Uncertainty Literature Review

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1. Introduction

Think back to the last time you made some sort of data visualisation. What was the purpose of that visualisation? Was it to better understand your data? Was it to help you make a decision? Was it to to communicate that decision to someone else? Now think about the last time you expressed some form of uncertainty. Was it a set of numerical confidence intervals? Maybe they were expressed as a set of values in a table. Did you consider visualising your uncertainty instead? There are many stages in our analysis that benefit from the power of data visualisation, however this does not mean it is always done with success. Visualization is an important step in exploratory data analysis and it is often utilised to **learn** what is important about a data set. The importance of data driven discovery is highlighted by data sets such as Anscombe's quartet (Anscombe 1973) or the Datasaurus Dozen (Locke and D'Agostino McGowan 2018). Each of the pairwise plots in these data sets have the same summary statistics but strikingly different information when visualised. Anscombe quartet is shown in Figure 1, because describing the data is never the same as seeing it. Instead of having to repeatedly check endless hypothesis to find interesting numerical features, visualisations **tell** us what is important about our data. This powerful aspect of data visualisation is poorly or seldom used in later stages when we are communicating our findings, specifically with respect to uncertainty.

2. Defining Uncertainty

2.1 Uncertainty is goal dependent

Statistics is, at its core, the study of uncertainty. Therefore discussing uncertainty visualisation a a separate sub domain to "normal" data visualisation is inherently confusing. What is typically meant by "uncertainty" visualisation is "noise", that is, we want to present some signal cushioned by its natural variance. Unfortunately, this distinction between "signal" and "noise" is entirely goal dependent.

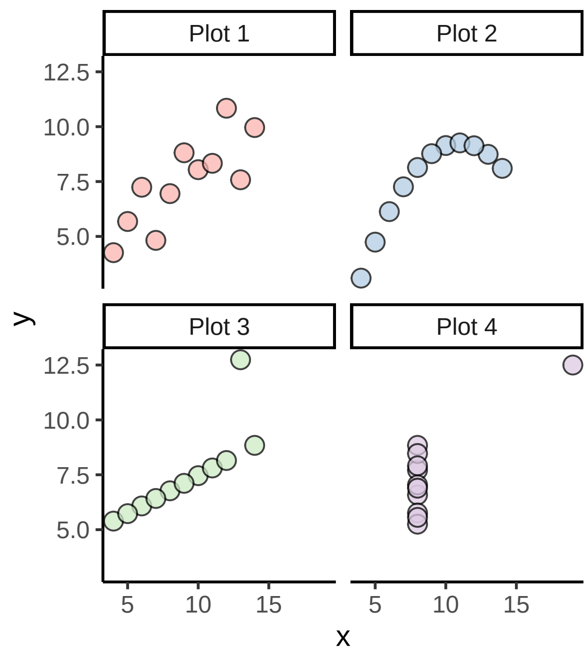

Figure 1: The four scatter plots that make up Anscombe's quartet. The four scatter plots are visually distinct but have the same mean, standard deviation, and correlation. The visualisation highlights the importance of plotting your data to identify interesting features that are hidden by other summary statistics.

The entire process of data analysis, from deciding what should be observed as data through to communicating that data in a plot is governed by human decision and the goal of analysis. This conceptual way of thinking about uncertainty has been rattling around in the philosophical discussions of uncertainty for quite a while.

Otsuka (2023) points out that the philosophy of statistics is build upon taking real world entities and boiling them down into probabilistic objects and this ontological process is largely dependent on our goals. For example, when we record coin flips we typically want to model the behavior with a binomial distribution, so we ignore the outcome of a coin landing on its side despite the fact it is a real world possibility.

Meng (2014) shows that the entire concept of signal and noise are relative and the noise for one goal can be the signal for another. This break down is done by considering the data source, the "resolution" of the problem and data, and the phases involved in the analysis. Meng (2021) highlights that data needs to be treated as an output from another process rahter than an value neutral input.

Carlin and Moreno-Betancur (2023) highlights a range of pitfalls that come up frequently when statisticians use regression models and they connect these pitfalls to the teaching of statistical methods as goal agnostic tools. Carlin and Moreno-Betancur (2023) suggest that every research question belongs to one of three distinct types: descriptive, predictive, and causal, each of which has its own appropriate statistical methods.

Amar, Eagan, and Stasko (2005)

Since uncertainty visualisation is largely goal dependent, hard and fast uncertainty visualisation rules are difficult to design. Additionally communication of statistics cannot ignore the ontological process discussed by Otsuka (2023) because the goal of communication is to map those statistical objects back to real world entities.

After all, the distinction between uncertainty and signal is largely determined by the goal of an analysis rather than any inherent properties of our data.

This leads to several unanswered questions. Is our goal in uncertainty communication to acknowledge and convey the inherrent randomness that exists in all statistical calculations and models? Is it to supress signal that could be the result of random variance? Is it to find the best way to convey the mass function of a random variable? A survey of the literature will leave the answers to these questions unclear, however this inherrent issue has not gone unnoticed.

- Should the visualisations change based on these goals?

need for task based understanding - several review papers acknowledge this issue is causing - **papers that talk about task specific stuff** - This problem of a task based philosiphy extends all the way back to philisophical uncerstandings of statistics and variance. - **notes from the Xiao-li Meng papers** - **notes from john paper** - While the statistics side brings up the purpose of a model or estimate for a philisophical consideration, it is a real, practical, and urgent problem for uncertainty visualisation. - **go through papers with endless different goals - review paper that has an entire paragraph discussing differnet findings for box plots based on the task**

need for statistics links - (no visual distinction between sample/pop variance) Bella et al. (2005) found that most participants were ignorant to the fact that error bars are used for both confidence intervals and standard error bars, two wildly different indicators of precision. (**also the paper sherry sent me**)

Uncertainty can only be defines within a specific problem. There is not a universal motivation agnostic "uncertainty" similarly as there is no motivation agnostic "signal". Therefore, in our following definitions of uncertainty, we will assume that the uncertainties we discuss are connected to some specific question.

2.2 Taxonomies

2.2.1 Taxonomies of Uncertainty

More commonly uncertainty is defined using a taxonomy rather than a strict definition.

Figure 2 is an illustration of the taxonomy presented by Walker et al. (2003). In this taxonomy, there are three things we need to consider for each "uncertainty" we encounter through the modelling process. First, we need to consider the source of the uncertainty. Is this uncertainty coming from inaccurate measurements or a poorly defined model? This is the *location* of the uncertainty. Second, consider how well you can quantify this uncertainty. Do you know exactly how much measurement error there is in each observation or are you not even aware if there is a measurement error? This is the *level* of your uncertainty, and it ranges from discrete to total ignorance. Finally, consider how this uncertainty came into existence. Is it a result of a naturally random process (epistemic) or is it due to imperfect information and could be improved (aleatory). This is the *nature* of your uncertainty. Walker et al. (2003) then goes on to describe mapping our uncertainty in a 3D space that is defined by its location, level, and nature, but I think the taxonomy is more easily understood as a series of questions we need to consider when we are trying to quantify uncertainty.

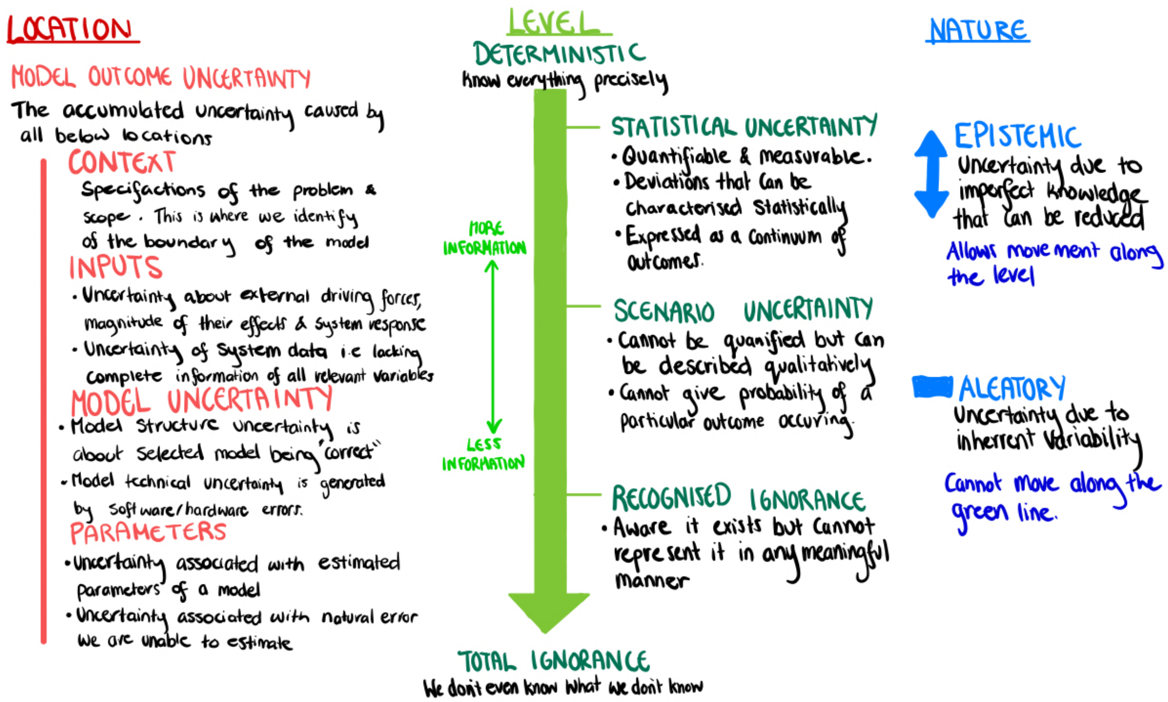

Figure 2: Depicts an illustration of the taxonomy described in Walker et al. (2003). From right to left the drawing shows the location, level and nature of uncertainty with examples of that category underneath. A specific source of uncertainty from the location can be mapped to a level of ignorance that can increase or decrease (i.e. moving up or down the green line) depending on the nature of the uncertainty. Identifying the location, level and nature of your uncertainty allows you to better understand it.

2.2.1 Taxonomies of Visual Uncertainty

3.General Attitudes...

3.1 Towards uncertainty in general

3.2 Towards uncertainty visualisation

4 Uncertainty Visualisation Best Practices

In this section we will first go over the current state of uncertainty visualisation research, which is currently a collection of evaluation studies and review papers, and discuss what it is doing well and what could be done better. Following that, we will provide general reccomendations from the literature.

4.1 The current landscape of uncertainty visualisation research

In section 2.1 it was mentioned that uncertainty must be defined within a specific motivating question, otherwise it inherently does not make sense. A large difficulty with the uncertainty visualisation evaluation studies is that this rule is not followed. There are a shockingly large number of evaluation studies that seem to pay no attention to the information that is relevant to the question they are asking, and show participants a selection of seemingly random visualisations from a statistical point of view.

- inferential uncertainty and outcome uncertainty ARE NOT THE SAME THING??? they visualise DIFFERENT DISTRIBUTIONS

We define two primary motivations for uncertainty visualisation. 1) To prevent deterministic conclusions from a random signal (uncertainty as noise) 2) To convey information about a variance, probability, or other random event (uncertainty as signal)

4.2 Take aways from the literature

5. Future work/Conclusion

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