Research Statement

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Charts and graphs are often the first or only contact we have with the data that are an increasingly inescapable part of our personal, professional, and political lives. Designers of **information visualization** therefore have tremendous power in shaping how people build up their view of the information around them, but this power also comes with responsibility. My work in visualization has led me to 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 focus on three themes of my visualization research.

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, even without formal statistical training.

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 how people 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 or variability of a group of bars). I have found that, in many cases, people are excellent visual statisticians, capable of accurately estimating means and averages in distributions [1], averages in time series data [2], means and lines of best fit in scatterplots [3] [4], or the proportions of colored words in paragraphs of text [5].

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. 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 [6]. 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.

Other areas where I have applied knowledge gained from studies on visual statistics are in new recommendations for univariate visualizations like histograms and density plots [7] [8], improved “robust” scagnostics [9] (diagnostic visual and statistical features of interest in scatterplots) that more closely align with human judgments, and Bayesian “surprise maps” [10] and “value-suppressing uncertainty palettes” [11] that highlight statistically informative regions of maps, and finally “color weaving” [2] for highlighting aggregate statistics in time series data. Part of this design work is the experimental validation that these new designs result in improved estimation or decision-making, and correct or diminish perceptual biases in how people build up aggregate pictures of data from charts. These new designs have been adopted by diverse users, from the use of gradient plots and other alternatives to error bars in R packages like *ggdist*, to the use of Surprise Maps to show Canadian census 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.

(Un)Ethical Visualization

Collecting and communicating data is about power, and with this power comes the potential for harm and misuse. I have used frameworks like virtue ethics to lay out our duties and responsibilities as visualization practitioners and researchers [12], 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 [13], mislead, distract, or even "bullshit" [14] audiences.

My work has exposed, through laboratory and crowdsourced studies, the ways that adversarial design choices such as histograms bin sizes [7] or axis bounds [15] 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 [6] or bivariate data [3] 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" [16] (charts that appear to convey a particular message that disappears on closer inspection), and designing and deploying testing regimes for surfacing mirages [16] and qualitatively validating visual augmentations [17] that can surface chart errors in useful ways.

Future Work

The misuse or misrepresentation of data, especially data derived from complex statistical or machine learning models, is rampant and damaging, leading to unjust, unequal, or just plain absurd outcomes. As an extension of my work on adversarial visualization, 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" [17] or "error checking" [16]. 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 bias or error in machine learning applications.

Data Science Beyond the Data Scientist

People with all sorts of backgrounds and from all walks of life are being asked to make sense of data and take action based on what they've learned. Yet, much of the effort in understanding and building for the analyst is geared towards experts, and so misses the **everyday data practices** of people who work with data but who do not self-describe as data scientists. Understanding these practices is key not just for designers of systems, but for those who want to be able to persuade or convince using data.

In collaboration with my peers, I have been engaged in deep qualitative studies of the very basic building blocks of visualization experience that are often overlooked by work that focuses only on expert users and bespoke systems. For instance, the usage of dashboards [18] has shifted considerably from the mere real-time display of key metrics to a set of complex and unique genres, each with different designs and analytical purposes. Likewise, the ability of tables and spreadsheets [19] to provide the ability to directly see and manipulate data is lacking in even tools that purport to provide richer analytical experiences. Of particular interest in my research on everyday data practices are initial forays into how non-data scientists react to the emerging genre of recommendation systems that make use of machine learning and statistics to attempt to automatically surface insightful charts and graphs. I found that, while people have (often unearned) trust in such systems [20], their own preferences and priorities [21] do not align with what these systems often provide. In a (slightly tongue-in-cheek) design probe, I examined how these recommendations can even seem "mystical" and uninterpretable [22].

Future Work

As ML and AI continue to integrate themselves into the way we think about data, there have been calls to make AI *transparent* and *explainable*. I am curious about the effectiveness of explainable AI (XAI) for non-expert users, and, employing the diverse methods of my prior work, plan to engage in a study of the **rhetoric of XAI for mass audiences**: beyond simple matters of trust or legal compliance, how do explanations of ML models or predictions persuade, convince (or bias)?

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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