Mining Cognitive Bias through Interactive Visual Analytics

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ABSTRACT

Cognitive biases is one of the human limitations in interactive visual analysis [2]. Specific cognitive biases in data analysis fields have been categorized in previous research [3]. As a result of these biases, partial or uniformed decision making processes might occur during the interactive visual analysis process. One solution to decrease these partial or uninformed decision making processes in visual analytics is developing metrics for detecting and quantifying cognitive biases using data mining techniques.

Without these computational strategies with which cognitive biases could be measured during interactive visual analytics in real time, the tendency of relying on evidence to support the preexisting beliefs could lead to partial decision making. These metrics are necessary to develop mitigation strategies of cognitive biases, which could lead to more reflective decision-making processes. In this survey, the computational strategies of characterizing cognitive bias and corresponding implemented data mining techniques in interactive visual analytics will be summarized.

KEYWORDS

cognitive bias; visual analytics; data mining

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1 INTRODUCTION

Visual analytic is the collection of techniques that analyzes datasets using their visual representations such as charts, graphs, or maps, which could help users with identifying patterns and more informed decision-making processes; however, in interactive data analytics the interactions of users also play could further impact users' decision making processes as a powerful role, which could be affected by the wide-recognized phenomenon: cognitive bias.

Identified cognitive biases which could impact the outcome of visual data analysis have been categorized.[3]. These biases could further influence the evidence analysts rely on and the outcomes of their decision making processes. Further, when analytic models in information visualization system are implemented with interactions of analysts, the impacts of cognitive bias might be amplified by the underlying learning models, which could further impact the decision making processes of future users.[8]. Even though cognitive biases arise from human intuitive decision making processes and can not be completely eliminated, they can still be detected and mitigated using deliberate reasoning processes such as quantifying metrics.[5] In this survey, we will summarize and categorize detection and quantification metrics of cognitive bias in interactive visual analytics.

2 PROBLEM FORMULATION

In this survey, the main problem is detecting and quantifying cognitive bias given the interaction data log from users. One general demonstration could be: Given detection mechanism m, interaction data D, the general quantifying method could be formulated as:

$$bias = m(D) \tag{1}$$

Cognitive bias detection could be simply formulated as a threshold problem:

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if m(D) > threshold:
    current interaction is biased
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The main challenges of detecting and quantifying cognitive bias in visual analytics are (1)the definition of cognitive bias in different visual analytics scenarios, (2)the preprocess of the user interaction data which could make the bias measurable and (3)the selection of specific techniques to quantify the cognitive bias. For example, re-designing mathematical computational methods or introducing concepts from machine learning fields, below is an existing metric example of quantifying the cognitive bias called vividness criterion[3] which utilized Markov chain to re-organize interaction data from users.

- **Data Point Coverage**
  The Data Point Coverage metric was developed to determine if data points are partial explored compared with an unbiased baseline model in interactive data analytics[8].

$$\widehat{K}(D_u) = \frac{N^k - (N-1)^k}{N^{k-1}} \tag{2}$$

$$b_{DPc} = 1 - min(\frac{K(D_U)}{\widehat{K}(D_U)}, 1) \tag{3}$$

  In this metric, the input D_U represent the set of data points interacted by user U. $K(D_U)$ represents the size of the data points interacted by user U. k represents the number of interaction iterations. The data point coverage metric outcome calculated from Eq.2 would determine how biased are the

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users when they focus too much or ignore certain sets of data points.

3 EXISTING WORKS

3.1 Anchoring Bias

- **Anchoring Bias in Visual Analytics**
  Anchoring bias is the tendency that people heavily rely on initial information to make the decision. For example, a mug with a price of $100 seems to be expensive; however, people's minds might be changed if the mug was labeled with original price of $800. Wall et al. proposed an example of anchoring bias in visual analytics: environment[7]. In the designated task, participants were asked to categorize anonymized basketball players into five positions using the visual analytics tool called InterAxis (Figure 1). Descriptions of five positions in basketball team will be differently elaborated using different attributes, which will be randomly assigned to participants. One description is provided based on role attributes such as statistic from players(number of rebounds, number of free throws), the other one was provided based on attributes regarding size such as height and weight. If participants heavily rely on corresponding attributes to categorize the players, anchoring bias might occur in their interactions.

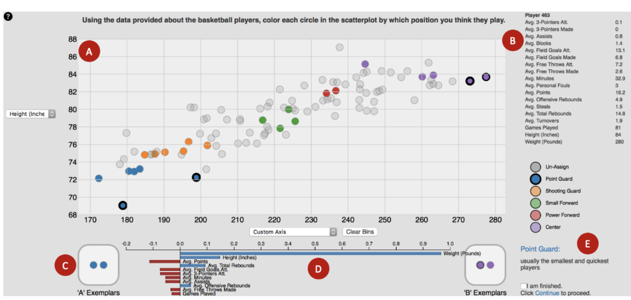

Figure 1: The Interface of InterAxis

- **Anchoring Bias Measurement in Visual Analytics**
  The Attribute Coverage(AC) metric from Wall et al. [8] was implemented to measure the attention distributed to each data attribute as anchoring bias.

$$\widehat{K}(D_u, Q_{am}) = \frac{Q_{am}^k - (Q_{am} - 1)^k}{Q_{am}^{k-1}} \tag{4}$$

$$b_{AC} = 1 - min(\frac{K(D_U, Q_{am})}{\widehat{K}(D_U, Q_{am})}, 1) \tag{5}$$

Similar to the data coverage metric in formula 3, Q_{am} donates the set of Q categorical or quantiles from attribute *am*. $\widehat{K}(D_u, Q_{am})$ donates the expected number of unique values for attribute *am*. The bias will be quantified within the range of [0,1]. We could reason from formula 5 that the b_{AC} would be greater if user only interact with data point within partial range.

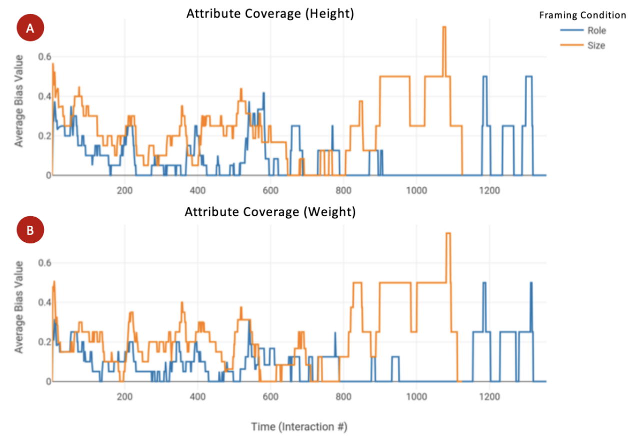

Figure 2: Attribute Coverage metric for the attributes Height and Weight overtime

Figure 2 supports the hypothesis that AC metric could detect and quantify anchoring bias in the user study with visual analytics environment. It could be observed that both height and weight attributes are partially considered to categorize players with description regarding size information compared with the experiment with description regarding role information.

- **Discussion**
  In this research project, the authors implemented a real-time metric to capture anchoring bias in a formative user study. The results showed that the interaction data from participants could reflect the exists of anchoring bias through the Attribute Coverage metric, which also encourages the development potential computational strategy for characterizing other cognitive bias and the proper bias intervention during users' interactions. One limitation of this study could be the lack of consideration regarding visual saliency[7], which means that emerging data clusters in the interface when user visualize different attributes could also draw participants' attention like anchoring bias. This limitation could encourage the improvement of unbiased behavior models in all cognitive bias detection user studies by adding the impacts of "biased" behaviors which is not from cognitive bias.

3.2 Weighted Average Illusion

- **Weighted Average Illusion in Visual Analytics**
  Weighted average illusion is a cognitive bias in visual analytics proposed by Hong et al. in 2021[4], under which the reader of a scatterplot could be make biased mean value estimation due to the impacts of size and opacity of each data point.(Figure 3)
- **Weighted Average Illusion Quantification in User Study with Visual Analytics**
  The authors conducted the user study where participants will estimate the mean value of a given scatterplot(the data point with means of x and y as coordinate). The experiment was separated into 2 groups, one studying the impacts of size,

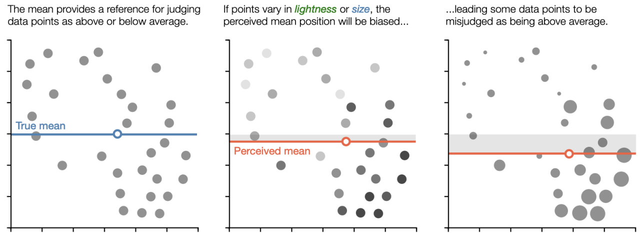

Figure 3: Weighted Average Illusion Example

the other studying the impacts of opacity, each with 3(encoding ranges) x 3(correlations) different conditions.(Figure 4)

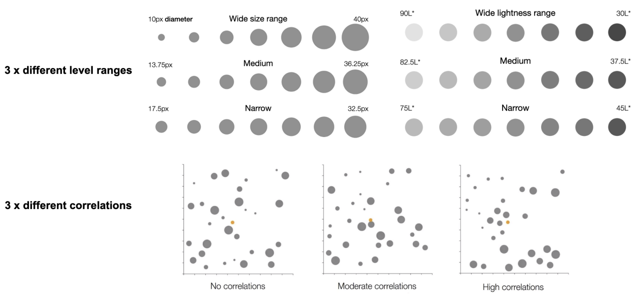

Figure 4: Experiment Design

The authors quantified the bias as the projection of error vector against the corresponding correlation direction of each scatterplot.

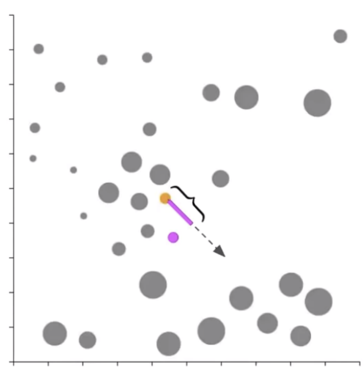

Figure 5: Weighted Average Illusion Quantification

In Figure 5, weighted average illusion was quantified as the length of the purple segment. As the results of the study, the authors concluded that (1)perceived mean of a scatterplot is biased towards larger or darker points, (2)bias always increased as correlations between position and the third data dimension increased and (3)widening size ranges also affected bias as correlations increased.

- **The Prediction of Weighted Average Illusion**
  Besides quantifying metrics for weighted average illusion, the author also proposed the method to predict users' mean estimates using linear regression:

$$R_x(j) = \sum_{k=1}^{N_{types}+2} W_k X_K(j) + Q_x(j) \tag{6}$$

$$R_y(j) = \sum_{k=1}^{N_{types}+2} W_k Y_K(j) + Q_y(j) \tag{7}$$

  In this formula, the data point (R_x,R_y) is the mean estimate, N_{types} donates different node types given size, lightness, $Q_x(j)$ and $Q_y(j)$ donate independent and normally distributed random bias and W_k represents the weight learned from user's mean estimates in the study.
- **Discussion**
  In this project, the new cognitive bias concept: weighted average illusion was proposed, along with the corresponding quantification and prediction methods, the authors further showcased how irrelevant channels such as size and lightness of each data point in scatterplots impact position mean perception. This work provides more insights for the design of future visualization tools, which could be helped with modeling potential bias through users' interaction and avoiding biased decision making processes. One limitation of this study could be the robustness of the prediction model. Few encoding ranges were implemented in the study, increasing the range could help the learning processes with producing more robust weights.

3.3 Confirmation Bias

- **Confirmation Bias in Visual Analytics**
  Confirmation bias is one of the most common occurred cognitive bias under whose impacts people tend to pay more attention to those hypotheses which support their pre-existing beliefs and ignore those which against their pre-existing hypotheses. In visual analytics environments, confirmation bias also occur in the form of disproportionally selecting information that supports their prior expectation. For example, in graduate school application review, given a visualization of GPA from students with different research interests, the reviewers might spend more time on applicants with backgrounds they are interested in.
- **A Framework for Confirmation Bias Detection in Visual Analytics Environment**
  While the computational strategy for characterizing confirmation bias is still lacking, a framework was designed to detect confirmation bias in visual analytics environments by Nussbaumer et al. in 2016 [6]. ,the framework proposed the statistical method to detect confirmation bias. One traditional method to detect confirmation bias is selective exposure experiment[1], where biased will be detected based on the change of questionnaire answer before and after user studies. The author brought interesting insights about converting confirmation bias detection to a classifying problem. In this framework, interaction data is collected during the

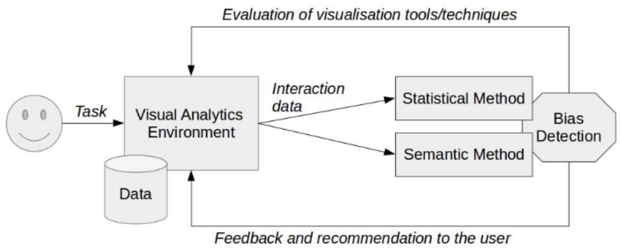

Figure 6: Framework for confirmation bias detection and feedback

visual analytics tasks, the data will be further classified into biased and unbiased interactions based on the results from selective exposure experiment. The labeled data will be used to train a machine learning model, which could be used in visual analytics environment for detecting confirmation bias automatically based on users' interactions.

- **Discussion**
  There is still no research work regarding the development of computational strategy for characterizing confirmation bias automatically in visual analytics environments. The authors proposed one potential detection strategy which combines traditional psychological methods and machine learning together. However, the question of model choice is still open, since the form of confirmation bias could be different due to different visual analytics scenarios. The potential research direction could be investigating how would confirmation bias look like in visual analytics in terms of user interactions. For example, user studies with casual inference tasks could be conducted, the corresponding biased interaction could be stopping early after obtaining result from the correlation between only two data attributes. Then the bias could be further formulated as the proportion of attention given to data points which supports participants' pre-existing beliefs.

4 FUTURE DIRECTIONS

In this survey, we concluded that the situation of the development of computational strategies are significantly different between each cognitive bias. For example, weighted average illusion could be detected and predicted in scatterplots; however, confirmation bias still could not be detected automatically in visual analytics. The first future direction could be summarizing examples where cognitive bias occurs in visual analytics, since defining the biased behavior is prior to detecting and mesuring it. Computational strategies should be designed based on different visual analytics scenarios. Future considerations should also be given to the intervention strategies of cognitive bias. The proper balance should be established between un-biased thinking and steady experiment flow since frequent bias feedback could produce much interruption which might lead to poor user experiences.

REFERENCES

[1] Jonathan L Freedman and David O Sears. 1965. Selective exposure. In *Advances in experimental social psychology*. Vol. 2. Elsevier, 57–97.
[2] Gerd Gigerenzer and Henry Brighton. 2009. Homo heuristicus: Why biased minds make better inferences. *Topics in cognitive science* 1, 1 (2009), 107–143.
[3] Richards J Heuer. 1999. *Psychology of intelligence analysis*. Center for the Study of Intelligence.
[4] Matt-Heun Hong, Jessica K Witt, and Danielle Albers Szafir. 2021. The Weighted Average Illusion: Biases in Perceived Mean Position in Scatterplots. *IEEE Transactions on Visualization and Computer Graphics* 28, 1 (2021), 987–997.
[5] Daniel Kahneman. 2011. *Thinking, fast and slow*. Macmillan.
[6] Alexander Nussbaumer, Katrien Verbert, Eva-Catherine Hillemann, Michael A Bedek, and Dietrich Albert. 2016. A framework for cognitive bias detection and feedback in a visual analytics environment. In *2016 European Intelligence and Security Informatics Conference (EISIC)*. IEEE, 148–151.
[7] Emily Wall, Leslie Blaha, Celeste Paul, and Alex Endert. 2019. A formative study of interactive bias metrics in visual analytics using anchoring bias. In *IFIP Conference on Human-Computer Interaction*. Springer, 555–575.
[8] Emily Wall, Leslie M Blaha, Lyndsey Franklin, and Alex Endert. 2017. Warning, bias may occur: A proposed approach to detecting cognitive bias in interactive visual analytics. In *2017 IEEE Conference on Visual Analytics Science and Technology (VAST)*. IEEE, 104–115.