins. However, 500 years of practice means that the convention for separation of type from visualization persists. Infographics in newspapers and magazines do use a variety of annotations around and within a chart, including variation in type size, weight and color, such as the example shown in Figure 3 right.[15] The current use of typography in infographics largely follows from the principles of graphic design to create a *typographic hierarchy:* differentiating text components such as the title, lead paragraph, data source, axis labels, call-outs and so forth. As such, the typographic elements are aiding the organization of the information on the page, but are not explicitly representing data. This thesis does not address traditional use of type in graphic design as there are many excellent type design and resources such as, Lupton's *Thinking with Type,*[16] or Bringhurst's *The Elements of Typographic Style.*[17] This thesis is concerned with larger questions regarding text inside visualizations.

In interactive visualization, text may be hidden and revealed on interactions such as tooltips or zoom. However, not all visualization media are interactive (e.g. print) or not interactive for the full audience (e.g. presentations, videos, etc). Further, some experienced media outlets recognize users do not interact, e.g. Archie Tse of *The New York Times* explains: "If you make a tooltip or rollover, assume no one will ever see it. If content is important for readers to see, don't hide it."[18] This thesis is focused on making text directly visible in visualizations, not hidden in interactions.

Text visualization is a very recent area of research effort that focuses on the analysis and visual representation of text as data visualizations. Perhaps the most famous text visualization is the *tag cloud* (also known as the word cloud) as shown in Figure 4. Tag clouds do not show much data: they show words and typically only one

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[15] Jeremy Ashkenas, Matthew Ericson, Alicia Parlapiano And Derek Willis *The 2012 Money Race: Compare the Candidates.* 2012. http://elections.nytimes.com/2012/campaign-finance Accessed 2016/07/24
[16] Ellen Lupton, *Thinking with Type: A Critical Guide for Designers, Writers, Editors and Students*. (Princeton Architectural Press, 2010).
[17] Robert Bringhurst, *The Elements of Typographic Style.* (Hartley & Marks. 2013).
[18] Archie Tse. "Why we are doing fewer interactives." Malofiej 2016. https://github.com/archietse/malofiej-2016/blob/master/tse-malofiej-2016-slides.pdf.

more data point represented by the text size. Note that color is random, location is random and the size is ambiguous – it is not obvious whether the area of the text indicates the quantity or the font size. Tag clouds are considered a poor visualization by many visualization researchers: they may perform well for keyword collection and identification,[19] but lose relational information, [20] are poor for navigation, suspect as a tool for abstract understanding, and primarily useful visceral user engagement.[21] Tag clouds have many broader criticisms, such as Jakob Nielsen's: "A one-paragraph summary [of each report] would probably be more enlightening, be faster to scan, and would take up much less screen space, allowing for more items to be summarized on any given page [than tag clouds]."[22]

Figure 4. A tag cloud is one of the most popular text visualization techniques. Word size represents data – such as word frequency in a document. Word location and color are often random.[23] Image created by author. (via wordle.net).

This thesis *does* focus on text visualization and more broadly the use of text in any visualization to show data. Text analytics are covered lightly, as, the key focus of this thesis is to provide a framework that can be used to synthesize many new types of visualizations using text based on the use of typographic attributes.

[19] Anna W. Rivadeneira, Daniel M. Gruen, Michael J. Muller, and David R. Millen. "Getting our head in the clouds: toward evaluation studies of tagclouds." In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 995-998. ACM, 2007.
[20] Byron YL Kuo, Thomas Hentrich, Benjamin M. Good, and Mark D. Wilkinson. "Tag clouds for summarizing web search results." In *Proceedings of the 16th international conference on World Wide Web*, pp. 1203-1204. ACM, 2007.
[21] Marti A. Hearst and Daniela Rosner. "Tag clouds: Data analysis tool or social signaller?." In *Hawaii International Conference on System Sciences, Proceedings of the 41st Annual*, pp. 160-160. IEEE, 2008.
[22] Jakob Nielsen, "Tag Cloud Examples," Nielsen Norman Group, last modified March 24, 2009. https://www.nngroup.com/articles/tag-cloud-examples/
[23] Tag cloud created on http://wordle.net on June 6, 2015 using text of Lewis Carroll's *Alice's Adventures in Wonderland,* from http://www.gutenberg.org/files/11/11-h/11-h.htm

A:3. Missed Opportunity: Text preprocessing

Interactive data visualization has become a broad area of research in the last 25 years largely centered on computer science (e.g. conferences such as *VisWeek*, *EuroVis* and *PacificVis*) with focus on different visualization techniques, interactive techniques, related data analysis, evaluations and applications. In visualization, a key step is visual encoding: the transformation of data into a visual representation. Early researchers such as Bertin[24], Card[25], organized the *design space* of visual encoding more or less into a) data types (nominal, ordered and quantitative), b) visual attributes (e.g. location, size, color), c) marks (i.e. point, line, area), and d) composition of those marks into a layout. This can also be thought of as an encoding pipeline which transforms data into a visualization as shown in Figure 5.

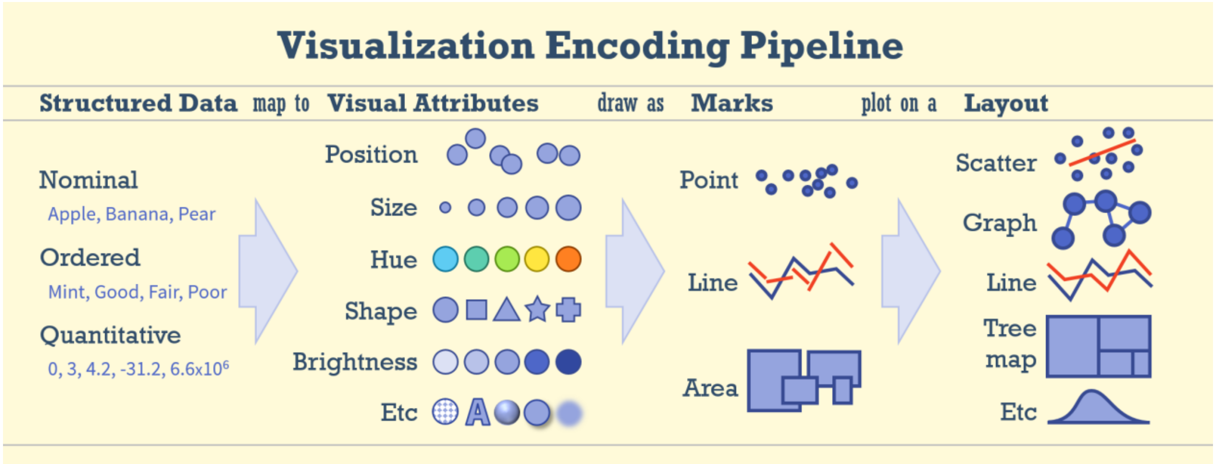

Figure 5. The visualization encoding pipeline: source data of different data types are mapped to different visual attributes which are then represented as different types of marks and composed into a layout. Image created by author.

This framework of data types, visual attributes, marks and layout, is powerful at explaining the construction of visualizations, such as some well-known visualization techniques shown in Figure 6. For example, the bubble plot (left) encodes quantitative data as x location, y location, and size; categoric data as hue; and renders these as point markers in a Cartesian layout. The treemap (Figure 6 right) represents quantities as size and hue; and renders the data as areas laid out with a space filling algorithm. The tag cloud (previously in Figure 4) encodes word frequencies as size; and in this particular example applies random hues; then renders the words at randomly placed points. The framework continues to aid the education and creation of new visualization techniques, such as introductory textbooks as well as formal declarative grammars (such as Wilkinson's *Grammar of Graphics*[26] or Wickham's *ggplot2*).[27]

[24] Jacques Bertin, *Semiology of Graphics,* trans. William Berg (Madison, WI: University of Wisconsin Press, 1983), 42–97.
[25] Stuart K. Card, and Jock Mackinlay, "The structure of the information visualization design space," *Proceedings of IEEE Symposium on Information Visualization 1997,* (IEEE, 1997), 92–99.
[26] Leland Wilkinson, *The Grammar Of Graphics*, 2nd ed. Springer Science & Business Media, 2005.
[27] Hadley Wickham, *ggplot2: Elegant Graphics for Data Analysis*, Springer, New York, 2009.

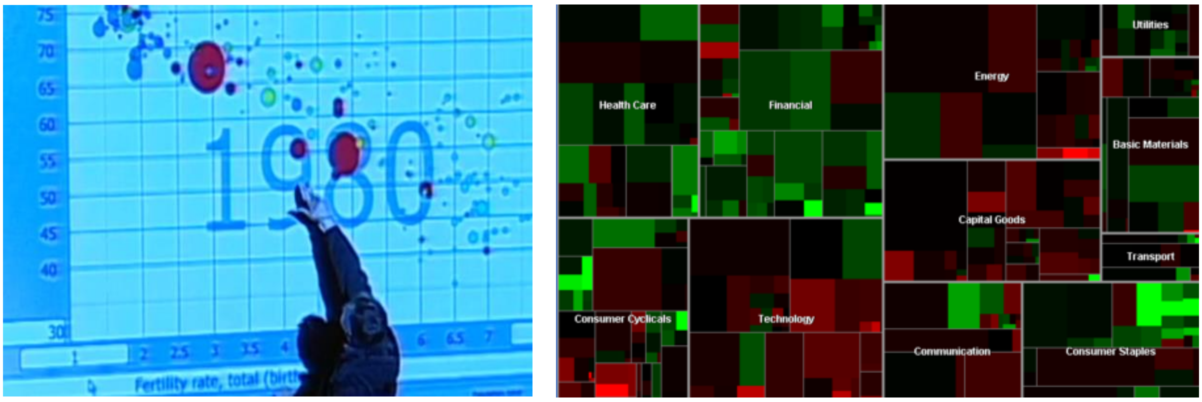

Figure 6. Popular visualizations as framed by visualization design space. Left: A *bubble plot* uses x location, y location, size and hue[28]. Right: A *treemap* uses size and hue[29]. Images copyright © 2006 TED Conferences LLC; copyright © 2016 MarketWatch, Inc.

Visualization of text can be added into this framework. The common approach is to simply **preprocess text** into the one of the forms of data handled by the remaining visualization pipeline, as shown in Figure 7. While this approach does work to create text-based visualizations, it has issues. First, many Natural Language Processing (NLP) tasks operate at the level of words: tokenization, stemming, lemmatization, part-of-speech tagging, removing stop words and punctuation, counting, frequencies, entity extraction; and some sentiment, emotion and topic modeling techniques are word-centric — thereby losing information contained in the original context. NLP is an active field of research because the meaning of text is much more complex than collections of words. While some NLP techniques operate across words (e.g. parse trees, dependencies, referents and summarization), corresponding visualizations may use grids, trees and lines but with plain text (e.g. Annis).[30]

Secondly, the approach assumes that the same data, attributes, marks and layouts are to be used for visualization (e.g. a tag cloud treats each word as a category, with size based on word frequency, point marks of the actual words and set into a random layout, alphabetic layout or semantic layout). There may be many other possibilities. These assumptions – a focus largely on words, using words as separate unique categories, represented with traditional attributes such as size and color, drawn point marks of words – need to be reconsidered and this is a primary objective of the thesis.

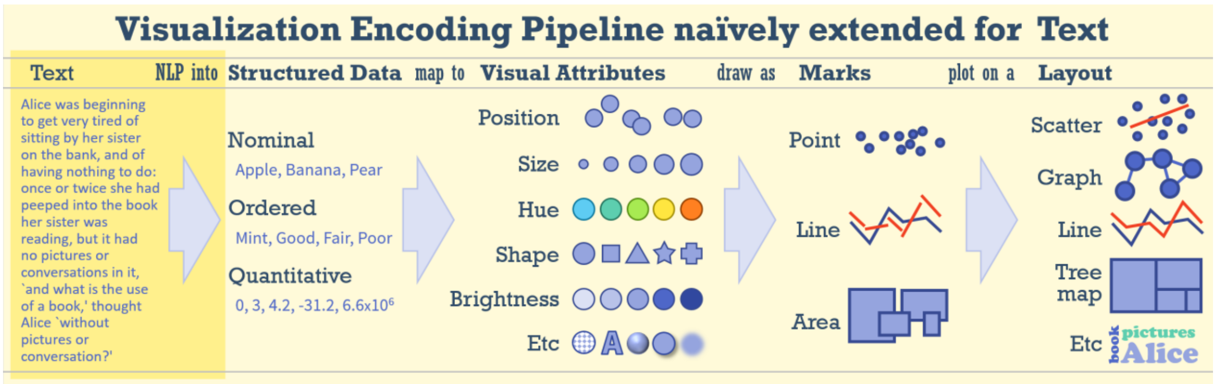

Figure 7. The visualization encoding pipeline, extended for text visualization (compare to Figure 110). Image created by author.

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[28] "Hans Rosling: The best stats you've ever seen," TED2006, filmed by TED Conferences LLC, February 2006, https://www.ted.com/talks/hans_rosling_shows_the_best_stats_you_ve_ever_seen?language=en .

[29] Martin Wattenberg, "Map of the Market," *Martin Wattenberg - Data Visualization: Art, Media, Science* (personal website), last modified: Sept. 13, 2012, http://www.bewitched.com/marketmap.html

[30] Thomas Krause and Amir Zeldes: "ANNIS3: A new architecture for generic corpus query and visualization." in: *Digital Scholarship in the Humanities* 2016 (31). http://dsh.oxfordjournals.org/content/31/1/118

Very rarely do modern text visualizations venture into the un-researched typographic attributes of fonts, such as **bold** and *italic* which are not expressed in the traditional visualization encoding pipeline. One finds little discussion of literal encoding as a type of encoding data and the implications. There are few examples of visualization manipulation beyond a sentence length or manipulation of individual characters in words.

If one ventures outside of visualization community, however, beautiful historic examples with rich typography can be found in other domains. For example, in Carey and Lavoisne's genealogical tree from 1820 (portion shown in Figure 8), bold indicates major branches, all caps indicate regions, small caps indicate sovereign rulers, italics represent spouses and symbols add other information, e.g. + indicates death. Text ranges from individual words to phrases to even two embedded sentences near the top. This one historic example hints that the pipeline shown in Figure 7 is deficient. This thesis will provide many more historic examples as a means to aid in the definition of the design space of text in visualization based on real-world uses.

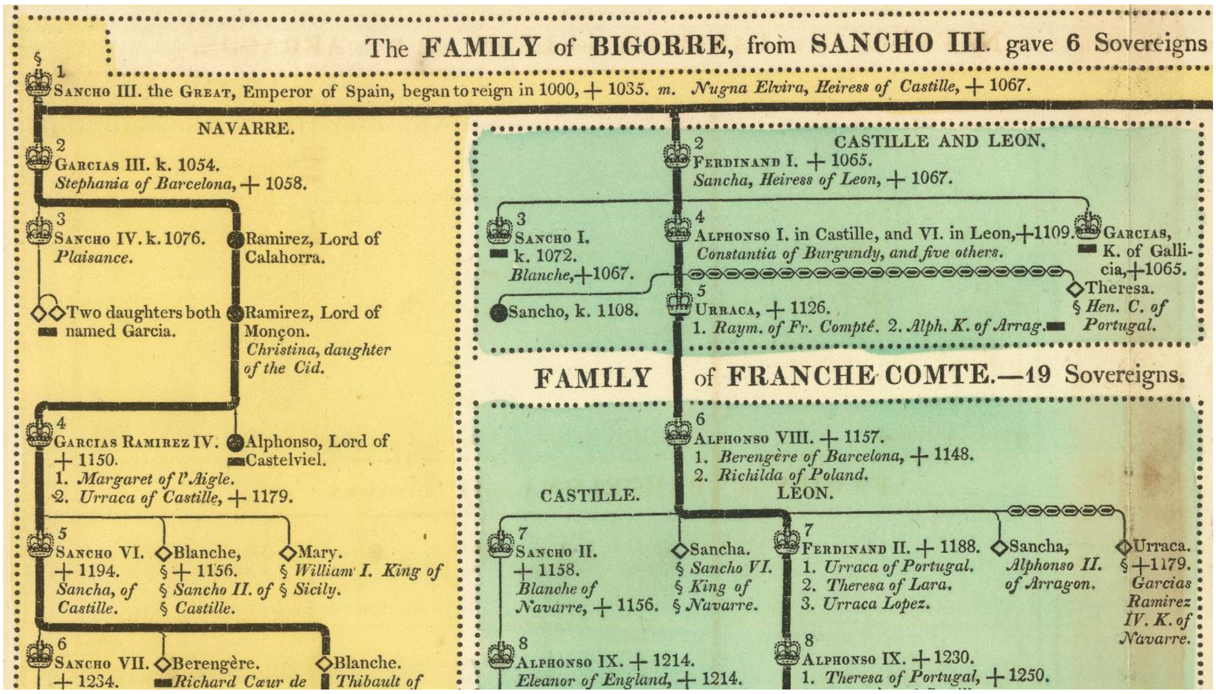

Figure 8. Portion from one of many family trees in Carey and Laviosne's *A Complete Genealogical, Historical, Chronological, And Geographical Atlas* (1820) using bold, italics, small caps and all caps to encode additional information.
Copyright © 2015 David Rumsey (www.davidrumsey.com), used with permission. Mathew Carey, *Spain from 1000 to 1814*. 1820. Philadelphia. Accessed June 6, 2015.

A:4. Text Visualization Skeptics

As discussed earlier in *A:2: Missd Opportunity: 500 years of separation*P5, there is a 500 year bias against mixing text and visuals. Most visualizations experts have no formal typographic training, and the separation of type from image has been reinforced from an early age through the thousands to millions of examples that they have seen throughout their career, such as easy readers with the text printed below the image, through textbooks where equations are plotted separately from the explanatory text to research papers where figures are neatly separated for associated text.

A:4.1. Text is not preattentive: therefore not a visualization attribute

Text, to be understood, must be read. Reading is a slow linear process. Perception of visual differences in hue or size, however, can be extremely fast and appear to visually “pop-out” from their surroundings. This property is described as being *preattentive,* that is, it is known that visual attributes such as size, hue, orientation can be perceived almost immediately, with a fixed response time regardless of the number of items in the display. Some examples of known preattentive attributes are shown in Figure 9.

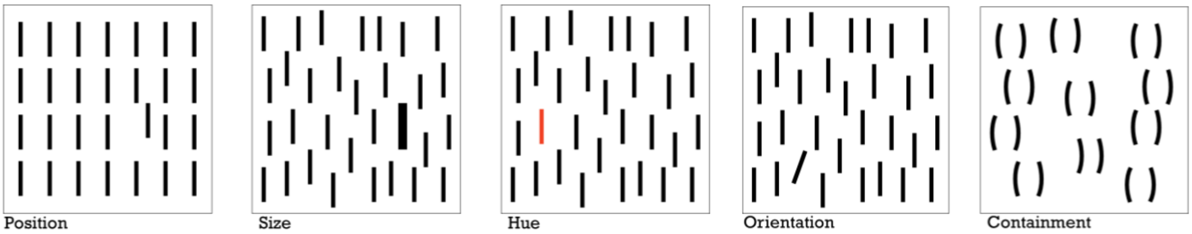

Figure 9. Illustration of some known preattentive visual attributes. The outlier in each square is fast and easy to perceive. Image by author.

Text may require linear reading of each word as opposed to rapid parallel perceptual processing across a number of simultaneous visual markers. However, visual attributes can be applied to text, thereby making the outlier quick to perceive. This allows attention to focus on reading a singular item bypassing the need to cognitively process all the other items. As can be seen in Figure 10, the one differently formatted name in each block is easily identified, whether the attribute is a traditional commonly understood preattentive visual attribute, such as color or size (top left), or typograph attributes such as bold, italic, font family, capitalization, and so on.

Note that the degree of preattention varies based on the degree of difference between the target and the other items.[31] For example, a red target will be easier to detect than a dark blue target among black items. Prior research on orientation shows that a difference of two degrees is noticeable, but a difference of 15 degrees is needed for effective preattention,[32] thus a steeply sloped italic will be easier to detect than an italic with very little slope among an otherwise plain (roman) font.

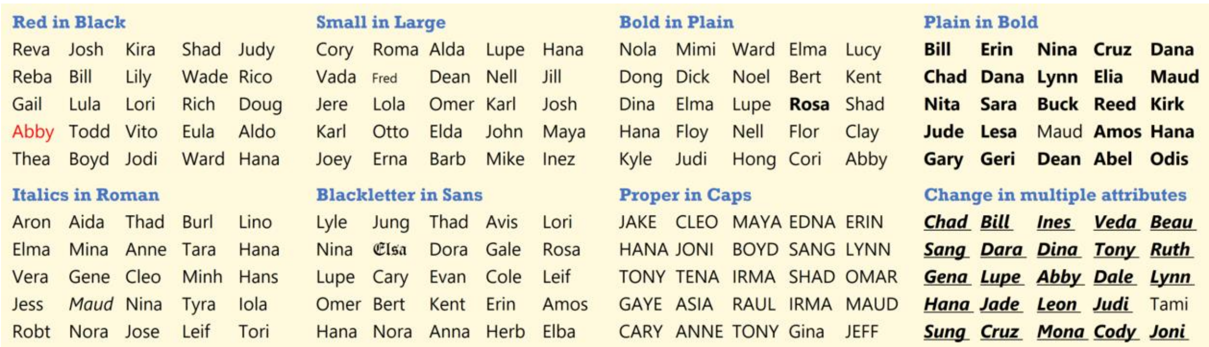

Figure 10. Different visual attributes are used to draw attention to a name: both well-researched visual attributes can be used (such as color and size); or typographic attributes such as bold, italics, font family, etc. Image by author.

This text differentiation is already in search interfaces and associated techniques such as *keyword in context*, even if not used in visualization. There are other benefits to text that will also be covered, such as identification, scaling to categories with high cardinality; serendipitous discovery; and so forth.

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[31] Jeremy M. Wolfe, "Visual search." Attention 1 (1998): 13-73.

[32] David H. Foster and Patrick A. Ward. "Asymmetries in oriented-line detection indicate two orthogonal filters in early vision." Proc. R. Soc. Lond. B 243, no. 1306 (1991): 75-81.

A:4.2. Many text visualizations already exist

There are already hundreds of existing peer-reviewed text visualization techniques. The online *Text Visualization Browser* (http://textvis.lnu.se/) is a non-exhaustive survey of many peer-reviewed text visualization techniques, with 249 examples logged from 1976-2015, excluding the authors' contributions (as of Jan 22, 2016). As per the left list in Table 1, 40 of these have no text, 103 have simple plain text (such as axis labels, node labels, document titles or tweet content) and only 106 (only 43%) use some form of visually encoding additional data into text. When text does encode additional data, the middle list in Table 1 shows which combinations of visual attributes were used - size and hue together occur most frequently (such as text size used to indicate magnitude and text color to indicate category). In many cases, two or more visual attributes are used to encode data. The right list shows the count of visual attributes used. Size is used most frequently, closely followed by hue. (See *Appendix: Supplemental Materials*P257 for detailed analysis).

Table 1. **Table summarizing use of text in 249 peer-reviewed text visualizations** from 1976-2015 on Text Visualization Browser (http://textvis.lnu.se/). See text for description of each list.

Use of Text	Number of Visualizations
No Text	40
Plain Text	103
Text encoding data	106
TOTAL	249

How Text Encodes Data	Number of Visualizations
Size + Hue	36
Size	23
Hue	16
Size, Hue + Orientation	5
Size + Intensity	3
Size, Hue + Intensity	3
Size, Hue + Underline	3
Bold	3
Orientation	2
Intensity	2
Hue + Underline	2
Hue + Case	2
Size + Orientation	1
Size, Hue, Orientation + Bold	1
Size, Hue + Bold	1
Hue + Orientation	1
Hue, Intensity + Bold	1
Italics + Underline	1
TOTAL	106

Text Attributes	Number of Visualizations
Size	76
Hue	71
Orientation	10
Intensity	9
Bold	6
Underline	6
Case	2
Italics	1

Size: Of the 106 visualizations with text encodings with additional attributes, 76 change text size to encode data. Size is highly preattentive (meaning that it can be perceived almost instantaneously). However, having some large words reduce the number of words that can be displayed overall thereby reducing data density. Size variation also interrupts readability for longer passages of text.[33] As noted by Bertin, size cannot be used for associative perception, e.g. estimating counts of items by area, feasible when each item has similar area.

[33] Thomas Sanocki and Mary C. Dyson. "Letter processing and font information during reading: Beyond distinctiveness, where vision meets design." *Attention, Perception, & Psychophysics* 74, no. 1 (2012): 132-145.

Hue: While hue is popular, there can be difficulties using hue. Text legibility depends on contrast between text and the background[34]. For example, it can be difficult to read colored text over varied backgrounds as shown in the stem and leaf plot in Figure 11 where red text may occur over an orange bar.

Tag clouds: Out of 106 visualizations, we counted 39 tag clouds. That is, 37% of peer reviewed text visualizations encoding data into text are variants on tag clouds. As mentioned earlier, (Figure 4P8) tag clouds have many known problems making them less than ideal for text visualization.

Figure 11. A stem and leaf plot of a railway timetable. Information is added to the leaves via foreground color, background color, background shape, added dot and added outline. Attempting to add a lot of information constrained to a few attributes can result in difficult to perceive combinations such as the difficult to read red text over an orange line.

Font attributes are rarely used: Only 14 of 249 examples in the Browser use any kind of font attribute to encode data. In some cases, the use of these font attributes is fairly simple, for example, to indicate a selection highlight. Interestingly, some of these text visualization systems mix and match software components including list boxes, email lists or search result components and these components do use attributes such as bold or underline for example to differentiate a title or indicate a link – while the visualization component immediately beside uses text without using any font attributes! This suggests that visualization developers rarely consider these attributes, even when in plain sight. Perhaps they do not have the requisite design knowledge to apply font attributes; or perhaps the existing design spaces constrain their abilities to notice the opportunities. Regardless, the design space of visualization needs to be re-examined.

[34] Arthur Robinson, *The Look of Maps*, (University of Wisconsin Press, 1952): 94.

A:5. Design Spaces and Visualization

Visualization researchers recognize that there is a significant design component to the creation of visualization systems.[35] As a first step, one needs to consider the scope of the design space in visualization.

A:5.1. What is a Design Space

Visualization researchers use the term *design space*. The term is used in many domains including semiconductors, pharmaceuticals and human-computer interaction. Some definitions:

- [A design space is] The set of possible designs and design parameters that meet a specific product requirement. Exploring design space means evaluating the various design options possible with a given technology and optimizing with respect to specific constraints like power or cost.[36]
- [A design space is] The multidimensional combination and interaction of input variables (e.g., material attributes) and process parameters that have been demonstrated to provide assurance of quality.[37]
- Design Space Analysis creates an explicit representation of a structured space of design alternatives and considerations for choosing among them. Different choices in the design space result in different possible artifacts.[38]

A design space defines a range of design parameters which can be used to construct possible solutions. It can be a powerful aid as it frames the exploration of many potential design alternatives. However, a design space may also be limiting, as the designer may not search outside the boundaries implied by the design space. Furthermore, designing data visualizations is difficult because there are many trade-offs between design alternatives and a small design space will result in a higher probability of missing a good design. Figure 12, adapted from Munzner[39], illustrates a design exploration through a design space. First, there are many possible design solutions, some of which are poor and some of which are better, as Munzner explains:

> *"The vast majority of the possibilities in the design space will be ineffective for any specific usage context."*

The novice visualization designer (left image), unaware of the visualization framework, will be limited to a small portion of possible solutions. In the middle image, the established design space uses the accepted visualization framework. This is a broader design space than the novice's and can yield better results. However, the designer that can use an expanded design space (right image) has more potential solutions, including new techniques not feasible under the previous conception of the design space.

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35 C. L. Paul, R. Rohrer and B. Nebesh. "A *Design First* Approach to Visualization Innovation," in *IEEE Computer Graphics and Applications,* (1), 12-18.

36 The National Technology Roadmap for Semiconductors. (SIA Semiconductor Industry Association, 1994), page C-4, last modified Sept. 11, 1998, accessed Jan. 31, 2016. http://www.rennes.supelec.fr/ren/perso/gtourneu/enseignement/roadmap94.pdf .

37 ICH Harmonised Tripartite Guideline, Pharmaceutical Development Q8(R2), page 7, in association with *International Conference on Harmonisation of Technical Requirements for Registration of Pharmaceuticals for Human Use*, published August 2009, accessed Jan 17, 2016, http://www.ich.org/fileadmin/Public_Web_Site/ICH_Products/Guidelines/Quality/Q8_R1/Step4/Q8_R2_Guideline.pdf

38 Allan MacLean, Richard M. Young, Victoria ME Bellotti, and Thomas P. Moran. "Questions, options, and criteria: Elements of design space analysis," in *Human–computer interaction 6*, no. 3-4 (Taylor & Francis: 1991), 201–250.

39 Tamara Munzner, *Visualization Analysis and Design,* (Boca Raton, FL: CRC Press, 2015), 13.

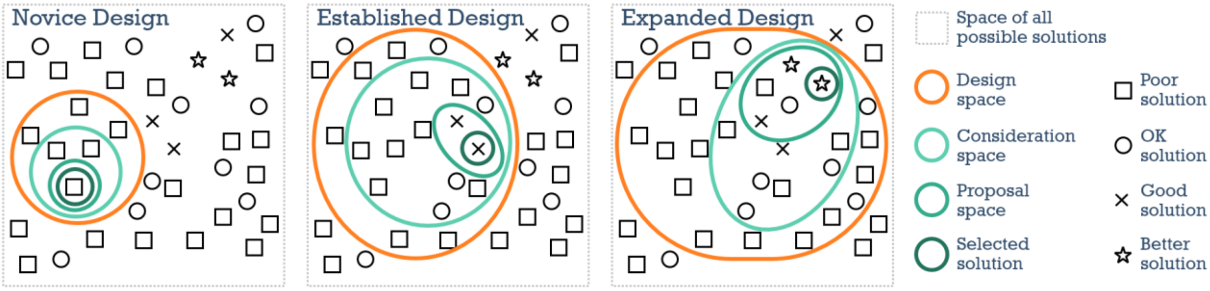

Figure 12. Design as a search through a design space. The expanded design space (right) has more alternatives and potentially better solutions than the narrower design spaces. Image created by author, redrawn and extended based on a drawing by Munzner.

The middle image representing established design approaches and current best practices indicates a potential constraint on design exploration. Communication theorist Marshall McLuhan said: "*We shape our tools and then our tools shape us*."[40] Therefore, to go beyond the existing framework, it is desirable to explore and characterize a broader design space. To effectively assess the use of text in visualization, it is necessary to first define the expanded design space.

A:5.2. A Method to Expand a Design Space

Many project oriented approaches to design do not focus on the design space. For example, user-centered design techniques are focused on user perceptions, behaviors, needs and experiences. The user-centered approach is focused on the problem space, that is, characterizing the problem to help direct the design approach and find an optimal solution. While user-centered design may result in a single unique solution that goes beyond an established design space, it does not seek to frame the larger design space.

The goal of this thesis is expand the design space for text in visualization by defining the design space then using the design space to create new applications. The steps to systematically explore and expand are:

A. **Identify gaps** in the existing domain's parameter space, with emphasis on areas with greatest potential.
B. **Research background** across a wide variety of disciplines to identify the new parameters and characterize those parameters both in terms of their originating disciplines and relating them to well researched parameters in the target domain.
C. **Identify new unique considerations** for the new parameters that may impact effectiveness and evaluation.
D. **Identify new application areas**, then design, implement and evaluate new kinds of solutions based on these new parameters.
E. **Evaluate the overall results** via broad evaluation techniques of critique and metrics, which can span across many visualization instances.

These steps are similar to the methods of other researchers that attempt to define and illustrate design spaces. Bertin, for example, starts with a decomposition of information graphics and maps (A); itemizes the constituent components and characterizes each of them (B,C). Bertin's popularity is due in part to the many illustrations

[40] Marshall McLuhan, *Heritage Minutes: Marshall McLuhan,* last modified Feb. 17, 2016. https://www.historicacanada.ca/content/heritage-minutes/marshall-mcluhan

showing applicability of the framework to many types of visualizations; the use to create new visualizations; and the use for different kinds of analysis (D).

Similarly, Edward Tufte in *The Visual Display of Quantitative Information,*[41] extensively researches primary documents (B), identifies problems with some approaches (A), and extracts themes and guidelines common across document to define specific approaches for effective visualizations (C). These approaches are then illustrated with revised examples of existing visualizations (D).

Outside of visualization, Le Corbusier in *Towards a New Architecture,*[42] criticizes the limitations of architecture (A) and extends the design space by borrowing from engineering (ocean liners, automobiles, grain elevators, etc) (B,C) and proceeds to create new designs for architecture and urban planning (D).

The approach has limits: Tufte's data dense non-interactive visualizations are not necessarily accepted as effective for analytical visualization. For example, Stuart Card at a panel at VisWeek 2017 indicated that information visualizations must be interactive and William Wright on the same panel claims that visualization "has to move". Le Corbusier is criticized for failed urban renewal and failed public housing, which results in part from factors beyond Le Corbusier's framework (e.g. socioeconomics). To address this potential shortcoming, evaluations of individual techniques are included in the new applications. More importantly, broad evaluation across the entire framework and all applications is explicitly attempted in the overall evaluation (E) by creating metrics and by engaging in broad cross-disciplinary critiques. Furthermore, it should be noted that the method is not strictly linear: feedback from later steps, such as failures in the development of new applications (D) or the expert opinions from critiques (5) are used to refine the criteria and characteristics of the framework (B,C). This should create for a more robust result, although some aspects such as interaction have been left for future work.

A:5.3. Identifying Gaps

While data visualization as a research field is more than 25 years old (e.g. see early work by Jacques Bertin, William Cleveland and Jock Mackinlay), there are many gaps and underexplored areas, such as novel visual attributes, encodings, interactions and evaluations.

At a high level, interactive data visualization transforms data into a visual representations (such as sizes, shapes and colors) perceived and decoded by a viewer. This sequence can be represented by a more comprehensive pipeline than previously shown in Figure 5P9 which focused only on visualization creation. Figure 13 illustrates the broad interactive visualization pipeline. It starts with encoding on the left side (i.e. data is mapped to visual attributes drawn as marks and plotted on a layout). This, in turn, leads into steps in human comprehension on the right side (wherein the visual patterns are instantly perceived, inspected with directed attention and more complex relations reasoned about). This process is supported (in interactive visualizations) with an interaction feedback loop. (Diagram based on Chen and Floridi,[43] Ware[44] and Proctor and Vu.[45])

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[41] Edward Tufte *The Visual Display of Quantitative Information*. Graphics Press, 1983.
[42] Le Corbusier. Towards a New Architecture. (trans. by Frederick Etchells) London: J. Rodker, 1931. New York: Dover Publications, 1985.
[43] Min Chen and Luciano Floridi, "An analysis of information visualization", *Synthese,* 190, no. 16 (2013): fig. 1, pg. 3422.
[44] Colin Ware *Information Visualization: Perception for Design,* (Waltham, MA: Morgan Kaufmann, 2013).
[45] Robert Proctor and Kim-Phoung Vu: "Human Information Processing: An Overview for Human Computer Interaction," in *The Human Computer Interaction Handbook*, Andrew Sears and Julie Jacko eds.; Taylor & Francis: New York. 2008

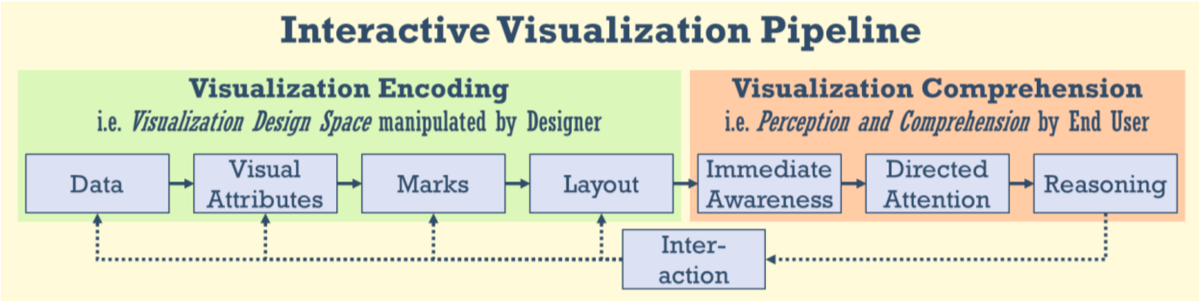

Figure 13. Visualization pipeline from data to comprehension. Visual encoding is a step unique to data visualization. Simplified from a diagram by Chen and Floridi. Image created by author.

Each step in the visualization pipeline can enhance the data or introduce unintentional noise and error. As each stage builds on the prior stage, error accumulates. There will be a gap between reality and perception due to incomplete data, design choices, limitations in perception and comprehension, and so on. This gap will always exist and can be identified at different stages as well as in the overall structure. Therefore, a reexamination of the overall design and each stage of the interactive visualization pipeline can identify gaps. For example, low-level gaps at individual stages may exist due to assumptions in the original concepts, such as no consideration of text as a data type. Those assumptions may have been based on technical limitations in those times, a narrower scope of uses, or other factors. More broadly, sometimes entire steps are not considered: for example, evaluations such as time and error studies may overly focus only on perception, thereby missing the target goal of comprehension. Within this thesis regarding text and visualization, the focus is primarily on the encoding side of the pipeline (in green), with less emphasis on comprehension (orange) and interaction (below) – there is much future work to be done in these areas.

A:5.4. Gap in Visual Attributes

The visual encoding step is unique to data visualization, as opposed to tabular reports, summary statistics or analytics. Most visualizations today primarily rely on encoding data into the visual attributes of position, size and color, and these attributes have been well researched. Beyond these attributes, the list of visual attributes can vary considerably depending on the compilation of research.

Table 2 shows a compilation of visual attributes as identified by various researchers in different domains over the last few decades.[46] Different researchers may group attributes in various ways - the groupings shown here are the authors.

[46] **Ber83:** J. Bertin, *Semiology of Graphics*, University of Wisconsin, 1983. **Cle85**:, W. Cleveland & R. McGill. "Graphical perception: Theory, experimentation, and application to the development of graphical methods." *Journal American Statistical Assoc.* 79, no. 387 (1984): 531-554.**Mac86:** J. MacKinlay. "Automating the design of graphical presentations of relational information." *ACM Trans. on Graphics*, 5(2), 110-141, 1986. **Wil99**: L. Wilkinson, *The Grammar Of Graphics*, Springer 2005. **War00**: C. Ware. Information Visualization: *Perception for Design,* Morgan Kaufmann, 2000. **Maz09**: R. Mazza. *Introduction to Information Visualization*. Springer 2009. **Bra10**: R. Brath. "Multiple Shape Attributes in Information Visualization" *IEEE Information Visualization*. 2010. **Ili12**: N. Iliinsky. "Properties and Best Uses of Visual Encodings." Complexdiagrams.com, 2012. **CF13**: M. Chen & L. Floridi. "An analysis of information in visualization." *Synthese*, 2013. **Mun15**: T. Munzner, *Visualization Analysis and Design*, CRC Press, 2015. **Bör15**: K Börner. *Atlas of knowledge: anyone can map*. MIT Press. 2015. **HE12**: C. Healey, & J. Enns. "Attention and Visual Memory in Visualization and Computer Graphics." in *IEEE Transactions on Visualization and Computer Graphics*, Vol. 18, No. 7, 2012. **Mac95**: Alan MacEachren, *How Maps Work: Representation, Visualization, and Design*. Guildford, 1996. **Tyn10**: J. Tyner, *Principles of Map Design*. Guildford Press, 2010.

Table 2. **Table of Visual Attributes**. Visual attributes for encoding data as defined by various information visualization researchers and preattentive vision research up to early 2015 (including authors' prior research on shapes).

Table of Visual Attributes

		Information Visualization Researchers											Vision Research	Cartog-raphy	
Visual Group	Visual Attribute	Bertin 83	Cleveland 85	MacKinlay 86	Wilkinson 99	Ware 00	Mazza 09	Brath 10	Iliinsky 12	Chen & Floridi 13	Munzner 15	Börner 15	Preattentive Perception	MacEachren 95	Tyner 10
Transform	Position	X	X	X	X	X	X		X	X	X	X		X	X
	Length		X	X		X	X		X	X	X	X	X		
	Size (Area)	X	X	X	X	X	X		X	X	X	X	X	X	X
	Orientation	X		X	X	X	X		X	X	X	X	X	X	X
	Volume		X	X		X					X	X			X
Shape	Shape	X		X	X	X	X	X	X	X	X	X		X	X
	Angle		X	X				X		X	X	X			
	Curvature							X			X	X	X		
	Line Ending						X	X	X	X			X		
	Closure							X		X		X	X		
	Edge Type							X		X		X			
	Corner Type							X		X					
	Icon, glyph, etc.									X		X			
Color	Brightness	X		X	X	X	X		X	X	X	X	X	X	X
	Hue	X	X	X	X	X	X		X	X	X	X	X	X	X
	Saturation			X	X	X	X		X	X	X	X		X	X
Texture	Granularity	X		X	X	X	X		X	X	X	X		X	X
	Pattern				X	X	X		X		X	X			
	Orientation				X	X					X	X			
Relation	Connection			X			X		X	X	X				
	Containment			X			X		X		X				
Optics	Blur				X					X		X		X	X
	Transparency				X					X		X		X	X
	Stereo Depth											X	X		
	Concave/Shade									X			X		
	Light Direction									X			X		
	Shadow									X		X			
	Partial occlusion									X					
Movement	Flicker					X				X		X	X		
	Speed					X				X		X	X		
	Direction									X		X	X		
Miscellaneous	Numerosity												X		
	Spatial Grouping												X		X
	Arrangement													X	X
	Resolution													X	X
	Artistic Effects												X		
Text	Text Labels				X		X		X	X		X			
	Font Family											X			
	Oblique											X			

Note: For Preattentive Perception see Healey & Enns 12. Tyner 10 summarizes earlier cartographic research work.

The column labelled vision research is a list of attributes that have been identified by perceptual psychologists as preattentive, that is, attributes that can be automatically perceived regardless of the number of items in a display. Preattentive visual attributes are desirable in data visualization as they can demand attention only when a target is present, can be difficult to ignore, and are virtually unaffected by load.[47] Interestingly, cartographers, who use typographic attributes such as bold and italic to encode data routinely into labels, do not discuss typographic attributes when considering visual attributes for geographical visualizations such as choropleth maps and cartograms (this will be explored further in the upcoming section *B:1.2: Historic Cartographic Examples*P33). Note how text is indicated by only a few authors and how typographic attributes are largely absent with the exception of (oblique and font family) for a single researcher.

Some of these attributes are rarely used to encode data and have not been thoroughly researched, such as shape and text. There are many possible reasons that some attributes are highly utilized while others less so. For example, size and hue may be popular because they have strong visceral appeal. Or, size and hue are popular because are easy to code (e.g. scale transformations and RGB colors are easily accessible in most programming languages). Or, perhaps they are known to be easily perceived, as shown by preattentive research. Alternatively, computer scientists involved in data visualization may have limited use of other visual attributes as they have limited knowledge of visual design vocabularies and grammar. For example, anyone having taken a course in computer graphics, computer vision, image processing or data visualization will be familiar with geometric transformations (e.g. size) and color (e.g. RGB). But it is unlikely that a visualization developer will have formal training in typography or perhaps unable to associate their knowledge of typography to visualization.

Technological limitations and change may also be a factor behind the use of these attributes. For example, the resolution of most displays has been limited to 72 pixels per inch until the late 2000's limiting the use of finely detailed attributes such as texture, shape and text. However, much higher resolutions are now prevalent (e.g. mobile devices and retina displays). With fine detail available, each of these attributes may have additional parameters and hence capabilities that have not been previously explored, such as serifs, italics and so forth. The typographic gap in visual attributes is a starting point for investigating typography in visualization. Some visualization researchers have discussed typographic attributes. For example, Börner[48] includes font family and obliques in a large grid of visual attributes, but not bold nor capitalization. Interestingly, Bertin does consider typographic attributes in his original 1967 edition of *Sémiologie Graphique* in French – but only in four pages in an appendix, not referenced in earlier matrices and diagrams in the book and furthermore, the *only* four pages of his work not translated into the English edition in 1983. Bertin includes font family, italics, condensed/expanded letter space and font weight. Bertin later follows with a brief five page article in 1980,[49] however, it has been cited only once in 38 years (discussed in more detail later in *D:1.2.iii*P218).

Instead, what is required is a full framework as implied by the visualization encoding pipeline (Figure 5P9) and the larger information visualization comprehension pipeline (Figure 13P18). The pipelines imply that there will be other assumptions at other stages to consider, for example:

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[47] Richard M. Shiffrin and Walter Schneider. "Controlled and automatic human information processing: II. Perceptual learning, automatic attending and a general theory." *Psychological review* 84, no. 2 (1977): 127.
[48] Katy Börner. *Atlas of knowledge: anyone can map*. MIT Press. 2015.
[49] Jacques Bertin, "Classification typographique : Voulez-vous jouer avec mon A" in: *Communication et langages,* n°45, 1er trimestre 1980. pp. 70-75. doi : 10.3406/colan.1980.1369 http://www.persee.fr/doc/colan_0336-1500_1980_num_45_1_1369

- Literal text is not considered as a base data type in visualization frameworks.
- Text may not conform well to mark types of point, line and area.
- Perception and comprehension both need to be understood for perceptual efficiency: for example directly reading text in a visualization may offer benefits over cross-referencing legends.

A:6. The Value of Text Visualization

Even though there is a gap in the existing frameworks for text in visualization, there should be compelling needs driving text visualization. Text visualization represents a significant opportunity for research and development from many perspectives.

Huge Volumes of Unstructured Data: There are large amounts of unstructured data: some pundits suggest 80% of all data;[50] and, 100,000 words per day are consumed by the average American (35% print, email, web; 65% radio, TV dialogue, phone, etc.).[51] However, current visualizations of text rarely use typographic features to encode data other than the actual text. Furthermore, most text visualizations frequently operate at the level of manipulating individual words – not individual letters, syllables, sentences, documents. For example, *scimaps.org* is a repository of curated exemplars of knowledge maps (data visualization to gain insights into the structure and evolution of large scale information spaces[52]). While 80% of 144 knowledge visualization examples on *scimaps.org* use text, only a *few* use font attributes to encode data. Similar results could likely be found in other text visualizations (e.g. processing.org, d3.js, the Guardian, Bloomberg, etc.) This suggests a missed opportunity.

Unstructured Data Analytics Market: The market for structured data visualization is $4.1B (USD) and growing annually nearly 10% with ten major established companies[53]. Text visualization is a nascent market with no dominant text visualization companies, although there are dominant providers of texts in specific domains, e.g. Springer (science), Lexis-Nexis (law), Bloomberg (news), Project Gutenberg (open source books), and so on. If one draws parallels to the market for structured data analysis (e.g. relational databases) vs. unstructured data analysis (e.g. search), the unstructured analysis market opportunity emerged many years after the structured market and a similar situation may exist in the opportunity for structured visualization vs. text visualization. If this is true, there is a huge potential market for text visualization in ten years.

Computer Science Research: Furthermore, the fields of data science, machine learning and natural language processing are rapidly expanding resulting in many innovations in text analytics such as topic extraction, social sentiment estimation, opinion analysis, entity extraction and disambiguation, text classification and so forth. The results of many of these analytic approaches require human interpretation – meaning that data visualization techniques should be highly desirable to aid detection of patterns, identify anomalies, and so forth.

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[50] Seth Grimes.. "Unstructured Data and the 80 Percent Rule", *Breakthrough Analysis,* August 1, 2008. http://breakthroughanalysis.com/2008/08/01/unstructured-data-and-the-80-percent-rule/

[51] Roger E. Bohn and James E. Short. *How Much Information?: 2009 Report on American Consumers*. University of California, San Diego, Global Information Industry Center, 2009.

[52] "Knowledge Maps and Information Retrieval (KMIR) Workshopt at Digital Libraries 2014," last modified April 21, 2016, http://www.gesis.org/en/events/events-archive/conferences/kmir2014 .

[53] "Data Visualization Applications Market - Forecasts and Trends (2015 - 2020)", *Mordor Intelligence*, 2015, http://bit.ly/1OdIZMj accessed: October 3, 2015.

Text Analysis: Current public discourse is becoming fragmented with real concerns regarding fake news, alternative facts, and deliberate misinformation. Anti-climate change, anti-vaccination, unproven health remedies, unsubstantiated claims, opinion biased by conflict of interest vie for attention with legitimate news, fact-based research and balanced opinion. The analysis of texts, poetry, music and so on has long been the focus of the humanities, and these users have different needs than the sciences. As outlined in one visualization for digital humanities workshop:

> *"There are differences in the rhetorics of proof and discovery (and so differences in data culture and use); there may be no ground truth; and tasks may differ such as close readings and critical engagements with texts."*[54]

The need for tools to assess content of unstructured text is great.

Many Applications: There are many potential application areas for the visualization of text. This includes any application primarily centered on textual documents such as dyslexia research, document skimming, poem analysis, prosody, character descriptions, opinion comparison, topic review, language analysis, summarization, plagiarism, and so on. Visualization of text can provide value beyond documents - structured data with text fields can also benefit: financial markets, set memberships, drug labels, etc. Finally, many well-known visualization techniques can be enhanced with text, such as line charts, scatterplots, and stem-and-leaf plots.

In short, there are many valuable opportunities for new and enhanced text visualization.

A:7. Conclusion

The contribution of this section has shown how the integration of text into visualizations has largely been overlooked due to cultural conventions; and how the use of text within visualizations has largely followed very simple extensions of the current visualization approaches (such as pre-preprocessing text to fit the conventional visualization pipeline and then using conventional encodings to represent attributes associated with text such as size and color). The representations currently in use in visualization are limited by the underlying assumptions which frame the current design space of visualization.

Given current research and industrial interests in better utilization of text analytics such as natural language processing, there is economic value in having a broader set of visualization techniques available to aid human interpretation of text and related text analytics. At a minimum, typographical variation such as bold, italics and font family can visually differentiate labels for faster perceptual access than linearly reading each label.

What is missing is a critical re-evaluation of the design space of visualization with regards to text. The method for this re-evaluation starts with the initial identification of gaps in our awareness and knowledge of typography's relevance to visualization as covered in next part of the thesis, *PART B. The Design Space of Text in Visualization*, while new application areas and evaluation of results will be in subsequent parts.

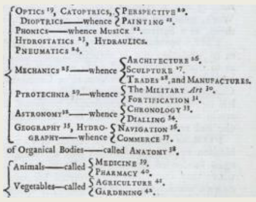
[54] Second Workshop on Visualization for the Digital Humanities. http://vis4dh.dbvis.de/

PART B. The Design Space of Text in Visualization

Description of Part B

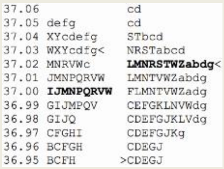
Defining the design space of text in visualization:

B:1. Starts with a cross disciplinary review of text encoding data across domains including…



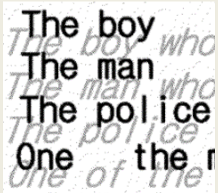
TYPOGRAPHY PAGE 24

CARTOGRAPHY 33



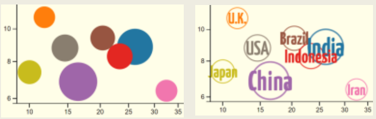
TECHNICAL APPLICATIONS 40

VISUALIZATION 46

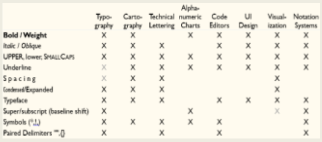


UI GUIDELINES 50

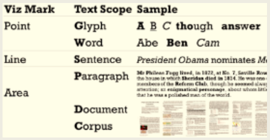
B:2. This review indicates **four unique text-specific extensions** to visualization:



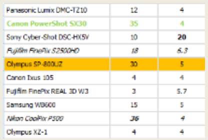
LITERAL ENCODING 52 with FUNCTIONAL, 53 PERCEPTUAL 53 & OPERATIONAL 57 benefits



TYPOGRAPHIC ATTRIBUTES 58

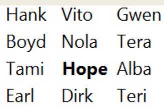


MARK TYPES FOR TEXT 59



UNIQUE LAYOUTS 61

B:3. **Additional perceptual considerations** are required for text, including…



PREATTENTION & GESTALT 63

LEGIBILITY & READABILITY 66

TYPE COLOR 67

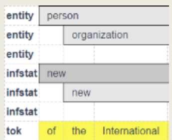
ATTENTION & REASONING 69

Humpty Dumpty sat on a wall.

TEXT SEMANTICS 69

TYPOGRAPHIC SEMANTICS 70

LANGUAGE 71



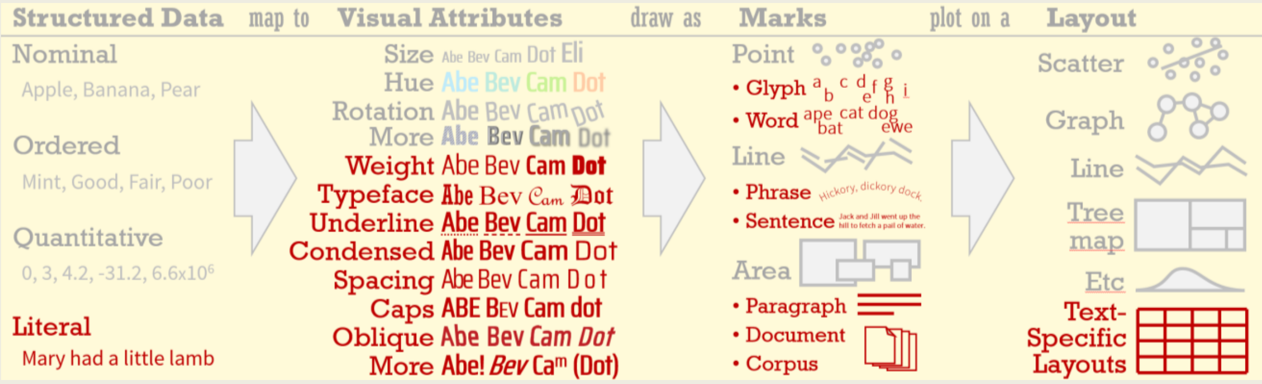
INTERACTION 73

B:4. **Typographic attributes** are characterized for use in visualization:

ABC123αβγ ALPHANUMERICS 75 | #|?$ SYMBOLS 76 | AAAAAA WEIGHT 77 | AAAA ITALICS 80 | AB AB ab CASE 82 | AAAAAA UNDERLINE 84

AAAAA TYPEFACE 86 | AAAA WIDTH 90 | 1AB BASELINE 92 | ([<A>]) DELIMITERS 93 | a a a FONT DESIGN 94 | AAAA NON-TEXT ATTRIBUTES 99

B:5. All the above define extensions for the **key contribution** of the thesis: **TEXT IN VISUALIZATION DESIGN SPACE** 102



B:1. Cross-Disciplinary Research and Relation to Visualization

To define the design space of text in visualization, design principles from related domains are investigated to leverage best practices accumulated over centuries of expert knowledge. This will not only aid identification of useful attributes, but also aid characterization and unique perceptual considerations to create a richer, more-informed design space.

While there is low exposure to typography in the visualization community, other domains, such as typography, cartography, mathematics, chemistry, programming and so on have a rich history with type and font attributes which informs the scope of the parameter space. However, some of these communities have not explicitly researched to role of typographical attributes in their use – the research approach used here is to review original documents as primary sources to assess the use of text and type attributes. This historically-informed research approach is rarely used in information visualization and future research could consider additional sources and additional applications in visualization research.

B:1.1. Historic Examples from Typography

Typographers embed additional data into texts using font attributes in examples from hundreds of years ago, such as the examples already discussed in the medieval scribe's diagrams in Figure 1P5 and the typographic genealogy diagram in Figure 8P11.

i. Typographic Trees

Hierarchical structures are needed in texts, such as, tables of contents or genealogical diagrams. The table of contents for Chambers' *Cyclopaedia*[55] uniquely creates a readable paragraph split into a hierarchy enhanced with typographic attributes as shown in Figure 14.

Chambers uses typographic formats to distinguish different types of information:

- Hierarchical structure is expressed with variously sized curly brackets
- All caps are used for the top level (i.e. KNOWLEDGE)
- Italics for broad topics (e.g. *Natural*)
- Small caps for specific fields (e.g. METEOROLOGY)
- Regular roman font for explanatory text (e.g. consisting in the Perception of Phenomena,…)
- Superscript numbers reference detailed descriptions (e.g. [2])

[55] Ephraim Chambers, *Cyclopaedia*, (London, UK: self-published, 1728), page ii. http://digital.library.wisc.edu/1711.dl/HistSciTech.Cyclopaedia

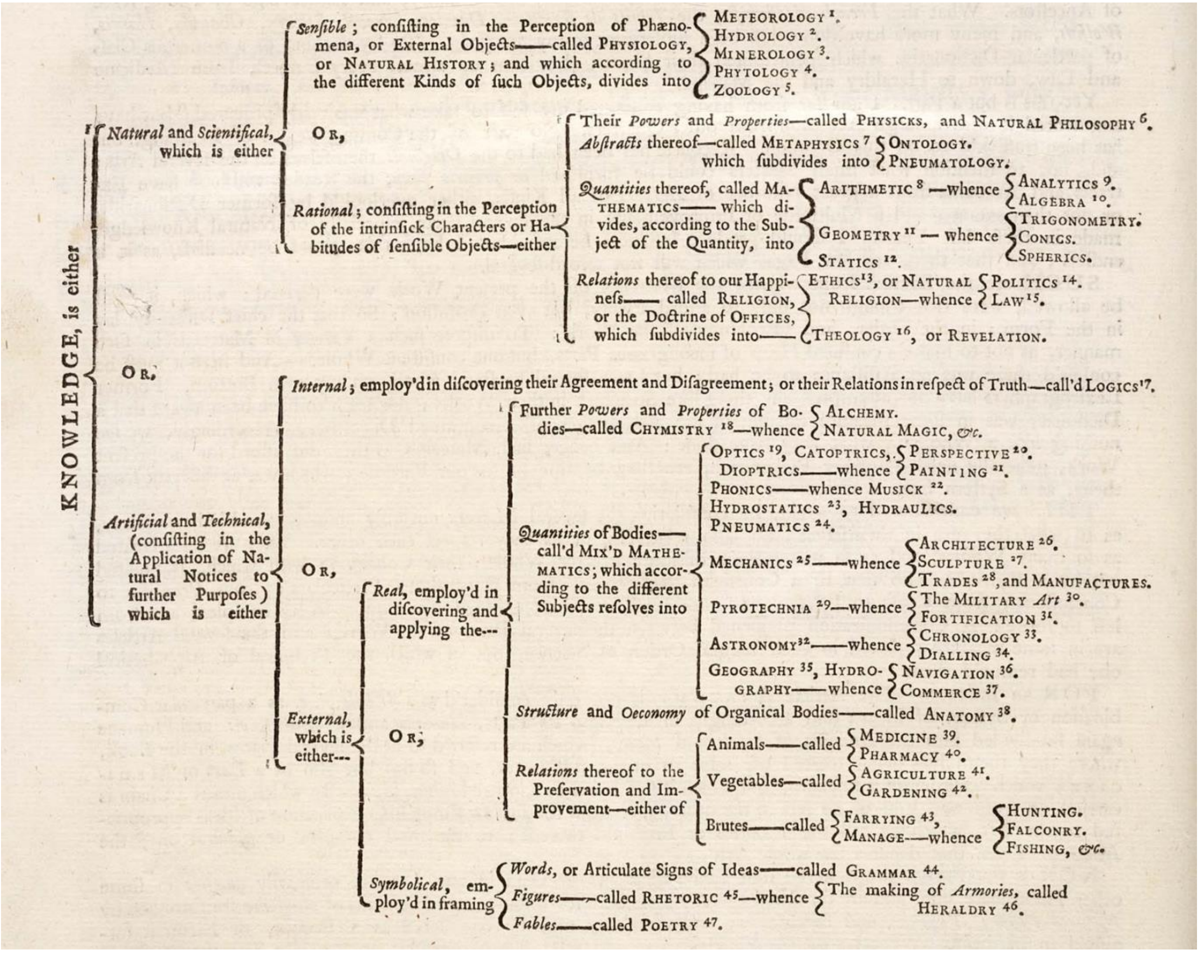


Figure 14. Table of contents from Chamber's *Cyclopaedia* (1728) using italics, small caps, roman and superscript to differentiate between topics, fields, descriptions and chapters respectively.

Curly brackets were used for hundreds of years in various publications to indicate not only trees of text, but also more complex directed acyclic graphs, such as Figure 15 from Loys Vasse's *Lodoici Vassæi Catalaune* (1541)[56] – which predates the similar visualization technique of word trees[57] by more than four centuries.

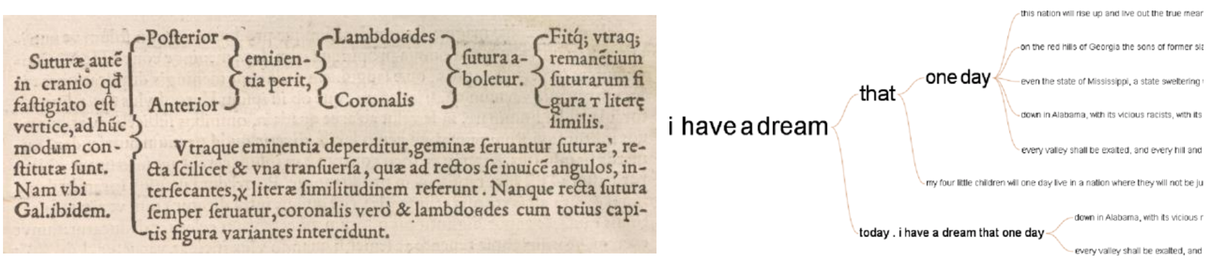


Figure 15. Left: A complex sentence formed with splitting and joining curly brackets from 1541. Right: Portion of a word tree from 2008.

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56 Loys Vasse, *Lodoici Vassæi Catalaune[n]sis, in anatomen corporis hvmani tabulæ quatuor.* Cambridge University Library classmark: N*.3.17(B)(6). Ex officina Michaelis Faezandat, in domo Albretica, e regione D. Hilarii, 1541 Parisiis. http://cudl.lib.cam.ac.uk/view/PR-N-00003-00017-B-00006/51. Accessed Nov. 10, 2016.

57 Martin Wattenberg and Fernanda B. Viégas. "The word tree, an interactive visual concordance." *IEEE transactions on visualization and computer graphics* 14, no. 6 (2008): 1221-1228.

Genealogical trees also occur frequently in historic documents. An engraved tree for the French royal family[58] from 1720 borrows typographic techniques of bold, italics and a large heavy-weight font (Figure 16):

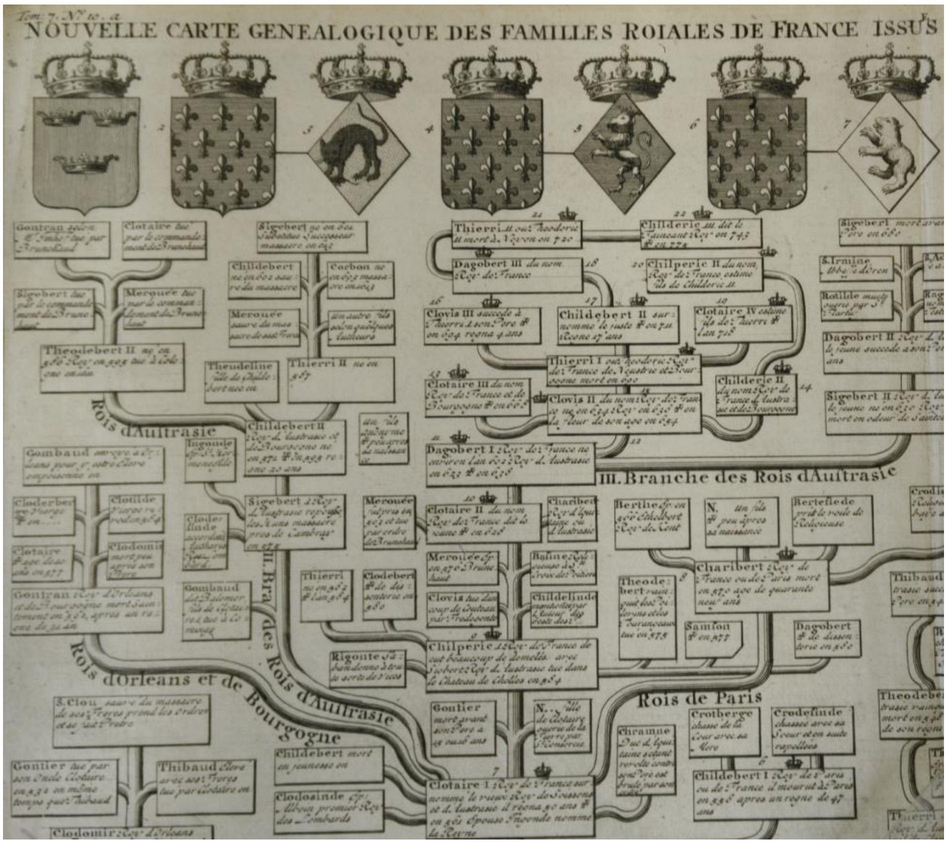


Figure 16. Nouvelle carte genealogique des Familles Roialles de France from *Suplement A L'Atlas Historique*.
Image part of the Collections & Archives at the Department of Typography & Graphic Communication, University of Reading

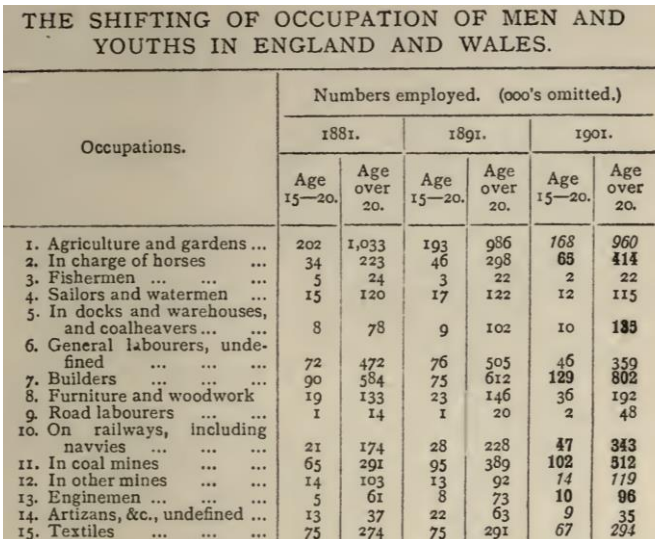
One hundred years later, Carey and Lavoisne's *A Complete Genealogical, Historical, Chronological, and Geographical Atlas* (as shown previously in Figure 8P11) creates information dense genealogical graphs using many different typographic features that were available to the contemporary typographer at that time. A wealth of information is presented at each node differentiated as follows:

- Large bold uppercase is used for large branches, such as **FAMILY of FRANCHE COMTE**
- Roman uppercase is used for small geographic branches, such as NAVARRE or CASTILLE
- Mixed case is used for direct descendants, such as Ramirez, Lord of Calahorra or Blanche
- Small caps are used to indicate sovereign rulers, for example, GARCIAS III or FERDINAND I
- Italics indicate spouses, for example, *Stephania of Barcelona*; or *William I. King of Sicily*
- And additional glyphs, such as crowns, crosses, dots and diamonds are used to add more information.

[58] Henri Abraham Chatelain and Nicolas Gueudeville, Nouvelle carte genealogique des Familles Roialles de France from Suplement A L'Atlas Historique, 1720. Imprint of v. 2: A Amsterdam, Chez l'Honoré & Châtelain, libraires. https://archive.org/details/gri_33125011099708 Accessed Jan 1, 2017.

ii. Typographic Tables

Tables are detailed organizations of information such as statistical data and timetables. Typographical attributes are intrinsic to tables to differentiate between information and draw attention to particular values. Figure 17 left uses italics in the final two columns to indicate values which have fallen from the prior period, and bold to indicate values which have increased significantly.[59] Figure 17 right shows a portion of a timetable from *Bradshaw's Guide for Great Britain and Ireland 1944*, where city names use variants of plain text, small caps and bold; and the schedule uses symbols, wide text, reverse text and so on.


THE SHIFTING OF OCCUPATION OF MEN AND YOUTHS IN ENGLAND AND WALES.

Occupations.	Numbers employed. (000's omitted.) 1881. Age 15—20.	1881. Age over 20.	1891. Age 15—20.	1891. Age over 20.	1901. Age 15—20.	1901. Age over 20.
1. Agriculture and gardens ...	202	1,033	193	986	*168*	*960*
2. In charge of horses ...	34	223	46	298	**65**	**414**
3. Fishermen	5	24	3	22	2	22
4. Sailors and watermen ...	15	120	17	122	12	115
5. In docks and warehouses, and coalheavers	8	78	9	102	10	**135**
6. General labourers, undefined	72	472	76	505	*46*	*359*
7. Builders	90	584	75	612	**129**	**802**
8. Furniture and woodwork	19	133	23	146	36	192
9. Road labourers	1	14	1	20	2	48
10. On railways, including navvies	21	174	28	228	**47**	**343**
11. In coal mines	65	291	95	389	**102**	**512**
12. In other mines	14	103	13	92	*14*	*119*
13. Enginemen	5	61	8	73	**10**	**96**
14. Artizans, &c., undefined ...	13	37	22	63	*9*	*35*
15. Textiles	75	274	75	291	*67*	*294*

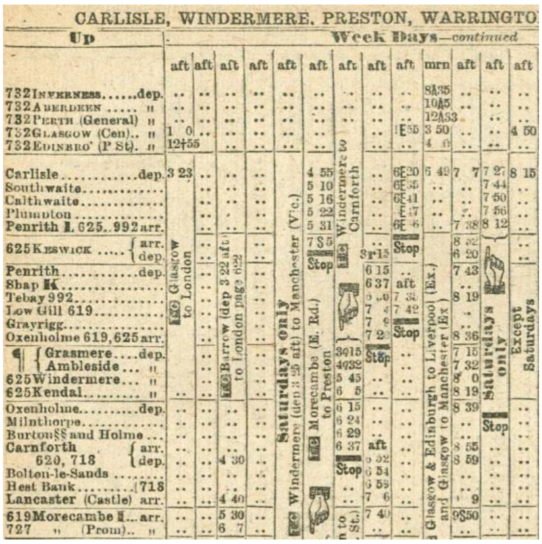


Figure 17. Left: Small portion of a table using bold to indicate significant increases and italics to indicate significant decreases. Right: Portion of railway timetable varying small caps, bold, reverse, wide serif font and tall sans serif. Public domain. Left: https://ia802702.us.archive.org/8/items/statisticalstudi00bowluoft/statisticalstudi00bowluoft.pdf page 5. Right: Bradshaw's Guide for Great Britain and Ireland No. 1328. Henry Blacklock & Co. Ltd., Manchester, UK. March 1944. http://archive.org/details/BradshawsGuideForGreatBritainAndIrelandNo.1328March1944

iii. Multi-lingual Labels, Captions, Phrases and Texts

Labelling Across Languages: Different words, phrases and classifications may need to be compared. Different font families can be used to distinguish which set a particular phrase belongs to. In an example from biology, Haeckel's *Pedigree of Mammals* chart[60] (Figure 18 left) differentiates across classification systems with either roman, italic, blackletter or a slab-serif typeface. Laroon's book of illustrations *The Cryes of the City of London Drawne after the Life*[61] (Figure 18 right) consistently labels 66 etchings in three languages, with English in a roman font, French is a italic font, and Italian in a slightly condensed script font with flourishes.

[59] Sir Arthur Lyon Bowley, Statistical studies relating to national progress in wealth and trade since 1882, London, King, 1904. https://archive.org/details/statisticalstudi00bowluoft page 5. Accessed Nov. 10, 2016.

[60] Ernst Haeckel, *The Evolution of Man: A Popular Exposition of the Principal Points of Human Ontogeny and Phylogeny*. (D. Appleton and Company: New York, 1897) 187-189. https://archive.org/details/evolutionofmanpo021897haec (accessed April 22, 2016)

[61] Marcellus Laroon II, *The Cryes of the City of London Drawne after the Life*, (London: Pierce Tempest, 1688). Page 2: http://www.britishmuseum.org/research/collection_online/collection_object_details.aspx?assetId=430139001&objectId=3062527&partId=1 (accessed April 28, 2016).

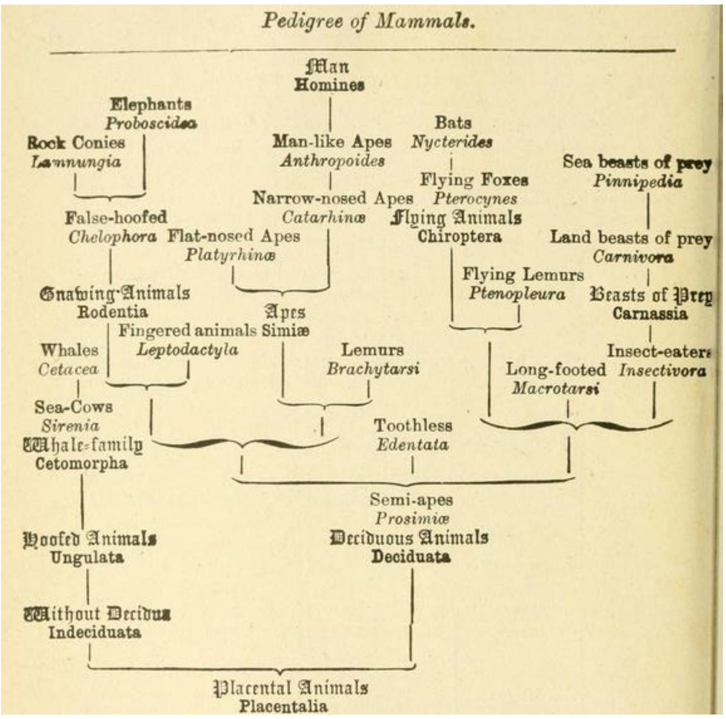


Figure 18. Left: Haeckel's pedigree chart from 1897 uses different fonts to indicate different classifications. Right: Laroon's illustrations from 1688 use different font families to indicate different languages. Left: not in copyright, available via archive.org. Right: Copyright © 2016 The Trustees of the British Museum. Licensed under Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International (CC BY-NC-SA 4.0).

Many historic examples of multilingual illustration captions can be found. An early example by Neiuhof in 1666 differentiates between two languages using small caps vs italic (Figure 19 left). By 1733 Bloemaert (Figure 19 middle) indicates four languages: French with a serif all caps, English in italic, German in blackletter and Dutch in a heavyweight serif. In the late 18th century, Pyle (Figure 19 right) labels with languages (English, German, Italian, Latin and French) with three font styles (plain serif, blackletter, italics).


Figure 19. Multi-lingual labels on illustrations differentiated by font from mid-1600's to late 1700's.
Joan Nieuhof, *Gesantschaft der Ost-Indischen Geselschaft in den Vereinigten Niederländern an den Tartarischen Cham und nunmehr auch Sinischen Keiser*. 1666. Jacob Mörs, Amsterdam. http://digi.ub.uni-heidelberg.de/diglit/nieuhof1666 page 373. (accessed July 3, 2015). CC-BY-SA 3.0 DE. || Cornelis Bloemaert, "Arion", Le Temple des Muses (Amsterdam: Chatelain, 1733) [Print, 247mmx 173mm]. British Museum. [Museum Number: 1914,0214.237] http://www.britishmuseum.org/research/collection_online/collection_object_details/collection_image_gallery.aspx?assetId=562664001&objectId=1540334&partId=1 (accessed April 28, 2016). © The Trustees of the British Museum. || Robert Pyle, Feeling, (London: Carington Bowles in St. Pauls Church Yard, 1766-1799) [Print, 158mm x 1103mm]. British Museum. [Museum Number: 2010,7081.1474] http://www.britishmuseum.org/research/collection_online/collection_object_details/collection_image_gallery.aspx?assetId=966668001&objectId=3350969&partId=1 (accessed April 28, 2016). © The Trustees of the British Museum. All images licensed under creative commons attribution (CC-BY-SA 3.0 DE; CC BY-NC-SA 4.0)

Similarly, early books showing multiple languages may utilize different fonts. Polyglot phrase books, such as de Berlaimont's *Colloquia*[62] (Figure 20) displays phrases from eight languages across eight columns, with, for example, German in blackletter, French in italics and Latin in roman font.

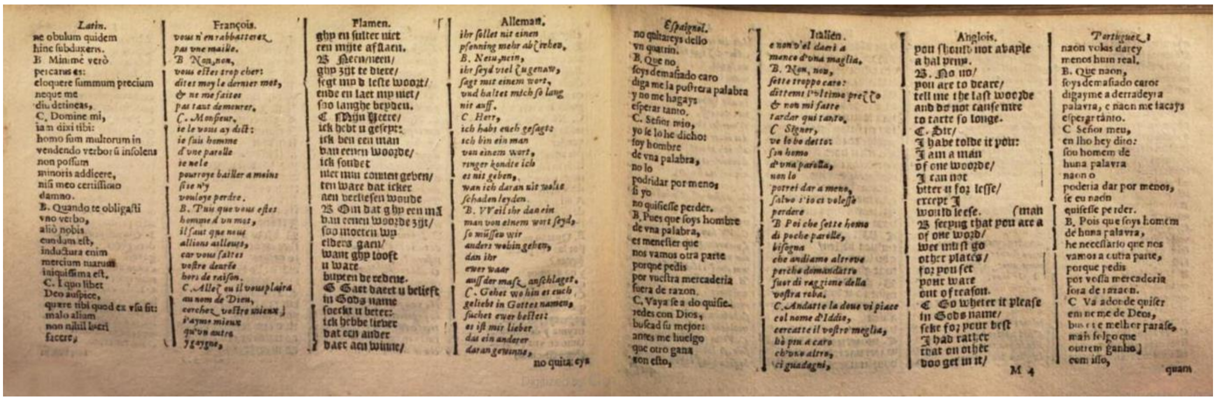

Latin. François. Flamen. Alleman. Espagnol. Italien. Anglois. Portugues.

Figure 20. de Berlaimont's *Colloquia* from 1631, a phrasebook with 8 languages differentiated with 3 font families. Not in copyright: available at books.google.com.

Typographically differentiated multilingual persist through to modern uses, such as, the humorous use of different typefaces to indicate the languages of various speakers in the comic *Asterix* as seen in Figure 21.

Figure 21. Different languages indicated in different typefaces in *Asterix the Legionary*. Copyright Dargaud, Paris, 1967.

Rather than separation of different languages into separate columns or regions of a page (e.g. polyglot Bibles, Figure 22), some historic texts mix languages and various typographic attributes directly in the flow of text, such as seen in the legal references from 1726 in Figure 23, which includes Latin, Hebrew, Arabic and Greek, and includes changes in typeface (e.g. blackletter, center left column), italics, and small caps.[63]

[62] Noël de Berlaimont, *Colloquien oft t'samen-sprekingen met eenen vocabulaer in acht spraeken, Latijn, François, Nederduytsch, Hoochduytsch, Spaens, Italiaens, Enghels, ende Portugijsch*, (apud viduam & haeredes Simonis Moulerti, 1631), M4. https://books.google.ca/books?id=BkNlAAAAcAAJ (accessed April 30, 2016).
[63] John Selden, David Wilkins and John Adam. *Joannis Seldeni jurisconsulti opera omnia, tam edita quam inedtia. Vol.II.* Typis S. Palmer, Londini. 1726. pp 257-258. https://archive.org/stream/joannisseldeniju02seld#page/n3/mode/2up (accessed Jan. 12, 2018).

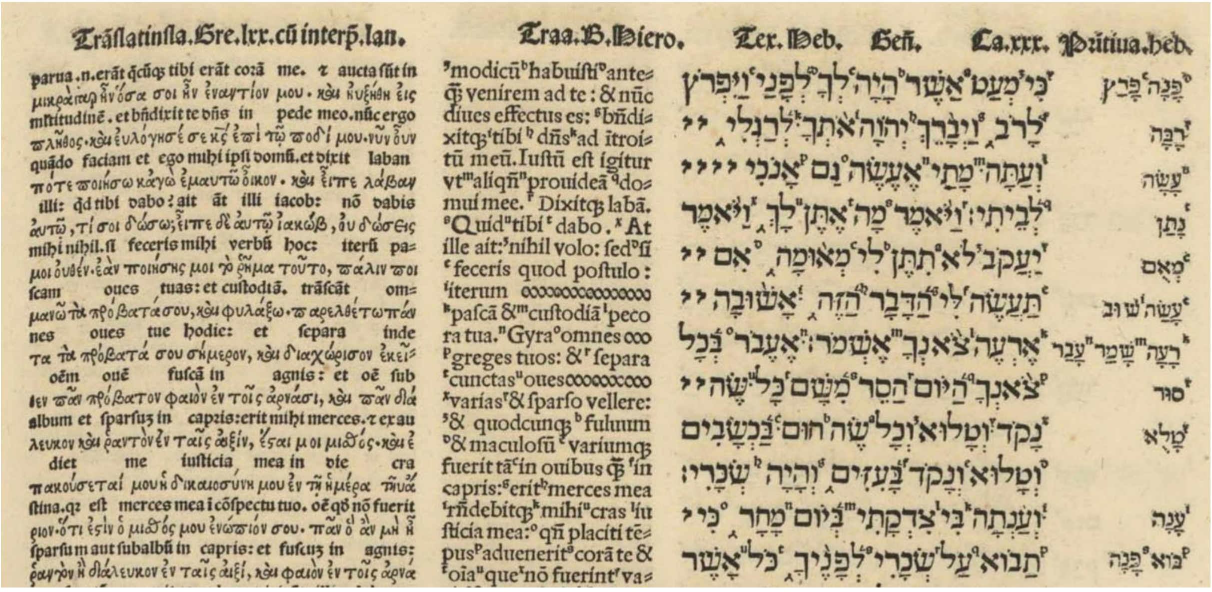


Figure 22. Small portion of polyglot bible with Greek, Latin and Hebrew in adjacent aligned columns. Not in copyright, available at https://en.wikipedia.org/wiki/Complutensian_Polyglot_Bible or https://archive.org/stream/complutensianpolyglot/pdf%20spanish/1/Imgenes1a100#page/n97

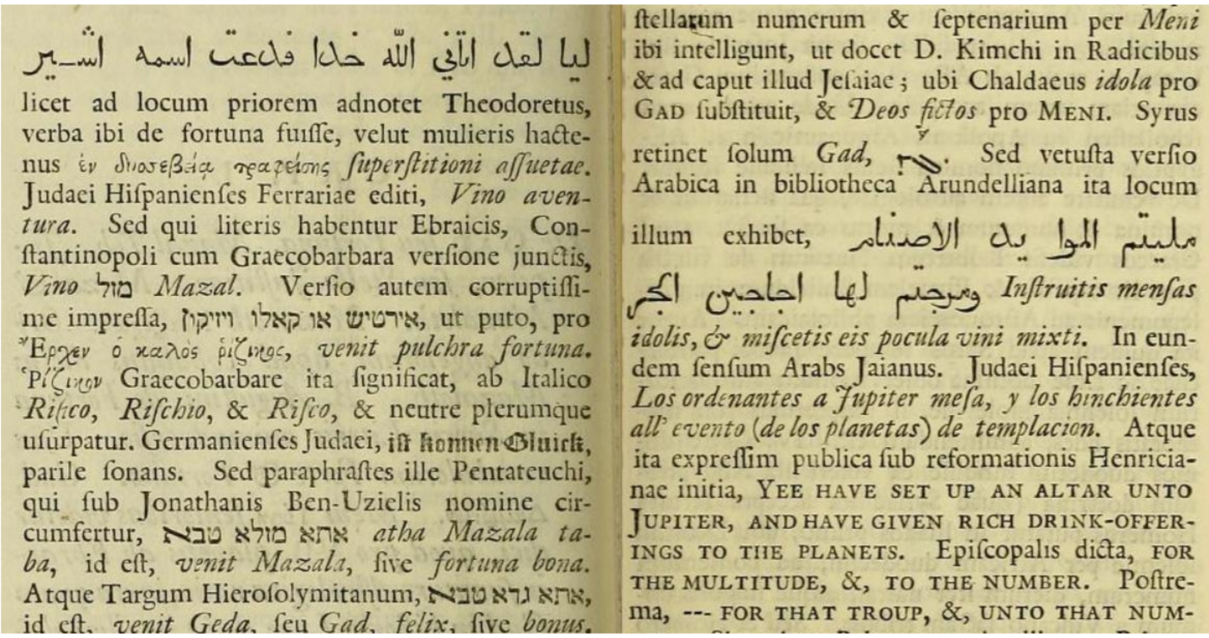
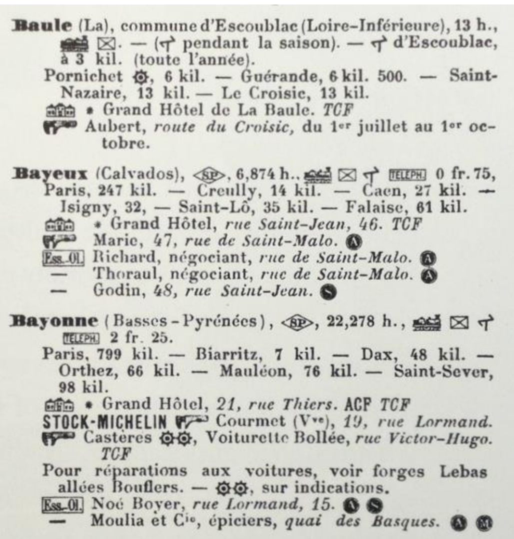


Figure 23. Legal reference simultaneously using Latin, Hebrew, Arabic and Greek plus changes in typeface, italics and small caps. Not in copyright: available at archive.org/details/joannisseldeniju02seld page 257-258…

iv. Typographic Document Organization

Typographic variation is frequently used to structure content within a text. Page numbers, running headers, paragraphs evolved with the invention of the printing press. The addition of headings, sub-heading, captions, tables, footnotes also grew over time. The application of different typographic formats to the different components of text are referred to as a *type hierarchy*. Conventions for type hierarchy are discussed in various typography texts with some authors being more proscriptive such as Bringhurst.[64]

Some texts are designed for quick, non-linear access such as dictionaries, indexes, catalogues and tables. Different typographic formats and symbols delineate and distinguish elements, enabling the viewer to focus on the information of interest. Figure 24 shows an example from a *Michelin Guide* (left) where town names are set in a high-stress heavy-weight font, commune in a plain font surrounded by parentheses, addresses in italics, and stations in a narrow all-caps sans serif. Note also the use of custom icons such as envelope, telegraph, hotels and calipers. Similarly, a catalogue from the early 1900s in Figure 24 right uses large all caps to differentiate sections, bold sans serif to indicate items, plain text for descriptions, and so on.



Baule (La), commune d'Escoublac (Loire-Inférieure), 13 h., ⊠. — (pendant la saison). — d'Escoublac, à 3 kil. (toute l'année).
Pornichet, 6 kil. — Guérande, 6 kil. 500. — Saint-Nazaire, 13 kil. — Le Croisic, 13 kil.
• Grand Hôtel de La Baule. *TCF*
Aubert, *route du Croisic*, du 1er juillet au 1er octobre.

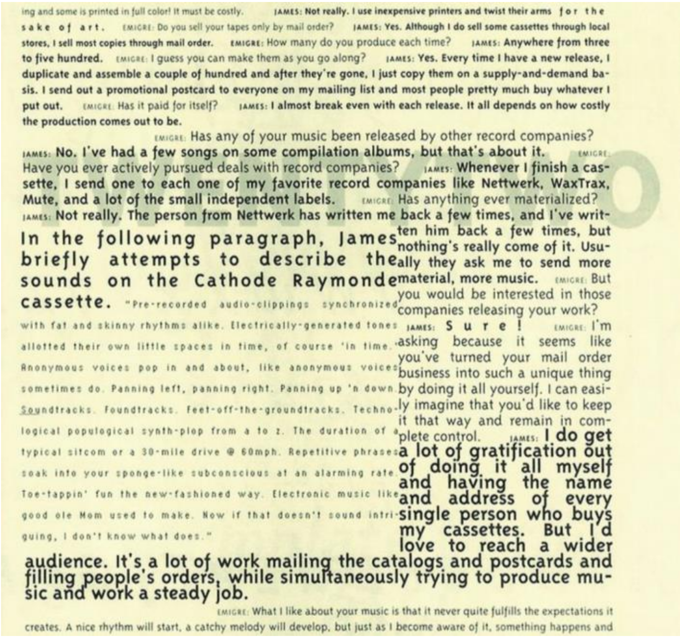
Bayeux (Calvados), 6,874 h., ⊠ TELEPH 0 fr. 75.
Paris, 247 kil. — Creully, 14 kil. — Caen, 27 kil. — Isigny, 32, — Saint-Lô, 35 kil. — Falaise, 61 kil.
• Grand Hôtel, *rue Saint-Jean, 46. TCF*
Marie, *47, rue de Saint-Malo.*
Ess.-Ol. Richard, négociant, *rue de Saint-Malo.*
— Thoraul, négociant, *rue de Saint-Malo.*
— Godin, *48, rue Saint-Jean.*

Bayonne (Basses-Pyrénées), 22,278 h., ⊠ TELEPH 2 fr. 25.
Paris, 799 kil. — Biarritz, 7 kil. — Dax, 48 kil. — Orthez, 66 kil. — Mauléon, 76 kil. — Saint-Sever, 98 kil.
• Grand Hôtel, *21, rue Thiers. ACF TCF*
STOCK-MICHELIN Courmet (Vve), *19, rue Lormand.*
Castères, Voiturette Bollée, *rue Victor-Hugo. TCF*
Pour réparations aux voitures, voir forges Lebas allées Boufflers. — sur indications.
Ess.-Ol. Noé Boyer, *rue Lormand, 15.*
— Moulia et Cie, épiciers, *quai des Basques.*

Figure 24. Left: portion of Michelin guide from 1900. Right: portion of a catalogue. Guide Michelin, Pneu Michelin, 1900. https://archive.org/details/b21539595. Right image Chalmers of Oban Scottish Wool catalogue, 1910's, part of the Collections & Archives at the Department of Typography & Graphic Communication, University of Reading.

By the mid-1980's, post-modernists challenged established typographic conventions. They broadly experimented with typographic attributes in new ways to convey information in texts and create multiple readings – as seen in magazines such as *Emigre* (Figure 25 left), *Octavo, Ray Gun*, or post-modern books such as Avital Ronell's *The Telephone Book,* or Johanna Drucker's Letterpress books (e.g. Figure 25 right[65]).

[64] Robert Bringhurst, *The Elements of Typographic Style,* (Hartley & Marks Publishers, 1992)
[65] Johanna Drucker, "Letterpress Language: Typography as a Medium for the Visual Representation of Language", *Leonardo*, Vol. 17, No. 1. (1984), pp. 8-16.


ing and some is printed in full color! It must be costly. JAMES: Not really. I use inexpensive printers and twist their arms for the sake of art. EMIGRE: Do you sell your tapes only by mail order? JAMES: Yes. Although I do sell some cassettes through local stores, I sell most copies through mail order. EMIGRE: How many do you produce each time? JAMES: Anywhere from three to five hundred. EMIGRE: I guess you can make them as you go along? JAMES: Yes. Every time I have a new release, I duplicate and assemble a couple of hundred and after they're gone, I just copy them on a supply-and-demand basis. I send out a promotional postcard to everyone on my mailing list and most people pretty much buy whatever I put out. EMIGRE: Has it paid for itself? JAMES: I almost break even with each release. It all depends on how costly the production comes out to be.

EMIGRE: Has any of your music been released by other record companies? JAMES: No. I've had a few songs on some compilation albums, but that's about it. EMIGRE: Have you ever actively pursued deals with record companies? JAMES: Whenever I finish a cassette, I send one to each one of my favorite record companies like Nettwerk, WaxTrax, Mute, and a lot of the small independent labels. EMIGRE: Has anything ever materialized? JAMES: Not really. The person from Nettwerk has written me back a few times, and I've written him back a few times, but nothing's really come of it. Usually they ask me to send more material, more music. EMIGRE: But you would be interested in those companies releasing your work? JAMES: Sure! EMIGRE: I'm asking because it seems like you've turned your mail order business into such a unique thing by doing it all yourself. I can easily imagine that you'd like to keep it that way and remain in complete control. JAMES: I do get a lot of gratification out of doing it all myself and having the name and address of every single person who buys my cassettes. But I'd love to reach a wider audience. It's a lot of work mailing the catalogs and postcards and filling people's orders, while simultaneously trying to produce music and work a steady job.

In the following paragraph, James briefly attempts to describe the sounds on the Cathode Raymonde cassette. "Pre-recorded audio-clippings synchronized with fat and skinny rhythms alike. Electrically-generated tones allotted their own little spaces in time, of course 'in time.' Anonymous voices pop in and about, like anonymous voices sometimes do. Panning left, panning right. Panning up 'n down. Soundtracks. Foundtracks. Feet-off-the-groundtracks. Technological populogical synth-plop from a to z. The duration of a typical sitcom or a 30-mile drive @ 60mph. Repetitive phrases soak into your sponge-like subconscious at an alarming rate. Toe-tappin' fun the new-fashioned way. Electronic music like good ole Mom used to make. Now if that doesn't sound intriguing, I don't know what does."

EMIGRE: What I like about your music is that it never quite fulfills the expectations it creates. A nice rhythm will start, a catchy melody will develop, but just as I become aware of it, something happens and

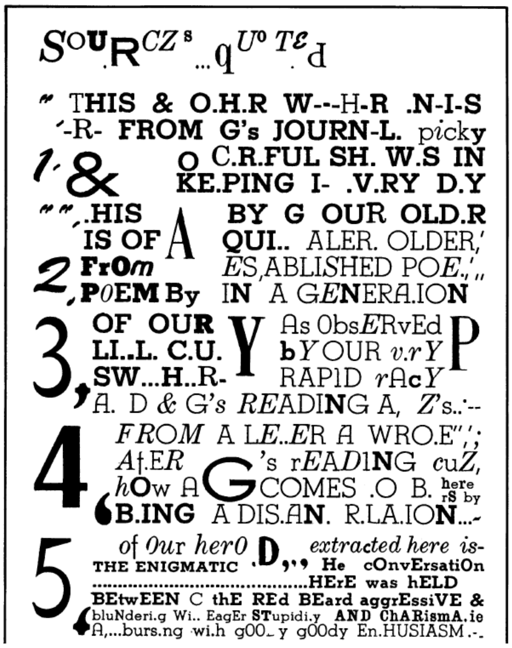


Figure 25. Post-modern typography. Left: *Emigre* magazine, number 22 (1992) varies type size, font, letter spacing, line spacing, etc. Right. Drucker's books create new readings of texts by varying typeface, italics, baselines, weights, size, etc., within and across words; creating new unexpected layouts; altering spellings; and so on. Copyright respective publications. Left: accessed 06/17/2017: s-media-cache-ak0.pinimg.com/736x/45/51/0b/45510b49b2b620af06f344112f6b93f6.jpg)

Beyond the historic examples, students of graphic design study years of typography at both a high level (using typography and typographic attributes to compose and layout texts) to the detailed analysis and design of new fonts. At a high-level, in addition to type-hierarchy, designers will also study text layout and the use of *grid-systems* to organize blocks of text – which create a convention to facilitate rapid access when scanning books, magazines and so on (e.g. Lupton, Squire, Bringhurst). At a low-level, typographers are concerned with the design of effective letterforms (e.g. Cheng, Willen and Strals), which will be discussed in later sections in this thesis.

B:1.2. Historic Cartographic Examples

Cartographers have long used variation in typography to indicate data. The *Gough map* is a medieval hand-drawn map with towns labelled in black text, counties in red text (in boxes) and London labelled in gold.

Figure 26. Portion of the *Gough map* with different types of place names in different colors. The Gough Map, author unknown, 1360, Shelfmark: MS. Gough Gen. Top. 16. Photo by Author. Bodleian Libraries, University of Oxford, digital.bodleian.ox.ac.uk/inquire/p/e4dc07a6-3ec8-414a-aa92-2e9815f93276 . Used with permission under Creative Commons 3 license.

After the invention of the printing press in the mid-1400's, the use of colored text became difficult. However, other typographic attributes such as italics or case were used to indicate different types of data. This differentiation occurred whether the cartographer was creating hand-engraved text (such as Mercator's 1540 map of Flanders shown in Figure 27 and discussed in Osley[66]) or text set with movable type, as seen in Figure 28, a snippet of Munster's *Geographia Universalis* (1540).

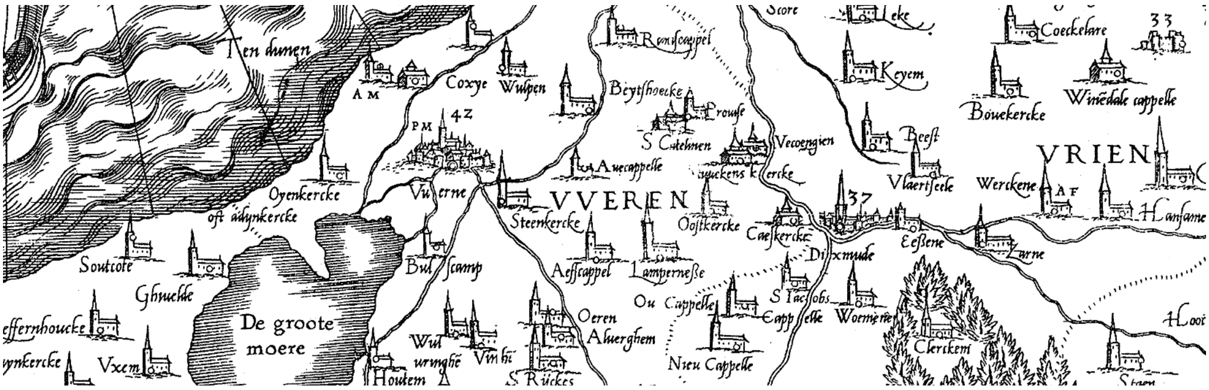


Figure 27. Mercator's 1540 hand-engraved map of Flanders with labels in allcaps roman, mixed case roman and mixed case italic with flourishes. Gerardus Mercator, Map of Flanders, 1540. (image via Wikipedia).

[66] A.S. Osley, *Meractor: A monograph on the lettering of maps, etc in the 16th century Netherlands, etc.* (New York: Watson-Guptill Publications, 1969)

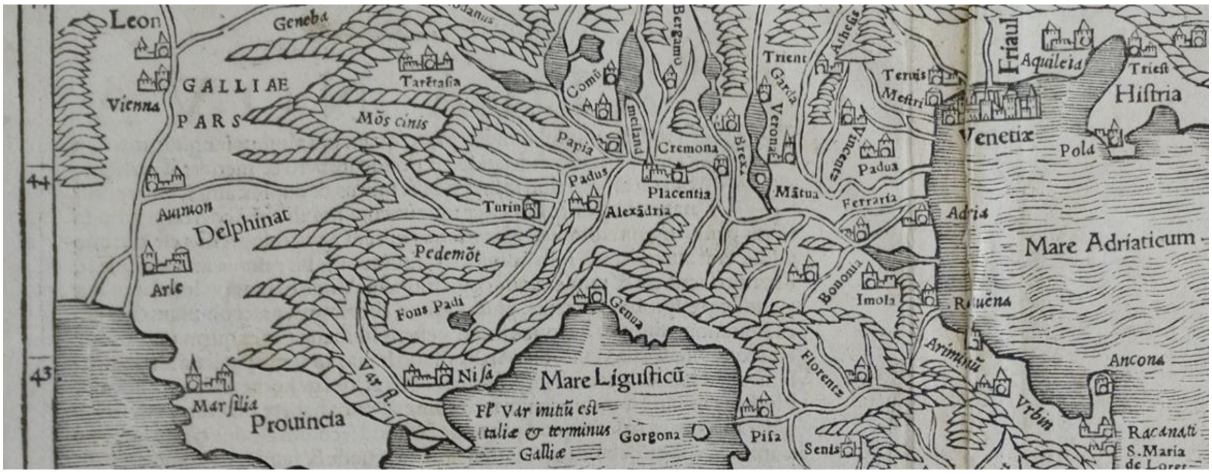
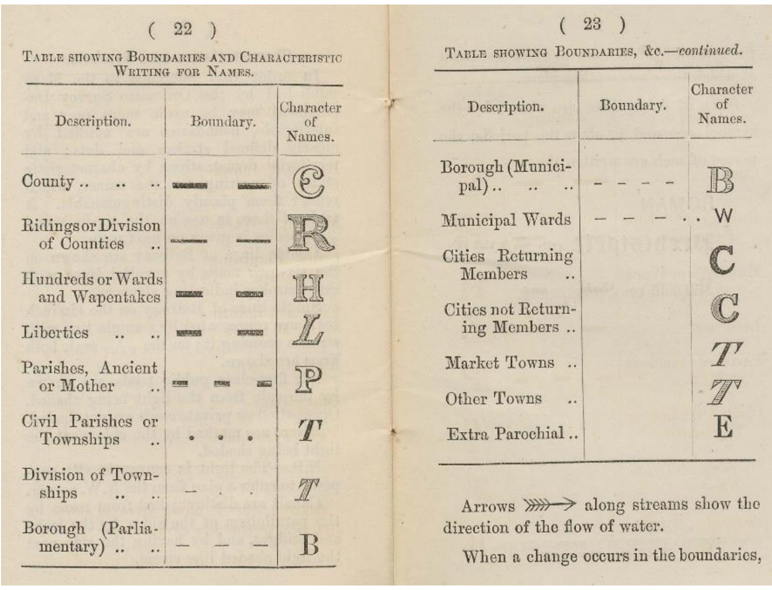


Figure 28. 1540 Map by Sebastian Munster from 1540. Typeset text varies with all caps, roman mixed case and italics. Sebastian Munster. Italia XIIII> Nova Tabula in Geographia Universalis, University of Basel(?) 1540. Isotype collection, Maps 83. Image used with permission. See also: www.swaen.com/munster1540.php

By the 19th century, cartographers expressed quantitative data with combinations of typographic attributes. In George André's, *The Draughtsman's Handbook of Plan and Map Drawing* (1874), a recommended ordering of type is provided: "The different types of lettering are arranged in the order of importance as follows: 1, the upright capital; 2, the inclined capital; 3, the upright roman, or ordinary small type; and 4, the small italic."

In 1888, the Ordnance Survey published a comprehensive guide[67] to the use of type styles indicating an ordering of names from counties down to towns as shown in Figure 29.



(22)

TABLE SHOWING BOUNDARIES AND CHARACTERISTIC WRITING FOR NAMES.

Description.	Boundary.	Character of Names.
County		C
Ridings or Division of Counties ..		R
Hundreds or Wards and Wapentakes		H
Liberties		L
Parishes, Ancient or Mother ..		P
Civil Parishes or Townships ..	• • •	T
Division of Townships		T
Borough (Parliamentary)	— — —	B

(23)

TABLE SHOWING BOUNDARIES, &c.—*continued*.

Description.	Boundary.	Character of Names.
Borough (Municipal)	- - - -	B
Municipal Wards	— — — . .	W
Cities Returning Members ..		C
Cities not Returning Members ..		C
Market Towns ..		T
Other Towns ..		T
Extra Parochial ..		E

Arrows along streams show the direction of the flow of water.

When a change occurs in the boundaries,

Figure 29. Guide to Ordnance Survey maps indicating type styles from counties down to towns. Image courtesy of Eric Kindel, Department of Typography & Graphic Communication, University of Reading.

[67] Sir Charles W. Wilson. *How and Where to Obtain Ordnance Survey Maps of the United Kingdom with a Description of their Scales and Characteristics,* Second Edition. 1888. Edward Stanford, Charing Cross, London. Pages 22-23.

As typography expanded with more typefaces, more weights, underlines and small-caps, maps evolved to use these many typographic attributes simultaneously within a label to indicate many data attributes. Figure 30 shows a portion of an Ordnance Survey map and legend (Hodson 1926) where city labels indicate five different data attributes:

- *Text* indicates the literal name of the city.
- *Case* differentiates between town (uppercase) vs. village (lowercase).
- *Italics* are used to indicate an administrative centre, i.e. a county town.
- *Font size* is used to indicate population category.
- *Font family* indicates country: serif for U.K., slab-serif or serif variant for Scotland.

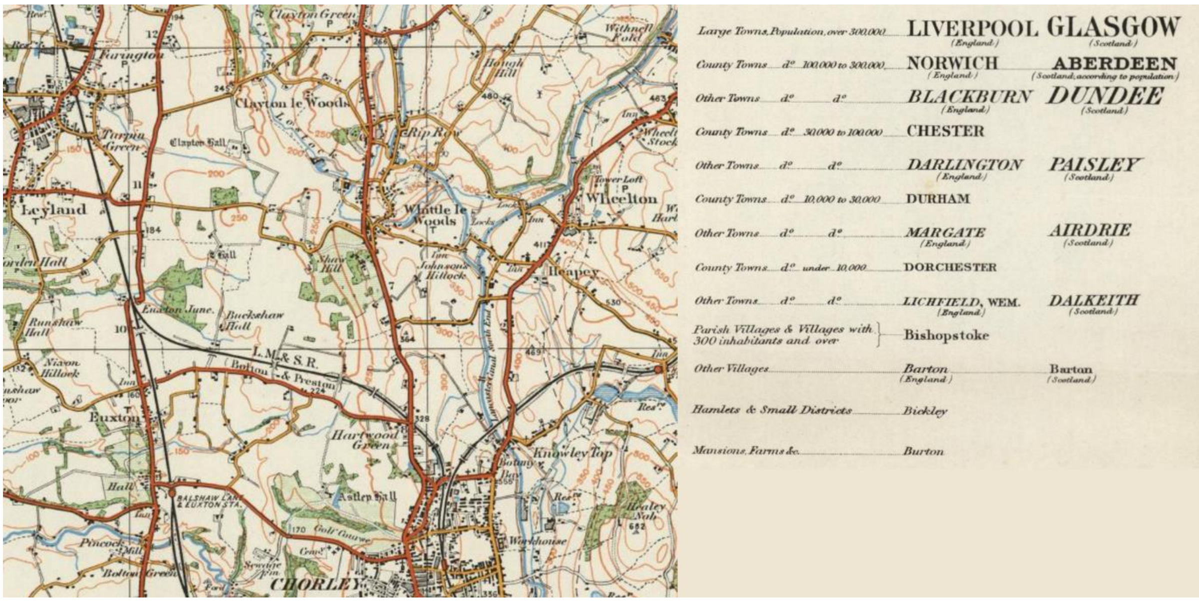


Figure 30. 1920's Ordnance Survey Map where format of town names indicates five data variables. Ordnance Survey Leeds & Bradford. Hodson, Yolande. 1999. Popular Maps, The Ordnance Survey Popular Edition One-Inch Map of England and Wales, 1919-1926. London: The Charles. davidrumsey.com 10/15/2016. http://www.davidrumsey.com/luna/servlet/s/1sy7l9

Similarly, Stieler's Atlas (1925) uses different typefaces, case, italics (both forward and backward), underlines and spacing (Figure 31). Whereas the Ordnance Survey map used font size to indicate the quantitative variable population, Steiler uses size, case, weight and italics to create an ordering:

1) Large uppercase roman (for the largest cities)
2) Uppercase roman
3) Uppercase italic
4) Lowercase roman
5) A lighter weight lowercase roman
6) Lowercase italic
7) A slightly smaller lowercase italic (for the smallest towns)

Steiler also adds a second ordered variable to town names using underlines to indicate the scope of an administrative center ordered double thick underline > double thin > thick > thin > dash > dotted underline as seen in a portion of the legend of Stieler's Atlas in the lower half of Figure 31.

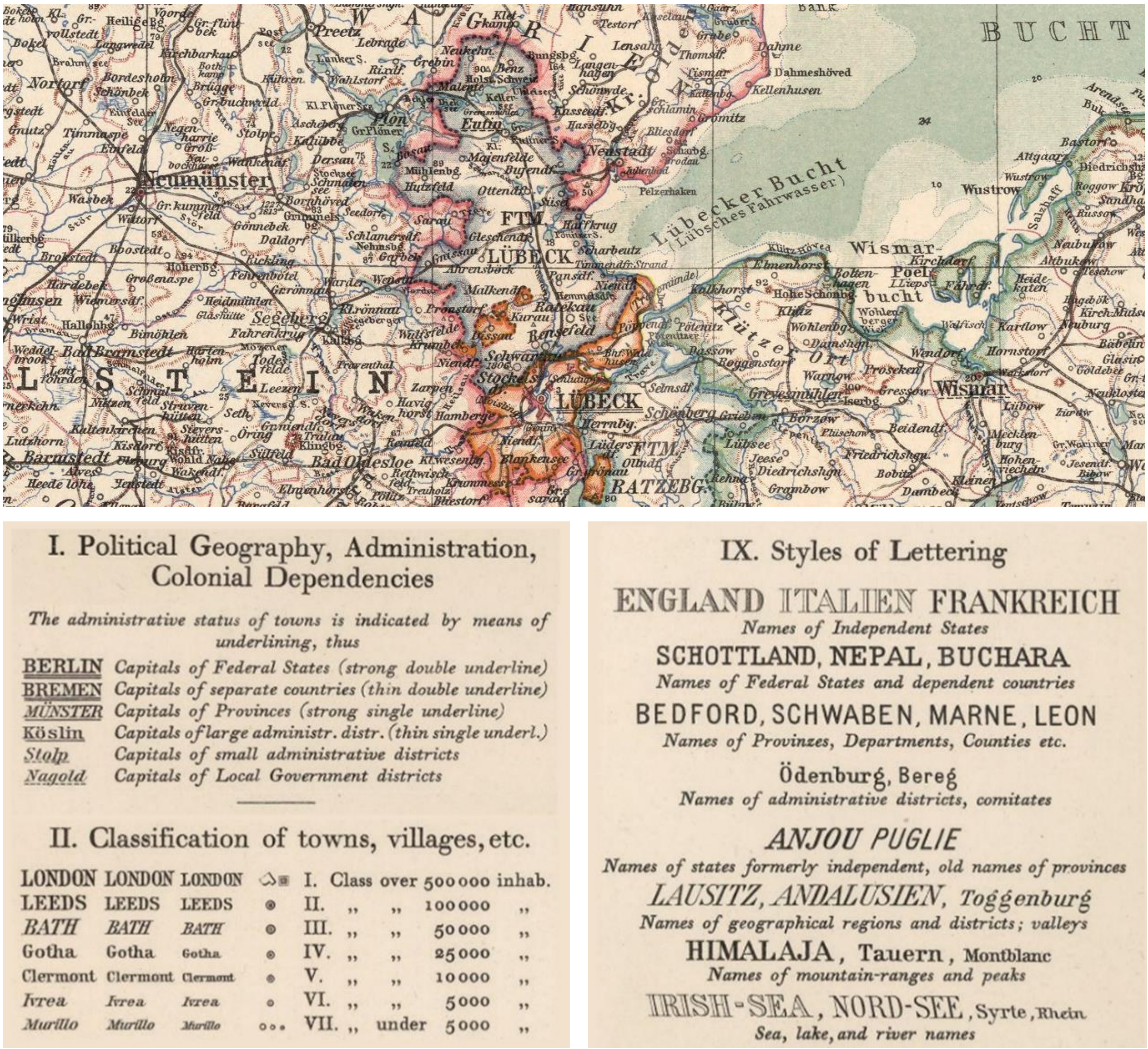


Figure 31. Example map using various typographic attributes to encode data including different font families (e.g. high contrast sans serif, low contrast slab serif, and outline font); italics (forward and reverse); case; variable number of underlines; and spacing (to indicate extents).[68]

While the above two maps show a few data variables encoded into labels, maps may need to express many more variables. General Sherman's *Map of Georgia and Alabama* (1864) records 15 variables per county including the population of whites, free colored, slaves, and military men as well as quantities of wheat corn, rice, cotton, sugar, horses, cattle, swine, etc. A small portion of this large 39 x 26 inch map is shown in Figure 32. This early data-rich map was credited by Sherman as having helped his armies identify supply routes, find food, and plan routes with the best chances for enlisting supporters and avoid opposition.[69]

[68] Adolf Stieler and H. Haack, Stieler's Atlas of Modern Geography, (Gotha, Germany: Justus Perthes, 1925), http://www.davidrumsey.com/luna/servlet/s/c2dd4y and http://www.davidrumsey.com/luna/servlet/s/791qv7

[69] Susan Shultan, "Sherman's Maps" *The New York Times,* New York, November 20, 2014. http://opinionator.blogs.nytimes.com/2014/11/20/shermans-maps/?_r=0 Access Nov. 5, 2016.

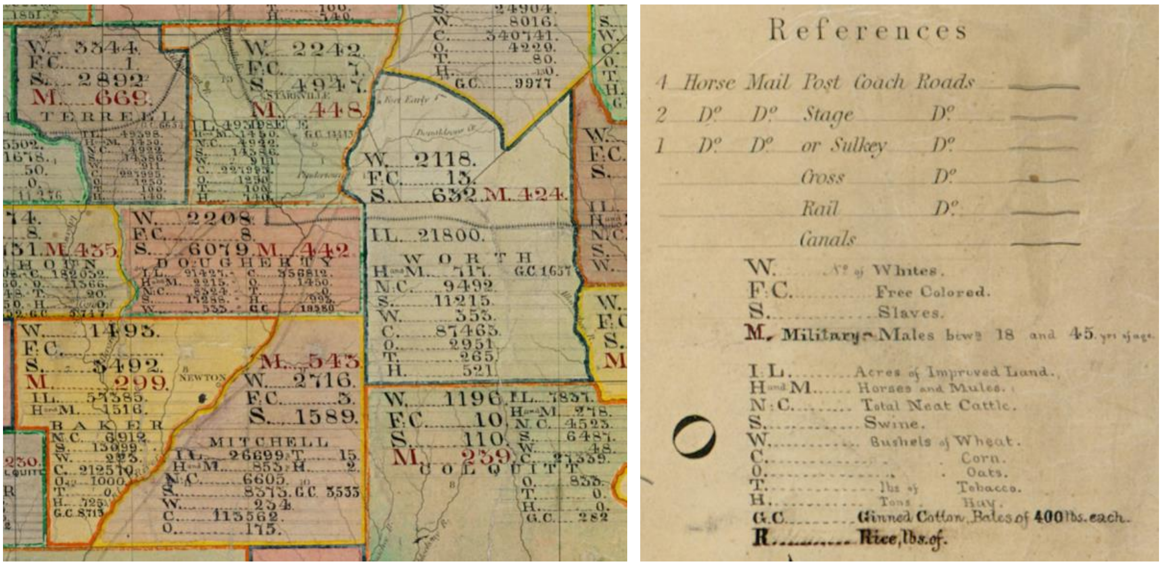
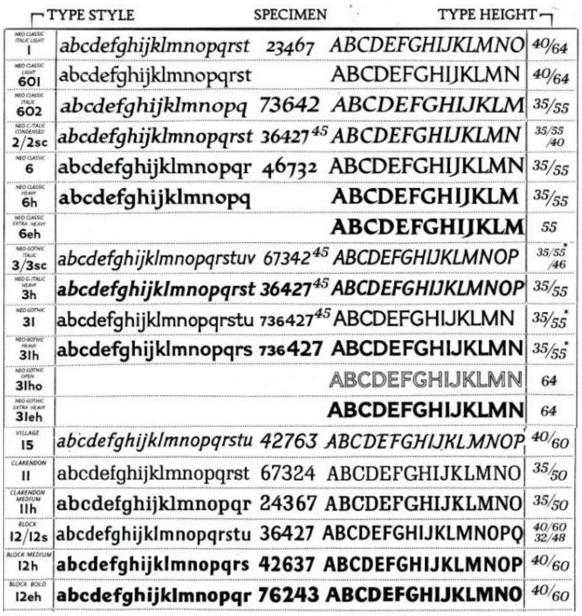


Figure 32. Small portion of General Sherman's map of Georgia (1864) with text annotations indicating 15 quantitative values for each county. From National Archives. See http://opinionator.blogs.nytimes.com/2014/11/20/shermans-maps/?_r=1

The typefaces created by typographers were sometimes found deficient by cartographers who created their own fonts. For example, Figure 33 shows a variety of fonts at National Geographic. Note the variations in weight and type family, while maintaining a consistency in look and feel across the entire set of fonts.



TYPE STYLE	SPECIMEN	TYPE HEIGHT
1	abcdefghijklmnopqrst 23467 ABCDEFGHIJKLMNO	40/64
601	abcdefghijklmnopqrst ABCDEFGHIJKLMN	40/64
602	abcdefghijklmnopq 73642 ABCDEFGHIJKLM	35/55
2/2sc	abcdefghijklmnopqrst 36427^{45} ABCDEFGHIJKLMN	35/55 /40
6	abcdefghijklmnopqr 46732 ABCDEFGHIJKLMN	35/55
6h	abcdefghijklmnopq ABCDEFGHIJKLM	35/55
6eh	ABCDEFGHIJKLM	55
3/3sc	abcdefghijklmnopqrstuv 67342^{45} ABCDEFGHIJKLMNOP	35/55 /46
3h	abcdefghijklmnopqrst 36427^{45} ABCDEFGHIJKLMNOP	35/55
3l	abcdefghijklmnopqrstu 736427^{45} ABCDEFGHIJKLMN	35/55
3lh	abcdefghijklmnopqrs 736427 ABCDEFGHIJKLMN	35/55
3lho	ABCDEFGHIJKLMN	64
3leh	ABCDEFGHIJKLMN	64
15	abcdefghijklmnopqrstu 42763 ABCDEFGHIJKLMNOP	40/60
11	abcdefghijklmnopqrst 67324 ABCDEFGHIJKLMNO	35/50
11h	abcdefghijklmnopqr 24367 ABCDEFGHIJKLMNO	35/50
12/12s	abcdefghijklmnopqrstu 36427 ABCDEFGHIJKLMNOPQ	40/60 32/48
12h	abcdefghijklmnopqrs 42637 ABCDEFGHIJKLMNOP	40/60
12eh	abcdefghijklmnopqr 76243 ABCDEFGHIJKLMNO	40/60

Figure 33. Portion of National Geographic's Map Type Faces Chart showing variants with case, italics, and a variety of font families including serifs, sans serifs, graphic and script. Designed by Ernst Riddiford Copyright 1946 National Geographic. via http://voices.nationalgeographic.com/2012/02/09/national-geographics-cartogaphic-typefaces/

Typographic conventions for categories in maps have been identified by various researchers. For example, Cuff and Mattson[70] surveyed cartographic labelling conventions including uppercase, italics and serif/sans serif as shown in Table 3.

[70] D. Cuff & M. Mattson, M. *Thematic Maps: Their Design and Production.* (NY. Methuen. 1982).

Table 3. Table indicating Lettering Conventions of major map publishers (redrawn based on Hodges[71]).

Feature	Publisher	National Geographic		National Atlases		Atlases		
		Reference	Magazine	U.S.	Canada	CIA	Goode	Oxford World
Water	Salt	*CAPS*	*Mixed*	*CAPS*	*CAPS**	*Mixed*	*CAPS**	*CAPS**
	Fresh	*Mixed*	*Mixed*	*Mixed*	*Mixed*	*Mixed*	*Mixed*	*CAPS**
Land Features	Other	*CAPS**	*Mixed*	CAPS	-	CAPS	*CAPS*	*CAPS*
	Peak	*CAPS**	*Mixed*	Mixed	-	*Mixed*	*Mixed*	*CAPS*
	Range	*CAPS**	*Mixed*	CAPS*	-	CAPS	CAPS	*CAPS**
Cultural	City	Mixed	Mixed	CAPS*	CAPS*	CAPS*	***	Mixed
	Park	*CAPS*	*CAPS*	*CAPS*	-	-	CAPS	*CAPS*
	Political	CAPS	CAPS	CAPS	CAPS	CAPS*	CAPS	CAPS
Thematic	Notes	*Mixed*	*Mixed*	Mixed	Mixed	*Mixed*	*Mixed*	*Mixed*
	Legend Item	Mixed	Mixed	Mixed	Mixed	Mixed	Mixed	Mixed
	Legend Head	Mixed	Mixed	CAPS	CAPS	Mixed	Mixed	Mixed
	Title	CAPS	**	CAPS	CAPS	Mixed	CAPS	Mixed

Brewer's *Designing Better Maps*[72] indicates use of typeface, italic/roman, hue, alignment for categoric data and size, weight, scaling (condensed/expanding), brightness, case and spacing for ordered data. Krygier[73] indicates the use weight, italic, size, hue, brightness, case, spacing and condensed/expanded. Krygier also recognizes but recommends against underlines. Muehlenhaus[74] discusses qualitative attributes including font family (recommending sans serifs), oblique and type arrangement; and quantitative attributes including case, value and weight. Note that cartographic texts discuss visual attributes and typography in completely separate sections (e.g. MacEachren, Tyner, Muehlenhaus, Krygier), and generally typographic attributes are not considered elements for thematic maps, even though they share many similarities to visual attributes.

Web-based interactive maps typically have carefully designed basemaps, upon which specific markers relevant to a user task such as a search or wayfinding are projected. These basemaps are constructed using tools such as Mapnik or Tilemill which provide a high-level of support for high quality typography on the maps (Figure 34 left). Tilemill, for example, exposes style sheets for configuring attributes, including font size, typeface (which includes weights, italics, small caps), case, fill color, fill opacity, label spacing, label orientation, label path, clipping and so on. Given that the text is being drawn overtop a background which may have a variety of colors, there is control for a text halo, that is an outline around to text to help visually separate the text from the background and improve legibility.

Some cartographers are exploring novel uses of type on maps. Axis Maps (www.axismaps.com) goes to the extreme of type on maps, eliminating all other graphics and plotting text only to define geographic features such as streets and neighborhoods (Figure 34 right) as novelty maps. These, in turn, have been computationally automated.[75]

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71 E.R.S. Hodges. "Cartography for the Scientific Illustrator." In *The Guild Handbook of Scientific Illustration*. ed. D.G.Cole, (New York: Van Nostrad Reinhold, 1989).
72 Cynthia Brewer. *Designing Better Maps: A Guide for GIS Users.* (ESRI Press. 2005).
73 J. Krygier. *Making Maps: A Visual Guide to Map Design for GIS*. (Guildford Press, NY, 2005).
74 Ian Muehlenhaus. *Web Cartography: Map Design for Interactive and Mobile Devices*. (CRC Press, 2014).
75 S, Afzal, Maciejewski, R., Jang, Y., Elmqvist, N., & Ebert, D. S. (2012). Spatial text visualization using automatic typographic maps. *IEEE Transactions on Visualization & Computer Graphics*, (12), 2556-2564.

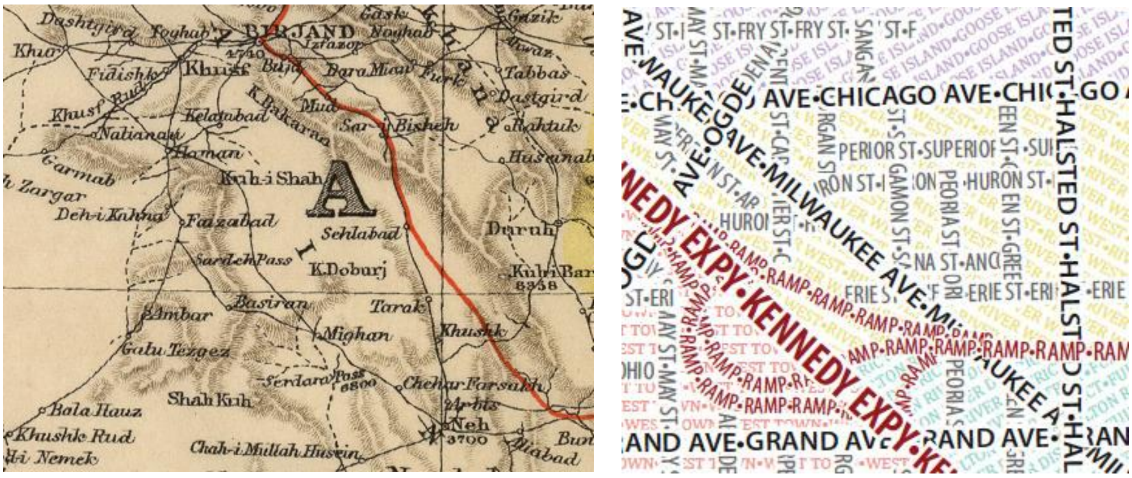

Figure 34. Left. Map generated with Tilemill (by Coleman McCormick). Right. Typographic maps. Images copyright respective authors.

Kate McLean's smell maps[76] transform smells into contour maps where contour lines instead utilize text (Figure 35 left). National Geographic created an interactive map of surnames[77] indicating frequency of surname per state (by size) and ethnic origin (by color). (see also flickr.com/photos/29846735@N05/5502759781/).

Figure 35. Left: Kate McLean's smell maps: contour lines with descriptive words. Right: National Geographic's map of US surnames by state. Images copyright respective authors.

Some cartographers have expressed concern with (lack of) typographic innovation in maps. For example, Skupin:

> *"[There is] a certain myopia and lack of imagination when it comes to the full potential of using text within maps."*[78]

[76] Kate McLean, Smellmap Amsterdam, 2014. Sensory Maps. http://sensorymaps.com/portfolio/smellmap-amsterdam/ Accessed Dec. 5, 2016.
[77] National Geographic. *What's in a Surname?* 2011. http://ngm.nationalgeographic.com/2011/02/geography/usa-surnames-interactive Access Jan 1, 2017.
[78] André Skupin, *Mapping Text*, Glimpse Journal, Issue 7, 2011. Salem, MA.

B:1.3. Technical Applications

Various disciplines have used type for labelling, notation and charting which providing interesting use cases of ways to encode data with typography:

i. Labelled Technical Drawings

Technical drawings (as used in surveys, engineering, architecture, medical and botanic illustration) use different typographic elements to emphasize, delineate or otherwise add information to text. Similar to cartography, architectural and engineering drawings need to label a lot of information on a drawing such as a floor plan or a machine part. Specifically contract drawings, also referred to as working drawings, are particularly dense with titles, labels, dimensions, annotations and notes. These labels are typically referred to as lettering. Historically, many of these tend to be hand-lettered with differentiation created using font attributes such as italics, underlines, tracking and font size, such as Figure 36 left.

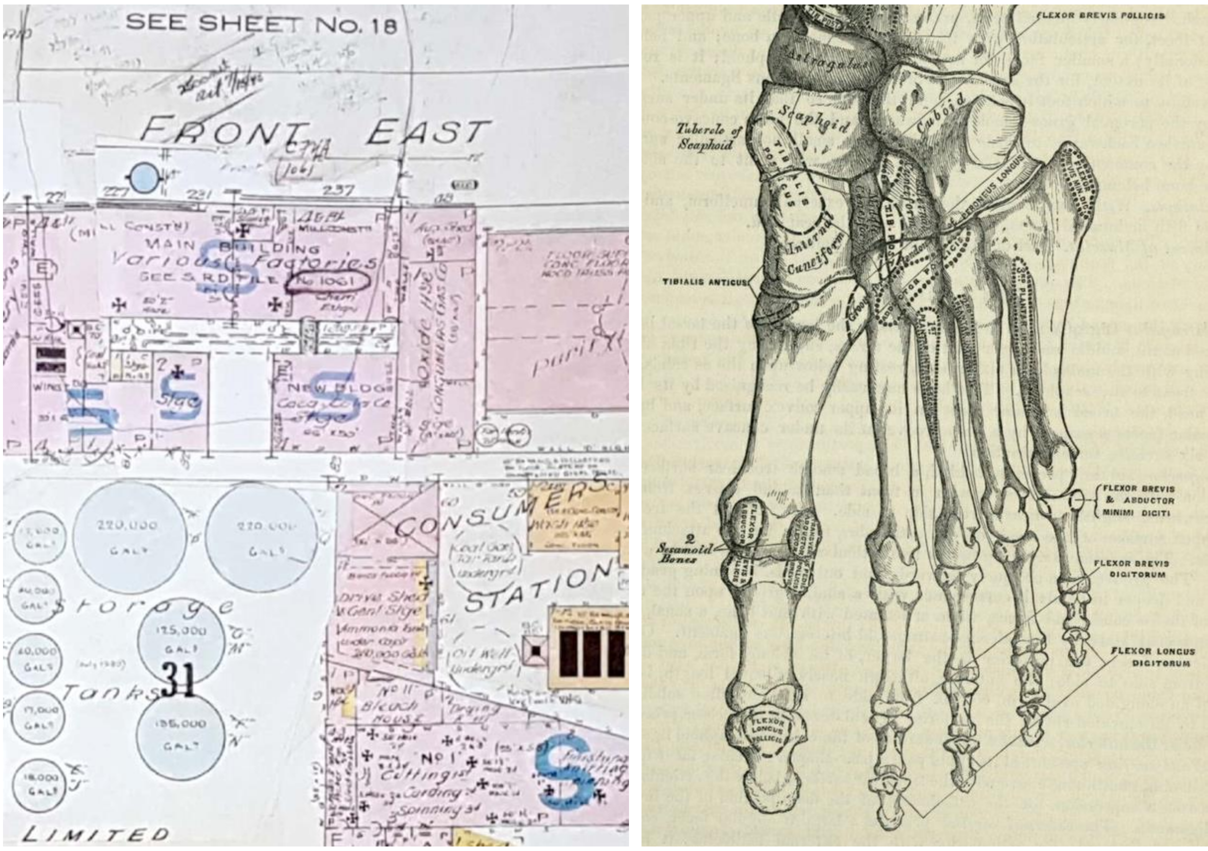

Figure 36. Left: Fire insurance drawing from approximately 1900. Note various sizes, small caps, italics/roman, tracking (spacing), and some different font styles (e.g. “31”, “SEE SHEET”). Right: Illustration of bones using typographic variation including small caps, italics, spacing and parenthesis. Left: Photo by author. Right: Source: Historical Medical Library of The College of Physicians of Philadelphia, Creative Commons Attribution-NonCommercial-ShareAlike 3.0 Unported License

Similarly, medical illustrations use typographic variation to differentiate between classes of information such as Henry Van Dyke Carters’s wood block illustrations in *Gray’s Anatomy*,[79] (Figure 36 right) which uses variation

[79] Gray, Henry, 1825-1861. Anatomy (London : J.W. Parker, 1858), figure 97. Ac 11B (Historical Medical Library of The College of Physicians of Philadelphia)

in small caps, italics, spacing and parenthesis. More advanced hand-lettering provides different font types (Sans Serif, Serif), outline fonts and so forth as seen in Figure 37.

Figure 37. Many variants of hand-lettering for technical drawings. From public domain Frank T. Daniel's *A Text-book of Free-hand Lettering.* (D.C.Heath & Co., 1909).

Lettering can also be created mechanically using stencils, templates or a pantograph (e.g. Keuffel and Esser's Leroy system). In some cases, more formal lettering could be applied using techniques such as dry-transfer decals (e.g. Letraset).

ii. Alphanumeric Charts

In finance, starting in the late 1800's, *figure charts* (Figure 38) evolved plotting individual security prices in a matrix organized by time (horizontally) and price (vertically).[80] This textual representation evolved over the decades, for example, Wyckoff[81] outlined figures and visually linked successive observations. By the 1930's these had evolved into *point and figure charts*[82] replacing the columns of figures with X's and other characters to denote particular price thresholds.

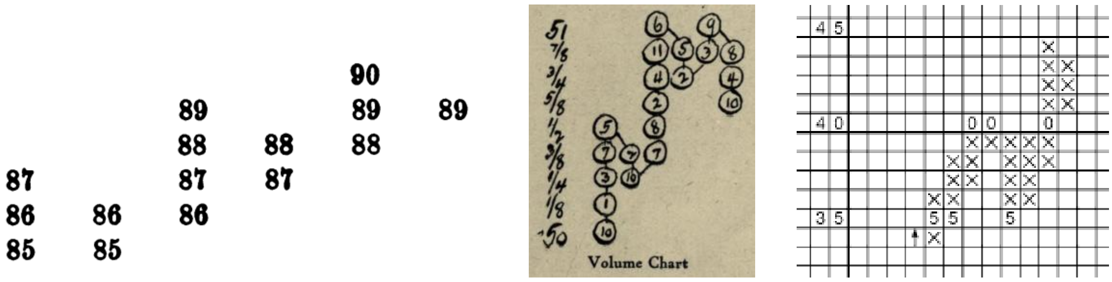

Figure 38. Left. Hoyle's *figure chart* records daily price movements as a successive columns of numeric figures indicating the range of price per day. Middle. Wyckoff's figure chart records the volume of stock at each price level as a series of connected numeric figures, incrementing horizontally when the price reverses direction. Right: The point and figure chart of DeVilliers and Taylor. Left two images from online books at archive.org. Right image copyright DeVilliers and Taylor.

Livermore[83] created his own variant tracking only the minimums and maximums, discarding the intervening levels and using text color and text underlines to indicate information (time is on the vertical axis and price on the horizontal axis in Livermore's variant, Figure 39 left). The current convention for point and figure charts is

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http://www.cppdigitallibrary.org/items/show/2370?advanced%5B0%5D%5Belement_id%5D=48&advanced%5B0%5D%5Btype%5D=contains&advanced%5B0%5D%5Bterms%5D=Gray%2C+Henry%2C+1825-1861.+Anatomy Accessed Oct 6, 2016.

[80] J.S. Hoyle. *The Game in Wall Street and How to Play it Successfully.* Oglive Publishing Co., New York. 1898.

[81] Richard Wyckoff *Studies in Tape Reading*. The Ticker Publishing Company. New York. 1910. Access 05/22/2015 via https://archive.org/stream/studiesintaperea00wyckrich#page/n7/mode/2up

[82] Victor DeVilliers and Taylor, Owen. *Devilliers and Taylor on Point and Figure Charting*. 1933.

[83] Edwin Lefevre. *Reminiscences of a Stock Operator,* The Sun Dial Press, Garden City, NJ, 1923. https://archive.org/details/JesseLivermoreReminiscencesOfAStockOperator

to use X's to indicate rising prices and O's to indicate falling prices, with other characters, for example, to indicate the start of a month or color to differentiate columns, as shown in Figure 39 right.

Figure 39. Left. Livermore's chart records minimums and maximums only. Note use of font color and underline color. Right. A modern computer based point-and-figure chart. Left image copyright from appendix from Livermore's book. Right image is from a Bloomberg terminal, copyright Bloomberg, used with permission.

Rather than stack alphanumeric characters in alternating columns, they have also been stacked to form distributions. An early example from 1937 is the chart *Percent of Population Receiving Relief, by State, from the General Relief Program*,[84] with each state having a unique numeric code, located vertically based on the relief metric and stacked to form a distribution (a small portion of the chart is redrawn in Figure 40 left). The arrow indicates the median and the shaded area (dashed) indicates the inner quartiles.

Market profile charts are financial charts that use characters to indicate the time of day that a commodity trades at a specific price level. A common encoding uses A-X, a-x to indicate half hour intervals starting at midnight with uppercase for trades in the morning, lowercase in the afternoon. Characters are aligned vertically by price and stacked horizontally forming a histogram, enabling a macro-reading (the distribution) and a micro-reading (the individual characters) as shown in Figure 40 right.

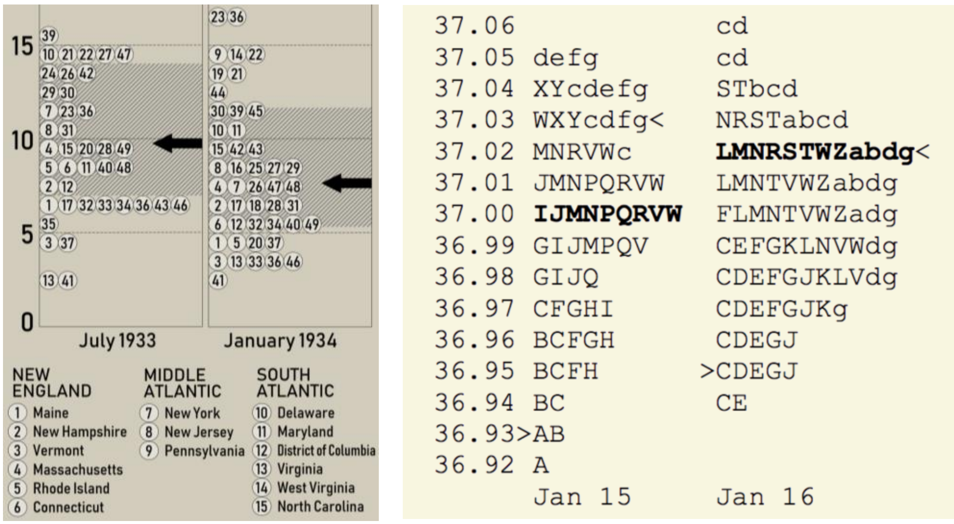

Figure 40. Left. Distributions are formed by stacked numeric codes in this 1937 chart "Percent of Population Receiving Relief, by State, from the General Relief Program" Right. A market profile chart. Left: Public domain, redrawn by author. Right image by author.

84 Willard Cope Brinton, *Graphic Presentation*. Brinton Associates. New York. 1939.

Some visualization experts have expressed doubt regarding the effectiveness of stacked letters.[85] However, there are at least eight commercial vendors that produce market profile charts – i.e. an economic validation of the approach. As of early 2016 these vendors include Sierra Chart, Windotrader, CBOT, Bluewater Trading Solutions, Pro Realtime, CQG, Market Delta, E-Signal as shown in Figure 41. Given the many possible data attributes and analytics that one might associate with a character in a chart, it can become a challenge to encode them. Variants beyond *position, letters* and *case* include:

- *color*: of the foreground letter or background square
- *bold*: to indicate a row or potentially as a highlight to one time interval, e.g. MarketDelta
- *superscripts*: e.g. eSignal.
- *added symbols*: asterisks, less than, greater than, etc.
- *added shapes*: circles and diamonds

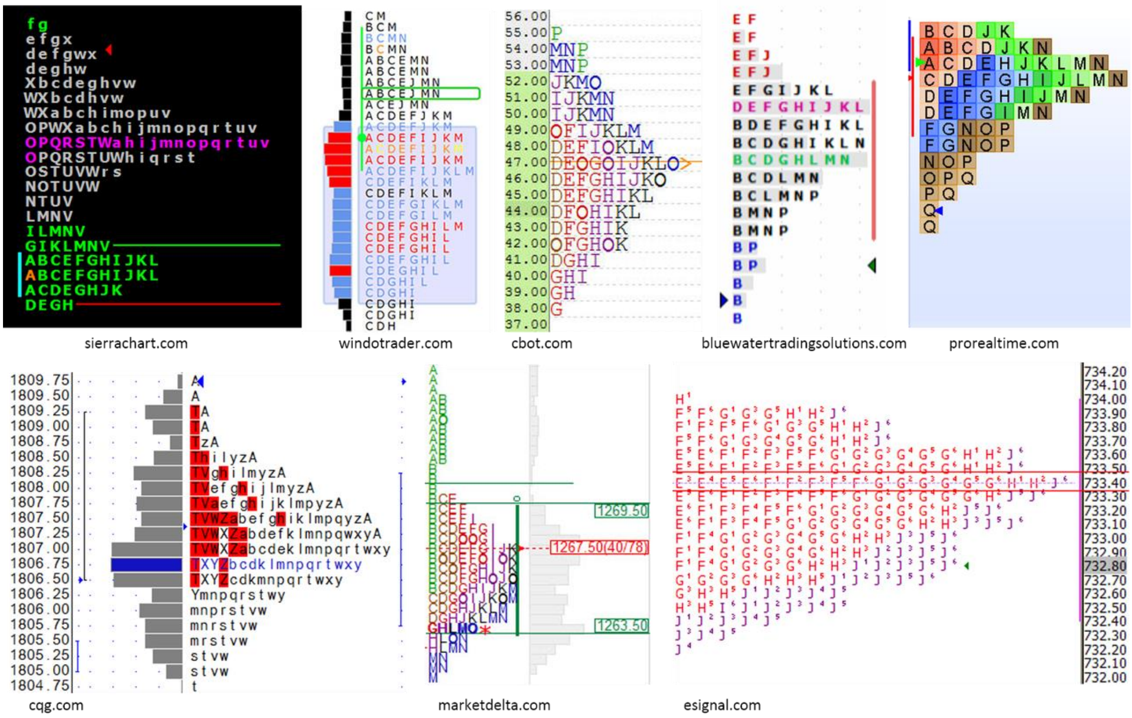

Figure 41. Many variants of *Market Profile* charts by various commercial software vendors. Note the additional information added via foreground/background color, bold, superscript, added marks, symbols and outlines. Images copyright respective companies.

Tukey's *stem and leaf plots*[86] are statistical charts which similarly stack characters to form distributions: the numbers along the vertical axis correspond to bins of the distribution and characters correspond to the next significant digit (Figure 42 left).

[85] Public conversation with visualization experts at TextVis 2015: IUI Workshop on Visual Text Analytics. Atlanta, GA. March 29, 2015.
[86] John Tukey: Some graphic and semigraphic displays. *Statistical Papers in Honor of George W. Snedecor* 5 (1966).

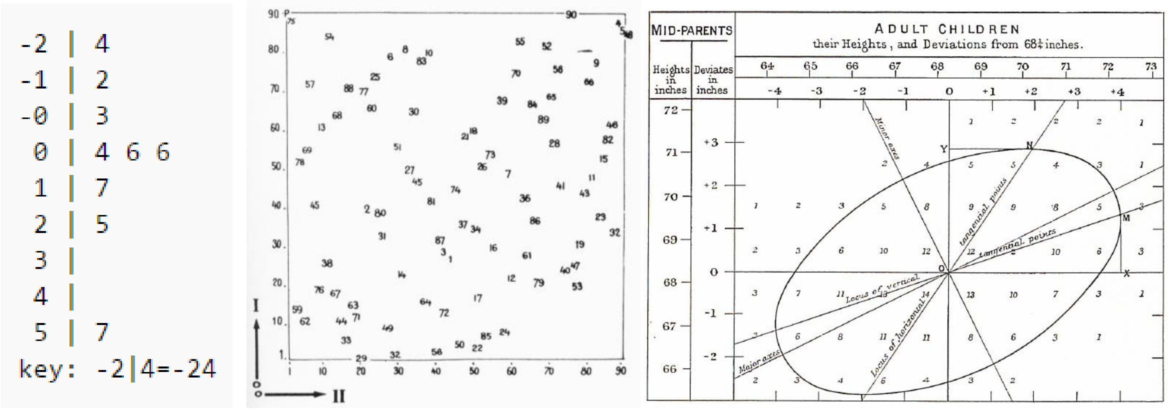

Figure 42. Left: stem and leaf plot. Left image from Wikipedia, middle image from Bertin page 249, right image from Tufte 1983 page 145 (from Karl Pearson, The Life, Letters and Labours of Francis Galton; Cambridge 1930, vol III-A, 14.) Images copyright respective authors.

Bertin's *Semiology of Graphics* has very few examples of alphanumerics on charts other than labels (e.g. axis labels, scatterplot labels) although there are a few examples of scatterplots with labels only (no other marks) as seen in Figure 42 middle, or numeric tables with added graphical marks.

Tufte's first three books provide seven examples of alphanumeric charts that include variation of font attributes. For example, Japanese railway tables (e.g. Figure 11P14) are similar to stem and leaf plots, varying font size, background shape and provide additional tiny glyphs above text. Tufte also calls out table-graphic with data points set as text in a grid (in a fine italic serif font) with lines of fit (e.g. regression, locus) overlaid and with additional labels (in bold sans-serif font) as seen in Figure 42 right.

iii. Notation Systems

Many domains have borrowed or extended the expressive capabilities of typographical attributes to create rich notation systems. These systems use attributes such as case, superscripts, symbols, delimiters, and so on to emphasize, delineate or otherwise add information to text.

Chemical formulas are a notation system using a mix of font attributes to describe molecular relationships (via Wikipedia):

- *Case* is used to distinguish atomic elements e.g. N, O, C, Na, Cl, with lead character in uppercase and a successive character in lowercase, if any.
- *Preceding superscripts* denote isotopes, e.g. ^{2}H, ^{235}U.
- *Trailing subscripts* denotes the number of atoms in the molecule, e.g. H_2O, CO_2, $C_6H_{12}0_6$.
- *Trailing superscripts* denotes the charge on an ion, e.g. Na^+, or Cu^{2+}.
- *Paired brackets* indicate ionic compounds that do not exist as discrete molecules, e.g. $[SO_4]^{2-}$.
- *Symbols* may be used to indicate structures, such as double bonds with =, e.g. $H_2C{=}CH_2$, or @ to indicate a trapped atom, e.g. $M@C_{60}$.

Mathematical notation evolved over hundreds of years (via Wikipedia and jeff560.tripod.com/mathsym.html):

- *Parentheses, brackets, etc.* used for grouping symbols, e.g. f(x), [], {}.
- *Line* (viniculum). Used as a divider for stacked numerics and an operation, e.g. a list of numbers to be added; or as division. The line, used as division, can be used to group symbols. The line is similar to text underline, but treated independently. The line may be part of a symbol extended across a group of characters, e.g. division symbol, square root symbol. Line may also be used in statistics, e.g. overline for mean, e.g. $\bar{x}$
- *Superscripts* and subscripts, e.g. exponents x^2, 2^x.
- *Symbols* such as arithmetic operators (e.g. +,-,/,=,<) and set operators (e.g. ∈, ∩, ∪).
- *Typefaces and alphabets*. Greek letters (e.g. α, β, Σ) are used as well as different fonts such as script (i.e. calligraphy, e.g. $\mathcal{H}$, $\mathcal{R}$), blackletter (i.e. Fraktur, e.g. $\mathfrak{H}$, $\mathfrak{R}$) and a blackboard bold (e.g. ℍ, ℝ). Glyphs may also be reoriented or have added marks to create a unique meaning (e.g. ∀, ∃, ∄, ∅).

iv. Software Code and Code Editors

Computer software code, which is built on conventions from mathematics, have created many conventions in markup notation. For example, HTML or XML use a variety of typographic attributes such as:

- *Symbols* such as colons, commas, semicolons, etc., to indicate syntax such as statements or operations such as assignment.
- *Quotes, parentheses, brackets*, etc. used for grouping tokens, e.g.

```
<div class=”body”> Text here </div>
```

- *Case* is usually not specified by the programming language, but conventions use case to differentiate types of operators or types of variables (e.g. `IF_DEF, gGlobalVar, ClassName`).

Code presentation has evolved to enhance code comprehension. In the 1980’s Baecker and Marcus characterized a range of visual attributes (including color, size, italics, small caps, bold, font family) for enhancing source code (Figure 43 left). These are now commonplace in many modern software code editors. For example, WebStorm (Figure 43 right) uses attributes such as background shading, text color, bold, italic, underline (straight and wavy), plus user conventions (e.g. CamelCase) and programming language syntax requirements of scope (e.g. ‘’,[],{},<>) to enhance code readability.

Figure 43. Software source code has long used typographic attributes to enhance comprehension. Left: Baecker and Marcus[87]. Right: WebStorm.

[87] Ron Baecker and Aaron Marcus, Human factors and typography for more readable programs, (ACM, 1989).

B:1.4. Text in Visualization

As discussed earlier in the analysis of the *Text Visualization Browser* (Table 1P13), most text visualizations use either un-differentiated text or text labels use familiar visual attributes of size, hue and intensity despite having unique typographic attributes. There are other repositories of visualization that can be reviewed – perhaps other collections will have different biases.

Scimaps.org is a juried collection of 144 exemplars of data visualization specifically with regards to mapping science. Many of these are posters with various notations surrounding a central visualization. As a collection, it includes a wide variety of different visualization types, including graphs, timelines, grids, maps, scatterplots, treemaps, tag clouds, Euler diagrams, infographics and so forth. In the 144 examples there are 116 examples of visualizations using text in the visualization (poster titles, institutional logos, blocks of explanatory text and so forth are not considered; only text within the visualization is considered). Out of these, 63% vary type using traditional visualization attributes of size, hue or brightness in the visualizations e.g. treemaps, tag clouds and labelled node-link graphs. Only 28% use font-attributes, such as bold or italics. Out of these 40/144 which use typographic attributes, in most cases these attributes are not used to encode additional data:

- *Composition*: In many of these examples, font-specific attributes (e.g. bold, serif/sans-serif, uppercase and/or italics) are used in a traditional typographic role to simply differentiate compositional elements such as title, subtitle, labels, axes, tooltips, and explanatory text. In these cases, the font-attributes are not adding additional data, rather just providing structure to the different classes of information. More than half of the examples using font-specific attributes use type in this manner (Figure 44).

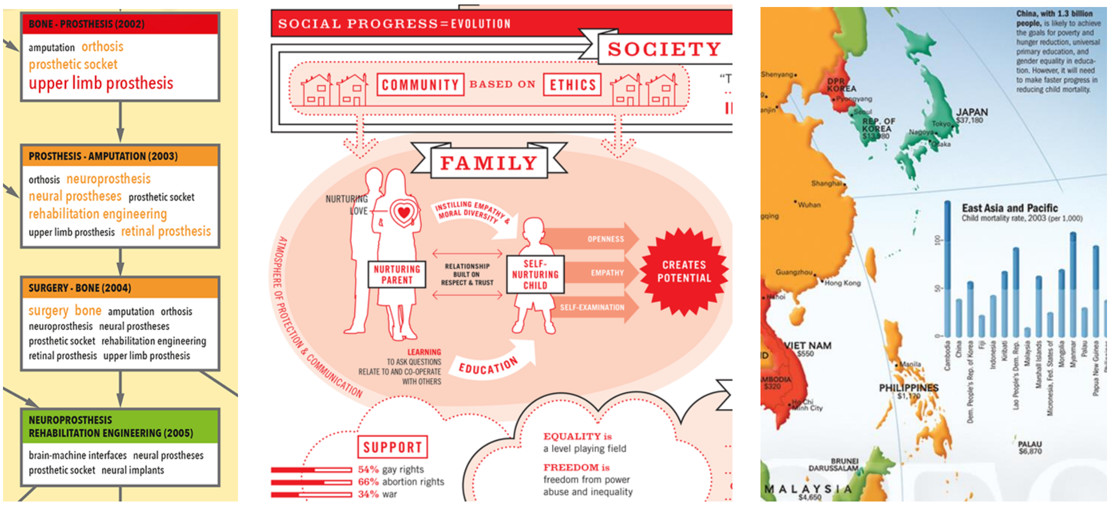

Figure 44. Left: Bold caps differentiates a box title from the box content.[88] Middle: An infographic mixing a wide variety of font attributes: typeface, case, condensed, but only for differentiation and establishing relative importance among many elements.[89] A choropleth map with chart overlays and commentary uses font-attributes to differentiate between the various elements.[90] Images © respective owners, accessed from Places & Spaces at scimaps.org.

[88] David Chavalarias and Jean-Philippe Cointet. 2013. "Phylometric Patterns in Science Evolution: The Rise and Fall of Scientific Fields." PLoS ONE 8:2.

[89] David McCandless and Stefanie Posavec. 2009. Left vs. Right Political Spectrum. Courtesy of Information is Beautiful. "8th Iteration (2012): Science Maps for Kids," Places & Spaces: Mapping Science, edited by Katy Börner and Michael J. Stamper.

[90] The World Bank and National Geographic Society. 2006. The Millennium Development Goals Map: A Global Agenda to End Poverty. Courtesy of The World Bank and The National Geographic Society. In "5th Iteration (2009): Science Maps for Science Policy-Makers," Places & Spaces: Mapping Science, edited by Katy Börner and Elisha F. Hardy.

- *Differentiate between datasets*. Some designers use one or two type attributes such as bold, italics or uppercase to differentiate between two classes of data in a visualization. For example Brad Paley's Map of Science[91] uses a small grey sans serif font to label topics and a larger, light-weight, italic font to indicate areas of study (Figure 45 left).
- *Cartographic borrowing*. Some designs are maps or borrow representational techniques from cartography, making use of typographic attributes such as spacing, italics and size to indicate different types or ranges of information. For example André Skupin's self-organizing knowledge maps[92] use GIS software to render the results including cartographic labeling techniques such as bold, spacing and so on (Figure 45 middle). Ellingham's 1948 chart, illustrating relations between science,[93] is a hand-drawn map placing closely related topics close together, with labels varying in size, capitalization, italics and spacing (Figure 45 right).

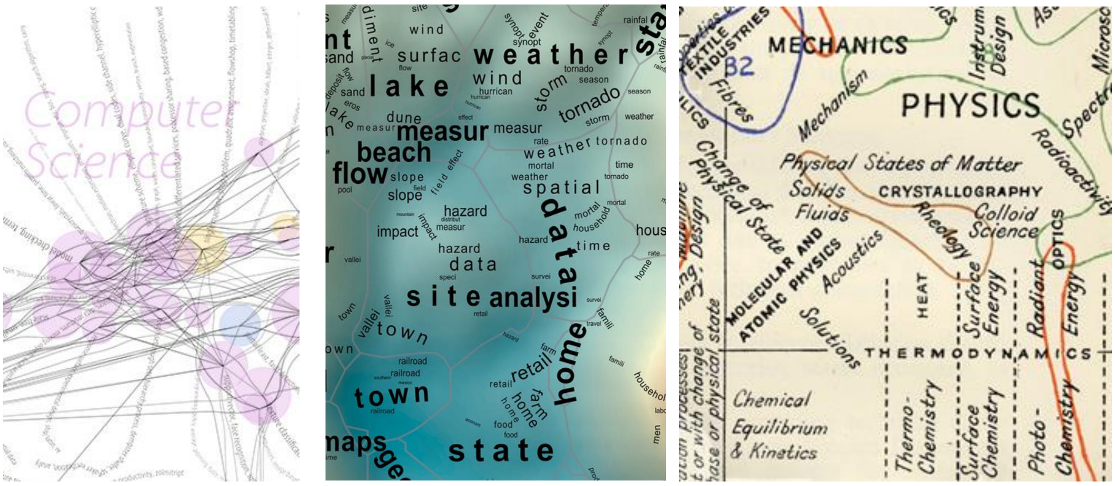

Figure 45. Left: In Paley's Map of Science, large thin italics indicate major research areas while tiny grey font indicates specific topics. Middle: Skupin's knowledge map borrows cartographic labeling techniques such as size, bold and spacing to encode information into the label. Right: Ellingham's 1948 chart of science and technology indicating different levels of topics and relations by proximity. Copyrights: © 2010 Brad Paley, 1948 The Royal Society; © 2004 The National Academy of Sciences.

A summary of the attributes used across these curated visualizations at *SciMaps.org* are outlined in Table 4. Size and color dominate. Case, followed by bold, are the most used font-attributes, however in more than half of these visualizations, they are used in traditional typographic roles, such as differentiating a title (as shown in Figure 44 above). Full analysis of scimaps.org is in the *Appendix* in *F:4.2*P261.

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[91] Brad Paley. Map of Science. 2010 version. http://www.wbpaley.com/brad/mapOfScience/ accessed Aug 24, 2016

[92] André. Skupin, "In Terms of Geography," courtesy of André Skupin, San Diego State University, San Diego, CA, in "*1st Iteration (2005): The Power of Maps,*" Places & Spaces: Mapping Science, edited by Katy Börner and Deborah MacPherson. http://bit.ly/1R97oms

[93] Harold J. T. Ellingham, "A Chart Illustrating Some of the Relations Between the Branches of Natural Science and Technology," courtesy of The Royal Society, in *7th Iteration (2011): Science Maps as Visual Interfaces to Digital Libraries*, Places & Spaces: Mapping Science, edited by Katy Börner and Michael J. Stamper, accessed Nov. 2, 2013. http://bit.ly/1hlJ6VK

Table 4. Visual Attribute use in Knowledge Map visualization as curated on *SciMaps.org*

Use of Visual Attributes in 144 visualizations catalogued on scimaps.org (as of July 12, 2014)		Number of items	Percent of total
Number of visualizations		144	81%
Number of visualizations with text		116	81%
Traditional Visualization Attribute	Size	62	43%
	Color	42	29%
	Bright	4	3%
	Angle	10	7%
Font Attribute	**Bold**	12	8%
	Italic	7	5%
	UPPER & lower	22	15%
	Underlines	0	0%
	Spacing	4	3%
	Typeface	7	5%
	Condensed	2	1%
	Superscript	0	0%

While font-attributes are not broadly used in visualization, there are a few interesting examples which go beyond the scope of simple labels (i.e. words, proper nouns). For example:

- *Sub-word*: Poem Viewer represents phonetic units as colored blocks anchored above their corresponding words (Figure 46 left).[94]
- *Sentences*: WordTree (previously Figure 15 right) shows common phrases across multiple sentences.
- *Multiple sentences*: projSnippet leverages web and visualization conventions with text size, foreground text color, background area color, underlines and grouping to organize titles, keyword-in-context phrases and URLs into a scatterplot (Figure 46 middle).[95]
- *Documents*: The Bifocal Display uses 3D perspective to show broader context around and organization of snippets or full documents, by presenting a readable portion of content in the center and surrounding context in 3D perspective (Figure 46 right two images).[96]

Figure 46. Visualizations ranging from sub-word phonetics to snippets to documents. Copyrights belong to respective authors.

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[94] Alfie Abdul-Rahman, Julie Lein, Katherine Coles, Eamonn Maguire, Miriah Meyer, Martin Wynne, Chris R. Johnson, A. Trefethen, and Min Chen. "Rule-based Visual Mappings–with a Case Study on Poetry Visualization." In *Computer Graphics Forum*, vol. 32, no. 3pt4, pp. 381-390. Blackwell Publishing Ltd, 2013.

[95] Erick Gomez-Nieto, Frizzi San Roman, Paulo Pagliosa, Wallace Casaca, Elias S. Helou, Maria Cristina F. de Oliveira, and Luis Gustavo Nonato. "Similarity preserving snippet-based visualization of web search results." *IEEE Transactions On Visualization And Computer Graphics* 20, no. 3 (2014): 457-470.

[96] Mark D. Apperley, I. Tzavaras, and Robert Spence. "A bifocal display technique for data presentation." In *Proceedings of Eurographics*, vol. 82, pp. 27-43. 1982. See also: https://www.interaction-design.org/literature/book/the-encyclopedia-of-human-computer-interaction-2nd-ed/bifocal-display

There are also interesting experiments not necessarily cataloged in the *Text Visualization Browser* or *SciMaps.org*. Some examples are shown in Figure 47: FatFonts[97] is a specialized font that varies font weight per character such that the ink varies in proportion to the numeric value represented; and TextViewer[98] with variation in size and multicolor underlines. Note that FatFonts typically outperformed comparable color gradients and detail on demand techniques on reading and comparison tasks, particularly for errors rates although speed varied more widely depending on the task.[99]

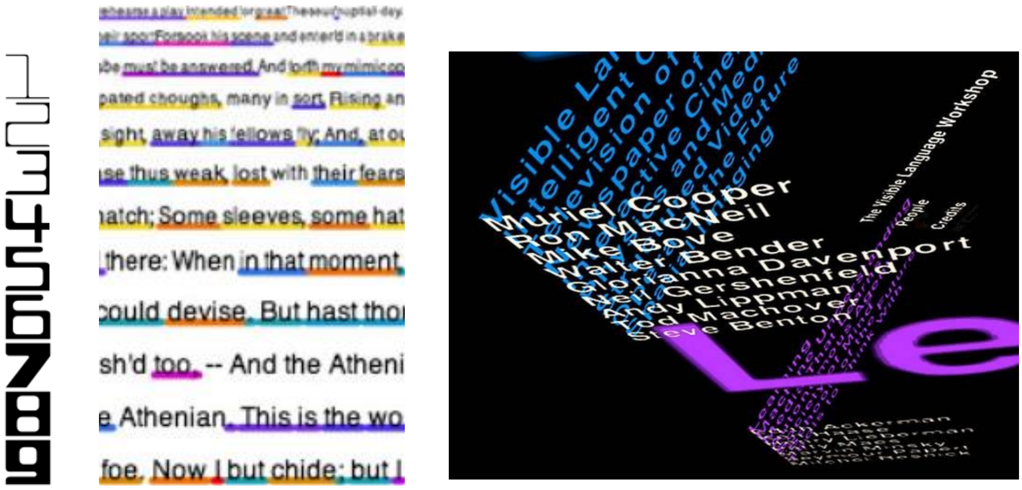

Figure 47. Visualizations using font attributes including, FatFonts, TextViewer and Visible Language Workshop. FatFonts are licensed under a Creative Commons Attribution ShareAlike 3.0 Unported License; and © 2011 Michael Correll, Michael Witmore and Michael Gleicher. Visible Language Workshop image via http://www.grahamfoundation.org/grantees/5014-messages-and-means-muriel-cooper-at-mit-19541994.

In some document visualizations, there are techniques to present both the text of interest and surrounding context such as fisheye representations,[100,101] text highlighting (e.g. keywords in search such as Adobe Reader) and text scaling to increase visibility of keywords.[102,103]

Muriel Cooper's Visible Language Workshop explored interactive 3D typographic workspaces: Small's Talmud[104] project uses a variety of type attributes to create a typographic hierarchy and user interface through combinations of type size, upper/lower case, color, size and font family and raises issues with 3D type.[105]

Wong et al[106] ingeniously scales text forming links in directed graphs to indicate edge direction as shown in Figure 48 left. Maharik's *Digital Micrography*[107] constructs complex images out of lines of tiny readable text, using the even texture of typography to form areas, together with smooth fields and scaling to form clear

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[97] Miguel Nacenta, Uta Hinrichs and Sheelagh Carpendale, "FatFonts: combining the symbolic and visual aspects of numbers." in *Proceedings of the International Working Conference on Advanced Visual Interfaces*, (ACM, 2012) 407–414.
[98] Michael Correll, Michael Witmore and Michael Gleicher, "Exploring Collections of Tagged Text for Literary Scholarship," *Computer Graphics Forum*, vol. 30, issue 3, (Wiley, 2011) 731–740.
[99] Manteau, Constant, Miguel Nacenta, and Michael Mauderer. "Reading small scalar data fields: color scales vs. Detail on Demand vs. FatFonts." In *Proceedings of the 2017 Graphics Interface conference*. Canadian Human-Computer Communications Society, 2017.
[100] Jock Mackinlay, George Robertson, and Stuart Card. "The perspective wall: Detail and context smoothly integrated." In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 173-176). ACM 1991
[101] M. D. Apperley, I, Tzavaras, & R. Spence, A bifocal display technique for data presentation. In *Proceedings of Eurographics* 1982.
[102] A. Stoffel, H. Strobelt, O. Deussen,& D. A. Keim, "Document thumbnails with variable text scaling". In *Computer Graphics Forum*. Blackwell Publishing. June 2012
[103] G. Buchanan & T. Owen, "Improving skim reading for document triage". In *Proceedings of the second international symposium on information interaction in context*. ACM 2008.
[104] David Small. *Talmud project*. http://www.davidsmall.com/portfolio/talmudproject/,1999. accessed 03/22/2014
[105] David Small, Suguru Ishizaki and Muriel Cooper. "Typographic Space", in *Proceedings of CHI 1994*.
[106] Pak Chung Wong, Patrick Mackey, Ken Perrine, James Eagan, Harlan Foote, and Jim Thomas. "Dynamic visualization of graphs with extended labels." In *Information Visualization, 2005. (INFOVIS)*. IEEE Symposium on, pp. 73-80. IEEE, 2005.
[107] Maharik, Ron Israel. "Digital micrography." PhD diss., University of British Columbia, 2011.

boundaries and maintain readability, as shown by the examples in Figure 48 middle. Xu and Kaplan perform *Calligraphic Packing*[108] using shorter texts with greater distortion to form representational images.

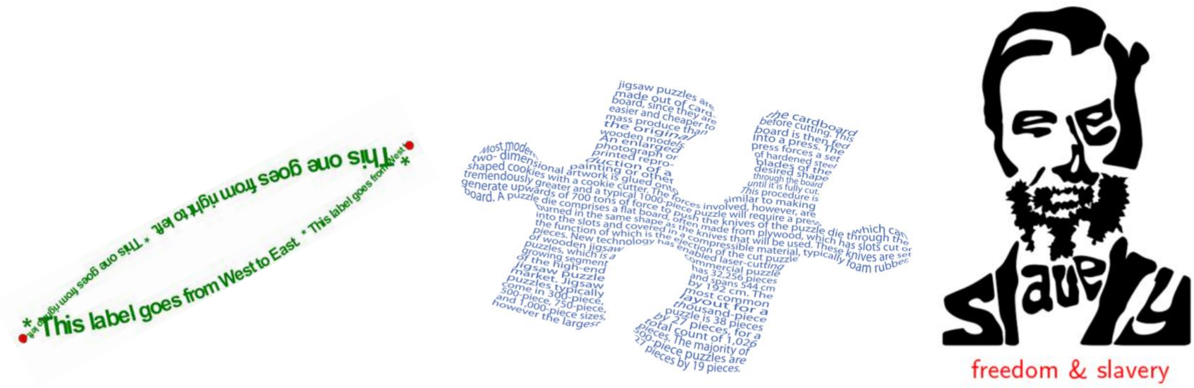

Figure 48. Left: Scaling of text indicates directed edges on a graph. Middle: Digital micrography fits small readable text into complex shapes. Right: Calligraphic packing fits a small amount of text into images.

B:1.5. User Interface Typography Guidelines

User interface (UI) and user experience (UX) guidelines provide recommendations regarding the use of type in user interface design and web design. These guidelines have changed as technology has improved, e.g. increased pixel densities, improved font rendering and wider availability of fonts. Early guidelines (1990's) recommended against italics, weights, small caps due to low resolution.[109] Modern web interface guidelines (e.g. *Fluid Web Typography*[110]) now include recommendations to more broadly use type attributes including type family, weight, italics and capitalization. However, given that higher resolutions are still not pervasive, some modern type experts still recommend against using the more subtle elements of type attributes, for example Bosler (same reference) states:

> *"Serif typefaces do not read well as body copy due to poor pixel resolution, so save the serifs for larger text."*

On the other hand, in the same book, Jason Santa Maria claims advancements in typography in mobile devices:

> *"By the time of iPhone and iPad, people were doing much more high-fidelity work with how they would render a web page."*

Guidelines recommend use of type attributes to create an information hierarchy (i.e. traditional use of type to differentiate between headings, sub-headings, body text, call-outs, bylines, etc.); differentiate among types of interactions; or web specific recommendations (e.g. underlines are a specific convention for indicating hyperlinks).

Interestingly, typographers focused on type design for use on interactive screen have noted the potential for new creative uses of type with higher resolution displays, e.g.:

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[108] Xu, Jie, and Craig S. Kaplan. "Calligraphic packing." In Proceedings of Graphics Interface 2007, pp. 43-50. ACM, 2007.
[109] P. Kahn and K. Lenk. "Principles of typography for user interface design." *Interactions*. New York.. pp 15-29. 1998
[110] J. Teague. *Fluid Web Typography*. New Riders, Berkeley, CA, 2009.

"New devices have such high resolution displays that individual pixels become imperceptibly small… The new devices are radically transforming what is possible in digital visual design." –Aral Balkan[111]

Another use is to increase the rate of reading by changing the presentation of type temporally. For example, rapid serial presentation flashes individual words in sequence for faster reading. This may also include font formats, such as italics. For example, see US patent US 20070061720 A1. Alternatively, setting type in motion can be used to aid speed reading, such as US patent US 8310505 B2, which also may include typographic enhancements (Figure 49).

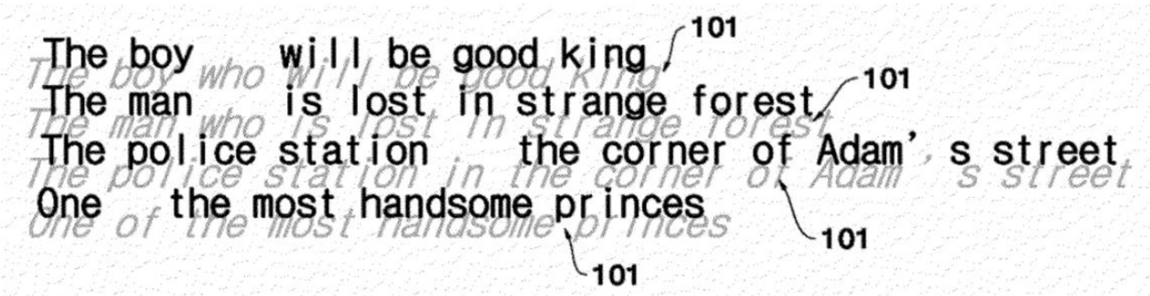

Figure 49. Patent drawing for moving type for a speed reading application. Public domain.

In search interface design it is common to use typographic techniques to differentiate elements in search results. Each matching document is presented with the document's title and associated metadata (e.g. date, author, size) and a portion of the search result (i.e. the *document surrogate*[112]). Each element in the surrogate is formatted with different typographic attributes to aid quick, non-linear access to the elements of interest – similar to the way that a dictionary uses typography to differentiate elements in a definition.

Weaver's search systems[113] expose HTML markup to attributes to the application making various font-attributes available to the interface, e.g. University of Oklahoma Western History Archive Improvise system.

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[111] Aral Balkan, *My Device Runneth Over: Type on Screen by Monotype,* Monotype. Woburn, MA. 2012.
[112] Marti Hearst, *Search User Interfaces,* Cambridge University Press, 2009. http://searchuserinterfaces.com/book/sui_ch5_retrieval_results.html
[113] C. Weaver. Embedding interactive markdown into multifaceted visualization tools. *IUI Workshop on Visual Text Analytics*, 2015.

B:2. Text Extensions to Visualization

The many examples of text and typographic attributes discussed in the preceding section can be organized relative to the encoding portion of the visualization pipeline. The implication is that the use of text in visualization is broader than typographic attributes such as bold or italic. The rich capabilities of text and typography extend each of the dimensions of the visualization design space as shown in Figure 50.

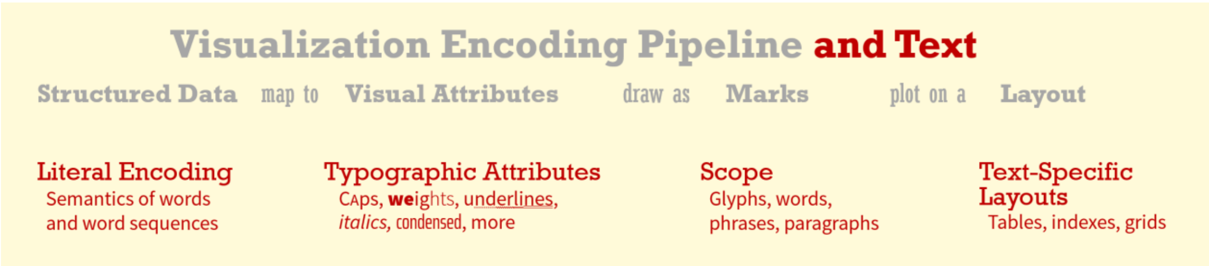

Figure 50: The visualization encoding pipeline, with each step extended with additional typographic capabilities in red. Image by Author.

1. In the first step, literal encoding is a different form of data *not* acknowledged in the traditional visualization pipeline (Figure 5[P9]), although fundamental to the use and effectiveness of any visualization using text, as seen in previous 30 images.
2. At the second step, mapping data to visual attributes, there are many use cases and many examples where typographic attributes such as bold, italics, case, underlines and so on are used to convey data in addition to the literal data of the text (e.g. Figure 14[P25], Figure 18[P28], Figure 30[P35], etc.).
3. At the third step, there are compelling examples where the usage of text units goes beyond the scope of words – down to individual glyphs (e.g. Figure 41[P43]), or extended to phrases and sentences (e.g. Figure 19[P28] - Figure 23[P30]).
4. Finally, other types of layouts become feasible such as tables or grids of text.

B:2.1. Literal Encoding

Literal encodings are unique to text. In most of the prior examples, text is used to literally indicate data: e.g. on a world map a city is represented as text literally identifying the name of the city. However, literal encodings are rarely discussed in visualization: the common design space framework for visualization usually only considers three types of data: nominal (aka categoric), ordered, and quantitative (Figure 5[P9]). Instead of considering text as a different form of data, some researchers consider text as a visual attribute – as shown in the *Table of Visual Attributes* (Table 2[P19]). Some researchers do not identify text in their visual attribute lists at all. There may be different reasons for this. Bertin, for example, does not include text as an encoding, however, Bertin narrowly defined his visual attributes as *retinal variables,* explicitly focusing on low level visual channels into which data is transformed for thematic representations. (Note that Bertin did identify text attributes such as bold, italic and typeface in four pages in an appendix to the original French edition of *Sémiologie Graphique* which was not included in the later English translation – discussed later in *D:1.3.iii*[P218]).

i. Functional Benefits

While literal text does not pop-out preattentively, it offers a variety of functional benefits:

1. **Visualization Purpose**. The goal of a visualization is not necessarily to simply analyze patterns by preattentive visual attributes, such as, a pattern of dots in a scatterplot. Bertin defines other purposes, including communicating key information and organizing a large amount of information. Text is common in historic visualizations that organize large amounts of information, such as maps (e.g. Ordnance Survey maps, Figure 30P35), genealogical charts (e.g. Figure 8P11) or tables (e.g. Periodic table of the elements). It is doubtful that these data-dense visualizations which organize information could function without text.
2. **Text is the primary subject**. Some visualizations are primarily about text. The simplest example is the tag cloud, which could not exist without text as an element within the visualization. Similarly, other visualizations related to text analytics presumably will have a strong need to explicitly represent literal text: extracted entities, topic analysis, sentiment and emotion analytics, keyword analysis, word stemming, ontologies, taxonomies, and so forth.
3. **High number of categories**. Many visual attributes do not support categories of high cardinality. For example, hue is typically limited to 10 or so values (Ware). Texture and/or shape can support more, however, there may be significant design effort required. Brath's *High Category Glyphs in Industry*[114] discusses the relative merits of different types of encodings used for high cardinality categories as used in more than two dozen industrial visualizations. Brath notes text labels can readily support a very high number of different categories and text was most frequently used when more than 30 different categories were encoded. Note that text can either be fully explicit (such as "China, Russia, Japan") or codes (such as "CHN, RUS, JPN"). The effectiveness of a code depends on the viewer's familiarity with the code. Some codes, such as country ISO codes are mnemonic, facilitating decoding even if the user does not know all the codes.
4. **Reduced Design Effort**. While it is feasible that pictographic icons can be quick to decipher, designing effective icons typically requires significant effort by expert graphic designers to create a series of icons which work together.
5. **Unambiguous**. Text literally encodes the specific identification of the item of interest. Icons can potentially be fast and easy to decipher, but they can also be ambiguous. For example, Clarus the dog-cow is an early icon from Macintosh computers considered by some users to be a dog and others to be a cow (e.g. en.wikipedia.org/wiki/Dogcow). Textual glyphs are highly learned and are unambiguous in well-designed fonts.

ii. Perceptual Benefits: Fast, Efficient Identification

In general, many visualization evaluations focus on testing time and errors, such as the rapid perception of the presence of a particular visual attribute. However, real-world user tasks may be much more complex requiring full decoding and comprehension of data. If the goal of a visualization is overall more efficient completion of tasks, then the performance of the entire system must be considered. For example, going beyond detection one

[114] Richard Brath, "High category glyphs in industry." In: *Visualization in Practice at 2015 IEEE Symposium on Information Visualization* (VisWeek 2015). IEEE (2015).

must consider how efficiently a visual representation can be decoded. At the level of active attention focused on reading text the following perceptual benefits are feasible:

6. **Identification by Reading vs. Interaction**. Reading labels is very fast compared to interactions such as tooltips.

   Word recognition is fast: The parallel letter recognition model of words states letters within a word are recognized simultaneously and the letter information is used to recognize the words.[115] The model shows that word perception is extremely fast. The parallel ltteer moedl also how epxalins trasponsed letetrs or wdros can still be read.[116]

   Automatic word recognition is a common explanation for the Stroop effect (wherein it is slow and difficult to name the color of a word as opposed to reading a word naming a color, such as red)[117] which theorizes that reading is an automatic habit which is difficult to voluntarily stop. An alternative explanation is the relative speed of processing model, which hypothesizes that it is faster to read the word than to label the color. Both explanations imply that reading words is fast. More generally, automaticity is the ability to perform a well practiced task with low attentional requirements: the user is unaware that the tasks are occurring, does not need to initiate the tasks, does not have the ability to stop the process and the task has low cognitive load.[118] The implication for text in visualization is that text (particularly a small number of words) will be automatically read and that the cognitive cost of reading the text will be low.

   Interaction is slow: Alternatively, interactions such as tooltips can be used to identify items in a display. Interaction requires additional cognitive effort, as the viewer must also determine their interactive response, engage in motor skills and progressively refine those skills to achieve the target.[119] For example, the use of tooltips requires that the user must formulate a physical task to achieve the identification, requiring the user to accurately move the mouse to a small target requiring effort and constrained by Fitts' law.[120] Zoom and pan with *level of detail* appearance of labels is an alternative approach to showing top level labels. Interactive maps often use this form of interactive labeling. However, zoom-based labelling is rare in visualization, perhaps because of the extra effort to implement zoom; perhaps because zoom does not fit well with some visualization paradigms (e.g. zoom on a parallel coordinates display? Radar plot? Pie chart?); or visualization does not have a set of heurisitics for which labels to turn on/off at different zoom levels, unlike cartography, which has built up heuristics for labelling over centuries. Zoom and pan also requires a sequence of multiple interactions, typically with a zoom followed by pan to recenter the item of interest and then another zoom if the target label has not appeared.

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[115] Kevin Larson, The Science of Word Recognition. ATypI. 2003. https://www.microsoft.com/typography/ctfonts/WordRecognition.aspx accessed 01/17/2017.

[116] Matt Davis, *Aoccdrnig to a rscheearch at Cmabrigde*…, Blog post 30/10/03, url: http://www.mrc-cbu.cam.ac.uk/people/matt.davis/Cmabrigde/

[117] Colin M. MacLeod. "Half a century of research on the Stroop effect: an integrative review." *Psychological bulletin*, 109(2), 1991 163-203.

[118] John A. Bargh. "The Four Hoursemen of Automaticity: Awareness, Intention, Efficiency, and Control in Social Cognition." In *Handbook of Social Congnition.* R> Wyer and T. Srull eds. 1994. 1-40.

[119] Robert Proctor and Kim-Phoung Vu: "Human Information Processing: An Overview for Human Computer Interaction," in *The Human Computer Interaction Handbook*, Andrew Sears and Julie Jacko eds.; Taylor & Francis: New York. 2008.

[120] P. M. Fitts, "The information capacity of the human motor system in controlling the amplitude of movement". *Journal of Experimental Psychology*. 47 (6): 381–391. June 1954. doi:10.1037/h0055392.

7. **Fast Decoding**. In any form of visualization the viewer must both perceive the information of interest and then decode it. When a visualization encodes quantitative data as bar lengths, a viewer can very quickly compare relative bar lengths to estimate a ratio. However, when visually assessing categoric data encoded as discrete instances in a visual attribute (e.g. using color to indicate categories), the viewer needs to recall the mapping between the colors and categories. With text, the viewer can directly decode the item.

   For example, in Figure 51, ten countries are depicted in a scatterplot. On the left, circles indicate country by hue; on the right, country is indicated with an explicit label. To decode the image on the left, the viewer requires both the colored dots and the legend and must cross-reference between the two. In the image on the right, the viewer may be able to directly identify the country based on the label, thereby more quickly decoding the glyph by reducing the need for cross-referencing.

   This is essentially a recognition vs. recall benefit (e.g. Nielsen Norman[121]). Seeing text and recognizing the identity literally expressed (e.g. USA) is easier than seeing some other form of representation (e.g. grey dot) which in turn requires the viewer to recall the relationship between the identity and the representation (e.g. the grey dot is USA).

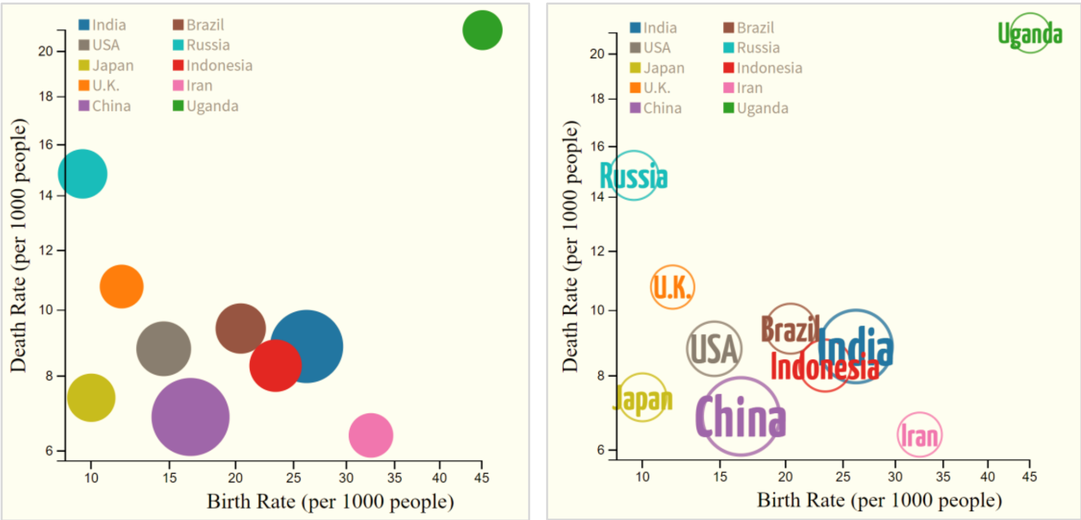

Figure 51: Left: birth and death rate for 10 countries indicated by hue. Right: same plot using labels. Image by Author.

8. **Reduced cognitive load on short term memory**. In addition to faster decoding, tasks reliant on short-term human memory can benefit from explicit text. Short term memory is limited in terms of the number of items that a person can retain, and can benefit if the amount of short-term memory required is reduced.

   For example, a comparison task on Figure 51 may ask "which country has the higher population: Uganda or USA?" Using the left image, the viewer has to first commit "Uganda" to memory, find it in the legend then commit "green" to memory. Then the user needs to find the green dot and remember its position. Then the user needs to repeat the process for USA. Now the user needs to visually compare

[121] R. Budiu, "Memory Recognition and Recall in User Interfaces," Nielsen Norman Group, July 6, 2014. https://www.nngroup.com/articles/recognition-and-recall/

the two dots and decide (e.g. the grey dot is bigger); and then decode "grey" back to "USA" to provide the answer. In the label example on the right, the viewer can read "Uganda" and "USA" directly at the marker. There is no requirement to use color as an intermediary, thereby freeing up short term memory resources.

iii. Perceptual Benefits: Aid to Reasoning

Beyond attention, problem-solving tasks require more cognitive resources to complete more complex tasks. In common visualizations, this may be tasks such as determining the segment in a Venn diagram that corresponds to a particular logical condition, or tracing a path in a network. More complex reasoning can be aided by the appropriate visual representations, as shown with force diagrams, pulley combinations and so forth (e.g. Diagrams conference).

The central idea of the **situation model** is that readers construct mental representations of what they read at multiple levels: 1) surface: words and syntax; 2) propositional content; 3) situation model incorporating and organizing content with respect to world knowledge from memory.[122] An example of a situation model applied to text is a description of items and their spatial relations: the surface is simply the word list; the proposition is the relations and the situation model is a mental construct of spatial layout. A question regarding the spatial relation between two objects can be answered using either the propositional information and a set of logical inferences, or a visual query of the situational model.

Real-world knowledge can also be embedded in the situation model. Prior knowledge associated with label or sentence is available to use: for example, with maps, prior knowledge regarding named places can be used to aid in reasoning tasks, such as preconceptions about birth rates or death rates in countries (Figure 51). This prior knowledge may act as an aid to the viewer, for example, to help the viewer orient themselves to the visualization based on expected relationships and potentially predict and confirm where expected data points may occur, provoke inquiry if there is a mismatch between expectation and the visualization, or assist in the generation of new hypotheses.

Learning and problem-solving tasks have been shown to be improved when textual instructions are directly integrated into diagrams.[123] Other studies in multimedia have shown improved performance when information is provided through both text and images with close spatial positioning and/or linkages between the two.[124] More broadly, Larkin and Simon's findings indicate that diagrammatic representations of content aid problem-solving by:

1) Spatially organizing information together reduces search effort;
2) Grouping related information together reduces need to cross-reference between labels;
3) Visual relationships support perceptual inferences.[125]

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[122] Stephen Payne. "Mental Models in Human-Computer Interaction". In *The Human-Computer Interaction Handbook.* Andrew Sears, Julie Jacko eds. Taylor & Francis: New York. 2008

[123] Paul Chandler and John Sweller, "Cognitive Load Theory and the Format of Instruction" in *Cognition and Instruction*: 8(4) 1991, 293-332. http://ro.uow.edu.au/edupapers/128

[124] Hari Narayanan and M. Hegarty. "Multimedia design for communication of dynamic information" in *International Journal of Human Computer Interaction Studies,*57, pp. 279-315. 2002.

[125] Jill Larkin and Herbert Simon. "Why a diagram is (sometimes) worth ten thousand words." *Cognitive science* 11.1 (1987): 65-100.

Extending Larkin and Simon's findings to text and visualization implies improved performance for text directly integrated into a visualization. Benefits extend across all three of Larkin and Simon's findings:

1) Spatially grouped text items makes it feasible to quickly find the target text of interest. For example, consider alphabetically ordered indices (e.g. the Michelin Guide in Figure 24$_{P31}$), siblings in a genealogical tree (e.g. Figure 8$_{P11}$), or tables of text (examples in *B:2.4. Unique Layouts*$_{P61}$). Local context will be discussed further in *C:1.3. Labels offer local context*$_{P112}$.
2) Text within a visualization element provides immediate identification of the text item as opposed to linking or drill-down. For example, the labelled cities on the map in Figure 30$_{P35}$ provides immediate identification (as opposed to a satellite image), plus additional typographic attributes indicate additional data immediately with respect to the item of focus.
3) Perceptual inferences can be made across collections of labels, such as: density of labels indicate common nodes across classification schemes in the graph by Haeckl in Figure 18$_{P28}$, the alignment of text along paths to form lines and areas (e.g. Figure 35 left$_{P39}$ and Figure 34 right$_{P39}$ respectively), the clustering of lower case letters in the market profile chart indicating higher prices in the morning (Figure 40 right$_{P42}$), greater number of entities in the longer stacks in stem and leaf plots (Figure 42$_{P44}$), scale of text to indicate link direction (Figure 48 right$_{P50}$), and so on.

Visualizations which instead bury detailed text under interactive tooltips, linked visualization components, or in spatially separated paragraphs or legends do not gain in these benefits.

iv. Literal Operations

Quantitative data can be transformed via mathematical and statistical operations: sum, percentage, range, min, max, mean, standard deviation, z-score, etc.; all of which can be visualized as quantitative data as well. Similarly, literal text allows for various textual operations which enhance various uses:

- **Ordering.** Text can be ordered and sorted (alphabetically), facilitating search and lookup.
- **Summarization.** Text can be summarized, meaning that longer texts can be reduced to shorter texts while retaining most of the original meaning.
- **Comparison, similarity and translation.** Text can be compared and assessments made regarding similarity. Tools such as thesauruses and dictionaries aid in understanding similarity. Translation extends comparative analysis to produce and understand equivalent meaning across languages.
- **Tone, opinion, sentiment and emotion.** Text can be evaluated assigned quantitative values, for example, for opinion (e.g. ratings), tone (e.g. news tone in GDELT), sentiment (e.g. score for positive or negative), or emotion (e.g. relative emotion).
- **Categorization and Topic Analysis**. Organization of large texts have followed many different classification schemes and tagging of topics by keywords; such as general purpose classifications (e.g. Dewey, Library of Congress) and domain specific (e.g. ACM, IEEE).
- **Natural Language Processing and Machine Learning:** All of the above techniques are evolving with NLP and machine learning to automate many of the above, plus additional analyses such as n-gram frequency analysis to detect language or determine authorship.

B:2.2. Typographic Visual Attributes

Based on the preceding review of font usage and attributes across domains, the following font attributes are used to encode additional information into text, beyond the primary encoding of the literal text. Table 5 shows a list of typographic attributes with a black X indicating the use of that attribute in various domains. Light grey X's indicate a use of an attribute in a domain, not shown in the thesis, but can be found in other examples, e.g. the use of spacing to create emphasis on one word in a paragraph of blackletter text.

Table 5. **Font Attribute Usage Across Domains**

	Typo-graphy	Carto-graphy	Technical Lettering	Alpha-numeric Charts	Code Editors	UI Design	Visual-ization	Notation Systems
Bold / Weight	X	X		X	X	X	X	X
Italic / Oblique	X	X	X		X	X	X	X
UPPER, lower, SMALLCAPS	X	X	X	X	X	X	X	X
Underline	X	X	X	X	X	X	X	X
S p a c i n g	X	X	X				X	
Condensed/Expanded	X	X	X				X	
Typeface	X	X	X		X	X	X	X
Super/subscript (baseline shift)	X			X			X	X
Symbols (*,!,)	X	X	X	X	X			X
Paired Delimiters "",{}	X		X		X			X

This font attribute list confirms the hypothesis that there are approximately ten font attributes that can be used to encode additional information within text and labels.[126] These attributes will be characterized in the upcoming section: *B:4. Characterization of Type Attributes*P75.

[126] Richard Brath and Ebad Banissi. "The design space of typeface." *Proceedings of the 2014 IEEE Symposium on Information Visualization* (VisWeek 2014). 2014.

B:2.3. Mark Types and Scope of Text

In a traditional visualization framework, there are usually only three types of mark: point, line and area. The point is the fundamental element used in creating a visualization. Sets of points can be:

1) displayed as individual **points**, such as dots, bubbles or icons;
2) connected as **lines** (e.g. in sequence to form a path, or branching to form networks); or
3) formed into **areas** or surfaces.

Each point, line or area may also have many visual attributes, such as hue, brightness, size and shape.

The notion of a single point mark in visualization is considered as an atomic unit (i.e. a glyph[127]). This atomic unit might be configured with multiple constituent parts, such as a background shape, a fill color and a foreground pictograph, each of which may be adjusted to indicate data, e.g. 
. These marks traditionally do not have properties, such as bold, italic, case and so on; are not used in sequences to form sentences; and so forth.

With text, a point mark may reference a different scope of characters. Firstly, in text visualization, a point marker is usually at the level of a single word, such as a word in a tag cloud, or a city name on a map. The overall word can be manipulated with font attributes such as case, weight, bold (e.g. Figure 31 P36). However, each character within a label can be manipulated independently, such as the use of individual characters in the market profile charts (Figure 41 P43); in post-modernists' type manipulation (e.g. see the right image in Figure 25 P32); the use of characters and symbols in mathematical equations and molecular notation (*B:1.3.iii* P44). Similarly, sheet music and pronunciation guides often split apart syllables. Thus, visual attributes can be applied to the full label, or subsets thereof, such as syllables or individual characters.

A line mark is typically a sequence of data points connected as a line: with additional semantics conveyed by the connection of the points. This is analogous to a text phrase, sentence or news headline: a sequence of words having additional semantics when assembled to form a statement.

An area mark is a set of data points forming a closed shape, often with visual attributes associated with the enclosed area, such as fill color or texture. Larger quantities of text are traditionally represented as areas: wrapped rows (or columns) of text filling a larger space. Unlike areas within a visualization, within text there are various conventions for assembling successive groupings of text. For example, text may be assembled into:

- *Books*: paragraphs, chapters, documents and corpus
- *Journals, magazines and newspapers*: paragraphs, articles, issues, volumes
- *Poetry*: lines, stanzas, poems, collections
- *Computer code*: lines, methods, classes, application

Areas can be further differentiated. In some English language legal documents, entire paragraphs may be set in uppercase; spoken text in a novel is set in separate paragraphs denoted with quotation marks; or a block quote in a magazine article may be set non-aligned text in italics or in a different font (as is done for many quotes in this thesis).

[127] Rita Borgo, Johannes Kehrer, David H. Chung, Eamonn Maguire, Robert S. Laramee, Helwig Hauser, Matthew Ward, and Min Chen. "Glyph-based visualization: Foundations, design guidelines, techniques and applications." *Eurographics State of the Art Reports* (2013): 39-63.

From a typographer's perspective, one may consider that the scope of text varies from the level of individual glyphs, to words, to sentences, to paragraphs and documents, and to systems applied across many documents (i.e. a corpus, such as an e-mail corpus or an author's corpus). A summarization of these different types of scope and the relationship to visualization marks is shown in Table 6, for example, glyphs or words can be used as point marks in different applications. The sample column provides a few examples, such as, the use of individual glyphs or the application of formats to a subset of glyphs within a word.

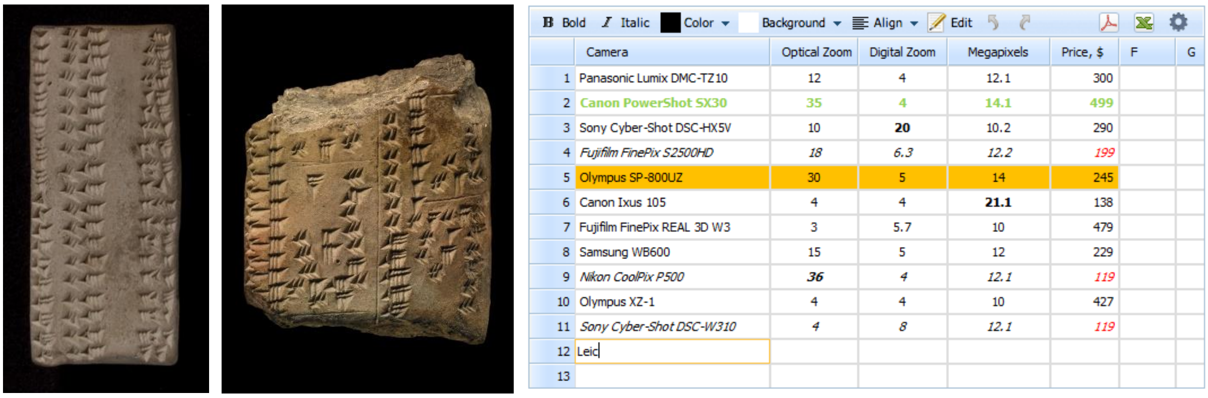
Table 6. **Expansion of Visualization Marks to Address Wider Range of Text Scope**

Viz Mark	Text Scope	Sample
Point	Glyph	**A** B *C* **though** **answer** **Gloucester**
	Word	Abe **Ben** *Cam*
Line	Sentence	*President Obama* nominates *Merrick Garland*.
Area	Paragraph	**Mr Phileas Fogg lived, in 1872, at No. 7, Saville Row, Burlington Gardens,** the house in which **Sheridan died in 1814**. He was one of the most noticeable members of the **Reform Club**, though he seemed always to avoid attracting attention; an **enigmatical personage**, about whom little was known, except that he was a polished man of the world.
	Document	
	Corpus	

B:2.4. Unique Layouts

Closely related to scope of text are unique, text-specific layouts. The layout of long sequential narratives structured with headings and paragraphs is only one type of text-specific layout. There are others, for example:

Tables have existed almost as long as written language, such as the fifth century BC Babylonian multiplication table[128] (Figure 52 left), the 7th century BC Assyrian table of reciprocals[129] (Figure 52 middle), statistical tabulations and timetables (Figure 17P27), calendars (Figure 1 rightP5) or the use of spreadsheets with conditional formats (e.g. Figure 52 right, using color, bold and italics).



	Camera	Optical Zoom	Digital Zoom	Megapixels	Price, $	F	G
1	Panasonic Lumix DMC-TZ10	12	4	12.1	300		
2	**Canon PowerShot SX30**	**35**	**4**	**14.1**	**499**		
3	Sony Cyber-Shot DSC-HX5V	10	**20**	10.2	290		
4	*Fujifilm FinePix S2500HD*	*18*	*6.3*	*12.2*	*199*		
5	Olympus SP-800UZ	30	5	14	245		
6	Canon Ixus 105	4	4	**21.1**	138		
7	Fujifilm FinePix REAL 3D W3	3	5.7	10	479		
8	Samsung WB600	15	5	12	229		
9	*Nikon CoolPix P500*	***36***	*4*	*12.1*	*119*		
10	Olympus XZ-1	4	4	10	427		
11	*Sony Cyber-Shot DSC-W310*	*4*	*8*	*12.1*	*119*		
12	Leic						
13							

Figure 52. Left, center: cuneiform tables on clay tablets. Right: spreadsheet with variety of conditional formats.

Use of tables are not commonly discussed in visualizations, although variants such as heatmaps and adjacency matrices are familiar to visualization researchers. Visualization techniques such as LineUp,[130] and UpSet[131] use tables as the initial starting point for organizing bars, glyphs and connections in grid-based matrices. Stephen Few has published guidelines on the use of visual techniques to create more effective tables.[132]

Tables are also broadly extensible to non-numeric data, such Figure 53 left itemizing medical symptoms and associated drugs using italics and bullets to organize items within table cells.[133] Periodic tables use attributes such as size, color, symbols, font, bold, super/subscripts to organize and differentiate between items in each cell and typically use common position of these items within cells to facilitate comparison across cells (Figure 53 bottom[134]). Various tables "in the wild" can be found mixing typographically enhanced text with visualization elements such as Google, Reuters, Bloomberg or the sample CNBC app in Figure 53 right (using font size, color,

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[128] Late Babylonian multiplication table for thirteen. British Museum #141493, 5th C BC. http://britishmuseum.org/research/collection_online/collection_object_details.aspx?objectId=1589110&partId=1

[129] Assyrian clay tablet containing a table of reciprocals. British Museum K.2069, 7th C BC. http://britishmuseum.org/research/collection_online/collection_object_details.aspx?objectId=311577&partId=1

[130] Samuel Gratzl, Alex Lex, Nils Gehlenborg, Hanspeter Pfister, Marc Streit. "Lineup: Visual analysis of multi-attribute rankings. In *IEEE transactions on visualization and computer graphics*. 2013 Dec; 19(12):2277-86.

[131] Alexander Lex, Nils Gehlenborg, Hendrik Strobelt, Romain Vuillemot, and Hanspeter Pfister. "UpSet: visualization of intersecting sets." *IEEE transactions on visualization and computer graphics* 20, no. 12 (2014): 1983-1992.

[132] Stephen Few, *Show Me the Numbers: Designing Tables and Graphs to Enlighten,* Analytics Press, Oakland CA, 2004.

[133] Tao Hoang, Jixue Liu, Nicole Pratt, Vincent W. Zheng, Kevin C. Chang, Elizabeth Roughead, and Jiuyong Li. "Detecting signals of detrimental prescribing cascades from social media. *Artificial intelligence in medicine* 71 (2016): 43-56.

[134] L. Bruce Railsback, "An Earth Scientist's Periodic Table of the Elements and Their Ions." *Geology,* Geological Society of America, May 2004. http://www.gly.uga.edu/railsback/PT.html

case, italics and bold to differentiate items along with small scale charts). The typographic community has studied tables and variants such as timetables, e.g. see Barman[135] and Kitts.[136]

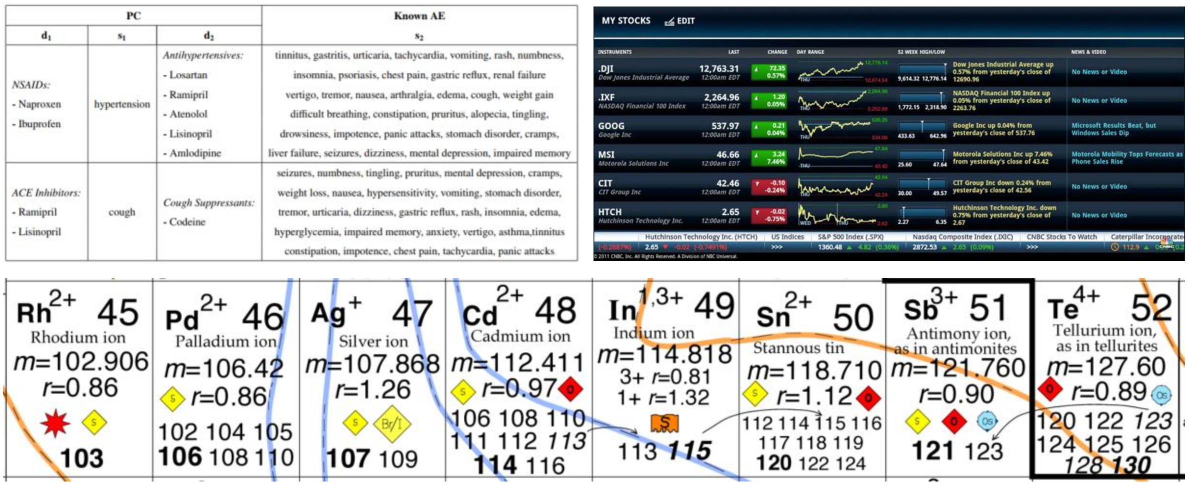

Figure 53. Left: table of symptoms and drugs. Right: Sample table in a stock market application using combinations of text and graphics in cells (this example from CNBC iPad application). Bottom: Subset of a periodic table. Copyright belongs to respective authors.

Lists and order lists and variants thereof (e.g. bullet points, indices, dictionaries) are sequential references, where each item may range from simple (e.g. shopping list) to complex items with many components, potentially separated with tabs (e.g. Tufte's *text-table*[137]). Lists are not suited to tables as some entries may be brief while other entries may be extremely long in comparison, making it difficult to use effectively in a table.

Graphic narratives, such as comics, are layouts with deep integration between text and graphics. Beautiful hand-made information graphics (infographics) integrate paragraphs with complex visual illustrations. Computer-generated visualizations, however, do not have these lines and paragraphs of text integrated directly into the visualization except for a few text visualization techniques such as word trees (e.g. Figure 14P25).

Magazines and websites may layout articles and content in a grid system, with running columns and boxes for core story content, with additional features such as call-out boxes, sidebars and footnotes to draw attention to a specific quote or additional explanation. Multi-column formats, such as broadsheet newspapers, may have contents such as headlines, photographs or illustrations spanning multiple columns.

135 Christian Barman, "Timetable Typography" in *Typography: 5,* Shenval Press, London WC1, 1938
136 Barry Kitts, "Printed Time" in *Octavo,* 86.6.
137 Edward Tufte. *The Visual Display of Quantitative Information.* Graphics Press, 1983. Page 178.

B:3. Considerations for Visual Perception of Text

In addition to the design space which determines how the visualization is constructed; human perception of these attributes must be addressed. One must consider how typography relates to initial perceptual mechanisms frequently discussed in visualization, such as preattentive perception and gestalt perception; and related typographic concepts of legibility, readability and type color. While much visualization perception research focuses on initial perception (typically measured by time and error studies) the higher levels of cognition such as directed attention and reasoning also need to be considered (Figure 54). Furthermore, similar to color which has learned associations in different cultures (e.g. red means stop), text also has learned meanings (e.g. A is typically ordered before B; or "Margaret Thatcher" is a deceased person, was Prime Minister of the U.K. in the 1980's, affiliated with the Conservative party, notable for deregulation, etc.)

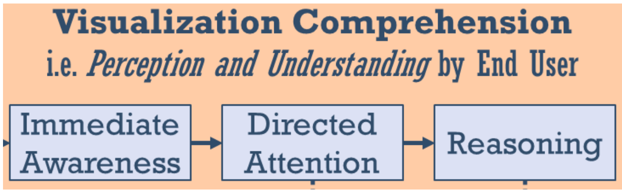

Figure 54. Visualization perception and comprehension. Image by Author.

B:3.1. Immediate Perception: Preattention and Gestalt

Perceptual psychologists and vision researchers have identified different visual channels, such as position, size, intensity, orientation and shape.[138] Each typographic attribute utilizes some combination of these perceptible visual channels. For example, font weight, at a macro-level can be understood to primarily alter the intensity of characters, which it achieves at a micro-level by varying the widths of letter strokes.

Some visual channels can visually pop-out (e.g. Healy and Enns[139]). For example, a red mark in a field of black marks will visually pop-out to the viewer (such as the examples in Figure 9 and Figure 10P12). The pop-out effect is *preattentive perception.* This is a property of the low-level human neurophysical visual system where some visual channels are perceived quickly and accurately regardless of the number of items in the display.

Some visual channels are stronger cues for guiding attention than others (e.g. Wolfe and Horowitz[140]). For example, intensity (luminance) is considered probably preattentive, and line width (size) is considered undoubtedly preattentive by Wolfe and Horowitz. Font weight, which uses both, is highly probable to be highly preattentive. Similar to the psychology perception studies for preattention, a psychology experiment can be constructed to measure which font attributes are stronger cues than others. One such experiment has been completed by Strobelt et al.[141] Figure 55 shows the typographic attributes tested in the left image; and the right image shows the resulting perceptual ranking from their study. The letters c and q indicate the use of the attribute for encoding categoric and quantitative data - for example, color is indicated as usable for categoric and

[138] Semir Zeki, *A Vision of the Brain,* (Boston, MA: Blackwell Scientific Publications, 1993), Pl. 6.
[139] Chris G. Healey and James T. Enns, "Attention and Visual Memory in Visualization and Computer Graphics," in *IEEE Transactions on Visualization and Computer Graphics* 18, 7, (IEEE, 2012): 1170–1188.
[140] Jeremy M. Wolfe and Todd S. Horowitz. "What attributes guide the deployment of visual attention and how do they do it?." *Nature reviews neuroscience* 5.6 (2004): 495-501, see Table 1.
[141] Hendrik Strobelt, Daniela Oelke, Bum Chul Kwon, Tobias Schreck, and Hanspeter Pfister. "Guidelines for Effective Usage of Text Highlighting Techniques." *IEEE transactions on visualization and computer graphics* 22, no. 1 (2016): 489-498.

quantitative encoding, while bold is not identified as useful for either encoding even though many different font weights were readily available in some of the fonts that they tested (e.g. Helvetica). In the ranking table, each typographic variant tested is indicated, with rank indicated A-F.

Technique	Use	Typical variations
Font color	c q	Saturation, luminance, hue
Background color	c q	Saturation, luminance, hue
Underlined	c q	Styles, thicknesses
Font size	- q	% increase
Font style	- -	Italics, subscript,...
Font weight	- -	Font weight
Rectangular border	c q	Styles of border, lines, thickness
Spaced out font	- q	Letter spacing
Text shadow	- -	Offset, intensity,...
Font family	(c) -	Sans-serif, Times, Helvetica,..

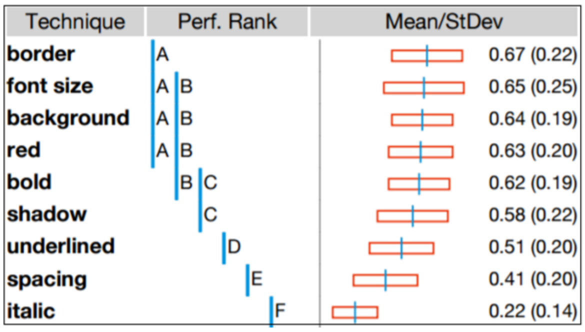

Figure 55. Strobelt et al's test of text highlight and corresponding ranking. Image by Strobelt et al.

The degree of preattention varies with the degree of difference between the target and the distractors.[142] This confounding factor was not considered in the preceding study. For example, the difference between Garamond plain/**bold** is less than Segoe UI plain/**bold,** or light/**black**). The difference between blackletter and Times is greater than Arial and Times. Some type attributes, such as *italic*, are typically designed to be subtle and only noticed in active linear reading: for example, more preattentive italics could be designed with *steeper slopes.*

Legibility and readability are not considered in Stobelt et al's experiment: for example they found that drop-shadows are an effective cue for making text pop-out from surrounding text, but did not consider that the text could be more difficult to decipher and were unaware that typographers recommend against drop-shadows in prose text. Similarly outline boxes around text are a good cue to make text visually stand-out but boxes around prose text will interrupt readability. Without considering legibility or readability, redacted text [redacted] perform [redacted] better than other forms of creating differentiation in a flow of text, but would result in the complete loss of readability which is not measured.

Some visual attributes are more accurate for perceiving magnitude (e.g. see Cleveland and McGill[143]) and the related concept of the number of distinct levels which can be perceived (e.g. see Ware[144]). For example, some channels are effective for encoding quantitative data (e.g. size), while others can only differentiate (e.g. shape). Table 7 shows visual attribute rankings for quantitative, ordered and categoric encoding by various researchers.[145] Note that the rankings generally align between researchers although there are inconsistencies. For example, shape moves from 7th place to 2nd place for categoric data for MacKinlay between 1986 and 2009; Mazza ranks size as not good for categoric encodings while MacEachren ranks size highly for the same use.

[142] David H. Foster and Patrick A. Ward. "Asymmetries in oriented-line detection indicate two orthogonal filters in early vision." Proc. R. Soc. Lond. B 243, no. 1306 (1991): 75-81.
[143] William S. Cleveland and Robert McGill. "Graphical perception: Theory, experimentation, and application to the development of graphical methods." *Journal Of The American Statistical Association* 79, no. 387 (1984): 531-554.
[144] Colin Ware *Information Visualization: Perception for Design,* (Waltham, MA: Morgan Kaufmann, 2013), 130.
[145] **Ber67:** Jacques Bertin, Semiologie Graphique, Gauthier-Villars, Paris, (1967). **Mac86:** Jock MacKinlay. "Automating the design of graphical presentations of relational information." *ACM Transactions on Graphics*, 5(2), 110-141, (1986). **Mac09**: Jock MacKinlay and Kevin Winslow. *Designing Great Visualizations*. Tableau. (2009). **Mac96**: Alan MacEachren, *How Maps Work: Representation, Visualization, and Design*. New York, NY: Guildford Press. 1996. **Maz09**: Riccardo Mazza. *Introduction to Information Visualization*. Springer Science & Business Media (2009).

Table 7. **Visual Attribute Ranking by various researchers.**

Visual Attribute Rankings by Encoding

Showing each researchers' rank and an overall average score (lower is better match)

	QUANTITATIVE						ORDERED						CATEGORICAL					
Visual Attribute: Researcher:	Ber67	Mac86	Mac09	Mac96	Maz09	Avg Score*	Ber67	Mac86	Mac09	Mac96	Maz09	Avg Score*	Ber67	Mac86	Mac09	Mac96	Maz09	Avg Score*
Position	Yes	1	1	good	suitable	1.2	Yes	1	1	good	suitable	1.1	Yes	1	1	good	limited	1.9
Size (inc length, area, volume)	Yes	2	2	good	suitable	1.8	Yes	7	5	good	limited	4.5	no	8	6	good	not	6.9
Angle (inc slope, orientation)	no	3	3	marginal	limited	5.6	no	8	6	marginal	limited	7.4	Yes	9	7	good	not	5.8
Brightness (value, intensity)	no	4	4	marginal	limited	6.2	Yes	2	2	good	suitable	1.7	no	5	4	poor	not	7.4
Color Hue	no	6	6	marginal	not	8.2	no	4	4	marginal	not	6.7	Yes	2	3	good	suitable	1.8
Shape	no	no	no	poor	not	9.0	no	no	no	poor	not	9.0	Yes	7	2	good	suitable	2.5
Texture	no	no		marginal		7.0	Yes	5		marginal		3.9	Yes	3		good		1.7
Saturation		5	5	marginal		6.7		3	3	good		3.0		6	5	poor		7.1
Arrangement†		no		poor	not	9.0		6		poor	not	8.3		4		marginal	not	6.0
Crispness / Resolution				poor						good						poor		
Transparency				poor						good						marginal		
Curvature					limited						limited						not	
Added marks					not						not						suitable	
Numerosity					suitable						suitable						not	
Concavity/Convexity					limited						limited						not	
Flicker					not						not						limited	
Motion					limited						limited						not	

Legend: best 1.0 3.0 5.0 7.0 9.0 worst

* A lower score indicates a better match. Average score based on rankings normalized 1-9, and averaged only if more than one author lists the attribute.

† Arrangement includes connection, containment, and spatial grouping

The column Avg Score aggregates researcher’s rank by converting into a normalized value then averaged. The table can be used to assess a typographic attribute’s appropriateness for encoding a data type. For example, font weight, which varies the stroke *size* of the letters and thus changes the visual *intensity* of the letters, can therefore likely be effective for encoding quantitative or ordered data, as both size and brightness rank highly (on average) in this table. However, font family, using *shape*, can be used for indicating categories but not quantities or ordering. It should also be noted, in most cases, font attributes do not have many distinct levels, limiting their use in any encoding to only a few different data levels.

Beyond the speed of perception of marks, there are other perceptual mechanisms that visualization and typography rely on. **Gestalt** principles, such as similarity, proximity, connectedness, closure and continuity perceptually organize elements within a scene.[146] For example, items which are similar tend to be perceived as a group, such as a set of red dots in field of blue dots in a scatterplot. Parentheses (more broadly paired delimiters) operate on the principles of symmetry and closure – that is symmetric objects (such as each half of a parenthesis) are perceptually grouped; and the concavities associated with brackets imply the enclosure ( ).

146 Dejan Todorovic (2008) Gestalt principles. *Scholarpedia*, 3(12):5345., revision #91314

B:3.2. Type Legibility and Readability

Legibility and readability are of paramount concern to typographers, cartographers and industrial designers.

Legibility is a perception issue concerned with the ability to clearly decipher the individual characters as well as commonalities within a font that increase letter identification.[147] Typographers and psychologists discuss factors at the level of characters (e.g. consistent stroke widths, open counters, wider proportions)[148], between characters (e.g. risk of error, run-together risk, x-height)[149], across a series of letters (e.g. predictability across letters, i.e. font-tuning),[150] and environmental factors such as illumination, distance and use environment (e.g. roadway signage, cockpits).[151] Studies indicate, for example, only 32% of the printed area of uppercase and 24% of lowercase letters are used by observers to identify letters, with letter terminators as the most important cue for letter identification.[152] Poor design choices such as stretching fonts, use of underlines or adding drop shadows can reduce legibility. For example, in Figure 56, the text Arnie and Amie are shown in three different fonts, each with dropshadows - the letter r and n run-together potentially being perceived as m rather than rn.

Figure 56. The letter r followed by n creates a shape very similar to the letter m characterized as "run-together risk". The legibility in this example is further compounded by drop-shadows. Image by Author.

Readability is a comprehension issue concerned with the ease of reading lines and paragraphs of text, and can also be affected by many factors such as line length, kerning, leading, x-height and font weight.[153] In Figure 57, the text is completely legible, but unreadable.

Figure 57. Text can be legible but unreadable, such as this text mirrored and flipped. Image by Author.

Readability is related to cultural conventions. Blackletter fonts are difficult to read for modern readers as they are highly unfamiliar. Gerard Unger says:

> *"Different fonts are not intrinsically more readable: rather it is the readers' familiarity that accounts for legibility and readability. When I designed Swift (typeface) in 1985 it was called hard to read with many angry angles. Now it is the standard used for many newspapers, used in dictionaries, and other major works."*[154]

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147 Thomas Sanocki and Mary C. Dyson. "Letter processing and font information during reading: Beyond distinctiveness, where vision meets design." *Attention, Perception, & Psychophysics* 74, no. 1 (2012): 132-145.
148 Sophie Beier, *Reading Letters, Designing for Legibility,* BIS Publishers (2012): 74-75.
149 Victoria Squire, Friedrich Forssman and Hans Peter Willberg, *Getting it Right with Type: The Dos and Don'ts of Typography*, (London, UK: Lawrence King Publishing, 2006), 31-32.
150 Isabel Gauthier, Alan CN Wong, William G. Hayward, and Olivia S. Cheung. "Font tuning associated with expertise in letter perception." *Perception* 35, no. 4 (2006): 541-559.
151 Jean-Luc Vinot and Sylvie Athenes. "Legible, are you sure?: an experimentation-based typographical design in safety-critical context." In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 2287-2296. ACM, 2012.
152 Jonathan Grainger, Arnaud Rey and Stephane Dufau. "Letter perception: from pixels to pandemonium." *Trends In Cognitive Sciences* 12, no. 10 (2008): 381-387.
153 Walter Tracy, *Letters of Credit: A View of Type Design,* (Jaffrey, New Hampshire: David R. Godine Publisher, 2003): 30-32.
154 Gerard Unger, conversation at University of Reading, Typography Department, 07/26/2016.

Since a visualization programmer has control over choice of font, shadows, spacing, and so on, issues of legibility and readability must be considered.[155] Visualization researchers are unfamiliar with the concepts of legibility and readability: e.g. Strobelt et al's study on text highlighting did not consider the impact of type attributes on the primary encoding of text (i.e. the literal text).

B:3.3. Typographic Color

The use of font-attributes in data visualization can leverage a core principle of typography referred to as color. This is the notion that there is a uniformity of weight, orientation, spacing and so on such that no letter or words should particularly pop-out in a paragraph. If one squints at a page of text, the paragraphs appear as gray blocks[156], as shown in Figure 58.

Figure 58. Blurred text from a typeset book. Words tend to be equally grey, delineated by white space, so that no individual words pop-out. Image by Author.

The even color of type is largely achieved by type designers fine tuning letter form shapes and their spacing. The font designer creates even color by adjusting the letterform shape and spacing between letters and specific letter pairs (e.g. kerning, ligatures) as shown in Figure 59. For example, a C, which is essentially an O with a gap is narrower to account for the lower amount of ink in the C. The letter G, which is similar to the C with an added crossbar, is wider than the C, has a smaller and narrower top to compensate for the extra weight at the bottom. The letter P is not simply the top half of the letter B: the upper portion has a bigger bowl and heavier strokes to compensate.

Figure 59. Typographers adjust letter shapes and widths for similar letters to compensate for the different amount of ink used in the letter. This example is the font Franklin Gothic Heavy. Image created by author, based on diagrams in Willen and Strals.

[155] C. Y. Suen, N. Dumont, M. Dyson, Y.C. Tai, X. Lu. "Evaluation of Fonts for Digital Publishing and Display," *International Conference on Document Analysis and Recognition*, 2011.
[156] Bruce Willen & Nolen Strals. *Lettering & Type: Creating Letters & Designing Typefaces*. Princeton Architectural Press, New York. 2009.

Figure 60 shows other font design techniques to maintain even weight and readability. For example, stems are offset (r) or taper (w) to avoid darker areas in crotches. Midpoints (x,o), may be shifted up so glyphs do not appear visually top heavy. Crossings are offset (x) to increase space and reduce dark areas.

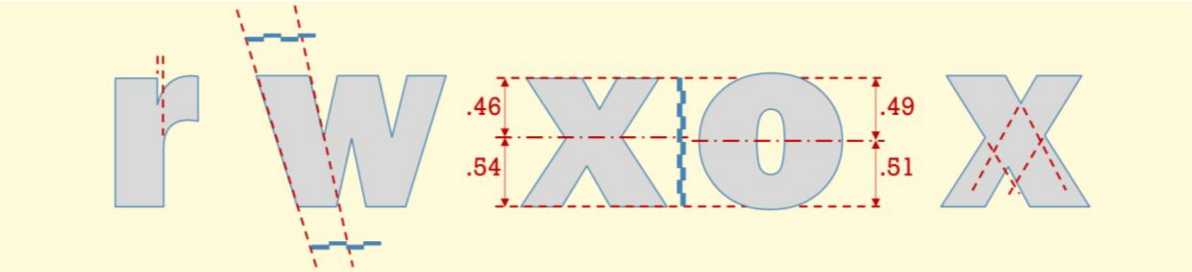

Figure 60. To maintain even weight and readability, many font design techniques are used such as offset and tapered stems, shifted midpoints and crossings. Font Franklin Gothic Heavy. Image created by author.

In addition to letter form shapes, kerning is the adjustment of spacing between letter pairs so that a consistent amount of white space occurs between letters. Most software can automatically adjust kerning, but various configurations and rules may not use the feature. Figure 61 left shows letters in signage where kerning is not available: even the non-typographer should be able to see the much larger gap between the VA compared to other letters in the image. In the middle and right images, kerning is automatic: note how the end of the V at the top right placed further right than the leftmost bottom of the A. AT are similarly kerned.

Figure 61. Kerning maintains consistent whitespace between letter pairs. Left image has no kerning – note large gap between VA, while right images have automated kerning. Images by author.

Similar discussions occur regarding consistency of other features in a font. The shape of a serif or the slope of a stem or other typographic details will be explicitly designed with respect to the overall type family. Willen and Strals provide a small example of successive refinements made to remove any anomalies (page 122).[157] This attention to detail provides both an even color as well as predictability across characters (i.e. font-tuning), which creates easier readability.

As a result, with an even weight across a field of type using the same font, the viewer does not perceive any particular letters standing out. It is precisely this idea of even color that creates a baseline from which font-attributes can be manipulated, such as underlines, bold, subscripts, to standout and be different from the rest of the text, creating a preattentive effect.

[157] Bruce Willen and Nolen Strals, *Lettering & Type,* Princeton Architectural Press: New York. 2009.

B:3.4. Directed Attention and Reasoning

Directed attention and reasoning were explicitly discussed in *B:2.1 Literal Encoding*P52. It itemized the benefits as:

1) fast word recognition (vs. slow interaction);
2) fast decoding (by reducing cross-referencing);
3) reduced cognitive load (by reducing reliance on short term memory);
4) a situation model constructed out of relations expressed in the text;
5) real world contextual information in the situation model which may be used as an aid to understanding the visualization; and
6) integrated text and visuals can aid problem solving tasks.

B:3.5. Text Semantics

Semantic content is added to text when words are combined in sequences. Consider the following sentences:

- **Jack and Jill went up the hill.**
- **Humpty Dumpty sat on a wall.**
- **The Owl and the Pussycat went to sea.**

Text, when processed into a "bag of words", loses the semantic content of the word sequence. These short sentences have meaning beyond the collection of words. Jack, Jill and Humpty all have height and can fall. Jack, Jill, the Owl and the Cat all went somewhere, Humpty did not.

Analytic and visualization approaches need to consider applications where a broader context of word sequence is maintained. Search user interfaces have evolved significantly beyond simple keywords and document metadata to include contextual titles, phrases and sentences in search results (e.g. Hearst, section 5[158]). Studies have shown superior performance for results containing text snippets.[159] Interestingly, the length of snippet should be proportional to the task. In navigation search tasks where the user is seeking a target document, short snippets allow more results to be displayed on a page (which aids finding the target without scrolling), whereas in informational tasks where the user is seeking to gain knowledge without regarding to the specific target document, long snippets provide greater context.[160]

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[158] Marti Hearst. *Search user interfaces*. Cambridge University Press, 2009.

[159] Charles LA Clarke, Eugene Agichtein, Susan Dumais, and Ryen W. White. "The influence of caption features on clickthrough patterns in web search." In *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*, pp. 135-142. ACM, 2007.

[160] Edward Cutrell and Zhiwei Guan. "What are you looking for?: an eye-tracking study of information usage in web search." In Proceedings of the SIGCHI conference on Human factors in computing systems, pp. 407-416. ACM, 2007.

B:3.6. Semantic Typography

Semantic composition[161] is the deliberate layout of text and choice of font to reflect the semantic content. In *The Destruction of Syntax* (1913), futurist poet Marinetti says:

> *"On the same page, therefore, we will use three or four colors of ink, or even twenty different typefaces if necessary. For example: italics for a series of similar or swift sensations, boldface for the violent onomatopoeias, and so on. With this typographical revolution and this multicolored variety in the letters I mean to redouble the expressive force of words."*[162]

Apollinaire uses typography and layout in the poems in *Calligrammes*[163] to convey meaning as well as words (Figure 62). Post-modernists, as shown earlier in Figure 25P32, also manipulated type for semantic reasons. Typographic design education typically contains exercises for students to typographically set nouns, emotive or action words (e.g. sink, swim, water, happy), which in turn, these techniques may be used in advertising.

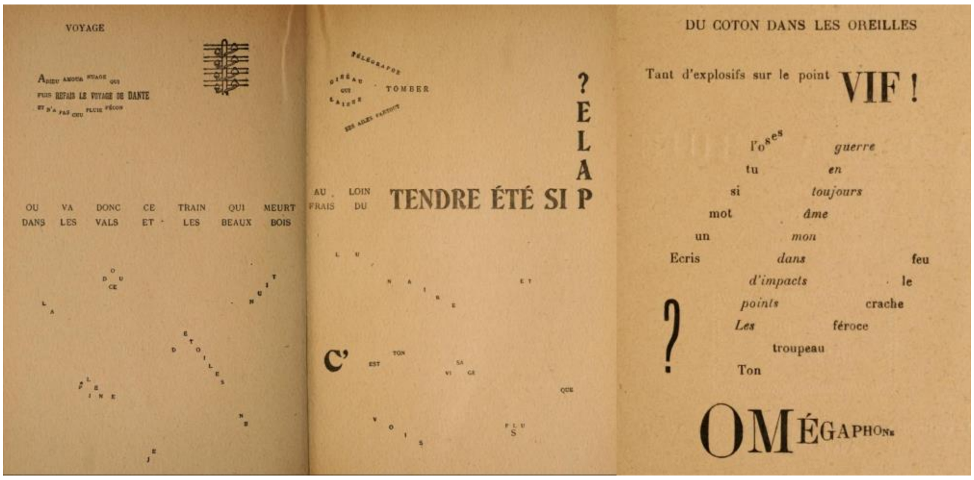

Figure 62. Example poems from *Calligrammes* (1918) wherein type is varied based on the semantics.

Type Character: Font families are often described with different adjectives and properties. Type designers point out that all typefaces contain semantic bias: every font has different emotive qualities associated with it. The most famous example is Comic Sans for changing the *voice* of any text written with it to imply the text is casual and informal. Blackletter may be associated with the medieval period or heavy metal bands. And Arial may be associated with being a plain, boring corporate font.

> *"There is no silver bullet for getting the voice right. It's more that you need to be aware that you're adding a voice to whatever you're building." – Aral Balkan*

Similarly, comics and manga have developed typographic conventions to convey semantic information in text bubbles and overlays for sound effects, such as small letters for whispering, drippy letters for sarcasm, rising baseline for rising voice, squiggly text for gasping and so on (Figure 63).

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[161] Peter Mayer, "Semantic Composition" in *Octavo* 86.2

[162] Filippo Tommaso Marinetti, "The Destruction of Syntax", *Lacerba*, (Florence, June 15, 1913): http://www.unknown.nu/futurism/destruction.html (accessed April 28, 2016).

[163] Guillaume Apollinaire, *Calligrammes* (Paris: Mercure De France, 1918) page 58 and 167. http://archive.org/stream/calligrammespo00apol#page/166/mode/2up (accessed April 26, 2016).

Figure 63. Example images from *Captain Courageous Comics*[164] with rising baseline, squiggly letters, underline, large sound effects words, script font for interstitials, and bold with italic for emphasis.

B:3.7. Language

Visualizations are used around the world. While many of the historic examples shown so far have focused on Latin-based languages (specifically with many examples in English), similar examples can be found in almost any language. For example, even the medieval English manuscripts mixing text and visualizations shown in Figure 1P5 have similar examples integrating text directly into visualization layouts in other languages. Figure 64 shows historic Arabic manuscripts from the Timbuktu Manuscripts project, a collection of largely unstudied and uncatalogued manuscripts. The number of manuscripts is unknown: only 160 are digitized at the *Mamma Haidara Library* in Timbuktu.[165]

Figure 64. Timbuktu Manuscripts ~ 13th century, weaving text directly into radial charts, tables and grids. Image https://en.wikipedia.org/wiki/Timbuktu_Manuscripts.

[164] *Captain Courageous Comics*, March 1942 No. 6 (New York: Periodical House, 1942) pg 14, 19 http://digitalcomicmuseum.com/preview/index.php?did=18084&page=14 (accessed April 27, 2016).
[165] The Tombouctou Manuscripts Project: http://www.tombouctoumanuscripts.org/

Unlike other visualization encodings, alphanumeric glyphs encode data relative to a particular language. Different languages may have different glyphs or variants. These glyphs are generally orderable although the order may only be known to a person familiar with the language. Glyphs may vary in shape positionally, for example, when used as the lead character or last character in a word (Figure 65 left). There can be complex characters, multi-level characters and baseline jumps. Glyphs, when combined in sequence, may have ligatures joining separate glyphs together, or even rules for combining glyphs together into compound glyphs, thereby making it difficult to apply a format to only a subset of letters in word (e.g. Figure 65 middle and right). Some joined letters may become very tall in some scripts requiring spacing adjustments in surrounding lines of text.

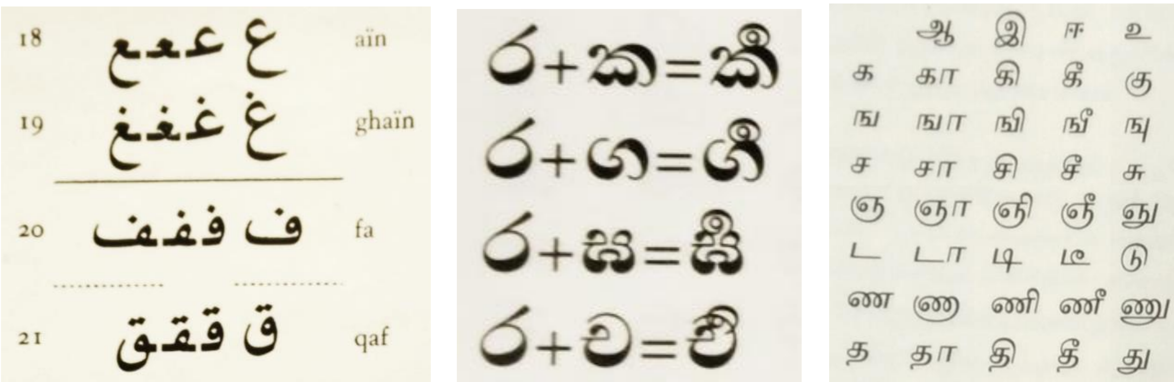

Figure 65. Example of glyph variants. Left: Arabic glyph variants depending on position of glyph within word. Middle: Examples of glyph combinations forming new glyphs in the script Sinhala. Right: Small portion of a ligature table showing combinations for consonants (left column) and vowels (top row) in Tamil. Images courtesy Fiona Ross, Department of Typography & Graphic Communication, University of Reading.

Font attributes may not be available in all languages. Uppercase, lowercase and small caps are not available in many Asian languages. For some less common languages, there may be very few fonts available to computer systems, (e.g. Cree, a language of northern native Canadians with unique characters, for example: ᐊᕕᒋᖠ), and therefore many of the font attributes identified simply do not exist in any available electronic font definition for that language (e.g. multiple weights, multiple widths, etc.). In discussion with Dr. Fiona Ross at University of Reading Typography Department,[166] it was noted that:

- Some Asian languages such as Bengali only have a handful of computer-based fonts – each with only a single variant (i.e. no bold, no italic, very few typefaces), however, there are many typographic attributes utilized in hand-painted signs.
- Underlines don’t exist in fonts for many languages.
- Uppercase doesn’t exist in most languages – there are many unicase scripts including Arabic and all the Brahmic-derived scripts.
- Condensed/extended don’t exist in fonts for many languages.

From an encoding perspective, some examples shown thus far include encoding information at the level of individual characters within words. For eastern languages (e.g. Chinese, Japanese) where a single glyph represents an entire word, this form of encoding is not available. Similarly, for eastern languages a line of 60

[166] Fiona Ross, conversation on 07/25/2016 at University of Reading, Department of Typography.

glyphs may represent far more words than a similar line of glyphs in a western language: encoding data onto words or a line of text may represent additional opportunities.

While Latin-based languages are oriented left-to-right, other languages can be right-to-left (e.g. Arabic, Hebrew) or vertically oriented (Japanese). Even for Latin-based languages, there can be language-based variations, for example, as Finnish words tend to be longer than other languages, thus paragraphs tend to be set wider in Finnish (conversation with Gerard Unger). More generally, each language will have different character frequencies, resulting in different texture and color of a page of text when set in different languages.

B:3.8. Text, Visualization and Interaction

This thesis is primarily focused on the direct depiction of text in visualization and not on interactive techniques. However, given the many differences of text compared to other text, the use of text in visualization implies potential new interaction techniques.

Text search is a highly familiar interaction and is enabled by default on most browsers. Web-based visualizations created in a technology that retains text in the browser (such as HTML, SVG or D3) automatically support browser-based search, thereby highlighting the literal search term. Term highlighting is a related, useful interaction. Audio-based techniques, such as speech recognition are an alternative input means which could support text search.

Web browsers have also familiarized users with hyperlinks. That is, hover on text for tooltips, and click (or tap) on text for either pop-ups or opening new documents are interactions that most users would find intuitive. Indicating whether text is a hyperlink or not is typically indicated by some font variation – originally text underlines in the 1990's but now other variations such as color or bold may be used to indicate the presence of hyperlinks. Note that in user-focused systems, such as a file browser, click variations such as click and hold may also be used as a point of access to rename a document, and the approach could be used to allow for in-place editing and enhancement of text: e.g. rename by typing, or changing data attributes by changing formats, such as ctrl-b to bold, ctrl-u to underline, ctrl-i for italics and so on.

Because text is orderable, interactions such as sorting can be applied. In tables, grouping is also a common interaction, assuming some categories, tags or hierarchy is available.

Advanced text analytics, such as topic analysis, sentiment analysis, entity recognition, opinion analysis is typically done non-interactively today, but with fast computing and appropriate visualization techniques, these could be done interactively. For example, the text analysis and visualization application ANNIS provides for interactive queries, rich text annotations and visualizations.[167]

[167] Thomas Krause and Amir Zeldes: "ANNIS3: A new architecture for generic corpus query and visualization." in: *Digital Scholarship in the Humanities* 2016 (31). http://dsh.oxfordjournals.org/content/31/1/118

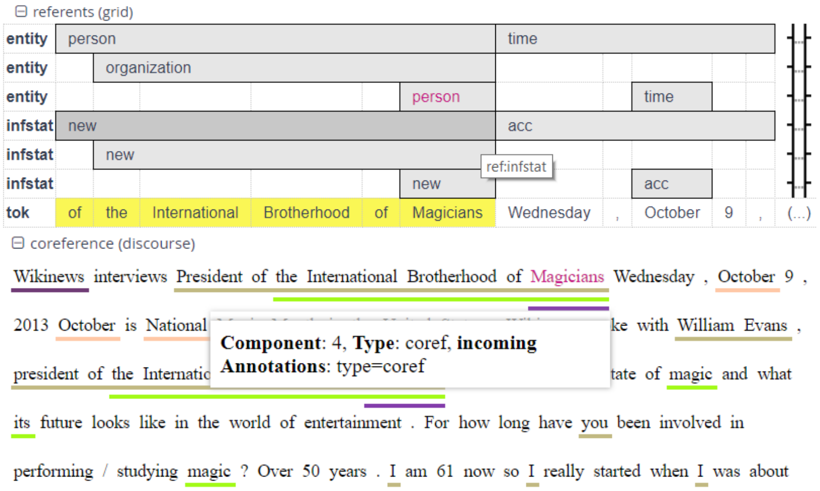

Figure 66. Example interactive visualization on conjunction with snippets of text from ANNIS, a search visualization environment for interaction with annotated information structure. Image via https://corpling.uis.georgetown.edu/annis/#_c=R1VN .

Speech-based interfaces are becoming more common for routine tasks (e.g. Siri, Alexa). Speculatively, text in visualizations can be easily converted into speech in potentially novel interactions. These interactions are beyond the scope of this thesis and are a potential area for future researchers.

B:3.9. Future Work: Extended Evaluation Techniques

As outlined in this section, there are many unique considerations for effective perception and understanding of text, different from typical visualization considerations. This implies that future testing and evaluation will need to evolve to consider effects of legibility, readability, typographic color, directed attentions, semantics of text, semantic typography, language and unique text interactions. The evaluation section (*PART D*) introduces two evaluation techniques novel to visualization, however, this section implies that there are many other kinds of evaluation to consider.

B:4. Characterization of Type Attributes

Each kind of typographic attribute has different qualities and conventions. Each of these can be characterized based on the guidelines from the various fields. For example, cartographers differentiate which typographic attributes are relevant to encoding quantitative values (e.g. weight, case) versus categoric values (e.g. font family, spacing).[168] Similarly, Baecker and Marcus provided detailed analysis of each typographic attribute relevant to the formatting of software source code. In typography, one can find fonts where attributes have a range of values.

B:4.1. Alphanumeric Glyphs

The individual glyphs that are used as part of an alphabetic or numeric system have several unique properties compared to other types of glyphs such as abstract geometry (such as circles, stars, squares) or icons (pictographs e.g. apple, cat, dog):

- **Literal**. As discussed in *B:2.1 Literal Encoding*P52, alphabetic glyphs can be combined to form words. As words, elements can be unambiguously, literally identified. There are hundreds of thousands of unique words that can be utilized as labels, whereas it can be much more difficult to define a high number of recognizable and uniquely identifiable icons or abstract geometry.[169]
- **Ordered Sets**. Alphanumeric glyphs have defined, well understood ordering, e.g. A,B,C,..X,Y,Z. Furthermore, there are different sets of ordered glyphs, such as different language alphabets, e.g. Latin, Greek, Cyrillic, Arabic, Hebrew, Katakana, etc. (e.g. A,B,C…; α,β,γ,…; а,б,в,г,…; ا,ب,ج,د...; א,ב,ג...; あ い う え お…) and numeric symbols e.g. Arabic, Roman, Chinese, Devanagari (1,2,3…; i,ii,iii,iv…; 一二三四五六…; १२३४५...). Ordering can be useful in many kinds of visualization techniques, for example:
    - *Table*. In a tabular layout, alphanumerics can be used to sort a column.
    - *Parallel Coordinates*. Similarly, a column of categorical data in a parallel coordinate display can be sorted alphabetically to facilitate finding and identifying an item.
    - *Hierarchical Layouts*. Some types of visualizations, such as treemaps[170] and sunburst charts[171], depict hierarchies with defined layout rules between parent and child. However, the layout between siblings may not be defined. For example, the convention for treemaps is to sort siblings largest to smallest with a recursive layout. This has documented issues, such as the relative location of siblings will change as the data changes, making it more difficult to utilize spatial memory when revisiting the visualization periodically. However, the siblings can be sorted alphabetically: size and color will still be as salient as before, but locating specific items can be faster because they will be in a consistent alphabetic order.
    - *Alphanumeric Charts*. Stem and leaf plots and related plots such as market profile charts, can order items alphabetically to aid perception of some patterns.

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[168] John Krygier, *Making Maps: A Visual Guide to Map Design for GIS*, NY, NY: Guildford Press, 2005.
[169] R. Brath. "High Category Glyphs in Industry", In Visualization in Practice at IEEE VisWeek 2015. 2015.
[170] Brian Johnson, and Ben Shneiderman. "Tree-maps: A space-filling approach to the visualization of hierarchical information structures." In *Visualization'91, Proceedings., IEEE Conference* on, pp. 284-291. IEEE, 1991.
[171] John Stasko, Richard Catrambone, Mark Guzdial, and Kevin McDonald. "An evaluation of space-filling information visualizations for depicting hierarchical structures." *International journal of human-computer studies* 53, no. 5 (2000): 663-694.

- *Legend*. A legend of generic glyphs needs to be organized by a visual attribute such as color or shape. A legend of alphanumic glyphs can be organized alphabetically, which facilitates rapid access.
- *Filters*. Similarly, alphanumerics can be listed in order in a filter component, such as a drop-down menu or scrollable side panel, for rapid access.

Perception and alphanumeric glyphs

Alphanumeric glyphs utilize the visual channel of shape. A well designed font will not have weight variation across a sequence of characters, so shape is the primary visual channel indicating differentiation. Some alphanumeric glyphs have been tested by psychologists for preattentive response, such as a C in the midst of O's or an L in the midst of T's, e.g. Healey and Enns[172]. However, this is not generalizable across all the characters of the Latin alphabet: Wolfe and Horowitz[173] are inclined to consider a preattentive response doubtful:

> *"One suspects that most of the evidence for letter identity and alphanumeric category reflects our inability to adequately define shape."*

Sequences of alphanumeric glyphs can be combined to create words which may be perceived quickly although not pre-attentitvely. There is a hypothesis regarding our abilities to perceive whole words automatically. Proponents suggest that we recognize the shape of words set in lower case font by recognizing patterns of ascenders and descenders. This has largely been discredited through experimentation.[174] The implications for visualization design is that individual words read extremely quickly, while lines of text require active reading which does not occur preattentively.

B:4.2. Symbols and Punctuation

Symbols and punctuation marks, such as !@#$%^&*|:?€£§ are conceptually much closer to glyphs and shapes as opposed to alphanumerics. Symbols may be ambiguous (e.g. * may be referred to as star or asterisk) and do not have any explicit well-known ordering. Punctuation increases readability, but may vary or not be available in some languages.

Symbols may be added to a string of text to denote specific operator, such as the ampersand in the middle of an email address. The use of symbols within strings has become more prevalent with social media such as #hashtags, @replies and so forth. Similarly, from a visualization perspective, symbols can be inserted into a string of text to refer to a particular quantity or category, such as the example shown in Figure 67. Indication of lengths via inserted symbols or other formats will be discussed in more detail in *C:8 – Quantitative Sentences*P193.

The midpoint of this string is |indicated with a vertical line.

Figure 67. An inserted symbol indicates data in relation to the overall string length. Image by Author.

[172] Christopher G., Healey and James T. Enns. "Attention and Visual Memory in Visualization and Computer Graphics." in IEEE Transactions on Visualization and Computer Graphics, Vol 18, No. 7, July 2012. 1170-1188.
[173] Jeremy M. Wolfe and Todd S. Horowitz. "What attributes guide the deployment of visual attention and how do they do it?." Nature reviews neuroscience 5.6 (2004): 495-501,
[174] Kevin Larson, *The Science of Word Recognition.* Advanced Reading Technology, Microsoft. https://www.microsoft.com/typography/ctfonts/wordrecognition.aspx

B:4.3. Bold and Font Weight

Text weight is a very strong cue for differentiation. Traditionally, with word processors on computers there are only two levels, **bold** or plain. But many fonts are designed with a wider range of weights: the highly popular font Univers has 9 levels of weight, the freely available font Source Sans Pro has 6 weights.

Bold originated during the industrial revolution with the need to create strong differentiation in text for early advertising.[175] In domains where bold does not exist, techniques have evolved to create bold fonts, e.g. with manual typewriters, a user can backspace over previous characters and repeat the same characters to double the amount of ink to create a bolder font. On blackboards, mathematicians create a bold font by doubling the vertical strokes with offsets that became known as blackboard bold (e.g. see LaTeX or extensive font families such as Segoe UI).

Not the same as brightness. Font weight and brightness both vary the intensity of letters. However, brightness will not be as effective: legibility of a font is related to the contrast between the font and the background (e.g. Robinson[176]), as can be seen in Figure 68.

Figure 68. Brightness is not the same as font weight: legibility remains higher using font weight. Image by Author.

Font weight, stroke width and character width. Font weight cannot be modified by changing the stroke thickness around the perimeter of a font – this will reduce legibility as bowls fill in, gaps between letters become too small, etc. A type designer will carefully design weights:

> *"Compensate of added heaviness by increasing tapers where strokes meet while maintaining similar curves, structure and height to ensure that the weight speak the same language as the rest of type family."*[177]

The left column in Figure 69 is *Arial* where stroke width around letters has been modified but letters have reduced legibility as they break apart at lightweights (e.g. m), touch each other at heavy weights and bowls are filled in (e.g. e).

Figure 69. Fonts with 6 levels of weight. Far left is Arial incorrectly weighted by adjusting the stroke thickness around the perimeter of the letters, thereby reducing legibility. Segoe UI is a font with many weights, as with most fonts, string length increases with increased weight. A few fonts are designed to maintain string length across different weights, e.g. fixed-width fonts and Thesis Pro. First three columns by author, final column from lucasfonts.com.

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[175] Michael Twyman,. "The bold idea: The use of bold-looking types in the nineteenth century." *Journal of the Printing Historical Society* 22 (1993): 107-143.

[176] Arthur Robinson, *The Look of Maps*. University of Wisconsin Press. 1952.

[177] Bruce Willen and Nolen Strals. Lettering & Type: Creating Letters & Designing Typefaces. Princeton Architectural Press, New York. 2009.

Changing the weight of the text will change the character width and thus string length in most proportional font families (Figure 69 column 2). If it is important to align strings, track the length of a string, or superimpose text, then, either: a) the variable length needs to be measured; b) use a fixed width font which has been designed to offer a variety of weights, such as *Source Code Pro* (Figure 69 column 3); or c) use a proportional font designed to maintain consistent lengths across weights, such *Thesis Pro* (Figure 69 column 4, www.lucasfonts.com). Consistent widths across weights may have applications such as superimposition (Figure 70), e.g. to compare keyword counts from different sources.

Figure 70. Different weights can be superimposed when weights maintain consistent length. Image created by author.

The amount of black associated with successive weights in a font family tends to be logarithmic, e.g. *Segoe UI* comes in 5 weights and the amount of ink associated with each level is as follows:

Light	12.9
Semilight	16.5
Regular	20.0
Semibold	**25.9**
Black	**39.2**

Figure 71. Ratio of ink to total space for font family Segoe UI (i.e. mean darkness). Image created by author.

Perception and font weight. Baecker and Marcus (e.g. *Human Factors and Typography for More Readable Programs*) used a variety of font attributes in their formatting of computer code. Constrained to laser printers in the late 1980's, their recommendations include limiting text to only two weights and used sparingly to emphasize individual words and phrases, such as key elements in a program such as function definitions, global variables and warning comments. In cartography, Krygier (*Making Maps: A Visual Guide to Map Design for GIS*) points out:

> *"Type weight variations imply ordered (quantitative) differences: Bolder implies more, lighter weight implies less."*

National Geographic's cartographic fonts include a few styles with at least three weights (e.g. font number 12 in Figure 33P37). In typography, bold is well understood as a means to create emphasis. Craig (*Designing with type: the essential guide to typography*) says:

> *"Bold is a thicker, heavier version of a typeface, typically used for increased emphasis. Next to italics, bold type is most widely used for emphasis. It is difficult to ignore words set in bold type!"*

Perceptually, font weight utilizes the visual channels of intensity and size, both of which are considered highly ranked visual attributes such as Cleveland or MacKinlay. 1) At a macro-level, the overall density of ink changes with different weights, effectively a change in intensity. 2) At a micro-level weight can be considered to be line thickness over the alphanumeric glyph's spine (see Lupton[178]) albeit with additional design enhancements to improve legibility such as tapering. Given the high ranking of intensity and size on most rankings of visual attributes (e.g. Bertin, Cleveland or Mackinlay), font weight is likely to be highly effective among font attributes.

In data visualization, font weight can be used in many different ways. A simple use is binary: differentiation between two different classes of information. However, as implied by cartographers, font weight can be used to encode ordered or quantitative data for a few levels.

Visualization example with weight encoding quantitative data: Font weight can be used to represent a few levels of ordered data or quantitative data, depending on the size of the text. A visualization using five levels of font weight with 9 point Segoe UI was presented to 40 people (Figure 72). All people could clearly perceive three distinct weights, with the majority of people being able to distinguish four weights. Only a few people were clearly able to see the all five weights at 9 point (hint: look near the bottom).

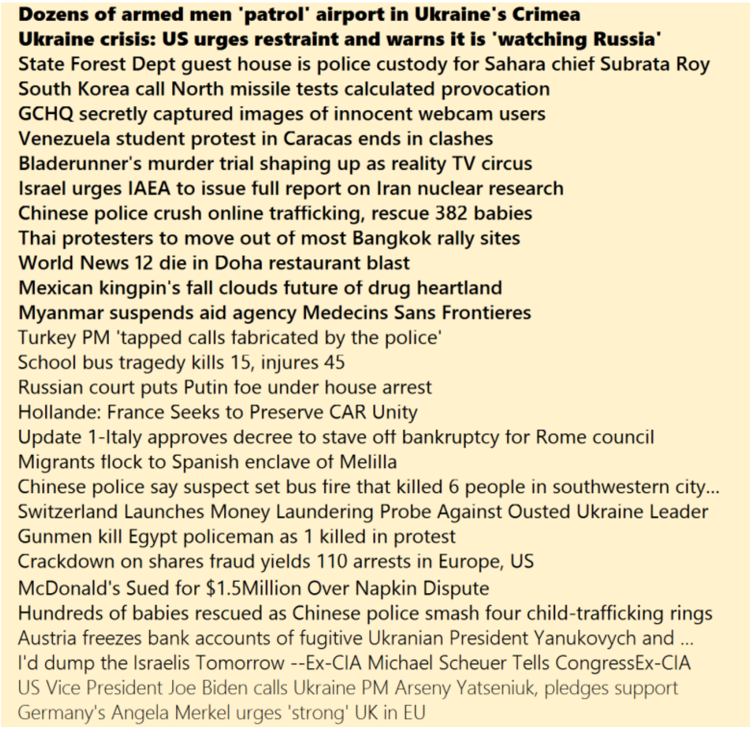

Figure 72. News headlines with the number of related articles encoded as five levels of font weight. Note that weight is proportional to normalized (log(numarticles)), with 0-.2 for light, .2-.4 for semi semilight, and so on. Image created by author based on dataset from Google news displayed on newsmap.jp.

[178] Ellen Lupton, *Thinking with Type*. Princeton Architectural Press, 2004.

B:4.4. Italics and Obliques

Italics and obliques are similar but slightly different font attributes. Both adjust the slope of the vertical axis of text. Obliques are sloped fonts made by geometrically skewing a font (e.g. Arial, Figure 73 top) while true italics are sloped fonts that have different letter shapes than their roman counterparts (e.g. Figure 73 Garamond) – e.g. note the different letter forms between: a, *a*; f, *f*; or g, *g*. Most sans serif fonts use obliques, although some create greater variation with italics (e.g. Figure 73 Segoe UI – e.g. note difference in a, f, or tail on b). Serif fonts tend to use true italics with more pronounced variation between roman and italic form (e.g. Figure 73, Century Schoolbook and Garamond). Most but not all serifs have true italics: e.g. *Bookman Old Style* and *Courier New* have oblique forms for italics.

AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
Arial

AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
Segoe UI

AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
Century Schoolbook

AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
Garamond

AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
AaBbCcDdEeFfGgHhIiJjKkLlMmNnOoPpQqRrSsTtUuVvWwXxYyZz1234567890
Courier New

Figure 73. Comparison between roman and italics for some fonts. Note the differences in letterforms. Image created by author.

Italic slope angle. There are no standards for slope angle: most italics slope to the right between 2 and 20 degrees.[179] Slope angle can be steeper: in Figure 74 left slope is 35 degrees.[180] In this example there are locations where text overlaps at right angles. With roman text (no slope), the primary orientations of straight segments in letterforms (e.g. L,T,H,E,F) are 0° and 90°. When this text overlaps other text at right angles, the straight segments of letterforms in different orientations will be aligned. With italicized text, the primary orientations will be offset, improving readability as seen in "crossed letters" (Figure 74 right).

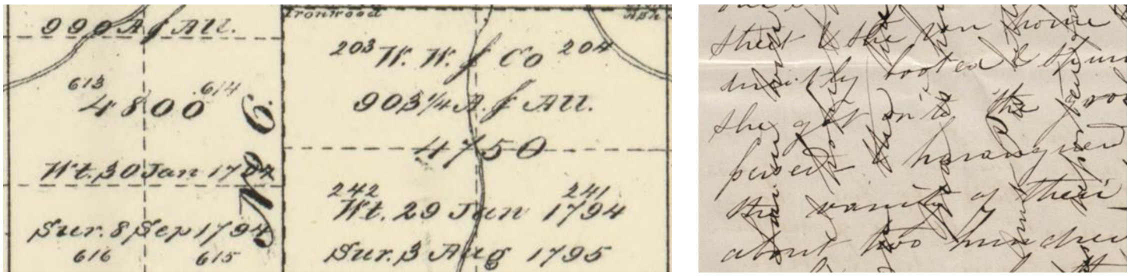

Figure 74. Steeply sloped italics from mid 19th century survey (left) and letters (right).
Public domain: https://www.loc.gov/resource/g3823w.la000811/ https://en.wikipedia.org/wiki/Crossed_letter

179 http://yin.arts.uci.edu/~studio/resources/type03/definitions.html
180 John C. E. Gardiner, A map of the original warrants of Warren & Forrest counties…. Pennsylvania Department of Internal Affaris, Harrisburg, 1881. https://www.loc.gov/resource/g3823w.la000811/

Italics do not need to slope to the right. In the font family *Quadraat*, the italic version is upright and readily distinguishable from the upright roman version of the same font (see Lupton[181] page 48). Reverse italics occur too, such as Figure 75 left.[182] Reverse italics are sometimes used in cartography to indicate water features, as seen previously in Figure 31[36] and in Figure 75 right.[183]

Figure 75. Reverse slope italics exist in some fonts and some map conventions use reverse italics to label water features. Left image in public domain, right image copyright by 010 Publishers.

Italics and perception. The primary salient attribute of italics is the uniform slope of the text. Slope and/or angle rank fairly highly on visual attribute rankings (e.g. Mackinlay 1986). Note that a switch from roman to italic font in the same font family maintains consistent font weight – there is no change in the intensity of italicized font. Italics offer an *associative* reading (Bertin *Semiology of Graphics*) when combining italic and roman (meaning that the italic and non-italic glyphs can be perceived uniformly at a macro level) unlike bold which does not offer associative readings – that is - bold should be disruptive to aggregate tasks while italics should perform more effectively for aggregate tasks (such as estimation of the number of items).

Visualization example with italic encoding quantitative data: Italics can be used to differentiate between two categories, as is done currently in prose text to create emphasis. Italics can encode quantitative information, by skewing the slope angle, for example, from a negative slope to a positive slope. In this graph visualization of emails (Figure 76), the oblique angle for each person's name encodes the recency of emails: the most recent senders are positively sloped (e.g. right side of graph) while the senders who have had no contact in a long time are negatively sloped (e.g. K. Slater on the left side or M. Murdock at the top).

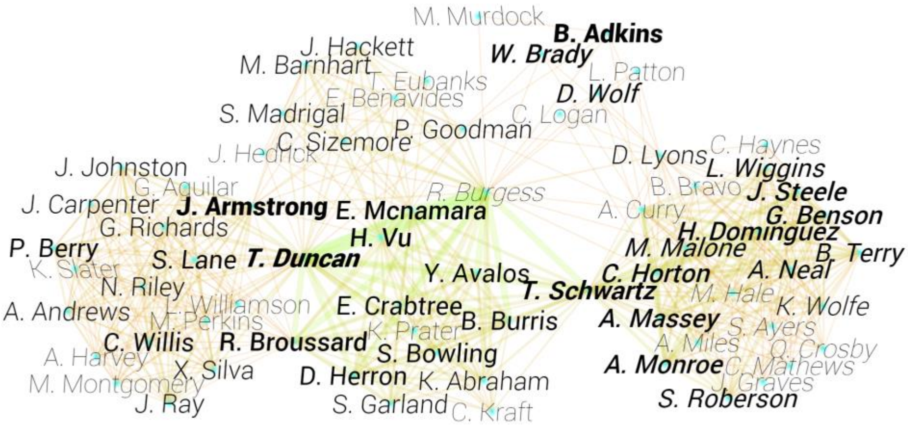

Figure 76. Slope angle indicates recency of contact. Slope ranges from reverse slope (old) to forward slope (very recent). Image created by author.

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[181] Ellen Lupton, *Thinking with Type: A Critical Guide for Designers, Writers, Editors & Students,* Chronicle Books, 2014.
[182] Charles Zaner, *The New Zanerian Alphabets* Zaner-Bloser. Columbus Ohio, 1900. Page 59. digitalservices.scranton.edu/cdm/ref/collection/zanerbloser/id/7180/rec/17 (accessed 2016/12/28)
[183] Paul Mijksenaar, *Visual Function: An Introduction to Information Design*, 010 Publishers, Rotterdam, 1997. Page 40. Full content online at: https://books.google.ca/books?id=-j7JcB2al7sC (accessed 2016/12/28)

B:4.5. Case: Upper, Lower, Smallcaps, Proper and CamelCase

Case evolved over a millennia. Lowercase letters were an outgrowth of rewriting documents and evolution of cursive writing. Lowercase offered greater economy enabling more words to fit on a line (e.g. Craig et al.)[184] Small Caps (i.e. small capitals) are smaller versions of capitals designed to be used together with lowercase text such that the height and weight match the lowercase. Uppercase has evolved conventions, e.g.:

- EMAIL: Upper case is considered shouting in e-mail etiquette. Essentially, capitals are a means for creating emphasis in a plain text medium when other font attributes are unavailable.
- NEWS HEADLINES: In financial news feeds, a headline with no body text (for example, breaking news at a live conference) is set in all capitals (e.g. Winkler).[185]
- Legal Documents. A word defined within a legal document will be capitalized to indicate that it is to be interpreted uniquely. Some laws require certain clauses (e.g. warranties) to be more conspicuous.
- SMALL CAPS FOR LESS EMPHASIS. Small caps may be used in text settings where regular capitals are required but might create unwanted emphasis such as acronyms such as NATO or NASA (e.g. Craig et al).
- SMALL CAPS FOR LEAD SENTENCES. Small caps may be used to set off the initial words of a sentence of a lead paragraph in a text, such as the beginning of the chapter.
- Titles With Each Word In Capitals: Titles, headings, news headlines (with a full news story) and proper nouns (in English) are often set with the lead character of each word capitalized. (see Winkler).
- CamelCase is a format used in computer software to create a token consisting of multiple words, removing spaces (as spaces delineate tokens) and capitalize the lead character of each word to improve readability. CamelCase has become more common in other uses, e.g. iPhone, eBay and so on.

Some caveats include:

- *All Caps does not work well in some fonts*. The extra decorative strokes in some script fonts (swashes) or ornamental effects in some blackletter fonts make the text less readable (e.g. Bosler).[186] For example: the, the, *the*, the vs. THE, THE, *THE*, THE (set in *Times*, *Segoe*, *Monotype Corsiva* and *Old English*). Note that some fonts provide variants which may adjust the appearance of swashes.
- *No All Caps?* Some cartographers recommend against use of uppercase: “A common myth among cartographers these days is that you should avoid using uppercase when possible. However, all caps can be successful to help differentiate between features.”[187]
- *No Uppercase*. Some glyphs do not have uppercase/lowercase variants: numerals and punctuation are not case sensitive. Some languages do not have uppercase/lowercase.
- *Small Caps need Context*. Small caps, by themselves appear as capitals, so small caps need to appear adjacent to either full-sized caps or lowercase in order to judge whether they are small caps.

Uppercase offer some specific benefits according to typographers:

- Capitals are more assertive (i.e. stand out more) than italics (Craig et al.)
- Capitals, as opposed to changing font size, enable you stay in the same font and point size (Crag et al.)

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[184] James Craig, Irene Korol Scala and William Bevington. *Designing with type: the essential guide to typography* - 5th Ed. Watson-Guptill Publications. 2006.
[185] Matthew Winkler. *The Bloomberg Way: A Guide for Reporters and Editors*, New York, 11th edition, 2009, Bloomberg Press.
[186] Denise Bosler, *Mastering Type. The Essential Guide to Typography For Print and Web Design*. How Books. Cincinnati, OH, 2012.
[187] Ian Muehlenhaus, *Web Cartography: Map Design for Interactive and Mobile Devices*. CRC Press, 2014.

- Uppercase can be set on tighter spacing between lines (i.e. leading) because there are no descenders to interfere with successive lines (Lupton).

In cartography, case can be used either for categoric data or ordered data. Uppercase implies more. As shown in Lavoisne's genealogy chart (Figure 8P11), an ordering is created from ALL CAPS to SMALL CAPS to Proper Nouns (for family branch, sovereign ruler, family member).

Uppercase and lowercase can work at the glyph level and applied to individual characters, words, lines and paragraphs of text, as shown by various conventions (e.g. use of small caps on the leading line of an opening paragraph in some books). On longer strings, uppercase and lowercase can be MiXeD.

Perception and case. Uppercase letters, are larger in both height and width than their lowercase counterparts. Size is a highly ranked visual channel. "Uppercase letters ask to be noticed".[188] Small caps, however, are specifically designed to fit in with lowercase. In some fonts, small caps may be wider than their lowercase counterparts (e.g. *Garamond*), but in other fonts may have similar widths (e.g. *Franklin Gothic* or *Rockwell*) as seen in Figure 77. (Note: a typographer indicated that these are not true small caps, rather Microsoft Office interpolated small caps, and true small caps may need to be licensed separately.) Regardless, the differentiation between small caps and lowercase is based largely on shape, which is a weaker cue in visual ranking tables.

Figure 77. Upper case letters are bigger than lowercase letters. Small caps are less differentiated. Image created by author.

Visualization example with case encoding ordered data**.** One simple example of case can be used to encode ordered data in a word list. Latent Dirichlet Allocation (LDA) is a statistical topic modeling technique to automatically extract topics from a corpus of documents. Each topic is characterized by a list of words, typically ordered by probability within a topic. Figure 78 shows the words associated with three topics, where the words are ordered using upper case, small caps and lowercase according to word frequency in the topic.

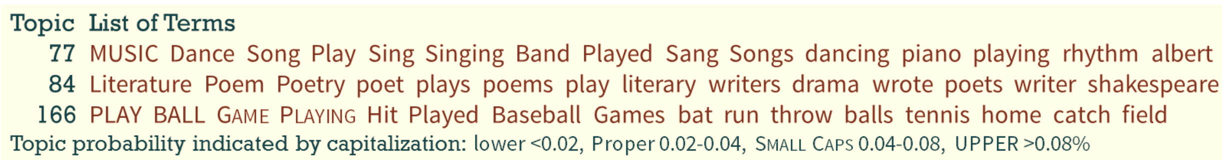

Figure 78. Word lists corresponding to three automatically detected topics. Capitalization indicates word probability in a topic: UPPERCASE most probable, followed by SMALL CAP, then Leading Cap, and lowercase for lowest. Image created by author.

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188 Elizabeth Wilhide. *How to design a Typeface*. Conrad Octopus Ltd in association with The Design Museum. London. 2010.

B:4.6. Underline

Underlines have been used for centuries by readers and editors of texts to indicate passages of interest. In English, "underscore" is used as a synonym for "emphasis." However, many current texts on typography and cartography recommend against underlines (e.g. Krygier, Bosler), for example "if you feel the urge to underline type, STOP and use bold instead" (Krygier). There are many reasons for this negative recommendation, such as:

- Underlines interfere with descenders (e.g. g,j,p,q,p,y, sometimes f,z,Q,J, punctuation (,}), old-style numerals 3,9 and subscripts), such as this text set in italic *Georgia*: *Queue 329 jiggly puffs (quietly).*
- Underlines are distracting. Unlike bold or italic, underlines are separate to the text adding graphical noise to the block of text. This may interrupt readability more than other techniques for enhancement.

Conventional uses of underlines vary by domain: such as indicating hyperlinks, wavy (for spelling errors), ~~strikethroughs~~ (for deletion in legal documents), structuring information (e.g. tables), editor conventions (e.g. single for italics, wavy for bold, double for small caps, triple for uppercase and dashed to remove formats, see Lupton) and ordering data in labels on maps (e.g. dotted, dashed, thin, thick, double). See Figure 79:

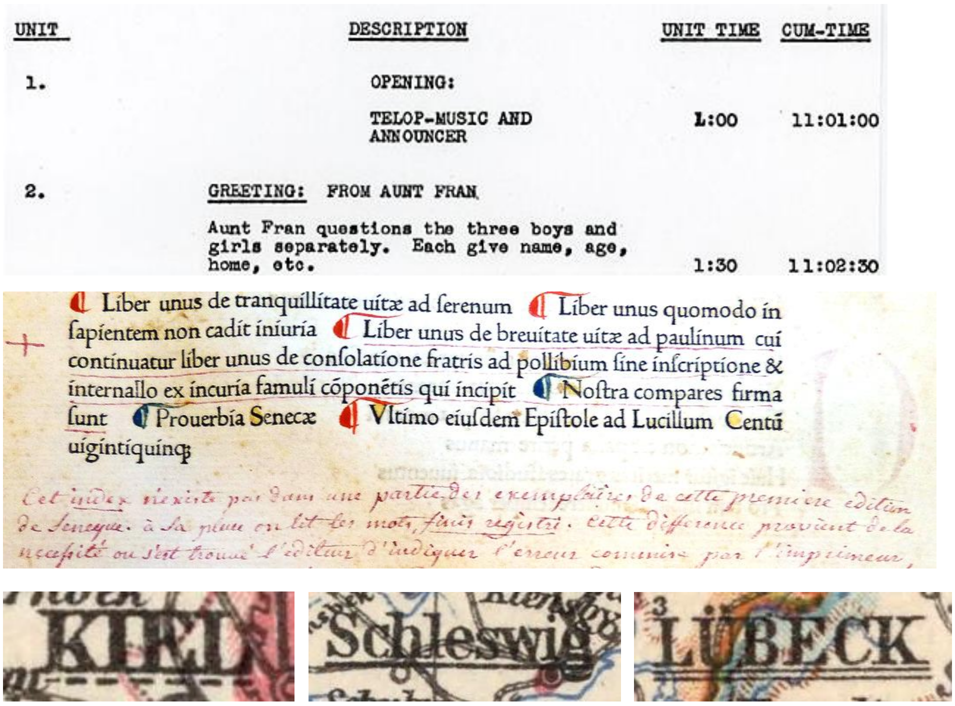

Figure 79. Top: Portion of a typewritten TV script using underline (and case and layout) to structure information. Middle: Underlines added to both typeset text and handwritten notes. Bottom: Variants of underlines on city labels to create an ordering (dashed, solid, double). 1) lib.umd.edu/LAB/exhibits/leadingrole/fn-images/FN-show2.jpg 2) Naples: Mattia Moravo, 1475; ISTC is00368000. via Penn Libraries: flickr.com/photos/58558794@N07/9629599118/in/photostream/ 3) From Stieler's *Atlas of Modern Geography*, 1925, via davidrumsey.com

Using underlines effectively. The deficiencies of underlines can be addressed:

- *Distraction*. A solid underline may be distracting: less distracting variants are dashes and dots.
- *Uppercase* letters in many font families do not have descenders. The same sentence discussed earlier renders with minimal interference set in uppercase: QUEUE 329 JIGGLY PUFFS (QUIETLY).
- *Breaking Underlines*. Instead of crossing descenders indiscriminately, underlines can break around descenders. The text will be clearly legible and underlines visually carry across their gaps using the

Gestalt principle of common fate. This is technically automated in some browsers or feasible via code[189] (e.g. Figure 80 left) and seen on some sites, such as newyorker.com (Figure 80 right).

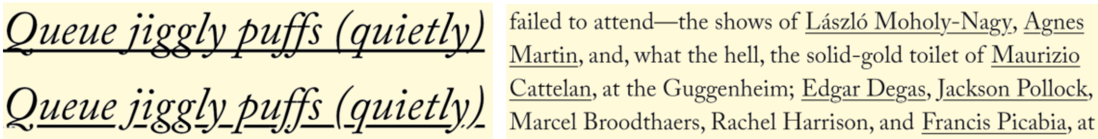

Figure 80. Breaking underlines do not interfere with descenders (left) and as used on the website newyorker.com. Left image created by author, right image copyright newyorker.com.

Unique capabilities. Underlines offer some unique advantages:

1) *Layout Retention*. Underlines do not change character width, whereas bold, italic and case do.
2) *Strong Emphasis*. Underlining, like bold, is difficult to ignore.
3) *Separable Attribute*. Underlines are visually separable from the character glyphs. This may be desirable for encoding multiple data attributes into multiple font attributes, where the viewer needs to respond on the basis of one variable or the other instead of holistically (e.g. see Ware Information Visualization: Perception for Design).
4) *Separate Hue*. Since an underline is separate from the text, its color may be independent of the text.
5) *Versatile*. Unlike other font attributes, underlines can be applied to spaces between words or applied to a fraction of a character width.

Perception and underlines. Underlines are perceived the same as lines: i.e. they have attributes of width, length and style. The effectiveness and applicability of underlines to visualization is likely high. Some visualizations today use almost-underlines to create labeled bar charts (Figure 81 left, middle).[190,191]

Visualization example with underline encoding quantitative data via length. The same chart from Figure 81 left is redrawn directly using font underlines in the word processor – no graphical libraries nor charting software required – in Figure 81 right.

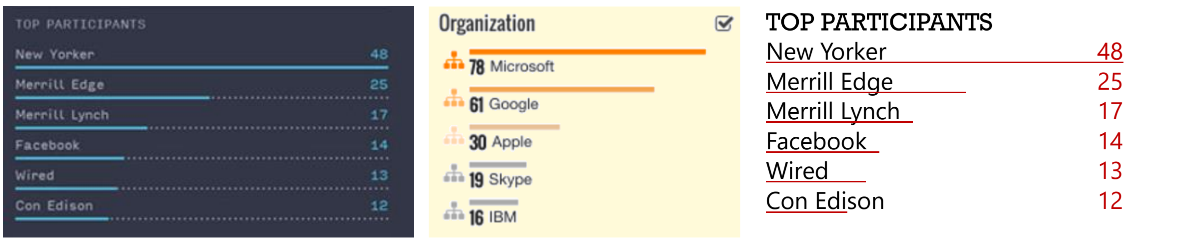

Figure 81. Feltron's 2013 Annual Report uses quantitative lines under text; a Microsoft PowerBI facet view uses an overline to indicate quantities. Right is a bar charted created directly with text underlines. Image copyright respective organizations

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[189] Andrew Patton, *Towards a more perfect link underline*, Acusti.ca, http://www.acusti.ca/blog/2014/11/28/towards-a-more-perfect-link-underline/ retrieved Jan 20, 2018.
[190] Nick Felton, *2013 Annual Report,* Feltron. http://feltron.com/FAR13.html retrieved Jan 20, 2018.
[191] Patrick Baumgartner, *New Power BI Custom Visuals Enable Browsing and Analyzing Collections of Text*, Microsoft PowerBI Blog, https://powerbi.microsoft.com/en-us/blog/new-power-bi-custom-visuals-for-browsing-and-analyzing-collections-of-text/ retrieved Jan 20, 2018.

B:4.7. Typeface

The terms typeface and font are (now) used interchangeably to refer to a family of fonts such as *Garamond*, *Helvetica*, *Comic Sans*, and so on. There are thousands of typefaces: *fonts.com* lists more than 150,000 while *Google.com/fonts* provides more than 650 free webfonts. In many cases, unique typefaces are designed for specific applications, such as highway signs (*Interstate*), phone books (*Bell Centennial*), low resolution screen display (*Verdana, Georgia*), etc.

i. Typeface for Categoric Data

Many typefaces are visually similar: hard to differentiate, particularly when used at small sizes - such as labels in a visualization. Some serifs and sans serifs are similar except for tiny serifs making it easy to miss the difference in a large amount of text (given that attention is directed to reading and the small change is not detected by font tuning,[192] which can result in change blindness[193]). Figure 82 shows a superimposed sans serif (yellow) m over other fonts in blue – notice the similarity to the plain serif m at the far left.

Figure 82. Comparison of typefaces by superimposition to show commonality (adapted from Legros and Grant[194]). Areas of green are common; areas of yellow or blue unique. For example the sans serif is highly similar to the plain serif. Image by author.

For use in visualization to distinguish categories, typefaces need to be differentiated. There are many type classification systems. The *McCormack Type Classification* system uses five basic categories, relevant to visualization due to its simplicity. Paraphrased from Ambrose and Harris:[195]

- Sans Serif typefaces such as *Helvetica, Arial, Univers, Franklin Gothic* and *Futura* have a clean and simple design that makes them ideal for headings and signage, but may make them difficult to read in long passages. Stroke width tends to be fairly uniform in most popular sans serifs.
- Serif typefaces were derived from Roman inscriptions. Most typographers consider serif typefaces as highly readable for longer passages of text (see Dumont[196] for summary). Serifs vary widely in serif size, shape, brackets and the variation in stroke widths, and, not all serifs are highly readable. A plain serif, such as *Times Roman*, has tiny serifs and low variation in stroke widths (Figure 82 far left), while some serif typefaces have extreme variation in stroke width such as *Bodoni* – in Figure 82 second image the vertical strokes are wide but become very thin as they approach horizontal.

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[192] Thomas Sanocki,. "Visual Knowledge Underlying Letter Perception: Font-Specific Schematic Tuning." *Journal of Experimental Psychology: Human Perception and Performance*, 12 no 2. 1987.
[193] Ronald A. Rensink, J. Kevin O'Regan, and James J. Clark. "To see or not to see: The need for attention to perceive changes in scenes." *Psychological science* 8, no. 5 (1997): 368-373.
[194] L.A. Legros and I. C. Grant. *Typographical Printing Surfaces, the technology and mechanism of their production.* London. Longmans, Green and Co. 1916.,
[195] Gavin Ambrose and Paul Harris. *The fundamentals of typography*. Ava Publishing, 2006.
[196] Nathalie Dumont, The influence of typographic features on legibility. In C. Y. Suen, N. Dumont, M. Dyson, Y.C. Tai, X. Lu. Evaluation of Fonts for Digital Publishing and Display, *2011 International Conference on Document Analysis and Recognition*, 2011.

- **Blackletter typefaces** are based on the calligraphic writing style prevalent during the Middle Ages, some ornate (e.g. *Old English),* others simpler (e.g. *Rotunda, Textura*). Letterforms tend to be angular, highly different from modern typefaces, as shown by the fifth example in Figure 82.
- *Script typefaces* imitate handwriting. Examples include *Monotype Corsiva*, *Lucida Calligraphy* and the popular *Comic Sans*.
- **Graphic typefaces** are typically designed for specific themed purposes, such as signage and logos. Examples include *Cooper Black, Hobo, Rosewood* and *Stencil*.
- **Monospace typefaces** (not part of McCormack) are visibly identifiable, differentiated by the uniform rhythm of characters. Examples include *Courier*, *Consolas*, and *Source Code Pro*.
- **Slab serifs** are a distinctive variant of serif (also not part of McCormack but explicitly separated in the Vox system).[197] Examples include *Rockwell, Glypha*, and *Roboto Slab*.

ii. Mixing Fonts

In traditional typographic use, different fonts are used at different sizes to create a typographic hierarchy to aid the viewer navigate the text structure (e.g. title, heading, caption, byline, etc.), and categorize different blocks of text. Typographers recommend choosing fonts that are visibly different from one another yet complimentary - to make the effect deliberate and noticeable while remaining harmonious. Many cartographers recommend using only one or two fonts (e.g. Muehlenhaus, Bosler, Krygier). Bosler provides a grid indicating fonts that pair well with one another (e.g. **Cooper Black** and Franklin Gothic can be paired, but **Cooper Black** and Lucida should not be paired). Many newspapers, magazines and dense websites use more, e.g. *The New Yorker* website uses at least three different fonts with different sizes, weights, case and colors (Figure 83 left). *The Atlantic* website uses at least three fonts varying in spacing, case, weight and color (Figure 83 right).

Figure 83. Different typefaces (combined with size, color, weight and case) are used organize stories on news websites differentiating between departments, titles, authors, lead sentence, date, etc. Copyrights: Left: newyorker.com, right: theatlantic.com, accessed 2016/12/30.

Besides information hierarchies, other examples of mixed type include:

1) multi-lingual labels (such as Figure 18P28);

2) features on maps (e.g. the many fonts of National Geographic maps in Figure 33P37);

3) 19th century handbills (e.g. Figure 84 left); and,

[197] Allan Haley, Richard Poulin, Jason Tselentis, Tony Seddon, Gerry Leonidas, Ina Saltz, Kathryn Henderson, Tyler Alderman. *Typography Referenced: A Comprehensive Visual Guide to the Language, History, and Practice of Typography*. Rockport Publishers, Beverly, MA. 2012.

4) differentiation of speakers in text (e.g. Figure 84 right, the title character always speaks in authoritative uppercase, his spouse in a soft rounded font, etc.).[198]

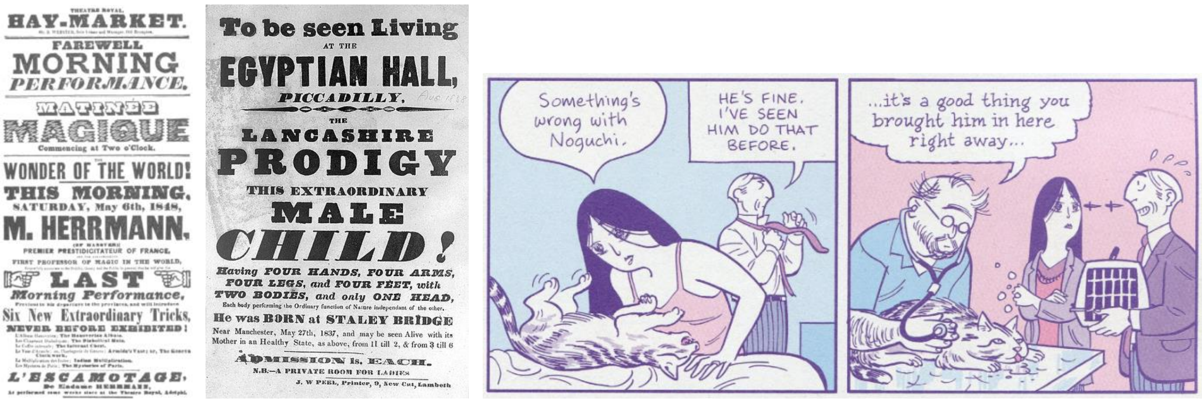


Figure 84. Left: Sample 19th century handbills mixing many font types. Right: Each character in the graphic novel *Asterios Polyp* speaks with a unique typeface. Left images from Wikipedia.org. Right: copyright Asterios Polyp, David Mazzucchelli, Penguin Random House, 2009 Used with permission.

iii. Perception and encoding with typeface

Font families are best used to encode categoric information as it is difficult to find a collection of fonts with an intuitive ordering. Krygier states: "Typeface is best used to symbolize nominal information." One challenge is to find a set of different fonts with comparable weights. Using the earlier adaptation from the McCormack classification a set of different fonts with similar weights can be created such as Figure 85:

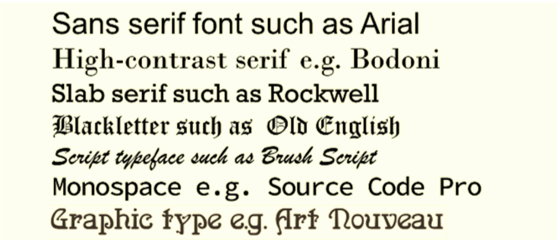


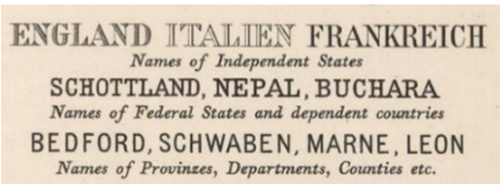
Figure 85. Very different fonts with similar weights for potential use to encode categoric data. Image created by author.

Assuming the weight of two different fonts is consistent, then the perception of difference rests on the nuances of the letterforms, which may be expressed by shape variation at the ends of the glyphs (e.g. bracketed serif, slab serif, no serif), proportions within the glyph (e.g. widths or x-height) or other variations such as stroke variation (contrast and angle of stress), path of the strokes and so on. All of these attributes are based on perception of many subtle differences largely based on shape. Since shape is not a strong cue in visual attribute rankings, change in font will not be particularly noticeable, especially if the differentiation between fonts is low.

[198] Mazzucchelli, David. *Asterios Polyp*. Pantheon, 2009.

iv. Typeface for Ordered Data

It is feasible to assemble an ordered set of typefaces, similar to Steiler's Atlas labels for levels of administration (Figure 86 left). In Figure 86 right, common typefaces are ordered from the most ornate high-stress typeface (blackletter), through a high-contrast serif type (Bodoni), to a no-contrast slab serif (Rockwell) to a plain common sans serif (Arial). Note that font weight may interfere with the perceptual ordering – care must be taken to ensure that similar weights (or consistently ordered weights) are used for the chosen set of fonts.



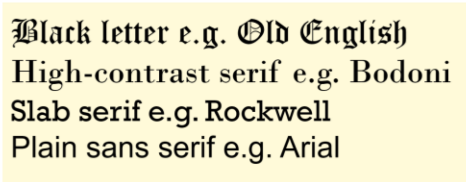


Figure 86. Typeface ordered by degree of ornateness. Left: ordering of administrative areas from Steiler's Atlas. Right: an ordering of ornateness using common fonts available in a word processor. Left image vis davidrumsey.com, Right image created by author.

Visualization example with typeface encoding ordered data. Below is a snapshot encoding the names of passengers of the *Titanic*, using an ornate high-stress serif font for first class (top row), a simpler serif font for second class (middle row), and a very plain sans serif font for third class (bottom row). While not preattentive, the viewer can visibly detect the differences and decode the passenger's class.

Figure 87. Some passengers from the Titanic with typeface indicating passenger class. Image created by author.

B:4.8. Width: Stretch, Condensed/Expanded and Spacing

Stretching, condensed/expanded and spacing are techniques that compress or extend the length of text:

Spacing (referred to as *tracking* for horizontal spacing between letters, and *leading* for vertical spacing between rows of text) is an adjustment to the size of the gaps between letters. Spacing can be used to indicate quantities and is often used to indicate the extents of an area in cartography[199]. Based on the long history of use in maps one may assume that it has both some degree of effectiveness and some familiarity with map users.

Condensed and expanded typefaces are variants of a typeface made specifically with different widths but otherwise retain the characteristics of the particular typeface. Condensed type is relatively new, only in the early twentieth century, it became more common to also design a condensed version of a font (e.g. Morris Fuller Benson)[200] Condensed type is typically used in situations where space is tight.[201] Extended types are wider versions of type and are often used for headlines to (dramatically) fill a space.[202] Condensed and expanded type are not available in many typefaces, except some sans serif super families such as *Helvetica* and *Univers.*

Stretching is a geometric scaling transformation on text either squishing or stretching it horizontally. This technique is generally scorned by typographers:

> *"There is a difference between true condensed and expanded typefaces and those created by stretching or compressing the letterforms. True condensed and expanded typefaces are individually designed as members of a specific type family. Stretched or compressed typefaces lack the integrity of the original designs and legibility suffers." (Craig 2006)*

> *"Correctly condensed fonts retain readability despite a reduction in character width." (Haley et al 2012)*

> *"You can change the set width of a typeface by fiddling with its horizontal or vertical scale. This distorts the line weight of the letters, however, forcing heavy elements to become thin and thin elements to become thick. Instead of torturing a letterform, choose a typeface that has the proportions you are looking for, such as condensed, compressed, wide or expanded." (Lupton 2004)*

Figure 88 (left) shows text at set in Gill Sans Bold. In the middle is the same text squished horizontally. Note how the even line thickness on the original O has become distorted and top heavy in the squished version. Right, same text set in Gill Sans Extra Condensed Bold. The font designer has maintained even line weights on the narrow font and adjusted letter forms to maintain legibility (e.g. a, g, r, e).

Figure 88. Left: original text in Gill Sans bold. Middle: same text squished horizontally. Right: same text in Gill Sans Extra Condensed Bold. Note even light thickness and adjusted letter forms. Image created by author.

A few fonts have been explicitly designed to allow for modest horizontal scaling (±25%), such as Gerard Unger's typeface *Swift* - which has been used in the *Oxford English Dictionary* at narrower scales.[203]

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199 John Krygier, *Making Maps: A Visual Guide to Map Design for GIS*, NY, NY: Guildford Press, 2005.
200 Peter Bil'ak, "Family Planning or How Type Families Work." In *Font. The Sourcebook*. Black Dog Publishing. 2008.
201 James Craig, Irene Korol Scala and William Bevington. *Designing with type: the essential guide to typography* - 5th Ed. Watson-Guptill Publications. 2006.
202 Gavin Ambrose and Paul Harris. *The fundamentals of typography*. Ava Publishing, 2006.
203 Discussion with Gerard Unger at course *Typeface Design Intensive*, University of Reading, July 18-29, 2016.

Emphasis or differentiation can be achieved by combining condensed or expanded typefaces from within the same family, such as the example, *Bloomberg Businessweek* magazine in Figure 89.

Figure 89. Title using variation in font width to distinguish between given name and surname. Image copyright *Bloomberg Businessweek*, 2014/03/13: (https://www.bloomberg.com/news/articles/2014-03-13/world-wildlife-fund-ceo-carter-robertss-career-path)

Perception and stretching/condensed/spacing. Similar to weight, spacing works visually by varying the density of ink for some portion of text by adjusting spacing between individual characters and rows. It requires a sequence of characters (e.g. word, line or paragraph) to be a salient differentiation. Spacing was sometimes used with blackletter type to emphasize text, such as word täglichen in the middle of the paragraph in Figure 90.[204]

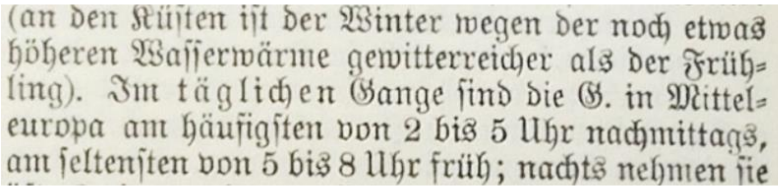
(an den Küsten ist der Winter wegen der noch etwas
höheren Wasserwärme gewitterreicher als der Früh=
ling). Im täglichen Gange sind die G. in Mittel=
europa am häufigsten von 2 bis 5 Uhr nachmittags,
am seltensten von 5 bis 8 Uhr früh; nachts nehmen sie

Figure 90. Blackletter text with the leading words in each paragraph indicated by wide spacing. Public domain.

Condensed type is different. The narrower width of letters can be noticeable. Essentially the change in width is directly associated with the highly ranked visual attribute of length. However, subtle changes in width may not be noticeable and in particular may not be noticeable with narrow glyphs such as i, I, l, r, 1.

Visualization example with condensed encoding

In the following example (Figure 91), city names are shown. The letters that are used in common abbreviation are in a normal width font. The remaining letters are shown in a very narrow font. Assuming that the most distinguishing letters are retained in an abbreviation, this representation keeps the distinguishing letters wide (to dominate the word), while retaining the less distinguishing letters (so that the word is still readable) while reducing the overall length of the word. The technique could be useful for labelling in dense plots.

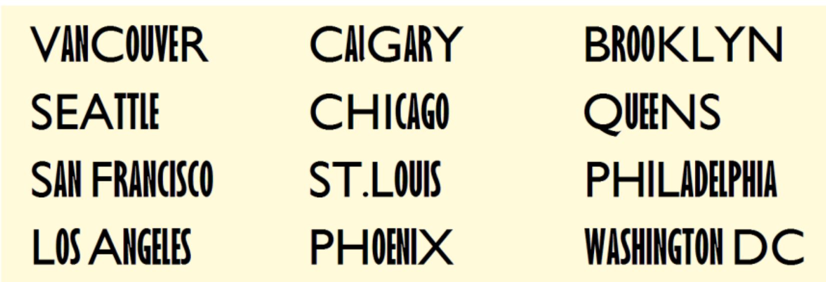

Figure 91. City names with letters normally retained in an abbreviation are set in wide letters while letters discarded in the common abbreviation are shown with a narrow width. Image created by author.

[204] *Meyers Lexicon*, Bibliographisches Institut, Leipzig, 1927.

B:4.9. Baseline shifts, superscript, subscript and text on path

A baseline shift adjusts the vertical positioning of subsequent letters. Common usage in blocks of prose text are superscripts and subscripts. Super/subscripts change two attributes of adjacent letters: the relative vertical position and relative size. Given that baseline shifts are in relation to other text, it cannot be used in isolation as it can only be understood relative to the baseline established by adjacent text.

Traditionally a baseline shift is binary - there is no conception of a super-super-script. Furthermore, the use of multiple baseline shifts may make the actual baseline ambiguous. Instead, multiple baseline shifts are similar to text on a path. With text on a path, letters are shifted to different locations and orientation relative to the path.

Typographically, superscripts are commonly used as a mechanism to insert a cross-reference marker in a text flow. This marker is offset and smaller such that it does not directly impact the flow.

In natural language processing hundreds of topics may be generated, and the challenge is to label each word uniquely and unambiguously in a text. Superscripts have been used in topic analysis representations to indicate topic membership of each word in context of the original prose.[205]

Perception and baseline shifts. Change in position uses one of the strongest encoding cues - location. Subtle shifts in location are highly perceptible and location encoding ranks above all other visual attributes for effectiveness. There is also a relationship to Gestalt principles such as *law of common fate* and *law of similarity*. For common fate, all the letters in a sequence sharing the common baseline are perceived as one, whereas the superscript, with a different baseline, is perceived as different. For similarity, all letters sharing the baseline have similar size and similar location, whereas the superscript has a different size and location. As such, superscripts and subscripts should have the potential to visually pop-out.

Visualization example using superscripts to positionally encode quantitative information. Given that superscripts can reside in a text flow with low interruption to the reading of the text, it is feasible to add information via superscripts. These superscripts can encode literal information in the superscript text and positioned within a sentence to indicate quantitative information. Figure 92 uses three-letter country ISO codes positioned relative to the beginning of the sentence to indicate the quantity of illiterate women per country. Note that inserting superscripts in the middle of words and figures (e.g. [IDN]5[ZAR]0[EGY]0 or il[CHN]literate) reduces the ability to read words quickly, suggesting that superscript placement relative to words rather than individual characters may be preferable for readability with a tradeoff in the accuracy of the positioning. Positional encoding will be discussed further in *C:8 – Quantitative Sentences*P193.

Figure 92. A sentence using superscripts to indicate countries with high number of illiterate women. Image created by author.

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[205] Mark Steyvers, Padhraic Smyth, Michal Rosen-Zvi, and Thomas Griffiths. "Probabilistic author-topic models for information discovery." In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 306-315. ACM, 2004.

B:4.10. Symmetric-Delimiters and Paired-Delimiters

Symmetric delimiters and paired delimiters are typographic symbols that are always inserted as a pair into the flow of text, such as (parentheses), [brackets], {braces}, *asterisks*, “quotes”, †daggers†, etc. This class of attributes can be set and displayed in pure ASCII, and with the simplest of text editors, e.g. chat, vi or notepad. Uses vary: for example, parentheses can be used around single characters to indicate optional plurality, e.g. color(s). Asterisks may be used around words to create emphasis in an environment where bold or italics do not exist, such as chat (e.g. I am *angry*). Quotes may be used around longer texts (e.g. “To be or not to be”), tags in markup (e.g. this text will be bold) or programming code (e.g. */ this is a comment /*).

Symmetric delimiters, i.e. delimiters that are symmetric across a vertical axis, such as (), evoke enclosure through the use of mirrored shapes. While complete enclosure is not explicit, the Gestalt law of symmetry explains that symmetric items are visually perceived as belonging to the same group – i.e. they are understood to form a pair. The law of closure explains how the paired concavities relate (to each other) (even if adjacent in sequence): concavities enclose e.g. (), {}, [], <> rather than the opposite e.g.)(, }{,][, ><.

Non-symmetric markers can achieve a similar effect, to a lesser extent since the law of closure is not applicable. Symmetry is created around the middle of the word by repeating the same symbol at the beginning and end of the *word*.

Nesting delimiters together may make readability difficult – such as nested functions (in Excel) where repetition of round brackets reduce the ability to parse which bracket pairs with its corresponding bracket (e.g. =indirect(address(row(3),column(4)))). This can be addressed by using an additional visual attribute (usually color) to differentiate between pairs.

Preattentive principles are not necessarily strong for paired delimiters - shape is considered a visual attribute that is weaker in preattentive properties, and unlike bold or italics or other font attributes that apply continuously across a sequence, there may be a significant gap between the pair of delimiters. Figure 93 shows a visualization example using paired delimiters (parentheses) to indicate one standard deviation along each line of text. For example, the mean *Citicorp Center* review is “Average” with standard deviation not varying significantly from “Average”; whereas the mean review for the *New York Public Library Map Room* is midway between “Very Good” and “Excellent” with a standard deviation from just below “Very good” to just above “Excellent”.

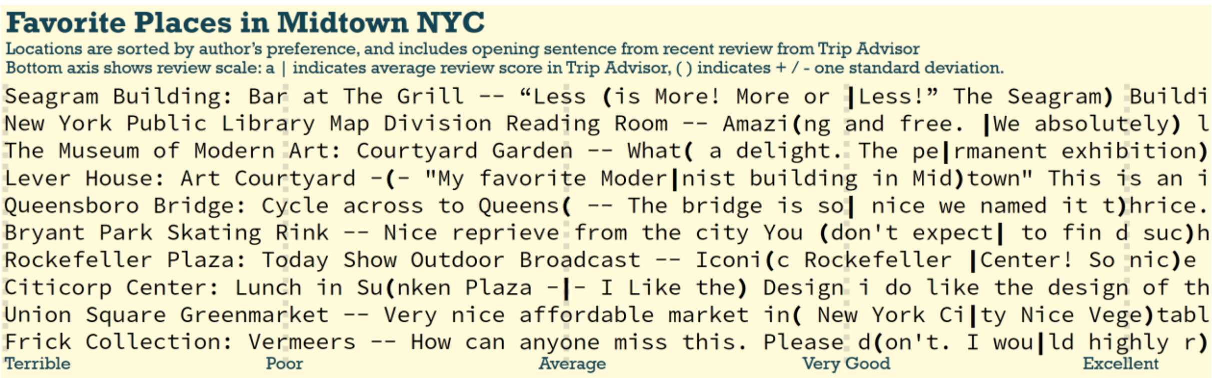

Figure 93. Online reviews of sights in New York City. Horizontal axis shows review score. Vertical bars indicate the mean review, parentheses indicate one standard deviation around the mean. Image created by author.

B:4.11. Font Design: X-Height, Contrast, Stress, Serifs, Etc.

There are many low-level font attributes intrinsic to a particular typeface and not exposed to the user as a parameter or configurable setting. These are attributes that are manipulated by a font designer during the creation of a font. Given the many variations, there are field guides to type identification such Figure 94.[206]

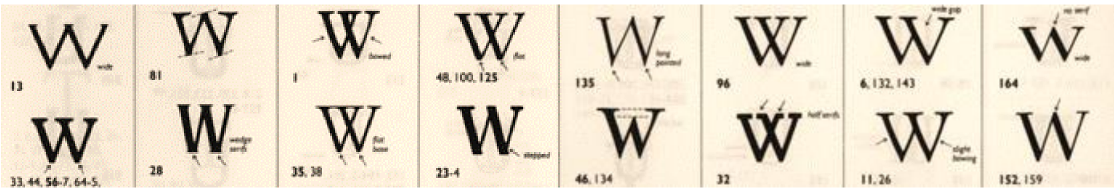

Figure 94. A few of the many variations of the letter W with arrows and dashes indicating distinguishing features. Image copyright *Rookledge's International Typefinder*.

i. Extrinsic vs. Intrinsic Font Design Attributes

Currently weight, italics, case, underline, typeface, baseline shift, delimiters are attributes commonly accessible in HTML5. However, type attributes available to designers have varied over time. Michael Twyman[207] differentiates between *intrinsic* features of characters, that is, features pre-determined by the typographer or the composition system; and *extrinsic* features, which are features that can be controlled by the users of type. For example, with the printing press using metal type, colored type becomes technically difficult: type is *intrinsically black*, so instead italics or capitalization is used to create emphasis. Or, with mechanical typewriters, there is no extrinsic access bold and italic: underline and capitalization become the means of emphasis. In medieval manuscripts, the scribe has complete extrinsic flexibility across the entire system: medieval scribes also used a wide variety of ligatures and completely flexible layouts – very difficult to replicate with current technologies.

Potential visualizations discussed so far in this thesis have assumed access to rich typographic features. However, some computer technologies work with a limited subset of capabilities: for example, visualization using Twitter's 140 characters as a medium would be limited to standard alphanumerics, some symbols and delimiters, all caps/no caps and emojis. On the otherhand, newer technologies such as parametric fonts and variable fonts may expose more typographic attributes to visualization designers.

ii. Intrinsic Font Attributes: x-height, serif, contrast, axis

Some intrinsic attributes apply across all the characters within a font (e.g. contrast and lower-case x-height) while some apply to only a few specific characters, e.g. ball terminals occur only on a few characters such as lower-case a. The following are more broadly applicable local level parameters across - paraphrased from Cheng[208] and illustrated in Figure 95:

- *X-height* refers generally to the height of lowercase letters. As a proportion of the capital height it typically ranges from 50-75%. Increasing the x-height increases the apparent size of letters.
- *Serifs*: are the short strokes at the ends of the horizontal and vertical strokes. Serif shapes and size can vary considerably (or non-existent in sans serif fonts).
- *Contrast*: The difference in thickness between the thinnest and thickest strokes in each glyph.

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[206] Christopher Perfect and Gordon Rookledge. *Rookledge's Classic International TypeFinder: The Essential Handbook of Typeface Recognition and Selection*. Laurence King, London. 2004

[207] Michael Twyman. "The Graphic Presentation of Language", in *Information Design Journal,* 1982. p. 2-22.

[208] Karen Cheng. *Designing Type*. Yale University Press. 2005

- *Axis*: (angle of stress), is the angle at which thinnest part of the letter occurs, typically visible in rounded characters. The angle of stress is not related in any way to the angle of an italic or oblique font.

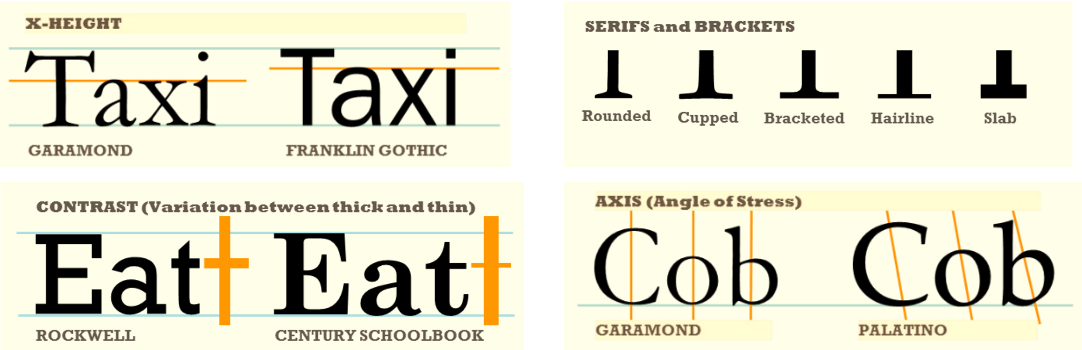

Figure 95. Examples of x-height, serifs, contrast and axis in some popular fonts. Image created by author.

iii. Type Systems and Parametric Fonts

A *type system* is a family of fonts that vary in a few attributes and share the same construction principles.[209] Type systems are relevant to visualization as they create an *ordering* of visual parameters. An early example (1950's) is Adrian Frutiger's *Univers*, designed as a continuous space defined by two axes: font width and font weight (Figure 96 left). Gerrit Noordzij presented a higher dimensional type system, including an ordering of high contrast serif to low contrast sans serif; an ordering of angle of stress (thick/thin stroke orientation) and weight (Figure 96 right, Bil'ak p. 162).

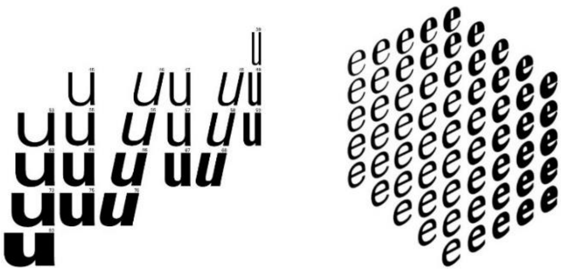

Figure 96. Left. The font family Univers was planned with a unified set of weights and widths. Right. Gerrit Noordzij's type system varies attributes not typically exposed to the font user, such as contrast (the ratio of thick to thin portions within a letter, shown vertically in this diagram). Images copyright respective companies/authors.

Parametric Design exposes many more parameters. Donald Knuth's programming language Metafont defined letterforms with geometric equations. Knuth claims in the introduction to *Computer Modern Typefaces*:[210]

> *"Infinitely many alphabets can be generated by the programs in this book. All you have to do is define the 62 parameters and fire up the METAFONT system, then presto – out comes a new font of type!"*

Knuth's MetaFont has a few global parameters that impact most of the glyphs in the alphabet, such as: *body height*, *x-height*, vertical and horizontal stroke width, letter-width; etc. Many Metafont variables are highly specific to a few glyphs, such as *dot size* (for the dots on i and j); *ess* (for the stroke breadth only on letter s); *variant g* (for two types of g, e.g. g vs. g), *beak*, *apex correction* and so on (Figure 97). Despite Knuth's claims of infinite fonts, METAFONT focuses on a broad family of fonts based largely on roman-style serif and sans-serif fonts – it would not be capable of generating script fonts, blackletter, etc.

[209] Peter Bil'ak, "Family Planning or How Type Families Work." In *Font. The Sourcebook*. Black Dog Publishing. 2008.
[210] Donald Knuth. *Computer Modern Typefaces.* Addison Wesley Publishing. 1986.

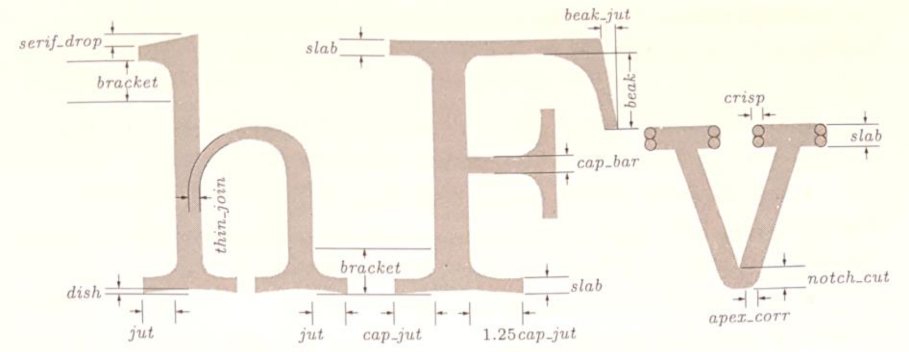

Figure 97. Sample variables from Knuth's METAFONT. Image copyright Don Knuth.

Later technologies, such as Apple's *GX* and Adobe's *Multiple Master* fonts use linear interpolation to create intermediate letterforms. *Elementar* is a comprehensive system of pixel fonts generated by a series of Python scripts by Gustavo Ferreira. *Kalliculator* is a tool that generates typefaces based on the strokes of the letterforms by Frederik Berlaen. *Prototypo.io* is a web-based tool for generating fonts. It provides 30 low-level parameters, such as x-height, width, thickness, slant, serif width, serif height, bracket curve (Figure 98 left) and can generate various unique fonts such the reverse-oblique, low x-height, bell-bottomed, serif font created with the parameters shown in Figure 98 right.

Figure 98. Parameters in Prototypo (left) and samples of the resulting font (right). Screen captures created by author

Many of parameters are mutually exclusive and all combinations can be generated, as shown in Figure 99.

	Plain	Boxy	Bulge Bracket	Wide Serif	Low x-height
Plain	Ferdinand	Charlotte	Cleveland	Rigoberto	Marcelino
Boxy	Millicent	Elizabeth	Cornelius	Magdalena	Georgette
Bulge Bracket	Dominique	Katherine	Claudette	Rosalinda	Christian
Wide Serif	Kimberlee	Christina	Gabrielle	Alejandra	Anastasia
Low x-height	Augustine	Josephine	Katharine	Annabelle	Johnathon

Figure 99. Parameters adjusted to make a boxy font, bracketed serifs, wide serifs, low x-height and all combinations thereof. Image created by author.

Some of these parameters have enough variation to create an ordering. Figure 100 shows a generated font with five ordered levels of x-height and five levels of curviness ordered angular-smooth-boxy and all the permutations.

	Curviness 1	Curviness 2	Curviness 3	Curviness 4	Curviness 5
X-height 1	Jacqueline	Concepcion	Christoper	Sanjuanita	Christiane
X-height 2	Marguerite	Earnestine	Clementine	Candelaria	Charolette
X-height 3	Antoinette	Evangeline	Georgianna	Marquerite	Clementina
X-height 4	Bernadette	Evangelina	Florentino	Margarette	Florentina
X-height 5	Kristopher	Antionette	Cristopher	Hermelinda	Margaretta

Figure 100. A sans serif font with five levels of x-heights and five levels of curviness. Image created by author.

OpenType *Variable Fonts*, announced in late 2016,[211] promises procedural control over type attributes exposed by the font designer providing the programmer or user interpolation between defined extremes (Figure 101).

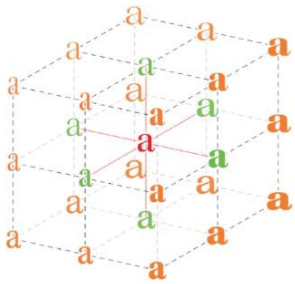

Figure 101. Illustration of variable fonts. Green letters indicate versions created by the font designer, orange indicates letters interpolated based on the defined versions. Illustration copyright John Hudson.

While OpenType Variable Fonts potentially create new capabilities for the visualization designer to access and adjust many more font parameters, it should be noted that fonts aren't necessarily designed for a broad range of parametric values that will interpolate effectively. For example, consider the professionally designed font *Gill Sans*: the font comes in a variety of widths, and the shape of some letters change at extremely narrow widths (e.g. a, g) to improve legibility and readability Figure 102. This would not be feasible with a Variable Font.

Figure 102. Font shapes may change significantly in a set of professionally designed variations of a font attribute, in this example Gill Sans regular, condensed and extra condensed. Image created by author.

iv. Typeface vs. low-level attributes: details, skeletons and graffiti

Is a typeface simply the result of a particular configuration of low-level attributes such as serifs, x-height and stress? If yes, then the earlier review of typeface as a font attribute is repeated in this section by decomposing typeface into constituent elements. However, the author contends that a simple combinatorial approach of low-level type parameters is insufficient to generate all possible fonts:

- *Details*: There are many typographic details and it impossible to parameterize all of them. For example, there are hundreds of variants of serifs and swashes, some highly ornamental.

[211] John Hudson, *Introducing OpenType Variable Fonts,* Sept 14, 2016. https://medium.com/@tiro/https-medium-com-tiro-introducing-opentype-variable-fonts-12ba6cd2369

- *Skeleton:* The underlying path which forms the different strokes of a letter is typically not considered a font parameter. While the skeleton of a common serif font such as *Times* and a common sans serif font such as *Helvetica* may be similar, the skeleton of a blackletter font will be very different.
- *Letterforms:* Beyond simple skeletons, letterforms can vary dramatically. For example, artist Evan Roth[212] compiles graffiti alphabets – a small example is shown in Figure 103. One might notice very different potential parameters in the shapes of fonts, such as:
  - *Rounded to Angled Curves and Corners.* For example, on the U (right column) the degree of curvature varies and may not be symmetric. Hard corners may instead be round, e.g. E.
  - *Uneven Tops and Bases:* For example, tops of the U vary, E and I bases may be angles or curved.
  - *Crossing Strokes:* Strokes do not neatly join but may greatly overshoot the crossing.

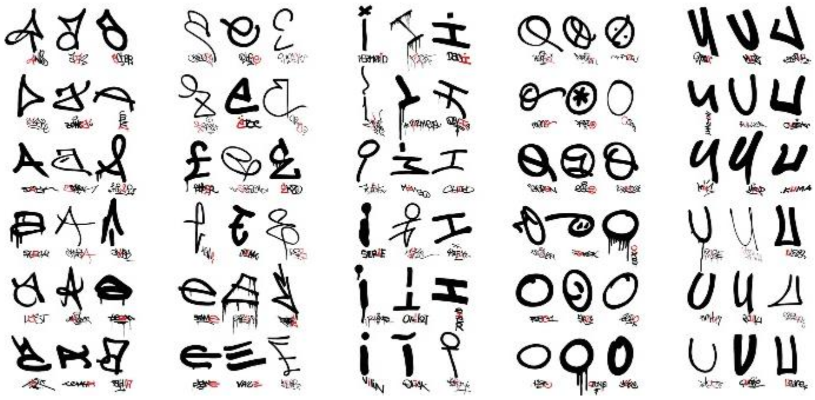

Figure 103. Sample letterforms for A, E, I, O and U by various street artists, compiled, normalized and organized by artist Evan Roth. Copyright Evan Roth, used with permission (evan-roth.com/photos/data/graffiti-taxonomy-paris/AEIOU-52x28in.jpg).

Visualization Example: Figure 104 shows an example visualization using x-height per letter to indicate which letters are frequently misspelled in common English words based on Wikipedia edits. In this example, 5 levels of x-heights have been created using Prototypo. For example, the tall *a* in *because* indicates that this letter is frequently misspelled. Similarly *er* and trailing *a* in *caterpillar* are frequently misspelled and so on. Note that the use of x-height is not an effective cue for the lowercase letter *l* – from this representation it is impossible to determine whether the *ll* in caterpillar is a source of spelling errors.

Figure 104. Sample visualization using x-height per letter to indicate which letter are frequently misspelled in common English words. Image created by author.

[212] Evan Roth. *Graffiti Analysis*. 2011. http://www.evan-roth.com/project-index/ Accessed Dec. 4, 2016.

B:4.12. Size, Color, Shadows, Outline and other Visual Attributes

Beyond the type-specific visual attributes discussed to this point, there are many other visual attributes of type which can be manipulated including: **fill color**, **background color**, **size**, texture, outline, **drop-shadow**, **blur**, orientation and so on.

Text color, notably, has been used since medieval times on hand-written documents (rubrication), continued in some liturgical texts despite the challenges of multi-printing colors with a printing press,[213] through to techniques with added hand-coloring or registration across multiple presses on 19th century handbills and posters, to modern *chromatic fonts* (also *layered fonts*) as shown in Figure 105.

Figure 105. Colored text has been used throughout centuries, despite technical challenges with multi-color printing. Left image: http://daten.digitale-sammlungen.de/~db/0003/bsb00036985/images/ Middle images courtesy of Gerry Leonidas, Department of Typography & Graphic Communication, University of Reading. Right image: https://www.colorfonts.wtf/ Retrieved Jan. 28, 2018.

Size is used extensively in many map labels, visualizations, and texts to indicate data or otherwise structure a type hierarchy. The variance in type size, between largest and smallest text, is highly constrained in map labelling (e.g. Figure 30 and Figure 31P36) and index texts (e.g. Figure 24P31). In word clouds (Figure 4P8), as well as some newspaper titles and handbills, this variance can be very large, thereby allowing one or a few words to completely dominate the display over all other words. An early visualization by Richard Brath and Peter MacMurchy (Figure 106) doubles or triples sizes of nouns, providing for high-level skimming in context of the full text. Reading research indicates that mixing large and small text within a string reduces reading efficiency.[214]

The author of these Travels, Mr. Lemuel Gulliver, is my ancient and intimate friend; there is likewise some relation between us on the mother's side. About three years ago, Mr. Gulliver growing weary of the concourse of curious people coming to him at his house in Redriff, made a small purchase of land, with a convenient house, near Newark, in Nottinghamshire, his native country; where he now lives retired, yet in good esteem among his neighbours.

Figure 106. Running text set at two sizes: doubling the size of nouns in context of the full text. Image by Peter MacMurchy, courtesy of Uncharted Software, used with permission.

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[213] Michael Twyman, *The British Library Guide to Printing: History and Techniques.* British Library. London. 1998. p. 29.

[214] Thomas Sanocki and Mary C. Dyson. "Letter processing and font information during reading: Beyond distinctiveness, where vision meets design." in Attention, Perception, & Psychophysics 74, no. 1 (2012): 132-145.

Beyond size and color, many other traditional visual attributes from Table 2P19 have been applied to text. These have not been thoroughly researched in visualization as applied to typography. In general, non-typographic visual attributes are beyond the scope of this thesis, but important to consider within an expanded typographic design space and there are many typographic examples, such as:

- **Texture**. In the first example in Figure 107, Italo Lupi[215] uses filled textures on letter forms. These stylized letters may require some effort to decode.
- **Scale**. Customized, highly stretched letterforms may still be readable, as seen in the word "Kunst" in the poster by Mark Imboden[216] in the second example in Figure 107.
- **3D**. In the third image in Figure 107, multiple orientations of 3D text are used while retaining a legible message.[217]
- **Transparency and Outline**. Italo Lupi[218] uses transparent, outlined, 3D letterforms. Letters remain legible even with overlap and orientation (right image Figure 107).

Figure 107. From left to right: A) Letter forms filled with coarse textures. B) Custom vertically scaled letters. C) 3D extruded letters; D) Transparent outlines letters. Images copyright IDEA Magazine.

- **Blur**. Optical effects such as blur can be applied to text, such as Figure 108 left.[219]
- **Shape**. Text can be used as a texture (e.g. Figure 58P67) and used to fill a shape, such as the map area in Figure 34 rightP39, the puzzle shape in Figure 48 middleP50, expressive silhouettes such as Figure 108 middle,[220] or the shape of a country in an infographic (Figure 108 right).[221]

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215 Italo Lupi. Calendar for GRAFICHIE MARIANO Printing 1194. In IDEA Magazine May 1, 1996, figure 137. http://magazines.iaddb.org/issue/IDE/1996-05-01/edition/256/page/72

216 Mark Imboden. "Exhibition of Artists from Central-Switzerland in Stens". 1995. In IDEA Magazine May 1, 1996, figure 52. http://magazines.iaddb.org/issue/IDE/1996-05-01/edition/256/page/61

217 Makoto Saito. Batsu 1994 fashion advertising poster. IDEA Magazine May 1, 1996, figure 52. http://magazines.iaddb.org/issue/IDE/1996-05-01/edition/256/page/61

218 Italo Lupi. Report for DePEDRINI Colour Sector. In IDEA Magazine May 1, 1996, figure 136. http://magazines.iaddb.org/issue/IDE/1996-05-01/edition/256/page/72

219 Gan Hosoya, "Sapporo 1972, Olympic Winter Games" IDEA Magazine May 1, 1996, figure 4. http://magazines.iaddb.org/issue/IDE/1996-05-01/edition/256/page/54

220 Alan Fletcher. Poster for the first Annual Pentagram Lecture held in conjunction with the Design Museum, 1991. In IDEA Magazine May 1, 1996, figure 68. http://magazines.iaddb.org/issue/IDE/1996-05-01/edition/256/page/61

221 David McCandless. "What does China censor online?", Information is Beautiful. https://informationisbeautiful.net/visualizations/what-does-china-censor-online/

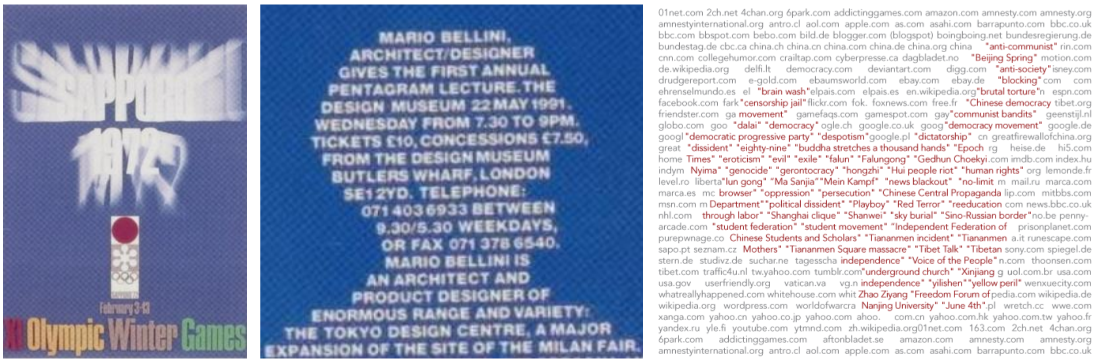

Figure 108. Left: Motion blurred text. Middle: Shape filled text. Right: Silhouette filled with text as texture.
Left images copyright IDEA magazine; Right image copyright David McCandless.

There are many more historic examples of other attributes applied to type, for example:

- **Superimposition**, that is, text overlaid on other text, with both texts still legible and readable, such as the left example in Figure 109 by Theo Van Doesburg[222] from the De Stijl art period (1922).
- **Unit grid**, that is, pre-set font sizes selected to fit within a grid, e.g. 1, 2, 5 characters per cell, as shown in the second example in Figure 109, a 1927 Bauhaus period art poster by Herbert Bayer.[223]
- **Text distortion,** such as the example of psychedelic text from the late 1960s in Figure 109 (third image)[224]; which may have been inspired by early 20th century Art Nouveau (such as the poster Figure 109 right[225]) and the late 19th century Arts and Crafts movement in England.

Figure 109. From left to right: A) Portion of De Stijl period text superimposition from 1922; B) Bauhaus period text modularly aligning with grid from 1927; C) *Grateful Dead* poster with distorted text by Wes Wilson 1967; D) Motorcycle poster by Théophile Steinlen 1899. Images not in copyright, except Grateful Dead poster copyright Wes Wilson.

These other attributes are not broadly discussed in this thesis, as these attributes have been explored and identified by other researchers; and they are broadly applicable to any type of glyph or point mark. It should be noted that when these attributes are applied to typography, one still needs to consider text-specific concerns such as legibility, readability and type color (i.e. the even density of type). Furthermore, there are many potential useful and novel applications of these attributes, particularly when applied to different layouts, different scopes of text and/or combined with other type attributes – this is an area with much opportunity for future work.

[222] Theo van Doesburg and Kurt Schwitters "Kleine Dada Soiree", 1922. In IDEA Magazine May 1, 1996, figure 24. http://magazines.iaddb.org/issue/IDE/1996-05-01/edition/256/page/24
[223] Herbert Bayer, Europaisches Kunstgewerbe 1927. In Figure 47 from IDEA Magazine May 1, 1996. http://magazines.iaddb.org/issue/IDE/1996-05-01/edition/256/page/32
[224] Wes Wilson. Grateful Dead Poster. 1967. Via wes-wilson.com. Attribution-NonCommercial-NoDerivs 3.0 Unported (CC BY-NC-ND 3.0)
[225] Théophile Steinlen. Motocycles Comiot. 1899. Public domain. Available at: https://en.wikipedia.org/wiki/Th%C3%A9ophile_Steinlen#/media/File:Steinlen-Motocycles_Comiot.jpg

B:4.13. Font-Attribute Summary and Application to Visualization

Table 8 itemizes font-specific visual attributes as discussed in this chapter on each row. This is a primary contribution of the research to the visualization domain. The central columns relate typographic attributes to perception. Perceptual psychologists and vision researchers identify different *visual channels*, such as position, size, intensity, orientation and shape.[226] Each font attribute utilizes some combination of these perceptible visual channels. For example, font weight, at a macro-level can be understood to primarily alter the intensity of characters, which it achieves at a micro-level by varying the widths of letter strokes.

Some visual channels are stronger cues for guiding attention than others (e.g. Wolfe and Horowitz[227]), and can visually **pop-out** (e.g. Healy and Enns[228]) as established in decades of perceptual psychology experimentation. This is summarized in the column labelled *preattentive potential*. For example, intensity (luminance) is considered probably preattentive (P), and line width (size) is considered undoubtedly preattentive (HP). Font weight, which uses both, is recorded as highly probable in this table. Strobelt et al's ranking is provided in the green tinted column, although Strobelt did not test all attributes listed here, and furthermore only tested limited variants (e.g. for font weight Stobelt only tested normal and bold, not lightweight vs. heavyweight).[229]

Table 8. **Characterization of font-specific visual attributes for encoding data:** showing attribute, related visual channel, preattentive potential, best encoding and example.

Group	Font Attribute	Visual Channel: Position	Length/Size	Intensity	Orientation	Shape	Containment	Preattentive Potential†	Strobelt rank	Best for encoding: Q: quantitative O: ordered C: categoric G: grouping/relationship L: literal	Example
Glyphs	**Alphanumeric Text Glyph**					◆		D		**L**, **O**	ape bat cat dog 123 456
	Symbols					◆		D		**C**	! ? # @ #comment $var
Font Family Attributes	**Font weight**		•	◆				**HP**	2	**Q** (2-9 levels)	1.0 2.0 3.0 **5.0** **8.0**
	Oblique / Italic				◆			**HP**	6	**C**, **Q** using slope angle	-2.0 -1.0 0.0 *1.0* *2.0*
	Case inc small caps		•			◆		**P**		**C**, possible O (2-3 levels)	BIG AVG. Small tiny
	Typeface					◆		**P**		**C** (2-6 levels)	Swiss French German *Italian*
	Underline	◆	•					**HP**	4	**C**, **O**, **Q** (using length)	plain dash single double
	Condensed		◆	•				**HP**		**Q**, **O** (2-4 levels)	1200 **2000** **3000**
Sequence	**Squished**		◆	•				**HP**		**Q**	anorexic thin plain wide **fat**
	Spacing		◆	•				**HP**	5	**Q**, **O**	tall grand venti
	Baseline shift (e.g. subscript)	◆	•					**HP**		**C** (2 levels)	Normal High Low
	Delimiters						◆	D		**G**	(but) *and* <or>
Font Design	**X-height**		◆					**HP**		**O**, **Q** (few levels)	ick ick ick
	Contrast / Stress angle					◆		**P**		**O** (few levels)	LOW MED. HIGH
	Serif length / Bracket size		◆					**HP**		**O**, **Q** (too small to see?)	see prototypo.io

◆ / • indicates primary / secondary visual channel for font attribute † HP: Highly probable, P: probable, D: doubtful

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[226] Semir Zeki, *A Vision of the Brain,* (Boston, MA: Blackwell Scientific Publications, 1993), Pl. 6.
[227] Jeremy M. Wolfe and Todd S. Horowitz. "What attributes guide the deployment of visual attention and how do they do it?." *Nature reviews neuroscience* 5.6 (2004): 495-501, see Table 1.
[228] Chris G. Healey and James T. Enns, "Attention and Visual Memory in Visualization and Computer Graphics," in *IEEE Transactions on Visualization and Computer Graphics* 18, 7, (IEEE, 2012): 1170–1188.
[229] Hendrik Strobelt, Daniela Oelke, Bum Chul Kwon, Tobias Schreck, and Hanspeter Pfister. "Guidelines for Effective Usage of Text Highlighting Techniques." *IEEE transactions on visualization and computer graphics* 22, no. 1 (2016): 489-498.

Some visual attributes are more accurate for perceiving magnitude (e.g. see Cleveland and McGill[230]) and the related concept of the number of distinct levels which can be perceived (e.g. see Ware[231]). For example, some channels are effective for encoding quantitative data (e.g. size), while others can only differentiate (e.g. shape). Font weight, using size and intensity, can be used for encoding quantitative or ordered data, while font family, using shape, can be used for indicating categories. This is shown in the second last column of Table 8. In most cases, font attributes do not have many distinct levels, limiting their use to only a indicating only a few different data levels.

Glyphs (a,b,c,β,δ,ς,وُ,の,み) can be used to encode literal data. Alphabetic or numeric glyphs can also be used to order data, based on a learned ordering. Both literal encoding and ordered encoding are not constrained to a few values like other attributes, however, these are highly unlikely to be pre-attentive.

The final column provides an example of the font attribute including variations the attribute across a few levels. The examples show some potential orderings, for attributes which are orderable, for example, orderings can be created using font weight, oblique angle, case, underline, condensed, squish, baseline and x-height.

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[230] Cleveland, William S., and Robert McGill. "Graphical perception: Theory, experimentation, and application to the development of graphical methods." *Journal Of The American Statistical Association* 79, no. 387 (1984): 531-554.
[231] Colin Ware *Information Visualization: Perception for Design,* (Waltham, MA: Morgan Kaufmann, 2013), 130.

B:5. Synthesis of Text in Visualization Design Space

All of the preceding sections can be organized to define the design space for text in visualization. Figure 110 illustrates all of the text extensions (in red) in relation to the broader visualization pipeline – *this is one of the most important contributions of this thesis*. This is the design space of type in visualization. Compare this image to Figure 5P9 and Figure 7P10.

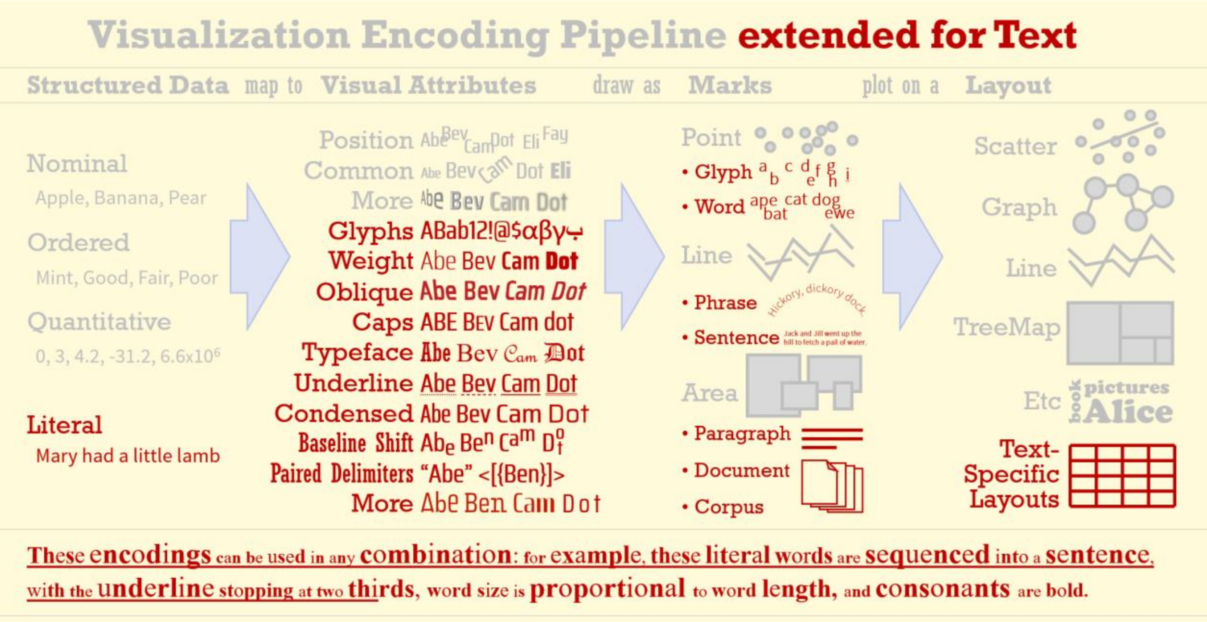


Figure 110: The visualization encoding pipeline, extended to text in red. See Table 8P102 for full list of typographic visual attributes and their characterization. Image by Author.

Unlike Figure 7P10, text is not relegated to a pre-processing step. Text is a primary data type; can be enhanced with visual attributes to convey additional data including typographic attributes; can be represented at any level from glyph to document; and can be used in a wide variety of layouts including text specific layouts:

1. **Data Encoding**. Type can be used to encode all data types including categoric (e.g. typeface), ordered (e.g. lower case, small caps, uppercase) and quantitative (e.g. font weight); plus the literal encoding of the text itself (i.e. *B:2.1*P52); which opens possibilities for significantly different kinds of visualizations. Unlike other encodings, each literal encoded mark can express hundreds of thousands of unique words as well as more complex phrases and sentences providing for richer context and deeper interpretation as elaborated in *B:3: Considerations for Visual Perception of Text*.P63
2. **Marks and Type Scope**. As discussed in *B:2.3 - Mark Types and Scope of Text*P59 the visualization conceptualization of marks as point, line or area can be expanded to seven kinds of marks: glyphs and words (types of point marks); phrases and sentences (types of line marks); and, paragraphs, documents and corpora (types of area marks).
3. **Typographic Attributes**. As detailed in *B:4 - Characterization of Type Attributes*P75 each of the 15 typographic attributes can represent more than one or two levels of data: they each have a range of potential values, although in many cases limited to 3-5 levels (see Table 8P102). Some work well with

categoric data, ordered data or quantitative data. In many newer fonts, multiple font weights are available. Font oblique angle can be skewed to various angles including reverse angles. While uncommon, orderings can be made with underline or case. And so on. Furthermore, the other 30+ visual attributes (e.g. size, color, transparency, 3D, blur, etc., see Table 2P19) are also available to visualizations using type.

4. **Layout**. New kinds of text specific layouts are feasible as discussed in *B:2.4: Unique Layouts*P61. Furthermore, almost all other visualization layouts – whether well-established layouts such as bar charts, line charts, Venn diagrams and choropleth maps – or, new types of visualization layouts invented in the last 50 years, such as dynamic graphs, mosaic plots and parallel coordinates, can be enhanced with new typographic techniques. There are potentially hundreds of different possible layouts, for example, *The Periodic Table of Visualization Methods* (www.visual-literacy.org/periodic_table/periodic_table.html), has more than 100 different variants of visualization layouts.

The implied design space of typographic encodings is vast: 100,000 words x 6 mark types x 15 typographic attributes (each with 3-5 levels) and 30+ other visual attributes (each with 2-100 levels) x 100's of layouts implies an enormous number of permutations. Additionally, multiple combinations of encodings may be used together at any scope, e.g. **The underline stops in the middle of this sentence, the size of each word is proportional to the word length, and consonants are bold.**

To organize this vast design space, data encoding and type scope can be combined to create a 4 x 6 framing of possible applications as shown in Table 9. The typographic scope is listed vertically, data types are listed horizontally, and cell intersections identify potential new types of encodings, applicable to any layout or visual attribute. As an example, cell *OW* indicates embedding *O*rdered data into *W*ords, where the ordering could be achieved with varying levels of font weight (e.g. ape, **bat**, **cat**). Cell *CG* indicates embedding *C*ategoric data into *G*lyphs, for example, where individual glyphs can be manipulated to encode meaning, such as silent letters indicated with a lightweight font as shown in the glyph row (e.g. **Glo**u**ce**s**ter**).

Table 9.**Matrix for categorizing type use in visualization - by typographic scope vs. data type**.

Mark	Scope	Literal	Categoric	Ordered	Quantitative	*Scope samples*
Point	Glyph	LG	CG	OG	QG	**A** B *C* **though** **answer** **Glo**u**ce**s**ter**
	Word	LW	CW	OW	QW	Abe **Ben** *Cam*
Line	Sentence	LS	CS	OS	QS	*President Obama* nominates *Merrick Garland*.
Area	Paragraph	LP	CP	OP	QP	**Mr Phileas Fogg lived, in 1872, at No. 7, Saville Row, Burlington Gardens,** the house in which **Sheridan died in 1814**. He was one of the most noticeable members of the **Reform Club**, though he seemed always to avoid attracting attention; an **enigmatical personage**, about whom little was known, except that he was a polished man of the world.
	Document	LD	CD	OD	QD	
	Corpus	LC	CC	OC	QC	
Encoding samples		ape bat cat d09 ελκ	ape bat cat d09 ελκ	ape bat cat **d09** **ελκ**	ape bat cat d09 ελκ	

This 4 x 6 scope vs. data type matrix can be used to review the existing text visualization research. For example, the scope of textual encodings used in the examples at the *Text Visualization Browser* (http://textvis.lnu.se/) is outlined in Table 10. Note that this table does not include a column for ordered use of visual attributes: ordered attributes have been included in the counts for the quantitative column, under the assumption that an ordered encoding is a low resolution encoding of quantitative data.

Table 10, **Scope of text used in text visualizations in Text Visualization Browser**.

	Encodings Across All Visualizations					Font-Specific Encodings	
Scope of Text in Visualization	None	Literal Only	Categoric Encoding	Quantitative Encoding	Total	Categoric Encoding	Quantitative Encoding
None	40	0	0	0	40		
Glyph		0	1	1	2	0	0
Word		87	19	68	174	7	0
Line		9	3	7	19	2	0
Paragraph		8	4	3	15	5	0
Document		0	2	3	5	2	0
Corpus		0	0	0	0	0	0

Forty out of 249 visualizations do not use text. Out of the remaining 209 visualizations, 173 operate at the level of words: that is, for 83% of the examples the scope of the text is words. These may be *LW* (Literal Words), such as labels on a scatterplot; *CW* (Categoric Words), such as color-coded words; or *QW* (Quantitative Words) such as variably-sized words. Beyond words, larger scopes of text encoding data occur infrequently. Sentences occur 19 times (e.g. a title, a tweet or a keyword in context). Paragraph scope occurs 15 times (e.g. an abstract or a few sentences). No examples exist depicting text at the level of a corpus: current examples of corpus visualization reduce documents down to marks such as a dot per document in a graph, or lists of words describing a topic. In general, word-based visualizations of text may currently be common because larger text sources, such as documents or corpora, can be reduced down to word lists using a natural language processing techniques such as word frequencies, entity extraction, topic classification and so on. At the sub-word level, only two text visualizations are listed - one for the analysis of suffixes and the other phonetic units.

With regard to font-specific attributes (e.g. bold, italic, underline), there are very few visualizations (final two columns) and are all categoric encodings - there are no font-specific quantitative encodings. While Table 10 does indicate that there is some exploration across the scope and encodings, there is clearly a strong bias to words. Furthermore, as indicated in Table 1P13, the existing use cases are almost entirely biased to use of size and/or hue to encode data, and as discussed earlier there are various issues with these visual attributes (e.g. readability, information density, contrast, loss of associative perception). Also, as indicated by Table 10, there is very little exploration with font-specific encodings.

What next?

Given the goal of expanding the design space, there should be many demonstrable applications. Simply outlining the parameters of a design space does not provide any indication of how these new capabilities might be used. How can they generate new value? Value is unlikely to be uncovered by simply converting an existing successful technique to use a different parameter. For example, simply changing a tag cloud to use font weight instead of font size is perhaps more space efficient but viscerally less appealing and doesn't solve any new problems (Figure 111).

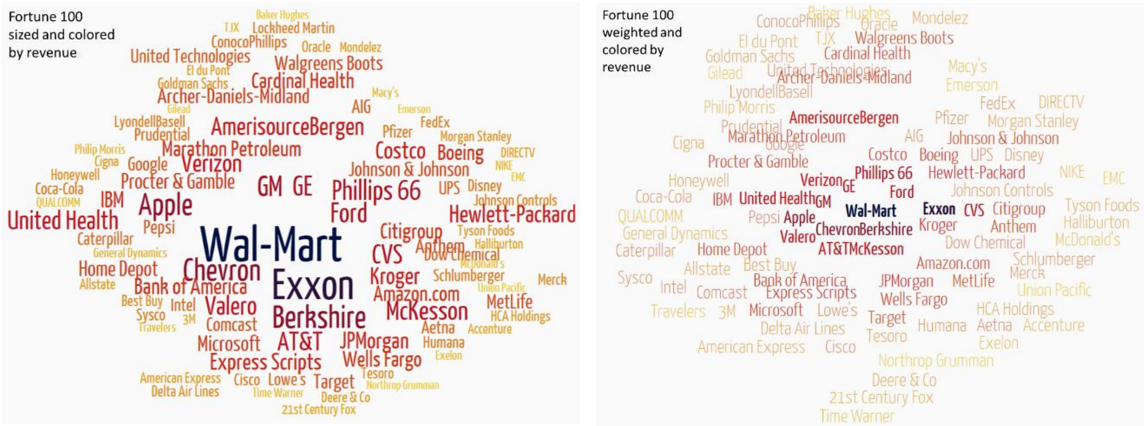


Figure 111. Tag cloud using size (left) or using font weight (right) to encode the revenues of Fortune 100 companies. Images created by author based on data from fortune.com.

The application of this design space is vast and will be explored in the next section: *PART C. Applications of Typographic Visualizations.* The 4 x 6 type scope vs. data type matrix (Table 9) is used as one means of validation. If the text visualization framework presented here is valid, then it should be feasible to construct visualizations for many different combinations of data type and mark scope. This helps guide different applications to focus on. For example, there is little need to focus on cell *QW* (*Q*uantitative *W*ords) as many examples already exist (e.g. tag clouds, such as the image above). Instead, the next section will show that there are a very wide variety of new and extended typographic visualizations, relevant to a wide variety of applications, and usable with very many well-known visualization layouts.

PART C.
Applications of Typographic Visualizations

Description of Part C

This new typographic visualization design space can be used to Generate New Visualization Designs;[109] or, create new kinds of **uses and applications** of varying Scope of Encoding (in some cases leveraging historic techniques) to enhance many well-known *visualization layouts*:

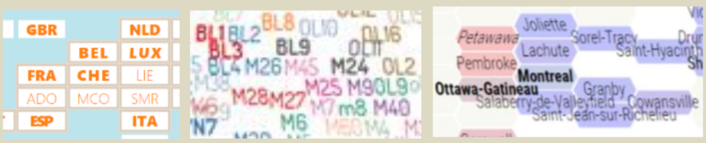
C:1. LW: Literal Words 111
Alphanumeric point marks, which are fundamentally **labels,** are applicable to *scatterplots & graphs* for immediate identification, higher information density and enabling serendipitous discovery.

C:2. LS: Literal Sentences 124
Lines in visualizations are represented as **microtext on paths** for *line charts & parallel coordinate plots* enabling differentiation across many more lines and inclusion of literal content.

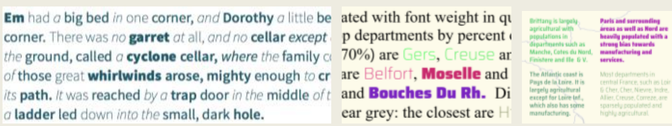
C:3. LX: Literal Elements 137
Text as stackable units creates **distributions** for *new variants of stem & leaf plots,* simple descriptive statistical content analysis.

C:4. CD: Categoric Documents 144
Areas of labels with formats indicate **set membership**, e.g. *Venn, mosaic, stacked bar & graphs* enhance element identification, membership quantity estimation and membership differentiation.

C:5. OW: Ordered Words 164
Font formats create **ordered markers** and are applied to *thematic maps* for improved performance in identification & location tasks.



C:6. OP: Ordered Paragraphs 176
Font formats facilitate **text skimming** such as *paragraphs & spark words* for rapid non-linear access to key text.



C:7. CG+OG: Formatted Glyphs 190
Font formats applied to **word subsets** aid *spelling, pronunciation, and prosody.*

C:8. QS: Quantitative Sentences 193
Font formats over a portion of a sentence shows **magnitude**, creating a *bar chart embedded in text,* with more legible text than the equivalent simple bar chart, or text-based treemaps.

Ideating New Kinds of Visualization (following Bertin)

The next step is to use this design space to create new kinds of typographic visualizations. This framework should be useful to facilitate the ideation of new visualization approaches, as well as useful to create new visualizations in response to particular applications. This PART will show how text can be applied to many well known visualization techniques and new visualization techniques implying new areas and new opportunities for visualization.

As a simple starting point, consider Bertin's example in *Semiology of Graphics* (pages 100-138) where 90 different visualizations are generated from a dataset of 90 French departments with attributes of department name, code, population for three occupations and proportions for each of those (Figure 112 data table at left). A subset of these are shown in Figure 112: bar charts, scatterplots, maps and so on. Note no typographic encodings are used in any of Bertin's 90 examples other than simple labels.

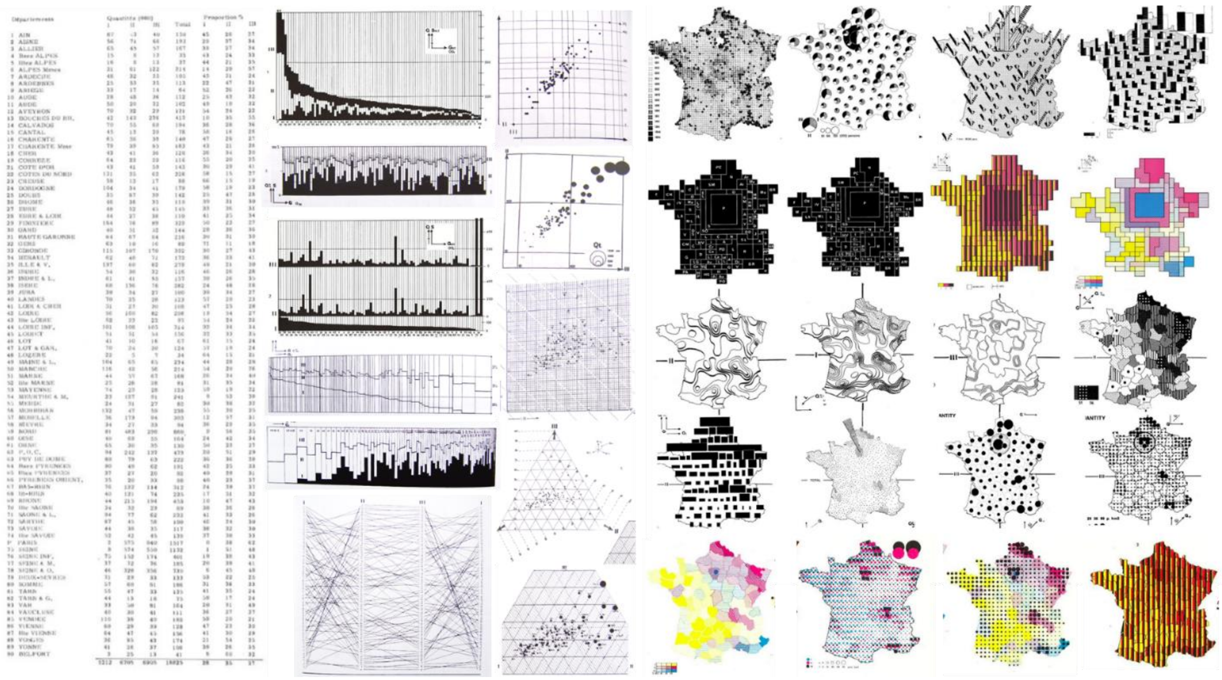
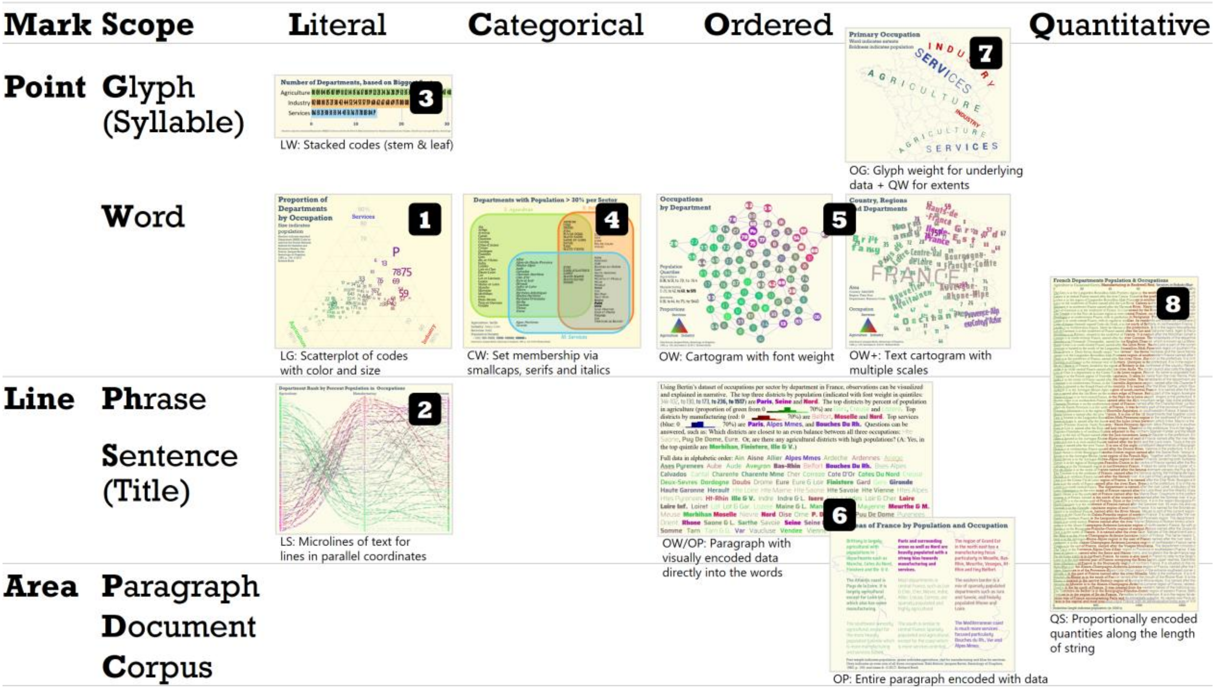


Figure 112. Some of Bertin's example visualizations of occupations by department.

Using the previous chapter's typographic framework for text in visualization, many extensions and unique visualizations can be generated *using Bertin's same dataset*. The application of text and font attributes to visualizations do not need to be constrained to common typographic nor visualization conventions: font attributes can be applied to subsets of words, sentences can flow along paths, internal properties of glyphs can be modified (e.g. x-height, font width). Table 11 shows ten typographic visualizations created using the same dataset as Bertin.

Table 11. **Some typographic visualizations using Bertin's occupations by department dataset in** Figure 112.



Each of these thumbnail images represent unique visualization approaches using different data type encodings x scope. Each of these will be discussed in upcoming chapters in this part of the thesis:

C:1. **LW: Literal Words** used as point marks (i.e. labels)PAGE:111
C:2. **LS: Literal Sentences** used as microtext to form lines in visualizations124
C:3. **Lx: Literal elements** used as units to create new variants of stem and leaf plots137
C:4. **CD: Categoric Documents** using labels to create areas and indicate set membership144
C:5. **OW: Ordered Words** specifically used to create multivariate thematic maps164
C:6. **OP: Ordered Paragraphs** using font formats to facilitate text skimming across paragraphs176
C:7. **OG+CG: Glyph Formats** used to creating ordering and categories in letters and syllables190
C:8. **QS: Quantitative Sentences** applying formats over a portion of a sentence to indicate magnitude193

Each chapter will define the potential application area for the particular data type encoding and scope. Each chapter will provide multiple examples of issues with other visualization techniques; illustrate a number of text-based examples that may overcome other limitations; and itemize potential benefits over other visualization techniques. A brief evaluation of the particular technique within each example is included in most chapters. A much broader evaluation across the entire framework follows in a subsequent portion of the thesis.

C:1. LW: Literal Words: labels as point marks

Many traditional visualization techniques use simple point marks to encode data, such as dots in a scatterplot, circles in a graph, squares in a heatmap, or glyphs as shown in Figure 113. These marks typically encode data via position, and also a secondary data attribute, typically presented by color, size or shape.

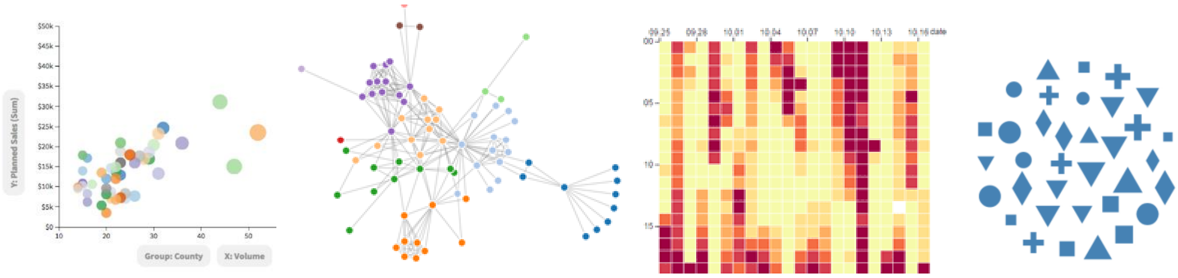


Figure 113. Examples of point-markers in popular visualization techniques. Images all from d3js.org, BSD license 2017.

C:1.1. Alphanumeric codes instead of Point Marks

Figure 114 left shows a typical bubble plot (this is the same visualization as Figure 51[55], with a larger dataset of 150 countries). In this example, country birth rate (x) vs. death rate (y) and population is indicated via (dot radius). Macro patterns, e.g. the crescent shape, are visible.

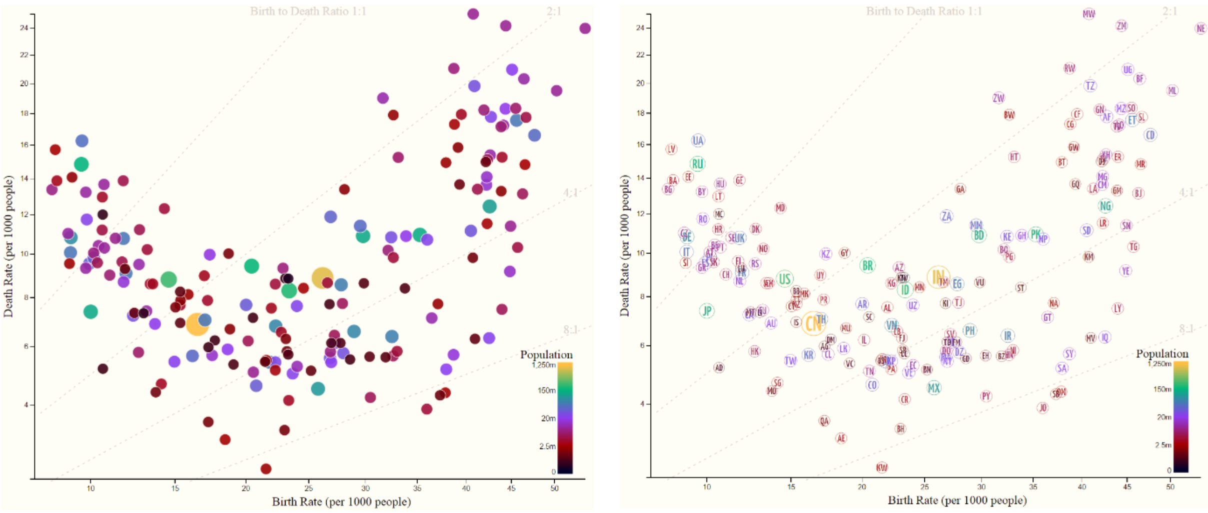


Figure 114. Birth rate vs. death rate by country with size and color proportional to population. Left uses dots, right uses country codes. (See Figure 118[116] for larger version). Images created by author.

Figure 114 right shows the same birth rate vs. death rate dataset as left plot, instead using 2-letter country ISO codes as a label-based scatterplot. The primary mark per data point is the 2-letter glyph. A secondary outline circle is also provided to make the marker location unambiguous (i.e. a text label without an added mark requires an additional note to indicate whether the data point is centered on the text, at the bottom of the text, left aligned, etc.).

C:1.2. Labels are fast and specific

Labels, unlike a dot or glyph, do not require additional effort to decode. The original example discussed in *B:2.1 Literal Encoding*P52, uses a small dataset with a simple legend. In this example, there are many more data points: the non-text version would not be able to support 150 uniquely identifiable colors, so slow interactions would be required to reveal the country names (e.g. tooltips). In the label-based version, the viewer can simply shift visual attention to any marker of interest to identify the item.

C:1.3. Labels offer local context

The use of labels can facilitate the ability to discern micro-level relationships in local areas. For example, in this dataset, toward the upper left are countries such as LV (Latvia), UA (Ukraine), RU (Russia), BG (Bulgaria), etc. – i.e. countries associated with the former east bloc (These countries have a higher death rate than birth rate – i.e. a shrinking population.) While it may be feasible to encode regional or other group-based memberships based on a data value, instead the viewer can use their pre-existing knowledge to recognize patterns by explicitly representing the individual identities as text. In this example, "former east bloc" is unlikely to be a category that exists in this dataset. (There are many, many geographical country groupings: Benelux, Scandinavia, Baltic, Nordic, Hanseatic, Germanic, Euro-zone, European Union, Euro, Eastern Europe, etc.)

Interactive techniques could potentially reveal these patterns, but the interactive techniques would require more interaction, greater cognitive load and more time (as discussed in *B:2.1.ii: Perceptual Benefits: Fast, Efficient Identification*P53). Without labels, local identification can be achieved via: a) tooltips (slow and reliant on short term memory overload); b) lasso selection and a linked visual listing entities such as a table (but a table does not reveal local relationships); or c) zoom with automated level of detail turning labels on/off - which is rare in infovis but common in maps (note: maps have 500 years of labelling heuristics, but infovis does not have labelling heuristics). Direct depiction via text provides immediate access without interaction.

In general, text labels identifying entities can facilitate the local pattern recognition by providing a context around any given point. The utility of local pattern detection is supported by various researchers:

1. **Tobler's First Law of Geography** states: "Everything is related to everything else, but near things are more related than distant things."[232] Many visualization layouts attempt to locate related objects close together (e.g. graph layouts, scatterplots, hierarchical treemaps and set visualization). Labeling entities in any of these layouts supports identification of local related entities to a given entity.
2. **Edward Tufte and Micro-Readings.** Edward Tufte popularized the concept of micro/macro readings; that is visual displays with large amounts of high-density information with the ability to visually read these at various levels ranging from high-level macro patterns such as trends, clustering and outliers; down to low level localized patterns, such as individual observations and local peers. Tufte summarizes this with "to clarify, add detail."[233]

   Tufte's approach is somewhat similar to Shneiderman's visual information-seeking mantra:

[232] H. J. Miller, "Tobler's First Law and Spatial Analysis", *Annuals of the Association of American Geographers,* 94(2), pp. 284-289. 2004. Blackwell Publishing, MA.
[233] E. Tufte. *The Visual Display of Quantitative Information.* Cheshire Press. 1983.

overview first, zoom and filter, then details on demand.[234] In Shneiderman's approach, interactivity is used to reveal the micro-data information whereas Tufte plots it directly. In Tufte's case, paper is exceedingly high resolution whereas in Shneiderman's case, computers in 1996 are fairly low resolution (72 DPI) with graphics hardware not necessarily suited to managing and manipulating thousands of elements. Now, modern displays have higher pixel density (e.g. 200-350 DPI) and greatly enhanced graphics capabilities which enables the potential for Tufte-inspired information dense displays which support the depiction of local detail – such as text.

3. **Jacques Bertin and Categories.** Bertin suggests that shapes can be used to represent categories of high cardinality and provides an example map with 59 different glyph types (each glyph representing a different type of manufacturing, see p. 157 in *Semiology of Graphics*). Bertin points out the global patterns with respect to a particular shape-type cannot be seen. Instead the viewer must linearly scan across glyphs and can only see local patterns. Furthermore, the viewer cannot easily ascertain if a local pattern is meaningful without comparison to the global pattern (e.g. a local concentration of a particular glyph type is meaningful only if the global concentration of that glyph type is not the same).

   Labels, however, are different. When labels identify unique entities (e.g. countries, people, companies, cities, etc.), a comparison to the global is not needed. Each label occurs only once and the viewer can use pre-existing knowledge about those entities to infer new knowledge. Figure 115 is Bertin's ternary plot of occupations by department code. In Bertin's example in *Sémiologie Graphique* (p. 107), examples are provided with dots; or dots and labels. In Bertin's black & white examples, the use of both dots and labels clutters the display. Here, all the information is available as labels which are also redundantly encoded with color. These labels are alphanumeric codes – like ISO codes, they may be recognizable by users familiar with the codes, for example, these codes are used in addresses (i.e. postal codes) and on license plates.

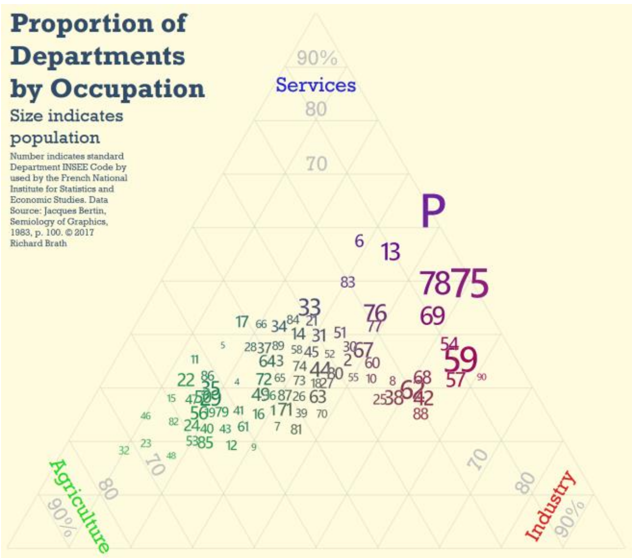


Figure 115. Bertin's ternary plot with literal codes. Images created by author.

234 B.Shneiderman. "The Eyes Have It: A Task by Data Type Taxonomy for Information Visualizations." In *Proceedings of the IEEE Symposium on Visual Languages*, pp 336-343, Washington. IEEE Computer Society Press, 1996.

4. **Thudt et al's Serendipity.** Serendipitous discovery is the fortuitous unexpected discovery by accident. It is researched in library sciences and summarized by Thudt et al[235] who note that serendipity is most closely associated with coincidence: wherein related ideas may manifest as simultaneous occurrences that seem acausal but still meaningful. Related ideas can be expressed and recognized in language (e.g. words, phrases, sentences) providing different cognitive associations than visual associations. As such, the integration of text in visualization offers the potential for more opportunities for serendipity. Interestingly, Thudt's et al's visualization designed specifically to encourage serendipitous discovery, *The Bohemian Bookshelf*, provides five different visualizations, four of which utilize text either directly (i.e. Author Spiral and Keyword Chains) or indirectly (i.e. images of covers in the Book Pile and Cover Circles).

As such, the expertise of previous researchers implies value in direct visual access to local detail. While an experiment has not been done to test this, future work could include a comparison of two visualizations (one using labels, the other using dots or glyphs) and create tasks that go beyond simple identification or comparison to one requiring local insights. Given that the domain background may vary by subject, this experiment may be difficult to configure, perhaps requiring an upfront survey to assess prior knowledge of a topic area.

C:1.4. Text vs. Glyphs

Instead of text, micro-level information could be encoded with icons or glyphs. However, ready-made charting software has a limited number of icons, e.g. Excel provides only nine different markers (e.g. square, circle) and D3,js provides six built-in symbols. A renewed interest in glyph design explores multiple attributes in glyphs (e.g. Brath[236], and Borgo et al[237]).

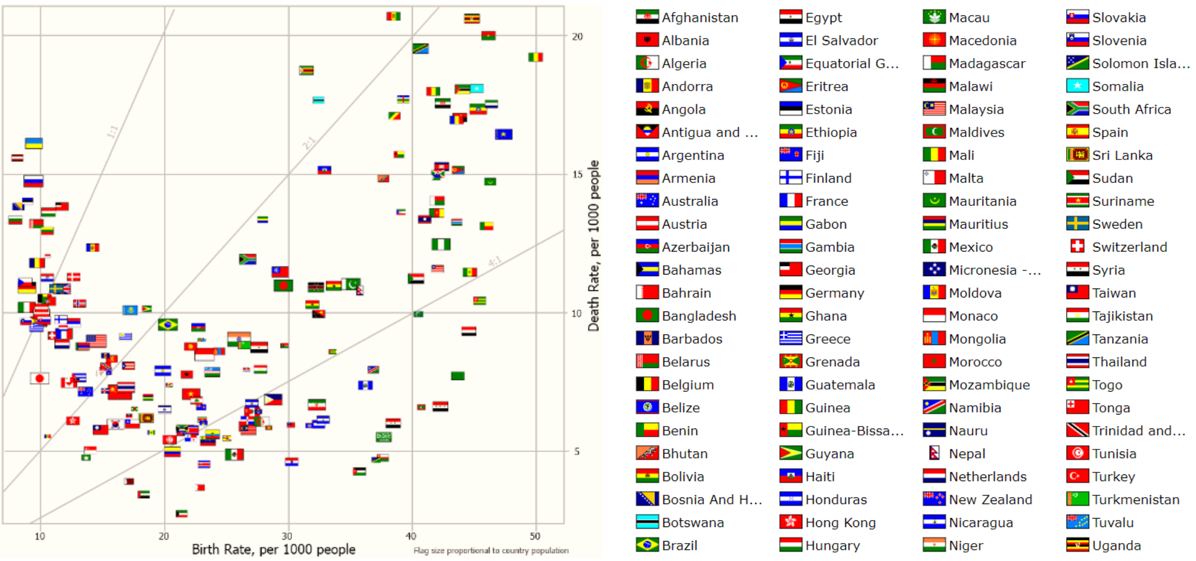


Figure 116. Same birth rate vs death rate scatterplot using country flags; with half of legend shown at right. Images by author.

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235 Alice Thudt, Uta Hinrichs, and Sheelagh Carpendale. "The bohemian bookshelf: supporting serendipitous book discoveries through information visualization." In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1461-1470. ACM, 2012.

236 R. Brath.: "Multiple Shape Attributes in Information Visualization: Guidance from Prior Art and Experiments." *IEEE Information Visualization*. 2010.

237 R. Borgo, J. Kehrer, D. H. Chung, E. Maguire, R. S. Laramee, H. Hauser, M. Ward, M. Chen: "Glyph-based visualization: Foundations, design guidelines, techniques and applications." In *Eurographics State of the Art Reports, EG STARs*, Eurographics Association. 2013.

Figure 116 uses flags instead of dots or alpha-codes. While flags are usable, many people are likely not familiar with more than a dozen flags, thus requiring either a legend or interaction to make the glyphs comprehensible.

Both labels and glyphs can uniquely identify hundreds of items, beyond the fidelity of most other visual channels[238] (e.g. color 10-20). However, the potential advantage of labels over other glyphs (e.g. flags), include:

1. **Mnemonic:** Some text codes may be easy to decipher by their target audience. In the birth rate/death rate scatterplot the top left corner has country codes such as UA, LV, RU, EE, BG which have some similarity to the corresponding country names Ukraine, Latvia, Russia, Estonia, Bulgaria.
2. **Alphasort**: Alphanumeric symbols can be sorted. Given a specific alphanumeric label, e.g. (TV), a legend in sort order aids the viewer to quickly find the target. Conversely given a specific icon of interest (e.g. green, red and green stripe flag), the viewer may need to linearly search through all flags in the legend until the matching entity is found.
3. **Glyph design**: While it may be feasible to design intuitive glyphs, the design task may be difficult when a large number of categorical glyphs are required, e.g. Bertin's map with 59 categories (*Semiology of Graphics*, p. 157).

C:1.5. Occlusion and Spatial Separation

In all cases (dots, glyphs, text), occlusion interferes with tasks such as estimation of number of points, perception of data attributes for largely occluded points, and identification of those points. As shown in Figure 117, solid flags (left) obscure the lower flags. With text, the open letterforms provide visibility to lower letters and thin white strokes on the letters helps legibility (Figure 117 third image). However, there remains perceptual uncertainty with some partially obscured text. Future work could consider strategies for improving text discrimination when text is overlapping, such as font size, outlines, transparency and color variation.

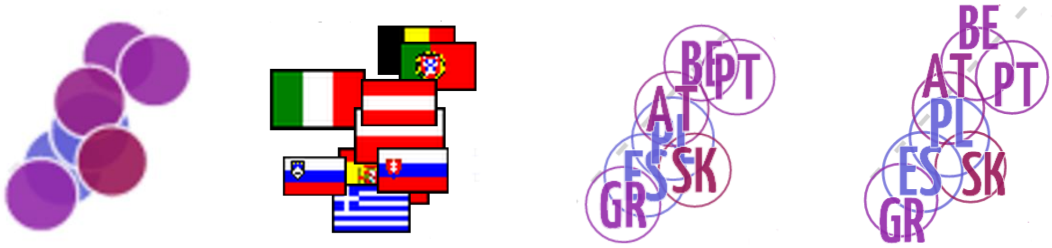

Figure 117. Partial occlusion interferes with visibility and identification. Images created by author.

Alternatively, clear spatial separation of glyphs will result in better legibility. The rightmost image in Figure 117 shows the same labels algorithmically nudged to reduce overlap while maintaining circle positions to indicate the original data location. The slight deviation of positions does not alter macro-level readings, such as the overall crescent-shaped distribution of the points or individual outliers (e.g. Latvia, LV, top left or Kuwait, KW, bottom) as shown in Figure 118. Interaction, such as hover, could dynamically move, show, highlight labels and/or their original positions, allowing a user to animate back and forth between an unmodified and legibility enhanced layout.

[238] R. Brath. "High Category Glyphs in Industry", In *Visualization in Practice* at *IEEE VisWeek 2015*. 2015.

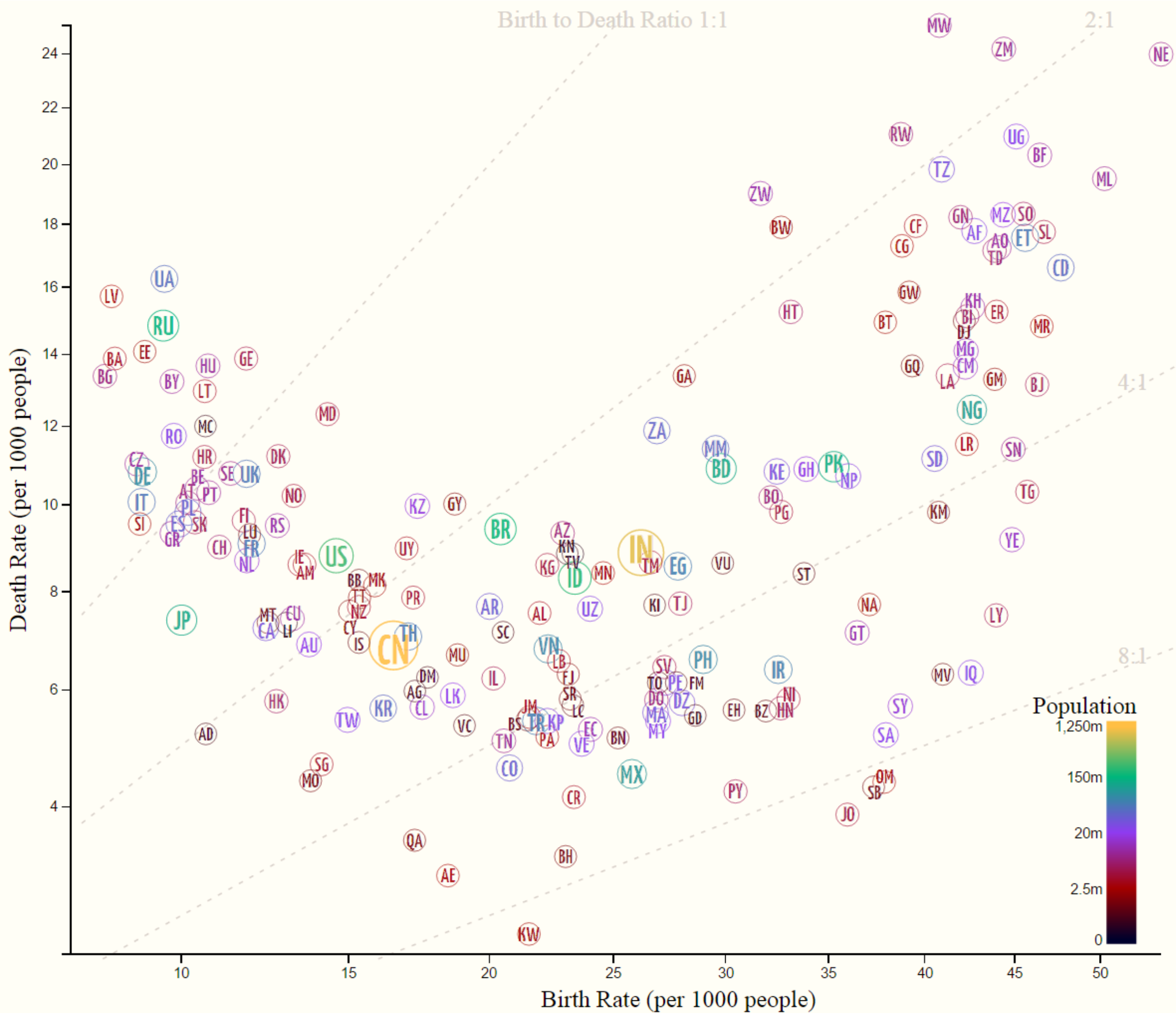

Figure 118. Legibility improves without glyph overlap while overall macro patterns remain visible. Image created by author.

C:1.6. Full Labels instead of Mnemonics

Alphanumeric codes maybe effective if available and the intended viewer can readily decode the mnemonic. In some cases, no mnemonic abbreviation is available. For example, Figure 119 shows statistics for U.S. National Parks. Similar to the previous figure, collision detection is used to reduce label overlap improving legibility. Narrow fonts (e.g. Arial Narrow, Gill Sans Extra Condensed, Roboto Condensed) are designed for use in tight spaces and are used here for labels.

Long labels could potentially hinder macro-level readings such as overly weighting one portion of the plot if long names are concentrated in one area. Furthermore, long labels (e.g. *Black Canyon of the Gunnison*) could have more prominence over short labels (e.g. *Zion*). Cartographers have similar issues labelling maps (e.g. Rome vs. San Francisco) and in practice use a set font weight (e.g. based on city population) regardless of label length. Large scale macro patterns are visible, such as the large central blob, outlier to the lower left (*American Samoa*) and cluster to the bottom right.

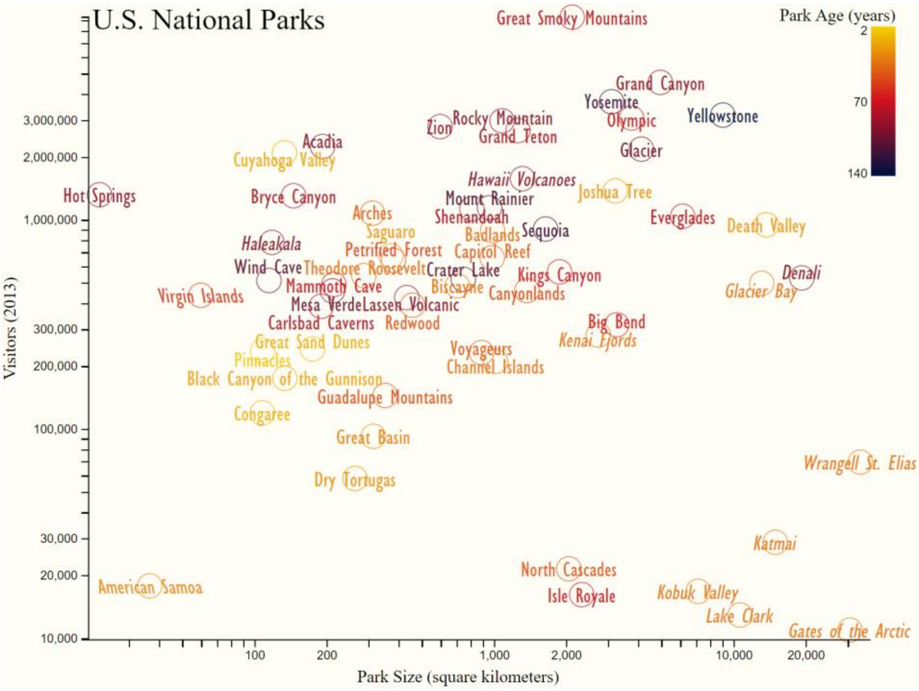

Figure 119. Long labels on a scatterplot of US National Parks. Images created by author.

Local relationships, such as a pair of very close dots, may become less visible with long labels and the underlying circles may need to be referred to. This could be mitigated by filling the circles to be more prominent while adding a faint halo to the text to maintain legibility, as shown in Figure 120.

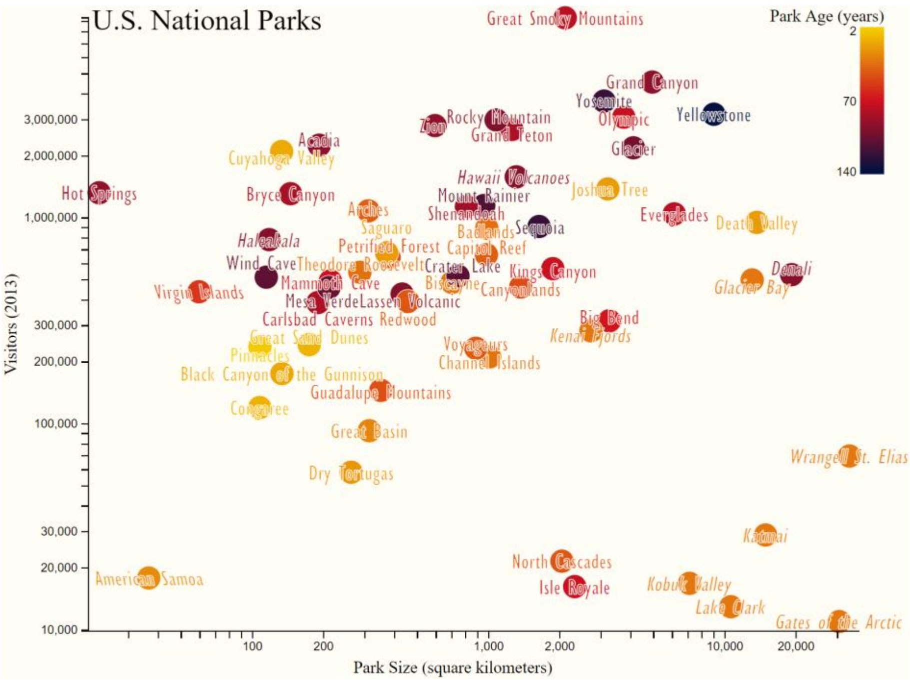

Figure 120. Same plot, with filled points and halos on labels. Images created by author.

There are other mitigation approaches to address issues with long labels, which will be considered in other sections and summarized in *D:1.2.ii Label Length Bias* and Speed: P216.

C:1.7. Hierarchical Labels

Figure 121 is a knowledge map of the top 500 U.S. stocks. Labels appear at three different levels of hierarchy. The smallest, opaque black labels indicate stock tickers of the companies (e.g. aapl). Very large transparent labels indicate ten major sectors (e.g. Health Care, Industrials). Mid-size transparent labels indicate industries (e.g. Biotechnology, Hotels, Road & Rail). Within each level, collision detection separates labels of the same size to avoid occlusion. Across levels, labels are permitted to overlap: difference in size, color, weight and contrast aid legibility, although some text is difficult to read (note: an alternative layout such as a treemap could be used to reduce overlap; or a different algorithm for generating text contrast could result in more readable text).

Hierarchical labelling allows a user familiar with the subject matter to navigate via labels: e.g. identify top level *Utilities*, then *Gas Utilities* then the single red markers labeled *WEC* and *gas*. The preset text sizes per hierarchical level facilitates perceptual association of individual letters into words despite the overlap of words of different sizes (similar to the orientation aiding separation of words in the historic cross-letters in Figure 74P80). The viewer can shift attention as needed to focus on a particular level (e.g. individual stocks) or across levels.

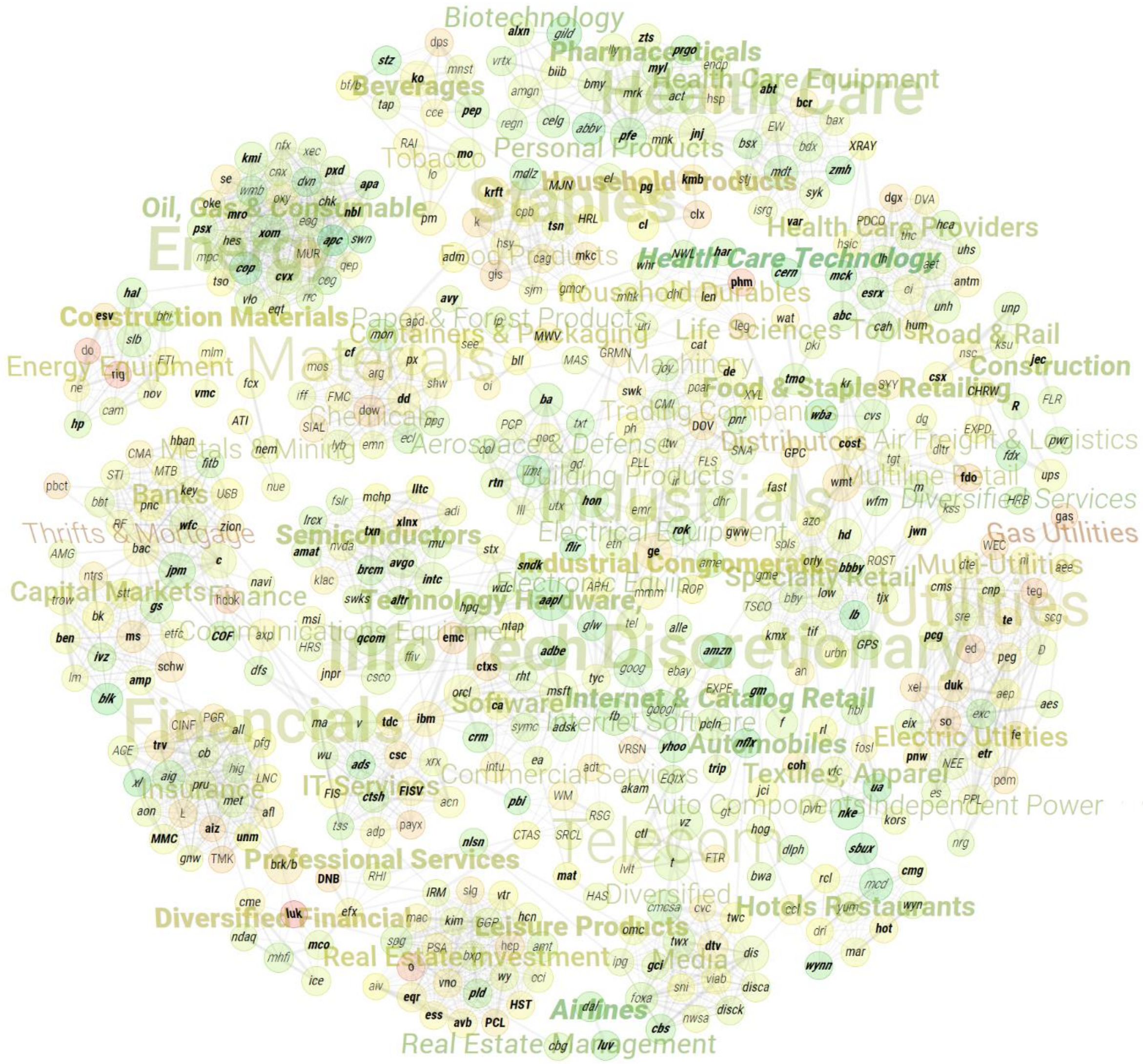

Figure 121. Hierarchical labels indicating the largest 500 U.S. stocks. Image created by author.

C:1.8. Cognitive Model

It has been discussed that a label should be faster to decode than a dot with a legend or interaction. This can be evaluated experimentally, or using an experimentally derived cognitive modelling method such as Card et al.'s GOMS[239] or Lohse's UICE.[240] Lohse, in particular, applies both models to estimate task performance with regards to various charts, and achieves time estimates with both models comparable to the same tasks performed in experiments. The GOMS model generally has fixed times per task but Lohse's UICE model has more tasks with variable times without explanation as to how these variations are to be derived. Therefore, the GOMS model is used in this analysis, following similar task sequences as previously shown by Lohse.

i. Modeling a Simple Identification Task

A simple task could be identification of a particular point in a plot, such as a minimum point or maximum point. An example of a very simple identification task is "Which country has the lowest birth rate?" in Figure 51P55. To achieve this goal, a sequence of fixations is required to collect the relevant information to complete the task. In the label plot (Figure 51 right), the viewer must do three steps:

1) Identify which axis is "Birth Rate" (i.e. the X axis). The eye movement to jump to an axis and associated time to perceive information at that fixation is 230ms. The time to read each label is 300ms. There are two axes to consider, so the total time is 2 x (230+300) = 1060ms. Lohse's examples only show the reading of a recognized target and skipping non-matching targets. This implies one reading action of 300ms of the axis label "Birth Rate". Total step time is 760ms.
2) Find the lowest dot (near the top left). Similarly this is an eye movement and perception step requiring 230ms.
3) Read the country name (i.e. "Russia"), which is 300ms.

All total, the GOMS model predicts that the task will require on the order of 1590ms in the simple labelled scatterplot. In contrast, in the bubble plot (Figure 51 left), there are more cognitive steps to complete the same task:

1) Find axis of interest (1060ms).
2) Find lowest dot (230ms).
3) Identify dot color (i.e. cyan). This requires matching the hue (cyan) to the objective (lowest birth rate) in working memory (70ms).
4) Find the cyan square in the legend. As the target is not in the first column in the legend, this may require two saccades (eye jump plus perception at new fixation point for 2 x 230ms).
5) Read the text adjacent to the cyan square (i.e. "Russia") which is 300ms.

The GOMS model predicts the bubble plot will require 2120ms. Overall, the bubble plot requires 3 cognitive steps while the bubble plot requires 5 steps. The estimated task time for bubble plot is 530ms longer than the label plot: 33% more time required.

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239 Stuart Card, Thomas Moran, Allen Newell, *The Psychology of Human Computer Interaction*, Lawrence Erlbaum, 1983.
240 Jerry Lohse, "A cognitive model for the perception and understanding of graphs." In Proceedings of the SIGCHI conference on Human factors in computing systems, pp. 137-144. ACM, 1991.

Applying the same task to a plot with more data points will show additional benefits performance benefits. For example, a similar question can be asked for the National Parks scatterplot (Figure 120P117), such as "Which park has the smallest area?" This plot has 59 data points, so a scatterplot version cannot use discrete colors to uniquely identify datapoints – instead a scatterplot version would need to use interaction such as a tooltip or selection. In this case, the label plot will have the same performance of 1590ms (identify target axis → find lowest dot → read label). However, the interactive scatterplot will have a somewhat different sequence:

1) Find axis of interest (1060ms).
2) Find lowest dot (230ms).
3) Move mouse to dot. This may require a) mental preparation for the interaction; b) moving the hand to the mouse if not already there; and c) moving the mouse to the target, as described by Fitts' Law. GOMS puts a lower bound of 1100ms on this mouse movement (assuming the hand does not need to move to the mouse). Using software from MacKenzie,[241] similarly sized dots required 1100-1300ms, close to GOMS.
4) Most tooltip implementations have a 100-200ms delay prior to showing a tooltip, to avoid having spurious tooltips appear as the mouse moves across the display. Alternatively, a click can be used to invoke a tooltip or popup, although a mouse click is slower at 200ms.
5) When the tooltip appears, there may be more information in the tooltip than just the country name. This in turn may require an additional saccade to move to the correct text item within the tooltip. However, assume that this particular tooltip has only the country name, so no additional saccade is required.
6) Then, read the text in the tooltip (i.e. "Hot Springs"), which takes 300ms.

Overall, this assuming the fastest interactive sequence – with no hand move, a fast responding tooltip and no saccade into the tooltip – the time required will 2790ms. This is 1200ms longer than the label plot (75% more time required).

A similar result would be computed using an even larger scatterplot, with some additional caveats. Consider "Which country has the lowest birth rate?" using the full dataset of 187 countries as shown Figure 114P111. First, labels need to be legible to be readable. Partial occlusion will slow reading down or interrupt it altogether. This can be overcome with collision detection and nudging (assuming there is sufficient white space to nudge) as in Figure 118P116. Secondly, this particular example uses codes instead of words. The lowest birth rate can be identified as "BG" and the viewer needs to decode this back to "Bulgaria". For a user familiar with the codes, there is no additional effort than reading any other alphabetic label – note the prevalence of short mnemonic codes on display screens in expert user environments such as stock screens, infrastructure displays, and other industrial environments. A mnemonic code, such as BG for Bulgaria, may aid decoding by triggering recognition. For a user completely unfamiliar with these codes, a legend or interaction will be required. Interaction will simply make task performance equal to the slow interactive scatterplot, while retaining faster decoding for the expert and for the user able to recognize the mnemonic code.

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[241] I. Scott MacKenzie, Fitts' law. In K. L. Norman & J. Kirakowski (Eds.), *Handbook of human-computer interaction*, pp. 349-370. Hoboken, NJ: Wiley. doi:10.1002/9781118976005 and http://www.yorku.ca/mack/FittsLawSoftware/

ii. Modeling a Comparison Between Two Named Points

A more complex task will have different results. Consider: "Which country has the higher birth rate: Brazil or India?" This task requires that the viewer *locate* two specific entities and then *compare* them. First, consider the small bubble plot with only 10 data points in Figure 51 P55 with steps and tasks as shown in Table 12. This bubble plot has twice as many cognitive steps, takes 970ms longer (28%) and requires greater utilization of short term memory than the label plot.

Table 12. **Comparison of two specific points in a label-based plot and a bubble plot**.

LABEL PLOT

Step	Cognitive Parameter	Time
1	Scan to Brazil in plot area (3 saccades)	690
	Read word Brazil	300
	Match to working memory Brazil	70
2	Scan to India (1 saccade)	230
	Read word India	300
	Match to working memory India	70
3	Scan to axis	230
	Read word Birth Rate	300
	Match to working memory	70
4	Comparison: is Brazil > India?	1200
	Total time estimate for label plot	**3460**

BUBBLE PLOT

Step	Cognitive Parameter	Time
1	Scan to Brazil in Legend (2 saccades)	460
	Read word Brazil	300
	Match to working memory Brazil	70
2	Scan to hue beside name Brazil	230
	Match hue to working memory Brazil	70
3	Scan to India in Legend	230
	Read India	300
	Match India to working memory India	70
4	Scan to hue beside name India	230
	Match hue to working memory India	70
5	Scan to grey circle	230
	Add grey circle to working memory	70
6	Scan to brown circle	230
	Add brown circle to working memory	70
7	Scan to axis	230
	Read word Birth Rate	300
	Match to working memory	70
8	Comparison: is blue > brown?	1200
	Total time estimate for bubble plot	**4430**

However, the effort becomes more difficult for both the bubble plot and the label plot when the number of points is higher. Asking the same question of Figure 118, the location task is slow and tedious when attempting to locate two specific countries amongst 185 other countries. Serial reading of 187 discrete pieces of text will require 46 seconds assuming 4 words per second; attempting to do this using a tooltip will be even slower. Interactive techniques are an obvious solution. Filtering data (e.g. based on continent), or search based on country name; will reduce the number of items in the display. This reduces the number of points that need to be reviewed. Assuming a few seconds to use the interaction, the number of points is reduced significantly and the task effort will then be similar to the previous example with only 10 points.

It should be noted even in this example with 187 items, the label plot offers advantages for completing the task over the bubble plot:

- In the case of filters, such as reducing data down to two continents, the label plot will be lower effort than the use of interaction such as tooltips, similar to the time estimates with ten data points.
- In the case of search, an individual point can be explicitly found, e.g. "India", but then doing a second search to find the second point may clear the first result: the explicit label plot will aid the viewer in re-finding the point within a general area, as opposed to a dot.
- In a non-interactive environment, such as PDF publication or projected presentation in a seminar, the task is still solvable with the label plot. With the bubble plot it is not solvable.
- Secondary cues provide an astute viewer with ways to optimize their search through labels. For example, knowing that both India and Brazil have large populations and that population is encoded with both size and color, the viewer can narrow their search to the largest 15 countries, achieving the result in a few seconds rather than a minute. Alternatively, the viewer can use context cues from the text. For example, recognizing a few labels are geographic peers, such as countries in Eastern Europe or Africa, allows the viewer to skip across points in that part of the plot thereby pruning their search and reducing their search time.

C:1.9. Label Conclusions

A significant contribution of this thesis is the use of literal text as a form of encoding data in visualizations. Use of labels over simple geometry or glyphs offers several benefits:

1) Multiple levels of information are immediately visible, such as the micro-level individual countries and the macro-level crescent shaped pattern in Figure 118 P116. The micro-details are available without reliance on interaction such as filtering or tooltips - which are much slower than shifting visual attention.
2) Cognitive load is reduced as the viewer does not need to refer to a legend, or rely on short term memory when comparing multiple points cross-referencing a legend, or rely on tooltips and memory. Overall task times are predicted to be faster or at least the same using cognitive modelling, for scatterplots of 10, 59 and 187 datapoints for identification and comparison tasks.
3) Local patterns can also be perceived. For example, there is the potential to see serendipitous patterns otherwise not visible, such as the declining population in the former east bloc in Figure 118P116.
4) Information visualization is fundamentally lossy. Use of labels over abstract glyphs retains greater information, reducing lossiness and increasing data density.
5) In the U.S. park scatterplot (Figure 119P117) two additional dimensions are layered in via text and italics, beyond the base scatterplot x, y, color and size. The use of additional font attributes to indicate data will be explored in many of the upcoming examples.
6) Hierarchical navigation can be aided by attending to distinct classes of labels for each level of hierarchy.

The magnitude of the above benefits over non-textual techniques should be tested experimentally as future work. There is some research regarding readability of partially obscured text (for example, if the bottom half of a string of lowercase text is obscured, it is less likely to be readable than the same text where the upper half is obscured e.g. Maria[242]) but more research could be done in future work.

From a technical perspective, one should consider collision detection as a simple technique for nudging text to reduce overlap and provide increased legibility. Markers, such as dots or circles can be used to indicate the point location that the text refers to if high accuracy is required. Consider a thin halo around the letters to improve legibility if the text is overlapping other graphical elements. Furthermore, mnemonic codes can be used if space is at a premium and codes known to the intended audience exist.

[242] Jason Santa Maria, "How We Read," in A List Apart. Aug. 5, 2014. https://alistapart.com/article/how-we-read

C:2. LS: Literal Sentences – lines as microtext

Sentences are similar to line-based visualizations, such as line charts. Line charts are frequently used for timeseries analysis. A simple line chart with one line doesn't require labeling: the title can unambiguously indicate the line. But when a few lines are added, cross-referencing between a label and a legend requires some cognitive effort. One of the benefits of diagrammatic representations is reduced cross-referencing: for example, the need to refer back and forth between a line in a chart and a legend with a description[243]. Furthermore, for some types of data, legends can be quite verbose increasing the effort to cross reference between the details in the legend spatially separated from the line. The unique contribution of Literal Sentences is to 1) replace lines in line charts as very small text - i.e. microtext, smaller than normal reading text at 3-6 point size but still visible and readable, and 2) to further extend this text with font attributes to indicate additional data.

C:2.1. Twitter Retweets

Figure 122 plots retweets over time for the most popular Donald Trump tweets beginning in late August 2015. Instead of a separate legend with a long line of text associated with a line chart; the tweet content directly replaces the line in the chart.

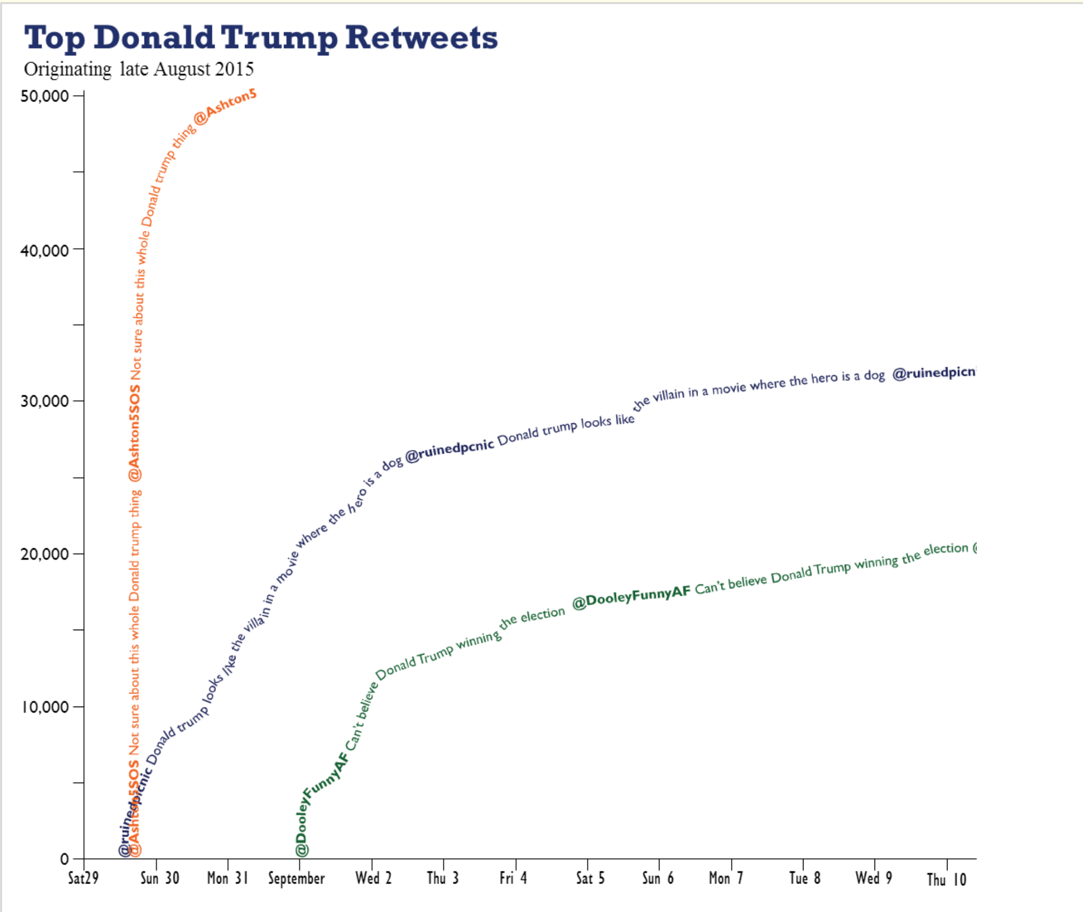

Figure 122. A timeseries chart where a line is replaced by literal text removing the need for a legend.
Image created by author, based on dataset courtesy Uncharted Software.

[243] Jill H. Larkin and Herbert A. Simon, "Why a diagram is (sometimes) worth ten thousand words," in *Cognitive Science* 11, no. 1 (Wiley: 1987): 65–100.

By replacing the line with the content, the next question of the viewer can be immediately addressed in context (what is that item?). In this example, the very quickly retweeted tweet (orange) was likely due to the huge fan-base of the original author (@Ashton5SOS: Ashton Irwin, drummer for band *5 Seconds of Summer*, which has a large number of teenage fans), whereas the slower growth blue line likely grew in popularity due to the comedic content.

C:2.2. Historic precedence of text on paths

There may be concern regarding the readability of non-horizontal text. Some guidelines recommend against text at angles such as axis labels (e.g. Wallgren[244]). However, path-based text is a longer string of text than a short label. There are many historic precedents of text along paths such as early word balloons, for example from a late medieval book of hours[245] or an early renaissance woodcut[246] as shown in Figure 123.

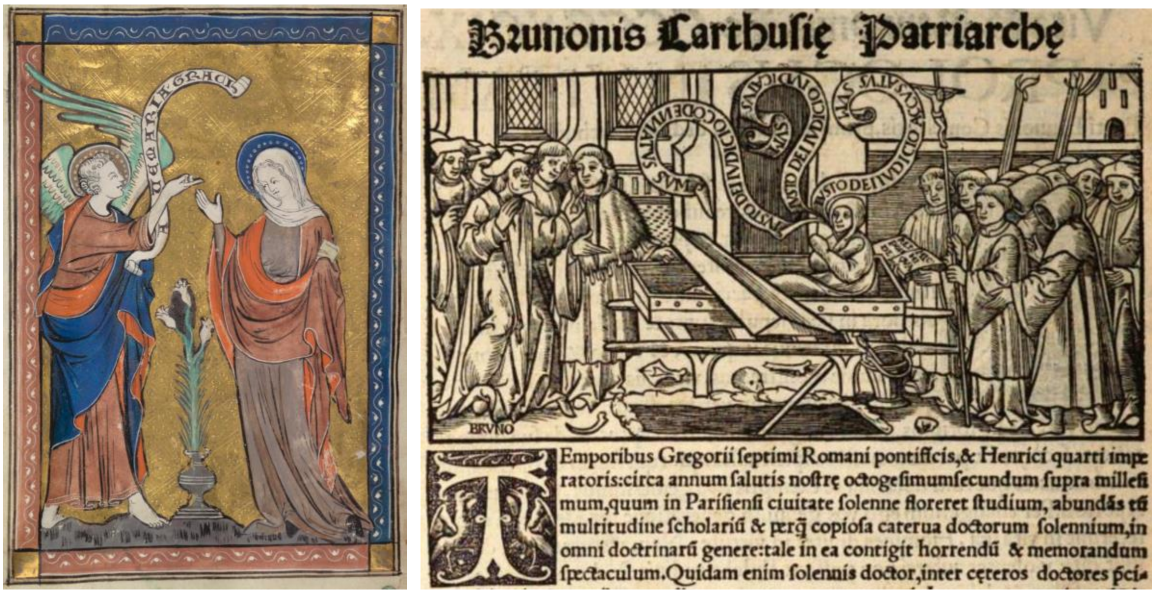

Figure 123. Historic word balloons with lines of text flowing along curving scrolls. Left. Annunciation from Medieval Book of Hours early 1300s. Right: Multiple word balloons as scrolls from 1524. Left image Creative Commons Attribution-NonCommercial 3.0 Unported License (CC BY-NC 3.0). Right image not in copyright available at archive.org.

More recent examples exist as well. While moveable type set in rectilinear arrays may not have facilitated free form text layouts, some authors experimented with text freed from straight left-to-right lines such as concrete poets. Apollinarie's concrete poems from the early 1900's playfully adjust type layout based on subject matter as shown in the poem *Visée*[247] (Figure 124 left). Modern graphic design tools, such as Photoshop and Illustrator provide easy-to-use tools to set text along paths. The programmable graphics format SVG natively provides functionality to place text along paths. Within the field of information visualization Brad Paley's *Map of*

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[244] Anders Wallgren et al. *Graphing Statistics & Data: Creating Better Charts*. Sage, 1996.
[245] Author Unknown. Book of Hours (Sarum Use). Early 1300s. East Anglia. http://cudl.lib.cam.ac.uk/view/MS-DD-00004-00017/16 Accessed Aug 23, 2016.
[246] Bruno Carthusianus. *Brunonis Carthusianorum Patriarche sanctissimi, theologi Parisiensis Scholae doctissimi: & Remensis ecclesiae canonici moratissimi: Opera & vita post indicem serie literaria indicanda*. Venundatur Jodoco Badio Ascensio, Paris, 1524 https://archive.org/details/bub_gb_3FEGaBmWN0UC (page 999). Accessed Aug 24, 2016.
[247] Guillaume Apollinaire, « Visée », in Calligrammes. Poèmes de la paix et de la guerre (1913-1916), Paris, Mercure de France, 1918. https://archive.org/details/calligrammespo00apol (pg. 88).

Science[248] has long flowing labels, in this case the nodes represent scientific topics and labels are a long list of topic words: to avoid overlapping labels, the paths for labels bend to avoid collision or cross each other at right angles to better maintain readability (Figure 124 center). Ben Fry's Tendril[249] renders the text of webpages as twisting 3D cylinders with hyperlinks spawning new orthogonal cylinders of text.

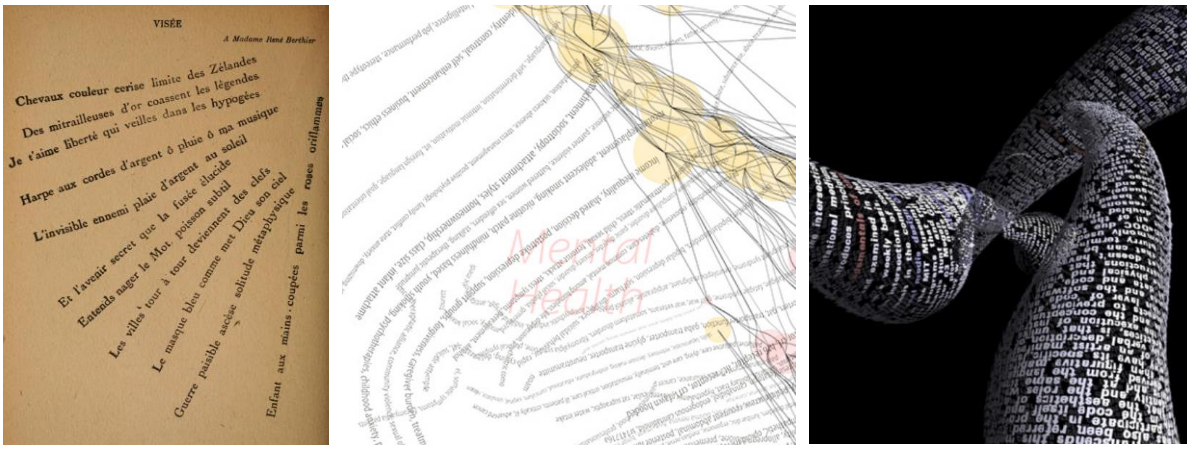

Figure 124. Left: Apollinaire's concrete poem *Visée.* Middle: Long twisting topic labels identify nodes in Paley's *Map of Science*. Right: Fry's *Tendril* with twisting cylinders of text. Left: Not in copyright, available at archive.org.. Middle: Copyright W. Bradford Paley. Right: Copyright Ben Fry.

C:2.3. Timeseries Chart Books and Chart Libraries

The visualization technique of Literal Sentences replacing lines in line charts may have application in financial charts. In financial services, time series charts have been used for more than 200 years, going back to William Playfair's charts and Japanese candlestick charts. By the early 1900's, organizations maintained and updated these physical paper charts, potentially having many charts forming *chart rooms* and *chart libraries* as seen in Figure 125.[250]

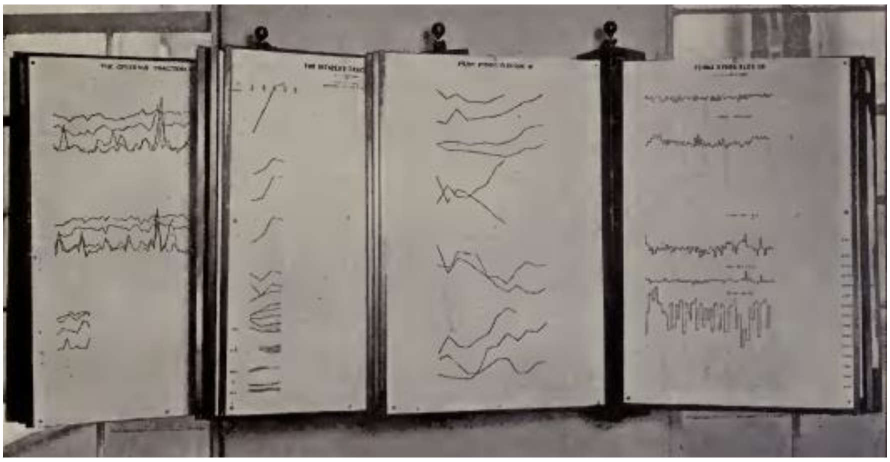

Figure 125. Hanging boards pivoting on a central pillar for organizing a large number of timeseries charts from the 1910's.
Not in copyright, available at archive.org.

248 Brad Paley. Map of Science. 2010 version. http://www.wbpaley.com/brad/mapOfScience/ accessed Aug 24, 2016
249 Ben Fry. *Tendril.* http://benfry.com/tendril/ accessed: Aug 28, 2016.
250 Willard Cope Brinton, *Graphic Methods for Presenting Facts*. The Engineering Magazine Company. New York. 1914

Although personal computers in the 1980's made it possible to interactively plot financial timeseries charts, variations of non-interactive charts have persisted through to today. The current notion of a financial chart book or chart library is a collection of time series charts which exist in a non-interactive format. Chart libraries may consist of hundreds of these charts. These charts may be consumed in many different ways, such as paper output (e.g. a chart book), a large PDF file, or used as content embedded into commentary, such as financial research reports. In spite of highly interactive computer systems, these non-interactive charts continue to persist.

The author has had occasion to view, analyze and discuss these chart libraries with users and experts in the capital markets,[251] including a large mutual fund company, a large bank, a market data provider and so forth. Users and experts claim benefits for these non-interactive charts including:

- *Ability to quickly flip through many charts*: Flipping through paper or pages in a PDF file is considered faster than stepping through a software system that dynamically retrieves data and updates charts.
- *Familiarity*: The users have seen these particular charts many times through their careers (e.g. weekly or monthly) and may also return to them for reference as needed. Off-the-shelf financial charting software systems may not store all their preferences, may not maintain consistency over time (e.g. scales change), may not retain user created notes and trend lines, and so forth are some reasons provided for favoring these charts.
- *Interactivity is not required*: The users want to be able to see all the series and the full scope of data: common computer-based visualization interactions such as zoom, filtering, changing scales, and so forth are expressly not desired. For example, they have become familiar with the sizes of items and may even refer to some aspects of such a chart with physical dimensions, e.g. "a quarter inch movement in a line".
- *Higher Resolution*: Some practitioners will print these charts out as a physical chart book. The print version can be higher resolution than the screen version. High quality 1200 DPI printers, in theory, provide 15 times more resolution (120m dots) than current state of the art 4k screens (8 megapixels)

While these charts are not used interactively, they are for the most part created computationally. They may be created with heavily customized off-the-shelf software (e.g. Excel) or other custom software. These chart libraries are considered a proprietary confidential asset to a financial firm, therefore it is typically difficult to get extended access to many of the charts. The author was able to review all the timeseries charts in one organization's chart library. This library consisted of 262 timeseries charts. Most of the charts (57%) displayed 5 or fewer timeseries. However, 31 of the charts (12%) displayed 11 or more timeseries, with the current maximum a chart with 23 timeseries, summarized in Table 13.

Table 13. **Number of series represented on charts in a financial chart library**.

NUMBER OF SERIES	NUMBER OF CHARTS
1-5	148
6-10	83
11-15	21
16-20	9
21-25	1

[251] Richard Brath, Lancelot Comrie, David Keller, Elaine Knuth and Eugene Sorenson. *Challenges in Financial Visualization*, IEEE VisWeek. 2014.

Note that this firm also had other timeseries charts, for example one with 83 series, however these charts with a higher number of series were consumed only in an interactive format, typically toggling on only a few series at a time for comparison; whereas in the chart library all the charts were always plotted with all the lines.
There are various challenges with these charts when the number of series is more than ten:

- *Differentiation*: Charts typically differentiate between series using hue, however, it can be difficult to scale beyond ten unique hues.[252] Strategies used included a combination of hues and brightness (e.g. bright red, dark red, bright green, dark green, etc.); or hue and dash (e.g. red continuous line, red dash line, green continuous line, green dash line).
- *Labeling*: Labels associated with each series are typically indicated in a separate legend. With many different series, it can become difficult to cross-reference between the line in the chart and the legend entry, for example the hue differentiation may be subtle. Larkin and Simon[253] for example, noted one benefit of diagrammatic reasoning is reduced cross-referencing, however this benefit is lost with a separate legend.
- *Other Layouts*: Small multiples, horizon charts and so forth were not acceptable alternatives: lines needed to be superimposed on a common scale for detailed visual comparison.

C:2.4. Line Labeling Alternatives

There are some alternatives to legends for these many line time series charts.

- *Labels at the line start or end*. Rather than a legend, labels can be depicted at the start or end of the line. This can be challenging if there are many lines starting or ending at similar values.
- *Labels in the plot area*. Rather than rely on the legend, some users add textual annotations in the plot area of the chart, placing a straight line of text near the target line, potentially with a leader line to visually connect the label with the line. This has the benefit of reducing the cross-reference to the legend (e.g. Figure 126 left[254]). However, it does clutter the plot area and some users are adamant against this. This is consistent with the arguments that labels can make it more difficult to see patterns formed by data, for example, as discussed in Cleveland[255] or Few[256].
- *Labels aligned to paths*. In historic hand-drawn examples of timeseries charts - such as Playfair, or pre-computer generated charts - the authors' hand-letter charts and can thus easily align text to shape of the line (Figure 126 right[257]). This has the benefit of reducing clutter and more directly associating the label with a line as opposed to the straight line of text:

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[252] Colin Ware. *Information Visualization: Perception for Design*. Elsevier. 2013.
[253] Jill Larkin and Herbert Simon. "Why a diagram is (sometimes) worth ten thousand words." *Cognitive Science*. 1987.
[254] Willard Cope Brinton, *Graphic Presentation*. Brinton Associates. New York. 1939.
[255] William Cleveland, *The Elements of Graphing Data*. Hobart Press, Summit NJ, 1994.
[256] Stephen Few. *Beautiful Evidence: A Journey through the Mind of Edward Tufte*. 2006. https://www.perceptualedge.com/articles/b-eye/beautiful_evidence.pdf. Accessed: 12/12/2015
[257] Willard Cope Brinton, *Graphic Methods for Presenting Facts.* The Engineering Magazine Company. New York. 1914

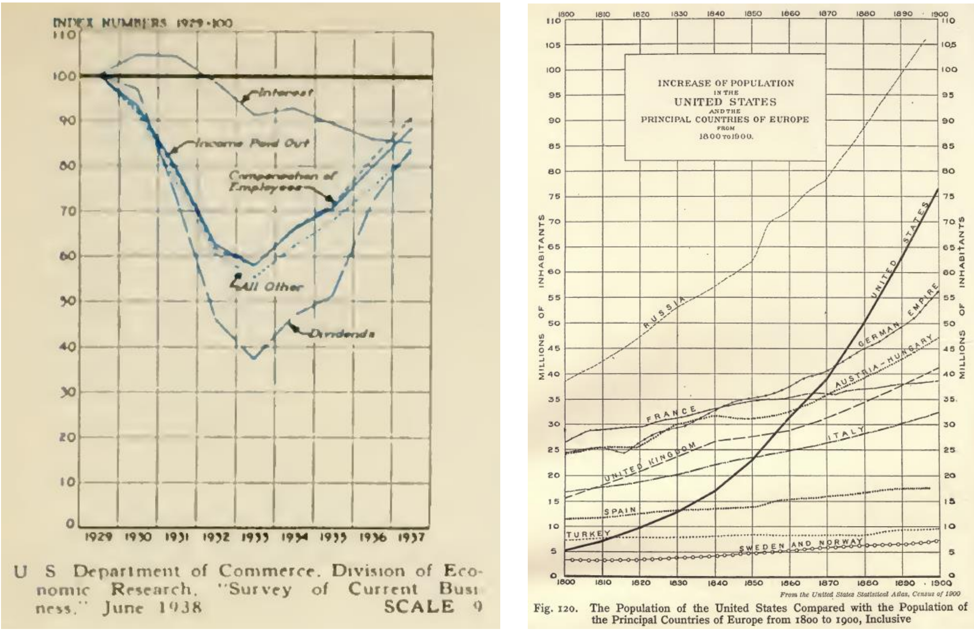

Figure 126. Left: time series labeled with straight lines of text and leader lines cluttering the plot area. Right: time series labeled with text aligned to the path of the timeseries: result is less cluttered. Images not in copyright, available at archive.org.

Labels aligned to graphical shapes are common in on-line maps (e.g. Google street map), however, they are uncommon in current time series visualizations. Directly labeling lines has challenges with occlusion (labels obscuring each other or the lines).

C:2.5. Literal Sentences for Congested Line Charts

Line charts with 20 or more lines can be difficult to create. The chart in Figure 127 left, shows 37 lines in one chart indicating unemployment rates from 2000 – 2014. Using color to differentiate lines does not work, as it is not feasible to have 37 perceptually distinct line colors.

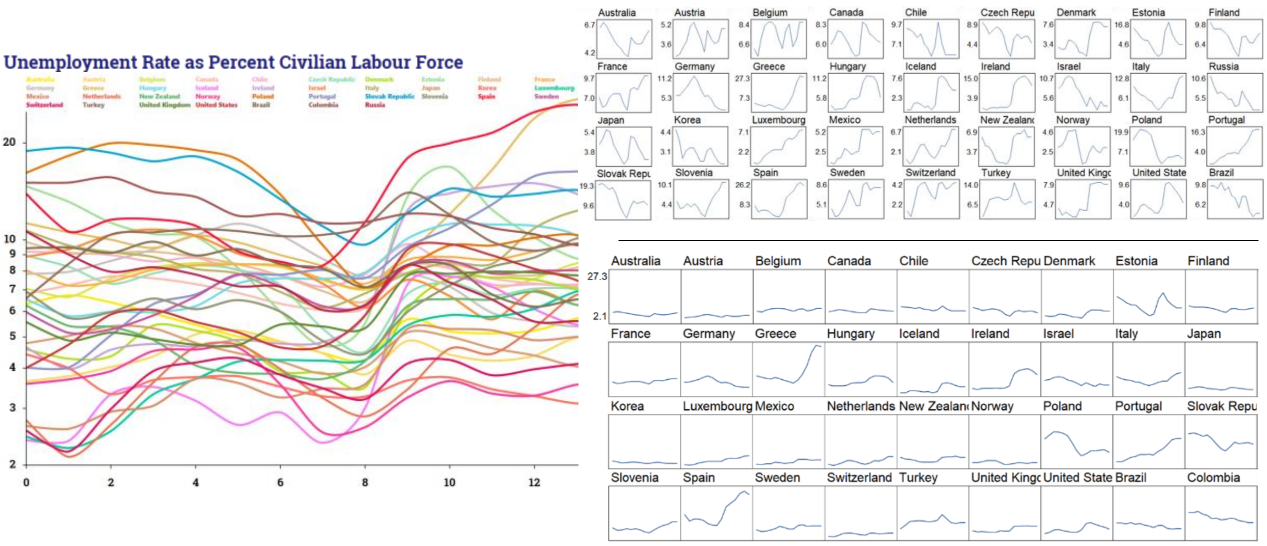

Figure 127. Many timeseries. Left: overlaid lines but colors insufficient to identify. Top right: sparklines but magnitudes difficult to compare as each sparkline has a different vertical scale. Bottom right: small multiples with a common vertical scale but loss of trend detail in most series. Images by author.

Other techniques to make arrays of small charts – such as sparklines, horizon charts, small multiples and so on – solve some issues. The top right set of charts in Figure 127 shows 36 sparkline charts of the same data. However, it is very difficult to compare magnitude when each chart is at a different scale: for example, does Denmark or Estonia have higher unemployment at the end of the time period?

The bottom right set of charts in Figure 127 share a common vertical scale, making the vertical distances comparable between charts. But some countries are squished into a few vertical pixels (e.g. Austria), making it difficult to get a sense of any detail in the trend. It is also difficult to compare particular time periods, for example, which country has the lowest unemployment in 2010. To do this comparison in this array of charts requires making a note of the particular point on each chart and relying on short term memory to compare relative positions. The benefit of direct visual inference feasible when all lines are superimposed on a single chart is lost when split into an array of charts.

Instead, the approach for directly labelling lines as shown in Figure 122P124 can be extended to charts with many lines. Using local labels means that cross-referencing a legend or visually following a line back to an end label is not required - the label is local to the area of inspection. There are alternatives as to how the labels can be utilized:

- *Labels aligned to paths*. Similar to river labels on maps, labels can be aligned to lines. Within a congested line chart, some care must be taken to reduce overlap. In Figure 128, a line chart showing unemployment rate for 37 countries is shown, with labels both at the end of the series and a few labels along the length of the timeseries (in 7 point font). A simple collision detection algorithm has been used to push the labels apart to minimize overlapping labels.

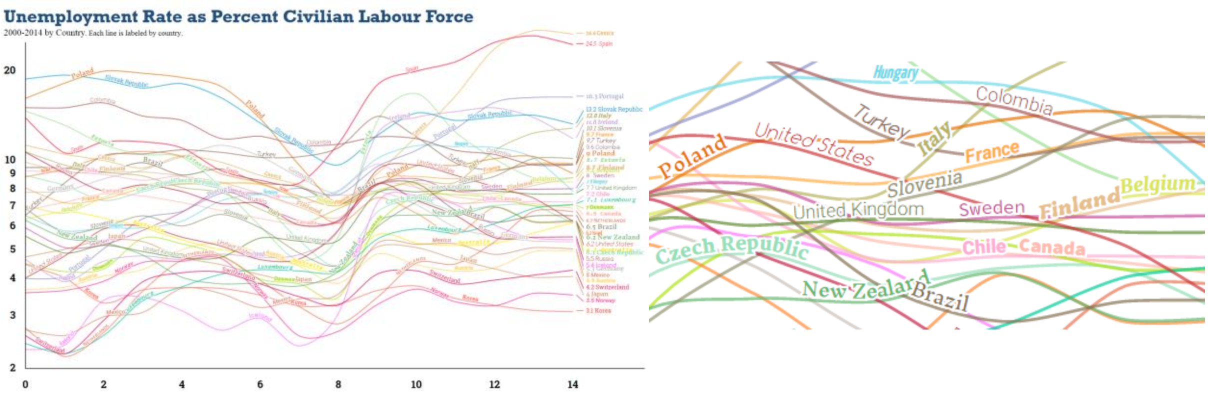

Figure 128. Congested time series chart with path labels, overview left, close-up right. Images created by author.

- *Text as lines*. With high resolution displays, lines can instead be drawn directly as continuous micro-text, similar to the continuous text in *Automatic Typographic Maps*[258]. In Figure 129, lines are replaced with five point microtext and appear perceptually similar to a dashed line.

[258] S. Afzal, R. Maciejewski, Y. Jang, N. Elmqvist and D. Ebert, “Spatial text visualization using automatic typographic maps.” *IEEE Trans. on Visualization & Computer Graphics*, (12). 2012.

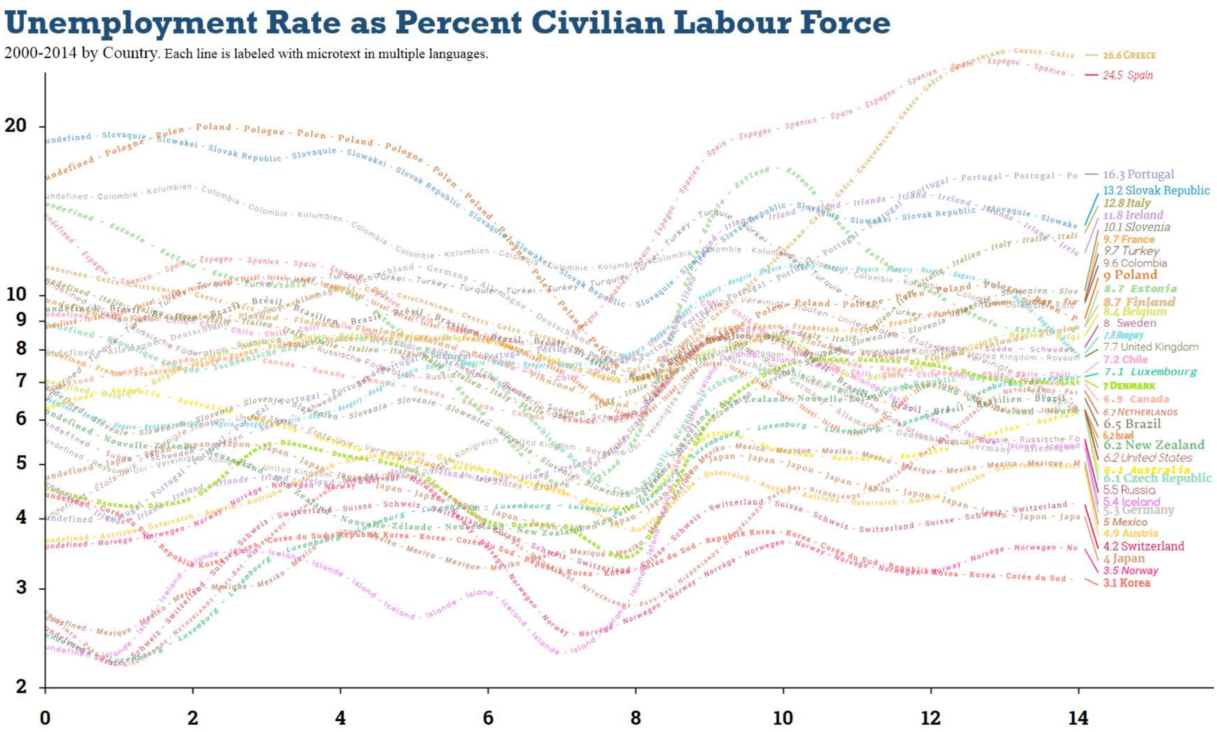

Figure 129. Congested timeseries chart with 37 lines, each line directly encoded as text. Image created by author.

Since lines cross and overlap, some consideration must be given to text legibility at intersections.

- *Halo*: In geographic maps, labels may be placed over top various other graphics. A halo may be added around the text to make the text more legible (e.g. TileMill text-halo-fill). In a congested line chart, however, there may be significant areas of overlap between lines. Adding a halo is feasible, but many other microtext lines may be partially occluded reducing line visibility and reducing legibility of partially obscured text (Figure 130 left).
- *No halo*: In Figure 130 right, no halo is provided around text. At holes in letters and gaps between letters, the color of text beneath appears through the higher text, and provides a better indication of line density than halos. Assuming different colors of text, one can visually trace other microtext lines and maintain some degree readability through crossings, although not through areas of high congestion. For example in Figure 130 compare Israel (red, near bottom) in both the left image (with halo) and right image (without halo). The path of line is more easily discerned through the many crossings in the non-halo representation. Or, Finland, in the left image (brown) is complete obscured, while in the right image, although often mixed with other text, can be somewhat discerned with some effort.

Figure 130. Left: each text label has a white halo to improve legibility of the topmost label however, many labels are partially obscured reducing readability. Right: text is over-plotted across other text - crossings between lines remains decipherable, except in the densest regions. Image created by author.

Another benefit is that the labels can vary: rather than repeat the same text, the microtext can be multilingual, extending the usefulness of the chart across nationalities, as seen on close inspection of Figure 129 and Figure 130. Also note: to increase the differentiation between lines, different colors and different type attributes are used (much as one might use different dash patterns for dashed lines). No two lines share the same combination of type family, italic, bold and condensed. This design choice follows Ware: "Graphical patterns similar in terms of color, spatial frequency, and so on tend to interfere more and fuse more with one another than those with dissimilar components."[259] Furthermore, the type has been tuned to have a slightly wider than normal spacing to reduce occlusion but not too much, so that words still remain fairly readable.

C:2.6. Evaluation of Lines as Microtext

The microtext timeseries were evaluated by six different experts in capital markets who use non-interactive chart books and chart libraries. This light touch study was approved by LSBU ethics committee. All the participants have at least 12 years expertise in capital markets specifically with financial charts and visualization; and have affiliations or certifications in professional financial analysis. All use financial charts in their daily work. All work in a capacity where they may be sharing their charts and observations with other people, such as clients.

The youngest participant was 35, the oldest 65, with an average 50. All were Caucasian men - as were most of their clients. All had limited time availability: questions and tasks were kept simple.

A small group of six expert users were provided with variations of the chart with 37 lines (as in Figure 129), including 1) plain line chart with endpoint labels; 2) line chart with labels on lines ("river labels") at 7 point; and 3) line displayed as microtext at 5 point. Note: 1 point = 1/72 inch = 0.35mm. This is 7 point and 5 point.

The experts were provided with the following tasks and questions:

1. *Initial Question*: How many lines do you have at a maximum in your charts? Why?
2. *Chart Tasks*: Then each of three Unemployment Rate as Percent of Civilian Labour Force charts were presented in sequence: first standard lines with end-labels only; followed by one of the two micro-text versions the followed with the other (i.e. Figure 128 and Figure 129). For each variant the following two questions were asked:
    a. Which country was top (or bottom) in year x?
    b. How did country x fare relative to its peers through the 2008 recession?
3. *Follow-up Question*: Are these techniques relevant to the kinds of analysis that your team does? Can you identify use cases where you would consider using this kind of chart?

With respect to the first question, the number of lines on a chart, only one participant out of six claimed that he did not need to plot more than 15-20 lines. Another claimed that while most charts used a low number of lines, there were cases where they could go much higher - beyond 50. The most insightful answer came from an analyst: the community is constrained by their tools and it is very difficult to make an effective chart with more than 10 lines therefore people have been conditioned to keep their charts simple. However there are actually many cases where one would want to view more lines if feasible, assuming the tools and representation were

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[259] Colin Ware, *Information Visualization, Perception for Design,* 3rd edition. Morgan Kaufman. 2013. pg. 212.

appropriate. This user pointed out that many peers and subordinates used Excel, which was poorly suited for working with many simultaneous lines.

When presented with the first task (highest/lowest country in year x with just a line chart), the response was either a dismissive comment (e.g. “That’s not going to work.”) occurring for 4/6 experts or taken as a challenge (i.e. attempting to trace the line to find the right answer, requiring 10-15 seconds to do so). If the initial answer was dismissive, the second task country x through recession) was not asked.

For the second chart, the participants responded almost instantaneously with a visceral response, such as “Wow, this is exciting”, or “I really love this.” One interesting aspect was 4/6 experts physically traced their response using their finger. For example, for the top in year x question, the expert might slide across the x-axis to the year, move up to the target line, move across to the first local label to the answer (requiring 2-4 seconds). This is a physical cue of the subtasks used to solve the problem.

The second task (how did country x fare through the recession) was done typically by tracing vertically near the beginning of the recession until the target was identified, tracing across through the recession to a matching label on the opposite side to confirm they were on the same line. This was followed with an observation relative to the peers, e.g. “I’d say that Switzerland did quite well” or “I don’t think things were good for Portugal.”

The third chart progressed much like the second, often eliciting a second visceral response equal to the first. Two experts did not complete the task for the third variant. For the remaining 4/6 there was not a significant difference in time.

Most experts felt compelled to compare and contrast the two techniques. Opinion was divided:

- The font sizes were slightly smaller for the text as lines variant (5 point) compared to the labels on path (7 point). For the oldest participant, the slightly smaller size was borderline legible and he had some difficulty reading the labels whereas he could read the slightly larger path labels. He preferred the larger labels but speculated that he might prefer the smaller labels if size varied depending on the space available.
- One participant found the microtext as line variant extremely compelling and referred to it as a very clean layout. He specifically noticed and called out the font variation (i.e. weight, case, typeface) as an effective means for creating differentiation.
- One participant had a strong preference to the path labels (river labels). The approach represented the best legibility for the entire chart as the labels tend to push out to the less dense regions on the chart while the most congested areas of the chart retained high legibility by having only thin, accurate lines through these areas. He wanted labels at the end removed to make the chart even cleaner. The microtext as line approach was not preferred as the labels were less legible when overlapping and multi-lingual labels were a distraction to the core content.
- One noticed the multilingual labels and hypothesized that the approach could make the charts more broadly accessible to his global audience.
- One participant hypothesized that the labels on a path may be appealing because of its nostalgic familiarity from cartography.

- The text as line was identified by one viewer as more stimulating than the other two: any local anomaly or pattern could draw you into the chart by having a meaningful label immediately visible thereby engaging the viewer to spend more time with the chart.
- Overall, 3/6 preferred the microtext only approach, 2/6 preferred river labels and 1/6 did not express a preference.

The final question provided responses that ranged across user types, user locations, and data types. Users identified various timeseries datasets that could benefit from using these techniques such as index analysis, peer analysis, economic analysis and state analysis. There was some discussion as to the nature of the data - the example dataset had low volatility (i.e. the lines did not zig zag up and down) - and how would the approach fare under different datasets. Various enhancements were suggested, such as:

- Labels as lines could indicate other data, such as values at high points and low points, rate of change, political leader during time periods, or other more detailed content (such as the Tweet content in Figure 122P124).
- Bold could be used to highlight specific information part way along a path.
- Interactivity could combine both the benefits of the textual static view with selection for ability to easily focus on any subset. As shown in Figure 131 left, simple browser search can be used to highlight topics in Twitter hashtag trends, in this example, showing three different hashtags referring to Hurricane Irma, including one with a misspelling. In Figure 131 right, retweet trend for top tweets are plotted with one line specifically selected and Tweet details provided in a tooltip.

In addition, one insightful comment was that the application area was much broader than capital markets - understanding trends across peer groups are applicable in many policy areas. In most of these cases, the reports will be published and distributed and not interactive. Any decision maker would benefit from these techniques.

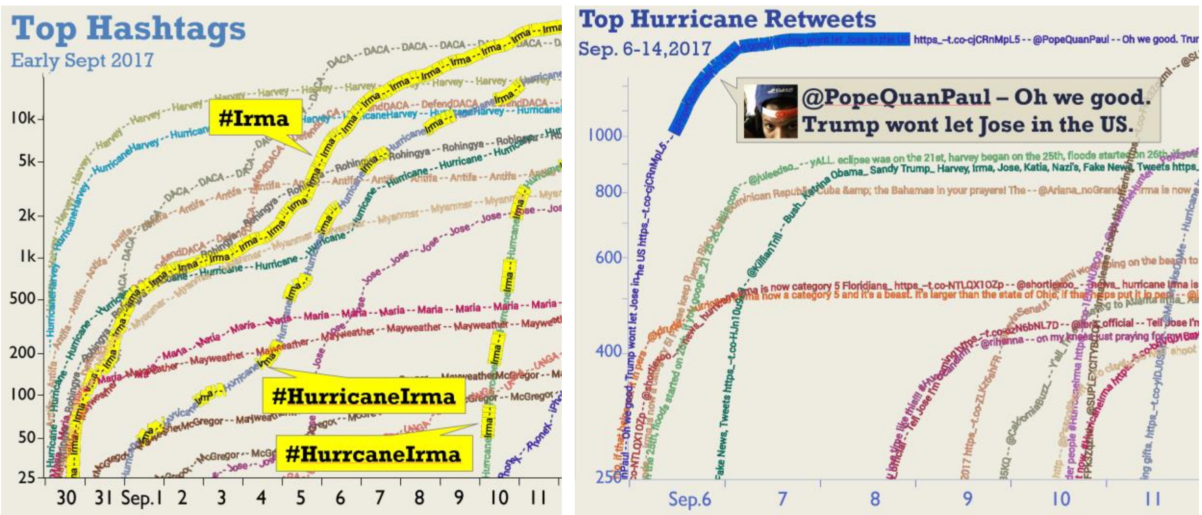

Figure 131. Microtext line charts. Left: chart of top twitter hashtags with search term "Irma" highlighted (occurs in three different hashtags). Right: One line highlighted with a tooltip showing content. Image created by author.

C:2.7. Microlines Applied to Other Layouts

Microlines can be applied to other visualization techniques that utilize lines, particularly in applications where there are many lines and potential use cases where there is a need to differentiate among them. This could include parallel coordinates, contour plots, spider charts, edges on graphs, subway diagrams, mindmaps, bumpcharts, dendograms and so forth. Figure 132 shows a parallel coordinates chart of Bertin's occupation by department data (similar to Bertin's chart in *Sémiologie Graphique* p. 109) where the lines are replaced with detailed department names. In addition to the broad patterns and individual lines visible in a parallel coordinates chart, each line is immediately identifiable.

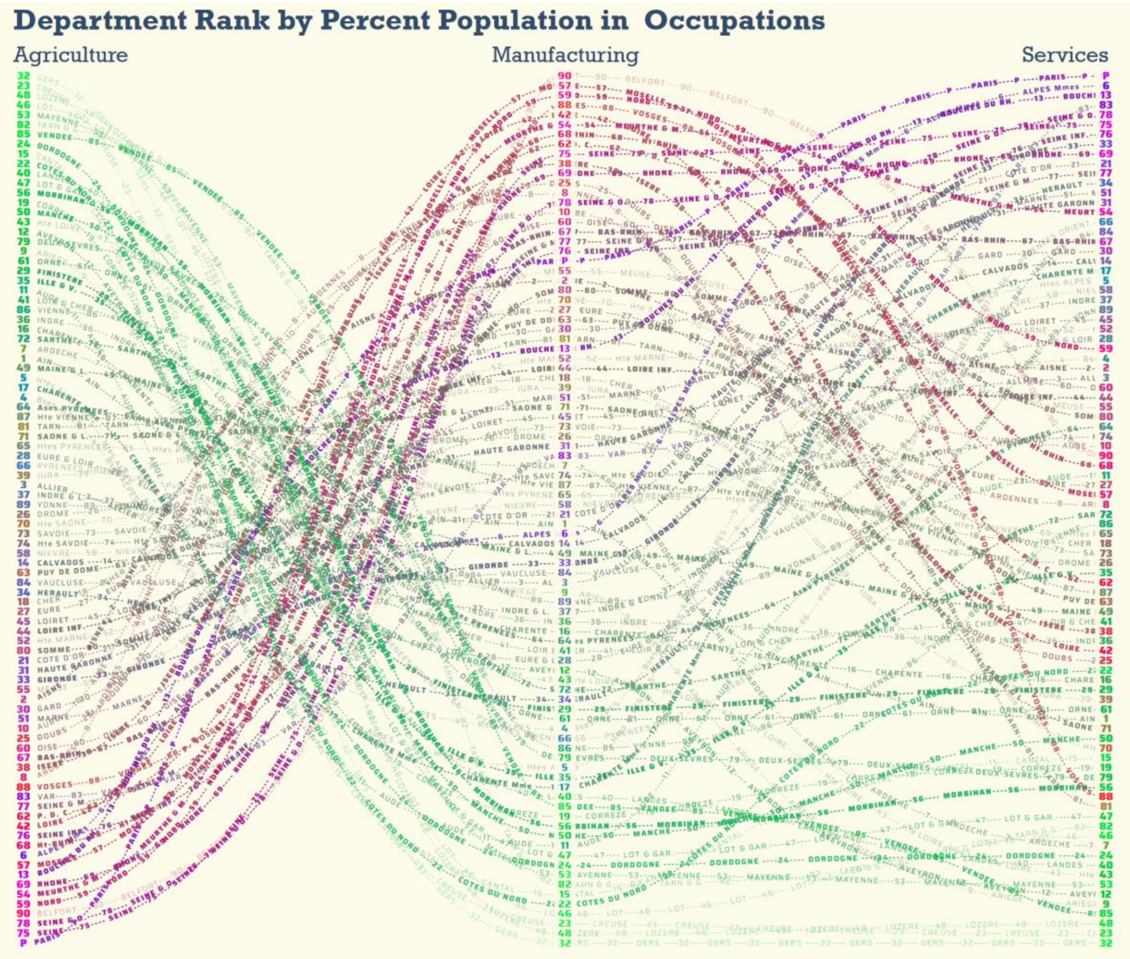

Figure 132. Parallel coordinates chart, with microtext lines showing department names, colored by proportion of each occupation (green for agriculture, red for manufacturing, blue for services). Image created by author.

C:2.8. Lines as Microtext Summary

The application area of timeseries visualization with many lines seems like a rich area for further investigation, with many potential applications outside of financial markets. However, a broader evaluation should be done for this broader audience - unlike financial market chart users, this broader community may have less familiarity with charts and visualization literacy.

Minimal font size is also an area for additional investigation. While one older participant found 5 point text borderline legible another participant had undergone cataract surgery one year earlier and had no difficultly reading the small 5 point text. In paper-based cartography, tiny fonts have been used for centuries. Minimum font sizes in cartography are defined as 3 point (Robinson et al)[260] or 4 point (Hodges)[261], with guidelines recommending 5 point or 6 point as a minimums (same texts). Similarly, information graphics in print had very small minimum point sizes, e.g. Brinton recommended a minimum size of 4 point, which was the smallest size supported by Monotype machines at the time.[262] Reference texts such as dictionaries, timetables, phone books, bibles, indexes and guarantees use small font sizes: the third edition of *Webster's Third New International Dictionary of the English Language* in 1961used 5½ point Times.[263] Note that type designers have unique design considerations for small fonts, and specialized versions of small fonts exist.[264] Non-scientific ad hoc tests with teenagers indicate some can read text as small as 2 or 3 point text. These references utilized extremely high quality metal-based printing technology of the time, with crisper details than the office printer used by the author. Lighting, glare, paper quality and other factors can also affect legibility and these were not controlled.

Microtext lines are a promising extension to information visualization. Microtext goes beyond previous type-based approaches by:

1) using text smaller than most visualization labels, but staying large enough to remain readable without interaction;
2) uses lines of text to embed additional information beyond simply labeling the area or line, e.g. multilingual labels; or the added context of phrases and sentences
3) the approach can be extended to use additional font attributes to differentiate between categories.

Technically, SVG text-on-path feature was used to create the examples shown, programmed in JavaScript and facilitated using the D3.js programming library (d3js.org). In the examples with few crossing lines, simple medium to heavy weight sans serif fonts seem to work best for legibility on screen (e.g. Source Sans Pro) – this may be due to font-tuning technologies (e.g. ClearType) unavailability to text at angles meaning that fine details such as serifs being poorly rendered. For uses with many overlapping lines, such as Figure 129P131, a variety of colors and a variety typefaces with wide variation in characteristics (such as width, x-height, stress) were used to increase differentiation between lines. It is assumed that the variation in hue and typeface design details will aid in the perception of differentiation and facilitate perception as lines of text move through congested areas, but this should be tested in future studies.

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260 A. Robinson, J. Morrison, P. Muehecke, A. Kimerling and Guptil S. *Elements of Cartography*. Wiley, New York, NY, 1995.

261 E.R.S. Hodges, "Cartography for the Scientific Illustrator." In *The Guild Handbook of Scientific Illustration*. ed. D.G.Cole, (New York: Van Nostrad Reinhold, 1989).

262 Willard Cope Brinton, *Graphic Presentation*. Brinton Associates. New York. 1939.

263 Paul Luna. Clearly Defined: Continuity and innovation in the typography of English dictionaries. Typography papers 4, 2000, 5-56.

264 Michael Hernan, *Compact Typography: The design of typefaces conceived for small size applications.* Master of Arts Thesis, University of Reading. 2009.

C:3. Lx: Literal Stem & Leaf Plots

Stem and leaf plots were introduced in the earlier section on *B:1.3.ii Alphanumeric Charts*P41 including many samples from domains such as statistics, biology, finance and schedules (e.g. Figure 40P42, Figure 41P43, Figure 11P14). The construction of a basic stem and leaf plot is straight-forward as indicated in Figure 133. Cox[265] identified benefits of stem and leaf displays including 1) more information is retained than a bar chart; 2) reveals fine structure while showing the distribution and 3) allows easy perception of measures based on ordered values (e.g. range, median, quartiles). In addition, stem and leaf plots are spatially efficient: unlike table cells listing the full numeric value, the stem is listed only once for potentially many leaves. This also allows the viewer to shift from macro tasks (identifying the stem) to micro tasks (identifying a specific observation).

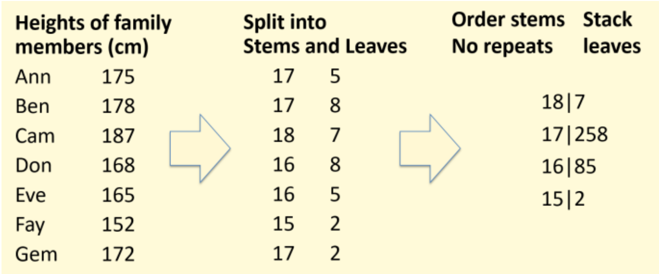

Figure 133. Process to create a stem and leaf plot from a simple dataset. Image created by author.

Cox also points out limitations including: 1) problems with large datasets, 2) whether extra digits are useful to the task and 3) comparison can be awkward.

Using text and typographic attributes, there are potential enhancements:

A) *Use Font attributes*: In addition to visual attributes such as color, typographic attributes such as bold, italic, underline and so forth, can be used to add data. The contribution of this section is to extend font attributes to stem and leaf plots.

B) *Use Text for stems and leaves*: Numerically oriented stem and leaf plots typically use one or two characters. However, in the context of text visualization, the scope of the textual unit (i.e. token) can vary depending on the application: e.g. individual characters, words, or phrases. These textual stem and leaf plots can also use font attributes to indicate additional data.

C:3.1. Font Attributes for Statistics in Stem & Leaf

In the earlier stem and leaf plots shown, additional data is encoded into the display using attributes such as foreground color, background color, background shape and dots as shown in Figure 11P14 – which can lead to issues such as reduced legibility. Instead, font attributes can be used, as they have been specifically designed to maintain legibility whether used singly or together. Figure 134 shows the plot of mountain heights (from Tufte[266]), with quartiles in bold, median in bold italic; standard deviation with underline, and mean with underline italic.

[265] N. Cox. “Speaking stata: Turning over a new leaf.” The Stata Journal. 2013.
[266] E. Tufte The Visual Display of Quantitative Information. Graphics Press, 1983.

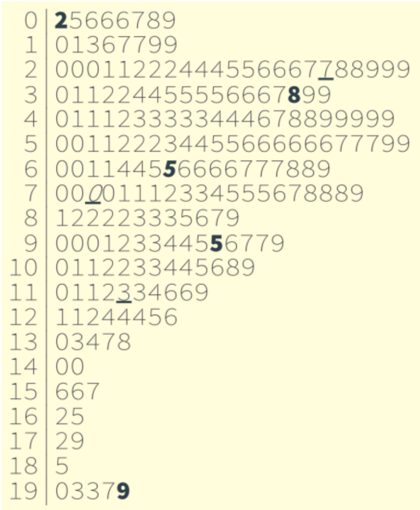

Figure 134. Stem and leaf plot with statistical value indicated via font attributes. Image created by author.

C:3.2. Glyph Stem & Leaf: Bigrams and State Statistics

Instead of leaves representing the final digit of a numerical value, a simple extension for text analytics is to use stems and leaves to represent numeric codes instead of numeric values – essentially a bar chart with each item explicitly labelled. Figure 135 shows simple stacks of French department codes by the largest occupation in each department.

Figure 135. Departments by largest occupation. Image created by author.

Type attributes can be used to add more data to the leaves. *Bigrams* (more generally *n-grams*) are sequences of adjacent letters used to provide the conditional probability of a token given the preceding token. Frequency of bigrams can be used for statistical language identification, prediction for auto-completion and cryptography. Figure 136 (left) shows English language bigrams that occur more than 0.5% of the time based on bigrams calculated from the Leipzig Corpora Collection (corpora.uni-leipzig.de). In this case, the stem and leaf approach is used as a layout to organize the first and second token, forming a distribution of letter pairs. The leaf stack length indicates the frequency of the stem token.

On the left half of the image, the stem indicates the first letter of the bigram, the leaf indicates the second letter. Font weight indicates the bigram frequency. At a micro-level, TH is among the most frequent bigrams in English as indicated with a heavy weight H. At a macro-level, bigrams starting with E are most common in bigrams occurring more than 0.5%. The right half of the same image uses the second letter as the stem and the first letter as leaves, e.g. TH is frequent, and the only pair with a trailing H out of the top 54 English language bigrams.

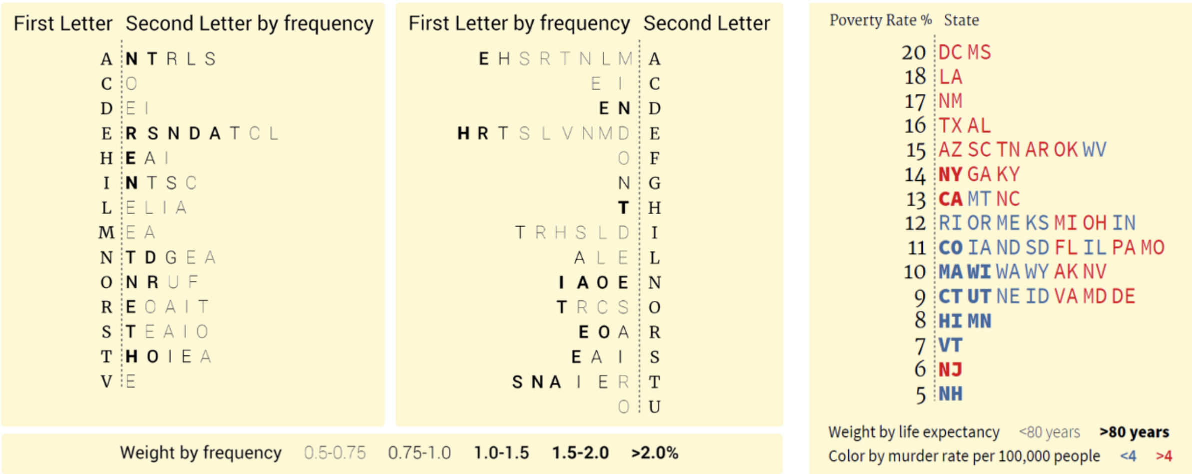

Figure 136. Left: Bigrams in the English language. Font weight indicates frequency of occurrence. Right: U.S. States: stem indicates poverty rate, font weight indicates life expectancy and color indicates murder rate. Image created by author.

Leaves do not need to be restricted to a single alphanumeric character. Figure 136 right shows U.S. states with stem indicating poverty rate and additional data via hue and font weight. Multi-attribute correlations are visible, e.g. higher murder rates (red) and lower life expectancy (non-bold) are associated with higher poverty rates (top portion of plot).

C:3.3. Word Stem & Leaf: Character Traits and Death Rates

Leaves do not need to be restricted to tokens of the same length, e.g. words can be used instead. Text analytics such as sentiment analysis is popular, with Twitter and news feeds being analyzed to produce sentiment scores and visualizations in both research[267] and industry.[268] Beyond the raw score, specific words associated with sentiment can be extracted and displayed to provide added context, (e.g., *Tile Apps*[269] depicts Twitter words sized by frequency).

Character trait analysis is an extension of text analytics for sentiment and emotions, instead collecting the specific adjectives used as opposed to categorizing adjectives to sentiment or emotion. Figure 137 illustrates a character trait analysis by identifying adjectives that occur within +/- 3 words from a character in *Grimms' Fairy Tales*, with the stem indicating the character and the leaves indicating descriptors. Adjectives are ordered left to right based on frequency with font weight indicating the level of frequency (note that kings tend to be old while princesses are beautiful; witches are not frequently wicked but more likely to be old).

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[267] J. J. Kaye, A. Lillie, D. Jagdish, J. Walkup, R. Parada, and K. Mori, Nokia internet pulse: a long term deployment and iteration of a twitter visualization. In *CHI'12 Extended Abstracts on Human Factors in Computing Systems* (pp. 829-844). ACM. 2012.

[268] *Bloomberg Introduces Sentiment Analysis Tools*. www.tradersdna.com/news/bloomberg-introducestwitter-sentiment-analysis-tools/. Retrieved 12/29/2014

[269] D. Cheng, P. Schretlen, N. Kronenfeld, N. Bozowsky, and W. Wright. Tile based visual analytics for Twitter big data exploratory analysis. In *Big Data, 2013 IEEE International Conference on* (pp. 2-4). IEEE. 2013.

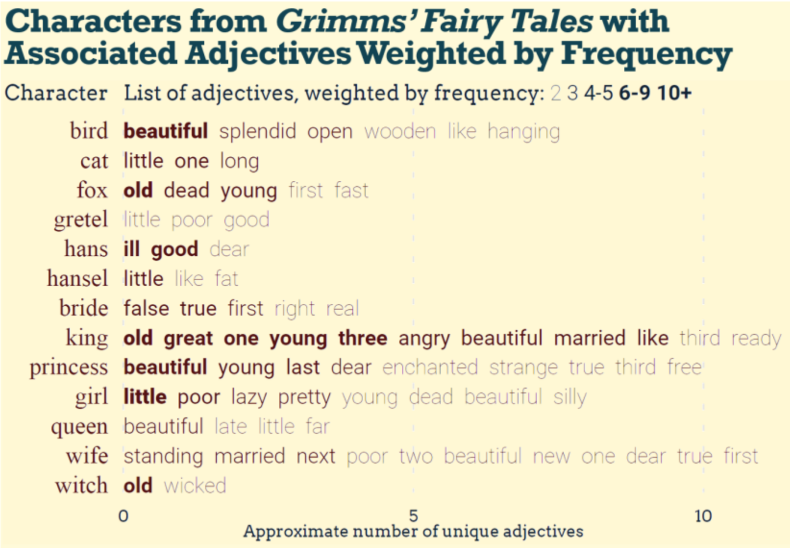

Figure 137. Adjectives associated with characters from *Grimms' Fairy Tales*. Image created by author.

One challenge with variable length tokens is spacing: if the space provided per word is based on the longest word, then there will be a lot of wasted whitespace. Also, uneven whitespace across a string of adjectives is more difficult to read than word spacing based on typical text spacing (e.g. Tracy[270]). Here, words are placed in sequence with an expected single space between words. A horizontal scale indicates the approximate number of words, based on average word lengths in the plot. Longer word lists should experience reversion to the mean: at the grid line for 10 average words, the number of words for king is approximately 9.3, for princess 9, for wife 10 - i.e. an error rate of only 10% in this example.

Figure 138 shows two stem and leaf plots with font attributes on a subset of Titanic passengers (left image for third class passengers, right image for first class passengers). The stem indicates surname and the leaf indicates given name. In this example, 1) font weight represents survival: e.g. bold indicates death, 2) italics represent gender: e.g. italic indicates female, 3) capitalization represents age: e.g. all caps indicates children, and 4) font family represents class: a plain font for third class, a serif font for first class.

Since there are many binary attributes indicating membership for different sets, back-to-back stem-and-leaf plots can be used to more clearly show membership for a specific attribute. Figure 138 shows females on the left and males on the right. In the right image (first class) higher survivorship is clearly visible among women (i.e. there is less bold on the left side of the plot). Although there are survivors among the first class men, capitalization reveals that almost entirely the dead men are adults ("women and children first").

270 Walter Tracy. *Letters of Credit: A View of Type Design*. Jaffrey, NH: David R. Godine Publisher, 2003.

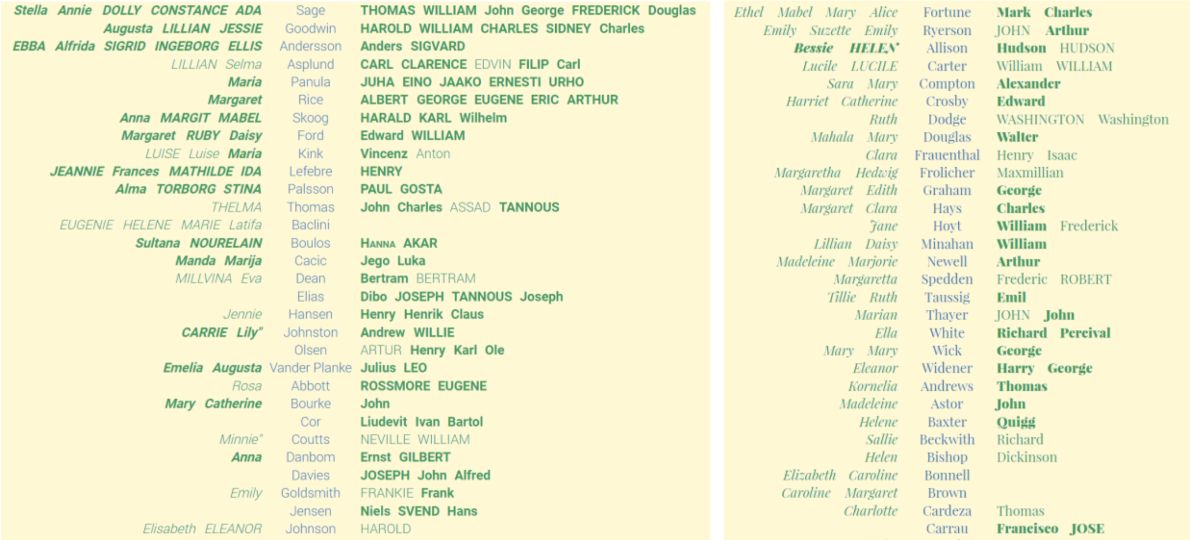

Figure 138. Titanic passengers. Left: third class families; Right: first class families. Stem indicates surname, leaf for given name, bold indicates death, italics for women, allcaps for children. Image created by author.

The greater proportion of heavyweight font for third class passengers left image vs. first class passengers right image is clearly visible: far fewer first class passengers died. Similarly, only two first class children (allcaps bold) deaths are visible in the subset shown while many of the third class deaths are children.

C:3.4. Phrase Stem & Leaf: Financial Performance and Psalms

Figure 139 shows a stem and leaf plot for the performance of 500 stocks aggregated into 150 different industries. In this example, a different strategy is used for variable label length: instead of placing each word in sequence, a fixed width is provided for each label. Long labels are compressed using a narrow version of the particular font with narrow inter-character spacing (i.e. tracking), while short labels use a wide version of the same font with a wide inter-character spacing. In this example, the font is Gill Sans (Plain, Condensed and Extra Condensed).

Figure 139. Distribution of stock market returns across 150 different industries. Image created by author.

Another approach to scalability with long names and many items is to rotate the stem and leaf plot 90 degrees as shown fully in Figure 140. This plot shows a horizontal distribution of earnings performance of 500 companies. In this orientation, the plot more closely resembles a bar chart. There is no layout error in counts as the height is consistent for each item. Phrase length is irrelevant – some phrases can be short (e.g. The Gap) and some can be long (e.g. Molson Coors Brewing Company). In this example, font color indicates sector (e.g. Tech, Financial, Retail), font weight indicates stock trading volume.

Figure 140. Distribution of earnings surprise for 500 companies. Image created by author.

The horizontal approach can be extended to longer phrases. Figure 141 is a visualization of common phrases repeated in the *Book of Psalms* from *The King James Version of the Bible* (www.gutenberg. org/ebooks/10). The source text is split on punctuation marks into phrases. Commonly repeated phrases are shown on the centerline. Phrases immediately prior the common phrase are above the centerline, phrases immediately following are below. Font weight indicates frequency. For example, the phrase “O give thanks unto the Lord”, is very commonly preceded by “Praise ye the Lord”, although on one occasion is preceded by “I will exalt thee”. Notice the common phrase “I will praise thee” is frequently followed by “O Lord”, while on one occasion it is followed by “O Lord my God” – this may potentially be indicative of a transcription anomaly leading the researcher to investigate prior versions of the document.

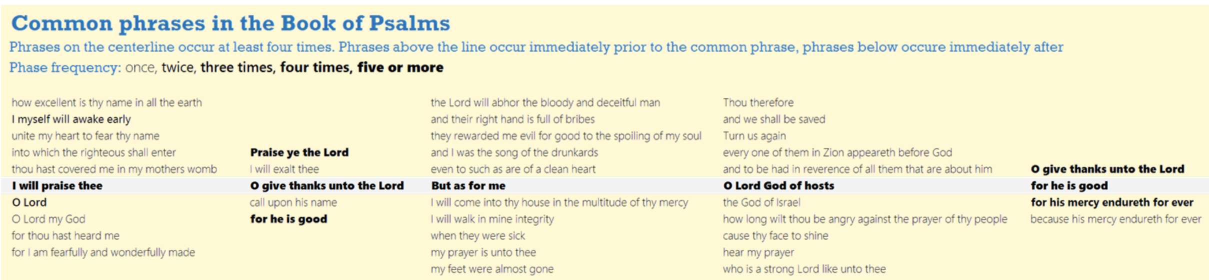

Figure 141. Subset of common phrases in the *Book of Psalms* (centerline), with preceding phrases (above) and following phrases (below). Phrase frequency indicated by font weight. Image created by author.

C:3.5. Literal Stem & Leaf Conclusions

The contribution of this chapter is to provide many new design extensions to this existing visualization technique. Text and font attributes can be used to create many novel variants of stem and leaf plots, including 1) use of font attributes to indicate data; 2) text markers to indicate either categoric or numeric values for either stems or leaves; 3) text markers which range from single character, to words to phrases; 4) horizontal and vertical orientations. Applications include text analytics such as n-gram analysis, character analysis and set analysis.

One issue identified is variable length leaves, and various strategies were used: 1) tokens packed together with a horizontal axis based on average token size; 2) consistent token size and use of multiple font widths to accommodate for variance in token width; and 3) a vertical orientation so token width is not relevant.
None of the examples here discuss interaction. The interaction of stem and leaf plots with other well-known visualization techniques (e.g. linked interaction[271]) or emerging visualization techniques (e.g. object constancy[272] or sedimentation[273]) should be considered. Sedimentation, for example, could be used to increase scalability.

Scalability is not addressed, although Figure 140 shows hundreds of phrases in a stem & leaf plot while retaining legibility, and implies thousands of characters can be depicted legibly. Interactive techniques such as zooming, tooltips and/or sedimentation could allow for much larger stem and leaf plots showing macro patterns zoomed out and details on interaction.

Stem and leaf plots are less common than other techniques such as histograms and scatterplots and more prone to errors in interpretation (e.g. Baker et al[274]). Some of the techniques shown here could be utilized to improve interpretation for novice users, for example, redundant encoding of the primary measure of the distribution using color or font-weight could be evaluated to determine potential improvement in performance.

Technically, text based stem and leaf plots are easy to create. Some of the examples above were created using formulas or macros in Excel, and reproducing the prior examples were simply created directly in a text editor. For character-based stem and leaf plots, fixed width fonts – such as Courier, Source Sans Pro or Lucida Console – should be used instead of more common proportional fonts, so that columns line up based on characters.

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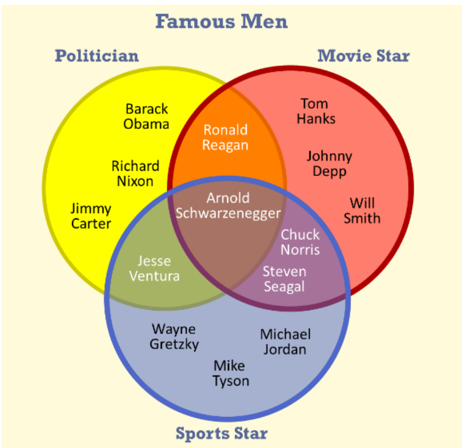
[271] R. A. Becker and W. S. Cleveland. "Brushing scatterplots." *Technometrics* 29, 2. 1987. 127–142.
[272] J. Heer and G. Robertson. "Animated transitions in statistical data graphics." *Visualization and Computer Graphics, IEEE Transactions on* 13, 6. 2007. 1240–1247.
[273] S. Huron, R. Vuillemot, J.D. Fekete. "Visual Sedimentation." *IEEE Transactions on Visualization and Computer Graphics*. Nov. 2013.
[274] R. S. Baker, A. T. Corbett, K. R. Koedinger. "Toward a model of learning data representations." *Carnegie Mellon University Research Showcase*, 2001.

C:4. CD: Categoric Document – labels to create areas for Venn, mosaic, bar, graphs and maps

Some documents are big tables or lists. Many visualization techniques show counts of things from lists. Distributions, treemaps, mosaic plots and sometimes pie charts and bar charts may represent counts of things by the area they depict. Venn diagrams and mosaic plots sometimes use areas to indicate counts by their areas. However, these visualizations depict only the summary and the underlying elements have disappeared. Immediate access to items may be desirable: for example, the viewer's task may be to locate where a particular item occurs rather than the overall tallies. Or they may be interested in adjacent items to a particular target. And so on. With only sums, getting to the underlying data requires additional interaction, such as a tooltips or clicks. Interactions are quite slow compared to simply shifting attention and thus it is desirable to directly depict the items that make up the sum.

Furthermore, there are many different font attributes, which can be combined together and remain distinctly legible, i.e. high-dimensional glyphs can be constructed using labels and adjusting many different font attributes. One application domain where high-dimensional glyphs are relevant is set visualization, such as Venn diagrams, mosaic plots and some graphs. In set visualization, elements are the individual items belonging to sets. In some set visualizations, the individual items are represented explicitly, such as dots, glyphs, images or words, as shown in the example in Figure 142 left.



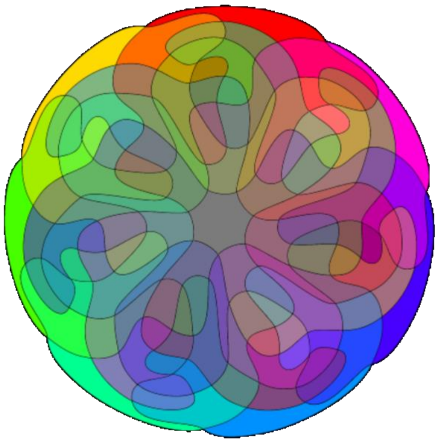


Figure 142. Left: Venn diagram showing some famous men by profession. Right: Venn diagram illustrating 128 different combinations in a Venn diagram of 7 sets. Left image by author, right image by Santiago Oritz.

However, Venn (and Euler) diagrams can be difficult to extend to many sets. Figure 142 right shows 7 different sets in a Venn diagram by Santiago Oritz.[275] These high dimension Venn diagrams are difficult to visually parse: to comprehend the set membership at any point, it is difficult to trace around the complex looping shaping. Even with a dataset about color, strange shades of bluish-greenish-greyish colors do not clearly identify which sets they belong to – as hue can really only express three unique dimensions.

[275] Santiago Oritz, 7 Sets Venn Diagram showing 128 color combinations from mixing 7 colors. http://moebio.com/research/sevensets/ Accessed Sept. 10, 2016.

Understanding elements and their relations to sets are important tasks in set visualization. Alsallakh et al's recent state-of-the-art report[276] on set visualization techniques identifies 26 analysis tasks on sets. More than half of the tasks (14/26) are related to elements, attributes on elements, or summaries about elements, such as:

- Find elements that belong to a specific set (task A1)
- Compare attribute values of two sets or subsets (task C3)
- Does one set contain more exclusive elements than another set (task B12)

Explicitly representing elements as labels has many potential benefits, including:

1. Both macro-level densities and micro-level identification can be made available.
2. Directly reading text is faster than relying on interactions, such as a tooltip.
3. The overall information density of the visualization is increased.
4. Serendipitous patterns otherwise not visible may be revealed.

Our unique contribution here is to extend labeled elements by varying font attributes, such as bold and italics, to indicate set membership and counts. This approach can yield additional benefits:

5. Noticeable changes in font attributes indicates differences in membership.
6. Membership for any element can be decoded based on the font attributes.
7. Intuitive mappings can facilitate decoding these attributes.
8. Text can scale to a high number of sets (10) and a high number of elements (1000's).
9. The aggregation of text elements can indicate counts.
10. The approach is scalable across a wide variety of set visualization techniques.

C:4.1. Review of Set Element Representations

Given the importance of elements to set analysis, it is useful to consider how elements are represented. This includes whether they uniquely identify the element and how they convey multiple data attributes. In the STAR report, there are 48 unique visualization examples, of which 28 explicitly represent elements. These elements are represented as:

- *Dots*. Simple dots are often used to represent one or two data attributes, such as color or brightness to identify set membership. For example, TwitterVenn[277] (Figure 143 far left) uses dots to indicate search results in a Venn diagram.
- *Labels*. Labels can uniquely identify items. In all cases additional attributes were not encoded in labels, but rather other visual attributes such as the background color, lines connecting labels, etc. e.g. ComED[278] (Figure 143 second image).
- *Glyphs*. In 5 cases, glyphs (e.g. pies, bars, and icons) are used to encode attributes such as set membership (e.g. Figure 143 third image).[279] Sometimes glyphs are used together with plain labels.

[276] Bilal Alsallakh, Luana Micallef, Wolfgang Aigner, Helwig Hauser, Silvia Miksch, Peter Rodgers: "Visualizing sets and set-typed data: State-of-the-art and future challenges" in *Eurographics conference on Visualization (EuroVis)–State of The Art Reports.* pp. 1–21 (2014)
[277] J. Clark. Twitter Venn (2008), http://www.neoformix.com/2008/TwitterVenn.html, accessed 04/02/2016
[278] Nathalie Henry Riche and Tim Dwyer: "Untangling Euler diagrams." in *IEEE Transactions on Visualization and Computer Graphics*, 16(6), 1090–1099 (2010)
[279] Gary L. Brase, "Pictorial representations in statistical reasoning." in *Applied Cognitive Psychology,* 23(3), 369–381 (2009)

- *Images*. In 3 cases, images are used. In two of these the images supplement otherwise undifferentiated labels (BubbleSets[280] and Vizster[281]).
- *Shapes*. In one case (Figure 143 last image) unique shapes of countries identify the individual elements, assuming that the viewer has a reasonable geographic literacy.

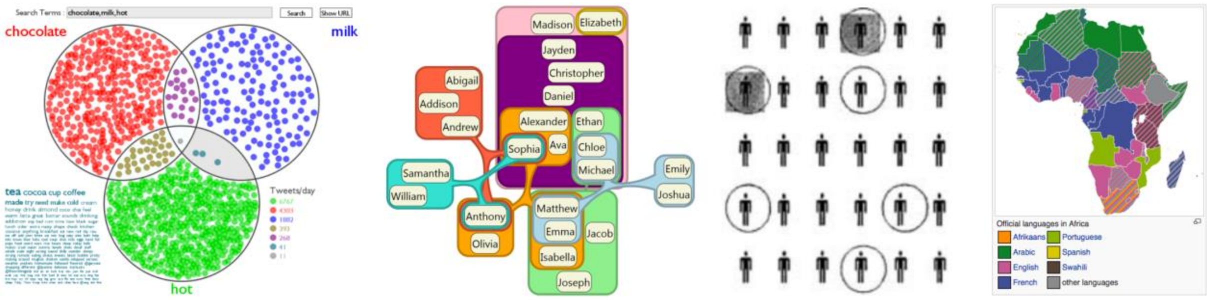


Figure 143. Set elements represented as a) dots, b) words, c) icons and d) geographic shapes. Images copyright respective authors.

In no case do the element representations illustrated in the STAR report use more than two visual attributes. For example EulerGlyphs uses hue and outline to encode memberships. Although there is some use of labels and/or a visual attribute or two to indicate elements in sets, the existing use suggest that much more could be done:

- *Identifiable Elements*. Uniquely identifiable elements adds information and context regarding the members of the sets which may be relevant to the task. Viewers can use their existing knowledge regarding the specific elements to augment their understanding of the sets (as shown by the named elements in Figure 142 left). Only 12 out of the 26 STAR report examples represent elements such that they are uniquely identifiable.
- *Multi-attribute Elements*. Adding more data to the elements with different visual attributes can help identify elements, membership in sets or other data.

C:4.2. Using Glyphs to Represent High Number of Dimensions

While identifying individual elements with multiple data attributes per element may not occur frequently in set visualization, other examples can be found more broadly in data visualization. Borgo et al.'s state-of-the-art report on glyphs[282] characterizes the design space of glyphs including common visualization attributes such as size, color, intensity, opacity, and shape; as well as semantic attributes such as text, symbols, icons, pictograms (as discussed earlier and summarized in Table 2P19). However, the guidelines surveyed focus on traditional visual attributes (color, shape, size, orientation, texture and opacity) although there is some discussion regarding metaphoric pictograms. There is no broader discussion for specifically identifying a large number of unique items. However, Maguire's PhD Thesis[283] does provide a broader discussion of high-dimensional glyphs, automated approaches for constructing these glyphs and examples of glyphs with up to seven attributes, which

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280 Chris Collins, Gerald Penn and Sheelagh Carpendale, "Bubble sets: Revealing set relations with isocontours over existing visualizations." in *IEEE Transactions on Visualization and Computer Graphics* 15(6), 1009–1016 (2009)

281 Jeff Heer and Danah Boyd, "Vizster: Visualizing online social networks." in *IEEE Symposium on Information Visualization, 2005. INFOVIS 2005*. pp. 32–39. IEEE (2005)

282 R. Borgo, J. Kehrer, D.H.S. Chung, E. Maguire, R.S. Laramee, H. Hauser, M.Ward, M.Chen, "Glyph-based visualization: Foundations, design guidelines, techniques and applications." in: *Eurographics State of the Art Reports*. pp. 39–63. EG STARs, Eurographics Association (May 2013),

283 Eamonn James Maguire, "Systematising glyph design for visualization." PhD dissertation, University of Oxford, 2014. pp. 43-52.

consider combinations of hue, shape, components, connector lines, luminance, size, texture and orientation in foreground and background to create composite glyphs, such as some of the examples shown in Figure 144.

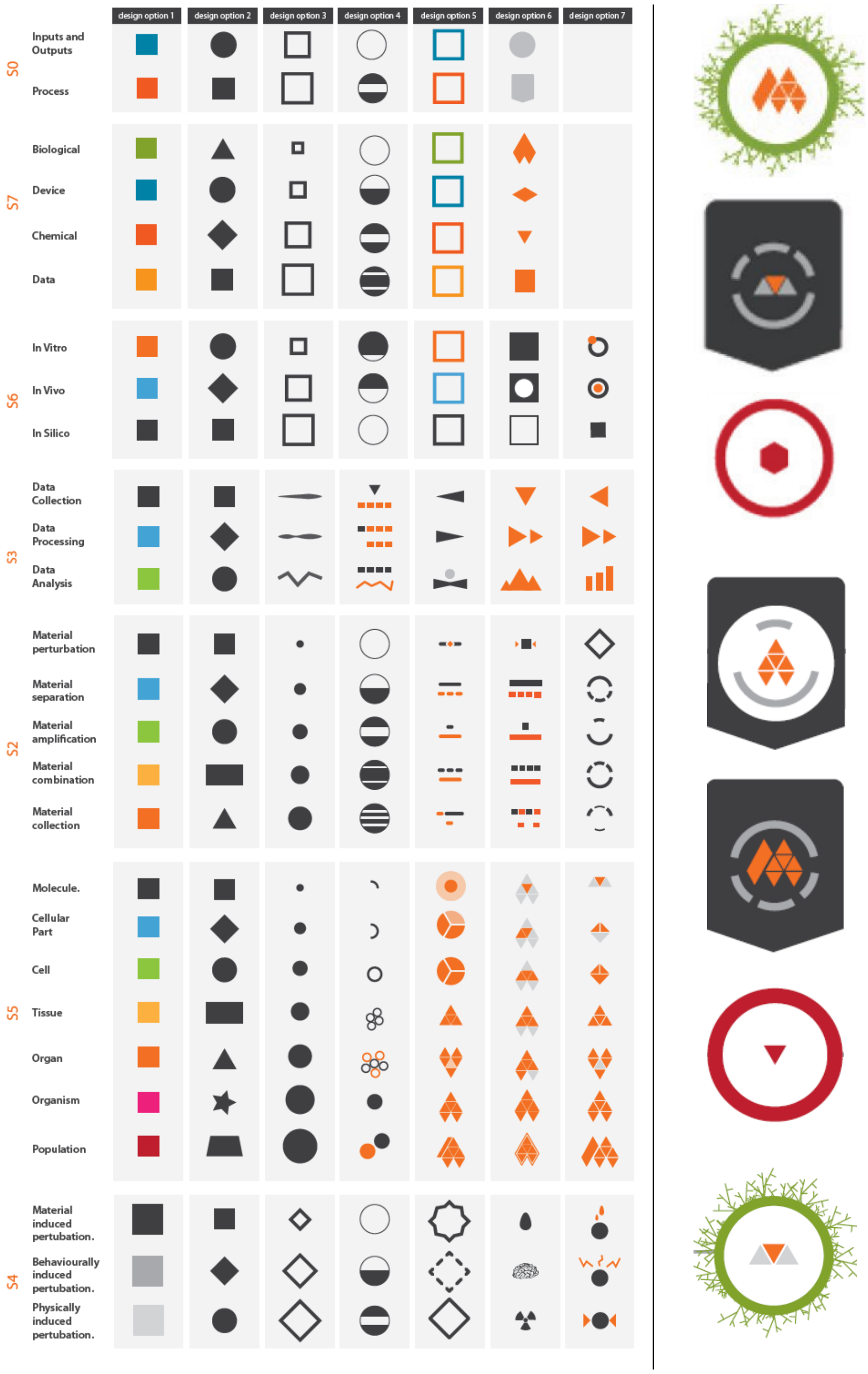

Figure 144. Maguire's high-dimensional glyphs. Left: exploration of visual design alternatives for each of seven different data attributes to be combined into a singular glyph. Right: sample glyphs based on one particular configuration of the visual attributes. Image copyright Eamonn Maguire.

Brath[284] itemizes approaches for uniquely encoding a high number of categories in glyphs as 1) icons; 2) geometric shapes, e.g. circles, stars; 3) textures, i.e. imagery combining shape and color, e.g. logos and flags; and

[284] Richard Brath, "High category glyphs in industry." In: *Visualization in Practice at 2015 IEEE Symposium on Information Visualization (VisWeek 2015)*. IEEE (2015)

4) text labels. Icons, shapes and textures can be difficult to create for a large number of categories, without pre-existing libraries of glyphs (e.g. logos, symbols, images), or automated techniques e.g. Setlur et al[285]. However, abstract concepts (e.g. GDP, CPI) may be difficult to encode; some glyphs may be ambiguous (e.g. Clarus the dog-cow); while other glyphs are difficult to add attributes (e.g. a French flag rotated 90 degrees is confused with Netherlands' flag).

High dimensional typographic labels are common in cartography. Figure 145 (previously, Figure 30P35) is an example Ordnance Survey map and legend from the 1920's where city labels identify the literal names of cities, and also indicate set membership in four different sets via:

- *Case* differentiates between town (uppercase) vs. village (lowercase).
- *Italics* indicate whether the city is an administrative centre or not, i.e. a county town.
- *Font size* is used to indicate population category.
- *Font family* indicates country: serif for U.K., slab-serif or serif variant for Scotland.

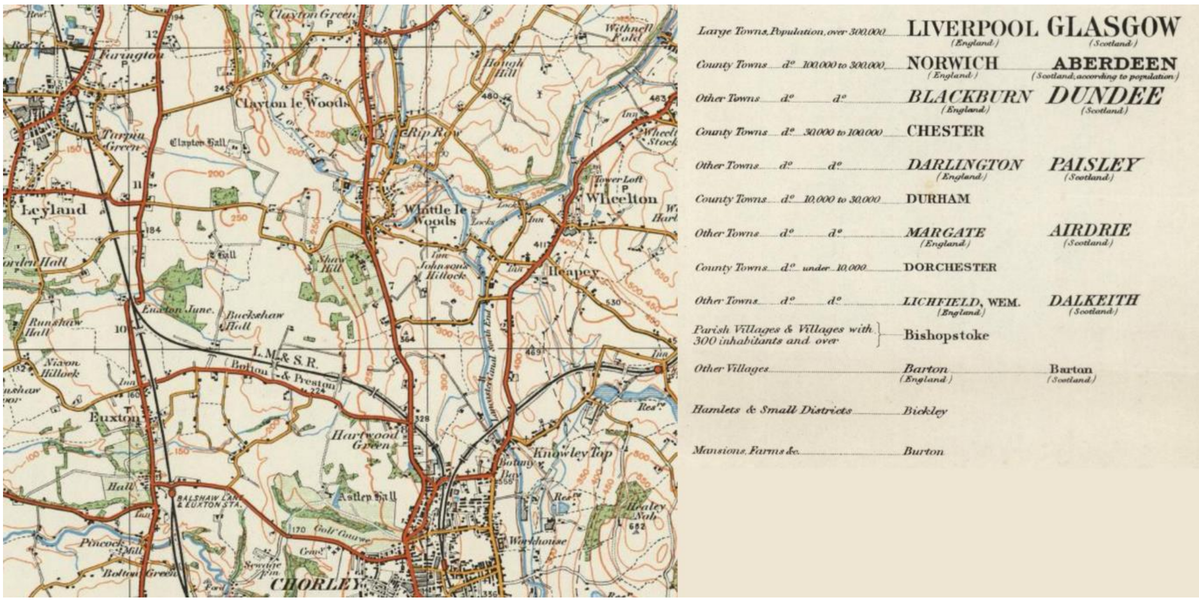

Figure 145. Ordnance Survey[286] map labels indicate set memberships via font size, family, italics and case.

The map in Figure 31P36 uses a different group of typographic attributes to indicate set memberships for geographic features including different font families (e.g. high contrast sans serif, low contrast slab serif, and outline font); italics (forward and reverse); case; variable number of underlines; and spacing (to indicate extents).

In the next sections, different set visualization techniques are shown extended with labeled elements and font-attributes, including Venn and Euler diagrams, mosaic plots, cartograms and graph-representations of sets.

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[285] V. Setlur, J. D. Mackinlay, "Automatic generation of semantic icon encodings for visualizations" in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. pp. 541–550. ACM (2014)

[286] Yolande Hodson, *Popular maps: The Ordnance Survey Popular Edition One-inch Map of England and Wales, 1919-1926*. (1999), http://www.davidrumsey.com/luna/servlet/s/s15w94, accessed: 04/02/2016

C:4.3. Typographic Venn and Euler Diagrams

Figure 146 shows a three-set Venn diagram of Bertin's dataset of occupations by department. Membership is determined by the proportion of population working in a given department: a department is assignment to particular occupation if the proportion of the population is greater than 30%. For example, the department Ariège has 51% of the population in agriculture-related occupations, and only 27% and 22% employed in industry and services – thus Ariège is a member of the set Agriculture. Paris, on the other hand, has 38% employed in industry, 62% employed in services and zero employed in agriculture – thus Paris is a member of the sets Industry and Services.

In the resulting area-proportional Venn it can be seen that the circle for Agriculture is larger than the circle for Industry – but difficult to estimate how much larger. Some memberships are very difficult to estimate: the ratio of departments belonging exclusively to Industry (pure red) versus belonging exclusively to Services (pure blue) requires a visual comparison the areas of complex curved polygons. Area estimation is known to be poor compared to estimation of other visual attributes such as length (e.g. Heer and Bostock[287]). Furthermore, areas depicted with regular shapes, such as circles, cannot be 100% accurate. This further increases the degree of error associated with area-proportional Venn diagrams.

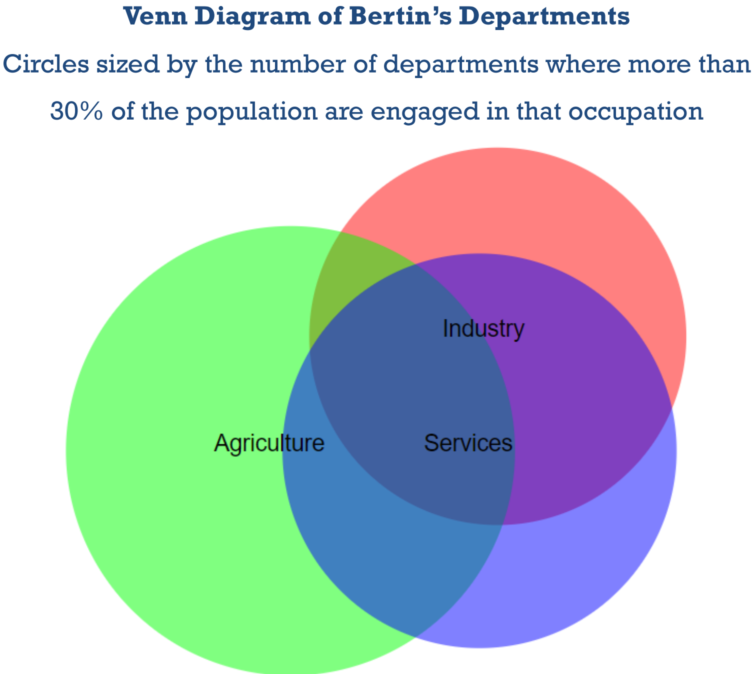

Figure 146. Venn diagram where areas are proportional to the number of elements in each segment. Image by author, generated using BioVenn.nl.[288]

[287] Jeff Heer and Mike Bostock. "Crowdsourcing graphical perception: Using Mechanical Turk to assess visualization design." In *ACM Human Factors in Computing Systems* (CHI), 203–212, (2010).

[288] T. Hulsen, J. de Vlieg and W. Alkema. "BioVenn - a web application for the comparison and visualization of biological lists using area-proportional Venn diagrams." In *BMC Genomics* 2008, 9 (1): 488

Figure 147 shows the same data as a three-set *typographic* Venn diagram. An underline indicates agriculture, industry in small caps, and services in italic. Individual elements are visible and readable and relative sizes are more easily comparable as stacks of text than area-proportional diagrams.

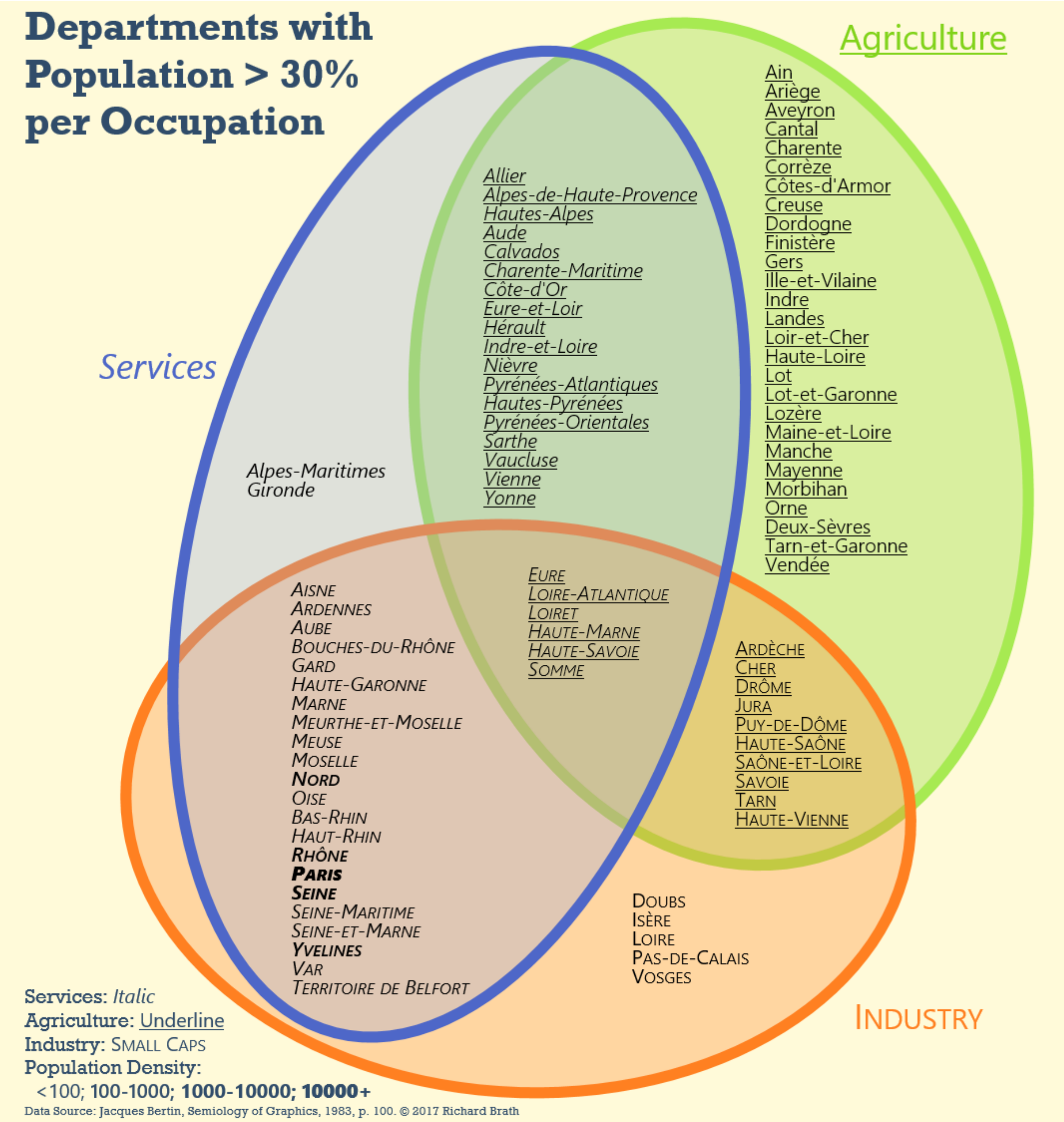

Figure 147. Venn diagram of occupations by French departments. Image by author.

Figure 148 goes further, with a four-set typographic Venn diagram indicating each member of the U.S. Senate as of 2014-2016 by name, with each element indicating *seven* data attributes:

- *Text* shows the name of each senator.
- *Slope* indicates the political party membership. Right-leaning text indicates Republicans, while left-leaning text indicates Democrats. Independents are represented with no leaning at all.
- *Bold* indicates senators who have served more than one term.

- *Underline* indicates senators who have a graduate or professional degree.
- *Hue* indicates gender: blue for male, magenta for female.

Beyond the four sets depicted by the Venn diagram, additional data is encoded:

- *Case* indicates age. Those over 65 are indicated in uppercase.
- *Font family* indicates ethnicity. Most senators are plain Caucasians (in a sans serif font), with a couple Latinos (in a curvy font), an Asian-American (in a serif) and a couple African-Americans (in a rectangular font).

At the level of individual elements, the names of individual senators are readable. Set memberships can be seen, either by assessing the containment of elements relative to the set outlines, or by the font attributes. For example, MAZIE HIRONO is a female (purple), Democrat (left-leaning italic), over age 65 (all caps), first term senator (not bold), with an advanced degree (underline), and is an Asian-American (serif). **BERNIE SANDERS** is male (blue), independent (no italics), over age 65 (all caps), multi-term senator (bold), with no advanced degree (no underline), and is Caucasian (plain sans serif font). At a macro-level, the use of stacked text elements allows stacks to be visually compared similar to bars in a bar chart. The viewer can attend to the stacks without regard to the individual names. Many visual comparisons of quantities can be done at the level of set relations. e.g.

- There are far more men than women senators.
- There are more Democratic women senators than Republican women senators.
- There are more Democratic women senators with advanced degrees than corresponding Republican women.
- There are no first-term Democratic women without an advanced degree.

Instead of using an area-proportional Venn diagram, the use of stacked text elements allows for the separation of the depiction of logical relations (i.e. the curved lines and fills depicting each set) from the quantities of elements (i.e. stacked text). Issues with attempting to algorithmically size areas of Venn outlines so that areas represent quantities are easily side-stepped, e.g. Wilkinson.[289] Each stack can be ordered too: in this example alphabetic order facilitates visual search within subsets.

Figure 149 shows a similar Venn diagram of the U.S. House of Representatives, indicating name and six additional set attributes. An interactive version of this visualization can be found online here: http://codepen.io/Rbrath/full/QEGBOo/

[289] Leland Wilkinson, "Exact and approximate area-proportional circular Venn and Euler diagrams." *IEEE Transactions on Visualization and Computer Graphics* 18.2 (2012): 321-331.

Figure 148. Venn diagram of the United States Senate representing 100 senators. Image created by author.

Figure 149. Typographic Venn diagram representing all 435 members of the U.S. House of Representatives and six attributes. Image created by author.

C:4.4. Typographic Mosaic Plot of Titanic Survivorship

A larger scale example is the data repository `encyclopedia-titanica.org`, which provides detailed biographies of 1308 passengers of the Titanic. However, one must either search or browse through lists of names: a macro view of the passengers is not available on this site. The *Titanic* dataset is a popular sample dataset for data visualization. There are 1308 passengers, all of which can be categorized by age, gender, class and survivorship. Visualizations of the *Titanic* data typically reduce the data down to summaries then plot the sets, for example, as a mosaic plot,[290] Venn diagram,[291] Parallel Sets,[292] treemap,[293] and so forth.

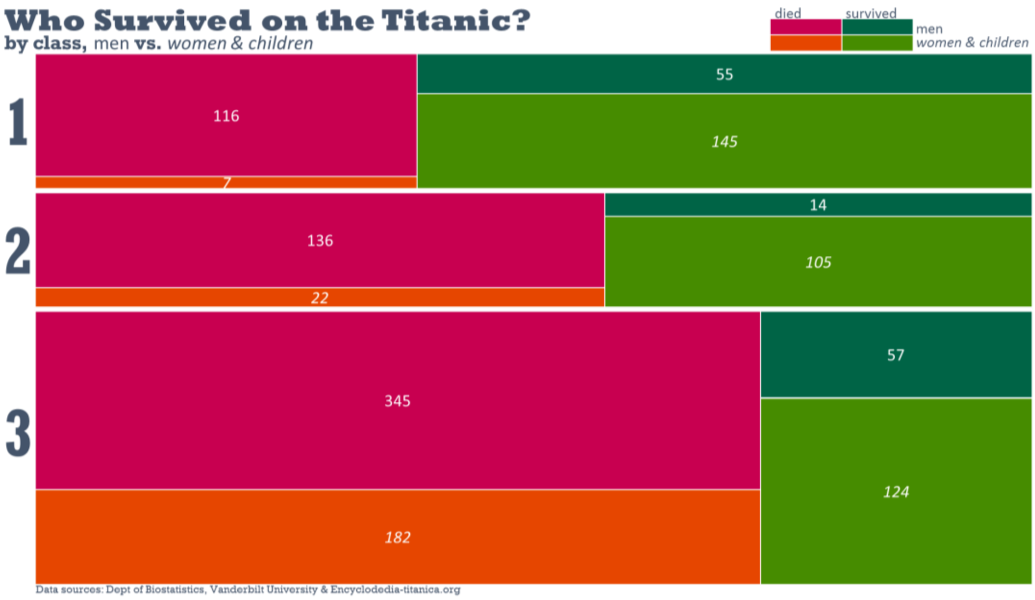

Figure 150. *Titanic* survivorship by class (1,2,3 – horizontal bands) and men vs. women & children.
Image created by author.

Figure 150 shows a typical mosaic plot of *Titanic* survivorship with horizontal bands indicating class (1,2,3), vertical split indicating survivorship (reinforced with red/green); and an additional split to indicate men (the upper portion of a band) vs. women & children (lower portion of a band). Only high-level macro patterns are visible, such as the higher rate of death for third class passengers. The detail elements are missing – which are important to 14 of the 26 analytic set visualization tasks identified by Alsallakh et al.[294] Unfortunately, the area-based visualization summaries do not retain the individual elements which are needed for half of the tasks.

With high resolution displays, thousands of individual items can be explicitly labelled and the overall area formed by a group of labels indicates the counts of the individual items. Figure 151 displays all 1308 passengers on the *Titanic*, similar to the previous mosaic plot, this time indicating the names of all passengers on board. On

[290] Pedro M. Valero-Mora, Forrest W. Young, and Michael Friendly. "Visualizing categorical data in ViSta." *Computational Statistics & Data Analysis* 43, no. 4 (2003): 495-508.
[291] Richard Brath, "Multi-attribute glyphs on Venn and Euler diagrams to represent data and aid visual decoding." In *3rd International Workshop on Euler Diagrams*, (2012): 122.
[292] Robert Kosara, Fabian Bendix, and Helwig Hauser. "Parallel sets: Interactive exploration and visual analysis of categorical data." *Visualization and Computer Graphics, IEEE Transactions on* 12, no. 4 (2006): 558-568.
[293] Robert Kosara, "Treemaps", on *Eagereyes.org*. https://eagereyes.org/techniques/treemaps accessed Sep 17, 2016.
[294] Bilal Alsallakh et al. "Visualizing sets and set-typed data: State-of-the-art and future challenges." In *Eurographics conference on Visualization (EuroVis)–State of The Art Reports*, (2014): 1-21.

a 17 inch 1920x1080 display the type in this plot is a small but readable 6 point providing access to all the micro-data. Within each horizontal band, both type and color are used to split between:

- Gender: men (plain/above) and women & children (italic/below); and
- Survivorship: died (red serif/left) and survived (green sans serif/right)

In the text-based approach, macro-patterns are still visible, such as the higher proportion of survivors in first class relative to other classes. At the same time, the detailed names of each individual are immediately accessible. Similar to the Vietnam Veterans Memorial, each person is made visible.[295] Macro-questions can be asked of this graphic (e.g. "Were women and children really first across classes?") and micro-questions (e.g. "Did the Astors' survive or die?").

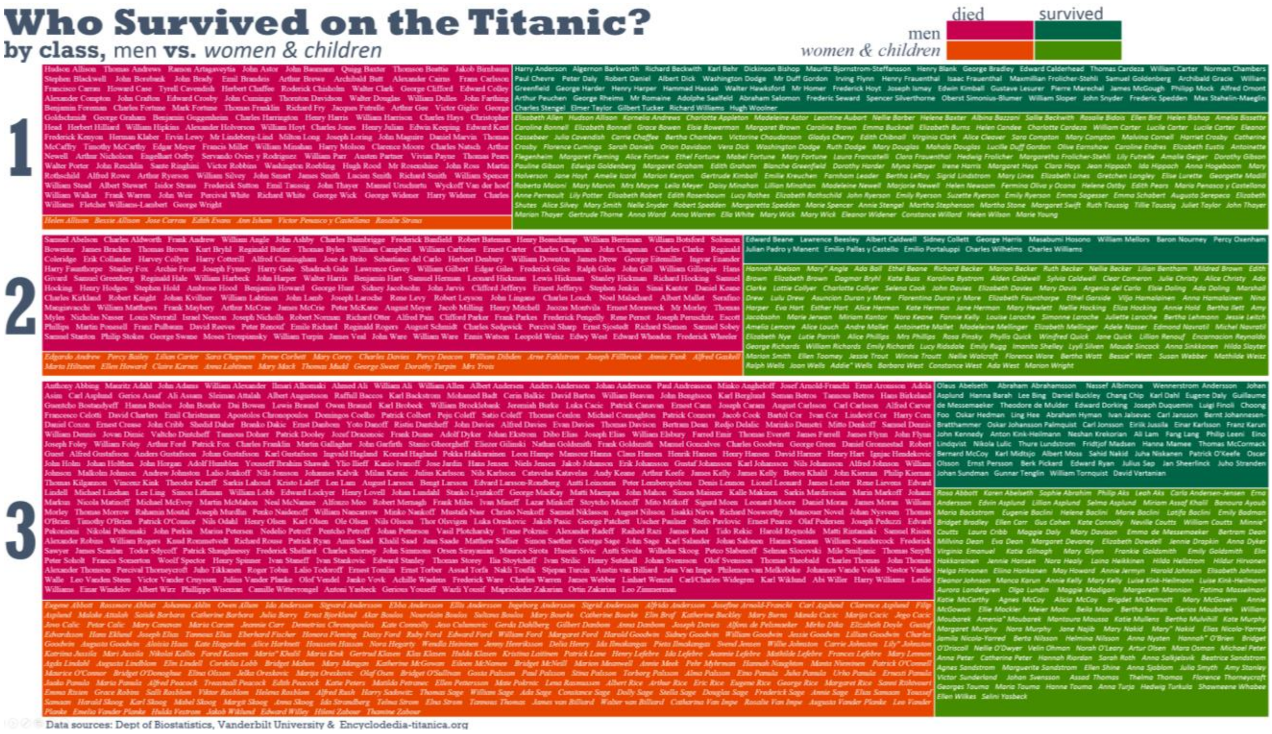

Figure 151. 1308 passengers on the Titanic, organized by class (vertically), survivorship (horizontally, serif/sans serif; red/green) and gender (plain/italic). Image created by author.

One problem using text labels to create quantitative areas is the potential for errors in the sizes of areas. This includes:

String length. Bias in sizes that can occur if there is a concentration of long labels in a portion of the plot. For example, surviving first class women and children names are on average 36.7 characters long while deceased third class men average only 22.0 characters - the names former segment are 67% longer than the latter. In this plot, names have been shortened to a familiar name and a surname, so that all passengers are reduced to similar visual length. For example, the passenger *Cardeza, Mrs. James Warburton Martinez (Charlotte Wardle Drake)* is recorded with eight words in the passenger list, and is reduced in the visualization to *Charlotte Cardeza*. The

[295295] Edward Tufte, *Envisioning Information,* Graphics Presss, Cheshire CT, 1990. Pages 42—44.

much shorter name, *Bird, Miss Ellen* is shortened to *Ellen Bird*. When the passenger names are reduced to two words, the above two segments are 13.9 and 13.6 characters respectively - a 2% difference.

Small box sizes. The algorithm used here nudges rectangle sizes larger to fit text. As a result, there is a margin of error between the areas if represented accurately compared to areas adjusted to fit text. This is most acute at the smallest sizes (as shown in the fourth column of Table 14). For example, the thin horizontal orange strip in Figure 151 (representing deceased first class women and children) has only 7 members and the height of the box is 8 points tall instead of 6.5 points tall – making this rectangle approximately 20% larger in area than it should be.

Table 14. Area Errors in Mosaic Plot with Sizes Adjusted to Accommodate Running Text

Data		**Mosaic: Wide boxes**		**Mosaic: Tall boxes**	
Actual value	Pct of Total	Pct of Total	Pct diff to actual	Pct of Total	Pct diff to actual
116	8.9%	9.1%	2.9%	9.0%	1.8%
7	0.5%	0.6%	20.2%	1.0%	85.6%
55	4.2%	4.6%	9.7%	5.2%	23.7%
145	11.1%	11.1%	0.2%	10.8%	-2.3%
136	10.4%	10.5%	1.4%	10.2%	-2.3%
22	1.7%	1.7%	3.6%	2.4%	42.2%
14	1.1%	1.3%	22.1%	1.8%	63.9%
105	8.0%	7.8%	-2.3%	7.4%	-7.2%
345	26.4%	25.2%	-4.5%	24.9%	-5.5%
182	13.9%	13.4%	-3.5%	13.7%	-1.8%
57	4.4%	4.6%	5.1%	4.5%	3.4%
124	9.5%	9.9%	4.1%	9.7%	2.4%

Aspect Ratio. The minimum height for a box is related to the height of a single line of text; whereas the minimum width for a box is related to the width of a word - which is a much larger size than height. The first version of the Titanic passenger mosaic plot (Figure 152) created splits in the opposite orientation resulting in many tall narrow boxes. These tall narrow boxes when adjusted for minimum widths, resulted in higher error rates, as shown in the sixth column of the table above.

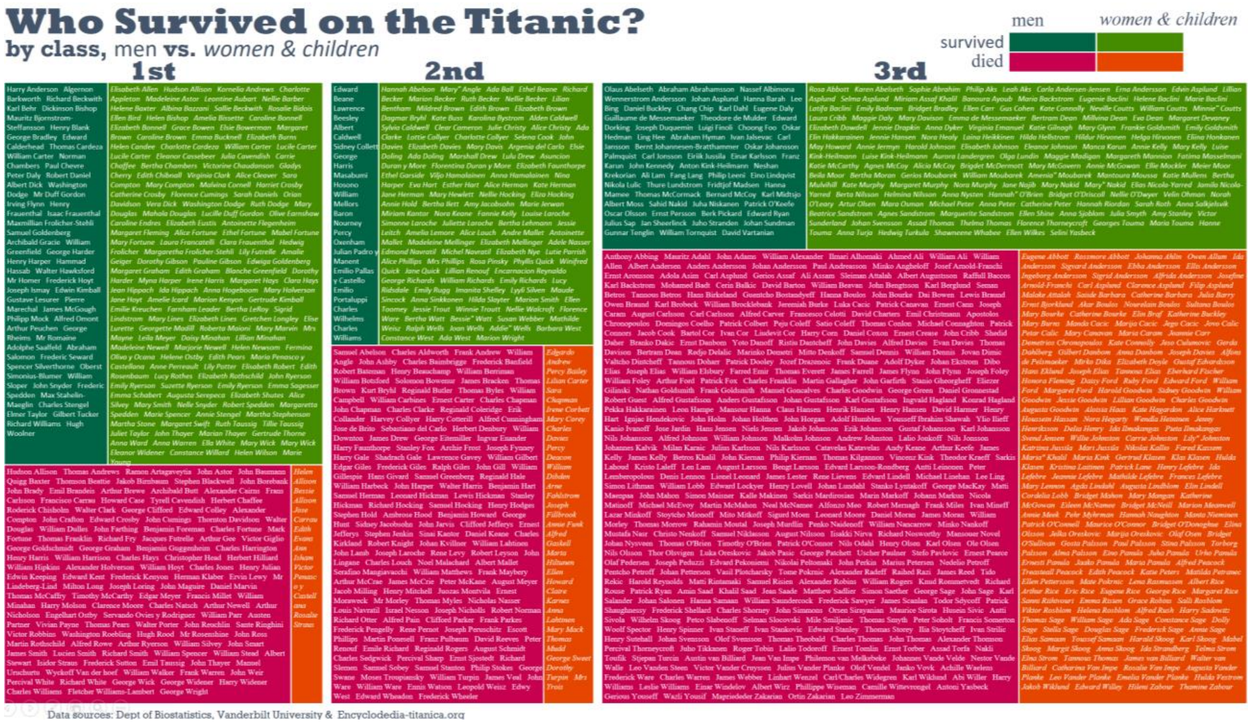

Figure 152. First version of labelled mosaic plot of Titanic passengers resulting in narrow vertical boxes with higher degree of error. Image created by author.

C:4.5. Typographic Stacked Bar of 3000 companies

Issues of area accuracy apply to any use of text in representations that use area to indicate magnitude. Diverging from set representations for a paragraph, stacked bar charts represent part-to-whole relationships – i.e. the height of a total bar is the sum of the constituent bars stacked up (e.g. see Berinato[296]). Traditionally, stacked bar charts represent data with colored boxes without any details. However, the boxes used in stacked area charts can include the underlying elements represented as text, similar to the previous example. Figure 154 shows a stacked bar chart indicating the top 3000 public companies around the world, with bars indicating the number of companies per sector, with different countries making up each layer in the stack. In this example, the width allocated to each company name is set within a consistently sized box: companies with long names are arbitrarily truncated (e.g. *Kinder Morgan Management* becomes “Kinder Morgan M”), while short names have additional unused space. Given the fixed box size per company, the height of the bar stacks accurately represents the company counts.

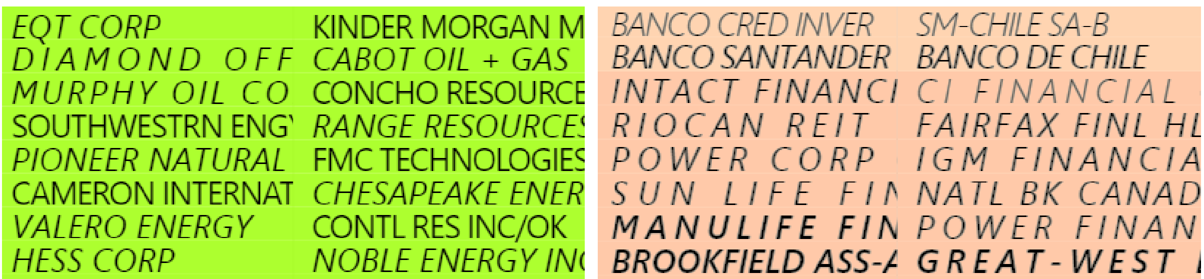

Figure 153. Close-up portion from two bars of the stacked bar chart from Figure 154. Image created by author.

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[296] Scott Berinato, *Good Charts: The HBR Guide to Making Smarter, More Persuasive Data Visualizations*, Harvard Business Review Press. 2016.

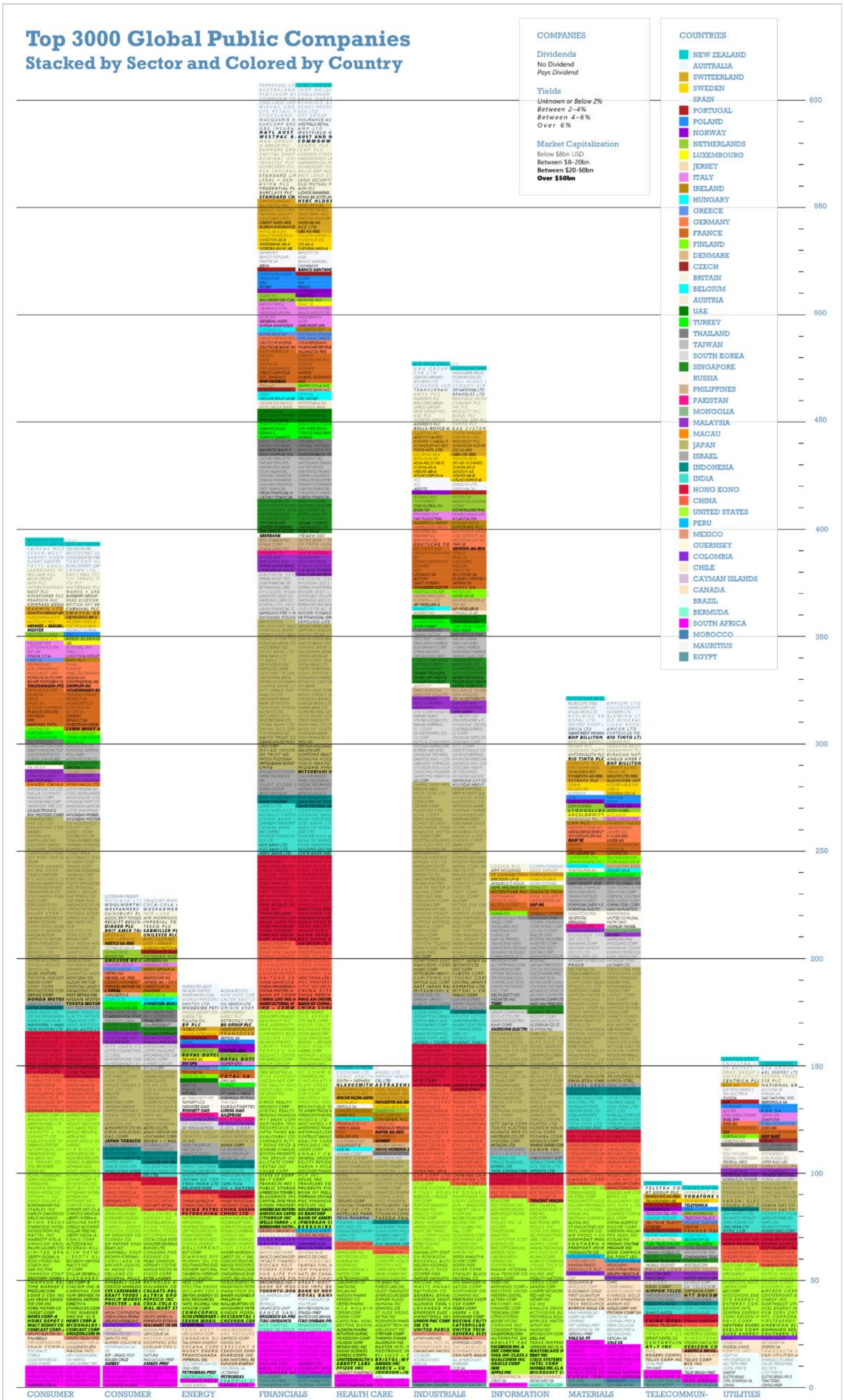

Figure 154. Stacked bar chart. The height of each bar indicates the number of companies in a sector, colors within the stack indicate the country associated with the company. Additional font attributes indicate other data. Image created by author.

C:4.6. Typographic Graph of Word-Emotion Association Lexicon

Node-link diagrams (i.e. graphs) are sometimes used to represent sets. In anchored maps[297] a circular layout is used to depict sets as nodes around a circle, and elements as free-floating nodes connected to respective sets. Using a physics-based graph layout model, element nodes are pulled based on set relations: elements belonging to only a single set are pushed outside the circle close to their set, other elements pulled to a position somewhere between their sets.

Node-link diagrams have scalability issues. With few elements, links can clearly show which set an element is connected to. However, when the number of elements is high, the many overlapping links makes it difficult distinguish membership.

Instead, element membership in sets can be encoded in font attributes. Links can be de-emphasized to reduce clutter leaving visible clusters of labels. Clusters can be visually inspected. If none of the elements stands-out from other elements in the cluster, all the font attributes are the same across elements and the cluster is homogenous. Furthermore, font attributes can be used to decode memberships.

The typographic graph in Figure 155 depicts 4463 words associated with eight emotions (based on Mohammad et al[298]). Words can be associated with more than one emotion. The eight large clusters around the perimeter are the words belonging to a single emotion. Each word is encoded with font attributes to indicate its set membership. Starting at 10am and proceeding clockwise: blackletter for anger, underline for fear, added exclamation for surprise!, spacing for t r u s t , baseline shift for joy, small caps for ANTICIPATION, lightweight for sadness, and italic for *disgust*. Word hue indicates sentiment membership. Positive sentiment is green, negative sentiment is red, neither is blue, and both is amber. Overall, membership in ten sets is encoded. The largest cluster (near the top right) is exclusively in the set trust.

In this emotion word dataset there are 256 (2^8) possible set relations of which 140 unique set relations exist. A legend and a callout (enlarged portion of the graph interior) are shown at the bottom Figure 155. Near the bottom left is a small cluster of words such as SIMMER, SUSPICIOUS and RAM - this cluster is homogenous with all the text in blackletter all caps indicating angry anticipation. To the right is a cluster immediately visible as heterogeneous – the font attributes are not consistent across all words in the cluster. For example, words such as WORRY, WILDERNESS and PLEA in underline lightweight caps indicate fear, sadness and anticipation. However, two other words positionally close to these words have very different memberships as indicated by their attributes: *p i o u s*, in spaced italics indicates both disgust and trust, while liquor in a blackletter with a shifting baseline indicates both anger and joy – the latter two words both being singular elements in these particular set intersections.

Unlike the *Titanic* example, variance in word length is not addressed. Average word length is 7.63 characters. The 24 largest clusters (each more than 50 words), have a standard deviation of 0.36 characters. As clusters become smaller, there can be wider variation: the 10 words in the cluster "angry anticipation" average only 6 characters.

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[297] Kazuo Misue, "Drawing bipartite graphs as anchored maps." In: *Proceedings of the 2006 Asia-Pacific Symposium on Information Visualization*-Volume 60. pp. 169–177. Australian Computer Society, Inc. (2006)

[298] Saif M. Mohammad, Peter D. Turney: "Emotions evoked by common words and phrases: Using mechanical turk to create an emotion lexicon" in: *Proceedings of the NAACL HLT 2010 workshop on computational approaches to analysis and generation of emotion in text*. pp. 26–34. Association for Computational Linguistics (2010)

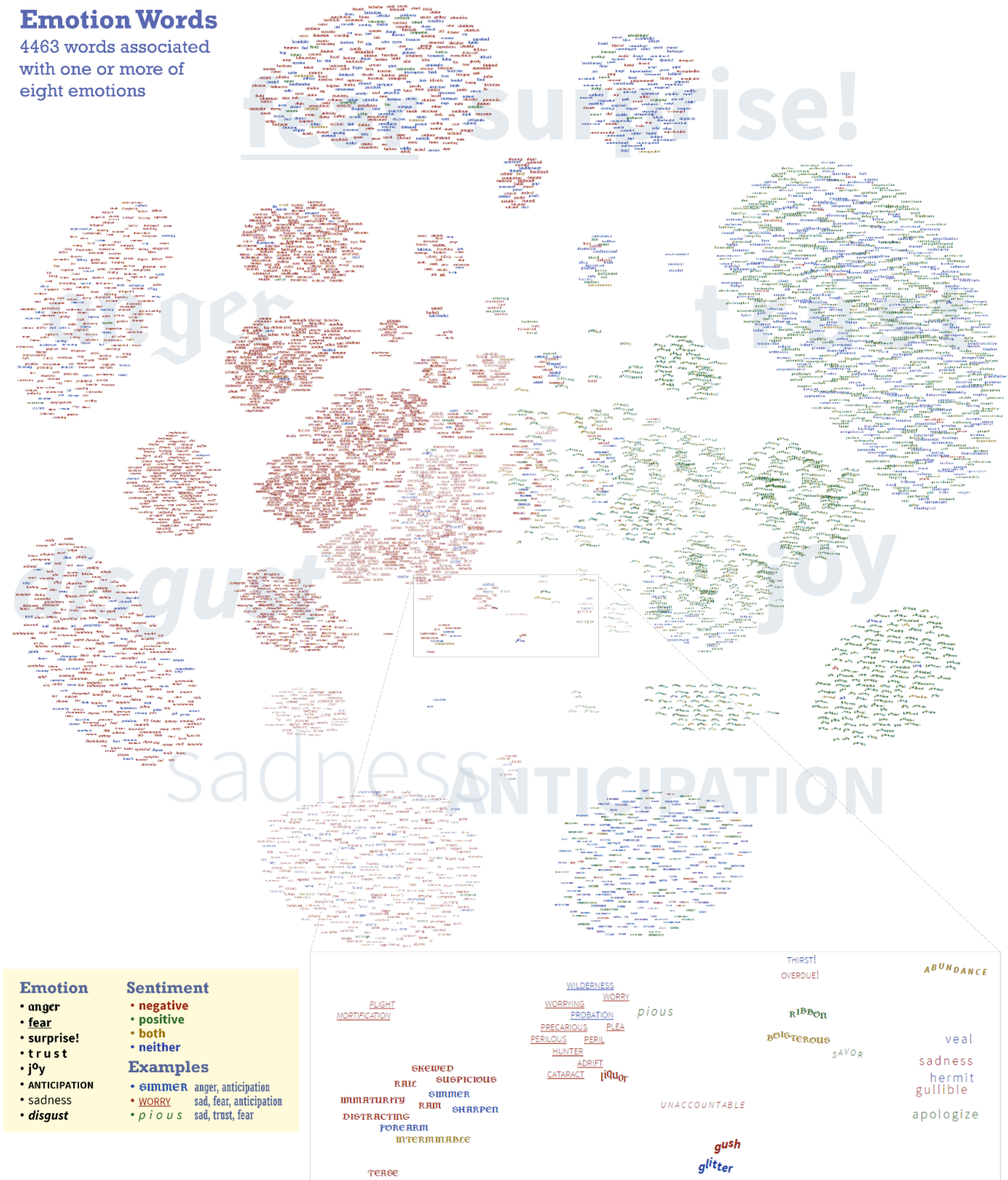

Figure 155. 4463 words associated with eight emotions, colored by sentiment, readable on a 4K display (or zoom to read). Subset shown in Figure 156. Image created by author.

Instead of focusing on area accuracy, the design attempts intuitive encodings. Anger words are in a blackletter font - sometimes associated with angry heavy metal bands. Surprise adds an exclamation mark - literally a mark indicating astonishment. Fear uses an underline - as the word *line* is associated with emotion fear in the lexicon. Joy uses a baseline shift - making the word appear bouncy. In addition, interactive techniques can be used to clearly indicate memberships, such as mouseover to reveal graph edges or tooltips to itemize memberships.

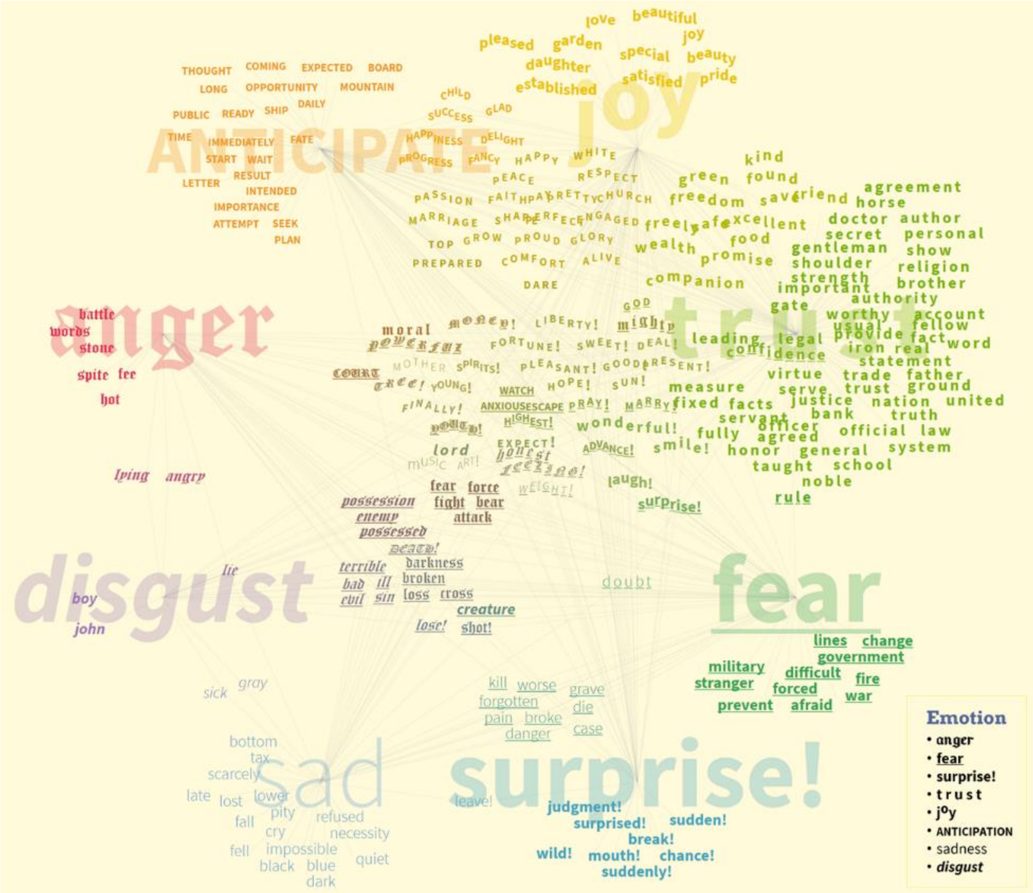

Figure 156. 250 most common emotion words, also showing graph edges and color encoding by emotion. Image by author.

C:4.7. Typographic Cartogram of Country Risks

Set elements are sometimes depicted on a map, such as geographic regions (e.g. countries, states, counties) or points (e.g. gas stations, hospitals, etc.) Set membership might be indicated by textures, icons, overlaid blobs, etc. Figure 157 is a close-up view of a map indicating many different types of risk associated with each country via icons. Long lines of icons require leader lines and varying alignment in congested areas. Countries are colored by summaries, but tiny countries are teeny dots difficult to see when zoomed out.

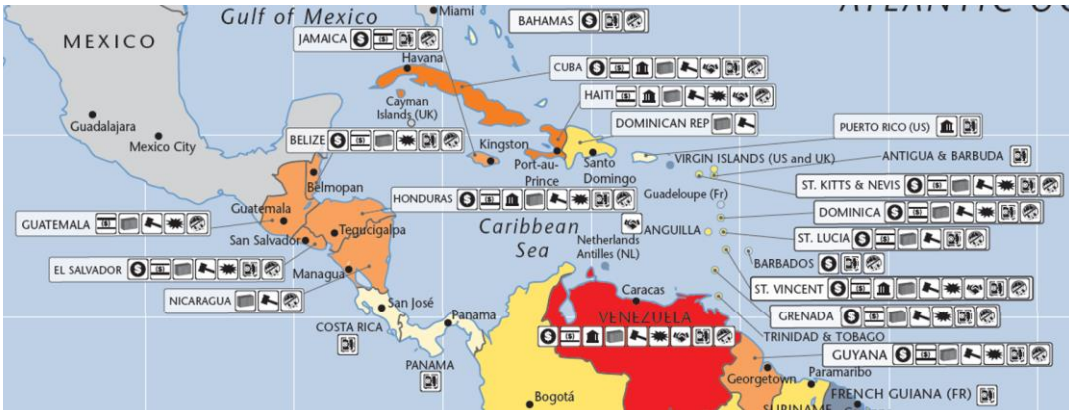

Figure 157. Close-up of a risk map indicating country risk types via icons (AON 2015 Risk Map). Copyright AON.

Encoding a high number of set memberships can also be done with positional encoding. If labels are constrained to a consistent fixed length (e.g. three letter country ISO codes), then font attributes can be applied to each character separately. For example, **U**SA, C**A**N, DE**U**, have bold applied to the first, second or third character independently to indicate set membership in three different sets.

Extending this across a variety of font and other visual attributes suggests a possible 20 or more unique indications of set membership into a single label. Figure 158 shows a typographic cartogram, where each country label indicates set membership by the formatting of each character. In this example, nine set attributes are conveyed in the labels, plus the background color and the literal label. Countries with no risks are plain (e.g. USA), countries with all risks are completely bold, italic and underline (e.g. Ethiopia ***ETH***) and those in-between have only some combination of attributes (e.g. Brazil *B***R***A*).

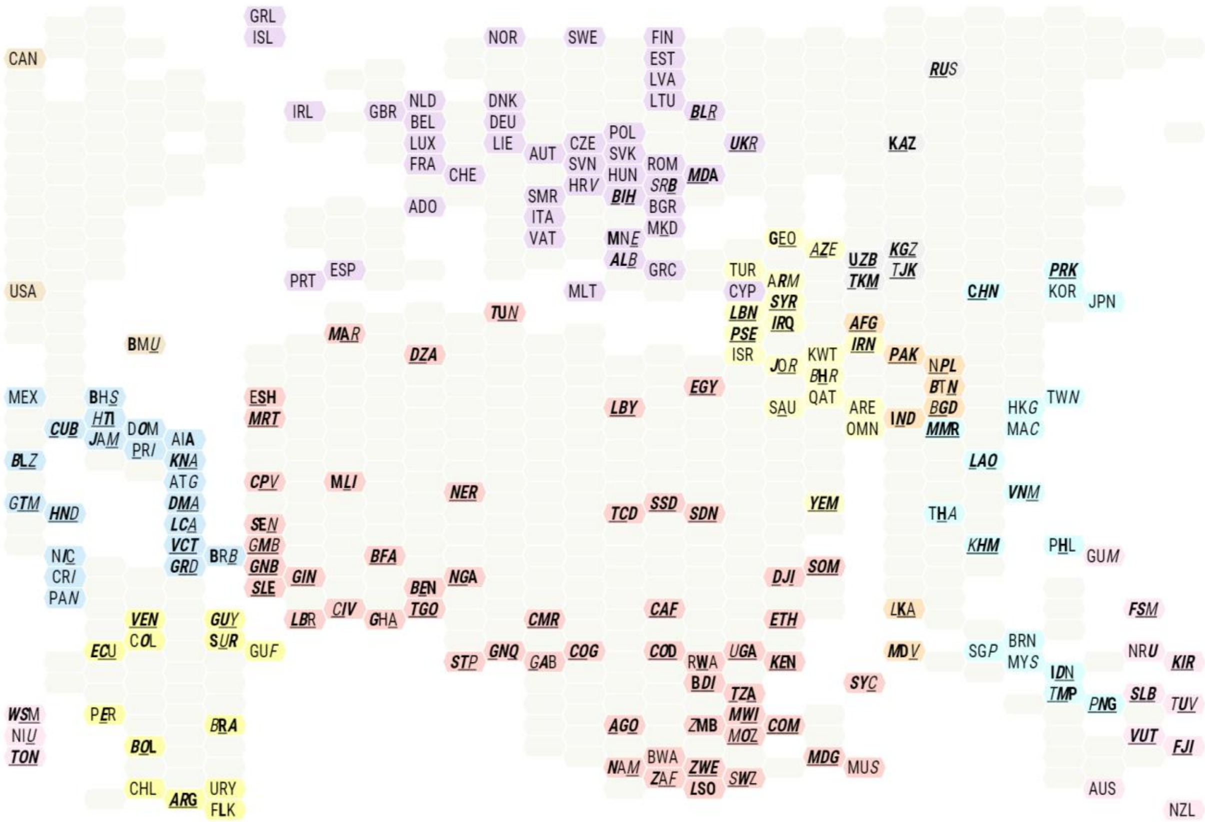

Figure 158. Country labels indicate 9 different risk types by bold, italic and underline applied independently to each letter of the three-letter ISO code. A country with no formats has low risk, a country with all formats across all letters is high risk. Image created by author.

C:4.8. Observations

One issue raised by a number of people was the issue of variable length labels biasing the sizes of areas formed with labels. Various approaches have been used here to offset the issue such as processing labels to be of similar length or using mnemonic codes. As the issue of variable length labels is more broadly applicable across many of the text visualizations herein, many different approaches to mitigate issues will be summarized in the later section (*D:1.2.ii: Label Length Bias and Speed: longer text is more prominent* on page 216).

Informal evaluation reveals positive initial feedback. One set researcher indicated that the use of typographic attributes was very promising particularly with regards to encoding many set memberships. In particular, when encoding many set memberships using different font attributes, the viewer can make integrative perceptual inferences without attention to the specific individual formats, including 1) noticing a difference in font attributes indicates a difference in set membership which aids visual separation between subsets; and 2) font attributes can be perceived as few (plain text) or many (bold, underline, uncommon typeface, etc.) providing an indication whether the element belonged to few or many sets.

Typographers pointed out that viewers sometimes do not notice a font difference when reading a line of line of text[299]: viewers attend to words, not fonts, and may miss a difference such as a shift between a common serif and a common sans serif font (e.g. inspect the word *such* in the preceding sentence). It is therefore necessary to use attributes which are noticeable or have a convention to be noticed (e.g. bold, italic, underline).

Interactivity can be an aid to perform different tasks. When many font attributes are used, tooltips can aid decoding memberships more quickly than identifying each font attribute. Furthermore, interactive features to toggle on/off any font attributes facilitates answering questions about subsets, making it easier to ignore a highly salient font attribute (e.g. bold).

Formal evaluation is non-trivial and there are many confounding factors. Evaluation studies should be done to assess ability to notice differences, ability to decode; ability to recall a font mapping; change in perception of areas when font attributes are manipulated; how legibility is impacted by layout; how readability is impacted by the application of multiple simultaneous font attributes; and limitations across different languages.

C:4.9. Typographic Set Diagrams Conclusion

Typographic sets are a significant contribution providing numerous enhancements to other set representation techniques:

1. **Labels** can uniquely depict elements. Furthermore, supplemental graphics, e.g. dots, image, etc. are not needed (e.g. ComEd in Figure 143P146 second image).
2. **Font Attributes** can be used to encode set membership, thereby providing clarification to some types of set visualizations where element membership may be otherwise ambiguous (e.g. graphs or maps as in Figure 145P148). Given the large number of font attributes (10) plus traditional visual attributes (e.g. hue, intensity, orientation), a large number of sets can potentially be encoded. This is a unique contribution.
3. **Area Proportions** are used in some set visualizations to indicate the number of elements belonging to a particular set relation. Areas can be represented with text-based set elements. At a macrolevel, a block of text can be seen as a texture covering an area. At a micro-level the individual text elements can be read. This is a unique contribution.
4. **Layout Agnostic**. Labeled, font-attribute elements can be used across a wide variety of set visualization approaches, including Venn and Euler diagrams, mosaic plots, graphs, maps and so on.

Technically, the set-based visualization examples here were primarily using SVG and JavaScript. One technical challenge for the visualization designer may be finding a typeface capable of rendering all possible permutations (e.g. bold, italic, underline, condensed, smallcaps). If using more than one typeface (such as Figure 148P152), then there is an additional challenge so that other typographic attributes are similar across both typefaces – e.g. is the slope angle of the italics similar across both typefaces, are the lightweight and heavyweight versions similar across both typefaces.

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299 Andrew Crompton, "How to look at a reading font" in *Word & Image,* Vol 30, Issue 2, 2014 pp. 79-89.

C:5. OW: Ordered Words - typographic cartograms

Reviewing cartography yields typographically rich maps such as the earlier examples in Figure 30P35 and Figure 31P36. In cartography, there are also thematic maps, such as choropleth maps and cartograms, which represent geographically related data using visualization techniques. These thematic maps tend to be devoid of labels or have minimal use of text and a variety of other issues.

C:5.1. Problems with Thematic Maps

Choropleth maps fill regions with different colors (e.g. Figure 159) to indicate data values: they have existed for almost two centuries[300] and they are extremely popular (e.g. 300,000 results on Google search). However, choropleth maps have many well-known problems:

- Regions with large areas (e.g. Canada, Russia) are much more visually salient than small areas (e.g. Ireland, Iceland).[301]
- Some small areas may not be visible at all (e.g. Singapore or Luxembourg on a world map).
- Not all viewers are familiar with geographic shapes (e.g. 63% of young Americans could not locate Iraq on a map of the Middle East in a National Geographic survey in 2006[302]).
- It can be difficult to depict additional data attributes on the map although it can be achieved with techniques such as added glyphs per country, or textures (e.g. stripes).

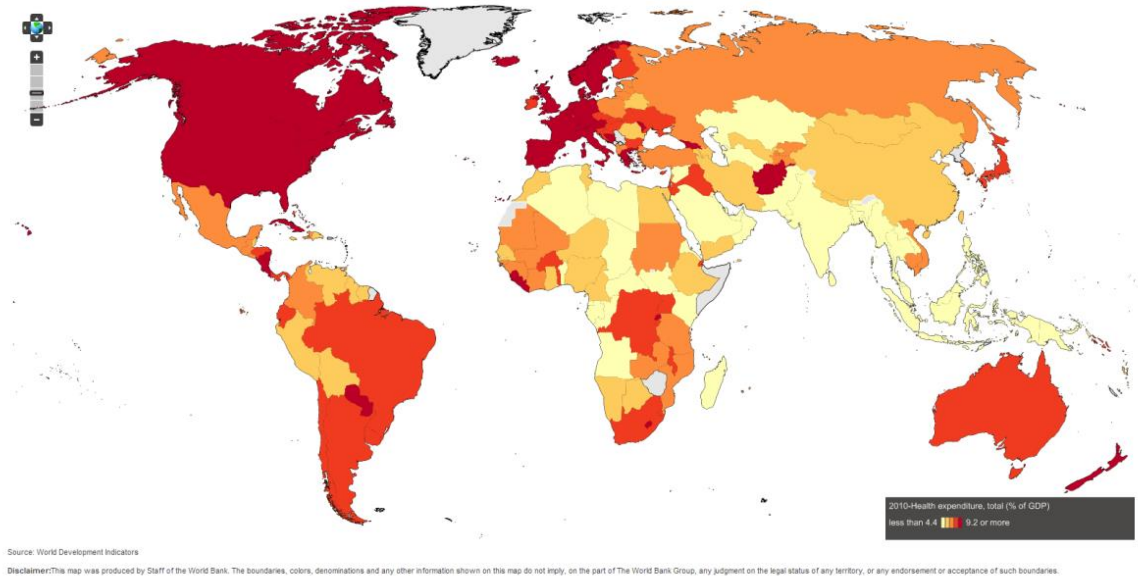

Figure 159. Health care spending as a percentage of GDP depicted on a choropleth map. What is the spending in countries with small area, such as Singapore or Caribbean nations? (image captured from worldbank.org[303]).

Similarly, cartograms are a mapping technique wherein geographic areas are adjusted to indicate data quantities. There are many types of cartograms, such as contiguous shape-preserving cartograms and Dorling cartograms, as

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[300] Gilles Palsky, "Connections and exchanges in European thematic cartography. The case of 19th century choropleth maps." *Belgeo. Revue Belge De Géographie* 3-4 (2008): 413-426.

[301] Mark Wilson, “Political voting maps are useless”, Fast Company, July 27, 2018. https://www.fastcompany.com/90208749/political-voting-maps-are-useless accessed July 27, 2018.

[302] Final Report: National Geographic-Roper Public Affairs 2006 Geographic Literacy Study. (NY, NY: GfK NOP, May 2006), http://www.nationalgeographic.com/roper2006/pdf/FINALReport2006GeogLitsurvey.pdf , accessed Feb. 17, 2016, 6-7.

[303] World DataBank, Health Nutrition and Population Statistics, “Health Expenditure, total (% of GDP) 2010”, accessed May 15, 2013. http://databank.worldbank.org/data/reports.aspx?source=health-nutrition-and-population-statistics

shown in Figure 160. Similar to the choropleth map, labels are minimal, some areas may be too small to be visible, and viewers may not be able to recognize distorted shapes. Furthermore, while these maps might represent data via both size and hue, they may be difficult to scale beyond two data attributes.

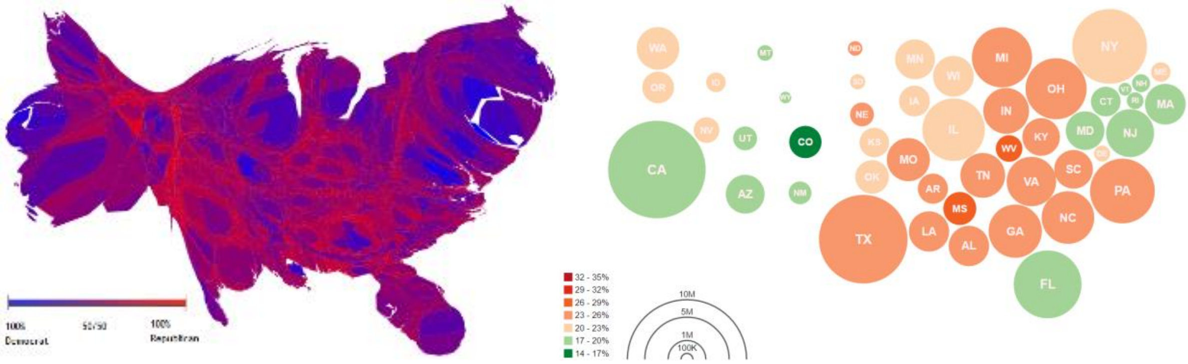

Figure 160. Left: a contiguous cartogram representing data by adjusting the area of each county, plus a second data attribute by color. Right: a Dorling cartogram representing states as circles, with size and color indicating data attributes. Left image: Wikipedia (en.wikipedia.org/wiki/Cartogram), Right University of Washington, used with permission (homes.cs.washington.edu/~j-heer/files/zoo/ex/maps/cartogram.html).

In general, thematic maps may be difficult to use to represent multiple data attributes. For example, three choropleth maps may be required to represent three different data values per country as shown in Figure 161. While this can be useful to answer simple questions (e.g. *Which country has the longest lives?*), it can be difficult to answer complex questions involving multiple variables. For example, asking *Are there countries with HIV and short lives even though they have high health expenditures,* of Figure 161 requires significant reliance on short memory to identify countries that match each individual condition which then need to be integrated to formulate an answer. While interactive techniques such as filtering could be used, the viewer would need to iteratively modify different parameters and could potentially miss near matches which may be relevant or miss serendipitous associations between geographically proximate countries.

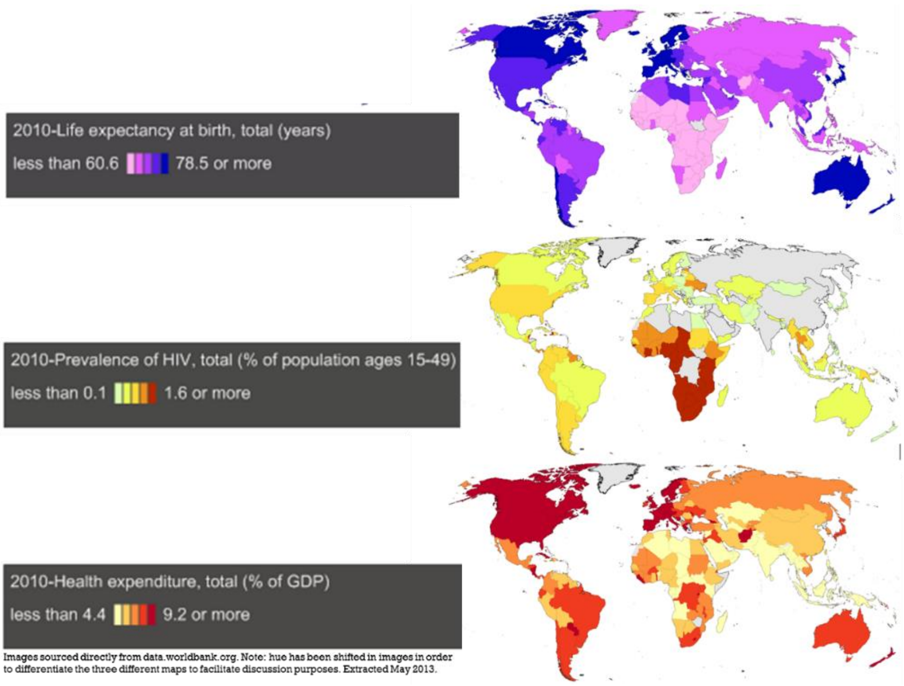

Figure 161. Three choropleth maps used to represent three data values. Answering complex questions across all three variables is difficult, e.g. Are there countries with HIV and short lives even though they have high health expenditures? Images copyright Worldbank, terms allow for non-commercial reuse.

C:5.2. Thematic Map split from Labelled Maps

How did thematic maps evolve and lose all the information associated with labels? The earliest choropleth maps are from Charles Dupin in 1819.[304] Simple shading and plain labels are used (Figure 162 left). Contemporary maps however use variation in typography such as spacing, capitalization, italics and size (e.g. Figure 162 right, from Carey and Buchon).

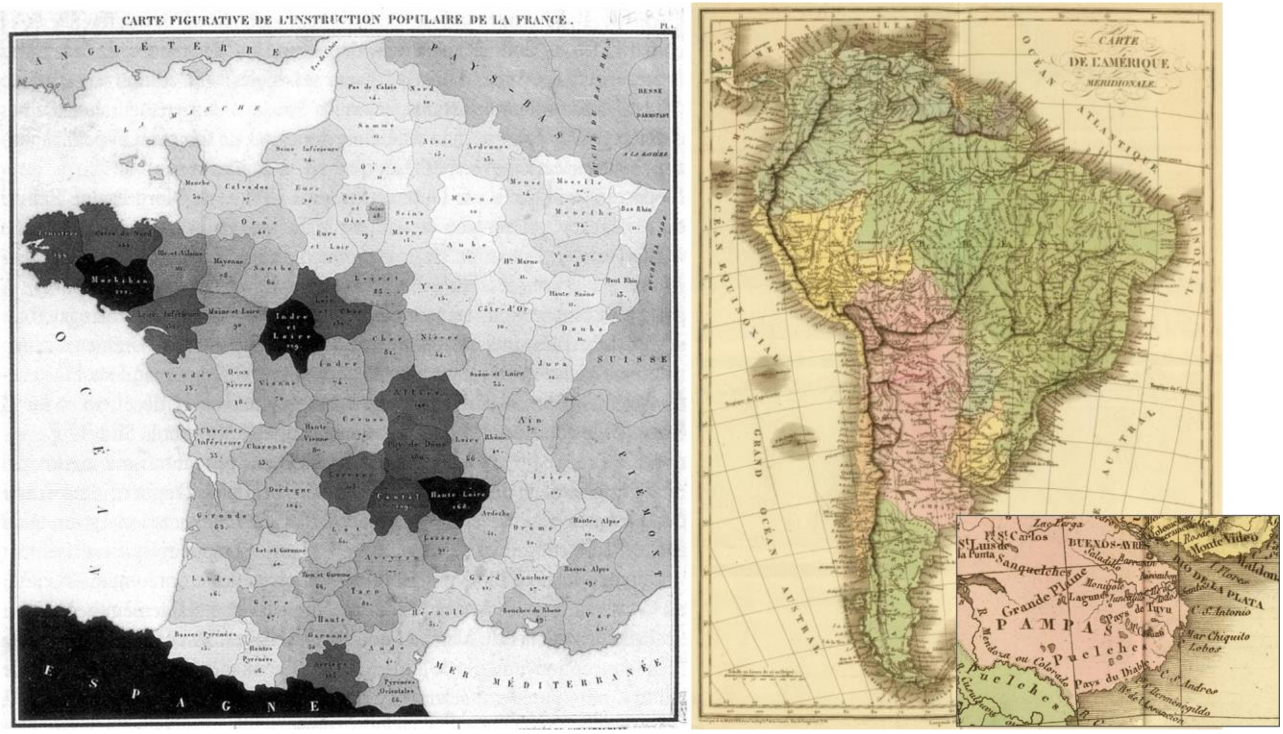

Figure 162. The first choropleth map from 1819 vs. a contemporary map with typographically varied labels. Images public domain.

A significant influence on Dupin was August Crome, who produced the map *Neue Carte von Europa* in 1782, which indicated the location of commodities across Europe (Figure 163). Crome starts with a contemporary base map, using the standard labelling conventions of the time, e.g. italics for rivers, all caps for country names, colors for country borders. Then he adds on top content related to his thematic investigation as symbols and codes. He can't differentiate symbols and codes using color, font size, case or italics, as those are already used in the base map, thereby leaving only codes, which do not visually pop-out (i.e. not preattentive). Dupin, however, starts with a much simpler base map, thereby leaving attributes such as brightness and color to indicate data. After Dupin, the convention for thematic maps has been to use brightness or color to indicate data – not labels.

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[304] Michael Friendly and Daniel Denis, *Milestones in the History of Data Visualization: An illustrated chronology of innovations.* York University. www.math.yorku.ca/SCS/Gallery/milestone/Visualization_Milestones.pdf

Figure 163. Crome's *Neue Carte von Europa*, 1782. Letter codes indicate commodity production. Image public domain.

C:5.3. Thematic Maps Using Text

A typographic approach can be used instead of these other thematic maps. A typographic approach has multiple benefits:

- *Labels*: Using explicit labels can aid the viewer's ability to identify and locate geographic entities.
- *Multiple Attributes*: Instead of being limited to size and color, labels can also utilize typographic attributes to encode data values.

C:5.4. Equal Area Cartograms

Instead of encoding the geographic entity's identification with shape, a label can be used instead. Labels can be placed such that each label is clearly visible and retains local proximity to adjacent countries. The label can literally encode the entity and use visual attributes to pop-out encoded data using traditional visual attributes and/or typographic attributes. Figure 164 shows two simple equal-area cartograms of U.S. States as squares (left) and rectangles (right). In both examples, data is indicated by the fill color.

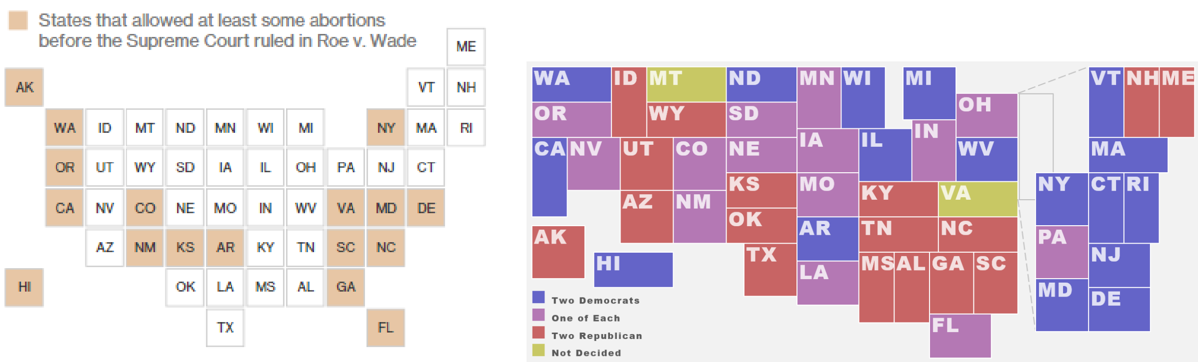

Figure 164. Equal-area cartograms. Left: squares indicate states and hue indicates abortion rights. Right: rectangles indicate states and hue indicates senate composition. Left image copyright Bloomberg.com June 26, 2015 (https://www.bloomberg.com/graphics/2015-pace-of-social-change/) used with permission. Right image by author.

Furthermore, while a choropleth map typically depicts only one numeric value via color, a label can depict multiple attributes. Typical visual attributes such as size and color can be used to represent data (e.g. see the label maps *Country Codes of the World*[305] or *UNODC Global Prevalence Estimates of Injecting Drug Users and HIV*[306]*)*. Alternatively, more data values can be represented using typographic attributes beyond traditional visual attributes of size and color.

C:5.5. Typographic Multi-variate Cartograms

Once a label-based cartogram has been created, the labels can be used as the basis to encode data, using a wide variety of visual attributes including font-specific attributes. Figure 165 uses font weight to encode 2010 GDP per capita, font spacing indicates GDP growth, font oblique angle to encode inflation (reverse slope for deflation, e.g. Ireland), and color encodes region. This representation can be used to answer simple questions of a single variable, e.g. *Are there countries with high growth rates?* (A: Yes, widely spaced China, Korea, Seychelles). Complex questions across multiple variables can be answered too, e.g. *Are there countries with high GDP, high growth and low inflation?* (A. Heavyweight, widely spaced, non-italic, e.g. Macao, Sweden); or, *Are there countries with low GDP, high growth rates and low inflation?* (A. Lightweight, widely spaced, non-italic, e.g. Kenya, Timor-Leste).

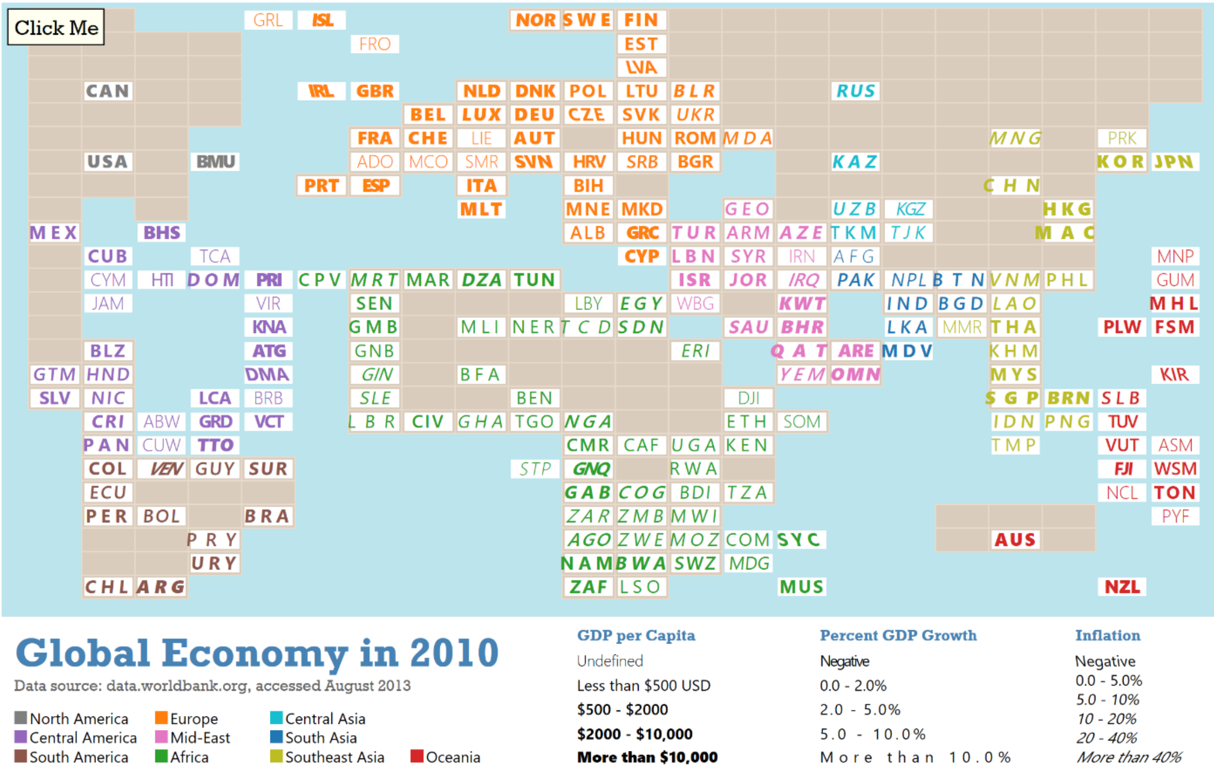

Figure 165. A Typographic Multivariate Label Cartogram indicating data via color, font weight, spacing and oblique slope angle. Image created by author.

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[305] John Yunker, "Country Codes of the World", Byte Level Research, (2007) http://www.bytelevel.com/map/ccTLD.html accessed April 14, 2016.

[306] Harry Pearce and Jason Ching. "UNODC Global Prevalence Estimates of Injecting Drug Users and HIV Among Injecting Drug Users", UNOHC, New York (2009). Available in Ellen Lupton, Thinking with Type: A Critical Guide for Designers, Writers, Editors & Students, 2nd ed. Princeton Architectural Press (2010): 44.

C:5.6. Scaling to Thousands of Labels

Text cartograms can scale to different layout algorithms and higher data densities. Figure 166 shows 2269 UK Postcode districts plotted directly by latitude and longitude on the right; with a cartogram of the same data on the right. In the left view, most labels are occluded and the plot only illustrates the post code densities. In the right view, each label is clearly distinguished and readable on a modern monitor. Visible patterns can be identified. For example, color indicates the occupation with the highest difference vs. national average. Green for agriculture in the west, blue for finance around east London, amber for mining in the north-east, etc.

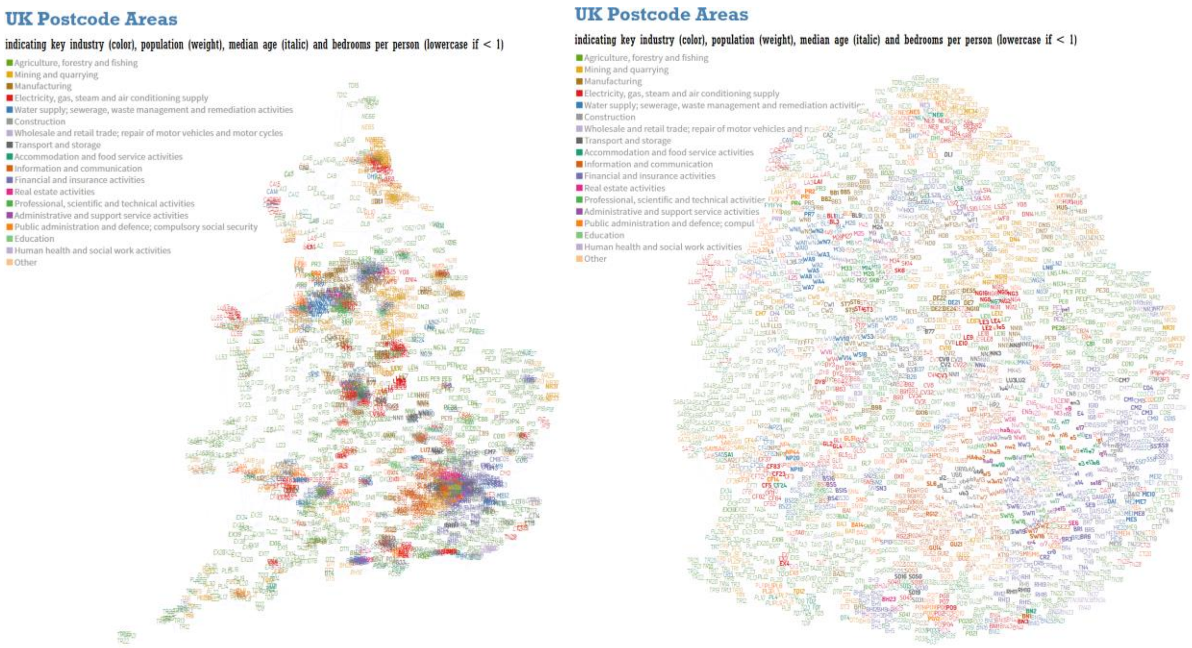

Figure 166. Left. 2269 UK postcode districts, located geographically, showing data by font weight, oblique angle, case and color. Right: Cartogram of the same data. Image created by author.

Figure 167 shows a close-up. Letters indicate postal code districts, e.g. Mxx for districts within Manchester. Weight indicates population within a district. Oblique angle indicates median age: reverse slope indicates a younger age, forward slope indicates older age. Case indicates number of bedrooms per person: uppercase if more than one bedroom, lowercase if less than one. In Figure 167 patterns in oblique angle indicate regional variation in age, e.g. most of the postcodes near the top left (LLxx indicating districts near Llandudno) slope right (indicating older median age) while districts within Manchester (Mxx) tend to slope left (indicating younger ages).

Figure 167. Closeup of Northern Wales, Liverpool and Manchester. Image created by author.

C:5.7. Scaling to Long Labels

In both preceding examples, short mnemonic codes were used for labels. In some applications only long labels of varying length are available. This creates two problems: 1) it is difficult to fit long labels into circles or squares; and, 2) elements with longer labels have greater visual area than elements with shorter labels, thereby making the element with the longest label more salient over the element with the shortest label (e.g. the label *San Francisco* is more prominent than *Rome*). Unfortunately, some types of labels do not have simple mnemonic codes. (e.g. while San Francisco's airport code is the mnemonic SFO, Toronto's airport code is non-mnemonic YYZ, and the nearby city of Cobourg does not have an independent airport).

Instead, labels can be associated with a consistently sized geometric container with a strong visual cue such as hue. Longer labels can exceed the container. Figure 168 shows a portion of a cartogram of central Canada census data – long labels exist for a number of entities in this dataset. In this example, labels identifying census area are directly associated with brightly colored fixed size areas, reducing the visual prominence of label length. For example, short heavy weight labels (e.g. *Montreal* or *Toronto*) are more prominent than long lightweight labels (e.g. *Saint-Jean-sur-Richelieu* or *Kitchener-Cambridge-Waterloo*).

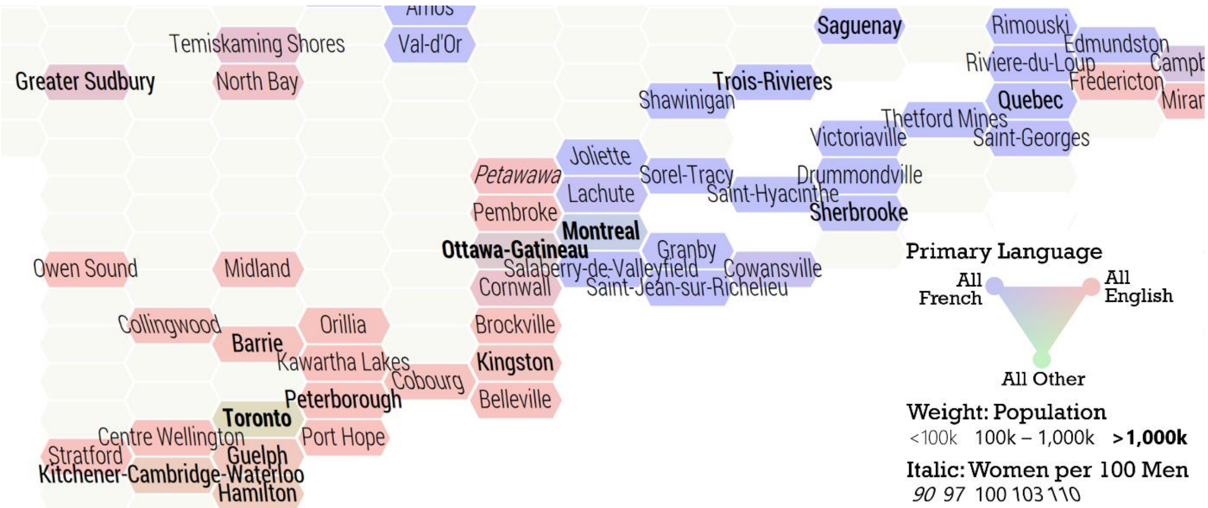

Figure 168. Close-up of Canadian cartogram with font weight indicating population, oblique slope angle representing the proportion of women to men, and hue indicating primary language (blue for French, red for English, green for other languages, with the target hue indicating the proportions for each language). Image created by author.

C:5.8. Positionally- and Proportionally-Encoded Labels

When labels are based on a sequence of characters, these characters can be manipulated individually. Instead of encoding a value by applying it to all characters, it can be encoded to a subset of characters:

Positional Encoding: By treating each character independently, each position can encode different data. For example, the cartogram previously shown in Figure 158P162 indicates nine different risk factors: bold, italic and underline applied independently to each letter of the three-letter ISO code. At a macro-level, country codes with few additional formats are less risky than country codes with many formats.

Proportional Encoding: Any typographic format can be applied to a sequence of characters to indicate a few quantities. For example, in Figure 169, the proportion of uppercase is used to indicate life expectancy: JPN has longer lives than USa, which in turn is longer than Mda, and in turn longer than zaf. Note that the data in Figure 169 is the same data as the earlier Figure 161P165.

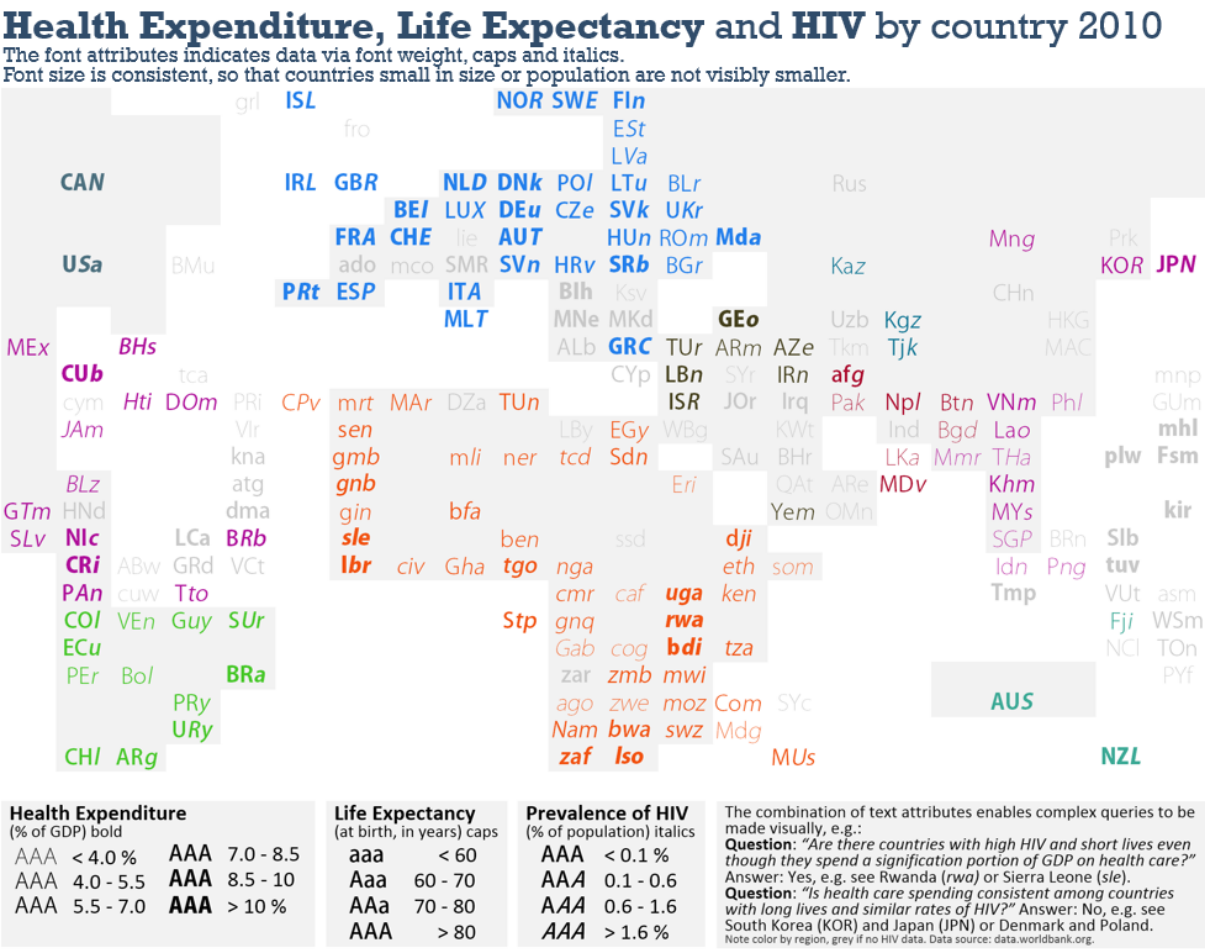

Figure 169. Label-based cartogram representing each country via unique three letter mnemonic country code, with additional data indicated via color, font weight, capitalization and italics. Image created by author.

C:5.9. Typographic Cartogram Layouts

Different algorithms have been used to produce the above cartograms.

Grid-based Cartogram: The cartograms in Figure 165 and Figure 168 use a regular mesh-based cell deletion approach (e.g. rectangular grid or hexagonal tiling). It starts with a large, regularly subdivided mesh such that each geographic entity (e.g. country, district, city, etc.) has a unique location in a particular cell in the mesh. Then, successive rows (or columns) are merged such that merging two adjacent rows (or columns) can retain all entities and no two entities occupy the same cell. This is repeated until no further merge operations can be completed.

Force Directed Cartogram: The cartogram in Figure 166 uses a force-directed layout based on an extracted mesh. First, all entities are placed on a plane using latitude and longitude. Then, a Delaunay triangulation is used to connect adjacent entities into a triangular mesh. Next, a force-directed layout is used to push apart entities which are close together (repulsive charge), while keeping adjacent entities adjacent (edge forces). This algorithm repeats until defined criteria has been reached (e.g. an energy threshold). The result of the force-directed layout still had various locations where labels are partially overlapped. This is due to the fact that the force-directed layout is an overall energy system and two points can still be close together given the nuances of the local connections. A final step walks through all the pairwise overlapping bounding boxes and pushes labels apart iteratively (until some stopping criteria or set number of iterations).

Non-Geographic: When a label-based approach is used, the labels can be arranged in other visualization configurations – such as scatterplots, Venn diagrams, distributions, tag clouds, heatmaps, graphs and so on. Figure 170 shows a scatterplot of countries plotting birth rate vs. death rate, with label size indicating country population and color indicating region. With a label-based representation, consistent markers (i.e. the label) can be utilized across different visualization techniques maintaining constancy thereby reducing cognitive load and reducing effort to learn multiple representations.

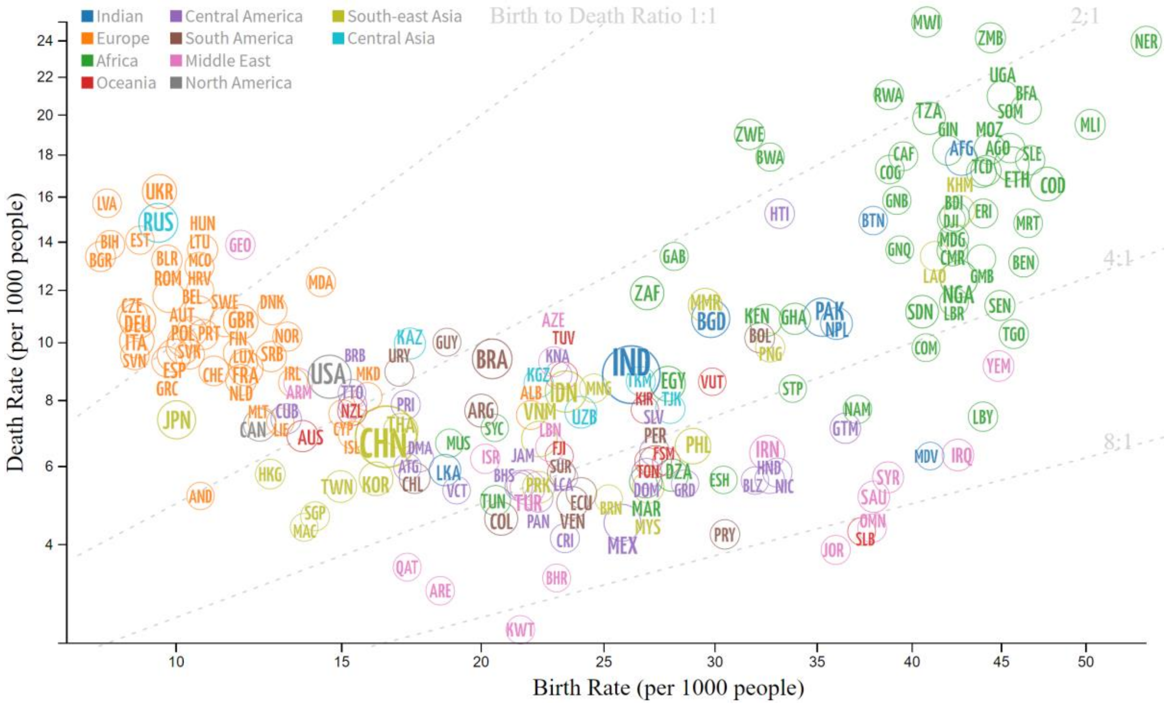

Figure 170. Country birth rate vs. death rate, label sized by population and colored by region. Image created by author.

C:5.10. Evaluation of Typographic Cartograms

There are many different aspects to the effectiveness of label-based cartograms. Two are considered here:

Information lossiness is an evaluation of the fidelity per visual attribute in an encoding; and an estimate of permutations across multiple attributes to compare relative lossiness[307]. A simple example is shown in Figure 171: both maps use 5 levels of hue. However, the colors of countries can be clearly identified in only 143 out of 187 countries in a choropleth map (at 520 x 310 resolution), while the corresponding label-based cartogram has all 187 countries with values readable (at the same resolution). In this example the choropleth has a fidelity of 76% compared to the cartogram. This approach can be extended to representations with many more attributes to consider the effect of tradeoffs be-tween different encodings. In general, label-based cartograms outperform choropleths and cartograms as many areas otherwise too small to be distinguished can be made visible and explicitly labelled.

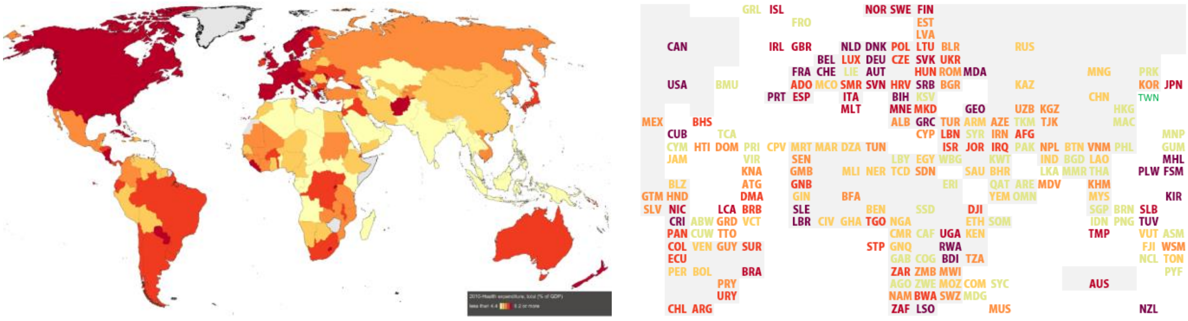

Figure 171. Comparison of a choropleth map and equivalent label-based cartogram. Choropleth via data.worldbank.org/indicators (accessed September 15, 2013), right image author.

Identification and location tasks go beyond lossiness. Using a similar approach to the previously discussed *National Geographic* map literacy survey, the two maps in Figure 171 were used with 17 participants in specific tasks (Table 15). This light touch study was approved by LSBU ethics committee. The identification task required the viewer to identify two circled countries in each map type. The location task required the viewer to indicate the color of two named countries for each map type. Viewers were either graduate students from computer science or employed in the domain of computer software development. Given that the participants were older and had higher education than the 18-24 year olds in the National Geographic study, countries used for the tasks were less commonly referenced in popular media, such as Niger, Albania, Ivory Coast and Slovenia. Each viewer had a set of eight questions evenly distributed between the two task types and the two map types.

Table 15. **Percent of correct responses on tasks for a choropleth map and an equivalent ISO code map**.

Task	Choropleth map (%)	ISO code map (%)	ISO code performance relative to Choropleth
Identify	15	65	4.4×
Locate	53	85	1.6×
Total	34	75	2.2×

307 Richard Brath and Ebad Banissi. "Evaluating Lossiness and Fidelity in Information Visualization" at SPIE 2015. 2015.

The labelled cartogram outperforms the unlabelled choropleth map in both tasks as shown in Table 15. For the identification task, ISO labels significantly outperform the choropleth with 65% correct answers vs. 15% correct. This may be due to the mnemonic nature of ISO country codes: e.g. on a choropleth map, an arrow may be pointing to a shape with few mnemonic affordances, whereas an arrow pointing at a mnemonic code such as SLE, may trigger recognition of Sierra LEone. Detailed data from this study is available in the *Appendix F:4.4*268. This small study should be repeated with a larger group of subjects to determine whether these differences are similar in a larger, more diverse population.

C:5.11. Beyond Simple Label Cartograms

The approaches outlined here are also applicable to other types of map layouts and visualizations. Figure 172 shows four maps using the dataset of Bertin's occupations by department:

- Top left is a cartogram focusing on adjacencies.
- The map top right uses a traditional geographic layout – however – unlike a choropleth map, the thematic data is in the labels thereby allowing multiple data attributes to be shown using size, weight, color and slope angle to form a multi-variate thematic map.

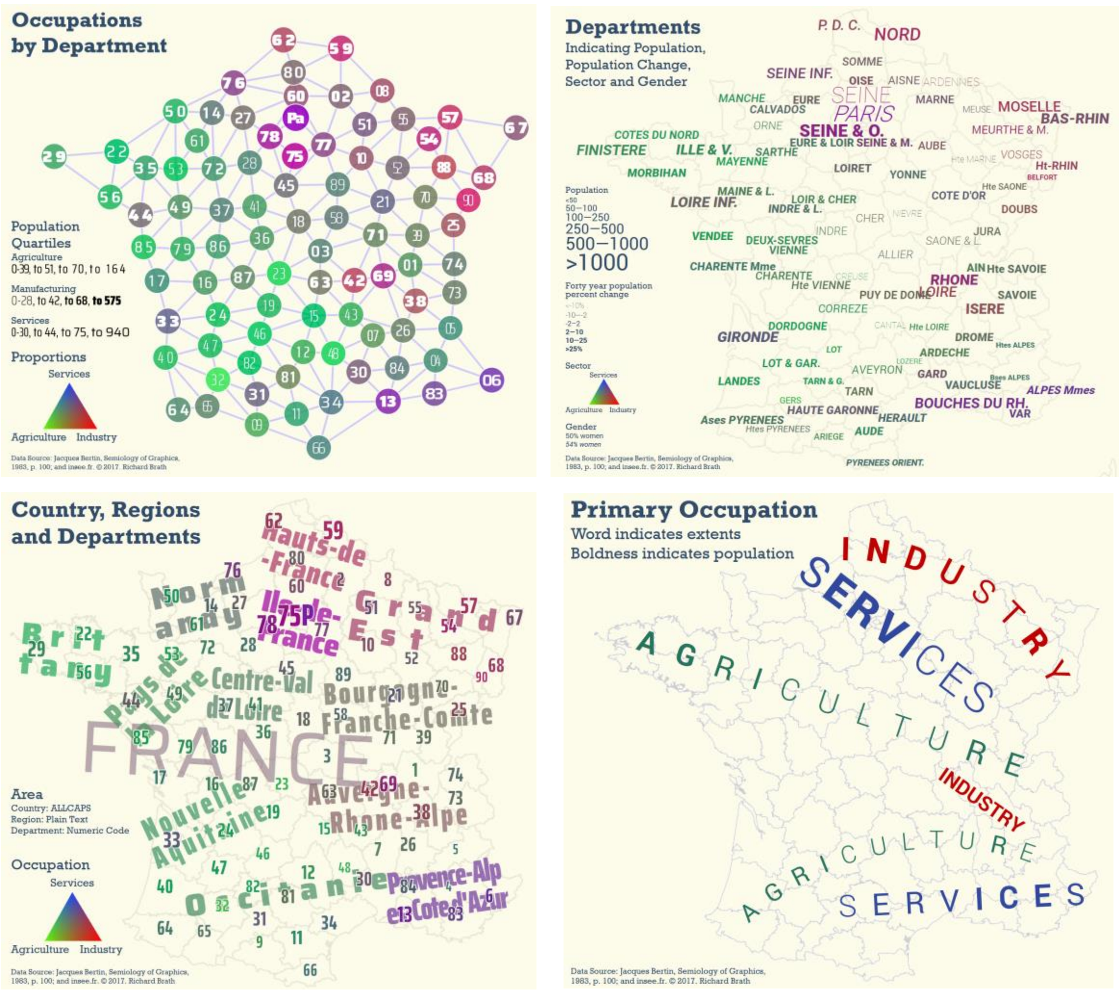

Figure 172. Variants of Bertin's occupation by regions. Image by authors.

- The labels in the map bottom left shows data at various levels of aggregation: department, region and country. Area-based visualizations, such as choropleth maps, treemaps and Voronoi diagrams, have difficulties showing aggregations. Instead, labels can convey the hierarchical level by size, with color and other attributes to indicate other data.
- Bottom right is a map where the names of the occupations are shown instead of departments: the departments are already given geographically, instead the primary occupation can be depicted literally.

C:5.12. Conclusions for Typographic Cartograms

Typographic cartograms are a contribution of this thesis. They are an alternative to thematic maps such as choropleth maps and cartograms. Labels have the potential to be more effective at tasks such as identification and location, reduce lossiness and can be used to encode multiple data variables into visual attributes beyond color, size and shape, for example, using bold, italics, underline, case and tracking. Furthermore, label-based representations can be used with other types of visualization layouts. Future work can include extensions to longer texts, e.g. sentences and paragraphs for linear and area-based features.

Many of the examples use mnemonic codes or even numeric codes over full labels. Extensive testing could be done to assess the tradeoff between shorter codes (saving space and potentially improving fast perception of formatting) versus longer labels (potentially cluttering the display but offering faster decoding by not requiring an association between the code and the full label). This will be highly impacted by user familiarity with the codes: expert users are typically deeply familiar with codes such as financial experts' knowledge of hundreds or thousands of stock ticker symbols (e.g. AAPL is Apple Computer Inc., VOD is Vodaphone, etc.), or electric grid operators' familiarity of codes associated with equipment codes, and so on.

All the examples shown are limited to the amount of text visible on the screen. Interactive techniques should be considered with respect to higher scalability. Similarly, multiple simultaneous visual attributes offer the possibility of serendipitous discovery of relationships across multiple variables, but may also confound perception if the analysis task were focused on a single variable: again interactive techniques should be explored further.

Technically, there are many possible algorithms for automated layout of cartograms which can be investigated further than the grid-based, hex-based and force directed techniques. Similarly, label-based positioning, orientation, curvature and deconfliction techniques should learn from automated labeling techniques in cartography, particularly since these techniques could be much more broadly applicable to other forms of text labelling across visualization, including earlier examples such as alphanumeric labels on the scatterplots (e.g. Figure 120P117), graphs (e.g. Figure 121P118), Venn diagrams (Figure 142 leftP144) and so on.

C:6. OP: Ordered Paragraphs - skim formatting

Text skimming is a reading technique of rapid eye movement across a large body to text to get the main ideas and content overview.[308,309] At a low level, the strategy requires the reader to dip into the text looking for words such as proper nouns, unusual words, enumerations, etc.

To facilitate skimming, the formatting of words in a document can be adjusted to make the salient words pop-out. First, each word in the document can be tagged by its usage frequency in the broad language. Then each word can be assigned a different font weight such that the least frequent words have the heaviest weight down to the most frequent words which have the lightest weight. Figure 173 shows the opening paragraphs of the Wright Brothers' *The Early History of the Airplane* formatted in this way to facilitate skimming. Words such as **fluttered**, **dubbed**, **helicoptere** and **torsion** visually pop out from the surrounding text. By using a font with multiple weights, it is feasible to differentiate between different frequencies of words – the least frequent words have the heaviest weight and each successive level of weight provides additional context; for example, the context immediately associated with **fluttered** is **awhile** and **finally sank** (indicating a flight sequence); or **screws, driven**, **opposite direction**, **rubber bands** are associated with **torsion** (indicating a mechanical configuration):

> Though the subject of **aerial navigation** is generally considered new, it has **occupied** the **minds** of men more or less from the **earliest ages**. Our personal interest in it **dates** from our **childhood** days. Late in the **autumn** of **1878** our father came into the house one evening with some object **partly concealed** in his hands, and before we could see what it was, he **tossed** it into the air. Instead of **falling** to the floor, as we expected, it **flew** across the room, till it struck the **ceiling**, where it **fluttered awhile**, and **finally sank** to the floor. It was a little **toy**, known to **scientists** as a" **helicoptere**," but which we, with **sublime disregard** for **science**, at once **dubbed** a" **bat**." It was a light **frame** of **cork** and **bamboo**, covered with **paper**, which formed two **screws**, **driven** in **opposite directions** by **rubber bands** under **torsion**. A **toy** so **delicate lasted** only a short time in the hands of small boys, but its memory was **abiding**.
>
> Several years later we began **building** these **helicopteres** for ourselves, making each one **larger** than that **preceding**. But, to our **astonishment**, we found that the **larger** the" **bat**" the less it **flew**. We did not know that a **machine** having only **twice** the **linear dimensions** of another would **require** eight times the power. We **finally** became **discouraged**, and returned to **kite-flying**, a **sport** to which we had **devoted** so much **attention** that we were **regarded** as **experts**. But as we became **older** we had to give up this **fascinating sport** as **unbecoming** to boys of our **ages**.

Figure 173. First paragraph of the Wright Brothers' *The Early History of the Airplane*, formatted to facilitate text skimming, by heavily weighting uncommon words so that they visually standout from other words. More samples with other fonts at: https://richardbrath.wordpress.com/2015/09/01/dickens-and-oz-formatted-for-skimming/) Image created by author.

C:6.1. Historic Precedents

While this may seem to be a new technique, there are many historic precedents. The notion of changing typographic formatting within prose text to provide a non-linear access to a linear string of text has been used in various historic applications including grammar, advertising, instruction manuals and modern search. Medieval examples include highlights on initial letters of keywords such as shown in Figure 174.

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308 Anne Arundel College, "Skimming and Scanning," last modified Oct. 27, 2007, http://www.aacc.edu/tutoring/file/skimming.pdf

309 BBC, "Skimming and Scanning", accessed Sept. 1, 2015. http://www.bbc.co.uk/skillswise/topic/skimming-and-scanning

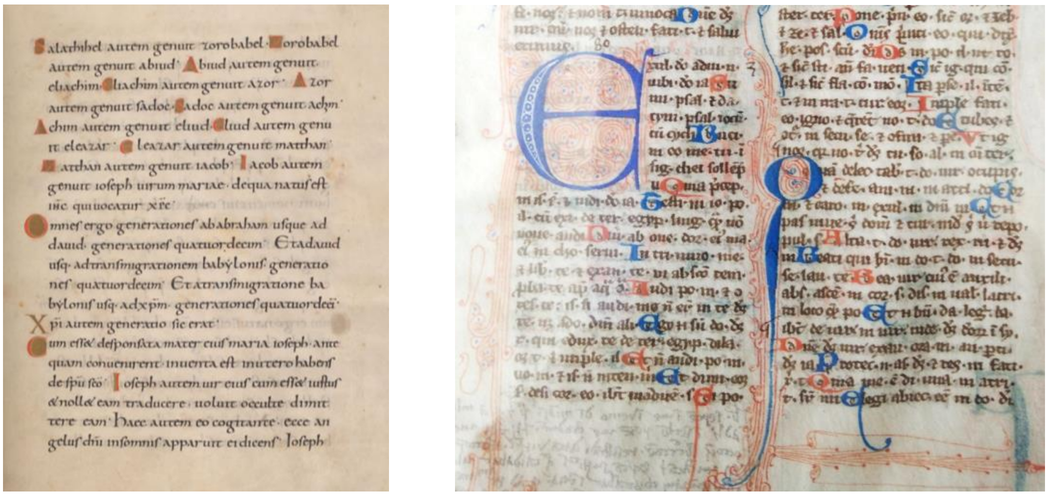


Figure 174. Left: Lindau Gospel 880 A.D. with initial letters on keywords illuminated. Right: medieval manuscript with leading characters on keywords enlarged, colored and illuminated with abstract curves. Left:: Lindau Gospels, Switzerland, Abbey of St. Gall, ca. 880–890, 320 x 250 mm, purchased by Pierpont Morgan, 1901, MS M. 1, fols. 14v–15r themorgan.org/collection/lindau-gospels/16 Photographic credit: The Pierpont Morgan Library, New York. Used with permission. Right: Author Unknown. Mid-late middle ages. Part of the Collections & Archives at the Department of Typography & Graphic Communication, University of Reading. Used with Permission.

An early printed example is the use of blackletter type, italic and roman type to, in effect, highlight keywords within a paragraph in this mathematics text[310] form 1724 shown in Figure 175 left.

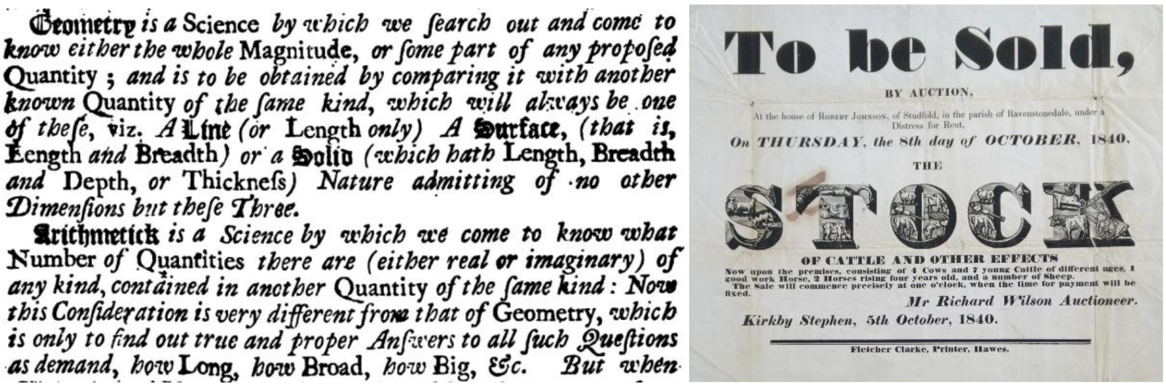


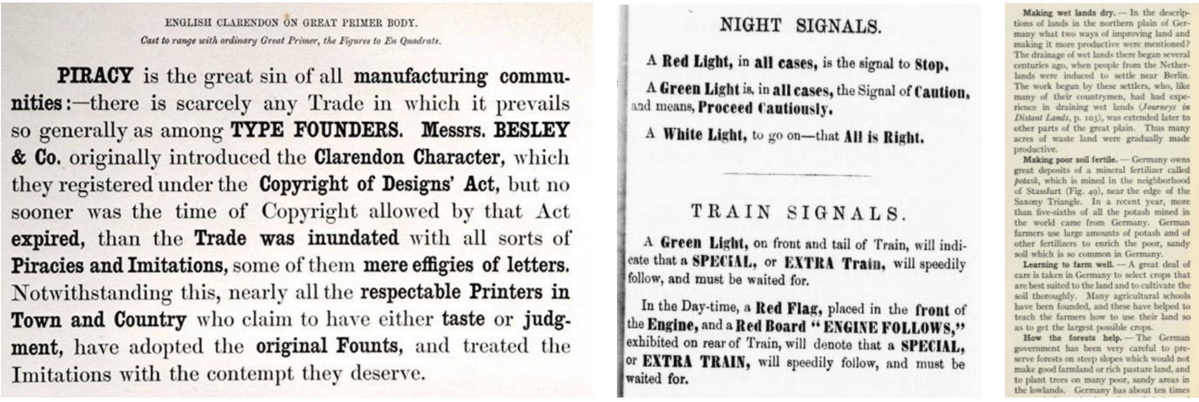
Figure 175. Left: text from 1724 with words highlighted using blackletter typeface or a non-italic type. Right: poster from 1840 using large-scale heavy-weight woodblock text to call out a key message. Both images from public domain.

By the early 1800's large scale advertisements were being printed, necessitating larger typefaces. These large letters may be heavy weight to create high contrast to make the ads stand out, such as the advertising poster[311] on the right of Figure 175 which can be read at a glance to convey "To be Sold, Stock", conveying the key message while leaving the details in smaller type. Bold evolved during this mid-800's time period meet the new demands for heavier typeface as detailed by Twyman.[312]

The original Clarendon typeface (1845) was a heavyweight type designed to be used together harmoniously with other text. Figure 176 left shows a promotional text[313] with new Clarendon type as well as uppercase to

[310] John Ward, *The Young Mathematician's Guide: Being a Plain and Easie Introduction to the Mathematicks* (4th ed.), A . Bettesworth, and F .Fayrham, London 1724. Page 2 Part 1. https://archive.org/details/youngmathematic02wardgoog accessed Aug 28, 2016.
[311] Fletcher Clark, *To be Sold,… Stock,* Hawes, 1840. Personal collection Gerry Leonidas, used with permission.
[312] Michael Twyman, "The bold idea: The use of bold-looking types in the nineteenth century." *Journal of the Printing Historical Society* 22 (1993): 107-143.
[313] Skylar Challand, Clarendon promotional sample, In "Know your type: Clarendon," from http://idsgn.org/posts/know-your-type-clarendon/ accessed Aug. 28, 2016.

make words stand-out from their context. An instruction manual[314] from a decade later (Figure 177 middle) uses the new bold capabilities to call out key text in a larger body of text, presumably facilitating rapid lookup for the novice signalman – e.g. **Red Light – all cases – Stop.** However, the additional effort to edit and assemble metal type like this presumably limited widespread adoption. Instead text could be restructured to place the key text at the opening of a paragraph and bolding this phrase, as shown in an early 20th century geography textbook[315] (Figure 177 right).



ENGLISH CLARENDON ON GREAT PRIMER BODY.

Cast to range with ordinary Great Primer, the Figures to En Quadrats.

PIRACY is the great sin of all **manufacturing communities**:—there is scarcely any Trade in which it prevails so generally as among **TYPE FOUNDERS. Messrs. BESLEY & Co.** originally introduced the **Clarendon Character,** which they registered under the **Copyright of Designs' Act,** but no sooner was the time of Copyright allowed by that Act **expired,** than the **Trade was inundated** with all sorts of **Piracies and Imitations,** some of them **mere effigies of letters.** Notwithstanding this, nearly all the **respectable Printers in Town and Country** who claim to have either **taste** or **judgment,** have adopted the **original Founts,** and treated the Imitations with the contempt they deserve.

NIGHT SIGNALS.

A **Red Light,** in **all cases,** is the signal to **Stop.**

A **Green Light** is, in **all cases,** the Signal of **Caution,** and means, **Proceed Cautiously.**

A **White Light,** to go on—that **All is Right.**

TRAIN SIGNALS.

A **Green Light,** on front and tail of Train, will indicate that a **SPECIAL,** or **EXTRA Train,** will speedily follow, and must be waited for.

In the Day-time, a **Red Flag,** placed in the **front** of the **Engine,** and a **Red Board "ENGINE FOLLOWS,"** exhibited on rear of Train, will denote that a **SPECIAL,** or **EXTRA TRAIN,** will speedily follow, and must be waited for.

Making wet lands dry. — In the descriptions of lands in the northern plain of Germany what two ways of improving land and making it more productive were mentioned? The drainage of wet lands there began several centuries ago, when people from the Netherlands were induced to settle near Berlin. The work begun by these settlers, who, like many of their countrymen, had had experience in draining wet lands (*Journeys in Distant Lands*, p. 103), was extended later to other parts of the great plain. Thus many acres of waste land were gradually made productive.

Making poor soil fertile. — Germany owns great deposits of a mineral fertilizer called *potash*, which is mined in the neighborhood of Stassfurt (Fig. 49), near the edge of the Saxony Triangle. In a recent year, more than five-sixths of all the potash mined in the world came from Germany. German farmers use large amounts of potash and of other fertilizers to enrich the poor, sandy soil which is so common in Germany.

Learning to farm well. — A great deal of care is taken in Germany to select crops that are best suited to the land and to cultivate the soil thoroughly. Many agricultural schools have been founded, and these have helped to teach the farmers how to use their land so as to get the largest possible crops.

How the forests help. — The German government has been very careful to preserve forests on steep slopes which would not make good farmland or rich pasture land, and to plant trees on many poor, sandy areas in the lowlands. Germany has about ten times

Figure 176. Left: a sample text from the mid -1800's using heavy-weight Clarendon as well as capitalization to call out specific words in the text. Middle: an instruction manual for railroad operators using the same formatting to call out key text. Right: an early 20th C. textbook pushing key information to the start of each paragraph with bold. All images public domain.

Other uses of type differentiation within text emerge as well. A patent from 1916 by Sheffield uses many typographic cues to highlight syntax, including various combinations of case, small caps, italics, weight (Figure 177 left). Sheffield says:

> *"My invention… shows visually the structure of sentences and the exact relation of their syntactic elements to each other so as to enable the intended meaning of sentences to be readily ascertained."*[316]

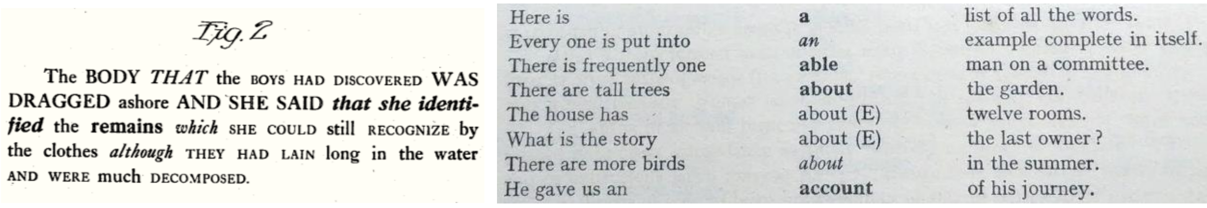


Fig. 2

The BODY *THAT* the BOYS HAD DISCOVERED WAS DRAGGED ashore AND SHE SAID ***that she identified*** the **remains** ***which*** SHE COULD **still** RECOGNIZE by the clothes ***although*** THEY HAD LAIN long in the water AND WERE **much** DECOMPOSED.

Here is	**a**	list of all the words.
Every one is put into	***an***	example complete in itself.
There is frequently one	**able**	man on a committee.
There are tall trees	**about**	the garden.
The house has	about (E)	twelve rooms.
What is the story	about (E)	the last owner ?
There are more birds	***about***	in the summer.
He gave us an	**account**	of his journey.

Figure 177. Left. Syntax highlighting from 1916. Right. Words explained through examples used within the context of a sentence. Left image public domain. Right image copyright C.K.Ogden, *Basic By Example*.

In the 1920's C.K. Ogden created *Basic English* as a simplified 850-word subset of English for international use and aid for teaching English. In his book *Basic by Example,* keywords are listed vertically in bold or italic within the context of sentences around them (Figure 177 right).

The advertising world continued to experiment with typography. Much like the earlier concrete poets (e.g. Figure 62P70), advertisers experimented with adjusting individual characters within words, or across texts to

[314] C.W. Hamilton, *Rules and regulations to be observed by the officers and men in the employ of this company*, John W. Harris & Co., 1858. Page 13. https://archive.org/details/cihm_92310 accessed Aug. 28, 2016.

[315] H. Barrows, E. Parker, M. Parker. *Geography Europe and Asia.* Silver Burdett and co., New York, 1934. Page 91. https://archive.org/details/geographyeuropea00barr

[316] Joseph Henry Sheffield, *Art of Printing,* US Patent Grant # 1456834A. Filed Apr. 10, 1916. https://www.google.com/patents/US1456834

express the semantics of the text. Figure 178 shows a text from an article about New York City using words and type to express the continually changing character of the city.[317]

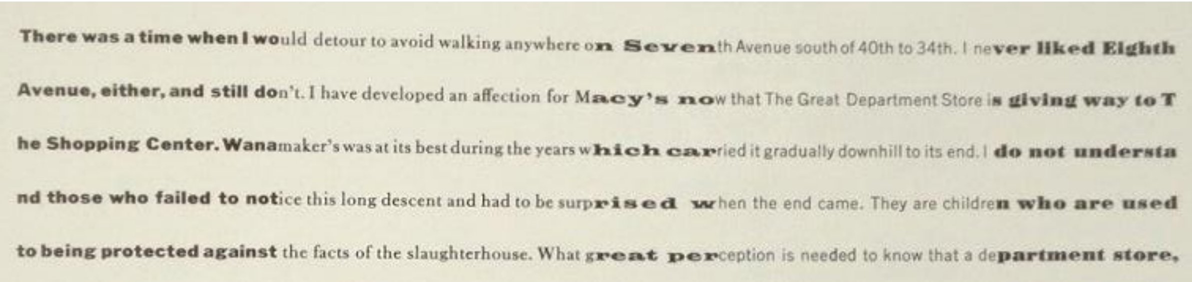
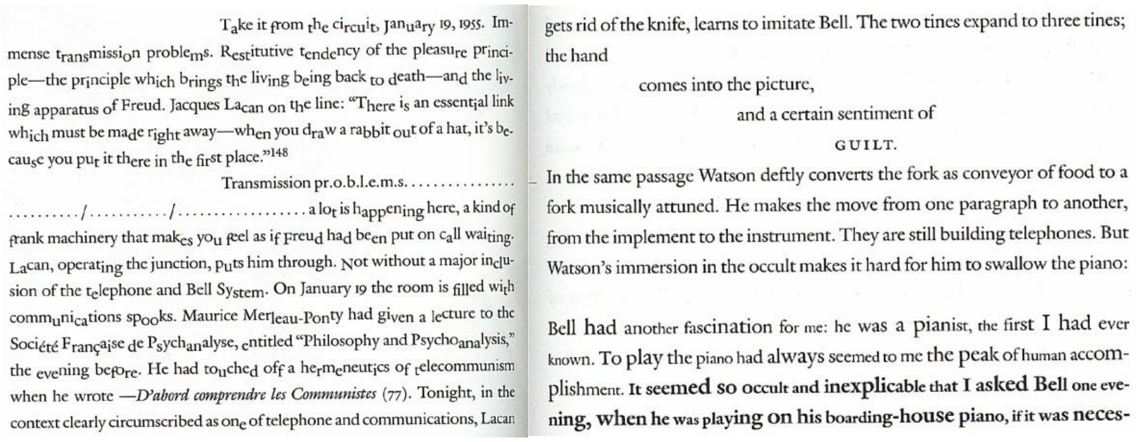

There was a time when I would detour to avoid walking anywhere on Seventh Avenue south of 40th to 34th. I never liked Eighth Avenue, either, and still don't. I have developed an affection for Macy's now that The Great Department Store is giving way to The Shopping Center. Wanamaker's was at its best during the years which carried it gradually downhill to its end. I do not understand those who failed to notice this long descent and had to be surprised when the end came. They are children who are used to being protected against the facts of the slaughterhouse. What great perception is needed to know that a department store,

Figure 178. Changing typefaces to express the changing character of New York City.
Original image copyright by Brownjohn, Chermayeff & Geismar.

Post-modernists go further. Deconstructivist Ronell adjusts a wide variety of typographic properties (e.g. tracking, sizing, weight, small caps) and deliberately breaks typographic conventions (e.g. interrupting words with punctuation, adding vertical gaps through text, adjusting layout, setting some text in Morse code) throughout her book *The Telephone Book*[318] to interrupt readability and convey semantics through typography (e.g. Figure 179).


Take it from the circuit, January 19, 1955. Immense transmission problems. Restitutive tendency of the pleasure principle—the principle which brings the living being back to death—and the living apparatus of Freud. Jacques Lacan on the line: "There is an essential link which must be made right away—when you draw a rabbit out of a hat, it's because you put it there in the first place."148

Transmission pr.o.b.l.e.m.s. ..../.........../.................. a lot is happening here, a kind of frank machinery that makes you feel as if Freud had been put on call waiting. Lacan, operating the junction, puts him through. Not without a major inclusion of the telephone and Bell System. On January 19 the room is filled with communications spooks. Maurice Merleau-Ponty had given a lecture to the Société Française de Psychanalyse, entitled "Philosophy and Psychoanalysis," the evening before. He had touched off a hermeneutics of telecommunism when he wrote —*D'abord comprendre les Communistes* (77). Tonight, in the context clearly circumscribed as one of telephone and communications, Lacan

gets rid of the knife, learns to imitate Bell. The two tines expand to three tines; the hand

comes into the picture,

and a certain sentiment of

GUILT.

In the same passage Watson deftly converts the fork as conveyor of food to a fork musically attuned. He makes the move from one paragraph to another, from the implement to the instrument. They are still building telephones. But Watson's immersion in the occult makes it hard for him to swallow the piano:

Bell had another fascination for me: he was a pianist, the first I had ever known. To play the piano had always seemed to me the peak of human accomplishment. It seemed so occult and inexplicable that I asked Bell one evening, when he was playing on his boarding-house piano, if it was neces-

Figure 179. Ronell's *Telephone Book,* varies many typographic attributes throughout the text including size, caps, weight, italics, baseline shifts, punctuation, spacings and so on; applies them to individual characters, words, lines, paragraphs and more broadly the layout. Copyright Avital Ronell.

Keyword in Context (KWIC) is a technique widely used in the presentation of search results, wherein a snippet of text containing the search keywords are highlighted in the context of a sentence or two of text. In this case, the user is providing the terms of interest, the system is providing the immediate context of the sentences those keywords are in, and keyword highlighting provides a means to quickly skim the context.[319] KWIC has been recognized as an effective technique aiding disambiguating of search indexes for many decades.[320] Figure 180 shows a Google search result for the ambiguous search "late gothic in England". The highlighted keywords aid non-linear access to the text focusing on keywords and their neighboring words thereby facilitating the viewer's ability to disambiguate which gothic period is of interest (i.e. medieval gothic ca.1200; or gothic revival ca.

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[317] Aaron Burns, *Typography*, Reinhold Publishing, 1961. page 49. Original document by Brownjohn, Chermayeff & Geismar
[318] Avital Ronell, *The Telephone Book: Technology, Schizophrenia, Electric Speech,* University of Nebraska Press. 1989.
[319] Marti Hearst, "5.2: KWIC, or Query-Oriented Summaries" in *Search User Interfaces,* Cambridge University Press, 2009.
[320] H.P. Luhn. "Keyword-in-Context for Technical Literature (KWIC Index)" in *ASDD Report RC-127,* August, 1959.

1740). Thus the user can identify relevant documents based on skimming the highlighted words and neighbors without needing to click through for details.

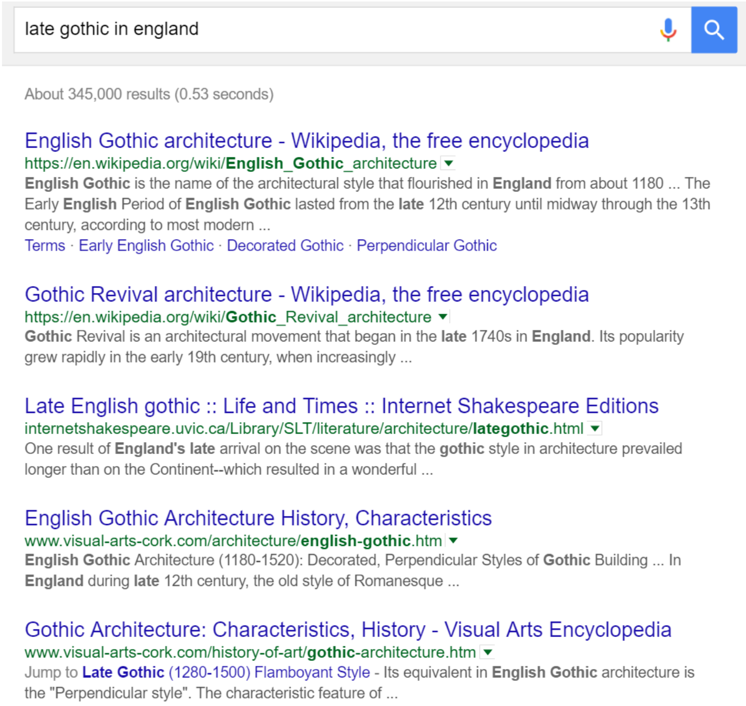
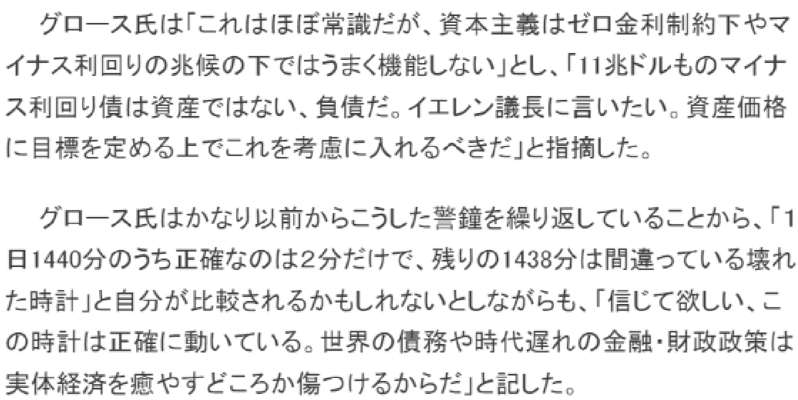


Figure 180. Google search for *late gothic in England* provides snippets of keywords highlighted in the context of source sentences. Image capture by author.

The notion of typographic variation to support skimming already exists in Japanese texts. Eiichi Kono, in *Computers and Typography 2,* explains that Japanese writing is a mix of Kanji pictographic/ideographic glyphs which are visually dense; plus Kana glyphs which are visually sparse. Kanji is used for core words while Kana are usually used for inflection, suffixes, prepositions and conjunctions. The resulting text is 30% Kanji and 70% Kana. Japanese is easy to read partially because the Kanji core text stands out as a much darker tone against a larger background of phonetic Kana.[321]



グロース氏は「これはほぼ常識だが、資本主義はゼロ金利制約下やマイナス利回りの兆候の下ではうまく機能しない」とし、「11兆ドルものマイナス利回り債は資産ではない、負債だ。イエレン議長に言いたい。資産価格に目標を定める上でこれを考慮に入れるべきだ」と指摘した。

グロース氏はかなり以前からこうした警鐘を繰り返していることから、「1日1440分のうち正確なのは2分だけで、残りの1438分は間違っている壊れた時計」と自分が比較されるかもしれないとしながらも、「信じて欲しい、この時計は正確に動いている。世界の債務や時代遅れの金融・財政政策は実体経済を癒やすどころか傷つけるからだ」と記した。

Figure 181. The Kanji glyphs from this news article are much more dense and complex than the surrounding Kana (Hiragana) glyphs enabling the reader to quickly skim the Kanji. News article from Bloomberg.co.jp.

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[321] Eiichi Kono, "English, Japanese and the Computer," in *Computers and Typography 2,* edited by Rosemary Sassoon, Intellect, Bristol, U.K. 2002. Page 54-68.

C:6.2. Automating Skim Formatting

Creating English text to facilitate skimming in the 19th century would have been laborious: editors would need to indicate which words to bold to pressmen who would need to have multiple different font cases simultaneously opened, manipulated and replaced throughout the process. Instead, simple algorithms can fully automate the process, such that the Wright Brothers' book in Figure 173P176 was formatted with five different levels of type weight and published on the web within minutes. The approach can be more generally extended using natural language processing *term frequency – inverse document frequency* (TF-IDF), in which the uncommon words are algorithmically determined based on their frequency relative to a corpus in the same domain.

For this project, six different public domain online books were selected from Project Gutenberg including popular fiction (Dickens' *A Tale of Two Cities* and Austen's *Emma*), children's books (Baum's *Wizard of Oz* and Burgess' *The Adventures of Buster Bear*), and more technically oriented works (Wrights' *The Early History of the Airplane* and Dillmont's *Encyclopedia of Needlework*). The baseline word frequencies for the English-language are based on Wiktionary word frequency lists from Project Gutenberg[322]. Texts are processed into unit words using Python NLTK toolkit (www.nltk.org). Each word is then ranked based on the Wiktionary frequencies. Typically, the thresholds used were as follows:

Word Frequency	Font Weight
< 100:	extra-light
100-500:	light
500-1000:	normal (book)
1000-20,000:	**bold**
20,000+:	**black**

These thresholds seemed to result in a distribution of weights such that there were not too many heavy weight words, nor too many light weight words. However, the Wright text used many more technical words, resulting in more uncommon words, resulting in too much text in the heaviest weight. If too many words are in the heaviest-weight, then skimming cannot be as effective because there are fewer words to skip across. In the case of the Wright text, the thresholds were manually shifted to 200, 1000, 5000, 20,000 which seemed to remedy the issue. Similarly, the children's text *Buster Bear* had very few infrequent words and the levels adjusted down. Presumably, counts of the number of words at each level could be used to automate the thresholds.

The NLTK parser and associated Python script has various logic to process the plain text. For example, in many Project Gutenberg texts, a single line of text surrounded by whitespace is used to indicate a sub-heading. A word surrounded by _underscores_ is intended to indicate italicization in the original text. Numbers were supposed to be extracted and assigned heavy-weights – but the word list has some numbers making those numbers appear in lighter weights. Handling of word-stemming and contractions was not addressed. Also, processing of quotes was not specially handled either, for example, plain quotes should be replaced with proper open/close quotes.

The Python script generates an HTML file wherein each word has an assigned class (1-5); and then an external CSS file is applied. Using CSS, different fonts and different weights can be easily applied. Using this approach, entire websites could be dynamically skim formatted, or books processed and output in print, eBook or PDF. Using CSS styling, it is easy to modify formats. For example, in Figure 182, the first few paragraphs of

322 https://en.wiktionary.org/wiki/Wiktionary:Frequency_lists#English accessed September 17, 2013.

A Tale of Two Cities by Charles Dickens, uses both capitalization and font weight to further emphasize the uncommon words (this particular capitalization/weight mix was a serendipitous result of a CSS error/font configuration error).

> It was the best of times, it was the **WORST** of times, it was the age of **WISDOM**, it was the age of **FOOLISHNESS**, it was the **EPOCH** of **BELIEF**, it was the **EPOCH** of **INCREDULITY**, it was the **SEASON** of Light, it was the **SEASON** of **DARKNESS**, it was the SPRING of hope, it was the WINTER of **DESPAIR**, we had everything before us, we had nothing before us, we were all going **DIRECT** to HEAVEN, we were all going **DIRECT** the other way-- in short, the PERIOD was so far like the present PERIOD, that some of its **NOISIEST AUTHORITIES INSISTED** on its being received, for good or for EVIL, in the **SUPERLATIVE** DEGREE of **COMPARISON** only.
>
> There were a king with a large **JAW** and a **QUEEN** with a PLAIN face, on the **THRONE** of **ENGLAND**; there were a king with a large **JAW** and a **QUEEN** with a FAIR face, on the **THRONE** of FRANCE. In both **COUNTRIES** it was **CLEARER** than **CRYSTAL** to the **LORDS** of the State **PRESERVES** of **LOAVES** and **FISHES**, that things in general were **SETTLED** for ever.

Figure 182. Dickens' *Tale of Two Cities*, formatted for skimming using both weight and capitalization. Image by author.

In the example in Figure 183, Jane Austen's *Emma* uses a serif font where the heavy weight uncommon words also use ligatures. Ligatures are connected letters, which for this particular font, uses a variety of uncommon historic ligatures, such as ct, st, sp. The design intent is that the use of ligatures on uncommon words will also draw attention to them.

> **Emma Woodhouse**, **handsome**, **clever**, and rich, with a **comfortable** home and happy **disposition**, seemed to **unite** some of the best **blessings** of **existence**; and had **lived nearly** twenty-one years in the world with very little to **distress** or **vex** her.
>
> She was the **youngest** of the two **daughters** of a most **affectionate**, **indulgent** father; and had, in **consequence** of her **sister's** marriage, been **mistress** of his house from a very early **period**. Her mother had **died** too long **ago** for her to have more than an **indistinct remembrance** of her **caresses**; and her place had been **supplied** by an **excellent** woman as **governess**, who had **fallen** little short of a mother in **affection**.
>
> **Sixteen** years had Miss **Taylor** been in Mr. **Woodhouse's** family, less as a **governess** than a friend, very **fond** of both **daughters**, but **particularly** of **Emma**. Between *them* it was more the **intimacy** of **sisters**. Even before Miss **Taylor** had **ceased** to hold the **nominal** office of **governess**, the **mildness** of her **temper** had hardly allowed her to **impose** any **restraint**; and the **shadow** of authority being now long passed away, they had been **living** together as friend and friend very **mutually attached**, and **Emma** doing just what she **liked**; **highly esteeming** Miss **Taylor's judgment**, but **directed chiefly** by her own.

Figure 183. Austen's *Emma*, formatted for skimming using weight, with ligatures used for the least common heavyweight words. Image by author.

Other type attributes besides weight could be used. In Figure 184 is the opening paragraph of T. W. Burgess' *The Adventures of Buster Bear*, using font width. Widths range from highly common words in an extra-condensed version of the font through to the least common words in an expanded version of the font. This example points to a potential perceptual conflict between preattention versus active reading: visually, the narrow fonts create more ink creating dark patches drawing preattention to the common words, but very narrow words could be harder to read than the wide words – in this configuration attention is potentially drawn to hard to read words.

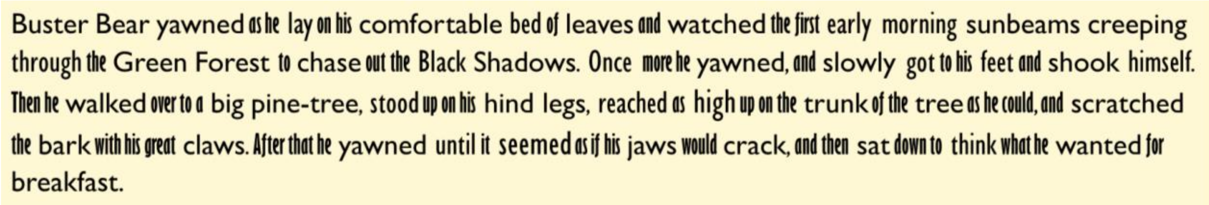

Figure 184. T.W. Burgess' *Adventures of Buster Bear*, formatted using font width. Image created by author.

Instead, Figure 185 shows the opening paragraphs of *Alice's Adventures in Wonderland* where the encoding ranges from uncommon words in a wide heavyweight font to common words in a narrow lightweight font, thereby maintaining the greater ink and visual dominance of the uncommon words. The cadence of the resulting textural rhythm is changed along with the dominance of the uncommon word: when reading the text, the formatting may have changed the semantics.

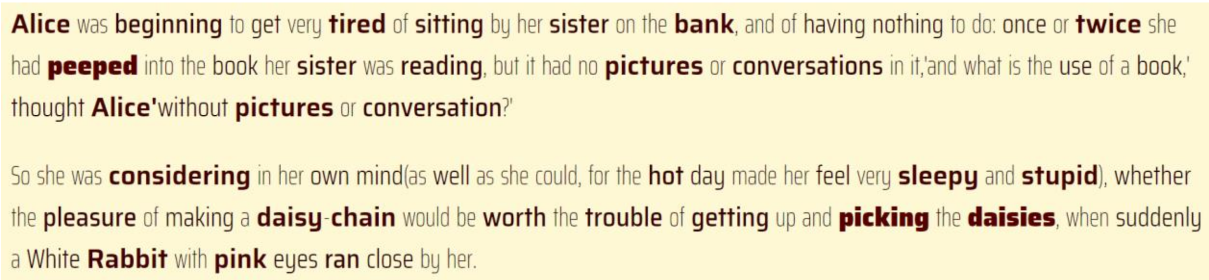

Figure 185. Carroll's *Alice's Adventures in Wonderland*, formatted using both font width and weight. Image created by author.

C:6.3. Evaluation and Other Considerations

Expert feedback has been collected via interviews with typographers, information visualization researchers and journalists, editors in news organizations and teachers. This light touch study was approved by LSBU ethics committee. There appears to be a strong appeal with responses ranging from visceral to observational:

- "Can you install this on my iPad now?"
- "I can see using this immediately in my own visualization research."
- "This is similar to how we use multiple underlines in our paper textbooks in college."
- "The ability to toggle is key: people who consume news all day will need to move back and forth between reading and skimming."
- "The technique can work well by aiding recognition of keywords instead of relying on searching (recall)."
- "Perhaps the same technique could be used to make the words pop-out that make the text more memorable, the way that Kennedy or Martin Luther King used spoken emphasis on words."

An informal online survey received 23 responses (see *F:4. Supplemental Materials*264 for the survey and the raw data). The participants reviewed two different texts: first, one unformatted fictional text, such as the opening paragraphs of *Alice in Wonderland,* followed by a second skim-formatting of a similar text, such as the opening paragraphs of *The Wizard of Oz*. Some participants received unformatted *Alice* followed by skim-formatted *Wizard*; while others received unformatted *Wizard* followed by skim-formatted *Alice*.

Participants were asked to identify a few skim-able words in each of the texts. As shown in the left chart in Figure 186, identification of skim-able words resulted in a wider range of words identified in the unformatted version (yellow bars, 20 unique words) versus the formatted version (blue bars, 14 unique words). In the skim-formatted version, 88% of words selected were of the heaviest weight (word frequency > 20,000). In the unformatted version, only 54% of the words selected were above word frequency of 20,000, however 90% of the words selected were of word frequency > 1,000. This indicates that participants were fairly adept at finding uncommon words regardless of formatting. Note that the task was not time limited as a real skimming task would require. Interestingly, in the unformatted version, 22% of words selected were capitalized proper nouns (Em, Kansas, Uncle, Henry) while only 3.5% of the selected words were capitalized proper nouns in the skim version. This suggests capitalization acted as a cue in unformatted text; and font weight acted as a stronger cue than capitalization in the skim format version.

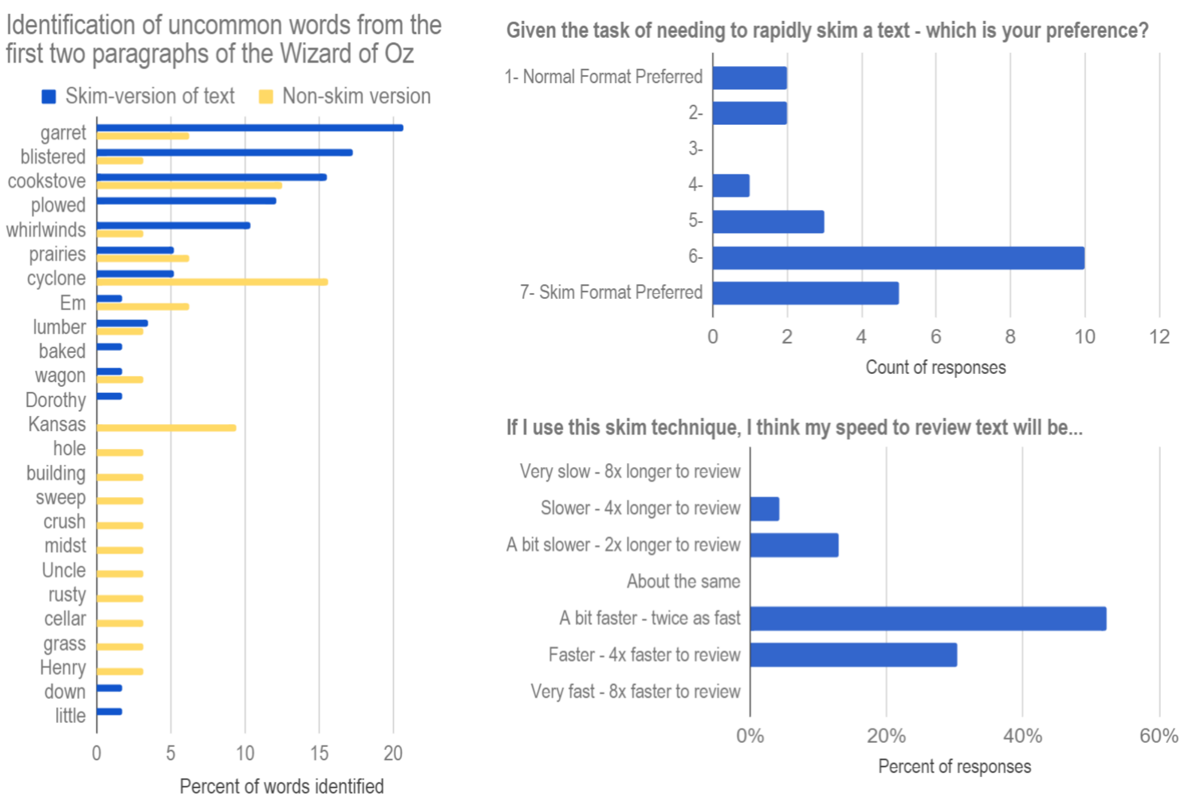

Figure 186. Left: Uncommon words identified by participants with skim and non-skim versions. Right: Participant preferences and perception of performance for skim formatting.

Participants expressed a preference for skim techniques, although not unanimous, as indicated by the charts on the right side of Figure 186. In free text responses, some users indicated 1) that other forms of highlighting, such as underline or background hue might be effective; 2) that bolding individual words interfered with reading – possibly introducing a different interpretation; and 3) that skimming focuses attention on words rather than the semantics. These are discussed below along with other considerations:

- *Other attributes or layout.* While bold and italic are used in these examples, other attributes may be more effective, such as other font attributes (e.g. underline), other visual attributes (e.g. color), or even modifications to the layout (e.g. Ronell's *The Telephone Book* also calls out text by adjusting white space around text, adjusting the layout, angle of paragraphs and so forth). Note that in various medieval examples (e.g. Figure 1P5, Figure 105P99), initial letters may highlighted instead of full words, or the use of capitalization on proper nouns (in English) or nouns generally (in German). One might consider skim formatting as a continuum of different types of formatting that both positively enhance ease of access of key information but at the same time disrupting the flow of reading. For example, italics may create the least disruption to the flow, whereas bold and underlines are somewhat more disruptive, while non-paragraph layouts and angular text may be highly disruptive to reading.

- *Adding parts of speech.* Word recognition research[323] suggests that short words and function words are frequently skipped for fixations of eye movement during reading. Thus, it may be desirable to further differentiate these words from the target words. An early variant of the skim formatting algorithm uses both inverse word frequency (to weight words as described earlier) and parts of speech tagging. Common, short, function words - specifically articles, conjunctions, pronouns, prepositions and infinitives - are italicized as shown in Figure 187 right. The intent is to increase the visual separation between the target words (heavy-weight infrequent words) and words least likely to be targets (light-weight, italicized function words e.g. articles, conjunctions, etc.). However, the use of multiple format changes may reduce readability and type guidelines recommend against changing too many type formats (e.g. Bringhurst).[324]

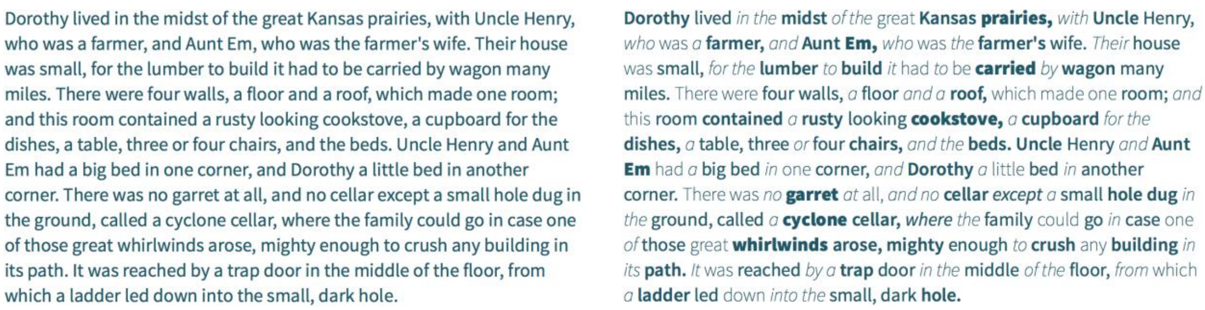

Figure 187. First paragraphs of the *Wizard of Oz*. On the right, weight indicates word frequency; italics further differentiates common parts of speech that may be skipped over while skimming. Image created by author.

- *Thresholds for weights and italics*. Decisions must be made at which word rank to switch to successively heavier weights. There are many confounding factors. Thresholds can be set so there are many heavy and lightweight words or few heavy and lightweight words with either choice resulting in the same average weight. Different texts will have different word usage: for example, technical articles will use many more infrequent words than most works of fiction. Also important is the choice of corpus

[323] Kevin Larson, "The science of word recognition." *Advanced Reading Technology*, Microsoft Corporation (2004). https://www.microsoft.com/typography/ctfonts/wordrecognition.aspx accessed April 17, 2016.
[324] Robert Bringhurst, *The Elements of Typographic Style.* (Hartley & Marks. 2013).

for the initial baseline word frequency: the Project Gutenberg corpus will result in different weights than the TV and movie script corpus. The choice of font family will have different rates of increase of blackness and different levels for the minimum and maximum weights. For example, sans serif fonts have a broader range of ink than serif fonts. There are also few fonts with five or more weights to choose from (and freely accessible). Fonts experimented with included *Source Sans Pro*, *Segoe UI*, *Cormorant*, *Glypha*, *Gill Sans, Saria, Roboto* and *Prototypo*. Note that the new OpenType Variable Fonts technology (2016), could be an alternative approach which allows for continuous scaling of some font parameters.

- *Interactivity.* A typographer pointed out that a text could be toggled back and forth between the skim formatted version and the non-skim formatted version. This, in effect, could be used to switch between a reading-mode (non-skim formatted) and a skimming-mode. More broadly, a number of different modes could be toggled to facilitate different linear/non-linear analyses of the text, such as, unformatted text; formatting of uncommon words (as described here); formatting of all nouns (e.g. with leading uppercase letter, as in German); formatting of all sentiment and emotion words; differentiation between all spoken text vs. descriptive prose; and so on.

  One challenge between toggling between these modes is the need to maintain word placement between modes to allow the viewer to maintain their reading position in the text. Word placement largely remains the same in Figure 187: some words are slightly longer (heavy weight) which are offset by other words that are slightly shorter (lightweight), meaning that the number of words in a line largely remains consistent. However, this could be problematic in longer texts: in Figure 187 line four the word *and* shifts to the next line in the skim formatted version. A better solution is to use a proportionally spaced font specifically designed such that letter widths are consistent across weights. Figure 188 shows two sans serif fonts. On the right, the highly popular *Helvetica* expands character width as font weight increases – the characters for the heaviest weight are 30% wider than the lightest weight. On the left, the font *Thesis Pro* maintains a consistent width was weight increases.

  Filtering is another potentially useful aspect: filtering out the text with lowest semantic value is potentially a means to further emphasize skimming text and condense the overall document; with interactivity to restore all text for reading mode.

Figure 188: Successive weights of fonts Thesis Pro (by LucasFont) on the left and Helvetica (by Monotype) on the right. Image created by author.

- *Sparktext.* Instead of data about word frequency or the semantic importance of text, other quantitative data associated with words could be depicted in visual attributes. Using Bertin's data indicating occupations of 90 departments across France, Figure 189 shows an explanatory paragraph and list of departments where the color and weight of department names indicate data. Tufte defines *sparklines* as data intense, design simple, word-sized graphics.[325] More broadly, Goffin et al[326] use *word-scale graphics,* which are word-size graphical elements used in the flow of text, and may be data-driven. Instead of a graphic, the information-carrying element can be *sparktext*, which represents both the literal word (readable directly in the context of the surrounding words), and also encodes additional data (e.g. categoric or quantitative data) through visual variables. In this particular example, the combination of red, green and blue indicates occupation and weight indicates total population. Because of their strong differentiation from the surrounding text, these sparkwords are skimmable when embedded into running text. Sparkwords are introduced here, but have not been further explored.

Using Bertin's dataset of occupations by departments in France, observations can be visualized and explained in narrative. The top three departments by population (indicated with font weight in quintiles: 34k-102, to 130, to 173, **to 236, to 1517**) are **Paris**, **Seine** and **Nord**. The top departments by percent of population in agriculture (proportion of green from 0 ___ 70%) are Gers, Creuse and Lozere. Top districts by manufacturing (red: 0 ___ 70%) are Belfort, **Moselle** and **Nord**. Top services (blue: 0 ___ 70%) are **Paris**, **Alpes Mmes**, and **Bouches Du Rh.** Districts which are closest to an even balance between all three occupations appear grey: the closest are Hte Saone, **Puy De Dome**, Eure. While many agricultural districts have small populations, a few are in the top quintile, such as **Morbihan**, **Finistere**, **Ille & V.**

Full data in alphabetic order: Ain Aisne Allier **Alpes Mmes** Ardeche Ardennes Ariege **Ases Pyrenees** Aube Aude Aveyron **Bas-Rhin** Belfort **Bouches Du Rh.** Bses Alpes **Calvados** Cantal Charente **Charente Mme** Cher Correze Cote D'Or **Cotes Du Nord** Creuse **Deux-Sevres** **Dordogne** Doubs Drome Eure Eure & Loir **Finistere** Gard Gers **Gironde** **Haute Garonne** **Herault** Hte Loire Hte Marne Hte Saone **Hte Savoie** **Hte Vienne** Htes Alpes Htes Pyrenees **Ht-Rhin** **Ille & V.** Indre Indre & L. **Isere** Jura Landes Loir & Cher **Loire** **Loire Inf.** Loiret Lot Lot & Gar. Lozere **Maine & L.** **Manche** Marne Mayenne **Meurthe & M.** Meuse **Morbihan** **Moselle** Nievre **Nord** Oise Orne **P. D. C.** **Paris** **Puy De Dome** Pyrenees Orient. **Rhone** **Saone & L.** **Sarthe** Savoie **Seine** Seine & M. **Seine & O.** **Seine Inf.** **Somme** Tarn Tarn & G. Var Vaucluse **Vendee** Vienne **Vosges** Yonne

Figure 189: A paragraph including *sparktext* indicating data through color and weight. Image created by author.

- *Larger scope and algorithmic detection of salient text*. The approach shown here uses a simple algorithm based on word frequency (and optionally parts of speech). While improved term-frequency based approaches may be better, the actual objective is comprehension of the most important information – i.e. semantics. Semantics are broader in scope than singular words. There are many possible algorithmic enhancements.
    - *Named Entities:* As per skimming strategies, in addition to reading infrequent words, other important items to detect and read include proper nouns and dates. Algorithmic approaches already exist for detecting named entities in text such as people, companies, dates, locations and so forth – these could be automatically formatted in the heaviest weight.

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325 Edward Tufte. *Beautiful Evidence.* Graphics Press. 2006.
326 Pascal Goffin, Jeremy Boy, Wesley Willett, and Petra Isenberg. "An exploratory study of word-scale graphics in data-rich text documents." IEEE transactions on visualization and computer graphics 23, no. 10 (2017): 2275-2287.

- *Negation, Qualification, Summation.* Sentences may be negated or otherwise qualified - a negation word on its own may not be relevant, but a negation word near another skim word might be. Prior research, such as Goldstein et al,[327] has characterized and scored sentences for query selection which could be extended for skimming – however, their work was limited to news stories and newsrooms have extensive rules regarding language usage and story structure (e.g. Winkler).[328]
- *Salience detection.* Instead of weighting words based on word frequencies, parts of speech, or entities, specific domain vocabularies could be used.[329] More advanced text analytics could be used to identify salient phrases and sentences, which in turn are weighted more heavily in relation to other phrases and sentences with lower scores. Entire phrases or sentences can be weighted to indicate saliency (similar to Figure 176 rightP178), which could be more suitable for interactive filtering as well. Similar to the notion of sparktext above, entire sentences or paragraphs can be formatted to indicate data, such as Figure 190.

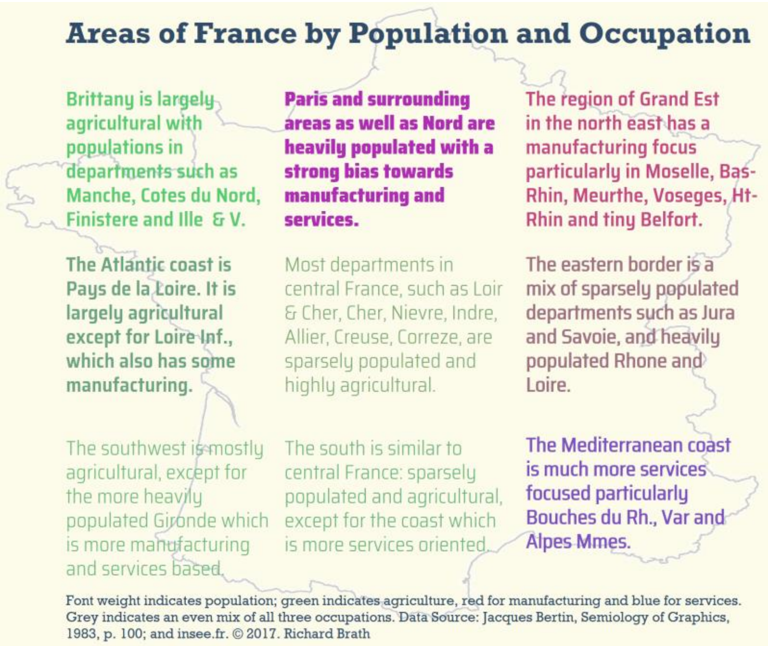

Figure 190: Paragraphs weighted and colored based on data. Image created by author.

- *Emotion formatting.* The emotional semantic content of text could also be considered and formatted appropriately (e.g. in addition to other semantic formats, or only emotion formats). For example, the semantic formats applied to emotion words as shown earlier in Figure 155P160 could also be used to indicate emotional content of the text; or formatted with the conventions used in manga and comic books (e.g. Figure 63P71).

[327] Jade Goldstein Mark Kantrowitz, Vibhu Mittal and Jaime Carbonelly. "Summarizing Text Documents: Sentence Selection and Evaluation Metrics," in *Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (SIGIR'99), pages 121–128. ACM Press New York, NY, USA, 1999.
[328] Matthew Winkler, *The Bloomberg Way,* Bloomberg Press, 2011.
[329] Philipp Mayr, Peter Mutschke, Vivien Petras. "Reducing semantic complexity in distributed digital libraries: treatment of term vagueness and document re-ranking" in *Library Review.* 57(3), 213–224 (2008)

C:6.4. Skim Format Conclusions

Skim formatting appears to be a promising use for font attributes in texts. Medieval texts, 19th century instruction manuals, Japanese reading strategies and keyword-in-context provides evidence that the approach of weighting the appropriate text facilitates skimming. The contribution of this section is to show that fully automated techniques can similarly create weighted keywords; and furthermore, that ordered levels of weights can be used to provide gradation across successively less frequent words. Additionally, we show that multiple algorithmic techniques can be combined together to increase the differentiation between the most important words and the least important words. Experts and potential users are excited about the approach, however, there are many nuances to consider for future work: including type of highlight, interactive toggling between skim and reading modes, thresholds for weights, novel sparktext extensions and extensions to highlight semantically important phrases and sentences – not words.

Note, that the approach has since been implemented in real-world applications. For example, the *Strippet Browser* (https://github.com/Microsoft/PowerBI-visuals-StrippetsBrowser), provides summary cards on mixed media content (e.g. news articles, social media), which automatically highlights entities in text content to facilitate skimming (Figure 191). The text is formatted with a change in both font family and font weight so that the skim content is differentiated even if the original formatting may have used bold or italics to emphasize content.

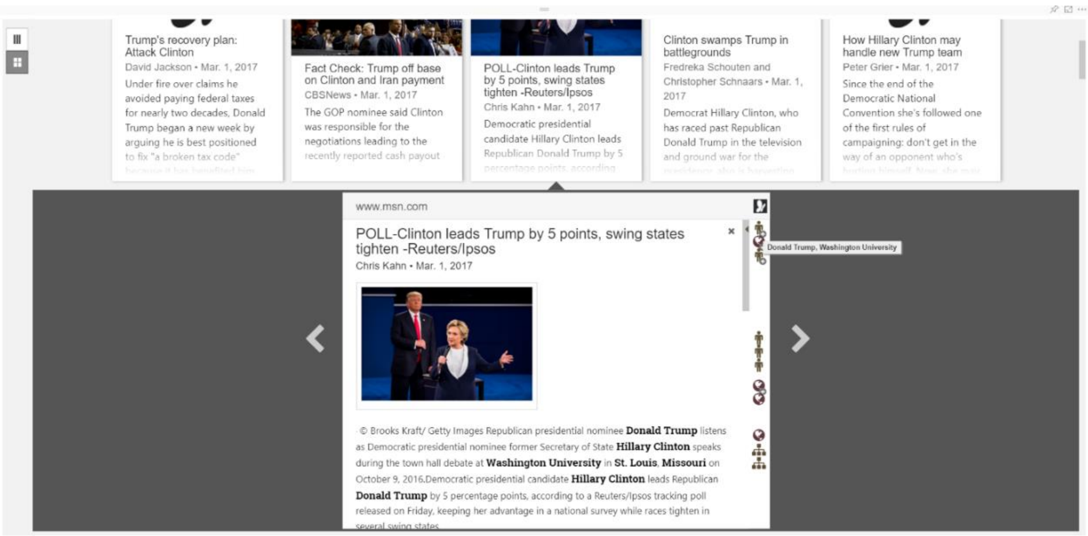

Figure 191: A commercial content browser which automatically detects and format entities (named people and places) to facilitate skimming while otherwise maintaining original formatting. Image provided courtesy Uncharted Software.

C:7. CG+OG: Glyphs for pronunciation & prosody

Typographic formats can be applied to subsets of words to indicate data. As discussed earlier, only two examples in the *Text Visualization Browser* focus on a typographic unit shorter than words. Already in this thesis there have been numerous examples of typographic visualization focusing on individual glyphs or syllables, such as:

- Alphanumeric charts (*B:1.3.ii: Alphanumeric Charts*P41),
- Stem and leaf plots extended to text visualization (*C:3: Lx: Literal Stem & Leaf Plots*P137),
- Use of expanded and condensed fonts to indicate letters retained in abbreviations (Figure 91P91), and
- Use of variable x-heights to indicate position of spelling errors (Figure 104P98).

Shimabukuro showed an approach to crowd sourced abbreviations and depicts retained glyphs via font size.[330] Glyph variation can also be used to indicate numeric data in proximity to the particular glyph: for example, the labels on the bottom right map in Figure 172P174 indicate population density in proximity to that glyph.

There may be new applications for embedding data at a sub-word level for applications related to intonation, pronunciation and prosody. For example English can be difficult to learn given many inconsistencies between spelling and pronunciation and many exceptions to rules. Historically, attempts have been made at spelling reform (e.g. Simplified Spelling Board), but rarely have these attempts been broadly accepted. Pronunciation guides in reference works such as dictionaries may accurately record pronunciation using the International Phonetic Alphabet[331] but this alphabet uses different glyphs and diacritic marks which completely transform the spelling of word (e.g. ˈhæpi, fɜː(r), ˈæktʃuəl, əˈbaʊt, dʒæm, /tʃeɪn via Oxford English dictionary). However, text formatting techniques could be used to indicate pronunciation while retaining the accepted spelling of the word: this would minimally disrupt reading, allow for closer inspection if the viewer is having difficulties pronouncing a word, and potentially aid learning as the primary letter sequence is not changed. Figure 192 shows a few difficult English words where lightweight glyphs indicate silent letters, underlines indicate long versions of vowels, and subscripts indicate the pronunciation of preceding letter sequences such as digraphs (e.g. ph pronounced as f). This example is only an illustration – the encoding shown here does not cover the full range of English pronunciation. The example is included as it generated strong positive response from a researcher familiar with data visualization, linguistics and English language teaching.

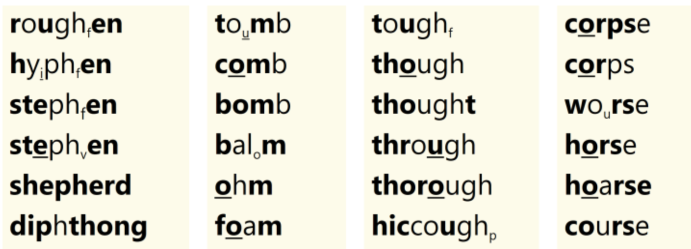

Figure 192: Words formatted with silent letters as lightweight, long vowels with underline and other sounds indicated in subscript. Image created by author.

[330] Mariana Shimabukuro, "An Adaptive Crowdsourced Investigation of Word Abbreviation Techniques for Text Visualizations," 2017. Master's Thesis. University of Ontario Institute of Technology.
[331] International Phonetic Association. https://www.internationalphoneticassociation.org/

Song in prose is often minimally differentiated from other text, for example, by being set in italics. However, this does not convey any of the prosodic song qualities such as the note pitch and note duration (Figure 193 left). While traditional music notation could be used, this would interrupt the flow of the text, require a lot of space, and would require that the reader is familiar with and capable of sight-reading music notation (Figure 193 right).

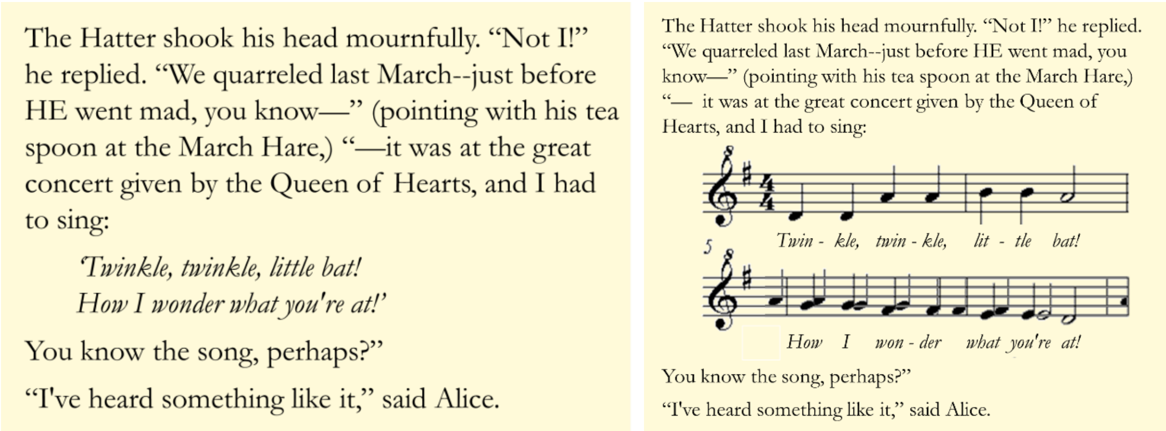

Figure 193: Song in prose does not convey melodic qualities. Music notation inline with text does convey melody, but only to the experienced music reader. Image created by author.

Patel and Furr[332] visualize prosody as an aid to the early reader: pitch, loudness and length variation are explicitly represented in the text as shown in Figure 194. In the left version, pitch is indicated by vertical shifts of the letters from their baseline, duration is indicated by letter spacing and intensity by letter brightness. While children were able to utilize the pitch modulation, readability was reduced and word boundaries were difficult to determine (this may have been predictable by typographers). The right version attempts to alleviate the readability issues: text spacing is retained to indicate duration while additional shading behind the text indicates pitch and intensity.

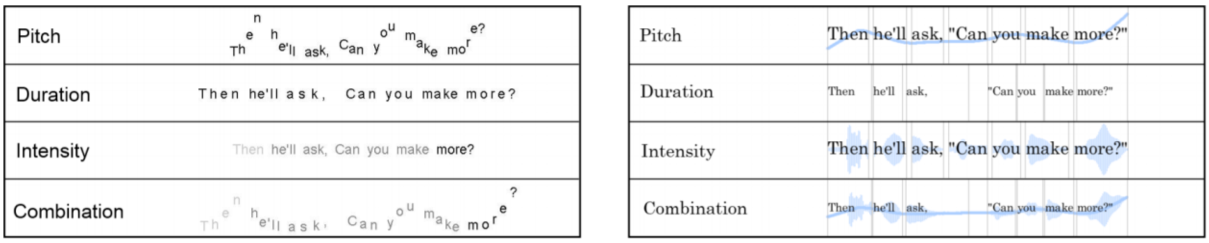

Figure 194: ReadN'Karaoke: left text manipulated to show prosody, right visual augmentation to indicate prosody. Image copyright respective authors.

Large baseline shifts reduce readability and make word spacing ambiguous. Intensity reduces contrast and reduces legibility. Instead, a typographic visualization approach could be used to maintain legibility and readability while maintaining the intuitive encodings for pitch and duration. In Figure 195, lower-case fonts have been compressed/expanded to indicate note duration; and the lower-case font x-height and baseline have been

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[332] Rupal Patel and William Furr. "ReadN'Karaoke: visualizing prosody in children's books for expressive oral reading." In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 3203-3206. ACM, 2011.

shifted to indicate note pitch (i.e. tall letters indicate deep pitches, short letters indicate high pitches). This approach maintains word height, letter alignment and clear delineation between words.

Frère Jacques, frère Jacques,
Dormez-vous? Dormez-vous?
Sonnez les matines! Sonnez les matines!
Ding, dang, dong. Ding, dang, dong.

Figure 195: Text encoding per syllable note pitch by character x-height and note duration by character width. Image by author.

These adjustments to glyph width, height and baseline may seem to be improved over the earlier prosody example, however there are many potential issues still to be considered, for example, x-height cannot represent a wide range of pitches; changes in x-height and font-width can be disruptive to reading; fonts with high aspect ratios are less legible, and so forth. Existing typographic research indicates negative reading effects with mixing fonts, cases or sizes within words,[333] suggesting caution for designers and a need for validation studies.

Technically, the above example is difficult to produce in current font technology: a font family with three different widths and seven different heights was required (i.e. 21 fonts). Adding in weight (to indicate intensity) would have required 105 fonts to have 5 levels. However, *variable fonts*, announced in Open Type 1.8 (discussed in *B:4.11: Font Design: X-Height, Contrast, Stress, Serifs, Etc.*P94) represents an important foundational technology which enables quantitative parameters to configure attributes of a font's definition: allowing a programmer to define the width of a character based on a data attribute, such as pitch duration.

The contribution of manipulating individual glyphs within words is exploratory: the intent is to generate examples which indicate the potential feasibility and utility of data-oriented glyph manipulation within words to create new applications. Many of the examples – spelling, abbreviation, pronunciation and prosody – suggest potential use in linguistics. Future work includes assessing appropriate applications, designing appropriate encodings and creating approaches to validate the work.

[333] Thomas Sanocki and Mary C. Dyson. "Letter processing and font information during reading: Beyond distinctiveness, where vision meets design." in Attention, Perception, & Psychophysics 74, no. 1 (2012): 132-145.

C:8. QS: Quantitative Sentences - proportional and positional encoding

Encoding quantitative data in text is a challenge. Size is most frequently used in existing text-based visualizations, however, size has issues, including: 1) in most word clouds, no legend is included thus leaving the mapping ambiguous as to whether area or height is used; 2) long strings tend to dominate the visual display, leading to potential bias; 3) strings on maps tend to use a few discrete sizes, thus being an ordered encoding rather than a truly quantitative encoding.

Instead, the novel technique of proportional and positional encoding of quantities should provide for more perceptually accurate encodings of quantities than text size. This approach was introduced earlier using short labels in *C:5.8: Positionally- and Proportionally-Encoded Labels*P171. More generally, both approaches can be applied to any length of text, such as sentences, paragraphs or even documents. Given that text is a linear sequence of words, any subset of this text can be differentiated to indicate a quantitative length:

Proportional encoding **highlights a subset of text by applying a typographic attribute along a subset of text relative to the quantitative proportion represented. For examp**le, the amount of bold applied to this paragraph indicates a quantitative value of 50%, as the number of characters in the paragraph is 342 of which the first 171 are bold.

Positional Encoding indicates a quantitative value by adding a unique format (such as an underline) or typographically differentiated characters (such as a subscript) at a position in a text relative to the pro**p**ortion indicated. For example, the bold underlined character in this paragraph indicates the quantitative value of 50%, as the number of characters in this paragraph is 422 and the 211th character is underlined.

C:8.1. Proportions along short strings (headlines, tweets, etc.)

There are various applications where short text strings (e.g. 20-150 characters) appear in user interfaces such as news headlines, search results (e.g. keyword in context), social media (e.g. tweets), titles for books, songs and video games; email subject headings, pull-quotes and so on. As such, there may be much more associated information, for example, dates, authorship, sources, subjects and document properties such as document length, number of readers, revision numbers, etc. Interfaces that list these text strings often don't list the other metadata; or they may use a grid with additional columns to itemize related information in a textual format that does not standout. A simple charting technique may not work well with these types of data: for example a bar chart ends up using most of the plot area for the labels, leaving little space for the bars, as shown in Figure 196. Labels could be truncated, however, keywords that uniquely identify the item or provide semantic context may be lost.

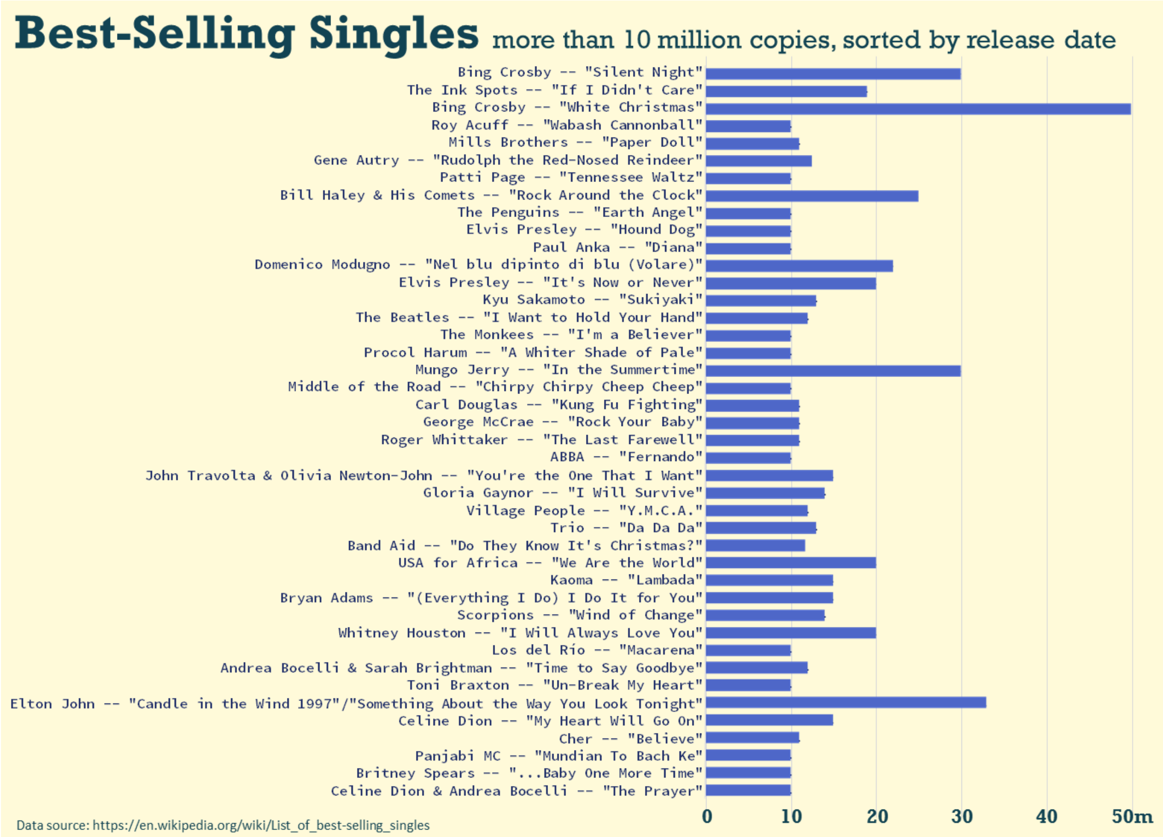

Figure 196. Bar chart with long labels identifying artists and songs: area for the bars significantly reduced in order to fit labels. Image created by author.

Other visualizations have been created based on use of these short text strings. For example, *NewsMap.jp* is a treemap of headlines where headline size indicates the number of related articles, and brightness indicates recency.[334]

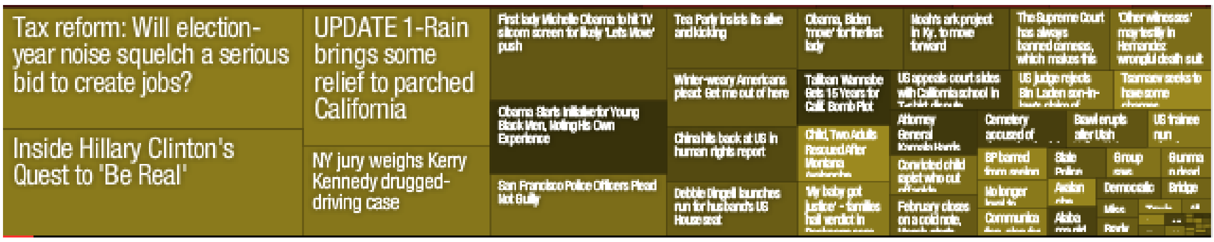

Figure 197. Portion of a *Newsmap*: box size/type size indicates number of articles, brightness indicates recency. Note some text is large, while other text is too small to read. Image by Marcos Weskamp.

However, any approach which uses size to encoded data into text has to make some text larger and some text smaller. As a result, some text is large and readable, therefore other text must be smaller and often much of this smaller text may be too small to read, such as the right half of Figure 197.

Similarly, color could be used, but as previously shown (e.g. Figure 11P14) there can be issues with various color combinations that reduce legibility. Furthermore, color cannot express many levels of differentiation and isn't particularly well suited to encoding quantities.

[334] Marcos Weskamp, "Projects: Newsmap" (2004), http://marumushi.com/projects/newsmap , accessed March 3, 2014.

Instead, Figure 198 shows a chart where the label data also encodes quantities as indicated by the length of bold applied to the text and referenced by the axis along the bottom of the plot. The label data and the quantity data have been superimposed into the same plot area, thereby reducing the overall area required for the plot. This superimposition allows the quantitative value to be encoded across the full width of the chart, not squished into a small remainder. This superimposition allows for a longer length to encode data, potentially allowing for greater resolution to be expressed as compared to the bars. Note that for this technique to work, strings have been padded to extend across the full display – or, better, additional useful information can be added, such as the initial lyrics of the song providing even more contextual information.

Figure 198. Chart showing best-selling songs, where the length of bold along the label indicates the number copies sold. This is the same data as Figure 196, has longer length to encode data and includes the first line of the lyrics. Image created by author.

Given all the text, either interactive techniques or analytic techniques can be used to highlight content of interest. For example, highlighting unique terms can provide a sense of the topics associated with songs as shown in Figure 199. In this particular example, the term *love* occurs four times in three songs (red highlight); while *Christmas* occurs five times but in only two songs (green); whereas *baby* occurs eight times in four songs (blue).

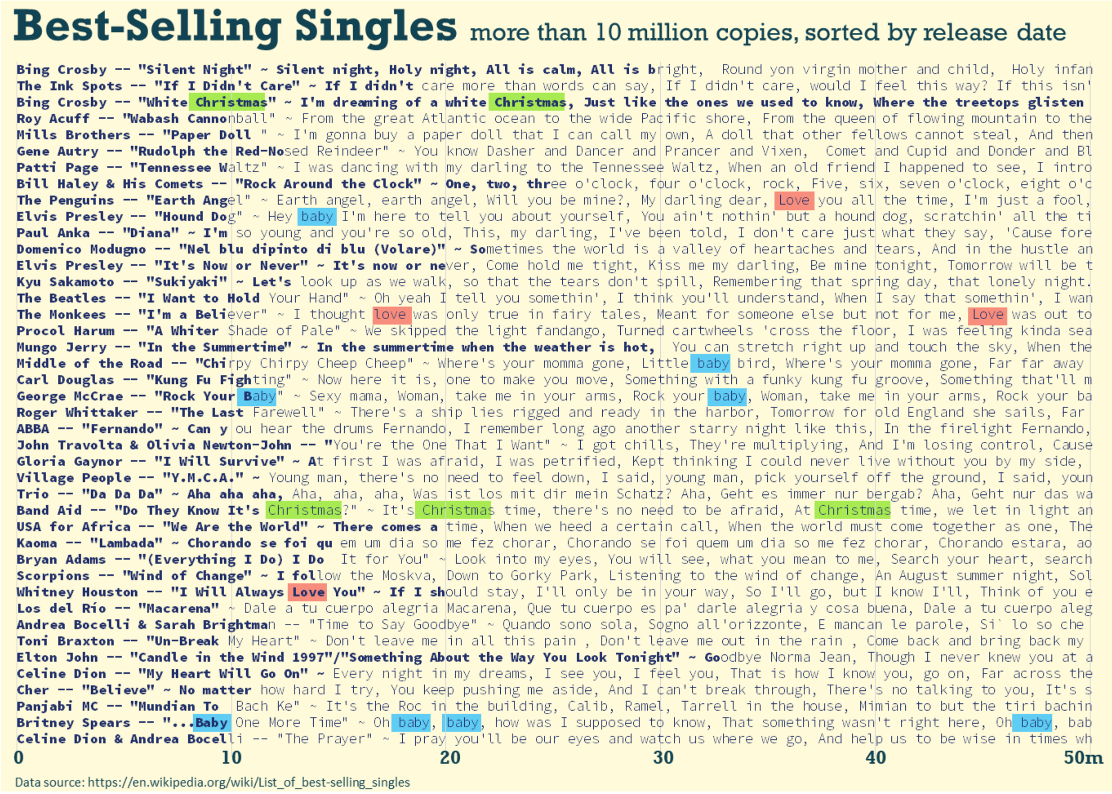

Figure 199. Chart from previous images with frequently occurring terms highlighted. Images created by author.

Proportional encoding easily works in-line in prose text, for example, with bullet point lists:

- Part A of this thesis is a brief introduction into the rationale for text in visualization.
- Part B uses historic review, characterization and feedback to frame the design space.
- Part C has many examples of applications using the design space, such as this chapter.

Note, in the above bullet point list underline length indicate relative size of each section.

Proportional encoding can be extended to more than a single value. Figure 200 shows four quantitative values from Bertin's occupations per department:

1) At a micro-level, each row corresponds to one department in France, with descriptive text automatically extracted from the opening paragraph of the Wikipedia entry for that department.
2) For each row, the proportion of color and typeface indicates the proportion of population in each occupation (as indicated along the top axis). The rows are sorted by the proportion of population occupied in agriculture. At a macro-level, it can be seen that the proportion of population in agriculture (green) is roughly inversely proportional to the population in manufacturing (red) – as indicated by the macro-level top-heavy green triangle offset by the bottom-heavy red triangle. This view is essentially the same as Bertin's stacked bar chart (*Semiologie Graphique* p. 108 top), with the additional benefit of literal text.
3) An underline indicates another quantitative variable – the total population in each department as referenced by the bottom axis. Agricultural departments tend to have small populations (short underlines near the top of the chart), while departments with large populations occur in some of the heavy manufacturing departments bottom). Anomalies can be seen – for example – Belfort, near the bottom has a tiny population even though it is heavily focused on manufacturing.

Figure 200.
The Departments of France:
- Each row is a department.
- The proportion of color and font indicates occupation (top axis)
- Underline length indicates population (bottom axis)
- Each row includes a description of the department, extracted from the first paragraph of Wikipedia.

Image created by author.

Figure 201 shows proportional encoding extended to indicate the upper and lower estimates for the number of volumes sold by top ten best-selling authors (according to Wikipedia). The ranges have been encoded with three different approaches:

- **Bold:** In the left image bold is used: note that bold can have accuracy finer than a single character by using a font with consistent width across weights, rendering the heavy-weight font to a texture, and then cropping the texture to the numeric values (notice the d in Harold, or e in Sidney). However, a per character format (such as bold, italic or case) will have some degree of error at gaps between characters and spaces between words.
- **Underline:** In the center image underline is used to indicate the range. Unlike bold (or italic or case), underline can span across gaps between words. Furthermore, underlines could be drawn to a fraction of a character width (for example by rendering the full string with underline and without, then cropping appropriate subsets of the string and compositing the results together).
- **Background Color:** In the rightmost image, a background color has been used to indicate the range. Yellow has been specifically used, as it is both familiar (like a highlighter) and maintains high legibility with a high contrast between the dark letterforms and the light color. Note that the extremely narrow ranges for Harold Robbins and J.K. Rowling are not particularly noticeable in any of the displays.

Figure 201. Range of values per author indicated via length of bold (left), underline (center), background highlight (right). Image by author. Images created by author.

Regardless of preference for color or underline, one powerful aspect of font attributes is that they can be combined together and uniquely identified. Using font-based techniques, multivariate quantitative metadata about documents can be depicted in addition to the title. Figure 202 shows a list of *Today's Featured Articles* from Wikipedia. Each line shows the title and a portion of the initial sentence of an article. The length of a particular format indicates a quantitative measure. For example, the length of bold is an indicator of the article length - articles regarding *Richard Nixon* and *Barack Obama* are particularly long while the article *Drymoreomys* is short. Underline indicates readership - the most read article is *The Green Children of Woolpit.* Note how some formats are easily perceived (e.g. bold) whereas others are require more focused attention (e.g. to detect the shortest upper case requires visually scanning all rows): this was predicted by the preattentive potential previously discussed (central column in Table 8P102).

Figure 202. List of articles from Wikipedia with length of format indicating article length (bold length), page views (underline), newness (case), and number of authors (italic). Image created by author.

The approach can be extended in a few ways. The quantitative data attributes can be used to sort the lines. This makes it easier to compare the relative areas of the particular format, such as viewing the slope or curvature associated with the sequence of quantities. Figure 203 shows two sets of movie reviewers' comments from the website *rottentomatoes.com* where the length of bold is used to indicate each reviewer's score. In this case, the original reviewer's commentary is truncated to a set length (and padded if the reviewer's quote was extremely short). Scores are normalized to a common range of 1-10. As the number of reviews vary per movie, the reviews are sorted based on score then sampled at equal intervals across the full range of reviews to extract a common number of reviews (e.g. 16 per movie). Plotting these reviews with the length encoding score reveals patterns. At a macro-level, the movie *Toy Story 3,* can be seen to have more dark bold, indicating higher review scores than the movie *Frozen.* The slope is an indication of dispersion: *Frozen* has a wider range of scores with one reviewer for *Frozen* providing a particularly poor review (almost no bold). In addition to the proportional text, the text is immediately accessible to read at a micro-level.

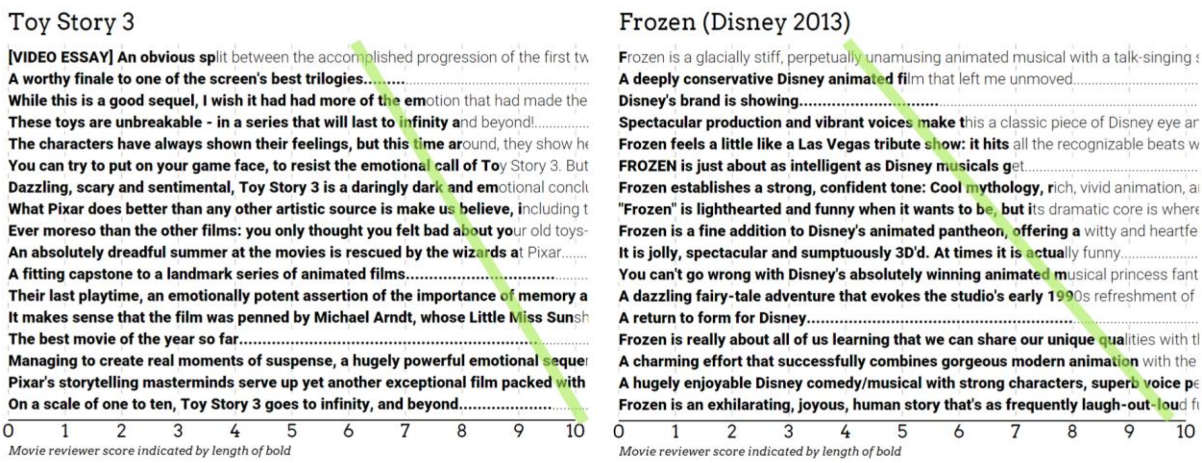

Figure 203. Movie reviews for *Toy Story 3* and *Frozen* with length of bold indicating score. *Toy Story 3* has more bold indicating a higher overall score. Reviews are sorted by score, Frozen has a lower slope indicating higher dispersion. Image created by author.

Any number of these distributions can be displayed, thereby providing a comparison across many different opinions across many different movies, such as the example shown in Figure 204. At a macro-level, the amount of black text indicates overall opinion, while the shape of the leading edge varies considerably across movies, as indicated by the comparison graph at the far right of Figure 204.

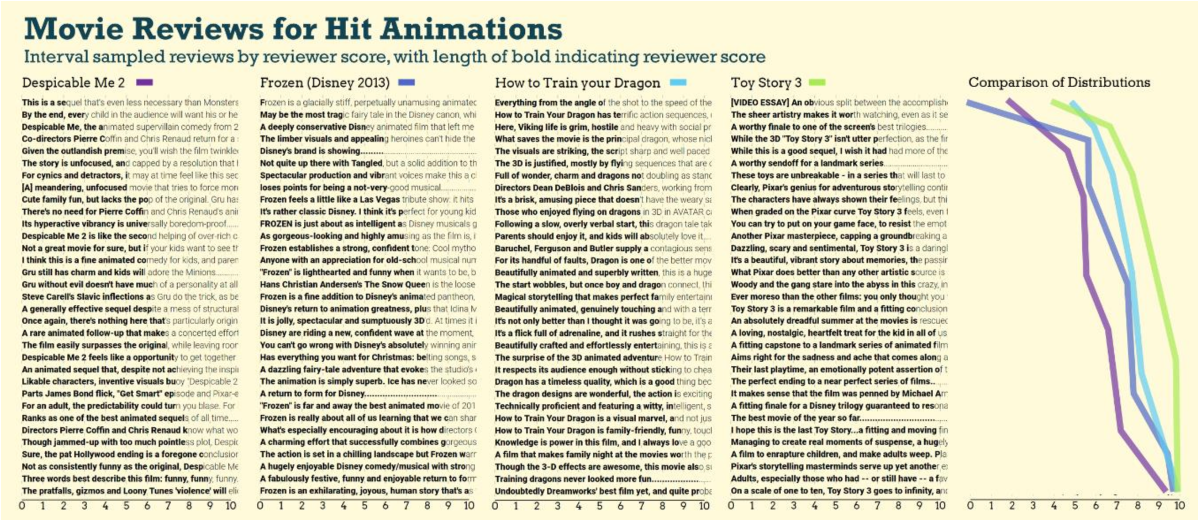

Figure 204. Movie reviews for four animations with length of bold indicating score. Note the different shapes of distribution the scores. Image created by author.

C:8.2. Evaluation of Proportional Encoding

Proportionally encoded lines of text are spatially efficient and perceptually efficient. A set of headlines and a single associated quantitative value were compared with three different encodings: 1) size (as in a treemap); 2) font weight (with 5 different weights applied evenly across the entire sentence to indicate 5 different data values); and 3) proportionally encoded (Figure 205). The treemap uses size within a fixed area, making some items large, and thereby decreasing the amount of space available to other items with some headlines too small to read. By contrast encoding data into font attributes allows a fixed text size to be used making all headlines readable. The three different encodings of news headlines were compared using different news data sets (e.g. few headlines, many headlines). The proportionally encoded headlines consistently outperformed the other two representations, with more readable headlines and overall lower information lossiness.[335]

Figure 205. Three variations of news headlines indicating number of related articles. Left: Treemap uses size (redrawn based on NewsMap.jp). Middle: font weight. Right: Length of bold. Image created by author.

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335 Richard Brath and Ebad Banissi. "Evaluating lossiness and fidelity in information visualization." In IS*&T/SPIE Electronic Imaging*, International Society for Optics and Photonics (2015): 93970H-93970H

In terms of perceptual efficiency, comparison of line lengths (used by proportional encoding) has the lowest margin of error (+/-2.5%). Comparisons of rectangular areas (used by treemaps) has a higher margin of error (+/-5%)[336]. Font weight used by itself is the least efficient as it only offers a few levels that can be readily perceived.

In terms of viewer preference, proportional encoding is quite different from other representations (e.g. bar charts and treemaps). An informal online survey (approved by LSBU ethics committee) received 23 responses specifically with regards to the movie review example (see *Supplemental Materials* in *F:4.3*264 for raw data). Understanding of the technique and preferences for the technique are given in Figure 206. While respondents understood the technique (as indicated in the left chart), but respondents were far from unanimous regarding their preference (right chart).

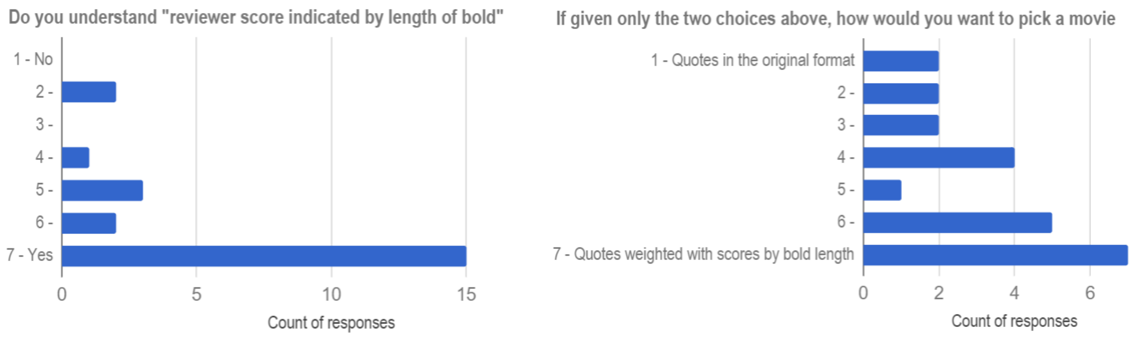

Figure 206. Understanding of proportional encoding vs. preference to use it. Image created by author.

The discrepancy between understanding and preference indicates potential issues which are expressed in free text comments. For example:

- “It incites to read only the bold character, in doing so it artificially push towards reading more out of the positive reviews.”
- “I automatically want to stop reading and skip to the next line when the bold ends.”
- “I'm reading for meaning and bold characters just end without a complete sentence - confusing because mixing two modes (quantitative score and text).”
- “Length of underline might be good too.”

The commentary indicates that the use of bold significantly interrupts the continuous reading of the text (i.e. readability, previously identified as a consideration in *B:3.2 Type Legibility and Readability*P66). This suggests that some other visual encoding – perhaps underline (as per the last comment above) or background color (e.g. Figure 201) may be better. From a visual perception perspective, background hue and underline are more readily separable from the text than bold, making it easier to attend to only one or the other separately.

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[336] Jeffrey Heer and Michael Bostock. "Crowdsourcing graphical perception: using mechanical turk to assess visualization design." in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, (ACM, 2010): 203–212.

C:8.3. Positional Encoding

Positional encoding is similar to proportional encoding. The same information encoded proportionally can instead be encoded by indicating the position along a string. Figure 207 shows the same data from the Wikipedia Featured Articles as Figure 202. Instead, the position along the x-axis indicates the quantitative value implied by the distance from the left edge to the formatted character. Double underline indicates the page views, the rightmost double underline occurs on *Green Children of Woolpit,* indicating that it is the most read story. Plain bold indicates article length, while italic indicates number of authors and color indicates topic. Note how it is more difficult to separately perceive the underline vs bold in this example as opposed to the earlier proportional example – in the prior example, the viewer could focus on a continuous underline, whereas here the underline is just a single glyph of similar size and weight to the bold glyph.

```
Action of 1 January 1800: The Action of 1 January 1800 was a naval bat
Mauritius Blue Pigeon: The Mauritius Blue Pigeon (Alectroenas nitidiss
Richard Nixon: Richard Milhous Nixon (January 9, 1913 – April 22, 1994
Metropolitan Railway: The Metropolitan Railway (also known as the Met
Rhodesian mission to Lisbon: Politics portalIn 1965, Britain's self-go
Over There (Fringe): "Over There" is the two-part second-seasonfinale
U2 3D: U2 3D is a 2008 American-produced 3Dconcert film featuring rock
First inauguration of Barack Obama: First term Second term The first i
1968 Thule Air Base B-52 crash: On 21 January 1968, an aircraft accide
Typhoon Rusa: Typhoon Rusa (international designation: 215, JTWC desig
Skye: Skye or the Isle of Skye (/skaɪ/; Scottish Gaelic: An t-Eilean S
Ranavalona III: Ranavalona III (November 22, 1861 – May 23, 1917) was
Pinguicula moranensis: P. moranensis var. moranensisP. moranensis var.
Green children of Woolpit: The legend of the green children of Woolpit
Otto Graham: Otto Everett Graham, Jr. (December 6, 1921 – December 17,
```

Figure 207. Position of formats encode quantities along a string of characters. Compare to Figure 202. Image created by author.

Proportional encoding is limited to indicating only one or two values along the length of a string with a particular format. With positional encoding, any number of markers can occur along the string length to indicate quantitative values, facilitating comparison across data points. A simple example is shown in Figure 208. In this case, the underlying text refers to the overall dataset and instructions to decode the data, while explicit superscripts indicate quantitative data via position as well as identification of each country via the character code in the superscript.

More[MEX] than[BRA] [IDN]5[ZAR]0[EGY]0 million women[ETH] in[BGD] the[NGA] world are[PAK] il[CHN]literate: the superscripts on this sentence indicate the number of illiterate women per country with sentence start indicating zero and sentence end indicating three hundred million illiterate [IND]women.

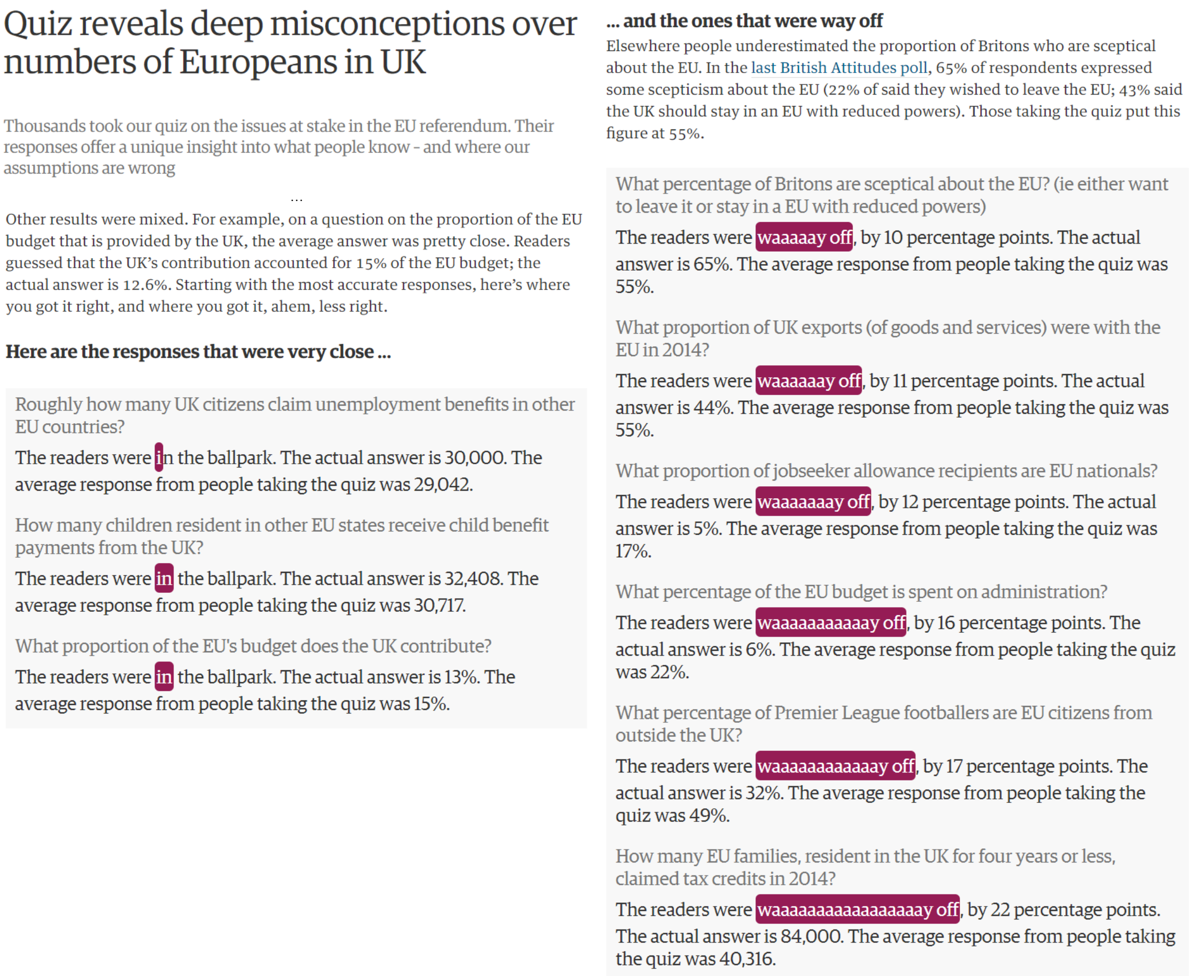
Data sources: UNESCO, World Bank, Wikipedia. MEX: Mexico. BRA: Brazil. IDN: Indonesia. ZAR: Democratic Republic of Congo. EGY: Egypt. BGD: Bangladesh. NGA: Nigeria. PAK: Pakistan. CHN: China. IND: India.

Figure 208. Position of superscripts encode quantities along a single sentence. Image created by author.

Note that the positional encoding in these examples uses position to indicate a quantity. In the earlier map example (Figure 158162), the position is used as an index to indicate a particular metric and the format is applied to indicate set membership.

C:8.4. Discussion

Proportional and positional encoding are new, but there are precedents. For example, this news post from *The Guardian* (Figure 209) uses background color and extends the word *way* by padding with extra letter a's for form a visual indicator of error. While the effect could be quantitative, in this example, the reporter simply uses more letters to convey greater error. However, the extension of the word *waaaay* more closely matches how one might extend the word in spoken text to indicate magnitude, thus perhaps a more intuitive semantic encoding.


Quiz reveals deep misconceptions over numbers of Europeans in UK

Thousands took our quiz on the issues at stake in the EU referendum. Their responses offer a unique insight into what people know - and where our assumptions are wrong

...

Other results were mixed. For example, on a question on the proportion of the EU budget that is provided by the UK, the average answer was pretty close. Readers guessed that the UK's contribution accounted for 15% of the EU budget; the actual answer is 12.6%. Starting with the most accurate responses, here's where you got it right, and where you got it, ahem, less right.

Here are the responses that were very close ...

Roughly how many UK citizens claim unemployment benefits in other EU countries?

The readers were in the ballpark. The actual answer is 30,000. The average response from people taking the quiz was 29,042.

How many children resident in other EU states receive child benefit payments from the UK?

The readers were in the ballpark. The actual answer is 32,408. The average response from people taking the quiz was 30,717.

What proportion of the EU's budget does the UK contribute?

The readers were in the ballpark. The actual answer is 13%. The average response from people taking the quiz was 15%.

... and the ones that were way off

Elsewhere people underestimated the proportion of Britons who are sceptical about the EU. In the last British Attitudes poll, 65% of respondents expressed some scepticism about the EU (22% of said they wished to leave the EU; 43% said the UK should stay in an EU with reduced powers). Those taking the quiz put this figure at 55%.

What percentage of Britons are sceptical about the EU? (ie either want to leave it or stay in a EU with reduced powers)

The readers were waaaaay off, by 10 percentage points. The actual answer is 65%. The average response from people taking the quiz was 55%.

What proportion of UK exports (of goods and services) were with the EU in 2014?

The readers were waaaaaay off, by 11 percentage points. The actual answer is 44%. The average response from people taking the quiz was 55%.

What proportion of jobseeker allowance recipients are EU nationals?

The readers were waaaaaaay off, by 12 percentage points. The actual answer is 5%. The average response from people taking the quiz was 17%.

What percentage of the EU budget is spent on administration?

The readers were waaaaaaaaaaay off, by 16 percentage points. The actual answer is 6%. The average response from people taking the quiz was 22%.

What percentage of Premier League footballers are EU citizens from outside the UK?

The readers were waaaaaaaaaaaay off, by 17 percentage points. The actual answer is 32%. The average response from people taking the quiz was 49%.

How many EU families, resident in the UK for four years or less, claimed tax credits in 2014?

The readers were waaaaaaaaaaaaaaaaay off, by 22 percentage points. The actual answer is 84,000. The average response from people taking the quiz was 40,316.

Figure 209. Magnitude of error indicated by padding a word with extra letters. Image by The Guardian. Accessed 2017/09/25. www.theguardian.com/politics/datablog/2016/jun/11/quiz-reveals-misconceptions-numbers-europeans-in-uk-eu-referendum

C:8.5. Proportional and Positional Encoding Conclusion

The notion of encoding quantities along the length of a string is a new encoding technique introduced in this thesis and a significant contribution to the field. Various aspects of the approach are explored, such as:

- increased information content than representations such as bar charts or treemaps
- accuracy of different attributes (e.g. underlines vs. bold); and the ability to increase accuracy by applying formats to partial glyphs
- ability to combine different formats to encode multiple values
- ability to order data to facilitate macro perception of cumulative distribution
- differentiation between proportional and positional formats

There are likely many enhancements to this technique which have not been explored; many potential applications which have not been considered; and the survey feedback implies that there is much more considered in evaluating the technique than just density/legibility and understanding. For example, readability is important as indicated by the reviewers for both a single quantitative value (such as bold), or, for many values represented simultaneously with different formats. The examples are largely limited to a single line of text – to facilitate length-based comparisons. Both techniques should be extensible to longer blocks of text with possibly area-based comparisons, or potentially use gradients, such as multiple levels of font weight, to indicate more than one value.

Technically, the approach is easier to implement using a fixed width font as opposed to a proportional font. With a fixed width font, the application of a format will be consistent across successive lines of text (e.g. Figure 198P195 or Figure 202P199). With a proportional font, the length of partial string length is based on the sum of the widths of individual characters, plus automated adjustments made for intercharacter spacing such as kerning and justification – and these calculations are not accessible in high level programming languages such as javascript, may be subject to some degree of error. For example, note the proportional fonts used with rows of text sorted by magnitude in Figure 200P197 and Figure 203P199 have small errors visible in rows with similar magnitudes.

PART D.
Evaluation of Typographic Visualization Design Space

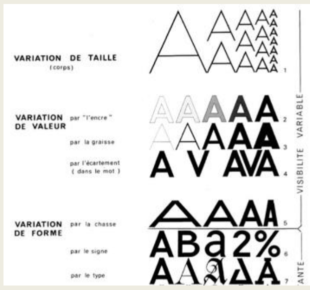
Description of Part D

Evaluation of the broad design space follows two main approaches: Critique and Metrics.[pages 206-248]

An evaluation approach needed and used in many fields is Critique.[p206]

- There are issues with existing Evaluations of User Interfaces.[206]
- Experts recognize the limitations: some suggest Critiqued Practice.[207]
- Critique builds on related concepts of Critical Thinking and Criticism[208]
- and the unique aspects can be characterized from Design Criticism.[212]

With critiques from experts across fields, there are Common Themes:[213]



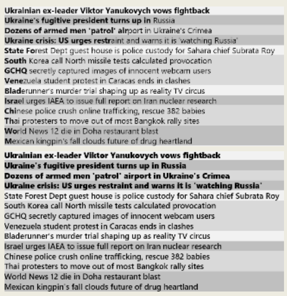
- Challenges and potential uses of Multivariate Encodings[213]
- Perception may skewed by Label Length Bias[216]
- Prior research by Bertin on Text seems to be Forgotten[218]
- There are many attributes: How many can be Combined?[222]

There may additional value to Economics and Innovation[224]
and Reconsideration of the Pipeline[224]

Experts from various fields have Domain Specific Critiques,[225] such as:

- Aesthetics, semantics and layout algorithms in Information Visualization.[225]
- Sparklines, interactivity, language and intuitive encodings by Typographers.[226]
- Perceptual bias, cultural conventions, and mobile devices by Cartographers.[230]

Measuring information content is done using Fidelity and Lossiness Metrics[232]



- A visual attribute encodes data with some reduction in Fidelity[234]
- which can be extended to estimate Multiple Dimensional Fidelity[235]
- and combined together to create a measure of Overall Lossiness[238]
- Estimates of fidelity enable Generalized Fidelity and Lossiness[239]
- with an Example,[241] application Text-based Visualization,[244] and Example without Dataset[245]
- the latter example points to some Limitations of the Metrics[245]

Each of the individual visualizations in the previous *PART C*P108-204 can be evaluated for specific goals as shown in the preceding examples. Techniques included *cognitive modeling* on the label plotsP119; measurement of *information density* on proportionally encoded lines of textP200; measured *encoding accuracy* on the typographic mosaicP154; measured *task performance* on labeled cartogramsP173; *user feedback* for skim formattingP183; *task observations* for microtext linesP132; and *user surveys* for skim formattingP183 and proportional encodingP200.

More important for this thesis is the evaluation of the design space. The design space is multi-dimensional with many different attributes and a wide range of possible applications making it difficult to evaluate the design space by experimental testing. For example, Lam et al's *Empirical Studies in Information Visualization* provides seven different evaluation techniques, however all are constrained to the evaluation of a singular project.[337] Instead, for evaluation across the broad design space this thesis introduces evaluation by *critique* and evaluation by fidelity and lossiness metrics.

D:1. Critique

D:1.1. The Need for Critique

Expert critique is a different approach to evaluate a large set of related techniques. While computer scientists in general are not familiar with critiques[338], the approach is well known among designers, architects, doctors and some engineers (e.g. Brooks[339]). Various visualization researchers recognize that there is a significant design component in the creation of visualization systems.[340,341] There are many different ways that a visualization can fail: for example, Munzner's nested model[342] identifies four levels with multiple evaluations per level. Yet, there are still many errors in visualization designs, as discussed by Forsell and Johansson.[343]

Instead, if it is given that the creation of visualizations involves design, then the visualization community needs to consider evaluation approaches used in design. In particular, many types of design education use critiques as a form of evaluation used frequently throughout the design process. Critiques can be used as a form of evaluation of visualization and is different than similar approaches such as heuristic evaluation, reviews or written criticism.

i. Evaluation of User Interface Designs

Some types of evaluation techniques may be inadequate as they may not consider the many potential points of failure. For example, a visualization which focuses on preattentive perception may achieve high performance on

337 Heidi Lam et al, "Empirical Studies in Information Visualization: Seven Scenarios," in *IEEE Transactions on Visualization and Computer Graphics*, 18 (9), (IEEE, 2012): 1520–1536.
338 Robert Kosara, "Visualization criticism-the missing link between information visualization and art" In *Information Visualization*, 2007. IV'07. 11th International Conference, (IEEE, 2007), 631-636.
339 Frederick P. Brooks Jr, *The design of design: essays from a computer scientist*, (Boston, MA: Pearson Education, 2010), 243–245.
340 C. L. Paul, R. Rohrer & B. Nebesh, B. "A Design First Approach to Visualization Innovation." *IEEE Computer Graphics and Applications,* (1), 12-18. 2015.
341 T. Munzner, *Visualization Analysis and Design*. CRC Press. 2014.
342 T. Munzner. "A nested model for visualization design and validation." *Visualization and Computer Graphics, IEEE Transactions on*, 15(6), pp.921-928. 2009.
343 C. Forsell and J. Johansson. "An heuristic set for evaluation in information visualization." In *Proceedings of the International Conference on Advanced Visual Interfaces* (pp. 199-206). ACM. 2010.

the time to perceive a target, however, the encoding may not be easy to decode: a metaphoric or connotative encoding could be slower to perceive but faster to decode.

Heuristic Evaluation: Heuristics have been compiled by different researchers (e.g. Forsell and Johansson, Ware[344] and Zuk[345]). A heuristic evaluation focuses on judging a design against established principles to assess the design's compliance to each heuristic and the approach has been used in visualization.[346] As described by Nielsen,[347] a heuristic evaluation is performed by having each evaluator inspect the interface alone then findings aggregated. The evaluator inspects user interface elements and compares them with a list of recognized usability principles. Heuristic evaluation does not provide a systematic way to generate fixes to the usability problems or a way to assess the probable quality of redesigns. Heuristic evaluation doesn't consider tradeoffs between design choices; assumptions associated with the heuristic that may not hold for the particular design; nor the possibility for conflicting heuristics. Tradeoffs can be more complex than simple functional and usability requirements: e.g. people are willing to trade aesthetics for functionality.[348]

User-Centered Design is another approach for creating effective design. User-centered design is focused on user perceptions, behaviors, needs and experiences. The user-centered approach is focused on the problem space, but users "typically cannot directly articulate their analysis needs in a clear-cut way" (Munzner 2014).

Models such as Munzner's nested model or Cen and Floridi's communication model might help identify areas to be evaluated, but the models do not capture tradeoff decisions. While models can be effective for framing the design process, models aren't inherently critical of their limitations.

Following a user-centered approach, a model-based approach or a heuristic approach may lead to a workable solution. However, there may be better alternative solutions. A user-centered approach is limited to user expertise – which may be low with regards to visualization. A model or heuristic approach is limited to the model constraints and knowledge-base of the designer or the heuristics. Past models, guidelines and findings may not be universal to new types of problems, domains, technologies, user capabilities, assumptions, etc.

ii. From Evaluation to Design Critique

The author's position is that the discussion should be expanded beyond evaluation to a discussion to include design and idea generation. For example, Stuart Card in 2003[349] says:

> *"The rise in the dependence of HCI on usability labs is basically a regression... Design is where the action is. You will just never get great systems out of usability testing; you would never get to the GUI interface by usability testing on DOS."*

Or Don Norman in the same panel:

> *"The design profession flourishes because they do things, they create. Usability languishes because good usability is invisible... Although we think we are indispensable, the world of business knows this to be false."*

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[344] C. Ware, *Information visualization: perception for design*. Elsevier. 2012.
[345] T. Zuk et al., "Heuristics for information visualization evaluation." In *Proceedings of the 2006 AVI workshop on BEyond time and errors: novel evaluation methods for information visualization* (pp. 1-6). ACM. May 2006.
[346] M. Tory and T. Möller, "Evaluating visualizations: do expert reviews work?" *Computer Graphics and Applications, IEEE* 25, no. 5 (2005): 8-11.
[347] J. Nielsen, *Usability engineering.* Elsevier. 1994.
[348] Y. Pan, D. Roedl, E. Blevis, E. and J. Thomas. Fashion thinking: Fashion practices and sustainable interaction design. *International Journal of Design*, 9(1). 2015.
[349] B. Shneiderman, S. Card, D. Norman, M. Tremaine, and M.M. Waldrop. "CHI@ 20: fighting our way from marginality to power." In *CHI'02 Extended Abstracts on Human Factors in Computing Systems* (pp. 688-691). ACM. April 2002.

Donald Schön, in *Educating the Reflective Practitioner*[350], argues that most research universities are based on technical rationalism. Technical rationality holds that professional practitioners solve well-formed problems by applying theory from systematically derived scientific knowledge. However, real-world practice does not present well-formed problems, but messy indeterminate situations with a context often larger than the immediate requirements. Instead, Schön argues for the constructionist view, wherein practitioners assemble models rooted in perceptions, appreciations and beliefs which are continuously updated with new evidence from attention, sense-making, boundary-setting and so forth. The designer's efforts (sketched and verbalized) provide the critic (i.e. expert practitioner) with evidence from which to infer the designer's difficulties and understanding forming a basis for the framing of questions, criticisms and suggestions. In effect, the critic is a coach. Schön provides examples across disciplines, including law, medicine, music, dance, art and architecture. Of medicine, he says:

> *"There is an implicit recognition that research based models of diagnosis and treatment cannot be made to work until the student acquires an art that falls outside the models. The medical practicum is as much concerned with acquiring a quasi-autonomous art of clinical practice as with learning to apply research-based theory."*

Fred Brooks, lead developer of IBM's *System/360* and winner of the *Turing Award*, supports Schön and says:

> *"The weakness of much academic formal education is its reliance on lectures and readings, as opposed to critiqued practice… Only rarely do computer science curricula do that."*[351]

Critique is not foreign to visualization: Kosara et al set out the basics of the design critique as applied to visualization in 2008.[352]

iii. Critical Thinking, Criticism and Critique

Critique, criticism and critical thinking are closely related concepts. Critical thinking underlies both critique and criticism. Critical thinking is defined by Oxford dictionary as "the objective analysis and evaluation of an issue in order to form a judgement". Hughes et al say "Three types of skills – interpretation, verification and reasoning – constitute what are usually referred to as critical thinking skills."[353] Critical thinking will disassemble designs and models, question assumptions, reconsider evidence and hypothesize new models. Critical thinking is useful for open-ended questions with potential ambiguity and tradeoffs – questions with more than one right answer such as design problems. Critical thinking is self-guided, self-disciplined thinking.[354]

Unlike critical thinking, criticism and critique are explicitly public. Criticism originates in the 18th century. It established a distinct public discourse based on rational judgement. Individuals gather for "equal interchange of reasonable discourse" in public forums such as clubs and coffee houses.[355]

> *Criticism is: "open to debate, it attempts to convince, it invites contradiction. It becomes part of the public exchange of opinion."*[356]

In modern English usage, the word criticism tends to be associated with the publications of the professional critic, such as a movie critic or fashion critic:

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350 Donald A. Schön. *Educating the reflective practitioner: Toward a new design for teaching and learning in the professions*. Jossey-Bass, San Franscisco, CA. 1987.
351 Fred P. Brooks. *The Design of Design*. Addison-Wesley. 2010.
352 R. Kosara, F. Drury, L.E. Holmquist and D.H. Laidlaw, D.H. "Visualization criticism." *IEEE Computer Graphics and Applications*, (3), pp.13-15. 2008.
353 W. Hughes, J. Lavery and K. Doran. *Critical Thinking: An Introduction of the Basic Skills*. 7th ed. Broadview Press. 2015.
354 L. Elder. "Defining Critical Thinking." website: criticalthinking.org/pages/defining-critical-thinking/766 (accessed 2016/06/11).
355 T. Eagleton. *The function of criticism* (Vol. 6). Verso. 2005.
356 P.U. Hohendahl, *The institution of criticism*. Cornell University Press. 1982.

> *"The role of the serious critic is that of an educator. By searching out the many examples of good design and appraising them constructively, he may convince the manufacturer or printer of the merits of good design associated with his product... Such constructive criticism in the press would teach the public, not only to appreciate, but to demand good design in the products they buy."*[357]

Or, more to the point:

> *"The critic has long been the arbiter of taste, determining for their readership what is considered good and what is bad."*[358]

There are calls for increased criticism in visualization, such as the many examples on the blogs of Robert Kosara (eagereyes.org), Kaiser Fung (junkcharts.typepad.com) or Edward Tufte. Following in the model of the professional critic, this approach can lead to a better appreciation of good visualizations. However, discourse in written criticism occurs slowly making iterative dialogue difficult.

As opposed to criticism, critiques (as used in education of design) are face to face interactions between designers and critics. The notion of critique can have subtle variations in meaning when applied to literature, philosophy or design. For the purposes of this thesis, critique will be used in a design context and specifically refer to critique as used in the architectural design process.

iv. Design Critique

The author has past experience in more than a hundred critiques through the completion of five years of undergraduate architectural education leading to a degree and two years of professional practice. This included experience at a variety of different architectural offices around the world and working with architectural students from other universities. In the last 20 years the author has worked in a visualization firm and used techniques borrowed from critiques to evaluate and advance design ideas. Some unique qualities of design critique are listed below: more detailed analyses are available (e.g. Schön).

1) Sketches and design artifacts: Critiques are used frequently during an architectural design project. In both architecture education and professional practice, designers typically work in an open office continuously ideating, expressing and refining design ideas through sketching, physical models, virtual models, mockups, diagrams, illustrations, annotations and other representational embodiments of the design ideas.

Sketching, in particular, is a simple medium that can be utilized by both the designer and critic to reveal qualities and relations unimagined beforehand. These dynamic modifications function as quick exploratory experiments which are not restricted or slowed by real-world constraints (Schön).

Design critiques are applicable to user interfaces and visualizations, particularly where the design process similarly generates sketches, walkthrough, wireframes, Wizard of Oz prototypes and other visual artifacts (e.g. Buxton).[359] The notion of sketching has also been applied to visualization design, such as collaborative sketching,[360] or as a method to generate design alternatives.[361]

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[357] A. Havinden, "Does Today's Criticsim Help Design?" *Printing Review*, Winter 1952.
[358] A. Gerber and T. Triggs. in *Blueprint, The Magazine for Leading Architects and Designers*, Oct 2007, page 80
[359] B. Buxton, *Sketching user experiences*. Morgan Kaufmann. 2010.
[360] B. Craft and P. Cairns, "Sketching sketching: outlines of a collaborative design method." In *Proceedings of the 23rd British HCI Group Annual Conference on People and Computers: Celebrating People and Technology* (pp. 65-72). British Computer Society. 2009.
[361] J.C. Roberts. "The Five Design-Sheet (FdS) approach for Sketching Information Visualization Designs." *Proc. Eurographics Education Papers*, pp.27-41. 2011.

2) Broad scope: Given that design may have many tradeoff decisions with no single correct solution, a critique can be very wide ranging, going beyond immediate functional requirements and may consider the elements of the broader social, historic, theoretic contexts.

Visualizations have many design decisions which can be probed: e.g. user types, user capabilities, tasks, goals, workflows, data available, data types, data quality (nulls, certainty, provenance), data scale, latency, analytics, models, choice of visual variables, layouts, labels, titles, legends, navigation, probes, selection, animation, collaboration, speed of perception, accuracy of perception, ease of decoding, cognition and so on.

Furthermore, as noted by various authors (e.g. Goebel[362]), the theories of visualization are still evolving. The underlying science still has many gaps: e.g. visual variables for visualization based on preattention research but ranked based on accuracy of decoding. The list of visual variables varies per researcher (Table 2P13). There are many different tasks that visualization can be used for (analysis, monitoring, communication, ambience, etc.), but visual variables aren't considered with respect to different uses. And so on. A critique is willing to consider design alternatives within these gaps, and explore beyond the current conventions whereas other approaches (heuristics, models, feedback) may be constrained by current best practices (e.g. Santos).[363]

3) Unifying concepts and consistency: A design needs to define and follow a broad conceptual reasoning. The overall conceptual framework is important because smaller design decisions follow the larger rationale and make the design predictable and internally consistent. This consistency aids the user: e.g. letters within a font have similar widths, x-heights and terminals, which facilitates reading.[364] Mies van der Rohe's *Seagram Building* in New York breaks with centuries of architectural tradition introducing uniform floor sizes and heights; unadorned structure and large glass windows allowing light deep into an office building coincident with concepts of modernity, technology, the rise of professional managers and democratization of the workplace (Figure 210).

Figure 210. Left: Seagram building, an exemplar of modern design (Mies van der Rohe, 1958) compared to Chrysler building, completed a generation earlier (William van Alen, 1930). Public domain images from Wikipedia and Library of Congress.

Visualization systems may not have this internal consistency especially when cobbled together out of components. Such a system might meet functional requirements and heuristic checklists but do not have consistency of design. Different glyphs, encodings, sizes, styles, color, typography, layout, white space and

362 Randy Goebel. "A sketch of a theory of visualization." In *Information Visualization Theory and Applications* (IVAPP), 2014 International Conference on (pp. 218-221). IEEE. January 2014.
363 B.S. Santos, B.Q. Ferreira, and P. Dias. "Using Heuristic Evaluation to Foster Visualization Analysis and Design Skills." *Computer Graphics and Applications, IEEE*, 36(1), pp.86-90. 2016.
364 I. Gauthier, A. Wong, W. Hayward and O. Cheung, "Font tuning associated with expertise in letter perception." *Perception 35*, no. 4: pp. 541-559. 2006.

interactions reduce the ability to take what is learned in one part of the application and use in another.[365] Or, user mental models may be challenged by mixing representations and aggregations: a linked views visualization may include individual data elements explicitly represented as dots in a scatterplot, lines in a parallel coordinate plot, and summarized into bars within a bar chart – these different aggregations could instead be represented as explicit datapoints throughout – as dot in scatterplots, stacked into bars and stacked into distributions.

4) Broad context and case studies: Critique frequently cites other examples where similar problems were solved in a unique, innovative approach. Historic examples and case histories, with many illustrative artifacts, are utilized as references for both the critic and the designer. Visualization has a long historic context, which in turn could influence design choices such as the many text examples shown in *PART B*$_{23\text{-}108}$, or examples found in *Album de Statistique Graphique*, Gantt, Marey, Minard, Playfair and so on (e.g. see Friendly for overview).[366]

Visualizations need to work within cultural preconceptions, metaphors, and codes of users, e.g. Norman,[367] Byrne et al[368] and Jones.[369] A critique can help identify unseen associations.

5) Public, bi-directional dialogue: Unlike a review of a paper, a critique is a dialogue between the designer(s) and the critic(s). The designer may provide an overview of the design, an explanation of the rationale behind various design choices, defend various design decisions or suggest additional considerations. There is no anonymity for either side of the discussion. Tom Hanrahan, Dean of Pratt School of Architecture says:

> *"…it takes place in a space where people discuss the work together, in a personal way, and in a very public way. Ultimately there's a public arena where the work is discussed,…"*[370]

Criticism is open to debate, attempts to convince and invites contraction. Critique is willing to re-evaluate prior convictions and evidence in a different context. This helps reframe the problem and provides the potential for different design approaches. Discussion can generate multiple perspective, in public, where each attendee can individually draw their own conclusions.

6) Many kinds of critics: A typical evaluation study might use novice users in a controlled experiment. Novice users, without expertise, only provide information on the task directly evaluated. Peers and experts, however, can provide feedback on any part of a system with which they are familiar, beyond the scope of the particular experiment: they may notice problems at different levels or different assumptions within the proposed design. Experts can come from related disciplines. Within the visualization domain, experts can be sourced from the visualization community, the user community, or related fields (e.g. human-computer interaction, end-users, IT departments, designers familiar with interface or information design, cartography, etc.)

7) Frequent: Design is a continuous, iterative process making frequent refinements throughout. Critiques may range from short ad hoc critiques by peers, to short review with an expert, to a large scale critique by three or more experts in front of peers (Figure 211). Frequent feedback provides greater opportunity to experiment with design alternatives, "fail-fast" and increase iteration cycles which can help reach a better design result.

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[365] David Jonker. et al. "Aperture: An Open Web 2.0 Visualization Framework" In *System Sciences (HICSS), 2013 46th Hawaii International Conference on, IEEE*, pp. 1485-1494. 2013.
[366] M. Friendly and D. Denis, *Milestones in the History of Thematic Cartography, Statistical Graphics and Data Visualization: An Illustrated Chronology of Innovations.* http://datavis.ca/milestones/ (accessed June 12, 2016).
[367] Don Norman. *The Design of Everyday Things*. Basic Books. 2002.
[368] L. Byrne, D. Angus and J. Wiles. "Acquired Codes of Meaning in Data Visualization and Infographics: Beyond Perceptual Primitives." *Visualization and Computer Graphics, IEEE* Transactions on, 22(1), pp.509-518. 2016.
[369] J. Jones. "Information Graphics and Intuition Heuristics as a Techne for Visualization." *Journal of Business and Technical Communication*. 2015.
[370] T. Hanrahan in *Archiculture* (documentary film). Arbuckle Industries, Dec 17, 2014. 04:38. https://www.youtube.com/watch?v=62r3UPrOS9k (accessed June 8, 2016)

Figure 211. Critiques in the design studio: with peers; with an expert at a desk critique; within a larger forum of peers and experts. Images from the documentary film Archiculture by 2016 Arbuckle Industries, used with permission (www.archiculturefilm.com).

v. Objections to Use of Critique in Visualization

There may be objections to the use of critiques:

Science: Most visualization research and design in universities is associated with computer science and quantifiable scientific results are required. As Schön suggests, technical rationality has limitations. There are risks with evaluations that fit only within existing models (e.g. Tacoma Narrows bridge failure in 1940; or inadequate wind bracing of Citicorp tower).[371] If design is a component to the creation of effective visualization, then visualization needs to evolve beyond researching what can be measured. Similar to HCI, visualization will be better served by a transdisciplinary perspective that honors both the rigor of what is measurable as well as the nuances and subtleties of that which is not measurable.[372] Critique is a valuable addition to evaluation rather than forcing evaluations of experimental tasks which may not meet real user needs.[373]

Lack of Experts: Unlike architecture, medicine or graphic design, there are fewer visualization experts. However, experts can be engaged remotely. Furthermore, innovative solutions to similar problems may occur in human factors, graphic design, cartography, historic charts, typography, etc.

Need for History and Case Studies: The bitmaps in most papers are tiny and difficult to decipher. The original visualization may no longer be operable.[374] There is a need to identify better ways of documenting visualizations, their interactions, their use and how they handle various issues. Blevis argues that visual content (in his case, photographic essays) can be on par with the textual content in research papers.

Need for Design Rationale. Underlying concepts and design rationale may not be captured in research papers. Evaluations should consider whether design assumptions match the assumptions of the referenced technique.

Need for Secrecy. One objection that is expressed is the need for secrecy for funding or intellectual property reasons: non-disclosure agreements can be used to resolve this issue.

Assuming that objections to critique can be overcome, then critiques should be used in visualization evaluation and discourse. In this particular thesis, critiques have been successfully used to assess the progress and gaps and inform areas requiring additional focus as discussed in the next section.

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[371] J. Morgenstern, "The Fifty-Nine-Story Crisis" *The New Yorker*. May 29, 1995, pp 45-50.
[372] E. Blevis. Being Photo-Visual in HCI and Design. In Proceedings of the 2016 ACM Conference on Designing Interactive Systems (pp. 983-995). ACM. 2016.
[373] A. Dillon. "Reading from Paper versus Screens: A Critical Review of the Empirical Literature." *Ergonomics*, 35(10). pp. 1297-1326.
[374] R. Kosara, *The Bits Are Rotting in the State of Data Journalism.* July 13, 2016. http://bit.ly/29QArh1

D:1.2. Common Themes across Critiques

As this work is influenced by the prior knowledge of experts from across domains, it is ideal to seek out experts across domains for detailed, systematic analysis of these techniques. Critiques have focused on the larger body of work outlined herein and have been solicited throughout the development of this thesis. Early critical feedback has been incorporated into the framework and some of the examples (e.g. legibility and readability). Critiques have been received from typographers, cartographers and information visualization practitioners. The author has solicited specific critical analysis of various portions of a PhD thesis with 16 info vis experts, including three authors of visualization textbooks, five vis pioneers (authors of historic seminal research papers) and eight other vis researchers. Beyond vis, the author has solicited and received critiques from experts in typography, cartography, human computer interaction, financial services and bloggers. Some critical themes are common across domains:

i. Multiple Encodings: redundancy, noticing a difference, decoding the difference, intuitive mappings and semantic encoding

Redundant encoding. Many examples vary multiple visual attributes per label:

1) *Redundant encoding*: In some examples, multiple visual attributes encode the same data. For example, in the tag clouds in Figure 111P107, the labels use both color and size (left image), or both color and font weight (right image), to indicate the revenue of companies. This redundancy facilitates decoding as each attribute reinforces the interpretation. Redundant encoding can also facilitate differentiation in congested and partially occluded plots, such as the use of different colors and font styles per line in the microtext charts (Figure 129P131). This aids legibility when text is overplotted and aids visually tracing a path with more unique visual cues per line.
2) *Multi-attribute encodings* are used in many more examples. With a multivariate encoding, each visual attribute encodes a different data attribute, such as the typographic map in Figure 165P168 where text encodes unique country code (literal encoding), color encodes region (categoric encoding), font weight encodes GDP (ordered encoding), font spacing encodes growth (ordered encoding) and font slope encodes inflation (ordered encoding). These multivariate encodings depict more data elements per label but require more cognitive effort to decode and other perceptual problems described next.

Multi-attribute interference. Using multiple typographic attributes to convey multiple data points is an issue raised by most critics. There are well known examples of Gestalt patterns which are easily perceived as a single visual attribute but interfere with each other when combined. For example, hue and form are known to interfere with each other: given the tasks of discerning an overall horizontal or vertical separation within a field objects is a simple constant-time task when the objects vary only in hue or only in form. However when both hue and form vary, identification of the separation is slowest when it is conveyed by form (Figure 212).

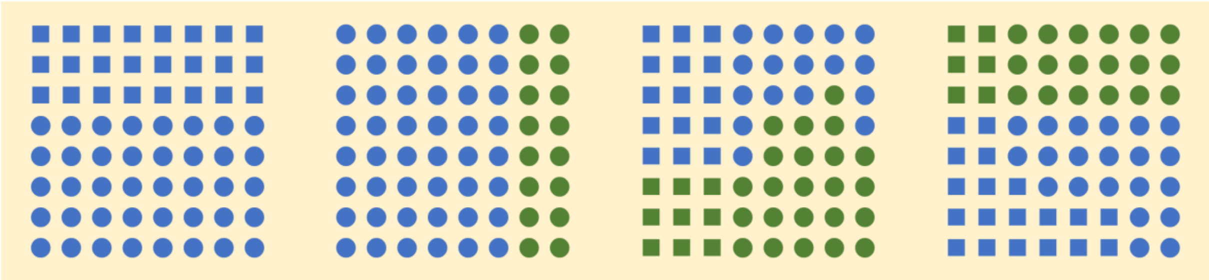

Figure 212. Multi-attribute interference: the vertical / horizontal boundary is fast to detect in a field where only one visual attribute changes (shape/color); slower to detect in a field where both change. Image created by author.

For example, in the proportionally encoded Wikipedia headlines (Figure 202P199), the length of uppercase is difficult to perceive, mixed with all the other changes in italics, bold and underline. Case alone might be easy to perceive. Understanding how these different attributes can be used together is important. Ware suggests that different visual channels should be used and these should be perceptually separable as opposed to integral[375]. Strobelt, for example, has evaluated the combination of some text highlighting cues.[376]

Noticing a Difference: Gestalt principles indicate that visually similar items are perceived as belonging together. The viewer immediately understands whether the two items are similar or different if their visual attributes are similar or different. When multiple visual attributes are used simultaneously, this difference can be effective. For example, in Figure 155P161 the use of font attributes readily distinguishes between adjacent elements belonging to the same set relations (homogenous attributes) or different relations (heterogeneous attributes). This differentiation can be perceived quickly and is meaningful even if the underlying mappings are not decoded.

Decoding a Difference: Decoding font attributes is a second step after noticing a difference. Short-term working memory only holds a small amount of information (3-7 items, e.g. Ware[377]). This implies cognitive challenges when encoding 10 memberships such as Typographic Graph (Figure 155P160), the five variable thematic maps (Figure 166P169: text, color, weight, slope and case) or the six variable proportionally encoded articles (Figure 202P199: text, color, weight, underline, italic and case). Furthermore, some typographic attributes rely on the same low level visual channel (e.g. case and font family both use shape) overloading the visual channel.

Encoding many different font attributes simultaneously onto a label may make it difficult for the viewer to decode all the memberships. In many use cases, interactivity can be used to aid decoding, for example:

- *Tooltips* can be used to immediately show memberships.
- *Toggle*. If the task is focused on a subset of set memberships, font attributes can be toggled on/off. Using SVG and JavaScript, toggling attributes can be done in a single line of code and has been implemented in some of the examples.
- *Search* can be used if the task requires locating a particular element. With SVG search can be done simply using the browser's find feature (ctrl+f).

[375] Colin Ware, Information Visualization: Perception for Design, third ed. (Waltham, MA: Morgan Kaufman, 2013): 157-172.
[376] Hendrik Strobelt et al, "Guidelines for Effective Usage of Text Highlighting Techniques," in *IEEE Transactions on Visualization and Computer Graphics,* 22, no. 1 (2016): 489–498.
[377] Colin Ware, Information Visualization: Perception for Design, third ed. (Waltham, MA: Morgan Kaufman, 2013): 157-172.

Some use cases, such as print, cannot use interactivity. However, some typographers were supportive of static multivariate encodings:

> *"I really liked the multivariate labels on the map. I like how it brings together all the different data. It's a bit like a puzzle that you can figure out, so it engages and stimulates you to analyze it. It could work on the back page of the Sunday paper."*

> *"The maps are a very interesting new way to deal with this data. We've done some projects with maps and healthcare data or with insurance data at a county level or zip level, and it's really hard to show what's going on in the urban areas and still show the other context. But these labels can show all the details."*

> *"As a type designer, I had never considered that so much extra information could be represented with type and that there are so many possible techniques for combining them. This is exciting."*

Intuitive Mappings: Decoding a multi-attribute label can be made easier when the mapping is specifically assigned to a connotative property rather than an arbitrary mapping. Many of the examples provided have deliberately chosen mappings, which are often recognized and commented on by audiences. For example:

- *Font oblique angle for political affiliation*. In Figure 148P152 the names of Democrats lean left, the names of Republicans lean right. American audiences viscerally react to the encoding (such as laughing or gasping). They also intuitively understand that independent senators (i.e. unaffiliated with either party) do not lean in either direction.
- *Font oblique angle for diverging scales*. More generally, oblique angles can slope from left to right working well for diverging scales where zero is indicated vertical non-sloping text.
- *Font weight for magnitude*. Using font weight for (non-zero positive) magnitude is used in many of the visualizations, for example, for income, counts, company size, etc. More ink associated with heavier font weights intuitively implies bigger data values.
- *Font width*: Can be used to indicate lengths, and in particular can be used to differentiate spoken characteristics of letters such as longer note duration in Figure 195P192.

Overall, critics are aware that the intuitive type is successfully taught and used in design, with some skepticism at how far the approach can be taken. Comments include:

> *"These techniques are really easy to understand. You can easily figure it out from the design choices for the encodings. You don't need any special training - the encodings make sense."*

> *"When you change the font features (i.e. font attributes) you change what text says. What you're doing is you are using the right features for the given applications so that the font feature properly expresses what you're trying to say."*

> *"When the choices are intuitive it makes the applications easy to understand."*

> *"It's very situational: it's all about using type the right way that best suits the task."*

> *"The music example is a bit of a stretch. I'm not sure I would have figured out the x-height being pitch without the explanation."*

Semantic Encodings: Going beyond intuitive mappings to semantic encodings was suggested by several critics from various domains, but is not explored in the thesis. Visualization researchers are aware of differences in font and the potential semantics associated with them. They are generally aware that *Comic Sans* semantically implies informality, that all caps semantically implies shouting and that manga manipulates type to indicate additional information such as urgency or sarcasm. How and where typographic semantic cues are best used within information visualization is still an open question for future research. There are many possible computational approaches to consider automating for semantic encoding:

1) Itemize conventions used in social media (e.g. ALLCAPS for shouting, strikethroughs for ~~unsupported~~ claims, etc.), poetry (e.g. concrete poetry, futurist poetry), comics and manga (e.g. WHISPER, ***ACTION***, *help!*, **POW!**, **DRAMATIC ENTRANCE**, **UGH!**, CREATURE, *transition*, ROBOT) to create a ruleset for semantic encodings. Digitized licensed fonts already exist which match these various conventions such as Comicraft, e.g. Figure 213 (via comicbookfonts.com), which could then be automatically applied to any subset of text classified by the ruleset.

Figure 213. Sample commercially available comic book fonts. Images via comicbookfonts.com and fonts.com.

2) As opposed to a heuristic ruleset, crowdsourced semantic attributes associated with fonts can be used (e.g. O'Donovan et al[378]). Current crowdsourced attributes are based on common popular web fonts (e.g. Arial, Times), not semantic fonts (such as comic book fonts, above, or the thousands of display fonts). Furthermore, the existing study confounds different font types, weights, italics and so forth.

3) Fonts already have descriptions associated with them, either by the designer or by convention of use (see discussion under *D:1.3.ii. Typographic Critiques*P226). These font descriptions can be converted into machine learning vectors, particularly focusing on descriptive adjectives and nouns associated with uses; which in turn could be combined with a computational analysis of content at some scope, e.g. sentence, paragraph, speaker in a play, etc., and then find the closest match in the high-dimensional vector space.

ii. Label Length Bias and Speed: longer text is more prominent

This concern seemed to be most prominent among visualization researchers and less prominent among typographers and cartographers. Labels instead of markers (such as dots) have a potential issue where longer labels may be more salient than shorter labels. For example, in the scatterplot of national parks in Figure 120P117, the length of park names varies widely, from the lengthy *Great Smoky Mountains* to the brief *Zion*. The concern is that long labels have greater prominence and can bias perception (e.g. Alexander et al).[379] Closely related are situations where a minimum label length (e.g. proportional formatting) or a maximum label length (e.g. names) is required.

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[378] Peter O'Donovan, Jānis Lībeks, Aseem Agarwala, and Aaron Hertzmann. "Exploratory font selection using crowdsourced attributes." ACM Transactions on Graphics (TOG) 33, no. 4 (2014): 92.

[379] Eric Alexander, Chih-Ching Chang, Mariana Shimabukuro, Steven Franconeri, Christopher Collins, and Michael Gleicher. "The biasing effect of word length in font size encodings." In *Poster Compendium of the IEEE Conference on Information Visualization.* 2016.

Label Length Solutions. There are many possible approaches, many of which have been shown in the various examples:

- **No adjustment.** Cartographers don't make adjustments to label lengths: *Rome* and *San Francisco* are labeled with a consistent font meaning the designer accepts that label lengths vary. Alexander et al show that viewers appropriately perceive even small variations in font heights and can respond appropriately – i.e. are not biased by length difference. Emotion Words (Figure 155P160) accepts this potential error and even uses encodings such as spacing (making strings wider) and baseline shifts (making strings taller) thereby increasing the error in the perception of areas. This may be somewhat offset by differences in density of characters, and mean reversion.
- **Mean reversion**. If using text in a sequence or clusters, a large number of words will tend to revert to an average word length, as shown in *Grimms Character Traits* (Figure 137P140).
- **Stack.** Alternatively, text can be stacked (Figure 140P142, Figure 148P152). With a common centerline or edge, the implied box around each length is consistent.
- **Use short mnemonic codes.** The equal area cartogram uses consistent three letter country codes (Figure 165P168): *Peru* becomes PER and *Philippines* becomes PHL.
- **Contract or truncate strings.** Some strings have well known contractions, e.g. Bklyn for Brooklyn. In the case of the *Titanic* passengers (Figure 150P154) all names are contracted to given name plus surname. Long strings can be forced to an arbitrary number of characters, followed by a period or ellipsis to indicate missing characters. See also Shimabukuro's thesis on crowd sourced abbreviations.[380]
- **Padding**. Extra content can be added to make all strings consistent length. Figure 202P199 adds a portion of the lead sentence to each title. Figure 203P199 adds ellipsis to make all strings the same length.
- **Condensed/Expanded (and/or intercharacter spacing)**. String lengths can be normalized as some fonts come in variable widths (e.g. expanded/condensed) and intercharacter spacing can be adjusted: the combination of these two could be used to compress long names and stretch short names as shown in Figure 139P141.
- **Make underlying point mark visually dominant**. Text labels can be associated with a consistently sized geometric container with a strong visual cue such as hue. This mark can be made with a wide aspect ratio to better suit long text. Longer labels can exceed the container as shown in Figure 168P170.
- ***Size** should NOT be used*! Size could be confused with the convention of using size to encode data commonly used on maps.
- **Toggle**. Use interactions to toggle between alternate marks, such as text and dots.

Area Comparison: Closely related to the bias in higher prominence of long labels is the related issue when groups of text are intended to be perceived as an area. A region formed of long labels will be larger than a region with the same number of labels that are short. This issue does not occur when using simple consistent icons to form areas. Various strategies can be used:

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[380] Mariana Shimabukuro,. "An Adaptive Crowdsourced Investigation of Word Abbreviation Techniques for Text Visualizations," 2017. Master's Thesis. University of Ontario Institute of Technology

- **Height**. Typographic Venn (Figure 148P152) uses stacked labels making perception of quantities a visual comparison of heights. Height comparison outperforms area estimation tasks as shown by Cleveland et al[381] and Heer et al[382]. The approach sidesteps the issue of variable string lengths.
- **Fixed length**: As per label length issue immediately prior, processing strings to have similar lengths (e.g. via truncation, padding, mnemonic codes or condense/expand) means that combinations of strings will have comparable areas.
- **Estimation of glyphs, not area**. Emotion Words (Figure 155P160) uses encodings such as spacing (making strings wider) and baseline shifts (making strings taller) thereby increasing the error in the areas formed by some types of labels. This is offset by differences in density of characters – that is – rather than perceiving the area, the viewer could perceive the relative number of characters within two comparable regions. This would need to be tested in future work.
- **Accept some degree of error.** Area estimation has a higher degree of error than height. Strangely shaped areas will also be more difficult to estimate and compare. Computational area measurement could be used to assess the degree of error and accept some error within the error bounds. Note the low error rate in the Typographic Mosaic most boxes (Table 14P156).

Speed and Accuracy of Perception: When adjusting labels, such as shortening or using codes, the level of error in perception of long strings vs. short strings may decrease – but there may be a corresponding increase in error in decoding the shorter string. Mnemonic codes in the typographic cartogram performed much better than a choropleth map for identification and location tasks as shown in Table 15P173. However, there was still 15-35% error rate: this error rate would be reduced to zero if full names rather than mnemonic codes were used.

Future work could include a set of experiments to evaluate whether there is a perception problem associated with longer strings, shortened strings and codes: perhaps people are conditioned by familiarity with map based encodings and aren't as prone to errors as anticipated – recent research indicates that people are not as biased as might be expected.[383] Assuming that problems do exist, then various alternative solutions should be evaluated.

iii. Why was Bertin's Research on Text Attributes Forgotten?

Most cartographers and a few visualization researchers are well acquainted with Bertin's research. Jacques Bertin was a cartographer and created the initial rational framework for visual encoding of thematic data with his text *Sémiologie Graphique* in 1967, which is a foundational reference for subsequent research in cartography and visualization. Interestingly, Bertin does discuss typographic attributes in the original French edition *Sémiologie Graphique* (1967), but restricted to four pages near the end of the work (pp. 412-415). These four pages (and only these four pages!) were dropped from the English translation in 1983. According to Bertin, literal text is a type of shape which is unambiguous. It is not selective (preattentive) and does not interfere with perception of visualization at an overall level. Bertin indicates that legibility of text is a key concern. Bertin's diagrams

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[381] William S. Cleveland and Robert McGill: "Graphical Perception: Theory, experimentation, and application to the development of graphical methods." in *Journal of the American statistical association* 79(387), 531–554 (1984)
[382] Jeffrey Heer and Michael Bostock. "Crowdsourcing graphical perception: using mechanical turk to assess visualization design." in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2010. 203-212.
[383] Eric Alexander, Chih-Ching Chang, Mariana Shimabukuro, Steven Franconeri, Christopher Collins and Michael Gleicher. "The Biasing Effect of Word Length in Font Size Encodings," Proc IEEE Information Visualization (InfoVis), Posters , 2016.

(*Sémiologie Graphique,* p. 415, fig. 2 & 3) identifies the following selective (categoric) typographic attributes: (1) the alphabetic glyphs, e.g. A,B,C; (2) font family, e.g. serif, sans serif, blackletter; (3) italic, including reverse italics; and (4) case, i.e. uppercase and lowercase; as well as the following orderable attributes: (5) condensed and expanded; (6) letter spacing, i.e. tracking; (7) size; and (8) font weight, e.g. bold, lightweight, black.

Bertin further expands on typographic encodings in the 1980 *Classification typographique: Voulez-vous jouer avec mon A*[384] (never translated to English). As shown in Figure 214, Bertin itemizes all the independent typographic attributes including size, intensity, weight, letter-spacing, condensed/expanded, letterform differentitaion including case, font fmaily, texture pattern, texture scale, italic/oblique, hue and serif/san serif. Bertin also indicates the scope of text ranging from letters to words, sentences, paragraphs, chapters and books. He differentiates between labels and running text and raises the issue of readability. Bertin claims that the eye can detect height differences as small as 1/20 mm (!). Bertin concludes that the independent attributes of type can be brought together in new ways to profoundly transform linear designs of catalogs and classifications.

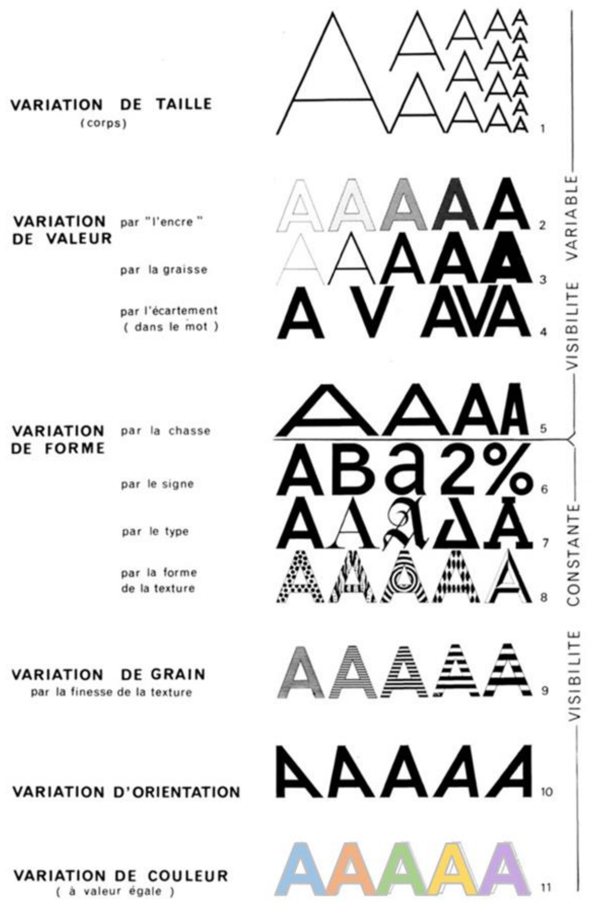

Figure 214. Bertin's typographic variables. Image copyright Jacques Bertin.

The critique goes beyond pointing out the overlap of Bertin's research **51 years** before this thesis. The more important question is: why was Bertin's work on typographic attributes skipped over, untranslated and remain obscure? There are many possible answers to speculate:

384 Jacques Bertin, "Classification typographique : Voulez-vous jouer avec mon A" In *Communication et langages,* n°45, 1er trimestre 1980. pp. 70-75. doi : 10.3406/colan.1980.1369 http://www.persee.fr/doc/colan_0336-1500_1980_num_45_1_1369

- **No compelling examples**. Bertin himself never provided any compelling examples of type. *Semilogy of Graphics* contains 400 pages packed with more than 1000 maps and visualizations illustrating many different combinations of visual attributes. However type occurs only in a literal use in a single example and there are **no** examples of type attributes used to convey data in either the book or article.
- **Technology**. Bertin published during the period of photocomposition and phototypesetting. Photographic techniques were faster and inexpensive compared to metal type and engraving – but sacrificed fine detail. Says Frutiger (designer of font *Univers*):

  > *"I nearly had to introduce serifs in order to prevent rounded-off corners – instead of a sans serif the drafts were a bunch of misshapen sausages!"*[385]

  This was immediately followed by early computers, also with poor representation of detail on screen (low resolution) and in print (e.g. dot matrix) resulting in jagged fonts: Frutiger again:

  > *"Coarse resolution would result in a stair-step effect on curves and diagonals that was referred to as the jaggies."*

  Only since Apple introduced *Retina* displays starting in 2012 did resolutions increase so that:

  > *"The human eye is unable to distinguish individual pixels when held at a normal distance, making web pages,* ***text****, images and video look incredibly sharp and realistic."*[386]

- **Thematic Map vs. Label Map Split***:* Bertin would have known of hundreds if not thousands of multivariate label based encodings in maps (such as the examples in *B:1.2.Historic Cartographic Examples*P33). Bertin's research may have been intentionally focused on the non-textual visual attributes to provide an explicit framework for these.
- **Thematic/Label Completely Different**. Bertin may have been unwittingly influenced by the 200 year split between label-based maps and thematic maps (*C:5.2: Thematic Map split from Labelled Maps*P166) – meaning that labelled maps were not considered by Bertin to be a thematic map.
- **500 Years of Separation between text and image**. As discussed in the introduction (*A:2: Missd Opportunity: 500 years of separation*P5) the long on-going bias to separate text from image may be an implicit goal in Bertin's work.
- ***Modernism****:* The *International Typographic Style* was part of the broader *International Style* sweeping across the world in the 1950's promoting international trade and communication. Modernism emphasized simplicity, cleaness, readability, as well as minimizing language-specific text in favor of non-language icons and symbols (e.g. see Tschihold on typography,[387] Le Corbusier[388] and Banham[389] on architecture). Modernists responsible for graphic communication would prefer simpler thematic maps and symbols. Isotype[390] was created during the early formation of modernism (Figure 215 left); followed by standardized symbols for international signage,[391] (Figure 215 right) then more broadly by standardized symbols.[392]

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[385] Heidrun Osterer and Philipp Stamm. *Frutitger – Typefaces: The Complete Works*. Walter de Gruyter, 2014. Page 80.
[386] Apple Computer Press Release. *Apple Launches New iPad*. March 27, 2012. https://www.apple.com/newsroom/2012/03/07Apple-Launches-New-iPad/
[387] Jan Tschichold. *The New Typography*. (R. McLean, trans.) University of California Press. Berkeley, CA. (1928/1995).
[388] Le Corbusier. *Towards a New Architecture*. Translated by Frederick Etchells. London: J. Rodker, 1931. Reprint New York: Dover Publications, 1985.
[389] Reyner Banham. *Theory and Design in the First Machine Age*. New York: Praeger, 1960.
[390] Otto Neurath. *From hieroglyphics to Isotype: a visual autobiography*. Hyphen Press, 2010.
[391] Roger Cook and Don Shanosky, AIGA Signs and Symbols, 1974. https://www.aiga.org/symbol-signs/
[392] Henry Dreyfuss, *Symbol sourcebook: an authoritative guide to international graphic symbols*. John Wiley & Sons, 1984.

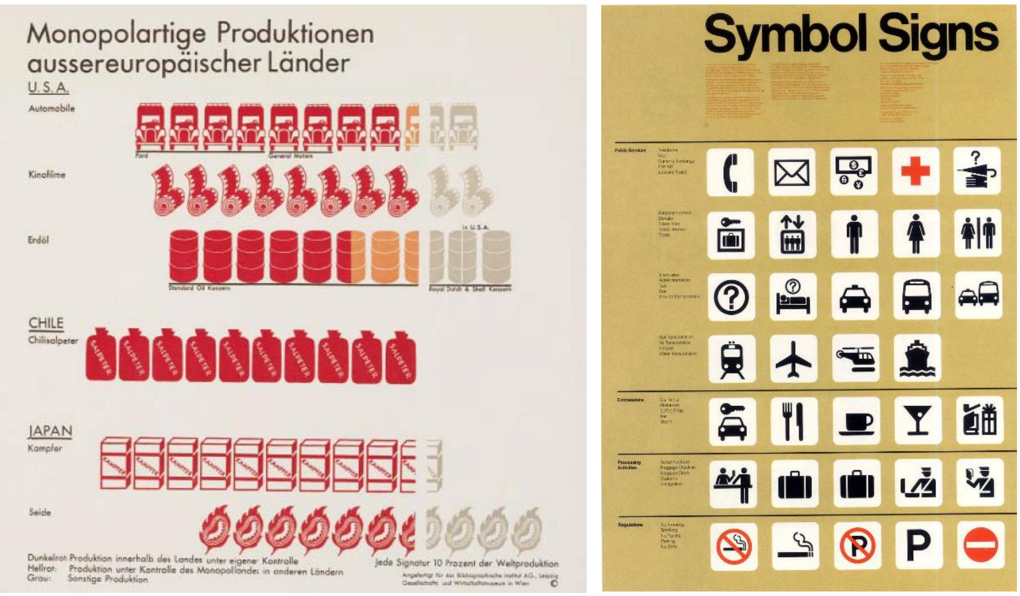


Figure 215. Left: portion of statistical visualization comprised of pictographic icons by Gerd Arntz from 1930. Right: standardized transport icons from 1974. Image: © Gerd Arntz Estate c/o Pictoright 2017, (http://gerdarntz.org/node/710/) used with permission. Right: free symbol signs from AIGA (https://www.aiga.org/symbol-signs).

- **Paper vs. Small Screens**. Paper is a medium suitable for very large displays at very high resolution and very fine detail (such as text). Computer displays in Bertin's time through to a few years ago were much lower resolution than paper, and have a smaller field of view. Mobile devices in particular have a very small field of view, meaning that a large map with thousands of labels can't be consumed in the same way: the viewer is always isolated to small zone with perhaps only tens of labels.
- **TLDR**. The Internet acronym TLDR means *too long: didn't read* and is used in reference to blog posts and other internet articles that viewers perform a superficial reading (e.g. first paragraph only). In an age of short attention spans and timeframes, visual journalism tends towards small simple graphics. A clear simple thematic map of a single variable is far easier to consume and more viscerally engaging than the label-based alternative. The *New York Times* claims to be shifting away from small interactive visualizations to larger visualizations with more commentary, although the visualizations seem to be largely high-resolution thematic maps with low labels.[393]

Regardless of Bertin's constraints and bias, the issue remains regarding the adoption of text and font attributes in visualization. This thesis presents a broader framework, and, many new use cases with illustrated examples to encourage adoption and spur creative new uses. At the same time device resolution is increasing thereby making the use of finely detailed text more feasible; and the increase in natural language processing, social media analytics and text analytics is increasing the demand to consume the results of text processing in ways beyond simple collections of words.

[393] Archie Tse. "Why we are doing fewer interactives." Malofiej 2016. https://github.com/archietse/malofiej-2016/blob/master/tse-malofiej-2016-slides.pdf.

iv. How many visual dimensions: 16-20?

One curiosity question that arises many times is the notion of how many different independent visual attributes can be combined together? The work here discusses a dozen typographic attributes, in addition to other well known attributes (e.g. color, texture, orientation).

A quick experiment can be made with a typographic graph: how many different sets can be depicted, each using a different visual attribute, so that all different combinations can be unambiguously represented. Using Pokémon as starting point, there are 151 different Pokémon, each with one or more of 16 different skill types. Using a visual attribute such as hue is problematic: given 16 different starting point colors, it is not feasible for the viewer to decode which colors are in any given combination. Pokémon of more than one type can end up with muddy, hard to distinguish, hard to decode colors, e.g.: purple + green = greyish brown; or orange + blue = brownish grey. The problem is that the original palette of 16 colors is being used to encode 16 separate categories. Attempting to combine these colors results in 128 possible colors (16×16/2). Unfortunately, human perception cannot readily identify 128 different colors.

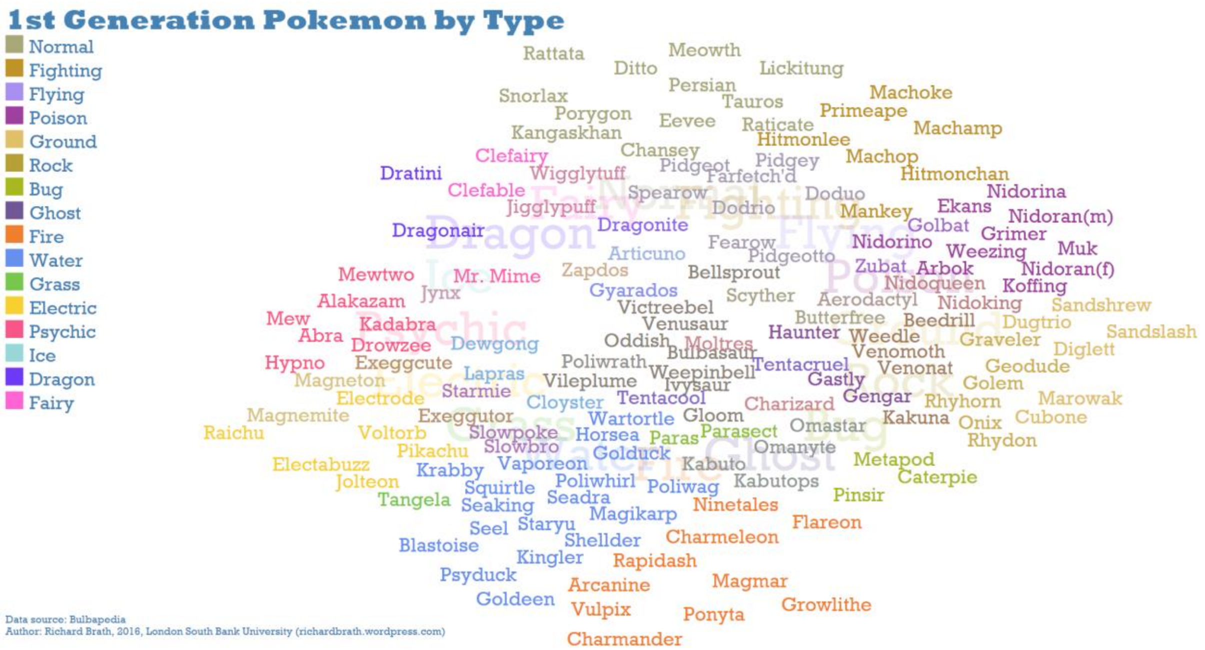
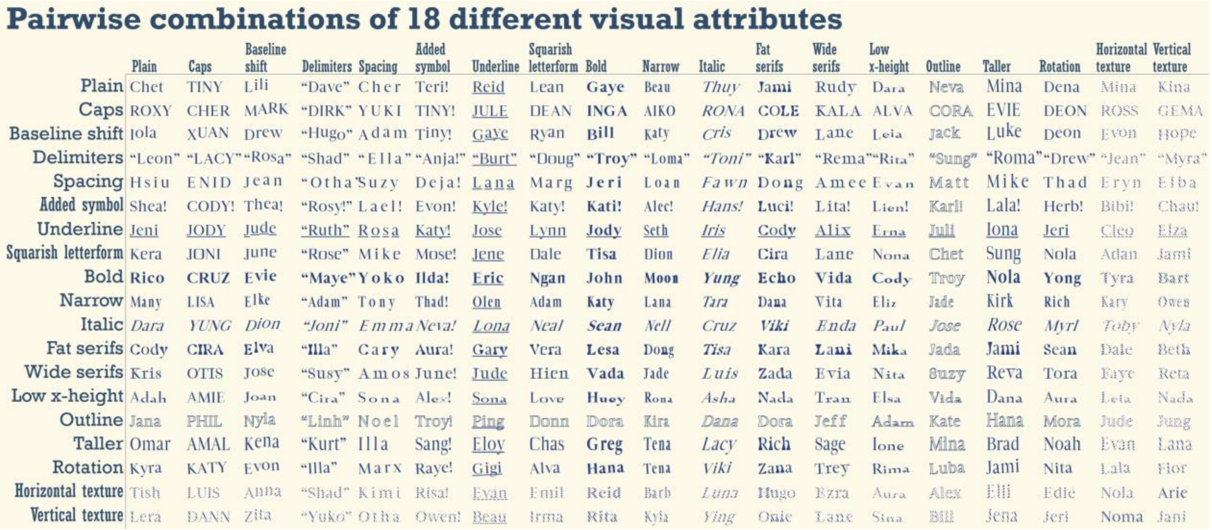


Figure 216. 151 Pokémon, set out and colored by their different skill types (large colored text). Some Pokémon have more than one skill type and the resulting color combinations cannot be decoded by the viewer. Image created by author.

Instead, 16 different visual attributes could be used. Each needs to be mutually independent, and usable in any combination. There are many attributes that could be used, as shown in Table 1, including common visual attributes (e.g. rotation, texture, motion, shape, shadow, outline, etc.) and typographic attributes (e.g. bold, italic, case, underline, baseline, serif type, etc.). Some combinations are not feasible or not recommended, e.g. shadows on text reduces text legibility; shape is difficult to combine with text; and motion does not work in print media.



Pairwise combinations of 18 different visual attributes

	Plain	Caps	Baseline shift	Delimiters	Spacing	Added symbol	Underline	Squarish letterform	Bold	Narrow	Italic	Fat serifs	Wide serifs	Low x-height	Outline	Taller	Rotation	Horizontal texture	Vertical texture
Plain	Chet	TINY	Lili	"Dave"	Cher	Teri!	Reid	Lean	Gaye	Beau	Thuy	Jami	Rudy	Dara	Neva	Mina	Dena	Mina	Kina
Caps	ROXY	CHER	MARK	"DIRK"	YUKI	TINY!	JULE	DEAN	INGA	AIKO	RONA	COLE	KALA	ALVA	CORA	EVIE	DEON	ROSS	GEMA
Baseline shift	Iola	XUAN	Drew	"Hugo"	Adam	Tiny!	Gaye	Ryan	Bill	Katy	Cris	Drew	Lane	Leia	Jack	Luke	Deon	Evon	Hope
Delimiters	"Leon"	"LACY"	"Rosa"	"Shad"	"Ella"	"Anja!"	"Burt"	"Doug"	"Troy"	"Loma"	"Toni"	"Karl"	"Rema"	"Rita"	"Sung"	"Roma"	"Drew"	"Jean"	"Myra"
Spacing	Hsiu	ENID	Jean	"Otha"	Suzy	Deja!	Lana	Marg	Jeri	Loan	Fawn	Dong	Amee	Evan	Matt	Mike	Thad	Eryn	Elba
Added symbol	Shea!	CODY!	Thea!	"Rosy!"	Lael!	Evon!	Kyle!	Katy!	Kati!	Alec!	Hans!	Luci!	Lita!	Lien!	Karl!	Lala!	Herb!	Bibi!	Chau!
Underline	Jeni	JODY	Jude	"Ruth"	Rosa	Katy!	Jose	Lynn	Jody	Seth	Iris	Cody	Alix	Erna	Juli	Iona	Jeri	Cleo	Eiza
Squarish letterform	Kera	JONI	June	"Rose"	Mike	Mose!	Jene	Dale	Tisa	Dion	Elia	Cira	Lane	Nona	Chet	Sung	Nola	Adan	Jami
Bold	Rico	CRUZ	Evie	"Maye"	Yoko	Ilda!	Eric	Ngan	John	Moon	Yung	Echo	Vida	Cody	Troy	Nola	Yong	Tyra	Bart
Narrow	Many	LISA	Elke	"Adam"	Tony	Thad!	Olen	Adam	Katy	Lana	Tara	Dana	Vita	Eliz	Jade	Kirk	Rich	Kary	Owen
Italic	Dara	YUNG	Dion	"Joni"	Emma	Neva!	Lona	Neal	Sean	Nell	Cruz	Viki	Enda	Paul	Jose	Rose	Myrl	Toby	Nyla
Fat serifs	Cody	CIRA	Elva	"Illa"	Cary	Aura!	Gary	Vera	Lesa	Dong	Tisa	Kara	Lani	Mika	Jada	Jami	Sean	Dale	Beth
Wide serifs	Kris	OTIS	Jose	"Susy"	Amos	June!	Jude	Hien	Vada	Jade	Luis	Zada	Evia	Nita	Suzy	Reva	Tora	Faye	Reta
Low x-height	Adah	AMIE	Joan	"Cira"	Sona	Alex!	Sona	Love	Huey	Rona	Asha	Nada	Tran	Elsa	Vida	Dana	Aura	Leta	Nada
Outline	Jana	PHIL	Nyla	"Linh"	Noel	Troy!	Ping	Donn	Dora	Kira	Dana	Dora	Jeff	Adam	Kate	Hana	Mora	Jude	Jung
Taller	Omar	AMAL	Kena	"Kurt"	Illa	Sang!	Eloy	Chas	Greg	Tena	Lacy	Rich	Sage	Ione	Mina	Brad	Noah	Evan	Lana
Rotation	Kyra	KATY	Evon	"Illa"	Marx	Raye!	Gigi	Alva	Hana	Tena	Viki	Zana	Trey	Rima	Luba	Jami	Nita	Lala	Flor
Horizontal texture	Tish	LUIS	Anna	"Shad"	Kimi	Risa!	Evan	Emil	Reid	Barb	Luna	Hugo	Ezra	Aura	Alex	Elli	Edie	Nola	Arie
Vertical texture	Lera	DANN	Zita	"Yuko"	Otha	Owen!	Beau	Irma	Rita	Kyla	Ying	Onie	Lane	Sina	Bill	Jena	Jeri	Noma	Jani

Figure 217. 18 different visual attributes applied to labels showing all pairwise combinations. Image created by author.

Figure 217 shows 18 different label variations across the top row and first column: the middle of the table shows all 162 pair combinations. Each cell is uniquely different from its neighbors. With some cognitive effort, the viewer can determine which attribute is different in each case. The attributes are plain serif, upper case, shifting baseline, surround quotes, tracking (i.e. spacing), exclamation mark, underline, boxy version of font, bold, narrow version of font, italic, deep brackets on serifs of font, wide serif version of font, low x-height version of font, outline version of font, tall stretched version, rotated, horizontal stripe texture, vertical stripe texture.

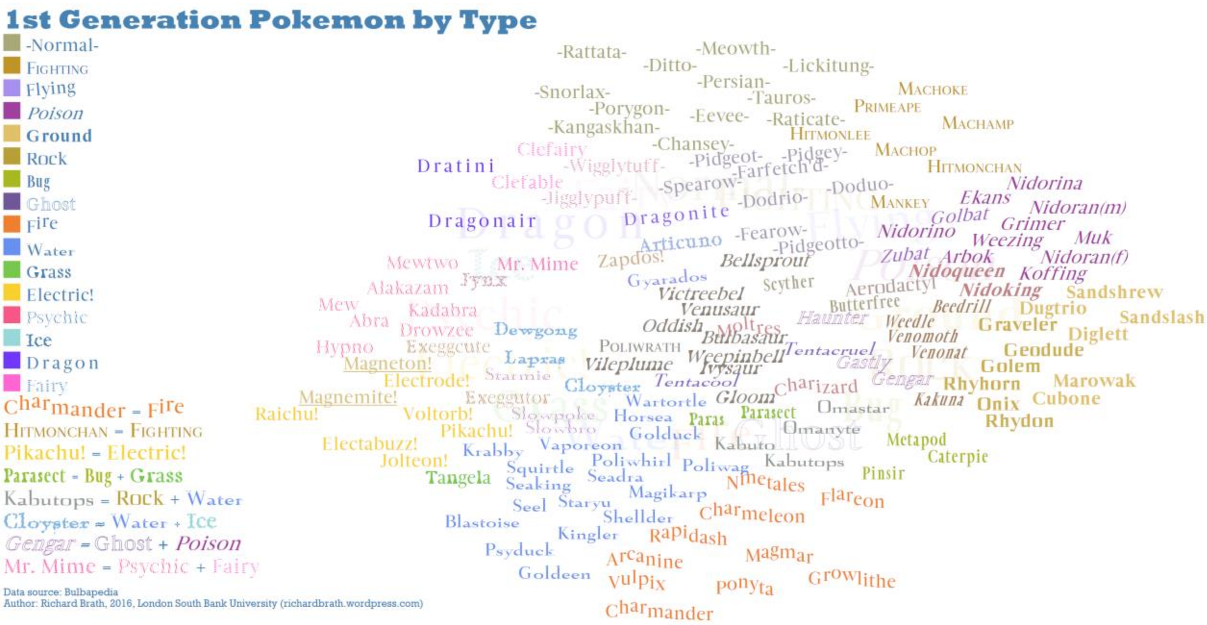


Figure 218. Pokémon skill types indicated with 16 different visual attributes in various combinations. Image created by author.

Figure 218 shows the same Pokémon with skill type indicated by attribute: small caps for fighting, slightly rotated text for flying, italics for poison, and so on. Attributes can be used together in any combination. Figure 219 shows some examples of combinations.

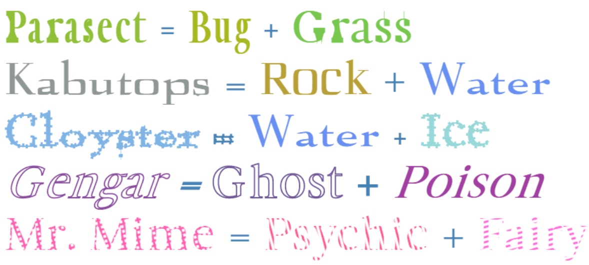


Figure 219. Examples of multiple visual attribute combinations in Pokémon names. Image created by author.

This quick experiment shows 16 different visual attributes, plus the literal name, plus the three dimensions of hue and the underlying x.y spatial layout all working together to encode a high number of dimensions. While addressing the question of curiosity, the solution is of questionable effectiveness and the use of many different visual attributes simultaneously is an open research area.

v. Economic and Innovation Discussion

Critiques suggest that there is some value in these approaches and that there is applicability at different levels from characters to words to longer text. Whether or not these techniques have economic value is an open question. One measure is perhaps the breadth of interest in a new technique. Research in font-specific attributes applied to visualization has gained interest from different domains including text visualization, information visualization, typography, and information search, including the author's research, as well as Strobelt.

Moreover, the frameworks define areas for future innovation that are untouched. For example, the analysis of document corpuses are often reduced to topics, keywords, graphs and such. But the design space suggests the possibility of textual views across an entire corpus - which is now technically feasible using extremely high-resolution display walls such as Hyperwall2, a 250 mega-pixel display. Or font-attributes such as paired delimiters may have some novel encoding potential for indicating groupings among non-alphanumeric attributes such as glyphs or table cells.

Finally, the cross-disciplinary context implies that, at a minimum, the use of text in visualization can be aesthetically enhanced, given the beautiful examples in high-resolution print environments such as maps and genealogical charts. Research into aesthetics can be challenging to do in evidence-based, experimental methods used in computer science. New methods for experimenting with aesthetics may be required.

vi. Visualization Pipeline Reconsideration

The analysis and discussion raises interesting questions about evaluation of the broader visualization pipeline (Figure 13[P18]). Optimizing a design for one stage of the pipeline may impact other stages. For example, an encoding that can be perceived quickly does not mean it can be decoded easily. In the labeled cartogram (Figure 165[P168]), textual encoding of countries may perhaps be slower to search for, but the decoding of countries may be faster, enhanced by mnemonic three letter codes which facilitate recognition.

Typographers, for example, point to Tall Man Lettering as an example where type is designed to perceptibly make some syllables stand out and be specifically disruptive to reading. This is used to differentiate key syllables in look-alike drug names, which appear on computer screens, tiny labels, dispensaries, hand-written prescriptions and other applications (Figure 220).[394] The goal is to reduce errors of confusion which can be fatal. The design solution is a counter-intuitive disruption of the differentiating syllable, which may aid comprehension.[395]

Sample Tall Man Lettering of Look-Alike Drugs

Uppercase	Lowercase	Tall Man
MEDROXYPROGESTERONE	medroxyprogesterone	medroxyPROGESTERone
METHYLPREDNISOLONE	methylprednisolone	methylPREDNISolone
METHYLTESTOSTERONE	methyltestosterone	methylTESTOSTERone
VINBLASTINE	vinblastine	vinBLAStine
VINCRISTINE	vincristine	vinCRIStine
HYDROXYZINE	hydroxyzine	hydrOXYzine
HYDRALAZINE	hydralazine	hydrALAzine

Figure 220. Tall Man letters accentuate differences in central syllables of similar drug names to reduce potential for error. Image created by author.

More holistic evaluations aligned with broader system goals need to be considered. This has long been an issue discussed between typographers and experimenters. For example, Dillon points out that ergonomists are so concerned with control over variables that the experimental task bears little resemblance to the activities that most people routinely do when reading.[396] Similarly, some visualization designers point to the need for broader evaluative techniques, such as Tory and Möller[397] and Kosara.

D:1.3. Domain-Specific Critiques of Text Visualization

Some criticisms are limited to specific domains, given a bias or depth of knowledge in that domain. Some of these are highly relevant across domains, some show lack of awareness of other domains.

i. Information Visualization Critiques

Information visualization critiques largely have focused at two different levels: that of individual words, since labels are pervasive throughout data visualization; and everything else (lines, paragraphs, documents, glyphs). Criticisms and discussion include:

- **Is this even data visualization***:* The biggest contention is whether or not text can be considered an element of visualization. Purists may define visualization as a process which utilizes visual encodings that are preattentive (automatically perceived) and text requires active attention to be perceived (controlled processing): therefore text is not visualization. However, font-attributes, such as **bold**, clearly utilize preattentive features, thus this argument is really focused on whether the framing of the design space includes literal encodings. Furthermore, the authors argue that literal encodings are part of the design space: for example, replacing a dot on a scatterplot with an alphanumeric character preserves

[394] "FDA and ISMP Lists of Look-Alike Drug Names with Recommended Tall Man Letters," ISMP Institute for Safe Medication Practices, last modified Dec. 17, 2010. http://www.ismp.org/Tools/tallmanletters.pdf
[395] Connor Diemand-Yauman, Daniel M. Oppenheimer, and Erikka B. Vaughan. "Fortune favors the (): Effects of disfluency on educational outcomes." *Cognition* 118, no. 1 (2011): 111-115.
[396] Andrew Dillon, "Reading from Paper versus Screens: A Critical Review of the Empirical Literature", *Ergonomics,* 35(10), 1297-1326.
[397] Tory, Melanie, and Torsten Möller. "Evaluating visualizations: do expert reviews work?." *Computer Graphics and Applications*, IEEE 25, no. 5 (2005): 8-11.

the initial reading of the scatterplot (i.e. location of data points), increases data density (by adding additional information with the character), and allows for perception of associative micro-patterns (i.e. local adjacencies) that otherwise would require interactive techniques to reveal.

- **Are these really new attributes**: One researcher considered font-attributes just variants on established attributes, for example font weight is effectively the same as intensity since both representations vary the amount of "ink" encoding the data. From a typographic perspective, these are not the same: font weight varies the stroke width, maintaining high contrast against a background regardless of the weight. Intensity, however, varies the brightness of the text thereby reducing contrast to the background and reducing legibility. At the end of 2015, nine examples in the *Text Visualization Browser* used intensity to encode data while none used weight, suggesting a lack of awareness that a similar effect to brightness could be achieved using font weight while enhancing contrast and legibility.

- **Aesthetics**: Some researchers expressed personal opinions that font attributes do not have the same visceral appeal as bright colors or size differential. This criticism indicates both strength and weakness of type. Type is unlikely to replace other existing visualization techniques when dramatic visual representations are desired. The corollary is that type variations may be particularly effective for other tasks such as analytical tasks, monitoring tasks and reading.

- **Layout Algorithms:** Unlike dots or icons, labels have an aspect ratio that is wider than tall. This impacts layout algorithms. Typographic Mosaic generated more accurate areas when favoring wider boxes over taller boxes. The initial Typographic Graph used a collision detection algorithm which assumed square proportions of elements and tended to push text apart vertically rather than horizontally, necessitating adjustments to the layout algorithm. Layout algorithms need to be adjusted for text, and need to work with both horizontally oriented text and vertically oriented text.

ii. Typographic Critiques

A subset of examples from *PART C: Applications of Typographic Visualizations*P108-205, were presented at a type conference (TypeCon2015)[398] followed by reviews with specific attendees (including at least one online review)[399] and direct engagement with typography experts and students at the University of Reading Department of Typography over a two week intensive typography course. Reviews have generally been positive along with appropriate skepticism for some techniques. Interestingly, after two years of research with critique from many information visualization designers, typographers raise different issues than visualization researchers:

- **Legibility** is a key concern to typographers but unexpressed by visualization researchers. Legibility typically was not an issue in the visualizations, except:

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[398] Richard Brath and Ebad Banissi, "Using Type to Add Data to Data Visualizations", *TypeCon 2015*, Denver (2015). https://richardbrath.files.wordpress.com/2015/08/typecon2015_paper_r2.pdf , accessed August 15, 2015.
[399] Nathan Willis, "Data Visualizations in Text", http://lwn.net/Articles/655027/ , accessed April 14, 2015.

- *Too many levels:* Too many levels or fine detail may not be perceivable, particularly at smaller sizes. For example, the use of five levels of font weight in headlines (Figure 205P200 middle) was problematic as not all levels are uniquely perceivable.
- *Text too small:* One viewer of microtext line charts (Figure 129P131) could not read the text as it was too small to be legible. Interactive control over font size was required.
- *Text format may create legibility issues:* Strobelt's formatting techniques, particularly drop-shadows, may have a negative impact on legibility.

- **Readability** is another important concern for typographers. In particular, a number of typographers expressed concern that changing more than a singular attribute can impact readability of text strings longer than a few words in length: for example, Figure 201P198 simultaneously varies weight, underline, italic and case which reduces readability. There are variations in opinions, also seen in typography texts: for example, Kane indicates multiple attributes can be combined to create contrast[400] whereas Bringhurst indicates that a sudden shift across multiple type attributes does not follow conventional typographic grammar.[401] Further typographic mixing many attributes examples can be found. For example, dictionary entries use text with many simultaneous variations in font attributes (Figure 221).[402] Tracy suggests that readability is not as important in works such as directories or tables where the viewer is not reading continuously but searching for an item of information.[403]

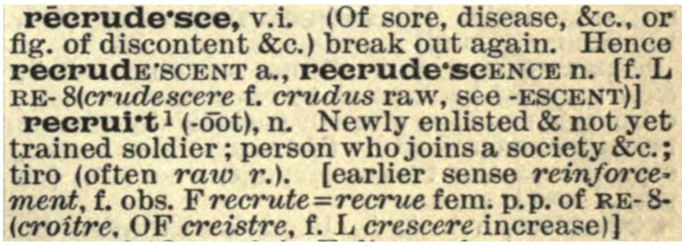
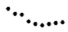

rēcrude'sce, v.i. (Of sore, disease, &c., or fig. of discontent &c.) break out again. Hence **recrude**'SCENT a., **recrude'sc**ENCE n. [f. L RE- 8(*crudescere* f. *crudus* raw, see -ESCENT)]
recrui't¹ (-ōōt), n. Newly enlisted & not yet trained soldier; person who joins a society &c.; tiro (often *raw r.*). [earlier sense *reinforcement*, f. obs. F *recrute*=*recrue* fem. p.p. of RE- 8- (*croître*, OF *creistre*, f. L *crescere* increase)]

Figure 221. Sample definitions using bold, italics, small caps, upper case, italics, paired delimiters and special characters. From *The Concise Oxford Dictionary of Current English* (1912). Not in copyright (accessed Feb 12, 2016 via archive.org/stream/conciseoxforddic00fowlrich).

If the primary task is reading, then even a singular strong cue, such as font weight, may be disruptive, because it is difficult to ignore. Some typographers consider italics as form of quiet emphasis, less disruptive to reading than a strong form of emphasis, such as bold.

- **Sparklines**. Most examples in this thesis put type into visualizations and a few modify type in place (e.g. in lines or paragraphs) to encode data. However, the thesis doesn't address visualizations embedded into running text such as sparklines popularized by Edward Tufte, such as this example distribution  or this timeseries plot of £/$(US) Oct 2015 – Sept 2017: from 1.55  down to 1.28. Sparklines are a promising technique, potentially useful on small screen devices where there is not a lot of space for both text and separate graphics. Technically, a sparkline created out directly out of

[400] John Kane, *A Type Primer,* Pearson Prentice Hall, Upper Saddle River, NJ (2011): 62-63.
[401] Robert Binghurst, *The Elements of Typographic Style* (Hartley & Marks, Publishers, 2004): 55.
[402] Paul Luna, "Clearly defined: Continuity and innovation in the typography of English dictionaries", Typography Papers 4, 2000, 5-56.
[403] Walter Tracy, *Letters of Credit: A View of Type Design,* (Jaffrey, New Hampshire: David R. Godine Publisher, 2003): 31.

numerical data and a font-file with no code (e.g. the experimental font *AtF Spark* used in the two sparklines above) enables easier sparkline creation in running text compared to mixing multiple technologies.

More broadly, sparklines represent an alternative to other inline techniques presented herein such as proportional encoding or skim formatting. For example, weights associated with words in skim formatting could be represented with bars per word, however, excessive bars embedded in the flow of text would interrupt readability. With respect to proportional encoding, presumably very narrow bars at the lead of each (line/phase/sentence) could be used, however at a cost of (a) using space that would accommodate a few extra characters; and (b) clutter up space in plots, such as a scatterplot with both dots and labels as opposed to labels only.

SparkWords are a variant introduced in this thesis: instead of embedding lines or bars into text, words are directly modified in place to indicate categoric or quantitative data regarding entities, such as the example in Figure 189P187 or this list of Canadian cities from west to east weighted by population:

<500k, 500-1m, 1-2, 2-5, >5m: Vancouver, Calgary, Edmonton, Saskatoon, Winnipeg, Toronto, Ottawa, Montréal, Québec, Halifax

Similar to Tufte's original intent to embed quantities into text, sparkwords can be read in the context of the content without needing to cross-reference a separate figure – however, like a sparkline, some additional information is required to provide an indication of the data range, such as the start and end numeric values with the currency sparkline above, the legend at the beginning of the list of Canadian cities above, or the parenthetical distributions in Figure 189P187.

- **Interactivity** is a potential means to address issues of readability, ease of understanding and also enhance functionality for any multivariate encoding. One typographer demonstrated that the skim formatting technique could be easily toggled back and forth between the non-formatted text and the skim formatted text. In skim formatting, some words are lighter (and slightly narrower) while some words are heavier (and slightly wider). On the balance the overall line lengths remain the same, preserving the relative positions of words across both formats (see the side by side comparison in Figure 222). This allows for an interactive toggling between both formats and the eye can maintain focus on a particular position in the text across the transition. Thus, interactive toggling can be a means to achieve the best readability and a highly-effective pop-out of skimming. Interactive font-attribute manipulation for skim formatting had not been considered prior to this.

  Another typographer noted how readers adapt over time to new fonts and layouts. An interactive approach to skim formatting could allow for incremental adaptation. As the reader becomes more accustomed to the system the encoding could be adjusted to an optimum level.

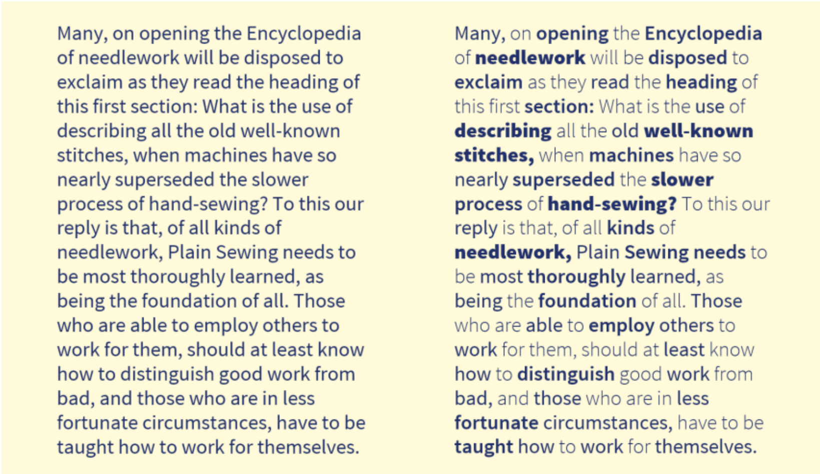


Figure 222. Side by side comparison of the opening paragraph of the *Encyclopedia of Needlework.* Note how relative word positions are maintained between the two versions. Image created by author.

- **Language**. Typographers are concerned about extensibility across languages. All examples shown use Latin-based character sets. Going beyond Latin, there are languages that do not have the same font attributes (e.g. case). Also, languages that represent words with single glyphs will have different considerations: inter character spacing is not available, encoding separate characters within a word is not feasible, and so on. More importantly, while typographic attributes are feasible in many languages, they may not be available in a digitized format. Scripts with hundreds or thousands of characters and many associated rules for forming ligatures can be difficult and laborious to digitize. For example, Bengali has a wide range of typographic attributes as seen in sign paintings, but computationally, only plain and bold exist. Devanagari has 37 consonants and more than 800 ligatures: compared to the Latin alphabet, it is much more expensive for a type designer to create a new variant of Devanagari, meaning few variants are available.

- **Intuitive Mappings** make it easy to decode multi-attribute labels. Most of the examples use encodings that have been specifically chosen as opposed to random assigned. For example, in Figure 165P168, heavier font weights intuitively indicate larger incomes. This, in turn, allows for multi-variate labels to be created that are engaging and stimulating rather than cognitively burdensome, although there is a tradeoff with the readability issue for multi-variate labels.

- **Semantic Encoding** is also an issue raised by typographers in addition to visualization researchers. Typographers have a deep set of semantic associations with various fonts. These semantics be explicitly documented by the designer or they may become inherited with use. For example, consider the descriptions associated with the fonts shown in Figure 223 (via fonts.com, Wikipedia, microsoft.com/typography, and font blogs):
    - *DIN*: is a font designed for industrial uses, widely used for traffic, administrative and technical applications.
    - *Bodoni*: is often associated with high fashion given high contrast and crisp serifs requiring high quality paper to print well. It is used with many fashion magazines and fashion logos.

- *Akzidenz Grotesk*: is used for publicity material, advertising, tickets and forms.
- *Cooper Black*: is a warm and friendly typeface with blunt rounded forms and blurred serifs.
- *Century Schoolbook*: is a round open sturdy no-nonsense font that generations of children have learned to read with.
- *Eurostile:* originally designed for headlines, signs and modernity in general, it has become it has been extensively used with - and is now associated with - science fiction, particularly *Eurostile Bold Extended*.[404]

Figure 223. Sample typefaces and their semantic associations. Image created by author.

In the visualization examples provided in *PART C*, these semantic associations of font are only marginally considered – for example, a blackletter font is associated with angry words in Figure 156P161. For the most part, this thesis does not consider the semantics of typographic attributes and how those might be encoded, nor does the framework as provided have any indication of how and where the semantic elements of typography fit. This is an area suitable for future work.

iii. Cartographic Critiques

Given that cartographers have long understood the use of both text and visualization, they share some similar concerns to both typographers and visualization experts, such as legibility, readability, semantics and Bertin, discussed earlier. Since cartographers do use text in visualizations, they are also aware of some issues when encoding with text. For example:

- **Perceptual bias with font attributes:** Interestingly, a cartographic critique pointed out that a typographic encoding can be intuitive but also has the potential to be misleading and lead to bias. For example, in Figure 165P168 the oblique angle of the letters indicate GDP growth, with reverse slope indicating negative growth, a positive slope indicating positive growth and vertical representing zero growth. Given that the familiar normal convention is to represent text with no slope, the visual mapping could be interpreted that the normal condition for GDP growth is zero, whereas most economists would indicate a growth rate of

[404] Dave Addey. "FontSpots: Euorstile" on *Typeset in the Future*. Nov. 29, 2014. https://typesetinthefuture.com/2014/11/29/fontspots-eurostile/

two percent may be considered normal. As a result there is a mismatch between the expectation and the representation that could cause bias in interpretation – e.g. a general viewer might assume that all text sloping slightly to the right as a favorable condition which may not be true.

- **Are low-level attributes the same as typeface (i.e. font family)?** The criticism is that the sum of all low-level attributes are the same as typeface (i.e. font-family). This has been discussed earlier in *B:4.11.iv. Typeface vs. low-level attributes: details, skeletons and graffiti*P97, i.e. type examples such as graffiti show that font features such as serif, contrast and x-height do not fully capture the design space of a font.

- **Cultural conventions***:* Given the long history of both typography and cartography, typographers are aware of many non-research related events impact on type in cartography. Cartographers have pointed out the role of modernism in shifting to increased use of language neutral maps (e.g. choropleth maps) as well as the role of regulation. For example, U.S. government accessibility requirements mandate that italics not be used on websites as italics are more difficult to read for people with impaired vision – thereby making it not feasible to use italics to indicate water features on web-based maps developed for U.S. government websites. This leads to the development of general purpose web maps without italics so that one version can be used across multiple clients.

- **Mobile***:* Cartographers are acutely aware of development of visualizations for small-scale mobile devices with touch-based interfaces. Whereas some critics were concerned with how the approaches described here scale up, scaling down is a different issue, not addressed in this thesis.

D:1.4. Critique Summary

The use of critique is a novel and important contribution of the thesis. As shown, early-on critique raised key issues – such as legibility and readability as key criteria, now incorporated into many parts of the thesis. Critique also prompted further investigation of alternative solutions to given problems – such as label length bias and area perception; as well as suggested new areas of future research, such as language constraints, semantic encodings and evaluation of multivariate encodings.

D:2. Fidelity and Lossiness Metrics

Given a wide variety of alternative representations, other methods of evaluation may be useful, particularly if an approach such as critique is indecisive. The process of transforming data into visual attributes is a fundamentally lossy process because visual attributes may encode information with lower number of perceivable levels than the original data[405]. For example, encoding data as brightness may result in perceptual estimation errors as much as 20% meaning that brightness should be limited to encoding only two to four numeric levels.[406] A means to measure the potential lossiness can be an effective design time evaluation tool for assessing alternative visualization designs. A novel approach for evaluating potential information lossiness is presented based on first evaluating the fidelity per visual attribute in an encoding; and then estimate permutations across multiple attributes to compare relative lossiness.

In an evaluation of infovis heuristics, Forsell and Johansson[407] identify Information Coding (originally defined by Freitas el al[408]) as the most frequent heuristic for explaining usability problems; that is, a problem in the mapping of data elements to visual attributes, such as inappropriate encoding. Chen and Floridi provide an analysis of information visualization from a philosophy of information perspective comparing a communication system with a visualization pipeline. Like communication, the visualization pipeline is subject to information loss, error and noise across each step in the pipeline (previously in Figure 13P18).

MacKinlay[409] defined expressiveness as a visualization that encodes all relevant information and only that information. In MacKinlay's expressiveness, an encoding transforms a data attribute in a one-to-one correspondence without removing or adding data. MacKinlay's expressiveness can be encoded as a grammar; which has been expanded upon by future authors (e.g. Wilkinson, Heer & Bostock). MacKinlay defines effectiveness as a separate consideration, broadly meaning that the presentation is clear. Whereas MacKinlay's effectiveness is like a grammar, effectiveness is akin to semantics.

One approach to selecting between different visual attributes is to create a ranking of visual attributes by effectiveness. In MacKinlay's APT, effectiveness is defined as the assessment that some visual attributes will be more suited to some types of data types, for example, MacKinlay presents a table ordering different visual attributes by effectiveness for different types of data (i.e. categoric, ordered, quantitative, see Table 7P65).

Visual attributes have different properties and effectiveness for different types of encoding and have been expressed by other researchers as well (see Table 2: Visual Attributes by ResearcherP19). The work of Bertin[410] characterized different visual attributes by length which indicates the number of unique levels that can be perceived for a given attribute. Bertin derived his recommendations for length based on his experience with printed visualizations, so for example, position of a mark along the plane is considered by Bertin to support 10 perceptible levels per centimeter. Size variation provides up to 20 perceptible levels. For some visual attributes Bertin does not provide the number of levels when mapping quantitative data to the attribute; but does provide

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[405] Min Chen and Luciano Floridi. "An analysis of information in visualization." Synthese, 2013.
[406] Colin Ware. *Information Visaulization: Perception for Design*, Morgan Kaufmann, Waltham, MA, 2013.
[407] Camilla Forsell and Jimmy Johansson, "An heuristic set for evaluation in information visualization," *Proceedings of the International Conference on Advanced Visual Interfaces*. 199–206. ACM, (2010).
[408] C. M. D. S. Freitas, P. R. G. Luzzardi, R. A. Cava, M. A. A. Winckler, M. S. Pimenta and L. P. Nedel, "Evaluating usability of information visualization techniques." Proc. 5th Symposium on *Human Factors in Computer Systems* (IHC) 2002, 40–51, (2002).
[409] Jock MacKinlay, "Automating the design of graphical presentations of relational information." *ACM Transactions on Graphics* (TOG), 5(2), 110-141, (1986).
[410] Jacques Bertin, *Semiologie Graphique*, Gauthier-Villars, Paris, (1967).

levels when considering the visual attribute for depicting categories, i.e. where discrete data categories must be differentiated. For Bertin, brightness (value) provides up to six levels, texture provides four to five levels, color is considered to have eight distinct hues and orientation has four levels. For Bertin, shape has an infinite number of levels, but does not offer any ability for association perception - i.e. objects of the same shape will not pop-out across a field but only associate with other shapes in the same vicinity.

Beyond Bertin and visual attribute lists, some research has measured accuracy of visual judgment for quantitative data for a few visual attributes, such as Cleveland and McGill,[411] who experimentally established error rates for perceptual estimation of visual attributes such as line lengths.

Rule-based systems for effectiveness have been used for automated visualizations. For example, AutoVisual[412] uses potential effectiveness (MacKinlay's effectiveness extended for interaction) and uses a priority ordering of variables in relation to task and mapping to either explicit representations (of the immediate inner world) or interactions such as the outer world or exploratory tools. AutoVisual optimizes for effective encoding, minimal required interaction, and fast response time; with additional rules to ensure legibility and also lowers priority ordering data variables with few levels (i.e. a data attribute with fewer than five unique values). VISTA[413] uses a set of rules to validate encodings. At a high level, composition rules determine combinations of multiple visual encodings; such as rules for merging marks, superimposition, union, transparency or intersection. At a lower level to assess effectiveness, the system has 150 rules for visual perception[414] e.g. quantitative data is better mapped to geometry than color.

User task, such as awareness, exploration or analysis, is an important consideration for effectiveness. For example, if the task requires rapid awareness among hundreds of indicators (e.g., hundreds of glyphs), a blinking indicator may be a highly effective encoding drawing immediate attention to it. For an analytical or exploratory task, blinking would be considered distracting whereas the ability to easily perceive differences in magnitude is important to these tasks. Amar and Stasko consider the analytic task to be more important to the representational primacy.[415]

For analytic tasks, such as the perception of differences in magnitude, visual fidelity is an important issue: some visual attributes only encode a few levels of differentiation. Lossiness occurs when the number of discrete data values that need to be shown is greater than the number of levels that can be perceived with the target visual attribute. Assessing the difference is the objective of this lossiness approach. This approach is an attempt to assess the visualization quality although this approach is at a scale that attempts to assess quality and trade-off decisions across very different kinds of visualization encodings rather than optimizing a particular visualization type (e.g. Lam et al[416]).

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411 William Cleveland and Robert McGill, "Graphical perception: Theory, experimentation, and application to the development of graphical methods." *Journal of the American Statistical Association*, 79(387), 531-554. (1984).

412 Clifford Beshers and Steven Feiner, "Autovisual: Rule-based design of interactive multivariate visualizations." *Computer Graphics and Applications*, IEEE 13.4 (1993).

413 Hikmet Senay and Eve Ignatius. "A knowledge-based system for visualization design." *Computer Graphics and Applications*, IEEE 14.6 (1994).

414 Hikmet Senay and Eve Ignatius. *Rules and Principles of Scientific Data Visualization*. Institute for Information Science and Technology, Department of Electrical Engineering and Computer Science, School of Engineering and Applied Science, George Washington University, 1990.

415 Robert Amar and John Stasko, "A Knowledge Task-Based Framework for Design and Evaluation of Information Visualizations", *IEEE Symposium on Information Visualization*. (2004).

416 Heidi Lam, Enrico Bertini, Petra Isenberg, Catherine Plaisant, and Sheelaugh Carpendale. "Empirical studies in information visualization: Seven scenarios." *Visualization and Computer Graphics*, IEEE Transactions on 18, no. 9. (2012).

The four-level nested design model for design and validation for visualization by Munzner[417] provides levels stepping through 1) domain problem characterization, 2) data and task abstraction, 3) encoding/interaction techniques, and 4) algorithm design. The lossiness approach here is specifically a measure for evaluation of the quality of visual encoding of data, that is, between-levels of data abstraction and visual encoding.

A broad survey of visualization quality metrics are presented in Bertini et al,[418] particularly with regards to measuring patterns generated by visualizations for high-dimensional data with the goal of helping users view the best configurations. However, the approach in this paper is focused on the visual mapping stage of the visualization pipeline (not data transformation nor view transformation); and in particular, on design-time evaluation of lower-dimensional visualization design alternatives, each with different visual mapping configurations and/or potentially novel visualizations. There are some similarities to Brath[419] with metrics such as maximum number of dimensions and dimensional score; but those were measures of the complexity of the encoding, not measures of information lossiness.

The unique contribution of this lossiness approach is that it goes beyond visual attribute ranking or rule based approaches for design alternatives. Instead this new approach 1) measures the visual fidelity of the attribute encoding per attribute, and, 2) provides a summarization of permutations across attributes to estimate a comparative lossiness between visualization design alternatives.

D:2.1. One Dimensional Fidelity

An information visualization encodes a number of different dimensions of data. A simple bar chart or pie chart encodes two dimensions of data: a set of categories and a set of values corresponding to those categories. In Figure 224, the bar chart shows values along a common scale making the difference between *black currants* and *cherries* quite visible, while the size difference on the pie chart may not be discernable.

Fruit	Qty
Apples	33
Black Currants	19
Cherries	17
Figs	13
Guava	11
Kiwis	7

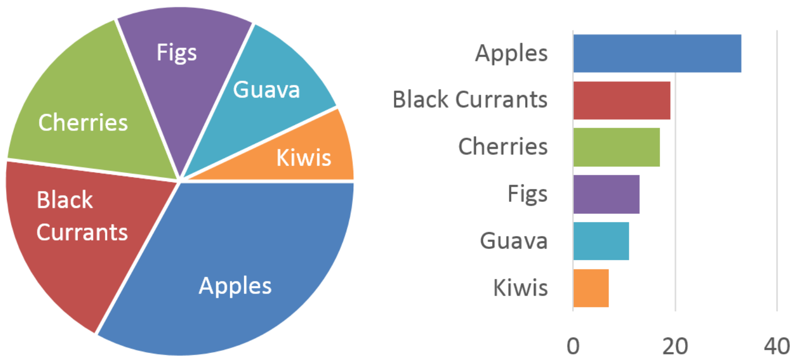

Figure 224. Pie vs. bar. Pie and bar each show the same data, each use the same chart area, but differences in similar sizes are more perceivable in the bar chart. Images created by author.

While these differences may be intuitively understood, the difference can also be articulated as a measurement of the number of discrete perceptible levels. With regards to perceiving quantities, Cleveland and McGill and later

[417] Tamara Munzner, "A nested model for visualization design and validation." *Visualization and Computer Graphics*, IEEE Transactions on, 15(6), 921-928. (2009).
[418] Enrico Bertini, Andrada Tatu, and Daniel Keim, "Quality metrics in high-dimensional data visualization: an overview and systematization." *Visualization and Computer Graphics*, IEEE Transactions on 17, no. 12 (2011): 2203-2212
[419] Richard Brath, "Metrics for effective information visualization." Proceedings of the *1997 IEEE Symposium on Information Visualization* (InfoVis' 97), (1997).

Heer and Bostock[420] provide metrics for accuracy judgments and error rates for different visual attributes, such as an average error rate of ± 4.5% on angle judgments vs. an error of ± 2.5% on adjacent length judgments aligned to a common scale. As such, the pie chart may be considered as having fewer perceptible levels than the bar chart. With regards to quantities, the bar chart provides a higher fidelity of data encoding than the pie chart and therefore has lower information lossiness.

To show this quantitatively using Cleveland and McGill's error rates, in the case of the bar chart, the bar *figs* is 39% of the length of the longest bar and the bar *guava* is 33% of the length of the longest bar, beyond the ±2.5% error rate for length discrimination. The bar lengths provide a fidelity of six uniquely perceivable levels. In the case of the pie chart, the angle subtended by the category *figs* is 13% of the total whereas *guava* is 11% of the total - within the range of ± 4.5% error rate on angle judgments. Similarly, the angles for *black currants* and *cherries* are close enough to result in potential error estimation as well. As a result, the pie wedges provide a fidelity of four uniquely perceivable levels. The bar chart, with a length fidelity at six levels, is superior to the pie chart, with an angle fidelity of four levels.

Error rates have been established for only a few visual attributes. Using Bertin's levels instead, one can inspect the bar chart and establish that the difference between any pair of bars is more than one millimeter, implying all lengths are clearly distinguishable, i.e. having six uniquely perceivable levels. For orientation, Bertin considers discrete angles of 30° increments distinguishable. In the pie chart, the angles of the wedges are 25, 40, 47, 61, 68 and 118 degrees. The angles for *figs* and *guava* at 40° and 47° are very close together resulting in potential error estimation; whereas the angle for *kiwis* at 25° is 15° difference from the next smallest wedge, half of the 30° increment and potentially not subject to error. Following this approach, *black currants* and *cherries* are also close and subject to error, and overall only 4 levels are perceivable for the pie chart. Using Bertin's values, the fidelity levels are the same as the results using Cleveland and McGill's error rates, that is, the bar chart lengths have six levels and the pie chart has four levels.

Lost information can be retrieved via interactions such as tooltips, however, tooltips are much slower than preattentive perception (the visual pop-out of lengths, areas and angles); and slower than simply shifting attention and reading a label already visible. This approach seeks to measure what is visible, not what is hidden and/or accessed via interactions.

D:2.2. Multi-Dimensional Fidelity

Consider three design alternatives shown in Figure 225. The end-user, a financial expert, needs a visual display of news headlines. Data of interest includes the news headline, recency and readership. It is important to note that the user community is interested in all the headlines - a headline with low readership may still be of interest. In all figures, the representation uses text to encode the literal headline and brightness of the background to encode recency. The only difference is the encoding of readership: Figure 225 top uses a treemap sizing text (redrawn based on newsmap.jp[421]), Figure 225 left uses font weight and Figure 225 right uses proportional string

[420] Jeff Heer and Mike Bostock. "Crowdsourcing graphical perception: Using Mechanical Turk to assess visualization design." In *ACM Human Factors in Computing Systems* (CHI), 203–212, (2010).
[421] Marcos Weskamp. "Projects: Newsmap", 2004. URL: http://marumushi.com/projects/newsmap. Accessed 03/03/2014.

encoding. Proportional string encoding applies a type attribute, such as bold, along a portion of a text string to indicate quantity with the proportion shown along a common scale.

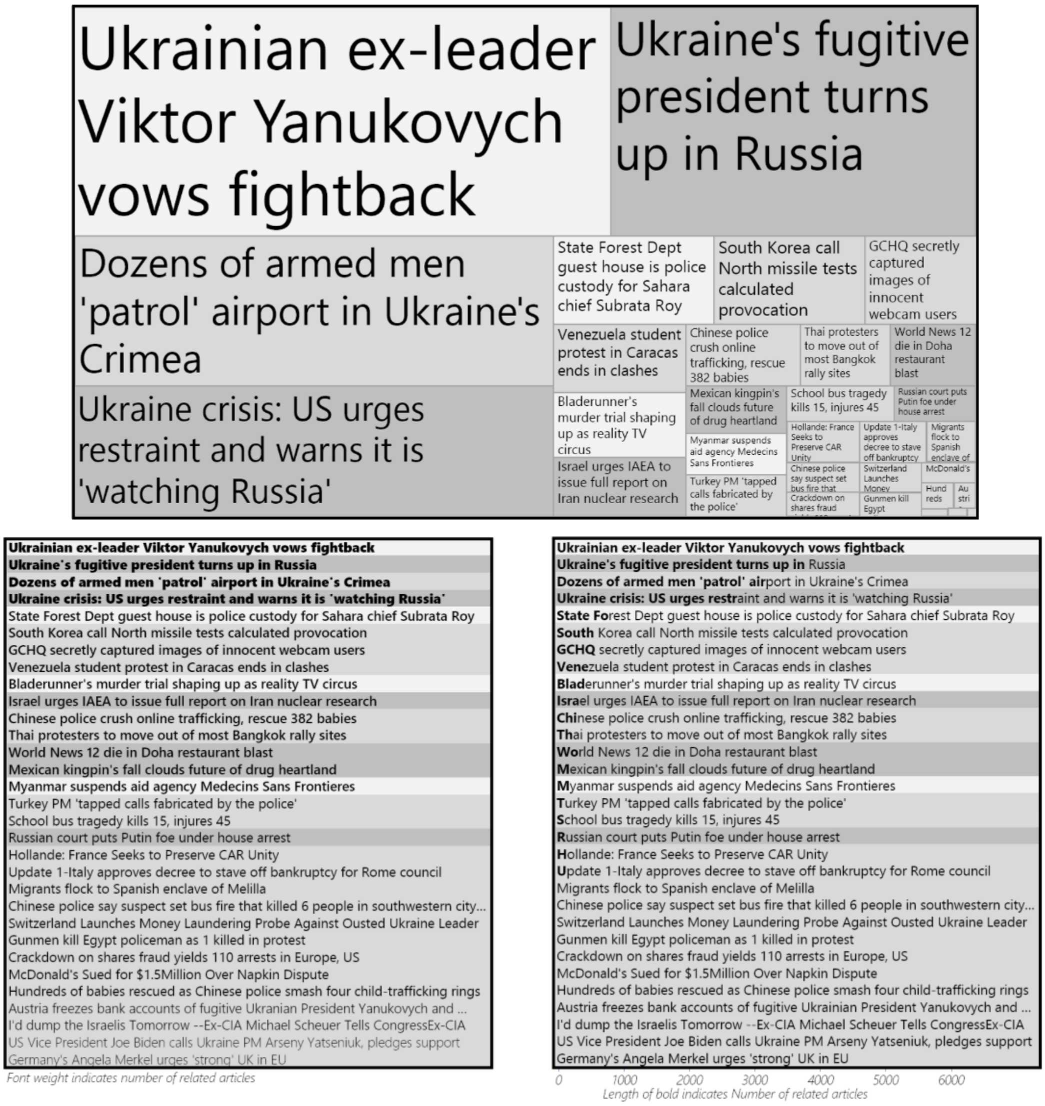

Figure 225. News headlines. Top: treemap. Size indicates readership, color indicates recency. Lower left: Same headlines and shading with font weight indicating readership. Lower right: Same headlines and shading with proportional length of bold indicating readership. Image created by author, top image redrawn based on newsmap.co.jp.

- The different encodings have implications in the number of levels perceivable, detailed below and summarized in Table 16.
- *Recency*: is encoded as the brightness of the background behind each headline. The same brightness encoding is used in all three examples and always applied to the background area behind the headline. For the purposes of evaluation comparative designs, the number of levels is irrelevant as it will be the same across all three variants and have a neutral effect on the result. However, to estimate the number of levels of brightness, according to Ware, is two to four levels. Since the brightness range is constrained (i.e. not too dark) in order to keep the text on top of the background legible, the number of levels of brightness may be considered to be slightly lower, at three distinct levels.
- *Readership*: is encoded in the treemap as area. Based on visual inspection and Heer's error rates (6% error rate), there should be on the order of 10-14 uniquely perceivable sizes in the treemap. In the font

weight example, the chosen font has 5 distinct weights. Font weights have not been formally evaluated, e.g. by Cleveland or Heer. Without a formal measure, and in need of an estimate, a group of experts was polled, and yielded answers of 3, 4 or 5 perceived levels, with 4 being most common. In the proportional encoding, the step size is minimally a single character, meaning that some small differences for the lowest readerships which are discernable in the smallest treemap boxes are not discernable in the proportional string encoding. Conversely, at the larger sizes, differences between two similar quantities may be difficult to discern in the treemap because areas of different aspect ratios have higher error rates (see Heer), while these differences are rapidly apparent in the proportional string encoding. There are approximately 10 uniquely perceivable sizes in this example.

- *Headline*: is encoded directly as text. However, the treemap results in text that is unreadable visually: if a headline is too small, shorter than 60 characters, or does not appear, it is considered unreadable. The same thresholds are used in all cases. In the case of the treemap, only 15-20 headlines out of 31 headlines were readable at a target resolution of 640x360 whereas in the other 2 representations all headlines were readable in a display that was only 52% of the area of the original treemap.

Table 16. **Number of levels per attribute for each news item visualization variant**

Variant	Recency	Readership	Headline
Treemap	3	10-14	15-20
Font Weight	3	4	31
Proportional	3	10	31

These measurements can be repeated for a number of different instantiations of the design, for example, at more extreme cases. These designs and measures were repeated for two additional variants, one very dense with 56 headlines in a tiny space such that all headlines cannot be displayed regardless of the design alternative (shown in Figure 226), and the other variant with 56 headlines displayed sparsely such that there is more than sufficient space to display all headlines. The results are shown in Table 17.

Initially, the treemap and the font-weight headlines were the only two design alternatives. The tradeoff between treemap versus font-weight headlines was visible in the initial designs and these fidelity metrics facilitated more focused consideration. The result was a design time dissatisfaction with both alternatives and spurred the design of the third alternative (i.e. proportional length encoding, see *C:8: QS: Quantitative Sentences - proportional and positional encoding*P193). The proportional length encoding provides a similar high fidelity for readership, like the treemap, and a similar high fidelity for readership, like the font weight variant; resulting in an overall seemingly superior design.

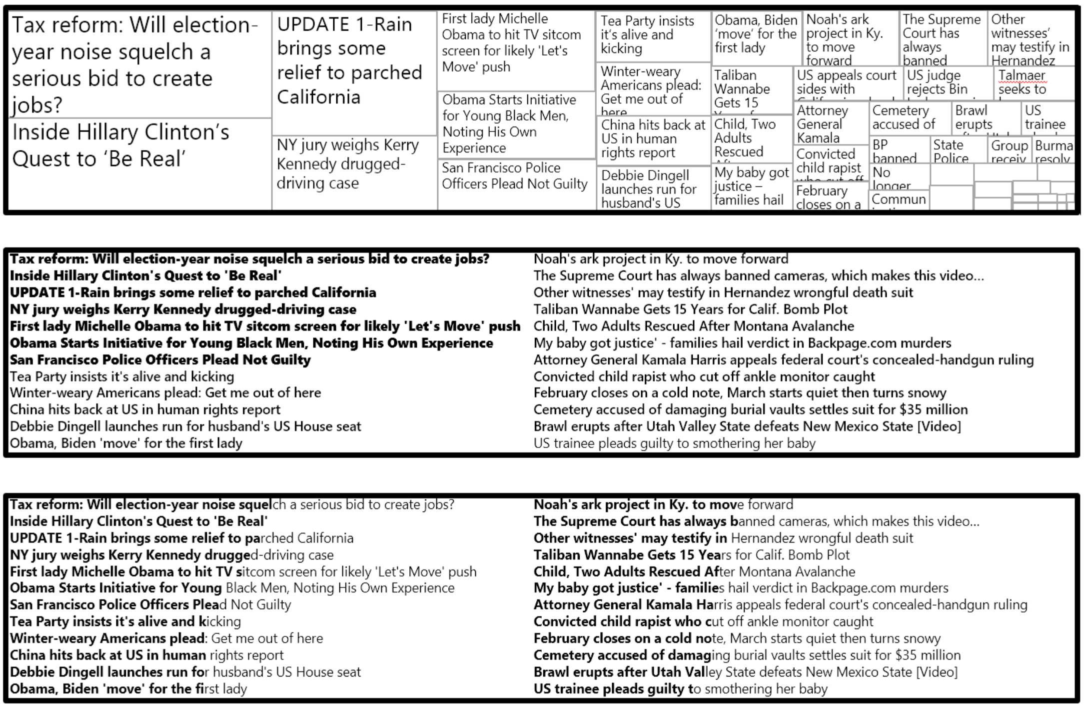

Figure 226. Another example of the news headlines (without background brightness). This example is dense with 56 headlines represented in a small area: in all cases, not all headlines are visible. Top: size indicates readership. Middle: text weight indicates readership. Bottom: proportional length of bold indicates readership. Image created by author.

Table 17. **Number of levels per attribute for each news visualization variant for dense and sparse variants**.

Variant	Recency		Readership		Headline	
	Sparse	Dense	Sparse	Dense	Sparse	Dense
Treemap	3	3	12	12	27	9
Font Weight	3	3	5	3	56	24
Proportional	3	3	12	10	56	24

D:2.3. Overall Lossiness

While the number of levels per each dimension is useful, some means of combining these values together into a single score is useful to evaluate different design alternatives. Visual attributes are typically combined together, for example, a bubble plot with bubbles at five different sizes and six different hues can represent 30 different unique combinations of size and color. The various permutations across combined visual attributes is multiplicative, in general, although there are caveats. For example, when combining hue and brightness, all hues with a brightness of zero are black reducing the number of permutations. This means in practice, the multiplicative combination of levels per channel represents a maximum potential permutations. The design and the perceivable levels should also take into account these interferences, for example, the hue and brightness combination can be addressed by varying brightness in a narrower range than extending to full black.

A relative comparison of the permutations per design variant then results in a relative lossiness score. This is analogous to the explanation that a computer hardware graphics card can display 16 million colors (i.e. 256 levels of red x 256 levels of green x 256 levels of blue) even though the card may only support a display size of 1920x1080 - i.e. 2 million actual pixels meaning that only a subset of the 16 million colors can be displayed at any one time.

Using this multiplicative approach, the relative lossiness of the three design variants is as follows in Table 18. Note that a lower score is more lossy, so the font weight encoding is the most lossy (at 0.7 relative to treemap) and the proportional encoding is least lossy (i.e. more preserved levels of the original data, with a score of 1.87 relative to the treemap.

Table 18. **Relative Lossiness of Alternate Headline Representations**

Design Variant	Recency	Readership	Headline	Total Permutations	Lossiness Relative to Headline Treemap
Treemap	3	12.0	17.7	637	1.00
Font Weight	3	4.0	37.0	444	.70
Proportional	3	10.7	37.0	1188	1.87

Based on this technique, the proportional encoding appears to offer the least loss. Font-weight appears to be more lossy than the treemap, although the metric is an "apples and oranges" aggregation: 1) Headlines express complex ideas whereas readership expresses a single quantitative value. Loss of a headline may have a higher weight than the loss of a quantitative value about a headline. 2) Headlines require active cognitive reading to be understood whereas sizes can be understood pre-attentively at-a-glance. While separate fidelity scores can be combined it is still useful to retain the constituent fidelity score per attribute.

D:2.4. Generalized Fidelity and Lossiness

The general approach to calculating fidelity and lossiness is as follows:

a. Fidelity Estimation

For each data dimension that is encoded as a visual attribute, the *fidelity* is calculated to determine the number of unique levels perceivable. The number of levels perceivable will be the lesser of the number of unique data instances and the maximum number of levels perceivable based on experiments and guidelines.

- *Example 1*: One data attribute from the Titanic dataset (http://bit.ly/1Y5Rc8b) is the class of the passenger, i.e. first, second or third. If this data attribute is encoded as hue, the number of unique levels perceivable is three. Some authors suggest that the maximum number of perceivable hues is eight to ten, but the number of unique instances in this encoding will only be three resulting in a utilization of only three levels for hue.
- *Example 2*: One data attribute from Fisher's Iris dataset (http://bit.ly/2oKX5yn) is sepal length, which has 35 unique values. If this data is encoded as brightness only, the number of unique levels is only four, using Ware's threshold of four levels of brightness. Even though current monitors can show 256 levels of brightness for gray, a maximum of four will be perceivable. If sepal length were instead encoded as bars compared along a common baseline and sorted, error rates of ± 2.5% suggest that at least 20 levels can be encoded.

To determine the number of levels perceivable, prior work estimating error rates or guidelines are useful. Some examples include Bertin, Cleveland and McGill, Heer and Bostock, and Ware summarized in Table 19.

Ideally, the visual attribute error rates and/or guidelines for levels would exist for all visual attributes. Some authors do provide guidelines for specialized attributes, e.g. for fonts both Brath (Table 8P102) and Stobelt et al[422] indicate which attributes are more highly preattentive than others, but in neither case do authors indicate the number of levels perceivable. A useful future task would be to collect and organize more of these values from multiple sources. However, not all visual attributes have experimental error rates nor guidelines. In these cases, an experiment should be defined to measure the number of levels perceived or the error rate. Such as experiment would be a large effort given the many different visual attributes available to be tested (Table 2P19).

Table 19. **Visual Attribute Error Rates, and Guidelines for Number of Levels**

	Estimation Error Rates		**Number Levels Guidelines**	
Visual Attribute	**Cleveland and McGill**	**Heer and Bostock**	**Bertin**	**Ware**
Adjacent positions relative to common scale *(T1 - adjacent bars within a chart)*	2.5%	2.2%	10 per centimeter	
Positions aligned to common scale *(T2 - between stacked bars)*	3.0%	2.5%		
Positions aligned to common scale *(T3 - between clustered bar charts)*	3.5%	2.8%		
Lengths non-aligned *(T4)*	5.0%	4.0%		
Lengths aligned in sequence *(T5)*	6.6%	4.6%		
Angle *(T6 - pie wedge)*		4.5%	4	4
Area *(T7 - circle)*		6.0%	20 *Bertin's examples tend to be square*	
Area *(T8 - rectangles aligned centers)*		5.5%		
Area *(T9 - treemap rectangles)*		6.0%		
Brightness			6	2-4
Hue			8	10
Saturation				3
Texture (multiple attributes: scale, orientation, pattern, contrast)			4-5	4-12
Shape / Glyphs			Infinite *but not preattentive*	32 combination of shape, color, etc.

In lieu of an experiment, the author has on occasion presented a sample design utilizing the target attribute to an audience of ten or more people and polled attendees to determine the number of discrete levels perceived. In practice, this approach tends to result in the majority of votes for only one level with a narrow distribution of votes. The author has repeated this approach with the same example in three different settings with three different audiences and achieved the same results in each case.

Another alternative is to collect user feedback from design review sessions. User feedback on high-quality design mockups can indicate where users believe that a particular encoding may be less effective than the designer believes, such as an inability to easily identify multiple levels of hierarchy in a treemap.

Finally, the design itself with sample data should be visually inspected. The particular combination of visual attributes, the size of the glyphs, the font used, or other interferences may show that the visual attribute has fewer levels of perceivable than anticipated.

[422] Hendrik Stobelt, Daniela Oelke, Bum Chul Kwow, Tobias Schreck and Hanspeter Pfister. "Guidelines for Effective Usage of Text Highlighting Techniques", *IEEE Transactions on Visualization and Computer Graphics* 22.1 (2016): 489-498.

b. Permutations and Relative Lossiness

Visual attributes can be combined together to show multiple data attributes. This is a multiplicative effect when 1) the visual attributes do not interfere with one another and 2) when the visual attributes are encoding different data. For example, hue and shape are independent: three shapes with three different colors yields nine distinct combinations. However, brightness and texture are not independent: texture requires brightness to be visible - therefore using texture together with brightness may reduce the number of levels of brightness that can be utilized. In general, when using this approach with combinations of visual attributes that are not independent, the impact should be taken into account when computing the number of levels perceivable per visual attribute.

In some visualizations there may be redundant encoding, i.e. two visual attributes are used to encode the same data. In this case, the same data is being encoded with two different visual attributes. As such, the two visual attributes are not defining a set of all possible permutations, but rather a one-to-one mapping between two visual attributes. In this instance, the number of levels should simply be the maximum of the two.

Number of permutations is the multiplication of all the number of levels perceivable into a total permutations. A higher value indicates a greater number of permutations and the potential to carry more information - i.e. less lossiness.

Number of permutations is computed for each design variant. Relative lossiness, is a simple transformation normalizing the number of permutations to a chosen design. A lower relative lossiness score indicates the potential for more information loss. Design alternatives can then be compared relative to the chosen design. Lower lossiness scores indicate lower amounts of information retained and higher lossiness scores indicate a higher amount of information is potentially retained.

Note that this lossiness score only measures information loss from the choices of visual attribute encoding. Information can also be lost at subsequent steps in the process of perception. For example, a scatterplot may lose some information due to over-plotting in the resulting visualization. Or, the viewer may have information lost in perception, for example, if the viewer has color blindness or if the viewer is unfamiliar with the representation and makes interpretation errors.

D:2.5. Post Hoc Lossiness Analysis Example

As a comparison, a well-defined design task with a known outcome can be evaluated using this technique to see if a lower lossiness alternative was chosen in practice. This particular design task occurred ten years ago for a client. This scenario is interesting because the design alternatives, which required significant implementation effort ten years ago, can now be prototyped by a wider audience of developers much more quickly and easily using modern visualization toolkits, however, understanding and assessing tradeoffs has not been made easier.

In this example, the user community needed to understand a hierarchy of data, each level with a magnitude and change measurement. For example, the Consumer Price Index (CPI), is a hierarchy of prices weighted by the proportion that individuals spend of each item (e.g. gasoline, rent, food), with a percent change in price in each item that can be aggregated up through the hierarchy to a total level. The users are interested in the magnitude and change throughout the levels and the initial starting point was dissatisfaction with a treemap as the hierarchy was not considered visible by the users and the intermediate aggregations were missing (e.g. tomatoes were displayed, but the total for vegetables was not). Figure 227 shows a sample treemap with CPI data.

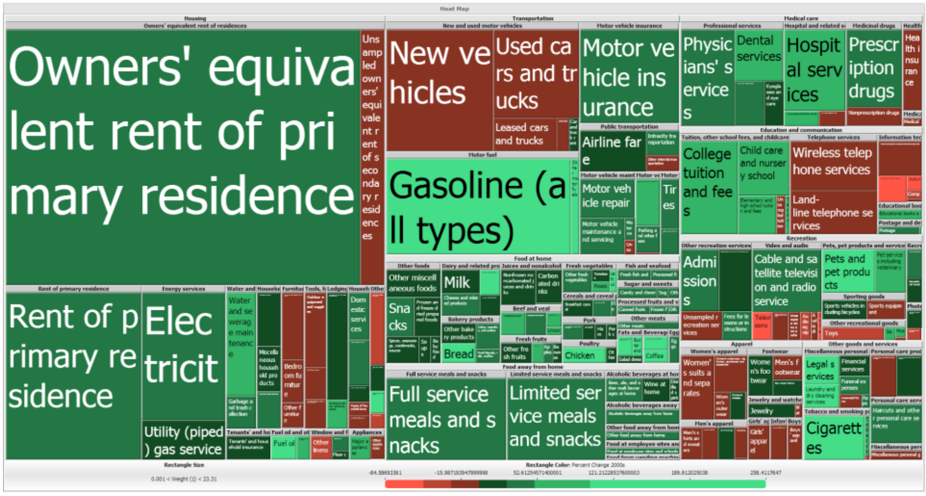

Figure 227. Treemap of US CPI data from www.bls.gov/cpi. Image created by author using Microstrategy software.

Design alternatives considered are shown in Figure 228, which included:

- *Treemap*, with size set to magnitude and color for percent change to prior period. This was the baseline.
- *Voronoi treemap*, with size and color set similarly. Similar to the treemap, users did not consider the hierarchy to be effectively visible.
- *Sunburst chart*[423] (i.e. a multi-level pie chart), with each successive level indicating another level in the hierarchy, with pie wedge size indicating magnitude and color indicating percent change. The sunburst clearly showed the hierarchy, colors and sizes. The only labels were around the perimeter, off the chart, indicating the category corresponding to the first level wedge.
- *2D Grid*. Each cell in the grid belonged to a region (clearly demarked) indicating hierarchy, with cell color indicating percent change and label size indicating magnitude. Labels were simply truncated at the edge of the cell (similar to long label truncation in Excel cells). Given the small sizes, labels indicated only the first three or four letters, except for the top level which contained larger cells and clearly labelled the category. Given the small label size, only three levels of label sizes would be discernable.
- *Grid with 3D bars*. Similar to the grid, with an added thin 3D bar. Bar height provides a greater number of levels than label size, but creates issues with readability of text in 3D and potential occlusion.
- *Org chart*. Each bubble on the org chart was colored by the percent change, each bubble varied in size based on magnitude.

Note that the target requirement would have hierarchies typically with 200 items and needed to display in approximately 400 pixels.

[423] John Stasko, Richard Catrambone, Mark Guzdial, and Kevin McDonald. "An evaluation of space-filling information visualizations for depicting hierarchical structures." *International Journal of Human-Computer Studies*, 53(5). (2000).

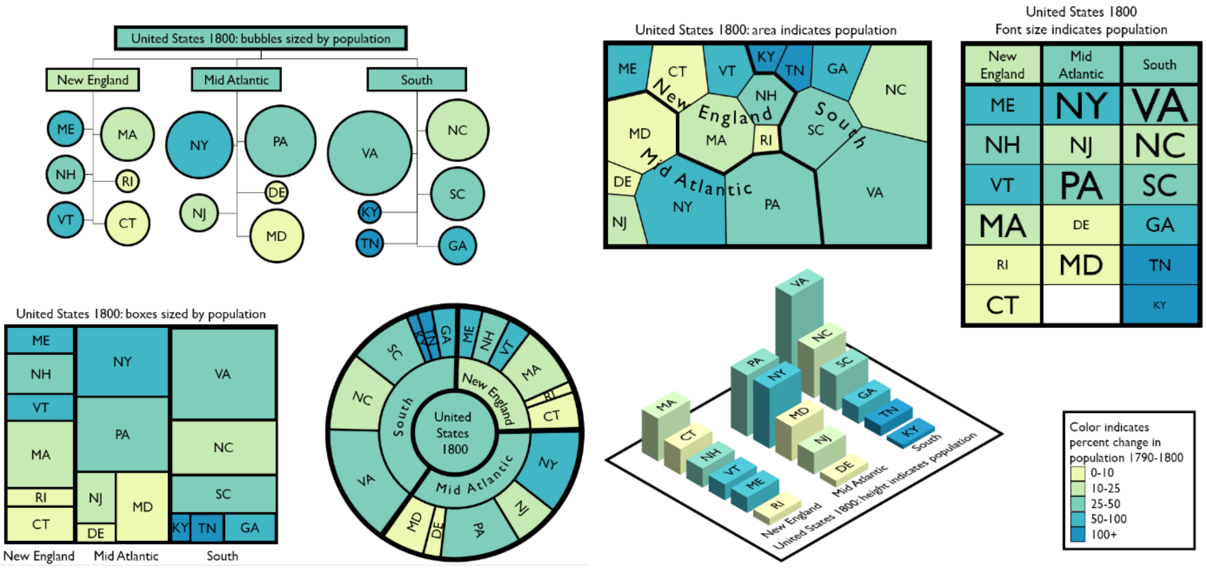

Figure 228. Design variants for depicting a hierarchy. Top row left to right: Org chart, Voronoi treemap, 2D grid. Bottom row: Treemap, Sunburst, 3D bars. Color is consistently applied in all designs. Image created by author.

Levels per each visual attribute, total discrete combinations and relative lossiness (vs. treemap) are shown in Table 20. The hierarchy column indicates the number of levels of hierarchy clearly visible. In the case of the treemap, users felt that the hierarchy was not particularly visible, therefore it scored only one level. In the case of the grid and 3D bar, clear amounts of whitespace or boundaries delineated the top level hierarchy, but the approach did not extend well through multiple levels, thus providing only two levels. The sunburst and org chart adequately displayed three levels of hierarchy.

Table 20. **Levels per attribute and estimated lossiness of design alternatives**.

Design Alternative	Hierarchy	Labels	Size	Color	Total Permutations	Lossiness Relative to Treemap
Treemap	1	25	12	7	2100	1.0
Voronoi Treemap	1	10	12	7	840	0.4
Sunburst	3	10	16	7	3360	1.6
Grid	2	50	3	7	2100	1.0
3D bar	2	10	16	7	2240	1.1
Org Chart	3	25	3	7	1575	0.7

The label column indicates the number of readable labels. The treemap is clearly capable of displaying many labels, as is the org chart (oriented left to right). The grid with truncated labels, however, is difficult to quantify using this approach. To a novice user, most labels truncated to only three characters would be useless, but for a domain expert they could be useful. Clearly some labels will be ambiguous regardless of viewer, e.g. *oth(er meats)* vs. *oth(er foods)*; and even domain experts may need more than a three letter cue for obscure categories. It is added here at 50, on the assumption that 50 of these labels will be useful to viewer somewhere between novice and expert.

The size column indicates the number of levels of sizes distinguishable based on metrics discussed earlier (Table 19). Based on Heer and Bostock, angle outperforms area estimation and the number of levels is proportionally higher for sunburst vs. treemap. Similarly, judging lengths with a common scale but not aligned with a baseline performs even better than angle and proportionally should have a value of 20 levels, however, these are 3D bars and the levels will be reduced by perspective effect and potential occlusion and therefore has been reduced to the similar level as sunburst. Note that the 3D bars also have the same labels as the grid, but given the small size, perspective distortion and occlusion, only the top level labels are considered in the table.

The color column has been set uniformly to seven levels, assuming 3 levels of green and 3 levels of red and one neutral color are visible. As all levels are the same, this column essentially has no effect on the total permutations column. The total permutations column is simply the multiplication of the preceding columns to express the total number of discrete combinations, and the final column adjusts these numbers relative to the treemap starting point.

In practice, the sunburst chart was implemented, has been successful and this is the chart that has the best lossiness score in the table above.

However, suppose that there were different user skills and tasks, and thus discretionary judgments were made differently. For example, instead of using levels of hierarchy, suppose the number of nodes displayed was used. If users are assumed to be expert users, then extremely short labels might be effective - perhaps 100 or even 200? Similarly, if users are assumed to be adept at 3D height perception the number of discrete heights could be higher. And so on. These adjustments result in values shown in Table 21.

Table 21. **Alternative calculations for levels per attribute and estimated lossiness of design alternatives**.

Design Alternative	Hierarchy	Labels	Size	Color	Total Permutations	Lossiness Relative to Treemap
Treemap	200	25	12	7	420000	1.0
Voronoi Treemap	200	10	12	7	168000	0.4
Sunburst	300	10	16	7	336000	0.8
Grid	210	150	3	7	882000	1.6
3D bar	210	10	20	7	294000	0.7
Org Chart	300	25	3	7	157500	0.4

In this alternate post hoc analysis, the grid with short labels performs best for expert users. Note that any design time decisions regarding encoding must be considered in the higher level context of the users, domain and task.[424] Thus the approach can work, although user goals and tasks and necessary, and best applied when making judgments about fidelity per attributes.

D:2.6. Lossiness in Text and Font Attribute visualizations

In many of the visualizations presented in *PART C,* new visualizations are derived from existing visualizations by adding text (e.g. Microtext line charts replace lines with text e.g. in Figure 122P124) or by adding additional information into text labels or lines of text using typographic attributes (e.g. Venn diagrams in Figure 148P152, Labelled graph in Figure 155P160, or paragraphs enhanced for skimming in Figure 173P176). In all of these examples, there is an implied before / after comparison with the before representation being a well-known

[424] Miriah Meyer, Michael Sedlmair and Tamara Munzner. “The four-level nested model revisited: blocks and guidelines.” *Proceedings of the 2012 BELIV Workshop: Beyond Time and Errors-Novel Evaluation Methods for Visualization*. ACM, 2012.

representations and the after representation being the same representation extended with additional data. In all of these enhanced visualizations, the after case has more data represented by additional visual attributes, with each added attribute creating more permutations. In effect, each extension creates a higher permutation space able to express more data.

D:2.7. Generating Lossiness Scores without Datasets

Up to this point, fidelity and lossiness has been applied to specific visualizations with specific datasets. Can the approach be applied more generally to generic information visualizations without data? For example, a dataset with three quantitative attributes could be represented as a parallel coordinates chart, a bubble plot, or a set of star glyphs.

In the case of the parallel coordinates chart, each quantitative value can be mapped to a position along an axis. Using Bertin's rate of one millimeter on a typical laptop screen this may be on the order 150 unique positions for each attribute. Total permutations are 150 x 150 x 150 = 3,375,000.

In the case of the bubble plot, assuming the same screen, the X and Y axis have similar number of unique positions. However the relative sizes of the bubbles have an error rate of 6% and Bertin suggests 20 sizes. Total permutations for the bubble plot are 150 x 150 x 20 = 450,000.

In the case of star glyphs, each glyph has three axes at different orientations, with the length of each axis indicating a variable. If each glyph is placed separately so that glyphs do not overlap, the number of glyphs determines the size of each glyph, which in turn impacts the number of the levels that can be perceived. Assuming 500 items, each glyph has approximately 1/20th the width and height available, resulting in only 8 or so levels per data attribute. The permutations are 8 x 8 x 8 = 512.

A comparison of these values shows that the parallel coordinates approach has the least lossiness, followed by the bubbleplot with star glyphs in a distant third place. In this generalized example, the parallel coordinates approach is superior (and perhaps the reason why parallel coordinates are a popular technique in exploratory data analysis where very little is known about data).

What is missing in this comparison is any notion of the data or the tasks required. Parallel coordinate displays the data with a high degree of fidelity per attribute, but visual separation between elements can be difficult (which is much easier both the scatterplot and star glyph displays). Some types of patterns can be easier to see in a scatterplot or star glyph than a parallel coordinate display. The star glyphs, with clear spatial separation, can more readily support labelling than either the parallel coordinate display or the bubbleplot. If a designer starts instead with a task, such as identifying individual outliers, the parallel coordinate display may not even be included in the design space as it may not be relevant to the task.

This example serves to show this approach is a design time tool for evaluating comparable visualizations for a target task and not an approach for ranking visualization techniques. Applying this technique without task consideration is a failure in the data and task abstraction step in Munzner's four level nested design model.

D:2.8. Limitations of Lossiness Metrics and Future Work

The measurement of fidelity and relative lossiness can be useful, particularly when evaluating design alternatives for accuracy. Many more visual attributes are feasible and it would be useful to extend accuracy research across a wider range of visual attributes and/or have methods for estimating the number of levels supported by a visual attribute in a particular context. As a proxy, as can be seen here, techniques for estimating the number of levels for fidelity include measured values in previous accuracy studies; polling experts or users; or visual inspection of a design that contains data. Some of these values may need to be adjusted based on well-defined thresholds, such as minimum legible screen sizes for fonts; or estimated, such as 3D occlusion reduces visibility of some items.

Understanding the higher level domain problem, including the users goals and tasks, is required to use this approach: this information helps frame judgments that are based on user needs and capabilities, such as ability to read truncated labels or expertise with 3D interfaces.

No aspect of the user task nor the relative importance of the particular data attribute to the task is directly captured in the metrics of fidelity and relative lossiness. A less important data attribute to the task does not require a dimension with high fidelity and more lossiness is acceptable. Thus, the components of relative lossiness could be to be weighted to match the task.

One particular shortcoming is that this approach only records the information discernable in the target display, not the speed at which the representation can be comprehended. Visual attributes that can be pre-attentively perceived, e.g. length, area, hue, brightness, etc., are mixed together with attributes that require active attention (e.g. complex shapes, text labels). The best lossiness score would be attainable with a fully alphanumeric table resulting in no lossiness, but also would have no information visualization properties, e.g. no information would pop-out, no patterns would be discernable at-a-glance. Similarly, glyphs based on complex shapes can have a high number of levels but also have slower to comprehend: Bertin provides examples where patterns are not visible in fields of complex icons. Amar et al also warns against representational primacy over analytic primacy and the ability to perceive patterns depends upon the visual system detecting pattern across pre-attentive visual attributes. Therefore, further extending this approach with the relative speed of perception of different visual attributes would be ideal. However, the simple visual attribute rankings (e.g. Table 7P65) do not clearly identify the reason for the ranking and some high ranking items are high because of accuracy of estimation not necessarily speed of perception or time to understand. Attribute rankings from perceptual psychology could be used instead, for example Wolfe and Horowitz[425] provide a table indicating visual attributes that might guide attention in visual search. Furthermore, all visual channels are weighted equally when creating an overall lossiness score. Weighting could better adapt the model for attributes such as labels or icons which provide a very high number of categorical levels (i.e. each unique label) at a cost of active reading.

The essence of an intuitive display or aesthetic appeal is not captured in fidelity and lossiness metrics. Some other metrics and clustering techniques do attempt to improve the intuitiveness and improve visceral appeal of the result.[426,427,428] One visualization expert reviewer agreed with all the logic for measuring the best performing design alternative in Figure 225, but commented that the treemap of headlines was still a more viscerally engaging representation than the other alternatives.

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[425] Jeremy Wolfe and Todd Horowitz. "What attributes guide the deployment of visual attention and how do they do it?" *Nature Reviews, Neuroscience,* 5(6), 495-501. (2004).
[426] Enrico Bertini and Guiseppe Santucci. "Quality metrics for 2d scatterplot graphics: automatically reducing visual clutter." *Smart Graphics* (77-89). Springer. (2004).
[427] Wei Peng, Matt Ward and Elke Rundensteiner. "Clutter Reduction in Multi-Dimensional Data Visualization Using Dimension Reordering." *Information Visualization, 2004. INFOVIS 2004*. IEEE Symposium on. IEEE, 2004.
[428] Leland Wilkinson, Anushka Anand and Robert Grossman,. "Graph-Theoretic Scagnostics." *INFOVIS*. Vol. 5. (2005).

In summary, this section suggests that design-time evaluation is multi-faceted and that metrics should include some combination of 1) fidelity/lossiness; 2) speed of perception; 3) intuitive displays and aesthetics; and that these should be considered in the context the user goals and tasks. These metrics could be readily available at design time with appropriate research to quantify levels and performance per visual attribute.

With regards to the use of text and font attributes, a key point of this fidelity and lossiness model is that the addition of text to a representation increases information density and reduces lossiness. That is, the addition of extra data into a representation using text (instead of dots or line), or the addition of data using font attributes, increases information density by adding an extra dimension of data. This extra dimension of data increases the permutation space and reduces the overall lossiness of the visualization.

Furthermore, with regards to specific typographic encodings, different alternatives can be compared. For example, for encoding quantitative data into text, the proportional encoding technique will be higher fidelity than using font weight or oblique angle.

Also, many typographic attributes are mutually exclusive and can be combined together without lossiness. This can be useful for set visualization (*C:4*P144) or other applications. For example, some older software systems (e.g. SCADA, financial systems, spreadsheets) or some web applications (e.g. reports) may not have access to a wide variety of visual attributes (e.g. texture, blur, shapes), but simple versions of font attributes are available in these environments, such as bold/not bold, italic/not italic, caps/non-caps, underline/no underline, superscript/not superscript). These five textual attributes can be used to create a 5 dimensional 2x2x2x2x2 permutation space of 32 unique combinations – which may be otherwise completely unavailable in these limited systems.

Overall, fidelity and lossiness provide a starting point for perceptual assessment of typographic attributes as alternatives to other visual attributes.

PART E.
Conclusions and Future Work

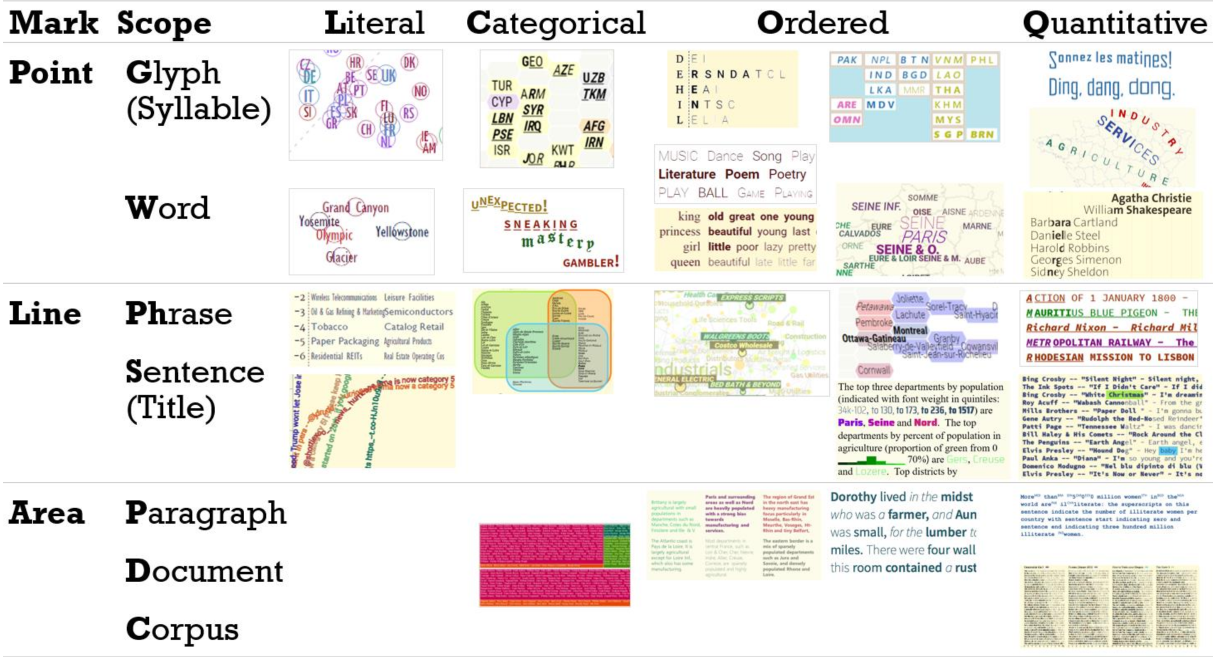
At the broad level of expanding design spaces, this particular investigation has shown how a systematic investigation into a design space can be used to re-frame the design space and create new applications.

E:1. Framework for Text in Visualization

Cross-Disciplinary Research: The method shows how interdisciplinary research can be used at multiple points in the process. Early, cross disciplinary reviews of background research were used to identify new parameters. Then a review of the framing of the design space in other disciplines helped frame the expanded space and also suggested possible applications (e.g. skimming, prosody). Finally, cross-disciplinary expert critiques exposed specific issues that may not be known in other domains; identified aspects missed in the evaluation of individual techniques; and broader issues in holistic evaluation. Cross-disciplinary expert critiques lead to a more robust definition of the design space and evaluation criteria, such as the introduction of criteria such as legibility and readability into data visualization.

Design Space: The starting points of the *Visual Attribute List* (Table 2P19) and the *Text Visualization Browser* (Table 1P13) both showed a low awareness of font-attributes used to encode data in visualization. In *PART B: The Design Space of Text in Visualization*P23-104, the characterization of attributes based on their source domains and in relation to visual channels, preattentive potential, and possible encodings creates an organized itemization for 15 typographic attributes. The 15 typographic attributes with four data encoding types and six typographic scopes across hundreds of different layouts which can be combined singly or together in any combination defines a very large design space. The example typographic visualizations shown in *PART C: Applications of Typographic Visualizations*P108-204, are just a small sampling from this design space. To recap, Table 22, shows the data encoding vs. typographic scope table with snapshots of the example applications.

Table 22. **Table showing examples of text visualization cross different text scope and data types**.



As discussed, these typographic visualization techniques can be applied to almost any visualization technique. Examples shown include scatterplots, distributions, cumulative distributions, grids, line charts, thematic maps, graphs, trees, Euler diagrams, mosaic plots, spark charts, stem and leaf plots, box plots / range bars, parallel coordinate plots, tag clouds, bar charts, stacked bar charts, lists, headlines, sentences, and paragraphs.

E:2. Open Questions and Future Work

The broad, multi-dimensional design space with many examples, use cases and wide variety of expert feedback opens many questions for future research into text, typography and visualization.

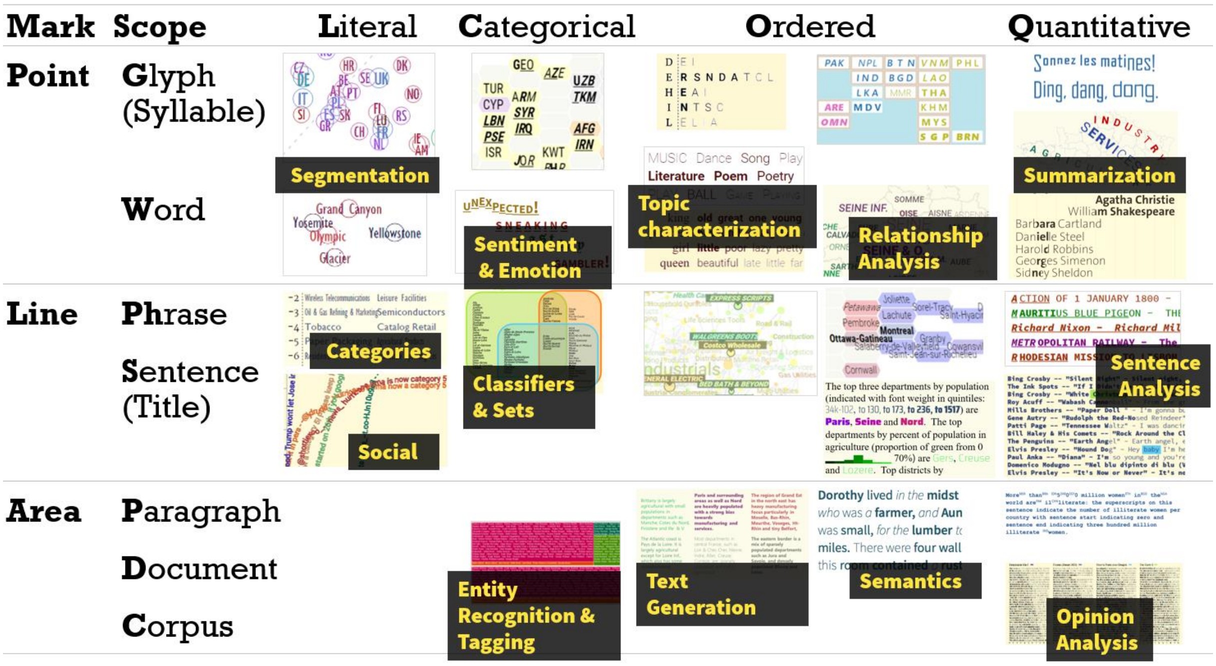
Literal encoding in a visualization context has many potential benefits as discussed earlier, but also potential issues, such as speed and effectiveness of decoding, noticeability of differences, increased salience of long words over short words, issues across languages and so forth. In some cases text may need to be padded (e.g. Figure 203P199); or other cases need text to be truncated or abbreviated (e.g. Figure 151P155).

Prior knowledge of the words and phrases visualized can help form associations beyond the data directly depicted (Figure 114P111). Words and entities are associated with sentiment, emotion and meanings (e.g. Churchill, Mussolini) which may or may not match meanings in the visualizations potentially leading to confusion.

Semantic associations with fonts, whether via heuristics, crowd-sourcing or font descriptions; can be used to create new meanings or enhance prior associations with words, characters, spoken text, etc. where appropriate - similar to the semantic depiction of words in comic books (e.g. **SMASH**, whisper, *help!*, *meanwhile…*).

NLP (Natural Language Processing) is closely related to text-based visualizations. Text visualizations can benefit from automated techniques such as translation and summarization. Similarly, NLP generates large amounts of text (such as entity detection, topic extraction, classifiers, relationships, and so on) which can be visualized using this framework. Table 23 shows the prior table with various text analytic techniques used in the visualizations, including social analytics, topic analysis, sentiment analysis, emotion analysis, classifiers, entity recognition, tagging, topic characterization, relationship analysis, semantics, summarization and opinion analysis. As the underlying text analytics are not the focus of the thesis they are only touched on, but the visualizations are highly relevant enhancements to these techniques.

Table 23. **Table showing examples and relation to text analytics**.



Legibility and readability are paramount in order for the literal encoding to be comprehended. With higher resolutions and larger monitors, the approach can scale to handle thousands of labels (e.g. Figure 155P160) and perhaps more with interactive zooming and aggregation techniques. Type becomes illegible at different sizes for different people: how small is too small and what interactions are expected? Type becomes more difficult to read when rotated and in steep perspective (such as Figure 47 rightP49).

Typographic attributes can be further characterized: for example, some types of typographic encodings (e.g. case and underline) are not available in all languages; or italic slope angle can be modified, both forward and reverse, but to what angle? Reducing text size, reduces the number of levels perceivable for typographic attributes weight, italic slope angle, etc. Typographic attributes typically available only to font designers (such as serif sizes, contrast, and width) are becoming widely accessible with new technologies such as Open Type 1.8 Variable Fonts support (e.g. Monotype[429]). Furthermore, attributes have expected or typical values: e.g. the common reading weight for text is 400 on a common font weight scale that ranges from 100 to 900 which logarithmically increases the amount of ink at each level – but weights at each level are not comparable across font families.

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[429] Monotype. (2017). Variable fonts: big news from TYPO Labs 2017. Blog post 17/4/2017. http://www.monotype.com/blog/articles/variable-fonts-big-news-from-typo-labs-2017

Other visual attributes such as size and color have not been explored, given the focus on typographic attributes. Note, for example, how cartographers tend to use a small range of type sizes to indicate quantities whereas tag clouds tend to use a very large range: why? Many of the techniques and applications could use these other attributes to create new designs.

Combinations of typographic attributes can be used to encode multiple datapoints into a single glyph or word (e.g. Figure 148$_{P152}$), however, some combinations will be confounding; or semantically difficult to decode.

Superimposition has been discussed, but no example applications of text superimposed over other text has been shown.

Gestalt principles indicate that visually similar items are perceived as belonging together: the viewer understands whether adjacent items are similar or different if their font attributes are similar or different (e.g. Figure 155$_{P160}$). This differentiation can be perceived quickly and is meaningful even if the underlying mappings are not decoded. However, what is the scale of difference required to be a noticeable difference across these attributes? For example, the variation in weight between bold/plain is quite different across font families designed for different purposes.

Type scope such as glyph vs. word only applies to languages with multiple glyphs forming words. Changing attributes mid-word provides a novel means of adding more fine grain data but could decrease word readability, particularly for a native English reader. This can potentially be usefully manipulated for the learning reader (e.g. Figure 104$_{P98}$). While the examples here range up to paragraph length, document length or corpus length encodings are not explored.

Sparklines and sparkwords provide word-scale visualizations embeddable directly into text, however, these graphics typically disrupt the flow of the text. Words and paragraphs embedding data via typographic formats (e.g. Figure 189 and Figure 190$_{P188}$) are a different form of word-scale visualization to be researched.

Interactions vastly expand the capabilities for users to interactively analyse data. Bertin provided an early physical model for interactive data analysis with re-orderable matrices, while modern interactive maps and visualizations regularly provide features such as search, sort, zoom, pan, filter and tooltips. There may be novel interactions with text visualizations, such as local search or toggling reading modes; and speech-based input may provide for new types of interactions well suited to text-based representations.

Text-specific layouts are under-explored. While variants of tables are common in both text and visualization, other forms exist too, such as poetic structures, document structures and unique formats such as dictionaries. The latter are designed for random access and quick skimming of multiple categories of content (pronunciation, part of speech, multiple meanings, etc.), similar to some types of exploratory analysis tasks.

Perception and understanding in visualization is a complex pipeline mirroring the visualization encoding pipeline in Figure 13$_{P18}$. Rather than rate of preattentive response or identification of perceptual areas; the broader sense of cognition, understanding, generation of hypotheses, and creation of insights need to be considered. This needs to be considered in the context of intended tasks – is a rapid response needed to avert a crisis? Or, is a deep reading assessing relationships and trade-offs across many variables required?

Applicability to glyph and icon design: The findings of this research apply beyond text visualization. For example, for visualizations using glyphs, icons or emoticons:

- *Legibility and readability*: Glyph visualization can benefit from some of the same evaluation criteria used in typography, notably legibility and readability. Readability implies that when glyphs are used together, in a sequence or group, that aspects such as line length and average weight may have an impact on performance.
- *Color*: The typographic notion of color is also applicable to glyph design. If a number of different glyphs are intended to be used together to convey information, the weight of ink should be consistent per glyph, otherwise a glyph will stand out.
- *Typographic formats*: While italics, bold, underline, etc., are not expected with glyphs, the design and use of glyphs can be extended to use these concepts, for example, these glyphs have italics and underline applied to a portion: 

More Future Work. The characterization of design space, the simple evaluations of the individual techniques, and the insights gained from the critiques suggest that there is much more work to be done. There may be aspects of the design space that require more detailed definition (such as fidelity); there are certainly more new types of novel visualizations within the design space that have not been explored; and certainly there are many more evaluations to be considered particularly at the level of individual visualization techniques and suitability to different types of tasks.

There are also higher level questions that span across the design space. For example, given multiple simultaneous font attributes what is the tradeoff between lower readability versus usability for some types of complex tasks involving a conjunction of data attributes? How can aesthetics and semantics be included in this framework? How can interactions, such as toggling an encoding on/off or adjusting font size enhance and make these techniques more usable? How can these techniques be evaluated with a wider range of datasets, at different scales and in different languages?

E:3. A Call to Action: Post-Modern Visualization

A critical analysis of the long accepted visualization framework provides an opportunity to reassess and extend our conceptualization of text in the use of charts, maps and visualizations. Hundreds of years of historic examples hint at many kinds of new types of visualizations and new use cases. The combination and permutations feasible between the many new facets introduced by text in conjunction with the many well understood aspects of visualization open an extremely wide design space for new forms to typographic visualization, each with many questions. Furthermore, the combination of these with interactive techniques such as sort, group, search, zoom, filter, pivot, and so on add many more potential permutations for new kinds of applications.

But, text offers far more than just an extended visualization framework:

Literal encoding adds information that cannot be ignored and triggers association with pre-existing linguistic knowledge. It shifts visualization from modernist, simplistic, preattentive-perception/Gestalt pattern analysis into post-modern, simultaneous, multi-level macro/micro patterns where the viewer can shift attention up and down levels of detail instantly for multi-level analysis. In addition to the visual cognitive modality of thematic maps and visualizations, text-rich visualizations enable language-based cognitive modality to be used simultaneously, thereby allowing for new ways of comprehending and reasoning about information in visualizations.

Post-modernism is defined by skepticism, a rejection of simplistic explanations of modernism and allowing for a plurality of viewpoints. Visualization with text introduces additional data, in different modes, levels and associations, which enables much more complex patterns and potentially contradictory patterns at different levels across modes. This suggests a pivot from visualization or visual analytics with representations focusing on one or two variables at a time into multi-facetted representations capable of expressing greater complexity than simply the permutations encoded in visual attributes. The semantics associated with text and with typographic enhancements are not neutral. The foundations of this work offers tremendous opportunities for future research across the breadth of implied design space for text in visualizations across disciplines ranging from psychology, perception, linguistics, philosophy, design, typography, cartography, statistics, natural language processing, human-computer interaction and visualization.

PART F. Appendix: Fonts, Acknowledgements, Supplemental Materials, etc.

F:1. Fonts Used and Font Recommendations

Many different font families were used in the creation of this thesis. For future researchers, some notes on the fonts may be useful:

Display fonts vs. Book fonts: There are many more "display fonts" available, that is, fonts designed for use as short titles, signage and generally used at larger sizes. Display fonts are typically not designed for use at smaller sizes. Graphic design considerations in display fonts may reduce differentiation between letterforms – for example, e.g. similarity between O and 0, I, 1 and l. Book fonts, however, have been designed for use at smaller sizes, with greater letterform differentiation and greater consistency across the letters to facilitate readability. Avoid display fonts – for example – Helvetica (and Arial) were originally designed as display fonts (e.g. note the similarity of I,l and 1 in Helvetica and tiny gaps in some letters), and compare them to Verdana, Tahoma and Georgia – all designed for use at small sizes on early low-resolution computer screens.

Free vs. Licensed fonts. There are many free fonts of poor quality available. Licensed fonts are generally of higher visual quality, provide a broader range of characters (e.g. extended Latin characters), and higher technical quality (some free fonts were difficult to layout with poor font metrics, some did not render well, and a few seemed to crash applications). Some "free" fonts appeared for a few months while the font was being developed, then disappeared when the final version was released.

High-quality free fonts: The following free fonts tend to be high quality and used extensively (all available at Google Fonts):

- **Fixed Width Sans Serif in Multiple Weights**: Source Code Pro
- **Proportional Sans Serifs in Multiple Weights**: Source Sans Pro, Roboto
- **Proportional Sans Serif in Multiple Weights and Widths**: Saira
- **Proportional Serif in Multiple Weights**: Cormorant (note, not much variation in weight)

System fonts: Most system fonts do not provide much variation: typically only one or two weights are provided. Segoe UI is a sans serif with many weights. Very few are available in multiple widths: Gill Sans, Rockwell and Arial are feasible. System fonts can provide a good selection of fonts for differentiation such as Bodoni/Didone (high-contrast serif), Rockwell (slab serif), Garamond/Palatino (humanist serif), Segoe/Verdana (plain sans serif), Times/Georgia/Century Schoolbook (plain serif) Consolas/Lucida Console (fixed width), Monotype Corsiva/Lucida Calligraphy (script).

Licensed fonts: At the time of writing, Prototypo (prototypo.io) was the only easy-to-use parametric font available; not particularly expensive and with prompt technical support. LucasFont's font super family *Thesis*, provides proportional fonts with variable weights, consistent widths, and serif/sans serif versions: although a license was not acquired and the fonts never tested in any of the visualizations.

F:2. Acknowledgements

Uncharted Software was highly supportive of the PhD such as time to attend conferences and LSBU meetings; access to staff for presentations, feedback and critiques; access to various information visualization resources such as historic publications and access to some customers; assistance with collecting some datasets such as social media datasets; travel fees to conferences; and so on.

Collaborative discussions have included a variety of people from various communities including information visualization: William Wright, Jock MacKinlay, Jeff Heer, Bob Spence, Tamara Munzner, Colin Ware, Chris Collins, Katy Börner, John Stasko, Enrico Bertini, David Jonker, Fanny Chevalier, Isabel Meirelles and more; typography: Gerard Unger, Gerry Leonidas, Fiona Ross, Paul Luna, Keith Tam, Richard Hunt, John Berry, Nick Shinn, Steve Ross, Eric Kindel; cartography: Cynthia Brewer, Alan MacEachren, Francis Harvey, Alexander Savelyev; HCI and Text Analytics: Marti Hearst, Eli Blevis, James Hodson, Craig Hagerman, Scott Langevin. And there are many others not mentioned – thank you for taking the time to discuss.

Presentations have included academic presentations to computer science, typographers and cartographers at: London South Bank University, University of Toronto, University of Ontario Institute of Technology, Columbia University, Dalhousie University, Indiana University Bloomington, University of Reading, Cadi Ayaad University Marrakech (CGIV2017 Keynote). Presentations to industry have included: Market Technicians Association Annual Conference, North American Cartographic Information Society Annual Conference, NYC Data Visualization Meetup and Strata Big Data Conference NYC 2017.

A number of historic documents are used to identify the use of font attributes. Libraries visited as part of this work include British Museum Prints and Drawings Room, Paris National Library Cartography Reading Room, Oxford Bodleian Library, New York Public Library Cartography Room, Boston Public Library Map Division, University of Toronto Robert Fischer Rare Book Library, Toronto Public Library Rare Book Division, University of Waterloo School of Architecture Library, National Library of Canada, Reading University Department of Typography Isotype Collection, St. Bride (Typography) Library London, London College of Communication Typography Collection, Prelinger Independent Research Library San Francisco and Powell's Books Portland Oregon.

F:3. Social Media Response to PhD topics

In the course of working on this PhD, various portions of this research have been posted in short snippets to a blog (richardbrath.wordpress.com). Instead of a scientific peer-review, this is a peer review by social media. The most popular blog posts generating the most tweets, likes and tweets are listed below in Table 24- presented with proportional encoding (count of number of tweets, retweets, likes, reviews). The blog post title hyperlinks to the corresponding blog post (left) and also links to the closest corresponding portion of the thesis document (right).

Table 24. Most popular blog posts related to this thesis (indicated via proportional formatting)

Blog Posting	Thesis Section
500+ years of increasing separation of text from visualization...	A:2
Visualizing Emotions	C:4.6
Venn Diagrams enhanced with Typographic Attributes	C:4.3
Potential uses of font attributes in visualization	C:6
Microtext Line Charts	C:2
Text Visualization and Search	Knowledge Maps
The Design Space of Typographic Data Visualization	B:5
The 19 Dimensional Word Cloud of Pokémon	D:1.2.iv
TypeCon 2015: Using Type to Add Data to Data Visualizations	PART C
Equal Area Cartograms and Multivariate Labels	C:5
Recent Publications	A:1
The Table of Visual Attributes (2013)	A:5.4

Two social media responses of particular interest include:

- Edward Tufte liked and retweeted *Venn Diagrams enhanced with Typographic Attributes*.
- Blog post *The Design Space of Typographic Data Visualization* was included on “The 10 Best Data Visualization Articles of 2016 (and Why They Were Awesome)” by Evan Sinar.[430]

[430] Evan Sinar, “The 10 Best Data Visualization Articles of 2016 (and Why They Were Awesome)” https://medium.com/datavisualization/the-10-best-data-visualization-articles-of-2016-and-why-they-were-awesome-ce30618ea06a

F:4. Supplemental Materials

Various analyses tasks to review a large number of visualizations or conduct surveys were done. Raw data and summaries are below.

F:4.1. Use of Visual Attributes on Text in 249 Text Visualizations

Analysis done Jan 22, 2016 using 249 visualizations catalogued at The Text Visualization Browser (textvis.lnu.se), not including the author's visualizations. NOTE1: Only the text in the primary visualization was considered, not including differentiation between chart elements such as body text, axis labels: must be per mark.

Name of Visualization Technique	No text	Plain Text	Tag Cloud?	Orientation	Size	Hue (foreground)	Hue (background)	Intensity	Bold	Italic	Underline	CASE	TEXT SCOPE None, Glyph, Word, Line, Paragraph, Document	Hue either fore- or background	Hue both fore- AND background	Num of Font-Specific Attribute	Other Attribute of note	Number of Dims in Text e.g. label + orientation = 2 dims
1 Stor-e-motion				X									Word			0		2
2 LDA Explore								X					Line			0		2
3 Matisse		Axis Label											Word			0		1
4 Sentiment Compass				X									Word			0		2
5 CrowdFlow	X												None			0		0
6 uVSAT							X						Document	X		0		2
7 Area (2015)		Cell Label											Word			0		1
8 EmoTwitter		Axis Label											Word			0		1
9 SocialHelix			Y		X	X							Word	X		0		3
10 CompareCloud			Y		X	X							Word	X		0		3
11 Visual Plagiarism					X		X						Word	X		0		3
12 Orcaestra		Node Label											Word			0		1
13 ThemeDelta					X			X-bkgd					Word			0		3
14 TextPioneer			Y		X			X-bkgd					Word			0		3
15 Q-SNE	X												None			0		0
16 Synemania	X												None			0		0
17 Lexical Episode						X							Word	X		0		2
18 LinkScope				X			X						Word	X		0		3
19 ShakerVis		X											Word			0		1
20 *Semantize										X	X		Paragraph			2		3
21 Network of Names					X		X						Word	X		0		3
22 mailVis		X											Word			0		1
23 MiTextExplorer									X				Line			1		2
24 ImgWordle			Y		X	X							Word	X		0		3
25 INVISQUE		X											Word			0		1
26 DiTopView			Y		X								Word			0		2
27 Footprint		X											Word			0		1
28 FAVe		X											Word			0		1
29 ConVis					X								Word			0		2
30 ProjSnippet					X	X					X		Paragraph	X		1		4
31 Semiato Storyline			Y	X	X								Word			0		3
32 EvoRiver			Y		X								Word			0		2
33 Text Variation		X											Paragraph			0		1
34 CosMovis		X											Word			0		1
35 Circular Cluster			Y		X								Word			0		2
36 I-VEST		X											Word / Line			0		1
37 PEARL		X											Word			0		1
38 FluxFlow	X												None			0		0
39 Laplacian Eigenmap	X												None			0		0
40 StarSPIRE					X		X				X		Paragraph	X		1		4
41 Overview		Cell Label											Word			0		1
42 Agave	X												None			0		0
43 RadCloud			Y		X	X							Word	X		0		3
44 V1 Declaratives	X												None			0		0
45 Emoticons	X												None			0		0
46 Lingoscope					X		X						Line	X		0		3
47 #SOTU							X						Document	X		0		2
48 Context-Specific Sentiment					X	X							Word	X		0		3
49 EmotionWatch		Axis Label											Word			0		1
50 dbo@ema						X		X	X				Word	X		1		4
51 TopicPanorama		X											Word			0		1
52 Text Re-use Grid									X				Word			1		2
53 VarifocalReader					X		X		X				Document	X		1		5
54 Impressions	X												None			0		0
55 CLICS		Labels											Word			0		1
56 Linea			Y		X	X							Word	X		0		3
57 News Views		X											Paragraph			0		1
58 SSE	X												None			0		0
59 Rose River			Y		X								Word			0		2
60 Tweet Bubble	X												None			0		0
61 Social Sentiment Sensor		X											Word			0		1
62 Opinion Flow			Y		X								Word			0		2
63 Typograph					X								Word			0		2

Name of Visualization Technique	No text	Plain Text	Tag Cloud?	Orientation	Size	Hue (foreground)	Hue (background)	Intensity	Bold	Italic	Underline	CASE	TEXT SCOPE None, Glyph, Word, Line, Paragraph, Document	Hue either fore- or background	Hue both fore- AND background	Num of Font-Specific Attribute	Other Attribute of note	Number of Dims in Text e.g. label + orientation = 2 dims
64 Poem Viewer							X						Character	X		0		2
65 Wine Reviews			Y		X								Word			0		2
66 Appraisal Patterns	X												None			0		0
67 Jigsaw			Y		X		X						Word	X		0		3
68 Sentiment Reln Map		X											Word			0		1
69 Sentiment Helix		X											Word			0		1
70 Geographical Public Sentiment	X												None			0		0
71 Electron Cloud Model	X												None			0		0
72 Fingerprint Matrices	X												None			0		0
73 Opinion Zoom		Scatter Label											Word			0		1
74 Dynamic Maps		Label											Word			0		1
75 Sw Dev Proj Emotions Viz		X											Paragraph			0		1
76 Serendip		Label											Word			0		1
77 Google+ Ripples					X	X							Word	X		0		3
78 ScatterBlogs2			Y		X								Word			0		2
79 UTOPIAN						X							Word	X		0		2
80 Texty		X											Line			0		1
81 Contextifier		X											Paragraph			0		1
82 Fisheye Word Cloud			Y		X	X							Word	X		0		3
83 SentiVis	X												None			0		0
84 Prefix Tags			Y		X		X						Word	X		0		3
85 Story Tracker							X						Word	X		0	Halo	2
86 Key Term Geo Map			Y		X	X							Word	X		0		3
87 Pixel Sentiment Geo Map	X												None			0		0
88 Topic Competition			Y		X								Word			0		2
89 Wikipedia Recent Changes		X											Word			0		1
90 Visual Sedimentation	X												None			0		0
91 Geo Temporal Assoc Creator			Y		X	X		X					Word	X		0		4
92 Token Cloud Vis		X											Word			0		1
93 Hierarchical Topics		X											Word			0		1
94 ForceSPIRE		X											Word			0		1
95 Distorted Doc Thumbnail					X								Document			0		2
96 Directed Social Queries							X						Word	X		0		2
97 webLyzard			Y		X	X							Word	X		0		3
98 TopicNets					X		X						Word	X		0		3
99 High Thruput Text Streams		X											Word			0		1
100 Suffix Distriubtion Vis		X											Word			0		1
101 Time Density Plots						X	X				X		Paragraph	X	X	1		4
102 Concept Recurrence Plots	X												None			0		0
103 Newspaper Quotation Thumbnails		X											Word			0		1
104 EventRiver							X						Line	X		0		2
105 VISA			Y		X	X							Word	X		0		3
106 Relaxed Evt Timeline		Topic Words											Word			0		1
107 ProjCloud			Y	X	X	X							Word	X		0		4
108 TopicTracker		Marker Label											Word			0		1
109 Money Trees		Node Label											Word			0		1
110 Emotional Tapestry		Cell Label											Word			0		1
111 iVisClustering		Axis Label											Word			0		1
112 Streamit		Topic Words											Word			0		1
113 Termite						X							Word	X		0		2
114 Stanford Dissertation Browser		Node Label											Word			0		1
115 DAViewer							X				X		Paragraph	X		1		3
116 Relative N-Gram Signatures		Doc Title											Line			0		1
117 News Auditor							X						Paragraph	X		0		2
118 RT Twitter Evt Detection	X												None			0		0
119 Whisper		Node Label											Word			0		1
120 Wordgraph					X	X							Line	X		0		3
121 Interactive 3D Vis of Semantic Network	X												None			0		0
122 Emotion Tracking Vis		X											Word			0		1
123 TypoMap				X	X	X							Word	X		0		4
124 TextWheel					X		X						Word	X		0		3
125 LeadLine			Y		X								Word			0		2
126 I-SI					X	X	X						Word	X	X	0		4
127 Semantic Preserving Word Clouds			Y		X		X						Word	X		0		3
128 TwitInfo		X											Word			0		1
129 SensePlace2			Y		X	X							Word / Line	X		0		3
130 Tag River			Y		X		X						Word	X		0		3
131 SentireCrowds			Y		X		X						Word	X		0		3
132 Opinion Blocks					X	X							Word	X		0		3
133 Eventscapes		X											Word			0		1
134 xLDD						X						X	Word / Line	X		1		3
135 Spatiotemporal Tags			Y		X	X	X	X					Word	X	X	0		5
136 ForAVis		X											Word			0		1
137 CyBis		X											Word			0		1
138 PaperVis	X												None			0		0
139 Comparative Reln Map		X											Word			0		1
140 Review Spotlight			Y		X	X							Word	X		0		3

Name of Visualization Technique	No text	Plain Text	Tag Cloud?	Ori ent ati on	Size	Hue (foreground)	Hue (background)	Intensity	Bold	Italic	Underline	CASE	TEXT SCOPE None, Glyph, Word, Line, Paragraph, Document	Hue either fore- or background	Hue both fore- AND background	Num of Font-Specific Attribute	Other Attribute of note	Number of Dims in Text e.g. label + orientation = 2 dims
141 Word Bridge			Y		X	X							Word	X		0		3
142 Linguistic Motion Charts		Node Label											Word			0		1
143 TextViewer					X	X					X		Document	X		1		4
144 CloudLInes		Node Label											Word			0		1
145 SolarMap		Node Label											Word			0		1
146 Topic View								X					Word			0		2
147 TextFlow						X							Word	X		0		2
148 Parallel Topics					X		X						Word	X		0		3
149 Tapestry					X								Word			0		2
150 Emotion Topic Diagram		X											Word			0		1
151 SparkClouds			Y		X								Word			0		2
152 Financial Blogs Vis		X											Word			0		1
153 Visual Backchannel				X	X		X						Word	X		0		4
154 Semantic News Analysis		X											Word			0		1
155 Facet Atlas					X								Word			0		2
156 VOSViewer					X								Word			0		2
157 Vox Civitas		X											Word			0		1
158 Tree Cloud			Y		X	X							Word	X		0		3
159 SIMPLE		X											Word			0		1
160 Character Flower	X												None			0		0
161 Opinion Seer		Node Label											Word			0		1
162 Parallel Tag Clouds			Y		X	X	X		X				Word	X	X	1		5
163 Bubble Sets							X					X	Word	X		1	Text Box	3
164 DocuBurst				X	X		X						Word	X		0		4
165 Opinion Cluster Thumbnails					X		X						Word	X		0		3
166 Topic Timeline Coordination							X						Word	X		0		2
167 Semantic Graphs									X				Word			1		2
168 Wordle			Y	X	X	X							Word	X		0		4
169 Phrase Net					X	X		X					Word	X		0		4
170 RSS News Feeds Sentiment	X												None			0		0
171 Document Cards					X								Word			0		2
172 Meme Tracker		Phrase											Line			0		1
173 AMAZING		Phrase											Line			0		1
174 Tiara			Y		X	X							Word	X		0		3
175 WET		Tooltip Label											Word			0		1
176 Exemplar-based Vis		Node Label											Word			0		1
177 Vibes		Glyph Label											Word			0		1
178 Hierarchical Document Map		Node Label											Word			0		1
179 STORIES		Node Label											Word			0		1
180 Skimmer					X								Line			0		2
181 Word Tree					X								Character			0		2
182 Document Spaces	X												None			0		0
183 BLEWS		X											Line			0		1
184 Sentiment Vis for eNulog	X												None			0		0
185 IVEA		X											Word			0		1
186 Ink Blots		X											Line			0		1
187 Tag Maps			Y		X								Word			0		2
188 Feature Lens			Y		X	X							Word / Line	X		0		3
189 Literature Fingerprinting	X												None			0		0
190 Topic Sequence							X						Word	X		0		2
191 Content temporal social based Event Visualization		Node Label											Word			0		1
192 Sentiment biased Topic Vis		Legend Label											Word			0		1
193 Storylines		Node Label											Word			0		1
194 Text-Image	X												None			0		0
195 Sequential Document Vis		X											Paragraph			0		1
196 Writeprints		X											Word			0		1
197 CrystalChat	X												None			0		0
198 Lexichron		X											Word			0		1
199 CiteSpace					X	X							Word	X		0		3
200 OCEAN		Annotations											Word			0		1
201 Docuscope						X							Word	X		0		2
202 Text Map Explorer		X											Word			0		1
203 Least Square Projection	X												None			0		0
204 MoodViews		X											Word			0		1
205 Sentiment Rose Plots	X												None			0		0
206 Sandbox					X								Word / Line			0		2
207 Opinion Observer		X											Word			0		1
208 Document Atlas		Node Label											Word			0		1
209 TextPool						X							Word	X		0		2
210 Pulse					X								Word			0		2
211 Gist Icons					X	X							Word	X		0		3
212 SmartINFO		X											Word			0		1
213 Gyro Knowledge Map		Node Label											Word			0		1
214 3D Explorer		Node Label											Word			0		1
215 IN-SPIRE Galaxies		Node Label											Word			0		1
216 Thread Arcs		Glyph Label											Word			0		1
217 Affect Color Bar		X											Paragraph			0		1
218 SATISFI		Adjunct Component											Word			0		1

Name of Visualization Technique	No text	Plain Text	Tag Cloud?	Ori ent ati on	Size	Hue (foreground)	Hue (background)	Intensity	Bold	Italic	Underline	CASE	TEXT SCOPE None, Glyph, Word, Line, Paragraph, Document	Hue either fore- or background	Hue both fore- AND background	Num of Font-Specific Attribute	Other Attribute of note	Number of Dims in Text e.g. label + orientation = 2 dims
219 Dynamic Discourse Analysis		Node Label											Word			0		1
220 Topographic Visualization of Evolving Text	X												None			0		0
221 Interactive Timeline Viewer		Title Label											Line			0		1
222 InfoSky		Node Label											Word			0		1
223 Arc Diagram		X											Word			0		1
224 Email Clustering		X											Word			0		1
225 ThemeRiver		X											Word			0		1
226 TextArc					X	X							Word	X		0		3
227 DUIS		X											Word			0		1
228 Netscan		Node Label											Word			0		1
229 Affect Inspector		Axis Label											Word			0		1
230 Compus	X												None			0		0
231 Patterngrams		Axis Label											Word			0		1
232 NIRVE	X												None			0		0
233 Data Mountain	X												None			0		0
234 Multiresolution Levels Strip Chart	X												None			0		0
235 Topic Islands	X												None			0		0
236 Multiresolution Levels Wave	X												None			0		0
237 Concept Shapes		Node Label											Word			0		1
238 Cat a Cone							X						Word	X		0		2
239 Lifestreams		X											Paragraph			0		1
240 ThemeScape		Peak Label											Word			0		1
241 TileBars		X											Line			0		1
242 Galaxy of News					X			X					Paragraph			0		3
243 Text Theme		Node Label											Word			0		1
244 InoCrystal	X												None			0		0
245 Document Lens		X											Paragraph			0		1
246 VIBE	X												None			0		0
247 SeeSoft		X											Word			0		1
248 Document SOM					X	X							Word	X		0		3
249 Tag Clouds (Stanley Milgram)			Y		X								Word			0		2
TOTALS and PERCENTAGES across the 249 visualizations:																		
Counts per attribute	40	103	39	10	76	42	33	9	6	1	6	2	**249**	71	4	14	2	
Percent of TextVis	16.1	41.4	15.7	4.0	30.5	16.9	13.3	3.6	2.4	0.4	2.4	0.8	**100.0**	28.5	1.6	5.6	0.8	

Based on the above itemization, various summaries can be computed. These summaries are used in Table 1.

Use of Text	Number of Visualizations
No Text	40
Plain Text	103
Text encoding data	106
TOTAL	249

How Text Encodes Data	Number of Visualizations
Size + Hue	36
Size	23
Hue	16
Size, Hue + Orientation	5
Size + Intensity	3
Size, Hue + Intensity	3
Size, Hue + Underline	3
Bold	3
Orientation	2
Intensity	2
Hue + Underline	2
Hue + Case	2
Size + Orientation	1
Size, Hue, Orientation + Bold	1
Size, Hue + Bold	1
Hue + Orientation	1
Hue, Intensity + Bold	1
Italics + Underline	1
TOTAL	106

Text Attributes	Number of Visualizations
Size	76
Hue	71
Orientation	10
Intensity	9
Bold	6
Underline	6
Case	2
Italics	1

F:4.2. Analysis of Text in Knowledge Visualizations at Scimaps.org

Scimaps.org is 144 currated exemplars of knowledge maps of science (knowledge maps are text visualizations which are representations of an entire domain). NOTE: "Y typ" indicates that the feature is used in a traditional typographic role meaning not data driven and only 2 variants (small/large, bold/not bold, 2 colors, etc.)

Item				Traditional Attributes				Typographic Attributes										
ID	Title	Type	Any Text?	Size	Color	Bright	Angle	**Bold**	*Italic*	UPPER & lower	Uline	Spacing	Typeface	Condensed	Super	Pair	Typgraphic Glyph	Mixed Language
158	Identify Emerge	Labeled Graph	Y (very few)															
159	Phylomemy	Org chart	Y	Y	Y			Y cat		Y cat								
157	Who Matters	Labeled Graph	Y	Y														Y
156	Hewlett	Grid	Y (ttip / axis only)		Y			Y typ	X Filter	X Filter								
155	Trend tagcloud	Tag Cloud	Y	Y	Y		Y											
154	Complexity Sci	Org graph?	Y	Y				Y typ	Y typ							Y typ		
153	Pulse Nation	Cartograms	N (single title)															
152	Polar Bear	Map	N (ttip only)															
151	Hurricanes	Map	N															
150	Moving Ocean	Map	N															
149	Movie Narrative	Timeline	Y	Y														
147	Khan Academy	Labeled Graph	Y	Y	Y		Y			Y cat								
146	Language Communities	Map (dots)	N (legend only)															
145	Interconnectedness	Labeled Graph (no edge)	Y	Y									Y sans/serif					
144	Manga Universe	Scatterplot	Y															
143	Knowledge Web	Labeled Graph	Y	Y	Y													
142	Gapminder	Scatterplot	Y	Y														
141	Left vs Right	Infographic	Y	Y	Y			Y		Y			Y					
140	Met Map	Infographic	Y	Y	Y								Y					
138	Time Spiral	Infographic	Y		Y		Y			Y				Y				
137	Shape of Science	Globe	Y															
136	Zones of Invention	Globe	Y															
135	Foreign Patent	Globe	Y	Y														
134	Illuminated Diagram	Labeled Graph	Y															
133	Illuminated Map	Map	Y	Y	Y													
132	History Sci Fi	Timeline	Y	Y typ	Y typ													
131	MACE Classification	Hierarchy Radial	Y	Y typ		Y typ			Y typ									
130	Seeing Standards	Infographic	Y	Y typ		Y typ				X acronymns								
129	Census of Antique Art	Rug Plot	Y	Y typ	Y typ													
128	Stream Sci Collab	Map Graph	N															
127	Design vs Emergence	Labeled Graph	Y															
126	Autism	Distribution	Y	Y typ	Y typ			Y typ										
125	Bible Arcs	Graph Arc	N															
124	Ellingham	Euler	Y	Y	Y (overlay #s)			Y typ	Y typ	Y typ								
123	Mondotheque	Physical	Y															
122	US Job Market	Labeled Graph	Y	Y	Y													
121	Nano	Labeled Graph	Y	Y typ	Y typ													
120	Knowledge Cartograph	Contour SOM	Y	Y														
119	Weaving Fabric	Ranking Timeline?	Y	Y typ						Y typ								
118	Literary Empire	Map	Y		Y													
117	Prix Ars Electronica	Labeled Graph	Y	Y						Y								
116	Speechome	Graph	N															
115	Connectome	Graph (Brain)	N															
114	Diseasome	Labeled Graph	Y	Y	Y													
113	Tree of Life	Hierarchy	Y	Y typ	Y typ													
112	Movies and Actors	Graph?	Y ?															
111	Bibsonomy	Scatterplot	Y		Y													
110	Research Collab	Map	Y	Y														Y
109	Co-PI Map	Labeled Graph	Y															

108	Websom	Contour SOM	Y									
107	PNL Inspire	Contour SOM 3D	Y									
106	Idealine	Timeline	Y		Y highlight	Y typ tooltip						
105	Indicator Assisted	Labeled Graph 3D	Y									
104	Topic Bursts	Labeled Graph	Y		Y			Y typ		Y		
103	VisIslands	Contour SOM	Y									
102	Lvis	Images 3D	N									
101	Vis Discipline	Scatterplot	Y									
100	Sci Map Kids	Infographic	Y									
99	DNA Development	Flowchart (Historiograph)	Y									
98	Emergent Mosaic	Images	N									
97	Lighthouse	Scatterplot 3D	Y									
96	Map www text	Cartograms	Y	Y	Y							
95	Cosmographia 1492	Map	Y	Y						Y		
94	PhD Thesis Map	Tubemap	Y	Y typ						Y typ		
93	Governing Values	Scatterplot of Shape	N									
92	In terms of Geo	SOM map	Y	Y			Y	Y			Y	
91	Sci and Society	Timeseries	Y									
90	Millenium Dev	Infographic	Y	Y	Y typ			Y typ	Y typ	Y typ	Y	
89	Chem R&D	Infographic	Y	Y typ	Y typ							
88	Boston Whales	Map	N									
87	Mobile Landscape	Map	N									
86	US Sci Vulnerable	Scatterplot ish	Y									
85	Death & Taxes	Infographic	Y	Y typ	Y typ	Y typ						
84	NIH Grants	Labeled Graph	Y									
83	Clickstream Sci	Labeled Graph	Y		Y							
82	Network Of Sci	Dashboard	Y	Y								
81	CoAuthor Net	Labeled Graph	Y									
80	Million items	Treemap	N									
79	Sky Chart	Map	Y	Y typ	Y typ		Y	Y typ	Y typ	Y	Y	
78	Periodic Table	Table	Y	Y typ								
76	Frequency Alloc	Treemap ish	Y	Y						Y typ		
75	Sci Outlook	Labeled Graph	Y	Y callout	Y callout							
74	Logic Land	Cartogram Game	N (ttip only)									
73	Oil Age	Infographic	Y		Y typ							
72	NYC Global Island	Map ish	Y									
71	Tech In Class	Labeled Graph	Y					Y typ				
70	Spam	Scatterplot	N									
69	Concept Maps	Labeled Graph	Y		Y typ							
68	Human Physiology	Labeled Graph	Y	Y typ	Y					Y typ		
67	Internet Splat	Graph (no label)	N									
66	Temporal Pattern	Timeseries	Y (axes)									
65	Map of Tenderness	Map	Y	Y typ						Y typ		
62	The Meal	Dining Room	N									
61	Universe	Map	Y	Y	Y							
60	113 Yrs Physical Review	Timeline w Links	N									
59	Structure of Sci	Labeled Graph	Y	Y	Y							
58	Anthrax Rsch	Timeline w Bubbles	Y									
57	Usenet Returnees	Treemap	Y	Y								
56	Abortion History Flow	Timeline Stacked Flow	N									
55	Sci Paradigms	Labeled Graph	Y									
54	Patent Hierarchy	Timeline w lots of text	Y	Y	Y							
53	Text Arc	Graph Ish	Y	Y	Y							Y
52	History of Sci	Labeled Graph	Y	Y								Y
50	Map of Science	Labeled Graph	Y		Y							
49	Science Wikipedia	Images	Y									
48	Structure of Sci	Labeled Graph	Y									
47	Medline Papers	Labeled Graph	Y									

46	Spatial for non-spatial	3D	Y															
44	Sci Roots of Tech	Alt	Y															
43	4Dtm	Infographic	Y															
42	Eco Footprint	Cartogram	N															
41	Patent Evolution	Timeline of Treemaps	Y															
40	Mark Lombardi	Labeled Graph	Y		Y typ													
39	Shrinking Planet	Timeline	Y															
38	Patterns of Patents	Physical	Y	Y	Y													
36	PeopleIknow	Labeled Graph	Y															
35	Poverty Map	Your are not here	Y															
34	New World 1544	Map	Y	Y						Y			Y					
33	Mappamundi DaVinci	Map	Y	Y														
31	Knowledge Discovery	Labeled Graph	Y							Y typ								
30	Map of Science 1996	Labeled Graph	Y															
29	Society for Neurosci	Labeled Graph	Y	Y	Y													
27	Map of Humanity	Map	Y	Y	Y typ water		Y	Y	Y	Y ?		Y						
26	Nova Anglia	Map	Y	Y			Y			Y								
25	World Map Old	Map	Y	Y			Y		Y	Y								
24	Air Travel Disease	Map	Y															
23	Tectonic Movements	Image Map	Y															
22	MidAtlantic Faults	Map	N															
21	Octagonal World	Map	Y	Y														
20	Where Sci Done	Map	N															
19	Tsunami beofre and After	Image	N															
18	1507 Globe	Map	Y	Y						Y								
16	GeoSphere	Image Sat Photo	Y															
15	Nova Terra 1659	Map	Y	Y						Y								
13	Anglo American Map	Map	Y				Y											
12	Helsinki Walked	Map Overlay	N															
11	Clover leaf Map 1588	Map	Y	Y									Y					
9	Napoleon March	Infographic	Y															
8	Dymaxion	Image Sat Photo	N															
6	Most Populous	Cartogram	Y		Y													
5	The Product Space	Labeled Graph	Y	Y typ	Y typ													
4	VCR	Labeled Graph	Y	Y typ														
3	Minard Cotton	Map W flows	Y	Y typ			Y											
2	Subjective Well Being	Map	N															
	TOTALS																	
144	Total	All	116	61	42	4	10	12	7	22	0	4	7	1	0	1	0	2
113	No Map	Not a map	96	45	37	4	4	10	4	13	0	2	5	1	0	1	0	1
31	Is a Map	Is a map	20	16	5	0	6	2	3	9	0	2	2	0	0	0	0	1

This summary is referenced in Table 4.

F:4.3. Online survey of Text Visualization Techniques

This light touch study was approved by LSBU ethics committee. Survey access via URL presented in seminars (also accessible here: http://goo.gl/forms/6lFYEKprpS). 23 responses received as of February 2018. Summary of survey and responses below.

A Survey: Visualization using Font Attributes

Font attributes, such as bold, italics, underlines, and so forth, are not commonly used in data visualization. This survey will show you some examples where font attributes are used with data visualization for different kinds of tasks. You'll be asked a few questions. Before we get started, a few questions about you, in part to prove that a real human being is carefully reading this survey as opposed to randomly clicking. No information is collected that personally identifies you.

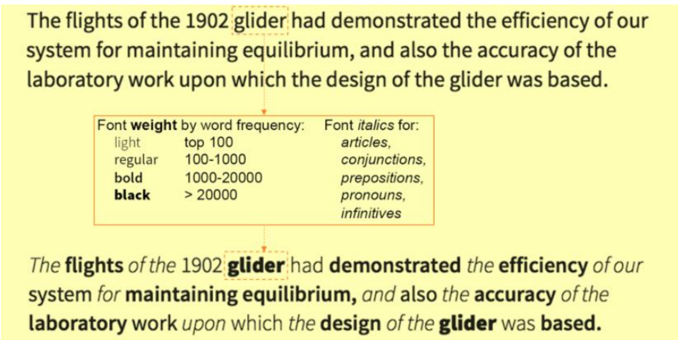
1. My occupation is:

Typographer	**0**	0%
Cartographer	**1**	4.3%
Computer Science / Software Programmer	**13**	56.5%
Other Designer	**1**	4.3%
Other Professional	**5**	21.7%
Student	**2**	8.7%
None of the above	**1**	4.3%

2. The numbers 2 and 3 add up to…
All responses were 5. This is a question to remove answers from robots or disinterested survey takers.

3. **Text skimming** introduced and text skimming technique introduced.

Skim formatting adjusts the formatting of text so that skim words - i.e. uncommon words - visually pop-out. Here's an example of a paragraph being reformatted:



4a. First pair of skim format questions. 8 responses. What are a few uncommon words that you see?

i. *Wizard of Oz* unformatted:

Dorothy lived in the midst of the great Kansas prairies, with Uncle Henry, who was a farmer, and Aunt Em, who was the farmer's wife. Their house was small, for the lumber to build it had to be carried by wagon many miles. There were four walls, a floor and a roof, which made one room; and this room contained a rusty looking cookstove, a cupboard for the dishes, a table, three or four chairs, and the beds. Uncle Henry and Aunt Em had a big bed in one corner, and Dorothy a little bed in another corner. There was no garret at all, and no cellar except a small hole dug in the ground, called a cyclone cellar, where the family could go in case one of those great whirlwinds arose, mighty enough to crush any building in its path. It was reached by a trap door in the middle of the floor, from which a ladder led down into the small, dark hole.
When Dorothy stood in the doorway and looked around, she could see nothing but the great gray prairie on every side. Not a tree nor a house broke the broad sweep of flat country that reached to the edge of the sky in all directions. The sun had baked the plowed land into a gray mass, with little cracks running through it. Even the grass was not green, for the sun had burned the tops of the long blades until they were the same gray color to be seen everywhere. Once the house had been painted, but the sun blistered the paint and the rains washed it away, and now the house was as dull and gray as everything else.

Responses:

- Kansas Em cyclone
- cookstove garret blistered

ii. *Alice in Wonderland* skim formatted:

Alice was beginning *to* get very **tired** *of* sitting *by her* sister *on the* **bank,** *and of* having **nothing** *to* do. Once *or* **twice** *she* had **peeped** *into the* book *her* sister was reading, *but it* had *no* **pictures** *or* **conversations** *in it,* "*and* what is *the* use *of a* book," thought **Alice,** "*without* **pictures** *or* **conversations?"**
So *she* was **considering** *in her* own mind (*as* well *as she* could, *for the* day made *her* feel very **sleepy** *and* **stupid),** *whether the* pleasure *of* making *a* **daisy-chain** would be **worth** *the* trouble *of* getting up *and* **picking** *the* **daisies,** *when* suddenly *a* White **Rabbit** *with* **pink** eyes ran close *by her.*
There was *nothing* so very **remarkable** *in that, nor* did **Alice** think *it* so very much out *of the* way *to* hear *the* **Rabbit** say *to itself,* **"Oh dear! Oh** dear! *I* shall be too late!" *But when the* **Rabbit actually** took *a* watch out *of its* **waistcoat-pocket** *and* looked *at it and* then **hurried** *on,* **Alice** started *to her* feet, *for it* **flashed** *across her* mind *that she* had never *before* seen *a* **rabbit** *with* either *a* **waistcoat-pocket,** *or a* watch *to* take out *of it, and,* **burning** *with* **curiosity,** *she* ran *across the* field *after it and* was just *in* time *to* see *it* **pop** down *a* large **rabbit-hole,** *under the* **hedge.** *In* another moment, down went **Alice** *after it!*
The **rabbit-hole** went straight *on like a* **tunnel** *for* some way *and* then **dipped** suddenly down, so suddenly *that* **Alice** had not *a* moment *to* think *about* **stopping** *herself before she* found *herself* **falling** down what seemed *to* be *a* very **deep** well.

Responses:

- waistcoat-poacket peeped
- waistcoat-pocket peeped daisy-chain

- cookstove, wagon
- prairie hole building cookstove cyclone
- sweep crush midst
- henry, em,cyclone,kansas
- kansas prairies uncle rust cookstove garret cyclone cellar whirlinds
- lumber kansas grass

- daisy-chain, waistcoat-pocket
- rabbit-hole waistcoat-pocket peeped daisy-chain
- waistcoat dipped
- alice,rabbit,hole,well
- daisies suddenly waistcoat rabbit-hole dipped
- waistcoat-pocket rabbit-hole daisies

4b. Second pair of skim format questions. 15 responses.

i. *Alice in Wonderland* unformatted.

Alice was beginning to get very tired of sitting by her sister on the bank, and of having nothing to do. Once or twice she had peeped into the book her sister was reading, but it had no pictures or conversations in it, "and what is the use of a book," thought Alice, "without pictures or conversations?"
So she was considering in her own mind (as well as she could, for the day made her feel very sleepy and stupid), whether the pleasure of making a daisy-chain would be worth the trouble of getting up and picking the daisies, when suddenly a White Rabbit with pink eyes ran close by her.
There was nothing so very remarkable in that, nor did Alice think it so very much out of the way to hear the Rabbit say to itself, "Oh dear! Oh dear! I shall be too late!" But when the Rabbit actually took a watch out of its waistcoat-pocket and looked at it and then hurried on, Alice started to her feet, for it flashed across her mind that she had never before seen a rabbit with either a waistcoat-pocket, or a watch to take out of it, and, burning with curiosity, she ran across the field after it and was just in time to see it pop down a large rabbit-hole, under the hedge. In another moment, down went Alice after it!
The rabbit-hole went straight on like a tunnel for some way and then dipped suddenly down, so suddenly that Alice had not a moment to think about stopping herself before she found herself falling down what seemed to be a very deep well.

Responses:

- waistcoat-pocket daisy-chain rabbit-hole
- considering Rabbit remarkable pleasure
- waistcoat daisy-chain
- hedge dipped daisy-chain
- peeped, sleepy, stupid, daisy-chain, daisies, rabbit, waistcoat, tunnel, dipped
- peeped waistcoat-pocket
- pictures conversations rabbit remarkable waistcoat-pocket
- waistcoat rabbit-hole
- curiosity peeped waistcoat daisy-chain remarkable tunnel
- peeped daisy-chain waistcoat
- waistcoat pop
- peeped daisy-chain dipped
- waistcoat daisy hedge
- daisy-chain waistcoat-pocket
- waistcoat-pocket, rabbit-hole

ii. *Wizard of Oz* skim formatted:

Dorothy lived in the midst of the great Kansas prairies, with Uncle Henry, who was a farmer, and Aunt Em, who was the farmer's wife. Their house was small, for the lumber to build it had to be carried by wagon many miles. There were four walls, a floor and a roof, which made one room; and this room contained a rusty looking cookstove, a cupboard for the dishes, a table, three or four chairs, and the beds. Uncle Henry and Aunt Em had a big bed in one corner, and Dorothy a little bed in another corner. There was no garret at all, and no cellar except a small hole dug in the ground, called a cyclone cellar, where the family could go in case one of those great whirlwinds arose, mighty enough to crush any building in its path. It was reached by a trap door in the middle of the floor, from which a ladder led down into the small, dark hole.
When Dorothy stood in the doorway and looked around, she could see nothing but the great gray prairie on every side. Not a tree nor a house broke the broad sweep of flat country that reached to the edge of the sky in all directions. The sun had baked the plowed land into a gray mass, with little cracks running through it. Even the grass was not green, for the sun had burned the tops of the long blades until they were the same gray color to be seen everywhere. Once the house had been painted, but the sun blistered the paint and the rains washed it away, and now the house was as dull and gray as everything else.

Responses:

- prairies whirlwinds blistered plowed garret
- whirlwinds blistered plowed
- cookstove whirlwinds blistered
- garret blistered baked
- prairies, em, lumber, wagon, cookstove, garret, cyclone, whirlwinds, plowed, blistered
- cookstove garret
- dorothy garret cookstove
- down little
- prairies cookstove cyclne whirlwinds plowed blistered lunber
- cookstove garret blistered
- garret whirlwinds
- cookstove garret plowed blistered
- cookstove cyclone garret plowed blistered
- garret
- cookstove, garret cyclcone whirlwinds, blistered

5. Given the task of needing to rapidly skim a text, which is your preference?

Normal formatting (left): 1	2	8.7%
2	2	8.7%
3	0	0%
4	1	4.3%
5	3	13%
6	10	43.5%
Skim formatting (right): 7	5	21.7%

6. If I use this skim technique, I think my speed to review text will be...

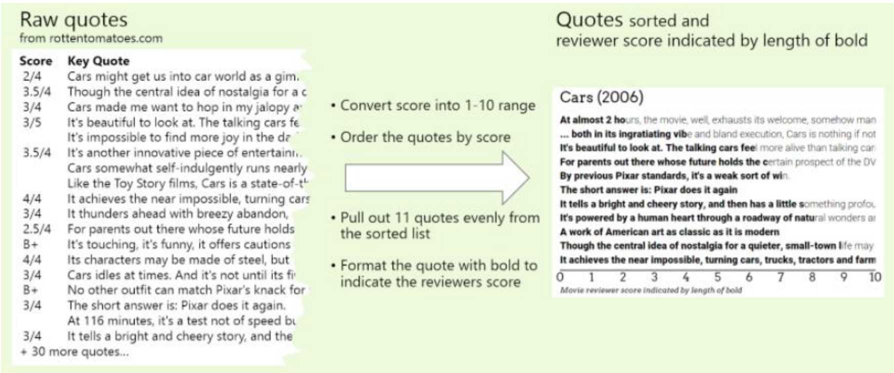
Very slow - 8x longer to review	0	0%
Slower - 4x longer to review	1	4.3%
A bit slower - 2x longer to review	3	13%
About the same	0	0%
A bit faster - twice as fast	12	52.2%
Faster - 4x faster to review	7	30.4%
Very fast - 8x faster to review	0	0%

7. I think some other variations should be considered, e.g. underline, highlighter or something completely different...

- Maybe bigger font sizes, similar to tag clouds.
- underline might be less distracting to the flow of sentences.
- Some common coordination words (then, so, and, or, ...) can be very important to correctly understand the text but they will be less visible with this technics. This is probably more right in scientific texts than in litterature.
- Reading the skim formatted text, i feel like the presentation is trying to impose an interpretation, so that place my mind reading in "double check" mode in order to avoid any hidden agenda due to the formatting, hence i do strongly prefer treading the normal formatting.
- Bold is best. Italics and underlines have specific meanings typically, and highlights create contrast differences that would be jarring to look at.
- Reading highlighed text marked up by previous readers seems to work well
- size symbols
- colored font
- Depends why I am skimming. Usually I skim for meaning - in which case, I think the bold is distracting. I would prefer larger spacing and clean blocks of text. If skimming for rare words, then bold is far better.

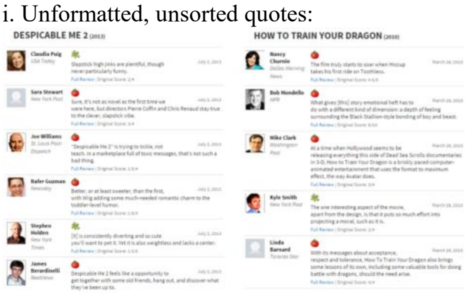
8. **Proportional encoding** introduction.

Suppose you want to see a movie. You could use a great website, say Rotten Tomatoes, to see the scores from professional critics or normal people.
But suppose you wanted to dig a bit deeper. You could read some of the key opinions. But there are hundreds of opinions per movie. And many movies. Which is the best opinion? The worst? And how does it compare?



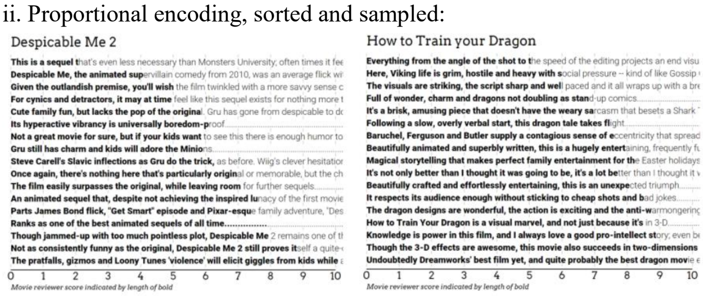
9. Which movie would you pick based on format?

i. Unformatted, unsorted quotes:



Despicable Me 2	11	47.8%
How to Train Your Dragon	12	52.2%

ii. Proportional encoding, sorted and sampled:



Despicable Me 2	3	13%
How to Train Your Dragon	20	87%

10. Do you understand “reviewer score indicated by length of bold”?

I don't get it at all. : 1	0	0%
2	2	8.7%
3	0	0%
4	1	4.3%
5	3	13%
6	2	8.7%
Sure, makes sense.: 7	15	65.2%

11. I understand it (proportional encoding), but I think there may be other considerations:

- In the presentation with bold text, comments are sorted by score. It seems not the case in the original presentation.
- I get it, the thing is that it incite to read only the bold character, in doing so it artificially push towards reading more out of the positive reviews.
- What if the sentence is too short?
- Reviews are truncated. What does this give in addition to average score?
- It could lead to malicious tempering by having some "bad" guy adding a review with a good "impression" on the first few words (being the last), which might make one side better than the other with "real" reviews.
- length of underline might be good too
- I automatically want to stop reading and skip to the next line when the bold ends
- Again, I'm reading for meaning and bold characters just end without a complete sentence - confusing because mixing two modes (quantitative score and text)

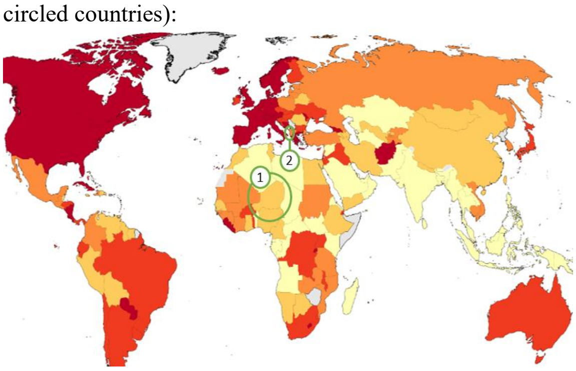
12. If given only the two choices above, how would you want to pick a movie?

Quotes in the original format (left):	1	2	8.7%
	2	2	8.7%
	3	2	8.7%
	4	4	17.4%
	5	1	4.3%
	6	5	21.7%
Quotes weighted with scores by length of bold (right):	7	7	30.4%

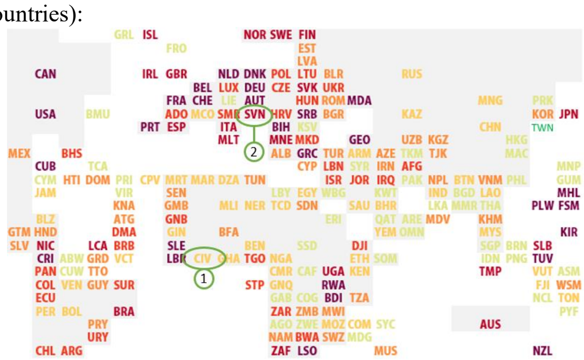
F:4.4. Choropleth map vs. ISO Code map Tasks

This light touch study was approved by LSBU ethics committee. The objective is to measure correct identification and location tasks across two mask types. Countries were used in all tasks were sufficiently sized to be visible in choropleth maps; and were not major countries, i.e. not in top 25 countries in the news, not largest population/size/economy in the continent. Sequence of questions and countries changed for different participants:

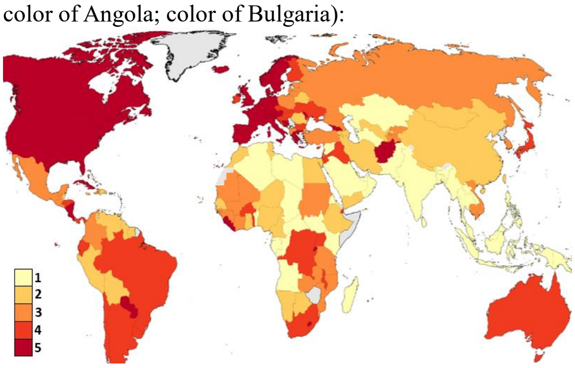
Sample identification task on choropleth map (name the circled countries):



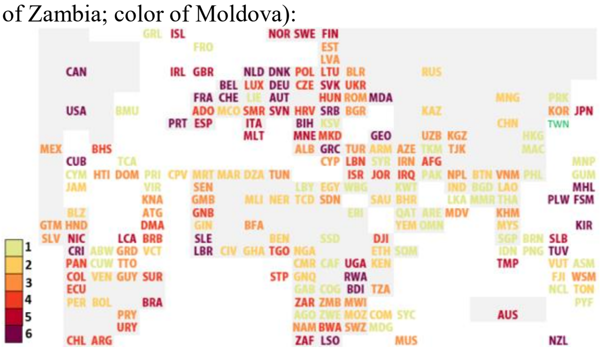
Sample identification task on ISO code map (name the circled countries):



Sample location task on choropleth map (e.g. what is the color of Angola; color of Bulgaria):



Sample location task on ISO code map (e.g. what is the color of Zambia; color of Moldova):



Results (nr = no response, interpreted as participant did not know the answer).

	QUESTION #							
	Identify circled country				Locate country record its color			
	Choropleth		ISO code		Choropleth		ISO code	
Respondent	1	2	3	4	5	6	7	8
1	wrong	CORRECT	CORRECT	CORRECT	CORRECT	wrong	CORRECT	wrong
2	nr	nr	nr	nr	nr	nr	wrong	CORRECT
3	CORRECT	CORRECT	nr	CORRECT	wrong	CORRECT	CORRECT	CORRECT
4	wrong	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT
5	nr	wrong	nr	nr	CORRECT	CORRECT	CORRECT	CORRECT
6	nr	wrong	nr	CORRECT	CORRECT	wrong	CORRECT	CORRECT
7	nr	nr	nr	CORRECT	nr	nr	CORRECT	wrong
8	nr	nr	CORRECT	CORRECT	nr	CORRECT	CORRECT	CORRECT
9	nr	nr	nr	nr	nr	nr	CORRECT	CORRECT
10	nr	wrong	CORRECT	CORRECT	wrong	wrong	CORRECT	CORRECT
11	wrong	wrong	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT
12	wrong	wrong	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT
13	wrong	CORRECT	CORRECT	CORRECT	CORRECT	wrong	wrong	CORRECT
14	nr	nr	nr	nr	wrong	CORRECT	CORRECT	wrong
15	wrong	wrong	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT
16	wrong	wrong	wrong	CORRECT	CORRECT	CORRECT	CORRECT	CORRECT
17	wrong	wrong	CORRECT	CORRECT	nr	nr	CORRECT	CORRECT
# Correct	1	4	9	13	9	9	15	14

	Choropleth	ISO code	Choropleth	ISO code
# Correct	5	22	18	29
% Correct	14.7%	64.7%	52.9%	85.3%

ISO-code map outperforms choropleth maps for both tasks. See discussion in *C:5 - OW: Ordered Words - typographic cartograms*, page 164.

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