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Interactive Visualizations: A Literature Review

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ABSTRACT

The idea that pictures tell a more compelling story than words is a long-standing tradition. Research provides many examples, dating back to the maps used by Napoleon. Visualizations are now an integral part of information system design as they address limitations of human cognition. They are more than a picture and should be viewed as a tool that facilitates analytic activity through different modes of interaction. This paper presents a literature review of taxonomies of interactive visualizations defined by task type and interaction type.

Keywords

Information Visualization, Interaction Techniques, Visualizations

INTRODUCTION

The idea that pictures tell a more compelling story than words is a long-standing tradition. Research provides many examples, dating back to the maps used by Napoleon. We are confronted with massive amounts of data, and visualizations are becoming even more important to Information Systems. Visualizations are now an integral part of information system design as they address limitations of human cognition. Visualizations are more than just a picture. They are now a tool that facilitates analytic activity through different modes of interaction. Visualizations use different interactive techniques to create a dialogue with the user for data analysis.

METHODOLGY

One of the most cited papers for interactive visualizations is by Yi et al. (2007). This literature review is based on a forward and backward citation search within the Web of Science research database, starting with this paper. The context of this literature review focused on the taxonomies that describe visual interactions and visualization tasks. Preference was given to papers or book chapters with titles and/or keywords that included information visualization, interaction, interaction techniques, taxonomy, and visual analytics.

VISUALIZATION

The term visualization is context-free, as it can mean different things to different people depending on the situation (Parsons & Sedig, 2014). The most common definition from visualization comes from Card, Mackinlay and Shneiderman: "[visualizations are a] computer-supported interactive visual representation of data to amplify cognition (Card, Mackinlay, & Shneiderman, 1999)."

Visualizations are a cognitive tool, much like a pencil or a calculator. People with cognitive tools are more effective thinkers than people without (Ware, 2005). The interactivity of visualizations further facilitates a deeper level of cognition but augmenting the human's ability. van Wijk's (2005) simple visualization model shows how insights are generated as the human participates in a feedback loop between reading and interacting with the visualization (see Figure 1). This model is also context-free, allow for the focus to be on the feedback loops between visualization and user (van Wijk, 2005).

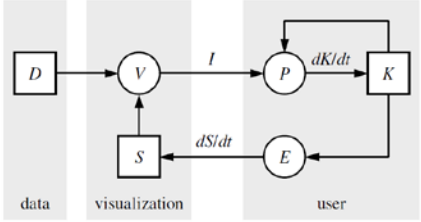

Figure 1: van Wiij's Simple Visualization Model

Interaction allows the user to define what data they see and how they see the data, creating a dialogue between the user and the system. The diversity of tasks prompting the need for interaction are too many to be theoretically founded in just one theory (Keim et al. , 2008). The theoretical support for visualizations is broadly classified into two groups: defining the visual representation and defining the manipulation of the visualization. Theories behind visual representation include graphical comprehension (Cleveland & McGill, 1984), preattentive processing (Ware, 2012), Gestalt

theory (Few, 2009), and graphical excellence (Tufte, 2001). Theories behind the manipulation of visualizations include but are not limited to cognitive fit (Vessey & Galletta, 1991), visual perceptual approaches (Baker, Jones, & Burkman, 2009) and human information processing. In reality, manipulation cannot be completely separated from the representations. These aspects are simply two sides of the same coin and must be considered together to identify the overall effectiveness of each fully. As interactive visualizations take a larger role in information systems, designers must know what tasks, visual representations, and interaction techniques are available and how they work in concert to facilitate analytical reasoning.

TASK TYPES

The number of people familiar with visualizations continues to grow as visualizations become an integral part to the design of information systems. Designers are placed in between a rock and a hard place, as they attempt to decide which type of visualization to use. They must decide on the most effective visual representation without being able to estimate every user's ability to read and interpret the visualization (Boy, Rensink, Bertini, & Fekete, 2014). Extant research provides insight to the tasks facilitated by use of visualizations, but it has been proven difficult to align each author's ideas with others: "alignment of approaches is difficult to attain and is mostly likely imperfect, as most authors and tool developers do not provide a definition of the terms they use (Börner, 2015)." Tasks can be viewed either by the goal the user is trying to obtain or by the intent the user has. A thorough search of taxonomies by task led to the identification of ten tasks most commoly referenced in literature.

Task	**Description**	**Source**
Identify	Establish characteristics of an object	Ward, Grinstein & Keim (2015)
Selection	Mark something as interesting	Bertin (1967)
Categorize	Place into divisions	Yau (2011) Borner (2014) Ward, Grinstein & Keim (2015)
Order	Assign an order or position	Bertin (1967) Yau (2011) Few (2012) Frankel (2012) Borner (2014) Ward, Grinstein & Keim (2015)
Compare	Notice similarities and differences	Yau (2011) Few (2012) Frankel (2012) Borner (2014) Ward, Grinstein & Keim (2015)
Time Series	Show changes over time	Yau (2011) Few (2012) Borner (2014)
Locate	Know the position of an object	Yau (2011) Few (2012) Frankel (2012) Borner (2012) Ward, Grinstein & Keim (2015)
Cluster	Group similar objects	Yau (2011) Few (2012) Borner (2014) Ward, Grinstein & Keim (2015)
Associate	Link or join in a relationship	Bertin (1967) Yau (2011) Borner (2014)
Correlate	Establish a direct connection	Few (2012) Borner (2014) Ward, Grinstein & Keim (2015)

Table 1: Task Types

INTERACTION TYPES

When considering the tasks, it is imperative to also identify the recurring techniques used to complete those tasks. Interaction techniques facilitate data exploration leading to theof generation new insight. Interactions explicitly place humans in the loop

where visualizations leverage the human perceptual system reducing the cognitive load required for data analysis (Endert, Chang, North, & Zhou, 2015; Sedig, Parsons, & Babanski, 2012). More systems are using interactive visualizations, as opposed to static visualizations, which in turn requires a a strong need to fully understanding the effectiveness of interaction techniques (Saket, Srinivasan, Ragan, & Endert, 2018). As with task types, interactivity types are difficult to narrow down to a cohesive set of terms. Table 2 provides a summary of research that investigates interaction techniques for visualizations.

Interaction	**Description**	**Source**
Overview	Birds-eye view; entire collection	Shneiderman, 1996 Yi, Kang & Stasko, 2007 Here & Shneiderman (2012) Few (2009) Figueiras (2015)
Zoom	Scale visualization to see specific subset of data points	Shneiderman, 1996 Few (2009) Figueiras (2015)
Filter	Reduce size of the search, hide data points conditionally	Shneiderman, 1996 Yi, Kang & Stasko, 2007 Few (2009) Figueiras (2015)
Details on Demand	Select an item to get details	Shneiderman, 1996 Few (2009)
Relate	View relationships among items	Yi, Kang & Stasko, 2007 Here & Shneiderman (2012) Figueiras (2015)
History	Track exploratory steps, allow back-tracking	Shneiderman, 1996
Extract	Save results of exploratory steps	Shneiderman, 1996
Abstract / Elaborate	show more or less detail	Yi, Kang & Stasko, 2007 Figueiras (2015)
Select	mark something as interesting	Yi, Kang & Stasko, 2007 Here & Shneiderman (2012) Few (2009) Figueiras (2015)
Reconfigure	change the arrangement, scale, or encoding	Yi, Kang & Stasko, 2007 Here & Shneiderman (2012) Few (2009) Figueiras (2015)

Table 2: Interaction Types

CONCLUSION

Schulz et al. (2013) define two abstractions for the design of visualizations: **Data + Task = Visualization** and **Data + Visualization = Task.** These abstractions demonstrate dependence between the data, visual representation, and the task. Humans are integrated into this dependence, as they use the visualization to carry out a task, as shown by van Wijk's simple visualization model. The more the user interacts with the visualization, they gain knowledge. The interactions allow a user to be in control of their understanding by providing the flexibility to create new views that help him/her go beyond just the visual representation (Keim 2008). The field of information visualization is continually adapting to changes with the big data revolution. These foundational items for task and interaction types provide a stepping stone for continuing to develop effective visualizations.

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