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Decision making in uncertainty visualization

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Abstract— In this position paper we investigate the role of decision making in uncertainty visualization. We introduce common decision making strategies identified by the cognitive science community [22]. These strategies are then used to reanalyze 21 design study papers that have previously been used as a foundation for defining visual parameter space analysis [26]. We found that current strategies in these tools relied mostly on one parameter at a time and are about filtering alternatives. Based on these results, we propose three questions for further discussion and research.

Index Terms—Uncertainty, Simulation, Decision making.

1 MOTIVATION

The literature on uncertainty visualization follows two main streams: perceptual studies and design studies. *Perceptual studies* such as by MacEachren et al. [18] help us to better understand how simple, low-level uncertainty tasks can be supported by visual encodings. While the results of such studies are generalizable across a range of humans, the approach is not accounting for higher-level aspects, such as cognitive skills, problem solving strategies, or decision making.

With these higher goals in mind, there has been an increasing focus on *design studies* [27]. In this qualitative approach, researchers work together with end users to better understand their data analysis tasks, and to create a visualization tool that supports these. In doing so, design studies provide us with instances of how actual problems were broken down into design decisions, going far beyond low-level perceptual reasoning. Design studies, however, are highly problem- and domain-specific. Therefore, while some of the knowledge gained in designing these tools is "transferable" to other visualization tools, the results are often not "generalizable" to the larger population.

In this position paper, we argue that there is a gap between these two lines of work. While there are general task taxonomies [7, 28] and models [31, 26] attempting to bridge the gap, we argue that a more systematic *user modeling* is missing. The visualization community has already started examining personality types and how those correspond to visualizations [11]. Beyond that, we advocate for a more thorough investigation and understanding of the overall *problem solving* strategies when extracting information from data, and the ultimate *decision making* processes. While these terms are not new to the visualization community, the literature from other domains such as Complex Problem Solving (CPS) [12] and Decision Theory [22] suggests that there is much more to say about these characteristics, than what we currently discuss in our community. For instance, people are known to have different strategies to go about decision making, filtering information, and adapt strategies based on, among other things, the number of attributes to consider, time pressure, and the mode of information display [22]. We deem a better understanding of such aspects specifically important for uncertainty visualization. Not only could they help to run better perceptual studies by directly accounting for user characteristic variables, but also support design study researchers by providing a better framework for problem and task characterization.

In this position paper, we seek to conduct some first steps towards such a more sophisticated understanding of the role of users in (uncertainty) visualization. Toward this goal, we make the following contributions:

- We introduce 6 different decision making strategies from the decision theory literature [22].
- We analyze a set of 21 design study papers, classifying them according to these strategies.
- We discuss and advocate the following questions: What are common decision making strategies? How can current approaches of task taxonomies and mantras be reconciled under the lens of decisions making? How can we better support *different* decision making strategies in our tools?

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2 DECISION MAKING STRATEGIES

In the following, we describe 6 different decision making strategies, taken from the book *"The adaptive decision maker"* [22], and discuss them in the light of visualization research. The strategies characterize how people make contingent decisions in which all alternative action possibilities—events that relate actions to outcomes—and the objective values are all available to the decision maker. All strategies assume that the decision maker (or user in our case) is selecting a decision item from a list of discrete choices. Each item has multiple *attributes* (objectives). These objectives are competing with each other in the sense that there is no clear optimal choice.

To better understand how these different strategies are supported by current visualization tools, we coded 21 design study papers on visual parameter space analysis tools (the same set as Sedlmair et al. [26]). We classified these papers based on the main strategy used, if any, by the users of the tools when describing the task analysis, user characterization, or case study. We found that $15/21$ of the papers described some sort of strategy when describing the task analysis, user characterization, or case study. Table 1 shows an overview of the results; specific examples will be discussed below.

2.1 Strategy 1: Weighted additive rule

The weighted additive rule considers all attributes of the various choices at once. Weights are assigned for the various attributes and the option with the highest weighted sum of attributes. A version of this strategy considers all attributes evenly but the selection is still made on the total weighted value.

Practical issues with this strategy include mapping attributes to numerical values and examining the effects of adjusting the weights. In our evaluation of design studies this rule is not directly supported. We considered that systems supporting the evaluation of distance functions such as in systems such as ParaGlide [4] as using this strategy.

2.2 Strategy 2: Lexicographic

Rather than considering all attributes at once the user can instead simply order the selections by the most important attribute to them. Ties within this attribute are broken by sorting by the second most important attribute and so on until a clear candidate appears at the top. This process has been named lexicographic.

Among our 21 reviewed papers, this is a relatively common strategy. Many visualization systems, for example, Tuner [30] and Luboschick et al. [17] allow the user to prioritize a few objective measures and evaluate the outputs based on those few. Naturally, when

Table 1: Classification of the 21 papers listed in Sedlmair et al. [26] according to which decision making strategies.

Strategy	#	References
Weighted additive rule	3	[2, 4, 6]
Lexicographic	5	[1, 3, 17, 19, 30]
Elimination by aspects	4	[5, 21, 29, 33]
Frequency of good/bad features	1	[10]
Satisficing	0	
Majority of confirming decisions	2	[8, 25]
None	*6*	*[14, 16, 20, 23, 24, 32]*

presented with more attributes than can be easily compared between, one can filter these attributes down to just the core set.

2.3 Strategy 3: Elimination by aspects

In elimination by aspects, rather than concentrating on finding the optimal options, a user might instead set thresholds and filter out unacceptable decisions. This process is repeated until a final choice remains.

Elimination by aspects is frequently employed in many visualization systems, such as in the system developed by Spence et al. [29]. The user can interactively filter objectives into acceptable and unacceptable regions and see that effect on the selections in the parameter space. Vismon [5] also uses a similar strategy.

2.4 Strategy 4: Frequency of good/bad features

If, like in the elimination by aspects strategy, one can articulate for each attribute a good and bad level then one could label each attribute of each decision option by this. The frequency of good and bad features strategy then depicts simply counting the number of attributes that are labeled "good", comparing it against the number of "bad" labels, and selecting the option with the highest difference.

We found that this strategy was never directly addressed in our study. The closest example we could find was the work by Coffey et al. [10]. In their system the user could browse through simulations and find similar ones which may be closer to what the user is looking for. The frequency of good and bad features between the choices of design physical instrument (a needle in this case) determined the final design decision.

2.5 Strategy 5: Satisficing

Satisficing does not consider the entire set of decision options holistically. Rather, when employing this strategy, one considers each option one at a time. Whether all attributes of the choice are considered or just a few depends on the person but either way the first acceptable option encountered is selected. We did not see any evidence in the literature of this strategy being employed. In some ways it is at odds with visualization tool development. Usually, one assumes that all data must be examined or all data is known up-front.

2.6 Strategy 6: Majority of confirming dimensions

As an alternative to looking at all decision options at once a user could instead examine them in a pairwise manner. The "winner" of each pairing is compared against the next choice and so on until a final optimal choice prevails.

This is also not very common in visualization perhaps because the pairwise comparison is quite labor intensive. Also, like satisficing, depending on the order that the options are considered one may get a very different outcome. In Fluid Explorer [8] and Paramorama [25] this is done by the user manually selecting an optimal candidate simulation from a list of simulation outputs.

3 Questions

Based on this analysis, we would like to address a number of questions during the workshop.

3.1 What are current decision making strategies supported by visualization tools?

In our study of 21 papers, we found that lexicographic and elimination by aspects were the most popular strategies by far. Both of these concentrate on one parameter at a time and are about filtering alternatives.

Some of the examples of strategy occurred in non-obvious ways. For example, ParaGlide [4] concentrated on a weighted strategy but did this through investigating a distance metric rather than directly adjusting the weights. This is not a very common strategy in the tools we examined, however, this is a major component in clustering evaluation tools. As far as we know, there is very little work on visualization tools that allows the user to directly see the effect of manipulating weights, such as LineUp [13], or ValueCharts [9].

3.2 How can current approaches of task taxonomies be reconciled under the lens of decision making?

Visualization systems are often designed around the visual information-seeking mantra "overview first, zoom and filter, details on demand" [28], or other strategies such as "global to local," or "local to global" [26]. Beyond that, task taxonomies, such as the one by Brehmer and Munzner [7], offer a more fine-grained resolution of of what features are required, for example, filtering or zooming. The interesting question is how this visualization lens on strategies relate to the strategies as discussed in the cognitive science community. Both are developed around how users go about solving tasks. However, while the visualization lens is mostly focused on the engineering aspects of the tools, the cognitive science decision making strategies are more focused on how these tasks can be combined to solve a problem. We believe that with a better understanding of the decision making processes used one could better decide which tasks to prioritize for which users. We propose that the task taxonomies can be linked with the different problem solving strategies in terms of which tasks support which strategies. This link will allow for more robust decisions about which tasks and which visual encodings to employ when designing a visualization tool.

3.3 How can we better support ***different*** decision making strategies?

A major design decision for a visualization tool is a proper visual encoding. There is evidence that the visual encoding of information will influence which decision making strategy one employs [15]. On the other hand, in real-world decision making there is often no clear optimal decision to be made, so it is difficult to evaluate which decision making strategy is best. However, it seems that it is best to at least comprehensively examine all the options.

One of the strengths of a visualization tool is the ability to switch modes dynamically during data exploration. One could envision combining a global overview in combination with a focused pairwise comparison system. The global overview would remind the user of how much of the *global* space they have explored. In addition, one could also dynamically filter the remaining options to reduce the number of comparisons in a process not unlike active learning.

4 Conclusion

We are proposing to study more closely the impact that uncertainty information has on decisions and the implications for visual tool design. We have enumerated some common decision making strategies and evaluated if these are currently addressed by visualization systems today. We hope that our work will spark interesting discussions at the workshop, and will open new avenues for visualization research.

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