Cognitive Biases in Visual Analytics – A Critical Reflection

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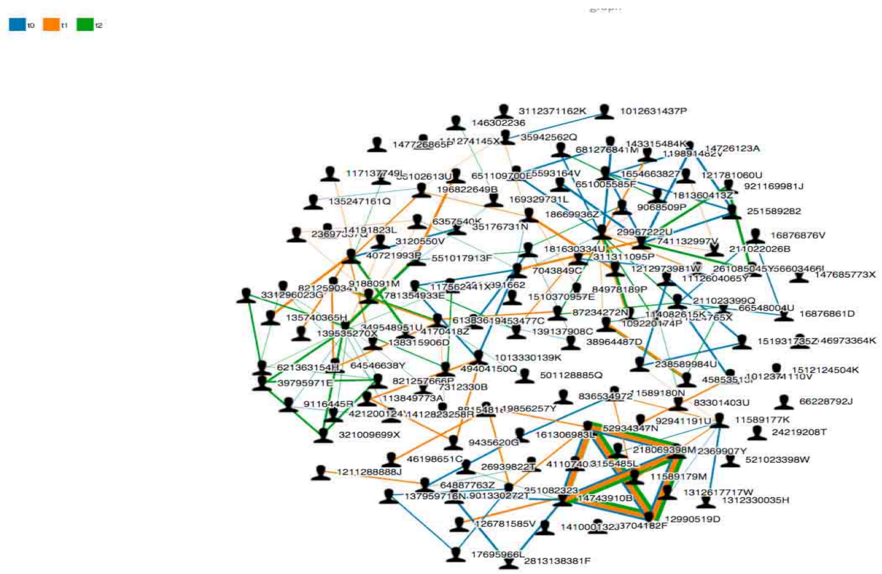

Figure 1: Node-link diagram of offenders who commit crimes together. The three colors denote three different years. When co-offenders are linked by more than one line, this indicates that they cooperated more than one year. The thickness of the line indicates the weight, that is, the seriousness of the crime according to the priorities of police forces.

Abstract

Cognitive bias research is an interesting and challenging area of research. Nevertheless, it is not entirely clear to what extent it is applicable in visual analytics. Visual analytics systems support reasoning processes in ill-structured domains with large amounts of data. It is difficult to apply cognitive bias research from laboratory studies based on a minimal amount of information to this area. In this paper, an alternative approach for bias mitigation is suggested: provide context and activate background knowledge. Advantages and limitations of this approach are discussed.

Keywords: everyday reasoning, dual process theory, expertise, bias mitigation.

Index Terms: • Human-centered computing~Visualization • Human-centered computing~Visualization design and evaluation methods

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1 Introduction

There is ample evidence that humans tend to commit cognitive biases under some circumstances [8]. Humans also have difficulties with logical thinking and reasoning [7]. Nevertheless, this kind of research has also been criticized [13].

It has been argued that the experiments that substantiate this research do not reflect realistic problem-solving processes. They often use puzzle problems or highlight abstract logical problems that are fairly artificial. These approaches specifically exclude context and background knowledge.

Visual analytics in general supports exploratory processes in ill-structured domains (e.g., in medicine, intelligence analysis, financial domain). In ill-structured domains, there are neither clear-cut solution methods nor easily identifiable solutions. In addition, visual analytics works with very large amounts of data, much of which is unnecessary and distracting. It is an open question to what extent research on cognitive biases is applicable in this domain. This paper reviews research from cognitive psychology and tries to clarify some of the open issues using an example from intelligence analysis.

2 Puzzle Problem Approach Vs. Everyday Thinking and Reasoning

Kahneman [8] is one of the most well-known representatives of a dual process theory of thinking and reasoning. He argues that there is system 1 that is fast but tends to be error-prone and system

2 that relies on logical thinking and therefore leads to more correct results. System 1 decisions tend to be influenced by cognitive biases because they rely on gut feeling more than on logical reasoning. This view has been criticized by some authors.

Evans [4], for example, argues that the concept of cognitive biases is based on a conception distinguishing between rational and irrational decision making. This conception presupposes some normative framework which enables researchers to differentiate between decision making processes conforming to the norm and others that do not. In general, formal logic or probability theory are defined as the normative standard and behavior deviating from this is seen as irrational. Evans, however, points out that human reasoning is, by design, pragmatic rather than logical. Therefore, an assessment of reasoning and decision making processes based exclusively on the norm of logical thinking might distract from the actual mechanisms governing these processes.

This discussion is especially relevant for visual analytics because thinking reasoning in this context are rather seen as exploratory and sensemaking processes than as drawing logical conclusions. Visualizations support looking at data from different points of view and formulation of competing hypotheses. A concept of thinking and reasoning based on some normative framework might be too restrictive to model these processes in the context of visual analytics.

Norman [11] argues that for the process of medical diagnosis there is evidence that the main source of error is lack of knowledge, not cognitive bias. This is overlooked in a discussion focussing on cognitive biases. In addition, he points out that extensive literature on the distinction between experts and novices shows that the true expert relies more on intuitive reasoning of the system 1 type, while novices apply deliberative rule-based methods.

Fiedler and von Sydow [6] provide an overview of research concerning cognitive biases based on Kahneman's basic assumptions. Based on this overview they argue that this type of research is too vague to serve as an underlying theory to explain how cognitive biases develop. It is not clarified which cognitive processes are executed when such biases occur. Many of the assumptions underlying the research in cognitive biases are not experimentally manipulated to test them systematically (e.g., the availability of information in the availability heuristics). Nevertheless, Fiedler and Sydow [6] point out that, despite its weaknesses, the resarch on cognitive biases has given rise to an extensive research program into thinking and reasoning processes that has clarified interesting issues.

Woll [13] provides an overview of the discussions about cognitive biases. He argues that there are methodological issues with the approach of Kahneman. Several researchers pointed out that the experiments conducted by Kahneman are fairly artificial and designed in a way to generate cognitive biases. Study participants have to make decisions based on scant information without any context. In contrast to that, decisions in everyday situations usually are based on redundant information. People often possess a considerable amount of background knowledge and decision making is a long-term process with several feedback loops. Woll doubts that the results from laboratory research on cognitive biases is applicable to such situations. In everyday thinking and reasoning people generally do not apply formal decision making processes, but rather adapt their strategies to the problem at hand and use these strategies very flexibly. Context and background knowledge play an important role.

I want to illustrate this line of argument using a well-known example from cognitive psychology – Wason's selection task. This task is one of the researched tasks in cognitive psychology (for an overview see Eysenck & Keane [5]). In this task, study participants see four cards, two of which show letters and two numbers. These cards also have numbers or letters on the other side of the card that is not visible. Participants then get a rule: If there is a vowel on one side of a card, then there is an even number on the other side of the card. The tasks the participants have to solve is which cards they have to turn around to find whether this rule applies or not. In this abstract form, this task is fairly difficult. It can be shown, however, that this task gets much easier when it is embedded in a concrete context (e.g. if a letter is sealed it has a 5d stamp on it instead of the rule concerning vowels and even numbers). There has been much controversial discussion about this phenomenon, and it is not entirely clear how the influence of context information can be explained, but in general this seems to be a fairly stable result. The model of pragmatic reasoning schemata has been proposed to explain this phenomenon [5]. This model assumes that there are rules that apply to certain classes of situations. In this context, knowledge about the world is essential.

3 Bias Mitigation Strategies

Several different cognitive bias mitigation strategies have been discussed in the literature. Nussbaumer et al. [12] especially discuss the following bias mitigation strategies: providing different views of the data to change the perspective; providing information about the uncertainty of the data; computerized critique questions; explicit prompts to rethink one's own hypotheses; discussion of hypotheses with peers; visualization of multiple hypotheses. Kretz et al. [9][10] especially study cognitive bias mitigation strategies in the context of intelligence analysis. They point out that there is still a lack of systematic empirical studies about the efficiency of bias mitigation strategies, especially in realistic contexts. They tested several different bias mitigation strategies and found that some of them are more efficient than others. In addition, it depends on the context which of the bias mitigation strategies are more efficient than others.

Bias mitigation strategies can have beneficial effects on the quality of decision making. In an evaluation of a system for intelligence analysts we could show that providing two different visualizations of one and the same data set motivated some users to adopt a verification strategy to make sure that their results were also supported by the second visualization or not [3]. However, many of these strategies require the users to spend additional time and effort. Given the time constraints under which, for example, intelligence analysts operate they will be reluctant to adopt such strategies.

Intelligence analysts have a considerable amount of background knowledge. They are able to use context to arrive at valid results. Based on the discussion about the importance of context and background knowledge it might be argued that this might help analysts to avoid cognitive biases. As described above, there is some evidence indicating that cognitive biases especially occur in laboratory situations where study participants are only provided with a minimal amount of information. As a consequence, it might be argued that by providing context and activating background knowledge cognitive biases can be avoided.

I want to illustrate this argument with an example from our work with intelligence analysts. Intelligence analysts often work with network visualizations of co-offenders, that is offenders who commit crimes together (Fig. 1). This system is described in more detail in Doppler-Haider et al. [3]. Figure 1 just shows a node-link diagram consisting of icons for the offenders and links to indicate that these offenders committed a crime together. In addition, there is some information about the temporal development of this cooperation and the seriousness of the crimes (which is indicated by the weight) that were committed. The goal of this visualization is to support intelligence analysts in the investigation of cooffender networks, for example, whether the criminal activities of a specific network increases or not or whether the types of crimes committed by such a network changes over time. Nevertheless, for a real task of an intelligence analyst the information shown here is still too little. Analysts need detailed information about the specific crimes that were committed to be able to assess their development and the specific contacts that the co-offenders have [1]. Such systems should, for example, provide specific information about the offenders and the crimes they committed. This information should be easily accessible from the node-link diagram shown in Fig. 1. On the other hand, experienced analysts already possess a lot of background information about the criminal activity in their area. This kind of information should also be activated. The information system should be designed in a way that analysts can easily combine their own background knowledge with the new knowledge provided by the system.

From informal observation of analysts we know that they need to interact a lot with the data to get a comprehensive overview and a feel for the data. Nevertheless, in practice it is not straightforward to decide which kind of data to provide to analysts, when to provide these data and how to activate their background knowledge.

Dimara et al. [2] conducted an experiment to find out whether adding context can increase the accuracy of task solutions when participants work with visualizations. They found that this is not the case. They found, however, that it does increase confidence and the user experience. This is a result that indicates that adding context is not a straightforward strategy. I would like to point out, however, that this experiment used crowdsourcing and fairly brief narratives to provide context. From the point of view of everyday thinking and reasoning it might be argued that this is still a fairly artificial situation. Nevertheless, the study indicates that providing context has to be designed with care to be successful.

4 Conclusion

Research on cognitive biases is a very interesting and challenging area of research. It is obvious that cognitive biases occur under certain circumstances. Nevertheless, it is not entirely clear how relevant this research is for visual analytics. Visual analytics operates in ill-structured domains. Therefore, it is often difficult to apply highly formal methods of reasoning (as, e.g., formal logic). Cognitive bias research usually is based on such formal methods as a normative foundation. This is one reason why it might be difficult to apply the results from this research in visual analytics. Another problem might arise from the fact that visual analytics per definition deals with large amounts of data. Most bias mitigation strategies suggest that users should look at additional data or check additional hypotheses. In contrast to that, users of visual analytics systems rather want to get rid of most of these data to be able to concentrate on the really relevant facts. Practitioners in such areas also operate under time constraints. This also makes it difficult to motivate them to consider large amounts of data or too many alternative hypotheses. In addition, bias mitigation research does not consider the importance of background knowledge or expertise which is essential for decision making in domains like medicine or intelligence analysis. All this makes it difficult to apply cognitive bias research in visual analytics.

In this paper, an alternative method of bias mitigation is suggested: provide context and activate background knowledge. I want to point out, however, that this method is not entirely straightforward. There is research suggesting that providing context does not always help. It is not entirely clear how best to provide context and activate background knowledge. More research in that area is necessary.

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