From Specific Information Extraction to Inferences: A Hierarchical Framework of Graph Comprehension

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We examined how graph readers extracted specific information, integrated information and made inferences from choropleth graphs. We present a hierarchical framework of graph comprehension suggesting how graph readers extract these different types of information. Our framework suggests the cognitive operations required to extract these different types of information build in a hierarchical fashion as the complexity of the type of extraction increases. Empirical data gathered in our laboratory is reviewed in support of our hierarchical framework and implications are discussed.

INTRODUCTION

In today's data rich world, we are bombarded by information nearly everywhere we look. Because graphs are generally an optimal way to represent data, this information is often displayed in some kind of graphical format (Larkin & Simon, 1987). For example, when reading the newspaper we often see many different types of graphs displaying data about things like population, stock prices, gross domestic product and unemployment. In order to be able to function in this data rich world, it is imperative that we have the necessary skills to interpret these graphs.

The skill to interpret the information displayed in graphs is so important to have, the National Council of Teachers of Mathematics has created guidelines to ensure that students learn these skills (*NCTM: Standards for Mathematics*, 2003). These guidelines are based primarily on the extraction of three different types of information from graphs: read-off, integration, and inference. Read-off's require the graph reader to extract one or two explicitly represented data points from the graph. Integration involves the comparison of multiple points in the graph (e.g. evaluating the trend in the graph). The most difficult type of information extraction is making inferences which require the graph reader to go beyond the explicitly represented data to make some prediction based on the current data.

What cognitive processes do graph readers use to extract these different types of information from graphs? The classical theories of graph comprehension suggest that graph readers first read a question to determine what information they are being asked to extract from the graph (e.g., What is the price of tin in 2001?). Parts of the question may be read multiple times (Peebles & Cheng, 2002). Next, the participant searches for the specific information on the graph, shifting from the axes to the main part of the graph and back again (Carpenter & Shah, 1998; Kosslyn, 1989; Lohse, 1993; Pinker, 1990). Once the information is found, multiple saccades occur between the main part of the graph and the legend in order to keep the information in memory (Carpenter & Shah, 1998; Trafton, Marshall, Mintz, & Trickett, 2002). Finally, the question itself is answered.

Classical theories of graph comprehension have focused primarily on the extraction of specific information from simple graph types generally displaying relatively few data points. Do these theories account for how graph readers perform more complex extractions like integrating information and making inferences? Trickett, Ratwani, & Trafton (under review) examined whether the classical theories could account for the extraction of these different types of information and applied these theories to more complex graph types. Trickett et al. (under review) found that the classical theories were able to accurately account for the read-off of information in simple and complex graphs, but the theories had difficulty accounting for how graph readers integrated information and how graph readers made inferences from graphs.

When Trickett et al. (under review) applied the classical theories to integration questions, the theories had difficulty accounting for how graph readers combined the information from multiple data points, especially in the more complex graphs. For example, when there are 10 data points that need to be combined in order to extract the trend, the classical theories have difficulty with these operations. The theories cannot account for inferences because inferences require the graph reader to go beyond the explicitly represented data; classical theories do not specify how graph readers go beyond explicitly represented data.

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The purpose of this paper is to work towards a theory of graph comprehension that accounts for how graph readers read-off, integrate, and make inferences from graphs. In an effort to work towards this theory, we propose a hierarchical framework of graph comprehension supported by experiments that have been conducted in our laboratory. In this paper we detail the hierarchical framework and review the empirical data that have been collected in our laboratory in support of the hierarchical framework.

THE HIERARCHICAL FRAMEWORK

Following from the guidelines of the NCTM, a hierarchy of complexity exists in the extraction of information from graphs. Read-off's are the simplest type of information extraction, followed by integration and then inferences. Our framework suggests that the cognitive processes required to extract these different types of information scale up in a hierarchical fashion with the difficulty of the extraction type. The read-off of information is the most basic type of extraction from graphs. The more complex integration of information will require read-off's in addition to spatial transformations. Finally, in order to make inferences, graph readers will use the processes used for integration in addition to pattern extrapolation and mental models.

The cognitive processes required to read-off specific information from graphs is well specified by the classical theories of graph comprehension. In our experiments we replicated these processes. In order to integrate information in graphs, graph readers will use read-offs and spatial transformations. Spatial transformations are any mental manipulation of data in a graph, for example mentally moving one line next to another for comparison is a spatial transformation (Trafton, Trickett, & Mintz, in press). Spatial transformations allow graph readers to combine different areas of the graph, this operation can aid graph readers in comparisons and trend making processes.

When graph readers make inferences from graphs we believe they will use read-off's, spatial transformations, pattern extrapolation and mental models. Graph readers may not use all of these processes, but may rely on a few of these operations in order to make inferences. Pattern extrapolation is a process by which graph readers examine known data points and then, based on the pattern of these data points, make an inference (Bott & Heit, 2004). Mental models may also be used to make inferences (Trafton et al., 2000). Trafton et al (2000) has shown that expert meteorologists form qualitative mental models when making inferences from meteorological visualizations.

Although our framework suggests which cognitive processes graph readers will use when extracting different types of information from graphs, graph readers are likely to use the simplest process possible to extract the desired information. For example, when integrating information, if made possible, graph readers will use mostly read-offs because read-offs are a simple way of extracting information from graphs and require very little cognitive effort in comparison to spatial transformations. Thus, while the hierarchical framework suggests what cognitive processes will be used when extracting these different types of information from graphs, other factors such as cognitive effort are likely to influence which operations are performed. Our framework serves to identify which processes are likely to be used to extract the desired information from the graph.

EMPIRICAL SUPPORT

In order to illustrate the cognitive operations that are used to extract different types of information, we chose to use choropleth graphs. Choropleth graphs use different colors, shades of gray, or patterns to represent different quantities. Choropleth graphs were chosen for multiple reasons. First, they are more complex than the graph types used in more traditional studies of graph comprehension and better reflect how graphs are used in the real-world. Second, these particular graphs do not require a great deal of domain knowledge and can be presented to undergraduates without much training. Finally, choropleth graphs represent a class of graphs that are commonly used by scientists in such domains as meteorology, geology and oceanography.

Read-off and Integration

We presented choropleth graph's depicting the population of fifty fictitious counties to graph readers (Figure 2). Graph readers were asked both read-off and integration questions for each graph. The read-off question asked the graph reader to identify the current population of a specific county. The integration question asked the graph reader to identify the general trend in the graph (for more details of the method see Ratwani, Trafton, & Boehm-Davis, 2003).

We collected eye track data using an LC technologies eyegaze system operating at 60HZ. The eye track data were coded in two ways. First, we coded each gaze as either a reading gaze or a non-reading gaze. Gazes that were directly to county names were coded as reading gazes. Gazes that were to other parts of the graph were coded as non-reading gazes. Second, we coded the location of the gazes to the graph. A boundary edge gaze was defined as a gaze directed towards the edge of two different colored counties. An inner gaze was defined as a gaze to a solid color, either completely within one single county or to multiple counties of the same color.

When graph readers were answering read-off questions we expected their cognitive processes to follow suit with the classical theories of graph comprehension. Graph readers should first read the question, then search for the target county by reading county names, and then finally read-off the population value by looking at the legend. Based on the eye-track data this is exactly what we found. Graph readers made significantly more reading gazes than non-reading gazes when answering read-off questions, $\chi^2(1) = 32.0$ $p < .0001$, as Figure 1 suggests. Thus graph readers are searching for the desired county by reading county names when answering read-off questions.

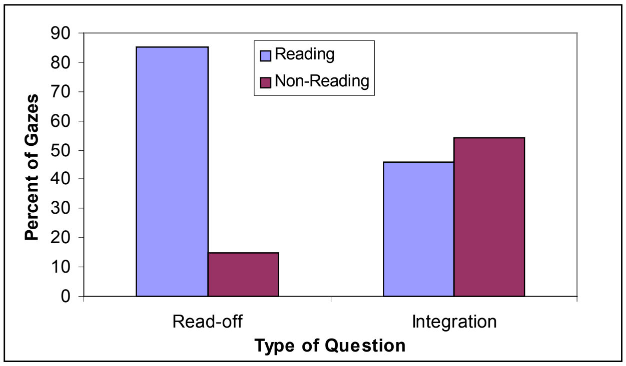

Figure 1: Number of reading and non-reading gazes.

Figure 2 is a sample of the eye track patterns observed when participants were asked to answer a read-off question. The graph reader first reads the question asking for the population of Palos Verdes County, then briefly searches for the target county by reading county names. Once the county is found, they quickly saccade to the legend to identify the population value. Each of the gazes to the graph itself are reading gazes in service of finding the target county.

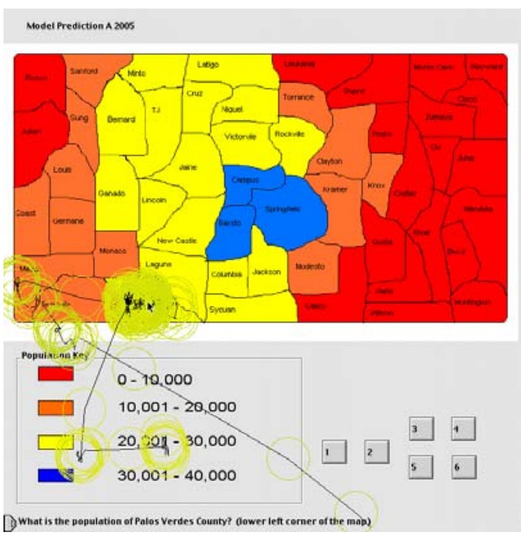

Figure 2. Eye track data when answering a read-off question.

Do graph readers use read-off's and spatial transformations when integrating information as the hierarchical framework would suggest? We believe graph readers will form clusters of proximate same colored counties by fixating on the edges of these clusters. Graph readers therefore should make a large number of fixations at the edges of these groups of same colored counties in order to form clusters. The explicit formation of these clusters is a type of spatial transformation that allows the graph reader to integrate information in the graph. We do not expect many fixations to the names of counties since graph readers should be more interested in the formation of clusters as opposed to individual county information.

The eye track data suggest that graph readers are making more boundary edge gazes and are not as interested in reading. Graph readers made significantly more boundary edge gazes as compared to inner gazes, $\chi^2(1) = 7.8$ $p < .01$. In addition, the number of reading and non-reading gazes was nearly equal, as Figure 1 shows. The boundary edge gazes are in service of the formation of clusters, a type of spatial transformation, which allows the graph reader to evaluate the trend in the graph. Yet, graph readers are still reading off some information as indicated by 50% of the gazes still being directed towards reading county names.

Figure 3 shows the eye track data from a participant answering an integration question. The graph reader's make gazes to the boundary edges of proximate same colored counties in an effort to form clusters. These clusters can then be used in the reasoning process to evaluate the trend. After forming clusters, graph readers evaluated the trend in the graph by using these clusters in their verbal responses.

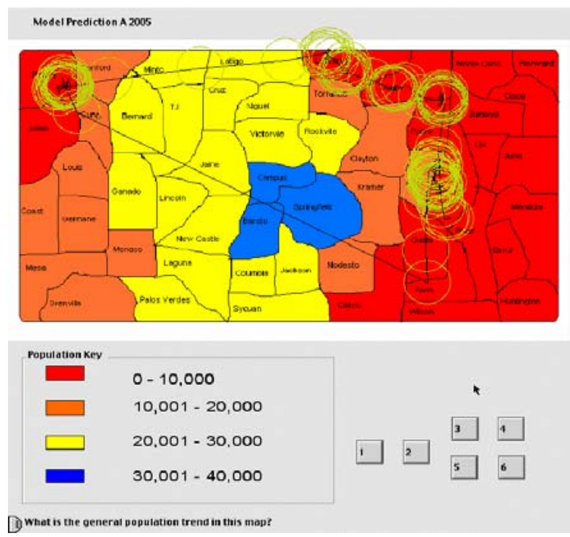

Figure 3. Eye track data when answering an integration question.

As the eye track data show when graph readers are answering read-off questions, the cognitive processes follow suit with current theories of graph comprehension. When graph readers are answering integration questions, the eye track data is in agreement with the hierarchical framework of graph comprehension. Graph readers are using spatial transformations by forming clusters of counties and graph readers are reading-off some specific county information.

Inferences

To examine how graph readers made inferences, we presented graph readers with a series of choropleth graphs depicting population over a 10 year period. Participants were presented with three choropleth graphs, one from 1990, 1995 and 2000; the graphs were similar to those used in previous experiments. The participants were asked to infer the population of a specific county in the year 2005. The population of the specific target county did not change in the graph, however, the surrounding counties did change in population. The surrounding counties changed in population (i.e. decreased or increased) such that there was a strong contextual indication that the population of the target county would either increase or decrease in the future time period (for more details see Ratwani & Trafton, in press).

Eye track data were collected using an LC Technologies eyegaze system operating at 60HZ. We coded the location of gazes to the graph in relation to the target county. Thus, gazes to other counties in the graph were coded by counting how many counties away the gaze was from the target county. We also coded when participants gazed at a county that changed in population compared to the previous graph they examined. For example, if a participant looked at county A in the graph from 1990 and then looked at county A in the graph from 1995 and county A changed in population over this time period, this was coded.

In order to make an inference based on these graphs one would have to examine the influence of the surrounding counties on the target county in each of the graphs and then across all three of the graphs. The hierarchical framework suggests that graph readers would have to use read-off's, spatial transformations, pattern extrapolation, and mental models in order to make these inferences. Once they examine all of the information in each of the graphs they can determine whether the target county will change in population. In this experiment we chose to focus on read-off's, spatial transformations, and pattern extrapolation. The use of mental models may be heavily dependent on domain knowledge. Because these graph types were selected for undergraduate university students to understand they do not require much domain knowledge.

Participants either responded that the population of the target county would change in the direction of the surrounding counties or that the population of the target county would not change. None of the participants responded that the target county would change in the opposite direction of the surrounding counties. Each participant was fairly consistent in their responses, that is they either always said the population would change or always said the population would not change.

The graph readers who said the population of the target county would not change appeared to only pay attention to the target county in each of the three graphs. These graph readers did not examine the surrounding counties when making an inference. As Figure 4 suggests, these graph readers primarily focused on the target county in the graphs. These graph readers made very few gazes to non-target counties and made few change gazes. Figure 5 shows the distribution of gaze location when graph readers made non-change and change responses. Graph readers who made non-change responses focused primarily on the target county, represented by the zero in the graph. These graph readers did not use all of the information displayed in the graphs as indicated by their eye movements. Because these graph readers simply focused on the target county they did not consider the heavy contextual influence of the surrounding counties.

Alternatively, the graph readers who said the target county would change in population used read-off's, spatial transformations and pattern extrapolation. Graph readers using this strategy appeared to integrate information in two ways: (1) they integrated information within the graph by examining the target county and surrounding counties, and (2) they integrated information across graphs by comparing particular areas that changed in population to see how the population increased or decreased.

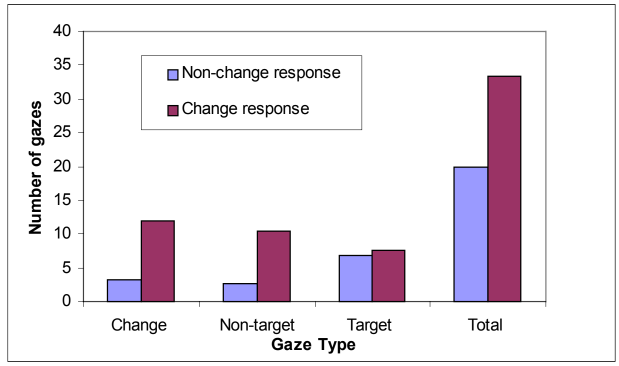

Figure 4. Location of gazes given an inference question.

As Figure 4 shows, when graph readers said the population of the target county would change, they integrated information within the graph by examining the target county and counties surrounding the target county. Figure 5 shows that graph readers who made change responses looked at more counties away from the target on average. Thus, they are integrating information within a graph by combining the target county information and the information from surrounding counties.

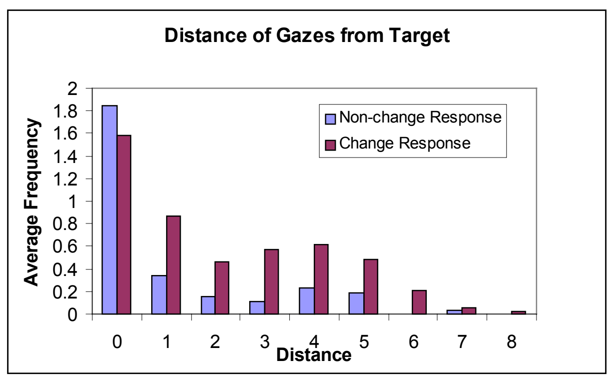

Figure 5. Distribution of the gazes to the graph by county location.

Graph readers who made change responses integrated information across the graphs by examining counties that changed in population relative to the previous graph they examined, as suggested by the number of change gazes in Figure 4. These change gazes suggest that participants are comparing the same county across graphs to see how the population is changing in the particular county. Graph readers who said the population of the target county would change went back and forth between graphs more often then graph readers who said the population of the target county would not change. Thus, information is integrated across graphs by comparing a few counties in each graph to understand how the population is changing.

Do these two strategies of making inferences fit with our hierarchical framework? Graph readers who did not use read-offs, spatial transformations and pattern extrapolation consequently did no evaluate all of the information in the graph and thus made a non-change response. Graph readers who appropriately evaluated all of the information in the graph did perform read-off's, spatial transformations, and pattern extrapolation and consequently made a change response.

GENERAL DISCUSSION

The hierarchical framework of graph comprehension serves to identify what cognitive processes are used when graph readers extract different types of information from graphs. Graph readers may not always use these processes; they are likely to use whatever processes are easiest for them to perform. Our framework suggests that the cognitive processes required to extract information depends on the complexity of the information being extracted from the graph. Reading-off information from the graph is the easiest and most basic type of information extraction. The classical theories of graph comprehension adequately account for this process. However, the classical theories do not adequately account for how graph readers integrate information or make inferences from graphs.

The integration of information and making inferences from graphs are much more difficult types of extractions. Our framework suggests the integration of information requires spatial transformations and read-offs. In order to integrate information in the choropleth graphs, graph readers explicitly formed clusters and then used these clusters to evaluate the general trend. This spatial transformation of the data allowed the graph readers to more easily reason with the data in the graph.

The processes used to make inferences build from the processes used to integrate information; graph readers use read-off's, spatial transformations, pattern extrapolation and mental models to make inferences. With the choropleth graphs used in our experiments, we focused on read-off's, spatial transformations and pattern extrapolation. Graph readers integrated information within the graph by combining target county information with the surrounding county information. Information was integrated across graphs by mentally comparing counties that changed in population across the three time periods.

Although we have shown that the hierarchal framework accounts for the processes used to make read-offs, integrate information and make inferences from choropleth graphs other graph types need to be examined. We believe our framework outlines the general processes that will be used to extract these different types of information. However, the specific processes, for example the specific types of spatial transformations performed, are likely to change depending on the specific type of graph being examined. Thus, other graph types such as line graphs and bar charts need to be examined to see how well the hierarchical framework accounts for the extraction of these different types of information in those graph types.

There is large body of empirical data examining how graph readers extract specific information from graphs. There are far fewer studies examining how graph readers integrate information in graphs, and even fewer studies examining how inferences are made. It is difficult to put forward a theory specifying how graph readers integrate information and make inferences from graphs when there is very little empirical data examining how these processes occur. What is needed is more empirical data systematically examining how graph readers make these extractions form different graph types. Once there is a greater body of empirical data examining these processes, a strong theory of graph comprehension can be put forward accounting for how these different types of information extraction occur.

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