GUEST EDITORS' INTRODUCTION

Visualization and Decision Making Design Under Uncertainty

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Uncertainty is an important aspect to data understanding. Without awareness of the variability, error, or reliability of a dataset, the ability to make decisions on that data is limited. However, practices around uncertainty visualization remain domain-specific, rooted in convention, and in many instances, absent entirely. Part of the reason for this may be a lack of established guidelines for navigating difficult choices of when uncertainty should be added, how to visualize uncertainty, and how to evaluate its effectiveness. Unsurprisingly, the inclusion of uncertainty into visualizations is a major challenge to visualization. As work concerned with uncertainty visualization grows, it has become clear that simple visual additions of uncertainty information to traditional visualization methods do not appropriately convey the meaning of the uncertainty, pose many perceptual challenges, and, in the worst case, can lead a viewer to a completely wrong understanding of the data. These challenges are the driving motivator for this special issue.

Visualization has become a core component of any decision or risk analysis pipeline, and tools for creating visualizations are quickly becoming more and more accessible. In addition, the visual literacy of the general public has been increasing due to the pervasiveness of visualizations in everyday life. As the appetite for decision making tools grows, so does the need to convey error, confidence, missing, or conflicting data visually.

However, practices around uncertainty visualization remain domain-specific, rooted in convention, and in many instances, absent entirely. Part of the reason for this may be a lack of established guidelines for navigating difficult choices of when uncertainty should be added, how to visualize uncertainty, and how to evaluate its effectiveness. Unsurprisingly, the inclusion of uncertainty into visualizations has been decried as a major challenge to visualization, and may play a role in other current communication challenges, like how to promote clear communication of experimental effects despite incentives for researchers to overemphasize small effects, or how to explain model workings and predictions in a way that is interpretable. As work concerned with uncertainty visualization grows, it has become clear that simple visual additions of uncertainty information to traditional visualization methods do not appropriately convey the meaning of the uncertainty, pose many perceptual challenges, and, in the worst case, can lead a viewer to a completely wrong understanding of the data. Numerous studies point to challenges people have in interpreting uncertainty—both conceptually and in visual presentation. Visualizing uncertainty may be perceived as conflicting with other goals of visualization authors, like conveying credible information. There is no single definition of uncertainty, since the term umbrellas concepts like confidence levels, distributions, and missing or erroneous data, among others. Additionally, there is little guidance to help visualization authors understand how different sources of uncertainty manifest in different scientific domains and how these uncertainties may warrant different visual approaches. Finally, large and heterogeneous datasets pose challenges based on their size and the need to assimilate data from multiple sources, all with uncertainty of different type and scale.

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CHALLENGES TO UNCERTAINTY VISUALIZATION

Representation and Modeling Challenges

Types of Uncertainty

Uncertainty comes in many forms, mathematical measures and conceptual ideas. We group these potentially disparate ideas into the term uncertainty, both for ease but also lack of understanding. Can we develop a taxonomy of uncertainty types to help define categories of uncertainty types that may be treated in a similar fashion?

Big Data Problems

The large scale of the data we are seeing today is just going to grow. Many of the techniques to handle this data use summarizations, sampling, or clustering, all of which introduce uncertainties in and of themselves, on top of the uncertainties within the data originally. In addition, data fusion and assimilation pose a challenge for uncertainty understanding since sources, types, and meanings of uncertainties may change between combined datasets. How can we handle these challenges? What kind of new algorithms need to be developed and what are the most appropriate uncertainty quantification techniques and statistical methods?

Propagation

Uncertainty arises in all stages of the decision making pipeline, from data gathering and generation, through visual presentation. Is there a way to better understand these uncertainties and provide guidelines to how these different stages of uncertainty effect understanding and decisions? Are there types of uncertainty that are less impactful and thus need less attention, or are there strong uncertainties in common algorithms that may suggest better algorithms or at the very least more attention by the community?

Comprehension Challenges

Challenges to Decision Making and Risk Analysis

Though decision making under uncertainty and risk are well studied fields unto themselves, the unique characteristics of decision making and analysis from visualizations raise questions that remain unanswered in those bodies of literature. For example, visualizations are often accompanied by text; should uncertainty be visualized for users to properly integrate it with text information? How does a visual channel change the perceived salience of uncertainty relative to text presentations?

Understanding User Differences

Risk interpretation changes from person to person, as does statistical literacy. The visual inclusion of uncertainty may result in differential effects across users of different risk profiles or ability levels. What do we know about the impacts of user characteristics and can we define guidelines for designing for specific audiences?

Perception

There are mechanisms within the human visual system that can decode things like mean value estimates from scatter plots without explicit depiction, raising the question of when explicit representations of uncertainty like intervals are needed over displays of raw data. How can we better understand the perceptual system's strengths and leverage those for visualization of uncertainty?

Social Challenges

Ethical Risks and Incentives

Depending on the situation, conveying uncertainty may not add value for users or decision-makers, may conflict with the visualization author's incentives, or may have other ethical implications. What are common uncertainty communication scenarios, where incentives and ethics may collide, what types of attitudes and rationales are at play in these scenarios, and can we define a normative way that a visualization researcher should respond? What can we conclude about the ethical ramifications of not including uncertainty?

Collaboration

Decision making is often a collaborative process that involves different types and levels of expertise. Collaboration can help reduce uncertainty, but can also generate new uncertainties due to compounded cognitive and relational factors. For example, uncertainty such as measurement error may be taken into account by a modeling expert using a quantitative form, but the same uncertainty can be translated to a qualitative form (e.g., confidence in a decision) at a later stage of analysis by a decision maker who uses that model. How can we make sure human understanding of uncertainty in one stage (e.g., at modeling stage) is properly translated to adequate forms of uncertainty at later stages of analysis? How can we reduce the cost of the coordination and synchronization between the different parties involved (e.g., between uncertainty modelers and decision makers)? How can we design uncertainty visualizations that take into account the various sources of uncertainty in the data as well as at the cognitive and relational levels? What are the triggers and barriers for revealing and communicating uncertainty in a collaborative context?

PAPERS IN THE SPECIAL ISSUE

Through the formal *IEEE Computer Graphics and Applications* review process of the 10 submissions, we accepted five papers for this special issue. In the article by Jin, Koesten, and Möller,[A1] the authors present different interface designs of sliders to support decision-making problems with three criteria. They present an exploration of the design space through an iterative development process with eight prototypes and the results of several evaluation studies with visualization experts and nonexperts. The article by Liu and Vuillemot[A2] investigates a user interaction based on a function for users to generate fuzzy data attributes in a dynamic way to convey the uncertainty categorization and to better support visual data analysis. The article by Tominski et al.[A3] explores how sets should be visualized. They develop a conceptual framework that brings together the information primarily relevant in sets (set membership, set attributes, and element attributes), as well as different plausible categories of (un)certainty and apply their framework to multiple visualization examples. The article by Gillmann et al.[A4] notes that while visual analytics (VA) has become a standard tool to process and analyze data visually to generate novel insights, each component can introduce uncertainty in the visual analytics process. The authors propose a taxonomy of potential uncertainty events in the VA cycle. Finally, Matzen et al.[A5] note that while visualizations are a useful tool for helping people to understand information, they can also have unintended effects on human cognition. This is especially true for uncertain information, which is fundamentally difficult for people to understand. The authors discuss the results of four experiments that compared visual and numerical representations of uncertainty and demonstrate that design choices are not neutral: seemingly minor differences in how information is represented can have substantial impacts on human risk perception and decision making.

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APPENDIX: RELATED ARTICLES

A1. Y. Jin, L. Koesten, and T. Möller, "Exploring the design space of three criteria decision making," *IEEE Comput. Graph. Appl.*, vol. 43, no. 5, pp. 26–38, Sep./Oct. 2023.
A2. L. Liu and R. Vuillemot, "A generic interactive membership function for categorization of quantities," *IEEE Comput. Graph. Appl.*, vol. 43, no. 5, pp. 38–48, Sep./Oct. 2023.
A3. C. Tominski et al., "Visualizing uncertainty in sets," *IEEE Comput. Graph. Appl.*, vol. 43, no. 5, pp. 49–61, Sep./Oct. 2023.
A4. C. Gillmann, R. G. C. Maack, F. Raith, J. F. Pérez, and G. Scheuermann, "A taxonomy of uncertainty events in visual analytics," *IEEE Comput. Graph. Appl.*, vol. 43, no. 5, pp. 62–71, Sep./Oct. 2023.
A5. L. E. Matzen, B. C. Howell, M. C. S. Trumbo, and K. M. Divis, "Numerical and visual representations of uncertainty lead to different patterns of decision making," *IEEE Comput. Graph. Appl.*, vol. 43, no. 5, pp. 72–82, Sep./Oct. 2023.

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