Bertin's Forgotten Typographic Variables

and

New Typographic Visualization

Richard Brath[a]* and Ebad Banissi[b]

[a]Computer Science, London South Bank University, London, U.K. and Uncharted Software Inc., Toronto, Canada; [b]Computer Science, London South Bank University, London, U.K.

Typographic variables were only briefly discussed by Bertin with no example applications. We extend Bertin's visualization framework with typographic attributes, literal encoding, and more variants of scope and layout. Then, we extend Bertin's examples using the new framework to create new typographic visualizations. The new approach raises many questions and opportunities for a new research agenda.

Keywords: text visualization, thematic maps, visual attributes, visualization framework

Subject classification codes: include these here if the journal requires them

1. Bertin and Typography

In four pages near the end of the original 1967 French publication of Bertin's *Sémiologie Graphique* are a passing discussion regarding typographic attributes, such as bold and italics, and their correspondence to retinal variables (pp. 412– 415). However, in the 1983 English translation *Semiology of Graphics*, the entire book is translated, except for these four pages! Why?

Bertin further discusses typography in a follow-on article in 1980, *Classification typographique: Voulez-vous jouer avec mon A*, refining and organizing typographic attributes. In this article Bertin identifies 1) that type uniquely encodes data literally, 2) alphabetic and numeric glyphs as two different systems for encoding ordered data, 3) type-specific attributes i) bold, ii) letter width (e.g. condensed and extended fonts) and iii) inter-character spacing can be used to encode ordered information; plus attributes iv) letterforms (e.g. a,b,c,1,2,3,$,%), v) font family (e.g. serif, sans serif, blackletter) and vi) orientation (italic slope angle), can be used for categoric data and associative perception (i.e. marks perceived as similar) .

Unfortunately neither of these typographic writings were translated into English, and the latter has been cited only once according to Google Scholar vs. 3337 citations for the *Semiology of Graphics* (English edition, i.e. definitively no references to typography). Regrettably, Bertin's typographic work has largely been forgotten.

Typography is rich design space, and when combined with visualization, it enables new types of visualization and new ways of understanding visualization. This article will speculate why Bertin's contributions were lost; show the rich capabilities of typography to convey data; provide a framework for designing visualizations with type; then extend Bertin's examples with new typographic visualizations; and provide a critical discussion. The primary contribution is the re-orientation of visualization beyond simple, preattentive, thematic diagrams to post-modern, multi-modal, multi-level analysis.

2. Why Were the Typographic Aspects of Bertin Forgotten?

Besides the lack of translation, a confluence of technological, social and cultural factors lead to the non-use of typography after Bertin:

Technical Regression

Bertin certainly would have been familiar with the incredibly detailed maps produced by expert engravers a generation earlier, such as Steilers’ *Atlas* shown in Figure 1, which uses capitalization, variable underlines, size and italics to indicate data in addition to the literal text to create rich multi-variate labels.

Figure 1. Small portion of map with place names varying font size, italics, typeface, capitalization and underline styles to indicate data (Stieler and Haack, 1911) via davidrumsey.com.

High quality typography has not been readily available for visualization for multiple generations. By Bertin’s time, phototypesetting was displacing engraving as it was faster for composing professional fonts. But, it lacked the precision of metal type as the optical lens tended to soften details. Adrian Frutiger, designer of the widely used font *Univers*, said of phototypesetting: “Instead of a sans serif, the drafts were a bunch of misshapen sausages!” (Osterer and Stamm, 2014).

Phototypesetting was followed by desktop computers, which also suffered from poor quality. Until the current decade, low pixel resolutions of 72-96 DPI were standard. This resulted in stair-step visual effects on the curves of letters, did not allow for small fonts to be legible, and did not allow for fine detail to be visible (e.g. Khan & Lenk 1998).

Visual Convention Separating Text and Graphics

In historic visualizations created by medieval and Arabic scholars such as the genealogical diagram in Figure 2 left (Peter of Poitiers, 1225), text is interwoven into diagrams, charts and maps; with variation in text colour and letterforms to indicate additional information.

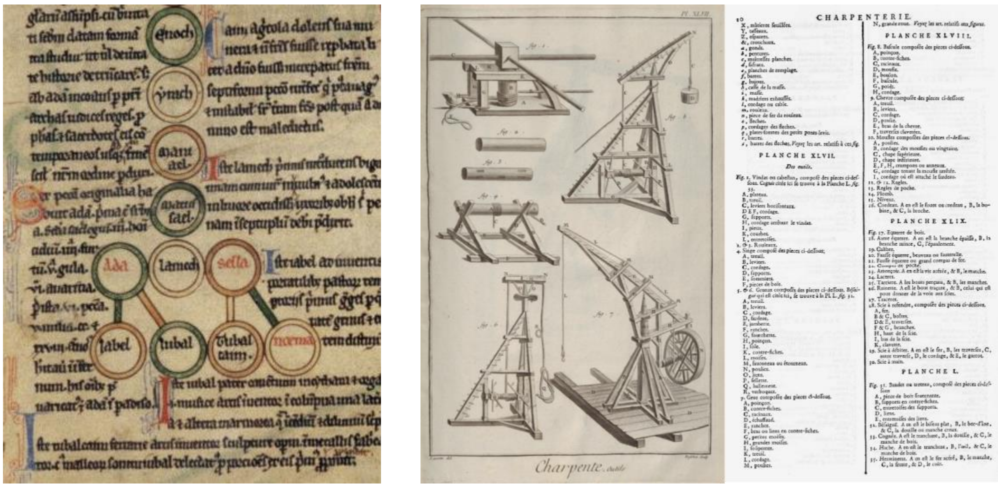

Figure 2. Left: Medieval genealogy chart (with colored text, rings and edges) interwoven into text. Right: Enlightenment Encyclopaedia separates text from image necessitating cross-referencing.

In 1439, the introduction of the printing press by Gutenberg changes the technical ease of mixing type and imagery. By the Enlightenment, text and image are completely separated and carefully cross referenced, such as Figure 2 right (Encyclopédie, 1751). By the 20th century, charts have largely relegated the role of text to simple labels, ticks, legends and titles around the perimeter of the visualization (e.g. Brinton 1939).

In Bertin's *Graphics and Graphic Information Processing* (1981), Bertin only provides a few paragraphs on text (pp.184-185). Bertin explicitly calls out for separation of text from visual: "In any presentation of graphic processing, the *text must appear opposite the image*." However, this discussion is only with regards to explanatory text to augment the visualization.

While modern technologies (e.g. HTML5) are capable of mixing type and graphics, modern visualizations still tend to keep visualization and type separate – potentially a result of graphic design education following 500 years of convention. One third of text visualizations at the Text Visualization Browser (textvis.lnu.se) did not contain text as of 2015.

Modernism

In European post-war 1950's, modernism was sweeping the world, promoting styles that reached across national boundaries. Modernism emphasizes clarity, simplicity, economy of expression, (e.g. Tschichold 1928/1995) as well as minimizing language-specific text in favour of international icons and symbols, such as seen in the statistical graphics invented in early modernism by Isotype (e.g. Neurath 1930). A modernist graphic designer at the time of Bertin would favour simpler thematic maps and visualizations with fewer labels out of principle.

Thematic Maps vs. Reference Maps

Bertin differentiates between maps used to inventory detailed information (i.e. typographically dense reference maps, such as the example in figure 1) and thematic maps leveraging visual attributes such as hue, size and brightness (i.e. retinal variables) for visual analysis of data. Bertin may have considered the two uses mutually exclusive: note how *Sémiologie Graphique* has more than a *thousand* visualizations, *none* of which leverage typographic attributes such as bold or italics! Furthermore, Bertin identifies that text uniquely *literally* encodes data, however in discussion of perception (levels of organization, i.e. associative, categoric, ordered, quantitative) in the introductory chapters, he does *not* include literal perception.

Bertin may have excluded typography to focus specifically on graphics. Perhaps he was biased by the long-standing separation between thematic and reference maps: Charles Dupin's first choropleth map in 1819 was influenced by August Crome's *Neue Carte von Europa* in 1782 (Figure 3). Crome uses symbols, one- and two-letter codes to indicate various resources on a map, but these letter codes appear similar to other labels indicating countries, rivers and cities. With low typographic variation between the codes and the labels, it is difficult to perceive any patterns without tediously searching through all the labels. Had Crome more effectively utilized type variation to differentiate between commodities, subsequent thematic maps may have used typography to indicate thematic data.

Figure 3. Subset of Crome's *Neue Carte von Europa*, 1782. Letter codes indicate commodity production but with little differentiation between categories. Image via Wikipedia.

Disappearance of Type as a Thematic Variable

Despite Bertin's written viewpoints on type, typographic attributes do not appear in visualization research reference texts (e.g. MacKinlay 1986, Ware 2013, Munzner 2015). In cartography, many authors note the ability of type attributes (bold, italics, capitalization, spacing, etc) to convey data; however, these are not discussed in thematic sections of the reference text and are typically in sections more concerned with label placement (e.g. Brewer 2005, Tyner 2012, Muehlenhaus 2014).

As a result, Bertin's framework has become widely popular, but with little focus on typography. Figure 4 illustrates the commonly used visualization framework which has largely been adapted and extended from Bertin's original. Structured data of different types (Bertin's *level of perception*) is mapped to various visual attributes (*retinal variables*) which are then represented as marks (*types of signification*) and composed in a layout (*imposition*).

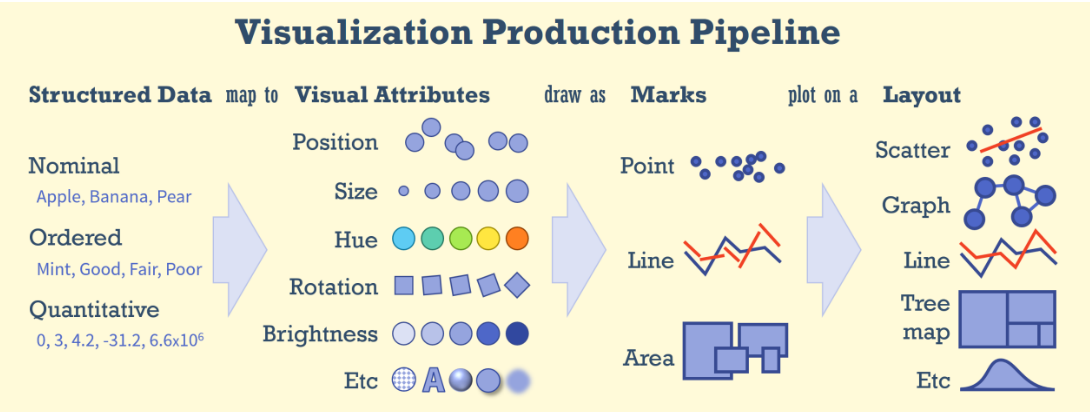

Figure 4. Bertin's framework as a visualization pipeline transforming data (left) into visualizations (right).

3. Type Encodes Data

First, we review existing examples of typographic visualization to confirm and extend Bertin's framing of typography applied to visualization.

Historic Typographic Visualization

Reference maps, such as Steilers' *Atlas* in Figure 1, vary many typographic attributes. Going beyond Bertin's list of attributes, for example, this map has an ordering of underlines (dot, dash, single, double) to indicate different levels of administrative areas.

Typesetters also ingeniously use typography to create rich encodings of data into text such as Chambers' *Cyclopaedia* (1728) in Figure 5. Interestingly, Chambers' uses a continuous narrative paragraph as opposed to the now more familiar table of contents. Chambers' table of contents is a paragraph configured into a branching tree using *brackets*, differentiating between subject areas with *italics*, specific topics in *small caps*, and numbered with *superscripts* to aid cross-referencing in following sections.

Cartography and Geographic Information Society (CaGIS). DOI: 10.1080/15230406.2018.1516572

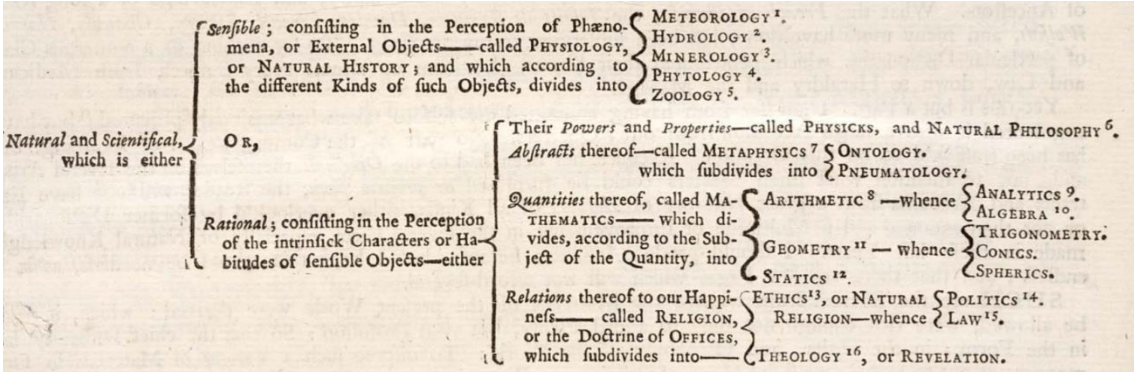

Figure 5. Portion of Chambers' *Cyclopaedia* introduction using italics, small caps and superscripts to organize the contents into a decomposable readable paragraph.

Beyond labels, Figure 6a shows an example of Victorian training material with keywords highlighted using *bold*, and bold *all caps* for the most important content (Hamilton 1858). Figure 6b shows a *market profile* chart using stacks of characters to indicate trading prices for stocks: at a micro-level, specific characters denote time intervals, symbols denoting open/close price, case to differentiate between morning and afternoon, and bold to indicate tallest stack. At a macro-level distributions are formed by the stacks. Figure 6c is a contour map where contour lines are narrative descriptions (McLean 2014). Figure 6d is a font designed so that the amount of ink is proportional to the numerical value (Nacenta et al 2012).

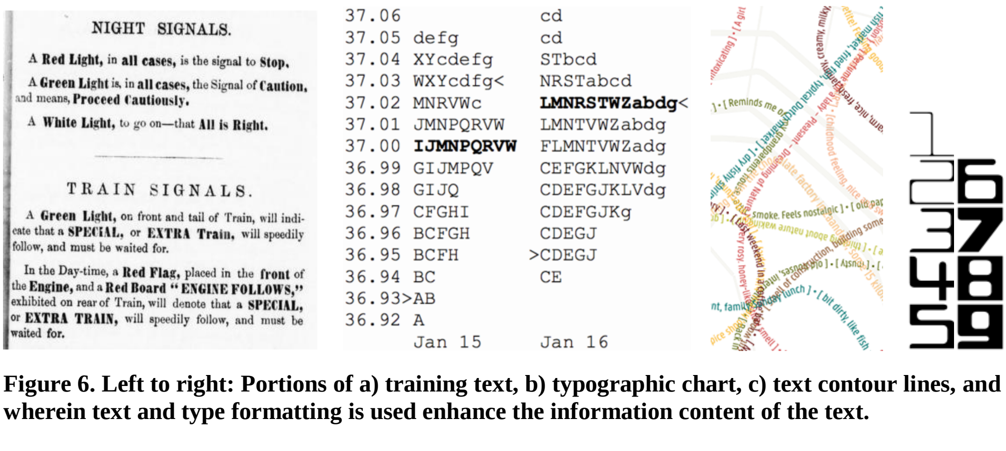

Figure 6. Left to right: Portions of a) training text, b) typographic chart, c) text contour lines, and d) a font wherein text and type formatting is used enhance the information content of the text.

Type variation is also used to indicate significant information in domains such as mathematical notation (e.g. $\mu_e(A) = inf\{\lambda_*(O) \mid O \in \mathcal{O}, A \subset O\}$), molecular notation (e.g. $[As@Ni_{12}As_{20}]^{3-}$), and software code (<div class=“body”>Text </div>). Note the use of features such as different typefaces, alphabets, superscript/subscript, paired delimiters (e.g. <>, [], “”) and symbols.

In the supplemental materials are other historic examples using typographic variation to indicate additional information beyond the literal text, such as timetables, data tables, reference guides, maps, illustrations, and financial charts.

Type and Preattention

Much of Bertin’s interest in information analysis using visual representations focuses on *preattention*, that is, visual patterns that can be perceived instantaneously. Bertin’s retinal variables (size, hue, brightness, size, shape, texture) and other visual attributes (e.g. blur, containment) have been shown in psychology research to be preattentive (e.g. Wolfe and Horowitz, 2004).

Many type attributes are similar to preattentive attributes: for example, type weight is similar to size as it increases the thickness of strokes on letters; italics are similar to orientation; font families rely on variation in shape cues. As shown in Figure 7, the anomalous type attribute can be readily detected visually in each group of labels.

Figure 7. Typographic attributes can be used to draw attention to a name.

Furthermore, early research (Strobelt et al, 2016) confirms the preattentive effect of typographic attributes but doesn’t consider related issues such as legibility and readability.

More broadly, philosophy, arts and criticism have move beyond the universalism of modernism to multi-layered interpretations across relevant contexts in post-modernism. Reconsider Figure 1: even though this map was not designed to be preattentive, patterns are clearly visible. For example, the left side of the map is more typographically dense - using larger, heavier weight, more uppercase text (i.e. densely populated Rhine valley) whereas the right half uses smaller, lighter text (i.e. sparsely populated Odenwald). At the same time, the text is immediately accessible for added levels of information, for example, not only can **MANNHEIM**, ***LUDWIGSHAFEN***, **Worms** and **Heidelberg** be individually identified, the large text size indicates the cities are large, while other noticeable typographic differences (case, italics, dash style) indicate other differences. Note that even though Tschichold's early modernist manifesto advocates clean sans serifs fonts, in the late 1960's he released his most widely-regarded font, Sabon, based on classic humanist serif fonts from the 1500s.

4. Typographic Visualization Framework

How do all of these typographic elements fit together into a visualization framework? The red text in Figure 8 illustrates extensions to the framework previously shown in Figure 4.

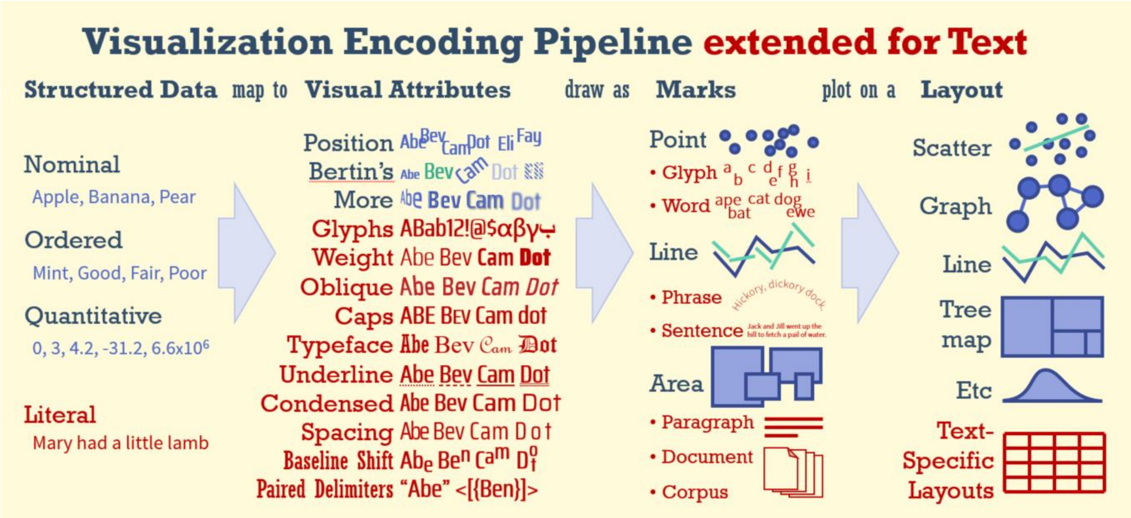

Figure 8. The visualization production pipeline. Traditional pipeline in blue, with type-specific extensions in red.

Data is extended to include literal encodings, specifically text. Visual attributes are extended with attributes such as weight, typeface, (e.g. Helvetica, Garamond, Blackletter), underline, width (e.g. condensed/expanded), spacing, case, oblique (italics), added symbols (e.g. !, $), baseline shift (e.g. superscript/subscript), and paired delimiters (e.g. "",[]). Marks are expanded so that point marks differentiate between individual characters (i.e. glyphs) and words; while lines range from phrases to sentences; and the scope of areas can range from paragraph to corpus. Finally, layouts can be expanded to include text-specific layouts such as tables and indicies.

Note that elements in this four dimensional framework can be assembled in any combination, resulting a large design space with exponential permutations. For example, any typographic attributes can be combined and used simultaneously with any other attributes, for example, **bold** + color + *italic* + size + underline + s p a c i n g + b r i g h t n e s s; which in turn can be combined simultaneously with literal, nominal, ordered, or quantitative encodings of various mark scope and layouts, 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.

5. Using the Framework to Generate New Typographic Visualizations

Sémiologie Graphique may have become popular because many examples were provided illustrating Bertin's framework. Bertin wonderfully spends 39 pages generating 90 different visualizations from one dataset of working populations for three occupations by 90 French geographic departments. A small subset are shown in Figure 9.

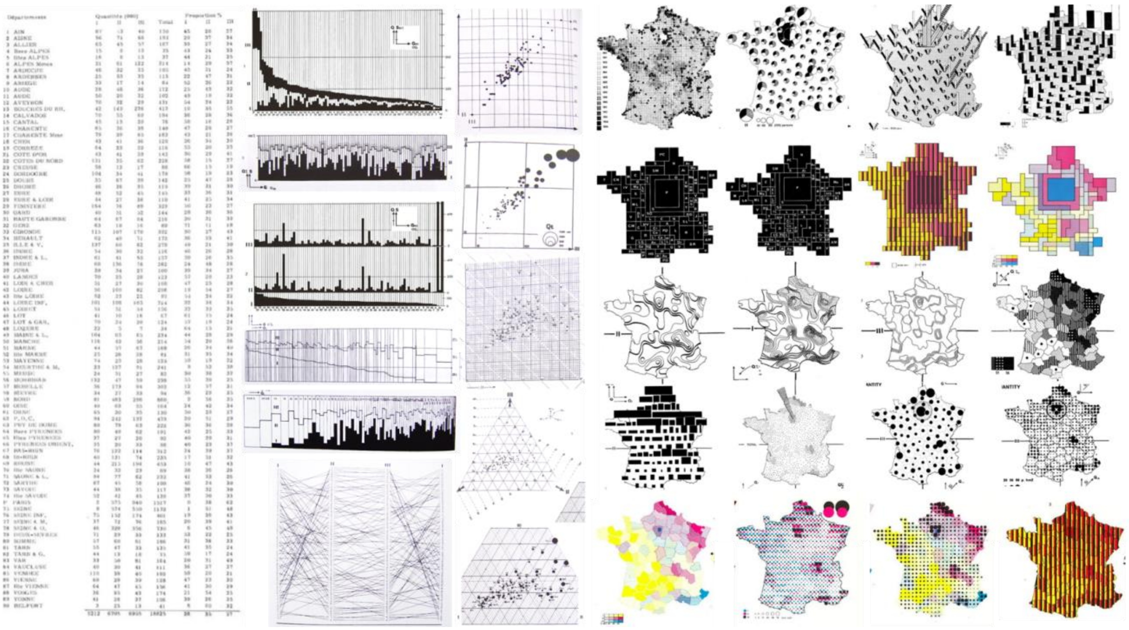

Figure 9. Table of data and sample of visualizations generated by Bertin for that data set.

Using the above typographic framework for text in visualization, many extensions and unique visualizations can be generated from Bertin's same dataset. Consider:

A. *Literal Areas*

Bar charts are among the simplest data visualizations. Using Bertin's data, a very simple bar chart can be constructed wherein the literal names of the departments are added to the areas of the bars as shown in Figure 10. This is somewhat similar to the earlier market profile chart made of out stacked text (Figure 6 middle) and stem & leaf plots more generally (BB 2017a).

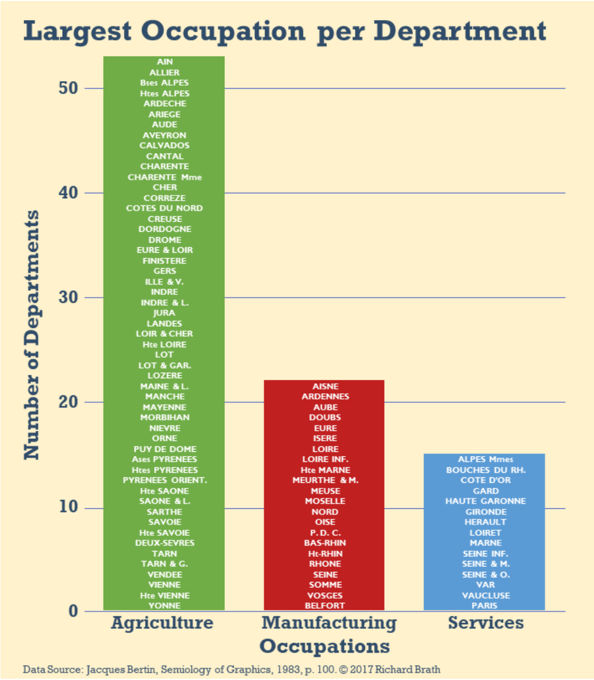

Figure 10. Bar chart with named departments.

The addition of this literal data introduces various benefits. The macro-level preattentive visual perception of the relative bar sizes is retained. Plus, the constituent members of each bar is readily accessible upon closer (micro) inspection (Tufte 1990) – which significantly increases the *data density* of this visualization.

Secondly, this micro-data is accessible *faster* than interactive techniques by simply shifting attention rather than relying on slower interaction such as tooltips (Proctor & Vu, 2008) or cross-referencing with a legend (Larkin & Simon, 1987) – for example, in Figure 2 right the viewer needs to constantly shift back and forth between the illustration and the written text.

Thirdly, while text is not preattentive, individual words are perceived extremely fast. The parallel letter recognition model states letters in words are recognized simultaneously (Larson 2004), and furthermore, automatic word recognition claims that reading is automatic and difficult to stop (MacLeod 1991). This leads to *serendipitous discovery* (Thudt et al, 2012) across local text, such as a known association between neighbouring labels (Robinson et al 1995) -- for example, in the agricultural column, labels such as “Alpes, Pyrenees, Savoie” may trigger recognition as mountainous regions, which matches an understanding that manufacturing and services tend not to occur in mountainous regions).

Fourth, there are 90 unique departments: most visual attributes do not support categories of high cardinality (i.e. Bertin’s length). Words can *scale* to high cardinality representing tens of thousands of unique entities and can be unambiguous, unlike icons e.g. Clarus the dog-cow (Brath 2015).

B. Literal Points

Point marks are often dots, but can be replaced with text instead. In some of the 90 examples by Bertin, dots are used on charts, and in a few cases these are additionally labelled. Using both dots and labels clutters the plot area. Instead, literal text can replace dots: the overall high-level visual patterns remain and individual points can be immediately identified. Figure 11 shows a ternary plot, similar to Bertin’s, where bubbles have been replaced with INSEE 2-letter department codes, sized by population. Even though this plot is made of text, high level preattentive patterns are visible: a clear subset of the plot area is covered with data, with a strong bias to larger sizes on the right. At a low-level, the text is readable, with perceivable patterns such as many high-number large departments along the right (BB 2015).

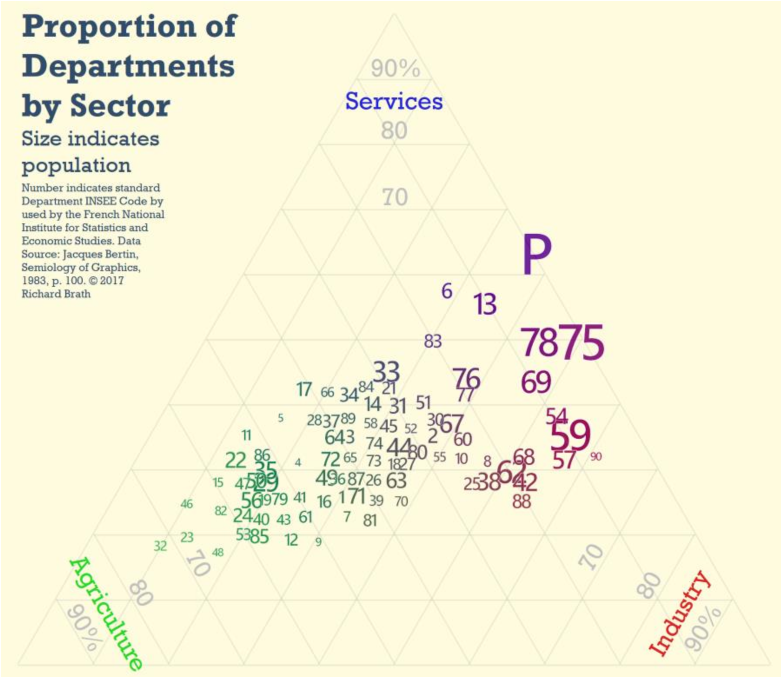

Figure 11. Ternary plot showing department codes instead of bubbles.

C. *Literal Lines*

Similarly, line charts can replace lines with text. This bypasses the issues of line charts typically limited to 20 or so lines due to perceptual limitations in differentiating between 20 or so line colors. Figure 12 shows a parallel coordinates chart with each column showing rank order of percent population (similar to Bertin's fig. 4, p. 90). Lines connect departments across columns: macro patterns such as the inverse relationship between agriculture and manufacturing are clearly visible with the many crossing lines. Plus, at a micro-level, the names of departments along lines provides identification and facilitates visual trace (BB2017b).

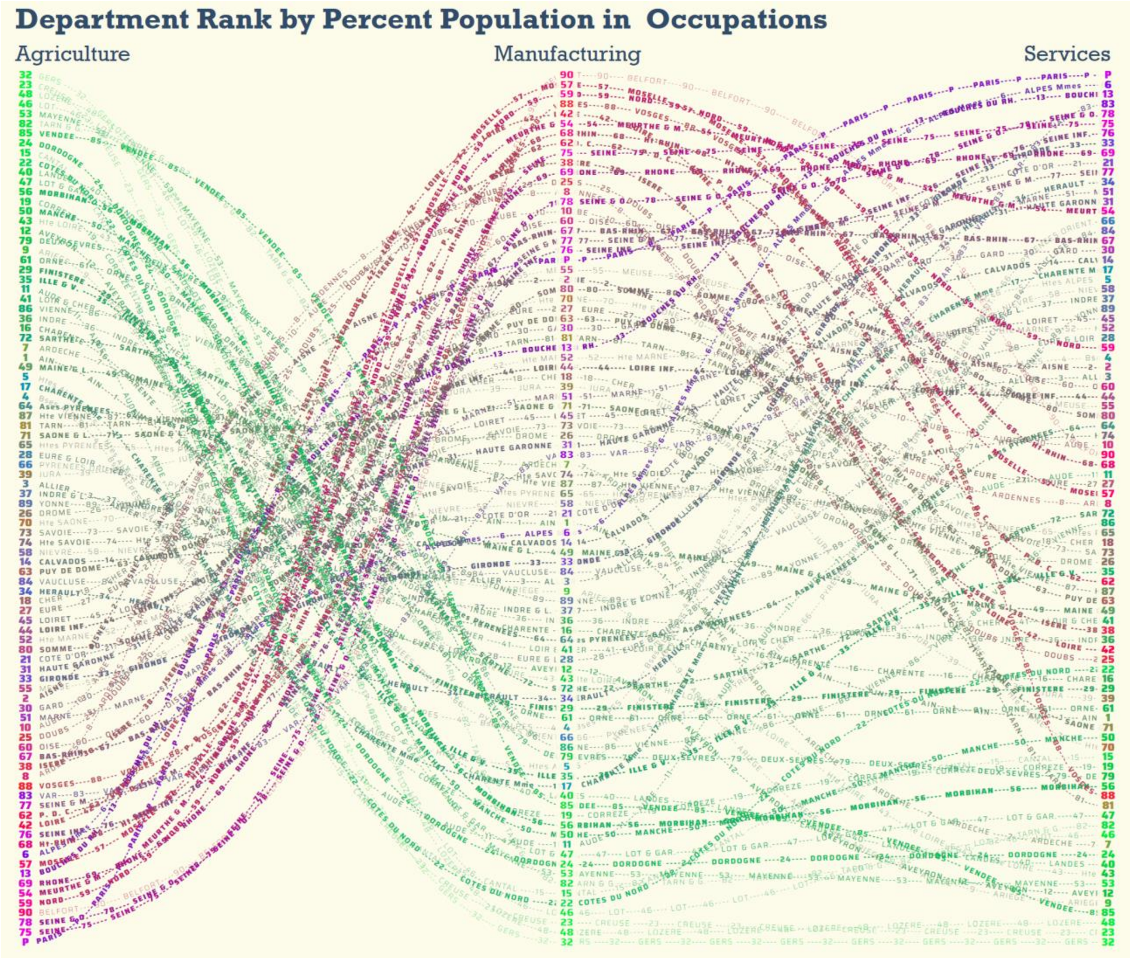

Figure 12. Ranking chart with lines of text connecting the same department across ranking columns.

D. Multiple Combinable Attributes

Font attributes are distinct and can be used together in any combination. Creating a thematic map composed entirely of labels allows typographic attributes to convey multiple data values. The map in Figure 13 shows:

(1) Named departments;

(2) Label size to indicate population (e.g. Paris and Seine pop-out as large labels, which indciates high population);

(3) Label weight to indicate population growth (e.g. Seines & O. has had significant population growth, Ardennes has shrank);

(4) Colour to indicate ratio of population among agriculture, industry and service sectors (e.g. the northeast is industrial, the centre is agricultural); and

(5) Italics to indicate ratio of women to men (e.g. Paris has more women than men).

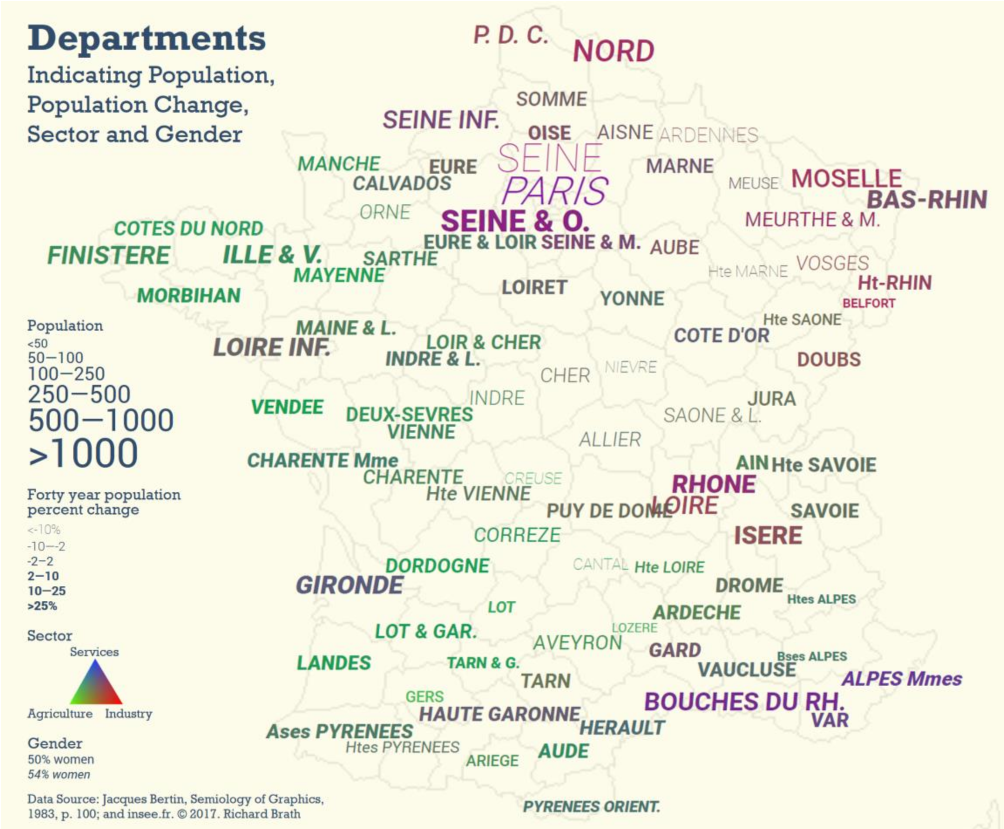

Figure 13. Thematic label-based map showing five different attributes per label.

This configuration allows for patterns of a single variable to be clearly visible, such as large text or heavyweight text. Furthermore, preattentive patterns are visible in multivariate data, such as small lightweight text in central France (small and shrinking populations). Similar patterns are perceivable in Figure 1 (note the large, heavyweight text on the left along the Rhine, the small sparse text in Odenwald on the right half).

This construct also enables multivariate questions to be answered, e.g. Q: Manufacturing departments with low population? A: Yes, Belfort (red, small) E.g. Q: Services department, with more women and growing population? A: ALPES Mmes (bluish, italic, heavyweight).

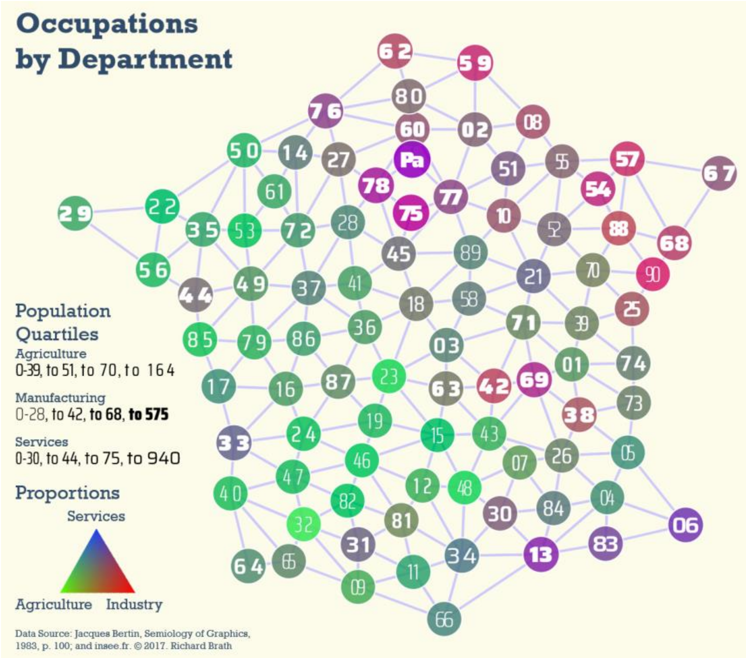

Figure 14. Cartogram with label attributes indicating three different quantities.

Figure 14 shows a cartogram where text attributes indicate three different measures of magnitude: agricultural population is shown with font spacing, manufacturing population with font weight, and services with font width. Many small departments are small across all three occupations, whereas large departments are more mixed: Paris is heavy, wide but tightly spaced (high manufacturing and services but low agriculture), with Nord (above Paris, 59) high in all three occupations, while 88 (Vosges, east) is heavyweight, but narrow and tightly spaced (high manufacturing, but low in services and agriculture). More generally, text-based cartograms can outperform many uses of choropleth maps, such as representing multiple variables and clearly depicting small regions (BB2017c).

E. Multiple Levels of Areas

Area based representations, such as choropleth maps and treemaps tend to have difficulties showing multiple levels of aggregation: for example, a choropleth map of countries around the world shows values per individual country but cannot simultaneously show the aggregate value per continent. Instead, many label-intensive maps use text at different scales to indicate features at multiple scales, such as continent, country, state and city. A similar approach can be used to express multiple levels of thematic data, such as Figure 15: the overall country summary is large all caps text; regions are indicated with text across the regions' extents; underlying text and individual departments are indicated with smaller numeric codes on top. Total, regional averages and departmental variation are all visible.

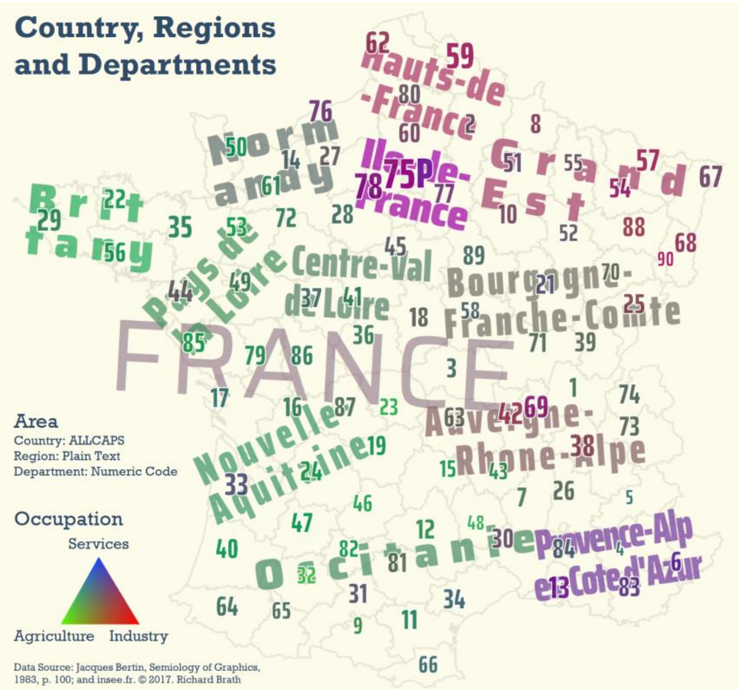

Figure 15. Labels at the level of country, region and district.

F. Character Scope

Instead of focusing on names of departments, occupations can be used. These occupations tend to group together geographically. In Figure 16, the extents of the label indicate the extents of that sector and weight of individual characters indicates population near the character. (Note, this particular example was hand-generated).

Figure 16. Labels indicate occupation and range; with weight of individual characters indicating population residing near those characters.

G. Paragraph Scope

Narrative visualization is an emerging area of research activity (e.g. Segel & Heer, 2010) with applications such as data journalism. Instead of the narrative explaining a separate visualization, multivariate labels can be directly embedded into the narrative along with other word-sized visualizations such as sparklines (Goffin et al, 2016), as shown in Figure 17. Similar to Figure 5, additional semantics are embedded directly into a paragraph.

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 17. A paragraph with multivariate labels embedded directly in the context of the narrative with both narrative and visual insights.

Narrative paragraphs with visualization can be extended beyond the formatting of individual words. Each sentence or paragraph can represent a summary of a subset of data; with formatting then applied to that summary. Figure 18 shows nine paragraphs, each with respect to a particular area in France (e.g. northeast, northwest), where each paragraph provides some summary text with font weight and color to match population and occupation. Patterns such as green in the west, heavyweight in the north are clearly visible without reading the text, much like the patterns visible in text in **Figure 7**.

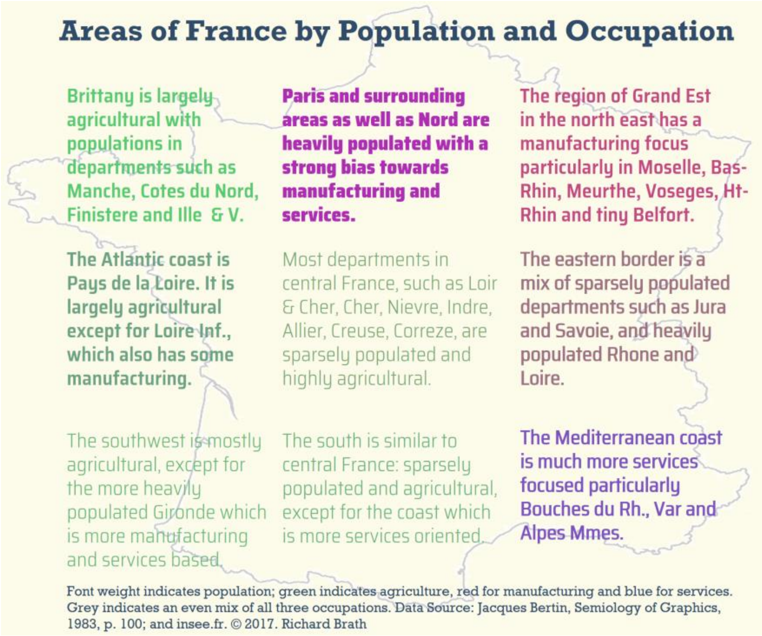

Figure 18. Nine paragraphs describing population and occupations, each colored and weighted by underlying data.

H. Quantitative Values Encoded Along Proportions of Text

Varying text weight or slope angle are ordered encodings: it is not feasible to make perceptual quantitative comparisons such as ratios. Using text formats along the length of a string allows relative string lengths to compared directly – length encoding is an accurate quantitative encoding (e.g. Cleveland & McGill 1984, Bostock & Heer 2010). Figure 19 shows one line of text per department, with font family and font colour varied to indicate proportion of population per occupation (top axis), and underline length to indicate overall population (bottom axis). In addition to acting as a stacked bar chart at a macro-level, the text (from Wikipedia) provides an introductory description per department for the viewer who is unfamiliar with French geography.

Figure 19. Proportions of font + colour indicate occupations per department; proportion of underline indicates population per department.

I. *Other Layouts and New Layouts*

Figure 20 shows an area-proportional Venn diagram, with each department name placed within its respective segment. Unlike an area-proportional Venn diagram with shaded regions, the text elements uniquely identify the set memberships of each department. It also provides the text in vertical stacks - a more perceptually efficient means of comparing relative sizes than estimating areas of complex geometric fragments. Furthermore, serifs indicate departments with high proportion of population in agriculture; smallcaps for high industrial population; italics for high service population; and, boldness to indicate population density (BB2016).

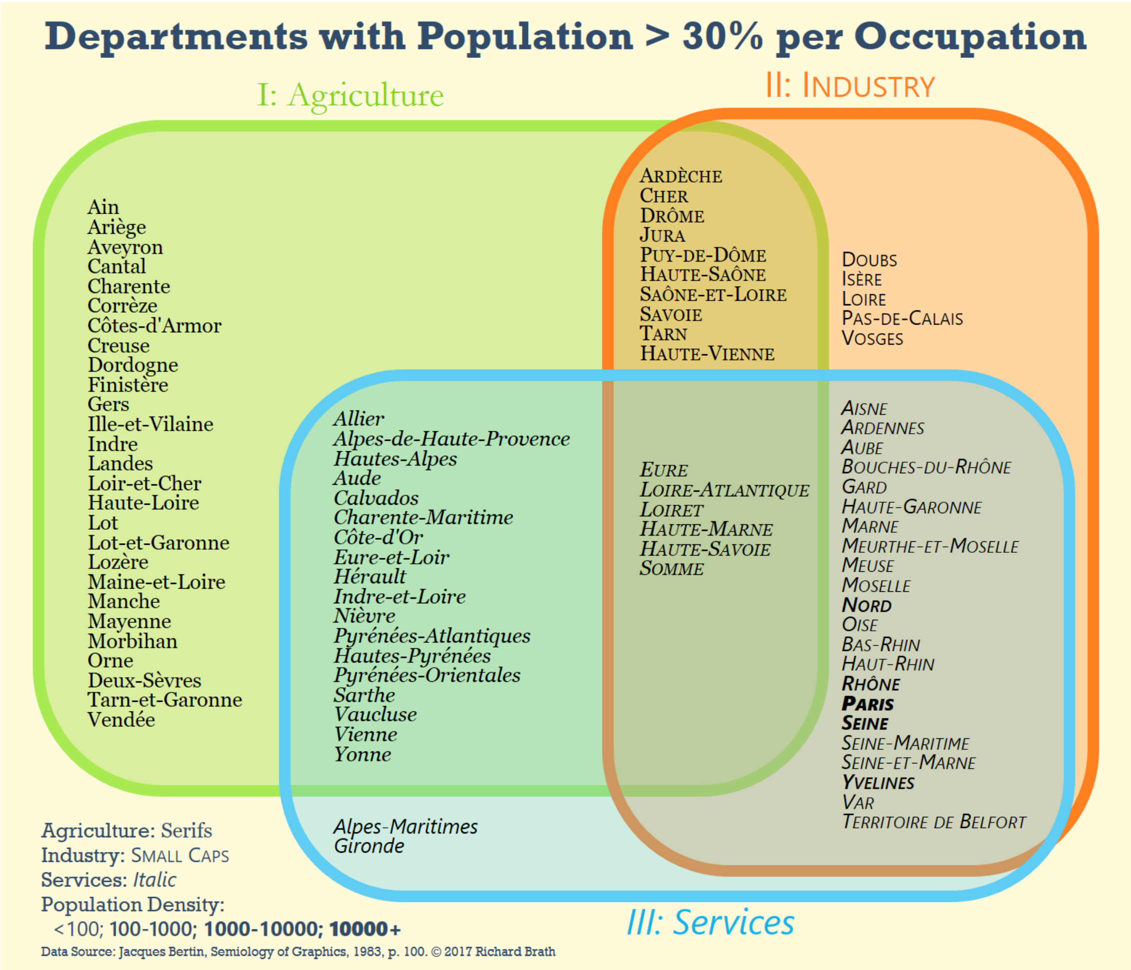

Figure 20. Venn diagram showing departments based on predominance in different occupations.

The breadth of these examples show that the framework makes a wide variety of typographic visualizations feasible. But one needs to consider relevance to real-world applications.

6. Applications of Typographic Visualization

There are many compelling use cases of typographic visualization, particularly in text-oriented applications:

In the Wild

The tag cloud is a highly popular visualization technique, but only marginally utilizes aspects of the framework. Many visualization experts are critical of tag clouds, because in most tag clouds, text color, position and orientation are arbitrary – only the literal text and text size are meaningful, yet size is ambiguous in most tag clouds as legends are typically not provided.

Software code editors are an incredible contemporary example of applied typographic visualization. Originating from *pretty-print* routines in the 1970's and formalized by Baecker and Marcus (1989), typographic encoding is now pervasive in most code editors. For example, WebStorm uses background shading, text color, bold, italic, underline (straight and wavy), plus user conventions (e.g. CamelCase), symbols and paired delimiters from the programming language syntax (e.g. $,%,'',[],{}) to enhance code readability.

Similarly, various versions of the *Periodic Table of the Elements* differentiate between a wide variety of properties for each element using techniques such as size, color (background and/or text fill), outline (cell or text), bold, superscript, subscript, added symbols and delimiters.

Tallman lettering (ISMP 2010) is an FDA standard used in health care for labelling drugs to reduce errors of confusion, which can be fatal. Tall Man lettering perceptually highlights differentiating syllables in look-alike drug names used on computer screens, labels, written prescriptions, etc, such as the example in Figure 21.

Uppercase	Lowercase	Tall Man
MEDROXYPROGESTERONE	medroxyprogesterone	medroxyPROGESTERone
METHYLPREDNISOLONE	methylprednisolone	methylPREDNISolone
METHYLTESTOSTERONE	methyltestosterone	methylTESTOSTERone

Figure 21. Sample Tall Man Lettering, which draws attention to the key differentiating syllable between similar drug names.

New Text Applications

New kinds of applications to aid reading, analysis and comprehension of text will become feasible such as (Figure 22 clockwise from top right): skim reading; pronunciation; prosody; social media trends; sentiment & emotion analysis; content analysis; and so on.

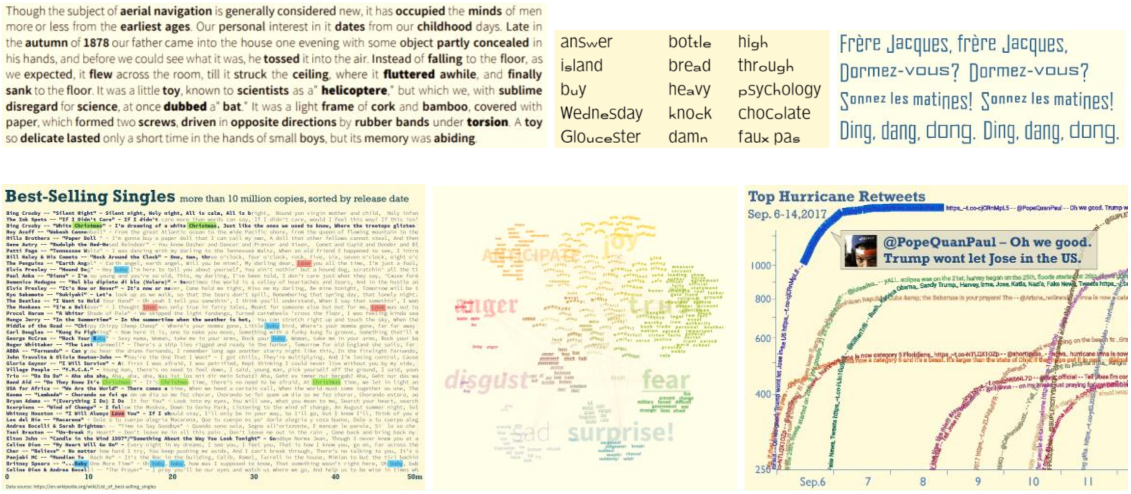

Figure 22. Example typographic visualizations for text analysis.

As implied by these examples, there are many potential applications in NLP (Natural Language Processing). 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 to aid analysis using this framework.

7. Discussion

As the examples show, there are a wide variety of visualizations possible using an extended text-based framework. This framework enables a breadth of many new types of visualization to be explored but also raises many questions beyond simple time-and-error evaluation. Critique by experts from visualization, typography and cartography provide many opportunities for future research and exploration.

Literal Text

Literal encoding in visualization 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 14 requires minimum length of two characters in order to use spacing); or other cases need text to be truncated (fortunately, Bertin's department names already contained abbreviations).

Prior knowledge of the words and phrases create associations beyond the data directly depicted, which allows for serendipity but also triggers associated sentiment, emotion and meanings (e.g. dove, hawk, Churchill, Mussolini) which may or may not match meanings in the visualizations.

Legibility is paramount in order for the literal encoding to be perceived. With higher resolutions and larger monitors, text visualization can scale to handle thousands of labels 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? (e.g. Beier 2012; Squire et al 2006).

Readability is a related issue of ease of comprehension. It is affected by factors such as line length, kerning (space between letters), or orientation (e.g. Tracy 2003). For example, type becomes more difficult to read when rotated and in steep perspective (such as this 3D scatter/bar/text plot of Bertin's data in Figure 23).

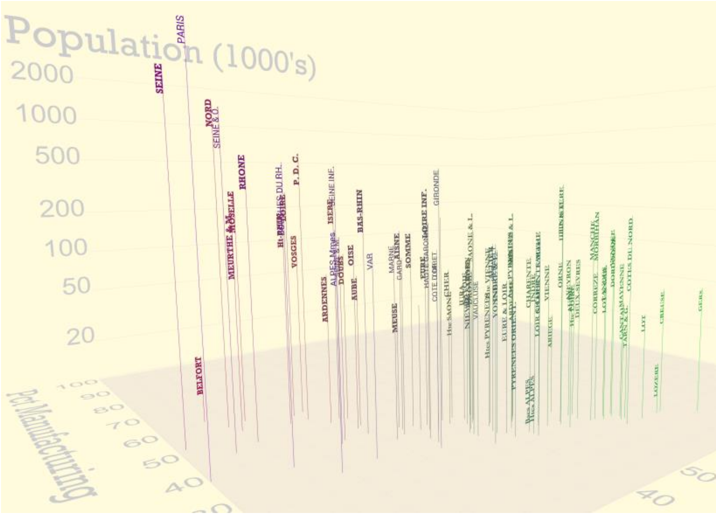

Figure 23. Text rotated in 3D. [Delete this example if too long.]

Typographic Attributes

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, width) are becoming widely accessible with new technologies such as Open Type 1.8 Variable Fonts support (e.g. Monotype 2017). 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.

Semantic associations with fonts (e.g. O'Donovan et al 2014) can be used to create new meanings or enhance prior associations with words where appropriate - similar to the semantic depiction of words in comic books (e.g. **SMASH**, whisper, *help!*, *meanwhile…*).

Combinations of typographic attributes can be used to encode multiple data points into a single glyph or word (e.g. Figure 13), however, combinations may be more difficult to read (e.g. Gauthier et al 2006, Sanocki and Dyson 2012), confounding or confusing, for example, the use of weight to convey population change in Figure 13 does not follow the usual map conventions where weight is typically used to indicate measures of magnitude.

Scope and Layout

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. While the examples here range up to paragraph length, document length or corpus length encodings are not explored.

Sparklines 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 17) are a different form of word-scale visualization to be researched.

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).

Interaction and Comprehension

Interactions vastly expand the capabilities for users to interactively analyse data. Bertin provided an early physical model for interactive data analysis with reorderable matrics (Bertin, 1981), while contemporary interactive maps and visualizations regularly provide features such as search, sort, zoom, pan, filter and tooltips. In Figure 13 each text attribute (weight, slope angle, hue, size, etc) could be toggled on/off independently to aid perception of patterns in only one or two variables.

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 (as in Figure 20). This differentiation can be perceived quickly and is meaningful even if the underlying mappings are not decoded – but assumes that viewers perceive the difference which requires research.

Perception and understanding in visualization is a complex pipeline mirroring the visualization production pipeline in fig. 7 (e.g. see Chen & Floridi 2013). Rather than rate of preattentive response; 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 tradeoffs across many variables required?

8. Conclusions

A critical analysis of Bertin's long-accepted framework provides an opportunity to reassess and extend our conceptualization of text in the use of charts, maps and visualizations. 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.

Text offers far more than just an extended framework. It shifts visualization from a modernist, simplistic, preattentive-perception/Gestalt pattern analysis into a post-modern, simultaneous 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. There are tremendous opportunities for a future research agenda across the breadth of the implied design space for text in visualizations, which can engage collaboration with disciplines ranging from psychology, perception, linguistics, design, typography, cartography, statistics and philosophy.

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