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Communicating qualitative uncertainty in data visualization

Two cases from within the digital humanities

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Qualitative uncertainty refers to the implicit and underlying issues that are imbued in data, such as the circumstances of its collection, its storage or even biases and assumptions made by its authors. Although such uncertainty can jeopardize the validity of the data analysis, it is often overlooked in visualizations, due to it being indirect and non-quantifiable. In this paper we present two case studies within the digital humanities in which we examined how to integrate uncertainty in our visualization designs. Using these cases as a starting point we propose four considerations for data visualization research in relation to indirect, qualitative uncertainty: (1) we suggest that uncertainty in visualization should be examined within its socio-technological context, (2) we propose the use of interaction design patterns to design for it, (3) we argue for more attention to be paid to the data generation process in the humanities, and (4) we call for the further development of participatory activities specifically catered for understanding qualitative uncertainties. While our findings are grounded in the humanities, we believe that these considerations can be beneficial for other settings where indirect uncertainty plays an equally prevalent role.

1. Introduction

Uncertainty in visualization research broadly refers to the issues, doubt or ambiguity that data workers face when interacting with data (e.g., Boukhelifa et al., 2017; Sacha et al., 2016). The origins of uncertainty that impact confidence in the data analysis process have been documented and these range from how the data is collected, modelled or even represented (Boukhelifa et al., 2017; Kale et al., 2019; Van Der Bles et al., 2019). Nevertheless, uncertainty is still often associated with its quantifiable dimensions such as modelling errors, with other types such as indirect, qualitative uncertainty being excluded from visualization representations.

This investigation forwards the agenda of critical data visualization studies towards representing and working with indirect, qualitative data uncertainty. Critical data studies have been increasingly drawing awareness to the problems of treating data as objective, complete and devoid of human interpretation. These studies explain how data are directly impacted by their author's intent and biases (Drucker, 2011), by the situated, local conditions that brought them about (Loukissas, 2019), as well as by the socio-technological infrastructure that stores and maintains them (Kitchin, 2021). The digital humanities, i.e., the interdisciplinary field that combines computational methods with the disciplines of the humanities, has also been prominent in the discussions of criticality, as researchers working with data from the humanities are well-aware of the incompleteness and biasing nature of historical records (Windhager et al., 2019). Visualization research is also increasingly becoming introspective to these topics, attempting to make visualization more critical (Dörk et al., 2013), ethical (Correll, 2019), rigorous (Meyer & Dykes, 2019) and feminist in all its content, form and process (Ignazio & Klein, 2020). By communicating qualitative uncertainty, visualizations can become more uncertain in and of themselves, allowing their readers to question, scrutinize and experience the underlying data and assumptions.

Still, while uncertainty may be communicated for reasons of transparency and accountability, there is an ambivalent relationship between communicating uncertainty in scientific data and gaining the trust of the public in the conclusions (Tak et al., 2014; Van Der Bles et al., 2019). Moreover, transparently communicating uncertainty in visualization does not ensure that scientific findings will be more accepted or adopted by the public, as eliciting trust in science requires a larger, more sustained engagement with the context of visualization use, i.e. its *social world* not just its visual design (Lee et al., 2021). Nevertheless, visualization research has found that experts prefer more, rather than less contextual information (Greis et al., 2017), and that they need to be aware of what they do not know in order to improve their trust in a visualization (Sacha et al., 2016).

Especially within digital humanities settings, humanists seem to be skeptical of visualizations that exclude uncertainty and present an idealized picture of the data (Boyd Davis et al., 2021). Accordingly, they advocate for the design of visualizations that highlight the "*partial knowledge representation, ambiguity, uncertainty, and observer dependence*" that exist in humanistic datasets (Drucker, 2015, p. 248). We build upon these calls and present two empirical cases of how this skepticism manifested itself within the process of designing a digital humanities visualization, and how this was eventually dealt with. Moreover, given the interdisciplinary nature of digital humanities projects, we demonstrate how the solutions for handling uncertainty may be impacted by the data practices of each discipline.

These two case studies were grounded in the Sagalassos Archaeological Research Project, which is a long-standing interdisciplinary project that studies the past and present of the Sagalassos region in south-west Turkey. The Sagalassos project can be considered the ideal research context to investigate indirect, qualitative uncertainties, both for its ample examples of partial, incomplete, and subjective archaeological datasets, as well as for the variability of disciplines that it employs. As an archaeological research project, the Sagalassos project organizes fieldwork campaigns where scientists excavate, survey and sample artefacts for further analysis. We followed one such campaign, observing how a consortium consisting of archaeologists, ecologists, human geographers, and urban planners analysed data of the region. Specifically, the first author observed the research activities of these scientists and documented how their artefacts were progressively 'datafied' into spreadsheets. These observations, together with our attempts to design visualizations for this context, uncovered the intricate research practices that imbued the data with uncertainty.

Reflecting on these findings, this paper proposes four considerations for data visualization research in relation to qualitative uncertainty. Specifically, we (1) discuss how uncertainty visualization should be approached within its disciplinary context, (2) propose that interaction design patterns can help experience it, (3) argue that the data generation process should be a fundamental part of digital humanities visualization research, and (4) call for the further development of participatory activities specifically catered for understanding indirect, qualitative uncertainty.

Figure 1. Example of archaeological assemblages of pottery fragments into types. These types will be later used to date these pieces and the site where they were found

2. Archaeological settlement data

The first case deals with the visualization of an archaeological dataset that collects information on sites of human activity since Neolithic times. For each sampled location, this spatiotemporal dataset documents whether there was a human settlement for a certain era. In case there was a settlement, the dataset documents its type as e.g., a hamlet, farm, town, or city. Through this dataset archaeologists wanted to uncover how human settlements varied, what motivated humans' choices to live in valleys or mountains and why some settlements evolved into villages, towns, and cities while others did not. To answer these questions, archaeologists needed to find patterns of appearance and disappearance of human settlements over time. While this seems to be a straightforward visualization task, the collection of this data is a complex error-prone process containing a number of tacitly understood parameters. Specifically, archaeologists organized excavations as well as field surveying to find artefacts (mostly pottery fragments) which they then assembled and dated to some cultural period (see Figure 1 for an example). If enough artefacts were found in a given area, archaeologists argued with relative confidence the existence of a human site. These sites were then classified into settlement types (e.g., a town instead of a village) depending on how wide the distribution of those artefacts in the location was. These assemblages are then dated and assigned to cultural periods based on the archaeologists' experience and background exposure to the artefacts of that region and period, which inevitably adds subjectivity to the classification. Moreover, given the vastness of the region (1200 km²), this dataset has been progressively captured over a period of 30 years, and since the technologies, methodologies, archaeological theory and research teams have evolved over time, the surveys from the first years are only broadly comparable to those from more recent years.

Our original visualization prototype, as seen in Figure 2, supported a distant temporal reading of these sites, following established ideas of distant reading from literary studies (Moretti, 2005). Being aware of this data generation process and of its implicit errors, namely underlying measurement errors that experts only account for qualitatively (McCurdy et al., 2019), the archaeologists approached this prototype with skepticism. While they could identify patterns, they did not trust their validity. We further collaborated with the archaeologists to deconstruct this skepticism and to understand how our visualization designs could be improved to account for such uncertainty. Our final visualization design (Figure 3) helped us achieve this with various simple techniques to address the implicit data errors as we have further documented in previous work (Panagiotidou et al., 2021). It depicted multiple views of the same data, included simple interactions such as scale changes, and added metadata regarding the collection methods overlayed on each site.

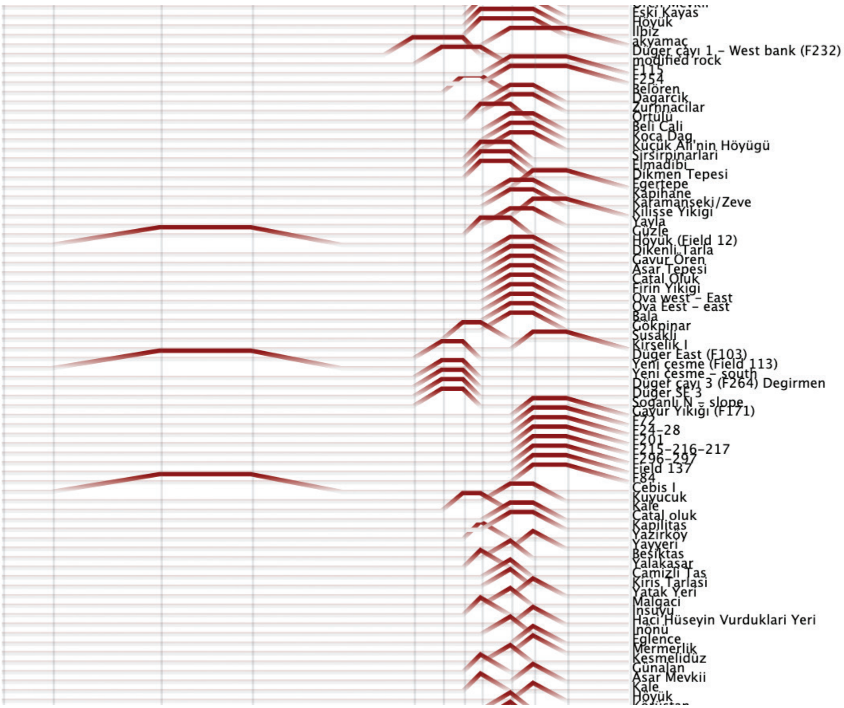

Figure 2. One of the first prototypes we created to permit the distant reading of the archaeological sites. The archaeologists approached it with skepticism because they knew how it hid the various implicit errors that brought uncertainty to their conclusions. Each line represents a site with the x-axis depicting time in eras. The text on the right of the line provides the name of the location and was only legible after mouseover

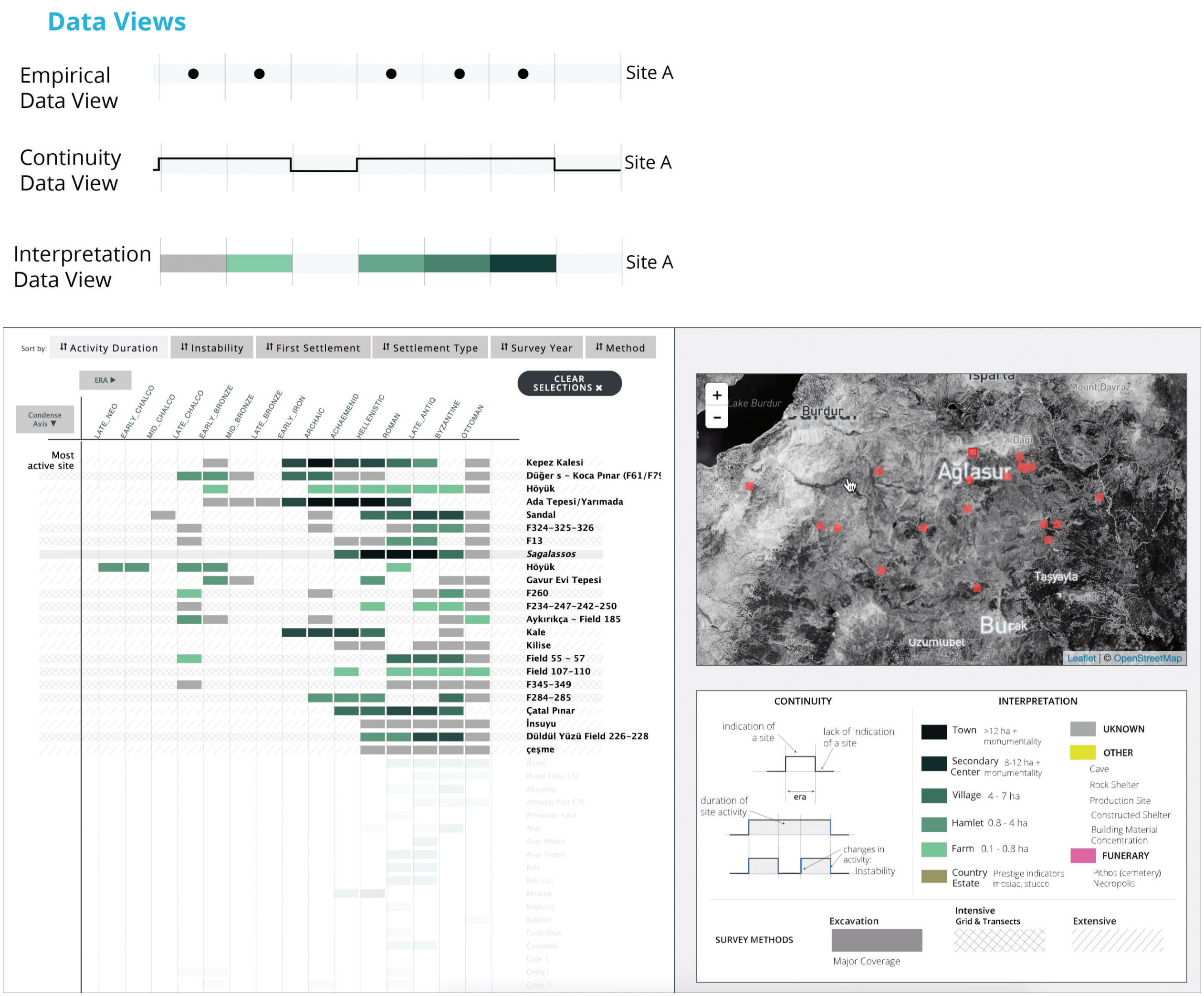

Figure 3.
Top: The example data views of the same site. The empirical view directly showed the empirical, sampled data while the other two views progressively allowed for more assumptions of continuity and the classifications into farms, hamlets, towns, etc.
Bottom: The final visualization design that accounted for uncertainty through various smaller interactive techniques such as the data views explained above, as well as the change of scales and the addition of metadata relating to the methods as background to each site

Specifically, in its basic view the visualization directly depicts the empirical, sampled data over a timeline (see Figure 3 – top). In the other two views, the visualization allows for further assumptions on the data and shows the site classifications as hamlets, towns, or cities. We used the interaction flow among these views to help archaeologists work with the uncertainty and eventually become more confident in the conclusions that they derive. We evaluated the visualization with 14 archaeologists of different experience levels and analysed their sense-making processes to examine their level of confidence. We found that while these dedicated views were not extensively used, they were able to trigger reflection and nudge archaeologists to hypothesize on the various data generation issues. Accordingly, even with our relatively incomplete visualizations of uncertainty (they still hid multiple data issues), we observed that these scientists engaged with the visualization and positively reacted to its use as an analytical tool. Through this exploratory study we thus argue that the interaction design technique to switch between the different data views helped unpack the origins of uncertainty by progressively *experiencing* them as needed, without needing to quantify them.

3. Synthesizing interdisciplinary socio-ecological data

The second case focuses on how the datasets of the archaeology, ecology, human geography, and urban planning teams of the Sagalassos project are integrated into a single visualization. Specifically, we tried to synthesize the previously mentioned archaeological dataset with modelled historical pollen data and land-use data collected from a contemporary town near the Sagalassos archaeological site. The goal was to understand the role of change in long-term socio-ecological patterns in the region. Through a series of participatory workshops (see Figure 4) we found that indirect, qualitative uncertainties were present in the datasets of all three disciplines.

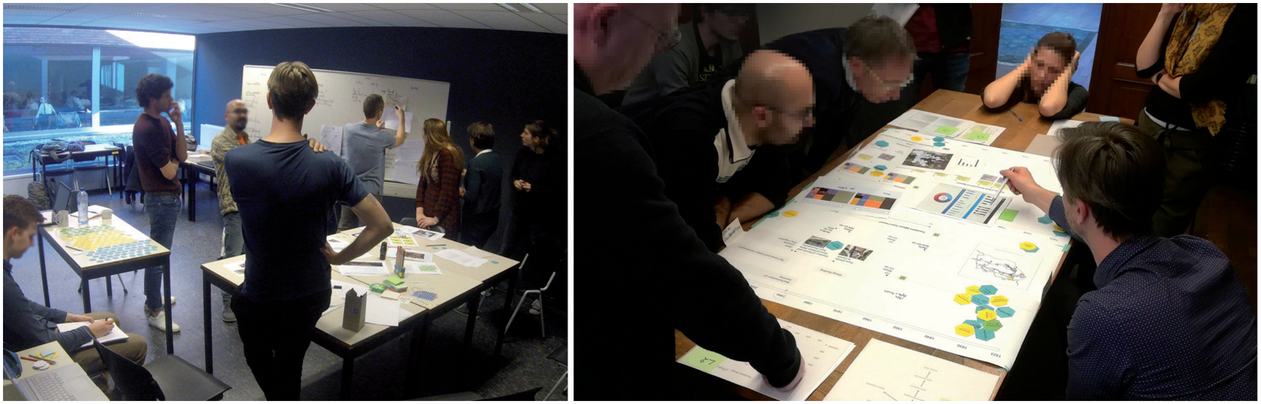

Figure 4. Snapshots from two of the participatory data activities with the interdisciplinary consortium. These sessions helped reveal how human geographers approached the uncertainty of their household survey dataset

The historical pollen data from ecology were used as indications of the vegetation species that covered the region during different time periods, such as nut, fruit or wild trees. By comparing those crop types with historical climate data, ecologists could assess if changes in the regions' forest cover were due to anthropogenic factors or to climate phenomena. These historical pollen datasets were the outcomes of three separate dissertations. The author of each dissertation used different climate models and different archaeological base assumptions of settlement locations to create their models. Their comparison, therefore, was imbued with underlying implicit uncertainty regarding the specific choices of each dissertation.

Similarly, the human geographers and urban planners used modern land-use data to understand the impact that various institutional factors had over the land-use choices of the locals. For instance, they were interested in seeing how subsidies and other centralized policies stirred the locals towards specific crop types. While this was studied on the contemporary scale, the aim was to create conceptual bridges to connect the institutional effects with historical moments of the town, e.g., during Roman Imperial times. There were various datasets for answering this research question, ranging from governmental data, across standardized household surveys to hand-drawn mental maps and interviews with the town residents. Such diversity of data naturally included many sources of uncertainty, such as the self-reported aspects of the interviews and mental maps, and the well-known limitations (to these researchers) of the governmental data to capture an accurate description of the local conditions.

In previous work we showed that while in all three datasets (including the archaeological data) the uncertainties referred to methodological aspects of the data, each discipline took a different approach to handling these (Panagiotidou et al., 2022). We argue that these differences are related to the epistemological backgrounds of each discipline (i.e., their approach to knowledge creation) and to the way that they generate 'data'. For example, in our sessions we observed that ecologists were concerned with alternative, hypothetical cases of the uncertain data and referred to the authors of the datasets as a way to establish confidence in their analysis. In visualization prototypes of this data, they added separate options to interactively show or hide the impact of the various dissertations on the final pollen synthesis. The human geographers on the other hand, brought additional datasets and points of view to the topic. They essentially minimized the effect of the uncertainties through the additional data, or in the case of the interviews and self-reporting, they simply accepted the uncertainty as an inevitable part of the process. As for the archaeologists, when unsure of emerging patterns, they often referred to the need to revisit original locations and examine the artefacts on which these conclusions were based. Moreover, we observed that when discussions took place in interdisciplinary settings, the scientists did not bring up these data issues. Instead, they seemed to either trust their colleagues' practices or to be unaware of the underlying issues.

In contrast to the previous case study, where the archaeological practices could be examined in depth so that the experts could be more confident in their insight making, here the variation among the participants and their data did not permit a singular solution. Thus, so that we could design a visualization for these scientists, we approached uncertainty differently for each group of scientists. For the ecologists, closer connection to the data's authors was warranted. Relational approaches to depicting information came closer to how human geographers understood and handled their indirect uncertainties. As for the archaeologists, they required a more direct relation (Manovich, 2011) to their underlying artefacts through the use of photographic thumbnails. We thus find that the visualization of uncertainty is subject to interpretation and can be affected by the scientist's views and experiences, the data, and the settings of its analysis. Therefore, we argue that the visualization of uncertainty should be dealt with within its situated, socio-technological context, one possible parameter being the scientist's epistemological background.

4. Towards communicating qualitative uncertainty in data visualization

While our two cases are anecdotal and originating from a single research setting, they still demonstrate the multitude of issues that exist in digital humanities visualization projects. Reflecting on our learnings, we thus offer four considerations towards a visualization practice that takes indirect, qualitative uncertainties into account.

First, we propose that qualitative dimensions of uncertainty be designed for in the interaction design of the visualization, as well as its visual encoding. Interaction design is a fundamental characteristic of visualization that refers to the "*interplay between a person and a data interface involving a data-related intent*" (Dimara & Perin, 2020). We suggest that this interplay be designed to highlight the effects of uncertainty. This can be achieved by means of visual 'what-if' scenarios, by representing the provenance of the data or by depicting pluralistic nature of the data through multiple views. In our first case, by including different levels of interpretation, we showed how interactions helped unpack the origins of uncertainty, thereby experiencing them iteratively without a need for quantification. Previous research has explored experiencing quantifiable uncertainty through the use of animation (Kale et al., 2019). While we are not aware of a direct equivalent for qualitative uncertainty, various interaction patterns for visualization have been developed that could be applicable. Using small interactions, ambiguity on overlapping characters in books can be explored as an assumption by merging these as needed when doing character analysis (Stoffel et al., 2017). Within the digital humanities, elaborate interaction patterns allow humanists to navigate through the different degrees of detail of cultural collections (Glinka et al., 2017). Such approaches can be re-examined through the lens of uncertainty as *indirect* uncertainty visualization techniques (Deitrick, 2012) that focus on the experience of uncertainty rather than on its explicitly depiction of glyphs or other marks.

Second, as these two case studies demonstrate, the data generation process in humanistic research significantly influences what gets counted as data and how complete and certain that data is. Specifically, we presented two different stages of the data generation, the first relating to the methodological practices of a single discipline and the second relating to the frictions that emerged after attempting to synthesize data from different disciplines. Previous research examining uncertainty in digital humanities projects equally documents the critical role that the data generation process plays in humanistic data (Boyd Davis et al., 2021; Franke et al., 2019; Windhager et al., 2019). In fact, by excluding the early stages of data generation from the scope of what is considered relevant to visualization research, researchers may be overlooking multiple sources of indirect uncertainty. To avoid the pitfall of presenting a visualization as neutral, we propose including visualization as part of a broader research process that commences much earlier than the abstracted data. This can be achieved, for instance, by expanding existing visual analytics models to include the data generation stages. We believe that explicitly accounting for the data generation stages in visual analytics models can prompt researchers to take the underlying uncertainty of the data into account. This could also help educate future generations of visualization practitioners to be more accountable of what they are depicting.

Third, we argue that uncertainty should be understood within its situated, socio-technological setting, and should be seen as a property of the scientists, as their context of inquiry as well as their data. As observed in our second case study, data uncertainty was not handled or valued the same in the different disciplines, and these differences may be related to the specific data practices of each discipline. As documented by previous research, reusing (historical) empirical data in the humanities requires their 'historization', i.e., their reading in light of the context of origin (McAllister, 2018). Similarly, data from the social sciences are perceived as co-constructed by the researcher collecting them, making it difficult to separate their meaning from their original author (ibid). The case studies from ecology, in turn, highlighted the importance of social interaction when it comes to establishing data trust (Zimmerman, 2007). Still, not all scientists within a discipline will hold a uniform approach to uncertainty and given the blend of methods that are prevalent in today's interdisciplinary fields, it would be limiting to generalize.

One of the goals of communicating uncertainty in visualization is to provide a feeling, experience or sensation so that it can inform users' actions (Padilla et al., 2020). Even if cognitive parameters in how to 'read' the visual encodings of uncertainty remain constant, how scientists trust and make decisions based on that same data does not. There is a need for more ethnographical and design research on uncertainty experience and its handling, so as to better understand how to design for it. Moreover, to design for such experiences of uncertainty, we need to consider them as a core part of a visualization design study and accordingly approach them in a human-centred way.

Finally, we suggest the development of participatory visualization activities specifically catered for understanding uncertainty. In the participatory process of our case study, we developed a close and deep understanding of the scientists' uncertainties as well as their handling of these uncertainties. Such an effort, however, was opportunistic, not pre-planned. There is a need for structured methods which can help visualization experts understand and design for the various uncertainties of the data. The goal of such methods should be (1) to help *identify* the origins of uncertainty by eliciting them from experts, (2) to help *assess* the impact of uncertainty on the broader research process, (3) to help understand how uncertainty is currently handled by the domain experts, and (4) to make it possible to *prioritize* the uncertainties that need to be accounted for in the visualization so as to increase confidence in the findings. Visualization research has adopted participatory activities to establish rapport among collaborators, to elicit requirements, to help design the visualization and even educate others on the potential of visualization (Hall et al., 2019; Kerzner et al., 2018; Marai, 2018). Accordingly, uncertainty activities can be modelled on such research as well as be informed by critical data approaches meant for lay audiences such as data literacy workshops and data biographies (Braun, 2018; D'Ignazio, 2017).

5. Conclusion

Visualizations tend to appear objective through their use of conventions such as clean layouts, the inclusion of sources and two-dimensional viewpoints (Kennedy et al., 2016). By exploring ways to communicate the underlying uncertainty of visualizations we have demonstrated the non-neutrality of data work. Building on critical visualization studies, we have presented two cases of how indirect, qualitative uncertainty manifested itself in a digital humanities project, and proposed four considerations for data visualization research in relation to indirect, qualitative uncertainty. While our findings are grounded in the humanities, we believe that these considerations can be taken up in other settings where indirect uncertainty plays an equally prevalent role.

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