Decision Making Under Uncertainty in Visualisation?

Geoffrey Ellis and Alan Dix

Abstract— Decision making under uncertainty can lead to irrational behaviour; such errors are often being referred to as cognitive biases. Related work in this area has tended to focus on the human's analytic and sensemaking processes. This paper puts forward a novel perspective on this, proposing that some cognitive biases can also occur in the process of viewing visualisations. Consequently, this source of error may have a negative impact on decision making. This paper presents examples of situations where cognitive biases in visualisation can occur and outlines a future user study to investigate the anchoring and adjustment cognitive biases in visualisation.

Index Terms—Cognitive bias, visualisation, decision making, uncertainty

INTRODUCTION

Over the years, there has been considerable effort in using visualisation to help users make better decisions, especially where there is uncertainty. In addition there is a wealth of studies which demonstrate that in certain circumstances, decision making under uncertainty can result in cognitive biases and irrational decisions [1]. However, there does not appear to be any effort on investigating whether or not visualisation itself, in the context of decision making under uncertainty, stimulates cognitive biases in the viewer.

This paper first reviews articles which mention visualisation and cognitive biases. The question of visualisation and cognitive biases is then discussed, providing examples of how particular cognitive biases could relate to the visualisation rather than the analytical or sensemaking process. Finally in Section 3, a study is proposed which investigates the anchoring and adjustment cognitive biases in visualisation.

1 BACKGROUND

The literature survey that was conducted revealed that apart from articles which use the term visualisation in the context of building mental models (many of which seem to also refer to clinical depression and anxiety disorders), the majority at least touch upon the reduction of cognitive biases through visualisation strategies (e.g. [2]). Confirmation bias is by far the most common bias mentioned. This is often discussed together with the driving force of user overconfidence or familiarity, and always in the context of sensemaking and/or reasoning. Several studies compare visual and non-visual presentation of data in an information seeking environment and again bring in confirmation bias, e.g. Phillips [3], however, issues relating to the visualisations are not discussed. Interestingly, despite many suggestions to the contrary, there is little evidence that visualisation-based debiasing strategies are particularly effective.

The closest related work can be found in visual processing of graphs and images. Gestalt principles of perceptual organisation determine how graphic items are grouped together as larger apparent objects, and has a marked effect on graph comprehension [4]. This process is similar to the heuristic basis of cognitive biases, in that it occurs unconsciously. Fendley [5] actually discusses cognitive biases in detail in relation to the comprehension of images and creates a decision support system to mitigate a selection of biases. It has also been demonstrated that different visual representation of common abstract forms can have a marked effect on their interpretation and the appearance of the visualisation itself can affect the interpretation of the data (e.g. visualisation style [6]). However, the latter and other work on graph comprehension is principally concerned with low level perceptual processing, which is not the principal focus of this paper.

2 COGNITIVE BIASES IN VISUALISATION

Before looking at some examples of cognitive biases in visualisation, we need to reflect upon uncertainty in understanding the graph.

2.1 Uncertainty in graph comprehension

This does not involve the higher-level analytics or sensemaking activity. In the latter, the user may be searching for information to confirm or disconfirm their current belief or to generate a new idea. The user is probably not aware of uncertainty anyway, as subconsciously we tend to avoid uncertainty and the accompanying feeling of unease or dissonance.

Simple examples of uncertainty in graphs would be a scatterplot where a trend is not obvious at first sight or where the user has to compare the heights of bars in different bar charts. Trickett and Trafton [7] suggest that the user has to resort to spatial processing when information cannot be gained through perceptual processing (e.g. direct comparison of heights is not possible). Spatial processing involves working memory and hence there is more chance of cognitive bias occurring. The next section illustrates how particular cognitive biases may arise when viewing visualisations.

2.2 Examples of cognitive biases

Let us consider some examples where users of visualisations are subject to different cognitive biases which result in less than optimal decisions.

Clustering illusion : The user sees a pattern in the plotted data (e.g. on a scatterplot) when the data is in fact a random distribution. Two things are occurring here, i) the user is unaware that a random sample does not generate an even distribution of points on a simple scatterplot or in coin tossing, a fairly balanced sequence of heads and tails; and ii) humans are predisposed to finding patterns, even very insignificant ones such as three points in a row amongst hundreds of scattered points. This cognitive bias is one that has already been identified, and is in fact a visualisation bias rather than analytic. The user is typically unaware of the data values, but is more aware of the position of graphic points on the display.

Completeness : The visualisation looks neat and tidy, with well-defined clusters or points that fall on a distinct trend line, and the user believes that this is *the* answer. This may result in the user accepting the result, without looking too hard at the actual values, and/or failing to explore the data further.

Anchoring and adjustment : When uncertain, the user latches on to a value or narrative which is readily available in their memory, even if this is, in hindsight, irrational (an example is given in Section 3). In addition, users are often conservative in that they tend not to move

- *Geoffrey Ellis is with the Data Analysis and Visualisation Group, University of Konstanz. E-mail: ellis@dbvis.inf.uni-konstanz.de.*
- *Alan Dix is with Talis, Birmingham, UK and the University of Birmingham, UK. E-mail: alan@hcibook.com*

Manuscript received 31 Aug. 2015; accepted 01 Aug. 2015. Date of Publication xx Aug. 2015; date of current version 25 Oct. 2015. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org.

too far from an initial starting point. This reluctance to change, for example an interactive control in a visualisation, may inhibit exploration of the data.

Framing : An example of framing is given in Section 4.

Mode : An error occurs when the user unconsciously gives greater weight than necessary to a particular visualisation or artefact within a visualisation, due to its greater perceived authority. For example, just presenting a simple chart rather than a table of numbers, may be enough to trigger this reaction in some people, even though the content is inconsequential. Fitting a trend line to a graph may also be given undue importance, because it has been generated automatically by the system.

Redundancy : Due to the fact that the visualisation can process and display a vast amount of data, the user perceives the result as being more accurate or correct than it actually is [8].

Sample : The user filters the dataset until only a small number, say 5, of the points are on display. These all lie on a straight line in the scatterplot. The user announces that there is an excellent correlation between the axis variables for the whole dataset. Unfortunately, the smaller the data sample the less representative it becomes of the whole, but the display gives the impression that it is a better fit and mistakenly more representative.

Availability : The user assembles a set of documents on the screen and proceeds to go about an analysis. People tend to use what is readily available (in this situation, what is on display) and so our users fails to search for further documents. The size of the display may also be a factor here in governing the number of documents that can usefully be displayed.

3 Outline of a User Study

Null hypothesis 1: the angle of lines in the 'anchoring pattern' does not affect the angle of the fitted line.

To investigate whether or not a user is susceptible to visualisation cognitive biases we need uncertainty and a user task that could be influenced by cognitive bias. People seem to be very susceptible to anchoring and there are many reasoning studies illustrating this cognitive bias. In one experiment [9] participants wrote down the last two digits of their social security number, and then bid for a bottle of wine in an auction. Consistently, those with higher social security numbers bid more for the wine.

In the proposed visualisation study, the 'anchor' value will be replaced with an 'anchor patterns', consisting of lines at different slopes (Figure 1a, 1b). These will be shown to the participants for a short time before moving to the task, which, instead of pricing the wine, is to fit a line to a random set of points in a scatterplot (Figure 1c). The randomness and spread of the points will provide the uncertainty. The participant will then drag out a line and then adjust the end points to give a good fit to the data (Figure 1d). Getting the user to set the initial line will avoid influencing them with a line at a particular angle.

In another study focusing on the adjustment bias, an initial trend line will be shown to the user (as in Figure 1d), set at different slopes, so not fitting the data points exactly. The investigation will determine if the initial slope influences the final position set by the participants. This could be repeated with and without the 'anchoring pattern'.

In addition to determining the exact format of the 'anchoring pattern', a pre-study will need to investigate, amongst other things, the amount of time to show the pattern, the spread and number of the scatterplot dots, and what, if anything, to tell the participant about the appearance of anchor pattern. There will of course be a control group who do not see any 'anchoring patterns'. Other variables need to be taken into account, such as the experience of the participant with scatterplots and their skill in fitting lines to a set of points. These should not be taken for granted, as Ali and Peebles discovered – many undergraduate students struggle to interpret line graphs even at an elementary level [10].

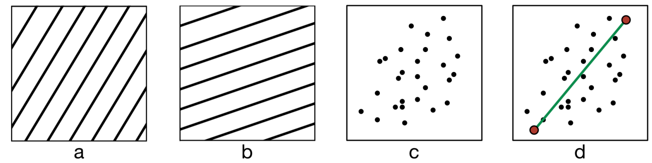

Figure 1. Illustration of proposed anchoring study. a & b are 'anchoring patterns', c is a target scatterplot and d is a plot with a trend line fitted by the participant.

4 Discussion and Conclusion

This paper proposes that the visual display of data may give rise to cognitive biases in the viewer, resulting in errors of judgement, irrespective of the higher level cognitive bias which may occur when they are in analytic or reasoning mode, focusing on the data content. For example, interpretation of the data can be affected by the type of visualisation, especially if the user is unfamiliar with the particular view i.e. does not have the graph schema (mental representation) to interpret it [4]. This can result in a framing error if the user unconsciously appropriates a graph schema for another graph type, which unwittingly does not fit. An example of this would be assuming that the slope of lines in a parallel coordinate plot represents and increase or decrease in a value.

Mitigation strategies for the set of visualisation biases have not been discussed, due to the available space, but this is clearly an area for debate and further investigation.

Although the workshop's focus is on visualization *for* decision making under uncertainty, identifying a possible source of error, which arises from using visualization under uncertainty is a valid contribution to the effort of improving decision making.

Acknowledgments

This work was supported by the EU project Visual Analytics for Sense-making in Criminal Intelligence Analysis (VALCRI) under grant number FP7-SEC-2013-608142.

References

[1] D. Kahneman, Thinking, fast and slow. Macmillan, 2011.
[2] T. Zuk and S. Carpendale, "Visualization of uncertainty and reasoning," in Smart Graphics, pp. 164–177, 2007.
[3] B. Phillips, V. R. Prybutok, and D. A. Peak, "Decision Confidence, Information Usefulness, and Information Seeking Intention in the Presence of Disconfirming Information," Informing Science: the International Journal of an Emerging Transdiscipline, vol. 17, 2014.
[4] S. Pinker, "A theory of graph comprehension," Artificial intelligence and the future of testing, pp. 73–126, 1990.
[5] M. E. Fendley, "Human cognitive biases and heuristics in image analysis," Wright State University, 2009.
[6] J. D. Daron, S. Lorenz, P. Wolski, R. C. Blamey, and C. Jack, "Interpreting climate data visualisations to inform adaptation decisions," Climate Risk Management, 2015.
[7] S. B. Trickett and J. G. Trafton, "Toward a comprehensive model of graph comprehension: Making the case for spatial cognition," in Diagrammatic representation and inference, Springer, pp. 286–300, 2006
[8] T. Lukoianova, F. Hall, N. Ave, and V. L. Rubin, "Veracity Roadmap : Is Big Data Objective, Truthful and Credible ?," vol. 24, pp. 4–15, 2014.
[9] D. Ariely and M. I. Norton, "How actions create--not just reveal--preferences," Trends in cog. sciences, vol. 12, no. 1, pp. 13–16, 2008.
[10] N. Ali and D. Peebles, "The effect of gestalt laws of perceptual organization on the comprehension of three-variable bar and line graphs," Human Factors: The Journal of the Human Factors and Ergonomics Society, vol. 55, no. 1, pp. 183–203, 2013.