The Cognition of Complex Visualizations

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Abstract

We explore current research on how complex visualizations are perceived, comprehended, used, and taught.

Introduction

How do people perceive, comprehend, and use complex visualizations, and when are they needed? Many domains (meteorology, scientific visualization, stock market analyses) deal with very complex data that must be displayed and used in novel ways. Unfortunately, very little is known about how these complex displays are used, how to best display complex graphical information, or how to design good complex visualizations for teaching purposes. This symposium will examine:

- how people understand and use complex visualizations;
- how people gain expertise in using complex visualizations;
- how to teach complex domains by using graphs and visualizations;
- how to visualize uncertainty across many variables;
- why a visualization is hard or easy to use; and
- how current models of graph comprehension scale up to more complexity.

Building Qualitative Mental Models

Greg Trafton

How do people use a complex visualization? Most current theories predict a straightforward process of reading off specific information, typically at the request of an experimenter. Many complex domains, however (many areas of scientific visualization, meteorology, etc.) need to deal with multi-dimensional data with complex interactions and anomalies.

I will present several recent studies that show that while experts mostly conform to the standard models of graph comprehension, there are some glaring holes in current theories. Specifically, experts do more than simply read off information. First, they extract primarily qualitative information from complex visualizations (e.g., "The wind is fast over San Diego") even when quantitative information is available and needed later. With this qualitative information, they build a complex mental representation (which we call a qualitative mental model, or QMM) to reason with.

I will present data that shows how experts build these complex mental structures by looking at complex visualizations. I will also present evidence from eye-tracking and protocol studies of experts and novices working in their own domain, showing how novices seem to conform to the standard graph comprehension models while experts do not.

The Role of Prior Knowledge in Complex Data Comprehension

Priti Shah & Eric G. Freedman

People are increasingly faced with the task of interpreting complex°multivariate quantitative data sets. Unfortunately, much research on graph interpretation has focused on how novice (college undergraduate) viewers use common formats° (e.g., bar and line graphs) for simple tasks (e.g., read a data point or describe a trend) and sparse (2-3 variables and few data points) and meaningless (axes labeled x and y) data.° In our presentation, we argue that models based on this research may not scale up to account for more complex data interpretation, which differs in several key features. Complex data interpretation usually refers to tasks involving many variables, complex interactions between the variables, and a large number of data points. Complexity extends beyond simply data complexity, however. Dealing with complex data coincides with complex tasks (e.g., making decisions or explaining data) rather than fact retrieval.° Complex data also involves the extensive use of prior knowledge and viewers with data interpretation skills (experts use complex data, not novices).° Finally, complex data is often presented via specialized displays that sometimes incorporate animation and interactivity. Models of complex data interpretation thus require considering data complexity, domain knowledge, graph reading skills, and display characteristics.

In a number of recent studies we consider how these factors play a role in viewers' interpretations. Our results suggest that domain knowledge and data interpretation skills influence viewers' comprehension and use of complex data. In addition, domain knowledge and data interpretation skills interact with data complexity and display characteristics. Specifically, prior knowledge reduces complexity in two ways:° experts know what to look for and also how to retrieve that information from complex displays.° Second, prior knowledge reduces the influence display characteristics on viewers' comprehension of data. Third, prior knowledge helps viewers integrate data and theory and understand implications of the data.° Finally, display characteristics such as interactivity and visual cues also reduce cognitive complexity.

We describe a model of graph comprehension based on these results. By incorporating the interaction of top down factors (e.g., domain knowledge) and the bottom up influence of display characteristics, our model builds on prior models but provides a more comprehensive description of complex data interpretation.

Visualizing Uncertain Information

Susan Kirschenbaum

There are many qualities that make visualizations complex. Perhaps the most clear-cut definition is the multi-variable visualization. The variables may be incompatible or difficult to display in a single visualization. For example, to display (in support of maneuver decisions) the course, speed, range, depth, time, and relative motion (how two moving objects relate to one another) of submarines moving through the sound field that is the ocean requires multiple complex visualizations. Weather forecasters have similar problems. The visualizations can be either graphs or, more often, geo-referenced displays.

Visualizations of these situations would be complex even without the added problem of uncertainty. However, the submarine world is characterized by the extensive uncertainty due to limited measurable data, indeterminate algorithmic solutions, and sound transmission characteristics underwater. Naturally, with multiple variables and uncertainties, there are many options for visualizing the problem. Some limit the number of variables; many ignore or discretize uncertainty. Alternatively, there are many ways to visualize uncertainty (Pang, et al., 1997). Even when uncertainty is not displayed, decision makers find ways to assess it by multiple comparisons; across variables of interest, and by comparing models with predicted, modeled, or measured data.

I will show evidence from verbal protocol and eye-tracking data of how decision makers interpret uncertainty in visualizations and of the impact of task and expertise on the effectiveness of various visualization options.

Designing representational systems to study complex visual cognition

Peter C-H. Cheng

Representational epistemology is the term I use to succinctly describe our work on the nature cognition with complex visualizations. The central theoretical claim of representational epistemology is that representational systems are fundamental to the highest forms of human cognition, such as problem solving, conceptual learning and scientific discovery. In such activities the acquisition and transformation of knowledge is essential, so understanding the nature of the representations that codify that knowledge will be critical. For instance, in the context of conceptual learning we theorize that an effective representation will substantially determine: what is learnt; how easily learning occurs; the nature of the conceptual structures that develop; the problem solving procedures that are acquired.

There are five common stages to our representational epistemological studies. First, a conceptually demanding knowledge rich domain is selected. Educational domains that we have addressed include mechanics, electricity and probability theory. The approach is also being applied to the intensive real-world problem of University examination scheduling. Second, the content and problem classes of the domain are analyzed to reveal the underlying conceptual structure of the knowledge, which includes the ontologies, perspectives, scale levels, laws, models, prototypes and extreme cases of the domain. Third, the existing domain representations are examined to uncover the conceptual problems they cause. Fourth, a new diagrammatic system is invented to encode the inherent conceptual structure of the domain. The novel representations that we have invented are Law Encoding Diagrams, LED. By directly reflecting the conceptual structure of a target domain in its representational structure a LED is a re-codification of knowledge that should support comprehension, problem solving and learning of the domain. The LEDs are of sufficient novelty and potential that papers describing them and their use have been accepted for publication in domain specific journals. Fifth, empirical evaluations of problem solving and learning with the new LED compared to the conventional representations of the domain are conducted in the laboratory or in Schools.

Studies conducted in the domains mentioned above show that LEDs improve problem solving and conceptual learning compared to the conventional domain representations. By generalizing over these different domains, contrasting the various LEDs and the existing representations, we are formulating principles for the design of effective representations for complex knowledge rich domains. Two classes are posited: semantic transparency principles that address how the underlying conceptual structure of a domain should be encoded in the inherent structure of the representation; syntactic plasticity principles that consider how a representation should be structured to support efficient problem solving.