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Semantic scaffolding: the co-construction of visualization meaning through reader experience

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Abstract

Information visualization has practical value – it is a means to gain insights, reveal patterns, shape decision-making and provoke a reaction from the reader. However, current evaluation methods are conceived in terms of the transmission of information, rather than use of visualization in practice. This has resulted in a divergence between the factors known to be important in practice (such as engagement and the reader's visual literacy), and the factors considered in the formulation of visualization design guidance. Even for the relatively simple case of static visualization, a new theoretical contribution is needed to describe the interaction between visualization design choices and the reader's prior knowledge.

In this research, a semiotics approach was used to extend the theory of visualization semantics, with the aim of developing an understanding of the context-specific meaning of visual features. The term *semantic scaffolding* is used in this thesis to describe the capacity for features in a visualization take on additional meaning when read in a specific context.

The first part of the thesis concerns the use of visual conventions and figurative images (e.g. illustrations) to convey meaning in information visualization. Content analysis of visualization exemplars examined whether the reader's prior knowledge is anticipated in information visualization practice. The analysis investigated the prevalence of visual conventions and figurative images in data visualizations and infographics. The content analysis showed that figurative elements and conventions are commonly used in exemplars of visualization practice. Visual conventions anticipate the readers' familiarity with the prior meaning of visual features. Figurative images convey descriptive information by anticipating the reader's knowledge of and ability to recognise the visual forms of objects.

Both figurative images and visual conventions are currently undervalued within the information visualization research community, because the way they contribute to meaning does not fit information transmission conceptualizations of visualization. By extending concepts from geospatial visualization, this research constructed a critical vocabulary for the descriptive information conveyed by figurative images. The critical vocabulary for figurative images articulates the increased expressive capabilities of information visualization layouts which use both figurative and abstract representation ('hybrid' information visualizations).

For the second part of the thesis, a new conceptual model was developed through the synthesis of existing models and experiments on visualization construction and interpretation. The new conceptual model developed in this project – called the *semantic scaffolding model* – assigns a specific role to the reader's prior knowledge in creating practical value. It is premised on the co-construction of meaning through visual encoding and the reader's context-specific knowledge (*semantic scaffolding*). Motifs, or intermediate level visual features (groups of marks or mark attributes encoding multiple data values), are a key component of the *semantic scaffolding model*. Motifs are created indirectly through the transformation of data into a visual form, but can be perceived as unitary visual forms with a coherent, context-specific meaning. Both intermediate level motifs and information-rich figurative images are visual features which can have practical meaning for the reader beyond the meaning encoded by the data-to-visual transformation.

The *semantic scaffolding model* and associated research is important in providing a technical language and set of concepts which can shape future research in the field of information visualization. To prevent a widening rift between information visualization research and practice, the design of experiments, evaluation measures and heuristics needs to shift away from the current focus on the encoded meaning of individual visual values. Instead, research needs to be designed around visual features and their practical meaning for the reader.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

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Publications during candidature

Peer-reviewed papers

Byrne, L., Angus, D., & Wiles, J. (2016). Acquired Codes of Meaning in Data Visualization and Infographics: Beyond Perceptual Primitives. *IEEE Transactions on Visualization and Computer Graphics*, *22*(1), 509-518.

Byrne, L., Angus, D., & Wiles, J. (2017). Figurative frames: A Critical Vocabulary for Images in information visualization. *Information Visualization*, 1473871617724212.

Conference abstracts

Byrne, L., D. Angus, and J. Wiles, A Theoretical Approach to Adaptive Visualization, in *Diagrams 2014 Doctoral Symposium*. 2014: Melbourne.

Byrne, L., D. Angus, and J. Wiles, How Visualization Provides Insights: Models and Misconceptions, in *Advances in Visual Methods for Linguistics.* 2016: Brisbane.

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Contributor	Statement of contribution
Lydia Byrne (Candidate)	Conception and design (80%) Analysis and interpretation (80%) Drafting and production (80%)

Daniel Angus	Conception and design (10%) Analysis and interpretation (10 %) Drafting and production (10%)
Janet Wiles	Conception and design (10%) Analysis and interpretation (10%) Drafting and production (10%)

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Daniel Angus	Conception and design (10%) Analysis and interpretation (10 %) Drafting and production (10%)
Janet Wiles	Conception and design (10%) Analysis and interpretation (10%) Drafting and production (10%)

Contributions by others to the thesis

My supervisors Janet Wiles and Daniel Angus contributed to the thesis through discussion and development of ideas as noted in the publications section.

Statement of parts of the thesis submitted to qualify for the award of another degree

None.

Research Involving Human or Animal Subjects

No animal or human subjects were involved in this research.

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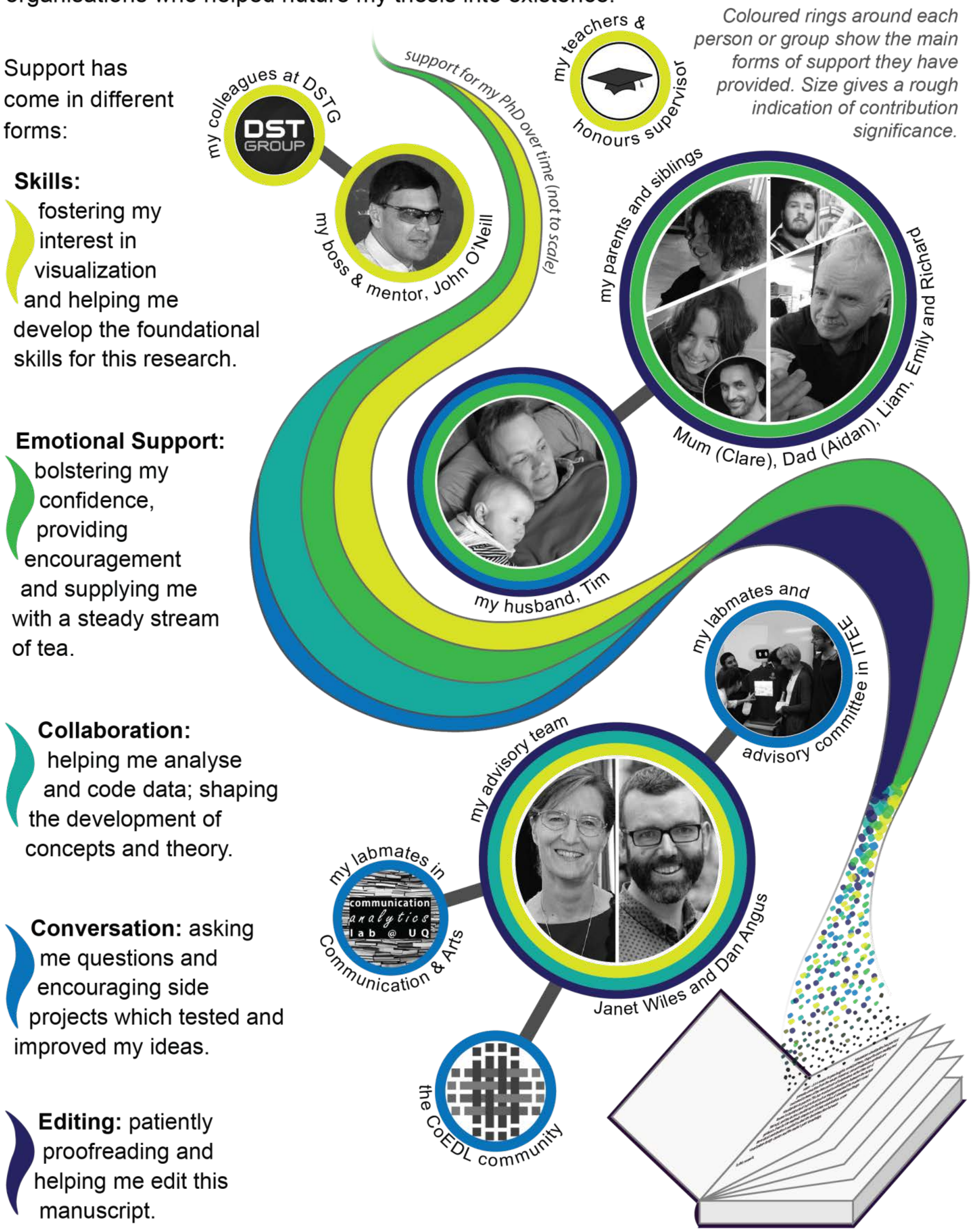

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Keywords

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This thesis is dedicated to my daughter, Paige. May you always stay curious, and have the confidence to search for answers to questions that others overlook.

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Abbreviations

EDA	Exploratory Data Analysis
VFR	Vickers, Faith and Rossiter
KIIBA14	Kantar Information Is Beautiful Awards 2014
GIS	Geographic Information System
UV-B	UltraViolet-B
SVG	Scalable Vector Graphics
CSS	Cascading Style Sheets
CO_2	Carbon Dioxide
HCI	Human-Computer Interaction

1 Introduction

The value of visual representation as a tool to analyse and communicate information is widely accepted both in research communities and broader society. However, existing design heuristics and evaluations of information visualization do not measure the attributes of visualization most valued in practice. Advocates of visualization argue that it transforms the reader's thinking – convinces [1], provides insights (see [2, 3]), amplifies cognition [4] and makes solutions to problems easier to perceive [5-7]. In short, information visualization is valued as a complementary resource to numerical calculations, supporting reasoning about data analysis as well as supporting analysis itself [8]. In contrast, user performance evaluations (and the design heuristics derived from them) in leading information visualization journals typically measure speed or accuracy in retrieving or recalling precise values encoded in a visualization (discussed further in Chapter 2) [9]. In other words, existing evaluation methods measure the ability of a visualization to replace numerical calculations, not fulfil its unique, complementary purpose. This thesis is concerned with the gap between what visualization is valued for, and what is measured in standard assessments of visualization (see Figure 1).

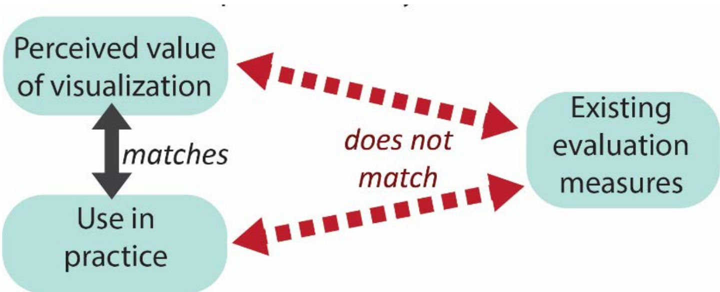

Figure 1: The gap addressed by this thesis

The gap in visualization evaluation can be attributed in part to the conceptual models of visualization underpinning existing research on visualization performance (as will be demonstrated in Chapter 2). Conceptual models (whether explicitly or implicitly stated) shape evaluation measures by specifying the attributes to be assessed and the factors which are necessary and sufficient to control during measurement. Current evaluation measures (reviewed in Chapter 2) assume an *information transmission* conceptual model of visualization, where data is encoded through a mapping from data to visual form, and then decoded by the reader through the reversal of the mapping. Consequently, measures focus on the explicitly encoded meaning of visual features and the reader's performance interpreting this meaning. The information transmission conceptualization excludes the reader's experience from the visualization interpretation process, and precludes measurement of aspects of performance which depend on experience. Yet visualization interpretation is known to be affected by the reader's prior knowledge and interests [10-15]. Moreover, the valued characteristics of visualization depend on the *practical meaning* of visual features; insights, emotional reactions, problem solving and transformation of thinking depend not only on the information encoded in a visualization, but on the significance of that information given the reader's existing knowledge, aim and motivation in reading [3, 13, 14] . More holistic visualization evaluation measures and design heuristics therefore require a conceptual model of visualization which accounts for the role of the reader's prior knowledge in creating visualization meaning.

The aim of this thesis is to develop a conceptual model of visualization which describes how visualization design choices interact with a reader's prior knowledge to affect the meaning of a visualization. The term *semantic scaffolding* has been coined here (adapted from [16]) to describe the process by which features within a visualization take on meaning not explicitly encoded through a mapping from data in a specific reading context. It expresses capacity for a visualization to provide a *scaffold* for additional meaning (*'semantics'*, to borrow the technical linguistic term). The right kind of model of semantic scaffolding will enable the articulation of research questions about the use of visualization to transform thinking. In doing so, the model will provide a foundation for the development of measures predicting the practical performance of a visualization (model requirements are discussed in detail in Chapter 3).

The development of a conceptual model has been approached from a semiotics perspective for this thesis, following seminal visualization theorists such as Bertin [17] and Wilkinson [18]. In the terminology of semiotics, visualization is a 'system of signs', like spoken (natural) languages. Information is able to be encoded and conveyed by a visualization because the designer and reader have access to a shared reference system (through the visualization key and axis labels) for what each visual object ('sign') means. Existing semiotic models of visualization have focused largely on the syntax of graphics: how visualizations can be deconstructed into (and constructed from) common elements [17, 18]. However, systems of signs also have a semantic component which determines how signs are imbued with and convey meaning. It is the semantics of the visualization sign system which is the most relevant to semantic scaffolding, and hence the focus of this thesis.

The first part of the thesis (Chapters 4 and 5) examines how a reader's visual literacy can be anticipated in order to encode information in a visualization design. In semiotic theory, *symbolic* and *iconic* signs are distinguished by contrasting relationships between sign and signified object [19]. Iconic representations have a 'literal' meaning, where the sign resembles the object. In this thesis, iconic visual representations are referred to as 'figurative' representations – following Bertin [17] – because of resemblance between the object and the sign. Symbolic representations involve an arbitrary-conventional association between the sign and the object (e.g. the word 'cat' is a symbolic sign). Figurative signs require the reader to have prior experience (possibly only indirect experience) of the represented object. Symbolic signs also often rely on prior experience, when their meaning is learned by users of the sign system. The meaning of a word like 'cat' is deeply ingrained through prior use by the community of English language speakers. Two underlying assumptions of the information transmission model are that visualization includes only symbolic signs, and that the meaning of those signs is 'free' – able to be redefined in each new use of those marks. For example, the bars in a bar chart can be used to refer to temperatures, frequency of bird sightings, product sales, or any other quantity, seemingly without confusion. In this thesis project, content analysis was used to challenge these assumptions (Chapter 4), and show that the information visualization sign system includes figurative representations and signs whose meaning is constrained by convention. Semiotics was further used to develop a conceptual model of the descriptive information conveyed by figurative representations within 'hybrid' information visualizations which combine both symbolic and figurative representation (see Chapter 5).

The second part of the thesis (Chapters 6 and 7) draws on existing semiotics models to synthesize existing knowledge of visualization interpretation into a model of semantic scaffolding. The semantic scaffolding model focuses on 'intermediate level' visual signs – motifs in a visualization representing more than one, but not all, values in the represented dataset. Intermediate level features are essential to the unique value of visualization (see Chapters 2 and 6). The semantic scaffolding model shows how their practical meaning is co-constructed by the data-to-visual-variable mapping and the reader's domain knowledge. It also shows how the motifs which may appear within a particular visualization layout can be anticipated in the design of a visualization.

A semiotics approach to the problem of reader experience in visualization highlights the similarities between visualization and spoken languages as systems of communication. The general discussion of the thesis (Chapter 8) points to the potential for concepts from the study of language to be applied as evaluation measures based on the semantic scaffolding model. Grice’s maxims – rules that conversation participants follow [20] – are adapted to describe principles for context-sensitive visualization design.

1.1 Research Scope

To make progress on the semantic scaffolding problem, the scope of this thesis has been limited. It focuses on the research rather than design perspective on visualization, and restricts the range of information visualizations considered to static visualization.

1.1.1 Research vs. Design

The thesis is motivated by the need for better evaluation measures of visualization, and thus focuses on information visualization research. Visualization and the visual representation of information can alternatively be seen through the lens of art and design [21, 22]. In contrast to research, the art and design perspective has always actively considered the uniqueness of each design context and the prior meaning of design elements in existing visualizations, and aims to make designers and the design process responsive to this context. However, design and research perspectives are often seen as complementary, with calls for a more empirical foundation for design models [23].

1.1.2 Static vs. Interactive Visualization

The scope of this thesis is restricted to static information visualization, in order to provide a manageable problem with general applications. Active reading of a static visualization — the thought processes, passive reading actions (e.g. eye movements) and social actions (e.g. sharing a visualization with others) prompted by a visualization are considered in scope, but not actions which change a visualization's form or data.

Many of this thesis’s findings, however, have relevance to interactive tools as well. Most interactive visualizations are composed of multiple static views, with reader actions used to transition between them. Understanding each component static view should therefore improve understanding of many interactive visualizations.

1.2 Structure of the Thesis

The research presented in this thesis has two related but self-contained parts, each examining a different type of interaction between reader experience and visualization meaning. Consequently, some chapters of the thesis can be read independently of each other (see Figure 2).

Two literature reviews establish the necessary background for the research. Chapter 2 (Literature Review: Visualization Value) documents a review of existing research on the value of visualization and how that value is measured. The review showed that existing measures do not capture the valued characteristics of visualization, in part because of a shared assumption that visualization is a straightforward channel for transmitting information. Chapter 3 (Literature Review: Visualization Models) outlines the need for a new conceptual model of visualization and the criteria it needs to satisfy, and reviews existing models of visualization.

Instead of a separate methodology chapter, the methodology for each of the two thesis parts is described in the initial chapters of each part (Chapters 4 and 6). Both methodologies draw on the theory of semiotics.

Part I (Chapters 4 and 5) provides an updated view of the visualization sign system. Content analysis was applied to 50 exemplar visualizations to examine the assumption in existing models that the meaning of visual components is purely symbolic, and redefined at each use (Chapter 4). Finding that the assumption is unjustified, a critical vocabulary was developed by extending existing concepts from geospatial visualization to explain how figurative images are not merely decorative, but capable of conveying information content (Chapter 5). Both Chapters within Part I consist substantially of reproductions of papers published in the course of the PhD research ([24] and [25] respectively). Some of the language has been updated to reflect the evolution of the research since publication.

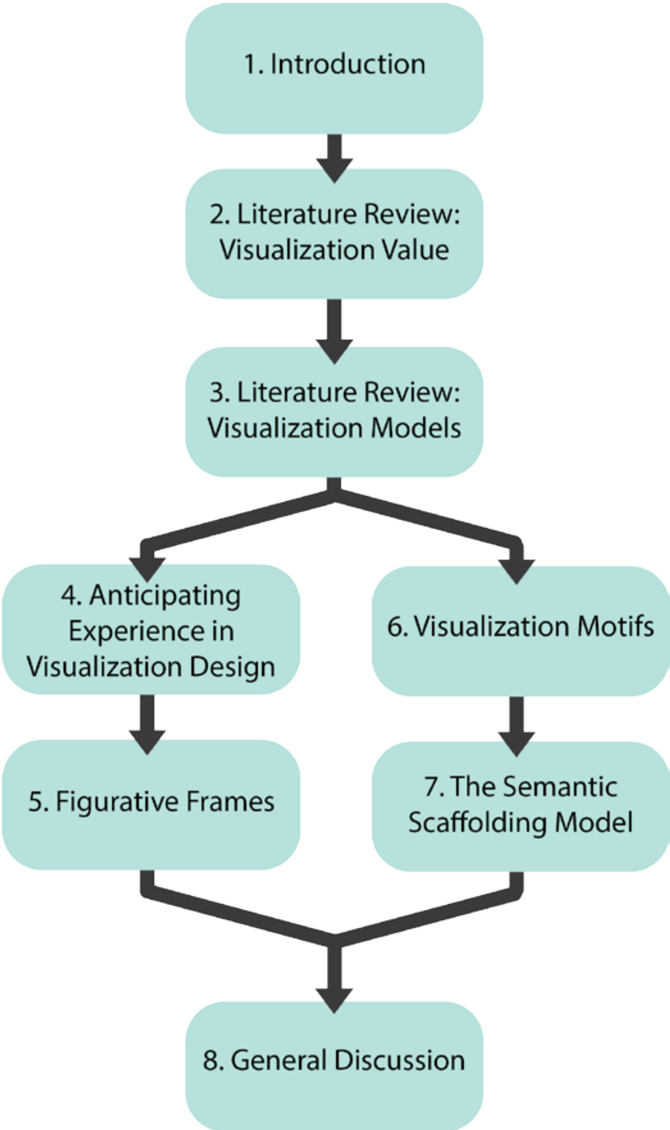

Figure 2: Dependencies between chapters in this thesis

Part II of the thesis (Chapters 6 and 7) describes the development of the *semantic scaffolding model* through synthesis of existing models and research on visualization interpretation. The model explains how semantic scaffolding is achieved through the interaction between the reader's prior experience and visual form (Chapter 7). Thus, the value of a visualization depends on the reader's recognition or discovery of correspondence between their existing domain knowledge and encoded visual motifs. Chapter 6 additionally develops a typology of the motifs which can arise in a visualization layout, derived from the geometry of visual variables used in the layout.

Together, the two research parts show that figurative elements and conventions are a means of achieving recognition of correspondence, and as such are currently undervalued within the information visualization research community (Chapter 8). In particular, figurative elements allow correspondences to be established with types of domain knowledge which are not achievable through abstract representation. The similarities between information visualization and spoken language revealed by the semantic scaffolding model provide a foundation for new evaluation measures which accurately reflect the unique value of visualization.

2 Literature Review: Visualization Value

The value of visualization – what makes a visualization ‘good’, what it is (uniquely) useful for – is discussed in several different forms. It has been the subject of visualization research (e.g. [2-6, 8, 17, 26]) and codified in evaluation measures and design heuristics (e.g. [27]). It is also visible to some extent in the visualizations used in practice. Those who use visualizations, and choose to use one visualization over another, believe that their choice will improve the analysis or communication task.

The capacity to measure visualization value enables both visualization research and design. A value that users say or demonstrate that they expect a visualization to deliver is an *articulation* of visualization value. A test which assesses or compares the performance of one or more visualizations (or their components) is a *measure* of visualization value. Research allows articulated values to be measured. For example, if a visualization is intended to provide more *accurate* communication than alternative forms of representation, evaluations measuring the accuracy of different visualization types will help isolate the characteristics which affect accuracy. The role of heuristics is to translate the characteristics affecting accuracy into guidelines for ensuring that visualization designs are accurate.

The literature review in this chapter revealed that there is a set of visualization values which are articulated but cannot be assessed by existing visualization measures. Analysis of the *practical* use of visualization – to conduct an action, make a decision or prompt a reaction – articulates values related to seeing 'patterns' with context-specific meaning. Existing visualization measures, on the other hand, assess values concerning information transfer, such as speed and accuracy. The review showed that information transfer measures are insufficient to understand the practical value of visualization.

The chapter is structured to provide both an overview and detailed analysis of the disconnect between practical visualization value and measures of information transfer. Section 2.1 uses a set of examples to illustrate the inadequacy of existing measures, and establish the language which will be used to describe the research problem in the remainder of the thesis. Section 2.2 examines the commentary and research on the purpose and benefits of visualization (practical visualization value). Section 2.3 concerns visualization practice and the values expressed through practice. Section 2.4 looks at evaluation of visualization, focussing on those measures of evaluation which have been accepted enough within the information visualization research community to be translated into design heuristics. The discrepancies between the three perspectives on visualization value are then analysed and the gap addressed by this research project identified in Section 2.5.

2.1 Overview

The gap in existing evaluation measures is exemplified by the contrast between two commentaries and a study on visualizations of correlation, described in this section.

One commonly cited demonstration of the value of visualization within the process of analysis is Anscombe's quartet [8]. The quartet consists of four sets of data pairs, developed to demonstrate that summary statistics are insufficient to understand the relationships within a dataset [8]. The datasets share *x* and *y* mean and variance, correlation and linear regression line, but scatterplot visualizations show strikingly different profiles (Figure 3).

Anscombe's quartet exemplifies an ideal of visualization practice – *actionable* knowledge about data which is obscured by other analytical methods, but revealed through visualization. Anscombe uses the quartet to demonstrate that in contrast to the precise but context-free values returned by numerical calculations, visualizations *"help us perceive and appreciate some broad features of the data ... [and] let us look behind those broad features to see what else is there"* [8] p.17. The visualization allows the reader to see whether a particular analytic question is appropriate, as well as judge the result of that analysis. The visual shape of each quartet suggests a different regression calculation to determine the underlying relationship within each dataset: quartet 1 suggests a linear regression should be calculated, quartet 2 suggests a parabolic regression, quartet 3 suggests removing outliers before calculating the linear regression, and quartet 4 suggests simply reading the *y* value as the main relationship in the data. In other words, the visual forms within the scatterplots correspond to different analytic actions. The scatterplot representation fosters extension of meaning from factual information about the relationships between values to actionable knowledge about how to investigate and characterise the relationships: an extension from 'what' to 'what next'.

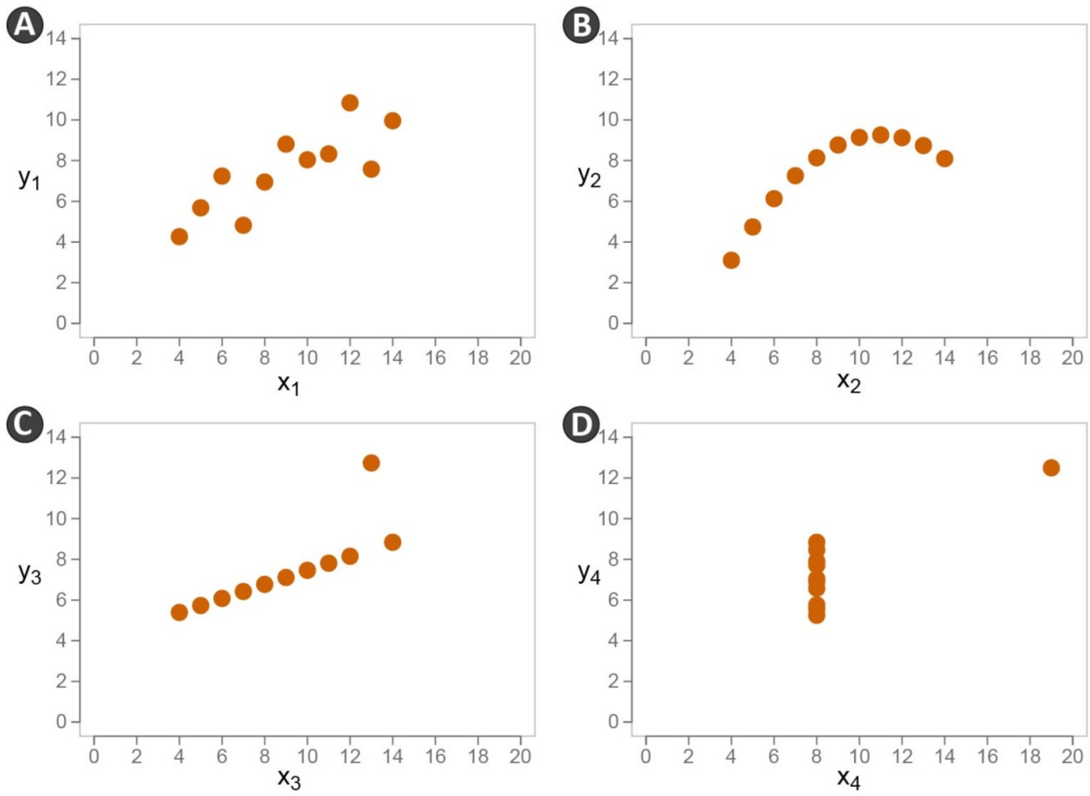

Figure 3: Anscombe's Quartet (redrawn from [8])

Anscombe's claim is about the value of visualization in general, but his example uses one specific visualization layout: scatterplots. Multiple visual representations of Anscombe's datasets are possible. Visualization evaluation is needed to determine which of the available alternative layouts can produce the same (or better) effect as Anscombe's scatterplots. Is a parallel coordinate plot version of Anscombe's quartet (Figure 4) equally able to suggest to readers appropriate regression analyses?

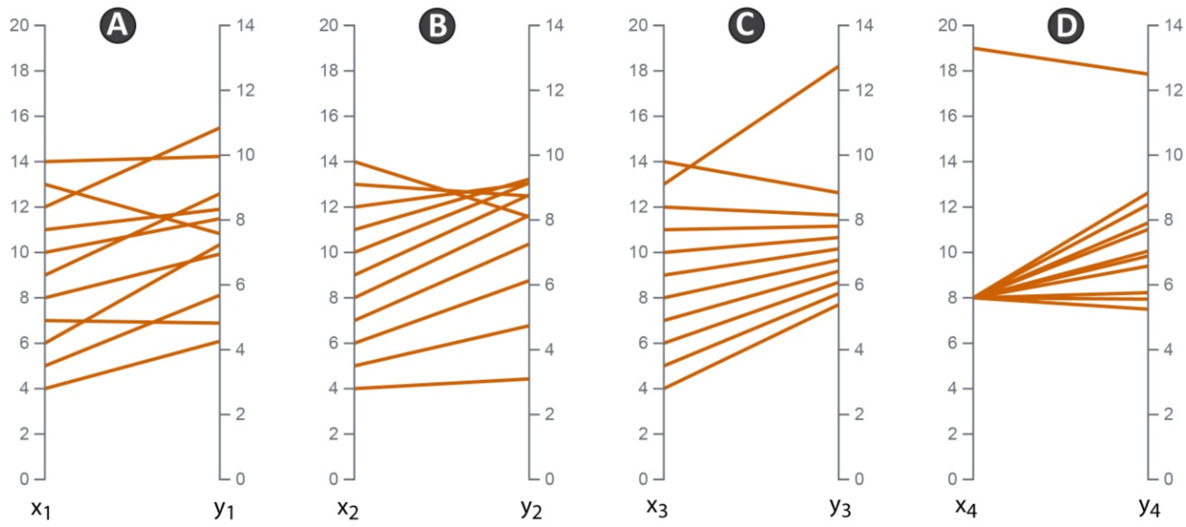

Figure 4: Anscombe's quartet as parallel coordinate plots

An evaluation study compared scatterplots, parallel coordinate plots and line graphs (among other layouts) as tools for determining correlation [28], but did not test the characteristics identified by Anscombe. The study compared how accurately the (linear) correlation value could be retrieved using different layout types. Subjects were asked to determine the linear correlation value from visualizations of datasets of varying levels of correlation. The change in visual form explored by the correlation study was incremental (correlation values of 0.3, 0.4, 0.5 etc), with readers asked to perform the same activity in each instance (report the linear correlation value). In other words, the correlation study measured the ability of a visualization to replace numerical calculations. In contrast, Anscombe's example highlights a categorical change in visual form (e.g. parabolic vs. linear shape), *where the categories are delineated by action* (calculate parabolic vs. linear line of best fit). The Anscombe quartet exemplifies the capacity for visualization to fulfil a unique purpose complementary to numerical calculations [8].

The value of visualization in Anscombe's example depends on *semantic scaffolding*: visual features taking on new, extended meaning through the reader's interpretation. For instance, the actionable knowledge provided by the 2nd scatterplot depends on the reader recognising that a curved arrangements of points means that there is a parabolic relationship in the data. In the parallel coordinate plot version of Anscombe's quartet (Figure 4) the appropriate regression methods can be associated with each dataset based on the plot only if the reader can understand the meaning of the shape in terms of analysis actions. For example, a constant relationship (x = 8, regardless of value of y, 4th dataset) appears as a fan shape in a parallel coordinate plot (Figure 4(D)), as opposed to the vertical line seen in Anscombe's scatterplot. The shapes which signal the appropriate regression calculation are visible in both layouts, but have different forms in each case. The visualization provides a scaffold for additional meaning to emerge through the interaction between prior experience and visual form.

Semantic scaffolding can be also seen in a second, more humorous, reminder of the need to visualize data rather than rely on statistics: the 'Anscombosaurus' (see Figure 5) [29]. As with Anscombe's quartet, the recognisable image in the scatterplot provides the reader with a different understanding of the dataset than statistical analysis. In an array representation the Anscombosaurus dataset is perceived as a random collection of numerical values, yet the visual representation is perceived as a commentary on statistical practice. The highly improbable T-Rex shape suggests that the data is derived from the visual image rather than the measurement of some relationship between variables. The humour relies on the audience's recognition that T-Rex is not a valid shape to find in a scatterplot. The Anscombosaurus shows that knowledge of valid and invalid scatterplot shapes must exist (at least in the minds of those readers who get the joke), and that that knowledge is used in the interpretation of a visualization.

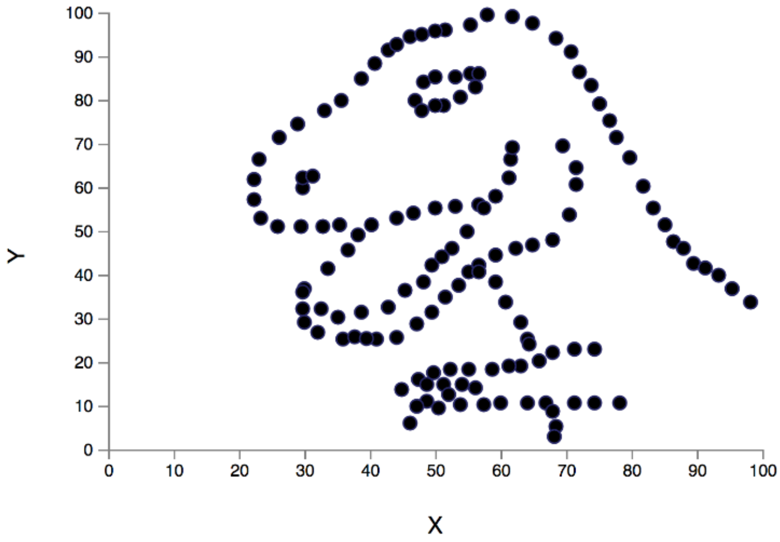

Figure 5: The 'Anscombosaurus', a humorous example created from artificial data– reproduced from [29] (open source)

The structure of the correlation study, and the underlying conceptual model of visualization on which it was based, precluded it from evaluating semantic scaffolding. It was assumed that the test subjects understood the visual shapes in each layout corresponding to (linear) correlation. Furthermore, the study subjects were asked to perform the same calculation (determine the correlation) regardless of any visual differences between datasets. In contrast, to test semantic scaffolding requires the possibility that recognition of meaning can fail. The study did not look for the presence or absence of shapes which might prompt a variation in response. This view, where interpretation is undifferentiated by task or visual structure, is symptomatic of an *information transmission* view of visualization.

The contrast between Anscombe's example, the Anscombosaurus and the correlation study exemplifies the gap between different expressions of visualization value. Visualization values identified in commentary or research examining the practical use of visualization typically depend on semantic scaffolding in some form (see Section 2.2 for details). In contrast, evaluations (measures) of visualization are based around a conception of visualization as an information channel which is incompatible with semantic scaffolding (see Section 2.3).

2.2 Practical Visualization Value

Commentaries and research on visualization value argue that information visualization has particular advantages for analysis and communication (e.g. [2-6, 8, 17, 26]). Visualization allows the two dimensional, non-linear representation of information, and can be read at multiple levels (local, intermediate and global [17], or details and overview [26]). Visualization is most commonly described as providing *insight*, although the term is not always clearly defined [2]. Insight and related expressions of visualization value involve the practical meaning of visual features – i.e. features within the visualization whose meaning is relevant to the reader’s current task or purpose. Practical usage encompasses providing the reader with new (convincing) knowledge, arousing the reader's emotions or prompting the reader's decision or action. Not every visualization delivers practical value to the same extent [5]. Realising the practical value of visualization depends on a number of factors: time [30], reader engagement [13] and alignment between the visual layout and the user's task [5].

An existing review of the purpose of visualization proposed ‘saving time on a task’ as a measurable alternative formulation of visualization value [2], while others have since suggested that ‘insights’ can practically be defined as information which is new to the visualization reader [3]. The purpose of visualization has additionally been described as *communication, analysis, to make decisions, to convey information, make comparisons, find patterns, see the important relationships, characterise the distribution of data, for enjoyment, browsing, to provoke a reaction, amplify cognition, distribute cognition* or *allow exploration* [2, 4-6, 31-33]. These descriptors are not always presented as the exclusive purpose of visualization, and many are elaborations of the concept of insights.

The descriptors of visualization value listed above, including the proposed definitions of *insight*, are concerned with the practical use of visualization. Descriptors such as *cognitive amplification, distribution of cognition, making decisions, solving problems, saving time, enjoying* and *emotionally responding to* a visualization, speak to an interaction between the information encoded by the visualization and the context in which it is read. *Problem solving, saving time, making decisions, cognitive amplification* and *distribution of cognition* all involve a task external to the visualization the reader is trying to complete, or an issue they wish to resolve. *Enjoying* or *emotionally responding* to a visualization involves interaction between the information encoded and the reader’s interest or expectations [13, 14]. The distinction between visualization for *communication* and visualization for *analysis*, which is often considered an important division within information visualization purposes

[34], can also be viewed in terms of practical meaning. For communication, the visualization is created to have a practical effect (whether informing, provoking emotion or prompting action) only on the reader, whereas for analysis both the creator and reader (often the same person) have a shared practical purpose in interpreting the visualization.

The theory of distributed cognition identifies two roles that artefacts, which include but are not limited to visual representations, can play in cognitive tasks [16, 35]. Artefacts allow information to be offloaded (i.e. stored outside of a person's memory) and they allow cognitive *scaffolding*. A representation which provides scaffolding changes the nature of the task required of the human in the system, allowing a person to substitute a difficult task (e.g. determining the speed of a vehicle) with an easy task (e.g. judging the position of a marker on a dial) [6, 16, 35].

Some accounts of practical visualization value identify characteristics of visualization which allow it to achieve its purpose. Visualization enables problem solving through correspondences between visual relationships and problem solutions [5]. Users can reliably tie a normal game of tic-tac-toe (naughts and crosses) where winning solutions correspond to straight lines of marks, but perform worse in forms of the game where winning solutions correspond to combinations of colours or written numbers [5]. Data visualization is two dimensional in nature compared to the linear stream of information provided by music or a written text [17]. As a consequence, data visualization is able to ‘show the whole picture’ – both details and overview [8, 26]. Visualization has inherent strengths as a perceptual channel [36, 37], particularly when looking at visual scenes built around aspects where vision is an accurate and rapid pattern-finding system [33].

Practical visualization value is intertwined with the concept of ‘intermediate level reading’ [17] or visualization tasks involving multiple visual elements [32, 38, 39]. Visualization represents information in a way that can be read at multiple levels [17, 26]. The data values corresponding to a single data element can be read at the local level (detailed view), and relationships describing the whole dataset (e.g. correlation) can be read at the global level (overview). In between the local and global levels, a visualization can be read at the intermediate level, to see relationships between a subset of values or variables in the dataset [17].

Visual pattern finding and associated strengths of visual perception involve detecting and judging objects in context [36]. When readers are asked to look up data values, tables outperform visualization, even without automated search tools [15]. Similarly, to determine a global property of the dataset – its average, variance, or line of best fit – statistics provides more precise answers than visual judgement [8]. What visualization has the unique capacity to do is bridge these two levels: to show how the values of individual data points combine to produce global patterns. When the reader makes a visual assessment (of central tendency, for instance) intermediate features make the calculations and assumptions underneath the metric explicit; the intermediate level relationships in a visualization both allow and require a reader to distinguish the contribution of each value to the end result. Intermediate level features also expand the scope of the representation: each visualization is simultaneously a visualization of multiple subsets of the dataset, many of which may be more interesting to the reader than the dataset as a whole.

The practical value of visualization depends on factors including time and interpretative skill. Studies of visualization use in practice show that the process of reading a visualization to gain insight is long and involved [30, 40]. The most useful insights from a new visualization tool in a biology lab were obtained after a month of use [30]. Practical visualization value also depends on successful interpretation. Learning to interpret a novel visualization involves multiple cognitive activities, all of which are liable to fail and disrupt the reading process [41].

Visualization comprehension depends on different types of prior knowledge [11, 42]. The concept of visual(ization) literacy – sometimes termed ‘graphicacy’ – describes learned skills required to read a visualization [11, 43]. Although the ability to make perceptual judgements is a universal skill [44], understanding the information conveyed through visual representations is not innate or automatic [10, 11]. Studies of visual literacy have shown lower than expected literacy among visitors to science museums who self-report being interested in maths and science, even for common techniques such as network diagrams [45]. Visualization literacy can reflect general competence and comfort with visualizations in general, or specific knowledge about a single layout type [11, 14]. When readers lack visualization literacy, they are liable to interpret a visualization incorrectly [10], or abandon attempts to interpret the visualization altogether [14].

In addition to learned reading skills, prior knowledge is also a factor in the reader’s willingness to read a visualization, and their interpretation of the visualization’s content [13, 14]. Existing knowledge about the topic of a visualization shapes which values a reader searches for and compares [41]. Visualizations for general public consumption (rather than specialist research or analysis tools) are read or dismissed in large part based on the reader's pre-existing interest in the topic [13]. The reader's interpretation can also be affected if the visualization uses a visual structure corresponding to a familiar metaphor [46, 47].

One factor with disputed effect on visualization performance is the use of figurative images within an information visualization composition. Figurative images have been assumed to decrease the performance of a visualization [33, 48]. However, multiple studies have found no consistent performance detriment [49-53] (the literature on figurative visualization is reviewed in more detail in Chapters 4 and 5).

In summary, visualization is valuable for a range of practical purposes, and this practical visualization value is realised through the context-specific meaning of visual features at multiple levels. In this thesis the term *semantic scaffolding* has been developed to describe the process by which practical meaning is constructed through visualization interpretation. Existing literature on visualization use shows that semantic scaffolding depends on the reader's engagement (potentially over an extended period) and prior knowledge.

2.3 Visualization in Practice

The visualization values embodied through visualization practice have not formally been reviewed for this thesis. However, a selection of examples illustrate the characteristics of visualization seen as useful in the communication of scientific research (see icons in Figure 6).

Each of the following examples are taken from a separate research paper, which included the visualization as a figure to convey a particular point to the reader. The visualizations make use of related layouts. Recurrence plots aim to show temporal dynamics of a system, focussing on how a system revisits previous system states (rather than representing the actual values of those states) [17, 54]. A matrix visualization has a superficially similar form to the recurrence plots, but notably distinct meaning, and is used to answer different questions (described in the following paragraphs). In their containing papers, specific visual features within the visualizations are used as a demonstration or proof of some relationship of interest to the paper's authors and intended readers.

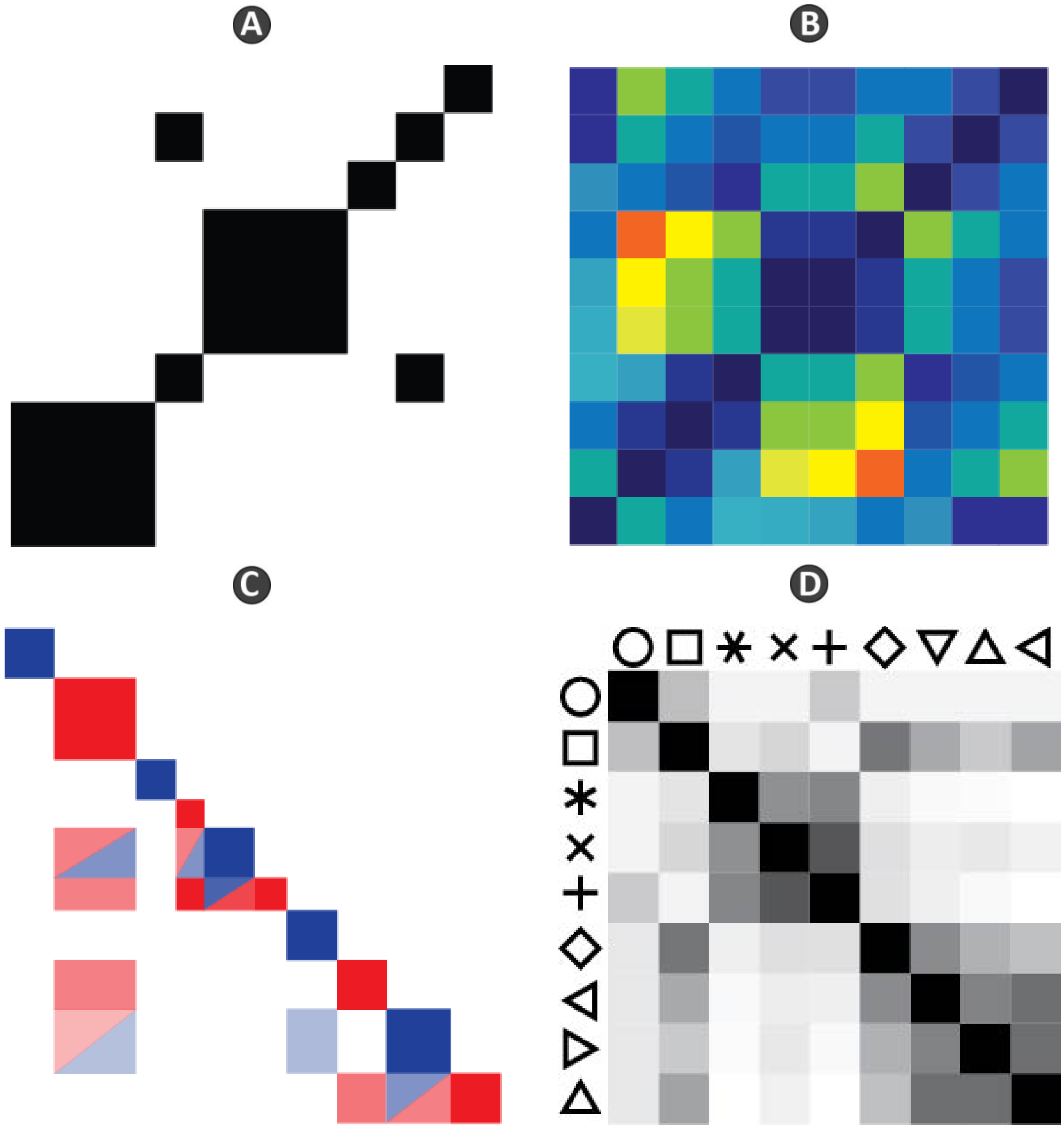

Figure 6: Four variations on recurrence plots/matrix visualizations used in practice, in icon form to allow comparison across the layouts. (A) each square of the black and white recurrence plot used by [55] indicates a match between the heart rate at times t1 and t2. The axes run left-to-right and bottom-to-top. (B) The colours of squares in the recurrence plot used in [56] show the difference between traffic speeds at times t1 and t2; orange points have a large difference, darker blue points have similar speeds. The axes run left-to-right and bottom-to-top. (C) Squares in the conceptual recurrence plot [57] show conceptually similar turns in a conversation. The opacity of each square shows the conceptual similarity, while the colour shows the speakers of each turn. The axes run left-to-right and top-to-bottom. (D) Squares in the matrix visualization [58] show perceived similarity between glyph shapes; darker points signal more similar glyphs. The axes run left-to-right and top-to-bottom. Figures are redrawn based on the respective references.

Different implementations of the recurrence plotting technique aim to answer similar questions about dynamics of time-varying systems, with small adaptations for different problems. To detect and characterise heart rate abnormalities, Marwan [55] uses a recurrence plot visualization where black points show matching heart rate trajectories at different times. Both axes show the same time interval, and the position (x = t1, y = t2) of a point in the plot indicates a matching heart rate trajectory at the times t1 and t2 [55]. In the paper, the visualization is used to distinguish one type of dangerous heart rate abnormality from benign behaviour. The distinguishing feature is the presence of larger clusters of points (similar to the large black squares in the icon-sized version in Figure 6(A)). An analysis of road traffic (see Figure 6(B)) uses a similar visualization with recurrence marked by colour instead of black points [56]. The difference between traffic speed (trajectories) at two different times (t_1 and t_2) in the day is reflected in the colour of the grid square at position (x_1, y_2). Dark blue represents the traffic speed recurring (minimal difference between speeds at the compared times), while warmer colours represent more contrasting traffic speeds. In the paper, the different visual position and size of low recurrence clusters (red and yellow areas) in the plots for different days is specified as proof of different traffic dynamics on different days of the week.

Both the heart rate and road traffic visualizations plot the internal dynamics of a single system, asking how the values at one time compare to another. Another variation of a recurrence plot applied to a diagnostic consultation between a patient and their doctor uses colours to distinguish participants – red for the patient, blue for the doctor [57] (see Figure 6(C)). Each square marker indicates that concepts are shared between the conversation turns at corresponding horizontal and vertical positions (shading shows the degree of similarity); the uppermost colour of the square shows the initial speaker and the lower colour shows the second speaker (i.e. the speaker who is repeating or referring back to earlier content). The conceptual recurrence plot also reverses the direction of the horizontal axis, so that turns in the conversation follow the direction of text down a page. Among other features, the authors highlight a stripe of points near the left of the plot starting with a red square on the diagonal as an indication that the patient's early explanation of their symptoms and concerns sets the agenda for the consultation [57].

The examples of recurrence plots have some shared (superficial) visual features, shared semantics (the meaning of visual features in terms of data) and shared usage. Except for the conceptual recurrence plot, the visualization looks like a square grid (the conceptual recurrence plot is half a grid). Points are scattered throughout the plot, not arranged in continuous lines or areas (in the traffic flow visualization, points of a particular colour are similarly distributed). Each plot contains a diagonal line stretching from one corner of the plot to the other. The shared appearance of the plots can be traced to their similar semantics; that is, the similarities between how each data set is mapped to a visual form produces visualizations of similar appearance.

Similar appearance does not guarantee similar semantics or similar usage. A distance matrix visualization showing perceived similarity between abstract shapes such as circles, squares, crosses and triangles has a similar appearance to the recurrence plot examples – a square grid with distributed points and a continuous diagonal line through the middle [58] (see Figure 6(D)). However, in contrast to the recurrence plots (examples (A-C)), only the co-linearity of points (other points with the same x or y values) rather than the positions are meaningful (i.e. the axes are unordered). The presence of multiple dark squares off the diagonal shows that the set of shapes are not perceived as being uniformly distinct. The visualization is used in the paper to support a recommendation for visualization design: the selection of shapes used in a visualization (of equally distinct categories) should correspond to a set of equally dark or pale squares when compared to each other in the distance matrix [58].

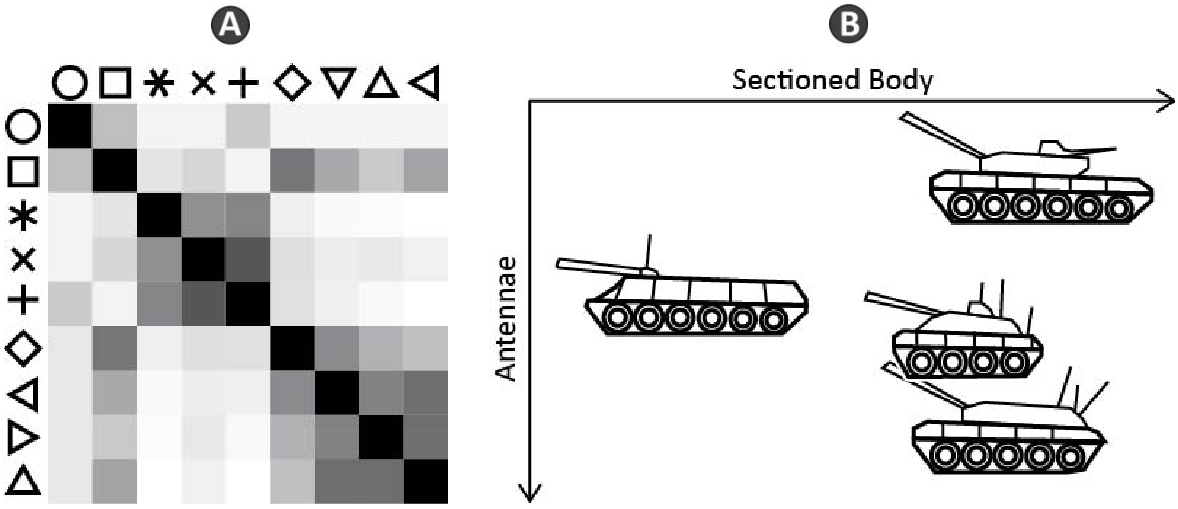

Figure 7: Figurative elements used within information visualization. (A) also shown in Figure 6(D). The glyphs compared in the visualization are figuratively represented along the axes. Redrawn based on [58]. (B) Figurative representations are used to describe tanks organized in a multidimensional scaled scatterplot. Redrawn based on [59].

The matrix visualization demonstrates a second technique observed in visualization practice – figurative visualization used in combination with abstract visualization. Two examples are provided in Figure 7, the first of which is also described in Figure 6(D)). The icons used as axis labels in the matrix visualizations are the same shapes as the shapes they represent, i.e. are figurative representations. The recognisable resemblance between shapes allows the authors to convey what they mean by a 'circle' or 'cross' icon, with the illustration standing in for textual explanation. Similarly, a scatterplot showing multi-dimensional scaling analysis of identifying attributes of different types of tanks in military training uses illustrations of each type of tank instead of abstract points in the scatterplot [59]. The illustrations are figurative representations of the actual tanks, allowing the visualization reader to compare the appearance of tanks which are more often confused (those close together in the plot) or more easily distinguished (further apart in the plot).

The value of visualization embodied in the examples above is consistent with expressions of practical visualization value (previous section). Specific visual features within each example are important for the associated domain problem. The features are at the intermediate, not local, level. The use of figurative visualization runs counter to some theories of visualization performance, but makes use of the reader's prior experience.

2.4 Evaluation Measures

Determining the value of a visualization requires measures of performance. A visualization can be evaluated either before (in the case of prediction) or after (in the case of assessment) it is created. All else being equal, predictive measures are more useful, since they can be used to narrow the range of design choices before effort is expended creating different visualization options.

A pair of systematic reviews of visualization evaluations within leading information visualization publication venues[1] characterised the different types of evaluation currently used and the prevalence of each type of evaluation over time [9, 60]. The articulation of the practical value of visualization discussed in the previous section falls under the systematic review category of 'process evaluations'. 'Process evaluations' assess how visualizations are used and integrated into the broader environment (e.g. measuring the success of a medical visualization in improving patient outcomes). Typical methods include case studies, observation and interviews with users [60]. In contrast, evaluations of visualization form, structure, features and characteristics are encompassed in the category 'visualization evaluations'. 'Visualization evaluations' assess how visualization features affect users' performance or experience, as well as the performance (e.g. speed) of visualization algorithms [9, 60]. The systematic reviews capture the rise in overall number of evaluations over time, with visualization evaluations outweighing process evaluations. This chapter explores the relationship between process evaluations (i.e. practical value) and visualization evaluations (in particular user performance). That is, how assessments of the form of a visualization align with the value of that visualization in practice. The term evaluation (also suitability measures) in this thesis refers to user performance evaluation.

[1] Lam et al. reviewed papers from IEEE Information Visualization, Eurographics/IEEE Symposium on Visualization (EuroVis), IEEE Information Visualization (InfoVis), IEEE Visual Analytics Science and Technology (VAST), and Palgrave's Journal of Information Visualization (IVS), while Isenberg et al. applied the same codes to papers from IEEE Visualization.

Different scientific disciplines have contributed to the development of visualization evaluation measures. Perceptual psychology, cognitive science, semiotics, information theory and design thinking have all contributed different approaches for judging visualization designs. Multiple different measures have been used to compare and recommend different visualization layouts, including error rates, accuracy, speed and memorability [9, 53].

The key question addressed in the review of existing visualization evaluation measures was whether they are capable of assessing the practical value of visualization (and the values embodied by visualization practice).

2.4.1 Perceptual Psychology

The field of perceptual psychology is concerned with the mechanisms and characteristics of perception, including visual perception [36]. Applied to information visualization, perceptual psychology has contributed measures of performance related to the accuracy, speed and sensitivity of visual judgements.

2.4.1.1 Judgement Accuracy

It is generally accepted that visualizations must not be misleading or distort the data [17, 61, 62] leading many to place accuracy as the overriding priority guiding the choice of a visualization design [27, 63, 64]. Measures of accuracy are based on the comparison of different basic perceptual judgements [27, 44, 65, 66]. Data values encoded in a visual property ('variable') such as position or angle in a visualization can be retrieved through a perceptual judgement comparing the difference in the visual variable value (the distance between positions or the size of angles). The accuracy of the reader's judgement varies based on the visual variable, for example the relative length of a pair of lines is more accurately judged than different areas of circles or blob shapes [27]. From most to least accurate, the commonly used visual variables are:

i. Position (same axis)
ii. Displaced position (i.e. on different axes with the same scale)
iii. Length
iv. Angle and Slope
v. Area
vi. Volume, Density and Colour Saturation
vii. Colour Hue [27]

For each variable, accuracy also depends on the values encoded (length comparisons are least accurate when one length is around 80% of the other, whereas a circular area ~55% of another is hardest to judge correctly) [44]. Other studies have supported and supplemented this ranking, for instance showing that the areas of rectangles are judged more accurately using side ratio 1:3/2 than 1:1 [66].

As a measure of visualization performance, judgement accuracy is used to prefer or recommend visualization layouts which use more accurately judged variables (for a small sample of such recommendations, see [27, 63, 67]). From the perceptual judgement perspective, the ideal visualization for any purpose is one which allows any two data points to be compared through a judgement of position along a common scale – for example a 1D scatterplot (Figure 8).

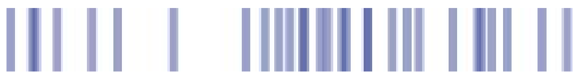

Figure 8: 1D scatterplot (artificial data)

While the accuracy of different perceptual judgements is well established, it is not always clear which variables a visualization 'uses'. In many visualization designs, it is possible to use multiple different judgements to retrieve the same value. For example, pie chart values can be read through angle, area or arc length [68]. Readers do not necessarily rely on the most accurate variable, or even a single variable, and different readers may use different combinations of variables to make the same judgement [68]. The ranked list of visual variables (above) may also be incomplete. Isotype-style graphs (which show a proportional number of stacked shapes) perform better than bar charts [69], suggesting an additional perceptual judgement of counting or 'chunking' comparison, which may be more accurate than length (see also [36]).

Judgement accuracy by itself is also not a sufficient criterion to choose between many available designs (in existing implementations). Implementations of judgement accuracy as a measure are typically based on transformations used to map data to a visual form (e.g. [63, 70, 71]). However, even restricting design choice to only the 'best' variable (position along a common axis) is not sufficient to differentiate between many alternative visualizations. For example, recurrence plots, scatterplots, and parallel coordinate plots can all be created using only position transformations (although parallel coordinate plots offer readers the choice between using position and angle as a variable for interpretation).

Determining the perceptual judgements involved in a specific practical use of a visualization is more difficult. Not all the information read from a visualization is built up from pairwise differences in values. In a scatterplot, for example, individual points are perceived as a unitary shape (formed from the points merged together) whose width, height and angle show the correlation between variables [39]. Thus, a scatterplot can use variables of length and angle, even though only position is involved in reading any individual value. Equally, the heart rate recurrence plot discussed in the introduction (case-study (A), Figure 6) is created by plotting points at horizontal and vertical positions based on data. However, the indicator of a problematic heart rate is dependent not on the position of points but on the size of clusters of points (i.e. an area judgement).

A further issue with the perceptual judgement approach as a measure of practical performance is that accuracy is sometimes given more weight than the performance difference between variables warrants and the practical task warrants. The difference in accuracy between high- and mid-ranked variables is not extreme: the mean error in length comparisons is ~1-3 percentage points worse than position, and area is ~4 points worse [66]. A few percentage points more accuracy may be critical in some applications, but many of the tasks associated with visualization (e.g. finding patterns, trends or outliers, making sense of large data inputs) do not depend on highly accurate comparison of specific pairs of values [8]. Examples can be seen in visualizations from the previous section which rely on visual features which are noticeable in a qualitative sense, not of a specific quantitative size. The heart rate and traffic flow examples examine whether the density and locations of square clusters is noticeably different from one experimental condition to the next [55, 56]. The doctor-patient example involves looking for a vertical cluster 'near' the left of the plot, which consists of reasonably saturated squares [57]. In visualization for communication and public consumption, readers remember the overall message of the visualization [52], and content which resonates with them personally [13]. Choosing the most accurate variables is also not the only means of conveying precise quantitative differences. In applications where precise values are important, these numbers can be annotated onto the visualization, or made accessible through interaction, or through tools other than visualization (e.g. direct calculation).

2.4.1.2 Perceptually-Sound Variable Scales

Measurements of perceptual judgement are also used to select particular subsets of a variable (choice of colours, choice of shapes) which maximise the chance of accurate reading. Colours are perceived differently by a significant minority of people (those with some degree of colour-blindness), and the colour space is not perceived uniformly (an equal change to the amount of yellow in a colour may be indistinguishable if the base colour is green, but not if the base is red). An alternative approach to recommending colour be avoided altogether is to use colours without these perceptual flaws – that is colours which are perceptually distinguishable to colour-blind users and when printed, and where the perceived difference between colours matches the difference between encoded data values [72, 73]. Specific colour-blind safe, print safe and uniform perceptual distance colour palates have been developed to aid design meeting these criteria [73]. Similarly, the perceived distance between sets of simple symbols (e.g. circle, square, cross, triangle) have also been measured to allow designers to use maximally distinguishable shapes within a visualization [58]. Another application of perceptual accuracy research is determining optimal dimensions and scales for line graphs based on the average slope of the line [74].

As a measure, the scope of perceptual soundness is restricted to choosing between layouts which vary only in their choice of scales. For example, it recommends a recurrence plot with a blue-to-cream colour scale (Figure 9(B)) over one with a rainbow colour scale (Figure 9(A)), but offers no guidance on whether the coloured recurrence plot is better than one using only black points (Figure 9(C)).

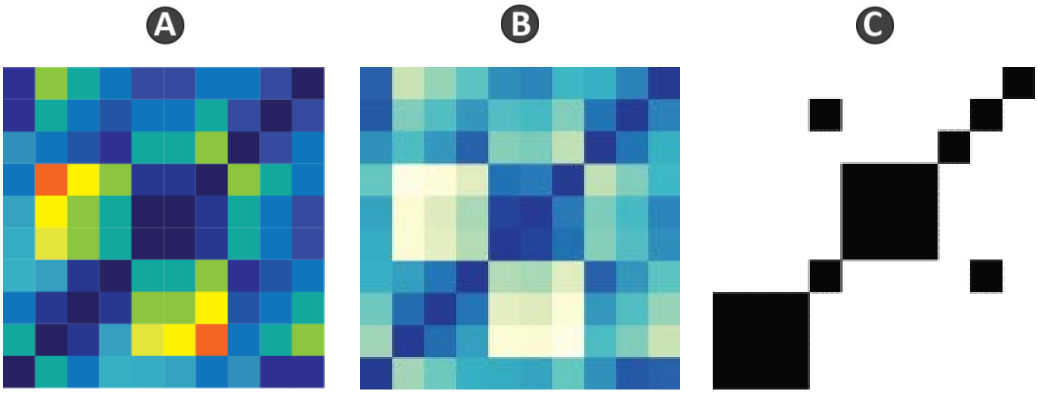

Figure 9: Different colour scales used in recurrence plots: (A) a rainbow colour scale, (B) a blue-to-cream colour scale, and (C) a black and white colour scale.

2.4.1.3 Pre-attentive and Distinct Features

An alternative, less commonly applied, measure from the field of perceptual psychology is the extent to which the variables stand out to the reader. The term ‘pre-attentive’ is used to describe objects (e.g. points, lines or shapes) which draw focus and are noticed faster than other features [36]. Visual variables of colour, brightness, shape, size, angle, and texture can all be used to create a pre-attentive effect, with visual objects perceived preattentively when their values in one or more of these variable dimensions contrasts with the values around them [36]. However, the contrastive effect is diminished when multiple attributes are used at once (e.g. a red circle stands out more amongst identically-sized blue circles than amongst a range of blue shapes of varying sizes) [36]. A visualization is better on this measure if important values are immediately apparent to the reader.

Visual variables also differ in terms of the number of distinct values which can be rapidly distinguished – they have different information capacity. For example, if arrow shapes take one of 4 different evenly spaced orientation values (0°, 90°, 180° and 270°), the reader will immediately be able to tell which shapes have the same (or different) orientation [36]. If the visualization contains shapes with 16 different orientations, the same immediate discernment is not possible. Information capacity has been used to develop suitable colour scales [73] and to judge the suitability of visual variables used in a design [17]. However, as a measure, it is sensitive to multiple factors and thus difficult to apply. For example, the number of distinct values depends not only on the visual variable, but on the size of the visual objects – subtle differences in the colour of large shapes are easier to distinguish than those in small shapes [36].

A related measure is the extent to which the visual values of a single object stand out or are separable from each other. The x and y coordinates of a point's position are easy to read separately, but it is very difficult to determine how much yellow and blue are part of a colour. Pairs of variables such as the height and width of a shape or hue and brightness are somewhat but not completely separable [36]. If a visualization uses difficult to separate visual variables within the same mark, the reader will have difficulty determining the underlying data values. Although well documented, the use of separability or variable capacity as a measure of visualization performance is rarely cited in the literature, compared to judgement accuracy.

As with judgement accuracy, pre-attentiveness (and related concepts) as a measure of practical performance is complicated by the difficulty of determining which variables a layout uses in practice. Furthermore, 'standing out' is a relative concept, and implies a judgement about which data values are more important. Similarly, whether visual variables need to be separable depends on a judgement about whether the data dimensions need to be considered separately or together.

The Minimalist Principle

Pre-attentive features are a key piece of evidence supporting the theory that visual compositions should show only the essential information and use minimal backgrounds [33], or the maximise the ‘data to ink ratio’ [62]. The rationale is that, all else being equal, important data values will be more likely to stand out if each object in the visualization can only take a small number of attribute values ([36, 63]). Another corollary of the ‘minimalist encodings enable data to stand out’ rule is the preference for simple small multiple layouts over complex single compositions [63].

Although popular, there is conflicting evidence about whether the minimalist principle consistently holds in practice. Multiple studies of figurative images – illustrations and icons – within visualization have shown no performance detriment, in contrast to the prediction of the minimalist principle [49-53].

For practical use, a visualization which contains more information than needed is better than one containing not enough. The negative effect of extraneous information in a display is smaller than the positive effect of having all the information for a task visually integrated [15].

2.4.1.4 Gestalt Cues

Gestalt cues are well known within visualization literature, but rarely applied to measure the suitability of a layout. A visual scene is perceived as a composition of objects and groups of objects (its ‘Gestalt’ or sense of the whole) based on proximity, similarity, closure, continuity, common direction, familiarity and 'pragnanz' (simplicity) [36, 75]. Different cues have different (quantified) relative strengths – shapes which are connected are perceived as part of a group before shapes which are close together, which in turn are grouped in preference to similarly coloured marks [76, 77]. Gestalt grouping cues provide an alternate set of variables to which data can be mapped, and have been used to create techniques for showing group structures [78] and network layouts [79-81].

In terms of suitability, layouts can be (but rarely are) assessed for their ability to produce meaningful Gestalt relationships (that is shapes which are grouped by Gestalt correspond to groups in the data) [11, 82]. As with pre-attentiveness, Gestalt cues work to prioritise certain groupings of visual objects in a visualization above others. Whether a particular grouping is good or not depends on which values in the dataset *should* be grouped, and thus involves a choice about the practical purpose of the visualization.

2.4.1.5 Visual Biases

Efforts have been made to translate discoveries about innate visual sensitivities to visualization evaluation. The tendency to look for and remember symmetry [83] has led to recommendations for designs which are always symmetric or where symmetry and asymmetry are meaningful features. At the extreme end of trying to exploit natural visual interpretation biases are techniques like Chernoff faces [84, 85]. However, these attempts have not delivered better performance in practice [86].

2.4.1.6 Mental Operations

An alternative measure to judgement accuracy is based on a model of mental operations through which values are assessed. The model suggests that attribute values in a visual composition are not compared directly, but that the reader uses a series of mental processes – anchoring to reference points, scanning, projection, and superimposition – to make the comparison [87]. The mental operations model accepts the perceptual judgement accuracy rankings, but argues that they apply to isolated pairs of values (i.e. two angles on a blank page, rather than angles positioned together in a piechart), and that basic judgement accuracy interacts non-trivially with properties of the layout. The number and difficulty of mental operations used to compare one value to another in a layout need to be considered in addition to the basic accuracy of the variable. In the mental operations model, a layout using variables with lower accuracy (e.g. angle rather than length) can nevertheless be less prone to error if it allows mental operations to be carried out more accurately – a prediction borne out by the evidence [87].

The importance of anchoring, in particular, in producing accurate visualizations is echoed in studies of visual references [83]. Particular points or lines in a visual layout (e.g. the line x=y in a scatterplot or line graph) form visual reference points through which readers interpret and remember data values. Reference points can be specific to the layout type: for example, the x=y line is only a reference line for charts, not geographic maps [83].

While references and mental operations appear to affect visualization interpretation, they have not been translated into a generally applicable evaluation method.

2.4.2 Semiotics

The field of semiotics is largely applied to visualization to explain how visual representations can convey meaning [17, 88], rather than as a basis for developing specific measures of visualization.

One area where the semiotics perspective has contributed to evaluation is in identifying ‘natural’ interpretations for variables. A ‘natural’ meaning is one which is intrinsic to the visualization system of signs, i.e. reflecting perceived relationships between visual properties. Data has classically been identified as nominal (unordered), ordinal, interval or ratio [89], which is sometimes been simplified to categorical (nominal), ordered (ordinal) and quantitative (either interval or ratio) [17, 90]. The distinction between unordered and the other types of relationships is reflected in the perception of certain sets of visual values [17]. Any set of visual objects with varying positions, sizes or shades (with no assigned meaning) are perceived as naturally ordered (e.g. from smallest to largest size). In contrast, sets of colour hues and shapes can be found such that there is no agreed precedence between one colour (or shape) and another. Thus colour hue and shape are more natural variables for conveying unordered data than size and shades [17]. Like perceptual judgements, data-type suitability is a measure of accuracy, but looks at interpretation rather than quantity accuracy.

Assessments of suitability combine naturalness and judgement accuracy to classify the mapping from data to visual form as being suited or unsuited to a specific data type (e.g. [17, 91]). Two principles underpin the classification:

i. the choice of variable should not imply an order when one does not exist in the data;
ii. (drawing on the perceptual judgement measure from psychology) the more precise the data-type, the more the variable needs to afford accurate judgement.

So, for instance, Bertin argues that position size (length or area) can be used for quantitative data, ‘value’ (i.e. brightness) can be used for ordered but not quantitative data (too inaccurate) or categorical data (shades inevitably suggest an ordered interpretation). Colour can be used for ordered or categorical data, but in the categorical case the colours should not be ordered in terms of hue. There is some inconsistency in the application of naturalness as a measure. The first principle is typically not applied to position – many (e.g. [17, 63]) suggest position is suitable for categorical data even though it implies an order, although some argue it is unsuitable for this reason [67]. Data type measures can also be applied to whole layouts as well as individual variables. Some layouts or types of mark are described as techniques for a specific combination of two or more data types – bar charts for categorical × quantitative data, for example [63, 90].

More specific data types have also been included as additions to or refinements of the classic typology. Continuous and discrete data have been differentiated within quantitative data, with lines suitable for visualizing continuous but not discrete data, and bars suited to the opposite case [91]. The suitability of lines for visualizing continuous data is also applied more specifically to visualization of time [63, 64]. Geographic data is another specialised sub-type of quantitative data identified as requiring special treatment (geospatial visualization) based on a natural analogy between real space and the space of a visual design [15, 61]. Although strictly speaking a classification of visualization types rather than a framework for assessment, Tory and Möller imply that the number of physical dimensions included in the dataset should be used to choose a visualization type which maintains the analogy between real space and design space [92].

A major limitation of data-type measures is that the suitability of a visualization changes when the encoded data is transformed from one type to another. In practice, data does not come fully formed as spreadsheets, but can be collected and processed to suit a chosen visualization. Any quantitative dataset can be transformed into an ordered set by binning values, and any ordered set can be treated as if it were categorical. Similarly, a categorical set can become ordered by applying a sort function. A quantitative set can be created by combining multiple ordered or qualitative datasets (for example cross-similarity or recurrence analysis). A visualization that encodes data through colour values is considered unsuitable when created from quantitative data. However, the same visualization is suitable if a transformation has first been applied to the data to reduce it to an ordered set. Data type is useful for classifying layouts, but does not assist measurement of practical performance unless some additional process is used to choose the type of the data.

2.4.3 Mathematical Measures

Visualization can be viewed through the lens of mathematics and information theory, concentrating on the functions which transform data values into visual objects and attributes. From a mathematical perspective, a visualization is suitable if the data to visual function is 'bijective', 'non-redundant' [67, 93, 94] or 'task faithful' [95]. Formally, the mapping from data to visual representation is injective (one-to-one) when every element (tuple) of data is represented by one and only one visual mark, is surjective (onto) when every mark on the page corresponds to an element of data, and is bijective when both conditions hold. In less technical terminology, injectivity in graphics specifies that the representation must *show each data value uniquely*, and surjectivity (and non-redundancy) requires that the representation must *show only the data* (and not any superfluous 'junk'). Task faithful visualizations involve (informally) injective maps from data to task, where only properties of the data which are relevant to the task need to have unique representation in the visualization [95].

One limitation with mathematical measures is that they are often based on idealised rather than realistic perception. For example, in the traffic-flow recurrence plot (Figure 6(B)), many of the colour differences corresponding to distinct differences in traffic speeds are indistinguishable to the human eye.

As with data-type suitability, practical performance from the mathematical perspective depends on what is considered ‘the data’ (and the task in the case of task faithfulness). In the traffic-flow recurrence plot, the visualization is not bijective if the data is traffic speed values, but is bijective if the data is differences between traffic speed values.

2.4.4 Design Approach

Design approaches emphasize learning from the experience of others, rather than from psychology experiments or mathematical deduction [23, 26].

2.4.4.1 Overview first, Zoom and Filter, Details on Demand

Shneiderman’s Mantra – Overview first, Zoom and Filter, Details on Demand – describes the order of high-level tasks a reader should be able to perform, based on Shneiderman’s design experience [26]. Although very influential, a literal interpretation has little importance for the suitability of static visualization (the focus of this thesis), since ‘zoom’, ‘filter’ and ‘demand’ involve interaction mechanisms. The sense in which it is relevant is the non-literal reading of the mantra which suggests that the tasks of ‘provide an overview of the whole dataset’, ‘allow users to focus their attention on part of the visualization’, and ‘show detailed information in a way which is accessible but not focus-pulling’ should be the aim of every visualization.

2.4.4.2 Common Layouts

An approach which draws on both the design perspective and perceptual psychology research is the development of repositories of visualization layouts which have previously been useful for a task. A repository (or library) of visualization techniques may include a small (e.g. [96], or large selection of techniques (e.g. [97-104]). Repositories often collect together different techniques with a common domain (e.g. visualizations of text analysis [104], or temporal data [101, 105]) or data type (e.g. set [100], networks [102, 106], or tree structured data [99]).

Repositories often include a recommendation for the use or purpose of each listed visualization. Recommendations may be based either on prior use (the design approach e.g. [104]) or synthesis of existing suitability research concerning visualization performance (the perceptual psychology approach e.g. [28, 105]).

One drawback of repositories is that inclusion of techniques is based on prior use and popularity. Furthermore, even when layouts are included, the repositories have limited capacity to distinguish between the suitability of alternative techniques. For example, the conceptual recurrence plot (previous section) is listed in a text visualization repository as a visualization which allows 'discourse analysis' of communication data through 'comparison', 'overview' and exploring 'region[s] of interest' [104]. However, 320 other techniques are also listed as capable of the same tasks [104][2]. Furthermore, it is not clear how the specific question which the conceptual recurrence plot is used to answer (‘did the consultation allow the patient to present their concerns in depth at the beginning of the conversation?’) is a specific instantiation of the tasks listed in the repository.

Repositories also fail to explain apparent similarities of form and function between visualizations. Domain specific repositories such as the text visualization [104] or temporal visualization [101] repositories ignore applications of the same or very similar techniques across domains. The heart rate and traffic flow examples (previous section) not only use visualizations with similar appearance to the conceptual recurrence plot, the questions they answer have underlying similarities which are reflected in the similarities of their visual forms. Data type repositories are equally constrained. A collection of visualizations for tree structures cannot explain why some tree visualizations (e.g. dendrograms) share visual elements with network diagrams, while others (e.g. tree map) are visually distinct. In short, repositories provide a useful resource capturing techniques which have worked in the past, but are limited in their ability to guide future use or to understand the suitability of new or adapted techniques.

2.4.5 Combined measures

Many of the evaluation measures outlined above are complementary – measuring isolated components of performance which contribute to the effective retrieval of information. The prospect of different measures recommending different visualizations raises the issue of visualization priorities. A large part of why measures reach different conclusions is that they are tailored towards different aims. Perceptual judgement places accuracy first, for

[2] As of 15 May 2017

example, whereas pre-attentive features aim to make visual patterns stand out, and Gestalt approaches aim to create intuitive groups. The question of visualization priorities is not which aim is more important, but the relative importance of each consideration and hence how much weight to give each measure.

A number of approaches have synthesized multiple measures into a single tool [63, 64, 71] or set of heuristics [67, 107]. The heuristic approach of Zuk et al. is the most straightforward of all the synthesis processes, simply collating criteria, recommendations or rules from multiple sources (Bertin – data suitability [17], Ware – pre-attentive features [36] and Tufte – minimalism [62]). Testing found the resulting heuristics were sometimes difficult to apply and ambiguous [108]. Automated approaches rely on limiting the layouts considered to a small set, using justifications such as minimalism and limiting designs to using only the most accurate variables [63, 64]. Both heuristic and tool approaches are based on information retrieval, not practical use of visualization.

2.4.6 Top-Down Assessment: Alternatives to (Predictive) Measures

The measures described above allow the suitability of a visualization design to be predicted before the design is deployed. Predictions are typically not expected to be perfect, however; even automated design tools such as Voyager [63] and the Tableau Show Me tool [64] present the user with multiple options to compare and choose between. As an alternative and complement to predictive measures, the performance of a selection of candidate designs can be measured directly (preferably with a sample of the target users).

2.4.6.1 Direct Comparison

Despite the time, cost, and limited applicability of the results, testing layout performance is reasonably (and increasingly) common, partly because of weaknesses in other measures of suitability, and partly because such testing is (justifiably) seen within the research community as a necessary task when introducing a new technique [9]. As with predictive approaches to suitability, testing of visualizations involves a choice about how to measure performance. In many cases, the same measures described in the previous subsections (Section 2.4.1-5) are used for direct comparison (for example speed and number of errors [109]).

However, direct comparison can only be applied after candidate visualizations have already been created, thus requiring considerable effort before testing. Furthermore, the need to narrow down the field of options to a number which is feasible to test means that testing cannot completely replace suitability measures. The repository approach (see above) can be used to close the loop between testing and prediction: existing techniques are recommended from a repository based on prior testing, and new techniques are added to a repository along with their test results compared to existing techniques. However, this feedback loop only works for an information transmission approach to visualization. The evidence that a visualization is useful for one practical task leaves open the question of its performance for other tasks.

2.5 State of the Art

The relationship between information retrieval and practical use of visualization has implications for how visualization performance and suitability is measured. From one perspective, the practical effect of a visualization follows information retrieval, and can be considered an independent secondary order effect. In other words, any alternate representation (whether another visual representation or other source of information) which provides the same information will have an equivalent practical effect. If true, the appropriate role for visualization performance measures is to assess how completely, accurately and efficiently a visualization allows the reader to access its information content – its suitability as a channel for information. Semantic scaffolding offers an alternative perspective. It suggests that specific components of a visual form take on practical meaning as a visualization is interpreted in context. The practical effect of a visualization, in other words, is inextricable from and mediated by the visual form. Following the semantic scaffolding view, the reader's experience and purpose defines which data values are retrieved, and, potentially, the performance of that retrieval process.

Existing measures from psychology, semiotics and mathematics are concerned with the suitability of a visualization as a visualization channel. This section will argue that specific issues with existing measures reflect a shared difficulty extending from information retrieval to practical use of a visualization. Similarly, repositories of existing designs struggle to provide enough specificity to guide visualization choice for a practical task. The limitations in existing measures thus lends weight to the alternative semantic scaffolding perspective. Further support for the semantic scaffolding perspective can be seen in factors known to affect the ability of a visualization to prompt a specific response which are not taken into account by existing measures.

2.5.1 Issues with Existing Measures

The flaws in existing suitability measures highlight some specific unresolved questions about visualization suitability (discussed above), but also reveal a set of broader issues around current theories of visualization form, purpose and interpretation.

2.5.1.1 Uncertainty

A common flaw shared by existing measures is ambiguity around how well measures extend from their foundational evidence into the functional use of a visualization. Uncertainty arises both in the isolated evaluation of a visualization using a single measure, and the relative importance of competing visualization priorities for a specific task.

Suitability measures based on knowledge of the fundamentals of visual perception assume that the data and perceptual judgements involved in a visual composition are stable. The application of individual suitability measures is hampered by uncertainty around fundamental components of a visualization when used for a specific task: its data and the perceptual judgements it involves. The results of mathematical (e.g. bijectivity) and semiotic (e.g. data type) measures depend on whether they are assessed against the dataset available to the visualization designer or the data required for the visualization task. Judging based on available data assumes that all data is relevant, and that (irreversible) transformations of data are never beneficial. However, the latter case involves further ambiguity – the task, and thus the data required, may be defined differently by the designer, the readers as a collective, a particular stakeholder (e.g. the client who commissions the visualization) or each reader individually. The perceptual judgements involved in a visualization are similarly difficult to determine. Even for low level retrieval of values, readers may use different judgements and combinations of judgements [68]. Visualizations are also read at intermediate and global levels [17], which may involve making judgements about shapes not actually present in the visualization, but perceptually merged together from the marks shown in the visualization (as seen in scatterplot correlation judgements [39]).

Furthermore, despite efforts to unify measures of suitability [63, 64, 67, 71, 107], there is uncertainty around the competing priorities of different measures. Approaches target aims as diverse as response speed (pre-attentiveness), accuracy judging quantitative values (judgement), and accuracy interpreting variables (data-type suitability); deciding what weight to give each aim is non-trivial.

Suitability measures – applied independently or in combination – can also be unable to suggest which of two alternative visualizations is better. It is not clear whether the lack of differentiation indicates that the designs are equally suitable, or whether there is a difference in suitability for which measures are yet to be developed.

2.5.1.2 Contradictions

A less prevalent, but more serious, issue identified in the review of measures is contradictions, between different measures of suitability, and between measures of suitability and performance evaluations. The presence of images (so-called 'embellishment' or 'chart junk') does not detract from performance in the manner predicted by the minimalist principle [49-53]. Similarly, conflict exists between the mental operations and perceptual judgement approaches [87], and between the 'pure' data-type suitability approach [67], and the more common hybrid approach which allows position to be used for both ordered and unordered data (e.g. [17]). The superior performance of stacked bar charts (length judgements) over pie charts predicted by the dominant judgement accuracy measure is contradicted by evidence in the case where only two values are represented [87].

2.6 Gaps

Several factors affect the ability of a visualization to fulfil a practical purpose which are not taken into account by existing measures.

Cognitive psychology literature has long recognised the need for theories of visualization comprehension to include and distinguish between different types of prior knowledge and the process of translating from perceptual judgements to meaning [11]. Yet existing measures of visualization suitability largely overlook both factors.

Measures of suitability are based around very short-term performance, yet studies of visualization use in practice show that the process of reading a visualization to gain insight is long and involved [30, 40]. The data on which pre-attentiveness and accuracy suitability measures are based involve fractions of a second differences in performance, or small differences in number of errors given seconds to perform the task [27, 36]. Even retrieving higher-level relationships (e.g. trends, correlations) is measured in tens of seconds [110]. What, then, accounts for the additional hours and even days of use, and how do different visual forms affect performance in longer timeframes? When readers solve more realistic analytics challenge problems, directed activities of the kind affected by suitability measures occupy only part of their time; searches for specific values or relationships are interspersed with other less directed activities such as browsing [40]. Factors affecting longer term use of a visualization, such as literacy [10, 12, 45], engagement [13], and memorability [52, 53] have been studied within visualization research, but not translated into measures which can be widely applied to assess the specific features of a layout.

2.6.1 The Semantic Scaffolding Problem

Understanding the relationship between visual form and practical purpose remains intractable because of fundamental limitations in the underpinning conceptual models of visualization. Existing measures of suitability are predicated on the concept of visualization as a channel through which all of the information content is transmitted to the reader, and only then used for a practical purpose. However, such measures have significant limitations when they are extended to practical tasks, and do not cover the range of factors known to affect such tasks.

Semantic scaffolding offers an alternative perspective to information retrieval as a neutral first step to achieving any practical task. The research project departs from the assumption that the practical use of visualization can be understood independently from visualization form. Instead, this project begins from the premise that the practical meaning of a visualization is inextricable from, and mediated by, the visual form.

The importance of engagement and prior knowledge in practical use of visualization (e.g. [10, 13]) invites a comparison between visualization and natural language discourse. Context plays a significant role in the use and interpretation of language. The suitability of a turn to its conversational context depends on more than just whether the utterance is grammatically correct and an accurate statement of facts. Instead, utterances take into account the existing knowledge, interests and perceived intentions of the other participants [20].

Visualization research has long drawn on knowledge of the structure and operation of (natural) language [1, 17, 18]. From a theoretical point of view, visualization *is* a form of communication, and thus subject to some of the same principles and constraints as natural language. The duality between speaker and listener is reflected in the dynamic between visualization creator and reader. Additionally, both data visualization and figurative representation can be said to have a grammar, complete with syntax and semantics [17, 18, 88, 111]. Theories of language have also had an impact on visualization design. Formal treatments of the grammar of graphics underpin many popular tools for visualization creation, including D3.js, ggplot and their derivative tools [112, 113]. The analogy with language (and the vocabulary for studying language) has also enabled the study of visual literacy [45, 114], visual rhetoric [1], and data visualization metaphor [46, 47].

In the study of natural (i.e. spoken and written) language, theories of *pragmatics* explain how context alters, adds to and transforms meaning during discourse [115]. It has already been established that visualization interpretation can be influenced by social, cultural and individual context [1, 13, 14, 116]. To understand the effect of context on visualization meaning in practice is to examine *visualization pragmatics*.

The semantic scaffolding problem addressed in this thesis is to explain how visual features take on extended meaning and significance to an audience in context. To guide visualization design, the understanding of contextual influences needs to identify specific implications for the choices which go into visualization design: the data structure, variables, visual form and composition.

3 Literature Review: Visualization Models

This chapter outlines the need for new visualization theory in order to address the semantic scaffolding problem. In particular, a (conceptual) model of visualization is needed which can describe the effect of the reader's experience on the interdependencies between a dataset, specific features of a layout, and practical tasks.

A review of existing models of visualization was conducted to look for existing models suitable for the semantic scaffolding problem. The review highlights strengths and weaknesses of different approaches to constructing visualization models. Existing visualization models show that visual layouts can be characterised as compositions built from common basic elements and operations, and that the data structure constrains the possible layouts. Models reinforce the finding from the literature review of visualization value (Chapter 2) that intermediate level interpretation is a fundamental component of practical tasks.

The approaches to visualization demonstrated by existing models show that different types of models provide alternative, but often complementary, lenses into how visualization works. Descriptive models (including process and classification models) can be seen as complementary to structuring models (including grammatical, semiotic and mathematical models). Structuring models can overcome the trade-off between specificity and complexity inherent in a descriptive model. Descriptive models provide input information and a means of checking completeness for a structuring model.

Gaps in existing models shape the methodology for the research presented in the remainder of this thesis. The methodology is split into two parts – presented at the start of Chapters 4 and 6 respectively. Part I addresses the role of experience-dependent meaning in visualization, particularly in the process of encoding data into a visual form. Part II constructs a new structuring model for the semantic scaffolding problem, focussed on features of a layout involving multiple data values – intermediate level features.

3.1 Theory vs. Experimentation

This section outlines the need for new theory rather than experimentation to solve the semantic scaffolding problem. It argues that while interesting and important experimental work remains within the field of visualization suitability, emerging evidence concerning the impact of prior experience on visualization interpretation (see previous chapter) calls for a theoretical response.

Calls for better research or more scientific rigour within the field of visualization are quick to focus on the need for more or better experiments [3, 9, 23, 117, 118]. However, science does not advance through experiments alone, but through the interaction between theory and experimentation, both of which depend on the other for validity. Experiments are required to support the claims made by theory, or determine which among competing theories is likely to be true. Conversely, theory is necessary to specify what variables are sufficient to control for in an experiment, in order to provide results with relevance and significance beyond the specific experimental context.

The mutual dependence of theory and experimentation is as true within the study of visualization as it is anywhere else. Consider as an example an experiment into the performance of different pie chart variations [68], leading to the conclusion, among other things, that donut charts are no less effective than pie charts. The study meets key benchmarks of quality, including a relatively large number of participants (96 with usable results), using a previously verified testing method [66], controlling for variables such as stimulus order and inner radius of the donut charts, and a 95% confidence threshold. In order to reach the study conclusions from the results, however, a number of assumptions are needed, each of which could potentially be flawed. Some assumptions are common across experimental paradigms: a 95% confidence level means that in up to 5% of cases the population's results will be outside of the mean and error range found in the study, even if the participants are perfectly representative of the target population. The experimental setting may affect subjects' behaviour [119]. Other assumptions reflect implicit or explicit beliefs about how visualization works. For example, the charts used in testing only have two segments, a highlighted segment and the remaining segment making up the full circle, but the study conclusions are generalised to charts with an unspecified number of segments. The study also assumes that the colour choice does not affect the result, that readers would have the same relative number of errors if the data values referred to a specific data sets instead of unspecified fractions, and that the current popularity of donut charts cited by the authors is not temporarily affecting the reading accuracy or perceptual mechanisms used to read pie charts.

Setting out the assumptions in the pie chart study is not intended to imply that the study is flawed, or that any of the assumptions are unreasonable. Instead, it shows that the need to make assumptions is an inherent feature of experimentation. Drawing conclusions from results by making assumptions is essential to the relevance of experiments. The interest of the study lies not in its specific details (i.e. how accurately a specific group of 96 people can read pie and donut charts of artificial data), but rather, a generalisation about performance. What is needed by the visualization research and design communities (and provided by the study authors) is information which can be used to predict the performance of pie and donut charts for future applications. Assumptions are necessary in order to generalise from the specific study context. Experiment design can increase the number of controlled variables, and choose whether or not to make a particular assumption, but experimenters cannot eliminate assumptions entirely.

Criticisms of the current experimental paradigm are not new (see [120, 121] for examples), but they serve to underline the need for complementary theory. If many studies support different aspects of a particular theory, it provides confidence in the assumptions behind the study. On the other hand, a study which refutes an otherwise well supported theory provides impetus to further examine the study assumptions (as well as the theory). Theory provides a frame to relate multiple experiments and use them to validate or counter each other. Additionally, theories accepted within a community guide the design of future experiments, because they provide the justification for making assumptions.

Although they are mutually supporting, the development of theory and experimental results do not always stay in step, giving rise to a situation where one or the other is in deficit [122]. Within a typical experimental project, most space is taken up by the details of the experiment, leaving little room to elaborate theory. Conversely, theories can be developed long before it is feasible for their hypotheses to be confirmed through experimentation. In particular, the acceptance of a theory’s plausibility or likelihood can be a necessary step towards gaining enough momentum and resources to conduct confirmatory experiments.

3.1.1 Deficit for the Semantic Scaffolding Problem?

In general, specific questions can be answered through experimentation, while abstract and general questions require theoretical development [123]. Understanding the role of the reader's experience in information visualization is an abstract problem. There is no clear set of design choices or aspect of interpretation on which to focus testing. Instead the question concerns the broad nature of the relationship between visual form and context-dependent interpretation. Thus, what is needed is a new theory of visualization which can posit testable explanations for how a particular visual layout meaningfully contributes to a specific problem (a task and audience). The goal of the new theoretical contribution will be to suggest new topics, tools and methodologies for research into practical visualization value that can be refined and extended as research progresses.

3.1.2 Theoretical Methodology

The remainder of this chapter documents the background literature underpinning the choice of a theoretical methodology for the semantic scaffolding problem. The following section (Section 3.2) provides an overview of the different types of theoretical models, the relationship between models and measures, and the overall benchmarks for model quality. Based on the general principles of good modelling, the specific requirements for the semantic scaffolding problem are discussed in more detail, drawing on the literature review of visualization value from the previous chapter. A review of existing visualization models revealed useful characterisations of visualization form, design, tasks and interpretation. However, existing models do not provide the required specificity or interconnectedness between factors affecting suitability. While no existing model is sufficient on its own, components from multiple models offer a basis for synthesising a coherent semantic scaffolding model.

3.2 Theory, Models and Measures

Theory development can take a variety of forms, ranging from simple hypothesis statements to complex mathematical formulas, each of which has its own characteristics and utility. The theoretical challenge taken up in this thesis is specifically to explain the relationship between components of visualization design and context-specific use of a visualization. Two types of theoretical development in particular are relevant to the semantic scaffolding problem: models and measures.

3.2.1 Models and Measures

A model is “an intentional symbolic oversimplification” of a phenomenon (a 'system') which enables research [124], or “a symbolic assertion in logical terms of an idealized relatively simple situation sharing the structural properties of the original factual system” [123]. Models come in many types and forms, developed for specific types of research: computational models which simulate the behaviour of the system, material models which construct a (simplified) physical copy of the system, mathematical models which describe the system as a set of interlinked equations. The theoretical development of research into a system may make use of and transition through models of different types, levels of complexity and precision [123]. As will be discussed in later sections, many different types of models have been developed to understand different aspects of visualization.

Conceptual models – sometimes termed mental models [125] – are the most unrestricted type of model, and represent a foundational act of theory development. A conceptual model of a phenomenon (whether an object, process or a combination of the two) is simply a description of the components and interconnecting relationships which explain how the phenomenon works [125]. The implicit claim made by a conceptual model is that it captures everything about the phenomenon that is important for the purpose of the model (and nothing more). Other types of model (e.g. mathematical models) can also be viewed as conceptual models, with constraints on the allowable forms used to describe the system components and relationships (e.g. the components must be quantified and related through equations). Comparison of different types of model of a single phenomenon (for instance visualization interpretation) is possible because each model has an underlying conceptual model (i.e. the model viewed as a conceptual model). Throughout this thesis, the term model implies conceptual model unless otherwise specified.

Models and measures are distinct, but interconnected. Measures assess one or more of the components or relationships involved in the phenomenon, producing a rating or quantity associated with those components or relationships. Models provide the basis for judging the weight and relevance of a particular measure. Measuring something not in the model has no relevance; measuring one component of a large model is relevant, but may be counteracted by measurements of the other components. Consider, for example, a standard model of business profit where "*Revenue – Costs = Profit*". Measuring the environmental impact of the business has no relevance to its profit (under this particular model), while measuring revenue alone provides only a partial indication of profit (high revenue can be associated with low or high profit, depending on the value of cost). A model also provides the basis for judging the completeness of a set of measures. A set of measures assesses (i.e. is an overall measure of) a modelled phenomenon if each component of the model is measured, and the resulting values are combined in accordance with the relationships in the model. (For example, a measure of revenue and a measure of cost combine to create a complete measure of business profit as modelled above, by subtracting the measured cost from the measured revenue). The measures of model components can be referred to as ‘component measures’ of the overall measure of the phenomenon.

Just as models provide a basis for judging a set of measures, measures also provide a means of judging the success of a model. Where a phenomenon is difficult to measure, the way that a model decomposes the phenomenon can make new measures harder or easier to develop. As such, a key indicator of the value of a model is whether it provides a pathway to developing measures. Partial success in developing measures is useful in its own right; the model of profit is useful even if only costs and not revenue can be measured – the business's chances of profits are increased by attempting to decrease costs regardless of revenue values[3].

In order to assess how well the form of a visualization enables it to provide practical value, both a model and measures will ultimately be needed. The scope of this thesis, however, is to develop the model and ensure it provides the foundation for measures, rather than developing the measures themselves. The model must capture the key components affecting semantic scaffolding, and show how these components are related. It is intended to provide a pathway for the development of measures which are repeatable and practical, for each of the components of the model.

3.2.2 Assessing Models of Visualization

Many models have been proposed to describe, organise and guide the practice of information visualization. To analyse whether any of the previously generated models are sufficient, and if not why not, it is first necessary to understand the yardstick for a good model.

Two explanations are often invoked to describe the challenge of good modelling: "the best [model of] a cat is another cat" [123], and "all models are wrong, some models are useful" [126]. The 'cat problem' as the former is known, illustrates the need for models to make simplifying assumptions, lest the model prove as difficult to understand as the phenomena it was created to study. One cat is a highly accurate model of another, but is equally intractable. The second explanation acknowledges that every simplifying assumption introduces inaccuracies; however, a model which is only partially accurate can nevertheless facilitate the acquisition of knowledge if it enables accurate synthesis of information about the phenomena [123]. For a principle derived from a model to be valid, the model only needs to accurately capture the factors and relationships affecting that principle. The quality of a model thus depends both on the modelled phenomena and the

[3] The model is important in developing the strategy of minimising costs. An alternative model which included, for example, product quality as a component which increased both costs and revenue would not support the same strategy.

purpose for which the model is being created (for example, a model of coins for commerce only needs to consider denomination, whereas a model for a collector needs to include factors such as production year and condition).

Both modelling considerations are important for the semantic scaffolding problem. Any model of visualization used to assess or predict practical value will necessarily be an oversimplification of reality, but may lead to useful conclusions provided it accurately reflects the relevant aspects of visualization, and reveals connections between new and existing research into visualization. More specifically, existing models of visualization can be highly useful models of the visualization creation process, interaction methods, or the range of layouts available, and yet be unsuited to analysing the practical use of visualization.

3.3 Model Requirements

What requirements, then, can be placed on a model of visualization for it to be useful in solving the semantic scaffolding problem? First, suitability (in context) sits at the intersection of data, visual form (i.e. design/composition), and interpretation, and thus the model must incorporate all three factors. Second, to be useful in guiding design, the model must relate suitability to factors which are controllable in the design process.

The importance of data, visual form and interpretation to suitability was a key finding from the literature review (see Chapter 2). Measures from psychology, semiotics and mathematics reveal aspects of design/visual form and interpretation performance which need to be accommodated in the model (e.g. variables used, groupings, pre-attentiveness, accuracy, cognitive naturalness). However, the limitations with such measures – particularly as highlighted by research into contextual interpretation – show the need for a model which is selective in how local-level performance factors apply. The model needs to do more than simply include visual form, task and interpretation as components; it needs to explain how the three components interact. In particular, it needs to show when a particular task changes the relative importance of different elements of visual form, or how they are interpreted.

The importance of foregrounding controllable components of design is a practical consideration. Designing for insight in visualization has been associated with a paradox: the visualization which best fosters insight can be identified when the data is well understood, but to understand the data requires a visualization which fosters insight [3]. To avoid the insight paradox and similar circular design recommendations, it is necessary to focus the model on factors which can be controlled by the designer, and in particular design choices which can be made based on information accessible to the designer. Thus detailed information about relationships between data values is considered out of scope of the model, but information about the data structure and its general content is within scope.

3.4 Existing Models of Visualization

A large number of existing models of visualization encompass design factors, tasks or interpretation. The existing models reviewed in this section are divided into process models, classifications, semiotic models and mathematical models. Process models describe the order of visualization activities, while classification models divide some component of visualization (e.g. data or tasks) into types. Semiotics has long been used as a lens through which to understand visualization, formalised through semiotic models. The primary aim of mathematical models, in contrast is not to provide a description of a visualization phenomenon, but to serve as the basis for analysing or reasoning *about* visualization through a mathematical formalism. (Excluded from this analysis are heuristics or prescriptive visualization measures such as Shneiderman's mantra. A review of prescriptive measures of visualization can be found in the previous chapter.)

Since many models of visualization have already been developed (often through intensive research and improvement over time), the aim of this thesis is to take advantage of existing work if possible. A comparison of existing models against the requirements of the semantic scaffolding problem was conducted to determine whether it is possible to use an existing model.

Model comparison can lead to a number of outcomes. One model can be chosen as the best model for the application at hand, or a new model can be synthesized from the combination of multiple models. Choice between models is required when models are incompatible – if model A is true, model B must be inaccurate. However, choice can also be driven by practical considerations such as the level of detail or scope required for a particular application. Synthesis requires that models are compatible (i.e. non-contradictory), and is useful when multiple models offer some contribution to a problem. Synthesis can involve merging or creating a structure to encompass multiple models. Merging (e.g. combining a list of time series layouts and a set of visualization layouts) is useful when models are similar in type and structure, but have different scope. The result is a model with the scope of the union of the input models. Structuring is useful when different models offer complementary descriptions of the same subject. Similarly, a large, complicated model (for example the result of multiple merges) can be made more elegant and easier to use through restructuring – for example using only a portion of the model, organising the model into dimensions, or abstracting to a higher level of detail.

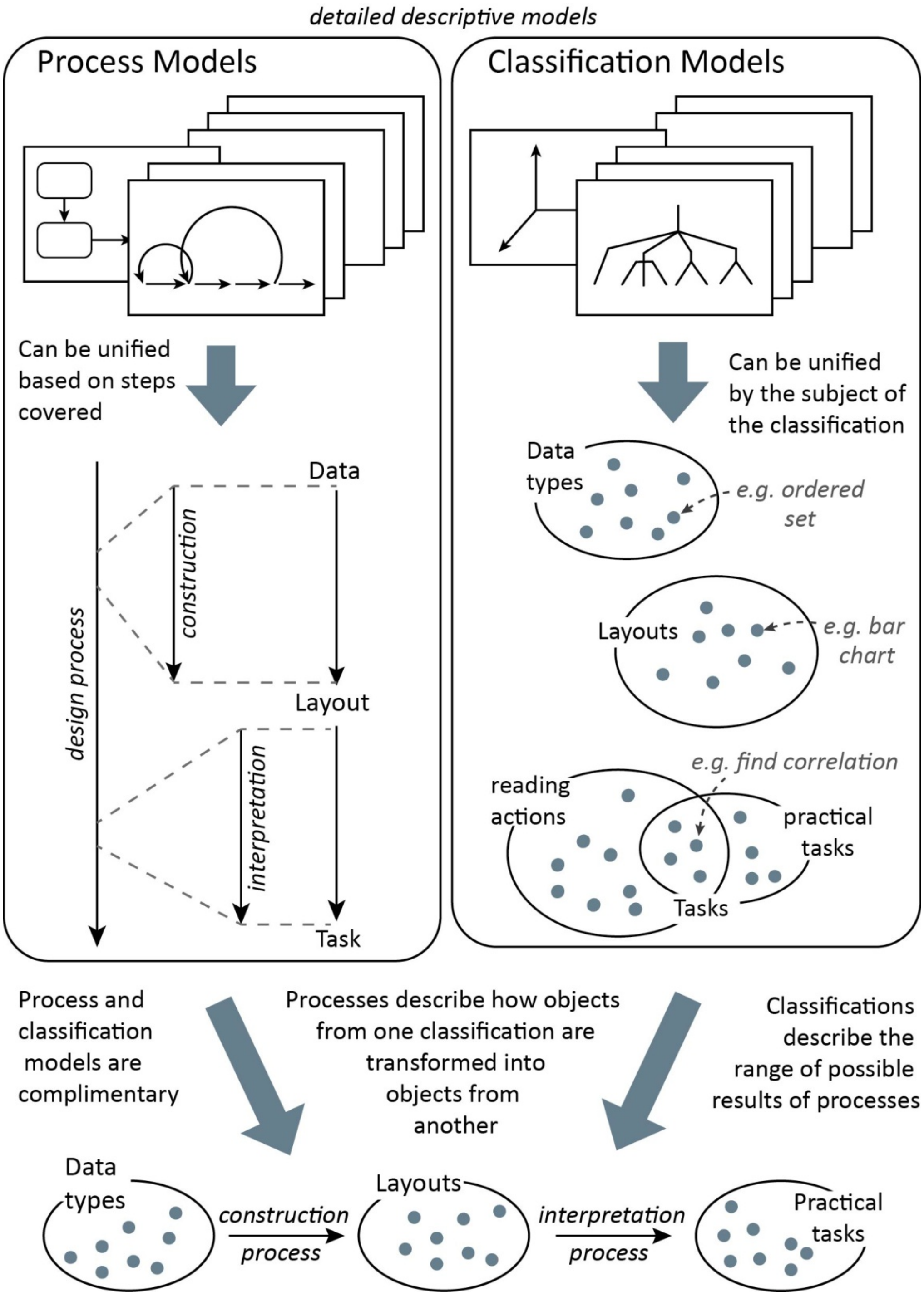

Figure 10: The complementary relationship between two types of descriptive model: process and classification models

In visualization, two sets of models – process and classification models – have a naturally complementary relationship (see Figure 10). Multiple process models exist describing the *construction* of a visualization from a dataset to a completed visual representation. Models (developed from psychology research) also exist describing the process of *interpretation*, beginning with a visual representation and ending with some information being obtained by the reader. The start and end points of construction and interpretation models correspond to the subject of multiple classification models. Multiple models describe data types, layouts (types of visual representation), and visualization tasks (types of information obtained from interpretation). A synthesized model can be envisioned which describes the range of data types (classification model), how data types are transformed into layouts (process model), the resulting types of layout (classification model), the interpretation of layouts (process model) and the resulting tasks (classification model). The inputs to this unified data-to-task model could be chosen or synthesized from existing process and classification models.

The prospect of a unified model raises two interrelated questions: first, would such a model help solve the semantic scaffolding problem, and if so, which input models are suitable as components? In other words what input models and restructuring are required to make the unified data-to-task model a semantic scaffolding model?

Just as different types of models have different uses in terms of explaining visualization, they have different requirements to be useful for the semantic scaffolding problem. Process models need to explain how meaning is encoded and decoded from visualization, but in a way which accounts for experience and can be traced to specific features of a layout. A construction process model would only be useful if it can explain how data values, sets of values and dimensions of value are encoded in a layout. In addition, it needs to explain how 'shared semiotic resources' (i.e. signs whose contextual and experiential meaning is shared by the designer and reader [116]) are encoded into a layout. An interpretation process model would only be useful if it can explain how a reader obtains information (i.e. answers questions) from a layout. In particular, it needs to explain how parts of a visualization (features and feature properties) are used in the completion of practical visualization tasks. An interpretation process is suited to the semantic scaffolding problem if it can explain how interpretation relies on experience. Classification models, on the other hand, need to describe the range of data, layouts and (practical) tasks involved in visualization.

The semantic scaffolding problem requires specificity. It needs a model which can be used to identify the meaning of specific features and properties of a visual representation. The 'meaning' of a feature or its properties needs to incorporate not just the translation in terms of the data, but the meaning *to the reader* – its practical significance.

The key problem of both process and classification models is that specificity comes at the expense of simplicity (and hence usability). Being able to explain the impact of design choices (i.e. the choice of a layout) on a task in context requires more than just an accurate model of the relevant visualization components and processes. The components need to be linked to show how design choices constrain and enable different practical tasks, given the reader's experience and reading context. As existing modelling efforts demonstrate, models of visualization components (data, construction, layouts, interpretation, tasks) do not always link together. Andrienko and Andrienko's [39] set of models for Exploratory Data Analysis (EDA) attempts to model data, layouts and practical tasks in detail (focussing on a restricted subset of information visualization – spatio-temporal data). However, the EDA approach explicitly rejects the possibility of linking the three models. Its authors argue that a formal treatment of suitability of visualization layouts (which they include as 'tools') for tasks is impossible, based on the number of distinct tasks at the level of specificity for which a layout is suited or unsuited [39]. The fundamental problem is that at the level of generality where tasks can be reduced to a manageable number, instantiation of those task categories for different datasets is too varied to be linked to a single layout or range of layouts:

> *"The spatial variation of the amount of forest and its structure, the dynamics of the crime rate in a country, the movements of storks or vehicles, the spatial and temporal distribution of earthquakes – these are just a few examples of possible behaviour types [which fall under the 'characterise behaviour' task]. It is clear that one cannot find or design a tool that would be equally appropriate for characterising any of these behaviours."* [39] p. 464

The EDA data-task-tools set of models is, in effect, a critique of its own modelling approach: developing extensive classifications of tasks, data and layouts and then trying to connect them will not solve the semantic scaffolding problem.

Structuring models resolve the trade-off between specificity and simplicity (see Figure 11). Structuring models – including semiotic, grammatical and mathematical models – use different types of formalisms to organise descriptions of visualization. They aim to distil common rules and properties governing visualization. In doing so, structuring models provide descriptions which are specific with respect to relationships between aspects of visualization, but generic enough to describe many visualizations at the same time. For example, Wilkinson's visualization grammar decomposes a layout into an arrangement of elementary components (e.g. points, lines, axes) which encode with different types of data (e.g. vectors, functions) [18]. Visualizations which use a particular element or arrangement of elements can be analysed through the structure of the grammar without needing to analyse each visualization instance.

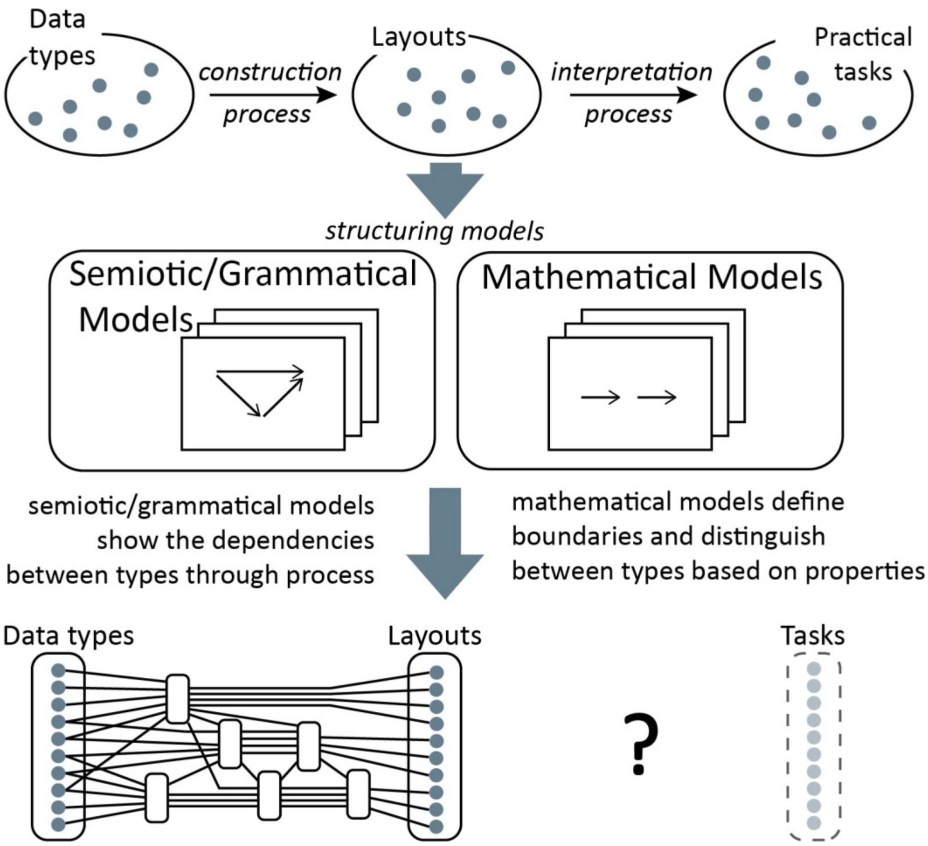

Figure 11: Structuring models resolve the trade off between specificity and simplicity inherent in descriptive models. Models exist which structure the relationships between data and layouts, but not layouts and tasks.

For the semantic scaffolding problem, the structuring models of interest (i.e. considered here) are those which link together data types, layouts and practical tasks. Most classification models include a structuring component – for example, visualization tasks can be decomposed into a WHY-WHAT-HOW structure [32]. However, as the EDA approach shows, a structured approach to tasks is not useful unless it can be linked to layouts, and vice versa.

The following subsections describe the overall landscape of existing models of each type, describing only representative sample models in detail. The main focus of the review is to identify the capacity of existing models to support the semantic scaffolding problem. For more complete descriptions of individual models, the reader is directed to the references listed in each subsection.

3.4.1 Descriptive Models

3.4.1.1 Process Models

At a high level, process models focus on either visualization construction [18, 37, 70, 95, 127], design [128, 129], or interpretation [3, 10, 15, 41, 43, 87, 130, 131]. In many cases, models differ in the number of stages posited or the boundaries separating stages, rather than contradicting one another about the nature of the process described. Process models can be written either in terms of states (e.g. 'scales') or functions (e.g. 'filter data'); however, a state model can easily be translated into a function model and vice versa (e.g. from 'scales' to 'create and apply scales' and 'filter data' to 'filtered data'). Another point of difference is whether the model shows explicit loops revisiting earlier activities.

The most well-known process models concern visualization construction models (also called visualization pipelines), which set out the steps required to transform data into a visual form (e.g. [18, 37, 70, 95, 127][4]. A sample construction model is Fry's seven stage process model: *acquire* data, *parse* the data, *filter* out irrelevant data, *mine* for patterns, *represent* the data visually, *refine* the visualization, and *interact* (see Figure 12) [37].

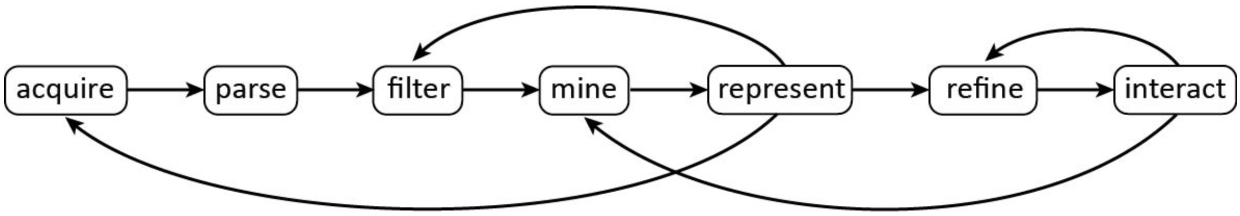

Figure 12: Fry's construction process model. Redrawn from [37].

A related but distinct type of process model describes the broader design process, the steps from a designer becoming aware that there is a problem to be solved with visualization and the delivery of a working solution. Many design process models exist for human computer interaction or computer science generally (e.g. [132]), but a few have also been created specifically for visualization, such as Munzner's nested design model [128] and Roberts et al. five design-sheet methodology [129] (see [129] for further examples). Design models typically include visualization construction, but focus more on the decision-making and mental activities involved (e.g. brainstorming, evaluation of options).

[4] Numerous other visualization construction pipelines exist focusing exclusively on rendering computer graphics, which are not included here.

Both design and construction models focus on the actions of the visualization creator; reading comprehension models, on the other hand, focus on the actions of the reader. Reading models do not overlap with construction models, but do contradict them either. The presence of evaluation actions in a design model (e.g. [128]) assume that reading takes place, but do not model the reading process explicitly. Reading models can be separated into those which describe the mental process of comprehending a single view [10, 15, 41, 43, 87, 131] and models which focus on active interaction with a visualization (e.g. zooming or selecting an alternative view) [3, 15, 130]. (The implicit reading model behind Shneiderman's mantra would fit into the latter category.) Spence and Van Wijk ascribe a different level of agency to the reader – Van Wijk's reader is capable of creating a new or updated visualization in response to her viewing [3], whereas Spence's reader is a consumer of visualization tools created by others [130]. The GOMES model attempts to predict the speed of a reader looking up values in a visualization (i.e. it is a quantified model), although, it must be said, not with much success [131].

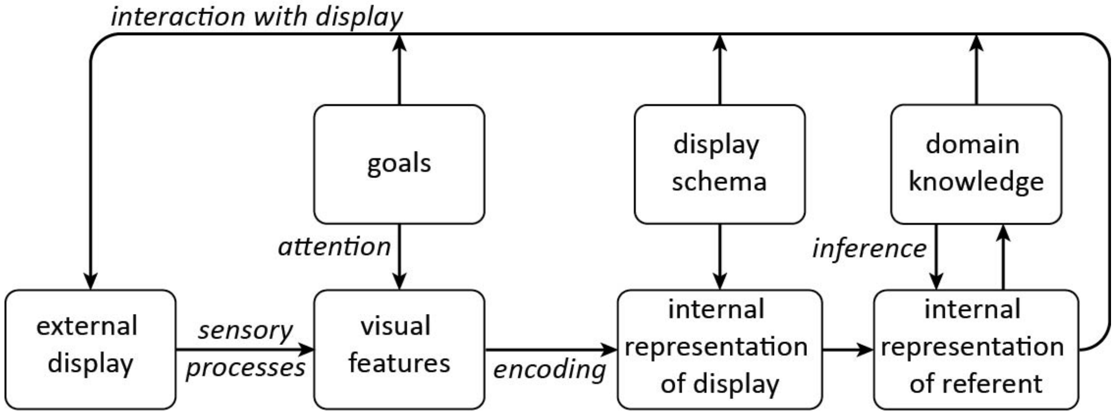

Figure 13: Hegarty's visualization comprehension model identifies two types of prior knowledge affecting interpretation: domain-specific knowledge of a visualization's content, and knowledge about how to interpret visualizations in general. Redrawn from [15].

A sample interpretation model is Hegarty's visualization comprehension model (produced in Figure 13) [15], which builds on prior models (e.g. [12, 43]). It is important for the semantic scaffolding problem because it is constructed to capture a number of findings about the effect of experience on visualization interpretation. Hegarty's model identifies two distinct types of experience affecting the derivation of meaning from a visualization – experience reading a particular type of layout, and experience with the domain [15]. Additionally, the model shows that the visual features which are observed within a visualization are affected by the reader's attention. In other words, readers may notice only some parts of a visualization, and the features which are noticed may vary between reading contexts.

Process models provide useful input information about the semantic scaffolding problem. Construction models highlight the functional (i.e. applying a formula or set of operations) nature of the transformation from data to visual form.

The usefulness of a process model as an approach to the semantic scaffolding problem depends on whether the component steps have an impact on practical performance. Fry's construction model (shown previously in Figure 12) applied to semantic scaffolding, for example, would need to provide insight into how execution of the *filter* or data-*mining* activities change the practical tasks for which a visualization can be used. Existing process models have two limitations in terms of determining practical impact. First, separate models are used to describe construction (and design) processes and interpretation processes. The separation makes it impossible to connect a design choice to a reader response. Second, process models in general are implementation-independent: they describe only the sequence of steps, not how each step must be undertaken. Implementation-independence is a strength for the application of a model as an instructional tool or guideline for tool builders. Process models describe things a designer or visualization construction system should do or (for interpretation models) take into account. A consequence, however, is that such models do not specify how the execution of one step constrains the execution of subsequent steps. Thus, even joining together Fry's construction model and Hegarty's interpretation model (Figure 13) does not allow the effect of design choices to be traced through the model.

3.4.1.2 Classification Models: Taxonomies, Typologies and Spaces

Classification models describe the range of data types, layouts and tasks which are associated with information visualization. Such models vary according to their scope, with some focussing only on a specific task or representation type (e.g. visualization of set data [100]), and others aiming to encompass the whole of information visualization (e.g. [17]). Models also vary in structure, including surveys or lists, taxonomies, typologies and design spaces. Section 2.4.4.2 of the previous chapter analyses visualization surveys as a tool for evaluating the suitability of layouts. The analysis of this chapter is focussed instead on the conceptualization of visualization expressed through the same set of surveys, as well as other classification models.

Data classifications describe the types of data which can be transformed into information visualizations [133-135]. The previous chapter outlined one such typology, which separates data into nominal (i.e. categorical), ordinal, interval and ratio types [89].

Layout classifications identify and organise the range of different visual forms which can be used for visual representation [39, 42, 63, 70, 71, 97-106, 136]. Layout classifications vary in terms of structure, scope (e.g. only tree visualizations [99]) and level of detail (dozens [17] to hundreds of techniques [104]). A representative sample of a high level classification is Bertin's design space of layouts ('types of imposition'), reproduced in Figure 14 [17]. It separates the space of visualizations into diagrams (i.e. plots or charts, which can have rectilinear, circular, orthogonal or polar axes), networks (freeform 'arrangement', rectilinear, circular or orthogonal – matrix – layout of nodes), maps, and symbols (which are not data visualizations).

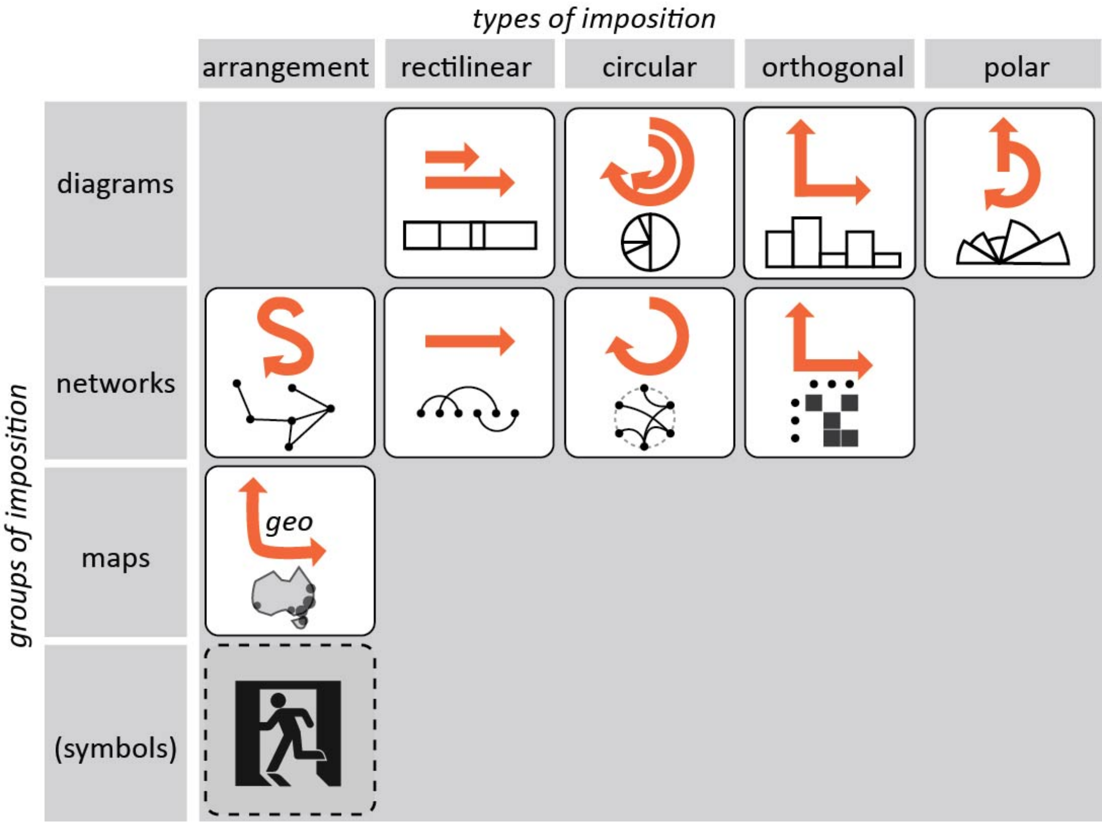

Figure 14: Bertin's layout taxonomy classifies layouts, redrawn from [17].

A number of task taxonomies and typologies have been developed to organise visualization tasks [7, 32, 38-40, 134, 137-145]. Tasks included in existing classifications can range from low-level interpretation actions to high-level visualization aims (including practical tasks discussed in Section 2.2). Andrienko & Andrienko's EDA task typology (summarised in Table 1) provides the classification of tasks most concerned with practical use of a visualization:

> *"an explorer does not only* ***look at*** *data but also* ***looks for*** *something "interesting". This may be, for instance, a salient pattern in a spatial distribution, a local anomaly, some indication of unusual behaviour, or an indication of a*

possible dependency between phenomena or processes. … [In contrast to other views of exploratory data analysis,] we understand "interestingness" as relevance to … the motive for doing the analysis." [39], p. 149

Although designed for exploratory analysis of spatial and temporal data, its tasks are described in terms applicable beyond spatio-temporal data.

Table 1: EDA task typology, reproduced from [39]

Elementary tasks		Look up
		Compare
		Relation seeking between values
Intermediate and global tasks	Descriptive tasks	Behaviour characterisation (pattern id and pattern search/inverse pattern id)
		Behaviour comparison
		Relation-seeking between behaviours and reference sets
	Connectional tasks (characterising, comparing and relation-seeking between behaviours of behaviours, e.g. correlations between behaviours)	Homogeneous behaviour (matching behaviour)
		Heterogeneous behaviour (contrasting behaviour)

Classification models reinforce the idea that data structures, layouts and tasks are three distinct and important factors required to understand visualization. Data type classifications identify a range of different data structures from which information visualizations can be constructed. One type of data missing from existing classifications is the information used to create figurative images (e.g. illustrations) in so-called 'embellished' visualizations (the concept of embellishment will be explored in Chapters 4 and 5). Classifications of layouts emphasize the importance of the position variable – with the different types and arrangements of axes providing a common means of distinguishing between layouts (e.g. [17, 105]).

A common feature of task classifications is the existence of 'intermediate level questions' [17] (also called 'synoptic' tasks [39], or tasks involving more than two 'targets' [38]). Intermediate level questions match the types of practical tasks seen in the recurrence plot and matrix examples examined in Chapter 2. The presence of such tasks within task classifications reinforces their importance to the semantic scaffolding problem.

The usefulness of classification models as an approach for the semantic scaffolding problem depends on whether the types they identify can be associated with variation in practical performance. Consider the scenario where two layouts (e.g. the two recurrence plots compared in Section 2.3) are 'the same' in a layout classification, but are suited to different practical tasks. The classification is either not detailed enough, or the boundaries separating layouts into different types have been drawn in the wrong places.

Overall, existing classification models provide a detailed description of the range of data types, layouts and tasks. However, no trio of data type, layout and task classifications has been linked together. Without this linking activity, it is difficult to know which (if any) classification models is suited to the semantic scaffolding problem.

3.4.2 Structuring Models

Structuring models of interest for the semantic scaffolding problem organise and efficiently summarise the relationships between different aspects of visualization.

3.4.2.1 Semiotic and Grammatical Models

Semiotics, or the study of how communication is enabled by systems of signs, provides a means of understanding different types of relationships between signs (representations) and the objects (information) they represent. Theories of semiotics have included the study of visual representation since its founding work by theorists such as Peirce and Barthes [19, 146]. Specific study of the sign-system of information visualization dates to Bertin’s semiology of graphics [17].

From general (i.e. not-visualization specific) semiotic theory, a key model is Peirce's semiotic triangle (see Figure 15) [19]. Peirce’s semiotic triangle shows how a sign is characterised by a triadic relationship between a representation (e.g. a word or image), a referent (object or data) and 'interpretant' (what the word of image means to the recipient) [19]. The representation (the word ‘dog’) is not the same as the object: in another sign system (e.g. another language such as Japanese), I would use a different representation (i.e. the word ‘inu’) to refer to the same object. Peirce’s semiotic triangle also captures the difference between the word ‘dog’, the object or concept I have in my head when I *say* the word ‘dog’ and the concept which comes to mind when you *hear* the word ‘dog’; I may have in mind a Great Dane and you might think of a Chihuahua [19].

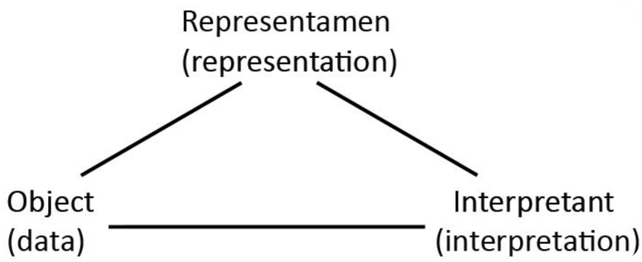

Figure 15: Peirce's semiotic triangle, based on [19].

Visualization-specific models based on semiotics include visualization grammars. A description of a grammar (including visualization grammars) includes the types of basic components which exist and the allowable constructions which can be assembled from those components [147]. Grammatical visualization models focus on setting out the elementary units of visual form which can convey meaning, and the grammar or syntax used to assemble such units into more complex compositions. A number of lists of visual variables and basic elements have been developed and progressively expanded [17, 18, 65, 78]. The two most influential examples of grammatical models are Bertin's *Semiology of Graphics* [17] and Wilkinson's *Grammar of Graphics* [18]. Bertin's syntax is focused on the use of the 2D space of the page (type and group of 'imposition' – see Section 3.4.1.2 above) and visual variables (shown in Figure 16), while the grammar of graphics centres on data-to-space transformations (e.g. coordinate transformations, scales) [17, 18].

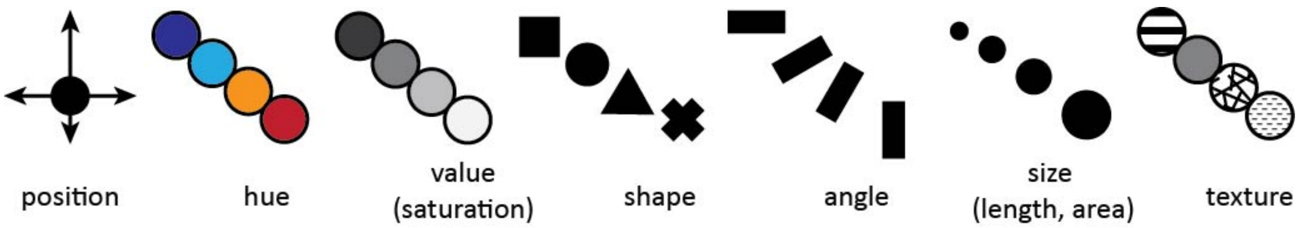

Figure 16: Visual variables, following Bertin [17]

Semiotics models provide a connection between process and classification models. Contingencies between components in a grammar (e.g. scales must be set before coordinates) determine a visualization construction order [18]. Additionally, a set of components or allowable constructions can motivate a partition of the design space, as seen in Bertin's separation of visualization into diagrams, networks and maps described above [17].

The interconnections between structure, process and classification has only been captured for visualization construction; it does not translate across to visualization reading and tasks. Both Bertin and Wilkinson discuss interpretation: Bertin shows how visualizations can be read at a local, intermediate and global level, while Wilkinson outlines the constraints which an automated reading system would need to satisfy. However, neither models expand on interpretation to the extent that they do for visualization construction, leaving the relationships between components of the grammar and tasks unexplored.

An alternative semiotic model is the category model of Vickers, Faith and Rossiter (VFR) [93]. The mathematical component of the VFR category model will be discussed in the next section, however, from a semiotics point of view, the VFR model is not a grammar. In the VFR model (see Figure 17), Peirce’s triangle is relabelled for a visualization-specific application: visual representations (signs) refer to data (the object), while *reading* produces what the authors term ‘evocations’ (interpretant), statements about the data interpreted from the representation [93]. The semiotic triangle also is embedded within a broader structure showing the origin of data in a system, and the ultimate aim of imparting knowledge. Importantly, VFR distinguishes between the specific and abstract form of the semiotic triangle, showing that a representation created from data is the instantiation of a general data structure ('Schema') and 'Layout' which together answer 'Questions' (the abstract form of interpretation or ‘evocations’).

The semiotics of visualization more generally (i.e. including diagrams and illustration as well as information visualization) has also been modelled and analysed [88, 111]. Like the semiotics of information visualization specifically, these more general models do not provide specifics about the relationship between form and meaning (i.e. tasks or questions), instead focussing on how the separate types of form and modes of meaning can structure the space of visual design.

3.4.2.2 Mathematical Models

A final set of models discussed here, many of which also fit into one or more of the previously discussed types, is mathematical models of visualization. Visualization has long been framed in terms of mathematical structures to describe datasets (e.g. [18, 39]) and mathematical functions to describe the transformation of data into visual forms (see for instance [18, 70, 93, 94, 148]). More elaborate mathematical models use formalisms from various branches of mathematics (analysis, economics, algebra and logic) to derive or define different characteristics of visualization.

The most common approach uses properties of the data-to-visual transformation function to define either boundaries of visualization types or visualization quality [93, 94] . For example, a bijective mapping (see Section 2.4.3) between the data and the visual representation is variously described as either a defining requirement (e.g. [94]) or a desired quality of visualization (e.g. [93]).

A second group of mathematical models embeds the data-to-visual function in a broader network of functions. Van Wijk's economic model (discussed previously as a comprehension model) adds reading and interaction functions, enabling the formulation of a cost function weighing the effort of creating a visualization against insights gained [3]. Quan et al. add an additional function from visual representation to task which allows them to introduce visualization property of faithfulness and 'task faithfulness' (see Section 2.4.3) [95].

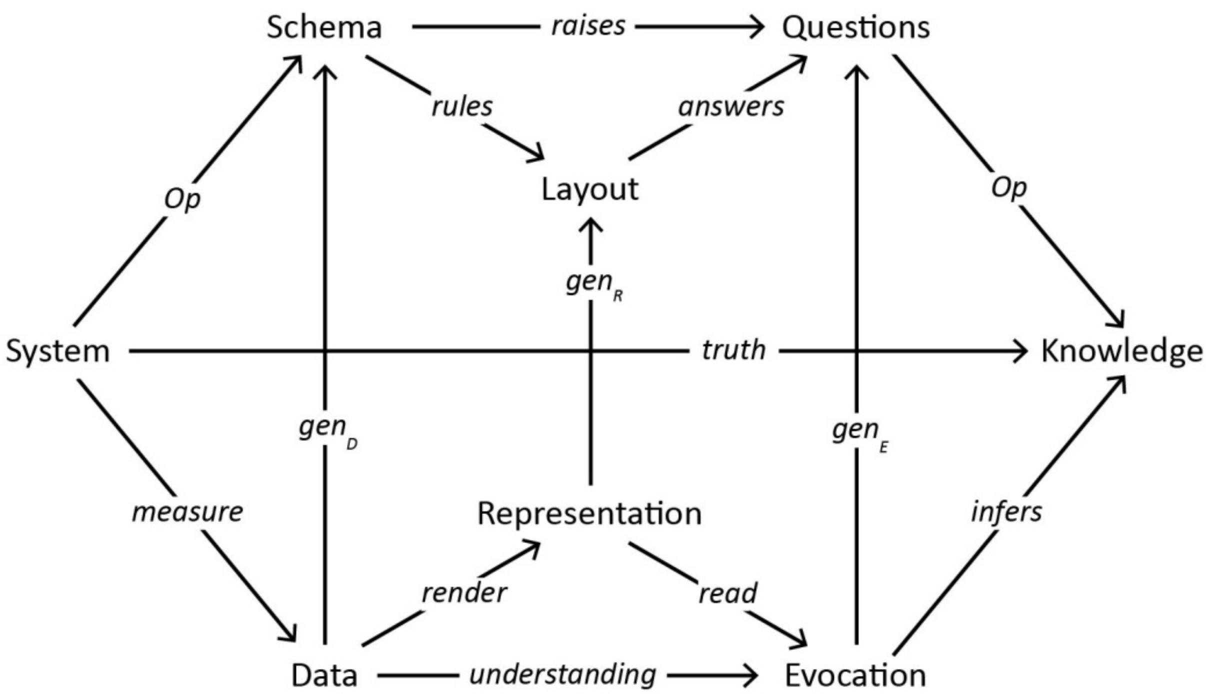

Figure 17: The VFR category model – redrawn from [93]

A small number of mathematical models draw on mathematical category theory, which examines properties of a collection (a 'category') of objects connected by functions (technically, 'morphisms', a more general concept of which functions are the most well-known subtype) [67, 93]. In mathematical terms, the VFR model (discussed above as a semiotics model) is a 'category' consisting of System, Data, Schema, Representation, Layout, Evocation, Questions and Knowledge objects, together with morphisms which describe the transformations between these objects in the visualization process [93]. Each alternative path through the VFR category shows an equivalent model of the visualization process. Visualization can be seen as the production of knowledge from a system (the path across the centre of the diagram), or alternatively the measurement of data about a system, the rendering of that data, which is read and used to infer knowledge (the 'W' shaped path through Data, Representation and Evocation). A particular path through the category may provide the most suitable model for solving one theoretical problem, but not another. The connectedness of the paths in the category construct ensures that the results from any one path remain translatable into the others. Similarly, given any two objects, any pair of alternate paths between them forms a self-contained sub-diagram which describes some aspect of visualization. In contrast to the process, classification and grammatical models, the VFR category model spans data, layouts and tasks.

Mathematical models can be used to develop definitions separating information visualization from other types of visualization, and define properties a visualization can satisfy (e.g. bijectivity). However, they do not characterise the range of data types, layouts or tasks which fit the mathematically derived definitions. As such, mathematical models (including the VFR model) are not sufficient by themselves to form a model for the semantic scaffolding model: there is not enough detail in the model to match layouts to practical tasks.

3.5 State of the Art: Visualization Models

There are two key gaps in existing models. First, none of the existing construction process models or structuring models describe the encoding of experience-dependent meaning. Second, there is a discrepancy between task classification and interpretation process models. Task classifications, especially those encompassing practical tasks, include tasks involving multiple data values. Interpretation processes, however, describe the interpretation of a whole visualization, or isolated values. Similarly, layout classification models describe complete layouts, and structuring models decompose layouts into unit elements. Neither type of model describes the multi-value visual features within a layout which correspond to intermediate level questions.

Existing models of visualization provide a rich set of inputs from which to synthesize a semantic scaffolding model. Classification models provide detailed descriptions of data structures (schemas), layouts and questions (tasks). Existing process models provide detailed descriptions of the visualization construction and interpretation processes. In other words, there are common processes involved in the transformation of any dataset into a layout and the interpretation of that layout for a task. Additionally, the specific relationship between characteristics of a layout (its grammatical elements and syntax) to elements of a data structure is captured by structuring models of visualization [17, 18]. The semiotic and mathematical VFR model provides an underlying framework suitable for the semantic scaffolding model, linking together the components of a data schema, layout, and questions in a structure adapted from Peirce's semiotic triangle [93] (see Figure 17). Existing models of visualization comprehension (e.g. [15, 43]) identify a number of top-down and bottom-up mechanisms which influence interpretation, including salience, visualization literacy (‘graphicacy’), priming, externally-directed attention, and domain knowledge.

In spite of the usefulness of existing models, there remains a need for a model which can trace the construction of practical meaning from data to specific features of a visual layout and through the interpretation process. It remains to be shown how specific encoding choices in a visual design can affect higher level visualization interpretation. How is the reader's experience anticipated in visualization design? In particular, there is no structure connecting (practical) interpretation and layout which provides the equivalent of the grammatical models structuring the relationship between layout and data schema. A structuring model is needed which links specific features of a visual form to contextually dependent, reader-specific meaning. Additionally, the structuring models provided by grammar and semiotics need to be translated into different units to describe layouts at the intermediate level.

3.6 Conclusions to Review of Models

The semantic scaffolding problem requires new theory rather than experimental research. A model encompassing three components of visualization – data structures, layouts and tasks – is needed to explain how practical meaning is co-constructed from visual features and the reader’s contextual knowledge. Existing models of visualization provide insights into the three components, and how they are interlinked through the visualization construction and interpretation processes. None of the models reviewed are sufficient on their own as a model of semantic scaffolding. However, the approaches to constructing models provide insights into how the semantic scaffolding problem can be approached. Process and classification models provide complementary descriptions of visualization, but models which are sufficiently detailed are too complex to be interlinked. Structuring models (e.g. semiotic, mathematical and grammatical models) resolve the trade-off between detail and complexity, but none of the existing models focus on structures important to the semantic scaffolding problem.

Based on gaps in existing models, the methodology for this research project has been divided into two parts. Part I explores the role of experience-dependent meaning in visualization construction, while Part II develops a new structuring model of semantic scaffolding focussing on intermediate visual features as the key structuring concept. The details of the methodology for each part are discussed at the beginning of chapters 4 and 6.

Part I

4 Anticipating Experience in Visualization Design

Acquired Codes of Meaning in Data Visualization and Infographics

The first part of this thesis (Part I) addresses a gap in existing models concerning the relationship between experience and meaning in visualization. Existing process models describe the role of experience in *interpretation*, both in terms of domain knowledge and visualization literacy [15]. It remains to be ascertained whether and how experience is anticipated in the design of a visualization. In the transformation of data into a visual layout, the choice of a layout is often expected to be based purely on factors of low-level perceptual performance (the information transmission perspective discussed in Chapter 2). Part I of the thesis asks whether design choice additionally relies on assumptions about the reader's prior knowledge. Do designers use particular visual forms because they expect the reader will be able to interpret those forms more easily and accurately (or find the content more engaging and persuasive) based on their previous experience with the represented domain and reading visualizations in general?

To the extent that experience is anticipated by visualization design, Part I of the thesis additionally explores whether experience-based meaning can be linked to specific visual features below the level of a whole composition (i.e. a whole layout). Compositional models of visualization layouts (e.g. grammars [17, 18]) show how layouts are constructed from common visual components (variables and marks). Existing models capturing the influence of experience on visualization interpretation have focussed on complete layouts – positing that experience allows a reader to recognise and successfully interpret a familiar layout [15]. The sheer number of distinct layouts suggests that visual literacy may echo the compositional nature of visualization layouts. In other words, readers most likely store an understanding ('interpretation schema') of how to read familiar components of a layout (perhaps alongside instructions for common whole layouts), and can piece these partial instructions together to read whole compositions. Some evidence for this hypothesis can be seen in studies which link socially constructed cues about visualization integrity and objectivity to visual components used across different layouts [116]. If it can be established that experience is relied on to encode meaning at the level of visual components rather than whole layouts, it provides further evidence for the component literacy view.

The material for the chapters in Part I are taken from papers published during the course of my candidature, which have been adapted slightly for the thesis:

- **This chapter:** Byrne, L., Angus, D., & Wiles, J. (2016). Acquired Codes of Meaning in Data Visualization and Infographics: Beyond Perceptual Primitives. *IEEE Transactions on Visualization and Computer Graphics*, *22*(1), 509-518.
- **Chapter 5:** Byrne, L., Angus, D., & Wiles, J. (2017). Figurative frames: A Critical Vocabulary for Images in information visualization. *Information Visualization*, 1473871617724212.

The papers are 80% my own work, and 10% each the work of my co-authors. My contribution to the papers included conceptualization, design of the code book (for Chapter 4), coding the data (Chapter 4), data analysis, writing and visualization design (Chapter 5). My co-authors contributed to the conceptual development, data coding (Chapter 4) and writing. The chapters differ from the papers in the language used to describe semantic scaffolding, which was developed later in the candidature, and the description of the overall methodology for Part I of the thesis.

4.1 Part I Methodology (Chapters 4 and 5)

The questions addressed in Part I are approached from a semiotics perspective. In the semiotic systems of natural language and the visual arts, signs (representations) draw on shared experience in multiple ways [15]. *Iconic* signs (which resemble the object they represent) are recognised through the listener and readers' prior exposure to the represented object. The *symbolic* meaning of representations, on the other hand, is determined and maintained by social convention and ongoing usage. The meaning of a word is learnt based on how it has previously been used, and reinforced when learners use the word to convey the same sense as their prior experience [19]. Speakers use words anticipating that their listeners – having shared knowledge of the same sign system – will understand the word's meaning. While information visualization is described as a semiotic system [17, 18], the meaning of visual variables is assumed to be 'free' and able to be reassigned to a new dataset for any new representation. Part I explores the extent to which the encoding of meaning in information visualization can be understood as a sign system not only in terms of the relationship between object, representation and interpretation, but also in terms of its reliance on the shared experience of a community of users who construct and maintain the sign system.

The anticipation of visualization experience in the design of visualization speaks to visualization practice. Thus, the first study documented in Part I uses content analysis to examine 50 exemplars of two categories of information visualization: infographics and data visualizations. The study looked for evidence of shared 'semiotic resources' – interpretations which are based on social, cultural or experiential cues common to the designer and reader. Content analysis was used examine the use of iconic ('figurative') representation and conventional symbolic representation in both categories of information visualization, identifying the presence of both types of experience-based meaning. Moreover, the study found evidence that infographics and data visualization reflect distinct communities of practice, supporting the shared semiotic system perspective. The implications of experience-based encoding on models of visualization construction are different depending on whether the representation is figurative (i.e. iconic) or abstract (i.e. symbolic). The use of experience in symbolic representation can be incorporated as an additional consideration for existing models. Information-conveying iconic representation, however, require an additional model to encompass the data, construction and layouts involved in figurative elements within an information visualization.

The second study within Part I of the thesis develops a conceptual model which captures the information content of figurative representations (the iconic signs of the information visualization system) within information visualizations and classifies the associated layout types. The concept of a *figurative frame* is constructed through an extension of concepts from geospatial visualization to explain how descriptive information is integrated within the overall content of an image-containing information visualization composition. The figurative frame conceptual model bridges a gap in existing models of visualization construction (from schema to layouts), capturing a more extensive range of 'data' types (i.e. information) represented through information visualization layouts. Analysis of the information content of figurative elements reveals how information visualization, as a sign system, smoothly blends together representations which rely on different levels and types of reader experience. It shows that experience can be engaged (i.e. required for successful interpretation) differently for different components of a visualization.

4.2 Introduction

It is well established that the interpretation of visual representation is affected by learned codes (i.e. experience) as well as innate perceptual mechanisms [36]. Many authors, both within information visualization [1, 149], and in related fields such as visual literacy [150, 151] and psychology [61, 152, 153], identify the existence of acquired codes of meaning in the interpretation of visualization. However, the contribution of experience to semantic scaffolding is not clear, particularly as a vehicle for encoding information.

The acknowledgement of the role of experience in interpretation is accompanied by a reluctance to include it in models of information visualization construction or suitability measures and 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 colour (symbols), which is based on acquired habits or learned conventions and can never claim to be universal”* ([17] p. 7). Standard grammars and taxonomies of visualization take their cues from Bertin, and either limit their scope to graphics [18], or embed information visualization within the realm of data graphics, excluding conventional meaning [4, 94]. Where imagery is included in information visualization, the emphasis is on machine generated images such as medical scans or geometric models, not familiar shapes [92]. 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 [108]. As seen in the literature review (chapter 2), existing visualization research to improve suitability has mainly focused on leveraging the current understanding of the human perceptual system [154].

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 [117, 155-157]. Researchers have also explored the boundary between art and information visualization [21, 22], drawing inspiration for information visualization designs [158] or analysing how abstract shapes and motion create affective responses [158-160].

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 [49], while a larger study found that pictorial elements in visualizations significantly increased their memorability [53]. The style of a visualization has been shown to change the type and perceived depth of insights users generate [161]. 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 [91]. Other research has explored the links between verbal metaphor and corresponding metaphors in information visualization in order to explain different accounts of user performance [46, 47]. Missing from the literature is an analysis determining how acquired meaning is anticipated in visualization 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 example is the use of a line graph to represent time series [64] 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 nature of the information visualization sign system. 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 [43], visual literacy [150] and memorability [49, 53] 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. Content analysis is applied here 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 [162]. 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 chapter 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 4.3). The key results focus on two areas: figurative visualization, and conventions around the depiction of time (Section 4.4). The results of the content analysis are used together with existing literature to distil a number of candidate guidelines for incorporating acquired meaning into design (Section 4.5), and set out an agenda for integrating acquired meaning into visualization practice and research (Section 4.6).

4.3 Content Analysis

Content analysis is used here 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*" [163], p.42. Krippendorff [164] provides an operational definition of content analysis by posing six questions that any such analysis should address:

- What data is analysed?
- How is the data defined?
- What is the population from which the data is drawn?
- What is the context relative to which the data is analysed?
- What are the boundaries (limitations) of the analysis?
- 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 [165]. 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 [166] 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 [167]. Content analysis approaches have previously been used in information visualization, for example to examine the use of rhetoric [1] and narrative [168]. 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.

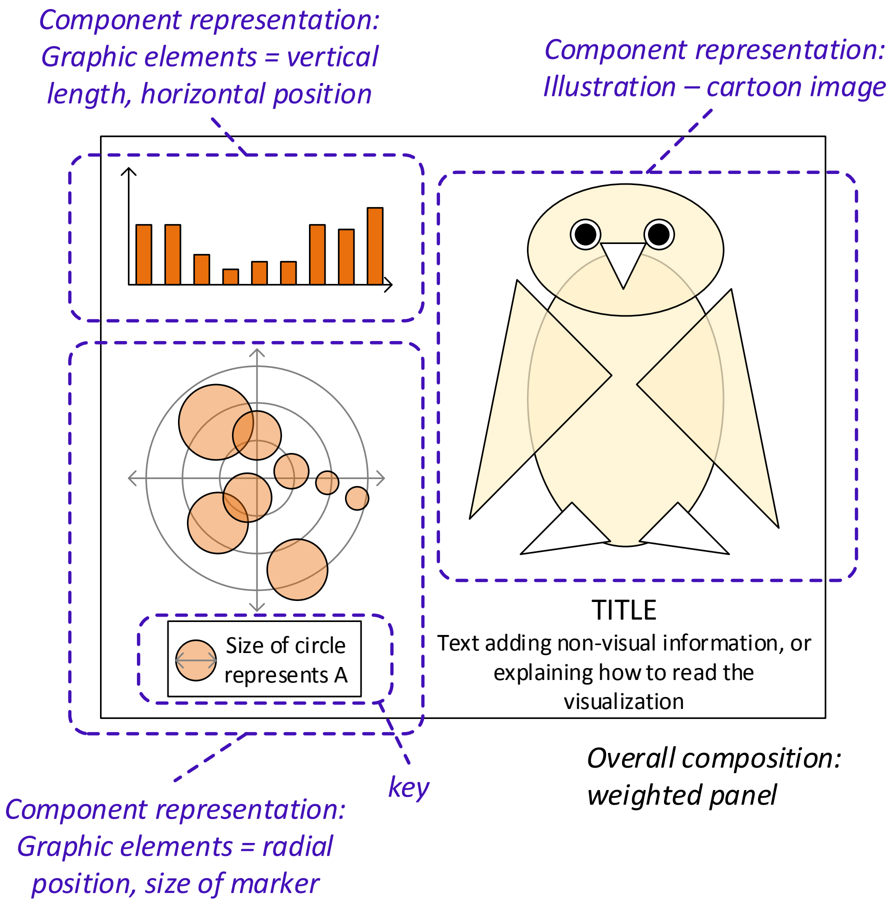

Figure 18: An illustrated guide showing how visualizations were decomposed for coding. A visualization is comprised of one or more self-contained component representations, classified as 'graphic', 'figurative' or both (hybrid). This visualization is a 'weighted panel' composition – it has three components, one of which is larger. (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.

4.3.1 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 [169]. 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 [169].

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 [169]. 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 [92], 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 [170]).

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 visualizations are closer to meeting the criteria that information visualizations are bijective mappings "composed of discrete and disjoint visual symbols" [94]. They do not fit the suggestion that data visualization is sometimes used to mean scientific visualization [94]. In contrast to several definitions of data visualization in the literature [4, 94], 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" [162]. Visualizations published in newspapers and magazines (the traditional outlet of the infographic [94, 162]) 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[5]. Visualizations were judged according to four criteria: appropriateness, originality, beauty, and whether they achieved their objectives [169]. 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

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

aspect of the visual arrangement is shared across visualizations, it suggests that a common visual language is being invoked.

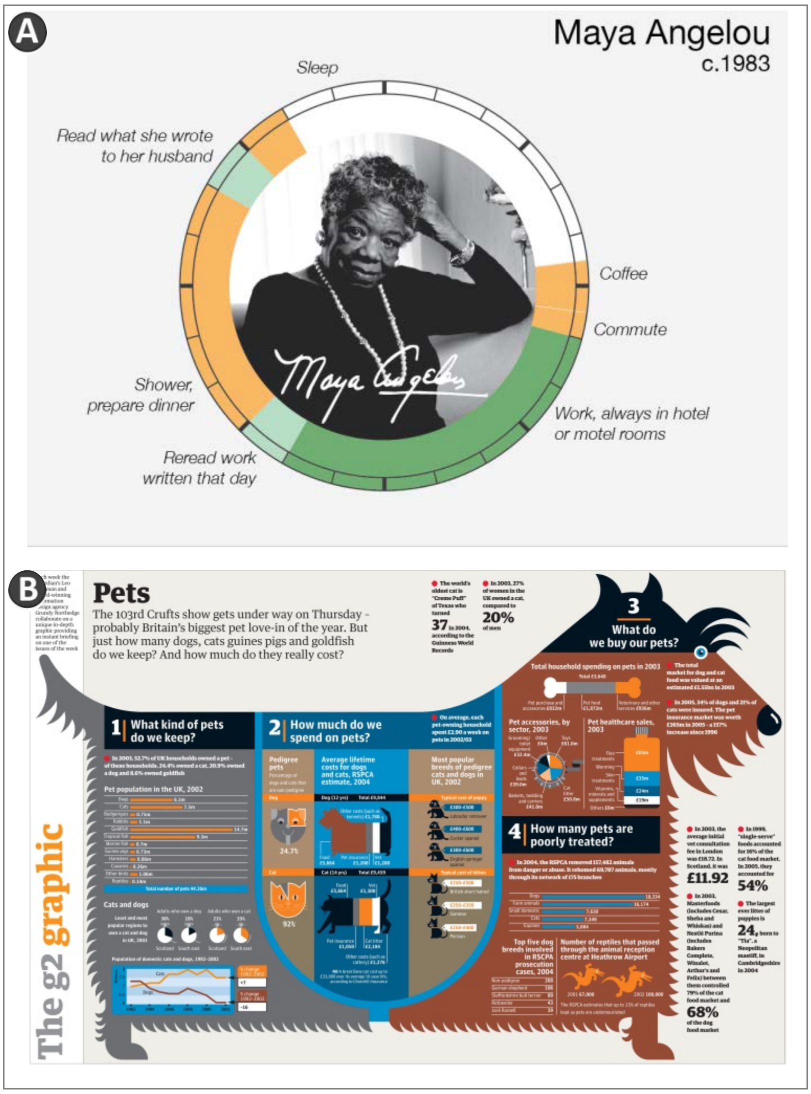

Figure 19: Hybrid representations. Figurative and graphic elements can be closely linked in a visualization. (A) A component of the visualization ‘Creative Routines’ [171], showing a graphic containing an illustration. (B) ‘Pets’ [172] showing graphics positioned within a figurative element. Reproduced 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.

4.3.2 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 needs to encompass and accommodate the arrangement of common elements into different designs. It also needs to 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.

4.3.2.1 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 [88].

Here we define a component representation as a portion of the visualization which can be repositioned without significantly affecting its meaning. A component representation is a 'panel' in the containing representation (see Figure 18).

At the top level of the composition is the whole visualization – the image in the KIIBA14 dataset. The dataset analysed 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 (or abstract) representation***: a representation where relationships within a dataset are revealed by mapping categorical, ordinal or quantitative data to visual variables.
- ***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 [17].

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 19). Hybrid representations or hybrid visual elements are counted as both graphic and figurative.

The first stage of coding considered the high level composition[6] 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;
- 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.

4.3.2.2 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[7] 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. [17]). In addition to being classified according to its figurative role, the presence of a map was

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[6] 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.

[7] Illustrations is used here to include imagery such as photographs.

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 colour 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. Colour meaning was chosen since it is frequently named in the literature [173, 174], 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 colour meaning when the colour 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 colour meaning.

4.3.3 Recognizing Acquired Meaning

The coded data was analysed 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 analysed 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.

4.4 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.

4.4.1 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 71% 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 20).

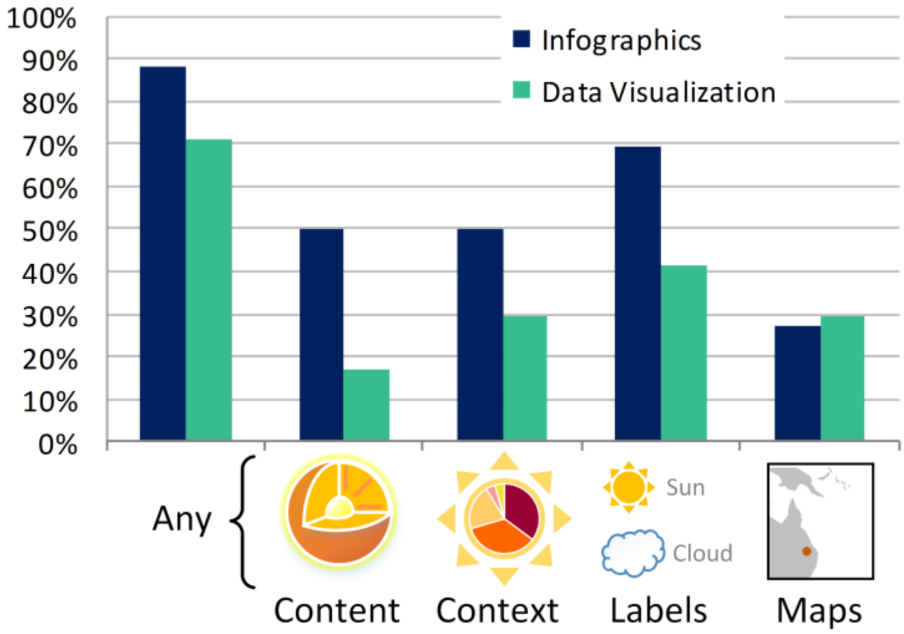


Figure 20: The percentages of infographics and data visualizations which contain different types of figurative elements. More infographics contain figurative elements across all three roles (content, context and labels), but this pattern does not hold for maps. The 'any' bars on the left do not equal the sum of the other bars, since visualizations may contain multiple figurative elements playing different roles, and maps additionally play one of figurative roles.

4.4.1.1 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 [17], with an illustration providing context to allow the reader to mentally place any geospatial graphical elements (see Figure 21(A) 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' [175] includes figurative elements, despite first appearances, since shape files of Manhattan buildings are used to define the shape of each point (see Figure 21(C)). The dataset contains only a single example of geospatial data *not* overlaid on a figurative map element [176].

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

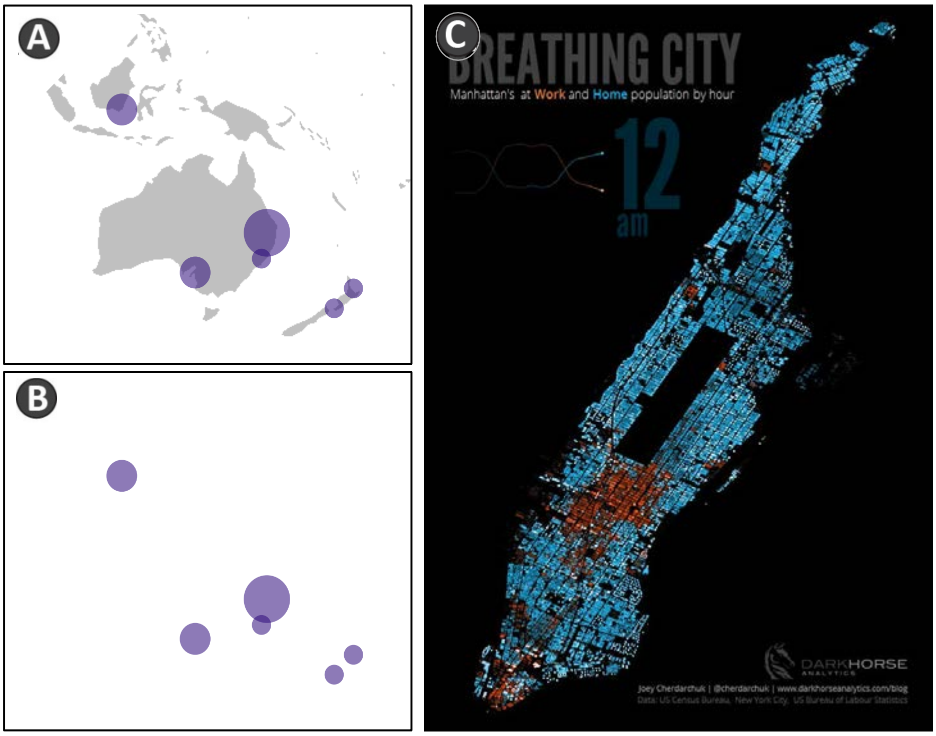


Figure 21: Recognizing the figurative aspects of a geospatial representation. (A) A map, and (B) not a map, show the same (made up) geospatial data with and without a figurative background. In (C), 'Breathing City' [175] provides an example of a map which is also a content bearing figure, since the shape 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.

'Breathing city' (Figure 21(C)) 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 22). The same component visualization includes maps as icons (labels), with country shapes used as location markers whose size indicates the quantity of aid received.

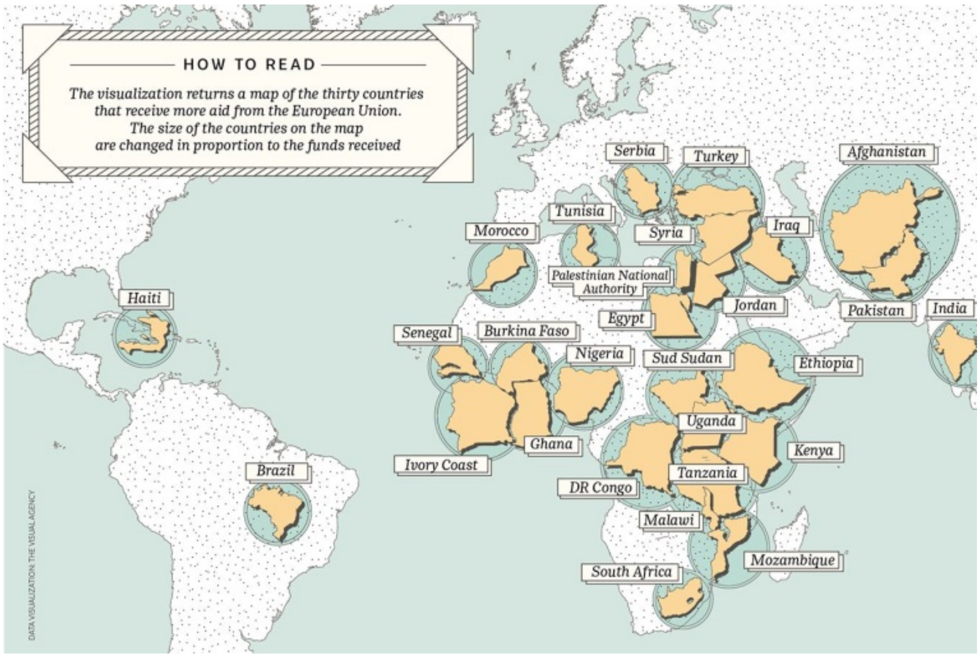


Figure 22: Maps in a context and labelling role. A segment from 'European Union Humanitarian Aid' [177] shows how maps can fit into multiple places in our proposed classification of figurative visualization roles. In the visualization, the map is used as an image the audience is meant to recognize, providing 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.

4.4.1.2 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 favoured 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.

4.4.1.3 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 [170] and human [178]) and inorganic objects (race car [179]) 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 ([180], [170] and [178]).
- ***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 [170], and skin tissue in a rectangular prism [178].

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 [179, 181] 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. [178], [170], [180]).

4.4.2 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 23). Six layouts were used more than once (see Figure 24).

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.

4.4.2.1 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).

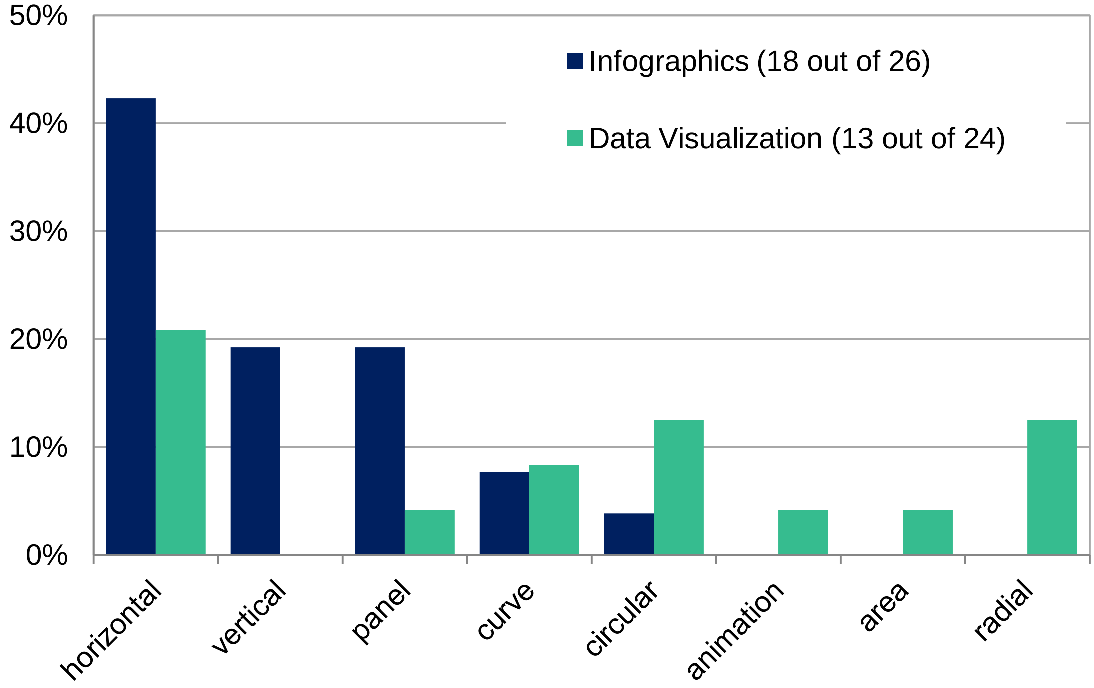


Figure 23: Layouts of time in infographics and data visualization. The height of each bar shows the percentage of 'time-containing' visualizations which include at least one instance of a particular layout. Of these subsets, linear (horizontal and vertical) layouts were the most frequently used.

4.4.2.2 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" [179] is shown in Figure 25. 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.

4.4.2.3 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.

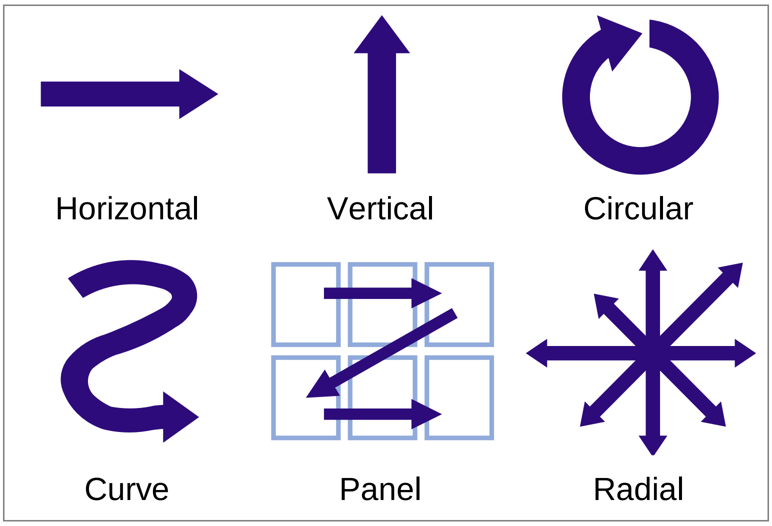


Figure 24: Arrangements of visual elements used to represent time more than once in the sample set.

4.4.3 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).

Literature discussing conventional codes often mention colour meaning (see for example [173]). Colour meaning was present but not prevalent in the data, identified in 12% of infographics and 8% of data visualizations. Colour 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.

4.5 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 [17] can be seen in the privileging of maps compared to other figurative elements in the data visualization category. The map of Manhattan in Figure 21 is analogous to the formula 1 car in Figure 25 – 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 Figure 23). In addition, infographics used icons as area markers far more than data visualization (5 instances in infographics compared to a single instance in the data visualization group), suggesting greater comfort in blurring the lines between figurative and graphic representations in infographics.

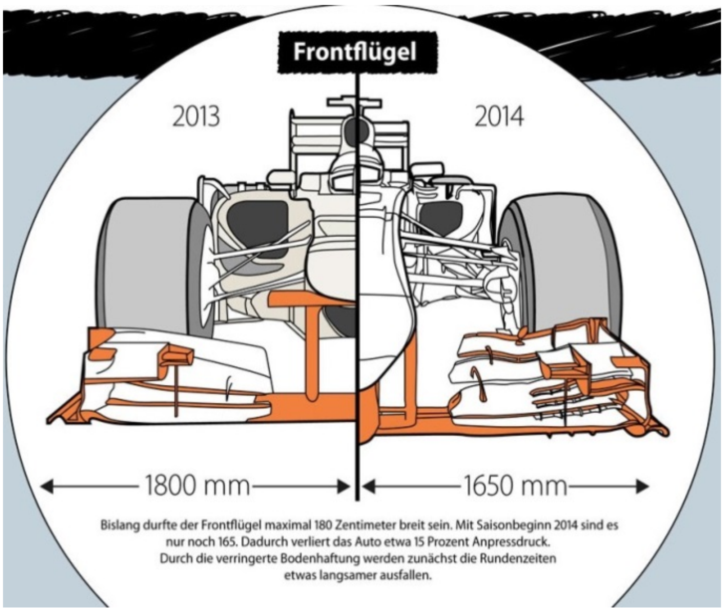


Figure 25: A panel arrangement representing time [179]. Panel representation of time is typical where the object changing over time is being represented figuratively. Reproduced with permission.

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.

The following section interprets the results of the content analysis in the context of existing literature, proposing a number of guidelines 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.

4.5.1 The Use of 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 colouring, magnification, and cut away. Based on these observations, the following guideline is proposed. **Guideline 1:** *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 (Figure 19(B)). 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 [49, 53, 182, 183]. In a labelling function, icons share the strengths of context images, but allow the abstract patterns of data to dominate the visual scene. **Guideline 2:** *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 (Guideline 1 and Guideline 2) also apply to maps. In particular, designers using maps as context or icons in the style of Figure 22 should provide enough detail to be confident that their audience will recognize the location from the information provided (see Guideline 2). 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 Guideline 1 outlined above. To apply the visualization technique of Breathing City (Figure 21) to a less recognizable city like the authors' home town of Brisbane, for instance, Guideline 1 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. **Guideline 3:** *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."* [184] *P. 165*

Regardless of the cause, using a realistic style for context appears to be another convention. **Guideline 4:** *Use a more realistic style for context than for content elements, if using figurative elements in both roles.*

4.5.2 Graphic Conventions

Analysing 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 [43] 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 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. **Guideline 5:** *Use conventions to create representations which are easy to read.*

4.5.2.1 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' [185] 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' [186] 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 analysed dataset. The distribution of representations of time (see Figure 23) 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. **Guideline 6:** *Conventions are tools, not rules – balance the ease of reading provided by conventions against other design considerations.*

4.5.2.2 Sources of Conventions

Traditional data classification models used in information visualization are based on the categorization of data into qualitative, ordinal, and quantitative types (see Section 3.4.1.2). 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. [187, 188]). 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 [64]. 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 [189, 190]. 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 [162].

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.

Guideline 7: *Discover and use the conventions within the target user community and subject domain.*

4.6 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.

4.6.1 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 4.5.2.1). 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 representation for comparing quantities, despite that fact that area judgements rank poorly in perceptual studies [27]. 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 4.5.2.1. 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 [17]. Learning about the visualization practice of the target audience (Guideline 7) 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.

4.6.2 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 chapter 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 [1]). Extensions of content analysis methods should be developed for use in analysing 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.

4.7 Conclusions to Chapter 4

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.

5 Figurative Frames

A Critical Vocabulary for Images in Information Visualization

The study of the KIIBA14 dataset (previous chapter) found that figurative elements are widely used in information visualization in practice. Although such elements are increasingly recognised as beneficial for memorability, the information encoded by a figurative image and how that information contributes to the overall content of the visualization lacks robust definition within visualization theory. The critical vocabulary for ‘hybrid’ information visualizations – which combine abstract representation of data with figurative elements such as illustrations – is underdeveloped. To support critical analysis of hybrid visualization, this chapter provides a model of the information content of a figurative image, which is termed the *figurative frame model*. The model is used to classify hybrid visualizations along two dimensions: information density in the images (defined as the number of features and preserved measurements) and integration of figurative and abstract forms of representation. The new vocabulary for analysing hybrid visualizations reveals how the figurative images expand the expressiveness of information visualization by integrating descriptive and abstract information, and allows the formulation of new measures of visualization quality which can be applied to hybrid visualizations.

Recent findings within information visualization present a challenge to the continued study of abstract visualization in isolation. Previously, taxonomies and assessments of suitability in information visualization covered only abstract representation excluding figurative elements, based on the principle that the ideal information visualization maximises the data-to-ink ratio (e.g. [33, 48, 63]). However, multiple recent experiments have shown that figurative images do not consistently impact performance [49, 50], and under the right circumstances can enhance memorability and engagement [49-53], presenting a challenge to some commonly held views of what constitutes ‘good visualization’. A more nuanced view of information visualization quality highlights the need for a vocabulary for hybrid visualization.

The enhancement of memorability and engagement provided by figurative images has been embraced by proponents of communicative and storytelling information visualization. These proponents recognise that visualizations are often designed with a primary aim of communication, rather than solely as an analysis tool [34, 191-193]. The practice and processes for including images as part of communicative information visualization has been explored from a number of different angles. Figurative images have been identified as a common component of both infographics and data visualizations for general public audiences (previous chapter) and are a key aspect of narrative visualization [1, 168, 194]. Particular attention has been given to so-called ‘embellished’ visualizations which use recognizable images instead of abstract shapes as data-encoding marks (e.g. pencils instead of bars in a bar chart, or animal shapes instead of points in a scatterplot) [33, 49-53, 195-197]. To this end, a toolkit has been developed to adjust the length or area of images to reflect data values, easing the construction of accurate embellished visualizations [198].

Less frequently considered is the information conveyed by figurative elements as part of an information visualization composition. Even within storytelling information visualization, images are often treated as ‘decorative’ additions to a visualization, whose merit is debated in terms of how their presence affects perception and comprehension of non-decorative ‘content’ (e.g. [49-51, 195]). However, including images within information visualization offers the potential to increase the overall amount and type of information which is communicated, not just to enhance abstract information. Within cartography, map images are recognized as a source of ‘configurational’ knowledge – knowledge of topological or geometric relations between objects [199]. Outside of geospatial information, there have been formal efforts within the information visualization community to convey both qualitative and quantitative information using figurative images. Early efforts include Otto Neurath’s isotype picture language which formalised a technique involving repeated pictograms to convey quantity of a qualitatively described concept [200]. More recently, the use of images to convey unfamiliar quantities has been codified in techniques for concrete scales (e.g. depicting how many sugar cubes are equivalent to the amount of sugar in an orange) [201]. Reference images of the human body have also been used to elicit information on medical symptoms [202]. Common strategies can be recognised across these techniques, and suggest the possibility of a more general vocabulary for content-rich images within information visualization.

Combinations of abstract and figurative visual representation in fields including art, graphic design, and public health have been the subject of research outside the field of information visualization [203-205]. The relationship between representational form and meaning can be understood through the theory of semiotics. Semiotics distinguishes between *symbolic* representations ('signs'), where the correspondence between the visual form and the meaning is arbitrary, and *iconic* representations where the meaning of the representation is based on intrinsic similarity between the representation and the object [206]. Abstract data visualization is a form of symbolic meaning, since marks and visual variables (e.g. position and colour) can be assigned any number of meanings. Recognisable images can be assigned (or take on) symbolic meaning (e.g. using a star shaped glyph to represent a car manufacturer), but they additionally convey iconic meaning (i.e. describe the depicted object). Figurative visualization corresponds to the use of recognisable images as iconic representations; that is, as a means of describing an object by producing its visual likeness. Figurative images are parsed far more quickly than abstract visualization [110, 207], provided the resemblance is recognisable. Iconic meaning also requires lower levels of visual literacy; children reading maps will sometimes confuse abstract marks such as red lines representing major roads as literal objects (red roads) – they understand the figurative correspondence of the map to geography before the abstract representation [15].

The impact (or lack of impact) of figurative images on comprehension speed and accuracy has received less attention than memorability and engagement, but has far reaching potential consequences. In experiments on images in information visualization, including images as part of a composition has not demonstrated a uniform detriment. Background images (but not images as marks) decreased performance in one study [69], and in another study embellishments did in some (but not all) cases slightly slow visual search [51]. However, in most cases images have made no difference to response time or accuracy compared to equivalent abstract visualizations [49, 50]. The absence of a clear rule 'images mean lower accuracy' complicates visualization suitability recommendations. Faced with the question 'what kind of visual representation should be used?' it is not clear when or why hybrid visualizations should be excluded. Whether the aim is to capture, communicate or analyse information through visual representation, designers and clients want the best possible representation for their aim, not the best visualization from an arbitrary selection of options. A vocabulary for describing hybrid visualizations is needed to distinguish between images which contain more or less information, and visualizations which combine descriptive and abstract information to different overall communicative effect. Such a vocabulary would provide a key component for a broader and more inclusive perspective on the visualization design space and visualization suitability.

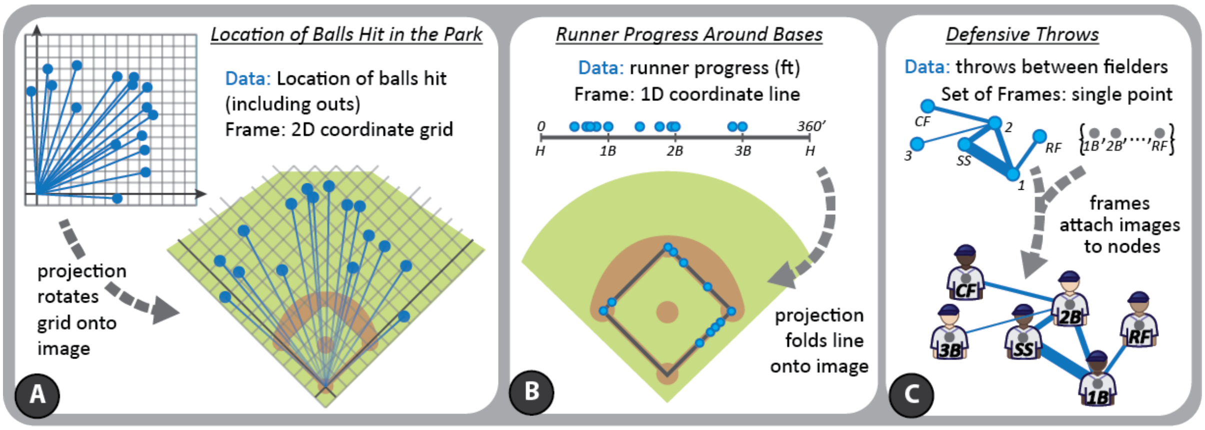


Figure 26: A figurative 'frame' is a data structure which underpins an image, and shows how data is integrated with recognizable descriptive information in images. Examples of baseball visualizations (artificial data) show how different frames provide a figurative context for different datasets. (A) A 2D coordinate grid frame shows the location of balls hit in the park; (B) a 1D coordinate line frame shows runner progress around the bases; (C) a set of single point frames shows defensive throws between fielders. Left visualization based on [208].

We introduce the concept of a figurative visualization 'frame' – a model of the information conveyed by a figurative image. The 'figurative frame' (shortened to 'frame' where convenient) captures the identity, key parts or features of the represented object or scene, as well as geometric information such as height or relative size of the component parts, which the reader is able to retrieve from a figurative image. Frames can range in feature density from a single element (where the reader is expected at least to be able to recognize the object e.g. the players in Figure 26(C)) to a coordinate grid akin to geospatial coordinates (the reader is expected to make quantitative assessments of distances between points on the image, e.g. Figure 26(A-B)). Visualizations with denser frames convey more descriptive information, while simpler frames convey more abstract relationships. The relationship between the frame and the abstract data visualization mapping captures the integration of configurational (descriptive) and propositional (abstract) information within a visualization. The extent to which abstract information is used as an anchor or to transform the frame determines the level of integration between the figurative and abstract representation in a hybrid visualization. More integrated visualizations convey more direct or explicit relationships between descriptive and abstract information.

In the current chapter, we present a set of concepts and associated vocabulary to critically analyse hybrid visualizations, taking into account existing information visualization models. A range of examples are used to explore the differences between abstract information visualization and figurative visualization, with particular attention to the communicative strengths and potential comprehension problems for each representation type. The concept of the ‘figurative frame’ is formally defined, drawing on established theory in cartography, a field which has grappled extensively with the challenge of combining descriptive and abstract information. Drawing on cartography and the survey of figurative images from the previous chapter, commonly used hybrid visualization techniques can be identified and positioned within an overall design space. Visual examples throughout the chapter are based on existing hybrid visualizations from sources that include scientific research papers, sports analytics and news media. These visualizations are adapted to provide straightforward examples, along with contrasting designs to allow comparison between minimally different alternative hybrid designs. Measures of hybrid visualization quality are identified from the figurative frame model and the known strengths and weaknesses of the different representation types. A detailed case-study shows how the different quality measures apply to alternative hybrid designs for different visualization aims. With these measures, the *figurative frame model* provides a high-level heuristic tool for creating and using hybrid visualizations. The discussion section outlines directions for future work to construct a stronger and more detailed heuristic design tool.

5.1 Data and figurative visualization

In order to discuss hybrid visualization it is necessary to have separate terms to describe visualizations with and without figurative elements, and an understanding of each type of representation on its own. Information visualization has been defined in a way that excludes figurative elements [4, 17, 18, 94], and describes figurative elements within a visualization as extraneous additions or even ‘junk’ (e.g. [48-50]). However, we argue that the term ‘embellished information visualization’ is insufficient to describe the full range of information visualizations containing figurative elements. To avoid confusion we use the terms ‘data visualization’ or ‘abstract representation’ (used interchangeably) to refer to visualizations or the components of a visualization without figurative elements (following [4]). Information visualization will be used to reference visualizations which contain data visualization components, but may additionally include figurative elements. Using this definition, a data visualization is also an information visualization, however the converse does not necessarily hold. Whether or not an information visualization contains figurative elements, its primary purpose is to capture, communicate or analyse information (i.e. to retrievably encode information) – distinguishing it from other visual forms such as art which aim primarily to evoke an aesthetic response [21].

5.1.1 Figurative visualization

An image or element of a visualization is figurative when the shape of the representation is recognizably similar to the shape of the represented object. Interpreting a figurative visualization requires the reader to recognize the depicted shape using prior knowledge. Figurative visualizations are open to misinterpretation, but also lend themselves to more natural interpretations. When describing simple line drawings, readers are more likely to see physical objects, providing a metaphorical description for an image only when they cannot think of a matching physical object [207]. Furthermore, recognition of objects in an image is faster and more intuitive than interpreting an abstract visualization [110, 207].

Figurative elements are included within information visualization for two main reasons: to enhance the comprehension of or engagement with the information encoded through data visualization, or because the information is inherently visual and cannot be communicated through abstract visualization techniques alone.

Figurative elements have been empirically shown to enhance a reader's ability to remember abstractly encoded information [49-53]. More specifically, the memorability effect appears to apply to the information involved in a dual figurative-abstract encoding [69]. Different figurative variations on a bar chart were compared: pictographs (bars made up of icons where each icon represents a fixed quantity of the represented object), figuratively shaped bars whose height was stretched to the quantitative value, charts with figurative labels on the axis, and charts with a figurative background (similar to Figure 27(B)). Values of abstract attributes were better remembered (in the very short term) when they were encoded as part of an element which also had a figurative attribute (pictographs and stretched figurative bars), than when a figurative element appeared in the background of the visualization [69]. A plausible explanation is that the level at which figurative images are placed in the visualization focuses the reader's attention and retention of the associated level of information – topic for background images, values for elements, and explanations for integrated visualization.

The second argument in favour of figurative elements relates to their expressiveness. The resemblance between the representation shape and the object shape allows the visualization to describe the geometry, topology or aesthetics of the object. However, figurative visualization relies on the reader's recognition of correspondence between an object and its representation, and so is susceptible to misinterpretation [17]. A reader may be unfamiliar with the object, and so fail to recognize its representation. Furthermore, two people can look at the same line drawing and recognize it as a representation of two different objects and each express certainty about their perceptions [207]. Additional ambiguity arises in the recognition of concepts [209] rather than specific instances of objects. A drawing of ‘a bird’ inevitably must have a shape that is closer to one species than another. To understand the representation, the reader must not only recognize the shape, but also infer the level of abstraction. A reader may recognize the shape but read the representation as a specific type of bird (e.g. an eagle) rather than the abstract concept. Similarly, a reader may infer an abstract concept when a specific instance is intended.

There are inherent limits in what can be represented figuratively. By definition, figurative visualizations show the shape of the object they represent – there is a fundamental correspondence between the drawn shape and the object shape. Hence, to be represented figuratively, an object must have some characteristic shape, or be depicted using a recognisable shape, which includes abstract, socially constructed or imagined objects, such as a low pressure front, country border and airspace no fly zone. Similarly, a concept design for an imagined object can be figuratively represented, even if it is unrealistic, such as a hoverboard, jetpack or unicorn. Figurative elements may be created any number of ways, including hand drawn on paper or screen, vector based, 3D modelling, photography or other imaging.

5.1.2 Data visualization

A data visualization is a set of visual marks (points, glyphs, lines, or areas) whose attributes (position, size, shape, colour, etc.) are determined by (mapped from) data values [18]. To interpret a data visualization the reader needs to read the key or axes to determine the meaning of visual attributes, which may be completely unrelated to prior meaning of that attribute in the reader’s experience.

Data visualization has a limited range of expression, as it can only be used to show relationships between data values or categories [17], however, it also has distinct advantages compared to figurative visualization. Data visualization can represent abstract properties, and can be used to place relevant variables in the same frame of reference [4]. Salient and accurate perceptual variables (e.g. position, length) can be used to prioritize information important to the problem at hand [44]. Additionally, since attributes of visual marks set through an abstract mapping depend entirely on data values, their relationships can be compared in isolation from other extraneous information [33].

Data visualizations are easy to create and replicate across diverse datasets. Techniques for data visualization have been developed and documented in surveys [97-101, 106] and grammars [17, 18], providing resources for the reuse and redesign of visualizations.

While less ambiguous than figurative visualizations, data visualization can also be misinterpreted. Through axes and keys, a data visualization explicitly describes the information encoded in the visualization, in contrast to figurative visualization. However, readers can misinterpret or fail to understand an unfamiliar data visualization because they fail to correctly identify the visualization mapping, for example not understanding what lines connecting points represent, or whether attributes such as colour are meaningful [41]. A survey of visitors to science museums found low levels of key visual literacy measures including interpretation of 'simple' data visualizations such as network representations [45]. When readers lack the visualization literacy required to confidently interpret a data visualization, they may misread a visualization to match their pre-existing beliefs – for example reporting that the visualization shows a trend opposite to the actual depicted trend [12]. By avoiding representational ambiguity at all costs, data visualizations risk misunderstandings due to the reader not being able to keep track of or correctly interpret abstract mappings.

5.1.3 Data 'metaphors'

While there is little evidence that including images in an information visualization negatively affects the comprehension of abstract information, there is also no reason to think that recognisable images should be used to communicate abstract information. Chernoff faces, which are data visualizations designed to look like a human face, aim to take advantage of human perceptual sensitivity to viewing faces, but are slower and more error prone to interpret compared to other data visualizations [86]. The strengths and weaknesses of figurative visualizations depend on the two defining characteristics of recognition and resemblance. A Chernoff face has a recognisable shape, but the shape has no resemblance to the object it is representing (abstract data), and so is a data visualization, not a hybrid visualization [84].

5.1.4 Hybrid visualization examples

A hybrid visualization combines abstract and figurative representation; aspects of the visualization have an interpretation based on resemblance, or on an abstract encoding, or both. A survey of data visualizations and infographics showed that images can be used in three roles: as backgrounds for abstract data, icons to label data, or as content (images whose primary purpose was to describe the shape or composition of an object) [24]. The following example considers the potential impact of the three image roles on the information communicated by a hybrid visualization.

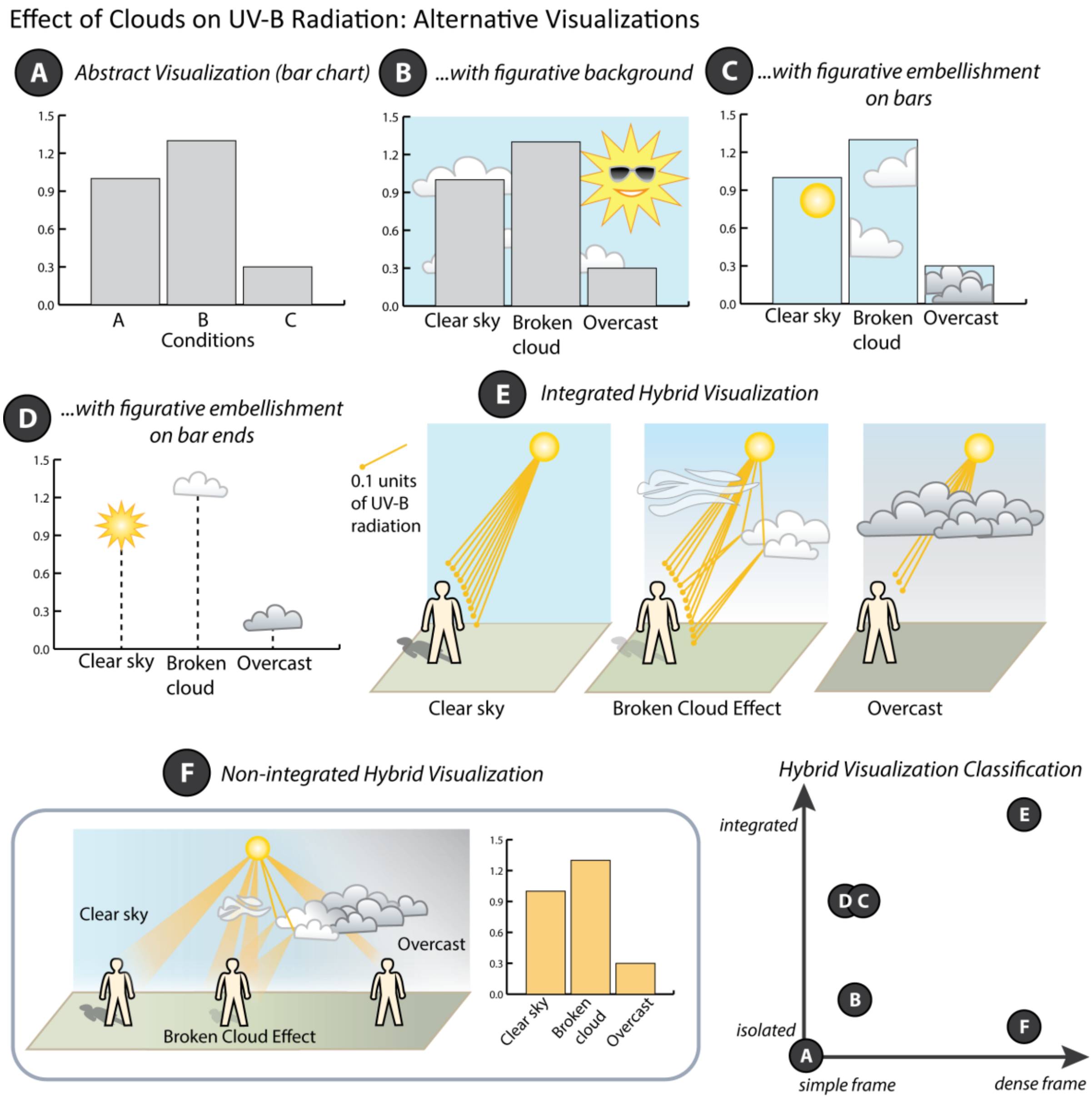


Figure 27: Alternative hybrid visualizations of the same dataset showing UV-B radiation under different cloud conditions;data source: [210]. (A) A purely abstract representation (bar chart) of the data. (B) A hybrid visualization using the same abstract representation technique as (A), but with a figurative background. (C) Figurative images on each bar describe the cloud conditions. (D) Figurative images describing the cloud conditions are attached to bar ends. (E) Each panel shows the different cloud conditions, with the number of rays reaching the person conveying relative UV-B radiation. (F) A figurative panel describes the cloud conditions, with the quantitative information conveyed by an adjacent bar chart. Bottom right: high-level design space classifying the different hybrid visualizations according to their integration and information density (see later sections).

A range of different information visualizations can be used to explain the effect of cloud cover on the amount of Ultra Violet-B (UV-B) radiation reaching a person and their consequent sunburn risk [210] (see Figure 27). For example, a bar chart (Figure 27(A)) shows the radiation dose for each condition through the abstract height attribute of bars. The data visualization can show how UV-B quantities vary as cloud conditions change, but does not explain what each condition involves. Instead, the visualization assumes the reader has a pre-existing understanding of the conditions (and the concept of UV-B radiation) which can be evoked by the axis labels. Adding a background image to the chart area (e.g. Figure 27(B)) can describe the overall topic (outside, sunshine), but does not differentiate between the different conditions. When the figurative images are used as labels for specific abstract elements (Figure 27(C, D)), however, the visualization provides a visual description of each cloud condition in addition to the comparison of their relative UV-B radiation values. The figurative bar fill in Figure 27(C) and figurative icons at the end of each bar in Figure 27(D) are independent of the abstractly meaningful bar height. Both the previous uses of figurative images at the global (27(B)) or element level (27(C, D)) can be described as 'embellished' data visualization, since without the figurative meanings the visualization is still a complete data visualization. The abstract and figurative interpretations can take place without reference to each other. At the most extreme end of separation between figurative and abstract representation, diagrams and data visualization can be used as separate visualization views (Figure 27(F)), with one view describing the different cloud conditions, and another comparing the associated quantitative UV-B values. In contrast, the figurative and abstract interpretations can be interconnected (Figure 27(E)). Here, the visualization uses an abstract ordered horizontal axis to set out the cloud conditions at different positions on the page, but each condition is depicted figuratively. The position attribute of line elements in the visualization have dual meaning. The lines have a figurative interpretation as rays from the sun which interact with clouds, but also have an abstract meaning as one-tenth of a unit of UV-B radiation received by the human recipient. The interconnected visualization shows a causal explanation for why the UV-B values arise *as a result of* the cloud conditions which is missing from the unconnected version.

Existing approaches to data visualization suitability provide a lens to evaluate each of the hybrid visualization examples as a vehicle for comparing UV-B values. The perceptual judgements (height, position or stack length) used for quantitative comparison can be identified in each case and compared in terms of accuracy [44].

Missing from existing theory is a means of evaluating the success of the images in providing descriptive information and connecting description and quantitative information. The UV-B examples suggest that hybrid visualizations can vary in terms of level of description detail provided by figurative images and in their ability to *explain* the connection between descriptive and quantitative information, or merely establish an association. The shift from background to content images (Figure 27(B) vs. 27(F)) provides increasingly detailed description, while the switch from background images to images-as-labels (Figure 27(B) vs. 27(C)) changes the relationship between the two types of information conveyed in a hybrid visualization, a difference echoed in the comparison between the most connected and most separate examples (Figure 27(E) vs. 27(F)).

5.1.5 Geospatial visualization

One domain which has established theory and practice for using hybrid visualization is geospatial visualization. Figurative images are used in the form of map images which provide a geographic and topographic description of space, and also as map icons showing the locations of landmarks or other objects. Abstract visualization in geospatial displays shows properties of locations, paths or regions. Both the figurative and abstract components in geospatial visualization are recognised as providing valuable information. Abstract marks reveal patterns of geographic distributions in the data [17], while the underlying map image provides knowledge of how the depicted locations relate to each other – 10 minutes of studying a map can provide better knowledge of the spatial layout of locations than living in an area for 10 years [211]. Recognisable map icons (and recognizable colours) aid map interpretation, although they can, of course, be misinterpreted [17, 212].

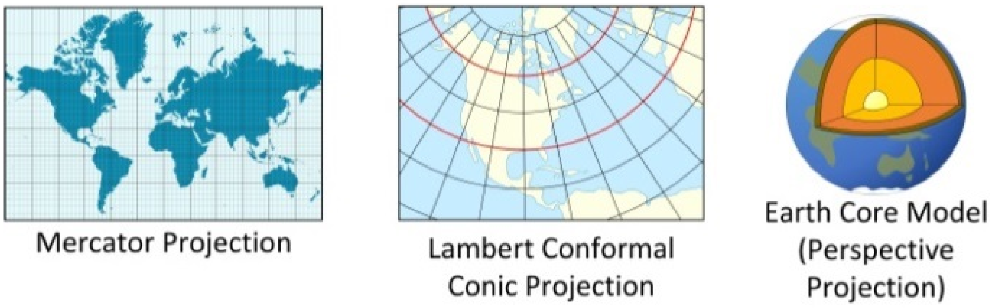


Figure 28: Alternative projections preserve different aspects of an object (the Earth) to create figurative visualizations which encode different information. Sources: Mercator and Lambert projections by Jecowa, distributed under a CC-BY-SA-3.0 license, and Mysid, after a USGS image.

Several principles have been developed for geospatial visualization which guide map image design and integration with data. One key factor is the choice of an appropriate projection used to display the three-dimensional (3D) world in a two-dimensional (2D) image. Projection appropriateness depends on the match between the distances, angles or areas the projection preserves, and the purpose of the map. A second principle is based on the concept of ‘generalization’, the idea that a map must choose a particular scale at which it is accurate, and omit some level of detail – for example smoothing edge contours of coastlines [213, 214]. Good generalization allows the reader to see relevant features clearly while not providing a misleading impression of shape or content (see [213, 214] for more detail). Techniques have also developed around the integration of figurative and abstract representation for geospatial applications – for instance cartograms which distort the map based on some data value, or using *per capita* operations to pre-process data to avoid simply revealing the underlying populations. The motivation behind techniques such as cartograms is to strike a particular balance between providing a clear view of patterns in the abstract data and a rich, detailed view of the geospatial features which may cause those patterns [17].

The approach of geospatial visualization offers a template for how to understand hybrid visualization more generally. The figurative frame concept presented in the next section provides a model which can generalise the geospatial case, and classify the range and dimensions of variation seen in the UV-B examples.

5.1.6 Visualization aims

Visualizations are used to capture, communicate or analyse information; to enable the discovery of new information, verification of existing beliefs, or to provide enjoyment [32]. Depending on a visualization’s aims, the topic, variable meanings, variable values, or causal relationships between variables may be more important to emphasize; engagement and memorability may be more or less important. It may be desirable to present results and hypothesized causes together, depending on the audience and purpose of the visualization. The aim of this chapter is not to advocate for one form of hybrid visualization in favour of others or in favour of purely abstract visualization, but instead to enable classification and analysis of distinct types of information visualization, and to identify appropriate measures of suitability for each type.

5.2 Frames

In this section, we explain the new conceptual model, which we call the *figurative frame model*. It is based around a mediating ‘frame’ which captures the intended information content of a figurative image (i.e. its iconic meaning), including the implicit reference system which connects the image to abstract data. In geospatial visualization, a map has “*coordinates, a projection and a defined accuracy*”, distinguishing it from images of a landscape, and determining how it can be used in geospatial visualization [215]. The *figurative frame* generalizes this set of properties to non-geospatial images. This section defines the frame concept, the range of forms a frame can take, and how the frame mediates between abstract and descriptive information.

Table 2: Figurative Frame Components and their Geospatial Equivalents

Term	Meaning	Geospatial Examples
Coordinates	The data structure which models the represented object	Latitude and Longitude (plus altitude)
Features	The essential information content of the image	Australia, Coastlines, state boundaries, forested areas, city locations, etc.
Projection	The mapping from the coordinates to the image	Perspective, Mercator, Albers, Conic projections etc.

A frame is a geometric model of an object which underpins a figurative image, and is recognisable to both designer and reader. Formally, a frame has three components:

- an abstract coordinate system,
- a projection from the coordinate system onto the figurative image, which accurately locates features onto the image, and
- a set of values in the coordinate system which correspond to key parts, points or surface properties ('features') of the depicted scene or object.

The three components and the geospatial visualization components they generalize are summarised in Table 2. The coordinate system is a structured space, each element of which references a location or position on the object or in the scene. Whereas geospatial visualization uses a single, standard coordinate system – latitude and longitude – figurative images can use a wide variety of coordinate systems, ranging in complexity from a simple unordered set to a 2D or 3D space. The projection specifies how coordinates map to the visual marks which make up the figurative image. Features are meaningful elements of the object, which have values in the coordinate system, and are present in the image. Features of a frame can include parts, boundaries, layers, angles of orientation or motion, key points, lines or areas of the object or scene. Every frame has at least one feature, its identity feature, which describes the represented object, including its level of abstraction, and is mapped to the whole image by the projection. Features are not necessarily marked out in the figurative image, as shown in examples below, but the coordinate system and projection mapping allow them to be located within the representation.

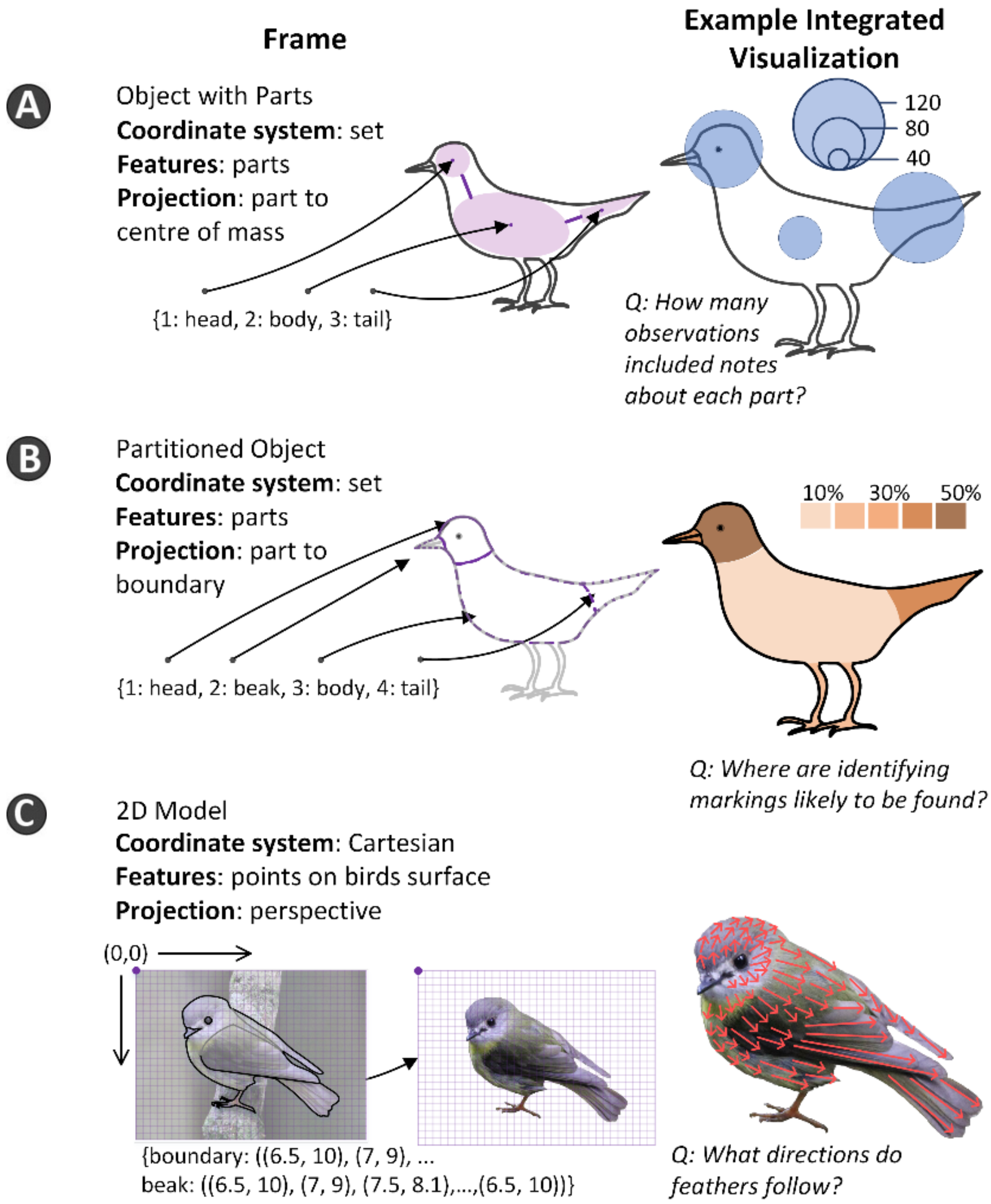


Figure 29: Frames with different coordinate systems or projections underpin different combinations of abstract and figurative visualization. Different figurative frames (left) can be used to combine abstract and figurative visualizations in integrated representations (right column, created from artificial data) to address specific questions. Photo credit (bottom image): T. Neville

For the reader, an understanding of the frame allows information to be obtained from a hybrid visualization. Applying an inverse of the projection mapping recreates the model of the object (the coordinates), which can be used to translate perceived relationships between the features (e.g. distance, angle, relative area, connectedness or attached data values) into inferences about the represented object. A line drawing of a generic bird, for example, may have a simple frame composed of a 3-element coordinate set (1, 2, 3), features ('a bird' [identity]: (1, 2, 3), head: 1, body: 2, tail: 3), and a projection which maps each coordinate to the central position of corresponding part on the drawing (Figure 29(A)). The frame allows the reader to associate each part of the bird with abstract markers whose size corresponds to the number of observations about that part (artificial data). A different projection, which mapped the same coordinates to bounded regions of the image (see Figure 29(B)), allows the reader to determine the data values corresponding to edge cases such as the neck. A photo representation, in contrast, uses a frame with a perspective projection, quantitative coordinate system, and more specific identity feature (‘pale-faced robin observed April 2016’) (Figure 29(C)), allowing the reader to compare feather direction between any points visible from the photographer’s perspective. The reader can also judge the relative size and geometry of features such as the eye, beak, wings and tail, and determine how these features affect the feather direction data shown through abstract marks.

The level and type of accuracy in a figurative image constrains the possible frame density. Only an image in which visually perceived distances (or angles) have an easily predictable relationship to actual distance (or angle) can use a 2D or 3D quantitative coordinate system. A range of projections which minimize distortion of one or more dimensions of measurement are well documented within cartography (e.g. [213, 216, 217]). Map projections (whose equations can be applied to any spherical object) exemplify distance and angle preserving images, but the geometry of perspective representation of 3D objects is also easily judged based on experience with everyday perception [218, 219]. In contrast, if the relationship between distances on the object and distances in the image is inconsistent the reader will not be able to invert the projection mapping to recreate a to-scale coordinate model. Thus not-to-scale images can only use ordered or set based coordinate systems. However, accuracy in a representation is tied to specificity: a scale image of a bird (e.g. Figure 29(C)) accurately captures the dimensions of an individual specimen, but not the species in general, let alone the generic concept of ‘a bird’. To represent hundreds of different species of birds with a single image, there is a maximum representational accuracy determined by shared attributes across the species. The maximum accuracy for ‘a bird’ can be captured equally well with a part or partition frame (e.g. Figure 29(A) and (B)) compared to a scale model.

The features included in the frame are also constrained by the level of detail in the image, and how the viewing angle and orientation of the image make some parts of the object visible and obscures others. A less complete or detailed image of an object has fewer or less precisely located features, corresponding to the concept of generalization in geospatial visualization [213, 214]. Where an image includes some features but not others (e.g. legs and beak but not feather outlines), the features included in the frame and how precisely they are specified in the coordinate system encode a particular view of which aspects of the object are important.

5.2.1 Reading cues

In contrast with geospatial visualization, where there is a single conventional coordinate system, and standard feature types (state boundaries, surface types), figurative visualizations more generally can have a wide range of frames, which the reader may never have encountered previously. Successful communication of information through a figurative image depends on the reader recognising the frame. Although parts of the frame can be explicitly described through captions, labels and guidelines, many conventional cues also typically exist which the reader can use to infer the frame.

As with communicating an abstract mapping, labels and guidelines play an important role in explicitly explaining a figurative frame. Gridlines and coordinate labels (as seen in the geospatial visualizations in Figure 28) can be used to show how a quantitative coordinate system projects onto an image. Similarly outlines or point markers can show a set-based coordinate system (see Figure 29(A) and (B), centre column). Labels and outlines can also be used to define and draw the reader's attention to features of frame. The overall visualization title and description additionally provides cues as to the type of frame used. Labels for visualizations can also explicitly indicate the precision of the coordinate system, using terms such as 'to-scale', 'sketch', or 'artist's conception'. Information accompanying a visualization similarly suggests parts of the image are frame features – the title of the UV-B visualizations (Figure 27) suggests that the sun, clouds and recipient are features of the frame in Figure 27(E), but that the sunglasses on the sun are not in Figure 27(B). Ambiguous images with explanatory captions are recalled more easily and recalled as being more like an image closer to the explanation [183].

The style and design choices of the image, as well as the surrounding context, also offer cues for identifying the frame. The level of realism in an image forms an implicit claim of accuracy with realistic images suggesting a quantitative rather than set based coordinate system, and more detail indicating more quantitative accuracy and a higher number of features. Similarly, the absence of detail or a 'sketchy' appearance implies a more generalised representation (see analysis of sketchiness as a data visualization variable [220]). In fields such as zoology which make frequent use of figurative images as a research tool, the interpretive guidance provided by less detailed figurative media such as illustration over photography is well established; illustration *"can emphasize only the most* *important information about a subject, leaving out distracting clutter"* p. 165 [221]. Context can also be informative – an image of a bird with its wings stretched next to another of the same bird with wings folded suggests different frame features than an image of a bird next to a lion. In the former, the wings and associated differences in the bird's posture are almost certain to be features of the frame; the same inference is not implied in the latter case.

A third mechanism by which the frame of an image can be inferred is through the type and position of associated data visualization marks. Consider example visualizations of gameplay in baseball (see Figure 26). When an image of a baseball pitch is used to plot the progress of hitters around the bases before being caught or tagged out (Figure 26(B)), all of the data points are positioned along the lines between each of the 4 bases. The distribution of the points suggests that quantitative scale in the image is only important for the 1 dimensional line around the bases; the scale of the remainder of the field is unimportant. The reader can infer a coordinate system consisting of the interval [0, 360ft], with an additional element representing the surrounds. Similarly, the features which are relevant for interpreting the data (in addition to the overall identity feature) are the bases and running line ([1st base (90 ft), 2nd base (180 ft), 3rd base (270 ft), home base (360 ft), running line: [0, 360 ft]]). By comparison, in a plot showing where the baseball is hit instead (Figure 26(A)), the 2D positions of line-ends are relevant, implying that scale matters throughout the image, and a 2D quantitative coordinate system is being used in the frame, with origin at the originating point of the line markers. A third example of a baseball hybrid visualization shows throws between fielders in a game of baseball; it makes use of icons in place of network nodes (Figure 26(C)). There is at most one link between each pair of fielders, and aesthetically similar links connect to images at different points (torso, head etc.), implying that the associated data concerns each represented player as a unit object, whose component parts are not important information content. Thus the reader can infer that each image uses a single point frame with only the identity feature.

One measure of figurative visualization success that can immediately be identified through the frame model is the reader's ability to discern the frame from the visualization and surrounding information (title, labels, captions etc.). 'Frame identifiability' offers a complementary measure to data visualization performance measures such as accuracy and error rate, capturing the ability of a figurative image to clearly convey the intended content.

5.2.2 Frames and types of hybrid visualization

Frames can be used to define two dimensions differentiating types of hybrid visualization: level of frame density and level of integration (Figure 27 shows the dimensions with the UV-B examples plotted).

The first dimension, frame density, is defined as the average number of features and preserved judgement types (distances, angles etc.) per figurative image in the visualization. It is one measure of the amount of information being conveyed by the figurative images in a hybrid visualization. The overall balance between descriptive and abstract information provided by a hybrid visualization can be gauged by comparing the frame density and the number of data dimensions. A visualization with high frame density and only a few dimensions of data is mostly descriptive, while low frame density and many data dimensions indicates a mostly abstract visualization. Visualizations with simple frames and only one or two data dimensions are balanced but simple in terms of their overall information content, while visualizations with complex frames and many data dimensions are balanced and information-rich overall.

The second dimension, integration, describes the extent to which marks in the visualization correspond both to frame coordinates and abstract data values. Integration can occur in two ways – first when data is attached to frame coordinates or features to show information about an object or scene (as in the baseball field examples in Figures 25(A) and 25(B)), and second when frames are positioned based on abstract data mappings (as in the baseball throws between players example in Figure 26(C)). The following two sections explore in detail how the different strategies of integration apply to both simple and complex frames, and the types of visualization problem to which each is suited. Two different integration strategies are identified: ‘frames as spaces’ and ‘layouts of frames’. Either strategy can be used to generate visualizations covering the same region of the hybrid visualization dimension grid (medium to highly integrated visualizations with frames of any density). The frames as spaces strategy has two subtypes – attached marks and abstract attributes; layouts of frames has one subtype – abstract layouts. Additionally there is a subtype – combined layouts – which uses both the frames as spaces and layouts of frames strategy. These different approaches to integration are explored in turn in the following sections.

5.3 Frames as spaces

A frame allows a figurative image to be used as a dimensionalized background (a meaningful or 'graphic' space [88]) on which abstract markers can be positioned, much as a map image forms the background of a geospatial visualization. Abstract data can be integrated with a figuratively represented object when data properties match one or more coordinates of the frame. Through matching coordinates, the data is 'anchored' to the frame structure and integrated into the figurative visualization either by utilizing unused visual attributes (colour or shading) or by adding abstract marks (point, line or area shapes). When the reader views the visualization, they make similar judgements to reading a data visualization (determining position, distance, hue etc.), but the inferred values are associated with positions on the figuratively represented object, rather than abstract dimensions.

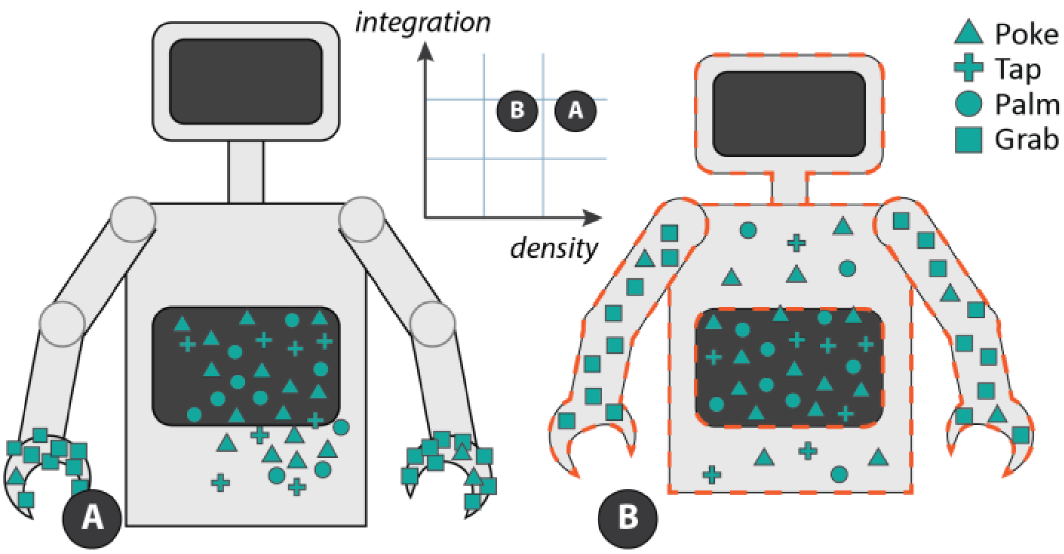


Figure 30: Matching figurative structures and abstract anchoring in touch interactions of a human with a robot (artificial data). (A) The figurative visualization is distance preserving (i.e. drawn to scale), and interaction markers are anchored to points on the robot, with a dodge operation used to reposition overlapping points (high frame density, high integration). (B) Distances are not preserved, and so interactions cannot be anchored to points on the robot. Instead, interactions are anchored to robot *parts* (indicated by dashed outlines), and the positions of the point markers only show which part of the robot was touched, not the precise location (medium frame density, high integration).

5.3.1 Anchoring data

When abstract elements are embedded within a figurative visualization, the data is 'anchored' to the frame. Specifically, an attribute of the data (the anchoring property) is identified with the coordinates of the frame. For example, in the baseball visualizations in Figure 26, hit location is anchored to the baseball field frame by mapping hit x and hit y to coordinates x and y of the frame. Data can be anchored to any feature defined in the geometry of the frame structure, including points, lines, parts, segments or networks. The anchored data can take the form of a single value (in addition to the anchoring value), or a tuple of values, and can be any data type – nominal, ordinal, interval or ratio. Data can also be anchored at different scales: to the object as a whole, to precise locations, to locations within a range or grid cell, or to components of the frame. Frame density determines the number of different places where data can be anchored to the visualization – the more coordinates a frame has, the more points available for data values.

A key measure of visualization quality for embedded abstract elements is that the level of detail in the coordinate system should match the type and range of the anchoring data property. To show data corresponding to specific locations on the represented object, the frame needs to preserve the spatial relations of the object. Similarly, if the figurative visualization is distance preserving, but the data is imprecisely located on the object, the resulting hybrid visualization is only as accurate as the data (see Figure 30). A mismatch between the type and resolution of data and the frame coordinate system creates a misleading or imprecise visualization, implying that data values relate to more specific locations than can be substantiated (detailed frame, less detailed data), or providing less information than is available (detailed data, less detailed frame). If data locations on an object or in a scene are quantitative, a scale image and quantitative (e.g. Cartesian or polar) coordinate system should be used. If data specifies information about object parts, then either a set coordinate system should be used, or parts should be specified as features of the frame (useful in the case where some data is about parts, and others is about quantified locations).

5.3.2 Attaching marks to a figurative visualization

One technique for integrating abstract elements within a figurative visualization is the superimposition of additional markers – points, lines or areas – at the data anchors (e.g. Figure 26(A) and (B)). In this form, the figurative element acts both to show the object and as a space for the abstract markers, providing context to the marker values.

Operations which work on marks in a data visualization can also be applied to abstract markers anchored to a figurative visualization, and interpreted in the same way. For example, a ‘dodge’ operation which separates overlapping points in a data visualization [18] can also be applied to separate points anchored to the same location on a figurative shape (see Figure 30(A)).

5.3.3 Abstract attributes: Setting attributes of a figurative visualization with data

The second technique for integrating abstract data within a figurative visualization is to make use of visual attributes not set as part of the figurative image. Figurative images may or may not include shading, texture, colour or transparency (opacity). When any or all of these attributes are not used in the figurative element, they may be defined based on data values anchored to the frame.

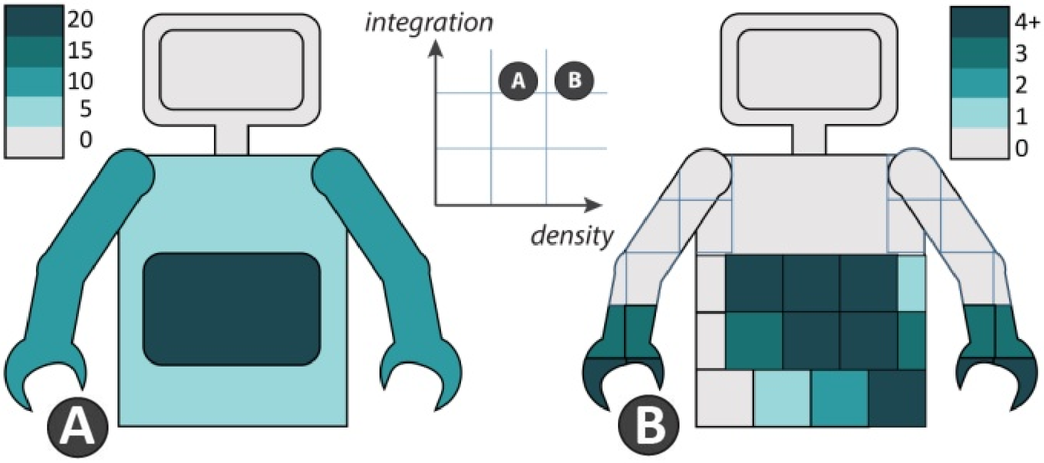


Figure 31: Abstract shading of a figurative visualization showing the number of touch interactions on a robot (artificial data). (A) The visualization on the left uses a frame with a partitioned structure, showing number of touches (normalized based on surface area) on different functional parts of a robot (medium frame density, high integration). (B) The visualization on the right uses a quantized structure, showing the number of touches within a grid cell (high frame density, high integration).

Each visual attribute (colour, shading, texture etc.) is applied in the same way. For example, the scale and geometry of the data anchoring and frame structure will determine how colour is applied to the figurative shape, while the data values and choice of colour scale will set the colour value. If data is anchored to frame features, the whole feature is coloured by the data value and colour scale (e.g. Figure 31(A)). If, on the other hand, data is anchored to coordinate regions (or points, or lines) on the frame surface, each region is coloured independently of its neighbours (e.g. Figure 31(B)). Colour scales may be categorical or quantitative depending on the type of data.

5.3.4 Interpretation

As an integration strategy, data embedded in a figurative element shows how values of some abstract property are distributed on or in the figuratively represented object or scene, relative to the descriptive information shown by the figurative frame features. It allows the reader to make the same types of queries as in a data visualization: to judge individual values, compare sets of values, or to summarise the distribution of values across the object (see [32] for data visualization tasks and queries).

The distinction between abstract elements superimposed on an image and images with abstract attributes is based on whether the abstract marks are perceived as part of or separate to the image. The perception of part or separate is in turn determined by Gestalt principles such as continuity [36]. Visualizations which define figurative attributes suggest that the abstract information is *about* the object (or scene), while visualizations which attach markers show information *on* an object or *in* a scene.

5.3.5 Measures of visualization quality

Abstract marks embedded in a figurative image are subject to the same measures of quality as marks in data visualization, as well as some additional measures relevant to hybrid visualization. The visual attributes (shape, size, shade, texture or hue) used to denote data values have different judgement accuracies as well as strengths for conveying ordered or non-ranked categorical values [17, 44]. Additionally, a good embedding of data in a figurative image will clearly distinguish the abstract marks or attributes from the background image.

5.4 Layouts of frames

The previous section explored the use of a recognizable figurative image as a background canvas to integrate abstract and descriptive information (frames as spaces). A second integration technique, commonly used in practice [24], is the use of multiple images in combination, positioned or adjusted based on abstract values (layouts of frames). Feature-types shared by multiple frames or abstract marks (for instance bounding boxes or angles of alignment) form an additional data-dimension, and can be used to specify relationships in the visualization. Frames capture the abstract and descriptive relationships between multiple figurative elements or a combination of figurative and abstract elements within a visualization.

Two types of visualization can be generated from a set of images (and their corresponding frames). The first is the use of images with very simple frames as glyphs or point markers in a data visualization mapping (as in Figure 26(C) and Figure 27(D)), often considered in the literature as an aesthetic treatment or embellishment of an abstract representation [18, 49, 51]. The second type applies layout operations to frames to create meaningful layouts of figurative and abstract components (as in Figure 27(E)).

5.4.1 Labels: simple frames

Figurative images are often used to label points, bars or lines in information visualization projects [24]. In Wilkinson's grammar of graphics, labelling is achieved through an '.image' function which sets the shape of a point in the final stages of the construction process [18].

Within the *figurative frame model*, figurative images used as labels have the simplest type of frame: a single coordinate element and the identity feature. The image visually identifies the object (through the reader's recognition of the identity feature), while other attributes of each image – such as size or position – provide abstract information. Any abstract layout which maps data values to a pair of coordinates can be used with simple-frame images, including bar charts (e.g. Figure 27(D)), scatterplots, network layouts (e.g. Figure 26(C)), pictographs (see [69]) and more. A reader can use their prior knowledge of the represented objects to find relationships in or explanations for an observed pattern in the abstract visual attributes (for instance needle-leafed plants clustering together on a graph of tree climate vs. deciduousness). However, the visualization does not provide any new descriptive knowledge.

The suitability of image labels for a particular problem depends on a number of factors. Images need to accurately reflect the data they are labelling, and need to be large enough within the visualization to be recognized, without obscuring each other or visual attributes (e.g. position values). Additionally, any attributes used in the image – shape, colour, texture – cannot be used to encode other data in the abstract mapping. Small, simple images are required to label large datasets, while complex images can be used for visualizing a smaller number of data points.

5.4.2 Abstract layouts of more complex frames

Images with more complicated frames can also be arranged in an abstract layout i.e. their position, size or other attributes defined using an abstract mapping based on data values. The abstract information conveyed in such a visualization is the same as in the images-as-labels case, but additional descriptive information is conveyed through the frame features. Features which are similar (or different) across multiple objects can be used to recognise relationships in the data, even if they are not part of the reader's prior knowledge (e.g. thin, straight wing shape can be correlated to long flight-times in a plot of the length of time different birds can stay airborne).

Abstract layouts of images create hybrid visualizations which allow the reader to compare, find relationships between, and summarise both properties and descriptions of a collection of objects.

5.4.3 Combined layouts

The hybrid visualizations described thus far include abstract marks on a figurative space (previous section), and images in an abstract arrangement (subsections above). However, it is also possible for hybrid visualizations to use a combination of both strategies.

When non-trivial frames are arranged in an abstract layout, additional data can be anchored to each of those frames and visualized through the addition of abstract marks or by modifying ‘free’ attributes of the image. The result is a nesting of the ‘layouts of frames’ and ‘frame as space’ strategies. A nested strategy allows the reader to compare properties of objects and properties of or related to their component features. However, the limitations on the size of images and number of represented objects relative to the display are even more pronounced than in the images-as-labels case. Images need to be large enough to allow the reader to distinguish both the image frame and the anchored marks or attributes.

A second type of combination is when abstract visualization techniques are used within the frame itself. A frame is a figurative layout: it arranges features according to their actual location in the represented object or scene. As such, an abstract property can be used to adjust or modify the figurative arrangement. When a frame is used as a space, the anchored marks or modified attributes are distinguishable from the image and have no figurative interpretation (i.e. are not part of the visual description of the object). In contrast, in a modified frame, features convey both descriptive and abstract information.

An example (see Figure 32) is provided by the panels of the highly integrated, complex framed UV-B visualization described previously (Figure 27(E)). Through a figurative layout, cloud features are positioned between the sun and the UV-B recipient against a background showing ground and sky. The figurative positioning of sun, clouds and recipient also defines areas in which UV-B ray frames can be placed to show recognizable interaction paths. An abstract mapping determines the number of UV-B ray features in the frame based on the quantity of radiation reaching the recipient (13 rays, where each ray represents 0.1 unit of radiation). The position of the rays in the final visualization is determined by an abstract stacking operation (as in a pictograph) constrained by limits imposed by the figurative layout. Additionally, the panels are positioned in order by amount of cloud coverage, using the width of the sky feature in the background frame (an abstract layout).

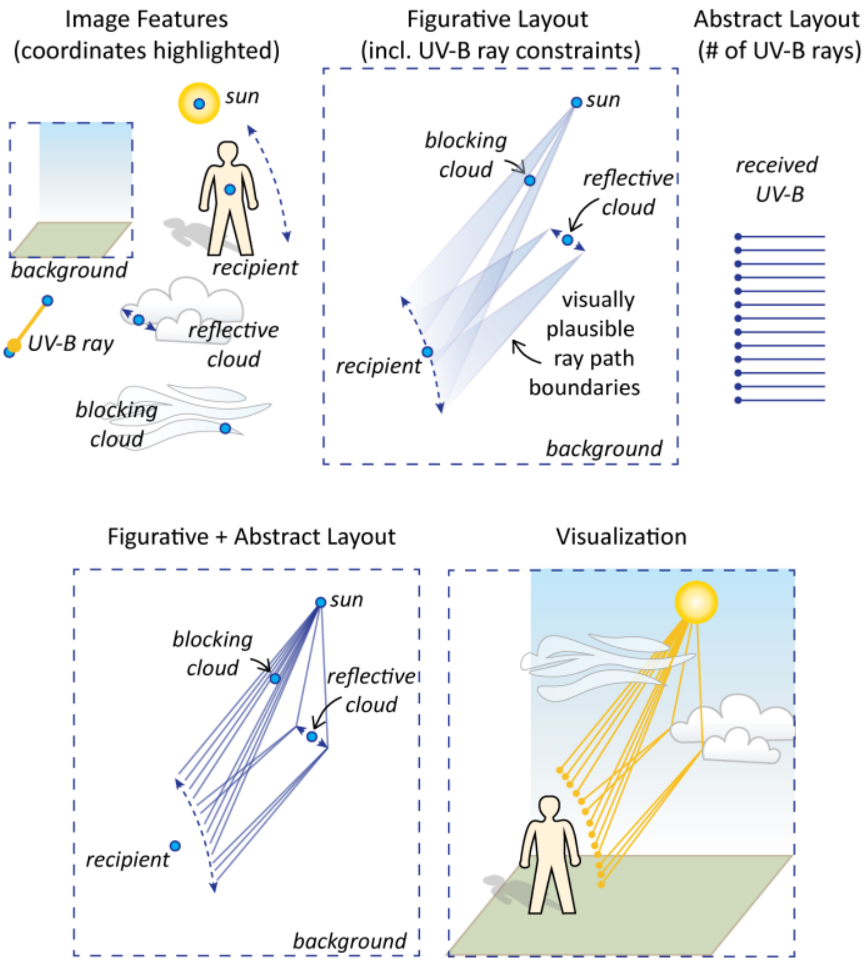


Figure 32: Combined figurative and abstract layouts applied to produce one panel of the integrated UV-B visualization shown in Figure 27

Modified frames are more integrated than either frames as spaces or layouts of frames – the abstract data is represented as an intrinsic part of the visual description. Integration can be a strength (it explains data) or a weakness (it conflates data and explanation), depending on the visualization aim and audience. Both the figurative and abstract interpretations need to be clear in a modified frame hybrid visualization, constraining the range of possible designs; different data values (e.g. a UV-B index of 1.3 vs. 0.8) need to be distinguishable, but marks also need to be recognized as features of the frame (i.e. part of the object description).

5.5 Case study: analysing hybrid visualizations

Having introduced the *figurative frame model* and the resulting classification of different hybrid visualizations, this section provides a case study of hybrid visualization analysis.

This section steps through the measures of suitability relevant to three different hybrid designs of the same dataset for a variety of particular audiences and aims.

Three hybrid representations

All three visualizations concern bird species identification and comparison. They focus on one set of hard-to-differentiate bird species: the cattle egret, little egret and intermediate egret, all of which are found on the mid- and north-east of Australia [222]. Three alternative hybrid visualizations (Figure 34, Figure 35 and Figure 36) show different information about the egrets, and have different levels of integration and frame density (Figure 33).

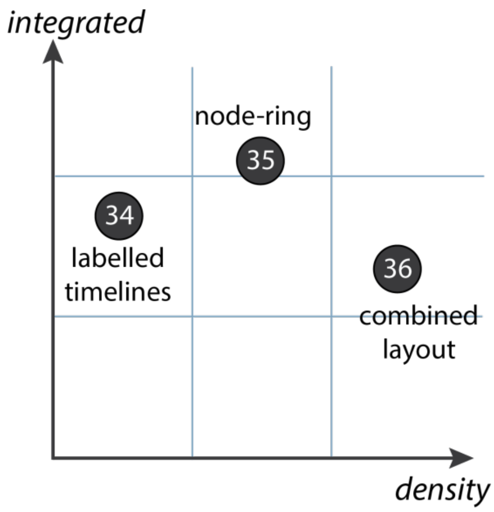


Figure 33: Integration and frame density of the three hybrid visualization designs (Figure 34, Figure 35 and Figure 36)

The first design uses an images-as-labels strategy as part of a timeline visualization comparing the breeding seasons for each egret species (Figure 34). Each figurative image has a simple single coordinate frame with only the identity feature. In the abstract component of the visualization, saturation gradient represents the sets of months when the birds are likely to be breeding, when they may breed if environmental conditions are suitable, and when breeding is highly unlikely [222].

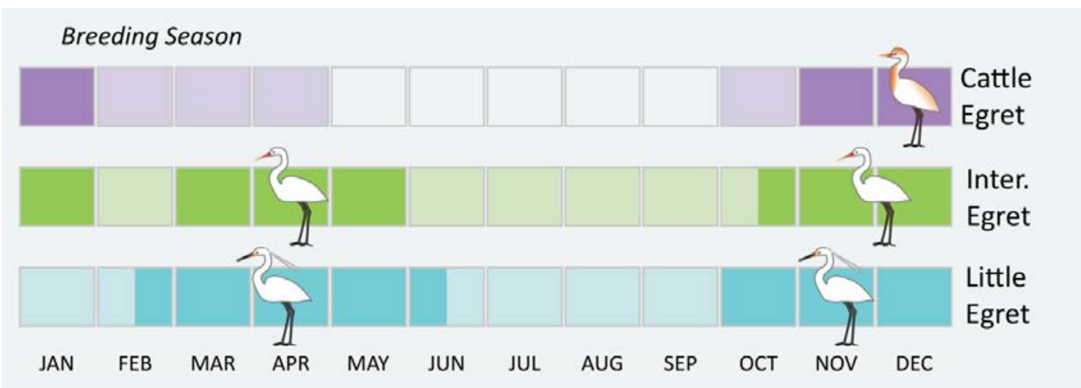


Figure 34: A timeline visualization allows comparison of the egrets’ breeding seasons.

A layout of frames approach is also used in the second hybrid design, however images have slightly more complex frames – each image shows at least one additional feature (the marking) as well as the identity feature (the bird part with that marking) (Figure 35). A tiling mapping is used to arrange the images according to bird location, and colour and pattern are applied as in a node-ring visualization [158] to show markings linked by their presence within a single species and plumage type. The stack of rings around each image indicates how the represented marking is shared across different species and seasons.

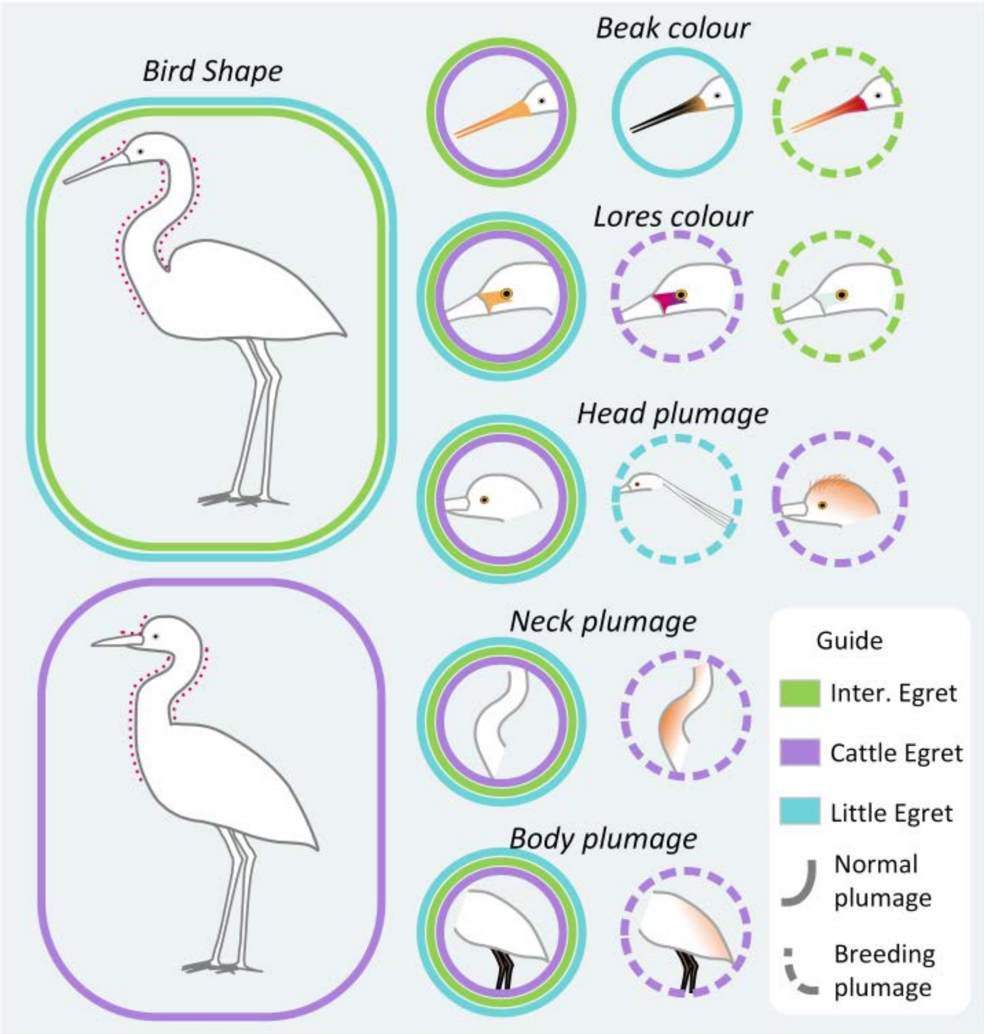


Figure 35: A node-ring based tiling of identifying marks emphasizes the commonality of features

The third hybrid visualization considered in the case study combines the frame-as-space and layout-of-frames approach. At the top level, it uses a faceting or small multiples approach [18, 223], in which all the information about a particular species is contained within a subset of the visualization. Within each facet, the visualization deploys the frame-as-space approach, with a radiating lollipop-shaped marker attached to the edge of any feature of the egret which changes plumage during breeding season. Each marker contains a second image (creating a layout-of-frames on the frame-as-space), showing the breeding plumage. The main images have frames of medium feature density – multiple features, but only a set-based rather than a quantitative coordinate system. The secondary images have a lower feature density, showing only one feature more than the identity feature. Integrated into each high-level facet is an abstract circular timeline showing breeding season; however, the timelines are only minimally integrated with the frame-as-space representation (shared colour, but separate position).

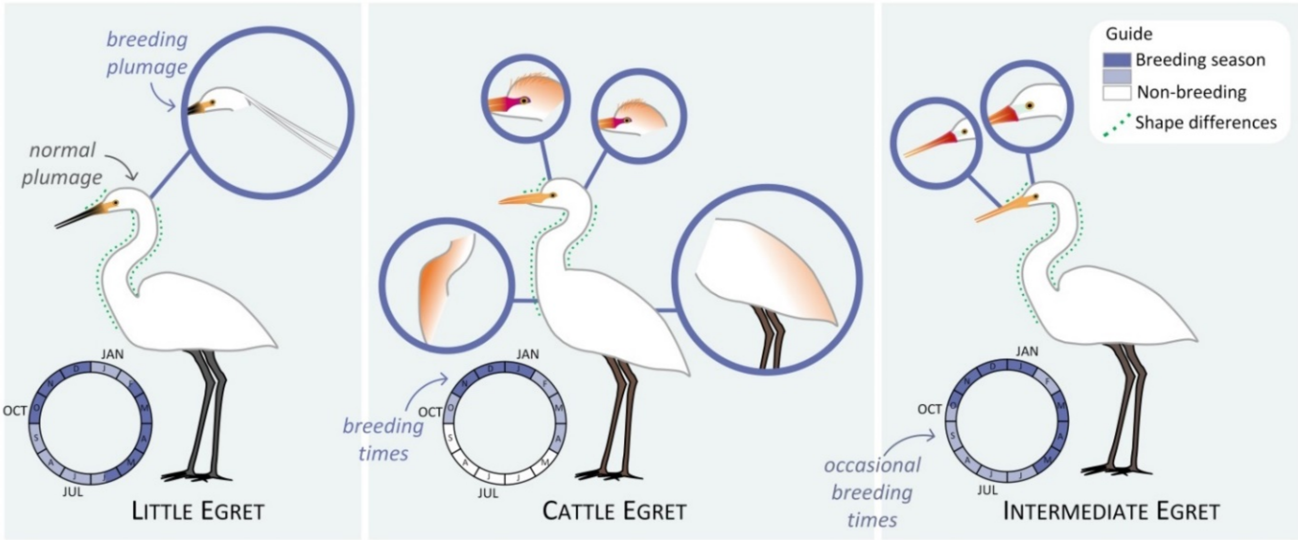


Figure 36: Egret identification showing plumage in normal vs. breeding seasons. The visualization is suited to assist novices in discriminating between similar species

5.5.1 Evaluating figurative frames and images

Visualization has the potential to aid in different challenges related to egret identification. Bird species are an important marker of biodiversity, and organizations are increasingly taking a 'citizen scientist' approach to collecting bird distribution data, recruiting the public to report bird sightings and participate in bird count surveys [224]. The quality of crowdsourcing approaches depends on accurate bird identification, which can be difficult for non-experts. Novice observers would benefit from a visual explanation of the normal and breeding plumage of each bird, as well as the times when each bird is likely to be breeding. For those training or giving advice to observers, on the other hand, it is important to identify the most easily spotted distinguishing characteristics to instruct novices to look for, since a bird may only be seen briefly. Visualization could also aid in planning the observation studies at appropriate times to compare breeding and non-breeding behaviour and habitat.

A suitable hybrid visualization will address the problem, as well as meeting general measures of data and figurative visualization quality (see Table 3). The suitability for a problem will depend on the type of hybrid visualization, compared to the required balance of description and abstract information. Visualization quality includes the choice of data visualization variables, the frame precision and the readability of the frame.

Table 3: Hybrid visualization suitability measures, and relevant chapter sections or references

Measures	Section/References
Appropriate balance of descriptive and abstract information	5.2 Frames
Use of frame-as-space technique if problem requires comparison *within* an object or scene	5.3 Frames as spaces
Use of layout-of-frames technique if problem requires comparison *across* multiple objects or scenes	5.4 Layouts of frames
Sufficient frame precision and features	5.2 Frames
Appropriate choice of variables and layout for abstract components (existing data visualization suitability)	See for e.g. [70, 108]
Readability of the figurative frame	5.2 Frames

Of the three example visualization problems, descriptive information is most important for the novice identification problem, and least important for observation planning. The novice identification problem requires a balance of abstract and descriptive information: abstract visualization is needed to compare the uniqueness of different markings, while descriptive information shows how easily each marking can be spotted. The combined layout (Figure 36) is the most suited to novice identification, since it provides the most descriptive information (i.e. has the highest frame density). In contrast, the minimal frames in the labelled timelines visualization (Figure 34) are suited to observation planning, since it focuses on the abstract breeding season data. The frames showing each marking in detail, in a layout which facilitates comparison across species and breeding season, makes the node-ring visualization (Figure 35) suited to the distinguishing characteristics problem.

Having matched visualizations to purposes, there remains the question of whether each visualization is a good visualization (as opposed to simply the best of the three presented options). One measure of hybrid visualization quality is whether the precision of the coordinate system and the choice of frame features are sufficient. The level of descriptive information provided by the labelled timelines visualization and node-ring visualization were already assessed as suitable for their associated problems; for the combined layout it is possible that a more realistic image would provide better guidance for novice observers.

However, individual birds within a species vary in terms of their size and markings, and can look different in motion in the wild, so a more realistic image would not offer a more accurate description of the species in general. Furthermore, additional features such as wing shape would not provide additional cues for distinguishing between the different egrets. User evaluations could be conducted to check the performance of realistic but less representative images as a means of instructing novices.

One interesting observation is that more complicated hybrid visualizations (i.e. those with higher frame density) are not necessarily more suited to expert rather than novice audiences. Readers who are highly familiar with an object may be able to recognise part of that object from a representation just of that part, drawn with low accuracy, whereas a less familiar reader may need to see the part represented more accurately within a more recognisable context. Working geneticists are less likely than biology students to include the details of shape and dimension in chromosome diagrams they generate to solve problems [225]. Furthermore, highly detailed illustrations can often be perceived as simpler than more minimalist representations [207].

Another quality consideration is the choice of variables and layouts for the abstract components of a hybrid visualization. Abstract visualization quality is discussed extensively elsewhere (see Chapter 2), so will not be addressed in this Chapter. One factor worth noting is that abstract visualization concerns can interact with the suitability of particular figurative frames, as exemplified by the hybrid node-ring visualization (Figure 34). The number of rings around each marking image shows how many of the egrets have that marking. Discounting the two leftmost ‘bird shape’ markings, the use of a common image size means that the overall size of each node corresponds to the prevalence of that marking – the reader can determine prevalence through an area judgement rather than judging line thickness. The cost of allowing an area judgement is that images cannot use frames with a common scale coordinate system and projection – the markings are not to-scale relative to each other. The ‘bird shape’ markings (left) are involved in the alternative end of a similar trade-off: if the images were reduced to the same size as the other marking images, the frame features (notably the head and neck shapes) would be difficult to identify, but an area judgement could be used instead of line thickness.

Finally, quality needs to take into account the frame readability. Too little is known about the interpretation of figurative visualization to predict the ease of reading a particular frame. However, it is possible to identify the different reading cues provided to help the reader recognise the frames of each visualization. In the labelled timeline, size provides a contextual cue that a minimal frame is in use – the images are too small to make out detailed features clearly. Text labels for each timeline provide a name for the identity feature, and help the reader ascertain the level of abstraction of the images (species, not individual specimen). In the hybrid node-ring visualization, highlighting techniques are used to emphasise the frame features. The head angle and neck of the 'bird shape' nodes are outlined with dotted lines to signal their importance in the image (i.e. to show they are frame features). In the remaining nodes, a line drawing style is used, with only the distinguishing marking coloured. The colour scheme indicates the sole non-identity feature for each image. The colour scheme also allows the image to represent a more abstract concept – an egret, of any of the three species, provided it has the relevant marking. The abstraction level can be inferred from the associated abstract marks – for the yellow 'lores colour' (2nd row, leftmost) node to apply to intermediate, cattle and little egrets, the image must show a concept more general than any one of the species individually. The combined layout visualization also uses highlighting and contextual cues, as well as annotations and guides to communicate the figurative frame. The egrets' neck and head shape features are highlighted by adding lines as in the node-ring visualization, explained through a note in the visualization guide. However, the primary means of frame explanation is comparison with surrounding images. Each anchored image (inside the lollipop markers) suggests a corresponding feature in all of the main egret frames. The features of the anchored images (breeding markings) are suggested by the focal point of the marker, and reinforced by differences with neighbouring anchored images and the corresponding part on the main non-breeding plumage image. Annotations indicate the concepts (including abstraction level) shown in the images. Identifying the reading cues in each visualization provides something for user evaluations to test, as well as supplying alternative strategies in case test readers struggle to comprehend the visualization.

5.6 Discussion

The main aim of this chapter is to introduce a vocabulary for critical analysis of hybrid visualizations. The *figurative frame model* and resulting classification allow a designer or visualization researcher to evaluate the inclusion of and balance between descriptive and abstract information, identify the cues available for the reader to understand the image's frame, and compare alternative hybrid visualization strategies.

The different types of hybrid visualizations and measures of hybrid visualization quality also have implications for the ongoing discussion within the information visualization community around the role of figurative images within information visualization, concepts of visualization quality, and the assessment of tools and techniques for hybrid visualization.

5.6.1 The ‘chart junk’ debate

As noted in the introduction, there has been debate within the information visualization community about the value of images in information visualizations. Early influential thinkers in the field have been critical either of figurative visualization in general [17] or of specific styles of figurative embellishment (labelled ‘chart junk’ [48]). However, their views have not been supported by evidence [49-53].

We contend that the distinction between different kinds of images is important and that frames provide a way to understand the relevant dimensions. Chart junk images have often been used to explore the effects of images on visualization interpretation [49-51, 195]. However, the term ‘chart junk’ was originally presented alongside exemplars of visualization which made use of figurative illustrations [48]. Moreover, empirical evidence suggests that while readers will more easily remember the overall content of a visualization if it contains relevant images, if the images are irrelevant, the user may struggle to absorb the message of the visualization [52]. In practice, images in visualization can be classified into three different information-bearing roles – providing background context, showing content and labelling points (previous Chapter).

The *figurative frame model* makes the information content of a figurative element explicit, and thus provides a means to distinguish between informative and irrelevant images, and between images in different information-bearing roles. Irrelevant images are figurative elements whose frame features have no connection to the topic or other data in the visualization. It is also possible to identify the difference between background supporting images and content images, using the frame model. Background images occupy the same space as a data visualization, but the data is not anchored to the image frame. Content images have a non-trivial frame (with relevant features), and can form a meaningful background space, or sit within or alongside abstract visual elements. The *figurative frame model* enables the recognition that images can play many roles, not simply embellishment.

5.6.2 Comprehension and ambiguity

In addition to objections against embellishment and chart junk images, figurative representation has been criticized on the basis that it is ambiguous [17]. While frames do not alleviate ambiguity, they do shed light on how visualizations can be misinterpreted, and help place figurative visualization interpretation challenges in the broader context of issues with visualization comprehension.

The *figurative frame model* differentiates between the designer's model of the object (the frame) and what is presented to the reader (the figurative element), revealing prerequisites for understanding. In particular, figurative visualization depends not only on the designer and reader sharing a visual sign system (in order for the reader to recognise the frame from the image) but also on common concepts and concept boundaries (in order to infer the correct level of abstraction).

Misunderstanding is not only a problem for figurative visualization: data visualizations can also fail to impart the intended understanding to their readers [41, 45]. The risk of misinterpretation and its mitigation should be seen as an inevitable aspect of communication, rather than something that can be avoided by restricting the range of representation types.

A third argument in favour of figurative elements used in this thesis (and well recognized in practice) is their expressiveness. When comprehension is measured for a given visualization, the assessment is based on what the visualization *can* show. Yet for some problems, the information a designer wants to communicate is not able to be captured in a data visualization. Figurative and abstract elements have unique communicative capabilities, and thus the information visualization community needs methods and layouts for creating representations of both types. A designer may not know which aspects of a visual sign system are known *a priori* by the readers. Strategically placed annotations and other reading cues can assist in recognising the frame of a figurative representation, thereby bootstrapping readers' interpretative abilities and hence reaching a shared understanding through the visualization itself. Measuring readers' comprehension of descriptive information from a hybrid visualization (i.e. frame recognition), and how different types of reading cues assist in comprehension, is an important future challenge for hybrid visualization.

5.6.3 Tools and techniques for hybrid visualization

Understanding the range of hybrid visualization designs provides a foundation for assessing the capabilities of tools used to construct such visualizations, and for the development of specific hybrid visualization techniques.

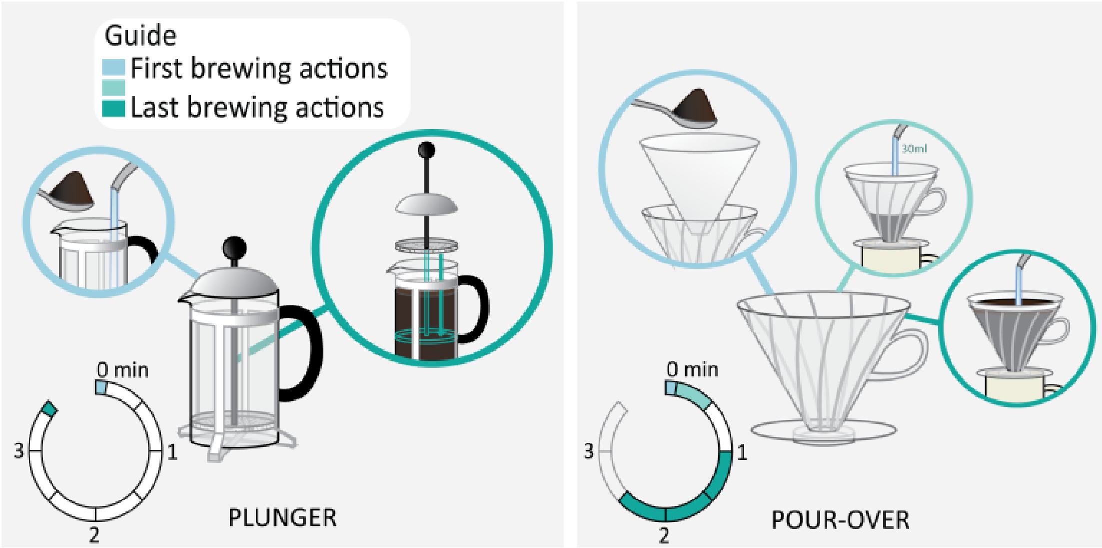


Figure 37: Application of the technique from the combined layout egret visualization to compare action and timing for different coffee making methods.

The classification of hybrid techniques can be used to evaluate the support for hybrid visualizations in existing visualization tools. Tools vary from accessible (e.g. excel, Tableau) to advanced (e.g. d3js, ggplot, p5js), and have the capacity to support different types of hybrid visualization. The capacity of a tool to implement particular types of hybrid visualization depends on its ability to satisfy three criteria:

1. include images within a visualization;
2. assist in finding a projection mapping which provides a common frame of reference for an image and abstract data; and
3. include images where the attributes (e.g. position, colour, and shading) of meaningful parts can be manipulated based on data values.

Images with minimal frames can be implemented in any tool which satisfies criteria 1 (i.e. most tools including Excel, Tableau and scripting languages). To use a figurative image as a space (as shown in Figure 30), the size and proportions of the background figurative image need to match the dimensions of the abstract space. Tools satisfying criteria 2 (e.g. Tableau) simplify the calculation of an appropriate projection mapping. For example, if an image of a baseball field is attached in Tableau, the annotations function can be used to find the coordinates of the home plate within the image. The retrieved coordinates can then be used to apply a transformation (i.e. projection mapping) to hit location data so that when plotted graphically, markers are accurately located relative to the baseball field image. Figurative images can be used as spaces even in tools when criteria 2 is not satisfied, since projection mappings can be calculated manually based on measurements of the image, but tools reduce the effort required. Satisfying criteria 3 (e.g. the Data Driven

Guides tool [197]) enables the implementation of frames-as-space visualizations where attributes are modified based on data (e.g. Figure 31), or combined layouts (e.g. Figures 27(E) and 11). For example in d3js, Scalable Vector Graphics (SVG) paths can be used to draw figurative shapes whose attributes can be set and manipulated through properties added to the paths (ids, CSS classes, data). The capacity of tools to meet criteria 3 is not always obvious. For example, Tableau allows the user to upload and use figurative shapes described by coordinate paths by deliberately mislabelling an array of coordinates as a custom polygon map with longitude (x) and latitude (y) values.

The hybrid visualization types described here (e.g. frames-as-spaces) are high level layouts or design strategies. One of the main advantages of data visualization is that more specific layouts (e.g. bar chart or ‘parallel coordinates plot’) are articulated independently of a specific tool or dataset, and so can be reused across different applications. Future efforts in understanding hybrid visualization could include the development of specific hybrid layouts useful for particular kinds of problem. For example, the hybrid layout used for the egret novice identification problem (Figure 36) could be generalized to a ‘time-varying object comparison’ technique, and applied to different datasets. It could be used to compare the timing of actions for different coffee-making devices (Figure 37). Articulating such techniques makes it simpler to create visualizations, and also provides a foundation for more detailed study of information visualization involving figurative elements. To create a novel hybrid visualization, a designer has to create or source figurative images of the subject, choose a figurative frame, and create a layout integrating abstract data with the frame structure coordinates. Each choice is an open ended design problem. In contrast, an existing technique guides each design step and also provides the designer with an advanced view of what the finished visualization will show. A technique requires a particular type of figurative frame and image fidelity, just as data visualization layouts require specific data types. The *time-varying object comparison technique* requires a ‘parts-of-the-whole’ frame which identifies changing parts of the object, and images detailed enough to distinguish these parts. A technique showing abstract data anchored to locations on an object (e.g. Figure 30(A)) would require both a quantitative coordinate frame and scale-preserving image. The more existing visualization strategies are codified, and the more their frame and image requirements are made explicit, the easier is the task of visualization designers in choosing appropriate strategies. Articulating figurative information visualization techniques also aids the scientific study of visualization. The ability to apply visualization techniques consistently to multiple datasets and to apply alternative techniques to the same datasets is a key enabler for controlled experiments measuring the performance of specific types of hybrid visualization.

User-centred studies based on the *figurative frame model* are required to refine the typology and measures proposed here, and provide more specific heuristics for hybrid visualization design. Future work could include testing the ability of visualization creators to construct figurative images which convey specified frames, as well as learning from and formalising successful strategies for communicating frame identity, precision and features. The *figurative frame model* also enables the articulation of specific research questions for evaluating hybrid visualization techniques. For example, studies of the effect of different mark types and styles on perceived figurative image precision would aid the development of more readable hybrid techniques. Similarly, the performance of different strategies for highlighting frame features (e.g. outlining, grid overlays, description in accompanying text, aesthetic style) and interference between such highlighting strategies and abstract data marks would allow the identification of compatible (or incompatible) combinations of abstract and figurative representation.

5.7 Conclusions to Figurative Frames

The *figurative frame model* introduced here provides a critical vocabulary for analysing the information content of an image and its relationship to abstractly visualized data. Generalizing existing concepts in geospatial visualization, a figurative frame consists of a coordinate system, a set of key features described in the coordinate system, and a projection from the coordinate system onto the figurative image. A frame captures the descriptive content of any figurative image, regardless of how that image is created (photography, illustration, 3D modelling). In integrated hybrid visualizations, the frame is the point of connection between the descriptive information and abstract data.

The frame model underpins a classification of different types of hybrid visualization according to their frame density and the level of integration between figurative images and abstract data. The classification differentiates between hybrid visualizations which provide more or less descriptive information, and visualizations separate or interrelate descriptive and abstract information. Additionally, two distinct integration strategies can be identified, revealing the different ways hybrid visualizations offer greatly expanded expressiveness in information visualization. The first is mappings in which the figurative element forms a background space akin to a background map image in a geospatial visualization. The use of a frame as a space provides a means of grounding qualitative or quantitative information about an object in its recognizable shape geometry. A second type is based on applying data visualization layouts to sets of frames, arranging images or image parts based on their qualitative or quantitative relationships. Abstract arrangements of frames allow the reader to discern relationships based on both descriptive and abstract information about objects, and can reveal interrelation between form and properties in a collection of objects.

Through the language of figurative frames, the increased expressiveness and information density offered by the inclusion of figurative images is made accessible to rigorous analysis. Hybrid visualizations can thus be integrated into the research agenda of the information visualization community, to complement their growing integration into visualization practice.

Part II

6 Visualization Motifs

The first part of the thesis (Chapters 4 and 5) explored how two types of reader knowledge – visual conventions and figurative shapes – can be anticipated to convey information. In conventions and figurative visualization, the reader recognises the correspondence between a visual form (e.g. horizontal axis, bird shape) and its conventional or iconic meaning (left-to-right direction, bird). Recognition (or discovery) of correspondence is a key concept in part II of the thesis. Part II has two components: a typology of visual motifs (this Chapter) and the semantic scaffolding model structure (Chapter 7). Together, these chapters document the development of a model which shows how meaning is co-constructed through the combination of visual form and the reader's experience.

The review of literature on visualization value (Chapter 2) and models of visualization (Chapter 3) revealed the need for a new conceptual model of visualization. Existing models, and the evaluation measures derived from them, do not adequately describe how features in a visualization take on specific, practical meaning through the interpretation process. The practical use of visualization depends on semantic scaffolding, i.e. forms within the visualization, particularly at the intermediate reading level, taking on extended meaning in context.

The methodology for both components of Part II is documented in the following section. Visual motifs are intermediate level forms in a visualization, created indirectly through the data-to-visual mapping. Motifs are important because they have the capacity to convey practical meaning beyond what was directly encoded in a visualization, but are still predictable. Because of these characteristics, motifs have been chosen as the structuring concept for the semantic scaffolding model. The semantic scaffolding model establishes the correspondence between visual motifs and concepts within the reader's domain knowledge. The typology of motifs provides the semantic scaffolding model with utility. The typology provides a means of predicting the visual motifs which may arise in a visualization, and thus anticipating the reader's experience through design. Different types of motifs – 'distribution', 'shape', 'gradient', 'enclosure' and 'path' motifs – are linked to properties of the layout design (see overview in Figure 38). The structure of this chapter on motifs is outlined following the Part II methodology.

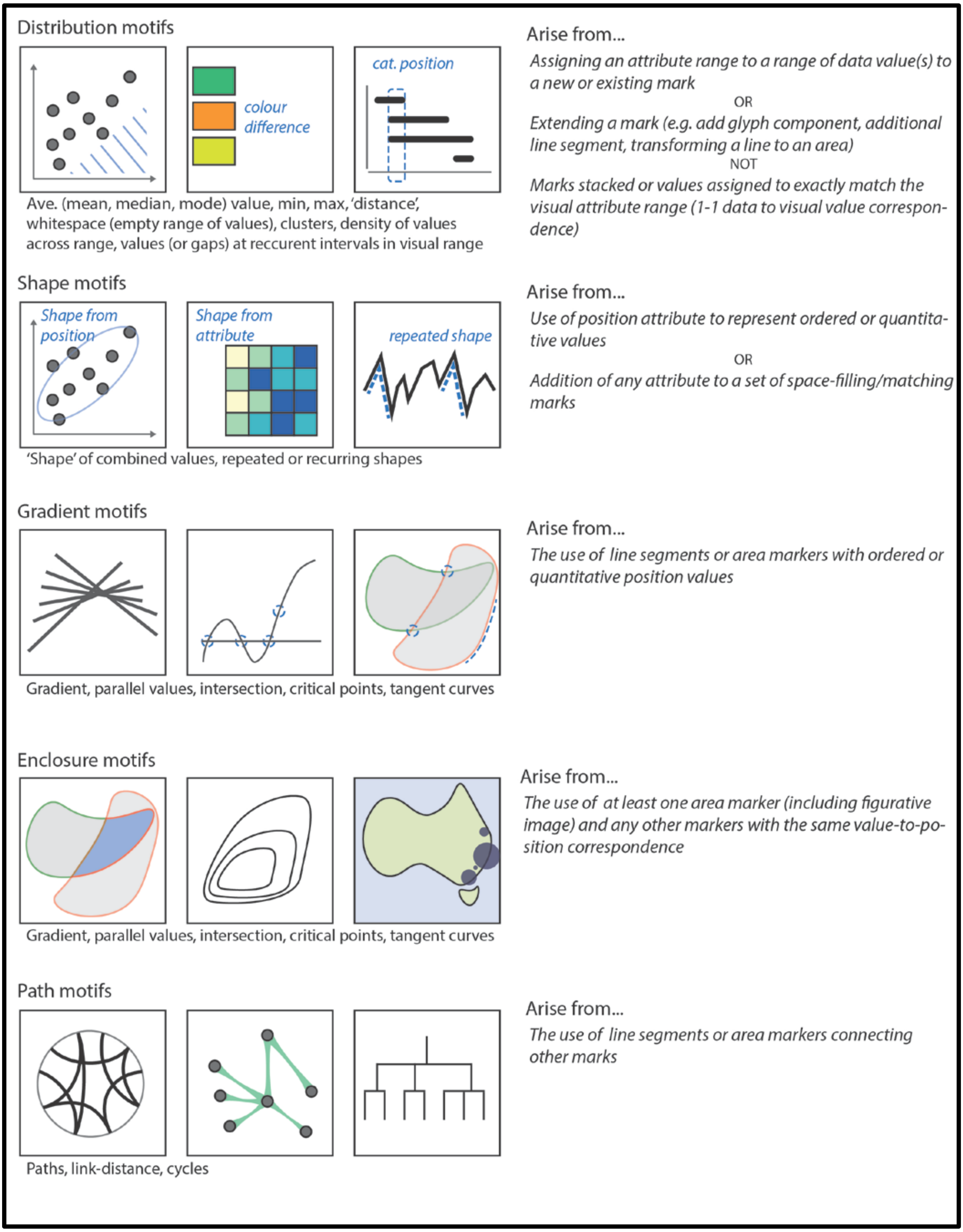


Figure 38: Motif typology overview

6.1 Part II Methodology

The semantic scaffolding model (including the motif typology) was created through synthesis of existing models and research on visualization. The method chosen for the semantic scaffolding model was to build on an existing structure that captures connections between visualization components. The importance of linking the data, layouts and tasks (see model review in Chapter 3) drove the choice of which components to incorporate into the overarching semantic scaffolding model.

The approach to model construction was suggested by a prior attempt to link existing models of data, layouts and tasks (Andrienko and Andrienko's Exploratory Data Analysis (EDA) set of models [39]). In the EDA approach, the component models were too complex to be interconnected [39]. Learning from this previous attempt, interconnections between data, layouts and tasks formed the foundation of the semantic scaffolding model, not its final stages.

The semiotics and mathematical model of VFR [93] was chosen as the underlying structure of the semantic scaffolding model, since it captures the relationships between data, layouts and tasks. Of all the models included in the review (Chapter 3), only semiotic models and mathematical models include (in particular the VFR model [93]) the necessary interconnections between the represented information (data schema), the visual form (layouts) and the interpretation for visualization tasks (questions).

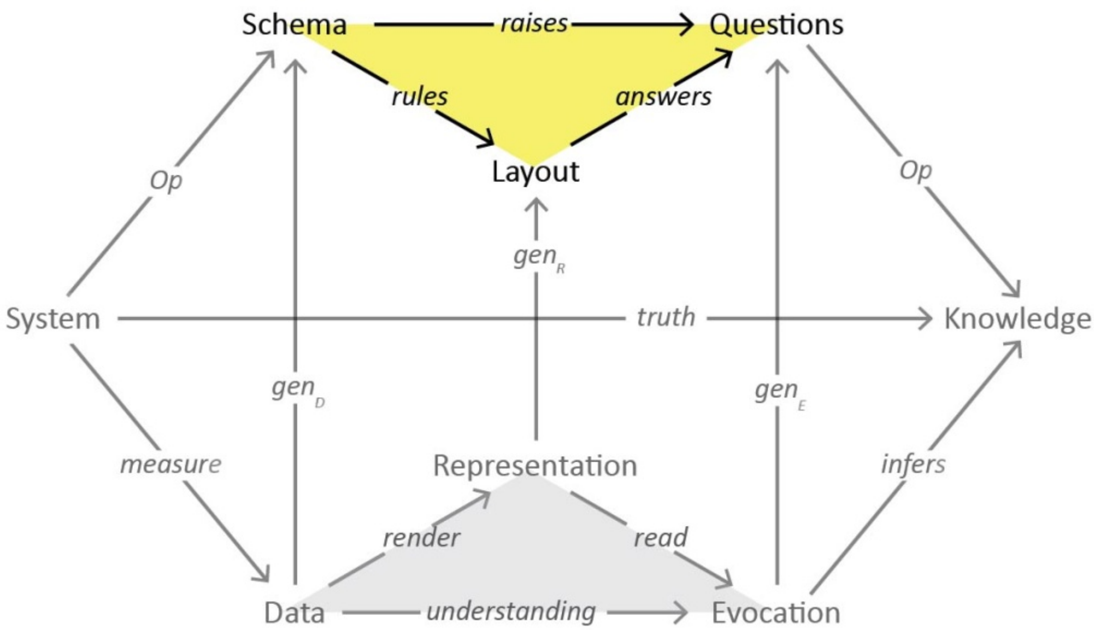


Figure 39: The VFR Layout Triangle (yellow highlight), and corresponding instantiated Representation Triangle (in grey) [93]

The focus of the semantic scaffolding model was restricted to the sub-category of the VFR model consisting of (data) Schema, Layout and Questions – the 'Layout triangle' (see Figure 39). The instantiated Data, Representation and Evocation sub-category (the 'Representation triangle') as well as the System and Knowledge objects were omitted. The Layout triangle is a generalised, abstracted version of the Representation triangle, and thus better captures the components which can be known ahead of visualization creation. The process of *operationalizing* a System (*measuring* in the instantiated case) to obtain a Schema is out of scope of this thesis. The transformation from Questions to Knowledge (the abstract version of *inference*) was also excluded, as it is incompatible with semantic scaffolding. Instead, the focus is on the direct connection between practical purpose and visualization form, rather than the subsequent use of information obtained from a visualization (see discussion of the information transmission perspective in Chapter 2).

The VFR category model provides high-level description of the relationships between components of the visualization process. However, it does not provide any detail as to the nature of the components themselves. In order to use the VFR category model to explore semantic scaffolding, it was therefore necessary to expand on the model. In particular, a structuring concept was needed in order to link data structures, layouts and practical tasks.

Visual motifs were chosen as the structuring concept for the semantic scaffolding model. The literature review (Chapter 2) suggested that meaning can be located in specific features of a visual form, and depends on experience and contextual interpretation. Additionally, both examples from visualization practice and the explicit expressions of visualization value (Chapter 2) suggest that practical use of visualization is intertwined with the concept of ‘intermediate level reading’ [17] or visualization tasks involving multiple visual elements [32, 38, 39]. Motifs are the visual forms corresponding to intermediate reading. Through the VFR layout structure, the semantic scaffolding model connects motifs to both data and practical tasks.

The two component models were developed using different methods. A typology of motifs (this Chapter) was developed from existing typologies of tasks and visual variables [17, 18, 32]. The existing task typology of Brehmer and Munzner [32] was used to derive abstract descriptors of motifs. The principles of mathematics and geometry were then applied to identify the range and variation of motifs possible within a visualization.

The theory of semiotics (embedded in the VFR structure) was used to identify the relationship between motifs and their meaning (Chapter 7). Information about visualization interpretation (reviewed previously in Chapter 3) and existing knowledge from cognitive science provided the inputs to show how the reader co-constructs the meaning of visual features.

6.2 Motifs

A motif is a collection of elements or regions of space in a visualization. Motifs are the visual relationships corresponding to intermediate (and global) level reading. The defining feature of motifs is that they involve relationships between more than one point of data. There are motifs which involve a small number of elements (e.g. cycles in a network visualization) or a large proportion of the visual marks (e.g. line of best fit), specific locations in the plot, shapes which can be formed anywhere in the plot, collections of marks, attributes or points within marks. The data-to-visual mapping creates motifs indirectly, through the composition of multiple visual marks and variables. This chapter presents a compositional typology of motifs, which describes the range of motifs possible within any information visualization, given its composition. The motifs possible within a visualization form the first component of the semantic scaffolding model (see Figure 40).

The importance of intermediate level reading and multi-element tasks with has been recognised from early [17] and ongoing development [32, 38, 39] within the field. However, the level of detail in current descriptions is low. Discussion has focussed on intermediate level questions, not the visual features which provide the answers to those questions. Detailed accounts of motifs are available for selected visualization types (e.g. networks [226]), but the general case is addressed only in terms of visualization tasks, and then only at the very abstract level. A number of taxonomies of visualization tasks acknowledge the existence and importance of tasks involving multiple values (simultaneously). Multiple elements in the visualization are the subject (the 'what') of the high-level 'characterising the distribution' task in Brehmer and Munzner's task typology [32]. Similarly, Schulz et al. include the number of elements as one of the dimensions of their task space [38]. However, both approaches provide limited insights into the kinds of features in the visualization which are the subject of such analysis (or produce different analysis results).

The motif typology was developed for this thesis to provide an expanded vocabulary for motif description, and allow motifs to be predicted from a visualization layout. The motif typology has been constructed using existing knowledge of visualization tasks, low-level visualization variables and marks (local features), and basic properties of mathematics and geometry.

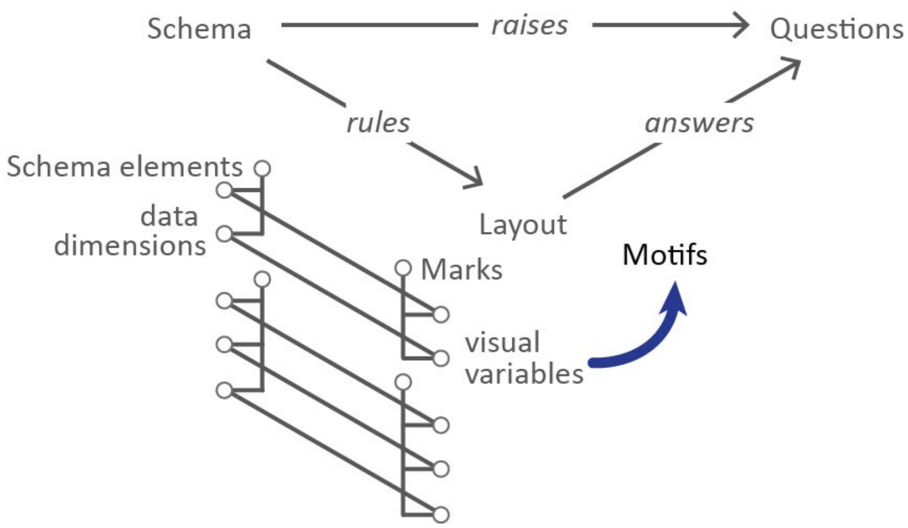


Figure 40: Part 1 of the Semantic Scaffolding model – the creation of intermediate level motifs

A summary of the motif typology, and the visual variable compositions which create each type is presented in Figure 38. The following sections describe the motif types (Section 6.3) and their relationships to different data-to-visual mappings (Section 6.4) in more detail. The characteristics of motifs which are important for the semantic scaffolding model are discussed in Section 6.5.

6.3 Motif Types

In the abstract, motifs can be characterised by differences (or similarities) between visual variable values and distributions of values. This characterisation has been derived by translating the task typology of Brehmer and Munzner [32] into visual features. Visualization tasks take the form of finding a value, comparing two or more values, and characterising the distribution of values [32]. Each task corresponds to a visual feature at the local, intermediate or global level: a visual variable value, a difference (or similarity) between a pair (or set of pairs) of values, and a distribution of values. Of these, the individual value is a local feature, while the pairwise relationships and distributions of values are motifs. *Differences* and *distributions* thus form abstract descriptors of motifs.

To some extent, the abstract difference and distribution descriptors produce equivalent motifs regardless of the marks and visual variables involved. 'General difference and distribution motifs' ('distribution motifs' for short) can be defined in generic terms, and then specified for any visual variable and any data-type (i.e. categorical, ordered or quantitative). Geometric properties of points, lines and areas give rise to additional motifs which cannot be replicated with other mark and visual variable combinations.

6.3.1 General Difference and Distribution Motifs

A set of data values encoded by a common visual variable range allows comparison of values, and a variety of motifs related to the distribution of values within the target range. 'Distribution motifs' are defined by a relationship between occupied and unoccupied of values of the visual variable range, including measures of central tendency (e.g. average values), clusters, density and repetition sequences of value differences.

Figure 41: Distribution of position values

A straightforward example of distribution motifs can be seen in the use of a single dimension of position to display quantitative/interval data values (Figure 41). The rules of the layout map a domain of data values [0, 123] to a range of positions on the page [0, 5cm]. Each horizontal position within the [0, 5] range thus corresponds to a value in the data domain. The correspondence between data domain and visual range of positions establishes two important relationships: distance and whitespace. The distance on the page between any two points is proportional to the difference between the two corresponding data values. Distance is necessary and sufficient[8] to calculate minimum, maximum, measures of central tendency (mean, median, mode), and outlying values (outliers, extreme, least common value). The absence of a point at a particular value ('whitespace') within the range of positions implies an absence of a data element with that value. The potential for empty values gives rise to motifs involving empty intervals, and sequences of filled and empty intervals. Distances and whitespace together underpin clusters (proximity-based groups) of different types, including intervals of a fixed length (e.g. 1cm) containing the most points, intervals from the start of the range containing at least 25% of points, partitions of the range into neighbourhoods whose component points are closer to each other than to the next neighbourhood and so on.

Distribution motifs appear slightly different when a visual variable other than position is used. For example, quantitative values can be encoded using a colour or angle range (Figure 42). Just as with position, the perceptual distance between any two colours within the colour range corresponds to the difference in their associated values. Similarly, colours within the range which do not appear in the visualization indicate values not appearing in the data (gaps in a colour space are harder to perceive than gaps in position, a factor

[8] Very minor technical detail: distance is sufficient for minimum and maximum calculations because any set of data (at a given point in time) is finite.

explored in subsequent chapters). Thus, the same motifs of minimum and maximum values (colours closest to the range limits), average colours, outlying colours, sequences and clusters can all occur in colour-encoded data.

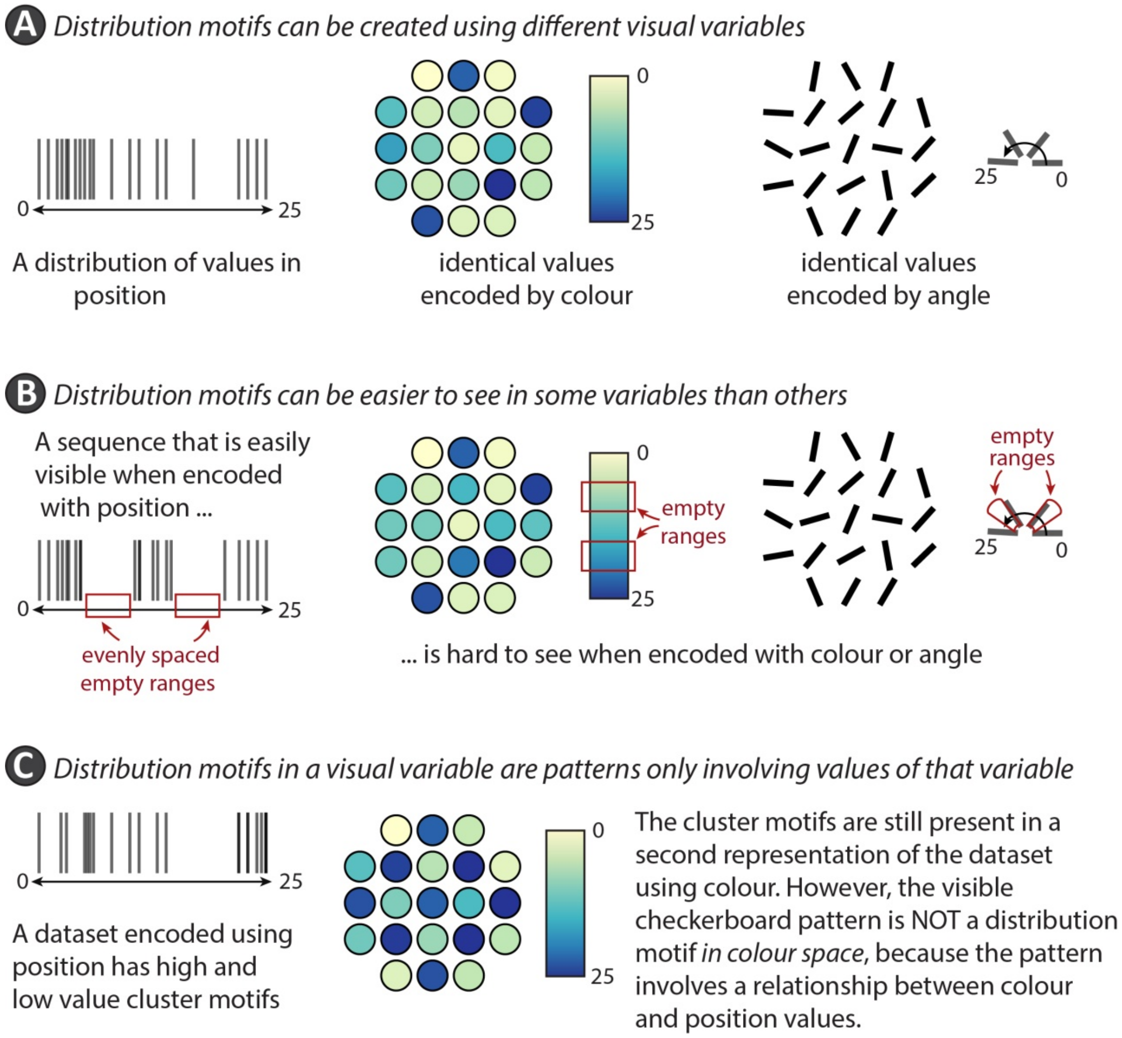


Figure 42: Three datasets encoded using different visual variables. (A) A dataset is mapped to values in position, colour, and angle. The colour and angle values are attached to marks which are additionally arranged in space (position) using a data dimension not used in the leftmost representation. (B) A sequence motif is easy to see in position but not in colour or angle space. (C) An alternating checkerboard pattern apparent in the colour representation is not a motif *in colour space*, as can be seen from the same data dimension represented using position. The alternating pattern *is* a motif in the combined space of colour × position, provided that the arrangement of marks in position space is not arbitrary. Some distribution motifs are less commonly used (and so harder to recognise) or naturally harder to perceive in different visual variables. For example, a sequence in colour space (Figure 42(B)) can be identified by comparing the colour range to the colours in the visualization, revealing a motif where colours from the first 1/6th of the range appear, and then the next 1/6th of the range is unused, the next 1/6th is present and so on. In contrast, what may at first glance seem like a sequence in colour space (Figure 42(C)), is in fact a sequence in the combined space of colour × position (discussed in subsequent paragraphs).

Representations of categorical or ordered data (rather than quantitative) affect the distribution motifs. When values are ordered, not quantitative, two pairs of evenly spaced values are not necessarily equally different, but order is preserved (i.e. if B < C than B – A < C – A). In effect, distances produced within an ordered space are qualitative not quantitative. As a consequence, motifs relying on distance are altered (summarised in the table below). Minimum and maximum values can still be calculated, as can mode and median values, but not mean. Outlying values can be computed based on rank (e.g. 5 highest and 5 lowest values), but not on ratios (e.g. more than 2 standard deviations from the mean). Empty intervals can be identified, but the sizes of the intervals cannot be determined from ordered values. Sequences based on recurring values can appear within visualizations of ordered data (e.g. angle A, angle A, angle B, angle A, angle A, angle B), but not sequences involving interval lengths (e.g. 10°, 25°, 40°, 55°, 70°). Similarly, clusters can arise which partition the space into a fixed number of consecutive values (e.g. the top 1/3, middle 1/3 and bottom 1/3), but not clusters based on relative distance. Categorically valued data yields an even more restrictive notion of distance: values are either the same or different, with no means of further differentiation. Distribution motifs for categorical data are thus restricted to patterns involving more or fewer common values (see Table 4).

Table 4: The effect of ordered and categorical data on (quantitative) distribution motifs

Quantitative Distribution Motifs	Equivalent Motifs for Ordered Data	Equivalent Motifs for Categorical Data
Minimum & maximum	Minimum & maximum	(No equivalent motifs)
Central tendency (mean, median, mode)	Mode, median	Mode
Outlying values (outliers, extreme values, least common)	Extreme values, least common values	Least common values
Empty intervals	Underpopulated intervals (interval size not comparable)	Least common values
Sequences	Sequences of shared and unique or empty values	(No equivalent motifs)
Clusters (by number of elements, relative proximity)	Clusters by number of elements with neighbouring values	Clusters by shared (i.e. identical) values

Distribution motifs depend on distance and empty (or relatively underpopulated) values, and thus are limited when visual attribute values are chosen to match data values exactly (i.e. a bijection between the data values and the visual range). Common examples in visualization practice include stretched bars or areas which fill the vertical visual space, or arranging values in a line or grid. If unused values in the data domain are left out of the visual range (essentially stretching the data to fill the visual range), distances are distorted and qualitative data is effectively reduced to ordered values. When every data value corresponds to a unique visual value, values cannot be shared or underpopulated, eliminating many of the distribution motifs (e.g. mode, empty intervals, sequences, clusters of common values). Matching data values to the visual range is design choice that curtails distribution motifs (but can have other benefits).

When multiple visual variable dimensions are used to encode multiple dimensions of data values, distribution motifs can appear within any of the individual visual variable dimensions, or in the combined space of two or more dimensions together. In the example discussed previously (Figure 42(C)), both position and colour (or position and angle) encode values. Colour-only (or angle only) distribution motifs appear (e.g. the mode is ). The position dimensions on their own do not yield distribution motifs because the mapping matches the data values to the visual range (i.e. the marks the grid). Motifs do occur in the combined position × colour space, such as the sequence of dark blue values alternating with paler colours. Combined space motifs depend on both dimensions. If the colour dimension was removed from the example in Figure 42(C), the marks would be indistinguishable from each other. If the position dimension was removed (i.e. the points were reordered randomly), the alternating (checkerboard) relationship between dark and pale colours would not exist. Distribution motifs in individual variable dimensions reflect a relationship between values *within* the single corresponding data dimension. Distribution motifs in combined space reflect a relationship *between* the associated data dimensions.

The data-to-visual mapping indirectly creates a set of distribution motifs whenever multiple data values are mapped into a visual space such that some visual values may be empty.

6.3.2 Geometric Motifs

The properties of two and three dimensional space give rise to a set of geometric motifs exclusive to the position variable. Geometric motifs still correspond to the abstract task ‘characterise the distribution’, but warrant a separate name since they are the exclusive to the position variable. Position has a unique capacity to create motifs [17, 43]. In contrast with other variables, shapes and other geometric motifs can be recognizably constructed from the relative positions of marks. A cloud of points, for example, can be viewed either as the cloud or as a collection of many discernible points, each of which makes an identifiable contribution (through its position) to the overall shape. Combining marks of different positions has the potential to create higher dimensional shapes.

In variables other than position, colour for example, equivalent group shapes do not arise. Although the rules of colour-mixing are well-understood [36], readers are not able to discern the contribution of unique component colours to a particular hue. Distinguishing a mauve formed from pale blue and red from the same shade of mauve created from pink and medium blue, for instance, is impossible unless the position variable is additionally used to separate marks in space as well as colour (as in large-dot printing). Furthermore, combined colours are perceived visually as a single colour.

Separate types of geometric motifs arise from point, line and area/volume marks. ‘Shape motifs’, as they are termed here, can be created from point, line, area or volume marks. ‘Path’ and ‘gradient’ motifs are formed from line marks and the boundaries of area and volume marks. Finally, ‘enclosure’ motifs require either area or volume marks.

Table 5: Examples of shape motifs

Geometric shape	Defining relation	Additional variables
Straight line	Two points establish a (straight) line	Length (for lines in 1, 2 or 3D space), slope (lines in 2 and 3D only)
Triangle	Three points, unless they are collinear	Area
Quadrilateral	Four points (no 3 of which are collinear)	Area
Plane	In 3D space, three points unless they are collinear	Slope
Circle	Any distance and point	Length (diameter), area
Ellipse	Any two distances and a point OR Any two points and a distance	Length (major axis), width (minor axis), slope (major axis), area

Shape Motifs

Shape motifs are created when quantitative (or ordered) data is encoded using dimensions of position or any non-position variable used in combination with position (see examples in Table 5).

Shape motifs capture geometrical relations between points in (Cartesian) space. Geometric relations include, but are not limited to, straight lines, planes (in 3D), triangles, circles, ellipses, parabolas, convex hulls. Any set of equations involving some combination of points, distances and angles defines a geometric relation which is visually recognisable in a two or three dimensional (position) space. Those relations are shape motifs (unless they are already defined as general distribution motifs).

In a visualization, shape motifs can appear as direct relations between mark positions (e.g. a line between the minimum and maximum points) and as approximations of mark positions (e.g. an ellipse which best matches the set of all points).

Shapes involve a selection of positions in the visualization, which may be chosen because of their internal significance within the visualization – minimum or average values, for instance – or because they correspond to important data values (a control or reference data sample, for example). The resulting shape can have meaning on its own, but also defines a relationship of other positions in the visualization. Geometrically closed shapes (e.g. circles, triangles, quadrilaterals etc.) separate positions inside and outside the shape. Open shapes (e.g. straight lines, parabolas) define positions as belonging to one or other side of the shape (positions can also be ambiguously related to the shape if it does not continue to the boundaries of the space). Shapes can also be formed so that the relationship between positions defines the location or proportions of the shape. An example is a line placed so that half the points in a scatterplot are below and half above the line. Shapes formed from positions not corresponding to data values are the shape equivalent of whitespace motifs in the distribution category.

The positions from which shapes are constructed can be point marks, or position values within line, area and volume marks. For instance, a peak in a line graph is a triangle shape motif formed from positions on the line mark, where the middle point of the triangle is a local maximum. Shape-forming positions can also be positions in space corresponding to specific data values, whether or not a mark exists at that value. As with distribution motifs, shape motifs are only relevant if the mapping from the domain of data values to the visual range preserves distances. The mapping also needs to include the possibility of empty values (i.e. the data values don't simply form a grid of points), unless another visual variable is also used to differentiate values at different positions (e.g. colour in a heat map). When an additional visual variable is used, shapes can be formed from one or more values of that additional variable. For example a cluster of red pixels against a blue background can define a shape, as can a pattern of 30° line segments in amongst other line segments.

Distribution and shape motifs can appear together to form more complex motifs. For example, maximum and minimum distribution motifs and the peak shape motif combine to produce a 'maximum peak' motif – the largest of all the peaks in the line graph. Similarly, a motif of recurring peaks in a line graph is formed from the combination of a distribution motif (a sequence) of a shape motif (a triangle or peak).

Gradient Motifs

Line and area marks[9] positioned in a visual space can form distribution and shape motifs (e.g. clusters, peaks), but can also create their own exclusive geometric motifs involving line gradients (i.e. slope) and intersections.

Gradient motifs are geometric relationships which can be defined by relationships between gradients but not points. Within a two dimensional space, lines have both a gradient and the potential to intersect. Straight lines have a single (constant) gradient value, and at most one point of intersection with any other straight line (including the axis lines). Continuous curved lines have a variable gradient, giving rise to 'turning point' and 'inflection point' motifs where the gradient is zero. Jagged lines (i.e. a sequence of points linked by straight line segments) may have a different gradient at each line segment, with points of gradient change (e.g. from positive to negative) in between. Both curved and jagged lines have the potential to intersect other lines at multiple points. Gradient motifs also include distributions of slopes and intersections formed from multiple lines, such as parallelism. Points where two, three, or any other number of lines intersect form gradient motifs, as do sets of intersecting lines of increasing or decreasing gradients (seen for example in the $y = -x$ or $y = x^2$ pattern in a parallel coordinate plot).

Any set of lines in a suitable space give rise to gradient motifs, including boundaries of area marks and surface paths on volumes. Sets of points which can be perceived as lines (e.g. through Gestalt principles [36]) will also give rise to gradient motifs. In a 2D or 3D quantitative space (i.e. the data dimensions corresponding to the visual space are quantitative), gradients and points of intersection have numerical values. When the space is ordered, positive and negative gradients can be distinguished, but gradients do not have meaningful numerical values (in terms of the data). Similarly, points of intersection can be related to the data order, but their position value does not necessarily correspond to a

[9] Or collections of points which are perceived as lines

quantitative value in the data domain. When one position dimension is quantitative and the other is ordered (or even categorical), gradients are numerically comparable if (and only if) they begin and end at the same value in the quantitative dimension.

Enclosure Motifs

Areas and volumes[10] give rise to 'enclosure' motifs, in addition to motifs of shape and gradient. Enclosure motifs describe properties of the area or volume enclosed by a mark, as well as motifs created from overlapping or intersecting areas and volumes. Areas and volumes enclose a region of observable size, which can have properties such convexity (straight lines connecting any two boundary or surface points remain within the shape) and shape (e.g. ellipsoid, star-shaped). When two or more areas (or volumes) overlap, a new area (volume) is created. The enclosed area (volume) has properties including size, boundary position (and associated gradient motifs), and centroid position.

6.3.3 Path Motifs

Links in a visualization – line marks used to denote connections between either points in space or other marks – also give rise to motifs above and beyond general distribution motifs. 'Path' motifs describe motifs formed from distributions of links in a visualization. Unlike gradient motifs, path motifs can arise regardless of whether the position of the line ends has quantitative, ordered or categorical meaning, or lacks consistent meaning (e.g. points are arranged aesthetically or relative to each other).

In contrast to other motifs, path motifs are well documented in the literature in the form of network motifs [226]. Path motifs include chains of links (paths of length *n*), cycles, and forks. When links are directed, additional source and sink node motifs are possible.

6.4 Determining possible motifs

In general, adding marks and visual variables adds motifs to a visualization, but both data and layout design choices influence how motifs are formed.

6.4.1 Data constraints

When data is structured or transformed in some way to constrain the relationships between data elements, the constraints are carried over to the visual representation. For example, in a data-tree structure, each data element has a single parent element (except the root element), and zero or more child elements (not connected to any other data

[10] Including sets of points and lines which are perceived as areas

elements except their own children). If the data-tree is represented in a network, the restricted relationship types restrict the path motifs which would normally arise from the use of links. Cycles of any length are not possible, since child nodes cannot connect to higher elements in the tree other than through their parent node. Another example of data constraints is symmetric data. The dataset for a recurrence plot is created by taking the (absolute) difference between all possible pairs of values in a series [54], so that the value of a point (a, b) is always the same as the value of (b, a). A visualization of this dataset will be symmetrical *as a result of the data transformation* used in its creation, and so will not contain a meaningful motif of symmetry (around the line a = b).

6.4.2 Variable Choice

Design choices in a layout can expand or constrain the motifs of a visualization depending on how they use the visual variable dimensions. Visual variables 'stack' onto marks – a mark can have position (in two directions), hue, saturation, size (length and width), shape, angle and texture [17] – with each additional variable dimension compounding the number of motifs. Not all variables are compatible with each other for all mark types, however. If a line mark is defined by position, it can be given the additional size variable of width, but not length. An area mark (whose perimeter is set by a mapping from data values to position) can have neither width nor length. Similarly, angle can only be used when the shape of the mark is distinguishable in different angles (i.e. a circle cannot be used with angle, while the angles of a square-shaped mark can only be used to encode a very limited number of data values).

6.4.3 Partitioning Variables

A second layout design choice affecting the motifs of a visualization is partitioning of a visual variable into multiple 'spaces'. Different visual variables have different 'intrinsic' or 'inherent' dimensionality, which limits the ways an additional dimension data values can be encoded. There are two dimensions each of position and size, but only one of angle and saturation. In other cases variable dimension is slightly more complicated, but still well understood. Colour hue can vary along two dimensions: blue-yellow and green-red, but these two dimensions are very difficult for the viewer to separate (orange and purple are perceived as unitary colours, not yellowy-red and bluey-red) [36]. Thus colour hue effectively provides only one intrinsic dimension of information encoding.

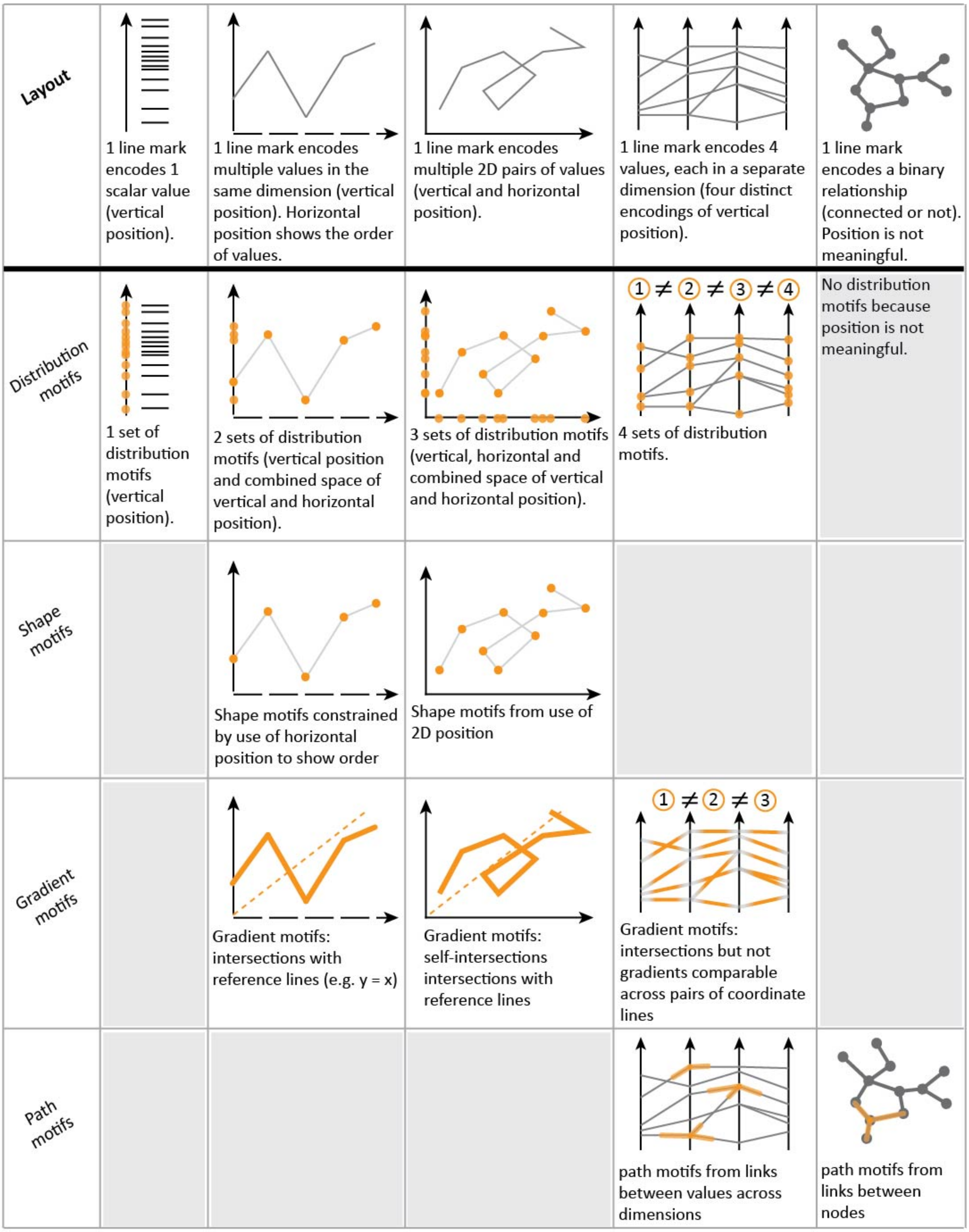


Figure 43: Creating multiple sets of motifs using the position variable

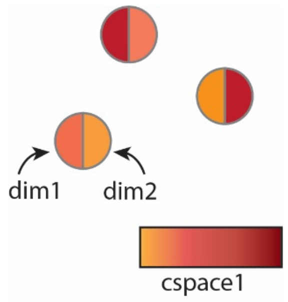
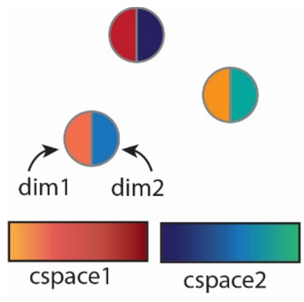
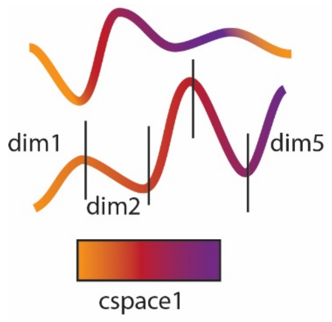
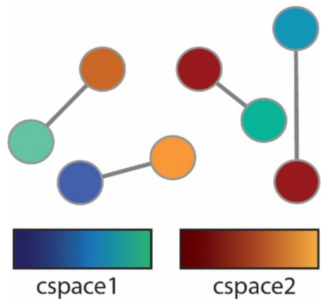
Use of colour	Motifs arising from use of colour
	Distribution motifs in dim1, dim2, combined space dim1 x dim2 and distribution motifs in dim1 and dim2 together (dim1+dim2)
	Distribution motifs in dim1, dim2 and dim1 x dim2
	Distribution motifs in dim1, dim2, dim3, dim4 and dim5, as well as distribution motifs from combinations of dim1 to dim5
	Distribution motifs in dim1, dim2 and dim1 x dim2

Figure 44: Encoding multiple dimensions of data values using the colour variable

The intrinsic dimension of a variable does not limit the number of data dimensions it can encode, but extending the encoding beyond intrinsic dimensions affects the motifs produced. Any variable can be partitioned into multiple ranges (‘spaces’), each of which encodes a different data dimension. Marks can also be partitioned to hold different dimensions of value. Example layouts (Figure 43) demonstrate that a single line mark can use the variable of position to encode a single scalar value, a sequence of scalar-valued pairs (2D vector data values), a single 4D vector value or a binary relationship between two values. The number of meaningful dimensions determines the number of sets of distribution motifs (see Figure 43). Neither *x* nor *y* position has meaning in the network visualization (0 dimensions of value), only vertical position is meaningful in the 1D scatterplot (1 dimension of value), both *x* and *y* are meaningful in the line graphs, whereas *y* has 4 different meanings at 4 distinct *x* positions in the parallel coordinate plot. Partitioning a variable adds motifs, but the scope of each set of motifs is restricted to within each partitioned space.

Non-position variables can also be under- or over-utilized in a single mark compared to their intrinsic dimensionality. Points, lines and areas can all be given multiple colour values, and the colour space can be partitioned to represent different value dimensions (see Figure 44). As with position, multiple colours can be used to encode multiple values in the same value space (e.g. the warmest and coolest temperatures in a day), or connected values in different spaces (e.g. train destination and arrival time). Since hue has only one intrinsic dimension, it does not have the same capacity to encode vector-valued data with a single visual value (compare to a single position in a scatterplot conveying a 2D vector value). Instead, the mark needs to be divided into parts to support multiple values. Either a consistent position within the mark encodes each dimension of value through hue, or the space of hues can be partitioned so that a particular range of colours consistently corresponds to a given dimension. When the colour space is partitioned, a particular hue either means dim1 or dim2, but not both (just as in the parallel coordinates plot (above) *x* position either means dim1, dim2, dim3 or dim4 (or no value), but only one of these dimensions). Other variables such as shape and texture can similarly be multiply encoded.

In summary, the motifs possible in a layout can be determined by adding:

+ Separate distribution motifs for every partition of a visual variable (scope restricted to the partition), unless the data values match the visual range
+ Combined distribution motifs for visual variables encoded on the same mark
+ Geometric motifs for each space containing 2D position (shape, line and area motifs depending on type of position use)
+ Path motifs if the layout uses links

…and then discounting:

– any motifs which are a result of the data structure or transformation used to create the visualization

6.5 Motif Characteristics

The concept of motif developed through the motif typology has a number of characteristics which make it useful as the structuring concept for the semantic scaffolding model.

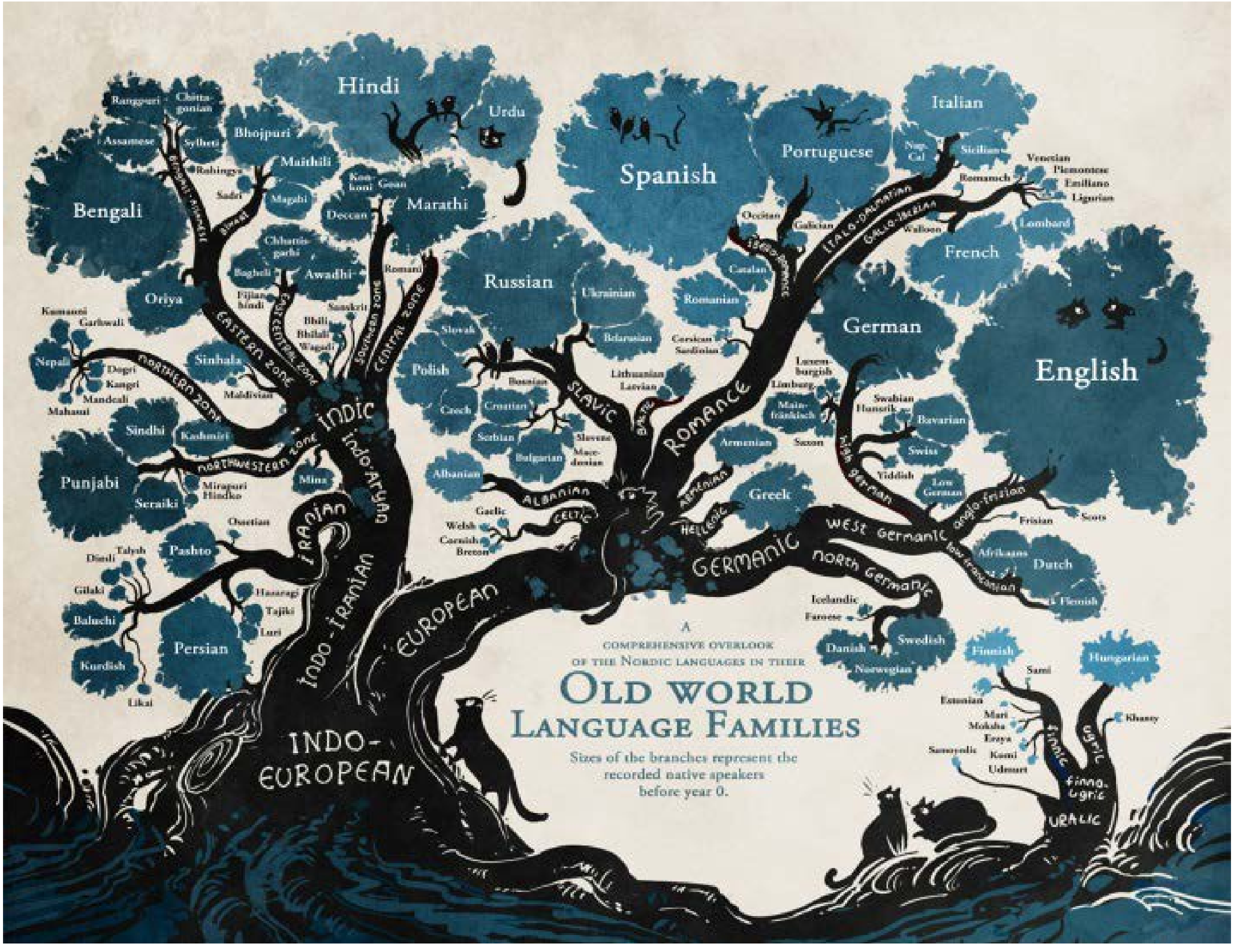


Figure 45: The tree shape in this visualization is formed by an aesthetic choice about the shapes and layout of the network nodes and links. Path motifs *are* present, formed by the data-driven links between nodes.

Indirect construction distinguishes motifs and variable values. A motif is indirectly formed from the relationship between component visual values. The motif value is derived from the values of the individual components. Many motifs have the same appearance as visual variable values. A checkerboard pattern can be created by points distributed in an alternating grid (a motif), or chosen as the texture to represent a particular categorical value (a variable value). Angles can be formed from straight lines whose ends are positioned based on data values (a motif), or the angle can be set directly based on a single data value (a variable value). Unlike motifs, a directly encoded variable value lacks individual visual components (i.e. squares in the checkerboard) which correspond to separate data values.

Motifs are also distinct from figurative visualization. If data is arranged on a purely aesthetic basis (i.e. without following a set of consistent rules or transformations), any shape can be formed. The shape can still encode information (see Chapter 5), however, the shape will reflect the deliberate intention of the designer, not an underlying relationship in the data. In a hybrid figurative-abstract layout (for example Figure 45) the abstract mapping determines motifs (e.g. path motifs), while the figurative components convey descriptive information.

Indirect construction of motifs provides visualization with the capacity to convey unintended and unexpected information. When visualization is used for analysis, a typical use case is for the analyst to transform the data from an array or database representation into a visualization. The expectation is that the analyst will see something new from the visual representation (e.g. [8, 30]). Since the analyst is choosing how data values will be mapped into visual variable values, the individual visual values cannot provide new information. Motifs, however, appear because of the interaction between visual elements representing data values. Motifs will be formed regardless of whether or not the analyst intends them to appear, and thus can be new, even to the visualization creator.

Motifs are distinct signs in the visualization sign system, as well as combinations of signs. Signs are distinguished by their mediating relationship between an object in the world (data in the visualization sign system) and the perceiver's interpretation [19] . Motifs fit the definition of a sign: they correspond to a relationship between data values, i.e. they represent objects (discussed further in Section 7.2), and are perceived as unitary visual forms, albeit forms with component parts [39]. A cloud of points in a scatterplot is perceived as a single shape [39]. Readers can use prior knowledge of motifs to recognise matching or similar motifs. For instance, readers compare lines in a line graph (but not in a map) to a mental reference line y=x [83].

As a structuring concept, motifs are the basis of a motif typology which is more suited to a model of visualization interpretation than existing visualization grammars. The motif typology is focussed on perception, not visualization construction. In the existing visualization grammar of Wilkinson, layouts are distinguished by differences in construction [18]. For instance, in Wilkinson's grammar a box and whisker schema is different from a layout with the same appearance created from two line segments plus a point mark. In the motif typology, the two layouts are the same because they create the same set of potential motifs (see Figure 46). Motifs depend on which visual relationships are meaningful, regardless of how those relationships were constructed.

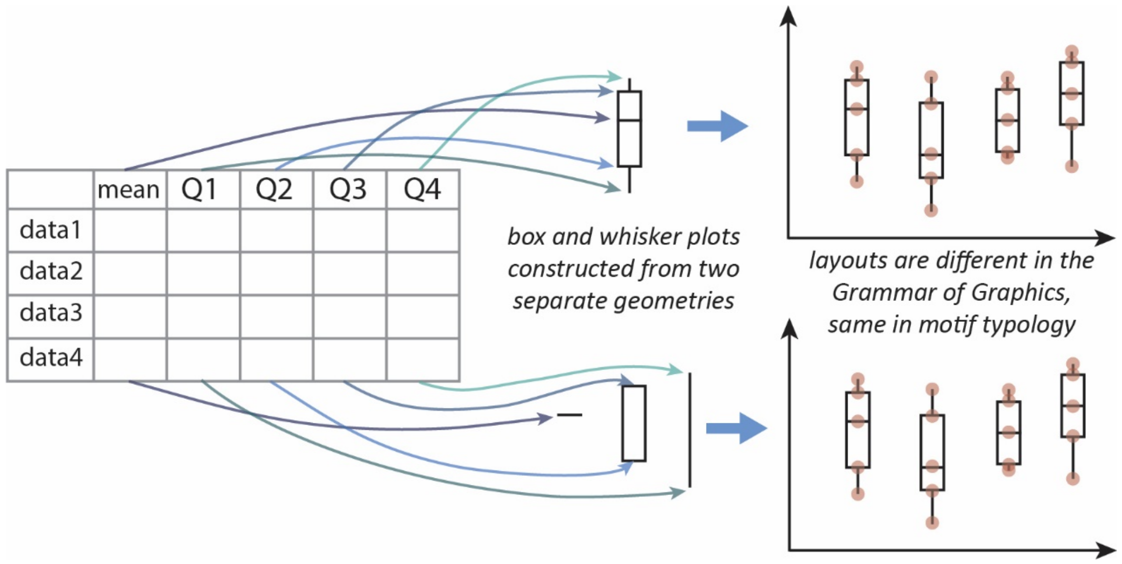


Figure 46: Box and whisker plots whose construction is distinct in Wilkinson's Grammar of Graphics [18], but have the same motifs. Orange dots on the plots highlight the points in the visualization corresponding to data values; the vertical distances and horizontal angles between these points are the basis of the box and whisker motifs.

The motif typology enables a distinction between the motifs *present* in a visualization, and those most easily *perceived*. The set of possible motifs which can be generated using the typology are the motifs present in a visualization. Gestalt principles can be used to identify highly salient motifs in a visualization [11]. For instance, the motif associated with a trend line is easier to perceive in line graphs (where the trend line is grouped by the principle of continuity) than in bar graphs [11, 91]. However, salience is affected by prior experience with the same or similar visual scenes [154], suggesting that readers will be able to see familiar or relevant motifs which are normally less salient. To conduct research on the meaning and interpretation of motifs (the subject of the following chapter), it is necessary to be able to identify the full range of motifs associated with a visualization.

6.5.1 Typology Limitations

There are a number of limitations of the motif typology, primarily around its specificity and application to a visualization layout. The different motif types have been described here, but not listed completely. Additionally, the typology relies on the user to identify the meaningful visual variables used in the layout, as well as the effect of the corresponding data types and data structure on the motifs.

The typology is initially intended for information visualization researchers, to aid in the development of visualization evaluation measures. To develop the typology into a tool for visualization design, a more detailed guide or automatic motif identification generator could be developed in the future.

6.6 Conclusions to the Motif Typology

Motifs are created as a result of the local level data-to-visual transformation. Properties of primitive visualization marks and visual variables determine the different types of motifs which can arise. Combinations of marks and variables add the capacity for additional motifs to a visualization, constrained by data structure and variable partitioning.

Any visual variable can create distribution motifs, which are visual relationships involving distance. The use of the position variable can also create geometric motifs, consisting of shape, gradient, and enclosure motifs. Path motifs are created from the use of links in a visualization.

The motif typology was created as a preliminary component for the semantic scaffolding model. Motifs form the structuring concept of the semantic scaffolding model, chosen because they are key to visualization value and have the capacity to provide information which is new even to the visualization creator. Based on the data-to-visual mapping and the data structure, the motif typology can be used to predict and describe the motifs which are possible within a particular visualization layout.

7 The Semantic Scaffolding Model

"[T]he comprehension of graphs is complex, with viewers spending the majority of the time interpreting a graph relating information from the lines on the graph to their referents, rather than viewing the patterns of lines themselves." [10]

Semantic scaffolding is explained in this thesis through a semiotic approach, by analysing the correspondence between sign and meaning. The distinction between form and meaning at the intermediate level (motifs and intermediate questions) is particularly important because of the unique characteristics of data visualization as a sign system. Any collection of marks or regions of space in a visualization can be a motif, but not every motif will have practical significance. The semantic scaffolding model shows how meaning of motifs is both inherited from the local level mapping and discovered or recognised by the reader based on their domain knowledge.

In the semantic scaffolding model, the practical use of a visualization is phrased in terms of questions. Following the underlying VFR model [93], questions are used as the generalised form of an interpretation. A specific representation may prompt an action (e.g. issue a weather alert), decision (e.g. choose which regression method to apply) or reaction (e.g. bitcoin generates a surprising amount of CO_2). The abstract form of that representation – its layout – prompts action-questions (e.g. 'should I issue a high-wind alert?'), decision-questions ('which regression method should be applied?') and reaction-questions ('does bitcoin generate more CO_2 than expected?'). Questions of the type discussed in this chapter are thus an expression of practical tasks.

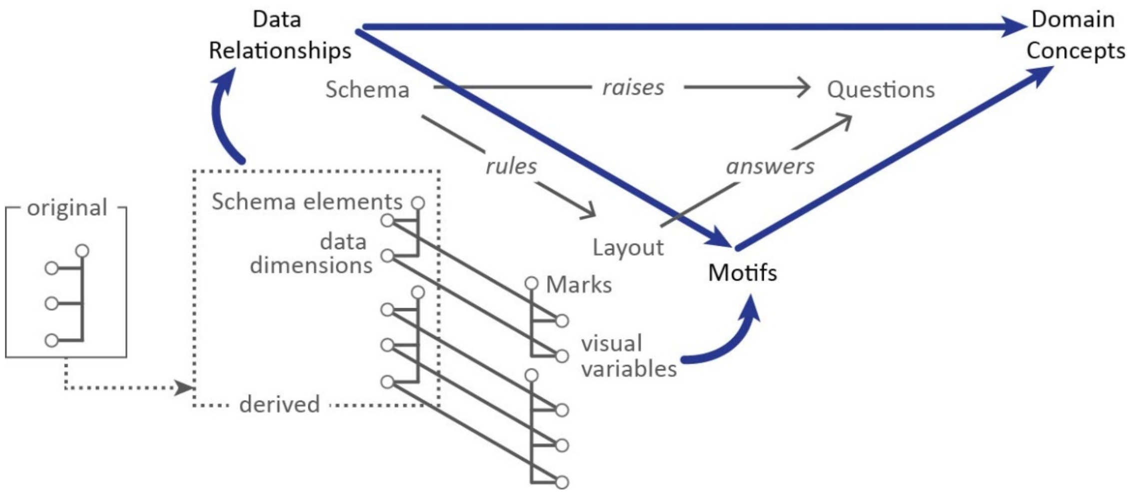


Figure 47: The completed semantic scaffolding model, showing the underlying framework of the VFR layout triangle.

7.1 Chapter Structure

The semantic scaffolding model is presented in this chapter by tracing how:

i. motifs correspond to relationships between elements in the data schema,
ii. the reader's understanding of the domain provides some data relationships with a cohesive meaning relevant to (practical question),
iii. the correspondence between motifs and relevant domain concepts is noticed and interpreted by the reader.

The completed semantic scaffolding model (shown in Figure 47) adds additional mappings to the VFR layout triangle (see Chapter 6), showing relationships between motifs, data relationships, and the reader's domain concepts. The term 'semantic scaffold' will be used to refer to the interlinked relationships between form and meaning established by the reader's interpretation of a visualization (as described by the semantic scaffolding model).

The structure of this chapter follows the structure of the semantic scaffolding model: a separate section explores each mapping within the scaffold (Figure 48).

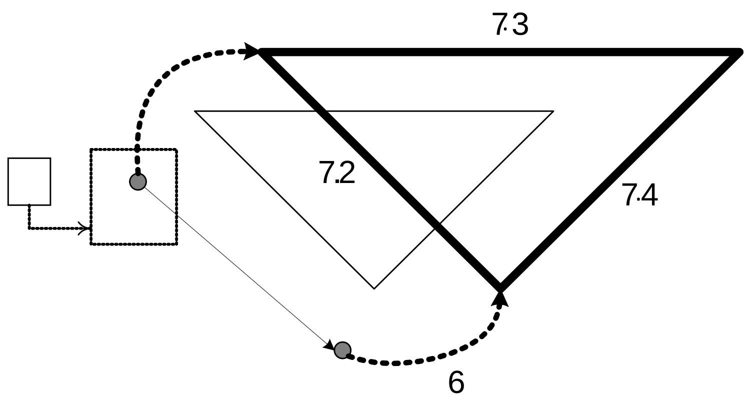


Figure 48: The structure of this chapter, as mapped to the semantic scaffolding model

7.2 Meaningful Motifs

The first component of the semantic scaffolding model is the correspondence between motifs and data relationships. Motifs are a relationship between multiple meaningful (i.e. data-encoding) visual values (see Chapter 6). As such, motifs represent relationships between data values, inherited through the data-to-visual mapping. In the semantic scaffolding model, the correspondence between data relationships and motifs is captured with a link parallel to the *rules* function (see Figure 49). The parallel between the *rules* mapping and the data relationships to motifs correspondence reflects the inheritance of meaning from the low level assignment of visual variables to data schema elements and properties.

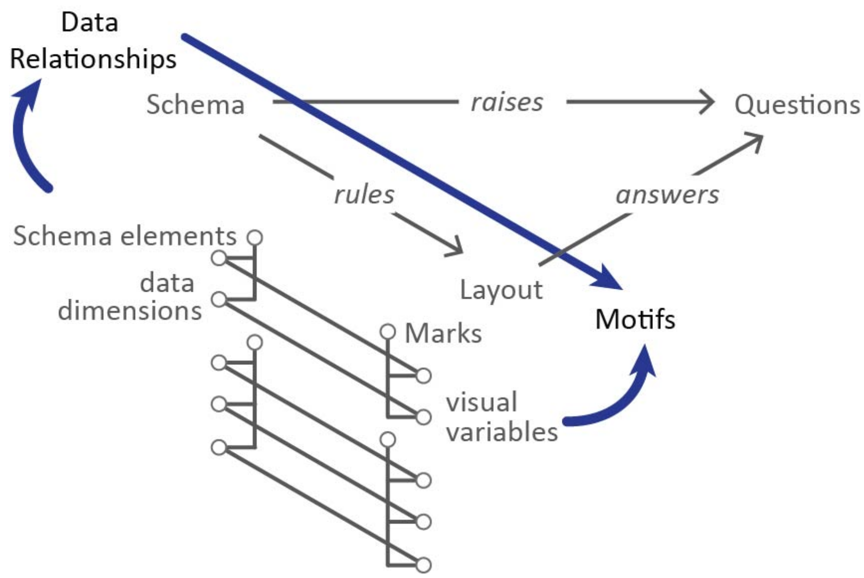


Figure 49: the correspondence between motifs and schema relationships

A motif's represented data relationship – its inherited meaning – is a translation of the visual motif relationship into a relationship between data values. Difference and distribution motifs have obvious translations: the visual mean of a set of angles, for example, translates to the mean data value encoded by angle. Similarly, data relationships involving simple differences and distributions are represented by distribution motifs, as demonstrated by a colour-shaded scatterplot of selected baseball team metrics from 2013 (Figure 50). The relationship 'teams with salary spending above $178m' is represented by a visual distribution motif in colour space: the set of points whose redness is greater than a specific shade of red (roughly a medium to bright red – see highlights on key in Figure 51). The relationship 'total strike outs and hits by teams with salary spending above $178m' corresponds to a distribution motif in colour *and* position space (blue highlights in Figure 51).

Translations of geometric motifs may be less transparent, as the data relationship corresponds to the relationship of difference or similarity which defines the geometric shape. Take, for instance, a triangle enclosing points between the line *y*=*x, x*=*a* and *x*=*b* in a 2D plot representing two student test scores (see Figure 52). The visual motif of the triangle corresponds to a data relationship where a large group of students have test 1 scores between *a* and *b* and scores in test 2 which are lower than in test 1.

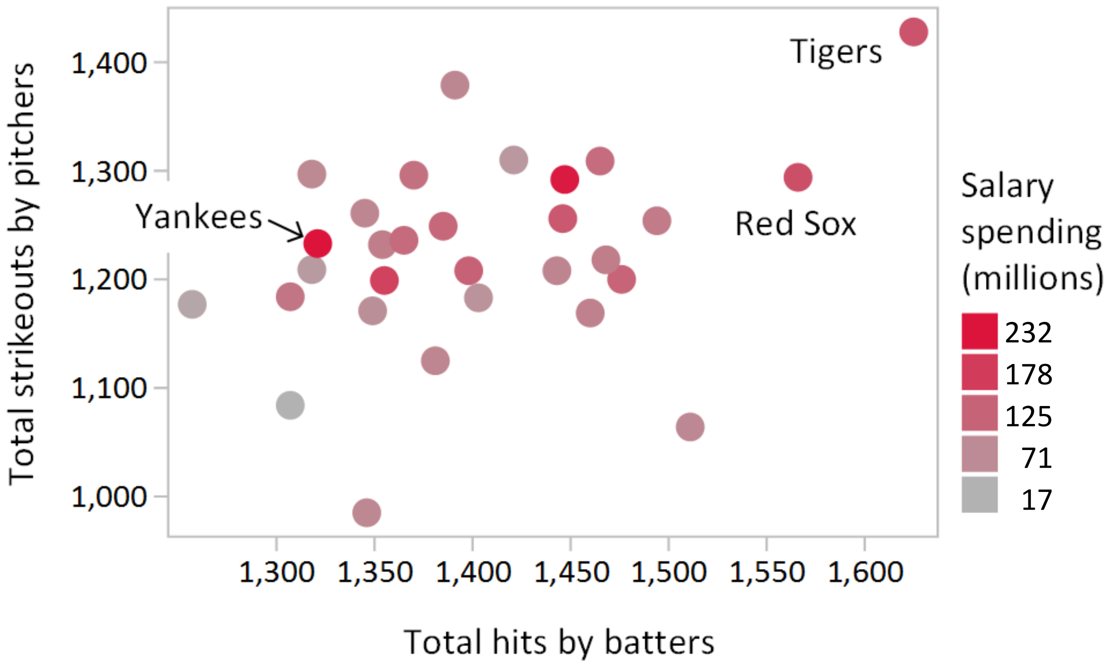


Figure 50: Salary spending vs. total hits by batters and strikeouts by pitchers by baseball teams in 2013. Data source: [227]

A motif represents a single relationship in the data, but that relationship can have multiple equivalent forms of expression. For instance, the triangle motif described previously (Figure 52) can equally accurately be described as students whose test 2 score is at least b, but no more than a, and lower than their test 1 score. Unlike local level visual features, the data relationships encoded by motifs are not explained (in general) by the key or axis labels. Instead, the reader must interpret the meaning of motifs based on the meanings of their visual components [10].

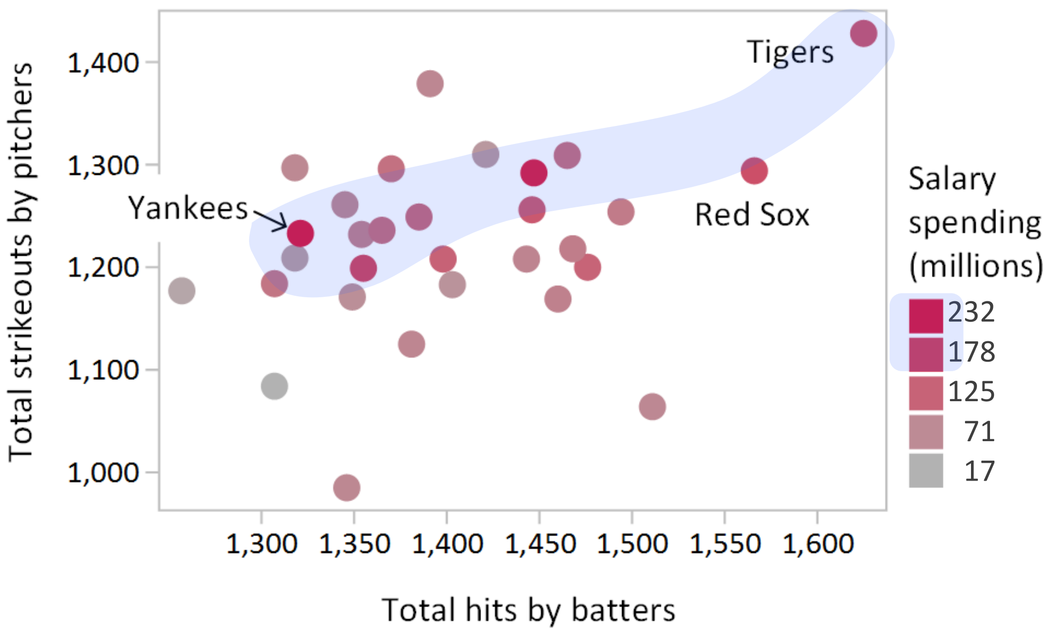


Figure 51: Salary spending above $178 million highlighted from Figure 50

The correspondence between data relationship and motif is one of the three triadic relationships defining a semiotic sign (in the tradition of Peirce) [19]. From a semiotics perspective, a motif conveys meaning because of two additional relationships: the interpreter's (i.e. reader's) knowledge of the object, and their recognition that the representation (motif) corresponds to that knowledge. The following sections show how the reader's prior experience affects these two relationships.

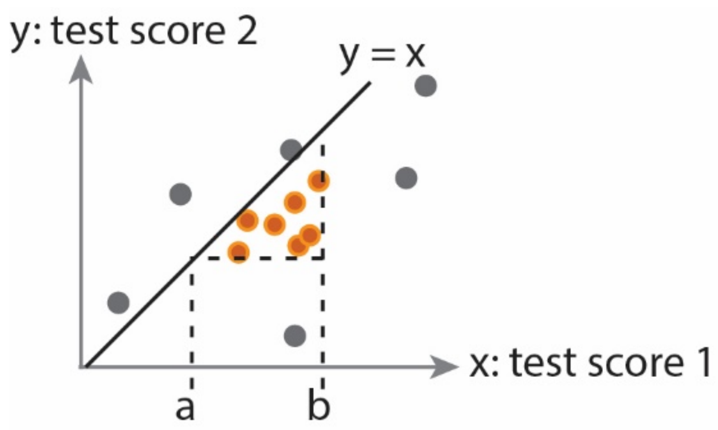


Figure 52: A triangle motif in a 2D plot of student test scores (artificial data)

7.3 Domain Knowledge and Questions

Concepts in the reader's domain-knowledge which relate to a collection of data elements provide a cohesive meaning to sets of visual elements. Domain concepts are an expression of the data relationship which is relevant to the reader's practical task. Through the correspondence between motif and data relationship, domain concepts elevate a motif from a collection of marks or attributes into a meaningful, cohesive structure. The idea has been captured in the semantic scaffolding model by adding a path which maps from the data relationship to domain concepts (see Figure 53).

7.3.1 Domain Concepts

A visualization is read in context, with the reader making use of their knowledge of the domain being visualized [15]. To understand the impact of the reader's existing knowledge on visualization interpretation, it is important to make a rudimentary characterisation of that knowledge.

Experience provides a reader with mental resources to describe, understand and act within a familiar domain [119]. Domain knowledge includes information and relationships between information, such as associations, classification, hierarchical relationships, properties and more. The reader's knowledge includes concepts about 'how to think' about different kinds of subjects – statistical measures, processes or transformations which can be used to operate on elements of the subject [119]. For example, readers with mathematics or physics training understand Fourier series as a transformation to reveal component frequencies, or convolution as a way of blending operators or derivative as a means of measuring rate of change. Domain knowledge also facilitates analytic actions, through process knowledge [119]. Process knowledge can be highly individualistic, with people developing their own cognitive units and activities for familiar processes [119]. As with factual and relationship knowledge, process or operations knowledge around a subject can be more or less comprehensive. A reader can be aware that complex systems have phases and attractors, or understand the relationship between speed and velocity, without being able to recall a detailed mathematical characterisation of these phenomena.

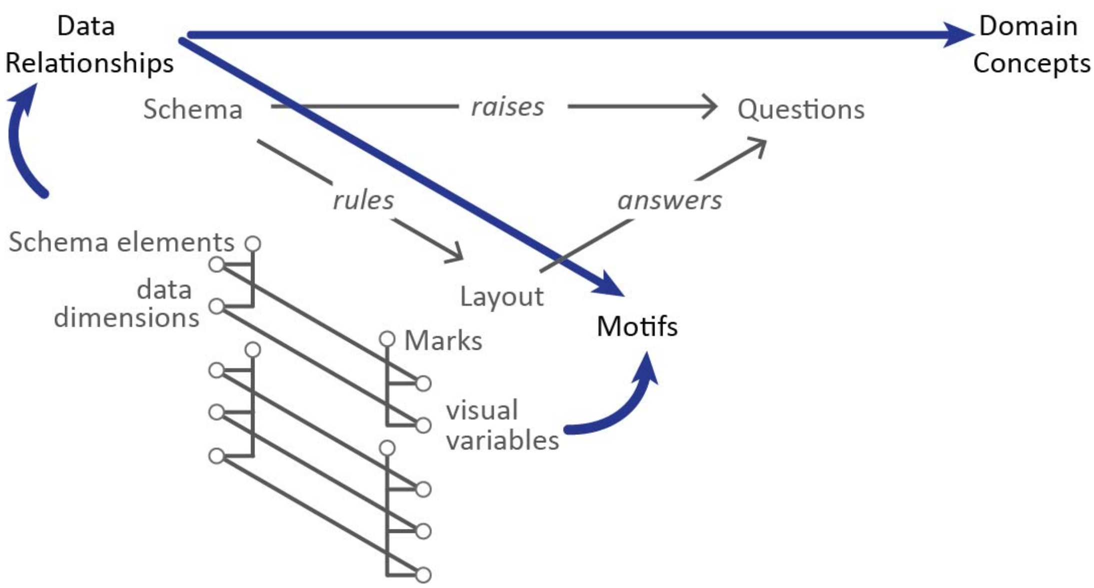


Figure 53: The data relationship to reader's domain concept addition to the semantic scaffolding model

Domain knowledge in the semantic scaffolding model refers to information related to a visualization's data schema which is known by the reader. The model distinguishes between information encoded *in* a visualization, and information related to the subject *of* the visualization. In existing visualization theory, the concern is primarily with encoded information (see Chapter 2). For instance, analysis of the data-type (ordinal, quantitative etc) and suitable visualization layouts for that data-type [90] concerns the encoded information. Similarly, the argument that the reader's familiarity with the data in a visualization limits the extent to which he or she can gain new information from that visualization [3] is based on encoded information. However, the information used to construct a visualization (the data) forms only a small part of the information available about a domain. In Culy's extended pipeline model, a distinction is made between a 'domain model' (the current state of knowledge about a topic) and a 'data model' (the structure used to create a visualization) [228]. Culy's extended pipeline is primarily concerned with visualization creation, however, not interpretation, and so is concerned with the visualization creators' domain knowledge. The impact of domain knowledge on tasks or questions must be due to the domain knowledge of the person carrying out the task, i.e. the reader.

7.3.2 Data Relationships to Domain Questions

In the semantic scaffolding model, domain knowledge provides task-specific interpretations of data relationships corresponding to motifs. Knowledge of concepts related to the data represented in the visualization (described in the abstract by the data schema) extends the meaning of data relationships.

An example can be seen in the baseball visualization described previously (Figure 50). The baseball visualization is created from a simple, four element data schema consisting of baseball teams, total hits by batters in the team over the year, strikeouts by the team's pitchers, and the total player salaries paid out by the team. In the visualization, each team is a separate point, 'total hits' maps to horizontal position, 'total strikeouts' maps to vertical position and 'team salary' is shown by colour. Team names appear when the reader hovers the mouse over a point (selected team names are shown in the static version in Figure 50). What questions does this visualization enable a baseball fan to explore? First, a reader can identify the strikeouts, hits, and salary of any team of interest, learning, for example, that the 2013 world series winning (Boston) Red Sox made around 1575 hits, just under 1300 strikeouts, and paid around 178 million in salaries. The reader might also ask whether there is a positive correlation between hits and strikeouts, suggesting a possible correlation between overall offensive and defensive performance (as indicated by hits and strikeouts respectively). Or the reader could compare how performance corresponds to results – the final four teams (Red Sox, Cardinals, Tigers and Dodgers) are all in the top right quarter of the graph, but the Detroit Tigers, who decisively led the group in terms of hits and strikeouts, were knocked out by the Red Sox in the American League Champions Series. Or the reader could ask what value for money a team achieved in 2013, or how many teams spend above the 178 million threshold at which teams have to pay 'luxury tax'.

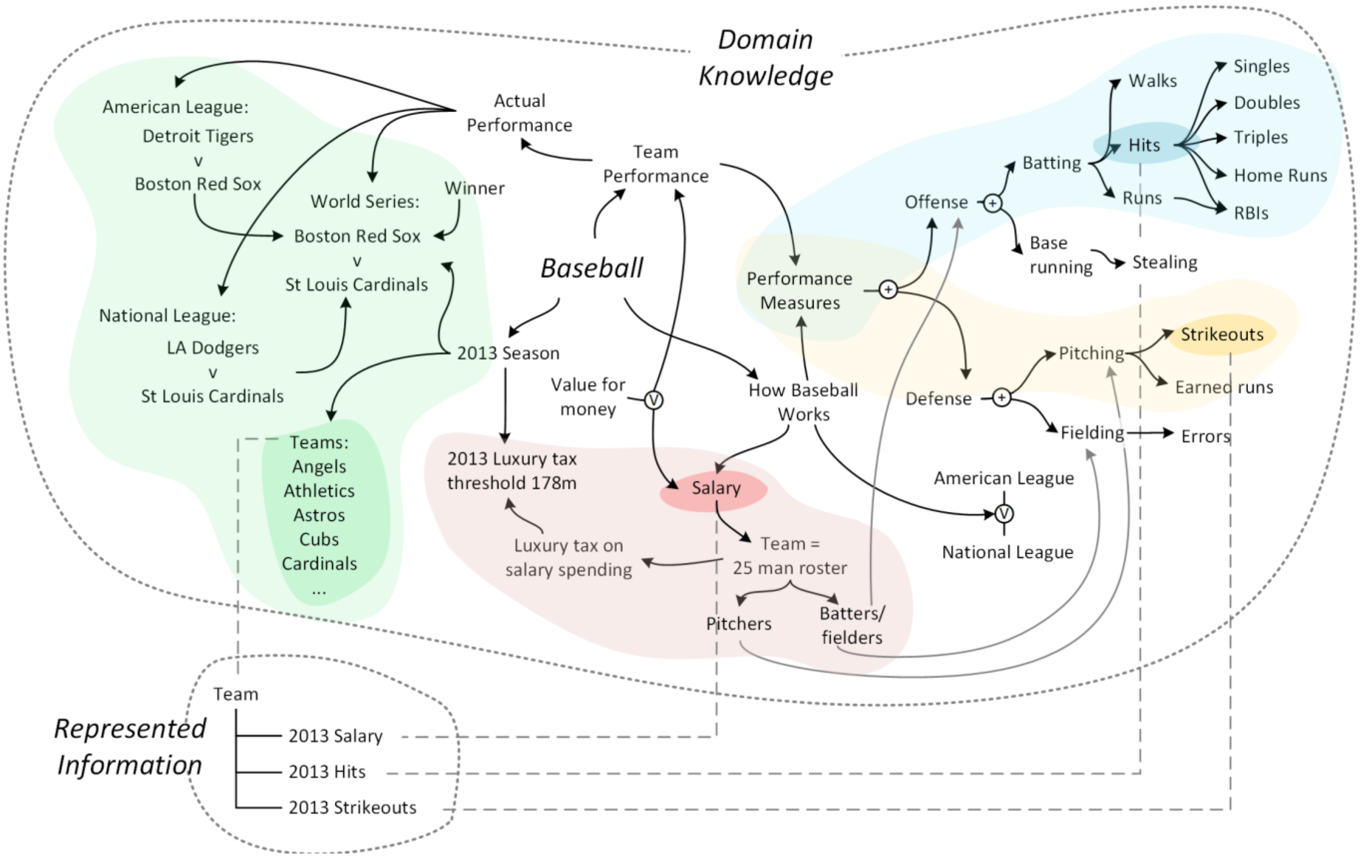


Figure 54: The relationships between data schema (bottom left) and a concept map representation of a domain schema (top) for 2013 Major League Baseball

The questions described above are contingent on knowledge of baseball. Figure 54 provides an illustration of how information represented in the visualization takes on more significance based on conceptual links within the reader's mental model of baseball, while Figure 55 shows the visualization annotated to show some of the places in the visualization which have additional significance based on the knowledge in Figure 54. Even basic interpretations, for example that higher total strikeouts and hits are better depend on a rudimentary understanding of the sport. Additional prior knowledge makes some teams more interesting than others (e.g. the winning Red Sox). Displayed information is interpreted in terms of external reference values, as seen in the observation that few teams exceed the luxury tax on team salaries, or the use of the final four teams to evaluate the metrics of hits and strikeouts. From domain expertise, the reader knows that a team's performance can be measured in terms of its offense and its defence, where strikeouts contribute to defence, while hits are key to offense. Through the domain understanding, a correlation between hits and strikeouts is transferred to a potential correlation between offensive and defensive performance. Awareness of other factors which affect offense and defence (e.g. walks, fielding errors) underscores that this is a *potential* not an *actual* correlation, and opens a path to further exploration (e.g. are strikeouts a good indicator of overall defensive performance?). Familiarity with baseball furnishes the reader with knowledge that a team's salary is split between the two player types: pitchers and batters (who also field). The two hypotheses about team spending depend on the division of salary into player types, and the link between player types and the metrics of hits and strikeouts. The data relationships corresponding to the motif identified from Figure 51 – 'teams with salary spending above $178m' – has an interpretation as 'spending above the luxury tax threshold'. The interpretation depends on specific knowledge that a luxury tax exists, and knowledge of its value. The next subsection (Section 7.3.3) generalises the relationships between domain knowledge and domain specific interpretation seen in the baseball example. It introduces the concepts of 'anchoring' and 'indicating' to describe the interpretation of data relationships in terms of the reader's domain knowledge.

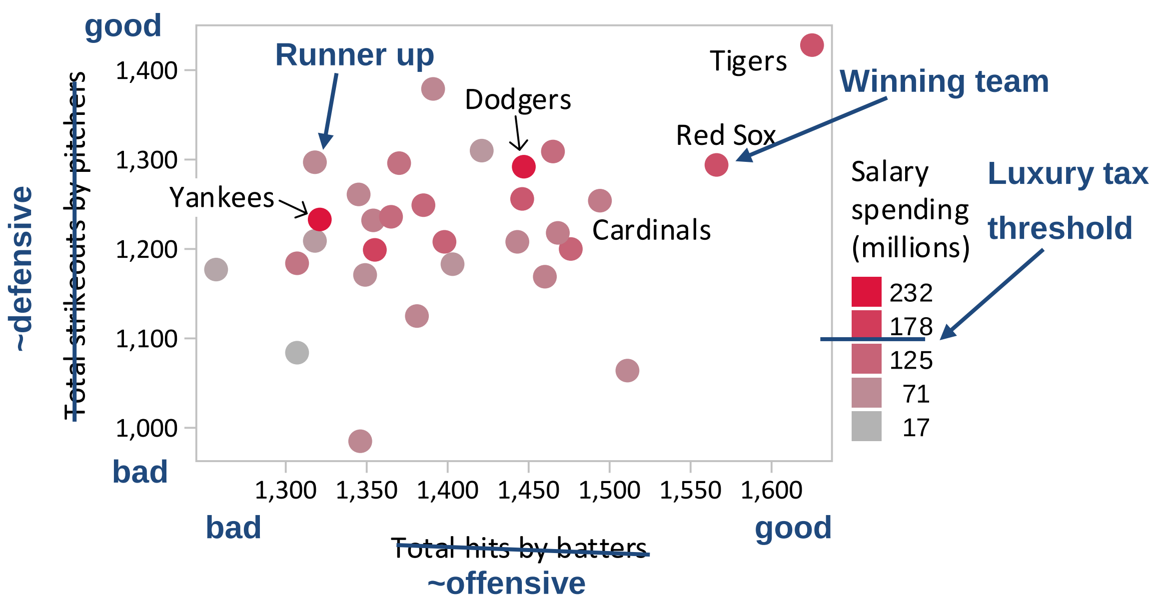


Figure 55: An expert-eyed view of the same visualization shown previously in Figure 47

7.3.3 Conceptual Anchors and Indicators

In the semantic scaffolding model, the extended meaning created by domain concepts is classified into two types: 'anchors' and 'indicators'. Domain knowledge extends meaning by adding additional significance to specific data values (anchor), and by connecting related but not identical concepts to values (indicators).

When data relationships correspond to a concept familiar to the reader, the visualization conveys information about that concept through the corresponding values. The values 'anchor' the concept to the visualization. Anchors can refer to a single data element, as with the Red Sox in the baseball visualization (the luxury tax value is an anchor for the data value $178m). Novices reading new visualizations often look for values with personal meaning, such as the make, model and year car that they used to own in a visualization of car performance [41]. As a result the visualization raises personally meaningful questions such as ‘how does my first car perform?’ or ‘how does my first car compare to other cars?’, not simply the generic question ‘how does a 2001 Holden Barina perform?’. Anchors can also be sets of values: In a doctor patient consultation, the length of the patient’s early conversation turns are believed to have significance for patient outcomes [229]. In a visualization of conversation dynamics between doctor and patient over time (e.g. [57]), the anchoring information raises the question ‘does the patient have a long early turn, and does its content reoccur throughout the conversation?’.

A second form of domain knowledge through which visualization meaning is extended is *indicator* concepts. In the sport of baseball, for example, the total number of strikeouts earned by a team over a year is not the same as the team’s defensive performance, but is an indicator for defensive performance. High strikeouts contribute to good defensive performance, even though it is possible to have good defence without high strikeouts or high strikeouts and poor defence.

Indicator concepts form the basis of proxy questions – questions asked as substitutes for the actual question of interest. As an established problem solving strategy, proxy questions are posed in place of a more complex or more difficult to answer questions, shedding light on the original question through the indicator relationship [230]. Their relevance to visualization interpretation can be seen in conceptual recurrence plot example of visualization practice cited earlier in the thesis (see Section 2.3). Repetition of related terms by participants in a conversation is an indicator that the participants are engaged in discussing a common theme [231]. The question 'are participants engaged in conversation' is difficult to answer, however the proxy question 'do participants repeat related terms across subsequent turns' can be answered using a conceptual recurrence plot [231]. Anchors and indicators are connected: an anchoring value is often an indicator for a broader concept.

7.3.4 Practical tasks and Analytic Affordances

The practical use of a visualization – whether an action, decision or emotional reaction – depends on the translation of data relationships into context-specific questions. Different prerequisites for action, criteria which prompt a decision, and beliefs are all part of reader knowledge for a practical task, which can be anchored or indicated by data relationships.

To say that a question *is* raised either by a schema or related domain knowledge presupposes that the reader is making a complete reading of the visualization, asking every possible question which is accessible to them. In reality, readers may browse a visualization, only seeking the answers to a few questions before moving on [32].

To account for the effect of limited browsing, the term ‘affordance’ is adapted from the field of Human-Computer Interaction (HCI). ‘Affordances’ is used in HCI to refer to actions which are *possible* for a particular user interacting with an object or interface, but which the user may not notice or put into place [125]. ‘Analytic affordances’ is used in the semantic scaffolding model to capture the idea of questions which can be raised by a particular user because they are within scope of his or her domain knowledge, but might not be raised in practice. Affordances only translate into actions when the affordance is perceived and the user chooses to act [125]. Similarly, analytic affordances only translate into questions when the domain knowledge for that question is mentally accessible (i.e. the analytic affordance is perceived), and when the reader makes a choice to ask.

The component of the semantic scaffolding model discussed in this section captures the way that relationships within a reader’s domain knowledge infuses particular data relationships with practical meaning. The previous section showed how the practically meaningful data relationships corresponded to motifs. The final component of the semantic scaffolding model (the next section) shows how the practical meaning of a visualization is realised when the reader *recognises* the correspondence between motif and domain concept.

7.4 Motifs to Domain Concepts

Recognising or discovering the correspondence between visual elements and their meaning is the most time-consuming component of visualization reading [10]. For a visualization to answer practical questions (i.e. questions about anchoring and indicator concepts), the reader needs to notice the visual motif corresponding to the question *and* interpret its meaning. The reader’s recognition (or discovery) of the correspondence between representation and meaning is the third triadic relationship in the semiotic triangle [19]. In the semantic scaffolding model, the correspondence between motif and context-dependent interpretation is captured through an arrow from motifs to domain concepts (see Figure 56).

Recognition of correspondence connects motifs to domain concepts. The motif typology (Chapter 6) can be used to determine the set of possible motifs for a particular layout. The motifs in the typology can *potentially* occur as meaningful motifs in a visualization using the right visual variable combination, but do not necessarily arise in every instance. Meaningful motifs will answer questions raised by the reader's domain knowledge provided two criteria are satisfied:

i. The reader sees the motif or its absence (i.e. the motif is salient to the reader);
ii. The reader recognises the correspondence between the motif and a domain schema concept (i.e. the motif is interpretable by the reader).

This section outlines the factors which affect salience and interpretability.

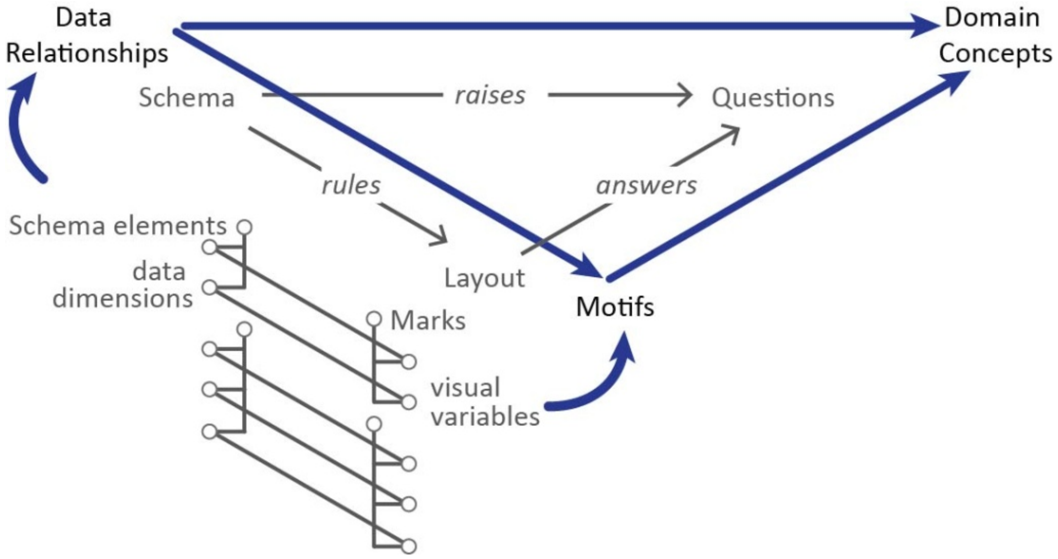


Figure 56: The final triadic relationship of the semantic scaffolding model, showing the reader's observation of a motif and recognition of the correspondence between the motif and domain concept.

7.4.1 Salience

Multiple motifs co-exist and overlap in any given visualization, and not all motifs are easily observed. Salience describes how readily apparent a motif (or its absence) is to the reader [36]. For instance, a sequence motif (Figure 57) where data only occupies alternate fifths of the value range overlaps with three cluster motifs (each of the occupied ranges). The motifs can easily be seen when data is mapped to position, but not when mapped to colour or angle. A motif that the reader fails to notice cannot convey information, no matter how relevant its corresponding domain concept.

The number of motifs possible in a typical visualization means that they are not equally apparent to the reader. In some cases, motifs are particularly salient for low level perceptual reasons – as a group they contrast from their surroundings in terms of colour, shape, size or angle [36]. In other cases, the motifs which are observed and highlighted by users of a visualization are not uniquely salient in low level perceptual terms. Instead social or individual factors (the reader's 'viewing code' [1]) make some features more readily apparent.

The salience of motifs depends on the combination of pre-attentive variable values, but also on Gestalt principles [82]. At the level of local visual features, individual marks (or parts of a mark) are particularly salient when they have a pre-attentive attribute (e.g. position, colour, shape, size, angle, or curvature) which contrasts from their surroundings [36]. Gestalt principles (see Section 2.4.1.4) determine whether a group of visual values (i.e. a motif) will be perceived as a coherent group [36]. The pre-attentiveness of the variable values of the group of marks determine whether a perceived group stands out compared to other groups in the visualization [36]. For example, a cluster of points in close proximity will be more salient as a group than a set of scattered points (due to the Gestalt principle of proximity), and a cluster of orange points in a visualization where the other points are blue will be more salient than a cluster of blue points in a visualization of purple and green points (due to the contrast between an object and its context affecting pre-attentive processing). Different Gestalt principles vary in strength, making it possible to predict – all else being equal – which of a set of competing groupings will be perceived [77, 78]. For example, if one set of marks in a visualization are connected to each other and an overlapping set are the same colour, the connected marks will be perceived as a group to the exclusion of the similarly coloured marks [77, 78]. Familiarity is also a Gestalt principle [75], causing readers to perceive familiar motifs (e.g. a checkerboard pattern) as coherent groups even if they are not grouped by other Gestalt cues.

The salience of motifs is diminished through occlusion by other marks [36, 67]. Occlusion of motifs is more likely when the mapping from data to visualization allows marks to overlap. Interference between different Gestalt principles can be viewed as a form of occlusion at the intermediate level, where one motif is less salient because a stronger Gestalt principle groups an alternative, overlapping, motif.

Some marks and motifs will be salient based on the choice of rules mapping data to visual attributes (most likely marks corresponding to outlying values). However, any chosen motif can also be deliberately made salient by the choice of the designer (or visualization user in interactive visualizations) to give preference to one data value above others, rather than letting the relationships within the data determine which values stand out [232]. Marks and motifs can be made pre-attentive by adding a contrasting variable value to the mark (i.e. highlighting) and given a stronger Gestalt grouping by outlining or adding a shared attribute to each mark in the group. Occlusion can also be prevented by adding transparency to other marks and motifs.

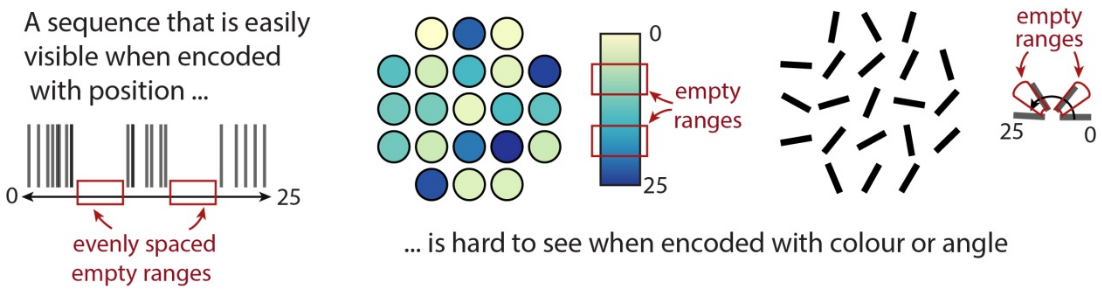


Figure 57: Overlap and varying salience of motifs (excerpt of diagram from Chapter 6). The sequence motif (data in alternate fifths of the value range) overlaps with three cluster motifs. Salience of the distribution motifs varies depending on the visual variable involved.

7.4.2 Interpretability

To be meaningful, the reader must connect a motif to a corresponding concept in the reader's domain knowledge. Like salience, interpretability depends on a combination of inherent and learnt factors.

Ease of interpretation is affected by the existence of visual conventions (see Chapter 4), domain expertise and visualization literacy [10, 11, 15]. Visualization reading builds iteratively on the reader's initial interpretation of the visual structure (i.e. the meaning of axes and marks) [41]. Faced with problems interpreting a visualization, the reader will adjust their prior understanding of the meaning of the visual structure, rather than starting over [41]. Similarly, visualization literacy can provide the reader with prior knowledge of the correspondences between domain concepts and visual features, through knowledge of the 'standard' or 'generic' meaning of a particular motif (e.g. the average slope of a line mark corresponds to the trend) [11]. Familiarity and confidence reading multiple types of data visualizations also aides interpretation [10, 13].

Recognising the correspondence between a domain concept and a motif is distinct from recognising the correspondence between the component visual elements of the motif and data values. The domain concept provides the motif with a coherent meaning beyond the aggregate meaning of its component parts. As such, a motif can appear and be salient to the reader, but not correspond to a coherent recognisable domain concept. The capacity for a convex shape in a visualization is relatively common, for instance, but there will rarely be a recognisable domain relationship corresponding to convexity. Informally, a convex shape implies that the data element encompasses all of the values in between its boundary values. (Formally, if (x_1, y_1) and (x_2, y_2) are within the data element corresponding to the convex shape, so are any values (a, b) satisfying $b = a (y_2 - y_1)/(x_2 - x_1) + y_1 - x_1(y_2 - y_1)/(x_2 - x_1)$ and $x_1 < a < x_2$). Either way, this data relationship will only be relevant for a limited number of datasets and problems. Simpler motifs (those involving fewer marks and variables) correspond to simpler relationships between data values. Thus, all else being equal, simpler motifs are more easily interpreted. More elaborate motifs like convexity become meaningful when they have a specific relevance to the visualization task, and this relevance is recognised by the reader.

When a motif is meaningful (i.e. interpretable) but not present, its absence in a visualization can still provide a useful insight to the reader. The absence of a motif which has the potential to arise indicates that the corresponding relationship between data values does not exist. An example can be seen in the application of conceptual recurrence plots to doctor-patient conversations [57] (introduced in Section 2.3 and revisited in Section 7.3.3 above). A vertical stripe of points near the left edge of the plot and a horizontal stripe of points near the bottom of the plot (both geometric motifs) are correlated with good doctor-patient conversations [57]. The two motifs are indicators for good doctor-patient conversations, and the absence of either motif signals that there may be something wrong with the conversation. Similarly, in the baseball example, the motif corresponding to high salary, good pitching but random batting (see Figure 51) can be identified even though it is only approximated in the visualization.

It is significant for models of visualization comprehension that the correspondence holds whether or not the actual visual pattern is instantiated in the visualization. It is a correspondence between domain knowledge and the *Layout*, not the *Representation*.

On the evidence to date, salience and interpretability are interlinked. Even a small amount of training in a domain area (10-15 minutes instruction) makes readers spend more time looking at task-relevant features in a visualization [233]. Understanding the meaning of a particular motif within a layout sets up an expectation that the motif may occur. It follows that the reader's prior understanding will make the understood motif more salient. For example, knowing that a vertical stripe in the left of the plot is an indicator for a turn that establishes conversation topic in a conceptual recurrence plot [57] will make the stripe easier to see.

7.5 Discussion

The semantic scaffold expands the factors to be considered in research on visualization encoding and interpretation. But it also catalogues some key constraints: motifs are (predictably) restricted by the choice and arrangement of visual variables (see Chapter 6), and the reader's domain schema restricts the sets of data values and relationships which provide anchors and indicators from which insights are formed. Most importantly, the interrelationships between domain knowledge, visual form and visualization reading expertise are untangled by the semantic scaffolding model. The semantic scaffolding model offers resolution to a number of unresolved issues with existing suitability approaches.

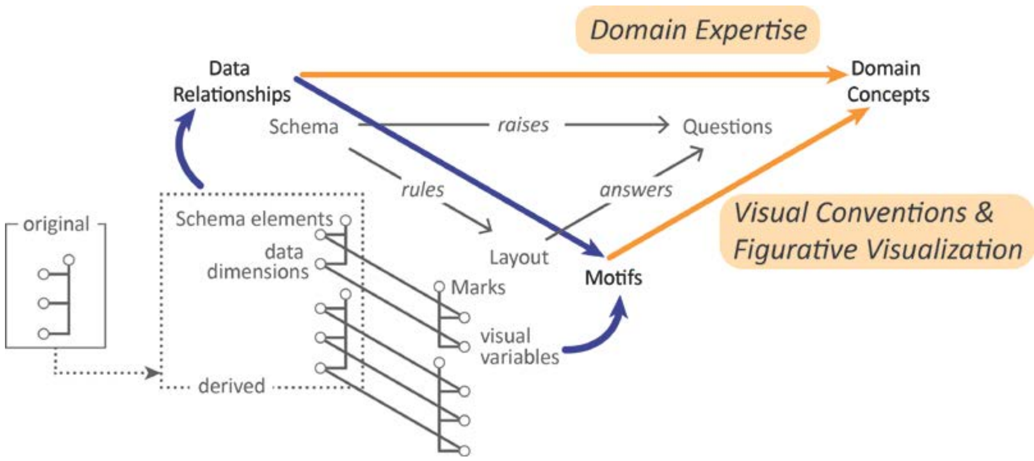


Figure 58: The effect of domain expertise and visual conventions in terms of the semantic scaffolding model

7.5.1 Reader Knowledge

The semantic scaffolding model explains the impact of different types of reader knowledge in visualization interpretation (see Figure 58). Visual conventions can provide a default interpretation for motifs, making them easier to interpret (the right arrow of the semantic scaffolding model). Domain expertise can make the links between data relationships and domain schema concepts clearer (the top arrow in the semantic scaffold), and thus make the correspondence between domain schema concept and motif easier to grasp.

7.5.2 Interpretation behaviour

The co-construction of meaning captured in the semantic scaffolding model explains a number of behaviours which have been identified in studies of visualization use [13, 14] [30].

The literature review (Chapter 2) identified the insufficiency of existing suitability approaches to explain how readers could take weeks to gain insight from a visualization

[30], or engage in complex patterns of directed answer-seeking and (relatively) undirected exploring [40]. The semantic scaffolding model explains both behaviours. In the semantic scaffolding model, the reader needs to do more than retrieve numerical values through perceptual judgements. When the reader begins with a practical task in mind, they need to translate their problem (i.e. task, questions or topic interest) into concepts which are indicated or anchored in the visualization. Translating a task may mean re-conceptualising existing domain knowledge into new units of analysis or defining and developing new concepts. Similarly, if, the reader begins by identifying intermediate level motifs, these motifs need to be translated into domain concepts, and their relevance assessed against the reader's interest. The observed patterns of switching between browsing and retrieval of a visualization can be explained as an iterative process of identifying a set of motifs which exist in the visualization and assessing their correspondence to relevant concepts.

The mismatch between user preference and user performance which arises in areas such as colour scales [234] also has a possible explanation based on the scaffolding model. Colour scales which are familiar give rise to more recognisable motifs. In a meteorological visualization, for example, a specific motif of contours and colours can be associated with the indicated action 'generate a weather warning'. Changing the colour map would break the association (learned knowledge of the correspondence) between the motif and the action, even if it improves perceptual accuracy. Colour maps with consistent correspondence between data values and colour values reduce the effort required to establish correspondence between concepts and motifs. The semantic scaffolding model allows a concrete, testable hypothesis to be articulated: readers will be faster and more accurate observing and recognising the practical meaning of the indicating motif.

7.5.3 Original vs. Processed Data Type

Data can be transformed from one type to another – making it difficult to assess a visualization as being ‘data-type suitable’ using existing suitability approaches (see Chapter 2 discussion). However, the semantic scaffold shows that there may be strong reasons for choosing one data format over another. The reader's fluency with domain concepts and methods associated with that data form for a particular subject make it easier to identify domain concepts corresponding to motifs.

A wide range of statistical and data processing techniques are available to transform data ready for a particular visualization technique (see, for example [18]). Pre-visualization transformations include simple operations such as binning data or sorting, applying scales such as a log transform, or more complex transformations such as calculating the Fourier transform, or performing k-means clustering [18]. In the semantic scaffold model only the data which directly affects the visual representation is included in data schema. The process of transforming a source schema into the data schema can be illustrated as an additional precursor process to the semantic scaffolding model, leading in to the data Schema (see Figure 59).

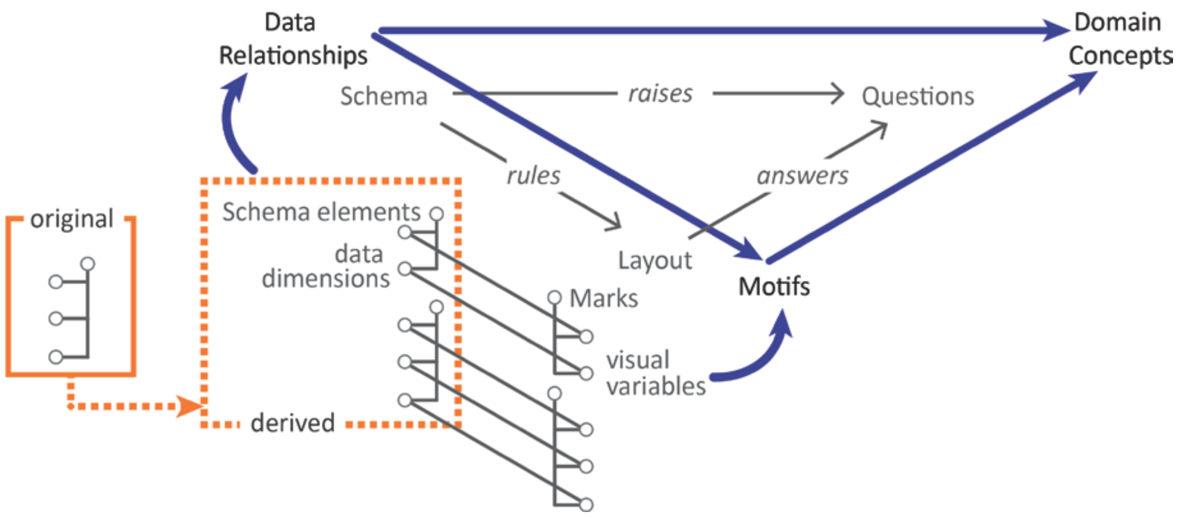


Figure 59: Data processing (highlighted in orange) transforms original data into the data schema for visualization

Pre-processing is used to change a dataset into a form amenable to visualization. The semantic scaffolding model can be used to show how it affects visualization interpretation. Transformations can make it easier to compare a particular property; for example it is easier to compare the gradients of two smooth curves through a line graph of two gradients rather than a line graphs of the original curves [27]. However, easier perception of visual relationships is not the same as easier interpretation.

Only the data schema is accessible to the reader through the visualization, not the original source data[11]. As a result, if the reader has knowledge related to original source data but not the schema, those questions will not be raised by the visualization. Where the data processing operation (e.g. Fourier transform) is well understood in the reader's domain knowledge, the visualization is able to raise questions about the original data as well the data schema. For example, if a log scale is used to visualize events over log(time) (see for e.g. [105]), readers familiar with log scales can ask 'what is the arrangement of events over time?', as they are aware of the relationship between log and linear scale. In contrast,

[11] Some applications make source data available, but the reader is then accessing a separate representation

the use of a more esoteric scale unfamiliar to the reader (e.g. non-metric multidimensional scaling) will not allow the reader to ask such questions.

In the semantic scaffolding model, the reliance on the reader's ability to understand and in some cases invert data transformations is reflected in the direction of the mappings from the original data to the schema elements, and from the schema elements to the reader's domain concepts. If the reader's domain knowledge contains a fluent understanding of how the data transformation can be reversed ('inverted', mathematically speaking), the original data will be accessible to the reader. Diagrammatically, the data transformation is applied from original to schema elements, and then the inverse transformation is applied from schema elements to the domain schema. Otherwise, the original data is inaccessible to the reader (the arrow from original data to schema elements is uni-directional), even if it can be retrieved in a mathematical sense. In contrast to existing models of visualization which emphasize the *existence* of an inverse in transformations of data (e.g. [94, 95]), the semantic scaffolding model additionally shows that the inverse must be *familiar and accessible* to the reader during interpretation. The semantic scaffold model can thus be used to explain transformations (namely those which are not intuitive to the reader) which make data easier to visualize but limit the explanatory power of the visualization.

7.5.4 Limitations

The semantic scaffolding model has a number of limitations. As with any new theoretical contribution, the model has not been verified through empirical evidence. Instead, its veracity is supported by existing research used as inputs (e.g. [10-15, 41, 93, 119]), as well as its ability to explain and organise otherwise unexplained phenomena such as reading time and domain knowledge.

Like the VFR model on which it is based, the semantic scaffolding model is a structuring model, not a process model. As such, it does not describe the *process* of achieving practical tasks through visualization. Instead it describes the relationships between the different components of visualization encoding and interpretation. The reader may begin interpretation focussed on their practical task, or may scan the visualization for motifs which stand out. The semantic scaffolding model applies equally to both scenarios.

While the semantic scaffolding model does not resolve the question of how measures trade-off against one another, it does provide a framework within which such questions can be asked. Multiple performance measures – accuracy [27], engagement [13], cognitive naturalness [17] – can co-exist within the model structure. For example, figurative elements can contribute to one aspect of interpretation (establishing correspondence between domain and visual), while not improving another (accuracy). Further work is needed to identify how to combine different measures within the framework of the semantic scaffolding model.

7.6 Conclusions to the Semantic Scaffolding Model

Building on existing semiotic models of visualization (the VFR model), the semantic scaffolding model captures the triadic relationship between sign, represented object and interpretation. In contrast to these existing models, the semantic scaffolding model is structured around the intermediate level. Intermediate level visual features – motifs – correspond to relationships between elements of the data schema. Data relationships can be expressed in multiple alternative forms, some of which will be more coherent and resonant to the reader than others. Domain knowledge can (but does not always) provide data relationships with a coherent translation into a concept relevant to the reader's practical task. Domain concepts with a direct translation into data relationships are *anchoring* concepts. Data relationships can also be *indicators* for domain concepts. For domain knowledge to be anchored to or indicated by motifs, the motif must be salient and interpretable. The semantic scaffolding model demonstrates that practical meaning depends on the reader seeing motifs in the visualization, recognising or discovering their correspondence with relevant domain concepts.

8 General Discussion

Language serves not only to express thought but to make possible thoughts which could not exist without it. – Bertrand Russell

Half of science is asking the right questions. – Roger Bacon

The semantic scaffolding model developed in this research project bridges the gap between the practical value of visualization (e.g. [4, 8]), and assessments of information transfer (e.g. [63]). The thesis has argued that the practical value of a visualization depends on the recognition or discovery of correspondence between the reader's existing domain knowledge and encoded visual motifs. The common use of figurative elements and conventions uncovered in the study of the KIIBA14 dataset (Chapter 4) reveals the extent to which the reader's experience is anticipated in visualization design. The semantic scaffolding model (Chapter 7) explains that anticipating the reader's experience through either type of acquired code of meaning can enhance the practical value of a visualization because it facilitates the recognition of correspondence.

The gap this thesis has identified is larger than the problem it has addressed. The identified gap is that state-of-the-art visualization suitability heuristics and evaluation measures do not assess the practical value of visualization. The thesis solves an underlying cause of this gap. The gap exists because practical value is currently expressed in imprecise, immeasurable terms which are unrelated to design choices. Terms such as 'insights', 'amplify cognition', 'seeing behind the broad features' are used without identifying the features that make visualization more or less likely to provide insights.

In this project, conceptual models and a critical vocabulary were developed to describe the practical use of visualization. Existing conceptual models are based on the assumption that visualization encodes meaning through a data-to-visual mapping which transforms data values into local level visual variable values. These models have allowed researchers to formulate and test questions about visualization as an information channel (for example 'how accurately do variables convey information?'). An alternative assumption was suggested by the field of language and communication. Semantic scaffolding assumes that the meaning of intermediate level visual features (motifs) is co-constructed by the reader's prior knowledge together with the data-to-visual mapping.

The outcome of the research is a technical language and set of concepts which allow the formulation of specific claims and questions that were not able to be articulated within previous frameworks. The figurative frame concept introduced in Chapter 5 enables the question 'are more integrated hybrid visualizations more persuasive?'. The semantic scaffolding model presented in Chapter 7 enables the question 'can recognition of correspondence be transferred across domains?'. The thesis does not answer such questions, but makes it possible to ask them. Research towards measuring different facets of practical value can now be framed methodologically as scientific questions within the framework of the semantic scaffolding model.

This chapter presents a structured discussion of the findings of the thesis project as they relate to the practical value of visualization (Section 8.1), visualization practice (Section 8.2), and the measurement of visualization performance (Section 8.3). An update to the state-of-art (Section 8.4) summarises the implications of the thesis for research and design. Finally, future directions for the semantic scaffolding model are explored, along with pathways for the development of measures of practical visualization performance (Section 8.5).

8.1 Practical Visualization Value

A review of visualization literature around suitability and visualization interpretation (see Chapter 2) revealed that existing suitability assessments are based on a conceptualization of visualization as a channel for transmitting information. This perspective assumes the reader retrieves all of the information from the visualization (or any subset with equal likelihood) as quickly and accurately as possible before making use of the retrieved information. Instead, analysis of practical use of visualization (i.e. visualization used for a specific purpose such as problem solving or entertainment) suggests that visualization interpretation is partial, and directed by reader knowledge, experience and interest [5, 8, 10, 13, 15]. Features in a visualization have specific meaning which cannot be entirely attributed to the encoded data, but also rely on the reading context (semantic scaffolding).

The semantic scaffolding model (and the literature supporting its component processes) enables the application of theories of language pragmatics to visualization. Studies of language pragmatics have developed theories which capture how cooperative conversation is realised through the interaction of language structure and speech context [20, 115]. In modelling intermediate level reading, the semantic scaffolding model highlights how motif interpretation is dependent on contextual factors. A variety of contextual influences on interpretation are captured in the model, from the reader's prior knowledge of the domain to their particular interest and motivation for reading.

Parallels between the semantic scaffold and theories of cooperative discourse are a consequence of the inherent similarities between visualization and conversation. Both visualizations and turns in a conversation have the basic function of conveying information to a target audience – the reader(s) of a visualization and the other participant(s) in a conversation. The visualization creator's intent to communicate particular information informs what is encoded in a visualization, while the reader's knowledge and interest determines the meaning understood from the visualization (Chapter 7). Similarly, visual conventions and prior experience are relied on for communication in both visualization (see Chapter 4, 5 and 7) and discourse. The creator/speaker and reader/listener can have different aims. Visualization creator and conversation speaker aims can include conveying a single tightly focussed message, leading the audience through a specific narrative, persuading the reader, or simply being interesting. Regardless of the creator/speaker's intentions, each audience member can also read or listen with the intention of learning something specific, following their interpretation of the creator/speaker's narrative or simply hoping to read/hear something interesting. The effect of the visualization or conversation turn (both in terms of information imparted and engagement generated) is specific to a moment in time – it is part of a dynamic system.

Through the analogy with discourse, the semantic scaffolding model is used to identify factors affecting suitability which have been overlooked, suggest practical strategies for improving suitability, and raise key research questions which need to be answered in order to develop a quantitative measure of suitability. The relevance of cooperative discourse and language pragmatics to visualization suitability both explains why traditional approaches to suitability have proved insufficient, and also offers a path towards measures of practical value. To contribute to a conversation, correct grammar and accurate vocabulary are insufficient [20]. Analogously, context-dependent visualization interpretation is not reducible to visualization grammar. That is, perfectly grammatical visualization can fail to provide insights to a reader because it is not relevant, or because the reader fails to establish the correspondence between a relevant concept and a visual motif. Similarly, even a visualization which is optimised for accurate perceptual judgement may fail to engage a reader or arrange information in a way that is easily interpreted.

The established theory of cooperative discourse sets out a set of four rules that participants follow to contribute ‘good’ or suitable turns to a conversation – known as Grice’s maxims (after their original proponent [20]):

- **Quality**: utterances are honest (true to the best of the participant’s knowledge)
- **Quantity**: provide an appropriate amount of information
- **Relevance**: provide information which is of interest or importance
- **Manner**: uses appropriate tone, language and level of formality. [115]

By following Grice’s maxims, considerate participants accommodate each other by choosing utterances which avoid confusing, offending, deceiving or inconveniencing the other participants. With the exception of **quality**, Grice’s maxims involve a match between what the context requires and what the speaker provides. Thus, better **quantity** is not necessarily achieved by more information, but by matching the amount of information the listener is seeking.

The merit of the semantic scaffolding model as a conceptual decomposition of visualization creation and interpretation can be seen by its match to Grice’s maxims; each maxim matches a different section of the model (see Figure 60). The **quality** or honesty of a visualization depends on the *rules* mapping from Schema to Layout. If the *rules* map data values to visual variable values consistently, then differences in visual values are a **quality** reflection of the data. If, on the other hand, the mapping from data values to visual values is inconsistent, then the honesty of the visualization is reduced. **Quantity** – or the amount of information provided – is altered by the transformation from the available data to the data schema used for the visualization. Data processing techniques such as filtering, averaging, binning and calculating metrics on data change **quantity**. So too does the inclusion or omission of descriptive information (which can be visualized figuratively). A visualization’s ability to provide information which is **relevant** to the reader is dependent on the match between the reader’s interests, and information contained in or implied by the Schema. Hence, the **relevance** of a visualization is reflected in the path from data relationships to the reader's domain concepts. Finally, the **manner** of a visualization reflects how well the form of the visualization supports successful interpretation by the reader. The idea that a visualization should be *intuitive* and easy to read is captured in the statement that it should have good manner. In other words, the visual elements present in the visualization and their meanings seem natural to the reader. In the semantic scaffolding model, manner matches the mapping from motifs to domain concepts.

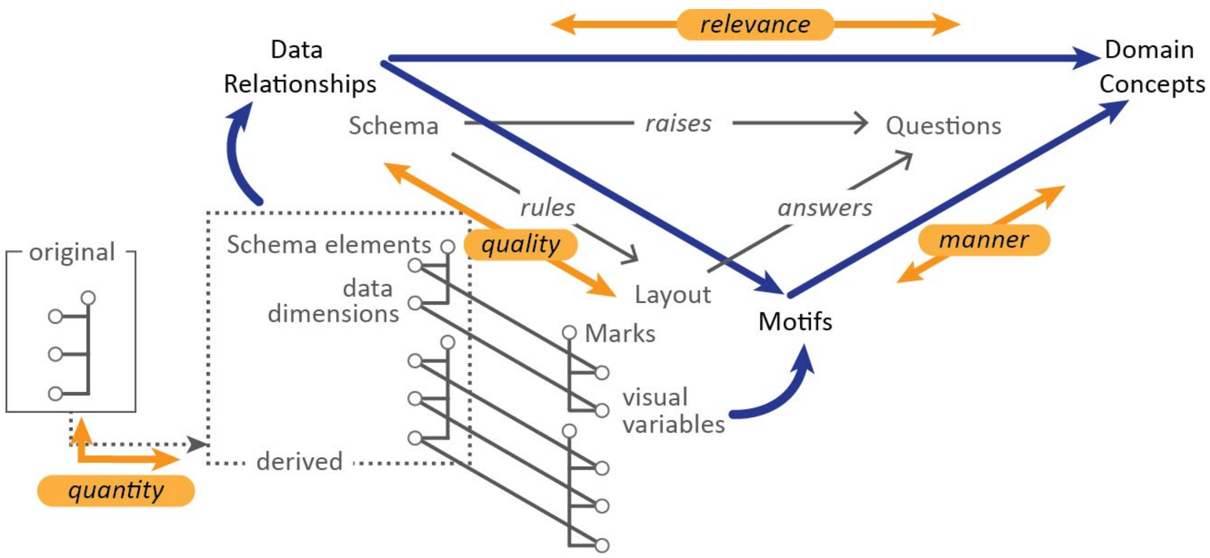


Figure 60: Applying Grice's maxims to visualization through the semantic scaffolding model

8.2 Visualization in Practice

A key finding of this thesis is that in practice visualizations anticipate the reader's prior experience. As shown in Chapter 4, exemplar data visualizations and infographics targeted at a general audience (the KIIBA14 dataset) commonly use visual conventions and figurative elements. At least one figurative element was used in 71% of data visualizations and 88% of infographics. Numerous different visual conventions were also identified. Both types of acquired codes of meaning reflect the role of the reader's experience in creating visualization value in practice (distilled into 7 guidelines summarised in Table 6).

The use of visual conventions in practice demonstrates the importance of recognition of correspondence. From a semiotics perspective, visual conventions reinforce the prior meaning of visual features, making the conventional meaning easier to recognise. The correspondence between motif and domain concept (captured in the semantic scaffolding model) becomes more familiar, allowing easier recognition of correspondence.

In contrast to existing examinations of visual literacy (e.g. [11, 45]), the conventions identified in Chapter 4 are at the intermediate, not global level. That is, Chapter 4 identifies conventional meanings of motifs rather than layouts.

The semantic scaffolding model offers an explanation for why conventions may be so widely used, and for the development of community level conventions. Whereas the translation of individual data values is explained by axis labels and keys, the context-specific meaning of a motif has to be co–constructed by the reader. Conventions allow the reader to rely on prior knowledge to recognise correspondence. Similarly, community-specific conventions reflect community-specific concerns.

Table 6: Guidelines for anticipating the reader's experience in visualization (from Chapter 4). Guidelines 1 - 4 relate to figurative images, while Guidelines 5 - 7 concern visualization conventions.

1. 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.
2. 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.
3. 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.
4. Use a more realistic style for context than for content elements, if using figurative elements in both roles.
5. Use conventions to create representations which are easy to read.
6. Conventions are tools, not rules – balance the ease of reading provided by conventions against other design considerations.
7. Discover and use the conventions within the target user community and subject domain.

The study of the KIIBA14 dataset showed the prevalence of figurative elements used as content, context and icons (see Guidelines 1 - 4 in Table 6). Figurative visualization anticipates the reader's prior experience in two ways. First, figurative visualization conveys descriptive information, leveraging the reader's existing familiarity with shapes and the visual forms of objects (see Chapter 5). Figurative elements are included in a hybrid visualization with the expectation that the reader will recognise the image's *figurative frame* – the identity and features of the represented object that the designer intends to convey. Although assuming a shared visual sign system risks misinterpretation, the payoff is more expressive visualization.

As noted in Chapter 5, when the assumption of a shared sign system holds (i.e. signs are part of the shared knowledge of creator and reader), interpretation of figurative elements is easier than abstract representation. The semantic scaffolding model suggests that the high interpretability of figurative elements aids interpretation of motifs formed from the abstract data in an integrated hybrid visualization. As shown in Chapter 5, figurative elements and abstract data can be integrated together through the frame-as-space and layout-of-frames strategies. In the frame-as-space strategy, abstract data is anchored to locations on an image, showing properties of or in the figuratively represented object (see Section 5.3). Features of the figurative frame are also domain concepts which the reader can recognise as corresponding to position motifs. For example, a cluster motif of line ends anchored to an image of a baseball field (see Figure 61(A)) corresponds to the concept 'centre-outfield hits', based on the 'centre outfield' location feature of the figurative frame. In a layout-of-frames strategy (see Section 5.4), multiple images are arranged based on abstract properties of the represented objects (see Figure 61(B)). Relationships between figuratively represented objects can be observed from the figurative images – in other words, the relationships are also figurative represented. An example is increasing cloud cover across different figurative illustrations of sky conditions (Figure 61(B)). The differences between interpreting figurative and abstract representation [207] suggest that motifs will be easier to interpret when they involve figuratively represented relationships.

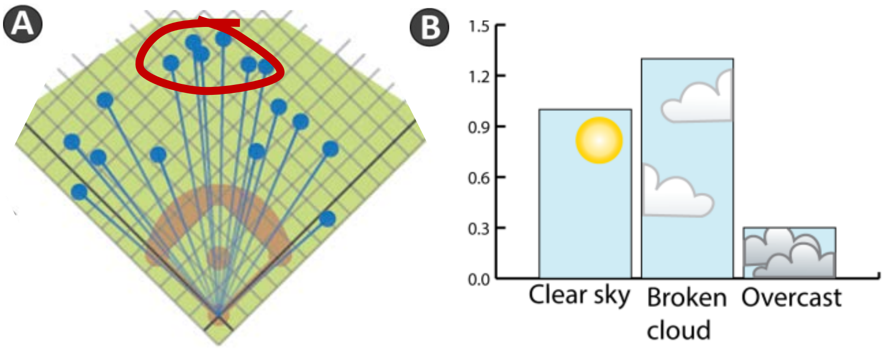


Figure 61: Recognition of correspondences between domain concepts and motifs in hybrid visualizations can be aided by figurative frame features. (A) A cluster motif (circled in red) corresponding to the concept 'centre outfield hits', based on a feature of the figurative frame used as a space – 'centre outfield'. (B) In a layout-of-frames strategy, the relationship 'increasing cloud cover' is observable from the figurative images. Replicated from portions of Figure 26 and Figure 27.

The study of the KIIBA14 dataset showed that the reader's experience was anticipated in exemplars of visualization design. The figurative frame concept and semantic scaffolding model explain why. Both types of acquired codes of meaning observed in practice aid the interpretability of a visualization, allowing the reader to leverage their experience to recognise the correspondence between domain concepts and motifs. Additionally, figurative representation expands the expressiveness of a visualization, allowing the communication of descriptive information.

8.3 Evaluation Measures

The aim of this thesis has been to move towards assessments of visualization suitability based around practical value – the ability of a visualization to provide semantic scaffolding. The review in Section 2.4 found that existing visualization approaches measure information transmission, not practical use.

Grice's maxims (described above in Section 8.1) offer high level (descriptive, not quantitative) principles which can be used as the foundation for measures of practical visualization performance. Applied to visualization, the maxims set out sufficient and necessary conditions for a visualization to be suitable for a particular context. The measures can be used to aid visualization suitability assessment, improve visualization design and guide research. The contribution of existing measures of suitability (e.g. judgement accuracy) and the implications of prior research to overall suitability can be placed in perspective using the high level measures.

In this section, each maxim is addressed separately, comparing the maxim to existing measures of suitability to critically assess how well visualization suitability is measured and identify gaps in existing measures. The semantic scaffolding model (through the analogy with discourse) suggests new measures for development and testing. Additional design strategies and research questions are also proposed, based on approaches in discourse and the insights from the semantic scaffolding model.

8.3.1 Improving Quality

The quality (honesty) of a visualization is relatively straight-forward, since it only depends on the construction on the visualization, not its interpretation. Measures for ensuring quality arise more often in visualization criticism than guidelines or heuristics.

Existing measures allow quantitative assessment of quality for abstract visualization – for example by measuring the combined error between the accurate visual values and the displayed values. In practice, quality can be difficult and time-consuming to assess, leading to the use of techniques providing quality assurance (e.g. links to the data source), or automated tools which are more reliable at the calculations required for data to visual transformations (e.g. [198]).

For hybrid and figurative visualization, the concept of a figurative frame introduced in Chapter 5 enables new measures of quality based on frame accuracy. As discussed in detail in Chapter 5, frame accuracy depends on the level of abstraction of the represented concept. An illustration of a specific car (e.g. the 2017 Red Bull Formula 1 car in Figure 25) has much more specific dimensions then the general concept of ‘a car’. More specific concepts offer more scope for violations of quality.

8.3.2 Improving Quantity

The maxim of quantity is followed when a visualization provides the appropriate amount of information. Amount of information can be viewed in terms of number of data points, size and cardinality of variable ranges (i.e. the number of values a data point can take for a given variable), schema size (i.e. the number of data variables), and data type (descriptive vs. relational; categorical vs. ordered vs. quantitative). Data processing (e.g. summary statistics, or binning [18]) and data collection are levers for changing the amount of information in a visualization. The challenge of quantity is ensuring that the amount of information provided suits the visualization's intended use. The appropriate information quantity depends on purpose of the visualization, the audience’s level of domain knowledge, their available reading time, and their expectations.

Existing approaches which address quantity consist of eliciting requirements and feedback from visualization stakeholders [128], and designing multiple views at different quantities so that readers can choose between them (as encapsulated by Shneiderman’s mantra, although achieving quantity is not its specified aim) [26]. Notably, existing measures do not speak to quantities of descriptive information required by a visualization problem.

Based on the reconceptualisation of visualization provided by the semantic scaffolding model, two improvements to measures of quantity can now be proposed. First, the figurative frame model (chapter 5) provides the critical vocabulary to articulate the required quantity of *descriptive* information shown in a visualization. As set out in chapter 5, different visualization contexts can require different quantities of descriptive and abstract information (affecting whether the visualization is a diagram, a data visualization or a hybrid visualization). At least some descriptive information is required when the visualization problem concerns the appearance or operation of an object or system (‘what is X’ or ‘how does X work’ type questions). A larger amount of descriptive information is required when the questions about appearance or function are specific and detailed. At least some abstract information (structured data) is required when the visualization is addressing relationships between object properties.

Visualization as discourse suggests a pragmatic approach to quantity, based on social conventions. While individual readers' preferences for desired amount of information are hard to gauge without asking directly (and sometimes even then), strategies from conversation can be applied to the visualization case. A discourse community establishes and maintains a standard of quantity that both speaker and listener learn to expect [235]. For instance, when presenting new research to other researchers, there is an expectation that evidence as well as summary results will be provided, whereas when making small talk at a party a simple statement will suffice. Analogously, the target venue and platform of a visualization establishes a standard of quantity. A visualization in a research paper, for example, will need to provide more detailed information than a visualization for a reader browsing news media. By the same principle, the amounts of descriptive and abstract information required may also vary based on the target venue. In some venues (e.g. a science museum), there may be an expectation that a visualization provides a detailed orientating description of the subject in addition to any abstract data.

8.3.3 Improving Relevance

The relevance of a visualization depends on whether it contains the information the reader is seeks or is interested in reading. Where quantity concerns the amount of information in a visualization, relevance concerns the information content and structure.

The semantic scaffolding model shows that relevance is determined by the relationship between the reader's domain knowledge and the data schema, not the layout. Although relevance is often acknowledged as an important factor in visualization suitability (e.g. [236]), existing approaches often conflate the maxims of relevance and manner (see next section), hiding the impact of the data structure. Existing approaches focus on matching a single task to its optimal layout (e.g. finding the best visualization for correlation [28] or comparing line and bar graphs for showing trends [11]). However, if the aim is to understand the profit of a company, a visualization of revenue against costs is far more relevant than revenue against time, regardless of the layout used. The schema structure is similarly important: if revenue and cost are not linked as properties of a single element (e.g. year, store or item), a pair of plots showing revenue vs. time alongside cost vs. store has limited relevance, even though both cost and revenue are shown.

Of the existing approaches to visualization design, relevance is addressed primarily through requirements elicitation (see for e.g. [128, 129]). Elicitation primarily focuses on obtaining a clear statement of the visualization's purpose and intended use, and identifying available sources of data. The semantic scaffolding model suggests that elicitation additionally needs to obtain an understanding of the reader's domain knowledge.

Several other factors affecting relevance can be identified based on the semantic scaffolding model (and supporting literature). The first is a match between the schema elements and the reader's mental model of the visualization topic. The reader's ability to solve a problem is affected not just by their problem solving skills, but by their familiarity with the terms and units chosen to articulate the problem [119]. A match between the reader's mental domain schema and the visualization data schema is easier to achieve when the reader has extensive factual/propositional and procedural knowledge of the domain. The higher the reader's level of domain knowledge, the more likely they are to be able to relate any given data schema to anchor and indicator concepts. Similarly, if the reader can conceptualise the problem in multiple ways (i.e. is good at re-configuring their mental schema), there are more relevant formulations of the problem available to be used as the data schema.

All else being equal:

i. Relevance is improved by matching the reader's mental schema to the data schema
ii. Relevance is improved by transforming the data into a set of relationships and elements which relate to the most domain schema concepts related to the visualization purpose

Where the visualization is designed for a specific set of tasks, relevance can be improved by identifying the intermediate level tasks, their relative importance, and the related domain concepts. Indicator concepts are particularly important for complicated, ill-defined tasks, and problems where the available data cannot provide a simple, straight-forward answer. In such cases, insight from the visualization is reliant on the reader making inferences and forming hypotheses from the visualization content, rather than simple deduction (Chapter 7).

Improving relevance using the factors suggested by the semantic scaffolding model requires that the visualization design process additionally elicits information about the target audience's domain model and conceptual framing of the subject (for example methods see [237]). Knowledge of the reader's domain model can be used to develop the visualization's data schema, but also to shape the reading context to be more conducive to interpretation. Explanation of the relationship between the data schema and reader's anchor and indicator concepts can be provided through visual, textual, or spoken accompaniment to a visualization, improving the visualization's relevance without changing the visualization itself.

8.3.4 Improving Manner

The maxim of manner measures the appropriateness of the (meaningful) visual form for the audience and setting. Manner concerns whether the form of the visualization makes the content easy to understand (to the target audience). For visualization, understanding will be automatic if the visualization: (i) supports visual chunks and (ii) the reader can map the visual chunks to relevant quantitative information [10]. In other words, a visualization has good manner if it encodes the most relevant information in visual motifs which are (i) salient and (ii) easily and accurately interpreted.

The contribution of this thesis to measures of manner is to emphasise the importance of the reader's discovery or recognition of correspondence. As noted in Section 2.5, the standard approach to assessing visualization layouts is to focus on information transfer (e.g. accuracy and speed). The semantic scaffolding model shows that discovery or recognition of correspondence between motifs and domain concepts is a key overlooked component in constructing practical meaning (Chapter 7). The utility of more commonly measured characteristics such as accuracy is contingent on recognition of correspondence. Accurately discerning visual values (either of individual data points or of relationships) will not aid the practical use of visualization unless the reader can identify the meaning corresponding to those visual values. For a layout to have good manner, therefore, it must foster the discovery and recognition of correspondence (i.e. it must be easy to interpret), as well as allowing fast and accurate judgement of visual values. Visual conventions and hybrid visualization (Chapters 4 and 5) are two different strategies for improving recognition of correspondence.

Interpretability measures are needed to gauge how the visual form makes the translation process hard or easy for the reader. Several factors improving interpretability can be hypothesized based on the semantic scaffolding model. The first, proposed in Chapter 4, is the use of visual conventions, whether deliberately or organically created. Visual conventions allow readers to use their prior experience with a feature to understand its meaning. Prior experience can also be leveraged through the use of familiar figurative elements as part of a hybrid visualization (see Chapter 5). The interpretability of familiar images potentially extends to abstract features (including motifs) within a hybrid composition. Marks positioned on or around figurative images imply a particular relationship between the figuratively represented object and the abstractly represented data. The hybrid composition thus constrains the likely meanings of features (e.g. a mark on a baseball field is likely to signify an object or event occurring within a game of baseball). For hybrid visualization, interpretability is expected to be affected by the choice of a figurative frame, and how well this frame is conveyed through the aesthetic style of the images (see Chapter 5). The frame identity and projection need to foster recognition based on the reader's experience with the represented object, while the frame features need to be distinguishable from the remainder of the image. Expressiveness (a measure of the information that a visual form is capable of encoding – see Chapter 5) also falls within the scope of interpretability; if a visualization is not capable of expressing a piece of information, it cannot be interpreted.

Another concept potentially affecting interpretability is the use of visual metaphors and analogies, which allow the reader to transfer understanding from one domain to another. The idea of visual metaphors and visual analogies has previously been explored in visualization, with inconclusive results [46, 47]. However, these previous studies have examined the effect of (familiar) verbal metaphors on low level visualization comprehension. The hypothesis from the semantic scaffolding model is that interpretability will be improved through the use of a coherent analogy (not necessarily familiar) which applies across multiple levels of a visualization. According to the semantic scaffolding model, interpretation can be challenging even when the visualization mapping at the local level is well understood, because the correspondence between motifs and the domain concepts they signify or provide indicators for still need to be deduced by the reader (Chapter 6). It follows from the model that cross–level analogies would provide the reader with an intuitive (metaphorical) meaning of a motif, based on their understanding of the local level mapping.

The number and separability of motifs may also affect interpretability. One finding from the motif typology is that different layout design choices affect how many motifs appear in a visualization and whether they share the same visual space.

The semantic scaffolding model demonstrates the need to extend measures of accuracy to the intermediate level. Visualization insight depends more on features at the intermediate rather than local level (see Chapter 6). The semantic scaffolding model suggests that the scope of existing measures of salience and accuracy should be changed to focus on the most relevant motifs (i.e. motifs corresponding to domain concepts relevant to the reader's problem or interests). More emphasis should be placed on intermediate level measures of salience (Gestalt principles and pre–attentive features of groups) than local level measures (pre–attentive features of individual marks).

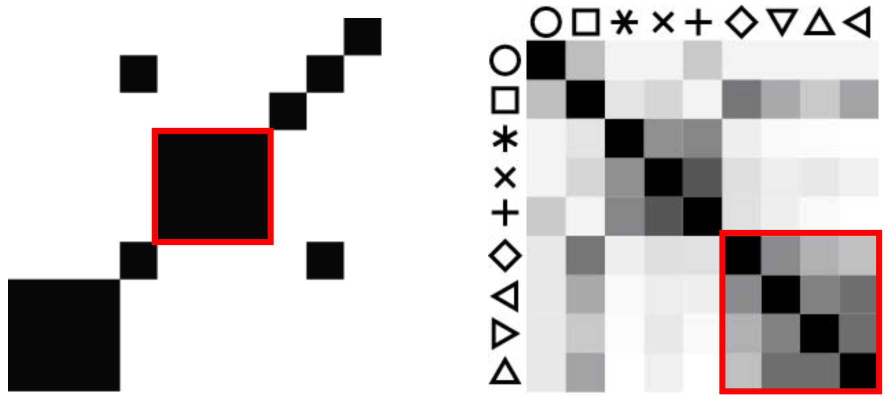


Figure 62: Motif variables vs. local level variables. The cluster motifs highlighted in red have area, length and width attributes that are not attributes of their component points.

The perceptual judgement measure of accuracy can be applied to properties of motifs just as easily as to individual marks. Accuracy depends on visual attributes [27], which are different at the local and intermediate levels. The visual attributes of a motif depend on the local level variables from which it is constructed, but are not the same as those variables. For instance, a contiguous cluster motif formed by the position attributes of points (see Figure 62) has area, width and length properties which are not properties of the component points. If the area property of the cluster signifies information which is more important to the reader than the position of the cluster, the judgement accuracy of the visualization should be measured based on area (low rank) rather than position (highest rank). Measuring accuracy only at the local level potentially misjudges the accuracy of visualization in conveying its key content.

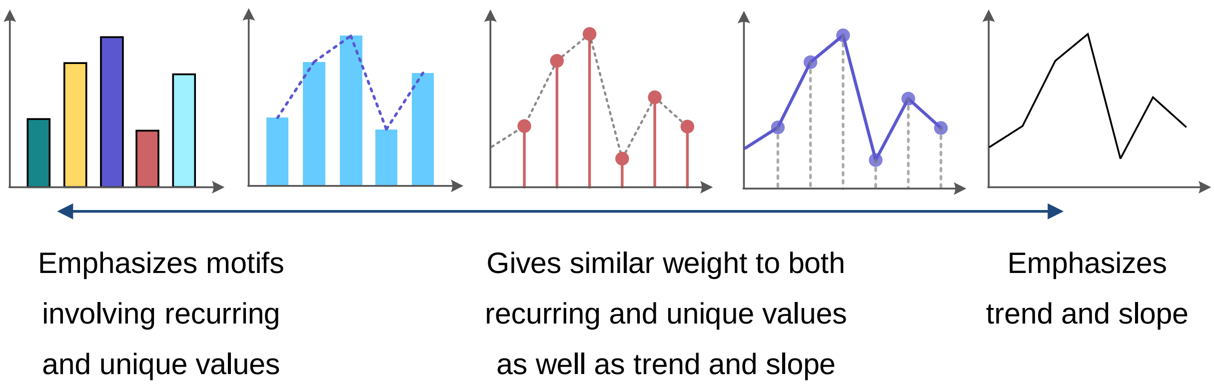


Figure 63: Choices of mark type for a layout with the same set of motifs

The intermediate level approach to salience and accuracy requires the most relevant motifs to be identified as a prerequisite for assessing manner. For example, design choices about the type of marks used, and the detailed format of marks should be evaluated in terms of relevant motifs. The same set of data values encoded by position give rise to motifs with different salience depending on the type of marks used – bars, lines, or points (see Figure 63). Similarly, the detailed format of marks (i.e. ‘aesthetic choices’ such as line width which are independent of data values) emphasize some motifs over others (also shown in Figure 63).

8.4 State of the Art

The semantic scaffolding model has implications for both research and design in information visualization. For research, the thesis provides a foundation to investigate and measure practical use of visualization. A better understanding of the practical value of visualization will have follow-on benefits for visualization design, as research allows the formulation of better heuristics and design guidance. Visualization design can also directly benefit from the work of this thesis: in particular the articulation of hybrid visualization types, motifs and the role of different types of domain knowledge in visualization interpretation.

8.4.1 Research

Understanding the context-specific meaning of visual motifs is a key foundational step towards measuring practical visualization value. Practical visualization value involves visual features within a visualization signifying a problem solution, available action, decision criteria or emotionally resonant concept. As described in Section 2.6, measures of practical value require a conceptual model of visualization which explains how the co-construction of meaning by visual form and reader experience can be anticipated in the visualization design process. Section 8.3 above shows how the development of measures is enabled by the semantic scaffolding model. The additional and extended measures proposed in Section 8.3 move beyond assessing information transfer, and offer a way to measure the success of a visualization in fostering the recognition of correspondence between motifs and the reader's knowledge in context.

This thesis has provided a critical vocabulary to describe the anticipation of prior experience in visualization. The vocabulary encompasses acquired codes of meaning, hybrid visualization (including figurative frames of varying integration and density), motifs and domain concepts (including anchors and indicators). Providing a language to describe and discuss these new concepts in visualization is a precursor to studying, understanding, and predicting the successful anticipation of prior experience.

8.4.2 Design

Research on practical use of visualization has the potential to aid visualization design by identifying layout characteristics associated with suitability for different contexts. More immediately, the semantic scaffolding model suggests a number of considerations for improving the visualization design process.

The design process can be conceptualized as starting from any of the three corners of the semantic scaffolding model (i.e. practical questions, data relationships and motifs), and adjusting the other components to match. Visualization design, especially in visual analytics, is often framed as creating a visualization to solve a particular problem, or answer a specific set of questions (e.g.[238]). In the design-from-questions scenario, the designer has freedom to choose or change both the motifs (by choosing a layout) and the represented data relationships (by choosing a data schema). When choosing a schema, the designer primarily needs to satisfy the maxims of quantity and relevance, while the choice of layout needs to satisfy the remaining maxims of quality and manner. Grice's maxims overlayed on the semantic scaffolding model identifies the maxims which pertain to the choice of schema and layout: schema affects the quantity and relevance maxims, and layout affects quality and manner. Alternatively, designing a visualization for context can be constrained by the need to use or adhere closely to an existing visualization layout due to legacy concerns, or represent a given dataset.

The semantic scaffolding model shows that motifs and figurative elements should be considered during layout design. For data visualization components, the design process should aim to find layouts where motifs corresponding to relevant domain concepts are highly salient, and easily interpreted by the intended audience. If the visualization is intended to address questions concerning what a system is or how it operates, then the layout should be a hybrid visualization including figurative elements.

Additional considerations for identifying data collection requirements are suggested by the semantic scaffolding model. Data should be collected and arranged so that the schema produces the most direct relationships to anchors and indicators, best maintains the perceived relevance to the audience. In order to construct such a schema, discussions with the visualization clients and stakeholders should elicit both descriptive and abstract information relevant to the problem, as well as visual literacy, conceptual anchors and indicators for the target problem as perceived by the target audience. Descriptive information can be used to identify the need for figurative elements as part of a hybrid visualization. The data schema should be chosen so that schema elements and relationships are easily connected to known conceptual anchors and indicators. Visualization quantity (amount of information) can be improved by understanding the target venue and expectations of the target audience (see Section 8.3.2 above).

If the schema is fixed, but the questions and layout are open-ended, conceptual anchors and indicators help to articulate the range of questions the visualization could answer. Looking for domain-specific concepts anchored to or indicated from relationships between data schema enables the designer to identify concepts which will correspond to motifs, not just local level visual features. Concepts identified as being 'in scope' of the data schema – anchored or indicated from it – can form the basis of further discussions with clients and stakeholders to identify which concepts are most relevant. The choice of layout should be driven by the need to represent the relevant concepts with salient and interpretable motifs. The motif typology (Chapter 6) can be used to predict the motifs which may arise, given the local level data-to-visual mapping.

For a given layout, the semantic scaffolding model can be used to tailor the design to a given application and audience. Highlighting relevant motifs improves their salience, while annotation and detailed guides can be used to explain the meaning of motifs, aiding interpretation.

8.5 Gaps

This thesis exposes a number of gaps and opportunities for further research. As discussed in Section 8.3, the semantic scaffolding model provides a foundation for measures of practical value, but such measures are yet to be developed. Three areas with implications for the development of measures of practical value are identified here as avenues for future research. One set of research questions concerns the quantification of the effect of experience on interpretation and salience. A second area for future work is the codification of a pragmatic approach to visualization design, based on the similarity between visualization and natural language revealed by the semantic scaffolding model. Finally, there are questions about how to combine and present layouts for multi-stage visualization use.

8.5.1 Measuring Experience

Gaps in measures of manner (see section 8.3.4 above) suggest a number of research questions concerning the relative contribution of attention and experience to salience and interpretability. In order to predict how a motif will be seen and interpreted, it is necessary to understand when experience and prior knowledge will outweigh ‘natural’, psycho-perceptual salience and interpretability. For instance, what type and length of training is sufficient to ignore a given Gestalt cue and see a competing motif (without prompting)? Similarly, if a reader understands that a particular motif is important for a task, do they see that motif to the exclusion of a more naturally salient motif?

The sensitivity of interpretation experience requires investigation, in order to improve the recommendations for using visual conventions provided in Chapter 4. The existence of professions which specialise in reading specific visualizations such as ultrasound technicians and meteorologists suggest that expertise may aid interpretation. Specialist professions which involve reading visualizations often express a preference for stable visualization forms (see for example [239]). Future research could identify how sensitive recognition of motifs is to changes in the visual form and problem domain.

Further measurement of the type of experience underpinning successful figurative visualization is needed. Chapter 5 developed high-level design heuristics for hybrid visualization. The heuristics could be developed in more detail through research into the translation of prior experience with visual objects into recognition of correspondence in figurative representation.

8.5.2 Pragmatic Visualization Design

The current research has made the case for the resemblance between natural language discourse and visualization. Since pragmatics is the term for language use in context, designing visualizations which adhere to Grice’s maxims – that is, are appropriate for their context – can be referred to as ‘pragmatic visualization design’. This thesis highlights the potential for a pragmatic approach to visualization.

In particular, pragmatic visualization design guidance should make it easier for designers to understand how their design choices affect the motifs which are possible in a layout, and their likely meaning for a target audience. One research path is to translate the motif typology into an automated tool for predicting the possible motifs, as suggested in Chapter 6. Methods for eliciting and capturing domain concepts also need to be developed.

In linguistics, Grice’s maxims are used for more than simply assessing a speaker’s linguistic competence. Instead, violations of Grice’s maxims can be often be interpreted as a lens into the speaker’s social behaviour [20]. Breaking one or more maxims can be evidence that a speaker is being deliberately uncooperative, perhaps to express their unwillingness to participate in conversation (for example, a teenager's quantity-violating reply of "stuff" to a question about their plans), or their feelings towards the listener (e.g. using obtuse or overly technical language – a violation of manner – to express superiority). Alternatively, violations of conversational maxims can be a form of politeness, allowing the other participants to infer that the speaker is trying to request or suggest something without expressing it directly (remarking that it is cold for example, rather than explicitly asking for a window to be closed).

In theory, context-sensitive visualization design could function in the same way. An information-rich visualization used when the designer knows that the audience would prefer something simpler (a violation of quantity) could be used as a polite way of saying 'this problem is more complicated than you assume' (see for example [240]). However, social use of Grice's maxims operates in an environment where both speaker and listener are intimately familiar with the maxims, to the point where conversational participants are often unaware that they are using and responding to these cues [115]. The relative lack of experience with visualization compared to speech suggests that there is a significant risk that the reader will simply assume that the designer is incapable of producing a suitable visualization.

8.5.3 Combinations of Visualization

This thesis has considered visualization use in a single moment in time – a static visualization display used for a single practical purpose. If a problem requires multiple transformations of thinking, a single, static view of a visualization may not be sufficient.

A challenge for future research is to determine how semantic scaffolding operates across multiple visualization views, and at multiple points in time. Complementary representations have been examined from an information channel perspective to determine whether readers are faster or more accurate retrieving information using a combination of visualizations (e.g. [241]). A semantic scaffolding approach would instead extend the idea of coherence generated through multiple representations [242]. How can visualizations be combined so that the correspondence between motifs and domain concepts from one view is leveraged by subsequent views for progressively better understanding of a problem?

8.6 Conclusions

Semantic scaffolding – the co-construction of meaning through visual encoding and the reader's context – is a key component of both the practical value of visualization, and its use in practice. This thesis has extended the theory of visualization underpinning visualization evaluation. New conceptual models provide an understanding of hybrid (figurative + abstract) visualization, intermediate level visual motifs, and semantic scaffolding. The research has synthesized existing knowledge of visualization interpretation to establish the role of the reader's prior knowledge in creating practical value. It shows how the reader's prior knowledge can be anticipated in the design of visualization layouts.

For a reader to gain value from a visualization, they must recognise or discover the correspondence between their existing domain knowledge and encoded visual motifs. Visual conventions reinforce the prior meaning of motifs. Figurative elements allow correspondences to be established with types of domain knowledge which are not possible through abstract representation. Figurative elements and conventions are a means of achieving recognition of correspondence, and as such are currently undervalued within the information visualization research community.

The importance of the technical language and concepts developed in this project lies in the path they provide for future research. The current focus of information visualization research on individual visual values and encoded meaning does not reflect the practical value of visualization. Instead, the design of experiments, evaluation measures and heuristics needs to be reframed around the practical meaning of visual motifs.

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