Implicit Uncertainty Visualization: Aligning Perception and Statistics

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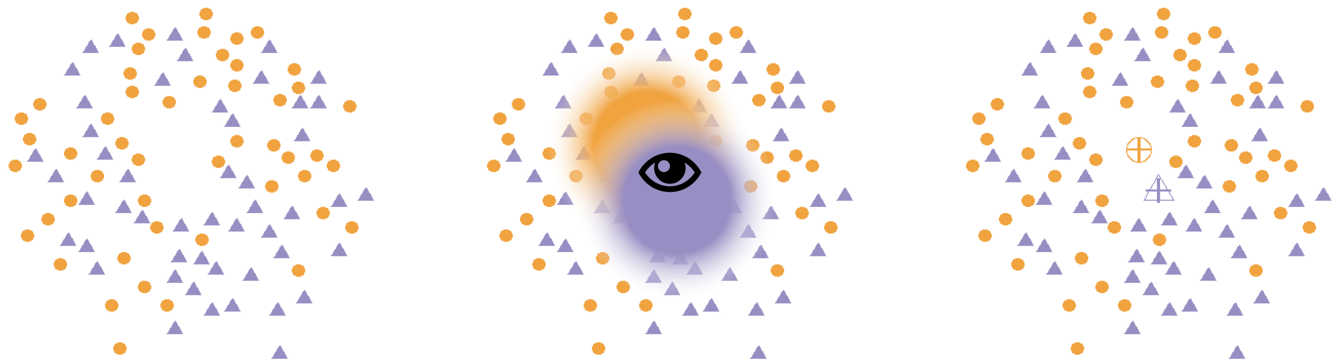

(a) Unadorned Visualization (b) Perceptual Estimation (c) Uncertainty-Aware Decision

Fig. 1: The implicit uncertainty visualization pipeline. Given these samples, which class of points is likely to have a higher average value, the orange or purple class? Humans are capable of estimating aggregate statistics from collections of objects. Viewer confidence in these perceptual estimations is modulated by many properties that are relevant for uncertainty quantification, such as difference in means and variance. Thus, *without the explicit visualization of uncertainty information*, viewers can both make *decisions* about data as well as estimate the *uncertainty* present in such decisions.

Abstract— In this work we present a brief argument for *implicit uncertainty visualization.* Instead of building complex models of quantifications of uncertainty in data, we rely on how viewers perceive aggregate information in visualizations to act as a proxy for these models. This perceptual uncertainty can take into account outliers and trends which might otherwise be difficult to quantify. Implicit uncertainty visualization also changes the design problem of how to visualize and communicate every relevant variable for uncertainty to a potentially simpler one: how to encode the data itself to make the perceptual extraction of summary statistics as easy as possible.

Index Terms—Uncertainty, perceptual psychology, visual statistics

1 Introduction

The visualization of uncertainty tacitly requires quantifying uncertainty. This quantification can be as simple as an additional per-datum confidence value, or as complex as a high dimensional model of error across the entire dataset. There are severe consequences to performing this quantification incorrectly. If our quantification is too simplistic then we may be blindsided by factors which are highly important for our inferences but excluded from our initial calculations. If our quantification is too complex we not only risk overfitting but also lose the ability to fluently communicate data to users who may not have the expertise in statistics to interpret our models. There are also design considerations which defy easy answers: how do we unify the "data map" (the data *per se*) and "uncertainty map" (the derived quantified uncertainty) [9] in our visualizations?

In this position paper we argue that there exists a viable alternative to the explicit visualization of quantified uncertainty: namely, *implicit* uncertainty visualization, where designers rely on the perceptual and cognitive uncertainty of viewers as a proxy for other forms of uncertainty modelings. Key to this approach is the capability of viewers to estimate statistics of interest from visualizations of the underlying data.

As a motivating example, assume with have a scatterplot with two classes of sampled points. A viewer might compare the sample means of the two classes, and use that comparison to drive an inference about the two classes in the real world. We can compute various values (the difference between sample means, variance, sample size, &c.) which contribute to a model of uncertainty for this task. Designers might choose which uncertainty models or relevant model variables to explicitly encode. For instance, a designer might choose to use dots representing the sample mean, and error bars representing some uncertainty about the spread of the means. However, viewers are capable of comparing sample means in scatterplots with high accuracy *without the designer explicitly encoding any information beyond the points themselves* [7]. Many of the variables which contribute to the ease with which viewers extract these means are the same as those which would contribute to explicit uncertainty quantification (for instance difference in means, or the spread of the points). In effect the viewer is in this case is being trusted to build their own uncertainty model without the explicit intervention of the designer. Figure 1 visually illustrates this process.

At first glance this approach might seem counterintuitive or even harmful: if we already know the statistics of interest, why not explicit visualize these statistics rather than rely on the viewer to esti-

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mate the uncertainty? Aside from the practical problems of providing distinct visual encodings for every single potentially useful statistic or model, and the difficulty of communicating the meaning of some of these more complex or esoteric values to the viewer, we believe there are additional benefits to taking the implicit rather than explicit approach. Some of these benefits are measurable through traditional time and error evaluation, for instance the ability of viewers to overcome insufficiently nuanced model building by, for instance, detecting and ignoring outliers. Others benefits are more qualitative: viewers might be more trusting of an uncertainty model if it is, in essence, a model they constructed by themselves, rather than one presented by the designer.

While naturally there are situations where the implicit approach to visualizing uncertainty is not appropriate (for instance, if the data are too large or complex for the human visual system to reliably estimate the relevant statistics), we believe that:

1. Situations where designers can rely on implicit uncertainty visualization to communicate uncertainty are common. In many cases we can rely on implicit uncertainty to perform just as well as more traditional uncertainty visualization techniques.

2. Designers can design for implicit uncertainty, just as it is possible to design for other viewer responses such as serendipitous discovery [10].

2 Implicit Uncertainty Visualization

Viewers have broad capabilities when it comes to statistical comparisons: with the proper encoding, viewers can compare means, detect outliers, estimate trend, and calculate many other aggregate statistics from visualizations [1, 6]. These capabilities are often rooted in basic perceptual machinery in how we store information about collections of visual objects [2]. This means that viewers can make use of aggregate statistical information without explicit statistical knowledge.

In some cases visual inspection can be *more* sophisticated than some statistical techniques. Anscombe's quartet is a famous example of datasets which have similar summary statistics, but which are immediately visually recognizable as different. By in essence passing off the problem of modeling information to the perceptual system, we relieve the burden of having to design and communicate complicated statistical models to viewers. This capacity for sophisticated model building and pattern recognition can be exploited for decision-making tasks. For instance "graphical inferences" can function as a sort of "visual t-test," letting non-statisticians assess the presence and strength of patterns that might be difficult to explain verbally or quantitatively [12].

The accuracy with which viewers estimate aggregate information, and (more importantly) the *confidence* they have in these estimates, is modulated by many of the same factors as in uncertainty quantification. For instance, the visual comparison of sample means is modulated by (at least) variance and mean difference [5], as are quantitative comparisons such as significance testing.

3 Designing for Implicit Uncertainty

Not all visualizations equally support, or even afford, the estimation of aggregate information (see [1] for a more thorough discussion of these affordances). Deciding on what encoding to use to represent the data in a way that viewers can employ implicit uncertainty visualization requires many of the same weightings of factors and tasks analyses that are part of more traditional uncertainty visualization. Through careful experimental design, designers can measure how different variables and encodings are connected to viewer confidence in decisions [3].

As implicit uncertainty visualization relies on perceptual rather than statistical machinery, there is also the problem of perceptual and cognitives biases which might skew judgments of uncertainty [11]. Even if designers do not explicitly encode particular aggregate values relevant to uncertainty, it might be necessary to make tweaks to the display of the underlying data to assist in de-biasing (see [4] for an example of such a tweak, or [8] for examples of how different visualizations choices effect decision-making under uncertainty).

4 Conclusion

Implicit uncertainty visualization may have the appearance of inaction, of doing nothing. However, we believe that choosing not to explicitly encode uncertainty information is an informed choice, a strategy designed for a specific class of datasets and tasks. Deciding to let viewers bear the brunt of estimating their own certainty requires nuanced designs; the choice of how to present data, even without adornment, can create measurable differences in certainty.

The research project ahead of us is to delineate when we can trust viewers to create their own uncertainty models, and when designers must explicitly intervene. Already empirical efforts seem to indicate that viewers of visualizations are good "visual statisticians" for a variety of estimation, comparison, and inferential tasks. Harnessing these abilities offers an alternative to traditional uncertainty visualization that avoids many of the major drawbacks in uncertainty quantification.

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References

[1] D. Albers, M. Correll, and M. Gleicher. Task-driven evaluation of aggregation in time series visualization. In *Proceedings of the 2014 ACM annual conference on Human Factors in Computing Systems*, pages 551–560. ACM, may 2014.

[2] D. Ariely. Seeing sets: Representation by statistical properties. *Psychological Science*, 12(2):157–162, 2001.

[3] M. Correll and M. Gleicher. Error bars considered harmful: Exploring alternate encodings for mean and error. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):2142–2151, 2014.

[4] M. A. Correll, E. C. Alexander, and M. Gleicher. Quantity estimation in visualizations of tagged text. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 2697–2706. ACM, 2013.

[5] G. Fouriezos, S. Rubenfeld, and G. Capstick. Visual statistical decisions. *Perception & Psychophysics*, 70(3):456–464, 2008.

[6] J. Fuchs, F. Fischer, F. Mansmann, E. Bertini, and P. Isenberg. Evaluation of alternative glyph designs for time series data in a small multiple setting. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 3237–3246. ACM, 2013.

[7] M. Gleicher, M. Correll, C. Nothelfer, and S. Franconeri. Perception of average value in multiclass scatterplots. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2316 – 2325, dec 2013.

[8] O. Inbar. Graphical representation of statistical information in situations of judgment and decision-making. In *Proceedings of the 14th European Conference on Cognitive Ergonomics*, pages 265–268. ACM, 2007.

[9] A. M. MacEachren. Visualizing uncertain information. *Cartographic Perspectives*, (13):10–19, 1992.

[10] A. Thudt, U. Hinrichs, and S. Carpendale. The bohemian bookshelf: supporting serendipitous book discoveries through information visualization. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1461–1470. ACM, 2012.

[11] A. Tversky and D. Kahneman. Judgment under uncertainty: Heuristics and biases. *science*, 185(4157):1124–1131, 1974.

[12] H. Wickham, D. Cook, H. Hofmann, and A. Buja. Graphical inference for infovis. *IEEE Transactions on Visualization and Computer Graphics*, 16(6):973–979, 2010.