Making and Trusting Decisions in Visual Analytics

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Abstract

Decision making and trust have both become rising topics in the research community of Visual Analytics (VA). Many efforts have been made to understand and facilitate making decisions with VA, as well as build and calibrate trust. However, previous research largely took VA as a tool to facilitate decision making, but did not explore the possibility to dissect each analytical step in VA as decision making and discuss how decision making theories can be utilized to improve the trustworthiness of decisions in VA. Therefore, this paper instead proposes such alternative take on the relation between decision making and VA, inspects the processes of visually analyzing data as decision making, and discusses how to leverage decision making theories to facilitate trustworthy decision making in VA.

Index Terms: Human-centered computing—Visualization—Visualization theory, concepts and paradigms; Human-centered computing—HCI theory, concepts and models—Visualization design and evaluation methods;

1 Introduction

Over the years, a large amount of research has focused on the pitfalls human might make in the visual analytical process. For example, humans are subject to change blindness where they do not notice visible changes in a scene [33], and cognitive bias such as confirmation bias allows people to focus on information that agrees with their preconceptions [34]. In particular, our paper in TREX workshop last year from comprehensively concluded how one not only should be skeptical about the trustworthiness of VA systems, but also need to calibrate their trust in one's own perception, knowledge, judgment, and situational state in order to make the right decision in VA [19].

Assisting decision making has also been seen as one of the fundamental goals of VA system since its birth. In 2008, when Keim et al. set the stage for VA, they pointed out that VA is to help people "ultimately make better decisions", and "state-of-the-art concepts of representation, perception, interaction and decision-making need to be applied and extended" for VA research [23]. This is also echoed in subsequent VA research, where making decisions with VA is often seen as the center piece and ultimate goal of using VA [10]. Recently, we have also seen some attempts of leveraging decision making theories to assist decision making in VA – FairVis from Ahn and Lin focused on identifying the biases in Machine Learning to promote fairer decision making [3]; Cho et al. investigated the anchoring effect and its implications on decision making with VA [5]; Padilla et al. presented a cognitive framework for decision making with visualizations [35]. These efforts all reveal some important underlying issues and propose means or frameworks to mitigate such pitfalls. Such efforts can also be seen as strategies to improve the quality therefore the trustworthiness of users' decisions with VA. However, if we take a closer look at the VA process – from selecting the data and algorithms to calibrating the parameters and visual layouts – in each step of the way, users need to identify the alternatives to choose from and gather information to make a choice between these alternatives. This constitutes a "decision making process". Therefore, we argue that each task users undertake in the VA system can also be seen as a form of decision making, and the process of making and trusting these decisions *in* the VA system is consequential for analysts to make and trust their final decision *with* the VA system.

To further clarify – making decisions *with* VA systems focuses on the final decision supported by VA – such as diagnosing a patient, choosing a stock portfolio or making political decisions, while making decisions *in* VA systems emphasizes each analytical decision in VA that leads to and supports the final decision – which area of the data to zoom in, how to transform and analyze the dataset, what visual encodings should be applied, etc. Analyzing the decisions made *in* VA systems is crucial as these decisions heavily influence but are markedly different from the final decision supported *with* the VA system. In this paper, we offer such alternative perspective on making and trusting decisions in VA – by taking each task and step in the VA system as a decision making process.

In Sec. 2, we introduce decision making theories regarding making the choice between different alternatives and discuss how they can help to make trustworthy decisions in VA, specifically compensatory and non-compensatory strategies. Then, Sec. 3 relates these strategies to bounded rationality and dual process theories to highlight how they can be leveraged in VA decisions. Subsequently, in Sec. 4 we reflect on how theories in decision analysis can be applied for making trustworthy decisions in VA. Finally, we conclude this paper in Sec. 5 by extracting some important takeaways and future research pathways regarding making and trusting decisions in VA. The structure of the mentioned theories in this paper can be seen in Figure. 1.

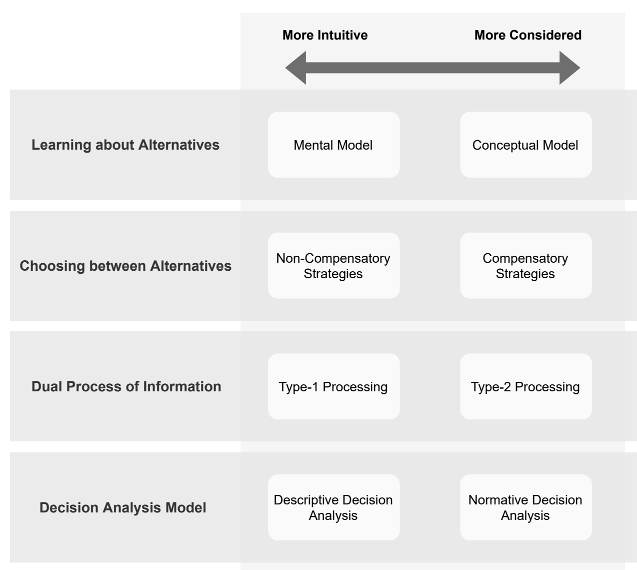

Figure 1: The structure of decision making theories mentioned in this paper.

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2 Choosing between the Alternatives

The central part of making a decision is to come up with alternatives to choose from and make a choice between these alternatives. In VA, many decisions are also done through choosing between alternatives, although sometimes in a more implicit way than making decisions with VA. For example, when analysts choose to focus on one part of the data, they are essentially choosing this subset of data against all the other subsets; when a clustering algorithm is chosen, a decision is made against other clustering algorithms; when a type of visual encoding is applied, analysts also implicitly decided that such encoding is more useful for their purpose than others. In short, each analytical action in the VA process, although sometimes not explicitly framed as a decision, can be always seen as a decision against other potential alternatives. Therefore, the strategies to choose between alternatives are fundamental to be analyzed to understand these analytical decisions.

2.1 Learning about the Alternatives

To make a good decision, decision makers need to first discover and collect information regarding the alternatives and how they work. In decision making, discovering information refers to the process of identifying a set of valid indicators that might predict the outcome of the decisions. It involves the process to learn about where to look for information regarding the alternatives that later the decision maker acquires and combines to make the decisions. [31] Such process relates to observing how different factors might influence the outcome through "lens of cues" that divides how real world works and how these factors are processed psychologically in a human's mind [18]. In Human Computer Interaction research, this is famously coined as the products' "conceptual model" and users' "mental model" [32]. Both theories assert that how things actually work and how one thinks they work might widely differ. Taking these ideas to the realm of VA – the smallest decision on data, algorithms and visualizations can also produce drastically different results, but the correlation between these factors and the yielded results can indirect and obscure, especially for novice users – a change in the inclusion of a few data points, a tweak on the parameters of an algorithm, or a modification for the specification of a visualization layout all could lead to radically different results. Without understanding the underlying mechanism, users can only make causal inferences about how these factors influence the outcomes.

Fortunately, in VA systems, there are usually means and resources that users can rely on to understand the system. On the one hand, designers of VA systems often more readily understand the underlying mechanism, and could design the system in a way that guide users towards the useful information. Ceneda et al. characterized the concept of "guidance" in VA as means to resolve a "knowledge gap" encountered by users to execute their tasks [4, 37]. For example, Tominski et al. designed a look-ahead radar view – an arc will appear when users are panning a graph visualization in the direction in which potentially interesting items lie (see Figure. 2) [41]. Streit et al. provided a guided view on users' analysis path taken as well as potential future steps that could be taken (see Figure. 3) [40]. We also previously explored the potential of using vibrotactile feedback as guidance for users' interactions, where we used vibrotactile cues to guide users to select certain number of data points or find a specific data point in a scatter-plot [20]. On the other hand, decision makers also might have knowledge about the data, algorithms and visualizations that could help them to know where to look at. Therefore, leveraging such knowledge to help users understand the underlying mechanisms and guide users towards important information regarding what to consider could greatly help to produce trustworthy results. VA systems should also reveal the provenance as well as important relevant information of their decisions to help users better judge the trustworthiness of the alternatives suggested by the VA systems.

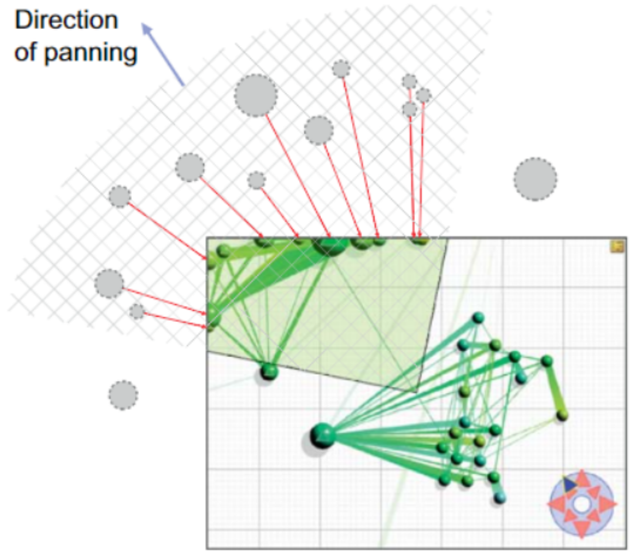

Figure 2: The look-ahead radar view [41] uses an arc to indicate direction in which potentially interesting items lie.

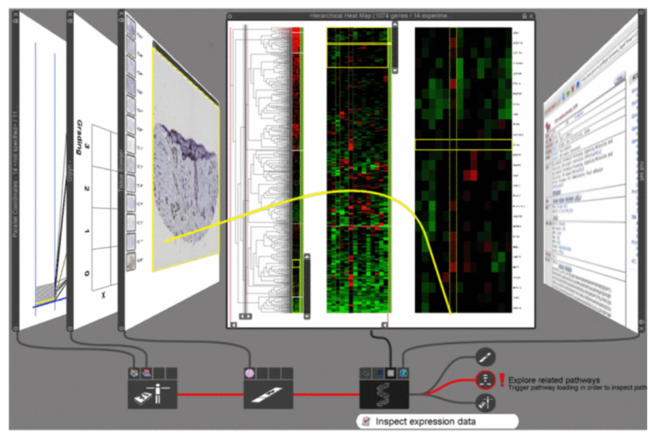

Figure 3: The Stack'n'Flip application [40] integrates the data with a map of analytical workflow to present the previous steps as well as recommend future steps to take for users.

2.2 Compensatory and Non-compensatory Strategies

To make a good decision, analysts unavoidably need to choose from a range of alternatives. In fact, one of the most important techniques to improve decision making is to "adopt the outside view and consider the opposite" [25]. For example, anchoring effect could be drastically reduced by asking people to consider arguments that are inconsistent with the anchor [30]. However, too many alternatives can also bring unnecessary burden to the decision-making – research shows that increasing the number of alternatives from 2 to 3 can greatly improve the quality of decisions, while when there are too many alternatives, the decision making quality deteriorates as much less time and effort are invested in evaluating each alternative [16]. Therefore, different strategies for evaluating the alternatives should be adopted for different contexts.

In decision making theory, there are two types of strategies to choose between alternatives. To make an optimal choice between a set of alternatives, ideally, we should be able to come up with an explicit set of criteria for the decision, and combine all the criteria together through some models – it can be as simple as *weighted* *additive* of the criteria [7], or more complex models such as *Analytic Hierarchy Process* [36]. Such style of decision making is known as *compensatory strategy*, which aims to evaluate the alternatives by combining all information and consider the trade-offs between different factors [31]. However, for decisions in VA, compensatory strategies can be hard to implement – the criteria for choosing which part of the data to explore first can be hard to determine, the number of alternatives for tweaking certain parameters for an algorithm can be infinite, and the value of putting the calculated results into certain type of visual encoding often can not be evaluated unless already visually presented. Moreover, as the decisions in VA are usually easily reversible, the "trial-and-error" type of interaction is commonly adopted in users [45] – in this case, analysts might temporarily settle with a "good enough" decision for the undertaken tasks, so the analytical process could move forward. Therefore, a *non-compensatory* strategy that does not consider all information but eliminates alternatives that do not meet some particular criteria is often used. For example, *"Take-the-Best"* is one of the most prominent heuristics which use the "best" piece of available information that discriminate two alternatives when analysts are making a binary choice [24]. In a similar spirit, *Elimination by Aspects (EBA)* considers the most important attribute among the two or more alternatives and eliminate the ones that do not meet certain cut-off value, then the next most important attribute is considered, until only one alternative left [24]. In the case where an excessive number of alternatives can not be avoided, the strategy of choosing the alternatives becomes increasingly important. Non-compensatory strategies like EBA can often help to filter out some potential candidates before going into deeper evaluations. For example, disjunctive rules accept alternatives that fulfill any requirements set on their attributes, conjunctive rules allow alternatives that fulfill all of the requirements, while lexicographic rules rank the importance of the attributes and "take-the-best" from the alternatives when one alternative is significantly better than the rest in any of the attributes [28] .

In real life, we often practice decision making in a hybrid manner – for example, when we buy on computer online, we might first filter the price range and certain specifications (non-compensatory strategy) to narrow down the candidates, and then evaluate the last few alternatives thoroughly by looking through all relevant product information and even comments or reviews (compensatory strategy). Decision support resembling non-compensatory strategies can also be seen in recent research for VA. For example, Tableau's "Show Me" [26] and suggests preferable visualizations based on the selected data to analyze, Draco [29] provides alternatives using users' specification as well as constraints from visualization design knowledge (see Figure. 4), and Voyager [46] recommends related views based on users' specified view (see Figure. 5). These research all utilize multiple views to exemplify the alternatives to choose from and use recommendations to help users avoid some flawed alternatives (non-compensatory strategies), therefore improve the trustworthiness of users' decisions.

In contrast, compensatory strategies examine all the possible variables and combine them in a structured way, therefore can provide reliable and stable pathways for making trustworthy decisions and greatly improve the comparability or reproducibility of the VA process. Implementing compensatory strategies in VA, however, remains a formidable challenge as to concretize the specific criteria regarding each decision in VA to consider and structurally present these criteria with regard to each alternative.

3 Decision Rationality and Dual Process

The non-compensatory strategies mentioned in Sec. 2 that only consider a limited subset of information also reflects another important concept in decision making and economics – bounded rationality. It asserts that humans make inferences with limited time, knowledge, and resources, therefore look for alternatives that "satisfice" – satisfy and suffice rather than a globally optimal one [38]. Proponents for these "fast and frugal" heuristics, often non-compensatory strategies, such as "Take-the-Best" and EBA, argue that they are not necessarily irrational, and showed that they can outperform in both speed and accuracy in some instances through a series of experiments [17, 27]. However, issues would also arise when taking the non-compensatory strategies to the extreme – seeking only information that confirms one's assumptions (confirmation bias), leaning to certain options that they were more exposed to (mere-exposure effect) or recently exposed to (recency bias) [9], then the decisions could be extremely biased and potentially untrustworthy. Previous research in decision making also shows that even though experts are good at identifying the important attributes about the alternatives for accurate and trustworthy decision-making, they tend to be poor at combining and synthesizing these attributes [12]. This is where such cognitive biases and pitfalls come into play.

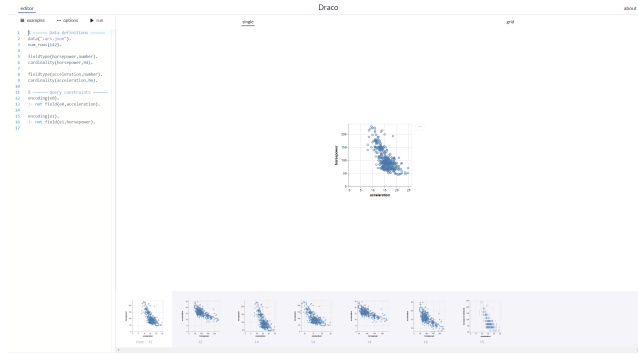

Figure 4: Drago [29] utilizes visualization design knowledge as a set of constraints, and recommends visualizations at the bottom of the currently specified view based on such constraints and the specifications from users to promote effective encoding.

Figure 5: Voyager [46] provides related views at the bottom of the specified view that suggest relevant visualizations based on the current visual encoding selected by users.

This extreme side of non-compensatory strategies and bounded rationality also relates to an important theory in decision making – Dual Process. *Dual Process* theory proposes that human reasoning consists of two relatively independent type of processes: type 1 – an fast, unconscious and implicit process with large capacity, and type 2 – a slow, conscious and explicit process limited by the capacity of working memory [14]. For example, to decide if a patient should go to a coronary care unit or regular bed, the doctor can use their past experiences (type 1) and/or medical instruments (type 2). Such dual process is also echoed in stereotype and prejudice studies – one of the most significant studies in the field by Devine concluded through a series of experiments that stereotypes can be unconsciously activated and applied (type 1) regardless of one's personal belief, while given enough mental resource and motivation, one with low prejudice level can inhibit the use of stereotype with their controlled cognitive process (type 2) [8].

In Visualization research, Padilla et al. proposed a cognitive framework in decision making with visualization based on dual process theory, and connected different thinking process in visualization with the two types of processing [35]. From the perspective of trust in VA, type 2 processing is more trustworthy, as the decision would be more structured and considered with more information. Such processing can be elicited with structured decision making strategies such as compensatory ones. However, type 1 processing still has its important value in efficiency, which is essential to ensure relatively good usability. Therefore, it becomes an important task for VA researchers to investigate when should which type of processing to be activated, and how to leverage type 1 processing to ensure interaction and decision efficiency while avoiding potential pitfalls.

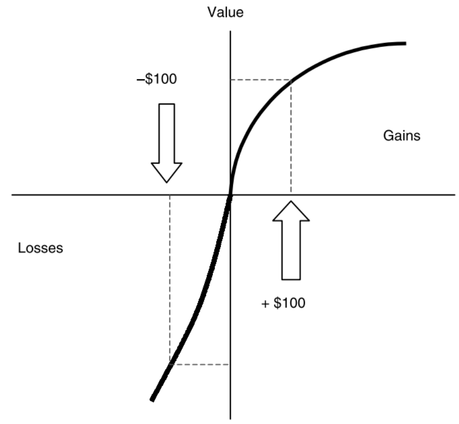

Figure 6: The value function of prospect theory [22, 31] where the value of loss is more significant than the same amount of gain.

4 Decision Analysis

Different from decision strategies, decision analysis aims to model and predict human decisions [31]. As Booth et al. pointed out in their paper on decision making modeling [2], relevant VA research, from Van Wijk's Value model, Green et al.'s Human Cognition Model, to Sacha et al.'s Knowledge Generation Model, has primarily focused on a *normative* approach – discussing what a rational human *should* logically do, in another words – the "best practices" in visual analytics. Particularly, Van Wijk's value model emphasizes that great visualizations lie in obtaining highly valuable knowledge with low cost of time and money [44]. From both theoretical and empirical analysis, other research in VA also attempt to formalize users' reasoning and sense-making process in terms of actions, tasks, and corresponding goals. This idea resonates with the prime example of a normative decision making model – expected utility hypothesis:

Expected Utility of each alternative is computed by the weighted sum of the utilities of its all possible outcomes, and it is assumed that rational individuals will maximize the expected utility and therefore choose the alternative with highest value of expected utility [1]. For example, when designing a visualization with the property of different cars from different country origins, an experienced user would most likely choose color or texture to encode the country origin property instead of size for a higher expressiveness, therefore higher expected utility. Although a normative approach does provide insights on the maximum potential of utilizing VA systems and what users should do to achieve that, researchers also become increasingly aware that what users *actually* do in reality is often based on heuristics and can deviate from the rational and logical course of reasoning. Perceptual differences, knowledge gaps, cognitive biases and situational factors could all contribute to such deviation [19].

To formalize such heuristics-based approach, research in decision making developed a different type of model – *descriptive* decision theories – to capture how people *actually* make decisions. Among them, *Prospect Theory* is the most prominent model for descriptive decision analysis – it maintains the idea of maximizing some form of expectation, but the expected utilities regarding the outcomes are considered relatively to a reference point (e.g., current wealth in the case of investing or betting) and cognitively distorted in a non-linear and asymmetric manner regarding gain and loss. Figure. 6 exemplifies the value of losing $100 is more significant than gaining $100. In situations with risks and uncertainties, human tend to be more risk-seeking when the choices lead to or are framed as losses, while more risk-averse when it comes to gains [22, 43]. Such dynamics with risk are important when people make decisions with the results of visualization – making life-and-death medical decisions, investing a huge amount of money, or developing policies that might influence the life of millions. Previous studies also show that high quality visualizations can well enhance the communication of risk, while perceptual errors can still arise and lead to the distortion of probability estimates [13, 15]. However, when analysts make each decision in VA, most of them are of low risk and easily reversible – one can always zoom out from a zoomed-in area of data, try out another algorithm, or use a different chart and visual encoding. This therefore can make VA decisions fundamentally different from many other decision-making scenarios – in many VA systems, users are often encouraged to explore and try out possible analytical paths – as the effort to recover from mistakes can be very low, and the risk of making a decision now is therefore nearly non-existent. Essentially, the effort going into making a decision is to reduce the risk of making an erroneous decision [6] – too much effort could be costly, while too little effort can greatly increase the risk. In the case of many potentially temporary and reversible VA decisions, investing too much effort is not worthwhile. This not only relates to the bounded rationality we discussed before – users often have limited time and resource to invest in making each visual analytical decision, we also need to consider with the "trial-and-error" style of decision making, how can we create feedback to users to help them make trustworthy decisions after the error.

With regard to risk, previous research also pointed out that the perceived risk and the actual risk of a decision can greatly differ from each other. Slovic et al. explain how risk is constructed in two ways – feelings as one's instinctive and intuitive reaction to danger, and analysis as one's logical and cognitive deliberation on risk management [39]. In particular, risk as feelings, or affect, can be mixed or influenced by other feelings, such as benefits – when a decision is framed as beneficial, the positive affective evaluation will lead to an inference of lower risk and decrease the perceived risk, and vice versa. Conversely, when an alternative is linked to negative affect, the corresponding perception of risk can increase and therefore overrated. With increased perceived risk, analysts can become more reluctant to make decisions and interact with the VA systems. This is also closely related to what our previous discussion regarding calibrating trust – the perceived risk of a decision also needs to be calibrated with regard to its actual risk for users to have the calibrated level of trust [19].

In addition to risk aversion in prospect theory, descriptive decision analysis also models many other issues regarding decision pitfalls, such as framing effect [11, 43], anchoring effect [42] and ambiguity aversion [21]. These predictive models can greatly contribute to warning flawed decisions made by users and highlight pathways for users to make trustworthy decisions.

5 Conclusions

In this paper, we advocate for a research focus on making and trusting decisions "in" besides "with" VA. To this end, we inspected relevant decision making theories – namely decision strategies, bounded rationality and dual process theory, as well as decision analysis models – with regard to making decisions in the VA process, and discussed their potential for making trustworthy decisions. From these discussions, we conclude the following potential research pathways for trustworthy decision making in VA:

First, both presenting a number of alternatives to choose from and providing relevant information regarding these alternatives contribute to trustworthy decision making. This not only helps users make more informed and trustworthy initial decisions, but also enables users to trace the provenance of their decision and analytical process, which is extremely important in an iterative VA process where users might later adjust their previous decisions. However, with bounded rationality, users tend to utilize their instinctive processing to capture limited amount of information. This also needs to be considered with regard to how to guide such processing towards more trustworthy decisions.

Second, descriptive decision analysis models can help to understand and highlight errors in user decisions. However, these models are yet to be adapted to the specific natures of making decisions in VA, for example – VA decisions are usually of low risk, easily reversible and iterative. Further inspections on these extended research from decision making community, such as on framing effect, anchoring effect, and ambiguity aversion [21, 42, 43], can greatly benefit VA research. Normative decision making model and different decision making strategies can be utilized to guide users to make more structured and trustworthy decisions. Normative decision model provides fundamental theories regarding expected utility that can be utilized in decision making strategies, and both compensatory and non-compensatory strategies also enable more accurate and trustworthy decision making with structured criteria or heuristics.

Finally, we can observe a common pattern of "intuition vs. logic" dichotomy from the decision making theories (see Figure. 1). However, both our discussion and research in decision making point out that decisions are usually not clean-cut through these diverging lines, and both sides of the models are very often combined together for most decisions. In addition, although these more intuitive models, strategies and processing can lead to some common pitfalls of cognitive biases, many decision making researchers also pointed out the high accuracy and efficiency of these intuitions are essential to human decision making. Therefore, it is vital for VA researchers to recognize the importance of facilitating and utilizing these intuitive approaches while avoiding the pitfalls they might bring along.

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