

Uncertainty of What and for Whom - And Does Anyone Care? Propositions for Cultural Collection Visualization

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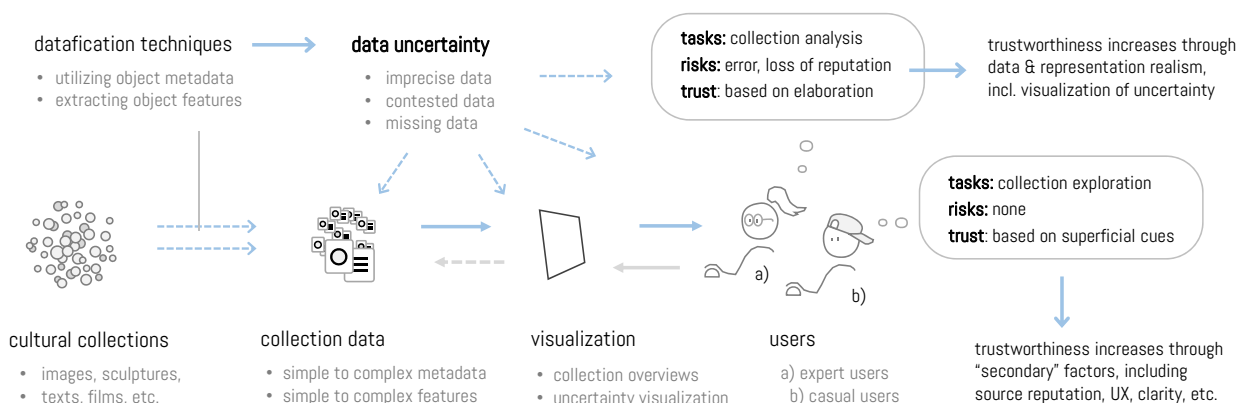


Fig. 1. Two stakeholder groups relying on two modes of trust-building for the visualization of cultural collections and data uncertainty.

Abstract—In cultural collections and art-historical bodies of knowledge, uncertainty is all over the place. Visualization approaches to corresponding data and topics are currently learning to deal with various aspects of uncertainty and ambiguity; yet, design practice and theoretical reflections cannot rely on a mature footing until now. With this position paper, we draw together theses about the role and relevance of uncertainty representations, which are commonly lauded for their contribution to truthfulness and the creation of trust. But when we look more closely at the main target groups of collection visualizations we arrive at two propositions: (1) Casual users will rather put trust into simpler and clearer visualizations with less visual complexity. (2) Humanist inquiry focuses on uncertainties about the meaning and relevance of cultural objects, whereas visualization commonly represents only uncertainties in well-defined metadata dimensions—A mismatch that reduces usefulness and probably also trust. By taking knowledge about different users into account, we aim to sharpen the standard rationale of uncertainty representation in our field and foster both advanced uncertainty visualization design for experts, as well as adaptive or lightweight approaches for casual users.

Index Terms—Cultural collections, visualization, uncertainty, trust, digital humanities, experts, casual users,

1 INTRODUCTION

The visualization of uncertainty is a topic of increasing relevance and interest for the visualization community since quite a while [7, 12, 14, 47]. In many areas, handling uncertainty is of obvious, vital importance—think of visualization in the fields of medicine, finance, meteorology, or national intelligence [7]. Recently it was also picked up in our research field of visualization of cultural collections (CC) [20, 43]. In general, representing uncertainty fits nicely with a certain academic standard rationale, which values veracity, rigor, and truthfulness above all else, and which holds a deep skepticism for (and would not put trust into) prettified or euphemized representations to begin with. Data and representation realism (i.e. the avoidance of stylized and superficial elements) thus often serves as a chief value, guiding interface design in all areas—and maybe even more so in areas like the humanities, where uncertainty and interpretive openness are ubiquitous. But are we seeing this clear enough? Is the representation of uncertainty of similar, essential relevance in all DH domains—and for all user groups?

This position paper critically reflects on visualization of uncertainty in the area of CCs. For this purpose, we have a closer look at the standard rationale to represent uncertainty, we weigh its various costs and benefits (section 2), and we examine the particular argument that

uncertainty visualization increases trust [36] (section 3). For a realistic assessment of this argument in our field, we have a closer look at its major stakeholder groups and at their motives to turn to CCs (section 4). To develop a more differentiated perspective on uncertainty visualization, we distinguish different data and uncertainty types (section 5), before deriving a more nuanced rationale for future visualization design and trust-building in the CC realm and other fields of DH.

2 UNCERTAINTY VISUALIZATION IN CULTURAL COLLECTIONS

Arguably, uncertainty is a standard condition under which large parts of collectors, communicators, and custodians of cultural collections are operating. This also becomes explicit during digitization endeavors, where uncertainty seeps in from every corner: Due to *original uncertainty in the object documentation*, or due to imprecision caused by *probabilistic datafication procedures*, uncertainty frequently appears as *fait accompli* for visualization developers: Practically every type of object information can be imprecise, it can be contested, or it can be missing completely. Obviously, such deficiencies then affect every further step of data processing. Various pipeline models thus elaborate on how given uncertainties are propagating through visual-analytical systems, to affect all further data *modelling, processing, representation, and sensemaking* procedures [22, 36, 46]. Quite frequently, data and collection owners prefer to spare themselves related computational and explanatory troubles and work with a sanitized core of data only, while keeping a lid on the all too messy remains.

Yet, uncertainty also is known to be connected to cultural objects on a top level of interpretation and inquiry: *What does an object actually*

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represent? What is its meaning? What motivated it? What is its worth, or why is it relevant? Given its pervasive nature, it is no surprise that visualization of uncertainty is a rising topic in the field of CC visualization [43,44]. Yet, looking more closely at the related work, mainly uncertainties in well-defined metadata dimensions are visualized, such as uncertain dates of origin [6,8,17,20]. But is this kind of uncertainty visualization actually relevant? Are we missing other aspects? And looking at the bigger picture—who cares about what?

The *scholarly standard rationale* for dealing with empirical data contends that a truthful representation of uncertainty increases the accuracy of visualizations and decisions. Especially in the world of visualizations and diagrams as “synthetic images”, the transparent handling of data quality is of utmost importance: “*Understanding the data and information and reaching sound decisions require knowing what pieces of information or data are accurate, complete, consistent, and certain, identifying which are not and by how much, and making the presentation accurate*” [12, p.43]. Uncertainty visualization strives to make these aspects explicit so that users can gain a more truthful understanding of the data, which provides the only reliable basis for well-versed decisions. “Accounting for such uncertainties in data is important for thorough data analysis, information derivation and informed decision making” [36, p.242].

On a negative side though, visual uncertainty indicators increase visual complexity and thereby also cognitive load [1,31,36]. Representing uncertainty requires to utilize at least one additional visual variable for encoding (e.g., degree of (im)precision), which raises the density of the visualization space and tends to decrease clarity and ease of use. So, is uncertainty visualization really worth the effort? Yes, it is, state Sacha et al. [36]: The representation of uncertainty positively affects the user’s trust in the visualization and the data. Though heavily cited, we are not aware of any empirical evidence that supports or evaluates this model. Therefore, we take a closer analytical look at one of its main propositions, namely that uncertainty visualization increases trust.

3 UNCERTAINTY & TRUST

According to Sacha et al. [36] the visualization of uncertainty is a central factor within the processes of knowledge generation and trust-building on the user side: On the computer side, uncertainty originates already at the data source and propagates through the whole visualization pipeline. On the human side, the user gets aware of these uncertainties due to various visual sensemaking loops and activities and integrates them in the generated knowledge. An important factor within the trust-building process is the user’s prior knowledge: If novel (uncertainty) information pieces match existing mental models they increase trust, but if they contradict the user’s prior knowledge, trust decreases and further sensemaking is required.

But the model by Sacha et al. [36] cannot give answers to two important questions: How do users without prior knowledge build up trust? And do users build up trust also if no uncertainty is presented? Against this background, an extended model of trust in information visualization has been proposed [28], which brings in critical new components:

- Trust—to begin with—is only relevant, when users are facing a certain risk or negative consequences from corresponding decisions [18,26].
- Trust as a systemic phenomenon results not only from the visualization itself (“trustworthiness”), but also from a users’ sense-making activities (“trust perception”). Yet, trust perception on the users’ side does not only come from cognitive elaboration and sensemaking loops as in Sacha et al.’s model [36], but also depends on their prior knowledge, their interests, dispositions, and their overall (socio-cultural) embeddedness [35,37].
- In the model of Sacha et al. [36] trust-building requires thorough inspection and diligent elaboration of visualizations and data (and the own mental model). But also less elaborated processes can be used for trust-building [18,19]. In this case, users do not engage

in laborious cognitive inspections and testing procedures, but initially and fundamentally rely on the monitoring of secondary cues, such as the reputation of source or author, familiarity with the institution, other people’s trust, high user experience, interface clarity, or emotional connection [28]. We consider these energy-saving short-cuts to play a major role to establish trust under non-experimental, real-world conditions for all types of users, but especially for non-experts—which have not been appropriately reflected by the visualization community up to now.

From this point of view, it is even more imperative to *know our users* and to familiarize with their needs, data and tasks [29]. This stance turns out to be specifically essential for the cultural heritage domain, where not so goal-oriented casual users without specific tasks and needs make up the lion’s share of the stakeholder population [27].

4 UNCERTAINTY FOR WHOM? – A USER TYPOLOGY

Who is the audience for visualizations of CCs? Obviously, the visual analysis of collection data can be of interest to experts, such as curators, collectors, art historians, anthropologists, humanities scholars. Yet even more so, CCs are explored by visitors of a different kind: consumers, tourists, connoisseurs, spectators, the interested public, in short: by non-expert, “casual” users; who are interested in culture, but not in a work-related way, but mainly for leisure purposes [9,27,42]. In contrast to the rather clear information needs of expert users, casual users are interested in the collection, but do not look for anything specific. Nevertheless, they want to take away something valuable—this can be knowledge, but also a personal connection with the collection or a positive emotional experience. Often casual users just want to spend time, kill time, get entertained, or procrastinate productively [27,34,42].

Even though casual users cannot specify tasks or search requests, there is plenty that visualization can do for them: They can provide an alternative way to find what might be available and develop an overview of the collection [42, p. 1]. Therefore, especially visualization and design strategies can support casual users which offer summaries, overviews, tableaus, and outlooks on the collection—arrangements similar to hallways, rooms, or galleries in real museums which they can stroll along [9], browse and skip through; with information spaces where *serendipitous encounters* [40] can happen, where eyes can wander around, search without a target, and zoom in on something interesting along the way.¹

When contrasting the hedonic and exploratory profile of casual users with the professional analytical intentions of collection experts, it becomes obvious that also *uncertainty* of cultural information will play a different role for both sides. We thus argue that any design rationale for uncertainty visualization has to be bifurcated along the expert/casual distinction—and that we further have to take preferences for traditional or digital modes of inquiry into account:

1. We consider **expert users** of CC data (historians, curators, analysts) *with digital tool literacy or visualization affinity* to be the major benefactor of uncertainty visualizations according to the standard rationale. As CC professionals they use various tools to obtain insights, to analyze and synthesize information, and to base their decisions and judgments on their findings. They will also take secondary cues into account for trust perception; but given the corresponding risk (such as erroneous interpretation and loss of reputation), they will require transparency along the whole data-to-visualization-pipeline to examine and validate the process. As such, the positive feedback loop of strengthened trust in (digital) tools due to representation of uncertainty [36] probably holds.
2. For **expert users** of CC data *without* digital literacy or visualization affinity, uncertainty visualization might make tools more

¹As a unique feature, CC data can be considered to be “autotelic”, providing an intrinsic value in and of themselves, due to their careful preselection according to their “aesthetic, historic, scientific, or social value” [16].

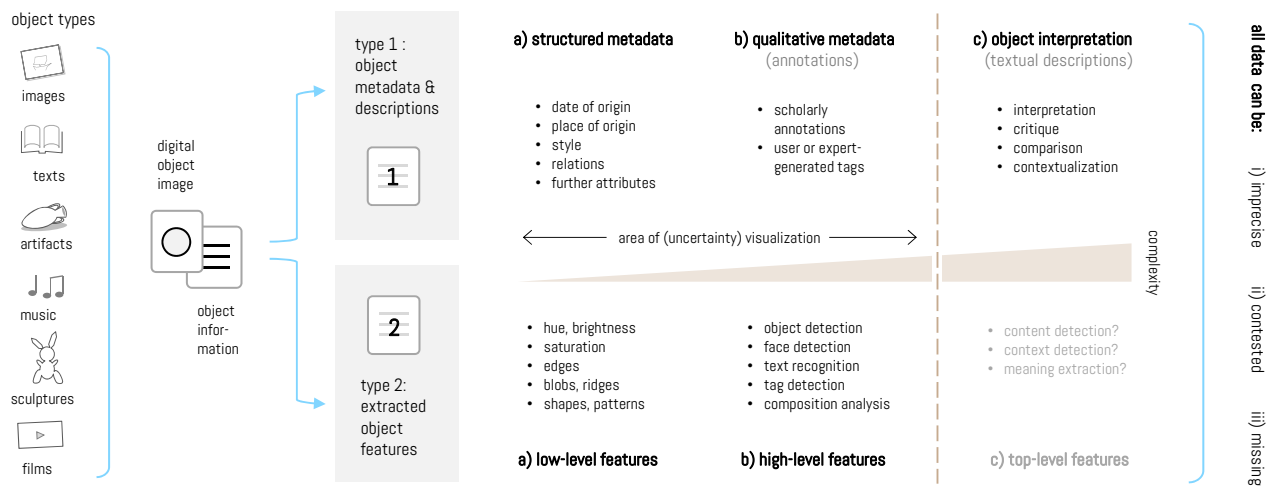


Fig. 2. Types of object metadata (top, commonly given before digitization) and object features (bottom, commonly extracted), which can be uncertain.

trustworthy: “The focus on veracity of sources is primordial in the field of art history. Distrust of any presented information before accessing its provenance is indeed essential to the practice of history research. This becomes even more critical when we factor in the initial distrust from researchers of art history in digital data analysis tools. Presenting sources of information in clear, verifiable manners is therefore decisive to building trustworthy tools.” [21, p.3]² However, visual complexity should be carefully balanced for this user group, so that a visualization is not overloaded [45]. Additionally, there is reason to assume that (until further notice) visualization designers will not be able to actually represent those uncertainties within their tools, which traditional (i.e. non-digital or post-digital) humanists, curators or art historians commonly deem essential (see section 5).

- For **casual users** we argue to revise the standard rationale and contend that uncertainty just is not exactly what they are into.³ Adding data quality indicators will increase visual complexity and thus decrease (easy) legibility [32, p.262]. Non-expert “users may also misinterpret the variability in this [uncertainty] representation as a sign that the data are not very trustworthy” [41, p.6].

Casual visitors of CCs do not face any obvious risks of getting the details of object data wrong. Trust—if relevant at all in this context—will not emerge from transparency and self-examination [36], but might rather emerge from the institutions reputation or from a robust and intuitive system design, which avoids confusion, ambiguity or dead ends, but is easily navigable and provides good approximations together with entertainment and splendid user experience.⁴

Proposition 1: Uncertainty visualization arguably is of obvious value for experts, whose judgments (and articles, keynotes, reputations, etc.) depend on correct inferences and decisions derived from truthful representations. In contrast, many casual users do not care about intricate conditions of uncertainties as they are not facing any analytical risks

²In addition, design strategies which have been suggested to increase the use of digital tools in art history include user-centered design, immersion in specific domain cultures, primacy of close reading or viewing perspective, as well as provision of high user experience [21].

³Exemplarily, in the context of spatial uncertainty, Beard [4, p.374] stressed that detailed uncertainty information might not be of interest to casual users due to the analytical efforts required to understand them.

⁴There might be some aspects of uncertainty, which move the imagination of casuals as well, such as: What is the (monetary) value of all this? Who is the creator of this painting? How did they do this? What is the meaning of it?—We will come back to the current state of addressing such questions further down.

or consequences from a simplified understanding. To the contrary, the increased visual complexity has negative consequences on the cognitive load and attraction power of a visualization; rendering attractive designs uncertain or complicated without added benefit is probably not rising feelings of veracity nor truthfulness at all. Regarding the practical consequences for CC visualization design, we thus suggest to either tailor systems to the needs for specific user groups, or—in case of systems intended for hybrid use—to strive for a simpler and clear visualization and add more complex layers only due to user interaction. In accordance with the notion of adaptive design, uncertainty visualizations then could be available on demand [5]. But what kind of uncertainty is relevant for the visualization of CC?

5 UNCERTAINTY OF WHAT? – A DATA TYPOLOGY

If uncertainty is an omnipresent property of information and knowledge in a given field, it also seems necessary to establish a more nuanced understanding of this concept. Researchers from various application fields have already proposed elaborate taxonomies of uncertainty [23, 33, 39, 47]. With regard to cultural object information we suggest to distinguish at least i) *imprecise data*, which can vary across various levels of magnitude or granularity, ii) *contested data*, which is any information that is subject of an ongoing debate, and iii) *missing data* in terms of residual knowledge about the “known unknowns” in the area of collection information [20]. But which data types can be subject to uncertainty?

Figure 2 establishes an overview on frequent data types in the fields of CCs. We refer to the two major information types as “object metadata” (top row), which are commonly already given by collection documentation, and as “object features” (bottom row), which are commonly generated by automated extraction procedures (such as image or text processing). What we consider essential in this arrangement is a certain gradient of conceptual and computational complexity, which increases towards the right-hand side of figure 2. On the left, structured metadata dimensions (such as time, place, style, etc.) provide the basis for most collection visualizations [43], but also qualitative annotations (generated by experts or visitors) can be utilized [30, 38]. Similarly, a whole range of options for automated feature extraction (bottom row) has become available to support distant reading or distant viewing approaches to CCs [3, 25]. While a lot of early work in DH or CC visualization was predominantly located on the left-hand side (utilizing low-level features), contemporary efforts, extraction algorithms, and machine learning technologies increasingly work towards the right side of the spectrum (high-level features) [24].

In a complementary fashion, though, both traditional humanities scholars and casual users are commonly reasoning on an even higher level, where they work with complex networks of object features (i.e.

concepts, propositions, or mental models), which resist automated extraction or detection (right-hand side). From their logical, syntactic, and inferential interplay arises the “meaning” of objects, which is generated either off the cuff during everyday sensemaking activities or by methodological controlled efforts of object interpretation, contextualization, and critique. In this context, it is mostly language-based reasoning, which is considered most suited to process these complex conceptual constellations—and assessments differ, whether digital procedures will ever be able to contribute directly to this human(ist) reasoning level.⁵

We consider such reflections on digital limitations to be relevant because it is arguably at the complex end of the spectrum, where humanist scholars and visitors are used to struggle with uncertainties. “*The past is a foreign country; they do things differently there*” [15]: Archives and museums are full of opaque objects, which require professional interpretation and contextualization—against the odds of accumulated historical uncertainties and adversities. Most of non-digital humanities research is plausibly dedicated to actually coping with this challenge—making various aspects and facets of meaning explicit within the tides of ever-evolving theoretical and methodological frames of reference. Humanists mostly do so in a text- or language-based fashion and they frequently prefer a polylogic, open-ended discourse, which abandons the idea of certainty for the sake of interpretative openness, novelty, provocation, critique, theoretical diversity, and a dynamic unfolding of plural perspectives [11]. It is in line with the “standard rationale”, to make this uncertainty-embracing way of coping with top-level uncertainty transparent. As a consequence though, we realize the area of (uncertainty) visualization to be operationally limited, and to share the stage with non-digital, language-based modes of representation, used to process the most complex facets of uncertainty in our field of study.

Proposition 2: Expert users—including the lion share of non-digital humanists—care deeply about uncertainty, but mostly about different types of uncertainty than those, which are commonly visualized by current interfaces. While it is plausible to argue, that this points out the future directions, where humanist approaches to interface design have to go (e.g., from the visualization of standard metrics of uncertainty to metrics that express interpretation [11]), we do not see any added value in assuming an easy way for digitization initiatives to lay ahead. Maybe—for the time being—it is better to become aware of the spectrum of cultural data complexity (Fig. 2), to honor the current state of the computational borderline—and to appreciate the complementary work that is done on each side without hegemonic ambitions. Paradoxically, this might imply—after suspending uncertainty visualization for casual users already—to deliberately restrict uncertainty visualization research and development to the actually not so relevant uncertainties in one’s own field.

6 CONCLUSIONS

Regarding collaborations of visualization and humanities researchers, the call for this workshop encouraged to “*explore ways in which trust can be built, strengthened, and maintained when communicating and transferring methodologies, designing tools and encodings, collecting and curating data, and deriving knowledge*”. Directing this focus of inquiry to our field of CCs, at least two major stakeholder groups come into play, featuring radically different needs and requirements to build up different sorts of trust. For both groups we assembled insights from existing studies, and by doing so also developed answers for other questions of the call:

⁵Accordingly, many fundamental debates are playing out along this line: Should we fear or hope for computational methods to cross into classical territories of reading and reasoning, of interpretation, (re)contextualization and evaluation—or should we just better learn to cherish spectral distributions of competences? While polarizing and binarizing debates are still aiming to eliminate parts of the spectrum, we consent to the notion that *intelligence amplification* (IA) trumps *artificial intelligence* (AI) as a guiding idea, and that digital methods—while not becoming strong AI—are here to stay, and to prosthetically augment, support, and amplify our sensemaking procedures [2].

- *How can we deal with different kinds of uncertainty (in data, methodology, research questions, visual encodings, and interpretation)?* By assembling different data, feature, and knowledge types, which are associated to cultural objects (see figure 2), we found that we cannot deal with all kinds of uncertainty on a visual level—and that we probably benefit from knowing that.
- *How can one make trustworthy visualizations for humanistic research? and What does trust mean for different communities and sub-communities?* We propose for visualization designers to respect two major limitations in the CC realm: While they can generate trustworthy visualizations for expert users along the standard rationale for uncertainty visualization, they should not forget about two demarcations: I) Complex “object features”, which guide traditional research (currently) withstand any datafication procedure. Art-historical top-level concepts such as meaning, content, relevance, or motivation will probably remain the subject of language-based propositional analysis and discourse until further notice. Thus it seems reasonable to develop visualization approaches as a deliberately self-restrained, ancillary perspective, ambitious development programs not precluded [10]. II) Casual users arguably have their own hedonic research agenda, which is not much concerned with questions of uncertainty. Occasionally, they ponder on specific uncertainties (How much is this? What does this mean? Could I do this too?)—yet, we do not consider these parameters to become accessible for quantification anytime soon. In contrast, visualization designers can build up trust for casual users by improving secondary cues of trustworthiness like minimizing visual complexity and maximizing attraction power.
- *How can trust be established in transdisciplinary projects?* Transdisciplinary approaches in the narrower sense require scientists and stakeholders from the public to collaborate on an equal footing. Exemplarily, the concept of crowd curation would argue for “interfaces that are open to annotation, commenting, co-creation, referencing and contextualisation” from the public and experts alike, and thus allow to represent multiple points of view [13, p.111]. Visualizations can obviously support sensemaking activities in this context too. Yet, as such projects are also frequently debated with respect to the scientific rigor of the generated data, they also introduce an additional uncertainty source to manage.
- *How much does trust rely on full understanding of methods, encodings, and other context, especially when collaborating across disciplines? and What do humanities researchers need to see and know to be able to trust visualization, as a tool and process?* Along with the standard rationale, we argued that trust for DH experts is enabled and deepened by transparent and truthful system designs, which allow to reenact all relevant processing steps from raw data to visualization, and to integrate the information with their existing mental models on the CC. By contrast, our extended model of trust-building [28] showed that trust for casual users does not emerge from a detailed structural and procedural understanding, but rather from an assembly of contextual cues.

Along with many other fields, we consider uncertainty visualization in the CC realm to be an important challenge and a major area of future work. Yet, based on a reflection of our specific field, we contend that the cart indeed has to pull the horse of visualization development: Two major user groups means two major types of tasks, associated risks, and processes of trust-building. Thus in visualization design, we can apply (A) a scholarly standard rationale of transparency, high level of detail, and uncertainty representation for visualization design on the expert side, while (B) casual users’ trust-building will benefit from an unburdened or adaptive approach, which foregrounds hedonic and generous design. Given the current lack of comparative evaluation studies in the area of uncertainty visualization in the DH, we hope for future work to shed light on these propositions, and to clarify, how much they might be generalizable for other DH fields, where autotelic data and casual users play a substantial role.

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REFERENCES

- [1] S. Antifakos, A. Schwaninger, and B. Schiele. Evaluating the Effects of Displaying Uncertainty in Context-Aware Applications. In N. Davies, E. D. Mynatt, and I. Siio, eds., *UbiComp 2004: Ubiquitous Computing*, LNCS, pp. 54–69. Springer, 2004.
- [2] R. Arias-Hernandez, T. M. Green, and B. Fisher. From cognitive amplifiers to cognitive prostheses: Understandings of the material basis of cognition in visual analytics. *Interdisciplinary science reviews*, 37(1):4–18, 2012.
- [3] T. Arnold and L. Tilton. Distant viewing: analyzing large visual corpora. *Digital Scholarship in the Humanities*, fqz013, 2019.
- [4] K. Beard. Roles of meta-information in uncertainty management. In C. T. Hunsaker, M. F. Goodchild, M. A. Friedl, and T. J. Case, eds., *Spatial uncertainty in ecology: implications for remote sensing and GIS applications*, pp. 363–378. Springer Science & Business Media, 2013.
- [5] G. Block. *Reducing cognitive load using adaptive uncertainty visualization*. Doctoral Dissertation, Nova Southeastern University, 2013.
- [6] M.-J. Bludau, M. Dörk, and F. Heidmann. Relational perspectives as situated visualizations of art collections. In *Proceedings of the ADHO Conference on Digital Humanities (DH2019)*. Utrecht, NL, 2019.
- [7] G.-P. Bonneau, H.-C. Hege, C. R. Johnson, M. M. Oliveira, K. Potter, P. Rheingans, and T. Schultz. Overview and state-of-the-art of uncertainty visualization. In *Scientific Visualization*, pp. 3–27. Springer, 2014.
- [8] S. Cottrell. Understanding textual uncertainty in dates using interactive timelines. In *Proceedings of EVA '17*, pp. 68–73. BCS Learning & Development Ltd., Swindon, UK, 2017.
- [9] M. Dörk, S. Carpendale, and C. Williamson. The information flaneur: A fresh look at information seeking. In *SIGCHI Conference on Human Factors in Computing Systems*, pp. 1215–1224. ACM, 2011.
- [10] J. Drucker. Is there a digital art history? *Visual Resources*, 29(1-2):5–13, 2013.
- [11] J. Drucker. Performative materiality and theoretical approaches to interface. *Digital Humanities Quarterly*, 7(1), 2013.
- [12] N. Gershon. Visualization of an Imperfect World. *IEEE Computer Graphics and Applications*, 18(4):43–45, 1998.
- [13] K. Glinka, S. Meier, and M. Dörk. Visualising the “un-seen”: Towards critical approaches and strategies of inclusion in digital cultural heritage interfaces. *Kultur und Informatik (XIII)*, pp. 105–118, 2015.
- [14] H. Griethe and H. Schumann. The Visualization of Uncertain Data: Methods and Problems. In *SimVis*, 2006.
- [15] L. P. Hartley. *The Go-Between*. London: Penguin, 1953.
- [16] International Council on Monuments and Sites (ICOM). Historic gardens, The Florence charter, Florence, Italy, 1982.
- [17] S. Jänicke, J. Focht, and G. Scheuermann. Interactive visual profiling of musicians. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):200–209, 2016.
- [18] K. Kelton, K. R. Fleischmann, and W. A. Wallace. Trust in digital information. *Journal of the American Society for Information Science and Technology*, 59(3):363–374, 2008.
- [19] H. Kong, Z. Liu, and K. Karahalios. Trust and recall of information across varying degrees of title-visualization misalignment. In *CHI 2019*, 2019.
- [20] F. Kräutli and S. Boyd Davis. Known unknowns: representing uncertainty in historical time. In *Proc. of EVA 2013, London*. BCS, 2013.
- [21] H. Lamqaddam, K. Brosens, F. Truyen, J. Beerens, I. de Brekel, and K. Verbert. When the tech kids are running too fast : Data visualisation through the lens of Art History research. In *3rd IEEE vis4dh workshop*. Berlin, 2018.
- [22] S. H. Lee and W. Chen. A comparative study of uncertainty propagation methods for black-box-type problems. *Structural and Multidisciplinary Optimization*, 37(3):239, 2009.
- [23] A. M. MacEachren, R. E. Roth, J. O’Brien, B. Li, D. Swingley, and M. Gahegan. Visual Semiotics and Uncertainty Visualization: An Empirical Study. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2496–2505, 2012.
- [24] L. Manovich. *Museum without walls, art history without names: visualization methods for Humanities and Media Studies*. Software Studies Initiative, 2012.
- [25] L. Manovich. Data science and digital art history. *International Journal for Digital Art History*, (1), 2015.
- [26] S. Marsh and M. R. Dibben. The role of trust in information science and technology. *Annual Review of Information Science and Technology*, 37(1):465–498, 2003.
- [27] E. Mayr, P. Federico, S. Miksch, G. Schreder, M. Smuc, and F. Windhager. Visualization of cultural heritage data for casual users. In *1st IEEE vis4dh workshop*. Baltimore, 2016.
- [28] E. Mayr, N. Hynek, S. Salisu, and F. Windhager. Trust in information visualization. In R. Kosara, K. Lawonn, L. Linsen, and N. Smit, eds., *TrustVis workshop*. The Eurographics Association, Porto, 2019. doi: 10.2312/trvis.20191187
- [29] S. Miksch and W. Aigner. A matter of time: Applying a data-users-tasks design triangle to visual analytics of time-oriented data. *Computers & Graphics*, 38:286–290, 2014.
- [30] J. Novak, I. Micheel, M. Melenhorst, L. Wieneke, M. Düring, J. G. Morón, C. Pasini, M. Tagliasacchi, and P. Fraternali. Histogram—a visualization tool for collaborative analysis of networks from historical social multimedia collections. In *18th International Conference on Information Visualisation*, pp. 241–250. IEEE, 2014.
- [31] L. M. Padilla, S. H. Creem-Regehr, M. Hegarty, and J. K. Stefanucci. Decision making with visualizations: a cognitive framework across disciplines. *Cognitive research: principles and implications*, 3(1):29, 2018.
- [32] A. Pang. Visualizing uncertainty in natural hazards. In *Risk Assessment, Modeling and Decision Support*, pp. 261–294. Springer, 2008.
- [33] K. Potter, P. Rosen, and C. R. Johnson. From quantification to visualization: A taxonomy of uncertainty visualization approaches. In *IFIP Working Conference on Uncertainty Quantification*, pp. 226–249. Springer, 2011.
- [34] Z. Pousman, J. T. Stasko, and M. Mateas. Casual information visualization: Depictions of data in everyday life. *Visualization and Computer Graphics, IEEE Transactions on*, 13(6):1145–1152, 2007.
- [35] M. M. Roghanizad and D. J. Neufeld. Intuition, risk, and the formation of online trust. *Computers in Human Behavior*, 50:489–498, 2015.
- [36] D. Sacha, H. Senaratne, B. C. Kwon, G. Ellis, and D. A. Keim. The role of uncertainty, awareness, and trust in visual analytics. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):240–249, 2016.
- [37] D. Sprague and M. Tory. Exploring how and why people use visualizations in casual contexts: Modeling user goals and regulated motivations. *Information Visualization*, 11(2):106–123, 2012.
- [38] J.-E. Stange and R. Kleymann. Towards Hermeneutic Visualization in Digital Literary Studies. *Digital Humanities Quarterly (manuscript under review)*.
- [39] R. Therón, A. G. Losada, A. Benito, and R. Santamaría. Toward supporting decision-making under uncertainty in digital humanities with progressive visualization. In *Sixth Intl. Conference on Technological Ecosystems for Enhancing Multiculturality*, pp. 826–832. ACM, 2018.
- [40] A. Thudt, U. Hinrichs, and S. Carpendale. The bohemian bookshelf: Supporting serendipitous book discoveries through information visualization. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1461–1470. ACM, 2012.
- [41] A. Toet, J. B. van Erp, E. M. Boertjes, and S. van Buuren. Graphical uncertainty representations for ensemble predictions. *Information Visualization*, preprint, 2019.
- [42] D. Walsh and M. M. Hall. Just looking around: Supporting casual users initial encounters with Digital Cultural Heritage. In *Supporting Complex Search Tasks*. CEUR-WS, Vol-1338.
- [43] F. Windhager, P. Federico, G. Schreder, K. Glinka, M. Dörk, S. Miksch, and E. Mayr. Visualization of Cultural Heritage Collection Data: State of the Art and Future Challenges. *IEEE Transactions on Visualization and Computer Graphics*, 25(6):2311–2330, 2019.
- [44] F. Windhager, S. Salisu, and E. Mayr. Exhibiting uncertainty: Visualizing data quality indicators for cultural collections. *Informatics*, 6(3):29, 2019.
- [45] Y. L. Wong, K. Madhavan, and N. Elmqvist. Towards characterizing domain experts as a user group. In *BELIV workshop*, pp. 1–10, 2018.
- [46] Y. Wu, G.-X. Yuan, and K.-L. Ma. Visualizing flow of uncertainty through analytical processes. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2526–2535, 2012.
- [47] T. Zuk and S. Carpendale. Visualization of uncertainty and reasoning. In *International symposium on smart graphics*, pp. 164–177. Springer, 2007.