SAND2020-7549C

Task Matters

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ABSTRACT

One of the major challenges for evaluating the effectiveness of data visualizations and visual analytics tools arises from the fact that different users may be using these tools for different tasks. In this paper, we present a simple example of how different tasks lead to different patterns of attention to the same underlying data visualizations. We argue that the general approach used in this experiment could be applied systematically to task and feature taxonomies that have been developed by visualization researchers. Using eye tracking to study the impact of common tasks on human attention to common visualization types will support a deeper understanding of visualization cognition and the development of more robust methods for evaluating the effectiveness of visualizations.

Keywords: Visual cognition, data visualizations, eye tracking, attention.

Index Terms: Human-centered computing ~ Visualization ~ Empirical studies in visualization

1 INTRODUCTION

What makes a data visualization effective? Evaluating visualizations can be very challenging and is the subject of much research and debate [6, 15, 19, 22, 24, 26]. Members of the visualization research community have called for evaluation approaches that assess how well visualizations support their viewers' cognitive needs [5, 9, 17, 29]. From this perspective, an effective visualization successfully exploits its viewers' cognitive processes to draw their attention to relevant information, minimize their attention to irrelevant information, and increase the likelihood of correct interpretation. In order to meet those requirements, visualization designers need to be able to account for the experience, expectations, and biases of the viewer *in addition* to the low-level, perceptual properties of the data visualization.

There is a growing body of research on how the perceptual aspects of visualizations influence viewers' cognitive processes. For example, researchers have demonstrated that increasing the visual saliency of task-relevant information can improve task performance [8, 11, 12, 14, 16, 18, 25] and that changing the visual representation of a dataset can change how viewers interpret it [7] and their biases in interpretation [21]. However, there has been relatively little research on how different high-level tasks impact viewers' attention to different aspects of visualizations. In this paper, we present a simple experiment as an illustration of why this is an important topic, in need of additional research.

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1.1 An Experiment on the Impact of Task

This simple example is taken from one task in a larger study. In this task, thirty participants recruited from the University of Illinois community were asked to describe either the trend or the outliers in a series of scatterplots. There were 32 scatterplots consisting of four unique plots for each of eight types of trends: positive linear, negative linear, flat, sinusoidal, positive logarithmic, negative logarithmic, positive quadratic, and negative quadratic. The simulated data were drawn from Gaussian distributions and the data points representing the trend were constrained to fall within two vertical standard deviations of the trend function. Half of the plots of each type had two outliers and half had four. The outliers were at least four standard deviations away from the trend function. An example is shown in Figure 1.

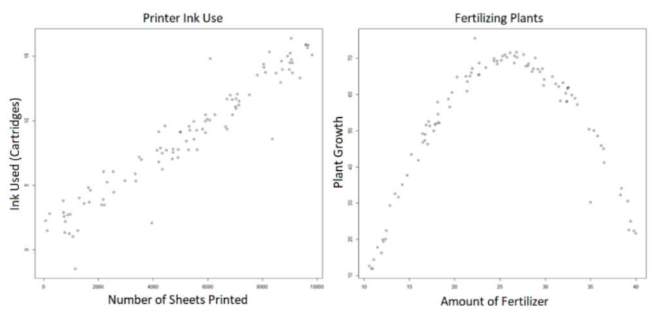

Figure 1: Two representative scatterplot stimuli, one with four outliers (left) and one with two outliers (right).

The stimuli were divided into two blocks. For one block, the participants were asked to describe the trend depicted by the scatterplot, and for the other block they were asked to describe the outliers. The task-block pairing and the order of the two tasks were counterbalanced across participants. Each scatterplot was shown on a computer screen for 10 seconds, or until the participant pressed a key to advance. While the participants were viewing the scatterplots, their eye movements were recorded with a Smart Eye Pro eye tracker. After the scatterplot disappeared from the screen, the participant verbally described the stimulus from memory.

1.2 Results

Two raters independently scored each participant's description of each scatterplot. The participants were generally successful at describing all five types of trends, but they had the most difficulty with describing the quadratic trends. When describing the outliers, participants missed one or more of the outliers on 200 out of 398 trials (50.3%). There were only 20 trials in which participants falsely identified an outlier (5.0%).

Fixations were calculated using Smart Eye's default algorithm, where any sample for which the velocity over the preceding 200 ms is less than 15°/s is deemed a fixation. The first fixation in each trial was excluded from the analysis, as was any fixation with a duration less than 100 ms. A mixed effects model (fit with the lme4 package in R software [2]) with a fixed effect for task and random intercepts for participant and stimulus (using Satterthwaite approximation for degrees of freedom) revealed that overall, participants had more fixations in the outlier task (mean = 22.83 fixations, stdev = 4.78) relative to the trend task (mean = 19.90 fixations, stdev = 5.37; $t(885) = 10.04$, $p < .001$). A similar mixed effects model with fixation duration as the fixed effect revealed that fixation durations in the trend task (mean = 325.38 ms, stdev = 293.92) tended to be longer than those in the outlier task (mean = 279.84 ms; stdev = 232.53; $t(20015) = 12.43$, $p < .001$).

Task also influenced which regions of the graph participants fixated most frequently. Each stimulus was divided into the following regions of interest (ROIs): Outliers, Trend, Title, X-axis, X-axis Label, Y-axis, Y-axis Label, and Other. The "Other" ROI corresponded to the white space inside of the scatterplot that did not contain any data points. The proportion of fixations to each type of ROI was calculated for each participant and stimulus (see Figure 2).

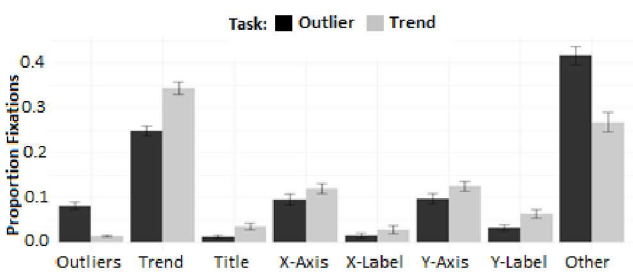

Figure 2: Average proportion of fixations to each region of interest.

The participants' task had a substantial impact on where they allocated their attention within the scatterplots. A mixed effects model was used to predict the proportion of fixations as a function of the fixed effects of task and ROI, with random intercepts for subject and stimulus (using Satterthwaite approximation for degrees of freedom). This analysis showed that for the trend description task, there were significantly higher proportions of fixations to the trend ROI as well as the title, axis, and axis label ROIs. For the outlier description task, the proportion of fixations was significantly higher for the outlier ROI and the "other" ROI (all t-statistics > 2.00 and p-values < .05). The high proportion of fixations to the Other ROI was likely due to participants searching the graphs for outliers as well as the relatively small size of the outlier ROIs.

2 Discussion

In this task, we observed differences in patterns of attention when participants were given different tasks that use the same stimuli. The behavioral results indicate that participants performed the two different tasks successfully, although some types of trends were more difficult to describe than others and some outliers were overlooked. The eye tracking data indicated that there are differences in the overall allocation of attention to different elements within the graphs. The trend and axes received a relatively high proportion of the participants' attention, regardless of condition, but the attention to the outliers and the area around them was dramatically influenced by the participants' task.

The classic experiment by Yarbus (1967) demonstrated that a person's task and goals impacted their eye movements, and numerous subsequent studies have found similar effects for visual search tasks using natural scenes [3, 10, 13]. Our simple experiment demonstrates that the viewer's task also changes patterns of eye movements when the stimuli are data visualizations. While this is a very straightforward example, where the attention to outliers increased when the outliers were important to the task, we posit that it is possible to characterize general patterns of attention that are associated with other common visualization types and tasks.

There are several taxonomies that break down common visualization types and common modes of interaction with visualizations, cf. [1, 4, 19, 23]. We suggest that it would be fruitful to apply methods from the visual cognition literature to the taxonomies that have been developed by visualization researchers. Using eye tracking to characterize how different tasks or goals within these taxonomies relate to different patterns of attention will help to further the understanding of how people make sense of data visualizations and where visual-spatial and cognitive biases [20, 27]. are most likely to impact their interpretations. Systematic research along these lines could also help to develop more widely applicable evaluation methods that take both bottom-up and top-down features into account to determine whether a visualization effectively meets the cognitive needs of its intended users.

3 Acknowledgements

This work was supported by the Laboratory Directed Research and Development (LDRD) Program at Sandia National Laboratories. Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525. This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

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