High Category Glyphs in Industry

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ABSTRACT

Encoding a high number of categories in a glyph may be necessary and can be encoded as label, icon, shape or texture. Number of categories, transparency, layout, compound glyph and legibility are considerations for the encoding.

Keywords: Glyphs, Icons, Labels, Categoric Encoding, Shape Attributes, Font Attributes.

Index Terms: K.6.1 [Management of Computing and Information Systems]: Project and People Management—Life Cycle; K.7.m [The Computing Profession]: Miscellaneous—Ethics

1 INTRODUCTION

There are many guidelines for multi-attribute glyph design, usage and application, e.g. [1,2]. The author has been directly involved over the last 25 years in the design and development of information visualizations (infovis) for industry, and some of these systems include the use of glyphs. While many of these systems involve rather simple or typical use of glyphs (e.g. encoding data to simple markers using size and hue visual attributes) there have been a number of cases where a glyph needed to encode multiple data attributes and one of those attributes that had a high number of unique categories (e.g. more than eight to ten), for example, countries (200 unique countries), states (50), stocks (thousands), different types of baseball pitches (~10), crop types (~20), common document formats (~10) and so forth.

The contribution of this poster is to itemize the techniques used to encode ten or more categories in glyphs from more than 20 industrial visualizations from domains such as finance, healthcare and broadcasting, as well as identify additional design considerations.

2 BACKGROUND

When the number of categories to encode is low, a strong pre-attentive cue can be used, such as hue. However, hue can be difficult to use beyond eight or so categories and may have other perceptual challenges (e.g. [3,4]).

For a higher number of categories, a different encoding of the data into the glyph is required, such as shape, pictographic icon, letter, or such. Compared to other visual attributes, these may not have the same degree of preattentive perception, or require active attention. However, it may still be highly desirable to have this information encoded visually as opposed to accessed via interactive techniques (e.g. tooltips, filters):

- *Fast access*. Interactive techniques, such as tooltips, require slower user input such as mouse movement, compared to visually encoded data, which can be accessed more quickly by simply shifting visual attention (e.g. [5,6]).
- *Lower lossiness.* Encoding data visually is typically a lossy process [7]. More information can potentially be retained with glyphs that encode a higher number of categories [8].
- *Micro patterns*. Even though the encoding may not be pre-attentive, micro-patterns [9] may be visible on detailed inspection that could otherwise be missed if reliant on interaction [10,11].

3 GLYPHS FROM INDUSTRY

There have been four different visual attributes used to represent a high number of categories referred to by the acronym LIST: *l*abel, *i*con, *s*hape and *t*exture. Table 1 summarizes glyphs from different projects that the author has been involved with that encode a high number of categories in a multivariate glyph. The first column indicates a project ID, the second indicates the number of unique categories encoded in the high category attribute. Columns 3-6 indicate the visual attribute used to encode the high number of categories, represented with the letter L, I, S or T. As these are multi-attribute glyphs, additional visual attributes are indicated with a +, for example, the project RTW has the high category attribute encoded as shape (square, circle, etc), which also has color and a text character added (A, B, etc) to indicate other data.

3.1 Texture

Texture has not been used often as an encoding for a high number of categories. Country flags and corporate logos are two cases where texture has been used (e.g. row PPR in fig. 1 below). Flags and logos are debatable as to whether they are icons or textures. Country flags are dependent on the unique combination of shapes and colors to form a unique identity. In a personal meeting with Dr. Colin Ware regarding shapes and texture in 2009, Dr. Ware considered flag glyphs as textures (a unique pattern combining elements of shape and hue) hence it is categorized as such here. Another possible differentiation - these textures utilize

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colors and cannot be properly perceived without their colors; whereas icons discussed later do not have color dependency.

		Representation				Additional Attributes						
Project ID	Num Categories	Label	Icon / Pictograph	Shape	Texture	Size	Glyph Hue	Background Hue	Overall Outline Hue	Brightness	Orientation	Other
MBS	15			S			+					~ transparency
WTR	20	+		S			+					~ transparency
I2S	20	+		S			+					added bar
I2F	20	+	I			+	+					0
FCN	20	L	I				+		+			superscript
RAP	20	L										halo hue
LLB	20	L						+	+			0
DIN	25	+	I				+					added bar
VDJ	30				T							0
NS1	30		I			+	+	+				0
AIR	50	L					+					0
AA1	50	L										case
PPR	100's				T	+					+	0
NMS	100's				T	+						0
CMI	100's		I				+					0
GET	100's	L	I	+				+				shape
TIK	100's	L		+		+		+				
RMA	100's	L				+		+				glow
NL2	100's	L					+			+		0
CML	100's	L					+		+			0
FMP	100's	L						+				spacing of chars
CES	100's	L										added bar, underline
BMO	100's	L					+	+		+		bold
Totals		13	6	3	3	6	12	7	3	2	1	12

Table 1. High number of category encoding per project indicated with L, I, S, T. Other glyph attributes indicated with +.

3.2 Shape

Shape has been used in a few applications. Unlike procedurally generated quantitative shapes (e.g. [12]) it can be challenging to generate a successful group of categorical shapes. Excel, for example, only has nine different shapes in the scatterplot, after which shapes repeat with different colors.

In one case, fairly simple procedurally generated categoric shapes (similar to [13]) were proposed (row ZZZ in fig. 1), but users did not like these shapes, possibly because they were quite abstract; or perhaps symmetry caused confusion. Instead, the users chose a set of shapes which were designed as *nameable shapes*, i.e. shapes that are recognizable and have simple names. In RTW, for example, the nameable shapes shown here are circle, square, star, pentagon, lemon, clover (trefoil), guitar pick, droplet and diamond. An extended version showing 24 unique shapes of similar proportions and area is shown in figure 2.

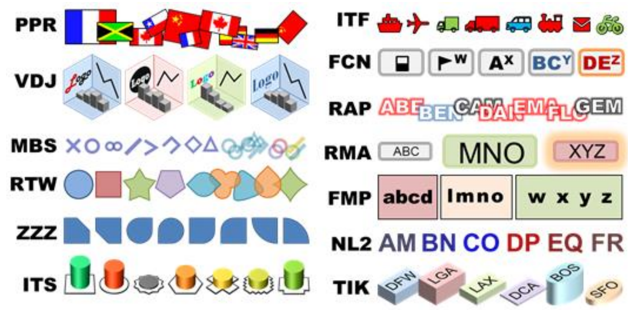

Figure 1: Sample high category glyphs redrawn based on industry projects. Each row corresponds to glyphs from a different project.

Another challenge is to create shapes which are visually comparable, that is, shapes that all have similar size and similar amount of ink. Note, for example, the shapes in fig. 2 which have similar areas, and MBS where the simple diagonal line has greater line thickness than the line of the circle or X.

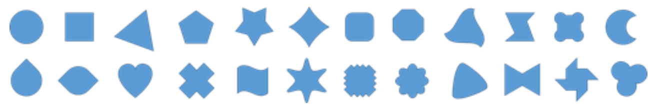

Figure 2: Sample of 24 unique categoric shapes, all nearly square proportion with similar areas.

3.3 Icon (Pictograph)

Icons are differentiated here from geometric shapes by being a pictographic representation, such as a boat or plane (ITF); or battery or pennant (FCN). Pictographic icons can be effective if they represent concrete objects [14], such as planes and trains or types of people [15,16].

In general, it can be difficult to design pictographs that can be unambiguously decoded. In one system there was no user training - the new functionality with glyphs appeared as a newly discoverable feature to a large community - unfortunately the "shovel" pictograph was interpreted as "the finger" pictograph by some users.

Furthermore, it can be much more difficult to design intuitive pictographs for abstract concepts such as CPI, GDP, or even a list of cities. The design task can be aided by collections of pictograms, either curated (e.g. [17,18,19]) or automated [20].

3.4 Label

A glyph label is typically a mnemonic code or abbreviation of 1-5 letters (or numbers) composed as part of the other items in the glyph; shown in examples FCN, TIK, RAP, etc. Note that in all cases, the labels are not full text strings, but codes or abbreviations easily decodable by the user community. For example, in one visualization, the full label for one node in the Consumer Price Index is *Window and floor coverings and other linens*, whereas the user community was familiar with the code associated with this category: SEHH (unfortunately, this is not a mnemonic code and thus not decodable outside the user community without additional interaction).

Labels are the most common means of representing a high number of categories in this review. Labels may be more common because labels do not require the design effort of a shape or icon.

In our work, we have seen examples which started at as icons (e.g. FCN), however, as the project had some success, more categories were added, necessitating additional icons. Sometimes, the new categories could be abstract concepts and so mnemonic codes were used instead. Thus, both icons and letters co-exist to describe categories such as FCN or a set of discrete financial event glyphs [21]. There are other common examples mixing alphanumeric and pictographs, for example, some font families include pictographs (e.g. Segoe UI Symbol); road traffic signs; or biological visualization (e.g. fig 3.6 in [2]).

Some label-based glyphs used other attributes of fonts, such as bold, case, superscripts or spacing, to indicate additional data. FMP uses spacing between letters to redundantly encode the same data as glyph width - which was eventually dropped as users felt that it did not add information but reduced readability of the acronyms.

4 Additional Design Considerations

These glyphs have been used in tables, scatterplots, nodes in graphs, stacks and other representations. Depending on the use, there are other considerations which may impact choice of encoding.

4.1 Number of Categories

When the number of categories is in the range of 10-30, shapes and icons may be used effectively. Project CMI had hundreds of icons, based on set of pre-existing icons familiar to the user community. Similarly textures can scale to a high numbers of categories, and these examples had pre-existing representations (flags and logos). In general, when the number of categories was above 30, labels were used, unless an icon set or texture set already familiar to the user was available.

4.2 Transparency and Layout

In some cases the glyphs were part of a scatterplot (or other dynamic layout) where it was necessary for glyphs to overlap and for the viewer to perceive density of glyphs (MBS, RTW). Shapes, assuming similar area/ink, were effective in this use case when the other visual attributes were also appropriately configured (e.g. hues of similar intensity). Labels have lower legibility if overlapping and transparent, thus RAP used opaque overlapping alphanumeric characters whereas, RMA and TIK used tweaks to the layout to ensure a minimum separation between adjacent glyphs. Similarly textures were opaque.

4.3 Legibility

In all scenarios, legibility is an issue. Typically shapes, icons and labels need sufficient contrast to be legible against a background, and strategies to aid this include either providing a dark outline around the shape, icon or characters; or providing a consistent container within which to place the shape/icon/label wherein the background color can be controlled. Conversely, when the shapes are intended to be used with high transparency, then simple shapes without reliance on fine details to differentiate between them, aids identification.

Legibility is also dependent on device resolution. In earlier visualizations (i.e. 1990's), lower resolution displays with low pixel per inch (PPI) limited the amount of detail that could be depicted, favouring representations such as simple polygonal shapes, flags, and plain fonts possibly varying only uppercase/lowercase or underline (e.g. PPR, RTW, RMA). User interface guidelines of that era recommended against detail in icon design and use of font attributes (e.g. [22]). With higher resolutions, techniques have shifted to include the use of fine details, such as pictographic icons or font attributes such as superscripts or fine control over character spacing [23] as have guidelines for modern user interfaces (e.g. [24]).

4.4 Additional Visual Attributes

In all cases the glyphs encode multiple data attributes. Hue is most frequently used, in a number of different ways. The color of the glyph (shape, icon, label) can be directly changed: e.g. NL2 encodes additional data in text hue (red, blue) as well as the saturation (vibrant to grey). Background color is used in some cases where glyph color is not. And an additional outline color may be used. Note that color is sometimes used more than once in some of these glyphs: FCN uses color to encode data on the letters and also uses color of the background shape outline. RMA uses the background color of the shape and also a glow around the shape.

Compared to color, size is used infrequently. This is due to use cases. In some cases, the intended perception is associative (i.e. Bertin's definition [25]) which size does not provide. In other cases, the layout constrains size, e.g. tables and stacks both require a constant size.

Most of the LIST encodings have reduced readability with orientation: text, flags and pictographs rely on an expected orientation. Even shapes may not be perceived the same as upside down (e.g. droplet vs. pin) or may be symmetric making some orientations unperceivable (e.g. circle, square, star).

In some cases, the glyph is made of compound elements, easily visually separable into components, such as a foreground icon on a colored background (FCN) or marker on top of a shape (ITS). In other cases, the representation is a singular object, such as colored shapes (RTW), colored icons (ITF) or rotated textures (PPR). A compound glyph may possibly aid the viewers by allowing them to focus on pre-attentive characteristics (e.g. size and color in RMA) while ignoring the easily separate high-category attribute at a macro-level view and then attending to the high-category attribute during detailed inspection.

5 Discussion

Beyond LIST, there are other possible encoding strategies for a high number of categories. For example, multiple visual channels can be combined together, such as a small set of shapes and a small set of hues, the combination of which results in the product of the two of sets for a high number of categories (e.g. red dot, red square, blue dot, blue square, etc., as in Excel's scatterplot). This is a completely arbitrary mapping with no metaphor to aid the user.

Another approach is to convert the categoric values to numeric values [26]. This approach uses clustering techniques to order categories, assign distances between categories, and possibly group categories together - the approach is specifically applied to location attributes, such as axes in parallel coordinates. The approach could potentially support other novel encodings within a glyph, although there is no specific metaphor or mnemonic that would correspond to the numeric positioning.

Conversely, the LIST approaches all have the potential for a metaphor or mnemonic to aid the users' ability to easily recall the mapping. In general, metaphoric visual representations can make it easier for users to decode the glyph with less effort required to learn and remember them (e.g. [27,28]). Recognizable textures, pictographic icons and mnemonic codes for labels (e.g. country ISO codes: US, UK, DE, JP, CA, RU, etc) all facilitate recall. Even simple shapes can be created which have mnemonic encodings, for example, the shapes associated with MBS in figure 1 represent baseball plays, from left to right, sacrifice fly, field out, double play, single base hit, double, triple, homerun, etc.

A significant unanswered question posed by this review is the potential benefit of any LIST encoding over another. First - do any of the encodings offer any hint of pre-attentive performance? None of these have been tested in lab so one can only hypothesize. All LIST encodings use shape - which generally ranks low on lists of visual attribute rankings (e.g. [29,30]) and Bertin specifically warns against the use of shape [25]. Texture, however, also uses color which typically ranks highly for categoric encodings - e.g. a viewer could focus on the color red if interested in the Japanese flag, although there are other red flags and therefore the viewer would need to do a slower conjunction search for red and circle.

Simple shapes could possibly have preattentive characteristics, for example, using shape elements previously identified in psychology experiments [31] such as curvature, vertical/horizontal/diagonal orientations, terminators and so forth, potentially creating an opportunity for preattentive perception.

The second part of this question, is whether the benefit of encoding for faster perception (e.g. simple shape or flags) provides an advantage over a representation with a metaphor or mnemonic that facilitates easy decoding. I.e. there is a trade-off wherein a preattentive encoding (e.g. flag or simple shape) is fast to perceive but possibly slow to decode, whereas a slower encoding (e.g. label) is slow to perceive (requiring active reading) but is fast to decode.

A broad strategy for choosing one encoding over the other does not exist, but a heuristic may be created. Assuming that we do not know the answer to the first question above and we err on the side that none of these encodings offer preattentive performance, then the encoding choice centers on choosing a representation that will be easiest for the viewer to decode:

1. If a pre-existing set of textures, shapes, icons or codes exist, first consider these.
2. If the number of categories is high (i.e. >30), labels may be the only solution. Consider short mnemonic labels, such as codes or abbreviations, if available and decodable by the user community rather than long descriptive strings.
3. If the number of encodings is lower (10-30) consider each of LIST encodings, with particular attention to an appropriate metaphor or mnemonic to facilitate decoding.
4. If there are alternative encodings possible, the use case may help determine which encoding is preferable. For example, in a visualization to engage the public, country flags are a colorful, visceral encoding; while in an analytic application, mnemonic labels may offer faster decoding performance over flags when analysing smaller countries.

6 Conclusion

Encoding a data attribute with a high number of categories may be necessary in some visualizations. Labels, icons, shapes and texture are potential visual attributes that can be used. Evaluation is an area for future researchers to consider the relative performance between these techniques. Extending techniques for systematising and automating glyph generation of high category glyphs is another area for future work. Investigation into the potential for visual attributes that make use of higher pixel densities such as detailed shapes, pictographs and font attributes are another area of potential further investigation.

REFERENCES

[1] R. Borgo J. Kehrer, D. H. Chung, E. Maguire, R. S. Laramee, H. Hauser, M. Ward, and M. Chen.. Glyph-based visualization: Foundations, design guidelines, techniques and applications. *Eurographics State of the Art Reports* (2013): 39-63.

[2] E. Maguire. *Systematising Glyph Design for Visualization.* PhD Thesis. University of Oxford. 2014.

[3] C. G. Healey. Choosing effective colours for data visualization. In Visualization'96. Proceedings., 263–270. IEEE, 1996.

[4] C. Ware. Information Visualization: Perception for Design. Morgan Kaufmann, third edition, 2013.

[5] P. M. Fitts and J. R. Peterson. "Information capacity of discrete motor responses." *Journal of experimental psychology* 67.2 (1964): 103.

[6] J. Lohse, "A Cognitive Model for the Perception and Understanding of Graphs" in *Proceedings of ACM Conference on Human Factors in Computing Systems 1991*: 137-144, 1991.

[7] M. Chen. and L. Floridi. An Analysis of Information in Visualization. In *Synthese* 190.16 (2013): 3421-3438.

[8] R. Brath & E. Banissi. "Evaluating lossiness and fidelity in information visualization". In *IS&T/SPIE Electronic Imaging. International Society for Optics and Photonics.* 2015.

[9] E. Tufte. *Envisioning Information.* Graphics Press. 1990.

[10] Timo Ropinski and Bernhard Preim. "Taxonomy and Usage Guidelines for Glyph-based Medical Visualization". 2008.

[11] R. Brath & E. Banissi. "Using Text in Visualizations for Micro/Macro Readings". In *Text Visualization 2015*. www.textvis.org

[12] D. Ebert, R. Rohrer, C. Shaw, P. Panda, J, Kukla, and A. Roberts. Procedural shape generation for multi-dimensional data visualization. In *Computers & Graphics 24.* (2000). 375-384.

[13] R. Brath. The Multiple Visual Attributes of Shape. In E. Banissi, F. Marchese, C. Forsell, J. Johansson, eds. *Information Visualization: Techniques, Usability and Evaluation.* Cambridge Scholars Publishing. 2014.

[14] F. Chevalier, R. Vuillemot, and G. Gali. Using Concrete Scales: A Practical Framework for Effective Visual Depiction of Complex Measures. *IEEE Transactions On Visualization And Computer Graphics,* Vol. 19, No. 12, 2013.

[15] Stephen Rose. *Social Stratification in the United States: The American Profile Poster*. The New Press. 2007.

[16] David Jonker, William Wright, David Schroh, Pascale Proulx, Brian Cort; Information Triage with TRIST. *2005 Intelligence Analysis Conference*. 2005.

[17] O. Neurath. *Gesellschaft und Wirtschaft*. Bibliographisches Institut AG. Leipzig. 1930.

[18] R. Modley. *Handbook of Pictorial Symbols.* Courier Corporation. 1976.

[19] H. Dreyfuss. *Symbol Sourcebook: An Authoritative Guide to International Graphic Symbols.* John Wiley & Sons. 1984.

[20] V. Setlur and J. D. Mackinlay. "Automatic generation of semantic icon encodings for visualizations." *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2014.

[21] E. Sorenson and R. Brath. *Financial Visualization Case Study: Correlating Financial Timeseries and Discrete Events to Support Investment Decisions.* In Information Visualization 2013 (IV2013).

[22] P. Kahn and K. Lenk. "Principles of Typography for User Interface Design" in *Interactions*. New York. Pp. 15-29. 1998.

[23] R. Brath and E. Banissi. "The design space of typeface". In *Visualization and Computer Graphics, IEEE Transactions on (VisWeek 2014).* IEEE Computer Society Press, 2014.

[24] J. Teague. *Fluid Web Typography.* New Riders, Berkeley, CA. 2009.

[25] J. Bertin. *Semiologie Graphique.* Gauthier-Villars, Paris. 1967.

[26] G.E. Rosario, E.A. Rundensteiner, D.C. Brown, M.O. Ward, S. Huang "Mapping nominal values to numbers for effective visualization." *Information Visualization 3*:80–95. 2004.

[27] D. Norman. *The Design of Everyday Things.* Basic Books, 2002.

[28] S. McDougall, O. De Bruijn and M. Curry. "Exploring the effects of icon characteristics on user performance: The role of icon concreteness, complexity, and distinctiveness." *Journal of Experimental Psychology: Applied 6* (2000), 291–306.

[29] W. Cleveland. *Elements of Graphing Data.* Hobart Press, Summit, NJ. 1985.

[30] J. MacKInlay. "Automating the Design of Graphical Representations" *ACM Transactions on Graphics,* 5. 2006.

[31] C. G. Healey and J. T. Enns. "Attention and visual memory in visualization and computer graphics." *IEEE Transactions on Visualization and Computer Graphics.* 18:1170-1188, 2011.