Revealing Uncertainty for Information Visualization

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ABSTRACT

Uncertainty in data occurs in domains ranging from natural science to medicine to computer science. By developing ways to include uncertainty in our information visualizations we can provide more accurate visual depictions of critical datasets. One hindrance to visualizing uncertainty is that we must first understand what uncertainty is and how it is expressed by users. We reviewed existing work from several domains on uncertainty and conducted qualitative interviews with 18 people from diverse domains who self-identified as working with uncertainty. We created a classification of uncertainty representing commonalities in uncertainty across domains and that will be useful for developing appropriate visualizations of uncertainty.

Categories and Subject Descriptors

H.5.m [**Information Interfaces and Presentation (e.g., HCI)**]: Miscellaneous.

General Terms

Experimentation, Standardization.

Keywords

Information visualization, uncertainty visualization, qualitative research, user-centered design.

1. INTRODUCTION

When information is shown in a computer interface, it often appears absolute. The native machine or language data types used to store numerical data employ a very high level of precision. There is no sense of the level of certainty in that data or the degree to which the data is only possibly true. However, in reality data is rarely absolutely certain. By developing ways to make the uncertainty associated with data more visible, we can help users better understand, use, and communicate their data.

There has been a significant amount of research on uncertainty in fields such as information theory [5] and probabilistic reasoning [12]. However, these fields focused on how to compute uncertainty by developing a formal mathematical method. In our study it became clear that uncertainty is a complex concept that occurs in various domains and does not always appear as a quantifiable probability.

Work on uncertainty within domains can inform the design of visualizations, but unfortunately uncertainty is referred to inconsistently within and among domains. Just within the domain of geography, for example, a previous review of models of information uncertainty resulted in an outline of challenges for future research [8]. These challenges include, "understanding the components of uncertainty and their relationships to domains, users, and information needs," "developing methods for depicting multiple kinds of uncertainty," and "developing methods and tools for interacting with uncertainty depictions." Within the amorphous concept of uncertainty there are many types of uncertainty that may warrant different visualization techniques. Before we begin to design these visualizations we need a better understanding of how users view uncertainty and how it is currently represented. To that end, we have reviewed existing work on uncertainty within a number of domains, created an initial classification of uncertainty, and empirically evaluated and improved upon the classification.

2. RELATED WORK

Much of the previous work on both the visualization of uncertainty and the classification of uncertainty occurs within isolated domains. The predominant consensus among papers on uncertainty appears to be that uncertainty has been defined many ways and is referred to inconsistently in a variety of fields. MacEachren *et al.* state, "Information uncertainty is a complex concept with many interpretations across knowledge domains and application contexts" [8].

2.1 Visualization of Uncertainty

Most research on visualizing uncertainty is found in geographic visualization, geographic information science, and scientific visualization. The main techniques developed include adding glyphs [14], adding geometry, modifying geometry [4], modifying attributes, animation [2], and sonification [7]. These techniques have been applied to a variety of applications such as fluid flow, surface interpolants, and volumetric rendering.

CandidTree shows two types of structural uncertainty based on the differences between two tree structures [6]. Olston and Mackinlay introduced visualizations to address two forms of uncertainty: error bars for showing statistical uncertainty and ambiguation for showing bounded uncertainty [10].

Unfortunately, most uncertainty visualizations are isolated efforts designated for a specific purpose. To move forward with the challenges of visualizing uncertainty and creating interfaces for interacting with uncertainty in data, we need a model of uncertainty that covers the needs of users in multiple domains.

2.2 Classification of Uncertainty

We began our research by examining the definitions and classifications of uncertainty developed within several domains for common themes and overlap. Within the domain of weather modeling, Pang and his colleagues have worked extensively on

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visualizing uncertainty in weather models [11]. Their model of uncertainty describes how uncertainty can be introduced at "acquisition," including issues with measurement or statistical variation; at "transformation," including any manipulation of data; or at "visualization." Within the domain of intelligence information analysts, Thomson *et al.* propose a typology of categories of uncertainty focusing on different types of uncertainty instead of sources of uncertainty [13]. Their categories include: accuracy/error, precision, completeness, lineage, currency/timing, credibility, subjectivity, and interrelatedness. One attempt to describe uncertainty outside any specific domain is a taxonomy of imperfect information, which includes "corrupt data/info," "imperfect presentation," "uncertainty," "info too complicated," "inconsistency," and "incomplete info" [3]. The taxonomy differentiates between uncertainty and concepts (e.g., incomplete info) that others (e.g., Thomson *et al.*) include within uncertainty.

In the domain of decision support and policy making, Walker *et al.* describe a way to convey uncertainty in a model to decision makers [14]. Their three dimensions of uncertainty include: location (context, model, or input), level (from deterministic to "total ignorance"), and nature (epistemic, meaning it could be clarified with more research, or variability, meaning uncertainty due to "inherent variability"). However, Norton *et al.* argue against this model by asserting that instead of seeing uncertainty as something additive that can be simplified to a level of uncertainty, we should view all the aspects of uncertainty associated with any decision [9]. This disagreement is an example of how epistemological differences between fields add to the difficulty of creating a unified classification of uncertainty.

Previous models of uncertainty have not been empirically evaluated and it is not obvious how to select between the models or integrate them into a single model.

3. CLASSIFICATION DEVELOPMENT

Based on our review of the literature on uncertainty from specific domains, we created our own preliminary classification of uncertainty spanning domains for the purpose of information visualization. We then refined our classification based on interviews we conducted with people from several different fields who encountered uncertainty in their own data.

3.1 Initial Classification

In the literature, we identified five common types of uncertainty discussed using different language in disparate domains. **Approximation** is often necessary in science and other domains, but it leads to uncertainty. Various techniques are used to attempt to measure or describe a phenomenon even when it cannot be measured or described with perfect precision. **Predictions** can be projections of future events, which may or may not happen. Prediction also is similar to developing an explanation of something that has already happened when the true explanation is not known. Model building is an example of a way to do prediction about the past or future. **Disagreement or Inconsistency** between experts in a field or across datasets is an indication of uncertainty. **Incompleteness** in datasets including missing data or data known to be erroneous also causes uncertainty. Lastly, **credibility** of data or of the source of data is another type of uncertainty described in the literature.

3.2 Qualitative Study of Uncertainty

To get a deeper understanding of uncertainty across domains, we conducted a formative interview-based study. We were particularly interested in gathering examples of uncertainty and learning how people currently represent and handle uncertainty. We then used the data to improve our classification.

3.2.1 Participants

We recruited 18 participants in the Greater Puget Sound area who self-identified as having aspects of uncertainty in their work. They came from both academic and industry settings including students, established researchers, and practitioners. Several participants worked in computer science with specialties including robotics, machine learning, databases, visualization, perceptual computing, and computer graphics. One participant was a former radiologist and other participants were from psychology, journalism, biology, bioinformatics, intelligence, bioengineering, and ecology.

3.2.2 Interview Methods

We conducted a 30-60 minute interview with each of the 18 participants individually. We took extensive field notes as well as audio recording. Some participants also provided screenshots or pointers to examples of uncertainty in their work. Interviews followed an interview guide, but were open-ended and exploratory. We began with open-ended questions about the uncertainty they encounter in their work. As they described uncertainty we asked for specific examples and asked them how they dealt with uncertainty. Towards the end of the interview we asked each person if they encountered disagreement, credibility issues, or incomplete data (if those issues had not previously been covered). We also asked participants to define uncertainty, asked them how they represented uncertainty or had seen it represented, and asked if they had seen any visualizations of uncertainty.

3.2.3 Analysis Methods

Within our team, we used affinity diagramming to collaboratively analyze our data [1]. This process began with individual thoughts and examples from the interviews broken out onto pieces of paper. The aim of this study was to evaluate and improve our classification. As we went through the pages, we tried to classify the thoughts and examples into our initial categories of uncertainty. When we discovered examples that did not fit our scheme we placed them in a new stack or adjacent to the stack with the closest fit. When we had multiple examples that did not fit into one of our existing classifications we attempted to redefine and iterate on our classification to accommodate the new type of uncertainty. About two thirds of the way through the data our classification stopped changing and the remaining examples fit into the new classification.

4. RESULTS AND DISCUSSION

We present our results in the form of an improved classification with descriptions of how the interview data guided the classification. One important concept introduced by our participants is the idea of levels of uncertainty. Visualizations showing levels of uncertainty could provide ways to show multiple types of uncertainty within a single dataset. We also present participants' definitions of uncertainty, how participants currently represent uncertainty, and what they do with uncertainty.

4.1 Definition of Uncertainty

Most participants had some difficulty providing a definition of uncertainty when asked, but there seemed to be agreement that uncertainty often happens in situations without complete knowledge. Participants used phrases like "imperfect knowledge," "inadequate information," and "lack of absolute knowledge" to describe uncertainty. Some participants saw uncertainty as a time when the probability of something is not 1.0 while others described it with more qualitative labels.

4.2 Classification of Uncertainty

One of the most important concepts resulting from our interviews is that multiple types of uncertainty are often associated with a single dataset and can be thought of as levels or layers of uncertainty. For example, Participant 5 described uncertainty about the measurements he got from scientists and then said that on top of that there was also "inference uncertainty" about the inference methods he chose. A few participants explicitly referred to "levels" of uncertainty. Participant 13 worked on computational photography and described the type of inference he used to try to remove blurring from images. He then distinguished uncertainty in the probabilistic inference from "another level of uncertainty" caused by noise in the sensor and lens variables. The sense of multiple kinds of certainty and different levels of uncertainty in a dataset or process are captured in our classification (Figure 1).

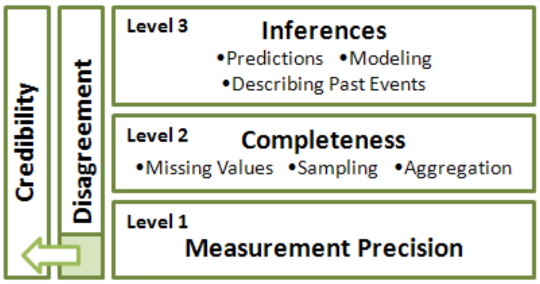

Figure 1. Improved classification showing layers.

4.2.1 Measurement Precision – Lowest Level

Uncertainty due to **imprecise measurements** came up frequently in our interview data and spanned domains. This category of uncertainty covers any variation, imperfection, or theoretical precision limitations in measurement techniques that produce data. Sometimes this imprecision is represented explicitly by a range that the true value is probably in (e.g., confidence interval). However, measurement precision uncertainty is often simply a data point that is known to be potentially flawed. In the example Participant 13 discussed above, there was measurement precision uncertainty from camera lens variability that was not constant enough to be modeled and adjusted for. He did not have a representation of certainty; instead, he had data points known to be somewhat uncertain.

4.2.2 Completeness – Middle Level

Completeness was an issue across domains as well. Some participants described **sampling** as a strategy for representing the values of some population. **Missing values** also represent incompleteness uncertainty. **Aggregating** or summarizing data in an irreversible way can also be a cause of uncertainty since once data has been summarized, information is lost and the data is no longer complete.

An important concept within completeness, that spanned domains, is **unknown unknowns**. Participant 18 distinguished the information you know (*known knowns*) from the information you know exists, but do not have (*known unknowns*) from the information you do not even know you are missing (*unknown unknowns*). The participants who discussed this distinction agreed that the *unknown unknowns* are the worst kind of missing information. When you do not know you are missing important information you are more certain than you should be.

4.2.3 Inference – Highest Level

Inference is a fairly broad category, spanning all types of modeling, prediction, and extrapolation. Inference has a tight relationship with decision-making: it is how data is infused with meaning and transformed into decisions. **Modeling** of any kind, ranging from probabilistic modeling to hypothesis-testing to diagnosis, falls in this category. For example, Participant 16 described the need to take a set of medical symptoms, either as a care provider or health consumer, and fit them into a model of illness. **Prediction** involves inferring future events by creating an abstraction of the causal relationship between current or past data and future occurrences. **Extrapolation** into the past, a complement to prediction, involves using data to try to recreate or make inferences about past events. For example, Participant 1 was interested in locations and paths of devices and people. He could use path data (inferred from location data) to try to identify where someone was in the past.

4.2.4 Disagreement – Spans Levels

Disagreement leads to uncertainty and spans the three levels. At the measurement precision level, disagreement happens when the same thing is measured multiple times or by different sources and the measurements are not the same. At the completeness level, disagreement comes from overlapping but not identical datasets. At the inference level, disagreement comes from two (or more) different conclusions being drawn from the same data. This could be two (or more) experts looking at a dataset and coming to different conclusions, or it could be applying two different mathematical models to a dataset to do inference. Participant 5 described an instance of disagreement at the inference level. Part of his work involved using multiple mathematical models of evolutions to predict the phylogeny of a virus. Each model produced a slightly different phylogeny and thus disagreement. Disagreement and credibility are often associated because as soon as disagreement occurs credibility is often called into question.

4.2.5 Credibility – Spans Levels

Credibility is a type of uncertainty that spans the three levels and is often difficult to measure. An information source that produces data that conflict with other data, has produced unreliable data in the past, or is otherwise suspect for some reason leads to uncertainty. Individuals may have different judgments about what constitutes a credible source. Participant 18, an ecologist, discussed building relationships with people and organizations over time and assigning different levels of credibility based on their level of expertise and on his experiences with them.

4.3 Levels of Uncertainty

As we classified examples of uncertainty into different kinds of uncertainty, we began to see a pattern in the way uncertainty compounds or stacks in datasets. Participants were not describing just one type of uncertainty, but instead were discussing uncertainty about multiple aspects of their work and occasionally used the word "level" to describe a higher or lower level form of uncertainty. After exploring this concept in the data, we assigned **Measurement Precision** to the lowest level type of uncertainty, **Completeness** to the middle level, and **Inference** to the highest level (Figure 1). **Credibility** and **Disagreement** are types of uncertainty that occurred along with, or on top of, each of the other types of uncertainty so they span the three levels. This does not mean that every dataset or project will involve every level of uncertainty, but many projects involved more than one level of uncertainty. One reason levels of uncertainty are so crucial and problematic in our participants' experiences is that uncertainty within one level, even if well-quantified at that level, rarely can be adequately transformed or accounted for at another level when the decision-making process requires a transition between levels.

4.4 Dealing with Uncertainty

The degree to which uncertainty in a dataset impacts an eventual outcome is hard to quantify. Participants described several strategies for dealing with uncertainty, but the predominant feeling seemed to be that the uncertainty was complex and difficult to describe, let alone deal with. Part of the problem might be that it is difficult to transform measurable uncertainty at one level into meaningful information at another level. It is also difficult to clearly convey the complexity of multiple levels of uncertainty to others. At some point, participants had to choose to do one of two things: live with the uncertainty or try to become more certain. Participants made this decision based on the potential impact of being wrong and based on how successful they felt they would be in improving their certainty.

4.5 Representations of Uncertainty

One of the challenges for visualizing uncertainty is that it is often not expressed in a standard quantification. We asked participants how they convey uncertainty and how they represent uncertainty.

4.5.1 Formats of Uncertainty

Some participants had quantifications of uncertainty they routinely used. In computer science, participants tended to define uncertainty in terms of probabilities representing a belief that something is true. The other quantification of uncertainty we saw was a range (e.g., confidence interval, error bound).

Many participants had uncertainty they did not quantify. Instead they used looser qualitative labels in communicating with others, but these labels were rarely stored with the data. Participant 8 described it in terms of t-shirt size: “small, medium, large, and XL.” These were not standardized definitions, but were constructs created and used within a group. Participants also used words such as “likely” and “probably” to convey their own belief in an assertion or value.

4.5.2 Visualization of Uncertainty

By far the most commonly mentioned visualization was error bars. Some participants expanded the idea of an error bar to apply to location as well, describing a point with a circle around it. One participant described a sphere surrounded by a buffer zone (or error bar). Other visualizations of uncertainty included showing distributions with box plots and using data plots with quartiles. Participant 5, who dealt with evolutionary trees, mentioned tree alignment, described color coding branches, and adding icons (often asterisks) to branches to indicate certainty. Several participants expressed frustration with the difficulty of communicating certainty to others in a useful way.

5. FUTURE WORK AND CONCLUSION

Our motivation for categorizing uncertainty across domains was to eventually create useful visualizations that provide a more accurate depiction of the data. Our next step will be to identify ways to visualize different types of uncertainty and find ways to convey the layers of uncertainty that exist within a dataset.

The classification of uncertainty we have proposed spans domains and will be useful for incorporating indicators of certainty into visualizations of data. Our classification is based on a review of literature from several domains and on interviews with 18 people working with uncertainty in several fields. We found that participant were aware of uncertainty at many levels in their data and expressed discomfort at their inability to be transparent about showing their uncertainty. Our classification better describes the broad range of uncertainty across domains, provides a structure for visualizing uncertainty, and will ultimately help develop visualizations that make uncertainty visible.

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