This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2015.2467321, IEEE Transactions on Visualization and Computer Graphics

Acquired Codes of Meaning in Data Visualization and Infographics: Beyond Perceptual Primitives

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Abstract—While information visualization frameworks and heuristics have traditionally been reluctant to include acquired codes of meaning, designers are making use of them in a wide variety of ways. Acquired codes leverage a user's experience to understand the meaning of a visualization. They range from figurative visualizations which rely on the reader's recognition of shapes, to conventional arrangements of graphic elements which represent particular subjects. In this study, we used content analysis to codify acquired meaning in visualization. We applied the content analysis to a set of infographics and data visualizations which are exemplars of innovative and effective design. 88% of the infographics and 67% of data visualizations in the sample contain at least one use of figurative visualization. Conventions on the arrangement of graphics are also widespread in the sample. In particular, a comparison of representations of time and other quantitative data showed that conventions can be specific to a subject. These results suggest that there is a need for information visualization research to expand its scope beyond perceptual channels, to include social and culturally constructed meaning. Our paper demonstrates a viable method for identifying figurative techniques and graphic conventions and integrating them into heuristics for visualization design.

Index Terms—Visual Design, Taxonomies, Illustrative Visualization, Design Methodologies

Introduction

Understanding how a visualization creates meaning is a key task for visualization research. Knowledge of the interpretation process plays an important role in both visualization evaluation and design. Successful visualization depends on a viewer decoding the visual scene into a message about the underlying data. While the perceptual aspects of this interpretation are well-studied, less attention is given to the conventions of practice that have developed within the visualization community. Socially constructed meaning is an overlooked factor and an untapped resource in creating visualizations which resonate with an intended audience.

It is well established that the interpretation of visual information is affected by learned codes as well as innate perceptual mechanisms [55]. Many authors, both within information visualization [24, 25], and in related fields such as visual literacy [4, 37] and psychology [21, 50, 51], identify the existence of acquired codes of meaning in the interpretation of visualization.

However, the acknowledgement of acquired meaning is accompanied by a reluctance to include it in information visualization frameworks or heuristics. The term 'graphics' is explicitly defined by Bertin to exclude elements which *"rely either on an explanation coded in another system (legends) or on a FIGURATIVE ANALOGY of shape or color (symbols), which is based on acquired habits or learned conventions and can never claim to be universal"* ([7] p. 7). Standard grammars and taxonomies of visualization take their cues from Bertin, and either limit their scope to graphics [56], or embed information visualization within the realm of data graphics, excluding conventional meaning [12, 59]. Where imagery is included in information visualization, the emphasis is on machine generated images such as medical scans or geometric models, not familiar shapes [48]. Similarly, a collection of multiple sets of heuristics for visualization design includes results from studies of perception and analysis of visualization tasks, but not consideration of acquired meaning [62].

Existing visualization research has mainly focused on leveraging the current understanding of the human perceptual system to improve visualization quality [22].

Increasingly, visualization researchers are calling for a greater understanding of culturally and experientially mediated responses to visualization. Understanding and making effective use of visual metaphors has been identified as a key challenge for visualization research [8, 20, 33]. Researchers have also explored the boundary between art and information visualization [28, 54], drawing inspiration for information visualization designs [17] or analyzing how abstract shapes and motion create affective responses [17-19].

Alongside this broadening theoretical outlook, a growing number of experimental studies have suggested that perceptual cues are insufficient to explain users' performance with visualizations. Contradicting theoretical advice against 'chart junk', a test of user performance found the use of images in or framing a graph did not affect response speed or performance, and aided retention [5], while a larger study found that pictorial elements in visualizations significantly increased their memorability [9]. The style of a visualization has been shown to change the type and perceived depth of insights users generate [53]. The possibility of a social convention around different uses of bar and line graphs has also been used to explain a stronger than expected experimental result [57]. Other research has explored the links between verbal metaphor and corresponding metaphors in information visualization in order to explain different accounts of user performance [60, 61].

Missing from the literature is an analysis determining how acquired meaning is actually used in practice.

Acquired meaning in visualization can take the form of overt figurative representation or more subtle visual convention. When designers include illustrations or similar images in a visualization they are relying on the audience's recognition of an object based on its shape. The audience's existing knowledge is explicitly called upon to understand the visualization's meaning. Even when the illustration shows something unfamiliar to the audience, visual cues and context ground the new information in existing knowledge. Acquired meaning can also be evoked more subtly through the use of conventions for how a particular kind of data is represented. An

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Manuscript received 31 Mar. 2015; accepted 1 Aug. 2015; date of publication xx Aug. 2015; date of current version 25 Oct. 2015.
For information on obtaining reprints of this article, please send *e-mail to: tvcg@computer.org.*

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2015.2467321, IEEE Transactions on Visualization and Computer Graphics

example is the use of a line graph to represent time series [36] or vertical tree structures for organization charts.

The contribution of this work is to evaluate the use of figurative visualization and visual conventions in visualization against competing theories around the role of acquired meaning in visualization. Bertin's concept of purely abstract mappings between data and representation – 'graphic purity' – suggests that good visualizations will avoid the ambiguity of acquired meaning and rely instead on abstract arrangements of perceptual primitives (visual variables). On the other hand, theories of graph comprehension [38], visual literacy [4] and memorability [5, 9] suggest that effective designs will make use of conventions and figurative elements to reduce the effort required for the user to understand and remember the message a visualization. We apply content analysis to identify uses of socially constructed meaning in exemplars of 'best-practice' drawn from two different categories of visualization: data visualization and infographics. Data visualization is grounded in the tradition of graphic purity, while infographics have no such ideal, and in contrast have traditionally made use of illustration [32]. Comparing the use of acquired meaning within these two categories provides us with an indication of how strongly the ideal of graphic purity shapes information visualization practice.

The paper describes the content analysis approach, including the choice of the sample set, the process of coding a visualization and the analysis of the coded dataset (see section 1). The key results focus on two areas: figurative visualization, and conventions around the depiction of time (section 2). The results of the content analysis are used together with existing literature to distill a number of candidate guidelines for incorporating acquired meaning into design (section 3), and set out an agenda for integrating acquired meaning into visualization practice and research (section 4).

1 Content Analysis

We use content analysis as a method for identifying acquired meaning in visualization. Tipaldo defines content analysis as "*a wide and heterogeneous set of manual or computer-assisted techniques for contextualized interpretations of documents produced by communication processes strictiore sensu (any kind of text, written, iconic, multimedia, etc.) or signification processes (traces and artefacts), having as an ultimate goal the production of valid and trustworthy inferences*" ([47] p.42). Krippendorff [30] provides an operational definition of content analysis by posing six questions that any such analysis should address:

1. What data is analyzed?
2. How is the data defined?
3. What is the population from which the data is drawn?
4. What is the context relative to which the data is analyzed?
5. What are the boundaries (limitations) of the analysis?
6. What is the target of the inferences made through any analysis?

The underlying assumption in content analysis is that the most frequently used codes will reflect the most important concerns in a communication system. Accepted practice for content analysis is to have multiple coders use the same coding scheme to independently code a dataset and to then cross-check the results for inter-coder reliability, a measure of the level of agreement between coders [31]. If there is high disagreement between coders it could be reasonably inferred that the coding scheme or data are prone to subjective bias. Krippendorf's alpha [29] is a widely accepted measure of inter-coder reliability as it can tolerate missing data-values, mixed data types, two to many coders, and has no minimum data size [35]. Content analysis approaches have previously been used in information visualization, for example to examine the use of rhetoric [25] and narrative [42]. Krippendorff's questions are addressed in the following sections, which look first at the dataset, then at the process of unpacking a visualization and coding it to allow recognition of different kinds of acquired meaning.

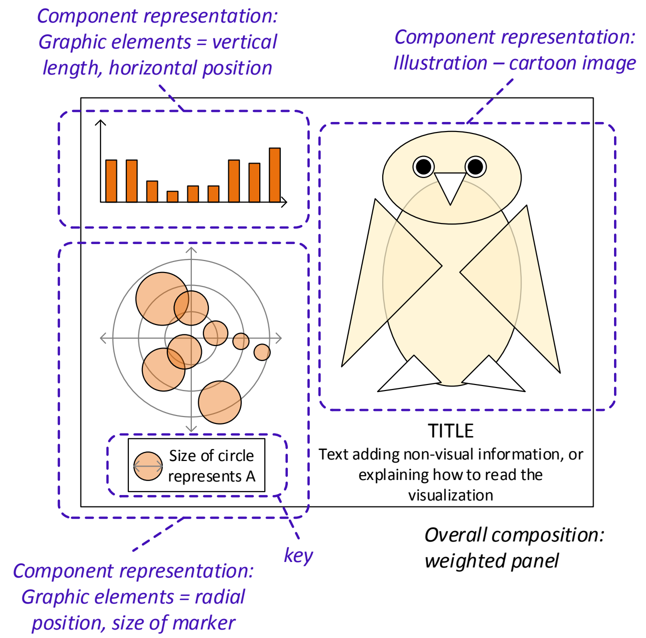

Fig. 1. An illustrated guide showing how visualizations were decomposed for coding. A visualization is comprised of one or more self-contained component representations, classified as 'graphic', 'figurative' or both (hybrid). This visualization has three components, one of which is larger (a 'weighted panel' composition). (right) The component representation is a figurative illustration; (left) both component representations are graphics. (left top) A composition of graphic elements using vertical length and horizontal position to encode data; (left bottom) an arrangement of graphic elements using radial position and the size of a marker to encode data, and which includes a key.

1.1 The Dataset

To identify how conventions are used in visualization, we selected a sample of visualizations from two categories of the Kantar Information is Beautiful Awards 2014 showcase: infographics and data visualization [1]. For comparison purposes we selected the sample to obtain roughly equal numbers from each category. Therefore, we used the shortlist for the Data Visualization category (24 visualizations in total) and the longlist for Infographics, discounting one of the entries as it was a multipage report (26 visualizations in total). We refer to this sample of 50 visualizations as the Kantar Information is Beautiful Awards 2014 (KIIBA14) dataset. The entire awards showcase can be viewed online [1].

The dataset includes visualizations published the National Geographic Magazine, the Washington Post, the Guardian and G2 newspapers, gallery installations, a report from a commissioned survey, a building installation, as well as online publications [1]. The result is a set of visualizations which are aimed at a range of audiences, and vary considerably in terms of data-quantity and data-complexity. In terms of Tory and Moller's design model of visualization [48], all of the categories of their high level taxonomy (given, constrained, or chosen spatial layouts vs discrete or continuous models) are represented in the dataset.

The dataset covers a broad range of topics, and includes humorous and general interest visualizations as well as pieces conveying new science (the infographic 'Deep Brain Dive' shows the result of imaging a mouse's brain at the 1 micron scale [49]).

Items in the KIIBA14 dataset are categorized based on the designers' own understanding of the terms (no guidelines are provided). The resulting partition between data visualization and infographics thus represents a naturalistic distinction between the two categories – nominated participation in one or other tradition. In comparison to existing definitions in the literature, the data

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visualizations are closer to meeting the criteria that information visualizations are bijective mappings “composed of discrete and disjoint visual symbols” [59]. They do not fit the suggestion that data visualization is sometimes used to mean scientific visualization [59]. In contrast to several definitions of data visualization in the literature [12, 59], neither set is interactive (interactive visualizations was a separate category of the awards). Only a small number of infographics in the dataset fit the stereotype of “illustration, large typography, and long, vertical orientation displaying an assortment of facts” [32]. Visualizations published in newspapers and magazines (the traditional outlet of the infographic [32, 59]) appear in both the infographics and data visualizations categories.

The chosen set of visualizations has a number of advantages for detecting conventions. Each visualization has been judged by a panel of experts as an exemplar of good visualization practice[1]. Visualizations were judged according to four criteria: appropriateness, originality, beauty, and whether they achieved their objectives [1]. The judges’ decision that a visualization has achieved its objectives validates assumptions the authors have made that an element will be understood without explanation (i.e. is conventional). The criteria of originality skews the sample set towards innovative visualizations, therefore entries in the showcase are less likely to be standard designs or copies of famous visualizations. Thus when the same combination of visual variables is used, or some aspect of the visual arrangement is shared across visualizations, it suggests that a common visual language is being invoked.

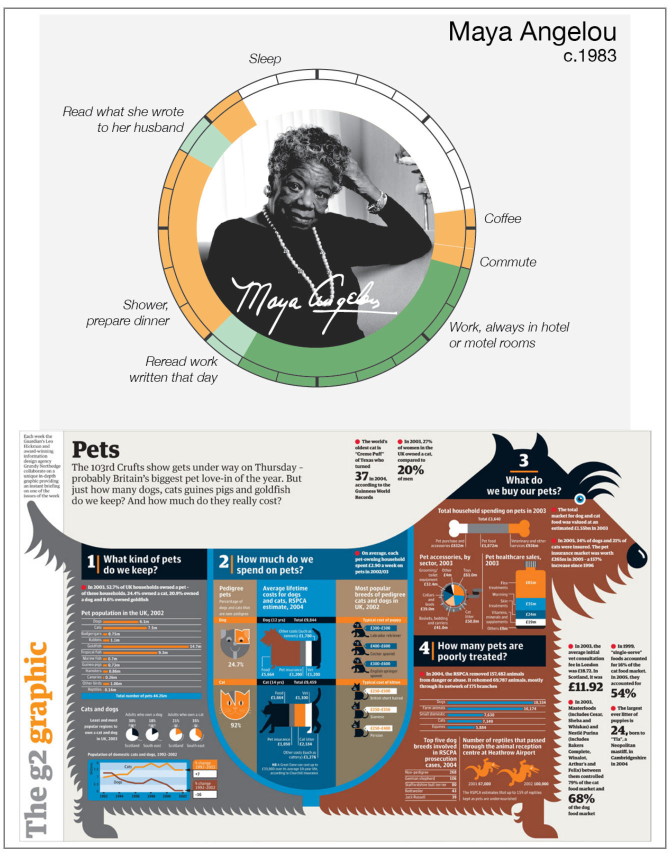

Fig. 2. Hybrid representations. Figurative and graphic elements can be closely linked in a visualization. (top) A component of the visualization ‘Creative Routines’ [40], showing a graphic containing an illustration. (bottom) ‘Pets’ [23] showing graphics positioned within a figurative element. Reproduced with permission.

A non-trivial portion of the dataset (20%) are in languages other than English, including German-language (four examples), Italian (four examples), Chinese and Portuguese (one example each). Visual conventions which can be identified from the set are likely to be conventions which exist within a broad international community of practice.

1.2 Coding a Visualization

In order to apply content analysis to the search for acquired meaning, the field needs a method for decomposing and coding a visualization. As demonstrated by the KIIAB14 dataset, visualizations can be complex multi-panel designs, showing different visual perspectives on a single subject. The content analysis code set should encompass and accommodate the arrangement of common elements into different designs. It should also recognize when common techniques are being applied as part of the composition of a visualization.

The first stage of our coding method was to decompose the visualization into its component panels and identify the overall composition and the visual elements at the base level of decomposition. The second stage was to identify how the data is represented through the visual elements. After being defined, the coding scheme was applied independently by authors Byrne and Angus, and the level of agreement tested using Krippendorff’s alpha.

1.2.1 Stage 1: Unpacking Composition

Many visualizations contain sections which could be viewed on their own as self-contained visualizations. Recursive definitions consider a visualization to be comprised of one or more ‘component representations’ which may in turn contain their own component representations [16].

Here we define a component representation as a portion of the visualization which can be repositioned without affecting its meaning. A component representation is a ‘panel’ in the containing representation (see Figure 1).

At the top level of the composition is the whole visualization – the image in the KIIBA14 dataset. The dataset analyzed here does not contain any interactive visualizations, however, the recursive model of visualization could be extended to multi-view interactive visualizations by considering the visualization system as a whole as the highest level, and each view as a lower level component representation. At the lowest level of the composition are arrangements of figurative or graphic visual elements.

A key aspect of the coding process is identifying component representations as either figurative and/or graphic, based on the following definitions:

- ***Graphic representation***: a representation where relationships within a dataset are revealed by mapping categorical, ordinal or quantitative data to visual variables [7].
- ***Figurative representation:*** illustrations, photographs, cartoons and schematic diagrams, where the meaning is based on the similarity of the shape of the representation to the shape of an external object or concept.

Figurative elements are connected figures or images, while graphic elements consist of combinations of perceptual primitives – point, line or area markers whose position, hue, shading, shape, angle or size encodes data. A graphic representation can contain figurative elements and vice versa (see Figure 2). Hybrid representations or hybrid visual elements are counted as both graphic and figurative.

The first stage of coding considered the high level composition[2] of the visualization and the presence of figurative and graphic elements. The composition of each visualization was classified as one of the following types:

- a *single* irreducible representation;

[1] The award judges are a combination of experienced visualization designers and researchers.

[2] if an image is used to frame the visualization as a whole, the high level for coding purposes is defined as the level inside this frame.

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- a *panel layout* where one or more component representations share the space roughly equally;
- a *weighted panel* where one component representation was noticeably larger than the others.

Additionally, coders identified whether each visualization contained at least one figurative and at least one graphic element.

1.2.2 Stage 2: Coding the visual elements

The second stage of coding examined the data being represented and how the variables or properties of that data were mapped to different visual elements.

Figurative elements can be classified into three distinct roles:

- ***Content***: Illustrations[3] are part of the content of the visualization when they show an object's identity or its contents or how a process works. We refer to these content-bearing illustrations as *figures*. Illustrations which do not provide additional information beyond what the user must already know to recognize and understand the shape are referred to as *images*.
- ***Context***: While they do not provide additional content, images can frame, reinforce or introduce the subject of the visualization, and can play a key role in catching the attention of audiences.
- ***Labels***: images can also be used instead of or alongside text identifying a graphic element.

Each visualization was coded for whether it includes any instance of figurative content, context or labels. Maps are a privileged form of figurative representation, often included as 'valid' graphical elements even when other figurative elements are excluded (e.g. [7]). In addition to being classified according to its figurative role, the presence of a map was coded to examine the effect of this privileging. Figures (i.e. content bearing illustrations) were additionally coded to show the presence of particular figurative conventions for showing content, for example the visual metaphor of a magnifying glass.

Each graphic element was coded based on four high level categories – representations of time, linear layouts, representation using area, and conventional color meaning. The high level categories were chosen to probe for a variety of conventions in the dataset. A quick survey of the dataset was undertaken to examine the subject of each work as well as how quantitative and qualitative information was encoded. The initial survey suggested that time was a commonly used subject in representations, and that area was frequently used to compare quantities. To test whether conventions can occur around a particular subject, time was chosen as a coding category, with linear axes chosen to allow comparison across subjects. Area was also chosen as a high level category because its frequency suggested potential conventions. Color meaning was chosen since it is frequently named in the literature [3, 46], and we wanted to test whether the conventions given as examples are in fact used in practice.

Since conventions are used across a community, we counted the number of different visualizations in which an element appeared, ignoring multiple uses of the same technique in a single design.

A visualization was considered to contain color meaning when the color scheme used for a set of visual markers had some recognizable association with the represented data (e.g. blue/pink for men/women). Natural or realistic shading of illustrations (e.g. blue for water on a map) was not counted as color meaning.

1.3 Recognizing Acquired Meaning

The coded data was analyzed to determine the prevalence of acquired meaning in the KIIBA14 dataset, the different forms of visual conventions present, and the contexts in which convention and figurative visualization were used. The presence and prevalence of figurative elements was read directly from the coded data. Identifying conventions required a slightly more complex analysis process, taking into account the presence of representational variation, and the placement of a visual element.

Conventions, including visual conventions, have two identifying characteristics. The first is prevalence; standard forms for representing an object appear frequently within a community of practice. The second is pervasive comprehension within the community. A convention does not need to be explained, it is assumed as common knowledge by visualization designers and their audiences.

Based on the characteristics of prevalence and assumed comprehension, it is possible to identify conventions from the coded data. To determine prevalence elements or patterns which frequently appeared in the sample of visualizations were identified. The coded data was analyzed to identify disproportionately common visual elements and examine the context in which they were used.

We then looked at guides, keys or explanations included by the designers within their own work to explain how to read their visualization. An absence of explanatory features suggests that the visual element is conventional – the designers and judges assume it will be widely understood without explanation.

A final indicator of conventional meaning is the placement of an element in the visualization. Designs requiring the reader to learn a new visual formalism are likely to be given prominence in the visualization, in terms of space and position. Elements which take up a small proportion around the periphery of the display area are therefore more likely to be conventional.

Conventions are socially constructed, and can be wide or limited to a small community. The scope of our analysis is the use of visual elements across the two categories of visualization from which we have sampled: infographics and data visualization.

As is typical of qualitative studies, the content analysis applied here uses a relatively small sample set, which limits our ability to generalize from the study results. The study findings are influenced by our choice of which aspects of visualization to observe – choices embodied in the coding process and coding schema described above. We chose a qualitative method because it allows us to explore how conventions manifest within visualization, and thus represents a good 'first pass' method, which can provide the foundation for quantitative analysis in the future.

Our analysis is limited to detecting conventions and acquired meaning at a high level of composition. Some visual elements may be tightly coupled, often occurring in the same irreducible component representation (for example maps with markers whose area shows quantities). However, the coding process did not capture how far apart in the visualization decomposition two elements are, and so cannot detect this kind of convention.

2 Results

The results of the content analysis are presented in three parts: the use of figurative elements, representations of time, and other candidate graphic conventions. Across these three areas there was high agreement between the two coders. Overall, there was 98.8% agreement, with a Krippendorff's alpha of 0.965.

2.1 Use of Figurative Elements

Figurative elements are frequently used within the dataset, particularly in the infographics category. Of the infographics, 88% contain at least one use of figurative visualization, as do 67% of the data visualizations. Furthermore, both the infographics and data visualization categories included multiple examples of each type of figurative element. Figurative elements were most commonly used as labels in both categories (69% and 42% respectively), while content-bearing figures and contextual images were much more prevalent in the infographics category (see Figure 3).

[3] Illustrations is used here to includes imagery such as photographs.

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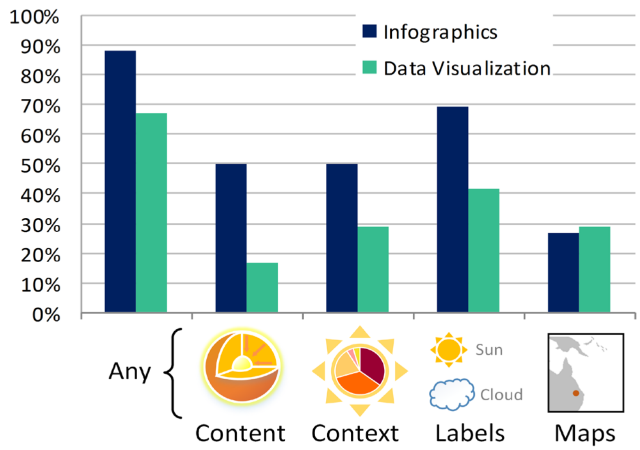

Fig. 3. The percentages of infographics and data visualizations which contain different types of figurative elements. More infographics contain figurative elements across all three roles (content, context and labels), but this pattern does not hold for maps. The 'any' bars on the left do not equal the sum of the other bars, since visualizations may contain multiple figurative elements playing different roles, and maps additionally play one of figurative roles.

2.1.1 Maps

Maps are such a common feature in information visualization that their figurative nature is often overlooked. Maps rely on the reader recognizing the shape of the country or region depicted [7], with an illustration providing context to allow the reader to mentally place any geospatial graphical elements (see Figure 4A and B). The figurative elements of a map can be recognized by looking for elements which are defined by shape files. For example, 'Breathing City' [13] includes figurative elements, despite first appearances, since shape files of Manhattan buildings are used to define the shape of each point (see Figure 4C). The dataset contains only a single example of geospatial data *not* overlaid on a figurative map element [26].

The dataset provides examples of maps falling into all three classes of figurative representation: figures, context and labels.

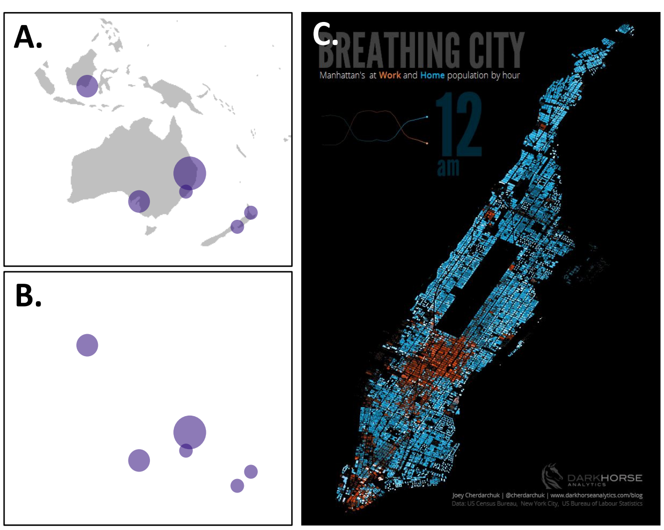

Fig. 4. Recognizing the figurative aspects of a geospatial representation. A (a map) and B (not a map) show the same (made up) geospatial data with and without a figurative background. In C, 'Breathing City' [13] provides an example of a map which is also a content bearing figure, since the shape of its points show the composition of Manhattan in far greater detail than the reader needs to recognize the city. 'Breathing City' has been reproduced with permission.

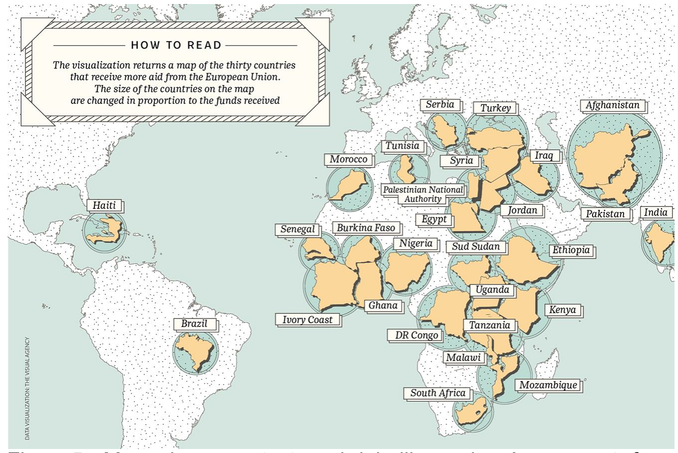

Fig. 5. Maps in a context and labelling role. A segment from 'European Union Humanitarian Aid' [44] shows how maps can fit into multiple places in our proposed classification of figurative visualization roles. In the visualization, the map is used as an image the audience is meant to recognize, providing context for where aid-receiving countries are located geographically and relative to each other. The location of markers on the map are themselves map segments – country icons used as labels. Blurring the boundaries between figurative and graphical representation, the size of each country icon encodes quantitative information. Reproduced with permission.

'Breathing city' (Figure 4C) is a figure, the shape of its points showing the composition of Manhattan in far greater detail than the audience needs to recognize and orient themselves. The background illustration of 'European Union Humanitarian Aid' is an image, providing background context for the quantitative information displayed in the visualization, but no more geographic detail than is already expected of the reader (shown in Figure 5). The same component visualization includes maps as icons (labels), with country shapes used as location markers whose size indicates the quantity of aid received.

2.1.2 Composition

The importance of figurative visualization in practice can also be seen from the composition of the visualizations in the sample set.

Infographics used the panel composition the most (50% of the time, compared to 21% for data visualization), while data visualization favored the single representation form (42% compared to 12% for infographics). The weighted panel layout was used consistently across the two categories in just under 40% of cases (39% infographics, 38% data visualization). Of these weighted panel layouts, a close inspection of the relevant visualizations showed that around half of the infographics used either a figure or an image as the main component, while nearly half of the data visualizations used a map.

2.1.3 Conventions in Figures

The figures (i.e. content-bearing illustrations) in the sample visualizations share a number of techniques for showing the nature or composition of an object, and how it fits into a known context:

- ***Outline:*** the object is illustrated through an outline style with either transparent or partially filled in shading. Outlining is used for both organic (mouse [49] and human [39]) and inorganic objects (race car [41]) in the sample set.
- ***Magnifying glass:*** a portion of one illustration is enlarged and overlaid or connected to the smaller scale image. A magnifying effect is used both with figures showing objects, and with maps ([6], [49] and [39]).
- ***Cut away:*** - a cross section of an object is shown by fitting the segment into a geometric shape – typically a rectangular prism. The cut away technique is used to show a segment of mouse brain in a cube [49], and skin tissue in a rectangular prism [39].

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The outlining technique was used in just over half of all visualizations with figures. Additionally, several examples use both figures to show content and images for context. In some cases a consistent style is used throughout the visualization, but in a few cases ([41, 58]) a realistic style or photograph is used for the contextual image, while a more abstract style (outline or silhouette) is used for the content.

While uncommon, the use of the magnifying glass (used in 3 visualizations) and cut away techniques (used in 2 visualizations) by multiple different authors in the highly flexible medium of illustration indicates that these are likely to be figurative conventions. The placement of some instances of each technique in the periphery of the overall composition further supports their conventional nature (e.g.[39], [49], [6]).

2.2 Visual Representations of Time

Many of the visualizations in both categories include some representation of time. More than half (54%) of the data visualizations and nearly three-quarters (73%) of the infographics showed the values or properties of objects changing over time. Time is shown running along horizontal, vertical, circular and curved axes, in a comic strip style panel layout, with animation, and using area, with varying frequencies (Figure 6). Six layouts were used more than once (see Figure 7).

The most common representations of time were horizontal and vertical – linear – layouts. Furthermore, linear representations of time were often peripheral in the overall composition of the visualization. None of the linear representations of time had an explanatory guide, and many did not have a “time” or similar label on the axis, simply numbering the units.

2.2.1 Direction

One pattern within the linear layouts of time was the direction of the axis. Horizontal layouts exclusively ran left to right. Vertical layouts were slightly less constrained. All five instances of visualizations which contained a vertical layout of time included an example where time ran downwards (small values higher up on the page), but two also included a representation of time running upwards (small values towards the bottom of the page). In comparison linear layouts of data other than time ran overwhelmingly left to right for horizontal layouts (93% of instances), and bottom to top for vertical layouts (88% of instances).

2.2.2 Time in figurative representations

Figurative representations of time used the panel layout (as too did some graphic representations). An example from the edge of “Revolution on Four Wheels” [41] is shown in Figure 8. The passage of time is indicated only by the different dates in either panel, suggesting that the reader requires little guidance to understand this representation.

2.2.3 Cyclical Representations of Time

Time was only arranged in a circular layout for particular sets of units: hours in a day, 12 hours, or days in a year. That is, circular layouts of time were restricted to cyclical ranges of time.

2.3 Other Graphical Conventions

Several other patterns were identified from the content analysis. The comparison of different quantities through the areas of shapes was used in 52% of all the visualizations. Circles were the most popular shape (especially in the data visualization category, where 79% of area markers were circles), followed by icons in the infographics category, and other geometric shapes in the data visualization category. Shapes showing area were often annotated with exact quantities (62% of visualizations with a set of area-varying shapes used annotations).

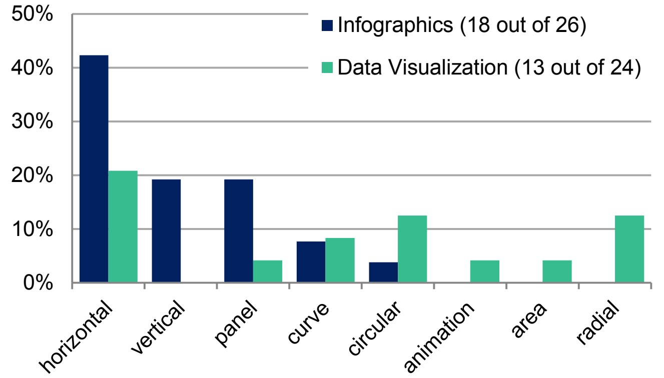

Fig. 6. Layouts of time in infographics and data visualization. The height of each bar shows the percentage of visualizations in each category which include at least one instance of a particular layout. Of these subsets, linear (horizontal and vertical) layouts were the most frequently used.

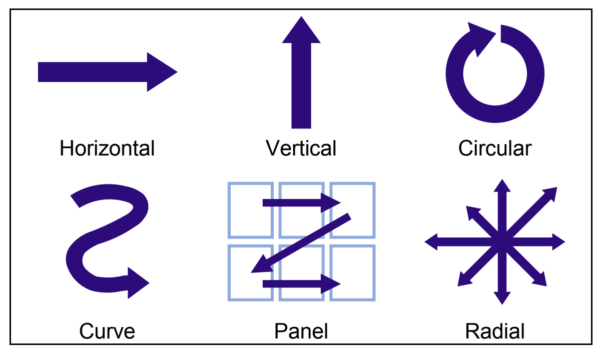

Fig. 7. Arrangements of visual elements used to represent time more than once in the sample set.

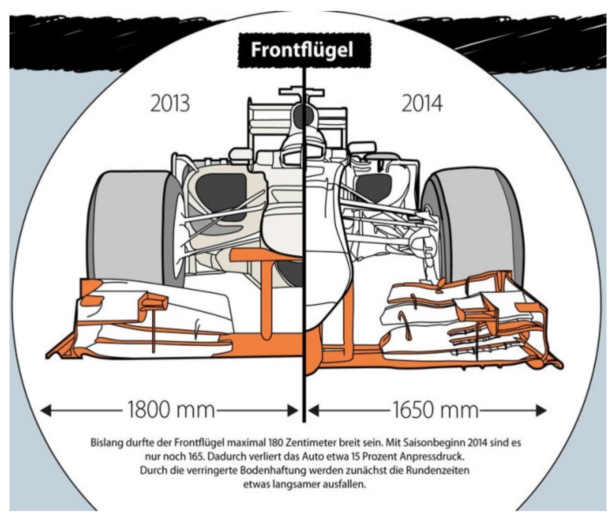

Fig. 8. A panel arrangement representing time [41]. Panel representation of time is typical where the object changing over time is being represented figuratively. Reproduced with permission.

Literature discussing conventional codes often mention color meaning (see for example [46]). Color meaning was present but not prevalent in the data, identified in 12% of infographics and 8% of data visualizations. Color meaning used to identify categories (for instance blue for men and pink for women) was explained with keys: authors did not rely on their audience knowing the conventional meaning.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2015.2467321, IEEE Transactions on Visualization and Computer Graphics

3 Discussion

Data visualization and infographics are grounded in different design traditions, which can be matched to their different use of conventions. The legacy of Bertin's exclusion of all figurative elements except maps [7] can be seen in the privileging of maps compared to other figurative elements in the data visualization category. The map of Manhattan in fig 4 is analogous to the formula 1 car in fig 8 – both are the outlined projections of a physical object. Figurative techniques such as magnification are also used identically in maps as in other figures. Yet of all figurative elements, only maps appear as frequently in data visualization as in infographics. In data visualizations figurative elements are rarely used to show content, and when they are, the content is often geographic. Although we did not formally measure the relative area taken up by contextual images as part of the study, non-map context images appear to make up a smaller component of the overall composition when they are used in data visualizations. Our analysis of representations of time shows that data visualization used a greater variety of layouts, while analysis of composition shows that a single graphic component was common (rare for infographics). Data visualizations often combined many facets of a subject into a single graphic composition. Infographics, which are grounded in a tradition of narrative, are far more likely in our sample to use a panel composition where different component representations can be read in sequence. Each component representation in a panel composition may itself be a simple statistical graph – we observed that representations of time in infographics use a smaller range of layouts and are far more likely to use basic horizontal and vertical axes (see fig 6). In addition, infographics used icons as area markers far more than data visualization (5 instances in infographics compared to a single instance data visualization shown fig 5), suggesting greater comfort in blurring the lines between figurative and graphic representations in infographics.

Data visualization projects in the KIIBA14 dataset do not meet Bertin's ideal of graphic purity, using acquired codes of meaning at nearly the same rates as infographics. Nor does it seem likely that the designers are unaware of this ideal. The privileging of maps over other forms of figurative element provides evidence that data visualization is influenced by its guiding theory. The dataset better fits a model where designers actively deviate from a 'graphically pure' approach in order to leverage their audiences' experience and prior knowledge to communicate effectively.

In the following section we interpret the results of the content analysis in the context of existing literature, proposing a number of guidelines (labeled G1 – G7) for the use of acquired meaning. These guidelines have particular application to information visualization designers working in a similar context to the KIIBA14 dataset – projects designed for a general audience, which aim at originality and beauty. The guidelines developed here could also be used to formulate hypotheses for quantitative research, to rigorously test whether the use of conventions leads to more effective visualization designs.

3.1 Figurative Visualization

A wide variety of figurative elements appear in both the infographics and data visualization exemplars. Most visualizations in the dataset used graphic and figurative elements in tandem, using each technique to represent different aspects of a subject. More importantly for efforts to integrate acquired meaning into theory, figurative elements fit into distinct roles, and conventions are used to convey common concepts.

The roles of figurative visualization vary according to how they leverage an audience's object recognition to communicate new information. Content elements (figures) show both known and unknown objects through shape, linking the two to provide the reader with the required reference point to frame new information. Figurative conventions enable the linking process – examples include outline and partial coloring, magnification, and cut away. **G1:** *Use figurative visualization to show the composition or nature of an object or how a process works. Link new information to a familiar context through outlining, magnification or cut-away techniques. Use panels to show changes in an object over time.*

Context and label images use the reader's recognition of a shape to explain or draw attention to graphic elements of the visualization. An example of context can be seen in the framing of 'pets' within the outline of a dog (fig 2, lower image). Existing research argues that the inclusion of recognizable contextual images will attract attention, as well as aid in understanding and retention of the represented information [5, 9, 10, 34]. In a labelling function, icons share the strengths of context images, but allow the abstract patterns of data to dominate the visual scene. **G2:** *To attract attention, to orient a general audience to an unfamiliar subject, or to make a visualization memorable, use* recognizable *images for context or labels.*

The figurative role of a map depends on how it will be used – the same GIS software can be used as context if the insight for the user concerns the positions of objects around a familiar location, or in a content role if the tool characterizes the location. In the KIIBA14 dataset maps were used in all three figurative roles: to show content, to provide context or in icon form as labels. As such, guidelines on using figurative elements (**G1** and **G2**) also apply to maps. In particular, designers using maps as context or icons in the style of fig 5 should provide enough detail to be confident that their audience will recognize the location from the information provided (see **G2**). For example, icons of the seven Australian states and territories would be recognizable enough to use as labels for an Australian audience, but need to be accompanied by text for an international audience. Maps showing content need to follow **G1** outlined above. To apply the visualization technique of Breathing City (fig 4) to a less recognizable city like the authors' home town of Brisbane, for instance, **G1** would advise linking the main figure to a map showing Brisbane's location within the recognizable landmass of Australia, in order to orient the reader. **G3:** *To ensure the recognition of label and context maps, and to orient the reader when a map plays a content role, adjust the level of detail and supporting information according to the reader's familiarity with representations of the location.*

The results showed the prevalence of outlining as a technique, as well as examples of less realistic illustrations being used to show content. Several explanations could account for the use of more realistic images as context and more abstract illustrations for content. One explanation is that the use of photographs in news media has produced a convention where photographs (or illustrations like them) accompany the story, but do not necessarily provide key information. A second explanation is provided by science illustrator Jenny Keller: *"In a good illustration, you can create a representative "average" or "typical" specimen from pictures of separate individuals, or emphasize only the most important information about a subject, leaving out distracting clutter."* [11] P. 165

Regardless of the cause, using a realistic style for context appears to be another convention. **G4:** *Use a more realistic style for context than for content elements, if using figurative elements in both roles.*

3.2 Graphic Conventions

Analyzing graphic representations of quantitative information, including time, showed that the visual language of graphics is highly flexible. For any given subject, there are multiple different representations which can be used. At the same time, clear conventions emerged around the use of particular arrangements and particular datasets.

Theories of graph comprehension [38] hold that familiarity with a particular type of graph leads a reader to understand such visualizations faster or with less effort (greater fluency). According to this model, conventions fulfil a useful function within

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visualization – they signal to the reader the kinds of judgements and comparisons to make as they examine the graph. An informal survey of guides and legends in the KIIBA14 dataset supports this view: unconventional graphic arrangements are more likely to contain detailed 'how to read' guides. **G5:** *Use conventions to create representations which are easy to read.*

3.2.1 Conventions and Exceptions

While conventions are used within the KIIBA14 dataset, they are not strict rules that designers always follow. The data visualization category provides examples where conventions were broken to construct an effective visual metaphor, and to create a perceptually efficient graphic arrangement. 'the depth of the problem' [27] shows the believed depth of the missing MH370 plane, showing heights and depths of familiar objects and events (e.g. the Washington Monument, the depth of the titanic) along a vertical scale. In contrast to convention, the vertical axis runs top-to-bottom. By breaking convention, the design establishes a highly effective visual metaphor of a cross-section of the ocean viewed at scale. 'What Teachers Think' [45] also breaks a visual convention observed in the dataset, in this case the convention of using circles as the shape for area markers. The designers instead use square markers arranged in sets of four to form windmill shapes, where each set represents the response of surveyed teachers from a particular country, and the size of each square within a set represents the proportion of teachers who agreed with one of four possible responses. The square shape allows the four grouped markers to be positioned so that they nearly touch, forming a highly salient group according to gestalt principles. At the same time, each square can vary in size without overlapping. The result is a graphic arrangement that allows comparison between teachers' survey responses at the country level by looking at the overall shape of each windmill, as well as comparison of each possible response by looking at the component squares.

Interesting patterns of convention and exception appear within the analyzed dataset. The distribution of representations of time (see fig 6) at first suggests a pattern where time is conventionally represented along a left-to-right horizontal axis, and other representations of time are simply exceptions to the convention. A closer reading of the 'exceptional' visualizations reveals an alternative explanation: visualizations of cyclic periods of time (hours in a day, days in a year) are represented using a circular layout, non-cyclic quantitative representations of time are represented horizontally, and the changes over time of a figurative object (i.e. qualitative changes over time) are represented using a panel layout. Three complementary conventions around time co-exist in the KIIBA14 dataset, with each convention applying to a particular subset of time-related data. The infographics category contains several additional exceptions to the horizontal convention where the time axis runs vertically. In these cases, the vertical axis is more likely to run top-to-bottom (4 out of 5 instances). One explanation is that multiple competing conventions are operating within the infographics community – a horizontal left-to-right convention, and a vertical top-to-bottom convention. In the KIIBA14 dataset the horizontal convention is more prevalent, but the vertical convention is also present within the infographics category.

Exceptions in the KIIBA14 dataset show that conventions do not override perceptual considerations. The example of time suggests that multiple conventions can usefully co-exist within a community of practice. Further research is needed to understand more precisely the relationships and interaction between conventions, perceptual cues, and other forms of acquired meaning (including novel visual metaphors, which were not considered in this analysis). While the details of how conventions and other codes of meaning interact are yet to be revealed, the combination of examples from the study are compelling evidence that conventions should be included as an additional constraint in the design process, not as rules to blindly follow. **G6:** *Conventions are tools, not rules – balance the ease of reading provided by conventions against other design considerations.*

3.2.2 Sources of Conventions

Traditional theories of graphic visualization are based on the categorization of data into qualitative, ordinal, and quantitative types [9, 26]. Data-type classification is insufficient for understanding visual conventions, as conventions around the representation of time in the KIIBA14 dataset show. The cyclic to circular convention only applies to time; other circular layouts simply fit data points to angular positions (e.g.[43, 52]). Similarly, most non-time vertical axes increase from bottom-to-top, whereas for representations of time the opposite is typically used. The presence of conventions which only apply to a particular subject (time) suggests that the subject of the visualization is important, and future theories will need to extend beyond data types in order to incorporate visual conventions. Steps in this direction are already underway within the field, with tools like Tableau encoding a preference for a line graphs to show time [36]. However, a one-to-one mapping between subject and representation type is overly simplistic, and ignores the possibility that subjects may be multi-layered.

Visual conventions appear to derive from existing conventions within language and culture. The direction of horizontal axes matches the direction of writing in all of the visualizations in the dataset. A search outside the KIIBA14 dataset for visualizations in a right-to-left language, Arabic, revealed examples where time ran right-to-left [2, 14]. Conventions may also have a narrow, specific origin and scope. For example, the top-to-bottom direction of vertical time axes may follow the layout of a timetable. Given that this convention was found only in the infographics category, it may also be influenced by the traditional long vertical layout and associated reading direction of infographics [32].

Since conventions can vary within local communities of practice, applying a formal methodology like content analysis forces designers to step away from their own expectations about the use and scope of conventions. Design choices can instead be based on evidence of a convention within the target field.
G7: *Discover and use the conventions within the target user community and subject domain.*

4 Implications for Practice

Successful codification of acquired meaning has implications for design and research. This section proposes that guidelines for the use of acquired meaning be reconciled with existing heuristics for design, and outlines a research agenda for integrating acquired meaning into existing theory.

4.1 Implications for Design

Analysis of the KIIBA14 dataset provides evidence that acquired codes of meaning are used in information visualization as an effective design tool, but that these codes are applied selectively. The implication is that designers should be aware of acquired codes of meaning, as well as perceptual cues. The two interpretation mechanisms provide different perspectives on what constitutes good design. Perceptual cues provide insight into how well a representation matches types of data based on an understanding of the human visual system. In contrast, acquired codes are concerned with leveraging a reader's familiarity with shapes and conventions to provide context for and effortless understanding of new information.

The KIIBA14 dataset reveals the potential for acquired codes to compete with each other and with perceptual cues (see section 3.2.1). Perceptual and acquired codes of meaning can guide design in opposite directions. An example of an apparent conflict between the two codes can be seen in the use of areas to compare quantities. Areas of shapes, particularly circles, are a conventional

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representation for comparing quantities, despite that fact that area judgements rank poorly in perceptual studies [15]. In the dataset, circles used for area comparisons are often annotated with the exact quantitative value represented. This suggests a more nuanced convention, where circles take advantage of the reader's acquired codes, but annotation compensates for the lack of perceptual precision. Recommendations for good use of acquired meaning do not invalidate recommendations based on perceptual cues. Instead, good use of acquired codes should take into account existing knowledge of perceptual cues, finding ways to reconcile the two.

Acquired codes, especially graphical conventions, are a mechanism for showing the reader something in a familiar way. But familiar is not necessarily best, as shown by the examples of exceptions discussed in section 3.2.1. Novel methods of visualization can provide new and engaging ways of looking at a subject. Knowledge of a convention is useful whether or not it is followed, since it suggests what is familiar and unfamiliar to an audience. In particular, when breaking a convention, keys and other guides to reading the visualization should be prominently positioned.

Use of acquired codes carries with it the risk that a particular reader will not be familiar with the convention used, or will not recognize the illustrated object [7]. Learning about the visualization practice of the target audience (**G7**) provides some mitigation of this risk, but does not remove it completely. The guidelines above could be enhanced by research into techniques for representing data that allow recovery or graceful degradation of communication when acquired codes are not recognized.

Conventions are by their nature based on an evolving community of practice. New conventions may develop which override existing ones, and conventions may only hold within a particular community – bioinformatics or business analytics, for example. The conventions identified by our analysis are not the only conventions, nor are they universal. The link between subject and visual convention supports the argument that design needs to be coupled with a deep understanding of the target domain and user community.

4.2 Implications for Research

A limitation of qualitative research such as content analysis is that findings generalize only to the extent that the dataset is representative of the domain. The KIIBA14 dataset is drawn from a single repository of visualizations which were chosen partly based on the criteria of beauty and originality. Visualizations designed for a technical audience (for example an air traffic control system interface) may not share either aim, and may not use acquired meaning in the same way. Nevertheless, articulating how conventions and figurative elements manifest within visualization is a key first step towards classification and further study, of acquired meaning.

The present paper has provided a demonstration of how acquired codes of meaning can be recognized and studied through examination of visualization practice. Further research is needed to develop fully-fledged theories of acquired meaning in visualization and integrate these theories with existing knowledge of perceptual cues.

Integrating acquired meaning into theories of visualization interpretation would benefit from reflective practice on the part of the visualization community. Curated lists of the acquired codes of meaning used within common domains of visualization would provide useful toolkits for working with multiple communities. Ongoing monitoring of the visual designs produced in different communities would add to the visual conventions identified here and allow the identification of emerging or changing conventions.

To enable reflective practice, methods for efficiently recognizing conventions within a target user community and subject area need to be further refined. The method used here places more emphasis on the prevalence of a technique across a sample of visualizations than previous content analyses (for example [25]). Extensions of content analysis methods should be developed for use analyzing acquired meaning. For example coding methods which take into account the distance between two elements in the visualization decomposition would allow the identification of more sophisticated conventions around the arrangements or combinations of different visual elements used in practice.

Another area for further study is to determine trade-offs and complementary relationships within acquired codes, and between conventions and perceptual cues. Looking further into the role of acquired meaning, questions arise as to how far methods for understanding acquired meaning and convention can be extended to cover traditional perceptual mechanisms.

5 Conclusions

An evaluation of the KIIBA14 dataset shows that the supposed ideal of graphic purity is not adhered to by data visualization designers. Instead, the pattern of acquired codes of meaning across the dataset provides evidence that conventions and figurative elements are used because they are an effective design resource. Both data visualization and infographics designers have made use of conventions, and used figurative elements to show content, provide context and to label data. Within visualization practice, learned conventions are used in consistent ways to leverage the audience's existing experience, expertise and expectations. Our analysis suggests that the interpretation of a visualization relies as much on figurative visualization and graphical convention as it does on innate perceptual cues. Content analysis offers a method for codifying the acquired codes of meaning operating within a community of practice and translating these conventions into heuristics for visualization design. The success of this method provides both the means and the motivation to integrate acquired meaning into the broader visualization research and design agenda.

Acknowledgments

The authors would like to thank the reviewers for their contribution. This research was supported by the Australian Defence Science Technology Organisation and an Australian Postgraduate Award to Lydia Byrne, the Centre of Excellence for the Dynamics of Language, and Australian Research Council grants to Janet Wiles.

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