

Visualizing Unquantifiable Uncertainty in Drug Checking Test Results

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ABSTRACT

We propose a visualization design space for representing unquantifiable uncertainty in percent composition drug checking test results using pie and cake charts. The design space generates alternatives for use in a visual drug report to facilitate decision-making concerning drug use. Currently, this communication does not capture the uncertainty in drug checking tests, leading to poor and potentially harmful decisions. The design alternatives aim to empower people who use drugs and facilitate harm reduction efforts. Our visualizations may apply to other drug checking services and to scenarios where end users need to understand unquantifiable uncertainty.

1 INTRODUCTION AND BACKGROUND

This paper explores a visualization design space for representing unquantifiable uncertainty of percent composition drug checking test results, where percent composition refers to the proportional contribution of a substance to a drug sample's makeup. In collaboration with a drug checking service team, we aim to produce a visual report that will support decision making by people who use drugs (clients). People who use drugs (clients) cannot be certain of drug composition because recreational drugs are un-monitored. Opioids—particularly Fentanyl and its potent chemical analogs—were responsible for 3,286 opioid overdose deaths in Canada between January 2018 to September 2018, of which 93% were ruled accidental¹.

Currently, drug checking test results are presented to clients during in-person conversations with harm reduction and chemical analysis staff. However, mistakes in regards to percent composition like Fentanyl composition could lead to overdose, injury, or death. For example, a drug checking researcher recounted how one client confused a test result of 91% confidence that a drug sample contained caffeine with 91% of the sample being composed of caffeine.

A global review of drug checking efforts [1] lists eight methods of communicating drug test results. None we saw a) present uncertainty in their reports, b) expose or resolve discrepancies between tests, or c) provide Fentanyl-specific indicators. These three aspects are, however, critical to our collaborating drug checking service.

Creating decision-support mechanisms which present complex drug content information is a broad goal. We describe the challenges of communicating unquantifiable uncertainty in drug checking test results; we propose a design space for showing unquantifiable uncertainty which decomposes proportional charts into six dominant visual marks; and we discuss how this design space can be further explored to this end. This abstract is limited to design explorations of percent composition visualizations displaying unquantifiable uncertainty, and we follow a design study methodology [10].

Characterizing Uncertainty. Walker and Marchau describe four levels of uncertainty within decision support systems [12]. Level

1 and 2 are shallow uncertainty, and medium uncertainty, wherein uncertain alternatives are somewhat describe-able. Level 3 and 4 are deep uncertainty, and recognized ignorance, where little to nothing is known of uncertain alternatives.

Drug checking results contain both what Potter et al. [7] call aleatoric and epistemic uncertainty. *Aleatoric uncertainty*—or statistical uncertainty—represents unknowns that arise from variations in measurements. Aleatoric uncertainty within our data is produced by chemical analysis processes which introduces level 3 uncertainty. *Epistemic uncertainty* represents unmitigated unknowns that arising from practical knowledge or measurement limitations. The test results also contain epistemic uncertainty, which leads us with level 4 uncertainty, or as we call it, unquantified uncertainty. However, providing uncertainty information in drug checking test results is critical for the described safety and, therefore, ethical reasons.

Visualizing Uncertainty. Research in uncertainty visualization highlights the risky exclusion, and beneficial inclusion, of uncertainty in data-driven decision making activities [9]. Correll [4] declares that, as ethically responsible visualization design researchers, “*We ought to visualize hidden uncertainty*”.

Pie charts display our percent composition data well and are highly recognizable. However, given the shortcomings of pie charts, we include a complementary alternative chart: the *cake chart* [2], which is essentially a linearized pie chart.

Olston and Mackinlay [6] introduce a technique called *ambiguation* we adapt to displaying unquantified uncertainty in proportional charts. Combining ambiguation and the application of Bertin's visual variables [3] (and extensions) to uncertainty visualization [5] we conducted design iterations to identify which visual variables we can manipulate to convey unquantified uncertainty.

2 A DESIGN SPACE FOR ENCODING UNQUANTIFIABLE UNCERTAINTY IN PERCENT COMPOSITION VISUALIZATIONS

Using the five design sheets methodology [8] to consider and reflect on design concepts, we distill six visual marks to visually encode uncertainty in both pie charts and cake charts, the visual variables useful for encoding uncertainty on separate visual marks, and demonstrate design space usage to generate uncertainty representations.

We identify visual marks that a) facilitate sharing design ideas between pie and cake charts, and that b) can be used to convey unquantified uncertainty, and identify two high-level graphical elements common to both pie charts and cake charts: a **percent axis** and a **segmented chart**, focusing on the segmented chart.

Fig. 1 shows our decomposition of pie and cake charts into the following visual marks: segment **labels**, **magnitude edges**, **boundary edges** and **areas**. **Segment labels** display (in written form) segment information such as names and numerical values. **Magnitude edges** are the edges of each segment that are proportionally sized to the percent contribution of the segment. Note that in pie charts the inner magnitude edge of each segment has length zero and the outer magnitude edge is of arc length. **Boundary edges** are the edges of each segment that are perpendicular to the percent axis, delimiting the segments. **Segment areas** are the inside shape of segments, delimited by magnitude edges and boundary edges.

Visual variables such as color, length, width and pattern can be used to encode uncertainty on each of the visual marks that constitute the segmented chart, as shown in Fig. 1. Though not shown here,

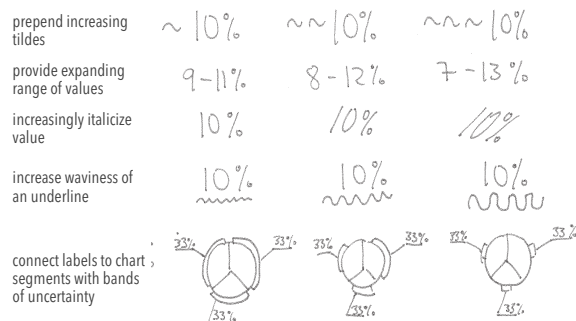
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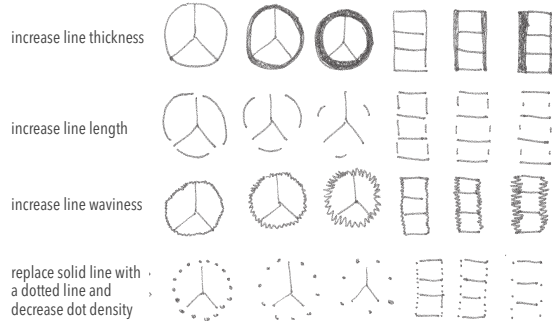
‡e-mail: mstorey@uvic.ca

¹<https://infobase.phac-aspc.gc.ca/datalab/national-surveillance-opioid-mortality.html>

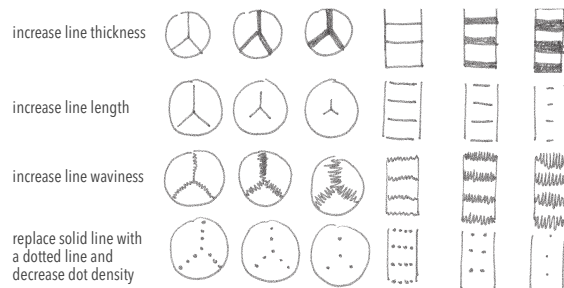
A: LABEL MARK VARIATIONS



B: MAGNITUDE EDGE MARK VARIATIONS



C: BOUNDARY EDGE MARK VARIATIONS



D: AREA MARK VARIATIONS

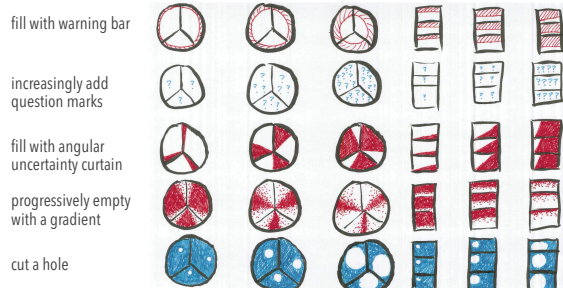


Figure 1: We show varying visual variables of label, magnitude edge, boundary edge, and area visual marks at low, moderate, and high levels.

combinations of changes to single visual marks in a chart, and to multiple visual marks across a chart were performed as well.

3 DISCUSSION, FUTURE WORK AND CONCLUSION

Decomposing proportional charts into visual markings enables us to manipulate visual variables controlling mark representation. We systematically explore this design space by varying visual marks via visual variables to introduce ambiguity within chart segments.

As was expected from the literature, some design variations convey unquantified uncertainty without disrupting chart readability, while others reduce chart readability and/or poorly depict uncertainty. We agree that pie chart angles are poor indications of segment size [11], and that some signification concepts more closely represent uncertainty within data than others [5].

As visualization researchers working within drug checking contexts, we must consider ethical and safety concerns if we are to empower people who use drugs to make as informed as possible decisions about their drug use. We hope effective unquantified uncertainty designs generated out of this design space could transfer between drug checking services, and to non-drug checking decision-support scenarios dealing with unquantified uncertainty.

Our future work involves further iterations in our design study, implementing and deploying selected designs into the drug checking service reports, and evaluating alternatives in lab and field settings. To conclude, determining “best” solutions is not straight forward due to the sensitive nature of this harm reduction application, and effectively visualizing unquantifiable uncertainty within percent composition drug checking test results is a challenging, but worthwhile, balance to find.

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