Research Statement

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The transformative power of data is undeniable, and **information visualization** is at the vanguard of this power; visualizations such as charts, maps, and graphs are often the first or only contact many people have with data, or the primary way that data are used to persuade or inform. My research in visualization is motivated by a desire to understand this power: to know how people build up larger pictures from the components dots of scatterplots or bars of bar graphs, how they square the perceived certainty of a map or a chart with an uncertain and changing world, and how charts shape the process of decision-making. As my understanding has grown, I have become increasingly aware of the ways that visualizations can result in harmful or unjust outcomes, and I have 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.

Ethical Visualization Practices

There is a common perception that visualizations are somehow “neutral:” the objective reporting of facts about the world. Even as public discussion on the use and misuse of data has come to grips with potential inequalities and harms in how data are *gathered* and *used*, how data are *presented* often receives short shrift. I am investigating this gap from two directions. The first is building up a theory of “black hat visualization” [1]: all the ways that ways that visualizations can harm and mislead. The second is creating ethical principles and safeguards for visualization designers and analysts.

My “black hat” work has explored, through laboratory and crowdsourced empirical studies, the ways that adversarial design choices such as histograms bin sizes [2] or axis bounds [3] 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 [4] or bivariate data [5] 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” [6] (charts that appear to convey a particular message that disappears on closer inspection), and investigated testing regimes [6] and visual augmentations [7] that can surface these mirages or other errors in useful ways.

Connected to my work on deceptive and misleading visualization (what to avoid doing as designers of visualizations) is the positive project of establishing guidelines, principles, and practices for **virtuous visualization**. It is my contention that *all* visualization research has ethical importance, and I have attempted to use frameworks like virtue ethics to lay out our duties and responsibilities in this space [8], 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). I have applied these principles in public speaking, organizing, and in scientific communication to argue for more equitable interdisciplinary work in the digital humanities [9], more stringent standards for visualizations in the COVID-19 pandemic [10], and the need for a stronger focus on social good in academic visualization [11].

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 building up a design language around visualization "linting" or "error checking." This work will also involve building up a stronger **theoretical grounding** for visualization, from clarifying fuzzily defined or pragmatically unhelpful terms like *visualization literacy* [12] to better articulating the roles of visualization designers.

Communicating Uncertainty

Uncertainty is an inescapable part of data but is rarely visualized, for instance because of the presumed lack of statistical expertise in the audience, an unwillingness to muddle an already fraught decision-making process with perhaps unnecessary information (as with the perhaps apocryphal quote attributed to LBJ: "Ranges are for cattle. Give me a number") or the sheer complexity of uncertainty information. 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, this 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.

A common choice for displaying uncertainty is to show a bar chart with error bars. In a crowd-sourced study, I discovered two biases with this encoding [4]. Firstly, the bar itself divides the chart into regions "inside" and "outside" the visual container of the bar. Viewers perceive outcomes that occur within the visual area of the central bar as more likely; this causes an asymmetric interpretation of the uncertainty of values. Secondly, although error bars are usually generated from procedures that rely on a *continuous* distribution, error bars create a *binary* impression that an outcome is either inside or outside the error bar (which may have very little to do with statistical significance or likelihood). I altered and tested two visualization techniques for showing mean and error, violin plots and gradient plots, which encode values in a continuous and visually symmetric way. I was able to confirm in experiments that these alternate encodings are still as easy to interpret as bar charts with error bars but are less susceptible to associated biases.

Another issue with uncertainty information is that it can be very tempting to ignore the uncertainty in our data when making decisions: for instance, we may interpret a candidate who is ahead in the polls as a sure bet in the actual election, regardless of the volatility in the polling data. My work on Value-Suppressing Uncertainty Palettes [13] is an attempt to make people more mindful of uncertainty, especially in decision-making. VSUPs are a form of bivariate map that reduce the number of categories as uncertainty increases, acting somewhat analogously to statistical effects tests in that they prevent people from speculating about minute differences when variability is too high for such differences to be reliable. 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 [14] 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.

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 [15], and comparing means and lines of best fit in scatterplots [5] [16]. However, in many cases, the best design for estimating aggregate statistics is not always the best for estimating point values, and vice versa [17]. "Color weaving" [15] is an example of techniques we have developed to support aggregate, rather than point, tasks. Color weaving relies on the local permutation of pixels in a heatmap to highlight group, rather than point, statistics. For instance, the noise of a local region of the heatmap corresponds to variance, and the perceived hue of a region corresponds to average value.

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 [2], improved "robust" scagnostics [18] (diagnostic visual and statistical features of interest in scatterplots) that more closely align with human judgments, and Bayesian "surprise maps" [19] that highlight statistically informative regions of maps.

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.

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