

Crisping up Vagueness Visualization

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ABSTRACT

Vagueness is a fundamental property of natural language, arising from ambiguity, underspecification, and context-dependent meaning. As large language models and conversational interfaces increasingly enable the collection of rich, freeform input, such imprecision becomes more visible in the resulting data. In this paper, I propose vagueness visualization: approaches that explicitly represent and preserve imprecision in language, supporting reasoning about meaning that is not fully determined. Drawing on prior work in linguistics, I position vagueness as a distinct phenomenon that persists even when data is structured, yet is often obscured by visualization techniques that impose precision. While existing approaches in uncertainty visualization provide useful foundations for representing non-exact data, they do not directly address the interpretive nature of vagueness. I therefore propose design implications for visualizing vague, language-derived data and reframe visualization as a mediating layer between human expression and formal representation.

Index Terms: Uncertainty visualization, Natural language, Vagueness, Human-centered data.

1 INTRODUCTION

Vagueness is a fundamental property of natural language, arising from ambiguity, underspecification, and context-dependent meaning [37]. People describe time as “early” or “recently,” severity as “bad” or “manageable,” [36]. These expressions do not map cleanly to precise values, and instead reflect how meaning is constructed and communicated in context. Importantly, vagueness is not merely a limitation of language, but a functional property: speakers rely on it because it is efficient, adaptable, and sufficient for communication without requiring unnecessary precision [37]. As a result, vagueness is often preserved as part of how meaning is conveyed rather than something to be fully resolved.

Vagueness in data not only arises from freeform language input, but also from how people express meaning through predefined categories. Structured inputs can rely on inherently vague terms, such as selecting “bad” to describe a symptom or “tall” to describe a person, where interpretation depends on context and implicit reference points. More importantly, recent advances in large language models (LLMs) and conversational interfaces have made this property more visible by enabling the collection of richer, freeform descriptions [14, 19]. As such data is incorporated into computational workflows, the vagueness inherent in language persists within representations, raising challenges for how it should be interpreted and communicated.

Despite this shift, visualization approaches often assume that data is well-defined and structured. In practice, vague expressions are frequently resolved, approximated, or discretized into precise representations, obscuring their underlying imprecision. This tendency reflects a broader focus in visualization on clarity and precision, even when the underlying data is inherently ambiguous [34].

I draw on prior work in uncertainty visualization as a complementary perspective. Uncertainty literature has traditionally addressed non-exactness through statistical representations such as variance, error, confidence intervals, and probabilistic distributions [4, 5]. These approaches assume that uncertainty arises from variability in otherwise well-defined quantities. While uncertainty research provides valuable techniques for representing non-exact data, it does not directly address vagueness as a property of meaning, which is interpretive, context-dependent, and not inherently probabilistic.

In response, I propose **vagueness visualization**: visualization approaches that explicitly represent and preserve ambiguity, underspecification, and context-dependent meaning in language, while supporting reasoning about interpretations that are not fully determined. Rather than resolving vagueness into precise values, these approaches aim to make it visible and actionable within the visualization.

While vagueness is well understood within linguistics and philosophy, it is rarely treated as a first-class concern in visualization. This paper argues for explicitly representing vagueness, treating data as fuzzy, evolving, and partially specified, and designing visualizations that preserve ambiguity, support refinement over time, and make visible the interpretive processes that shape meaning. In doing so, it suggests that future work in uncertainty visualization may benefit from engaging not only with probabilistic variation, but also with uncertainty in meaning itself.

To motivate this shift, I make the following contributions: I propose and formalize *vagueness visualization*, grounded in the concept of semantic vagueness from linguistics; characterize how it differs from traditional uncertainty in being interpretive, context-dependent, and non-probabilistic; and propose design implications, informed by my own work, that draw on techniques from uncertainty visualization to support representing and reasoning about vague, language-derived data.

2 RELATED WORK

To situate this work, I examine three complementary perspectives: linguistic vagueness, visualizing ambiguity and uncertainty visualization.

2.1 Vagueness in Natural Language

Vagueness is a pervasive feature of natural language, characterized by the presence of borderline cases where a predicate neither clearly applies nor clearly does not apply [37]. Foundational work in philosophy and semantics has long examined this phenomenon, with theories differing in how they formalize vagueness but converging on the view that meaning is often inherently indeterminate rather than simply noisy or incomplete [13, 38, 15]. For example, one influential approach formalizes this indeterminacy through *fuzzy set theory*, where predicates are associated with degrees of membership rather than binary truth values. For example, a person might belong to the category “tall” to some degree rather than being strictly classified as tall or not, capturing the gradual transitions that characterize vague categories [11].

In linguistic semantics, vagueness is often distinguished from imprecision, separating inherently vague predicates, like “tall,” from loosely specified references to otherwise precise concepts, such as “three o’clock” [36]. Both give rise to classical challenges

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such as the Sorites Paradox [21], illustrated by the question of when removing single grains of sand from a heap causes it to no longer be a heap. Each individual removal seems insignificant, yet repeated application leads to a contradictory outcome with no clear boundary. These distinctions highlight that vagueness is not a singular phenomenon, but arises in multiple forms across language.

Natural language also encodes vagueness through pragmatic mechanisms. Lakoff introduced the concept of *hedges*, linguistic modifiers such as “sort of” or “technically” that systematically alter the applicability of a predicate [28]. Similarly, the notion of *pragmatic halos* shows that even seemingly precise expressions are interpreted with tolerance, allowing for context-dependent flexibility in meaning. For example, saying “the meeting is at 3:00” may still be understood to include a few minutes before or after the exact time [29]. These perspectives emphasize that meaning is shaped not only by literal denotation, but by context and use.

Vagueness is also closely tied to how meaning is structured and interpreted. For example, gradable expressions depend on context-sensitive thresholds, where terms like “tall” or “severe” are evaluated relative to implicit comparison classes [26]. More generally, interpretation can shift across contexts and over the course of discourse, reflecting the dynamic nature of meaning in language [2]. These properties further reinforce that vagueness arises from interpretation rather than measurement alone.

Another important dimension of vagueness is *granularity*, where descriptions vary in level of detail depending on context [18]. Human reasoning frequently shifts between coarse and fine-grained representations, resulting in uneven specificity across different aspects of a description. As a result, natural language often contains a mixture of precise and underspecified information within the same account.

Taken together, this work characterizes vagueness as a multifaceted property of language, spanning logical indeterminacy, graded membership, pragmatic flexibility, and context-dependent interpretation. Rather than reflecting noise, vagueness emerges from how meaning is constructed and adapted across contexts. However, these perspectives are rarely carried into visualization, where representations often assume stable meanings. This gap motivates the need to represent vagueness explicitly and design visualizations that support reasoning about meaning that is not fully determined.

2.2 Visualizing Ambiguity

A growing body of work, particularly in digital humanities, engages directly with ambiguity as a fundamental property of interpretation rather than a problem to be resolved. This work is often grounded in practices such as *close reading*, where meaning is constructed through careful, context-sensitive interpretation of text rather than extracted as fixed structure [22]. In contrast to approaches that seek stable representations, digital humanities research treats meaning as inherently situated, contested, and often indeterminate.

Visualization systems in this space reflect this perspective by supporting multiple interpretations rather than converging on a single, authoritative view [23]. For example, *Poemage* visualizes the sonic structure of poetry in ways that allow for overlapping and competing readings [32], while work on literary corpora and entity networks emphasizes exploratory, open-ended analysis over definitive conclusions [6]. Related work in visual text analysis also highlights how meaning evolves and remains fluid over time. Systems such as *TextFlow* [10] support the exploration of topic evolution through splitting, merging, and interaction, enabling users to iteratively refine interpretations and reason about multiple plausible structures within text data. These systems prioritize interaction, interpretation, and the gradual construction of meaning, often valuing uncertainty as a productive feature of analysis rather than a limitation.

Importantly, this line of work implicitly treats ambiguity as a property of the data itself. Rather than assuming that uncertainty arises from noise or incomplete information, it acknowledges that multiple interpretations may be valid simultaneously, and that meaning is shaped by context, perspective, and analytical goals. As a result, visualization is not used to resolve ambiguity, but to expose, explore, and negotiate it.

Despite these contributions, ambiguity is rarely framed explicitly as a visualization challenge in its own right. Instead, it is often discussed in terms of interpretation, exploration, or humanistic inquiry, without being formalized as a property that visualization systems should represent and support. This perspective motivates a need to consider how ambiguity can inform visualization design, particularly in developing representations that make vagueness visible and support reasoning about meaning that is not fully determined.

2.3 Uncertainty Visualization

Uncertainty visualization has a long history of studying how to represent and communicate variability, error, and incompleteness in data [4]. Early work characterizes uncertainty as arising throughout the visualization pipeline, including data acquisition, modeling, transformation, and visual encoding [35], with subsequent reviews emphasizing challenges in representing and propagating uncertainty across domains [5, 24].

Much of this literature focuses on *quantifiable uncertainty*, where variability is expressed using probabilities, distributions, or bounded intervals. Common techniques include error bars, confidence intervals, and ensemble-based representations. A key insight is that uncertainty is often better understood when represented as a set of plausible outcomes rather than as abstract summary statistics [9], supporting more accurate judgments and better calibrated decisions [25]. At the same time, empirical work shows that encoding choices influence interpretation, and that uncertainty is often omitted in practice due to concerns about clarity and usability [8, 20].

Work on temporal uncertainty further illustrates this assumption. Even when uncertainty is difficult to specify precisely, such as uncertain start and end times, visual encodings such as gradients, intervals, or ambiguous boundaries can support different reasoning tasks [16]. However, these approaches operate only after uncertainty has been formalized into a representable structure.

More recent work explores *qualitative uncertainty*, arising from contextual, interpretive, and socio-technical factors rather than measurable variability [34]. Similarly, research on visual text analysis pipelines identifies uncertainty introduced through ambiguity, underspecification, and interpretation in language [17]. From a design perspective, ambiguity has also been framed as a feature rather than a limitation, enabling richer analytical reasoning. These approaches come closest to the concerns of this paper, but still assume that such uncertainty can be resolved or expressed within structured representations.

Despite these advances, most uncertainty visualization approaches assume that underlying data can be represented in structured, often numerical forms [7]. As a result, uncertainty is typically treated as variability around known values or models, with less attention given to uncertainty that arises prior to formalization, specifically, uncertainty in how data should be interpreted or structured.

In this work, I focus on uncertainty arising from indeterminacy in meaning. Rather than variability in values or predictions, this perspective considers uncertainty in interpretation: what is meant, what is inferred, and what remains unresolved. Here, ambiguity and underspecification are not artifacts to be resolved, but persistent properties of the data, requiring visualization approaches that support reasoning about meaning that is not fully determined.

3 OVERLAP BETWEEN VAGUENESS AND UNCERTAINTY VISUALIZATION

Although semantic vagueness differs from traditional forms of uncertainty, there are important areas of overlap that suggest existing uncertainty visualization research can inform its representation. In both cases, visualization must communicate that data is not fully precise, and must support users in reasoning under conditions of incomplete or indeterminate information.

A primary point of overlap is the need to represent non-exactness. Uncertainty visualization has developed a range of techniques for encoding variability, including intervals, distributions, gradients, and probabilistic overlays. These approaches move beyond single-value representations, instead communicating ranges or likelihoods. Similarly, vague expressions such as “early,” “frequent,” or “moderate” imply ranges of possible values rather than discrete points. This approach suggests that techniques for representing distributions or intervals may serve as a starting point for visualizing vagueness.

A second area of overlap is supporting interpretation under ambiguity. Uncertainty visualization often focuses on helping users interpret confidence, assess reliability, and avoid overconfidence in precise-looking representations. This approach aligns closely with the challenges of vagueness visualization, where users must reason about meaning that is inherently indeterminate. In both cases, visualization plays a role in shaping how users understand and act on uncertain information.

A third shared concern is avoiding misleading precision. Prior work in uncertainty visualization has shown that precise visual encodings can lead to overconfidence, even when underlying data is uncertain. Similar risks arise in language-derived data, where vague expressions are often transformed into specific values or categories. Visualization techniques that explicitly encode uncertainty, such as blurring, transparency, or non-crisp boundaries, may help counteract this effect.

Finally, both domains emphasize the importance of user trust and calibration. Uncertainty visualization research has explored how visual encodings influence trust, decision-making, and interpretation. These insights are directly relevant to vagueness visualization, where users must understand not only what the data represents, but also how much confidence to place in its interpretation.

Taken together, these overlaps suggest that vagueness visualizations can benefit from the representational and perceptual foundations established in uncertainty visualization. However, as discussed next, important differences limit the direct applicability of these techniques.

4 DIFFERENCES BETWEEN VAGUENESS AND UNCERTAINTY VISUALIZATION

Despite these overlaps, semantic vagueness differs from traditional uncertainty in several fundamental ways. These differences have important implications for visualization design, as they challenge assumptions underlying many existing techniques.

First, uncertainty in visualization is typically *quantifiable*, whereas vagueness is *non-quantifiable*. Statistical uncertainty can be expressed through probabilities, distributions, or confidence intervals, enabling precise encodings and mathematical interpretation. In contrast, vague expressions such as “a while,” “sometimes,” or “severe” do not map cleanly to numerical values. While it is possible to approximate them, such mappings introduce interpretation rather than measurement.

Second, uncertainty is often treated as *external to the data*, while vagueness is *intrinsic to it*. In traditional settings, uncertainty reflects limitations in measurement or modeling applied to otherwise well-defined data. In contrast, semantic vagueness originates from the data itself, specifically, from how humans express meaning.

As a result, vagueness cannot be separated from the representation without fundamentally altering the data.

Third, uncertainty visualization typically assumes a *single underlying truth* with associated variability, whereas vagueness allows for *multiple valid interpretations*. A probabilistic distribution represents different possible values of the same quantity, but vague language may correspond to qualitatively different interpretations rather than variations around a single value. This distinction complicates the use of traditional uncertainty encodings.

Fourth, uncertainty is often *reducible* with additional data or improved models, whereas vagueness is often *persistent*. While statistical uncertainty can decrease with more observations, semantic vagueness may remain even with additional context, as it reflects inherent properties of language rather than missing information.

Finally, the goal of uncertainty visualization is often to *support decision-making under risk*, while the goal of vagueness visualization is to *support interpretation and meaning-making*. This shift places greater emphasis on preserving ambiguity, exposing alternative interpretations, and supporting user reflection rather than resolving uncertainty.

These differences suggest that while uncertainty visualization provides useful foundations, new approaches are needed to address the interpretive and non-quantifiable nature of semantic vagueness.

5 MOTIVATING EXAMPLE: VAGUENESS VISUALIZATION IN HEALTHCARE

My work on patient-authored health narratives [1] motivates this exploration of vagueness in visualization. In this patient narrative context, visualization plays an increasingly important role in healthcare communication, particularly in supporting clinicians’ rapid understanding of patient histories during time-constrained encounters [31]. Narrative visualizations can provide structured overviews of complex experiences, helping clinicians identify patterns, relationships, and areas for follow-up [12]. However, these visualizations are often derived from patient-authored narratives, where information is expressed in natural language and is inherently vague.

In these settings, individuals describe their experiences using context-dependent expressions [3]. For example, patients frequently describe temporal information using phrases such as “early in the year,” “a few months ago,” or “in my twenties.” These expressions convey meaningful information but lack precise boundaries. Similarly, symptoms are often described qualitatively, such as “mild,” “severe,” or “getting worse,” where interpretation depends on implicit reference points such as personal baselines, prior experience, or clinical norms. These forms of vagueness are not errors; they reflect how individuals naturally communicate complex and vague experiences.

When visualized, these descriptions must be structured. Timelines require placing events at specific positions, forcing vague temporal expressions into fixed dates or narrow intervals. Likewise, qualitative descriptions are often mapped to discrete severity levels, typically without preserving the contextual reference points that give them meaning [30]. While these representations enable computation and visualization, they impose a level of precision not present in the original input.

This disconnect introduces clinically consequential distortions. During intake review, fixed temporal placements can anchor clinicians’ reasoning about onset, progression, or sequencing of events, while discretized severity levels can shift interpretation by implicitly redefining what counts as “mild” or “severe” independent of the patient’s context. As a result, visualizations can imply certainty and structure that were not present in the original account, shaping interpretation in time-constrained encounters.

In contrast, preserving imprecision in timing and variability in symptom descriptions, along with their underlying reference frames, can provide clinicians with critical context for assessing

reliability, probing vagueness, and guiding follow-up questions. Making this vagueness explicit supports more effective clinical conversations, where both patient and clinician can negotiate meaning rather than relying on potentially misleading precision.

More broadly, the way vagueness is represented can shape interpretation and communication. Visualizations that obscure imprecision or implicit reference points may anchor users to constructed certainty, while those that expose them encourage users to question assumptions and probe for clarification. For example, making terms like “severe,” “early,” or “getting worse” explicit in their ambiguity can surface differences in interpretation and intent. In this way, visualization can act as a shared reference that supports negotiation of meaning rather than assuming it, enabling more precise communication even when the underlying data remains vague. Visualizing vagueness is therefore not only a representational challenge, but also an important aspect of supporting interpretation and communication.

6 IMPLICATIONS FOR VISUALIZATION DESIGN

The similarities and differences between statistical uncertainty and semantic vagueness suggest both opportunities and limitations for existing visualization approaches. While uncertainty visualization provides a valuable foundation for representing non-exact data, semantic vagueness introduces challenges that require rethinking key assumptions about representation, interpretation, and interaction. Reflecting on these issues, which arose in my prior work [1], has led me to propose the following set of design implications for vagueness visualization.

Representing Vagueness Beyond Probability: Techniques from uncertainty visualization provide a starting point for representing non-exactness, such as ranges, gradients, and probabilistic encodings. However, because vagueness is not inherently probabilistic, these techniques must be adapted. Rather than representing likelihood, visualizations should convey possibility spaces or interpretive ranges, where multiple meanings coexist without implying a specific distribution.

Preserving Ambiguity Rather Than Resolving It: Where uncertainty visualization often aims to summarize variability, vagueness visualization must preserve ambiguity as a first-class property. This implication includes representing multiple plausible interpretations and avoiding premature discretization. Instead of collapsing vague input into a single structured value, systems should expose the range of interpretations that underlie the representation.

Making Interpretation Visible: A key difference between uncertainty and vagueness is that vagueness arises from interpretation. As a result, visualization should not only represent data, but also make visible the interpretive steps that produced it. This implication includes linking structured representations back to source language and exposing how vague expressions were translated into formalized values.

Supporting Progressive Refinement: Uncertainty visualization often assumes fixed data with variable confidence, whereas vagueness suggests data that can evolve over time. Visualization systems should support progressive refinement, allowing users to iteratively clarify, adjust, or reinterpret vague inputs. This implication shifts the role of visualization from static representation to interactive sensemaking.

Representing Context-Dependent Reference Points: Many vague expressions are inherently relative, depending on implicit comparison classes or contextual standards. Terms such as “tall,” “severe,” or “bad” are interpreted in relation to a reference point rather than as absolute values. Visualization systems should therefore make these reference frames explicit or allow them to be adjusted, supporting interpretation that reflects how meaning shifts across contexts.

Supporting Flexible Levels of Specification: Semantic vagueness often reflects variation in how specifically information is expressed. Users may describe some aspects precisely, such as exact dates or quantities, while leaving others intentionally coarse, like “early in the year” or “often”. Visualization systems should accommodate these heterogeneous levels of specification, supporting representations that combine precise values with imprecise ranges without forcing uniform precision.

Mediating Between Expression and Representation: These considerations suggest that visualization systems must do more than represent structured data. In settings where data is derived from natural language, visualization should mediate between user input and structured interpretation by exposing how meaning is constructed, supporting the exploration of alternative interpretations, and enabling users to validate or refine representations. This implication extends the role of visualization from displaying results to actively supporting the interpretation of inherently vague data.

7 DISCUSSION AND FUTURE DIRECTIONS

While language has long been used to represent data, such as structured interfaces that rely on inputs like “bad” or “often,” the rise of LLMs and conversational interfaces has expanded its use, making semantic vagueness more visible and consequential. As language-based representations become more prevalent in computational workflows, imprecision, ambiguity, and context-dependent meaning persist within the data. This shift highlights the need to better understand how visualization can represent and support reasoning about vagueness, rather than assuming it can be fully resolved.

More generally, vagueness visualization is relevant across domains such as personal informatics and journalism where data is often expressed through language. In these settings, how vagueness is represented can shape interpretation and downstream use. When vague input is transformed into precise representations, visualizations may suggest a level of certainty that was not present in the original data. Conversely, explicitly representing vagueness can preserve important context and support reasoning about what is known, what is inferred, and what remains unresolved.

The reification of vagueness visualization raises several open challenges. One key challenge concerns representation. While this paper suggests adapting techniques such as ranges, gradients, and non-crisp boundaries, it remains unclear which visual encodings are most effective for communicating different forms of vagueness. Further work is needed to understand how users perceive and interpret visual representations of imprecision, ambiguity, and under-specification.

Another challenge is evaluation. Traditional approaches in uncertainty visualization often rely on tasks involving probabilistic reasoning [27] or decision-making under risk [33]. In contrast, vagueness visualization requires evaluating how well systems support interpretation, reflection, and meaning-making. Developing appropriate evaluation frameworks for these goals remains an open area of research.

8 CONCLUSION

This paper proposes *vagueness visualization* as a first-order concern when representing and reasoning about semantic vagueness in natural language. Vagueness is interpretive, context-dependent, and often persists even after data is structured, in contrast to statistical or model uncertainty, which is typically quantifiable and tied to variability in well-defined quantities. I argue that because vagueness is inherent to how language expresses meaning, visualization must move beyond representing precise outputs to explicitly representing and preserving this imprecision, supporting reasoning about how meaning is constructed from ambiguous input.

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REFERENCES

- [1] Anonymous. HealthTale: A patient-centric health story visualization tool. Submitted for publication to IEEE Trans. Vis. Comput. Graph. (TVCG/IEEE VIS), 2026. 3, 4
- [2] C. Barker. The dynamics of vagueness. *Linguist. Philos.*, 25:1–36, 2002. 2
- [3] E. Basch, B. B. Reeve, S. A. Mitchell, S. B. Clauser, L. M. Minasian, A. C. Dueck, T. R. Mendoza, J. Hay, T. M. Atkinson, A. P. Abernethy, et al. Development of the national cancer institute’s patient-reported outcomes version of the common terminology criteria for adverse events (PRO-CTCAE). *J. Natl. Cancer Inst.*, 106(9):dju244, 2014. doi: 10.1093/jnci/dju244 3
- [4] 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: Uncertainty, Multifield, Biomedical, and Scalable Visualization*, pp. 3–27. Springer-Verlag, 2014. doi: 10.1007/978-1-4471-6497-5_1 1, 2
- [5] K. Brodlić, R. Allendes Osorio, and A. Lopes. A review of uncertainty in data visualization. In *Expanding the Frontiers of Visual Analytics and Visualization*, pp. 81–109. Springer-Verlag, 2012. doi: 10.1007/978-1-4471-2804-5_6 1, 2
- [6] S. Campbell, Z.-Y. Yu, S. Connell, and C. Dunne. Close and distant reading via named entity network visualization: A case study of women writers online. In *VIS Workshop on Visualization for the Digital Humanities (VIS4DH)*, 2018. 2
- [7] S. Carpendale, A. Thudt, C. Perin, and W. Willett. Subjectivity in personal storytelling with visualization. *Inf. Des. J.*, 23(1):48–64, 2017. doi: 10.1075/idj.23.1.07thu 2
- [8] M. Correll and M. Gleicher. Error bars considered harmful: Exploring alternate encodings for mean and error. *IEEE Trans. Visualization & Computer Graphics (TVCG)*, 20(12):2142–2151, 2014. doi: 10.1109/TVCG.2014.2346298 2
- [9] J. Cox, D. House, and M. Lindell. Visualizing uncertainty in predicted hurricane tracks. *Int. J. Uncertainty Quantification*, 3(2), 2013. doi: 10.1615/Int.J.UncertaintyQuantification.2012003966 2
- [10] W. Cui, S. Liu, L. Tan, C. Shi, Y. Song, Z. Gao, H. Qu, and X. Tong. TextFlow: Towards better understanding of evolving topics in text. *IEEE Trans. Visualization & Computer Graphics (TVCG)*, 17(12):2412–2421, 2011. doi: 10.1109/TVCG.2011.239 2
- [11] D. Dubois and H. Prade. Fuzzy numbers: An overview. In *Readings in Fuzzy Sets for Intelligent Systems*, pp. 112–148. Elsevier, 1993. doi: 10.1016/B978-1-4832-1450-4.50015-8 1
- [12] S. Dunn, T. Capel, A. Manataki, and B. Bach. Personal health data communication: Techniques, tensions, and implications for design from a clinician perspective. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI)*, pp. 1–16, 2026. doi: 10.1145/3772318.3790368 3
- [13] K. Fine. Vagueness, truth and logic. *Synthese*, 30(3–4):265–300, 1975. doi: 10.1007/BF00485047 1
- [14] Y. Fu, D. Bromley, and V. Setlur. DataWeaver: Authoring data-driven narratives through the integrated composition of visualization and text. *Computer Graphics Forum (CGF)*, 44:e70098, 2025. doi: 10.1111/cgf.70098 1
- [15] D. Graff. Shifting sands: An interest-relative theory of vagueness. *Philos. Top.*, 28(1):45–81, 2000. 1
- [16] T. Gschwandtner, M. Bögl, P. Federico, and S. Miksch. Visual encodings of temporal uncertainty: A comparative user study. *IEEE Trans. Visualization & Computer Graphics (TVCG)*, 22(1):539–548, 2015. doi: 10.1109/TVCG.2015.2467752 2
- [17] P. Haghighatkah, M. El-Assady, J.-D. Fekete, N. Mahyar, C. Paradis, V. Simaki, and B. Speckmann. Characterizing uncertainty in the visual text analysis pipeline. In *IEEE VIS Workshop on Visualization for the Digital Humanities (VIS4DH)*, pp. 25–30, 2022. doi: 10.1109/VIS4DH57440.2022.00010 2
- [18] J. R. Hobbs. Granularity. In *Readings in Qualitative Reasoning about Physical Systems*, pp. 542–545. Elsevier, 1990. doi: 10.1016/B978-1-4832-1447-4.50053-5 2
- [19] M. J. Hoefer, R. Rycheky, M. Gong, and S. Volda. TellTime: An AI-augmented calendar with a voice interface for collecting time-use data. In *ACM Conf. Intelligent User Interfaces (IUI)*, pp. 1366–1380, 2025. doi: 10.1145/3708359.3712116 1
- [20] J. Hullman. Why authors don’t visualize uncertainty. *IEEE Trans. Visualization & Computer Graphics (TVCG)*, 26(1):130–139, 2020. doi: 10.1109/TVCG.2019.2934287 2
- [21] D. Hyde. The sorites paradox. In *Vagueness: A Guide*, pp. 1–17. Springer-Verlag, 2011. doi: 10.1007/978-94-007-0375-9_1 2
- [22] S. Jänicke, G. Franzini, M. F. Cheema, and G. Scheuermann. Visual text analysis in digital humanities. *Computer Graphics Forum (CGF)*, 36(6):226–250, 2017. doi: 10.1111/cgf.12873 2
- [23] S. Jänicke, G. Franzini, M. F. Cheema, G. Scheuermann, et al. On close and distant reading in digital humanities: A survey and future challenges. *Computer Graphics Forum (CGF)*, 34(3):83–103, 2015. 2
- [24] A. Kamal, P. Dhakal, A. Y. Javaid, V. K. Devabhaktuni, D. Kaur, J. Zaientz, and R. Marinier. Recent advances and challenges in uncertainty visualization: A survey. *J. Visualization*, 24(5):861–890, 2021. doi: 10.1007/s12650-021-00755-1 2
- [25] A. Karduni, D. Markant, R. Wesslen, and W. Dou. A bayesian cognition approach for belief updating of correlation judgement through uncertainty visualizations. *IEEE Trans. Visualization & Computer Graphics (TVCG)*, 27(2):978–988, 2020. doi: 10.1109/TVCG.2020.3029412 2
- [26] C. Kennedy. Vagueness and grammar: The semantics of relative and absolute gradable adjectives. *Linguist. Philos.*, 30(1):1–45, 2007. doi: 10.1007/s10988-006-9008-0 2
- [27] Y.-S. Kim, L. A. Walls, P. Krafft, and J. Hullman. A Bayesian cognition approach to improve data visualization. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI)*, pp. 1–14, 2019. doi: 10.1145/3290605.3300912 4
- [28] G. Lakoff. Hedges: A study in meaning criteria and the logic of fuzzy concepts. *J. Philos. Logic*, 2(4):458–508, 1973. doi: 10.1007/BF00262952 2
- [29] P. Laserson. Pragmatic halos. *Language*, 75(3):522–551, 1999. doi: 10.2307/417059 2
- [30] M. Lor, T. A. Koleck, and S. Bakken. Information visualizations of symptom information for patients and providers: A systematic review. *J. American Medical Informatics Association (JAMIA)*, 26(2):162–171, 2019. doi: 10.1093/jamia/ocy152 3
- [31] H. Ma, X. Yuan, X. Sun, G. Lawson, and Q. Wang. Seeing your stories: Visualization for narrative medicine. *Health Data Sci.*, 4:0103, 2024. doi: 10.34133/hds.0103 3
- [32] N. McCurdy, J. Lein, K. Coles, and M. Meyer. Poemage: Visualizing the sonic topology of a poem. *IEEE Trans. Visualization & Computer Graphics (TVCG)*, 22(1):439–448, 2016. doi: 10.1109/TVCG.2015.2467811 2
- [33] L. M. Padilla, S. H. Creem-Regehr, M. Hegarty, and J. K. Stefanucci. Decision making with visualizations: A cognitive framework across disciplines. *Cogn. Res.: Princ. Implic.*, 3(1):29, 2018. doi: 10.1186/s41235-018-0120-9 4
- [34] G. Panagiotidou and A. Vande Moere. Communicating qualitative uncertainty in data visualization: Two cases from within the digital humanities. *Inf. Des. J.*, 27(1):52–63, 2022. doi: 10.1075/idj.22014. pan 1, 2
- [35] K. Potter, P. Rosen, and C. R. Johnson. From quantification to visualization: A taxonomy of uncertainty visualization approaches. In *IFIP Working Conf. Uncertainty Quantification*, pp. 226–249, 2011. doi: 10.1007/978-3-642-32677-6_15 2
- [36] U. Sauerland and P. Stateva. Two types of vagueness. In *Vagueness and Language Use*, pp. 121–145. Springer-Verlag, 2011. 1
- [37] S. Solt. Vagueness and imprecision: Empirical foundations. *Annu. Rev. Linguist.*, 1(1):107–127, 2015. doi: 10.1146/annurev-linguist-030514-125150 1
- [38] T. Williamson. Vagueness and ignorance. *Proc. Aristotelian Soc., Suppl. Vol.*, 66:145–177, 1992. 1