User-driven Expectation Visualization: Opportunities for Personalized Feedback

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ABSTRACT

In this paper, we define and motivate Expectation Visualization, an interactive technique for soliciting, and presenting personalized feedback on, a user's expectation of the data. Expectation Visualization (EV) addresses the common challenge faced by designers of how to engage users with visualized data on a deeper level. We describe the design space of EV, including how it can be used for data encoded in marks and mark attributes, and describing forms of training and personalized feedback. We propose three specific applications where the benefits of EV may be particularly useful. We conclude with ideas for future research.

Keywords: Human-centered computing, Visualization, Information visualization.

1 INTRODUCTION

Traditionally interaction in visualization has been understood as user-driven manipulation of views of an existing data set: for example a user might select, sort, or filter a view [3]. Such interactions allow a user to generate views that are particularly relevant to him or her. As rich interactive visualizations become easier to author and more ubiquitous in media and other outlets, novel interactions, particularly those that make the data personally relevant to a user, are desired.

One form of "personalized" interaction that researchers have argued for is the manipulation by the user of internal (mental) representations as he or she makes sense of visualized data [10]. Relating an external visualization to one's internal representation, or mental model, can lead to better comprehension of gaps in one's knowledge [4][13]. For example mentally animating a set of small multiples showing a physics process, or comparing the small multiples to an internal representation, can lead to deeper understanding of the process [6].

Prompting users to engage in self-explanation, the process by which users explain its concept or example to themselves, may be useful as a means of guiding a user to compare internal representations to an external visualization [1]. As a form of prediction, self-explaining stimulates greater engagement with the topic. For example, it has been proposed that a system might prompt more active processing of data by asking a user to guess the direction of the trend prior to viewing the data [7].

In most examples studied in psychology [4][6][13], the benefits of self-explaining and internal visualizations come only after considerable cognitive work on the part of the user, who must mentally imagine the difference between their internal representation and the external visualization. In this work, we consider a new possibility: What if visualizations allowed people to draw their expectations of the data prior to viewing? Seeing the data along with the expectation provides a form of personalized feedback, as it renders this gap between expectation and fact explicit. The act of drawing maintains a user's engagement, while the visual representation of the expectation against the result allows more detailed observations than may be possible through mental visualization alone.

In this paper, we define Expectation Visualization (EV), an interactive technique for soliciting and presenting personalized feedback on a user's expectations of the data. Expectation Visualization (EV) addresses the common challenge faced by designers of how to engage users with visualized data on a deeper level. In the rest of the paper, we describe the design space of EV including how EV could be applied to common visualization tasks and visual encodings. We propose specific types of applications in which the cognitive benefits of EV could be useful. We conclude by offering ideas for future work.

2 EXPECTATION VISUALIZATION DESIGN SPACE

We use a recent New York Times interactive graphic to motivate the design space of EV. We define the design space according to tasks and visual encodings. We discuss forms of training and presentation of personalized feedback.

2.1 Predicting Marks

We begin our characterization of the design space for EV by considering a recent New York Times graphic of this technique (Fig. 1). The interface presents a XY plot without any data shown, however the axes are labeled as *Parent's income percentile* and *Percent of children who attend college*. The user is encouraged to draw their guess for each income level in the chart (Fig. 1a). In the accompanying text, definitions of various visual trends are provided to help users to relate the graphical representation to their expectations (e.g.,  or ). After the user is done drawing the line, the true trend is presented as an overlay on the chart showing the user's expectation (Fig. 1c). Statistics describing how the user's guess compares to those of other users are presented in text below the chart.

In this example, the user's mental model is represented by a trend line. Two continuous variables are being considered, so a simple labeled XY plot is sufficient for the drawing interface. However other visual encodings and data types require different drawing interactions and interfaces. We envision how EV can be applied to other tasks and encodings in Table 1.

2.2 Extension to Mark Attributes

Visualizations are composed of marks (e.g., a bar in a bar chart, a circle in a scatterplot) and mark attributes (e.g., size, shape, color). While the above example provides interactive support for visualizing one's expectations by adding marks, it may also be possible to support interactive prediction of a variable, which will be encoded as a mark attribute. For example in a choropleth map, a user brush on color to predict the trend in a region for a continuous variable. In these examples, marks are presented and the user interacts to add value expectations (Table 2).

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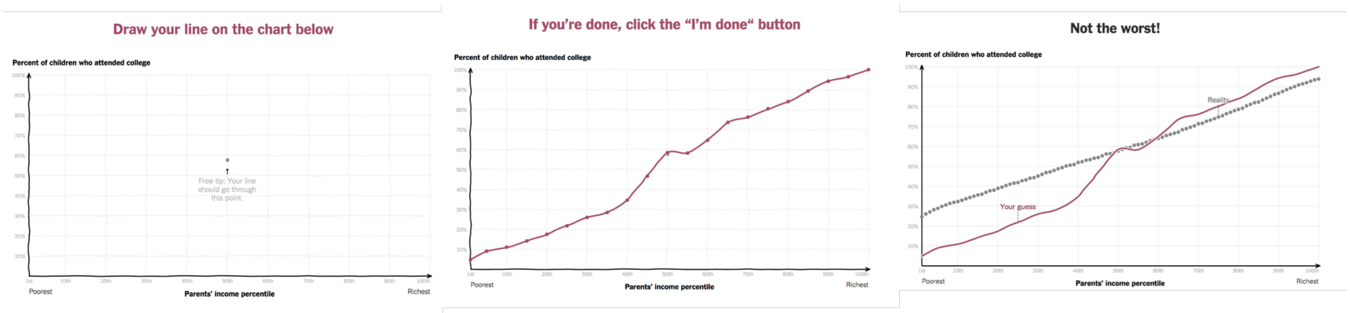

(a) (b) (c)

Fig. 1. A screenshot of 'You Draw It: How Family Income Predicts Children's College Changes'[1].

Table 1. Possible tasks and visual encodings for predicting marks.

Task	Drawing task	Encoding
Comparison between means	Draw bars, dots	Bar chart or dot plot
Uncertainty	Draw confidence interval, coverage interval	Bar chart or dot plot with error bar
Analyze a distribution	Draw probability density function, draw quartiles, annotate expected outliers	Histogram, violin plot
Identify clusters	Draw contour, drag and drop element to the cluster	Scatter plot, dendrogram, Node-line diagram
Judge correlation/fit	Draw line of best fit	Scatterplot
Analyze connectivity	Draw edges	Node-line diagram

Table 2. Possible tasks and visual encodings for predicting mark attributes.

Task	Drawing task	Encoding
Predicting values of variables	Brush on color, drag symbols to size	Map (choropleth graduated symbols), 3D+ scatter plot
Predicting categorical membership	Brush on color, draw shape	Bar chart, scatter plot

2.3 Training

We anticipate that EV could be especially useful for non-expert analysts, such as news readers and students. However, it might be necessary to train such users by providing a "drawing vocabulary'' that relates the expectation to the visual encodings. This vocabulary consists of sample marks and marks attribute along with definitions of what the example element represents.

For example, for the visualization presented in Figure 1, sample trend lines were given in the text (e.g. means the chances are the same for everyone). Another way to support novice users is by providing annotations directly on a plot structure to describe how to interpret the graph schema (e.g., indicating what data relationships different regions of an XY plot represent).

2.4 Forms of Personalized Feedback

Presenting the real data against the expectation in the same view, such as through an overlay, directly shows the user gaps between the facts and their expectation. However, personalized feedback on the user's expectation can also be presented in the form of a comparison to previous users. For example, an overlay on the user's drawing might instead depict aggregated estimates from other users. Personalized annotations can be added directly on marks that the user predicted which vary significantly from the true data or from those derived from aggregated user data. The discrepancy between the expectation and the true data can also be quantified and presented with a description of how much the user should adjust their internalized model to accurately perceive reality.

3 Potential Benefits of Applications

We expect EV to facilitate deeper understanding of graphical format. Based on the more active processing of the data that prediction can stimulate, we also expect EV could increase engagement and memorability of data and concepts. Furthermore, by visualizing the discrepancy of a user's expectation and providing personalized messages, EV could be used to motivate users to change their behaviour in certain ways.

3.1 Deepening understanding of data and graphical schema

The canonical self-explanation approach induces active processing that stimulates deeper understanding of a concept by showing a user a representation and then prompting the user to explain it to herself [1]. In our adaption of self-explanation in EV, the user makes her prediction before seeing the visualization.

We expect that predicting before seeing the visualization will cause novice users to devote more attention to the data and graphical schema. This may result in better understanding of the semantics of reference structures of a graph (e.g., the axes, legend, etc.). It could be useful for understanding units, time span or other domain specific aspects of a dataset.

Other aspects of the data schema including the nature of the variables, or the difference between observed data and a model derived from the data, may also be better understood depending based on how the drawing interaction is realized. For example, drawing a line to visualize their expectation of a trend may help the user to perceive the variable as continuous if the line drawing interaction is smooth, and to understand that their drawing represents a model instead of a set of data observations. If the system requires the user to draw a line as a discrete set of points, this might help the user understand that the true data is a set of measurements, not a model.

[1] http://www.nytimes.com/interactive/2015/05/28/upshot/you-draw-it-how-family-income-affects-childrens-college-chances.html

3.2 Engagement and Memorability

We expect EV to have benefits for increasing a user's engagement with the data and increasing the memorability of the data. The act of drawing is still relatively novel compared to typical point-and-select interactions, and therefore likely to engage users' interest. This "more natural" form of interaction may be particularly attractive to novice users who are new to data analysis.

Active processing, particularly via self-testing exercises [2], can improve memory for information [7]. By presenting personalized feedback, EV makes the information more relevant to the user, which is also likely to benefit memory [8].

3.3 Behavioral change

Personalized messaging is an effective way of motivating one to make a desired behavioral change [9][12]. Imagine a chart in a news article describing how temperatures in the world have risen over the last century. The chart is intended to deliver information, but also to urge readers to change their behaviors that affect global warming. By using EV, the feedback presented after the user draws their expectation provides individualized messaging that directly measures their awareness of the problem. We expect that seeing the gap between reality and their expectation will make a user more likely to change their behaviour than if they had only seen the data.

4 Future Work

There are multiple important next steps for research and application of EV. An important next step is to further specify how EV interactions should differ for different types of visualizations and data. This may also include identifying automated techniques that can be used to more easily compare users' drawings to a data schema. For example, if the variable the user is predicting is encoded in mark shape, a computer vision algorithm may be needed to classify the shape the user draws.

One important next step is to provide experimental evidence of EV's benefit for visualization comprehension. A number of questions arise regarding how particular applications of EV will influence a user's comprehension. For example:

- How should the true data be presented against the expectation?
- How often should dynamic feedback be presented?
- What forms of training are necessary for allowing novice users to use EV applied to different visualizations?
- How useful is personalized feedback compared to the true data vs. compared to other users' expectations?
- To what extent do the benefits of EV stem from the act of drawing vs. the act of prediction?

We are beginning to develop an interactive prototype for applying EV to different chart types in order to answer these questions and others.

5 Conclusion

We define and motivate Expectation Visualization, an interactive technique for soliciting and presenting personalized feedback on a user's expectation of a data set. We describe the design space of EV including application to mark and mark attributes and describing forms of training and feedback. We propose three specific applications where the benefits of EV may be particularly useful. We conclude with a roadmap for future research of EV.

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