Research Statement

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My research is focused on **information visualization,** the graphical communication of data. As my understanding of the power and promise of visualizations has grown, I have become increasingly aware of the ways that visualizations can result in harmful or unjust outcomes. I have therefore worked to contribute to a **critical data science** that is mindful of how data can mislead, bias, and dominate. I employ a mixture of methods in my research: theory-building, quantitative and qualitative experiments, and prototyping of novel visualizations systems and techniques.

In this document I lay out three of my current central research trajectories, but I maintain an interest in a wide variety of directions not included in this document including the digital humanities, visual rhetoric, and bioinformatics.

(Un)Ethical Visualization

It is my contention that *all* visualization work has ethical importance, and I have attempted to use frameworks like virtue ethics to lay out our duties and responsibilities in this space [1], such as our duties to visualize the "invisible" (such as hidden populations, assumptions, and labor), collect data with empathy (rather than the reduction of people down to numbers), and challenge structures of power (rather than use data science to replicate and reinforce existing inequalities). One way of making these ethical obligations visible is through the analysis of all the ways that visualizations can deceive, mislead, or distract audiences: what I call **black hat visualization** [2].

My work has explored, through laboratory and crowdsourced l studies, the ways that adversarial design choices such as histograms bin sizes [3] or axis bounds [4] can result in strong and reliable changes in what viewers notice (or don't notice) in charts and graphs. Even without malicious intent, choices in how we display confidence intervals [5] or bivariate data [6] can result in biases that impact decision-making and estimation. Building on these studies as well as prior work, I have worked on a taxonomy of "visualization mirages" [7] (charts that appear to convey a particular message that disappears on closer inspection), and qualitatively investigated testing regimes [7] and visual augmentations [8] that can surface these mirages in useful ways.

Future Work

I am worried that the misuse or misrepresentation of data, especially data derived from complex statistical or machine learning models, is rampant and damaging. As an extension of my black hat work, I am interested in building ***defensive* visualization systems** that reliably surface potential data quality issues or statistical fragility. This involves both ongoing qualitative work on "auditing" visual analytics for potential concerns as well as design work extending current design paradigms around visualization "linting" [8] or "error checking" [7]. I also wish to extend my positive project of laying out ethical guidelines and best practices for data visualization, especially for areas of ongoing public concern such as machine learning algorithms and their resulting predictions.

Communicating Uncertainty

Uncertainty information is often excluded from visualizations for reasons of complexity or presumed data literacy. As the general public is forced to reckon with important events with large amounts of uncertainty like machine learning predictions, unequally measured events, and data-driven forecasts, the further exclusion of uncertainty information will become untenable. My research focuses on investigating **biases in the visual communication of uncertainty**, either through an analysis of common visualization techniques or, when those are inadequate, the design and evaluation of novel encodings for inference, prediction, or estimation.

One of my first forays into this work was a crowd-sourced evaluation of the ways that one of the most basic and ubiquitous visualizations of uncertain data— bar charts with error bars—can bias or mislead [5]. For instance, these encodings generate a "within-the-bar bias" where values inside the visual area bar are perceived as likelier than those outside of bar. They can also produce dichotomous thinking. Alternative visualization strategies, like violin plots or gradient plots, can reduce these biases. For more complex data, in future work we created Value-Suppressing Uncertainty Palettes [9]: a form of bivariate map that acts somewhat analogously to a statistical effects test, where unreliable differences in value are "suppressed" into a narrower visual range. In a controlled study, we found that VSUPs promote caution in judgments under uncertainty without negatively impacting decision quality compared to other types of bivariate maps.

Future Work

People are increasingly exposed to decisions and recommendations made by algorithmic procedures like machine learning models. It can be tempting to view such black box systems as flawless or unbiased interpretations of the data (my work on a visual analytics tarot deck [10] is a slightly tongue-in-cheek attempt to curb this impulse). The illusion of the infallibility of "the model" elides inescapable uncertainty. I have begun to examine the complex relationship between trust, uncertainty, and performance in outputs from machine learning systems, with the goal of creating systems that **encourage skepticism** in their users while still being useful for automating or assisting in analytical tasks.

Improving Visual Statistics

Statistics is powerful, affording summarization and inference from massive amounts of data. The visual system is similarly powerful; it is capable of comparing, aggregating, and contrasting visual features quickly and reliably. Through careful design of the presentation of information, we can harness the strengths of visual perceptual system to allow people to act as **visual statisticians**, capable of making sound judgments about information in the aggregate.

Information on the perception of summary statistics like mean, variance, and trend is crucial to assessing our capabilities as natural statisticians. Through empirical methods developed in collaboration with perceptual psychologists, I have investigated the abilities of people, including those without statistical training, to estimate not just low-level visual features (such as the height of a particular bar in a bar chart), but also aggregate statistics (such as the average height of a group of bars). I have found that, in many cases, people are excellent natural statisticians, capable of accurately estimating averages in time series data [11], comparing means and lines of best fit in scatterplots [6] [12], or judging the proportions of colored words in paragraphs of text [13].

One goal of these studies is to highlight areas where we may need assistance; where our abilities as visual statisticians may be not up to the task, and also areas where existing visualization best practices conflict with how people see and interpret data. Areas where I have applied knowledge gained from studies on visual statistics are in new recommendations for univariate visualizations like histograms and density plots [3], improved "robust" scagnostics [14] (diagnostic visual and statistical features of interest in scatterplots) that more closely align with human judgments, and Bayesian "surprise maps" [15] that highlight statistically informative regions of maps, and "color weaving" [11] for highlighting aggregate statistics of time series data.

Future Work

Recent work by both myself and others has pointed to the potential for visual statistical judgments to exhibit systematic biases. I am investigating how we might provide **beneficial design "nudges"** to improve the quality of judgments in these cases (for instance, via directionality or other visual "attractors"). Or, when visual statistics are completely unreliable, how we might discourage unjustified conclusions. I am also interested in how visual statistics interfaces with existing protocols for graphical inference and sanity checking.

Summary

While my work explores a number of areas and I employ a diversity of research methods, a unifying component is my belief that people use visualizations to build complex pictures of the world, with implicit and explicit assumptions (both statistical and otherwise) that determine what people take away from the data. We can use qualitative methods to learn more about how people create meaning from visualizations, quantitative methods to explore potential biases in graphical judgments, and design thinking to explore new ways of viewing the world. My long-term vision is a world where visualization can empower everyone, not just statisticians or data scientists, to understand the data that are important to them in sound, reliable, and responsible ways. Achieving this goal will require a deeper understanding of how visualizations create meaning, more effective techniques for communicating statistical information (especially for non-statistical audiences), and a stronger ethical and moral grounding for how data are used in our society.

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