The Role of Perception and Cognition Costs in Models of Visualization Effectiveness

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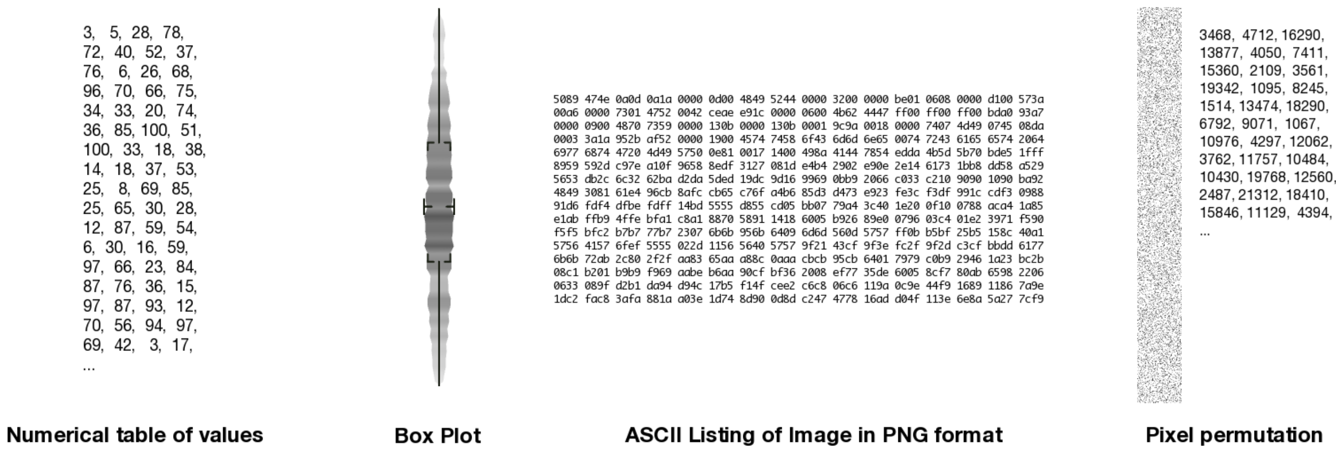

Figure 1: Perceptual and cognitive models of the costs in visualization processes should be essential parts of visualization effectiveness models. Since the alternative data representations have the same amount of information as the original boxplot figure, a model which fails to account for such costs must rate all these visualizations equally well, while they clearly are not all equally effective.

Abstract

The search of an appropriate, effective and comprehensive model for the effectiveness of visualization is one of the most important open theoretical problems in the field. Information theory provides an alluring set of tools and concepts which elucidate some of the goals of visualization. We argue here that any effectiveness model must include an equally effective model of perceptual and cognitive costs, since information content cannot by itself tell the difference between visualizations which vary wildly in their effectiveness. We argue that direct inspection of brain activity (in our case, through EEG) can be used to inform the research into such perceptual cognitive costs, and present a description of how this is being currently carried out.

1 Introduction

To say that Shannon's information theory has revolutionized the theory and practice behind communication channels is an understatement. It has changed the practice so fundamentally, and with such broad applicability and depth that it is fairer to say it effectively created the field as it is studied now. Visualization, on the other hand, seems to lack such a basis. Because the goal of visualization is much less well-defined than that of communication theory, it might seem foolish to look for a model that can yield comparably remarkable successes.

Still, information theory is an attractive candidate for modeling the effectiveness of visualizations. It is clear that at some level, a visualization tries to facilitate the transfer of information into the practitioner's mind, and information theory has much to say about how effectively we can hope to transfer information. In fact, information theory has already yielded applicable techniques for visualization. The principle of entropy maximization, in particular, is a well-known mechanism for picking visualization parameters which "increase the information output" of a picture or visualization. Examples include camera selection in both surface [13] and volume rendering [17], high-dimensional view selection [15], and isosurface navigation [3]. Even simple techniques like histogram equalization and banking to 45 degrees [7] can be seen as instances of entropy maximization.

Particularly relevant to our discussion is the work of Chen and Jänicke [5] who show how to interpret many concepts in visualization in light of information theory. Could we reduce, then, most or all of visualization to representing the original information in a way which loses the fewest amount of information? Alas, this cannot work: consider the task of comparing different probability distribution functions over a subset of the natural numbers (say, from zero to one hundred). While a visualization practitioner knows in their sleep that one appropriate answer to that question is to use, for example, a boxplot such as the one shown in Figure 1, the information content of this visualization is actually less than *simply writing out all of the numerical values*. We seem to be in trouble: a list of values is the folklore answer for the worst possible visualization, and yet it has exactly all the content of the original data. An even more extreme example is the one arrived by a random shuffling of the pixels in an image. Even with full knowledge of the actual permutation, it is impossible to get any visual information out of the plot.

One could hope to salvage the idea by an argument of economy: perhaps we must eliminate "useless" information in the visualization. After all, the box plot is much more economical than the list of distribution values. Consider, however, the printout of the compressed encoding of a PNG file of said boxplot: it is as economical as the PNG file, but the visual encoding of the image file is obviously much better than a character dump of the file.

In addition, this notion of "useless" information only makes sense in the context of asking a particular question about the data. And in that case we must again be careful with our models, since the most economical visualization for the question "is the median of this distribution less than 50?" is not one using Tukey bars, central moments or violin plots: it is simply the word "YES" or "NO" displayed on the screen.

So while there are good reasons to be wary of including perceptual and cognitive concerns in the communication channel induced by a visualization, these concerns must play a central role in a quantitative model of effectiveness. A model which lacks these notions is doomed to claim the representations in Figure 1 are all equally effective visualizations. We want to emphasize here that we share the vision of Chen and Jänicke that information theory has a large potential impact in the theory and practice of visualization. However, quantitative models of the perceptual and cognitive cost of processing these visualizations cannot be treated separately from the rest of the process.

2 Measuring the Cost of Processing Information Visually

While we do not yet have a model which takes into consideration these costs, we now discuss how these models might be constructed using data collected from physiological measurements of subjects during visualization tasks.

Ignoring reflexive actions like the proverbial knee-jerk, it is well-accepted that both learning and decision making processes must somehow process acquired data (in our case, through the visual system) to facilitate understanding [11]. The idea of using comprehension and cognitive measures to determine the effects of illustration has attracted attention in the fields of memory [9], aging [6], and the visualization of chart data [14].

Comprehension and cognitive uptake are typically studied using indirect methods. Agarwal and Karahanna note that individual attitude and behavior influence cognitive absorption and comprehension [1]. Additionally, measuring cognitive ability is known to be confounded by practice during a task, further complicating user studies [8]. In order to address the complications of determining cognitive assets, Brünken et al. suggest directly measuring cognitive load [4], using functional magnetic resonance imaging (fMRI). As part of ongoing collaboration with a team of neuroscientists and a clinical psychiatrist, we are employing electroencephalography (EEG) to directly inspect brain activity during visualization tasks.

Since EEG measures brain activity at high spatial and temporal resolutions, it provides a mechanism to monitor memory and cognition centers of the brain. Additionally, as cognitive activity is associated with specific frequency characteristics [12], we can use signal processing to help pinpoint the types of loads placed on the human cognitive system and its performance during visualization tasks. Some preliminary results suggest that different plot types with the same information content cause significantly different measurements in the brain activity of subjects being studied. In addition, these differences in the electric measurements are consistent with there being different cognitive loads. This first study was intended to determine whether EEG measurements are powerful enough to determine cognitive load for visualization tasks. We believe a similar study protocol can be used to investigate other visualization choices, hopefully leading to an experimentally-justified model of the cost of a visualization.

We note here that a model using only cognitive costs cannot possibly work either. For example, if we consider the question "does the distribution have median less than 50?", then the visualization with lowest cost will be the one which simply computes the appropriate answer and displays a large "YES" or "NO" on the screen. The problem here is that although such a visualization has low cognitive cost, it cannot have a large information content. Hence, we envision a model in which information-theoretical concerns are optimized together with cognitive costs.

3 Are any models possible, even in principle?

The shortcomings of purely quantitative measures of visualization quality become more evident when considering artistic elements in visualization. The minimalistic representations advocated by Edward Tufte [16] notoriously clash with the embellishments championed by designers such as Nigel Holmes [10]. In recent work, the arguments both for and against "chart junk" are put to the test by Bateman et al. [2]. This study examines the effects of stylized artistic decoration on the comprehension and cognitive recall of charts. While representations focused on maximizing "data ink" fit well into information-theoretical systems including entropy and capacity as discussed by Chen and Jänicke, Bateman et al.'s unintuitive result that "chart junk" sometimes appears to be helpful serves as a warning sign that modeling the effectiveness might require even higher-level information than the comprehension and cognition load we are studying.

Still, we believe the integration of even reasonably low-level cognitive concerns in a model of visualization effectiveness is the right place to start, and might serve as a valuable complement to the already-existing information-theoretical models of visualization.

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