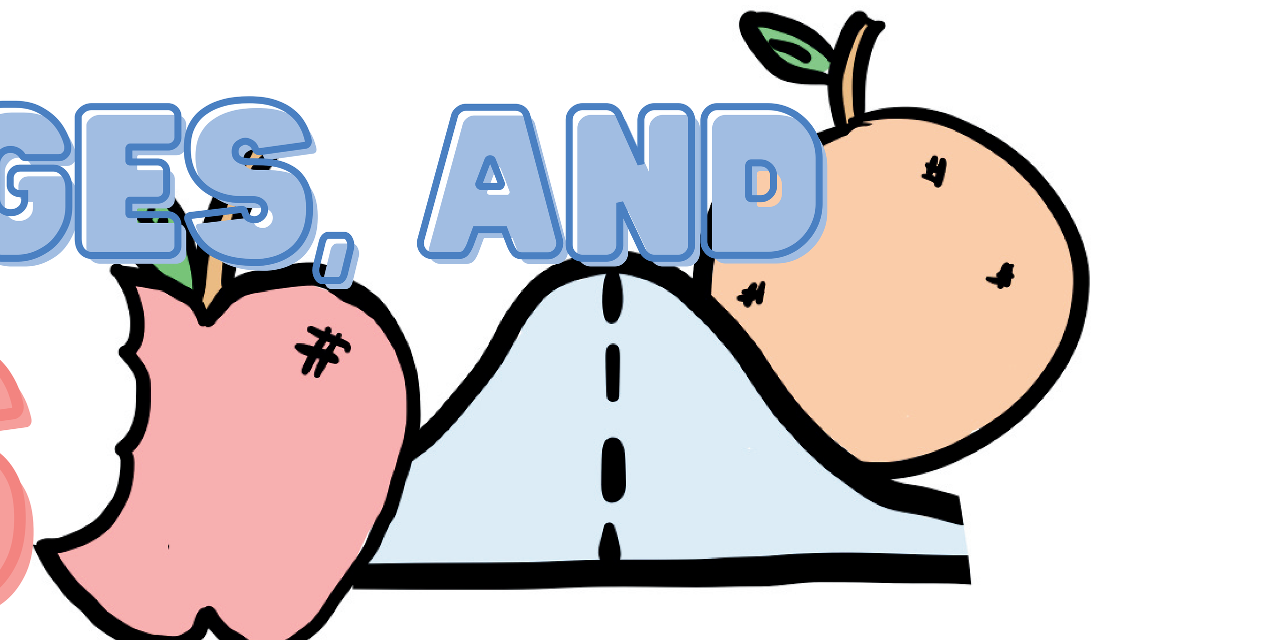
PLOTTING APPLES, ORANGES, AND DISTRIBUTIONS



HARRIET MASON: DIANNE COOK: SARAH GOODWIN: URSULA LAA: EMI TANAKA

IS VISUALISING UNCERTAINTY IMPORTANT?

- To make an accurate decision using an estimate of a numerical quantity, a thorough understanding of the uncertainty around that estimate is needed.
- The most effective expression of uncertainty information is through visualisation, which provides a more complete picture of risks than numerical summaries alone [5, 7].
- Presenting uncertainty information improves decision making and increases trust in predictions, both experimentally [4, 8, 10, 12] and in practice [1].

DO WE VISUALISE UNCERTAINTY ?

- Uncertainty information is complicated and difficult to express, so it is not conveyed as often as it should be.
- A survey found that only a quarter of visualisation authors included uncertainty in 50% or more of their visualisations [6].
- The most common reasons authors gave for omitting uncertainty information when it was relevant to the visualisation are provided in Figure 1 [6].

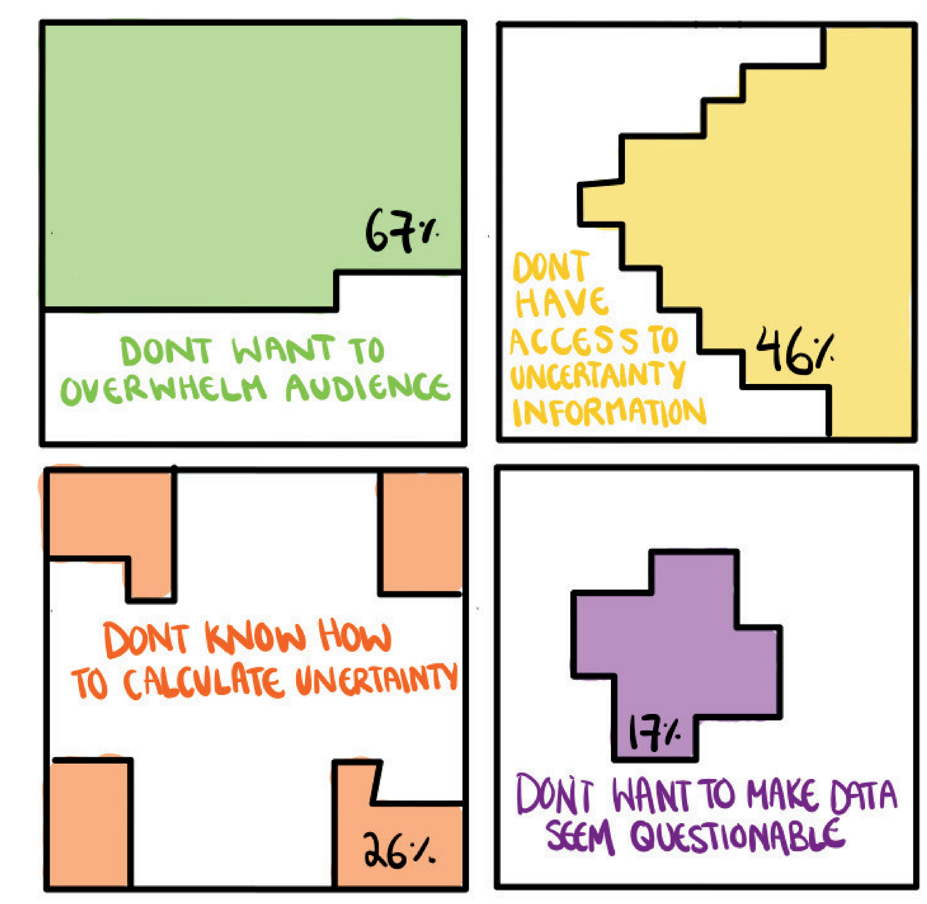
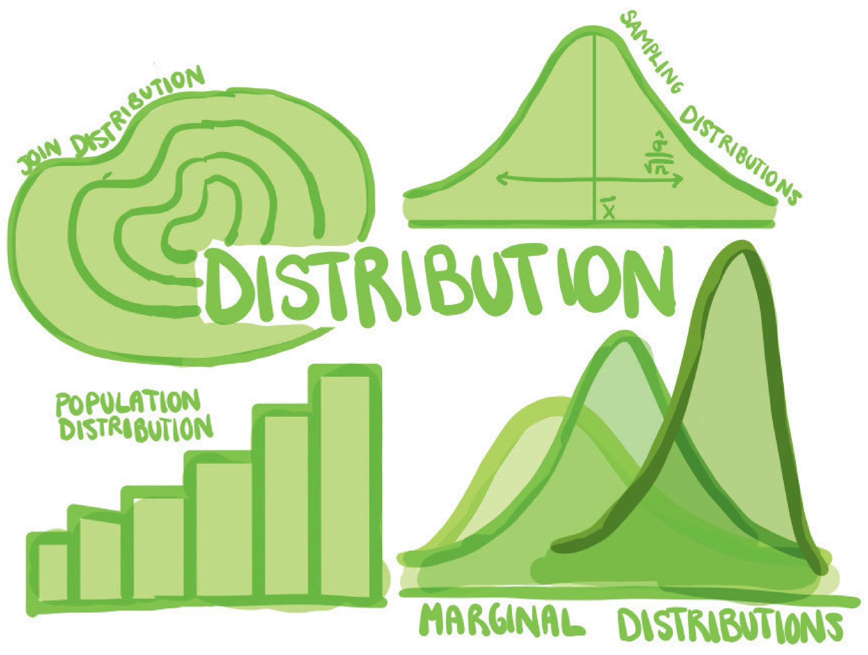


Figure 1: Common reasons authors don't visualise uncertainty

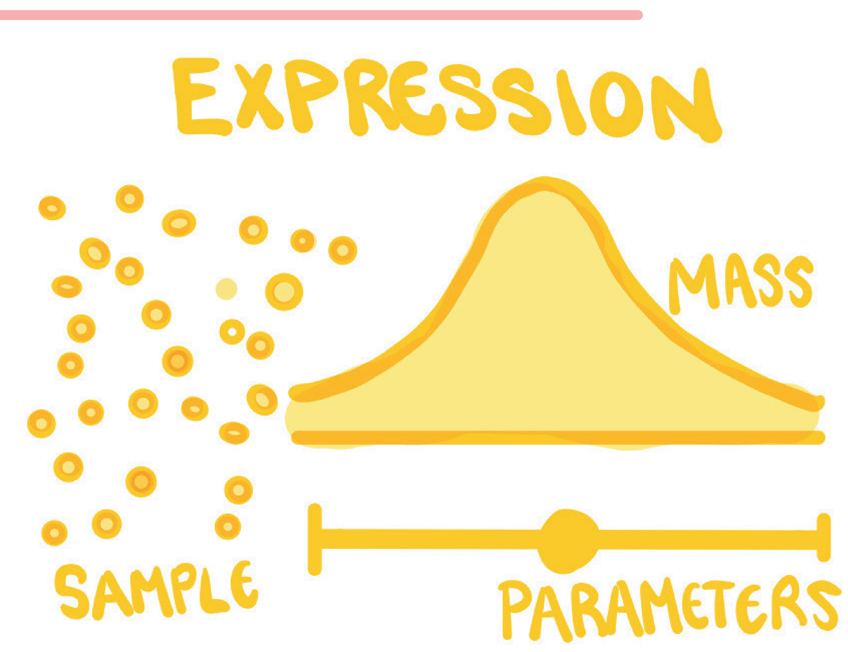
A TAXONOMY OF VISUAL UNCERTAINTY INFORMATION

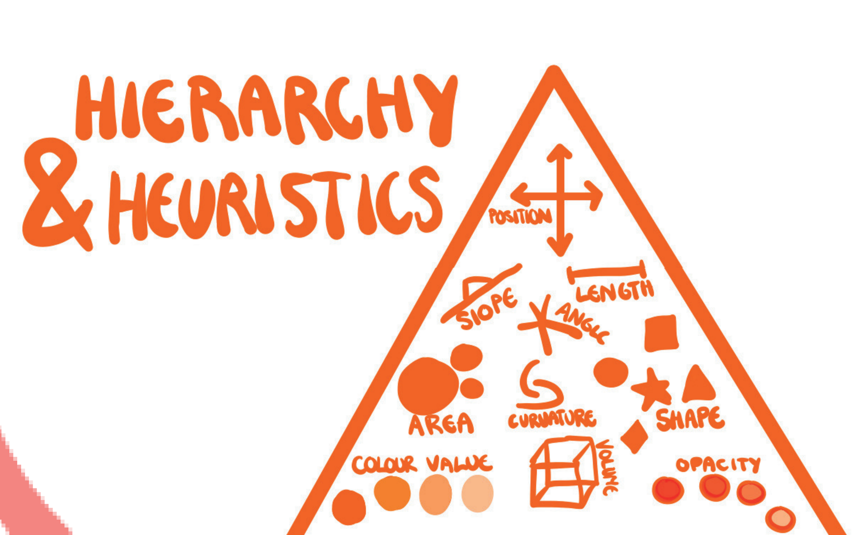
Each piece of "information" contained in a plot can be organised according to the distribution it represents, how it is expressed, and how easily that information can be extracted from the plot. One plot may contain multiple pieces of information. Figure 2 provides an example of how to apply this taxonomy



- **Distribution** the most important aspect of the taxonomy as it highlights the importance of identifying and displaying the most relevant variable or relationship.
- Very often, a single marginal distribution is expected to answer a wealth of questions related to uncertainty, even when that distribution is statistically irrelevant to the question.
- For example, error bars are often considered poor practice by researchers due to being unable to communicate uncertainty that it does not express [2].

- **Expression** highlights which feature of the aforementioned distribution is visualised.
- There are three common ways to express these distributions; its mass-specific parameters, or a real or simulated sample. These three expressions are depicted in Figure 3.
- Different expressions of a distribution seem to be better at answering different questions. For example, a sample is most appropriate to answer questions about the frequency of an outcome.



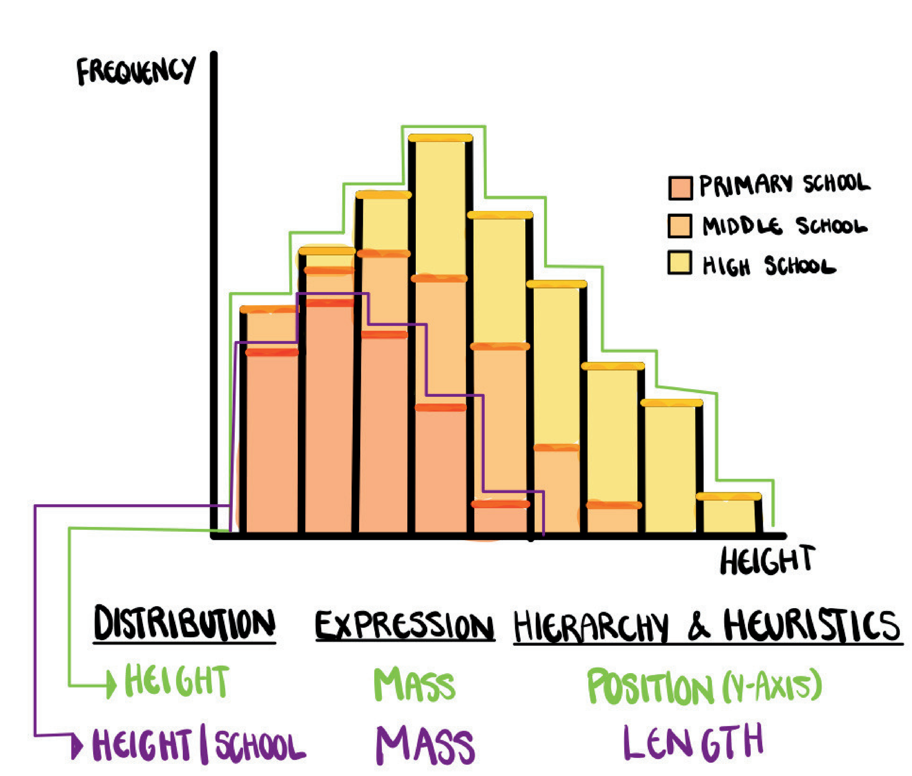


- **Hierarchy & heuristics** identifies how easily a user can extract the information depicted in a graphic.
- Hierarchy identifies how efficiently information can be extracted using elementary perceptual tasks [3]. Heuristics leverage the existing mental connections we have between visual features and variables.
- For example, uncertainty can be intuitively mapped to fuzziness where more fuzzy means more uncertain [11].

HOW DO WE FIND THE BEST VISUALISATION?

- To visualise uncertainty without overwhelming the audience, we need to know which visualisations are the most effective.
- Uncertainty visualisations are often compared to each other in experiments but in order to compare plots, they need to contain the same information [3] and no additional irrelevant information [9].
- There is currently no reliable or standard approach to assess the information contained in a graphic.
- Since there are numerous ways in which uncertainty information can be quantified and expressed, experiments comparing uncertainty visualisations suffer disproportionately from this issue.
- A system for identifying and organising the information contained in an uncertainty visualisation could alleviate this problem.

Figure 2: An example of how the taxonomy can be applied to identify the information in a stacked bar chart.



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Embodied Visualisation group

MONASH University

Contact Information
Harriet Mason
Monash University
harriet.mason1@monash.edu