Main takeaways

- Use SparkWords in the text that accompanies certain charts to facilitate cross-referencing;
- Visually encode the different hierarchical levels (using color or weight, for example) of certain numerical codes;
- Tallman lettering (use upper case letters to help distinguish similar labels).

The Design Space of SparkWords

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Figure 1: *Sample SparkWords encoding data as a) word weight; b) word size; c) colored background bar/fill per glyph; d) foreground color and weight per glyph or phrase; e) subset of bold; f) overlay text; and g) in table.*

Abstract

The design space of SparkWords is consistently-sized words; embedded in sequential text (e.g. prose, lists); embellished by adding data, including categoric, ordered or quantitative data, that is encoded by a variety of attributes (singular or multiple) applied to words or letters. The breadth of the design space is illustrated with historic examples and novel implementations.

CCS Concepts

• ***Human-centered computing*** → *Visualization techniques;* • ***Applied computing*** → *Document searching;*

1. Introduction

In this technique paper we organize the design space of SparkWords. SparkWords are consistently sized words used in-line in prose. Words or letters are enhanced with additional data, including categoric, ord*ered* or quantitative data. The encoded data is associated with the word and represented with common visual attributes (e.g. hue), typographic attributes (e.g. font **weight**, *italics*, CAPS), or graphical elements (e.g. bars behind or lines below).

Our contribution is to define the design space of SparkWords (Section 3) based on historic and infovis examples (Section 2). We provide novel examples including a) embedding multiple extrinsic data attributes into words to provide more contextual information in prose (4.1.1); b) using the same visual attributes from a visualization in the associated narrative to facilitate cross-referencing (in 4.1.2); c) more perceptually accurate mapping of quantitative data (4.1.3); d) glyph-level formatting to indicate data relative to a portion of a word or code, (e.g. hierarchical data 4.2.2); and, e) use in prose, lists, and tables (4.3).

2. Background

SparkWords are different than:

(a) Markup. SparkWords go beyond traditional markup of text (e.g. highlight keywords in context e.g. [Luh59, Hea09] or code syntax highlighting [BM90]), by: (i) encoding multiple simultaneous data attributes into a word (e.g. hue, weight and italic), (ii) manipulating glyphs individually, (iii) allowing for more accurate encodings of quantities by using lengths superimposed against words.

(b) WordClouds. WordClouds (e.g. [Fei10]) depict individual words without the contextual narrative text [Nie09] and embed quantitative data [FFB18]. SparkWords are in-line in prose context and encode additional data types. Further, most WordClouds use size to encode quantitative data. SparkWords are consistently sized with adjacent text: this maintains text layout without adjusting line heights, line lengths or reflowing text.

(c) Word-scale Visualizations. Sparklines were popularized by Tufte [Tuf96] and are now pervasive, e.g. in libraries [Mee18] and

SparkWords != markup, word clouds, sparklines

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fonts [Gal17]. Various researchers, e.g. [GWFI14, BW17, GBWI17] review hundreds of variants of word-sized visualizations and identify uses to show quantities, proportions, locations, trends, time, ranking and relations; means of relating the graphics to the text by visual cues such as underlines, highlights and frames; and interactions such as brushing, linking and overlays. Instead, with SparkWords, data is embedded directly into semantically associated words.

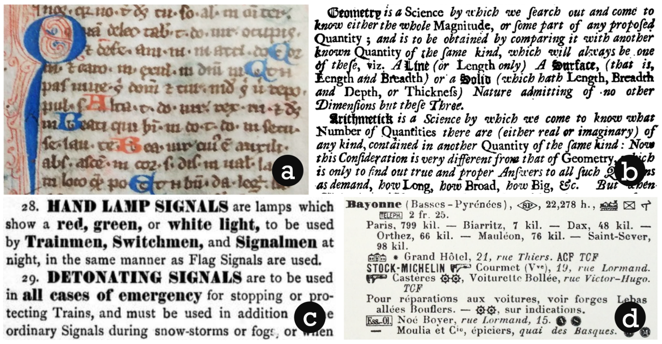


Figure 2: *Historic examples: a. Illuminated glyphs, b. Words highlighted in blackletter, c. Regulations with ordered formats, d.* Michelin Guide *with formats and icons for quick access.*

a.k.a. Gothic script

There are many historic examples of SparkWords, such as: (i) differentiation of text to facilitate skimming prose, such as medieval illumination of lead characters ordered black, red, blue, gold (Figure 2a [Unk50]); 16th. C. textbooks mixing blackletter, italic and roman type (2b, [War24]); 19th. C. instruction manuals using bold and caps to create ordering (2c, [Bro79]); (ii) rapid access to different classes of content (e.g. reference texts, fig. 2d, [Mic00]); and (iii) visualizing syntax (e.g. software code [BM90]).

Modern publications manipulate type to convey additional intent, e.g. Fry's *Frankenstein* (2011) with procedural font selection; comic books with semantic lettering (e.g. digitalcomicmuseum.com); and Ronell's post-modern *The Telephone Book* (1991) with deliberately disruptive formatting. *Tallman lettering* adjusts case to differentiate look-alike drug names to reduce prescription errors (e.g. vinCRIStine vs. vinBLAStine) [FPGG04, Gab06].

2.1. Related Information Visualizations

There are hundreds of text visualizations, (e.g. *Text Visualization Browser*, textvis.lnu.se), although most are not specific to narrative text. *FatFonts* vary font weight per character so that the ink varies in proportion to the numeric value represented [NHC12]. FatFonts are limited to numerals: they do not extend to alphabetic characters. *TextViewer* scales text across entire lines for a magnification effect and applies color underlines to individual words to indicate tag categories. [CWG11]. *Variable Text Scaling* changes word sizes either scaling horizontally or both vertically and horizontally, such that important text remains visible in document thumbnails [SSDK12]. *Skim formatting* varies font weight inversely proportional to word frequency to facilitate skimming [BB16].

Beyond specific techniques, Strobelt et al., review a wide variety of formatting techniques to highlight text in context [SOK*16]. Brath and Banissi define a dozen typographic attributes for visualization [BB16]. Parnow differentiates between *modifications* to the typography, such as a change in typeface; and the *addition* of separate graphics, such as a background box [Par15].

3. Design Space of SparkWords

Based on historic examples, infovis and text visualization research, the design space can be defined:

- *Word*. SparkWords are encodings applied to words: these encodings do no exist independent of the word.
- *Layout*. SparkWords are embedded into word sequences such as narrative, lists, tables and other sequence layouts.
- *Scope*. The format can apply to a word or two, down to syllables or single glyphs within a word.
- *Data Type*. The encodings support categoric, ordered and quantitative data.
- *Visual Attributes*. There are many visual attributes available, including traditional visualization attributes such as hue and intensity (see [CF13] for a comprehensive list) and typographic attributes (see [BB16, Bra18] for overview).
- *Multiple Attributes*. Attributes can be combined in a single word to redundantly encode data or encode multiple data attributes.

There are some constraints:

- *Legibility* is a perception issue concerned with the ability to clearly decipher individual characters as well as commonalities within a font that increase letter identification [SD12]. Attributes which make text illegible should not be used: e.g. brightness reduces text contrast, reducing legibility; blur and drop-shadows reduce the clarity of letterforms, reducing legibility.
- *Readability* is a comprehension issue concerned with the ease of reading lines and paragraphs of text [Tra03]. Word format affects reading (e.g. [GFD19]), e.g. blackletter is legible but difficult to read.
- *Not Size.* Sparkwords are used in-line in text, lists etc. Text size variation is used in some infovis (e.g. [SSDK12, WLM*14, Wea15]), but size variation is not commonly used by typographers in running text as it creates gaps of white space, disrupting typographic color [WS09]. Figure 1b was an early attempt to use size variation to encode data which received negative feedback from typographers: it disrupts reading by size, by extra wrapping, and it disrupts typographic color.

4. Design Experiments

The permutation space is enormous: dozens of attributes, in multiple combinations, across scope from glyph to words, and three different data types implies many thousands of combinations. A design space can be tested by creating instances across each parameter (e.g. [Ber67, BLB*17]): we create examples across scope, data type and layout.

4.1. Example SparkWords at Word Level

4.1.1. Categoric

Encoding binary categories with text has many existing use cases, such as keyword in context (in search applications), hyperlinks on web pages, etc.

National mapping agency for Great Britain

Multiple Attributes: Many visual attributes are mutually exclusive: formats can be combined to show multiple different categoric attributes (as occurs with cartographic labels, e.g. Ordnance Survey [Hod99]). For example, attributes of politicians can be encoded as textual attributes. *Donald Trump* can be shown as a right-leaning conservative via right-leaning text, and male gender via light blue. Politicians with multiple terms of service could be indicated with bold, for example ***John McCain*** or **Nancy Pelosi**. In this example, four attributes are indicated per name: literal text, color, weight and slope.

4.1.2. Ordered

Examples such as Skim Formatting [BB16] or Variable Text Scaling [SSDK12] encode ordered data about the words relative to their document context using font weight, width, or size. This can be more broadly extended to data beyond the words in their context. In many sparklines, the viewer is not given an explicit legend but the decoding can be inferred: e.g. labeling the starting and ending value of a sparkline indicates vertical scale. With more generalized SparkWords a legend is required if the viewer is intended to decode the values, as given directly in the narrative text immediately prior to the city names in figure 1a.

Single ordered values: In figure 1a, five different weights of text are ordered to indicate population. The viewer can read the text sequentially, or visually skip to the heaviest weights for the largest cities, such as **Vancouver**, **Toronto**, and **Montréal**.

An administrative division of France

In *Sémiologie graphique* (1967), Bertin illustrates examples with a dataset of occupations by department. Instead, observations can be visualized and explained in narrative. The top three departments by population (indicated by font weight: 34k-102, to 130, to 173, **to 236**, **to 1517**) are **Paris**, **Seine** and **Nord**. Top departments by percent of population in manufacturing (shown by proportion of red: 0 70%) are Belfort, **Moselle** and **Nord**. Top departments for agriculture (green: 0 70%) are Gers, Creuse and Lozere. Top services (blue: 0 70%) are **Paris**, Alpes Mmes, and **Bouches Du Rh**. Three districts closest to an even balance between occupations appear grey: Hte Saone, **Puy De Dome**, Eure. Agricultural districts with large populations are **Morbihan**, **Finistere**, **Ille & V**. Small departments with bias to manufacturing or services are Belfort, Doubs, Cote D'Or and Var.

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 3: *Paragraph of ordinal SparkWords with encoding explained in-line.*

Multiple ordered values: Like map labels (e.g. [SH25]), SparkWords can show more than one ordered variable. In figure 3, weight and color indicate four different ordered data attributes. The encoding is explained inline facilitated with histograms indicating data range and distribution per variable.

SparkWords cross-referencing a visualization: A consistent mapping of visual attributes between SparkWords in narrative explanations of visualizations can facilitate cross-referencing and reduce learning effort (i.e. the same encoding applies to both uses) without reliance on interaction [LLB18] (in some uses, interaction is not feasible or slow). In figure 4, a heatmap is paired with a narrative paragraph where the SparkWords use the same weight and hue as the corresponding cells in the heatmap.

Collision	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Animal	106	66	70	75	99	95	65	60	56	139	240	169
Bridge	26	17	25	12	8	18	15	14	12	14	14	18
Building	16	10	9	4	8	5	8	11	7	12	15	9
Cyclist	63	63	60	101	139	168	211	157	105	48	53	100
Ditch	135	120	103	93	72	91	111	100	85	131	120	95
Embankment	89	61	52	51	48	50	49	54	48	62	68	58
Fire	5	1	3	3	9	4	7	4	3	5	3	3
Guardrail	126	84	90	60	64	68	87	75	77	127	111	77
Hydrant	9	13	10	2	11	8	6	6	4	11	4	4
Jackknife	20	20	14	10	10	8	10	18	15	20	17	11
Parked vehicle	167	177	169	163	171	166	155	174	143	164	160	143
Pedestrian	149	118	124	156	160	152	132	131	145	124	134	150
Post	172	178	183	126	119	126	126	140	136	177	167	137
Rollover	137	104	115	126	136	137	153	168	104	150	133	144
Train	3	6	4	3	2	2	4	2	2	2	5	4
Tree	140	132	125	85	83	97	104	98	102	141	135	107
Wall	27	21	18	14	8	11	22	10	9	21	20	15

This heatmap of accident data shows clear patterns but key insights are not obvious. An observation or two could be highlighted. If there are many insights and comments, associated prose with SparkWords may be more effective. In this accident data, the most frequent collisions are in heavy-weight type: **parked vehicles**, **posts** and **pedestrians** (less than ½% in period, ½-3%, **3-10%**, **10+%**). Animals, cyclists, ditches and trees are also quite frequent. Severity of injury varies from **none** to non-incapacitating to **fatal**. Worst injuries result from collisions with **pedestrians** and cyclists. The least injurious accidents are fires and animals. Collisions with trains, buildings and roll-overs are also injurious, but infrequent.

Figure 4: *Heatmap with associated narrative where both use the same hues and weights to facilitate cross-reference.*

4.1.3. Quantitative

Varying hue, brightnesss or font weight provides only a few ordered levels on words at typical reading size (e.g. [War00]). For more accurate quantitative encoding, a visual attribute such as length can allow for more discrete levels to be comprehended [Ber67, HB10]. Length across the span of a word or two can be indicated by varying the length of a visual attribute across a subset of a word. E.g.:

The popularity of *Star Wars* characters is lead by Darth Vader at 16 million page views (Wikipedia), indicated by the length of the underline. This is more page views than the next top three characters combined: Obi-Wan, Luke, and Princess Leia. Rounding out the top characters are Han, Chewbacca, R2-D2, and C-3PO. Underline length is not constrained to full characters - formats can be cropped based on data. Thus, Princess Leia's underline extends fractionally under the *n* in *princess*.

Cropped lengths can be used with other formats. For example, background color is more visually dominant than underlines: Darth Vader, Luke, Princess Leia, and R2-D2. Shaded bars behind text is an approach already familiar from tools, such as Microsoft Excel. Here, the approach is generalized to running text.

Figure 1e uses bold to indicate a range of estimated book sales (read from left to right), e.g. Barb**ara** Cartland, has higher sales than Sid**ne**y Sheldon.

4.2. Example SparkWords at Glyph Level

In western languages (e.g. English, Greek, Arabic, Cyrillic), words are composed of separate characters (i.e. glyphs), each of which can be encoded with additional data.

4.2.1. Categoric

Project name

Individual glyphs can represent data about words. *Silenc* colors silent letters red, which are visibly removed with a physical transparent red filter [MMR12]. Going further, figure 1f shows English words where *ph* may be explicitly pronounced, one letter silent (light), or pronounced differently (superimposed red letter).

4.2.2. Ordered

Shimabukuro shows crowdsourced abbreviations with retained glyphs shown by font size [Shi17]. Instead of size, font width could be used. Here, letters dropped in common contractions are indicated using a narrow font, such as BROOKLYN, PHILADELPHIA, and WASHINGTON DC.

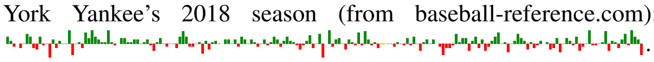
Frequency of letters spelled incorrectly in words can be shown with x-height (the intermediate height of lowercase letters), e.g. caterpillar, government, occasionally, and successful. For example, the tall second *c* in *occasionally* indicates it is frequently misspelled; and *ern* are frequently misspelled in *government*.

Coded hierarchies are frequently used by experts, e.g. financial markets, electrical grid equipment, product codes, etc. Figure 1d, is an example using NAICS industry codes. NAICS is a five digit hierarchy: e.g., 51 is the information sector, 515 broadcasting, 5152 pay media, 51521 pay TV. Each digit is colored by the changes at each successive level (bright red for big decreases, bright green for big increases) and font weight indicates size relative to peers at that level (thin < 10%, 10-40%, 40-90%, 90+% heavy). Expert users do not require descriptions: they know the codes. This enables a dense line of SparkWords to summarize data in a few words, e.g.: *The biggest contributors are:* 11221, 22111, 32742, 41111, 51521, *and* 62132. For non-experts, details can be exposed with a tooltip, or expanded to readable phrases as in Fig. 1d.

4.2.3. Quantitative

NAICS: North American Industry Classification System

Small spark bar charts are used in sports to summarize the results of a series of games, such as small bar charts used by Tufte [Tuf96] or this example summarizing the New York Yankee's 2018 season (from baseball-reference.com):



The chart shows the win/loss sequence (red/green) and score differential (bar height), but does not indicate the opposing team.

Baseball games are played in a series of two to four games per opponent. All teams have mnemonic three letter codes, e.g. NYY for the New York Yankees. Each letter can represent each successive game over the season. For example, the Yankees started the season with a 4 game series vs. Toronto (TOR4), where outline indicates win/loss (green/red) and fill height indicates score differential (a low fill is a loss by one run, a full fill is a loss by 10 or more). The *Yankees* then win 22 of the next 33 games: TBR BAL4 BOS DET MIA TOR4 MIN4 LAA HOU4 CLE BOS, sweeping series against Tampa, Minnesota, L.A., and Cleveland.

Three variations are shown in figure 1c. First is filled letters. Second is a tall thin font over a lightly shaded background bar, similar to prior superimposed tag clouds [LRKC10, LBSW12], although SparkWords are in narrative, and bars are per letter. The third provides high contrast between type and background - e.g. useful in sunlight or low quality print.

4.3. Layout

In addition to narrative, SparkWords can be used in:

Alphabetic Lists: The bottom half of figure 3 shows 90 departments in alphabetic order. The viewer can 1) read the list sequentially; 2) find named departments using the ordering to facilitate search; or 3) focus on a visual attribute (e.g. blue or heavyweight) to identify departments with that characteristic.

Spatial Lists: Figure 5 shows top hashtags in NYC, set out as a list, ordered to geolocate each topic by highest frequency. Rather than a tagcloud with variable sized words randomly placed on a map (e.g. [NTST11]), this layout offers: (1) Location: Every word is placed on its location (note *Wall Street*, *MOMA* and the underlying map). (2) Text is in lines, facilitating reading of sequences of words (e.g. *MOMA* is beside *art*, *Wall Street* is adjacent to *Brooklyn Bridge*, etc.) (3) Weight is a preattentive cue, e.g. the density of text from midtown to downtown is clearly visible.

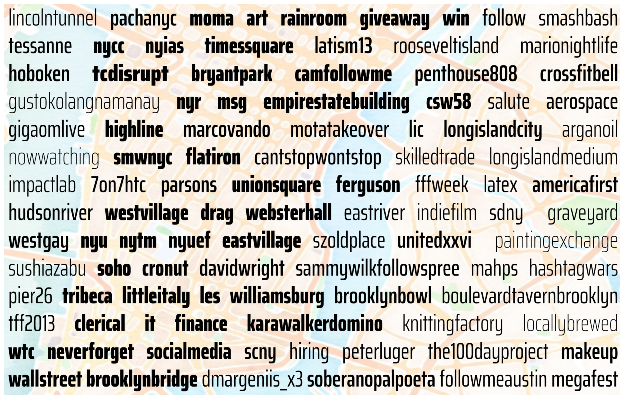


Figure 5: *Top hashtags in NYC located in proximity to highest frequency of use, e.g. wallstreet and brooklynbridge near bottom.*

Table: SparkWords also work within the confines of cells in tables, e.g. figure 1g shows top foods where calories are indicated by weight, water by underline, caffeine in green, sodium in red and cholesterol in blue. Unlike column-aligned, height-constrained word clouds [FFB18], this table includes semantics associated with rows and columns, and multiple encoded values.

5. Conclusion

SparkWords build on prior work and generalize their use to encode categoric, ordered or quantitative data; across letters, words or phrases; with single or multiple encodings; in various layouts. There are many applications, including: increased information density in data dense applications (e.g. finance); visually-facilitated cross-referencing between narrative and visualization; data-enhanced text to provide additional context; and glyph manipulation to reduce prescription errors or aid language learning.

There are many areas for future work. SparkWords do not require interaction, but could be enhanced with interactions [GWFI15, LLB18]. Different fonts and formats have semantic affect which has not been considered. There are many types of evaluations that should be done - detection, legibility, readability, comprehension, user acceptance, and so on.

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