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Understanding Visualization Discourse and Building Discursive Visualizations

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*Dedicated to my family,
Lia & Johanna*

Abstract

This doctoral thesis investigates the potential of discursive visualizations to entice readers of visualizations to discussions about data. Through a suite of surveys, interfaces, and user studies it explores key aspects of how people talk about data and demonstrates how these conversations can be integrated into visualizations. Discursive visualization describes a genre of visualization interfaces, engagement practices, and representation methods that aim to integrate discussions *about* visualizations *into* visualizations.

Data visualization has become a popular, ubiquitous medium in science, journalism, entertainment, and across a variety of online environments, including news outlets, social media, dedicated blogs, or expert groups. When discussing data visualizations, expert and novel audiences alike express their thoughts and observations about the data. Existing annotation systems have explored various facets and scenarios of these discussions about data visualizations, including collaborative sensemaking, public communication, or participatory data correction. However, considering the ongoing increase in potential audiences, use cases, and venues to encounter and talk about data visualizations, the potential of understanding discourse and the interfaces required for its integration remain under-explored. To explore the potential of existing discussions about data, I provide a structured analysis of public audience reactions to visualizations observed outside of controlled lab environments. My results describe ten reaction types on four reaction scopes as well as a description of intrinsic and extrinsic engagement drivers that motivate people to participate in discussions. Building on this knowledge, I design an interactive prototype that allows to annotate data visualizations with personal stories. Small but important details, for example where an annotation is placed or who write it are generally overlooked in prior research. My interface offers different viewing conditions to better understand the impact of such details on the reading experience, particularly focusing on the role of embedded audience annotations. My results inform the notion of 'collective storytelling' that describes a genre of visualizations providing a space in which audience annotations become the primary concern of visualizations. In a follow-up study, I design another prototype that introduces '*anchored annotations*' and '*discursive patinas*' as core mechanics to integrate discussions into visualizations, regardless of their specific chart types, topics, or desired reaction types. My evaluation shows that discursive patinas improve the ability to navigate discussions and guide people to comments that help to understand, contextualize, or scrutinize the visualization.

My studies demonstrate how discursive visualization supports collaborative sensemaking and allows for novel engagements with data *and* data visualizations, including collective storytelling, distant readings of discussions, and close readings of visualizations. Audience annotations are usually not required in visualization design. Yet, they are practical devices that are at the core of discursive engagements, as they allow to guide interpretation, offer contrasting perspectives, offer feedback, establish personal relevance, promote empathy for others, and help people reflect on their own experiences. Conceding space and visual presence to the audience challenges existing power dynamics in the relation between visualization creators and consumers. Offering a platform for discussions that are not considered when designing visualizations allows for a multiplicity of narratives to coexist. Integrating local knowledge into visualizations can point to missing, biased, or simply incorrect data, and improve the validity of the data as a whole. Based on these considerations, I see great potential for discursive visualization to provide the foundation for polyvocal, personal, and critical engagements with data.

Lay Summary

This research is about helping people to discuss data visualizations, for example bar charts or line charts. Of course, if a group of people is in the same room and reads the same chart, they can already talk about it. But if they live in different cities, it is hard to have such a conversation. That is why, in this research, I try to make the conversation part of the chart itself. This way, everybody can see it and add to it when looking at the chart.

This idea is not entirely new. Other researchers already built websites that made it possible to add comments to data visualizations in order to better understand it. But there are many more things to talk about when looking at a chart, as I found out by looking at comments in online communities. Especially when readers are not experts, other questions are also interesting to them, for example: Is there a story you can tell about the chart? How does this make you feel? Is there something you disagree with? Do you see yourself in the chart? Do you like the design? Is all the information in there correct?

I want to know how these comments can become part of the chart. I find it interesting to understand if reading comments changes how people think of the chart. I built two different websites that allow people to have conversations about charts. These websites are different from similar websites created by others because they help people point out exactly what part of the chart they are talking about. I look at how people use these websites, for example, where they click and what comments they write. I also interview them, so they can tell me what is interesting to them. In the end, my research is about helping people to talk about charts. Not just how to understand the chart, but also to present different perspectives that can change how people read the chart.

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Thank you.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

Tobias Kauer

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Introduction

1.1 Motivation

The fundamental hypothesis of my research is that discourse about visualization — how people talk about and react to it — is a valuable resource to support sensemaking as well as personal and critical engagements with data visualizations. Making this discourse accessible in the visualization can enhance its impact on the reading experience and help people to participate in the narrative framing of the presented data. In this section, I outline why I think this is relevant, how I approach this endeavor, and what I want to achieve with my research.

1.1.1 The Merits and Challenges of Data Visualization

From politics to pop culture, data visualization has become a powerful tool for conveying complex information in a clear and accessible manner. With the abundance of data generated daily, effective visualization plays a crucial role in facilitating decision-making processes, improving public understanding of intricate issues, and communicating insights across various domains. Data visualization is promoted as a way to make sense of complex data by presenting information in a digestible format. It is deemed useful to grasp patterns, highlight trends, and understand relations in the data (Keim et al., 2008). Especially novice audiences are more likely to stay interested and focused when presented with interactive charts, graphs, and infographics. This increased engagement can lead to better comprehension and retention of the information being presented (Borkin et al., 2013).

The last decade has shown a trend towards data visualizations as a pervasive medium that is considered by increasingly diverse audiences (Böttinger et al., 2020) for an ever expanding range of tasks (B. Lee et al., 2020). This trend does not happen in a vacuum, it is part of a wider transition towards a data-driven and datafied society (Van Es & Schäfer, 2017). Analysts and domain experts who are familiar with the use of visual analytics (P. C. Wong & Thomas, 2004; Thomas & Cook, 2006) and data-driven decision-making (Y. L. Wong et al., 2018; Padilla et al., 2018) are a well-researched audience. Recent work has put more emphasis on describing 'General Public' (Schuster et al., 2023)

audiences with little expertise (Burns et al., 2023), who are less data literate (D'Ignazio, 2017), and a merely have casual concern for data visualization (Pousman et al., 2007; Mayr et al., 2016). These audiences are not primarily interested in the visualization in a professional capacity, instead visualizations are used to learn about topics of personal interest (Peck et al., 2019), to raise awareness for social issues (Dörk et al., 2013), or simply to be entertained and to avoid boredom (Sprague & Tory, 2012). The trend of diversification in audiences, topics, and tasks is further amplified by the platforms and contexts in which visualizations are encountered. News media embed visualizations into their articles (Hullman et al., 2015; De Haan et al., 2018), social media users create, post, and discuss visualizations on a variety of platforms (C. Lee et al., 2021; Almahmoud & Karger, 2023), and projections (Valkanova et al., 2014, 2013) or data physicalizations (Huron et al., 2022) in public space are conspicuously present to passers-by (Hansen et al., 2020; Walny et al., 2020). Arguably, never before have so many people been directly exposed to and influenced by charts, infographics, and other visual representations of data. Given the omnipresence of data and the popularity of visualization for data-based communication, I want to point out critical perspectives on the narrative framing of visualizations and their potential for participatory engagement.

The popularity of visualization as a tool for communication goes hand in hand with the emergence of data-driven storytelling and narrative visualizations (Segel & Heer, 2010). By crafting compelling stories, visualization authors can guide readers through the data, and separate the signal from the noise to shape a coherent narrative (Silver, 2012). This requires careful curation of the data and authors make decisions, e.g. to select, normalize, filter, categorize, translate, map, arrange, aggregate or otherwise process data (Brehmer & Munzner, 2013). Preparing data for visualization design further requires addition (e.g., through annotations) or omission (e.g., removing seemingly irrelevant outliers) of information (Hullman & Diakopoulos, 2011). Data is often considered “*messy*” (OpenRefine Team, 2024) and there is an abundance of tools that help to “*clean*” (Tableau, 2024) and “*tidy*” (Wickham et al., 2024) it up by removing duplicates and outliers, unifying labels or categories, or getting rid of “*irrelevant observations*” (Tableau, 2024). Consequently, there is an ambition towards cleanliness extends to data visualization, which strives to “*reduce complexity*” (M. Chen et al., 2020), “*simplify datasets*” (Banerjee, 2024), and be overall “*easily digestible*” (Schwabish, 2020). Admittedly, the success of data visualizations as a medium may in part originate in its aspiration to be straightforward and easy to understand. However, cleaning data comes at the cost of losing context, nuances, and plurality. Even mundane transformations, e.g., unifying a date format to make it machine-readable, can eradicate meaningful details about a record. (Loukissas, 2019) . In consequence, the process

of preparing data for visualization can “*distort, hide, and disguise the complex reality of data, data practices, and phenomena from the real-world*” (Hengesbach, 2022). While providing one easy-to-follow narrative is what makes visualization enticing in the first place, it simultaneously makes it impossible to include a multiplicity of interpretations:

“A visualization is often delivered from on high. An expert designer or team with specialized knowledge finds some data, does some wizardry and presents their artifact to the world with some highly prescribed ways to view it. Can we imagine an alternate way to include more voices in the conversation? Could we effect visualization collectively, inclusively, with dissent and contestation, at scale?”

—Catherine D'Ignazio (D'Ignazio, 2015)

Data-driven storytelling generally promotes one narrative—chosen by the authors—over other narratives that might be equally plausible. Offering a plurality of narratives (Dörk et al., 2013) is often not considered when producing visualizations, and producing visualizations may come with the temptation to de-emphasize, appease, or ignore existing dissent in the data or its interpretations (D'Ignazio, 2015). D'Ignazio and Klein ask: “*[W]hat might be lost in the process of dominating and disciplining data? Whose perspectives might be lost in that process? And, conversely, whose perspectives might be additionally imposed?*” (D'Ignazio & Klein, 2020).

Beyond this visualization-specific issue, there is another, deeper-seated problem because the validity of data is limited. In contrast to the aforementioned bias introduced by visualization authors, this challenge concerns the problem that data remains only an imperfect representation of a phenomenon (Lin et al., 2022). Prior work in has pointed out a number of pitfalls that impact the ability of data to truthfully represent a phenomenon, e.g., sampling errors, collection errors, or false dichotomies (Correll, 2019). During the COVID pandemic in the United Kingdom for example, mistakes during manual data entry meant that 50,000 potentially infectious people were told to not socially isolate (Halliday et al., 2020). Further, data is shaped by existing power dynamics and hierarchies: Those in positions of power may influence what phenomenon is deemed relevant enough to collect data on and how that data is structured. For example, D'Ignazio and Klein point out how non-binary people are systematically underrepresented in surveys or demographic data (D'Ignazio & Klein, 2020) because existing forms only provide the option to enter 'male' or 'female' when asking about a person's sex. These examples show how data can be wrong by misrepresenting reality and lived experiences. Consequentially, visualizations that are created on this foundation, are equally wrong, and in need of correction.

In this thesis, I want to explore how visualizations can be used to elicit and integrate annotations that allow the audience to express potentially critical reactions and offer alternative narratives. By collecting annotations from the audience, I expect to contrast the data with partial and situated knowledge (Haraway, 1988) that is not based on *more* or *bigger* data' (Boyd & Crawford, 2011), but offers an alternative way of knowing and knowledge-making about the phenomenon (Rettberg, 2020). While visualization has mastered to represent quantitative information, it lacks the ability to integrate and represent more nuanced, ambiguous, and qualitative information.

Throughout my research, prior work on cartography has been a great inspiration. Similar to data, maps seek to present an objective truth to the readers. And similar to data, maps remain models of reality that can only provide imperfect representations. Drucker points out this similarity in her perspective of information visualization more generally:

"I think the ideology of almost all current information visualization is anathema to humanistic thought, antipathetic to its aims and values. The persuasive and seductive rhetorical force of visualization performs such a powerful reification of information that graphics such as Google Maps are taken to be simply a presentation of 'what is,' as if all critical thought had been precipitously and completely jettisoned."

—Johanna Drucker (Drucker, 2012)

Where can inspiration to make visualization less reified and more personal be found?; how can engagements be made less persuasive and more critical? Cartography, a field arguably older than data science or visualization, has long discussed the challenge of contrasting the physical geography of a place with its intangible context, e.g., its religious, cultural, symbolic, metaphysical dimension. For example, Ayers asks, "*how might we combine the obvious strengths of geographic understanding with the focus on the ineffable, the irreducible, and the particular [...]?* How might we integrate structure, process, and event? In sum, how might we combine space, time, and place?" (Ayers, 2010). One concept that is inspired by these questions are *deep maps*, which were first popularized by William Least Heat-Moon (Moon, 1999). Deep maps, like traditional maps, abstract and describe geographic space, but also "*include the discursive and ideological dimensions of place, the dreams, hopes, and fears of residents*" (Aitken et al., 2015). Building on this idea, participatory cartography has democratized map making by involving local communities, stakeholders, and marginalized groups in the creation and interpretation of maps. This empowers individuals to contribute to a discourse consisting of local knowledge (Geertz, 2008), spatial information, and cultural insights, fostering a more inclusive and representative mapping process. There are many examples of modern approaches to participatory deep maps, including maps of queer visibility (Kirby et al., 2021), maps "*that empower, challenge, and redefine stories*" about residents (Loukissas & Ntabathia, 2021), and maps about the struggle and desire

of urban dwellers (Maharawal & McElroy, 2018). In a prior publication that is not part of this thesis (Kauer et al., 2019), I investigated four existing collaborations in the fields of peacemaking, population demographics, and street ethnography. In these scenarios, maps rely on information from residents, for example to collect local knowledge on a street-level or to represent spatial narratives. Pairing these requirements with the premise of deep maps, I propose *participatory deep maps*, as an approach to allow for polyvocal and participatory mapping (Kauer et al., 2019). I contribute a set of challenges for such maps, that are relevant for the context of this thesis, as they question how personal stories can be collected from the audience and how impact the reading experience. Further, as Drucker criticizes the incapacity of conventional interfaces to “*alter data structures of a visualization through direct input*” (Drucker, 2017), I ask how such stories can be integrated into the visualization. Finally, I question how the additionally collected information itself can inform a visualization that works towards “*exposing multiple facets and enabling a variety of interpretations*” (Dörk et al., 2013) of the data and the surrounding discourse.

Integrating stories into maps is a rewarding challenge, as existing examples (see Chapter 2) demonstrate. How can this practice be translated into data visualization more generally? Also, at what point in the process of creating visualizations should other people’s input be integrated? It may not be possible or practicable to always involve diverse groups of individuals in the creation of any given visualization (Losev et al., 2022). One way to partially address this dilemma is to broadly discuss data visualization *after* its publication. Offering people a way to vocally and visibly share their perspectives, objections, and own analyses of the data on a public forum may be a path towards a more critical engagement with data. Against the aforementioned background of growing audiences, I see great potential for personal and critical engagements throughout a visualization’s extended life cycle, as a great diversity of topics and communities invite for more voices, more perspectives, and more narratives from the fringes to be integrated into visualizations.

In order to understand how people talk about visualization once it is published, I first want to have a closer look at existing formats that already display a rich source of social exchange around data.

1.1.2 Understanding Visualization Discourse

By making data accessible, engaging, and understandable, data visualizations offer a fertile ground for audiences to discuss presented topics and ideas. There are many examples of communities and platforms, in which the presentation of data visualizations invites readers to partake in a lively and diverse discussion. These discussions provide insights into how individuals engage with and make sense of the visualized data, which otherwise could only be done in lab-based user studies, but not in real-world settings.

Public audiences engage in discourse about data visualizations on social media platforms like *X* (formerly *Twitter*), *BlueSky*, or *Reddit*, or users share visualizations they find interesting or insightful, along with their interpretations and critiques. On *X*, hashtags such as #dataviz, #dataanalytics, or #infographics are commonly used to initiate discussions about data visualizations. The hashtag #TidyTuesday for example marks an ongoing challenge to visualize a given dataset and add to a discussion about best practices for clean visualization. Reddit communities like *r/dataisbeautiful* provide a space for users to share, discuss, and provide feedback on various data visualizations. Redditors (as users of the platform call themselves) ask questions about techniques, tools, and best practices for creating effective visualizations. They also seek feedback on their own visualizations or share interesting findings they've made through data analysis. These discussions often involve a mix of professionals, enthusiasts, and beginners, contributing to a diverse range of perspectives and insights.

In addition, international newsrooms like *The Guardian*, *The Financial Times*, *The New York Times*, or national media like Germany's *ZEIT ONLINE* or *Der Spiegel* have entire teams of data journalists dedicated to curating articles that use visualizations as a central device to communicate data and form data-driven narratives. Traditionally, these websites feature a comment section, which interested readers use to express their opinions, ask questions, or add additional insights related to the visualized data. In recent years, some news websites have heavily restricted or entirely closed comment sections, as they require significant resources to ensure that discussions remain civil, respectful, and free from hate speech or misinformation. This has—intentionally or not—further elevated the role of social media as a place for discussion, where news outlets post articles to reach new audiences and readers can comment mostly unconstrained.

Similarly, many blogs and websites are dedicated to data visualization, such as *FlowingData* (Yau, n.d.), *Nightingale* (Authors, n.d.-a), or the *Storytelling with Data* community (Authors, n.d.-b). These platforms feature articles that analyze and criticize data visualizations from various sources, discuss trends in visualization design, and showcase innovative approaches to data presentation. Audiences engage by commenting on posts, sharing their thoughts on social media, and sometimes even contributing their own guest posts or visualizations for publication. There hasn't been a structured survey that investigates these instances of public discourse about data. Little is known about how public audiences without specific expertise and shared incentives openly express their thoughts, feelings, and insights in response to data visualizations. Understanding how people discuss data visualizations is relevant for a number of reasons.

In order to outline the relevance of discourse for visualization, I want to first discuss different notions of the term 'discourse'. In a very wide sense, discourse often associated with being the sum of all statements about a topic. The discourse around climate change for example includes research articles, data, news articles, spoken conversations among peers as well as speeches by politicians, written words on this year's election posters as well as century old letters that first address the issue. Habermas discusses the role of discourse in the public sphere, where citizens engage in debate and discussion about matters of public interest (Habermas, 1981). He emphasizes the importance of an open and inclusive public sphere for democratic legitimacy, where individuals can participate in the formation of public opinion and decision-making processes (Habermas, 1981). This notion of discourse is particularly relevant to postmodern society, in which grand narratives about an absolute truth are widely rejected. Instead, cultural relativism suggests that personal views are always dependent on a specific context or perspective: different people can have different and potentially conflicting 'truths'. In this thesis, I am primarily concerned with written comments left with or around visualizations that are published on the web. This small cutout of the discourse can already take many shapes, including comments on articles, social media, or blogs, all, responses to those comments, or annotations on visualizations. Individual chapters of my thesis focus on slightly different aspects of how individuals express themselves after reading a visualization. Therefore, I use different terms to describe these expressions, including *reaction*, *annotation*, *comment*, or *externalization*. Conversely, I refer to *discussions* if the discourse design allows for further interpersonal exchange, e.g. if one can respond to my initial reaction.

There are a number of factors that affect the way readers engage with data visualization (Kennedy, 2015). For example, an individual's cultural, social, and emotional context plays a considerable role when making sense of data (Kennedy et al., 2016; Kennedy & Hill, 2018). Taking personal context into account when investigating discussions about data visualizations can help build more inclusive visualizations and improve data literacy. Moreover, providing space for personal expression can potentially include a multiplicity of voices, narratives, and perspectives into data visualizations.

In this thesis, I investigate the notion that *data is personal* (Peck et al., 2019) and want to understand how personal relations to data are expressed in public settings. Building this understanding existing discourse, I want to build interfaces — discursive visualizations — that elicit reactions from audiences.

1.1.3 Building Discursive Visualizations

In the settings mentioned above, discussions are created and displayed separately to the visualization. They exist as individual text snippets besides or underneath the visualization that have no explicit relationship to any specific part of the visualization. This approach works fine, as long as comments refer to the visualization as a whole. As soon as comments point out specific visual marks, patterns, trends, or relationships, it becomes a tedious task to associate information gathered from the discussion to data represented in the visualization. Existing annotation systems have worked towards integrating expressions created by the audience into visualizations. Most prominent are efforts for collaborative sensemaking: pioneering platforms like sense.us (Heer et al., 2007) or ManyEyes (Viegas et al., 2007) were first to consider the audience as a valuable resource to collectively read and understand data visualizations. Following in these platform's footsteps, CommentSpace (Willett et al., 2011) offered more structured mechanisms to aid the analysis process and help contributors to navigate the discussions. CommentSpace also discussed the relevance of "*managing and incentivizing participation*" (Weiner & Harris, 2003) to enable users to use more sophisticated interfaces. PixelClipper (Walny et al., 2020) or ActiveInk (Romat et al., 2019) offer ways to manipulate, cut, draw, or highlight elements of the visualization. These tools use various strategies to embed annotations within visualizations, including placing markers (Willett et al., 2011), but also placing text on the visualization (Heer et al., 2007), adding free-form drawings (Romat et al., 2019), or manipulating visual marks (Lin et al., 2022).

These existing systems have a different focus compared to my emphasis on personal and critical engagements. First, they are created in an effort for "*many users to pool their effort as they discuss and analyze the data*" (Willett et al., 2011), working towards a "*shared interpretation of the data*" (Willett et al., 2011). This narrow focus on social analysis does not consider other ways to engage in a discourse about data. While there have been efforts for annotation interfaces to challenge e.g., the validity of data aggregations or values (Lin et al., 2022), the potential for a broader discourse including critical, design-oriented, or personal expression remains vastly under-explored. Further, there is no robust understanding of the effect of integration (*where*) and origin (*who*) of comments. There have been no controlled studies that determine, whether a placement inside or outside the visualization changes how comments are considered. Similarly, it is not known whether comments from the audience or annotations from visualization authors provide different reading experiences. Finally, existing strategies to integrate annotations into visualizations lack the ability to precisely point out what element(s) of a visualization they refer to. For example, it remains unclear whether one-dimensional markers on a map put the scope on a specific place, the city it is located in, or a whole country. On the other hand, they lack the ability to *scale*, e.g., when multiple freehand drawings or labels overlap each other, rendering each other illegible.

To conclude: opening visualization to audience discussion may change how people engage with them, yet there are no interfaces that allow for broad participation beyond sensemaking: My work is motivated by the idea that letting people talk about data offers more than just a way to better understand it. Integrating discourse into visualization paints a broad picture of the data and its interpretation, but also points out its gaps, seams (Hengesbach, 2022), and oversimplifications.

I hypothesize that bringing data visualization and discourse about it closer together helps people to understand data's context and gives a glimpse of people's intricate, complex, and personal relation to data:

Visualization shows a message — discourse asks: *who created it?*

Visualization narrates, what data means — discourse asks: *what does it mean to you?*

Visualization connects the dots — discourse asks: *what is between them?*

In her 2015 essay 'What would feminist data visualization look like?', Catherine D'Ignazio asks: "*How can we devise ways to talk back to the data?*" (D'Ignazio, 2015). Inspired by this question, my thesis contributes interfaces and practices that challenge existing dynamics in visualization creation and reading engagement: They offer ways to lessen the epistemic authority of data; they rethink whose perspectives are included to shape what people learn when reading a visualization, and provide a platform for personal, analytical, and critical engagement with data outside the lab.

1.2 Thesis Outline

To approach the idea of discursive visualization, the overall strategy is to (1) understand existing discourse, then (2) understand the implications of integrating this discourse into a visualization in a narrow proof of concept prototype, to then (3) broaden this concept of integrated discourse to a wider platform for discursive visualization. I follow this strategy by structuring my work into three research questions (RQ1–3). This section provides an overview over these questions, with which methods I approach them, what results I get, and what contributions I draw from them.

Chapter 3:

Investigating Reactions to Visualizations on Reddit

While there is a plethora of discussions about data visualization, there is no structured analysis of them. There is no knowledge about *what* people say, what they *address* with their comments, and *why* they engage in the first place. Hence, I ask **RQ1: How do people react to data visualizations?** To better understand existing discourse about data visualizations, I turn to the */r/dataisbeautiful-community* on Reddit, a community of casual visualization enthusiasts who create and discuss data visualizations outside controlled lab settings. I collect comments from community members that directly react to visualizations and use a Grounded Theory approach to analyze them. I follow up with a structured survey to better understand people's motivation to participate in the discussion. Based on the results of my analysis, this chapter contributes a description of *ten reaction types* on *four reaction scopes* from visualization audiences in public forums, as well as a set of implicit and explicit *engagement drivers* for these audiences.

Chapter 4:

Investigating Audience Annotations in a Public Data Visualization

Prior work has shown how text elements next to visualizations (e.g., annotations, titles, or captions) provide a frame for interpretation that influences, how people make sense of the visualization or what they remember after reading it. Although investigations into RQ1 (Chapter 3) underline the potential of discourse for sensemaking and contextualization, it remains unclear if existing *separated* discussion interfaces fully leverage this potential and whether integrating discourse into visualizations can enhance its impact on the readers' viewing experience. Further, there are no studies that consider the origin of an annotation and compare how comments made by the audience compare to comments added by visualization authors. Hence, I ask **RQ2: What is the impact of audience discourse on the viewing experience?** In a time as the corona pandemic was subsiding, I am interested in people's memories about this period and designed and implemented a prototype

called '*corona moments*' that displays line charts of COVID-19 case numbers for different countries. I deploy this prototype and encourage the audience to place visual marks along the timeline and connect them to a textual comment that describes a moment that stuck with them. I am specifically interested in the impact of the different viewing conditions on the reader's experience: visitors are randomly assigned to one of three viewing conditions, altering the integration of comments (embedded vs. integrated) and their origin (audience vs. authors). Based on this prototype, in Chapter 4 I describe two connected studies that explore the design space between annotation integration and annotation origin. To approach the research question and narrow it to my specific research focus, I ask: How do annotations curated by visualization authors and annotations collected from the audience differ in their effect on the viewing experience; what is the impact of embedding annotations directly into visualizations? To answer these questions, I analyze interaction logs comparing the different viewing conditions, audience annotations, as well as two structured surveys that ask all visitors of the prototype about their experience and their motivation to share a comment. Based on the results, I contribute to a robust understanding of how different annotations impact the reading experience. Further, I present the concept of visualization as a space for *collective storytelling*, in which audience annotations can become the primary concern of a visualization, as reading them establishes personal relevance, promotes empathy for others, and helps people reflect on their own lives.

Chapter 5

Anchoring Discussions in Data Visualizations

The findings of Chapter 4 are limited to one specific chart type of one specific topic and one type of marker to embed annotations. Other existing discussion platforms have similar shortcomings, and further do not fully leverage the potential of integrating comments into the visualization: they do not provide mechanisms to exactly point out what area of the visualization is talked about. Also, they do not scale well and are overwhelmed with large volumes of comments. Based on this, I ask **RQ3: How can discourse be integrated into data visualizations?** I present an interface prototype called *viscussion* that allows selecting specific areas within a visualization to create what I call *anchored annotations* and connect textual comments to them. By layering and coloring these anchors, a meta-visualization emerges, showing what and where people comment. Inspired by human traces left on physical objects, I call these digital traces of communication *discursive patinas*.

To answer RQ3 (*How can discourse be integrated into data visualizations?*), I conduct user studies with students, domain expert groups, and visualization researchers. I qualitatively analyze statements from group discussions and structured. I conduct an open-coding of participants' comments and analyze interaction logs recorded across all user studies. Based on this data, I assess, how anchored comments are created and what parts of a visualization

people annotate. I further explore how discursive patinas shape the readers' experience of the discussion and how they can be used in future applications. Based on the results, I contribute discursive patinas as a device to improve the ability to navigate discussions and guide people to comments that help understand, contextualize, or scrutinize the visualization.

Chapter 6: Discussion & Conclusion

The final chapter summarizes the previous chapters and points out relevant limitations of my work. It then outlines the various aspects of design implications discursive visualization has on user interfaces, human factors, and future applications. The thesis closes with an outlook on future work to discuss, how the impact of the discursive engagement can be deepened, how future applications can cover a broader spectrum of use cases and techniques, and how rising technological trends can interactive with discursive visualizations.

1.3 Thesis Statement

This thesis investigates, how people discuss data visualizations and evaluates user interfaces that allow audiences to visually integrate their reactions into data visualizations. Doing so, my work provides mechanisms that help to shape, understand, and foster the wider discourse about data. What is part of that discourse determines, what information people get when reading visualization.

Through Grounded Theory, prototype designs, user studies, as well as interviews and surveys, this thesis develops the practice of *discursive visualization* as a way to entice professionals and novice audiences alike to engage in analytical, personal, and critical discussions around visualization.

1.4 Publications

This section lists the publications that are relevant to this thesis and refers to the chapters they appear in. This list also includes publications that are not part of this thesis, but inform the design of workshops or challenges relevant for my work. This thesis is written in first-person singular perspective: I use "I", "me", "my" to motivate and discuss my work. Due to the collaborative nature of paper-writing, chapters based on the publications below are written in first-person plural, where "we" and "our" refer to the authoring team of a given paper. For all publications, I outline my contribution to the manuscript and the conferences or journals they were submitted to.

Publications in this thesis:

- **Tobias Kauer**, Arran Ridley, Marian Dörk, Benjamin Bach (2021) *The Public Life of Data Investigating Reactions to Visualizations on Reddit*, Proceedings of the CHI Conference on Human Factors in Computing Systems
 - This paper forms the basis for **Chapter 3**. My role in the author team was to collect and prepare existing discussions about data visualizations for analysis; take part in the Grounded Theory analysis; carry out and analyze the survey; and take part in writing the paper.
- **Tobias Kauer**, Benjamin Bach, Marian Dörk (2022) *Many Voices: Audience Annotations in a Public Data Visualization*, **Under review** at IEEE Computer Graphics & Applications Special Issue on Critical Data Visualization
 - This paper forms the basis for **Chapter 4**. My role in the author team was to design and develop the prototype used in the study; run the study; conduct and analyze interviews; conduct and analyze two surveys; and take part in writing the paper.
- **Tobias Kauer**, Derya Akbaba, Marian Dörk, Benjamin Bach (2024) *Discursive Patterns: Anchoring Discussions in Data Visualizations*, IEEE Transactions on Visualization and Computer Graphics.
 - This paper forms the basis for **Chapter 5**. My role in the author team was to design and develop the prototype used in the studies; run the studies and collect data; analyze the collected data; and take part in writing the paper.

Other publications:

- **Tobias Kauer**, Benjamin Bach, Marian Dörk (2019) *Participatory Deep Maps: Towards Discursive User Engagement with Data Visualizations*, 2nd Workshop on Urban Data Visualization, IEEE VIS Conference
 - This short paper has not been included in this thesis, but describes challenges for participatory visualization outlined in **Chapter 1**. My role in the author team was to collect and describe motivating cases; review related literature; flesh out and describe challenges; design the conference poster; and take part in writing the paper.
- **Tobias Kauer**, Sagar Joglekar, Miriam Redi, Luca Maria Aiello, Daniele Quercia (2018) *Mapping and visualizing deep-learning urban beautification* IEEE computer Graphics & Applications
 - This publication has not been included in this thesis, but informed challenges in **Chapter 1**. My role in the author team was to design and develop the prototype used in the studies; run the studies and collect data; analyze the collected data; and take part in writing the paper.
- Christine Bell, Benjamin Bach, **Tobias Kauer** (2020) *Ways of seeing: Peace process data-viz as a research practice*, Sage Convergence
 - This publication has not been included in this thesis, but informed challenges in **Chapter 1** as well as the workshop design in **Chapter 5**. My role in the author team was to design and develop the visualizations described in the studies and take part in writing the paper.

Chapter 2

Background

My research sits at the intersection of data visualization, critical data studies, and annotation interfaces. I start this section by deepening the discussion of existing use cases for data visualization and critical perspectives on data as well as data visualization (see 2.1). I also want to showcase existing projects in participatory cartography (see 2.2) that were a great inspiration for my work. I will then outline the literature relevant to my research questions. First, I want to provide an overview of existing interfaces for discussing visualizations (see 2.3). I then provide a summary of related work that investigates different types of audience reactions (see 2.4) in order to set the scene for my approach of RQ1 in Chapter 3. Then, I review existing interfaces and visualization approaches that allow to integrate discussions into visualizations (see 2.5) and inform the design of my own prototype for discussion integration in Chapter 5 (RQ3). I finish this chapter with an assessment of prior work on personal engagements of the audience with data (see 2.6) to then study the impact of annotations (RQ2) in Chapter 4.

2.1 Visualization and Visualization Critique

Through visual representations of data like charts, graphs, and maps, data visualization aims to make complex data more understandable, accessible, and interpretable (Heer et al., 2010). It helps users to analyze large datasets, identify patterns, trends, correlations, and outliers, and make informed decisions based on the insights derived from the data (Brehmer & Munzner, 2013). There are two not clearly distinguishable categories of data visualization: exploratory and explanatory data visualizations. An exploratory approach allows to investigate novel datasets, to conduct analyses (Perer & Shneiderman, 2008), seek information (Dörk et al., 2011), or help investigate possibilities (Roberts, 2005). Exploratory analysis is generally supported through interaction (Dimara & Perin, 2019) and has a strong focus on revealing patterns and relationships, e.g. through coordinated views (Roberts, 2007). Explanatory data visualization, on the other hand, is used to communicate data with a focus on clear insights, which are carved out in advance (Segel & Heer, 2010). Explanatory visualizations are usually used for data-driven storytelling, in which data supports

a previously established narrative framing (Hullman & Diakopoulos, 2011). As a result, these narrative visualizations generally have stronger emphasis on key insights and offer contextual information (Ren et al., 2017) to be accessible also for readers with little data literacy. Across these categories, data visualization seeks to produce insights that might be missed with raw data alone. By communicating data-driven insights effectively to diverse audiences, visualization can transform data into actionable insights, for example to make informed decisions (Moore, 2017; Park et al., 2022), drive behavioural change (Pandey et al., 2014), or to raise awareness for social issues (Dörk et al., 2013).

Recent years brought forward more critical voices (Kitchin & Lauriault, 2014) and ethical considerations (Correll, 2019) about the process of designing visualizations and their impact on readers. Critical data studies scrutinize, how data is produced, used, and interpreted as researchers interrogate the power dynamics, biases, and inequalities embedded within data practices (Dalton et al., 2016). To that end, recent work has pointed out how data can be incorrect, inconsistent, inaccurate, incomplete, uncertain, relative, contextual, or situated (Correll, 2019). Data is not a neutral representation of the world, but shaped by existing power structures (D'Ignazio & Klein, 2020). There are clear discrepancies between what a visual design suggests and the characteristics of the visualized data (Hall et al., 2015), and visualization tends to unintentionally mask or intentionally hide aspects that point towards the imperfection of data (Hengesbach, 2022).

Existing efforts of critical visualization often remain theoretical. This thesis builds on existing work on visualization annotation, existing taxonomies of annotations, and their integration. This is done with the aspiration to foster a *practical* approach to critical engagement with visualizations: how and by whom can data be scrutinized and contested? How can data be corrected? What are alternative narratives other than the one prescribed in the visualization? How can the visual representation be improved? My research draws inspiration from participatory cartography and relies on existing studies of visualization annotation and audience engagement to better understand, how and why people actively engage with visualizations. In the following, I will provide an overview of existing work in these fields.

2.2 Participatory Cartography

Both maps and data visualizations aim to represent information visually. Maps typically represent geographical or spatial information, while data visualizations represent numerical or relational data. They are both used to communicate insights and patterns within the data or geography. Maps are often used to understand spatial relationships, while data visualizations help users interpret trends, correlations, and patterns in the data. Most

importantly, in the context of this thesis, both are designed with the audience in mind, with the aim of conveying information in a clear, concise, and engaging manner. They often simplify complex information to make it more accessible to the intended audience. Both are media for planning, decision-making, and communication alike.

While critical perspectives on data visualization have received increasing attention only in recent years (D'Ignazio & Klein, 2016; D'Ignazio, 2015; Dörk et al., 2013), critical cartography has discussed for many decades how maps are not neutral representations of the world, but are shaped by existing power structures (Wood & Fels, 1992) and hidden agendas (Harley, 1988):

"Maps are never value-free images. [...] Both in the selectivity of their content and the signs and styles of their representation, maps are a way of conceiving, articulating, and structuring the human world which is biased towards, promoted by, and exerts influence upon particular sets of social relations."

—J. B. Harley (Harley, 2002)

Rooted in this critical tradition, cartographers have approached map-making as a participatory practice that considers residents' stories as a valuable source for knowing a space and creating representations of it. People's local knowledge (Geertz, 2008)—their everyday local experiences and place-making practices (Yeh, 2016; Nugroho et al., 2018)—plays an important role because it provides unique insights and perspectives that might not be captured through traditional mapping methods alone.

In Chapter 1, I teased the idea of *deep maps* – maps that are not limited to represent political borders or geographic features, but also seek to include discursive dimensions of place. The following examples illustrate use cases for such maps and show their relevance for my thesis, specifically RQs 2 and 3.

The Anti-Eviction Mapping Project for example has created an archive that collects stories of displaced residents in the San Francisco Bay Area and other urban centers in order to build community, raise awareness, and express solidarity with the victims (Maharawal & McElroy, 2018). Through a process that is described as "*collaborative, multimodal, and—yes—quite messy*" (D'Ignazio & Klein, 2020), the project collects stories of evictions (Figure 2.1) and shows them on maps to stress the magnitude of the problem of housing injustice on a geographic frame while also sharing the stories of particular community members. Similarly, the project Queering the Map allows users worldwide to add written stories of queer moments and memories to a map (Kirby et al., 2021). Stories are submitted anonymously and appear as a marker on a map (Figure 2.2). Instead of clearly defining the audience, Kirby et al. (2021) coin the phrase "stories for someone", i.e., stories that do not address anyone

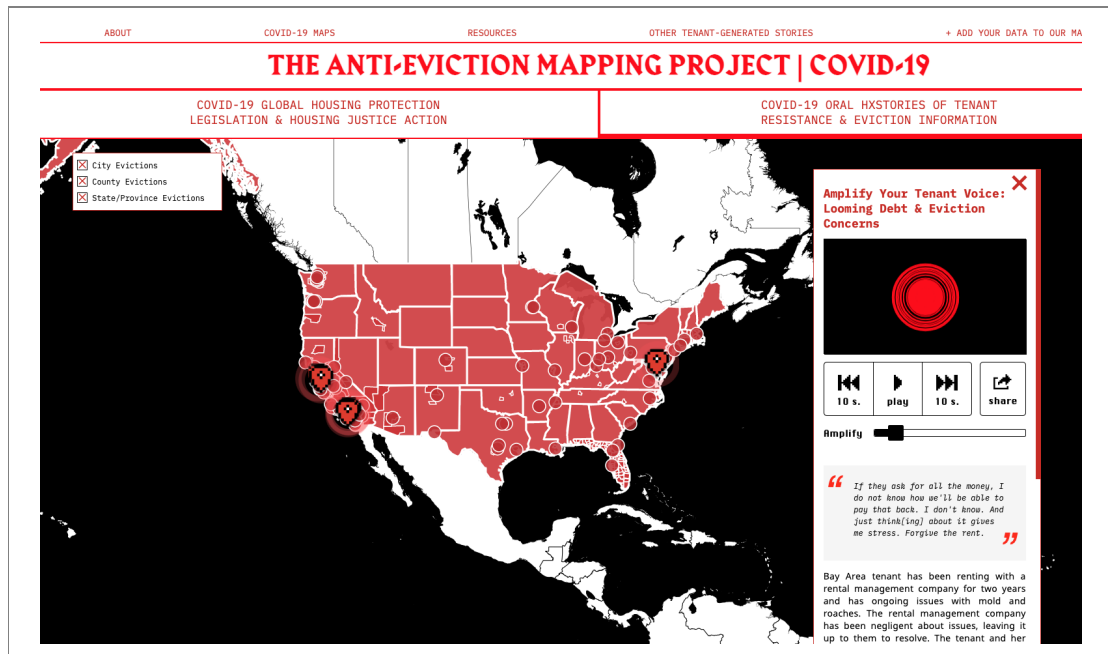


Figure 2.1: A map from the collection of the Anti Eviction Mapping Project showing personal stories of evictions throughout the COVID-19 pandemic (Maharawal & McElroy, 2018)

specifically, but are written to add to an archive of experiences. Maps hold the potential to open up spaces for people to meet, exchange, and make claims about the world, as observed by Loukissas and Ntabathia in their studies of map rooms as open data settings (Loukissas & Ntabathia, 2021).

To conclude, efforts in participatory cartography show the open-ended potential of visual representations to elicit and represent knowledge from everyday audiences. The work presented in this thesis aims to translate these efforts to the field of data visualization.

2.3 Visualization Annotation

Annotations in the form of comments and other textual information offer a way to provide essential context for data shown in visualizations and provide an important interpretation frame to the reader. They are widely used in data-driven storytelling to explain data, draw the reader's attention to specific parts of the chart, and to provide information unable to convey through visual means (Riche et al., 2018). They can include background information on the represented topic, the data sets used, or how the visualization is to be read, or personal insights by the visualization creator. Annotations may vary in length and scope: ranging from brief description to verbose treatise. They can be referring to an entire visualization or only parts of it. Hullman et al. (2011) point out that annotations serve an important role

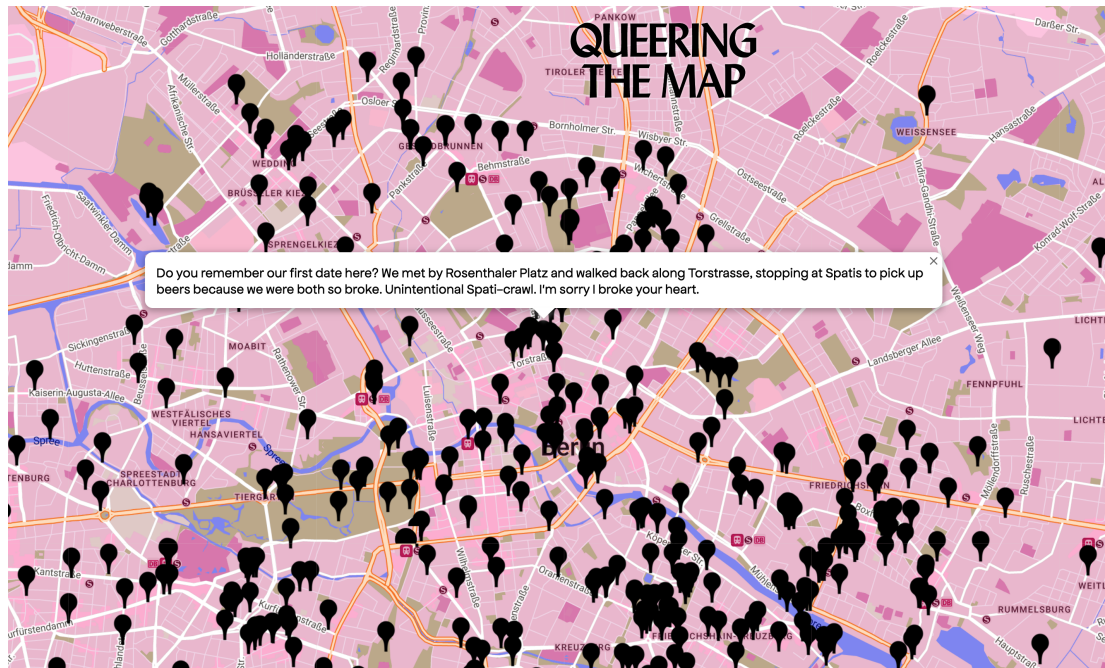


Figure 2.2: A story shared on the Queering the Map-website

in focusing readers' attention on specific areas of the chart, but have often been overlooked in prior research. This is particularly relevant, as annotations have a significant impact on how visualizations are understood and what readers remember about them (Kong et al., 2018, 2019).

This thesis primarily focuses on annotations created by the audience of a visualization. These annotations have been studied in the context of personal (Y.-S. Kim et al., 2019) and collaborative sensemaking (Viegas et al., 2007; Heer et al., 2007; Willett et al., 2011). Supporting data discovery through annotation is used to improve decision-making (Y. Chen et al., 2010), for example, in the context of business intelligence (Elias & Bezerianos, 2012). Prior research on collaborative data visualization has particularly considered task coordination, awareness, and communication (Isenberg et al., 2011). Similarly, expectation visualizations solicit and show readers' assumptions about data relations (Y.-S. Kim & Hullman, 2015).

Over the last twenty years, there have been a handful of research prototypes that provide a dedicated system for readers to comment on visualizations as a form of social data analysis. Introduced by Wattenberg and Kriss, social data analysis describes a "*version of exploratory data analysis that relies on social interaction as a source of inspiration and motivation*" (Wattenberg & Kriss, 2006).

Understanding these tools is necessary to understand, what kind of interactions and comments these interfaces afford. This section outlines existing tools and adjacent platforms (e.g., from social media or participatory cartography) and compares their approach to enabling and integrating discussions (Figure 2.9). While the compiled list of annotation tools may not be exhaustive, it provides an overview of the evolution of social analysis and highlights recent trends in discussions about data and data visualization.

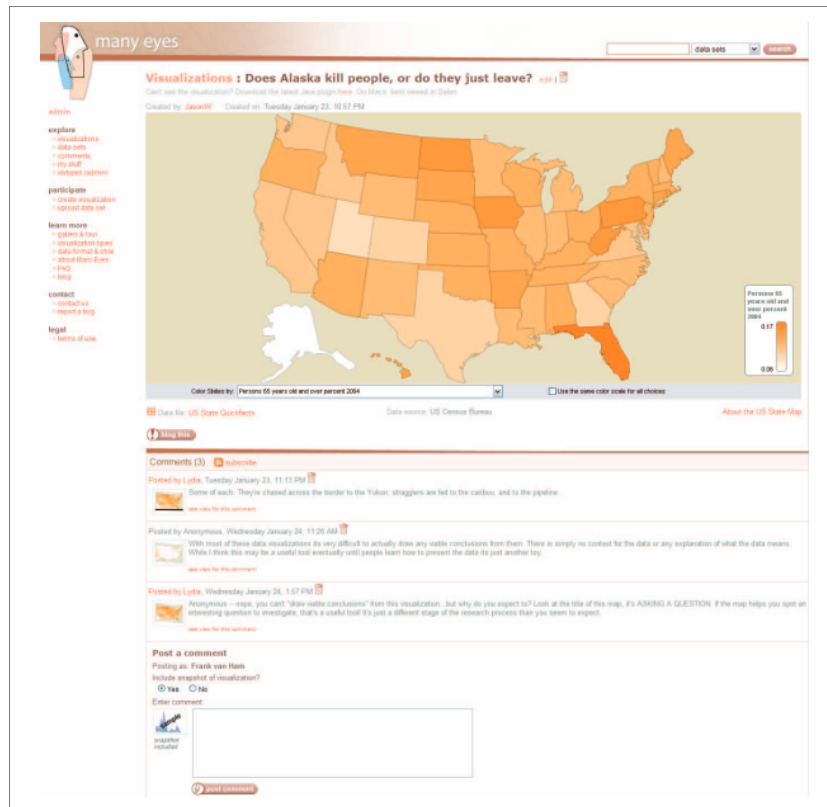


Figure 2.3: Discussion view of a visualization on the ManyEyes platform (Viegas et al., 2007)

Wattenberg's **NameVoyager** (Wattenberg, 2005) is a web-based visualization of historical trends in baby naming. While the website itself does not offer a comment function, there are many entries on blogs and discussion sites that discuss, how and why users use the visualization for social analysis. Wattenberg describes four distinct roles in social analysis (Bartle, 1996) (Achievers, Socializers, Explorers, and Killers), who exhibit unique traits, goals, and commenting styles.

ManyEyes (Viegas et al., 2007) is a publicly available platform to author and discuss visualizations. The tool offers authors a variety of templates they can edit with their own data to publish interactive data visualizations. Readers can talk about published visualizations in a separate comment section. ManyEyes combines the democratization of visualization authoring with a leap in social analysis and knowledge sharing. Doing so, ManyEyes marks an important step towards considering visualization as a social space.

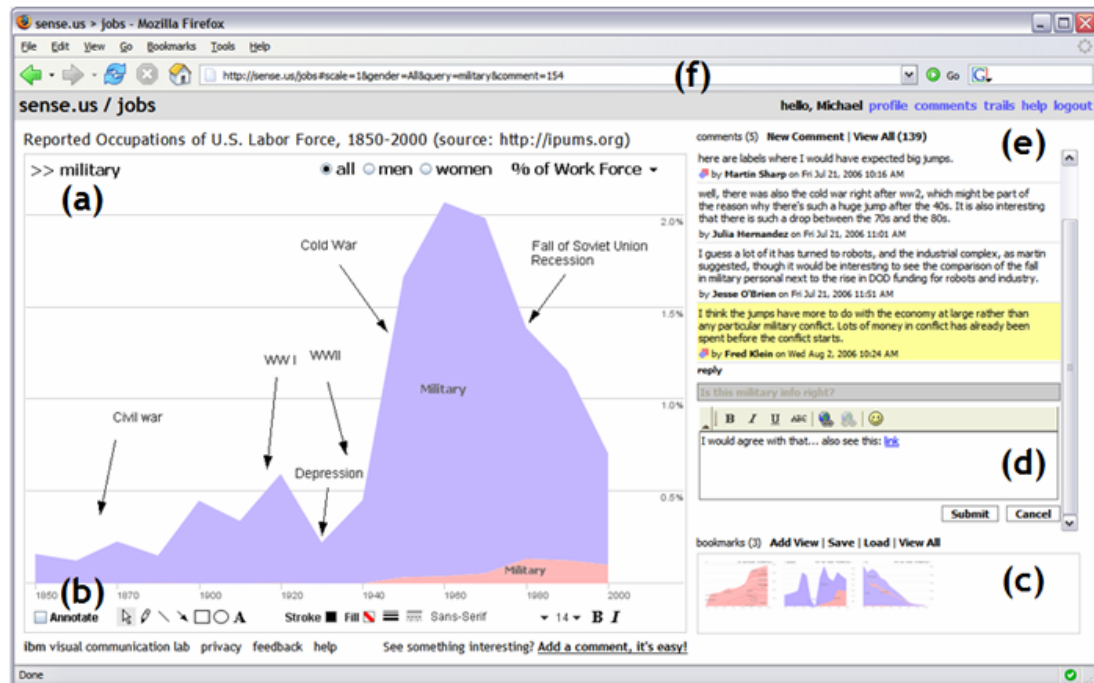


Figure 2.4: Discussion view of a visualization on the sense.us platform (Heer et al., 2007)

With **sense.us**, Heer et al. (2007) invite collaborators to comment and draw on data visualizations for the purpose of participatory sensemaking. The tool supports commenting specific visualization states and offers various ways for the readers to explore comments. The authors describe how most comments on the platform are concerned with data analysis and express observations, hypotheses, or questions. However, the lab study also found instances of 'personal' or 'playful' expressions that were 'social' in nature.

Click2annotate (Y. Chen et al., 2010) allows analysts to select a group of visual marks in a visualization (e.g., a cluster of elements in a scatter plot) and automatically generates an annotation that provides insights (e.g., number of elements, mean values) about that group. Analysts can then rate the quality of the annotation.

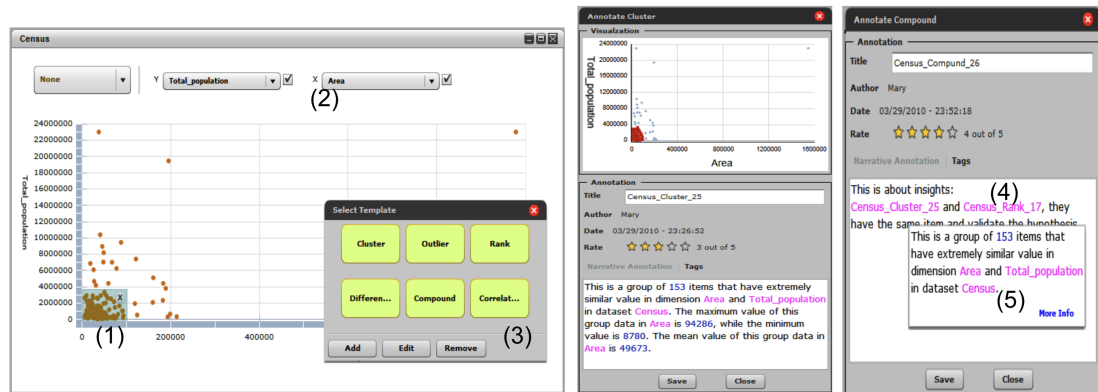


Figure 2.5: Annotation process on the click2annotate prototype (Y. Chen et al., 2010)

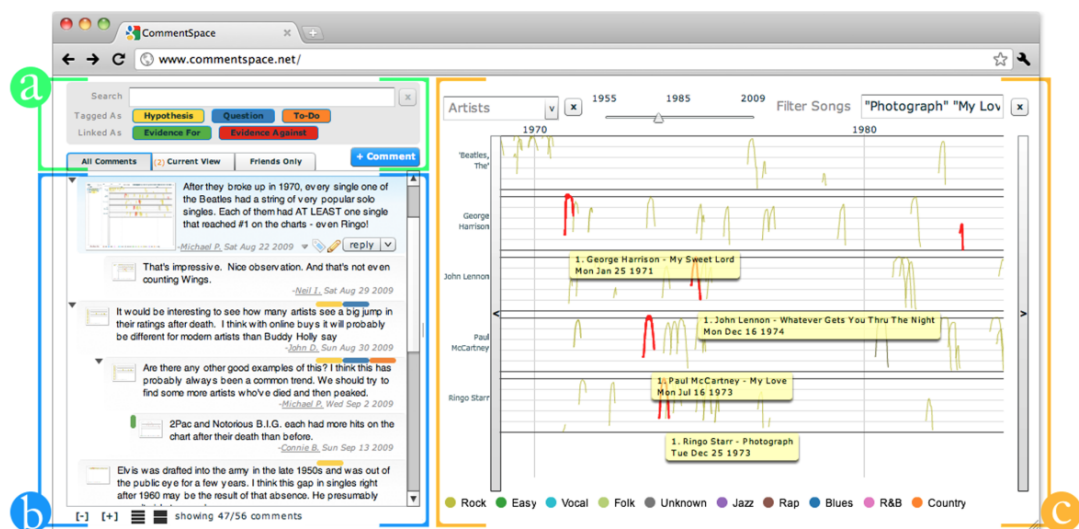


Figure 2.6: Discussion view of a visualization on the CommentSpace platform (Willett et al., 2011)

Expanding on the premise of sense.us, **CommentSpace** (Willett et al., 2011) provides a more structured approach to collaborative analysis. Here, Willett et al. invite analysts to use a small, fixed vocabulary to categorize their comments (question, hypothesis, to-do) and link them to data (evidence-for, evidence-against). The conducted lab study demonstrates how analysts shift from mere data exploration to more sophisticated, analytical tasks.

PixelClipper (Walny et al., 2020) provides a platform for conversations about data visualizations in public space. Readers can create custom cutouts (so-called 'clippings') of a visualization based on a grid and write comments about these portions of the visualization. Clippings are then shown alongside textual comments to provide a reference to the visualization content. A discussion of the tool's deployment outside of lab settings suggests that clippings provide entry points for audience engagement in public.

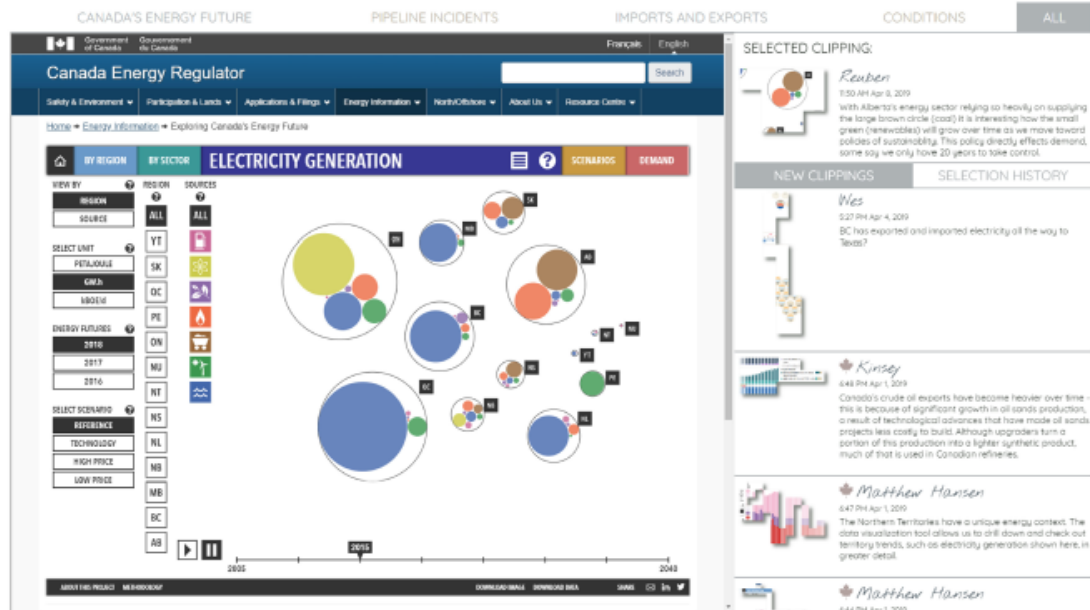


Figure 2.7: Discussion view of a visualization on the PixelClipper platform (Walny et al., 2020)

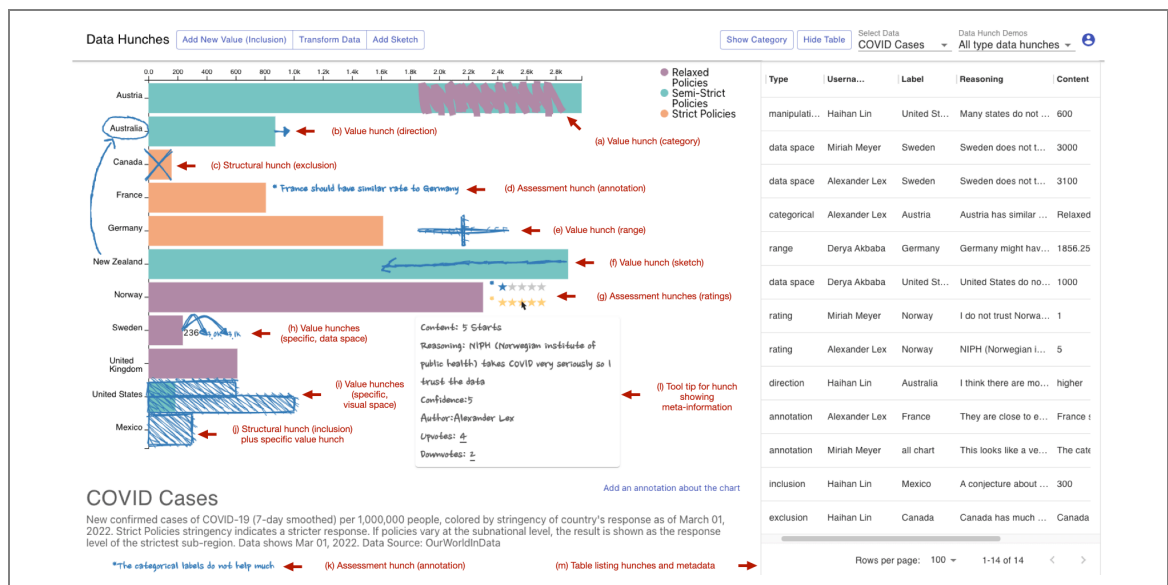


Figure 2.8: Discussion view of a visualization on the DataHunches platform (Lin et al., 2022)

Data Hunches (Lin et al., 2022) allows domain experts to express their ‘hunches’—their personal knowledge or intuition that builds on their experience with the topic—about data. This enables them to point out when they have issues with the trustworthiness of data, see problems with the structure of e.g., categories or relations, or think values are wrong or missing. Hunches are displayed as manipulations or additions to the original data and can

be enriched with additional comments or certainty scores. In that regard, Data Hunches demonstrates an important deviation from other tools, as they acknowledge that data is imperfect: Audience annotations are not merely used to understand data and enhance sensemaking, but to improve the underlying data itself.

It is important to note that outside this list, other systems exist that allow visualization *authors* to create and integrate annotations into their design, e.g., ChartAccent (Ren et al., 2017) Charticulator (Ren et al., 2018), or Voder (Srinivasan et al., 2018). Similar to work portrayed in this section, these tools support sensemaking and data-driven storytelling, yet annotations are entirely created by people who also design the visualization, and do not involve the audience and hence do not give them an opportunity to shape alternative narratives or contest the presented data.

	ManyEyes (2007)	sense.us (2007)	Comment- Space (2011)	/r/datais beautiful (2012)	Queering the Map (2018)	ActiveInk (2019)	Pixel- Clipper (2020)	Data Hunches (2022)
a Annotation <i>What can readers add to the visualization?</i>	none	freeform text shapes	none	none	marker	freeform, text, shapes, manipulate	clippings	freeform, text, shapes, manipulate
b Comments <i>Is there a separate list of comments?</i>	threaded	threaded filterable	filterable threaded	threaded sortable	none	none	sortable	none
c Linking <i>Are annotations and comments connected?</i>	none	on hover	none	none	none	none	none	on hover
d Attributes <i>What are properties of comments?</i>	none	none	3 tags 2 links	"Original Poster"	none	none	"facilitator comment"	hunch types (3) popularity confidence
e Encoding <i>How are attributes visually encoded?</i>	none	none	none	none	none	none	none	none
f Awareness <i>Are comments bound to data or states?</i>	none	state- and view aware	state- and view aware	none	none	none	none	none
g Charts <i>What visualizations are supported?</i>	dynamic templates	fixed set	any (if state in URL)	any	map	fixed set	fixed set	bar chart

Figure 2.9: Comparison chart of existing annotation systems and discussion platforms for data visualization

Taking a step back, reviewing existing platforms through Figure 2.9 shows several relevant patterns. First, the platforms that allow for a discussion of any kind of visualization (CommentSpace & /r/dataisbeautiful; Figure 2.9G) do not provide mechanisms to integrate comments into the visualization. This is only possible on platforms that limit the range of potential charts, either through templates (ManyEyes), specially prepared visualizations (sense.us, DataHunches, PixelClipper) or fixed sets of chart types (ActiveInk). The integration of comments into charts is at the heart of RQ3 and will be further detailed in Section 2.5. Further, current platforms under-utilize using attributes and their visual encoding. CommentSpace and Data Hunches allow describing comments with an additional vocabulary and provide categories for this characterization, e.g., hypothesis or specific

hunch-types On Reddit, the 'original poster' (OP, usually the original visualization designer) is highlighted in the comments. Similarly, on PixelClipper, discussion 'facilitators' visually stand out for the audience to understand their unique role in the unfolding discourse. On Data Hunches, readers can rate the popularity of a comment or their confidence in their hunch. However, none of these meaningful attributes are translated to be seen in the visualization. I will address the potential of this encoding in Chapter 5 (RQ2).

2.4 Types of Annotations

Working towards RQ1 (*How do people react to data visualizations?*), I want to outline various existing efforts to better understand how people talk about data visualization and to create taxonomies that describe their expressions. When evaluating the sense.us platform, Heer et al. (2007) also present a classification of annotations. Their classification focuses on sensemaking categories such as *observations*, *hypotheses*, *data integrity*, and social feedback (e.g., *socializing*, *affirmation*). One study analysed how the audience of ManyEyes (Viegas et al., 2007) engaged with the platform and found that "*although many visualizations on the site succeeded in sparking communication, very little of this communication took place on the site itself*" (Danis et al., 2008): Visualizations that were published on the site were often picked up by third parties, e.g., bloggers, who then hosted a discussion about the original post on their own platform. A study by Viegas et al. (2008) investigated these off-platform comments, along with comments on ManyEyes itself and the similar sense.us platform. Based on their analysis of 92 comments, they present a taxonomy of user reactions (Figure 2.10), including observations, questions, hypothesis, data integrity, socializing, system design, testing, tips, to do, and affirmation. In a different study, an analysis of 300 annotations sourced through a lab study (Vanhulst, Évéquoz, et al., 2018) identified six dimensions of comments (*insight on data*, *multiple observations*, *data units*, *level of interpretation*, *co-reference*, *detected patterns*).

As Figure 2.9 shows, some annotation systems use reaction types to let comment authors 'tag' their own comments. CommentSpace, for example, derives their vocabulary of fixed tags (question, hypothesis, to-do) (Willett et al., 2011) from observations made on sense.us and ManyEyes. Lin et al. (2022) introduce their own vocabulary of three 'hunch types', including *assessment* hunches, *structural* hunches, and *value* hunches, each of which offers different attributes, e.g., assessment hunches that include numerical scores to rate the status quo.

The existing taxonomy (Figure 2.10) by Viegas et al. (2008) provides a relevant starting point for RQ1 (*How do people react to data visualizations?*), in that it describes a broad range of expressions that are part of visualization discourse. However, revisiting the idea of investigating reaction taxonomies is a worthwhile approach in this thesis: I am particularly

Label	Many Eyes %	Sense.us %
Observation	46.3	80.6
Question	15.8	38.1
Hypothesis	11.6	35.5
Data integrity	9.5	15.7
Socializing	11.6	9
System design	11.6	9
Testing	4.2	5.6
Tips	4.2	4.1
To do	4.2	2.6
Affirmation	13.7	1.5

Figure 2.10: Comment categories on ManyEyes (Viegas et al., 2007) and sense.us (Heer et al., 2007), presented by Viegas et al. (2008)

interested in critical and personal approaches to visualization. While categories like 'data integrity' or 'socializing' hint at this kind of engagements, existing literature does not provide detailed descriptions of them and fails to explain the role of these categories for visualization discourse. Similarly, people's motivation to engage remain unknown. While Hullman et al. (2015) investigate audience reactions on a journalistic data visualization blog and found that "*comments drew on personal knowledge, opinions, experiences, or narratives*", what motives drive commenters to the discourse is not known. Against the background of changing audiences and novel platforms, revisiting contemporary discourse allows to assess how discourse changes over time and differs across communities.

2.5 Discussion Integration

As pointed out in RQ3, I seek to build interfaces that allow for visual integration of discourse into data visualizations. Prior studies about collaborative and personal sensemaking as well as existing work in digital cartography provide a number of approaches for this integration and discuss the effect it has on user engagement.

Studying annotation interfaces in the context of data exploration and analysis, Kim et al. found that analysts valued the benefit of annotations that are directly overlaid on the visualization as opposed to nodes on a separate canvas; and “*found that participants appreciated the ability to reference a part of a visualization [or] to pinpoint exactly the issues through the use of a pen is nice*” (Y.-S. Kim et al., 2019). Existing platforms employ a variety of strategies to integrate comments into visualizations (Figure 2.9a-d). While placing comments adjacent, but separate from visualizations worked well for early discussion platforms like ManyEyes (Viegas et al., 2007), there has been considerable effort to explore how to integrate comments more closely with visualizations (Figure 2.9a-c). While the discussions on CommentSpace (Willett et al., 2011) are more structured and (See e.g., Figure 2.9d), comments are generally not integrated into the visualizations but are linked to specific visualization states (e.g. specific views or filter settings). Similarly, sense.us (Heer et al., 2007) separates the list of comments that were made in a specific visualization state, but comments can be linked to freehand drawings, shapes, or text elements that are superimposed on the visualization. Tools for personal sensemaking that offer a single person features to analyze visualizations (instead of systems that let multiple users collaborate on a visualization) have similar features: ActiveInk (Romat et al., 2019) (Figure 2.11) and VoyagerInk (Y.-S. Kim et al., 2019) investigate techniques to draw and write directly on visualizations and to highlight, hide or manipulate visual marks with digital pens. Highlighting relevant data points or areas in a chart can help the viewer navigate and better understand the information. These tools have the advantage of not needing to anticipate other people’s externalizations: Only one user at a time manipulates the view, giving space to sophisticated ways to add annotations. Apart from visualization-specific platforms, mapping tools often allow placing markers, e.g., to describe something that happened in a specific place (Kirby et al., 2021) (akin to the concept of deep maps), or to help externalize and discuss implicit errors in visual analytics systems (McCurdy et al., 2019).

In an investigation of public receptivity to public data and visualizations, He et al. found that discussions “*generally integrate poorly with visualization and analysis tools*” (He et al., 2023). As mentioned before, comments are generally displayed in separate sections (see (Hullman et al., 2015) or section 1.1.2) and people use “*screenshots and external links rather than more malleable representations*” (He et al., 2023). Further studies investigating visualization comments on online news platforms, however, found that the majority of comments ignore the data or visualization itself (Hullman et al., 2015). Instead, comments focus on the context and framing of the story (Hullman et al., 2015), while only a fraction of comments refers to the data visualizations in the news articles (McInnis et al., 2020).

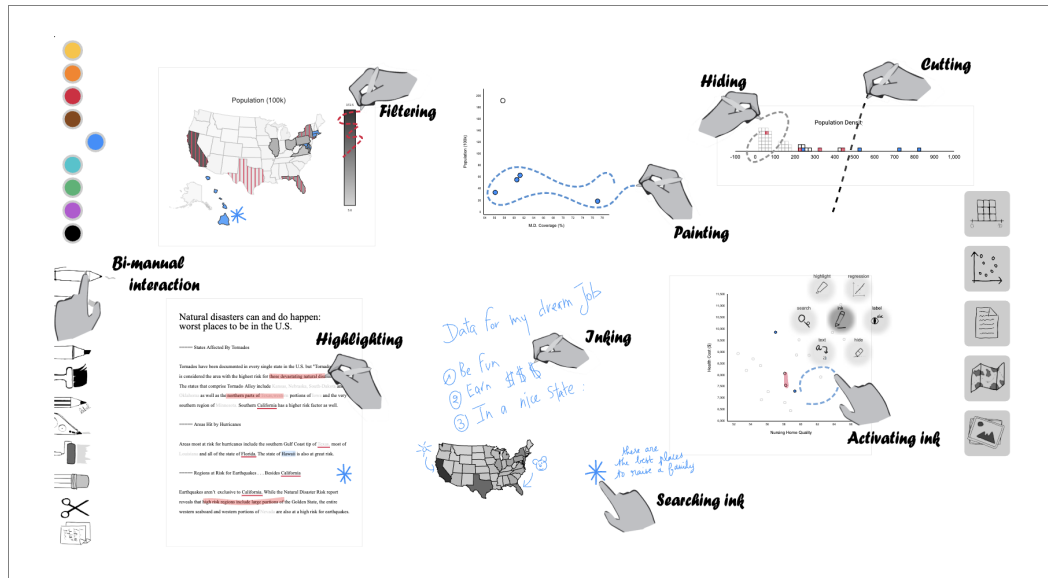


Figure 2.11: ActiveInk (Romat et al., 2019) platform for personal sensemaking

So, why are novel interfaces strategies for annotation integration not deployed more widely? The reasons for this can be manifold and challenging to address. Most importantly, establishing a practice of talking about data does not only require the right interfaces, but also an audience to use them. Most existing efforts aim to bridge the gap between visualization and discussion work with dedicated platforms (Figure 2.9) and try to bring the people to the visualization, instead of bringing the tools to the people. In the case of ManyEyes, for example, visualizations were often created on the platform and discussed elsewhere, e.g., on existing blogging communities (Danis et al., 2008). One notable exception to this is VizDat (Almahmoud & Karger, 2023), which offers Reddit users the ability to 'remix' an existing visualization (Figure 2.12). However, this feature is not available to all platform users, only to those who install a dedicated plugin—which again has the same drawbacks as dedicated platforms in that they do not leverage the power of an existing community.

Existing interfaces lack to satisfy two annotation characteristics: their scale and scope. The concept of *scale* reflects the interfaces' ability to accommodate a growing volume of comments without leading to visual clutter or compromising the readability of individual comments. Conversely, by *scope*, I refer to the mechanism for identifying portions of a visualization that are being commented on. Existing tools use a variety of mechanisms to place annotations in the visualization. Foreshadowing my work in Chapter 5, I call these integration devices 'anchors', as they mark the area comments hold on to. Anchors effectively encircle, point to, highlight, or cut out portions of visualizations they reference. The high flexibility in defining the scope comes at the expense of their capacity to scale with increasing numbers of contributions. Overlapping freehand drawings render each other illegible; for a

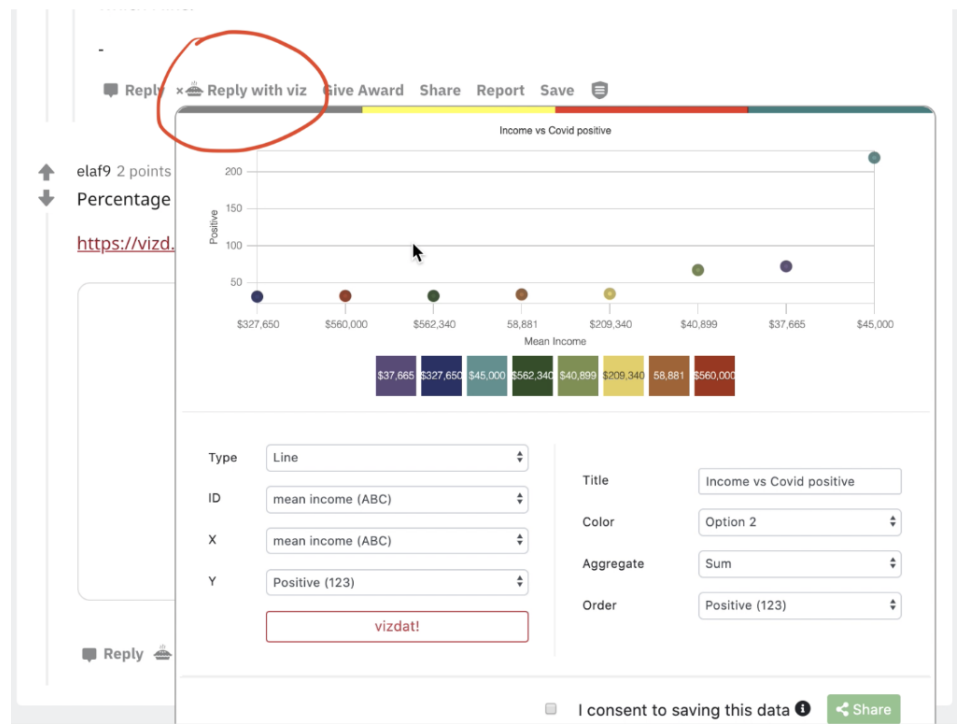


Figure 2.12: VizDat (Almahmoud & Karger, 2023) browser plugin to remix visualizations on Reddit

similar reason, clippings (Walny et al., 2020) or manipulations (Lin et al., 2022) from multiple viewers are not presented in one view. While this is not an issue for individuals or small groups, in public forums it quickly becomes an issue of scale when idiosyncratic scope definitions can impede the overall legibility.

In contrast to free-form annotations, interfaces using one-dimensional markers (Brown & Knopp, 2008; McCurdy et al., 2019) are highly scalable, at the cost of custom scope (see e.g., Figure 2.2). The uniformity and small size of markers help readers to quickly gauge where many comments are placed. Their identical size, however, can make it hard to understand the scope of what a comment refers to.

Existing discussions about data visualizations generally happen separated from them and have no visual integration (ManyEyes, CommentSpace). If comments are integrated, they have limited ability to scale and scope (Sense.us, PixelCXLipper). Further, platforms that allow for comment integration only allow discussion about a fixed set of visualizations or chart types: Sense.us and PixelClipper have a curated list of visualizations people can annotate, Data Hunches only allows annotations on bar charts. Only ManyEyes allows the audience to create and discuss their own visualizations. On all other platforms, it arguably would be cumbersome to translate existing strategies to new visualizations or chart types. Based on this, I pose RQ3: *How can discourse be integrated into data visualizations?*

2.6 Audience Engagement

The different aspects of the relationship between a visualization and its audience are often discussed as *engagement*, a term that however lacks a firm definition. For example, Haroz et al. haroz2015isotype refer to engagement as a measurement of effectiveness when interacting with visualization, alongside memorability or performance. Other sources describe engagement as a prerequisite for learning, ranging from *not-viewing* over *responding* to *presenting* (Naps et al., 2002). Similarly, Mahyar et al. describe engagement by the means of Bloom’s taxonomy of learning goals, ranging from *low* to *high* (Mahyar et al., 2015); *low* has been attributed to viewing and simple interaction, while *high* has been used to describe higher-level cognitive tasks such as hypothesis testing and decision-making. Similar notions to describe engagement refer to “*the [whole] processes of looking, reading, interpreting and thinking that take place when people cast their eyes at data visualizations and try to make sense of them.*” (Kennedy et al., 2016).

From another perspective, engagement has been used to describe how visualizations can get citizens informed about and involved in social issues (Dörk et al., 2013). In that sense, engagement is a process that may be triggered by a visualization, but eventually happens outside the visualization, e.g., in the form of social change and advocacy, rather than sensemaking and interaction. Often, such engagement will include other people. In context of co-located and in-person conversations about visualizations, Walny et al. (2020) provide a crucial differentiation between *direct engagement*, which is “*characterized by a visitor’s observable interactions with the space, artefacts, and people*”, and *data engagement*, defined “*by the extent to which a visitor connects with [...] the data behind the visualizations*”.

Some user engagement can be measured more easily, e.g., from interaction logs, questionnaires, and observations (Hung & Parsons, 2017; Walny et al., 2020; Conlen et al., 2019). Prior studies by Thudt et al. (2012), Wang et al. (2019), and Valkanova (2014) report on observations on how general audiences engage with visualizations in co-located and real-world settings. However, rather than aiming to collecting a wide range of reactions, these studies focus on understanding positive and negative impressions towards a designed artefact such as an interactive table-top application, a data comic, or a polling display. Data engagement and engagement beyond the artifact, on the other side, is hard to measure and assess. By relying on comments that users provide on the web, I explore a specific resource to understand engagement with visualizations, while at the same time being objective and neutral about the type of engagement.

In the context of this thesis, I focus on engagement as a personally motivated yet publicly visible approach to data that determines how and what one reads, contributes, and takes away from a visualization: A person’s particular situation, knowledge, and experience is highly influential when engaging with a data visualization (Kennedy et al., 2016; Kennedy & Hill, 2018). People’s cultural and social context as well as the emotional condition play

a considerable role when making sense of data. Any type of engagement can be related to current affairs and highly personal as reported by Peck et al. (2019); for example, well-established visualization tasks (e.g., information extraction, hypothesis-building) seem to be overshadowed by biographical or personal factors; people would not trust data that is sourced from institutions with a political identity different from their own—no matter the topic or insight. In other cases, people would deem charts more useful if they depicted a topic they had first-hand experience with—independent of the extracted information. Visualizations of early online communication demonstrate the wide spectrum of emotions shared publicly, while also proposing unique visual aesthetics to accommodate the personal nature of the data (Donath et al., 2010; Kamvar & Harris, 2011). (Peck et al., 2019). Likewise, when visualizations are shared online, people post comments on data visualizations to provide additional context and criticism (Hullman et al., 2015).

In data-driven storytelling, the provenance of such annotations is generally one-sided: Annotations are provided only by the visualization authors in order to establish a carefully crafted narrative, which advances a certain argument on a topic and amplifies their perspective on the data. Alternative perspectives are inevitably silenced, although readers might benefit from a plurality of possible interpretations (Dörk et al., 2013). One viable source of additional perspectives on the data presents itself in the form of its audience, which may offer personal experiences. Prior research described systems like sense.us and CommentSpace that allow for the audience to add comments to visualizations—however, they are purpose-built for social analysis in limited audiences, not for personal expression in public .

Akin to *footsteps* (Wexelblat & Maes, 1999) forming a path, there has been a long-standing interest in logging and displaying user interactions within web applications to generate social signals (Hill et al., 1992; Dieberger et al., 2000; Brusilovsky, 2008) that provide future users with information about past users' behaviour. Interaction histories have been visualized to provide *proximal cues* that help people find useful information (Pirolli & Card, 1999). Scented widgets (Willett et al., 2007), for example, add visual indicators, such as bar charts, to interface elements to enhance social navigation by recording and representing visitation patterns, indicating popular or neglected items within an information system. The idea of embedding visual cues to convey prior use can be extended to any kind of application without requiring any instrumentation, by superimposing patina heatmaps that aggregate application usage data (Matejka et al., 2013). HindSight (Feng et al., 2016) translates the footsteps analogy to visualization and changes the color of elements of a data visualization a single person has visited before, thus aiding a comprehensive personal analysis process. It is debatable whether these audience traces are part of visualization discourse. While they clearly are expressions of people's interest and activity, they also remain non-verbal and thus non-explanatory. Nevertheless, visualizing prior interaction data can change how users explore interfaces: personal interaction histories encourage users to engage more deeply

with presented data, as they increase the volume of data they consider (Feng et al., 2016). Visually supported social navigation aids users in exploring unfamiliar datasets or interfaces, fostering unique discoveries (Matejka et al., 2013). This is relevant for chapter 5 particularly, as I seek to better understand how the visualization of embedded discussions could facilitate the engagement with data visualizations.

To conclude, there have been studies that assess the role of people's feelings (Kennedy & Hill, 2018) or their personal interests (Peck et al., 2019) when engaging with visualizations. There have also been studies that determine the role of titles and captions in the viewing experience (Kong et al., 2018, 2019). In contrast, there have not been any studies that investigate how audience annotations impact the reading experience. Hence, I ask RQ2: *What is the impact of audience discourse on the viewing experience?*

Investigating Reactions to Visualizations on Reddit

Preface

At the onset of my Ph.D. in late 2019, I had the privilege to travel to Vancouver to visit my first ever academic conference. I presented two papers at IEEE VIS: First, my work on Participatory Deep Maps (Kauer et al., 2019), outlined in the introduction. Second, I talked about an article based on a prior collaboration with Nokia Bell Labs in Cambridge, UK, which discussed the visualization of generative AI data for urban planning (Kauer et al., 2018). In both papers, I speculated about the potential of opening visualizations for participation from the audience, e.g., to improve the quality of AI training data (Kauer et al., 2018) or add personal stories to maps (Kauer et al., 2019). Motivated by the feedback on these presentations, I was eager to start building interfaces and let people discuss *any* data I could find. However, I soon realized that I had little knowledge of *what* people would be willing to contribute to such discussions. For example, I simply did not know what kind of possible expressions, contents, topics, and motivations people would bring to the table when discussing data. To gain basic understanding of potential participatory behaviour, I spent most of February 2020 planning co-located workshops to annotate visualizations on a whiteboard with small teams of students. In March, before I could run the first pilot workshop, the term 'COVID' entered the collective vocabulary, and it soon became clear that the pandemic and, consequently, social distancing measures would make this format impossible to run. I now faced the challenge of doing an inventory of people's behaviour without being able to directly observe them or ask them about their motives in a co-located workshop setting. I initially tried to salvage the workshop idea and ran pilot workshops on the collaborative platform Miro¹, but soon realized that switching to an online setting to observe people was a blessing in disguise. Between baking sourdough and looking for dogs to adopt, the lockdown also sent me down various online rabbit holes, including Reddit's /r/dataisbeautiful² community. Instead of staging a controlled workshop

¹<https://miro.com/>

²<https://www.reddit.com/r/dataisbeautiful/>

to get people to talk about visualizations as initially planned, I could simply observe real discussions online. The following chapter is the result of my observations and discusses RQ1 (*How do people react to data visualizations?*). It was co-authored with Benjamin Bach, Arran Ridley, and Marian Dörk and was published under the title *The Public Life of Data: Investigating Reactions to Visualizations on Reddit* in the Proceedings of the CHI Conference on Human Factors in Computing Systems in 2021. For the purpose of this thesis, I combined the abstract, the original introduction, and the related work section into one continuous introduction.

3.1 Introduction

This research investigates how people engage with data visualizations when commenting on the social platform Reddit. Visualizations are published through a growing range of channels, including news articles (Segel & Heer, 2010), social media (Shu et al., 2020), blogs (Hullman et al., 2015), reports, government websites,³ and museums (Hinrichs et al., 2008). There has been considerable research on collaborative sensemaking with visualizations on existing platforms for social data analysis (Heer et al., 2007; Wattenberg, 2005; Elias & Bezerianos, 2012). In general, these target-specific groups of people, with specific tasks, and a common goal of sensemaking. Little is known about how public audiences without specific expertise and shared incentives openly express their thoughts, feelings, and insights in response to data visualizations. Motivated by the extensive social exchange around visualizations in online communities, I am interested in how ‘general audiences’ engage with visualizations online without a focus on social analysis. As our study suggests, engagement of these non-expert audiences can be very different and include motivations beyond (collaborative) sensemaking such as entertainment (Sprague & Tory, 2012). There is much more to learn about how people engage with visualization in the broadest sense, including aspects such as critique (Hullman et al., 2015), emotions (Kennedy & Hill, 2018), personal experience (Peck et al., 2019) and expertise, and potentially visualization literacy. A more profound understanding of these online social practices can inform the design of a future generation of annotation and collaboration tools as well as methods to allow larger and more diverse audiences to express their viewpoints and engage in collaborative exchanges and decision-making with visualization.

To widen our understanding of how people engage with data visualizations outside controlled lab settings, this chapter analyses user comments on the Reddit forum `/r/dataisbeautiful`. I study community members’ expressions and introduce the term *reaction* to describe these expressions; I define a reaction as *any verbal or textual expression upon*

³<https://www.ons.gov.uk>

viewing, reading, and/or interacting with a data visualization. Through iterative, multi-person coding of 475 comments, based on principles of Grounded Theory, I obtained a classification of 10 distinct reactions types: *observations, hypotheses, opinions, conclusions, clarifications, proposals, critiques, additional information, testimonies, and jokes* (Section 3.3). Reactions were found to point to four main *scopes* around these visualizations: *visual representation, data and data analysis, topic, and insights.*

These types and scopes provide us with a structured framework to analyze users' engagement, described by our reactions. Our findings highlight a broad and diverse range of engagement types and complement prior research (Hullman et al., 2015; Wattenberg, 2005; Viégas et al., 2008). An online survey with 168 posters of comments from our collection delivers additional information about the audience's demographic and individual motivations (Section 3.4). I found motivations to include both personal as well as extrinsic goals to actively contribute to a public discourse around data. Finally, I discuss how our findings can inform the design of future generations of tools for collaborative and public discourses based on data visualizations.

3.2 Data & Methodology

For our study, we chose to investigate Reddit for its abundance and variety of data visualization posts, the lively discussions in response to them, and the availability of the data for qualitative analysis. Reddit has 430 million monthly active users (*Redditors*) (Reddit, 2024) who share media, links, or self-created content in groups (*subreddits*) that focus on a broad range of cultural, political, or social topics. It has been conceptualized as a public sphere in which people engage collaboratively to express and form opinions (Dosono et al., 2017). Contrary to other social platforms like Twitter or Facebook, Reddit users remain semi-anonymous, do not form networks (Kilgo et al., 2016), and do not have "*an a priori built social network*" (Medvedev et al., 2017). Posts are generally public and can be commented on in hierarchical threads by anybody. Posts and reactions to them receive a score by the audience (*karma*), making Reddit "*the internet's largest social voting community*" (Gilbert, 2013).

Our study investigates textual reactions to visualizations expressed on the subreddit */r/dataisbeautiful*. What kind of content is allowed in this community is specified by a set of rules, stating that all posts must contain a data visualization that has at least one computer-generated element. The rules also enforce a standard by sanctioning sensationalized headlines ("*Clickbait posts will be removed*") and encouraging the transparent display of the data

sources. An additional set of rules is aimed at the audience to establish a code-of-conduct, inviting constructive feedback to the presented visualization and prohibiting intentionally rude or hateful comments. To extract data and content from Reddit, we use the official API through the Python library PRAW (2024).

blockbuster	Blockbuster Video US store locations between 1986 and 2019
breaking-bad	The absolute quality of Breaking Bad.
bushfire	Area of land burnt in Australia and area of smoke coverage shown as equivalent area over Europe
cases	COVID-19 spread from January 23 through March 14th. (Multiple people independently told me to post this here)
daylight	Hours of daylight as a function of day of the year and latitude
deaths	Coronavirus Deaths vs Other Epidemics From Day of First Death (Since 2000)
donations	Top 10 Highest COVID-19 donations with the percentage of their net worth
employment	To show just how insane this week's unemployment numbers are, I animated initial unemployment insurance claims from 1967 until now. These numbers are just astonishing.
garbage	The Great Pacific Garbage Patch
golf	Hardest Golfing President
google	Trending Google Searches by State Between 2018 and 2020
IMDb	Worst Episode Ever? The Most Commonly Rated Shows on IMDb and Their Lowest Rated Episodes
minecraft	Where is each ore found in a minecraft world?
net-worth	2020 Presidential Candidates by Net Worth
oil	US oil price
ramsey	What percent Gordon Ramsay's Kitchen Nightmares are still open?
rates	This chart comparing infection rates between Italy and the US
stimulus	Where the money goes in the US Senate's \$2T coronavirus stimulus bill
tuition	US College Tuition & Fees vs. Overall Inflation
tulsa	Attendance at Donald Trump's rally in Tulsa, compared to the number of tickets Trump claimed were requested.

Table 3.1: Original titles of the visualization posts from which the reactions were obtained. We use short tags to identify the visualizations throughout this chapter.

3.2.1 Data Selection

To find a suitable subset of comments for this study, we followed the following five-step procedure:

1. **Pilot studies:** We examined single visualization posts and their reactions and tested preliminary coding schemes on small numbers of them. In these pilots, we observed that some posts, e.g. visualization of quantified-self data and humorous posts, attract many inappropriate or off-topic reactions.
2. **Visualization selection:** We included the 26 most popular visualization posts according to their *karma* score over the span of one year (Oct-2019 to Sept-2020) in our study. From these 26 posts, we manually removed six posts that mostly attracted off-topic reactions and did not consider them for data collection.
3. **Data Collection:** We used the Reddit API to collect 68,000 reactions from the remaining 20 visualization posts.

4. **Filtering:** We filtered these reactions based on the following four criteria and ended up with a set of 792 reactions.

- As we intended to look only at direct reactions to the visualizations, we only included first-level comments but no replies to any comments.
- We ignored comments by the visualization author and by automated bots, identifiable through their username.
- We ignored comments that were deleted by the reaction authors or removed by moderators.
- We set a threshold of five upvotes for each comment to be considered, to remove comments off-topic, illegible, or otherwise irrelevant.

5. **Sample Sizing:** Since the number of reactions differed along the 20 posts, we randomly selected 25 reactions per visualization. Since some visualizations had less than 25 reactions, our final dataset contains 475 reactions.

Generally speaking, the visualizations we considered use common and well-known techniques such as bar charts, line charts, or heatmaps. Nine visualizations are animated, the other eleven are static images. While the range of depicted topics is broad, we found several visualizations about COVID-19, the 2020 presidential election or pop-cultural data like IMDb-ratings. Table 3.1 shows the list of visualizations included in our study, with titles and clickable links.

3.2.2 Open Coding

To obtain a high-level understanding of reactions, we engaged in open and close coding following Grounded Theory (Strauss & Corbin, 1994). Our goal was to find independent and non-overlapping concepts in the data, able to describe the range of users' reactions.

Our coding scheme developed over eight major iterations. Each iteration involved between two and four of the authors and refined both the set of comments and visualizations as well as our coding scheme. We started our open coding by independently coding a random set of comments. We then build a first scheme with four dimensions: *i*) types of reactions, e.g., observation, critique, clarification, etc, *ii*) a user's stance (negative, neutral, positive), *iii*) their conviction (weak, neutral, strong), and *iv*) any presented evidence (e.g., external, anecdotal).

Throughout the early iterations, we observed that many of these dimensions depended very much on the subjective interpretations of the coders. Through several iterations of close coding, we removed dimensions and categories that led to misleading coding. Each new iteration was tested with a new set of randomly selected comments to prevent us from fitting our scheme to a specific set of comments. In the final coding scheme, 20% of the data was coded by all four authors and discussed to reach consensus. The four authors independently used this scheme to categorize comments and test, whether the assumed

categories could exhaustively and without overlap characterize the actual data. We merged categories that were hard to discern from our data (e.g., observations and interpretations) and added new categories where comments did not fit any of the existing categories or to clarify important differences among comments within a category.

Throughout coding, we observed that many comments included notions about the commenter's personal perspectives. While we started out with an individual reaction type 'personal reference' many of these comments overlapped with other reaction types. We thus introduced an optional *personal* flag to tease out the role of personal qualifications in the reactions. Many of these personal comments included subtle expressions of first-person pronouns (I, me, my) or indications of experience (*as someone who [...]*), to articulate personal positions (*in my opinion [...]*).

3.2.3 Final Scheme

After our 8 major iterations, we converged towards a coding scheme with two dimensions: Ten *reaction types* (Table 3.2) and four *reaction scopes* (Figure 3.2). While we started out with the intention to only allow one type per reaction, we accepted that comments are often more nuanced and ambiguous to be classified as one type only. We attribute this to the very nature of human thought and expression. While we tried to minimize overlap between types of reactions as much as possible, we accepted some comments to contain two reaction types, rather than eliminating overlap.

3.2.4 Online Survey

We conducted a survey and contacted the authors of all 475 comments, 168 participants (35%) of which completed it. In the survey questionnaire, we asked for basic demographic information and compared them to the overall average of the Reddit user base, reported on (Duggan & Smith, 2013). 10% of the participants in our survey were not cis-male (overall on Reddit: 33%). Our two most prominent age groups were 19-29 years old (survey: 45%, overall: 50%) and 30-39 year olds (survey: 45%; overall: 9%) The participants lived most of their lives in North America (58%) or Europe (28%). 39% had a Bachelor's degree, 25% had a Master's degree, 24% had a high school diploma. 45% stated that they had some formal training with data, statistics or visualization. We asked the participants about their motivation for their reaction and report back on the results in Sections 4 and 5.



Figure 3.1: Examples of the 20 popular visualizations we obtained from [/r/dataisbeautiful](#). In total, we considered 475 reactions. Visualizations varied in their topics, aesthetic appeal, visualization techniques, and the use of animations.

3.3 Visualization Reactions

This section presents ten reaction types and four scopes. The reaction types describe the kind of contributions that people make when responding to a visualization. The scopes describe which aspect of a visualization the comment refers to. In the following, we start by explaining scopes and then present the reaction types. We include verbatim examples of reactions and show what visualization they refer to in a [tag]. We complement the results of our analysis with the motivations the posters shared in the survey. Direct quotes from the survey are indicated through a *background color*.

3.3.1 Scopes

Akin to Hullman et al.'s (2015) targets, scopes denote the part of a visualization post a commenter refers to. Since posts on [/r/dataisbeautiful](#) are structurally different from comments on a news blog and do not come with an accompanying article, we encountered four slightly different scopes:

Data—This scope describes reactions about the dataset. Comments referred to data quality and the ability to inform (*“What is the composition of the large corporation other? Loans? Grants? Tax credits?”* [stimulus]), data collection methods (*“do you mind discussing how you parsed the world file?”* [minecraft]), or the accuracy of data (*“The swine flu killed at least 18000 people in the end. I find this quite misleading”* [deaths]).

Visualization—Comments with this scope refer to the visual representation and its creation. Comments referred to representation aesthetics (*“Great Graphic”* [stimulus]), visual variables (*“Any meaning to the different colours?”* [cases]), or other design decisions (*“This map is using the Mercator projection, which can be a bit deceptive”* [bushfire]).

Insight—Whenever a comment refers to information that can be extracted from the visualization, we call this an ‘insight’. Comments referred to observed data points or trends (*“It really revved up in the last 4 days.”* [cases]), raised questions about a finding (*“We can see where it goes.... but... where does it come from?”* [stimulus]), or any other contemplation about the presented information (*“Why is there a seasonal trend to this? What month does that happen and any idea why?”* [employment]).

Topic—Comments with this scope referred to the topic illustrated by the visualization, rather than any specific insight. Generally, these comments were found to be independent of the specific information contained in a visualization: *“We had so much time to start quarantining people travelling from China. We all blew it.”* [cases].

The majority of the 475 comments referred to either an insight (188) or to the topic (187) (Figure 3.2). This supports Kennedy et al.’s (2016) findings that a visualization’s subject matter is an important driver for engagement—people engage with topics they are interested in. 117 reactions mainly referred to the data source, and 82 talked about the visual representation of that data.

3.3.2 Reaction Types

We now report on the ten reaction types that we identified. Each type indicates a distinct contribution that a comment makes in response to a data visualization. We provide a brief description, the frequency, and example reactions for each. We also discuss potential subgroups that are characterized by similar phrases or lines of argumentation. Table 3.2 provides an overview of the reaction types.

Observations point out insights that were made directly in the visualization or interpretations derived from its data: *“wow, House episodes rating are incredible consistent”* [IMDb]. These reactions consist of individual, often simple observations of outliers (*“May 24th, when Minnesota became the center of the world for a little bit.”* [google]) and trends (*“Wow that’s crazy I didn’t think a company could expand that quickly. And then to see it disappear as quickly is crazy”* [blockbuster]). Often, observations are a necessary prerequisite for other reactions, such as opinions and conclusions. Their scopes are predominantly insights, yet they are not merely about expressing what a person took away from a chart. Observations are often expressed in a humorous way and combine specific data points or trends with a joke: *“That line dips any lower it’ll hit oil”* [oil]. We also found a number of observational reactions that include subjective or personal expressions, such as *“I like”*, *“I’m surprised”*, *“I’m*

Type	Description	#
Observation	Stating the obvious; pointing out specific data points or trends; expressing insights and interpretations	62
Conclusion	Taking a step back to provide an overview of the presented information and draw conclusions or call to action	29
Hypothesis	Providing a speculative explanation to explain the presented information. This can range from tentatively asked questions to bold claims that introduce additional data to argue for an explanation	56
Clarification	Asking for information to better understand the data, a visualization or its insight	50
Proposal	Propose future work and possible adaptations of the data or visualization	43
Critique	Feedback to the visualization author, ranging from expressing constructive feedback and pointing out improvements to disagreement with the visualization and contestation of data.	90
Additional information	Introduce additional information to allow people to better contextualize or relate to the presented data. Includes background information, comparisons with similar data, trivia, and links to external sources with additional data.	58
Testimony	Providing personal information by speaking from first-hand experiences and sharing anecdotes or memories	41
Opinion	Providing a personal perspective by sharing opinions, but also feelings and emotional reactions.	92
Other	Unfitting in other categories, off-topic or not understandable reactions	19

Table 3.2: Reaction types, their meaning, and frequency of occurrence (#). The sum of occurrence is larger than number of reactions due to some double encodings

particularly amused by”, *“Fascinating that”*, and *“Wow, that is [...]”*. These expressions reveal genuine moments of surprise associated with finding something interesting and relevant. Moreover, they show people’s personal stance with respect to that observation. We flagged these observations as *personal* for subsequent analysis.

Conclusions take a step back and reflect on the observed information and its consequences. One characteristic group of conclusive reactions simply summarize the presented information and refer to insights the reaction author had: *“Season 5 was flawless, particularly those last 3 episodes [...]”* [breaking-bad]. Beyond that, we found a number of comments that put individual observations into perspective: *“When billions of dollars can be depicted using a thin, one pixel line, it truly shows just how much two trillion dollars is”* [stimulus]. Other reactions draw conclusions from the data to point out necessary next steps or make a call to action: *“This is exactly why any push for free college MUST tackle the irresponsible spending and ballooning administrative costs by colleges”* [tuition]. Conclusions can include a personal stance and can be motivated by expressing how this stance is not in line with the take-away message of the visualization: *“I wanted to summarise the data in a different way to how the [author] did”*.

Hypotheses provide speculative explanations for the presented information. While some hypotheses are phrased as short, tentative questions (*“Is it possible the only driver for cost of college is not inflation but rather demand?”* [tuition]), the majority of them introduces additional information and argues for a specific explanation of the presented data: *“[...]”*

This perfectly tracks with the drive to transfer our publicly shared national treasure into the private accounts of the exceptionally wealthy, starting with Reagan in the 80's. This is wealth inequality come home to roost. " [tuition]. Some of these claims introduce bold theories that are generally not externally verified: *"This is all incentivized by the government [...]"* [tuition].

Clarifications are questions addressed to the visualization author or the public audience. They are generally posed to better understand the presented information. We found a wide variety of clarification questions: Some people needed help with correctly interpreting the information (*"How is it negative, I don't know how these things work"*, oil) or encoding the visualization (*"What does the wideness of the color mean? [...]"* [minecraft]). Some intend to get more details about specific data points (*"What the hell happened in season 4 of the UK version?"* [ramsey]) or background information about the topic (*"Why is there a seasonal trend to this? What month does that happen and any idea why?"* [bushfire]). One recurring clarification seeks more information about the used datasets and how they are generated: *"Why is 'nation security' part of the 'large corporations branch?"* [stimulus]. These clarifications are generally phrased in a more critical tone, as they question the design decisions that were made to produce the used data. This critical stance is also observable in some sceptical questions that question the correctness of single data points: *"[...] your chart is showing that both poles go from 0 hours of daylight to 24 hours of daylight in what appears to be a single day. See day 82 for example. You sure your math is right?"* [daylight]. Such questions often co-occur with the reaction type critique and are a frequent case of double-encoding.

Proposals suggest future work and possible amendments to the dataset and adaptations of the visualizations. While we observed different kinds of proposals in the reactions, a majority of proposals suggested introducing additional data to the existing visualization to provide more context: *"Can we add the common flu to this and start on January 1st?"* [deaths]. Others were interested in using the same visualization to display another related dataset: *"Can I get one of these for every spending bill? [...]"* [stimulus]. On the other hand, reactions proposed to improve or change the visualization: *"Kinda wish the opening and closing were more distinctively different"* [blockbuster], sometimes with the intention to make the presentation more relatable: *"Please do British Columbia Canada! My wife doesn't get how bad and big it is"* [bushfire]. One participant described the motivation to react with the *"Desire for more than one perspective on a dataset"*.

Critique gathers reactions that express a form of resistance. In contrast to proposals, they identify specific issues with the current form of visualization or data—often in a harsh or ironic speech. The most predominant kinds of critique are contestations that scrutinize the validity of the used data for the visualization: The scope of 52 (out of 113, 46%) critical reactions is on the data. These data contestations are threefold: Firstly, people

	Observation	Conclusion	Hypothesis	Clarification	Proposal	Critique	Additional	Testimony	Opinion	Joke	Other	Total	Personal %
Topic	2	10	37	18	8	12	37	29	49	29	15	246	29%
Vis	3	3	1	8	12	37	6	1	21	5	2	99	34%
Data	6	2	10	19	31	53	20	3	12	9	0	165	22%
Insight	56	26	27	25	2	11	13	10	50	37	5	262	30%
Total	67	41	75	70	53	113	76	43	132	80	22		
Personal %	31%	24%	24%	27%	36%	23%	14%	91%	39%	23%	14%		

Figure 3.2: A heatmap indicating the absolute distribution of types across scopes. Values that stick out are e.g., how critical reactions most often relate to the data, whereas the scope of observations most often is an insight. Yellow cells indicate the relative distribution of personal flags. By design, testimonies and opinions most often have a personal notion.

point out missing data that they deem relevant to get a whole picture of the presented information: *“Should have included cancer and AIDS to humble down those COVID stats”* [deaths]. Secondly, people indicate that the presented data does not accurately represent the topic and should be generated in another way: *“It seems that this graphic uses worldwide statistics for Covid19, but USA only stats for some of the other outbreaks, in order to give an overly dramatic impression”* [deaths]. Thirdly, people contest the correctness of single data points, sometimes by introducing additional sources: *“This is wrong. Based on the Deutsche Bank info that came out last week. Trump is only worth about 600-700 M. [...]”* [net-worth]. This last point illustrates how contestations often co-occur with the provision of additional information. The motivation behind this kind of critique often is *“to combat misleading or unhelpful data visualizations”*. Beyond these contestations of data, we observe 36 (32%) criticisms of the visualization. The reactions point out hard to understand or possibly misleading representations (*“This chart succeeds at illustrating the wealth of Bloomberg, but does a very poor job of displaying/contrasting most of the candidates. Consider a log plot”* [net-worth]) and often co-occur with suggestions for improvement. Surprisingly many reactions address the aesthetic appeal of visualizations and we often observed harsh criticism for a perceived lack of beauty or the use of animation in charts.

Additional information is provided in order to contextualize the visualization. This can be background knowledge that helps to understand the subject (*“[...] The garbage patch is not a big island of floating plastic bottles, etc. It’s a big sparse conglomeration of micro plastics[...]”* [garbage]) or to put the presented data into perspective (*“Instead we had 13 million people watch the rally”* [tulsa]). Since additional information is used to explain existing or introduce new knowledge, we observe that these reactions are among the longest in our study (>500 characters on average), with them being double as long as the overall average. People’s motivation to provide additional information is to contribute to sensemaking by

adding what they deem relevant: *"I had information pertaining to the topic at hand and just wanted to point out that the data was more significant."* Others also have the discussion that can unfold from this kind of reaction in mind: *"[...] i decided to post it to add the idea to the conversation"*.

Testimonies are reports of first-hand experiences with the presented information, usually with a strong focus on the topic (70%). Testimonies express forms of local knowledge and anecdotal evidence of people's everyday lives, often times disclosing biographical or private information. The largest group of testimonies talks about a personal spatial relation to the presented information: *"I live along the east coast of Australia in an area not directly affected by the fire but heavily impacted by the smoke [...]"* [bushfire]; *"We don't have daylight savings here in India. Now I know why that's a phenomenon in the West. [...]"* [daylight]. Others relate to the topic through memories and experiences they have made in the past: *"I remember being a kid wanting to work at block buster one day. They were gone by the time I was old enough to work"* [blockbuster]. A third group talks about the impact the presented data has on their everyday lives and discloses information about their jobs or families: *"[...] I'm a little pissed I'm an essential worker throughout this and will be getting less pay than being unemployed [...]"* [stimulus]. The last example shows that testimonies frequently co-occur with opinions.

Opinions provide a personal perspective by sharing an individual judgement or point-of-view. This can be simple feedback to the visualization author (*"I really enjoy this graph. It really bothers me when people conflate millionaires and billionaires"* [net-worth]; *"This data is most certainly not beautiful"* [rates]). Often, opinions carry a notion of personal account, yet they do not disclose the same level of personal information as testimonies: *"I don't think I will ever get or understand the appeal to play golf. Played once and was bored out of my mind"* [golf]. Visualizations that depict everyday topics many people can connect with—such as pop-cultural data about TV shows—show a high number of opinionated reactions. On the one hand, people have opinions about the topic, people who watched the depicted TV show express how they liked it (*"Glad to see Person of Interest get some love. Always felt that was an underrated show."* [IMDb]). However, we also found some contestations when people relate their own experience to the data and express an opinionated contestation: *"How they gunna hate on Towlie? That's one of my favorite episodes!"* [IMDb]. This is backed up by the motivation to create these kinds of posts: *"I liked the show. I didn't agree with the visualization"*. This tension between an insight on the data and the commenter's own stance on that matter is a recurring theme we found in many opinionated reactions: *"Might as well call this 'Why I hate people: An animated explanation' "* [google].

How many redditors does it take to change a light bulb? Nine to express all prior types and one to make **jokes** about it. Across all visualizations, we observe many reactions that are primarily intended to be funny, including sarcasm (“*ah yes, the two presidents of the united states*” [golf]), pop-cultural references (“*Game of Thrones’ ending is why I have trust issues*.” [cases]), observational humour (“*Looks like every Facebook party ever organized*” [tulsa]), and puns (“*This chart points out the ultimate irony... It could not break into Bad...*” [breaking-bad]). 19 reactions we collected would not fit into any of the presented categories. This includes verbal insults, automated responses from bots or things we could not read or understand, e.g., “*Meanwhile a mysterious diplomat traverses his homeland searching unsuccessfully for a single hand to shake*” [bushfires].

3.4 The Personal and the Public: Why People Engage with Visualizations Online

While reaction types inform us about *what* type of engagement people shared, this section looks into the *why*, i.e., asking for the motivations behind people’s comments. Based on the 168 survey replies we obtained from comments, we report on findings about personal (intrinsic) motivations and motivations to support the public discourse (extrinsic).

3.4.1 Personal Perspectives and Experiences

A major theme that we observed when coding the reactions was that personal perspectives were expressed in many comments and throughout all types of reactions: testimonies, opinions, emotions (e.g., in observations), adding personal knowledge (e.g., in additional information), proposals, and critiques. Building on prior work on personal perspectives in data visualization (e.g., Hullman et al., 2015; Kennedy & Hill, 2018; Peck et al., 2019) we discuss four drivers for expressing personal experiences and perspectives and seek to understand what they add to the discourse around data visualization.

Expressing opinions—We observed that reactions expressing opinions, i.e., points of view or judgements about a topic, are an inherent part of the sensemaking process, as they act as an intermediary between the presented information and a viewer’s self-perception. This self-perception can be shaped by cultural values or political views, (e.g., “*[This] is a perfect encapsulation of Trump’s opportunism, his hypocrisy and lack of self-awareness*” [golf]) but also relate to personal preferences, e.g., how people react to the presented ratings of a TV show they enjoyed. Expressions of opinions vary in their expressivity, including typical phrases like “I think / love / hate [...]” or “in my opinion [...]”. Paired with a scope of topic or insight—specifically when talking about their own observations—they further indicate

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that people refocus on their own position and juxtaposing it to what the data suggests when making sense of it. Commenters are well aware of this dynamic that prefers personal relation to information: *"I believe my comment was upvoted because others agreed with it, not because it offered any insight or analysis."*

Matching knowledges—Other reactions demonstrate how people compare extracted information against their own existing knowledge. Often times, this simply results in people stating what they learned through observation and interpretation. In case of a mismatch between presented and existing knowledge, we observe two possible reactions. We found several reactions that imply how the new information challenges previous assumptions, often accompanied by an expression of astonishment (*"Bernie Sanders is 78 years old with a NW of only 2.5 million? That's honestly pretty surprising to me [...]"* [net-worth]). If, however, the viewer is not convinced by the presented data, they express their own knowledge in the form of critiques, motivated by not letting something they perceive as wrong remain uncommented: *"I have a compulsion for calling out bullshit by using my experience and education"*.

Sharing emotions—Redditors post emotional reactions that are evoked by the visualization. While many reactions contain emotions, they do not typically carry the central message of the reaction, but often set the underlying tone of a reaction. People prelude their reactions with how a visualization makes them *"feel"*, or what their *"gut feeling"* [garbage] about the data is. Some reactions, however, have feelings or emotions as a first class citizen: *"I'm simultaneously horrified yet excited to see how this looks [...]"* [cases]. In the survey, one participant points out how expressing emotions is the main driver of her reaction: *"I can't really explain my motivation other than wanting to share how this phenomenon 'feels', even if feelings [do not equal] science."* Another participant states: *"This was about the hard feelings I still have [...] and less about data as a motivation to post."* This emphasizes the role of emotional statements as a counter-weight against the typical impression of data and visualization to be rational and objective (D'Ignazio & Klein, 2016).

Claiming interest—We found some expressions that were shaped by a viewer's personal interest, which is clearly stated in their motivation: *"I appreciate data visualization as someone with a background in the sciences, and also have an interest in politics, and so I felt motivated to comment [...]"*. When formulating proposals, people often asked for an adaptation that they can better relate to personally, for example, in order to *"satisfy a curious itch"*. This might be a change of the visualization in order to better understand how the presented information affects them personally (*"Can we get another chart that outlines the reduction of state and federal funds dedicated to higher education? I know my state only contributes to less than 10% of the state's higher education system"* [tuition]), or the adaptation of new data, for example, to display the ratings of a TV Show they watched and want to learn more about. In the survey, a participant described his motivation to post a

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clarification with a *“genuine interest to get an apolitical answer [...]”* in order to learn more about particular aspects that were not further described in the visualization. People also ask for clarifications to express their *“Desire for more than one perspective on a dataset”*, which can be met by adding anecdotal evidence.

Adding anecdotal evidence—When considering a viewer’s personal involvement in the visualizations, testimonies get to the heart of what the previous drivers already indicate. They are expressions of inherently personal, sometimes even intimate, relations that complement the visualization with first-hand experiences. Against the background that visualizations can depict data that may be specific to a single country, time-period or demographic group, these reactions offer subjective perspectives that can help the audience to better relate to the data. Several participants confirm this motivation: *“I was looking to provide a human story behind the data. The bushfires in Australia earlier this year were devastating and my comment was intended to describe how the fires being discussed in the data is beautiful post was affecting millions of people”* or *“I am a regular reader of Reddit, and golf a lot. The data was interesting to me and I wanted to add some context to it for those that may not golf and do not quite understand if the rounds of golf represented are a lot or not very many. If an activity is foreign to someone a number matters little to them. Context or comparison to better understand the number can be helpful.”*

3.4.2 Informing the Public Discourse

We found that many personal reactions, though motivated by internal reasons, were meant to contribute to the public discourse and collaborative sensemaking among community members. For example, while some reactions only speak to the visualization author (*“To compliment the OP and give constructive feedback”*, *“encouragement [...] and asking for more information”*). Other comments aimed to add to a public discourse more broadly: *“posting my opinion to a wide audience”*. Below, we characterize four motivations of people to express themselves in public. Considering that reactions are also motivated by personal expression, it is important to note that these drivers are not mutually exclusive with the personal ones reported in section 5.1.

Participate in public sensemaking—Several participants explained their motivation to share their existing knowledge or gained insights with others as constructive and objective conclusion to share facts, findings, and implications from the visualization with others (*“[...] understand and share the implications of the data”*; *“share an interesting conclusion [...]”*; *“share an observation/trend”*).

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Adding one's own story—Personal experiences can constitute a crucial quality of the reactions to data visualizations we studied. The prospect of providing complementary human perspectives onto the data is particularly relevant for the discourse to humanize data, complement findings, *“providing local or ‘inside’ information”*, or to *“contextualize the data for others[...] I wanted people remember or know what it was like.”*

Rectifying what's wrong—Correcting wrong information goes beyond the previously described sensemaking. Similar to previous work (Hullman et al., 2015), we observed how people express critique about the topic, data, or visual representation: *“Data is often used to justify one side of things. Unfortunately data can be manipulated to make concepts, ideas, etc. seem better or worse [...]”*. While correcting old or introducing new information is an important motivation, we only see few cases that use and link to verifiable sources. In some cases, the source is named but not linked—or different authors provide different “correct” numbers fixing the data. The majority of reactions claiming that some of the presented data is wrong and suggest other data remain unverified and are intertwined with personal perspectives. Eventually, critique on the visual design is specifically important and points to increasing awareness of slants and biases in visualization: *“A lot of information is presented in a biased way, where the numbers are accurate but are portrayed in biased light. I try to rectify that”*.

Sparking discussion—Reactions can be an invitation for others to participate. Participants express reactions in order to further *“engage with the community”* and trigger more follow-up reactions: they want *“to bring attention to a particularly interesting data event and provide a starting point for further discussion”* and feel that the statements they make *“furthered the discussion around the topic”*. People are curious what other's make of their observations and opinions: *“I thought it'd be interesting to see how people would react to it [and] if others felt the same [...]”*.

Besides personal and public motivations, a third group of motivation can be summarized *“acquir[ing] upvotes”*, or having fun by contributing jokes: *“sparkles! I love sparkles”* [cases].

3.5 Discussion

In this section, we summarize and discuss our findings, reflect on our methodology, discuss implications for interface design to support engagement with visualizations, and relate our findings to other findings in the literature.

3.5.1 Main Findings

We found a great **diversity of reactions** in the visualization-focused online community /r/dataisbeautiful. Previous classifications (Vanhulst, Evequoz, et al., 2018; Vanhulst, Evéquoz, et al., 2018) and interfaces (Heer et al., 2007; Willett et al., 2011) primarily focused on annotations—a different, yet arguably comparable kind of audience-authored reaction—as tools for collaborative sensemaking. In contrast, reactions on Reddit serve a wider variety of purposes and express not only analytical insight, but also personal perspectives, critical questions, and additional information. Furthermore, the comments themselves constitute an integral part of the visualization community on Reddit and as such they also exhibit humour, sarcasm, and banter. The dynamic between the visualization and the people that comment on it is often times harmonic and sociable, for example, when expressing observations or evoking memories, but can also be tense and antagonistic, especially when critical comments and opinions are expressed.

We were interested in understanding how an open and potentially heterogeneous community reacts to visualizations, differing from lab studies and specific communities (such as university students and employers of a tech company) and a wide range of different types visualizations. Our results confirm findings by Heer et al. (2007) and reveal additional categories. Our taxonomy is meant to capture ‘exclusive’ categories in order to provide a better picture of individual types of reactions. Finally, we are most interested in how people report on their personal relation and their motivations in contributing to commenting, something entirely missing in the previous studies.

For example, we found various **levels of sensemaking** across almost all reaction types. While observations can be associated with low engagement in Mahyar et al.’s (2015) taxonomy, reactions such as hypotheses, clarifications, and conclusions indicate a higher level of engagement, often based on personal experience, wider contextual knowledge, or profound interest. A specific type of comments added comparisons and other information to help translate the insights of a visualization from one context to another. Eventually, critiques can be seen as a distinct form of sensemaking, given that they imply some sort of personal cognitive effort that includes understanding an issue, comparing it with previous observations or guidelines, finding a point of disagreement, and expressing this disagreement intelligibly. In many cases, the critiques we found were highly constructive, suggesting the means to overcome a particular weakness.

The **role of personal perspective and experience** is prevalent across all types of reactions and ranges from expressing opinions and emotions to contributing personal experiences (testimonies) and adding or providing evidence. We also found that critique is not necessarily expressed from a neutral or analytical perspective: more than one third of critical reactions have a personal notion to them. This supports many of the findings by Peck et al. (Peck et al., 2019) and also shows that personality does not only shape perception, but also

the sensemaking and communication after viewing a visualization. Confirming Kennedy et al.'s [kennedy2018feeling](#) observations about the role of emotions in engagements with data, we found multiple instances that expressed the relevance of people's *feeling of numbers*. Eventually, we identified several **drivers for engaging with visualization**, including personal motivations and contributions to the public discourse.

3.5.2 Reflecting on Methodology and Data

Our findings are characteristic for Reddit, specifically the `/r/dataisbeautiful` community. Reddit is featuring non-interactive content, other than e.g., many contemporary news outlets and their visual stories. Besides the ensuing discussions, Reddit content comes without additional information, e.g., such as in [Hullman et al.'s study hullman2015content](#). While related studies on personal perception ([Peck et al., 2019](#)) and feelings ([Kennedy & Hill, 2018](#)) have been carried out in co-located, synchronous workshops, or interviews, our study focused on an online setting. For the most part, we were able to support existing results and deepen our knowledge of the audience behaviour when reacting to visualizations and their motivation behind it.

We deliberately **ignored discussion threads**, i.e., the nested replies to comments, in order to focus on the primary reactions to the visualizations. However, we often resorted to replies in order to understand and agree on the meaning of single comment as these replies often clarified the initial intention of a comment. Future work should consider these discussions to better understand the audience's perception of reactions, for example, to find out how successful testimonies are in humanizing the data or determine whether people change their mind based on critiques. The reaction types provide a structured basis for such an endeavour and can be used to further analyze how discussions evolve.

To account for the complex nature of the expressions we encountered, we **iteratively adjusted the coding scheme**. Comments contained traces of different reaction types and this ambiguity required intense discussion among the authors. Correctly and consistently interpreting a reaction depends on inside knowledge about the topic, the specific online community, and the used jargon and abbreviations. Some of this is due to the varying familiarity with Reddit and the `/r/dataisbeautiful` community among the authors. Still, some comments could not be classified due to potential irony, missing context, or where the reaction would not fit in any of the ten categories.

More research is necessary to **generalize our findings** and determine whether they are specific to one online community or whether they apply to other platforms, communities, and even co-located (uncontrolled) settings. Our framework can serve as a reference point to understand how reaction types, their quality, and quantity change with context (e.g., online, situated, synchronous, asynchronous ([Isenberg et al., 2011](#))), audience, media (e.g.,

pen and paper, data physicalization, interactive), and goals of engagement (e.g., open, entertainment, collaborative sensemaking, design critique). Evidently, more research is necessary to understand these specific parameters that influence human engagement with data visualizations.

Our reactions are **based on textual comments**. Other sources of textual comments could include forums (Diehl et al., 2018). Other means of data capturing, for example through audio recordings, interaction, pointing, drawing, or specific functions in existing annotations interfaces, can provide complementary information while at the same time requiring specific analysis methods.

3.5.3 Design Implications and Future Work

Beyond the often discussed cases for engagement exploration and communication, our work informs mechanisms of questioning and contestation (critiques, clarifications), user contribution (testimonies, additional information, proposals, opinions), and more sensemaking tasks (observations, hypothesis, conclusion). Informed by these reactions (3.3) and drivers (3.4) for personal contributions, this section discusses design implications for user interfaces, complementing previous implications by Heer et al. (2007).

G1—Allow for **type-specific annotations** to capture the richness of observers' reactions and to support participation and discourse around data. Such rich annotations can entail audience-driven labelling of elements and regions of a visualization, highlighting relations between elements, linking reactions to data points, or drawing on the visualization. While some techniques are present in existing systems (e.g. Lyra, CommentSpace, Sense.us), our typology can be used to better tailor annotation features to suit the specific needs of individual reaction types. For example, interfaces could provide features to collect and categorize opinions such as done using Twitter for general discussions (Huron et al., 2013) and link them to the data. We can imagine visual polling interfaces in which user reactions drive visual properties of elements that are put to the vote, e.g., the roughness of a visual shape or a highly controversial opinion. Interfaces for data contestation could allow people to *rectify whats wrong* and provide features to express a critique of data points or the quality or provenance of the data set, and add details on the annotator's confidence or the provided additional information as evidence. clarifications and proposals aim to improve or re-create visualizations as proposed by Hullman et al., (2015), raising questions about data access and visualization creation tools.

G2—Supporting **personalized stories and visualizations** can capture an audience's testimonies and display them within the context of a given visualization. Driven by people's willingness to *provide anecdotal evidence* and *add their own story*, this allows for a juxtaposition of the data's bird's-eye perspective on a topic and a local, situated reaction to it and thus provides a more convincing narrative as proposed by one study participant: *"visualization*

is powerful - it's even more powerful when supplemented by real experiences". We imagine interfaces to provide personal testimonies in a more participatory and empowering way than 'just' annotating and commenting on a given visualization. Challenges are posed by allowing for easy authoring of such stories, as well as storage and navigating these stories. Eventually, such stories can include not only text, but other media such as photos, oral histories (Maharawal & McElroy, 2018), customized visualizations, or data comics (Zhao et al., 2015; Bach et al., 2017). This can help to include external information and adapt a given visualization to different contexts (e.g., using alternative geographic maps).

G3—Visualizing the discourse around a given visualization can help analysts and an audience understand controversial parts and aspects of a visualization and the data displayed. For example, similar to hotspots in a document (Hill et al., 1992), a visualization could display a heatmap to highlight parts with many reactions, broken down to different reaction types, e.g. opinions, contestations, clarifications, critiques, observations or, as suggested by Heer et al. (2007), keyword tagging. Complementary analytical charts could show specific insights and trends about reactions such as reaction type, frequency over time, types of opinions, or terms mentioned in critique posts using techniques from NLP and sentiment analysis. Showing which and how elements of a data set or visualization are reacted to could inform both further audience engagement as well as a detailed analysis into the content of the discourse. An eminent challenge here is again to design easy-to-use interfaces to submit reactions and to navigate an existing discourse and its reactions.

G4—Open discourse and annotation requires guidance and moderation. **Guidance** should help participants express reactions and participate a discourse. For example, besides explanatory messages, visualizations of discourse (G3) can provide cues and affordances to an ongoing discourse (Hill et al., 1992) and provide for *social navigation cues* (Heer et al., 2007). Scoring systems could allow audiences to interact with the discussion itself (Kauer et al., 2019). **Moderation** must prevent vandalism and misinformation as well as prevent discussions from going off-topic. Also, moderation can help to find agreement and resolving conflicts for contestations and critiques, eventually updating a given visualization or data alongside respective notifications to inform the audience of such updates.

G5—Gratify people's participation. While one goal of any (visualization-based) discourse should be to enrich an audiences' understanding of the data (see Sec 5, *matching knowledge, add anecdotal knowledge, participate in public sensemaking, sparking discussion, rectifying what's wrong*), we found many other motivations for people to engage with visualizations (express opinion, claim interest, share emotions, express humour) which could be leveraged by social media platforms in to attract attention to a topic and give the audience an enriched

channel of expression and participation. More simple motivations can include attention to one's comments or posting humorous comments. One challenge here is how to get people engaged in intellectually demanding reactions such as critiques and contestations, or suggestions on visualization redesign.

3.6 Conclusion

We see a huge research potential in providing more expressive and inclusive interfaces for engaging with and discussing content in data visualizations; this includes both online as well as offline media. To inform these interfaces, this chapter has investigated reactions to data visualizations on the social platform Reddit, seeking to better understand different types of reactions and the drivers that motivate people to express them in a public forum. We coded comments to popular posts containing data visualizations and developed a coding scheme of ten types of reactions. We extended prior classification systems and added personal relations to data and a wide variety of critiques on the presented visualizations and their data sets. In a subsequent online survey, we identified nine drivers of people to engage with a visualization and express themselves. We differentiated between drivers that share a rather personal motivation from those that primarily aim to inform the public discourse. Our results show a variety of ways for people to personally, analytically, or critically connect with data when they are visualised in online media. Our work demonstrates people's willingness to engage and put effort into presenting personal perspectives to a public forum. From our findings, we deduced five design implications to inform future interfaces for participatory data visualization systems that support a range of different reaction types.

Investigating Audience Annotations in a Public Data Visualization

Preface

One and a half years after I started working on the previous chapter, the COVID-19 pandemic was still unfolding. It was a paradoxical period marked by both shock and monotony. While I and most of my friends and family were widely unscathed, others had lost family members or had friends who were affected by Long COVID. My hometown of Berlin has introduced the ‘Corona-Ampel’, a system to regulate social distancing measures based on indicators like weekly COVID-19 infection rates.

To me, one of the most interesting findings of the last chapter was that people’s reactions to visualizations were deeply personal. Against this background, I was interested in the personal stories behind charts about infection rates. These charts felt omnipresent, as they were displayed in the evening news, news outlets, social media, and printed newspapers. After observing deeply personal reactions to visualizations in public, I was keen to build a dedicated platform to collect such stories about the COVID pandemic, using charts to represent and elicit stories and data alike. In the future work section of Chapter 3, I mentioned interfaces that allow for authoring of personal reactions that juxtapose *factual* data and *contextual* stories (G2). The following chapter explores the idea of building an interface for collective storytelling. Doing so, it explores RQ2: *What is the impact of audience discourse on the viewing experience?* The chapter is based on the manuscript *Many Voices: Investigating Audience Annotations in a Public Data Visualization*, written by me, Benjamin Bach, and Marian Dörk. It is currently under review for a special issue of IEEE Computer Graphics & Applications on critical data visualization. In the context of this thesis, I combined the abstract, the original introduction, and the related work section into one continuous introduction.



Figure 4.1: CoronaMoments platform with embedded audience annotations.

4.1 Introduction

This research investigates the effect of annotations in data visualizations on the reading experience. The prior chapter has shown that visualizations can elicit expressions of personal feelings, memories, and experiences, but little is known how these annotations, in turn, influence readers' experiences and relationships to the data shown.

In data-driven storytelling, annotations are generally provided by the authors of a visualization, who curate them to support the chosen narrative. In contrast to that, prior work on social analysis also considers annotations created by viewers of a visualization. In these expert-driven settings, annotations become collaborative devices that help to make sense of data by sharing observations (Heer et al., 2007), building arguments (Willett et al., 2011), or collecting arguments for correct data interpretation (Lin et al., 2022). The previous chapter explored public engagements with data visualizations and investigated the type and content of comments made by readers when considering visualizations. These *public reactions* are different from expert-driven annotations, as they are motivated by personal values (Peck et al., 2019) and include personal perspectives and experiences. However, there are no

interfaces that allow for an integration of personal reactions into the visualization itself. There is little knowledge about how annotations create a framing for a general audience and how interfaces for audience participation, personal expression, and informed discourse can be designed.

In this chapter, we present in-depth research into the role of annotations and their integration into data visualizations. With two connected studies, we want to better understand what kinds of annotations non-expert audiences would share in public visualizations; how different integrations of these annotations into the visualization change the reading experience; and what impact audience annotations have compared to annotations that are curated by the visualization author. Our longitudinal study is oriented towards the general public and situated in the context of the COVID-19 pandemic. Throughout the pandemic, data about new infections or deaths were widely used to justify public policies including e.g., mask mandates, social distancing measures, or travel restrictions. Hence, the media used a wide variety of visualizations to inform the general public about the development of these numbers. It is safe to assume that a majority of people worldwide have been confronted with visualizations about the pandemic. At the same time, people's lives were collectively disrupted—by a phenomenon whose severity often related to the numbers shown in data visualization. We capture this unique coincidence by designing and deploying an annotation interface called *CoronaMoments*, which shows policies and audience contributions as annotations in the context of a line chart of corona cases, worldwide or for a given country.

We built an online platform (Figure 4.1) that features two different ways of integrating annotations—separate or embedded—and allows switching between two annotation origins—stories collected from the audience or policies curated by the visualization authors. In a first study over eight months, we collected and analysed annotations from the visualization audience as well as interaction logs, including for example where people clicked, what annotations they viewed, in what view they created annotations themselves. We identified four types of public annotations—experiences, reflections, emotions, and actions—and observed how embedding annotations increases session duration, user engagement, and the number of submissions. Brief surveys indicate that a) viewers are more interested in exploring annotations than learning about the chart they annotate, and b) annotation creators use annotations to express their emotions and view their own submission in relation to others. In a follow-up-study, we conducted eight in-depth interviews with members of the audience to better understand their reading experience. We learn that exploring embedded audience submissions is what participants find most useful, as they are personally relevant to them: Participants are most likely to think about their own experiences after viewing similar annotations and empathize with the people who wrote them. Participants use the combination of data visualization and annotations to reflect about their experiences and contextualize them over the time of the pandemic.

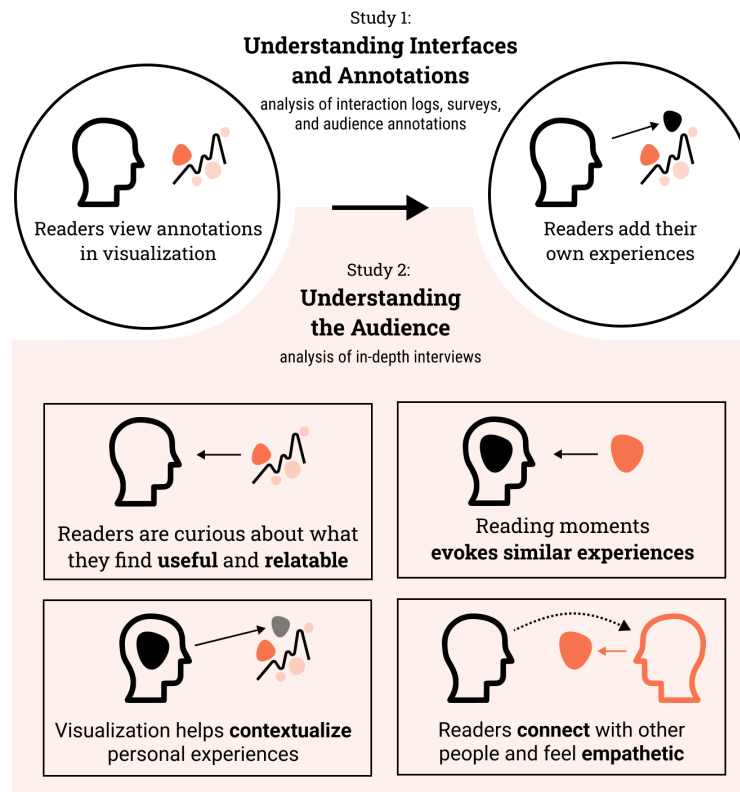


Figure 4.2: Two study setup that demonstrates the impacts of embedded audience annotations on the reading experience.

Externalizations may not only be leveraged for sensemaking and analysis, but can also relate to the audience's personal experiences and local knowledge. Visualizations of early online communication demonstrate the wide spectrum of emotions shared publicly, while also proposing unique visual aesthetics to accommodate the personal nature of the data (Donath et al., 2010; Kamvar & Harris, 2011). More recently, Peck et al. (2019) showed that people find those visualizations most useful to which they have a personal connection. Likewise, when visualizations are shared online, people post comments on data visualizations to provide additional context and criticism (Hullman et al., 2015).

In the previous chapter, we produced a taxonomy of reactions. Some of these reactions show personal perspectives and experiences related to the data such as personal opinions and knowledge, critique and potential misrepresentations. In this chapter, I am mostly interested in understanding *testimonies*, which describe people's experiences with the data in their everyday lives. Testimonies often disclose biographical information and personal relations to the topic. Allowing the audience to create annotations themselves, e.g., in

the form of comments on news websites or Reddit, creates a dynamic in which a largely heterogeneous audience is taking the role of both the author and reader of annotations. In my research, I examine the origin, integration, and content of annotations in a public data visualization.

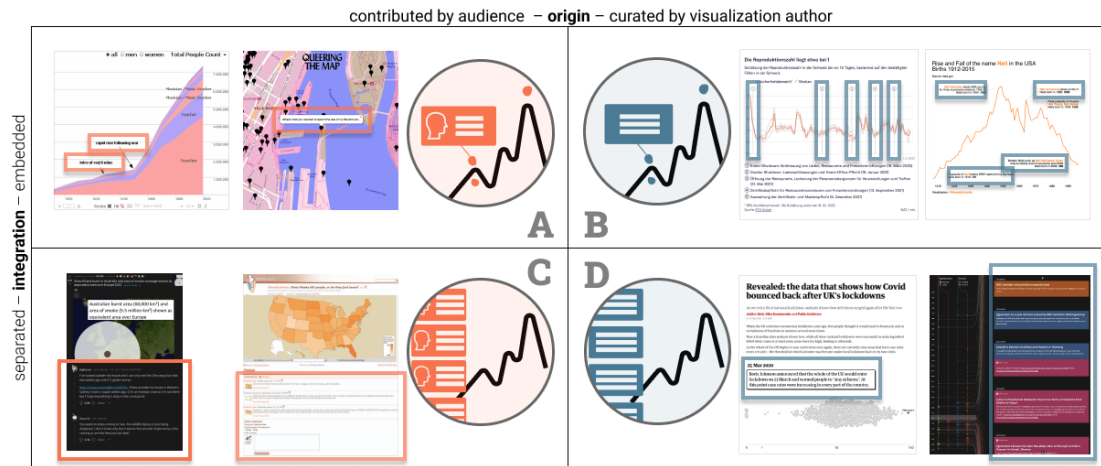


Figure 4.3: Our design space stretches along two dimensions: annotation origin and annotation integration. Each combination is illustrated by examples described in the related work : A) sense.us (Heer et al., 2007), Queering the Map (Kirby et al., 2021); B) NZZ (news outlet) (NZZ, 2024), example from storytelling with data (Nussbaumer Knaflic, 2018); C) Reddit (see thesis Chapter 3) (Kauer et al., 2021), ManyEyes (Viegas et al., 2007); D) Guardian (news outlet) (Kirk et al., 2021), Yemeni Timeline (Bell et al., 2021)

4.2 Approach

Annotations provide essential context for visualizations in various domains. With our research, we hope to better understand the origin and integration of audience annotations in public data visualizations. Here we describe a design space for annotations to inform our research, clarify relevant concepts, and present details of the study interface.

4.2.1 Study design space

Based on prior work on collaborative, personal, and public data visualization as discussed in the introduction to this chapter, two aspects emerge as the distinguishing dimensions to classify textual annotations in visualizations: **annotation origin** and **annotation integration**. The resulting design space—illustrated in Figure 4.3—informs the studies and discussion in the remainder of this chapter and helps frame our research questions.

Dimension 1: Annotation origin

Annotation origin refers to the source and authorship of annotations. There are potentially many characteristics of annotations related to their provenance and content, for example, how dynamic they are, whether annotations can be edited, how they are written, whether they explain the visualization etc. For simplicity and the sake of our study, we collapse these characteristics into two main categories.

- **Author annotations** refer to textual information provided by the author of the visualization piece. Author here refers to any wider team involved in analysing the data, creating the visualization, and writing (or curating) the annotations—as opposed to the audience the visualization is intended for. These annotations are static in the sense that the audience does not have control over their content. Author annotations are common in news media, data videos, data comics, infographics, scientific publications, and other means of storytelling. These annotations usually report on facts and insights from the data, such as important events, people, or other contextual information. Author annotations aim to inform the audience and are usually kept brief, factual, and clear. They aim to provide an expert lens onto the data, helping to understand the visual encoding and visual patterns in a visualization as well as drivers, reasons, consequences, or hypotheses around the data represented by the visualization.
- **Audience annotations** are reactions and reflections provided by the audience of a visualization through commenting. Audience annotations are dynamic in the sense that the audience can provide new annotations at a high pace. They capture the audience's thoughts about the represented topic and reactions towards the visualization and the underlying data. As opposed to author annotations, audience annotations hence contain deliberate subjectivity and relations to personal experiences and feelings; they can also express public opinions and perceptions. Audience annotations are common on newspaper websites with comment functions and on social media platforms.

From this dimension, we frame our first research question: *How do annotations curated by visualization authors and annotations collected from the audience differ in their effect on the viewing experience?* (**Q-Origin**).

Dimension 2: Annotation integration

The second dimension informing our research is the integration of annotations, by which we mean how annotations are visually and functionally situated with respect to the data visualization.

- **Embedded annotations** are placed 'inside' the visualization, eventually becoming part of the visualization. They are common in infographics or annotated charts (Segel & Heer, 2010) and could even include free-form pen-based annotations (Satyanarayan & Heer, 2014). In our case, annotations refer to individual time points inside a visualization, corresponding to the surrounding visual elements and patterns.
- **Separated annotations** are placed 'outside' the visualization, without any explicit reference to visual elements inside the visualization. Separate annotations are common in data-driven journalism, e.g., when insights from the visualization are discussed in the broader article, or in online communities with separate comment functions.

This dimension frames our second research question: *What is the impact of embedding annotations directly into visualizations on the viewer's experience? (Q-Integration).*

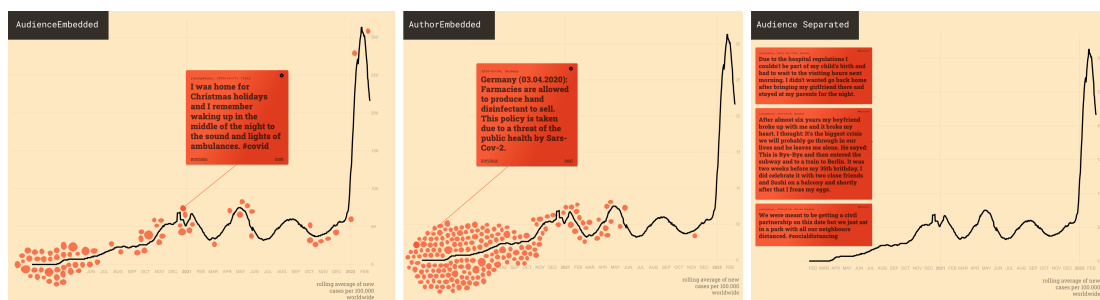


Figure 4.4: Three views of the CoronaMoments platform: (left) Embedded annotations collected from the audience, (middle) embedded annotations curated by the author, (right) separated annotations collected from the audience.

Possible views

The two-dimensional design spaces creates four types of annotation interfaces illustrated in figure 4.3 and named as follows:

- **AudienceEmbedded** allows for the audience to freely comment on the visualization. Comments are embedded into the visualization, able to reference specific visual elements or patterns, geographic locations, or any other data elements in the display.
- **AuthorEmbedded** shows comments by the author embedded into the visualization, e.g., highlighting specific events, outliers, or visual patterns. This interface is common in data-driven storytelling 2018, and data journalism 2024 (Figure 4.3B)
- **AudienceSeparate** also allows for the audience to leave comments, but comments are shown in a list separate to the visualization and with no spatial or visual connection to the visualization. Examples include interfaces like ManyEyes (Viegas et al., 2007), CommentSpace (Willett et al., 2011) or audience reactions on social media as described in Chapter 3.

- **AuthorSeparate** is the same interface as **AudienceSeparate**, but with author comments shown separate from the visualization. This interface type is widely used in news articles that use data visualizations and provide further explanations in the accompanying text. Examples can be found on the Guardian (Kirk et al., 2021) or in visualizations of conflict timelines (Bell et al., 2021).

We are interested in how the general public uses interfaces with varying annotation origin and integration. Since we as authors can not produce audience annotations ourselves, we need to first collect them. Doing so allows us to better understand, how they are structured and why people contribute them. Therefore, our third research question **Q-Annotations** is: *How and why do non-expert audiences use annotations to express themselves in public data visualizations?* Answering this question then allows us to further investigate the impact of the dimensions in our design space.

To pursue our research questions, we ran an experiment that is based on a visualization prototype designed to support the sharing of audience annotations as well as the display of author annotations. The topic and data sets for this visualization need to be carefully considered. If a participant cannot relate to the topic represented by the data and visualization, their engagement may stall?? Unfamiliarity with a topic may also imply assumptions or wrong information. For the purpose of this research, we need a topic and data set for which we can curate meaningful annotations while, at the same time, the general public should be familiar with the topic in order to be able to create annotations without being domain experts.

4.2.2 Pandemic context

The COVID pandemic affected the lives of many people around the world. Since the beginning of 2020, people almost inevitably had to change plans due to restrictions, were required to wear masks, and feared for their own, their friends', or their family's health. For months, real-time updates on new infections, deaths, or vaccination rates were present in the media through a large number (Zhang et al., 2021) of data visualizations. The general public is well familiar with the discourse, the data, and the visualizations about the pandemic. Data on infections and deaths are reliably available through public APIs for every country in (almost) real-time. Representing country-specific and up-to-date data for people from various locations makes them more interesting for them to view and comment on. For us as visualization authors, there is a plethora of information available that we can curate to create annotations that have a meaningful connection to the data, e.g., timestamped information about government policies. The framing of visualizations in the context of the pandemic is a particularly sensitive topic. What people learn from visualizations largely

depends on how they are framed (Kong et al., 2018)—which can potentially support the spread of misinformation about the pandemic (C. Lee et al., 2021). Visualization authors also need to consider that “*behind every data point is a person in a COVID-19 dataset*” 2020 and that showing numbers does not necessarily do justice to the people they represent.

For our experiment, we chose to create a visualization in the context of the pandemic and use multiple views ?? the visualization to collect audience annotations and answer our research questions.

4.2.3 CoronaMoments Interface

To run our studies, we built a web-application called CoronaMoments (Figure 4.1). It implements three of the four views described in section 4.2.1 with the concrete example of COVID case numbers for various countries. CoronaMoments mainly features a line chart of the rolling average of new cases per 100k. Per default, the visualization shows aggregated data and annotations for all countries worldwide and single countries can be selected from a list of 265 countries. The three views from our design space are implemented as follows (Figure 4.4):

- **AudienceEmbedded:** In this view, orange dots along the chart curve represent annotations left by the audience. Each dot is positioned based on its date. Clicking a dot shows the full text and metadata (submission date, country) of the annotation in a pop-up within the visualization. The pop-up is connected to its respective dot with a line. Visitors can place new dots in the chart to add their own annotations. The submission form suggests adding hashtags that were frequently used in other, already submitted annotations.
- **AuthorEmbedded:** Similar to **AudienceEmbedded**, this view shows orange dots embedded into the charts. Instead of audience annotations, each dot represents a single policy response for the selected country, collected by the CoronaNet research project (Cheng et al., 2020). We use the project’s existing categories as an equivalent to hashtags in personal stories. In this view, the audience can not add any annotations, as they are only curated by the authors.
- **AudienceSeparate:** This view shows the same audience annotations as in **AudienceEmbedded**, but displays them in a scrollable list besides the chart. The list is sorted chronologically by the date the respective annotation refers to. There are no orange dots embedded into the chart and no other visual relationship between the date mentioned in the comment and the chart. Visitors can add annotations through a simple button above and below the list, which opened the same submission form as in **AudienceEmbedded**.

Because interfaces that show a combination of data visualizations and additional information curated by the same authors are prevalent in data journalism, we chose not to design a separated view of government policies (AuthorSeparate). In doing so, we increase the number of visitors to the other three views and are able to solicit audience annotations from two thirds of our visitors. With this set of views, we are still able to do comparative analyses along the two design dimensions origin and integration.

Besides these differences, all design variants have the same basic functionality. In AudienceEmbedded and AudienceSeparate, annotations can be filtered by hashtags provided by the audience (e.g., “#lockdown”). In AuthorEmbedded, annotations can be filtered based on existing categories from the data provider (e.g., “Border Restrictions”). In both embedded views (AudienceEmbedded, AuthorEmbedded), visitors can click a button to *open a random moment* and can explore “next” and “previous” annotations based on their dates. In AudienceSeparate, annotations are ordered by date.

We intentionally kept the project description and narrative to a minimum. In an intro, we asked “*What stuck with us throughout this pandemic?*” and provide a short introductory sentence: “Since the start of the pandemic, we are confronted with charts about new cases daily. What are the stories behind the numbers?” (in AuthorEmbedded, we mentioned *events* instead of *stories*). We also did not provide any further guidance as to what kinds of annotations people could submit to (a) avoid bias and (b) promote freedom of expression. Upon visiting the website, a visitor was randomly assigned to one of the three views. Visitors could switch views through a small menu. The menu appeared after a delay of 20 seconds to make sure that visitors would familiarize themselves with the view that was randomly assigned to their session.

4.3 Study 1: Understanding Interfaces and Annotations

We conducted a first study to understand how people engage with the different user interfaces from our design space and to answer our research questions. This study was designed to be conducted outside a controlled lab environment to obtain ecologically valid answers from a broad audience. We are interested in people’s intrinsic motivations to engage with the visualization and contribute content, any supervision or compensation would make it impossible to understand what people would have shared or viewed outside the lab. Participants were not asked to disclose their name, identity, or any demographic information, as a prior study shows that *intentional anonymity* enabled participants to respond more freely when expressing personal stories, desires, or fears (Brown & Knopp, 2008).

4.3.1 Setup

In phase 1, we publicly promoted the *CoronaMoments* website through the Twitter accounts of the authors and the research groups. We created a dedicated Twitter handle (@corona_moments), infrequently posting screenshots of annotations to encourage further site visits. Phase 2 lasted six months, from October 2021 to March 2022. During this period, several major rises in cases in European countries occurred, yielding a range of incidence curves, each specific to the respective country. These rises were often labelled by the media with the virus variant that caused them, e.g., the “omicron wave” that hit Europe in late 2021 and early 2022. Coinciding with these events, the platform was launched and the research project was featured in the online and print version of a regional newspaper. During phase 2, we collected four kinds of information about the usage of the platform and the content of the shared moments:

- **Interaction logs:** After visitors consent to data collection, we record the timestamp of any click interaction on the platform, including clicking on audience annotations or policy measures, viewing random annotations, selecting countries, filtering annotations, or submitting annotations.
- **Audience annotations:** Annotations that visitors left when viewing AudienceEmbedded or AudienceSeparate were stored anonymously. Throughout study 1, we refer to these annotations as *moments*.
- **General survey:** After a few minutes, a brief survey invited visitors to share what they found most interesting on the CoronaMoments platform through a multiple-choice questionnaire.
- **Post-submission survey:** Visitors in AudienceEmbedded and AudienceSeparate who shared a moment were also prompted about their motivation for the submission. The form contained multiple choices (with multiple selections possible); the options participants could choose from are taken from engagement drivers for user participation in Chapter 3 : *Expressing opinions, matching knowledge, sharing emotions, claiming interest, and adding anecdotal evidence*.

4.3.2 Analysis & Findings

Throughout study 1, 77 personal moments were contributed on the CoronaMoments platform: 37 during phase 1 and 40 during phase 2, which was public. To answer [Q-Annotations], we analysed the moments and subsequent survey submissions. The vast majority of moments were submitted from Germany (69%), followed by the United Kingdom (12%), three or fewer submissions came from Italy, Norway, Netherlands, United States, Romania, Australia, Mexico, Greece, and Brazil.

Moments

To obtain a high-level understanding of contributed moments, we applied a Grounded Theory approach (Strauss & Corbin, 1994) that resulted in four categories: actions (30, 39%), reflections (29, 37%), experiences (25, 32%), and emotions (27, 35%). Since moment authors often touched on multiple topics, we refrained from building mutually exclusive categories.

Actions describe people's own behaviour during the pandemic and provide a rationale for the decisions they made: e.g., *"At Heathrow Airport on our way to see my family in America. We both felt safe knowing that everyone in the airport had taken a PCR test the previous day and had tested negative in order to fly. #testing #newnormal"*. Especially at the beginning of the pandemic, many actions describe last instances of activities that later became impossible: *"I attended my last in-person conference. News about the virus were spreading, but it all seemed far away back then. Everyone was making jokes about the new ways of greeting each other without shaking hands. #conferences #academiclife"*. Later into the pandemic, actions often refer to coping mechanisms that people employ to deal with the *new normal*, e.g., baking bread, buying plants, going hiking, or buying home-office equipment.

Reflections are another group of moments, in which people contemplate the pandemic and reveal realizations about themselves: e.g., *"I remember listening to a radio show talking about the 'novel lung disease from china'. This was before everything got very serious. I brushed it off as just another news item."* Reflections sometimes read similar to diary entries, as authors disclose intimate thoughts or share their inner monologue: *"Yesterday I realized that this pandemic has been going on for so long that I have become a different person in the meantime. There is no going back to my old self. I'm not sure about this new self either"*. Reflections often co-occur with descriptions of actions and evaluate give insight into behaviour evaluation of their behaviour in hindsight: *"Because of the shortage of medical masks, I started sewing masks from old bedsheets for my family and I. In hindsight it actually seems bizarre that it wasn't mandatory to wear masks in public spaces this long"*.

Experiences are shared by people in many moments. Compared to actions, experiences describe unintended events that people encountered or found themselves in without their own doing: e.g., *"I went for a walk with a friend and we suddenly ended up in a small corona deniers / anti maskers demo without really noticing because they were walking in smaller groups. And then everywhere we wanted to go, paths were blocked by the police."* Experiences often express a lack of control of the situation, e.g., when their lives are disrupted by restrictions, health concerns, or other people's actions.

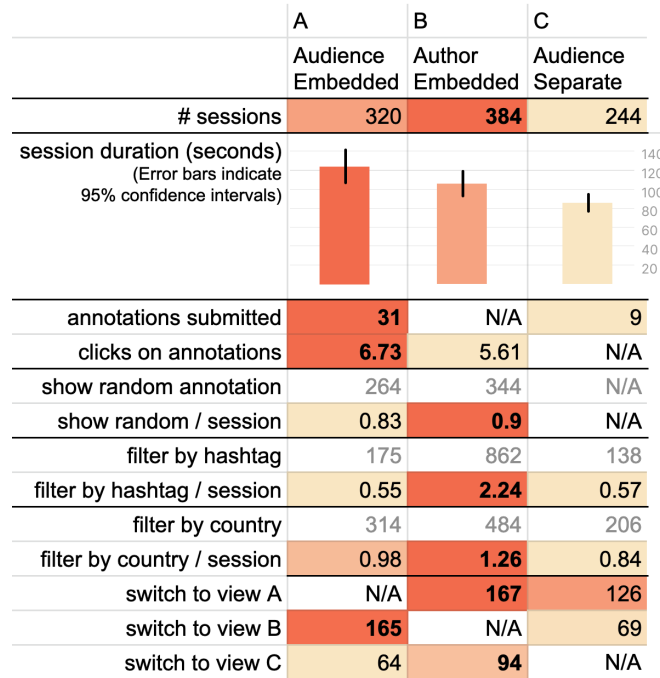


Figure 4.5: Comparison of interaction analysis for all views.

Emotions describe how people feel in the moments they submitted: e.g., “*Feeling grateful having received my booster jab today, which makes me feel like I was given an update and now I’m ready for the next round of the pandemic #vaccination*”. We found a wide variety of emotional expressions, including anxiety (“*Catching my first common cold since the pandemic had started and I was *very* anxious about the symptoms until I had the negative result of the covid test*”), joy (“*I adopted the sweetest black kitten and she is purrfect at keeping the loneliness bug away #covidpet*”), and anger and gloat (“*I called the police on a group of 40+ teenagers playing drinking games [...] It was pure joy seeing them busted*”). Emotions most often co-occur with other kinds of moments, as people describe the emotional context and consequences of their actions, reflections, and experiences.

We developed the above coding scheme through three iterations and discussions among the authors. One prior version classified moments as pandemic-specific events (e.g., *restrictions, ruptures, new normals*), which very well described the data with regard to the COVID pandemic, but left little room for further generalization of our findings. An initial attempt to categorize the moments according to their relation to the data failed because—other than expected—none of the moments explicitly mention the numeric incidence values around the temporal context of the annotations.

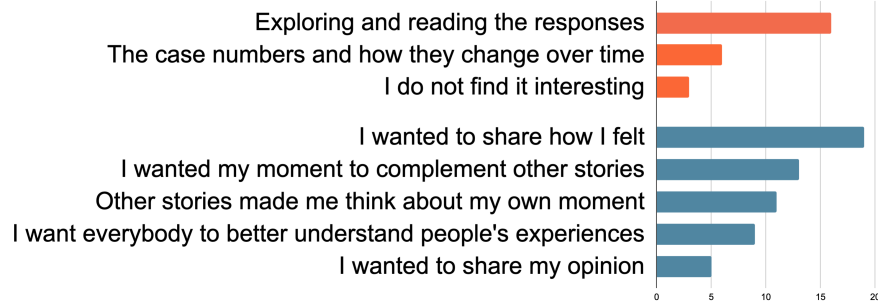


Figure 4.6: Survey responses of people who read annotations (red) and after they submitted own annotations (blue).

Apart from this analysis, we made several observations about annotation creation. For instance, people in study 2 were more likely to submit a moment in *AudienceEmbedded* (31, 78%) than in the *AudienceSeparate*. Also, people are more likely to comment about the beginning of the pandemic (74% of annotations refer to moments in 2020), irrespective of when people submit the annotation (58% of annotations are posted at least one year after the moment they refer to).

Interactions

We collected data about 2,409 unique sessions on the platform. We dismissed 259 sessions from the pilot phase. Since we did not optimize all three views to be equally accessible on small devices, we dismissed 607 sessions of people who accessed *CoronaMoments* from a mobile phone. 596 people did not consent to the data collection; their sessions were hence removed. Based on the remaining 949 sessions, we could observe several usage patterns.

View visits: *AuthorEmbedded* was visited most (40.2%), followed by *AudienceEmbedded* (33.7%), and *AudienceSeparate* was visited least (25.9% of all visits). Based on the timespan between the first and last interaction per session, people spent the most time in *AudienceEmbedded* (122 seconds avg.), followed by *AuthorEmbedded* (104s avg.) and *AudienceSeparate* (84s avg.).

Read moments: Similarly, visitors were more likely to click on and read audience annotations (avg. clicks per session: 6.7) than policy responses (5.6). Since in *AudienceSeparate* no clicks were necessary to read the moments, we cannot determine with confidence how many were read.

Switch views: People were randomly assigned to one starting view but could switch to see other views via a menu containing a brief description and preview icon for each view. The menu order was randomized. Table 4.5 shows the migration behaviour across views. From any starting view, people most likely switched to an embedded view.

Filter moments: The usage of UI elements to filter visible moments varies considerably across the views. In both audience views, few people filtered moments by hashtag (average 0.6 clicks per session), while this number quadruples for `AuthorEmbedded` (2.3). Filter by country shows a similar, yet less drastic distribution (`AudienceEmbedded`: 1; `AuthorEmbedded`: 1.3; `AudienceSeparate`: 0.8); so does opening random elements by clicking on the button “Show Random Moment” (`AudienceEmbedded`: 0.8; `AuthorEmbedded`: 0.9).

Surveys

Out of 949 visitors, 24 (2.5%) responded to a mini survey shown on the website after a few minutes of usage. The responses show that people across all views are more interested in reading responses (66%) than in the actual case numbers (25%). 12% of respondents expressed no particular interest in either (Table 4.6).

38 visitors (4%) responded to another survey *after submitting an annotation* to give an account of their motivation. Responses indicate that the main driver for audience annotations was people’s desire to share how they *feel* (50%) in contrast to sharing their *opinion* (13%). Other important motivations indicate the intricate relationship between people’s own experiences and what they read about others. Reading other people’s moments made respondents *think about their own moments* (29%) which they then shared. They wanted their own stories to complement the existing collection of experiences (32%). Nine (24%) participants were well aware of the public display when submitting and wish for their moment to help other’s better understand their experiences. Similar to the first survey, only two participants (5%) focus on the actual graph and point out something in the data.

Both surveys included a free text input for participants to further explain their motivation and interest in viewing and sharing moments. While none of the participants of the first survey made use of that option, we recorded several replies from participants who just submitted a moment. Two participants elaborated that their motivation for the submission was “*to share some current corona vibes*” and how it “*Feels good to reflect and write that down somewhere*”. Another one reflected on the impact reading other stories has on them: “*I found it touching to read other human experiences along time in the cases chart. It reminds me that I’m not alone despite the isolation and the social distancing*”.

4.3.3 Summary

Our coding scheme provides an understanding of the content of audience annotations in a public data visualizations (*Q-Annotations*) in the form of four high-level themes: actions, reflections, experiences, and emotions. Our findings also suggest that the integration of annotations changes user behaviour in that `AudienceSeparate` is less popular than the embedded views (*Q-Integration*): the log analysis shows that people spent the least amount

of time in AudienceSeparate and were more likely to switch to any of the embedded views than vice versa. 78% of the 40 moments written after the pilot phase (which only had provided one view) were submitted in the AudienceEmbedded view. The effect of an annotation's origin is two-fold: On the one hand, showing audience annotations correlates with slightly longer sessions and more interactions. On the other hand, in AuthorEmbedded people are more likely to engage with the visualization by filtering countries and categories. In short, we were able to characterize the contents of annotations shared in a public data visualization (*Q-Annotations*) and we found initial evidence for engagement differences according to integration and origin of annotations.

4.4 Study 2: Understanding the Audience

Next we conducted semi-structured interviews to obtain more qualitative information and better understand *why* the three views were so differently engaging and *how* the audience annotations frame the engagement with the phenomenon represented by the data.

4.4.1 Participants

We invited visitors of CoronaMoments as well as followers of the Twitter account to individual interviews. We recruited eight participants [P1–P8], all of whom had visited CoronaMoments at least once. We did not know whether each participant knew all views due to the anonymous nature of logging and audience submissions. Three participants identified as female, five as male; all participants had a bachelor's degree or higher. Participants came from a variety of fields, including the arts, HCI, journalism, and cultural studies. Five participants lived in Germany, two in the United Kingdom, and one in France.

4.4.2 Procedure

Interviews were carried out online via Zoom videoconferencing and lasted between 40–60 minutes. Participants were directed to the CoronaMoments website and had full control over the website on their computer. Each participant randomly started with one of the three views and then could switch to the other views, akin to study 1. Sharing their screen, we encouraged participants to freely explore each view in CoronaMoments for as long as they wanted. We watched participants using the platform and asked them to think aloud and express their thoughts while addressing a set of four main tasks.

At the beginning, an introductory question was asked (*"Can you explain to us, how the three views are different from each other?"*) that was aimed at establishing a shared understanding of the visualization's functionality. We encouraged participants to explore various annotations in each view (*"From each view, pick a response that stands out to*

you and explain why”). Following Peck et al.’s (2019) approach to invite participants to share their values in data visualizations, we asked participants to *“Rank the three views according to how useful they are to you”*. In a follow-up question, we asked *“What concept of usefulness do you have in mind when ranking the views”* and *“How do different elements of the visualization (stories, policies, and the chart itself) help you reflect on the pandemic?”*. During the interviews, we took notes of the responses, revisited all afterwards, and grouped similar statements into general themes.

4.4.3 Findings & Reflections

We report on the main findings from the interview study with regard to the perceived usefulness of annotations, in particular their capacity to contextualize experiences and stimulate empathy.

Usefulness

Embedded audience annotations considered most useful. Six out of eight participants ranked the three views of our study in the same order along descending usefulness: AudienceEmbedded, AuthorEmbedded, and AudienceSeparate. Hence, the two embedded views were rated higher than the separate view. This ranking reflects and extends our findings from study 1: people spend most time and read the most annotations in the view they find most interesting because in AudienceEmbedded they can explore people’s perspectives. For example, comparing the AudienceEmbedded and AudienceSeparate, all but one participant found the embedded version more useful and described the separate version as *“unproductive”* [P4] and a *“wall of text”* [P8]. Having a list of moments separate from the chart was perceived to disrupt the connection between annotations and data: *“It does give me insight, but I can’t correlate it to the data”* [P2]. In a way, this relation was surprising, given that few of the audience annotations directly referenced specific visual patterns or a particular time period in the chart, other than the beginning of the pandemic. We intentionally asked participants about their understanding of usefulness only *after* they ranked the views. This allowed us to get an unfiltered response first and a rationalization of that response later. In the following, we iterate over this finding and explain how the different views impact the participants’ understanding of data and annotations.

Usefulness linked to personal relevance. To most participants, usefulness manifests itself in *“translating a data set in a way that it becomes relevant to the viewer”* [P4]. Relevance was most often described as personal interest with respect to personal experience and reflecting on one’s own experience as well as learning about other people, comparing, and empathizing: *“What’s important to me is really just my personal context and curiosity about other people”* [P7]. This observation is understandable, given the public nature of our study and the potentially many personal annotations from the audience related to the COVID

pandemic this research is situated in. Another reason for this focus on personal relevance might be the missing goal in engaging with the visualization and comments in the first place. Again, we think this is representative for many contexts in which visualizations are encountered, as opposed to a shared analysis goal in collaborative sensemaking. Reading personal annotations is not a means to an end, but satisfies a curiosity. For example, participants highlighted how clicking on embedded personal annotations sparked their desire for exploration and other people's behaviours during the pandemic and how their stories relate to the data: *"What did people do in the first wave?"* [P5]. This includes comparing oneself with other people and understanding how one's own choices, thoughts, and actions resemble those of other people: *"It's useful to compare my own experiences with others and to see how other people were doing compared to me"* [P3]. Participants especially appreciated their seemingly unique experiences to be reflected in the annotations shared by others: *"It's information that I can relate to. It's something that is unique to me"* [P6]. In particular, the personal character of the shared annotations offered a *"qualitative perspective that you can't really get from the data"* [P2].

However, personal relevance was also found in author annotations. Two participants connected policies in AuthorEmbedded to their own life: they used country selection and category filters to find the exact moments that described border closures they were affected by: *"This one impacted me and it was a horrible one"* [P1]. More often, finding personal relation in public policy needs a bit start-up support. In one instance, after searching for a policy they could relate to without success, they randomly picked a moment about Belgian travel policy and pointed out how *"this one speaks to me because it's so long and hard to understand, I have to read it twice. it reminds me of my situation, not knowing what is allowed and what is not"* [P7].

Orientation

Chart as contextualization of own experience. When talking about the ways the interface helped participants with their own reflection, participants stated how the data representation supported them in looking back on the pandemic by setting mental anchor points: *"Having a chart support my memory helps recollecting memories at the right point in time"* [P4]. For some participants, the chart was sufficient to jumpstart reflections about their memories and feelings: *"the waves [in the chart] are meaningful in a way that they tell me how I felt in different months. They give me access to those points in time"* [P5]. Other participants explicitly expressed how the combination of other people's annotations and data representation help them with their own contextualization: *"Looking back two years later, it is interesting to see what happened: How do I remember it, how do others remember it. For this, the timeline helps a lot"* [P3].

Visual distribution of annotations as retrospective. The participants pointed to the visual impression of all embedded annotations as a whole that makes a difference, compared to the separated view. They mention how the distribution of annotations in the visualization—many annotations at the beginning of the pandemic and fewer towards the end (Figure 4.1)—represents participants' own experience of general fatigue: *"The frequency reflects my personal perception of the pandemic: in the beginning everything was new [. . .]. Two years later, all of this is not so 'interesting' anymore. One can understand why the entries are distributed like that"* [P8]. Participants did not reflect about their own experiences just by looking at the visualization of incidence values and reading the lists of comments separated from a visualization did not prompt similar reflections. It is the combination of data visualization and audience annotations integrated into a joint space of the interface that seems to stimulate orientation, contextualization, and reflection on their own personal experiences and those of others.

Empathy

Personal annotations evoke personal experiences. In all views, participants picked annotations they could personally relate to. For example, after reading personal stories, participants expressed how they had similar feelings: *"I read this and think to myself that I could have literally written it like that. It expresses exactly what I feel. It is good to know that I am not the only one who feels this way."* [P8]. Often participants have made comparable experiences, e.g., *"this person had to reschedule their wedding SEVEN times? I only had to do it twice"* [P4], and throughout the interview they *"go down memory lane"* [P4] and share their own stories about cancelled conferences, closed libraries, their first COVID tests, complicated travel plans and *"having similar discussions about similar topics"* [P3] when reading audience annotations. During this reflection process, some participants remembered the annotations they themselves posted or mentioned how they wanted to post the moments they just remembered (P1).

Personal annotations can promote empathy. While browsing personal annotations, participants would empathize with other people's fate, even if they had not made similar experiences: *"That might not be something that relates to you - but might make you feel happy about them"* [P2]. Personal annotations allowed the participants to change perspective and connect with other people through their shared experience: *"I have not heard this particular idea in my personal environment — but now I feel connected to that unknown person!"* [P8]. In two instances, people expressed how they take social distancing very seriously themselves, but show leniency towards people who break rules, for example, to celebrate life events: *"I can feel that. That person might go through so much deliberation before making such a decision"* [P1]. In these statements, participants express compassion for the authors of the audience annotations they encounter.

4.5 Discussion

According to our two studies, viewers of public data visualizations are willing to share personal annotations, which in turn can lead to higher levels of engagements with the interface, mainly because they support reflection, orientation, and empathy. In the following, we discuss these results, explore implications, and highlight important limitations.

4.5.1 Responding to Research Questions

Based on our insights from studies 1 and 2 we provide answers for our three initial research questions:

Q-Annotations: *How and why do non-expert audiences use annotations to express themselves in public data visualizations?* In our study, non-expert audiences use annotations not for collaborative analysis of data, but for personal expression. In contrast to existing work on commenting and collaborating in visualization (Heer et al., 2007; Willett et al., 2011), the observed annotations lack references to data, but provide a rich, subjective characterization of the time the data refers to. Prior classifications of audience reactions among other categories of expressions mention *testimonies*: reports of first-hand experiences and anecdotal evidences that more often relate to a visualization's topic than do its data (Chapter 3). The presented annotation categories provide a more fine-grained description of said testimonies, indicating that this type of audience reaction consists of personal reflections, reports of own actions, descriptions of emotions people felt, and experiences of situations they observed. The post-submission survey shows that people's wish to express their feelings is a strong motivator to share personal annotations. The process of creating annotations furthermore relies on other, existing annotations: reading annotations makes people think of their own stories, which they then can contribute as well.

Q-Integration: *What is the impact of embedding annotations directly into visualizations on the viewer's experience?* Embedded views are seemingly more useful, create slightly longer sessions with increased engagement. While the AudienceSeparate view allowed participants to quickly skim all annotations, embedding annotations sparks a 'desire to discover' and people are eager to explore annotations, particularly those from the audience. In contrast to existing interfaces that show annotations separately to the visualization (e.g., in online communities or on social media), embedded annotations help people navigate other people's stories and contextualize their own experiences. Furthermore, seeing the overall distribution of shared annotations within a data visualization can instil a sense of orientation in regard to the represented phenomenon, echoing the ideas of social navigation during which collective traces guide users in digital information spaces (Dieberger et al., 2000).

Q-Origin: *How do annotations curated by visualization authors and annotations collected from the audience differ in their effect on the viewing experience?* Audience annotations help to make a data visualization personally relevant to the reader. They can promote empathy for other contributors and allow people to relate their own experiences to theirs—and with that, they play an important role for continuous engagement and participation. The origin of annotations *does not* change the insights people draw from a visualization. However, audience annotations have a great impact on the represented narratives and change what people think about after reading a visualization and what they are willing to contribute themselves. The personal character of the audience annotations seem to foster a qualitatively different connection between the reader, the visualization, and the represented phenomenon.

4.5.2 Limitations and Reflections on Methods

Our work has some important limitations to take into account. We deliberately chose to only have anonymous submissions of annotation in order to allow for a greater freedom of expression. This means we know little about the demographics of our contributors. While our experiment allowed a public audience to participate, there are still entry barriers: the website was only available in English and was not optimized for small screens, which excluded some demographics and usage scenarios. We primarily propagated the link among our own networks on Twitter, which limited our potential reach. Therefore, we might have missed annotations, survey responses and recordings of interaction logs from a more diverse audience who potentially engage differently with visualizations (e.g., on mobile phones), have had different, marginalized experiences (e.g., members of high-risk groups), or find other things relevant. The same limitations apply for the participants in study 2.

The pilot phase of study 1 was run in two research labs and provided us with an initial set of annotations, which were necessary to have a meaningful comparison of different views. The limited diversity of the audience may have influenced the starting conditions of the experiment and follow-up annotations were potentially biased by existing ones. For example, the hashtag “#academiclife” was introduced during the pilot phase and later automatically suggested to annotation creators during the public deployment in phase 2. We do not know how responses would have differed with different starting conditions.

The annotation submission was framed around *stories* (“What are the stories behind the numbers?”) and invited people to “share their *moments*”, which potentially could have discouraged people from submitting a more diverse range of annotations. As outlined in section 4.2, we focused on audience annotation as subjective and personal accounts, as opposed to more objective reactions provided by authors. Chapter 3 provides an overview of other possible audience reactions, such as *testimonies*, *opinions*, *critique*, and more. Our work provides a better understanding of testimonies, but ignores other kinds of reactions.

Future work should investigate different framings for soliciting engagement, for example, asking public audiences to embed annotations that express their critique of the data, commentary on the visualization design, or maybe even arguments on a social or political topic.

We deliberately chose a topic and data people were well familiar with. Participants in our study, however, mentioned how they were tired of the pandemic, which may have affected general engagement and the number of annotations created. We observed that annotations did not refer to specific data points, but talked about the topic more broadly. More research is needed to understand how other topics, data sets, and visualizations change audience annotations and their contextualization of a visualization.

4.5.3 An open reference space for collective storytelling

Based on our findings, we conceptualize visualization as a space that leverages audience annotations as a mainstay for narrative framing and continuous participation. This space is *open* to the general public to participate without pursuing explicit goals and allows for contributions of local, situated, and partial knowledge (Haraway, 1988) from the non-expert audience. It uses representations of data as a reference frame, which helps the audience to contextualize their own knowledge and experiences in relation to the data as well as other people's annotations. In doing so, it enables a practice of *collective storytelling*, in which the framing of a visualization does not consist of a singular narrative provided by the visualization authors, but instead is dispersed into a plurality of voices. Compared to data-driven storytelling, in which visualization authors control the narrative with annotations they create, collective storytelling shifts this power and responsibility to the audience, which provides a plurality of narratives. We see five implications for visualization research and design.

Rethink roles of annotations and visualization. Data representations are typically the main protagonist of a visualization, while labels, captions, accompanying articles, and annotations are considered supporting structures that reinforce the message of the data. During the course of the presented research, we observed how these roles were gradually reversed and audience annotations became the primary concern of our visualization, while the chart was merely used for orientation. With that, audience annotations have great potential to increase engagement and provide for a longer lasting and more profound reading experience. Prior work indicates that titles and captions have great impact on what insights one can draw from a visualization (Kong et al., 2018). Our findings suggest that audience annotations are powerful devices that can become the integral component of a visualization. Yet, more research is required to fully understand whether audience annotations can change what insights people draw from a visualization.

Leverage personal relevance. One challenge in data-driven storytelling is to convey why the reader of a visualization should care about the topic or the implications of the data. Our study demonstrates how annotations from the audience established personal relevance for other viewers and promoted empathy for the people writing annotations. This has potential implications on future work for antropographics (Morais et al., 2021), asking whether providing human experiences as context in visualization has an impact on prosociality. We imagine embedded audience annotations as a future device in data journalism that helps viewers to better relate to articles they read.

Cold-start contributions. The engagement with audience annotations requires a set of starter annotations that act as a seed for further contributions to be made. The data visualization alone may not be sufficient to foreshadow the kinds of experiences to be shared and stories to be told. It takes editorial effort to set the tone with the first set of statements. This is a daunting task. The CoronaMoments platform was originally called “CoronaMemories”, in hindsight, with an overly optimistic undertone that it might be over soon. However, especially when representing (and responding to) a highly contingent phenomenon, the interface—both visualization and annotations—turn into a dynamic, if not volatile, space that refers to a moving target. The uncertainty about the further development of the represented topic requires careful and open-ended wording both in the interface as well as in the seed contributions.

Support and study discourse. Our work considered annotations as singular responses that relate to a specific time and the findings from the studies suggest audience annotations are written in direct and indirect reference to other existing annotations. Future interfaces can support comments to annotations and with that support a multi-party discourse inside a visualization. One challenge for such an interface is the visual arrangement of potentially multiple levels of annotations. We imagine these interfaces to reinforce the engaging effect of audience annotations, potentially providing for a greater variety of annotations for further analysis.

Prepare for moderation and manipulation. With a potential for vast participation comes responsibility to prevent harm. Prior work showed how visualizations can be used to promote misinformation—specifically in a pandemic context (C. Lee et al., 2021). Audience annotations need to have robust mechanisms for reporting and moderation of potentially harmful content. The combination of quantitative evidence and qualitative experiences can prove particularly convincing, if not deceiving, when constructed in a manipulative manner. There is a risk of misusing the authenticity and authority of crowdsourced statements on a contentious issue. More research is needed to address questions of trust and transparency in data visualizations that open the door to personal audience annotations. Depending on the

topic and audience, having a plurality of potentially conflicting narratives in one visualization may confuse readers. Future work should investigate mechanisms to provide orientation while preserving the original multiplicity of voices from the audience, e.g., through options for self-categorization, further use of hashtags, or audience-driven aggregation.

4.6 A call to annotation

From collaborative sensemaking to public storytelling, annotations are integral components of most data visualizations largely due to their communicative value. Data do not speak for themselves—and neither do visualizations. Considering that personal responses can play a big role in the use of data visualizations, we were interested to learn if and how such personal responses can become meaningful and useful components of a public data visualization. To explore the potential of such audience annotations in public visualizations, we developed and deployed a web platform visualizing the Corona case numbers and contextualizing these with annotations. We carried out two studies, first to collect audience annotations and to compare the role of annotation origin and integration on the engagement with the interfaces, and second, to better understand the impact that annotations have on the audience's reading experience.

Our findings suggest that audience annotations can fundamentally change the reading experience of public data visualizations. Audience annotations can become the primary concern of a visualization, as reading them establishes personal relevance, promotes empathy for others, and helps people reflect on their own lives. The annotated visualization provides an overview to contextualize and eventually express these thoughts as annotations, including accounts of emotions, reports on actions, experiences, and reflections. Based on these findings, we envision future visualization interfaces as open spaces for collective storytelling that allow public audiences to engage with data, visualizations, and other readers. In the face of complex and dynamic topics that are publicly communicated in the form of data visualizations, we see great potential—but also risks—of visualization annotations for public discourse and deliberation.

Anchoring Discussions in Data Visualizations

Preface

Publishing my first full paper of this thesis (Chapter 3) at CHI in 2021 was a great success for me. I am grateful to the anonymous committee member who took on the manuscript and shepherded the process until the paper was accepted. Trying to publish my work on coronaMoments (Chapter 4), however, I learnt that it does not always work like that. I wrote, submitted, got rejected, received reviews, rewrote, resubmitted, got rejected, received reviews, rewrote, resubmitted, got rejected, received.... What I felt was a unique opportunity—the idea that weekly updates on COVID-19 cases were so pervasive that basically everybody could relate to this data—turned out to be considered by many reviewers as a great weakness of the whole research design. I remain confident that my results contribute a valuable proof of concept to show how discourse about a visualization can be entirely driven by personal stories. However, the question remains: What would be an integration technique that works with any chart, map, dashboard, or infographic? Also, how do people discuss charts that are not about the pandemic, but about a range of topics they are either more or less familiar with?

Therefore, the following chapter explores the idea of generalizing the integration of annotations in visualization and discusses approaches to RQ3 (*How can discourse be integrated into data visualizations?*). The chapter is based on the manuscript *Discursive Patinas: Anchoring Discussions in Data Visualizations*, which was accepted at the 2024 IEEE VIS conference and will be published in the IEEE Transactions on Visualization and Computer Graphics. The paper was co-authored with Benjamin Bach, Marian Dörk, and Derya Akbaba. In the context of this thesis, I combined the abstract, the original introduction, and the related work section into one continuous introduction.

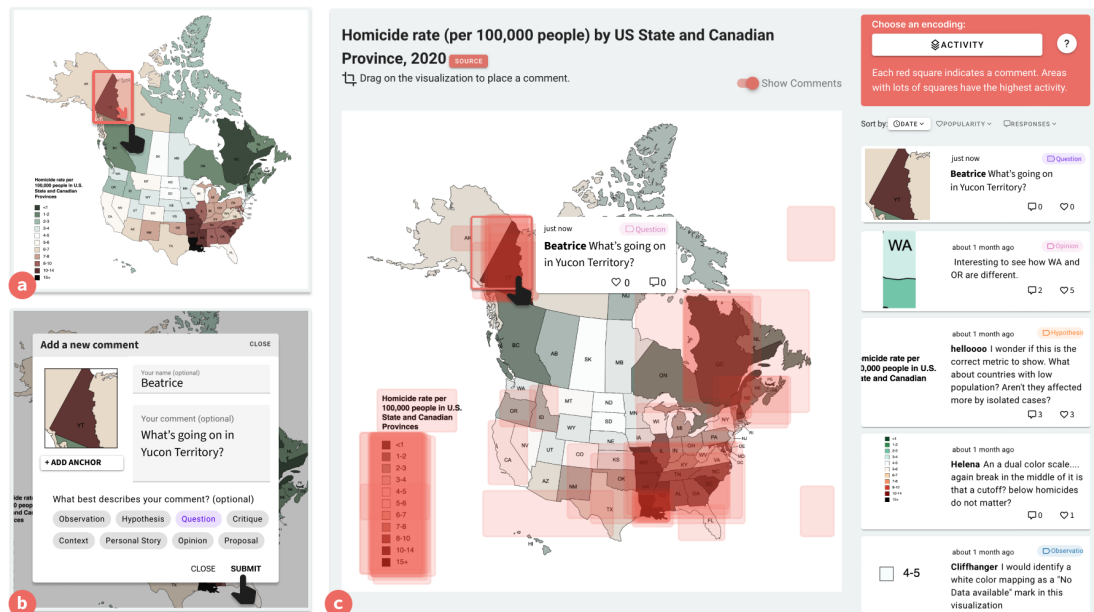


Figure 5.1: Our platform supporting discussions about visualizations through anchored comments (a, b) and discursive patinas (c). Drawing on the visualization creates an anchor (a) and a textual comment (b). The full interface shows all anchored comments as an emerging discursive patina on the visualization. All comments are also shown in a separate browsable list (c). Together, anchored comments and discursive patinas visualize the level of engagement of specific areas in a visualization that are being discussed across people.

5.1 Introduction

This chapter presents *discursive patinas*, a technique to integrate discussions into data visualizations, inspired by how people leave traces in the physical world. While data visualizations are widely discussed in online communities and social media, comments tend to be displayed separately from the visualization. There is a lack of ways to relate these discussions to the content of the visualization, e.g., to situate comments, explain visual patterns, or question assumptions.

In related work (Chapter 2) we can find two major approaches to visualization discussion on existing platforms. The first one focuses on textual comments that are displayed separately from the visualization, i.e., comments exist as individual text snippets besides or underneath the visualization with no explicit visual relationship to any part of the visualization (Hullman et al., 2015). Such interfaces are simple and scalable as long as the comments refer to the visualization as a whole; however, they do not support detailed comments about specific visual elements or data patterns in the visualization and do not visually relate comments back to the visualization (He et al., 2023; Hullman et al., 2015). For example, a comment might critique the scale on the legend or highlight a specific visual pattern in the visualization. To

mitigate this problem, the second approach allows for free-form annotations where users can highlight and otherwise express themselves directly *on* the visualization (Heer et al., 2007; Lin et al., 2022). While allowing for more direct comments, such free-form annotations can quickly clutter the visualization, especially in scenarios with hundreds of commenters, as is common on online platforms. Moreover, existing interfaces hardly convey the complex, diverse, and often highly dynamic nature of discussions. It is difficult to get an overview of what people are discussing, what kind of reactions they express, and which parts of a visualization spark the most conversation.

The challenge of getting an overview connects with the observation that discussions “*generally integrate poorly with visualization and analysis tools*” (He et al., 2023) since comments are displayed in separate sections or use “*screenshots and external links rather than more malleable representations*” (He et al., 2023).

Existing annotation and discussion platforms introduce various strategies to embed annotations within the visualization and connect them with segments of the visualization. Our contribution is driven by an assessment of the annotation interfaces through the lens of two anchor characteristics: their scale and scope. The concept of *scale* reflects the interfaces’ ability to accommodate a growing volume of comments without leading to visual clutter or compromising the readability of individual comments. Conversely, by *scope*, we refer to the mechanism for identifying portions of a visualization that are being commented on.

On existing platforms, annotations can effectively encircle, point to, highlight, or cut out portions of visualizations they refer to. The high flexibility in defining the scope comes at the expense of their capacity to scale with increasing numbers of contributions. Overlapping freehand drawings render each other illegible; for a similar reason, clippings (Walny et al., 2020) or manipulations (Romat et al., 2019; Lin et al., 2022) from multiple viewers are not presented in one view. While this is not an issue for individuals or small groups, in public forums it quickly becomes an issue of scale when individual scope definitions impede the overall legibility. In contrast to free-form annotations, interfaces using one-dimensional markers on maps or images (Brown & Knopp, 2008; McCurdy et al., 2019; Xu et al., 2014) are highly scalable, at the cost of custom scope. The uniformity and small size of markers help readers to quickly gauge where many comments are placed. Their identical size, however, can make it hard to understand the scope of what a comment refers to. With our research, we are particularly interested in resolving the tension between scale and scope of visualization annotations. In this chapter, we offer a mechanism to embed the discussion of — and on — the visualization.

We introduce an annotation interface designed to scale the number of comments about a visualization while closely relating the comments to the aspects in the visualization they refer to, thus re-negotiating the tension between scale and scope. The web-based interface *Viscussions* supports *anchored comments* that can be placed onto the visualization

using semi-transparent rectangles as visual marks. In contrast to traditional map markers (e.g., pins), these rectangles specify relevant areas in a visualization and can be styled to encode information about a comment, such as its reaction type, popularity, or the number of responses to the comment. This combination of visual encoding and scoping of comments can summarize aspects of the discussion within the spatial structure of the visualization. Similar to existing work on crowdsourced design critique (Luther et al., 2015), our intent is to foster constructive and critical discourse that is literally grounded in the data visualization. As the number of anchors and comments grows, meta-visualizations emerge that we call *discursive patinas* (Figure ??), whose designs are inspired by visualizing interaction histories (Matejka et al., 2013) as well as traces human interactions can leave on objects in the physical world (Hill et al., 1992). Discursive patinas are designed to follow Wexelblat's idea of physical traces "*to guide [...] actions, to make choices, and to find things of importance or interest*" (Wexelblat & Maes, 1999) within a visualization.

Across three complementary studies (Sec. 5.3) involving a total of 90 participants, we use *Viscussion* in different contexts to investigate the potential of anchored comments and discursive patinas. We study how discussions on data visualizations can serve not only as means for understanding data but also as a communicative space for critical reflection about biases in the data and assumptions in the visualization design (Dörk et al., 2013; D'Ignazio & Klein, 2020). Such critical engagements are intended, but not prescribed, and we intentionally invite for a broad spectrum of annotation contents. We report from three studies with a total of 10 sessions and 90 participants. A controlled study compared *Viscussion* to a baseline interface modelled after prevalent interfaces on social media and news outlets with juxtaposed (as opposed to overlaid) comments. A second study with domain experts explored the wider potential of *Viscussion* to facilitate discussions about visualizations relevant to the experts' domains. A final study was situated in an educational setting to investigate the instructive potential of *Viscussion* for reading and discussing visualizations. The results from the studies indicate that anchored comments can reduce barriers to understanding a visualization, add relevant context, and introduce alternative interpretations. Compared to the baseline interface, discursive patinas improved participants' navigation of the discussion by highlighting different areas of interest within the visualization. Overall, anchored comments and discursive patinas encouraged people to more carefully examine specific parts of a visualization, compared to when they only had the ability to create comments without anchors. Based on these results, we discuss how discursive patinas can support *close reading of visualizations* while at the same time allowing for *distant reading of the associated discussions*. We conclude by discussing future scenarios for discursive annotation interfaces that allow for critical readings of visualizations, provide design feedback, and support feminist approaches to data visualization.

In summary, we contribute a technique for integrating and aggregating discussions on data visualizations and report from a three-step evaluation on the impact of anchored comments and discursive patina on critical engagement with data visualization.

5.2 Anchored Comments and Discursive Patinas

This research investigates how comments on data visualizations could facilitate a critical and constructive discourse about a subject, its visual representation, and the underlying data. Assuming that anchoring comments in the visualization could facilitate a well-grounded discourse, we seek to close the gap between visualization and discussion, which translates to three design goals:

DG1—Anchor comments in visualization. Comments should be directly embedded as annotations in a data visualization, specifically targeting particular regions. The annotation mechanism should be type-agnostic to allow any kind of visualization to be able to record and represent comments. A comment’s visual appearance should convey its scope, i.e., location and spatial extent in the visualization. To cater to a wide range of users with varying visual literacy, from casual viewers to professional analysts, the commenting interface needs to have a low barrier to entry, making it straightforward to both read and add comments.

DG2—Provide discursive patina. The interface should accommodate comments at scale by effectively managing, displaying, and aggregating a large volume of comments in a way that gives an overview of the discourse unfolding on the visualization. The discursive patina emerging from the anchored comments should indicate where interactions between viewers are most concentrated, for example, guiding viewers to areas of high engagement or controversy within a given chart.

DG3—Balance discussion and visualization. While offering a visual synthesis of all comments, the superimposed visualization of the discussion should preserve legibility of the underlying visualization. The challenge is to integrate comments in a way that enhances, rather than detracts from the visualization. A balanced approach needs to ensure the primary function of the visualization, while enriching it with a discursive layer.

We address DG1 by allowing users to draw semi-transparent rectangles—anchors—onto the visualization to designate the region of the visualization their comment relates to. We address DG2 by styling those anchors according to data about their comments: number of replies and likes, type, timestamp, resulting in meta-visualizations, each showing how different regions of the visualization are referenced in the comments. Finally, we address DG3 by providing interactive control over the visual presence of the discussion and the particular

characteristics that are being emphasized (e.g., category, popularity, or relations). *Viscussion* is implemented as an open web-platform supporting the ability to upload visualization images, leave and browse comments, reply to others' comments, and explore discussions through different discursive patinas.

While designing these solutions, we addressed a range of problems related to *Which information to collect and display about the discussion? How to collect this information from user comments? How to visualize all the information in a clear way? and How to best balance the visualization of information about the discussion with the legibility of the underlying visualization?* In the remainder of this section, we explain the design, rationale, and solutions we found for anchored comments (Sec. 5.2.1) and discursive patinas (Sec. 5.2.2).

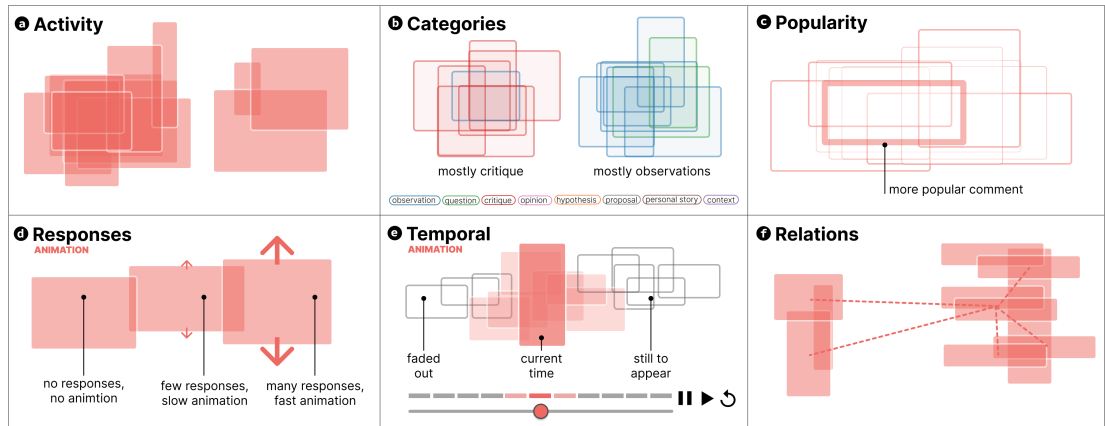


Figure 5.2: Illustrations of the six patina encodings: each encoding is driven by different metadata from single anchored comments.

5.2.1 Anchored comments

Drawing anchors. Comments are created by dragging the mouse over the region of interest in the visualization to create a rectangle selection (Fig. 5.1a). Pixel locations and dimensions of these anchors are recorded in a database, coupling the comment with the visualization (similar to PixelClipper (2020)). Each comment in *Viscussion* must have at least one anchor. Additional anchors can be drawn and associated with a comment in order to relate two or more regions of interest to that same comment (see Sec. 5.2.2).

Writing comments. Upon lifting their finger after drawing an anchor, users are presented with a form (Fig. 5.1b) to enter their comment. A thumbnail refers to the regions they just selected in the visualization. The form records the following information: *a)* user name (optional); *b)* the user's comment (optional, no length limit); and *c)* a group of optional categories to classify the comment. Categories for comments are adapted from

Chapter 3 and include: *observations, hypotheses, questions, critique, context, personal stories, opinions, and proposals*. These categories aim to capture structured data about the meaning of a comment. Immediately after pressing the 'submit' button, comments are published on the web platform, open for anyone to read them (Fig. 5.1c).

Browsing and reading comments. Comments are displayed as part of elements that include: the full comment text, the author's name, the selected category, the number of likes and responses, and the creation time. When hovering an anchor, the associated comment appears next to the anchor. All comments appear in a scrollable list on the right of the visualization (Fig. 5.1), with an additional thumbnail that previews the anchor. Hovering over a comment on this list highlights the associated anchor on the visualization. Clicking on a comment in the list or on an anchor on the visualization shows a conversation view of the comment on the right side, which includes the original comment and a threaded view of all its replies. The list of all comments can be sorted by date, popularity, and number of responses. By default, comments are sorted chronologically, with the newest comments on top. Switching to another patina encoding shows popularity scores or number of responses per comment sorts comments by those measures.

Responding to comments. The conversation view features a form to reply to comments, which includes a) the respondent's name (optional) and b) a text comment (optional, no character limit). Replies are explicitly linked to a comment and hence implicitly connected to the anchor of the original comment. All replies refer to the original comment; replies to replies are a future extension. Another way for a reader to express that they liked a comment is to press a heart-shaped button next to the comment, increasing its popularity score.

For each comment (excluding replies), the following meta-data is collected: a) anchors and their pixel coordinates in the visualization, b) categories selected by the user, c) number of likes, d) number of replies, and e) date and time the comment was created. These aspects are the basis for the design of different patina encodings.

5.2.2 Discursive patinas

All comment anchors are visualized as semi-transparent rectangles with a minimum opacity of 5%. This allows anchors to overlay each other, showing where comments accumulate and which parts of the visualization are most discussed. All anchors are in turn grouped and the group opacity is set to 50%. This ensures that the underlying visualization will remain legible in the presence of large numbers of overlapping anchors and therefore remain readable (DG3). To further support the legibility of the underlying visualization, we lower the saturation of the chart to 30%. This enables a balance between allowing strong colors

of the visualization to remain visible (e.g., to identify categories or color scales) while also providing visual prominence to the colors of the anchors. To visually identify comments on the visualization, each individual anchor has a stroke to signal the size and position. To help select anchors among many, smaller anchors are placed on top of larger ones.

Data about comments are encoded through visual variables of the anchors. To avoid too much information being encoded in the same visual mark, we designed six different encodings, leading to six different types of patinas. We mapped one facet of comment meta-data to one visual attribute per patina. We chose different visual attributes to give each patina an individual identity.¹

The default **Activity** patina encodes the parts of the visualization comments refer to. Comment anchors are colored red with an opacity ranging between 50% and 5% according to the number of anchors on the visualization. Overlapping patinas show which areas of the visualization are commented on most, i.e., spark most discussion. Fig. 5.2a illustrates how the area on the left attracts more comments than other areas, leading to a more salient color in that area.

The **Category** patina encodes the eight types of comments that users can use to tag their comment (*observations*, *questions*, etc.). This allows readers to gauge what people are saying about different regions in the visualization. Each category is mapped to the color of the anchor. Given the different hues, we further reduced the transparency of the anchor fills. Fig. 5.2b illustrates how clusters of similar categories are shaded in the assigned colors. The view can be filtered to only display single categories, e.g., to only view comments tagged as “critique” and so identify which parts of a visualization are often criticized.

We measure the **Popularity** of a comment with the total number of likes. This measure is mapped to the anchored comment’s stroke-width (Fig. 5.2c) ranging from 1px (least popular) to 10px (most popular). Anchors in this view have a white fill (5%) to put more emphasis on the anchor outline. This patina shows which parts of the visualization and discussion result in the most positive reactions. For example, this patina could show if people agree or like a particular pattern, feature, or information in a visualization.

The **Responses** patina visualizes the distribution of replies as a measure of the quantity of the discussion happening and shows which parts of the visualization are most discussed, potentially showing controversy (‘hot areas’). The number of replies per comment is encoded as the amount of animated jitter of an anchor (Fig. 5.2d): more jitter and movement indicates more replies. Otherwise, anchors use the default encoding (5% red fill; 50% red outline).

¹The supplemental material includes comprehensive examples of patina encodings.

The **Temporal** patina represents the dynamics of discussions. As more anchors pile up onto the visualization, it would be possible to lose information about the unfolding and different phases of a discussion. The temporal patina is an animation that fades anchors in and out in the order of their creation (Fig. 5.2e). When displayed, anchors use the default encoding (5% red fill; 50% red outline). All comments are grouped into ten segments based on their creation time. The animation cycles through the segments and filters the anchors present in the patina encoding. Comments are faded in during their corresponding cycle, remain for one cycle, and are faded out after that. An additional interface provides a progress bar and three buttons (start, pause, replay) to control the animation.

The **Relations** patina indicates the connections among multi-anchor comments. Some comments on a visualization may involve more than one region of interest, e.g., when commenting on the application of a color value from a legend to a visual element in the visualization, or when comparing two visual patterns (Fig. 5.2f). The relations patina shows anchors belonging to the same comment as visually linked by a dotted red line. The resulting patina can reveal interdependencies spanning a visualization.

Lastly, users can also select to view **no patina** at all, either by selecting the 'none' option from the encoding list or by disabling the 'show comments' toggle above the visualization (Fig. 5.1). As a result, no anchors are shown and the visualization is displayed with full saturation.

5.3 Evaluation

In evaluating anchored comments and discursive patina, we want to answer the following research questions:

Q1: *How are anchored comments used and what do people annotate?*

Q2: *How do discursive patinas shape the experience of the discussion?*

Q3: *What are possible applications of discursive patinas?*

We designed three complementary studies with 10 sessions and a total of 90 participants, each providing a different angle on our research questions. The complementarity was necessary to account for the fact that visualization annotation is very open process, that can require people to get familiar with the topic, may in fact require some expertise, and aims to reflect diversity in the comments and topics. Moreover, the amount to which people engage with visualizations and actually leave comments can vary strongly among participants, their relation to the topic, and general ability to express themselves or participate in discussions. Consequently, the three studies differed in their objective (understand open

annotations and motivations, understand collaboration, comparison with baseline), and have different setups informed by: the context of the discussions (education, shared discussion, guided), participants (domain experts, students), task (open annotation, collaboration), and scaffolding (controlled, open).

5.3.1 Open annotation sessions (OA)

The first study aimed to understand our interface in an open annotation and education setting. We invited ten participants (OA1 to OA10) to a 60-minute session and gave them tasks and exploration prompts. Unique to this format, participants *were not* familiar with the charts presented to them. We selected three publicly available visualizations portraying topics covering age distributions, recipe ingredients and economic data (see supp. material).

Additionally, we invited 60 undergraduate university students (OA11 to OA70) attending an introduction to data science and visualization course to use *Viscussion*. Over four consecutive weeks, we uploaded four different publicly available visualizations (see supp. material) to the platform and presented them to students. We introduced the platform features and asked students to use *Viscussion* to comment on the week's visualization. During class time, we encouraged them to explore anchored comments and discursive patina, and asked them to conduct a close-reading of the visualization: exploring the data, generating insights, posting questions, and following their peers' comments. We also invited students to asynchronously use *Viscussion* throughout the week, for those who wanted to contribute after the allotted class time had ended. After concluding all four sessions, we analysed the interaction logs and the participants' comments.

5.3.2 Domain expert workshops (DE)

After the first study, we felt that we lacked understanding of how *Viscussion* could support more nuanced discussions about visualizations. So for our second study, we invited domain experts from two university research groups to two separate workshops (total 13 participants) (DE1 to DE13). The workshops were conducted online via video calls, lasting one hour. We used these workshops to understand how experts used anchored comments (Q1) and read the discursive patina (Q2) when they engaged with visualizations from their own research and domain. In each workshop, we presented three data visualizations which either had been created by participants, used in their work, or reflected the subject of their research (see supp. material). One group (10 participants, 1 moderator) consisted of experts from law, design, and peace research who discussed charts and dashboards about peace data. The other group (3 participants, 2 moderators) consisted of experts from art history, art, and design and discussed charts from cultural collections and data journalism. We briefly introduced participants to the platform's features, including drawing anchors,

authoring comments, and switching patina encodings. Workshops were structured with two tasks that directed the attention of participants to the anchored comments and discursive patina functionality. Specifically, participants were asked to: explore the visualizations and annotate using anchored annotations; and to interact with and understand the patina.

For each task, participants had 20 minutes to use *Viscussion*. The workshops ended with a 20-minute group discussion moderated by the first author, asking for feedback and reports of participants' experiences. In the discussion, we asked participants where else they could imagine using anchored comments and discursive patinas (Q3). After concluding both workshops, we analysed the transcripts using an inductive approach to identify patterns in participants' statements.

5.3.3 Comparative evaluation (CE)

The final study aimed at understanding both the impact of anchored comments on participants' reading experiences (Q1) and how the discursive patina influenced participants' engagement with the underlying visualization and associated discussions (Q2). In this controlled format, we held three sessions with a total of 11 participants.

We compared *Viscussion* to a baseline interface designed to mimic common interfaces for visualization discussion and annotations (e.g., on social media, news outlets, or research projects, e.g., ManyEyes (Viegas et al., 2007) or PixelClipper (Walny et al., 2020)(viegas2007manyeyes, walny2020pixelclipper). The baseline interface *only* displayed comments juxtaposed to the visualization. Comments were ordered temporally, but could be sorted by popularity, number of responses, and filtered by categories. To achieve this, we used our *Viscussion* implementation and *removed* all functionality for anchoring, patinas, and thumbnails from comments (Fig. 5.3).

For the visualization examples, we turned to the */r/dataisbeautiful* community on the social media platform Reddit to find visualizations that were discussed extensively. Without a large volume of discussion, the patinas are not visually obvious. Using pre-existing visualizations with comments balanced the necessity for many comments that were also realistic in origin. Also, comments from this source remain meaningful in the baseline condition, as their comment text usually includes a reference to a part of the visualisation. The first author, who frequents and contributes to the community, chose an initial set of potential visualizations. Along with the rest of the authors, we narrowed our decision down to two visualizations that had discussions pertaining to different parts of the visualization.

The two selected data visualizations were homicide rates in North America and popularity ratings of TV shows (see supp. material). Each visualization had more than 250 comments and responses, which were scraped with the Reddit API.² The first author went through each comment, determined which area of the visualization the comment referenced, and created a corresponding anchored comment in *Viscussion*. For example, comments that mentioned the color scale were mapped to the color scale legend in the visualization; comments that mentioned specific data items, like states or TV shows, were mapped to contain the respective marks in the visualization. In twelve instances, comments could not be attributed clearly to a specific area in the visualization and were excluded from the study. For each comment, we also transferred the original upvote scores, the number of comment responses, and the creation timestamps from Reddit onto *Viscussion*. Each comment was further tagged with one of the established categories. To ensure similar numbers of annotations on both visualizations, we stopped after the first 100 comments, with the combined number of comments and responses being 250 for each visualization.

We recruited 11 participants (CE1 to CE11) through an open call promoted on social media and mailing lists across the authors' respective institutions. We conducted three sessions online via video with varying participant numbers (1; 5; 5 participants per session). Sessions did not require collaboration among the participants and were only carried out with multiple participants for efficiency. Each session was run by the first author, lasting 55 minutes on average. The participants first saw one of the two visualizations in the baseline view. They were prompted to explore the visualization and comment what stood out to them. Once participants completed this task, they were shown the second visualization in the patina view with the same instructions. There was no time limit for the tasks, and we asked participants to report once they were done. Across sessions, the order of visualizations was alternated to account for any learning bias.

After the tasks were completed, participants were directed to a structured online survey with questions about navigation strategies, notable observations, and reactions to anchored comments and the discursive patina (see supp. material). We concluded each session with a group discussion that lasted 20 minutes. To address Q3, we used the discussion to ask participants how they would use the technique in other contexts. After concluding both workshops, we analysed the survey responses and participants' statements.

²Reddit API

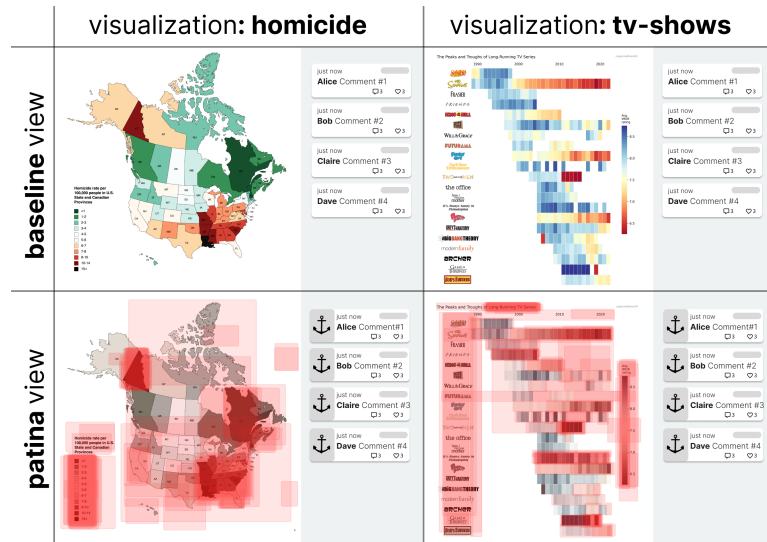


Figure 5.3: The different viewing conditions for the comparative study show the same two visualizations and associated discussions with varying levels of visual integration. *Top Row* — Baseline view: Comments are alongside the visualization with no interaction link to the visualization. *Bottom Row* — Patina view: Comments are anchored onto the visualization and a discursive patina emerges from overlapping anchors.

5.4 Results

Across all studies, we collected comments from participants through anchored comments (⚓), verbal recordings from think aloud and discussions (💬), and the post-hoc questionnaire (📄). The open annotation session (OA) yielded 77 anchored comments (65 of which in the timed session and 12 from the classroom setting). The domain expert workshops (DE) yielded 78 anchored comments. The comparative evaluation (CE) yielded 41 anchored comments. Across all studies, we collected interaction logs. In the following, we refer to participants by the study abbreviation, the participant number in that study, and the type of comment we cite, e.g., ⚓ DE6 is an anchored comment created by participant #6 in the domain expert study. No participant number indicates an anonymous submission.

5.4.1 Writing and reading anchored comments

Working towards answering Q1, we present five results (R1-R5) that show how anchored comments are created and used for visualization interpretation.

R1. Anchors highlight details, insights, and context. The vast majority (86%) of anchored comments use one anchor, the remaining comments use two or more anchors, resulting in a total of 212 anchors. We qualitatively analyze anchored comments in an open coding process. In three coding passes by two authors, we read each comment and its associated anchors to come up with and converge on eight categories that describe which parts of a visualization the anchors relate to (Fig. 5.4).

anchored comments	196	100%
single elements	50	25.5%
multiple elements (excl. comp. / sim.)	46	23.5%
comparisons	37	18.9%
similarities	20	10.2%
labels	19	9.7%
blank space	10	5.1%
legend	9	4.6%
axis	5	2.6%

Figure 5.4: Open coding of anchor usage, analysing what areas of the visualization are marked with anchors

Most comments relate to single (26%) or multiple visual marks (52%) in the charts, allowing participants to comment on the data or its representation. We observe how some comments that refer to multiple marks express insights about similarities and differences: Comparisons highlight changing trends in the data, e.g. *“Interesting to see how Washington and Oregon are different”* (⚓ CE); similarities point out elements that look alike, e.g. *“Estonia, Latvia, Lithuania all look so similar”* (⚓ OA1). In both cases, single anchors are used to refer to elements that are next to each other, while multiple anchors link elements that are further apart on the visualization.

While rare, comments on blank space (5%) allowed participants to express interesting opinions that were otherwise difficult to associate with a single part of the visualization. The comments in these areas mainly pertained to three topics: questioning the absence of elements, e.g. *“I wonder why this is empty. No data? Design choice?”* (⚓ DE); proposing missing elements that they wanted to see in the visualization, e.g. *“place for a legend?”* (⚓ DE8); or placing comments that are unrelated to the anchored area just to place them somewhere.

Anchors also pointed to contextual elements surrounding the visualization: Participants commented on labels (10%) e.g. *“I find this wording a bit cryptic”* (⚓ DE4); legends e.g. *“definitely too many colors and hard to see. why not just add the number??”* (⚓ CE7); and axes (3%) e.g. *“Does the horizontal axis indicate passing of time?”* (⚓ DE7).

Analysing anchors' sizes, we learn that anchors are generally used to refer to relatively detailed parts of the visualization with the median anchor size spanning 12% of the width and 11% of the height of the visualization.

R2. Comments guide visualization interpretation. Comments helped participants make sense of the visualization in three ways: by reducing the barrier to entry to understand the data and visualization, adding relevant context, and introducing alternative interpretations. Comments captured other people's preceding efforts to understand and explain the data,

which other readers then could use and consequentially comprehend without closer examination of the visualization: *"I looked at the most popular comments and found this experience quite compelling as a way to find interesting factoids without having to 'put in the work' of looking through the vis myself"* (☺ CE3).

Comments also guided the readers' attention to novel or hidden information about the visualization design: *"Sometimes people don't see things that are there already - like a hidden legend - or design decisions like the blue and the red it's not fully explained"* (☺ DE10). Together, comments about the data and visualization acted as scaffolds to new readers. Comments added context that otherwise would remain unknown: *"[Comments] focused me on others' observations and surfaced things I wouldn't have learned otherwise"* (☺ CE3).

Across comments, some were pertinent to the data, while others were more personal. One participant reflected on how they used the personal stories to make sense of the visualization: *"All the personal background stories [...] gave me some information about hypothesis why certain things were colored a certain way. In the end, the graph itself doesn't answer those kinds of questions, since it only showed the numbers"* (☺ CE7). Similarly, reading other people's interpretations of the data sparked reflection on assumptions participants had about the data: *"It's a nice opportunity to challenge what you think you know about a process or how you think you understand it. [...] It's nice to challenge your own assumptions"* (☺ DE7). Considering that comments don't require participants to *"put in the work"* (☺ CE3), an important caveat is the risk of bias. One participant acutely related their lack of effort, foregoing 'put[ting] in the work', at the expense of taking others' interpretation as accurate: *"The page is already showing me the impressions of other people. It does not allow me to first form my understanding and it's visually biasing me"* (☺ CE6). Ultimately, whether the comment supported an easier or more nuanced reading of the visualization or introduced productive discourse that sparked reflection, comments affected how the visualization was interpreted by new readers.

R3. Observations and questions are prominent comment types. For 71% of comments, participants selected a category; the most used categories were *observations* (27%), *questions* (15%), and *critique* (10%). Others were opinions (6%), hypotheses (5%), proposals (5%), personal stories (2%), and background information (2%).

Observations ranged from simple descriptions of visual marks, e.g. *"Crazy shape"* (⚓ 0A1) to conclusive insights into data similar to aforementioned comparisons, e.g. *"most activity in this time frame"* (⚓ DE12). Questions covered a broad range of topics, from asking for clarification of data, e.g. *"which demographic of people were used for this?"* (⚓ 0A), reasons behind visual patterns, e.g. *"Do the blank spaces tell us something?"* (⚓ DE10) or *"why is this shift here?"* (⚓ DE); or explanations of the encoding, e.g. *"are the colors explained somewhere?"* (⚓ DE8). Critical comments primarily point out frictions participants had

when trying to make sense of the visualization, e.g. *"I don't get what this dotted line is about"* (⚓ OA), but also raised awareness of questionable data or encodings, e.g. *"I think this is highly biased because it's just based on this one source and not a more broad survey"* (⚓ OA).

Participants used observations to point out areas of interest, e.g. *"The first thing that catches the eye is that the markers are populating a certain time frame [...]"* (⚓ DE10), but also to elicit more information from others, e.g. *"I posted some observations but did not really know their context so its useful to see what [domain expert] makes of them"* (☹ DE12). Others asked questions to interrogate the visualization and guide their own sensemaking process, e.g. *"My comments [...] were mostly questions because i didn't fully understand what [the visualization] is supposed to be telling me"* (☹ DE7). Most responses are reactions to the two most frequent categories (40% respond to questions, 30% respond to observations), with a disproportionately high engagement on questions that make up 15% of comments but attract 40% of responses.

R4. Anchoring changes how comments are written. The structured survey shows that a majority of participants agree (46%) or strongly agree (27%) when asked, whether anchoring comments changed their commenting behaviour. Participants reported that the presence of the patina reduced the amount of text that they wrote in their comments. We confirm this by comparing text lengths across comments in the separate conditions. The median comment length was 36% shorter when comments were written in the patina view (91 characters) compared to the baseline view (142 characters). In some instances, the reason was practical: the participant needed less text to describe what part of the visualization they were commenting on. Participants found the coupling between the comment and visualization useful because it prevented the need to *"write an essay"* (☹ CE2) and instead made it *"possible to comment, e.g., a specific row without describing it in words"* (☹ CE2).

Additionally, the act of choosing where to anchor a comment changed the types of comments participants considered appropriate to write. Participants correlated the position of the anchor with spatial significance, which made it difficult when they wanted to leave a general comment: *"Since I had to select specific areas, I did not really feel like I could make general comments even if I wanted to. I had to think about comments that would make sense for a specific area of the visualization (or that was pertaining to a specific area), so I kind of restrained myself from making some comments that I think I would have made otherwise"* (☹ CE9). In this instance, the generality of the comment clashed with the specificity of the anchor, which prevented the participant from leaving the comment.

R5. People's engagement varies across visualizations and settings. Within *Viscussion*, there was a variety of visualization types for participants to discuss. We observed that some visualizations attracted more comments than others. Among the visualizations that elicited more comments were visualizations with small multiples, dashboards, and maps. We describe

these visualizations as *information dense* as they describe a large number of entities, carry a lot of information, and can invite close inspection. Participants reported that information density fostered their engagement: *“Having lots of data points is more overwhelming but maybe it’s easier to annotate because there’s more things to take note of”* (☺ DE12). Further, the setting of individual user studies had an impact on engagement: For example, the open annotation session (OA) with students yielded 0.2 anchored comments per participant, while each domain expert (DE) on average wrote 6 anchored comments.

5.4.2 Discursive patinas for navigating discussion

Answering Q2, we observed two recurring themes in how participants used the discursive patina to explore and navigate the discussion. While these themes were mentioned across all evaluation studies, we primarily based our results on the comparative evaluation, which best highlighted the effect of the patina view compared to the baseline view.

R6. Patinas help navigate discourse. Participants described the discursive patina as a *“map”* (🗺 CE), *“heatmap”* (🗺 CE), and *“meta-visualization”* (🗺 CE) that helped gain an overview of the discussion: *“some areas were ‘more red’ than others, indicating that there were more comments made on that specific area of the visualization”* (☺ CE9). With the overlapping anchors creating a salient visualization of comments, participants used the saturation of color and overlapping areas to find where comments were concentrated. One participant remarks on how the patina illustrates the overall perception of the visualization, stating: the patina is the *“reception of the visualization among the readers”* (🗺 CE) that answers, *“what are the hottest findings”* (🗺 CE).

The baseline view, in contrast, made gaining an overview of the discussion difficult. One participant noted the chaotic nature of connecting discussions to the visualization: *“I don’t think I was able to analyze the discussion itself, for it looked to me like a rather disorganized discussion forum”* (🗺 CE). Other participants also found the baseline view particularly taxing. They described difficulty in locating what parts of the visualization the comments referred to. This was articulated by one participant who discussed the challenges of both trying to understand the visualization and also the comments concurrently: *“in the [baseline] interface it was really hard to pinpoint the particular discussion points. you are losing the visualization out of your sight and instead focus on the comment section”* (🗺 CE).

While all participants in the comparative sessions were prompted to explore different patina encodings (Fig. 5.2) only one mentioned them in the survey: *“to see what is most commented on, what is liked the most, and how things are linked. This is something completely new”* (☺ CE6). Based on the interaction logs, we learn that all comments have been written in the default ‘activity’ encoding and we do not know whether participants used different patina encodings to more successfully navigate discussions.

R7. Patinas can overwhelm and obstruct. Although the discursive patina helped users navigate discussions, our analysis also shows that the patina impeded their interaction with the underlying visualization. One participant wrote a comment using the interface to point this out: *“I’m reading comments and then I want to see the data but it’s a bit hidden by the overlay so it’s a lot of back and forth between the visualization with and without comments”* (⚓ CE). Others reported being overwhelmed by the patina: *“when you are entering the page the first thing you see are already the red annotations”* (📖 CE). Two participants decided to ignore the patina because they *“found that frustrating [and] switched to the list”* (☹ CE3), or switched off the [patina] view altogether in order to *“see the viz properly”* (📖 CE). They reported concerns that the patina may have distracted them from fully looking at the visualization: *“I didn’t actually look through the viz, so maybe there are things I might have noticed or cared about that I didn’t see?”* (📖 CE). In addition to visual obfuscation, participants also mentioned that they felt biased by the content of the patina. One participant reflected on how the patina prevented them from developing their own interpretation of the visualization: *“because the page is already showing me the impressions of other people, it does not allow me to first form my understanding and it’s visually biasing me”* (📖 CE).

5.4.3 Scenarios

Finally, we asked participants to speculate about scenarios in which they would want to use the *Viscussion* interface (Q3). To answer this question, we report participants’ statements and group them into three scenarios that arose during the discussions.

Scenario 1: Visualization design feedback. Participants suggested using the platform to provide feedback on visualization design through a productive dialogue between visualization designers and other team members. On the one hand, this would allow the team to point out friction points in the design and iterate, e.g., a visualization’s encoding, layout, or labels. On the other hand, visualization designers could use the feedback to better understand the underlying data: *“This could be used to talk about mock-ups, understand underlying data and get comments from your peers before you publish something”* (☹ DE11). One participant specifically talked about anchored comments as a precise tool to pinpoint design critique: *“In news outlets, you have very little comments about design critique. This interface is sparking this discussion, because comments are so localized”* (☹ CE6). The idea of design feedback was particularly popular in the domain expert workshops, as the visualizations in this format came from the participants and echoed prior design feedback processes that they had done together. One participant mentioned, how the platform could streamline this process and help with facilitate a dialogue with relevant stakeholders: *“A really useful application for this would be a dialogue with our funders. This would be a useful, quick, and interactive way for them to ask questions and discuss future development instead of writing big lists of*

questions to go through in meetings” (☹ DE6). This scenario came up in a workshop, when the discussion helped a group’s designer understand overlooked domain knowledge and its relevance to the visualization: *“Because I’m part of the creative team for this visualization it’s really interesting to see this feedback because there is domain knowledge i don’t know and it’s really relevant for my work”* (☹ DE9).

Scenario 2: Help with public sensemaking. As reported in R3, we found, many instances in which participants used the interface to pose questions and get answers. R2 shows how this dialogue can support readers in their sensemaking. Participants envisioned *Viscussion* as a public forum to discuss data visualizations. In this scenario, one participant mentioned how *“one answer allows you to see the visualization in a whole other way”* (☹ DE10). This public dialogue can be particularly powerful if data experts are part of it. One participant mentioned how they used the platform to elicit context from domain experts to better understand the underlying data: *“I posted some observations but did not really know their context so it’s useful to see what [Domain expert] makes of them”* (☹ DE12).

Scenario 3: Local knowledge collection. Participants envisioned how discursive patinas could support collecting personal stories from a variety of sources on the ground. Participants deliberated both on the opportunities and drawbacks of such a use case. While they saw the potential for anchored annotations to facilitate discussion among people with different perspectives, they also acknowledged that discussion moderation would become more important. One peace researcher: *“If we are talking about limitations, bringing together different experts brings together completely different approaches [and truths]. If we were doing something where we are engaging with different people to [...] feed in their perspectives, you need to carefully think about representation and balance who gets to be a part of that”* (☹ DE7). The participant noted the opportunity to foster *“ongoing discourse”* with users holding local expertise. They imagined how the visualization could benefit from input provided by people with *“very different expertise from in-country experts”*.

5.5 Discussion

With *Viscussion*, we set out to design an interface that allows to directly annotate information *on* a visualization and thus help relate comments to visualization content (DG1), to help understand an ongoing discussion (DG2), and to balance the presence of the visualization and information about the discussion (DG3). The results from our studies suggest that anchored comments are used for detailed comments and to contextualize those comments with information from the visualization (R1), often in the form of observations, questions, and critique (R3, R4), with detailed and information-rich visualizations soliciting the most comments (R5). Comments, in turn, can guide the sensemaking process and help people reflect on their own opinions (R2). We found that most of our participants

valued how patinas helped them gain an overview over the discussion and find entry points to begin exploring the visualization and discussion (R6). Other participants preferred the raw visualization and found patinas competing with the visualization (R7). Participants described scenarios that could benefit from anchored comments and discursive patinas, all of which imply an exchange between strangers and require the ability to read and write comments as well as to form discursive patinas pointing out issues, localizing questions, and contextualizing explanations.

In the remainder of this section, we reflect on these findings and our design goals, highlight limitations of our approach, and discuss implications for studying and designing discussion interfaces.

5.5.1 Close and distant readings

One immediate observation is that anchored comments support **close reading of visualizations** as people were more likely to annotate detailed visual patterns and visual marks. In the humanities, close reading refers to reading individual texts carefully, listening to what the text is saying and its method of delivery. Close reading in visualization is consequently strongly related to visualization literacy (Boy et al., 2014), reading visualization techniques, and understanding flaws (Pandey et al., 2015) and visual patterns in visualizations (Wang et al., 2020). However, while visual literacy tests evaluate the understanding of common visualization techniques (S. Lee et al., 2016) and criticality (Ge et al., 2023), those tests usually focus on common charts and question-based assessments. We think that close reading of complex visualization requires a much deeper engagement and open questions such as used in visualization evaluation (Bares et al., 2020): asking people to openly comment on what they see and observe, what they found most significant, what things meant to people, and what additional information would have been required. Anchored comments can guide people in these activities.

While anchored comments focus people on the close reading of visualizations, discursive patinas can be seen as supporting **distant reading of the resulting discussions**. Again, a method common in humanities research, distant-reading aims to examine large bodies of literature by taking a step back from individual texts and focusing on salient and abstract features across many texts, e.g., accumulation of specific words or phrases, genres, or literary figures (Moretti, 2013). Similar in our case, discursive patinas can support the distant reading of discussion dynamics by abstracting from textual comments and focusing on data across potentially elaborate discussions. In fact, across the workshops, participants commented on the discursive patina as a visual guide to the discussion and remarked how it helped them quickly spot where comments accumulated (R2). The different patina types are designed to offer multiple lenses to the discussions to debate questions such as: *What are the discussions about? Which topics dominate a discussion? Are there parts of a visualization*

that cause more argument? Are people actually discussing the visualization? How does a discussion unfold over time? While there has been considerable research on visualizations for distant reading of texts (Jänicke et al., 2015), discursive patinas are the first attempt to map discussions onto visualization, helping people to zoom in and out of the discussions of a visualization and the information they add.

5.5.2 Generalizability, scalability & expressiveness

The visual and functional characteristics of anchored comments and discursive patinas as implemented in *Viscussion* are deliberately independent of the underlying visualization. We carefully designed the anchors and patinas to ensure some expressiveness in the position and size, while also supporting a wide variety of visualization techniques. As noted previously (Lin et al., 2022), free-form comments may vary depending on the data type (e.g., networks) and thus call for more specific designs to balance expressiveness and scalability. With our design, we can point to examples that show up to 100 anchors at a time, which we posit is a scale impossible with simple free-form comments. Future iterations on anchor and patina design could include non-rectangular anchors, general lasso selections, or brushing. We can also imagine annotating individual visual elements or groups thereof, permanently linking comments to those elements.

Likewise, we can think about gathering more data about comments, e.g., assessing stances and topics from the comments texts as common in social media analysis. Such data could inform further user interface components, visualizations, and patinas, showing comments over time, the emergence of topics, or the convergence and divergence of sub-topics within the discourse around visualizations. However, in particular the patinas should be designed in such a way that they either focus on analytical tasks for understanding discussions, or as signposting *some* selected comments and regions as inroads into joining a discussion. Currently, patinas are designed to support both scenarios, but future iterations could specialize, taking inspirations from overlaid heatmaps, fog-of-war techniques, and blurs (N. W. Kim et al., 2017) that mask unexplored parts of a visualization, or other traces and autographic designs (Offenhuber, 2023).

5.5.3 Limitations

Limitations of the patina display: discursive patinas can **bias viewers' attention** towards areas with high comment density, overshadowing less-discussed but potentially significant parts of the visualization. This could lead to an unbalanced understanding, where viewers focus more on popular areas rather than interpreting the visualization without any social cues. Likewise, the anchoring mechanism encourages **local comments** about specific elements of a visualization, rather than high-level comments about the whole visualization.

This could potentially limit the scope of a discussions and prevent broader observations. Eventually, patinas unavoidably **obstruct the underlying visualization**. However, none of these issues was a design goal of our technique and *Viscussion* can simply switch off patinas.

Methodological limitations: Our complementary studies — from open and exploratory to more rigorous and controlled — are limited, as **not every anchored comment we analyse is created equal**. Hence, our results are limited by the people participating, the contexts they acted in, and the topic of the visualizations. Still, we are confident that especially the qualitative findings across different contexts and participants provide for a good understanding of the potential of patinas and potential improvements. In future, we hope to roll out *Viscussion* over a longer period of time, collaborate with newspapers, and explore the use patinas in more ecologically valid scenarios with more participants.

5.5.4 Critical readings of data visualizations

One particular design approach to supporting users' navigation of visualizations could be to disrupt the common *seamlessness* of data visualizations. Seamlessness points to the tradition of visualization design that strives towards clean, tidy, and easily digestible data (Helen Kennedy & Allen, 2016). As Hengesbach articulates, the problem of seamlessness is that “*it distorts, hides, and disguises the complex reality of data*” (Hengesbach, 2022). She further argues to keep or even add seams to point out i.e., complexities, uncertainty, ambiguity, instead of considering them as potential ‘tripping hazards’ for readers that need to be removed. Seams can provide visual cues that point to the partial and imperfect aspects of data. We saw this attention to seams in R2, when participants reflected on how their interpretations differed from those of others, as comments provided visual cues to these disambiguities. Anchored comments and discursive patinas can be seen as seams and tripping hazards to visualizations similar to traces in the real-world guiding our use of something: a pre-annotated copy of a hand-book, touch and wear marks on a mechanical device, etc.

Close reading of visualizations can also include questioning the design decisions behind the visualization and the data collection preceding any visual encoding. In particular, visualizations meant for a broad audience run the risk to make assumptions and statements that might upset people, e.g., missing consideration for accessibility or disputed frontiers on maps. Researchers have already articulated visions for feminist data visualization with its aim to reduce the power differentials between visualization authors and readers (Correll, 2019; ?). Such works draw on critical and feminist theories to suggest ethical approaches to data visualizations that expose the materiality of data, reveal the decisions of the designer,

and reduce the authority of the visualization. We speculate that discursive patinas could help groups of people collectively unpack the many ways that visualization and the underlying data are historically situated. Anchored comments can help pinpoint evidence for such hypotheses.

In that sense, we imagine anchored comments and discursive patinas to play a stimulating role in **open design processes**, in which visualization designers benefit from an already established practice to receive qualitative feedback (Choi et al., n.d.) from their colleagues. While data visualizations often aim for large audiences once published, they are often designed, improved, and discussed by a small, private group of individuals. In contrast, designing in the open invites readers to participate in the creation and iteration of the visualization. We point to successes in open design processes during early moments of the COVID-19 pandemic where visualization authors worked with interested audiences to *“iterate on the original theme, generating thousands of comments, and exceptional levels of engagement”* (Cotgreave, n.d.). To facilitate such and other scenarios, we can imagine guided tours (Walny et al., 2020) walking readers through visualizations to offer behind-the-scenes insights (e.g., rationale for design decisions), pointing out ongoing construction work and asking questions about the reader’s comprehension. As potential conversation starters, such designer comments could be visually distinct from other comments.

5.5.5 Future directions

Our results and reflections show that discussing visualizations is far from being an established practice and methodology. Across all studies, it took time for participants to not only read the patinas, but also to feel comfortable expressing their thoughts and engaging with the other comments. To some extent, this might be further illustrated by the fact that participants did not make full use of all patina types (R6). This might also be influenced by the willingness of participants to participate in discussions about visualizations in a study setting. This could be due to a mismatch between the topics and visualizations we chose for two of the studies, compared to the interests of our participants. It could also signal a lack of group cohesion, like those found in online spaces who are designed to attract like-minded people.

We attempted to rectify both of these constraints by pre-populating *Viscussion* with extant discussions. To kickstart the discussions—a problem common in these kinds of studies (Kauer et al., 2021)—we chose an initial set of comments from Reddit, rather than fabricating comments ourselves. Although Reddit is a source used by others to investigate user engagement (Almahmoud & Karger, 2023; Kauer et al., 2021), the comments are *not* integrated to the visualization and have hence been created in a different context.

Another promising direction is the support for anchored comments and discursive patina within interactive data visualizations. Interactivity brings interesting technical and aesthetic questions about anchoring comments within specific view parameters as well as the aggregation across a range of display states.

In any case, we identify a major obstacle for visualization research: current visualization design and practices ignore collaboratively reading and discussing visualizations. We see this as an opportunity for visualization research to understand the skills required to conduct *both* close reading of visualization and distant reading of discussions for future critical engagement with data, visualizations, and participation.

Chapter 6

Discussion

This thesis was motivated by two questions: How do people discuss data visualizations and how can I broaden this discourse and integrate it into visualization interfaces? Throughout the thesis, these motives have interacted, overlapped, and influenced each other. In this section, I want to bring them together by discussing the contributions and limitations of my work, moving towards a detailed conceptualisation of the term 'discursive visualization', to then finish with an agenda for future work.

6.1 Summary

To better understand existing discourse about visualizations, in Chapter 3, I did a structured analysis of real-world discussions in the */r/dataisbeautiful* community. The results motivated me to look beyond visualization as a tool for collaborative sensemaking, and to also consider it as a social practice that involves a wide range of motivations and expressions that shape people's engagement with data visualizations. While I am not the first to think of visualization as a social space (Viegas et al., 2007), revisiting this idea almost two decades after the first explorations provided new insights and perspectives. First and foremost, I found personal and critical engagements coming from an audience that confidently navigates the social space of visualization: people expressed emotions, openly called out misinformation, told personal stories, and shared their individual experiences. They did so with the public nature of their discourse in mind. Talking about data in a personal manner changes what others can learn from the visualization.

Motivated and intrigued by this, in Chapter 4, I was keen to learn more about people's personal approaches to data visualizations, how they engage with them, how they express themselves in their presence, and how these expressions impact the reading experience. Previous work investigated personal engagements with data Peck et al. (2019), but did not consider a backchannel for people's reactions to the presented data. My prototype provided just that and demonstrated a discursive interface that is — by design — entirely driven by personal stories. My results showed the relevance of integrating comments into the visualization, as this integration sparks participants' desire to discover, provides a sense

of orientation, and helps people associate stories and data. The interviews suggested that personal annotations change the reading experience in that they promote empathy and elicit personal experiences from audience members. In the overall structure of this thesis, Chapter 4 acts as a proof-of-concept: For one specific topic and one specific chart type, I demonstrated discursive visualization as a stand-alone format that does is not driven by a shared goal of collaborative sensemaking, but allows people to come together in a practice of collective storytelling.

My final study picked up the thread where the proof-of-concept ended. Prior work explored structured support for discussions about visual analysis and various ways to integrate such discussions into visualizations that were limited in their ability to simultaneously scale and scope comments. With anchored annotations, in Chapter 5 I offered a malleable mechanism to integrate annotations into visualizations, independent of chart formats, topics, or reaction types. While this approach had clear limitations — for example the missing support for interactive charts — it offered a more general idea of bridging the gap between the breadth of existing discourse I explored in Chapter 3 and its ability to impact the reading experience for a singular scenario in Chapter 4. Where single annotations provided details, context, scrutiny, or questions about a marked out portion of the visualization, the accumulation of anchors produced a discursive patina that zooms out from the particular and draws a map over the overall discussion. The transition between close readings of the visualization and distant reading of the discourse is unique to discursive visualization and paves the way for novel and critical engagements with data.

6.2 Limitations

My thesis explored the discourse about data visualizations on existing platforms and on platforms specially built to elicit discourse. Had I investigated other platforms than Reddit in Chapter 3, I would have seen different reactions because different platforms have another unique culture, social norms, or demographics. I do not know whether people would have had fundamentally different engagements with my prototype in Chapter 4 if the central subject had not been COVID but, for example, climate change data. The results in Chapter 5 emerged from user studies I carefully designed to ensure engagement and audiences in differently designed studies could have used the platform less active or in different ways.

This limitation is further amplified by the fact that at no point throughout my user studies, the discussion among participants became a sure-fire success. For example, I had to advertise the *coronaMoments* platform continuously on social media and mailing lists to collect voices from the public. Similarly, the participation of expert groups in user studies on the *viscussion* platform relied on existing collaborations, rather than organic growth and word-of-mouth advertising. Attempts to engage existing student communities in a self-contained discourse

about visualization largely failed. For both platforms, I can not guarantee that my reliance on active promotion did not bias the way discussions unfolded. Further, it is possible that participants who created the first annotations unintentionally set a social norm for all following comments and thus influenced what people thought was acceptable discourse. While this limitation is inherent to my research design that aimed at deployments outside controlled lab settings, it also speaks to the fact that the discourse I found and produced remains partial and incomplete.

While the *coronaMoments* platform included annotation support for an interactive line chart, *viscussion* only supported static images for discursive engagements. Throughout my thesis, I did not design or implement a more generalized support for annotation in interactive visualizations. Consequently, interactive visualizations (e.g. with filters, details on demand, coordinated view) or detailed maps (that require pan and zoom) could not be the subject of the discussion.

In hindsight, there is a missed opportunity to engage with critical approaches to the epistemology of data more deeply. I am confident that the focus I chose lead me to meaningful contributions on the creation and representation of discourse. My work allows participants to point out incorrect data or misleading interpretations. Yet, topics that have been discussed in the scholarship that motivated my work, e.g., data literacy (D'Ignazio, 2017), empowering protocols (Loukissas & Ntabathia, 2021), or colliding epistemologies (Brown & Knopp, 2008) remain underexplored in this thesis. With a a greater emphasis on these topics could my work could have also investigated, how data authority can be challenge more fundamentally. In a similar vein, my thesis stops at pointing out problematic data by putting an annotation as a visual 'warning label' on it. None of the studies have to ability to "alter data structures [...] through direct input" (Drucker, 2017), by deleting, updating, or otherwise updating the underlying information systems, databases, or repositories. While a visualization on the viscussion platform could include a rich discourse and data critique, this added context only existed siloed on the platform with little possibility to be fed back into the original data.

6.3 Design implications

Discursive visualization is primarily process-oriented and assumes that the appearance and narrative of a visualization remain malleable also after its publication. In my studies, I demonstrate how people's expressions can vary throughout this process. On the one hand, I observed statements from the audience which they formed when viewing the *just the visualization*, e.g., when expressing observations or critique. I provided a platform for these kinds of statements to be recorded, amplified, and visible to others. On the other hand, my

studies were able to elicit expressions that are not just reactions to the visualization, but *reactions to the discourse around the visualization*, e.g., when people were inspired to share their own stories after reading those of others (Chapter 4), or when participants used other people's annotations to challenge their own assumption of the data (Chapter 5).

Through demonstrating the potential of integrated audience engagement, my work has an effect on design of future visualizations as authors may anticipate discursive engagement and dedicate space or visual variables to accommodate anchors or annotations from the audience. In the following, I want to characterize the practice of discursive visualization and point out its impact on visualization practice.

6.3.1 User Interfaces for Discursive Visualization

At its core, discursive visualization is a collection of practices that allow audiences to integrate reactions into data visualizations. In doing so, discursive visualization assumes that data alone may not always be able to fully represent all facets of a phenomenon, and therefore relies on the audience to add their own interpretations, experiences, local knowledges and partial perspectives. Yet, knowing a phenomenon through data is inherently different to knowing it through qualitative context and integrating one with the other requires careful consideration of the process (When is one added to the other?); the design (How do they coexist visually?); and the desired activity (What is it used for?). In this thesis, I demonstrated a wide range of activities, including but not limited to collective storytelling, design feedback, critical readings, collaborative sensemaking, and data interrogations.

Discursive visualization starts with an empty canvas only showing a chart, a map, an infographic, a dashboard, but no pre-existing comments, and relies on building a continuous loop of recording and representing audience reactions, described as follows: *recording reactions* first requires a user experience (UX) that prompts people to react, for example a legend that is unclear to them, a question they know the answer to, or an outlier about which they can tell a story. The engagement drivers presented in Chapter 3 provide an exhaustive list of such experiences. Then, it requires a user interface (UI) to externalize, create, and integrate the reaction. This includes forms to enter text and additional metadata (e.g., timestamps, categories, data values), but crucially also a way to scope the reaction and relate it to a clearly marked point or area on the visualization. *Representing reactions* in discursive visualizations makes use of established principles in data visualization. By assigning visual variables like position, color, or opacity to annotation anchors, they can display information about the discussion without requiring the audience to read any text. Applying the same principles to the initial visualization and the ongoing discussion results in a meta-visualization that allows readers to traverse from distant reading of the whole discussion to zooming in on smaller portions of the visualization for closer inspection. Discursive visualization anticipates visual competition between representation of data and

representation of discourse, as they occupy the same space and both seek the readers' attention. Instead of offering guidelines to mitigate this problem, discursive visualization pleads for clutter, seamfulness, and visual tripping hazards that allow for critical readings of visualization. The two platforms presented in this thesis—*coronaMoments* and *viscussion*—provide examples of the required user experience and user interface to record and represent audience reactions. They cover different scenarios and granularities of information and employ different strategies to navigate the visual competition. By doing so, they are starting points of the development of future systems for discursive visualization. While the designed interfaces and contribution mechanisms enable people to integrate their expressions in the first place, how they are used is vastly determined by human factors, which I will briefly discuss in the following.

6.3.2 Human Factors in Discursive Visualization

In hindsight, many of the challenges I faced were not engineering challenges but concerned the social context in which the platforms were deployed and the people who used it. For example, identifying the engagement drivers in Chapter 3 theoretically should have provided a solid foundation to not worry about motivating participants to use the prototypes for a lively discussion of data. In practice, engaging in a discussion is more complex and requires deliberate consideration of how to incentivize people and provide them with a good understanding of the desired behaviour and expectations in the study. Existing reward systems and social norms, e.g., on Reddit, may play a greater role than anticipated: translating identified engagement drivers like 'letting people share their own story' to a platform with different systems and norms does not guarantee lively engagement. For example, it was almost impossible to create self-sustaining engagement on the *coronaMoments* platform in Chapter 4 because visitors of the platform had little incentive to share their stories without getting e.g., social rewards in return and without knowing who exactly would read their personal memories?

Making visualization discursive changed the relation between visualization authors and readers. While typically authors create and readers consume, Chapters 4 and 5 demonstrated how audiences could become 'prosumers' (Ritzer, 2014) who simultaneously read and produce, consequently creating discourse that became more important than the underlying visualization. While readers may not have been able to manipulate data, allowing them to add annotations granted them power over the look and feel of the visualization. This effectively gave them power over how visualizations are read by the wider audience, and changed the power dynamic between these groups. However, in the presented studies, the audience was always bound to remain reactionary. They could criticize encoding, suggest improved techniques, or point out wrong data, but it was up to visualization authors to implement such changes.

Although it was not explicitly discussed, in both studies, I introduced a third role into the network of actors: the facilitator. On the coronaMoments platform, the role of visualization author and facilitator were both embodied by me. On the viscussion platform however, these roles became clearly separated, as I was not the author of the visualization but instead uploaded third-party visualization?? onto the platform to discuss them with participants. In this case, authors may be present when discussing visualizations, but I took the role of facilitator to stimulate discussion, start conversations, or point people to questions they might know the answer to. However, the role of the facilitator and its influence on the discourse remains under-explored in the context of the studies. I consider their function to be similar to a panel moderator, who holds the communicative space open for all participants and serves the purpose of navigating narratives. The facilitator role requires special powers (e.g., deleting harmful content or misinformation), special visibility (similar to PixelClipper's 'facilitator comments' that differentiates comments from the facilitator from comments written by other audience members), and a special mandate to take on this role. Establishing this role again shifts the power balance, as different participants now have different privileges. Yet, especially for larger scale discursive visualization, a person to moderate and facilitate be necessary in order to manage large volumes of comments or to delete harmful comments and misinformation.

6.3.3 Applications for Discursive Visualizations

I see practical implications of my work for a number of real-world use cases that rely on visualization to communicate to broad audiences.

Newsrooms already use data visualization and data-driven storytelling as innovative formats to reach new audiences. As pointed out in Chapter 4, existing news platforms only allow to comment on the article as a whole, but not on specific parts of it. A deeper integration of social features into data-driven formats as demonstrated in Chapters 4 and 5 can help to measure and increase audience engagement. Existing methods to understand engagement are generally quantitative in nature (e.g., click rates, retention times, scroll position) and do not provide insight into readers' cognitive, emotional, or affective experience. As Chapters 4 and 5 demonstrate, discursive visualization can act as a crowdsourcing tool for this type of information. As seen particularly in Chapter 4, a deeper integration of comments further increases audience engagement. Newsrooms can use this information to address friction points in the readers' experience (e.g., unclear encodings) or identify popular bits to focus on in future articles (e.g., conversation-starting annotations). More interestingly, authors could bring audience engagement to the heart of the article. Several articles already exist that employ this principle (Bressa et al., 2024), for example NYT's '*You draw it*' project n.d. or ZEIT Online's n.d. poll on parties in the EU parliament. These articles reverse the established

data-driven format and first let readers themselves guess values or positions on a political landscape before revealing the underlying data. Discursive visualization adds to this space and could foster the development of similar future articles that put audience annotation at the center of attention.

In other scenarios, the same principles for social exchange around visualization apply with slightly different implications. For example, platforms like Datawrapper¹ or RawGraphs² already have active audiences who use the platforms' tools to author visualizations. There is a broad range of use cases on these platforms, ranging from exploring different templates to visualize datasets (Mauri et al., 2017) to using these tools as part of an established publication pipeline (Datawrapper, n.d.-a). Both platforms emphasize the relevance of an active community for mutual learning, creative inspiration, or to identify missing features. Datawrapper has a dedicated forum called 'River' (Datawrapper, n.d.-b) that allows creators to browse other people's visualizations and remix them. Discursive visualization has great potential to influence how people author visualizations by adding a social dimension to the design process. As explored in Chapter 5, entering a constructive dialogue and providing feedback to visualization authors is a promising scenario for helping people to learn how to improve their designs. Adapting mechanisms like *anchored annotations* for visualization authoring platform is not without challenges (see 6.4), but could benefit authors and readers alike.

6.3.4 Towards Discursive Engagements

For the past 15 years, many tools that allow experts to talk *about* data have been created. Throughout this time, the use cases, discourses, and audiences of visualization have changed. A strong motivation for my thesis was to follow D'Ignazio's call to "*imagine an alternate way to include more voices in the conversation*" and to devise ways to "*effect visualization collectively, inclusively, with dissent and contestation, at scale*" (D'Ignazio, 2015). Against this background, revisiting platforms to talk about data is a timely endeavour to work towards these aspirations.

My work explored practical ways that allow novices and experts alike to talk *back to* data. Discursive tools could well be used for social data analysis, which remains to be a conventional and frequently practised way to discuss data. Yet, moving towards personal and critical engagements with visualization lies at the heart of my thesis. These engagements may be less prominent in terms of in prior visualization research, but represent a practical approach to D'Ignazio's call for data feminism (D'Ignazio & Klein, 2020) and visualization practices often advocated for in related work. Critical and personal engagements deeply

¹<https://www.datawrapper.de/>

²<https://www.rawgraphs.io/>

rely on local knowledge, personal experiences, and a confidence in the value of partial perspectives and anecdotal knowledge. However, it requires more in-depth exploration and further research to assess how engagements unfold and how they shape the way data and data visualization is used in everyday life.

6.4 Future Work

I see various avenues to further deepen the knowledge gained through this thesis and apply the principles of discursive visualization to broader use cases and technologies.

6.4.1 Broaden applications with data-aware annotations

To address the limiting circumstance that only static images can be discussed with anchored annotations, future work could research interfaces for data-aware annotations. Heer and Shneiderman (2012) introduce the idea of data-aware annotations that are explicitly tied to specific data points. While they did not consider these annotations to be created by the audience, the idea of letting *readers* tie their reactions to data (not areas, as demonstrated in Chapter 5) could be a great starting point to introduce discursive features to interactive visualizations. This way, annotations could be displayed selectively (e.g., to be hidden when the associated data is not visible) or change position (e.g., to follow visual marks that move over time). There are, however, challenges to this approach. An early prototype of the *viscussion* platform used VegaLite (Satyanarayan et al., 2016) to render visualizations and added a data-aware annotation layer to it. While initial tests seemed promising from a technical perspective, I found it challenging to imagine a broad audience using a sophisticated language like VegaLite to create visualizations I could then discuss. Future research would have to find a balance between the availability of visualizations (either through simple authoring tools or existing resources like data-driven news articles, social media, or government institutions (Walny et al., 2020)) and a technical platform that can provide data-aware annotations for a large variety of chart types.

6.4.2 Discourse for Generative AI

Following the public release of ChatGPT (OpenAI, n.d.) in late 2022 and the subsequent explosive growth (Reuters, 2023) of large language models (LLMs), chat interfaces have become a popular way to interact with generative artificial intelligence. Novel platforms like DataChat (*DataChat*, n.d.), Talk to Data (Talk to Data, n.d.), Scavenger (*Scavenger AI*, n.d.), Visuo (*Visuo AI*, n.d.) allow analysts to *chat with their data*, often using visualization as an additional way to illustrate answers. Considering the use of natural language for such engagements with data, this trend has implications on discursive visualizations—and vice

versa, as in both cases, there is verbal back-and-forth about data. Anchored annotations could help analysts, for example, to inquire about visual outliers and point them out to the chat bot, allowing for more precise queries. More broadly, large language models could join discussions about data as additional participants that offer insight — admittedly with their own algorithmic bias. On the other hand, I want to again stress that discursive visualization assumes data alone to be insufficient to fully illuminate a topic and further context and narrative is required to gain a more holistic view. While state-of-the-art LLMs may be able to join conversations to assist analysis, the extent of their knowledge is limited by the data they are trained with. Contrary to human participants, they can not provide inherently different ways to understand the represented topic, e.g., by thinking critically about data, or adding partial perspectives and local knowledge. However, future work could investigate the role of chat bots as participants in discursive visualizations, be it to provide a starting point for engagement, populate otherwise empty discussions, or even as critical advocates that are trained using existing patterns to expose misinformation conveyed in data visualizations (Pandey et al., 2015; Lisnic et al., 2024).

6.4.3 Move closer to existing communities

As discussed, one limitation of my research design was that the reliance on people visiting my platforms to engage in discussion. Future work can benefit from turning this approach upside down and **move where the people are** by bringing discursive features to existing popular platforms. One approach to pursue this goal would be to invite news audiences to integrated discussions, as discussed in the previous chapter. Another approach would be to leverage the existing reach of public institutions, similar to PixelClipper's (Walny et al., 2020) role in a greater effort to make data accessible to citizens. In this scenario, governmental or civic stakeholders could present data visualizations about topics that are relevant to their work and invite existing stakeholders, interest groups, and the wider public to participate in a data-driven discussion, facilitated through discursive visualization.

Similarly, it stands to reason that using discursive approaches on communication platforms like Slack,³ Microsoft Teams⁴, or Discord⁵ could enable established teams and existing communities to use existing infrastructure that is already part of their everyday work to discuss their data through discursive visualizations. The domain expert workshops in Chapter 5 provide a starting point, e.g., for design feedback processes or for iterating visualizations within a team to then present it to the public.

³<https://slack.com/>

⁴<https://www.microsoft.com/en-us/microsoft-teams/>

⁵<https://discord.com/>

The functional scope of Slack workspaces for example can be extended via an API (Technologies, n.d.) that could be used to add, for example, anchored annotations to Slack comments. Ideally, the approaches mentioned above would further break up the borders between visualization authors and readers, for example by providing participatory authoring tools and ways to iterate or remix existing visualizations, as demonstrated in research (Almahmoud & Karger, 2023) and practice (e.g., on Datawrapppper's 'River' community). As mentioned in Chapter 5, participants in my user studies approached discursive engagement rather tentative, e.g., when students seemingly were not confident enough to freely express themselves. The fact that the environments I offered with platforms like *coronaMoments* and *viscussion* were unknown to them may have contributed to this caution. Bringing discursive engagements to well-known social environments may mitigate this and empower users to discuss and annotate more freely. Future research could leverage network effects of existing communication infrastructure to better understand community-specific use cases, discourses, and reading experiences. This requires inviting platform operators or admins as stakeholders in the process to make discursive features available. I hope the promising results of my thesis can act as supporting argument to bring discursive visualization to more online communities.

While leveraging the existing knowledge of communities can benefit our understanding of discourse, an equally important approach would be to understand how to give people in these communities the authority and capacity in the face of data authority. Just giving people the opportunity to express critique does not imply that everybody is able, confident, and willing to do so. This limits our understanding of what is required to empower people critically approach data. There is a great opportunity to expand the existing work on data literacy and investigate how e.g., different social settings, interface designs, and access to knowledge help people to critically engage with data and data visualizations.

Supplementary Material to Chapter 5

A.1 Survey Questions

- What was your strategy to navigate the discussion in the two different interfaces?
- What visual patterns stood out to you when looking at the comments in the [patina] view?
- To what extent do you agree with the following statement: “The displayed comments in the [patina] view influenced how I understood the visualization” (Likert scale from ‘*Strongly disagree*’ to ‘*Strongly agree*’)
- Text input: Please elaborate: Why and how did they influence you (or not)?
- To what extent do you agree with the following statement: “*The ability to draw comments directly onto the visualization influenced the way I wrote my comments in the [patina] view*” (Likert scale from ‘*Strongly disagree*’ to ‘*Strongly agree*’)
- Text input: Please elaborate: If you agreed, how did your comments change?

A.2 Visualizations used in comparative evaluation

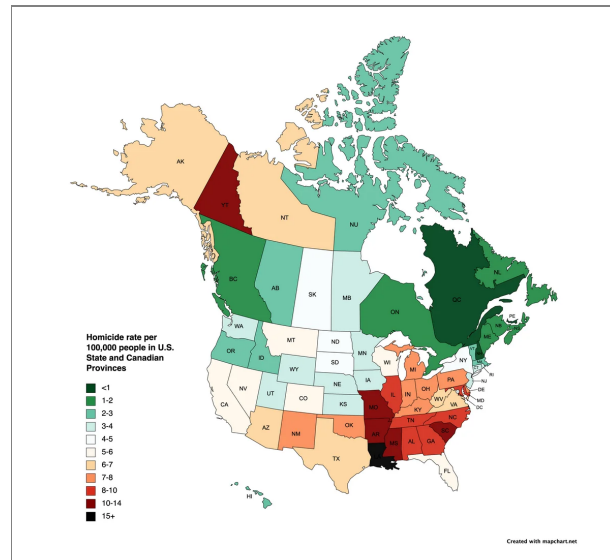


Figure A.1: Homicide rate (per 100,000 people) by US State and Canadian Province, 2020 (via Reddit)

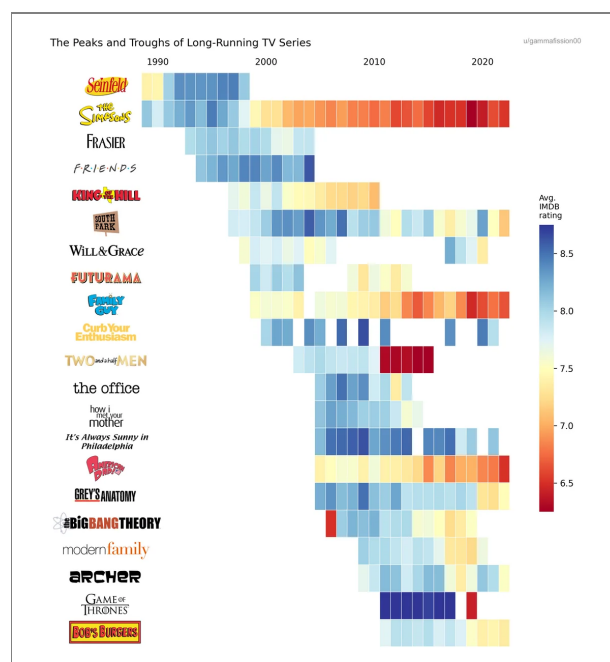


Figure A.2: The Peaks and Troughs of Long-Running TV Series (via Reddit)

A.3 Visualizations used in open annotation sessions

A.3.1 Workshop Setting

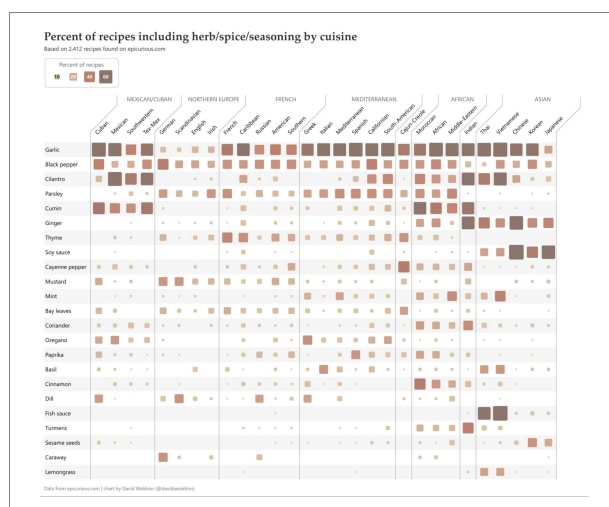


Figure A.3: Percent of recipes including herb/spice/seasoning by cuisine (via Reddit)

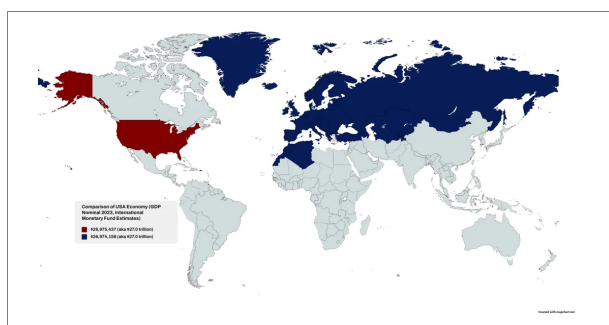


Figure A.4: According to the latest IMF estimates, the USA economy is now bigger than the European Union + the former Soviet Union + the United Kingdom + every other European country + Turkey + the Maghreb combined (via Reddit)

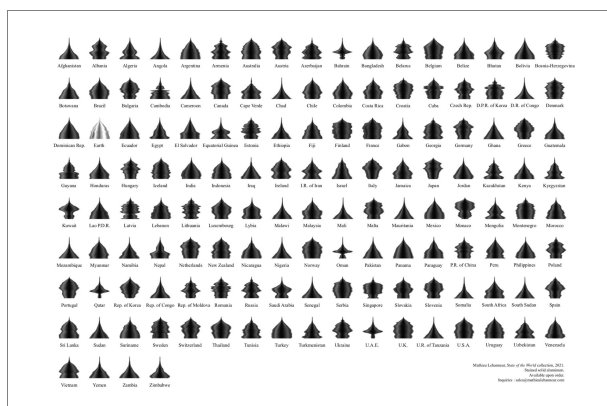


Figure A.5: State of the world collection(Mathieu Lehanne, 2021)

A.3.2 Classroom

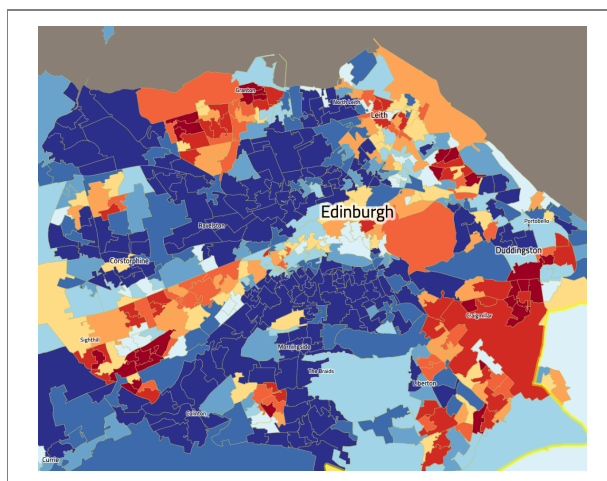


Figure A.6: Scottish Index of Multiple Deprivation

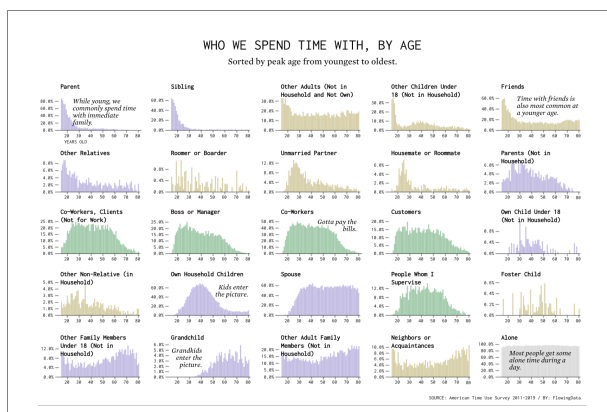


Figure A.7: Who We Spend Time with as We Get Older (Nathan Yau)

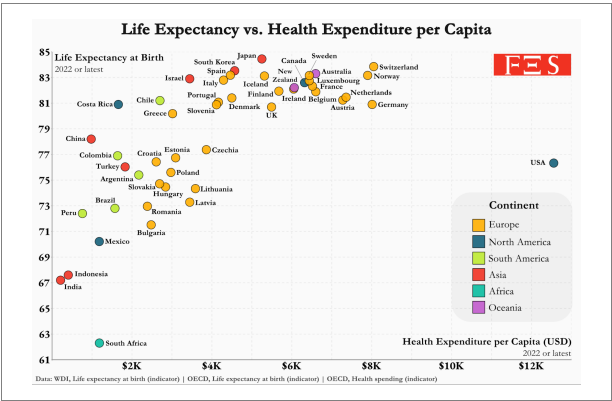


Figure A.8: Life expectancy vs. health expenditure, 2021 (OurWorldInData, 2021)

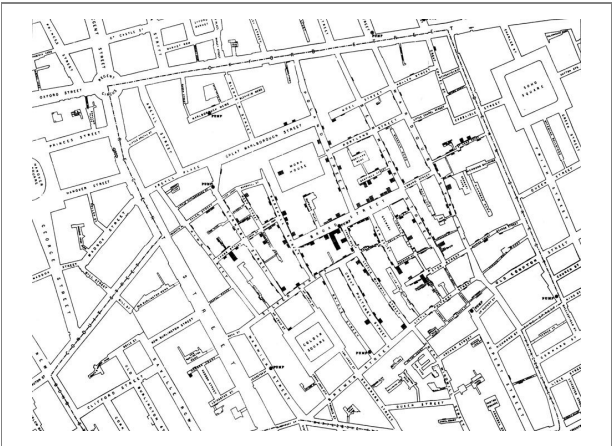


Figure A.9: John Snow Cholera Map of London (via UCLA)

Bibliography

- Aisch, G. (n.d.). *You draw it: How family income affects children's college chances*. Retrieved from <https://driven-by-data.net/2015/05/28/college-chart-game.html> (Accessed: 2024-06-01)
- Aitken, S., Cooper, D., Delozier, G., Ethington, P., Gregory, I. N., Hardie, A., ... others (2015). *Deep maps and spatial narratives*. Indiana University Press.
- Almahmoud, J., & Karger, D. R. (2023). Vizdat: A technology probe to understand the space of discussion around data visualization on reddit. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 7(CSCW1), 1–16. doi: 10.1145/3579544
- Authors, M. (n.d.-a). *Nightingale on medium*. <https://medium.com/nightingale/>. (Accessed: 2024-06-11)
- Authors, M. (n.d.-b). *Storytelling with data community*. <https://community.storytellingwithdata.com/>. (Accessed: 2024-06-11)
- Ayers, E. (2010). *Turning toward place, space, and time* (D. Bodenhamer, J. Corrigan, & T. Harris, Eds.). Bloomington: Indiana University Press.
- Bach, B., Riche, N. H., Carpendale, S., & Pfister, H. (2017). The emerging genre of data comics. *IEEE Computer Graphics and Applications*, 37(3), 6–13.
- Banerjee, A. (2024). *Ultimate python libraries for data analysis and visualization: Leverage pandas, numpy, matplotlib, seaborn, julius ai and no-code tools for data acquisition, visualization, and statistical analysis (english edition)*. Orange Education Pvt Ltd. Retrieved from https://books.google.de/books?id=o1L_EAAAQBAJ
- Bares, A., Zeller, S., Jackson, C. D., Keefe, D. F., & Samsel, F. (2020). Using close reading as a method for evaluating visualizations. In *2020 ieee workshop on evaluation and beyond-methodological approaches to visualization (beliv)* (pp. 29–37). doi: 10.1109/beliv51497.2020.00011
- Bartle, R. (1996). Hearts, clubs, diamonds, spades: Players who suit muds. *Journal of MUD research*, 1(1), 19.
- Bell, C., Bach, B., & Kauer, T. (2021). Ways of seeing: Data-viz as research practice. *Convergence*.
- Boe, B. (2024). *Praw: The python reddit api wrapper*. <https://praw.readthedocs.io/en/latest/index.html>. (Accessed: 2024-06-01)
- Borkin, M. A., Vo, A. A., Bylinskii, Z., Isola, P., Sunkavalli, S., Oliva, A., & Pfister, H. (2013). What makes a visualization memorable? *IEEE Transactions on Visualization and Computer Graphics*, 19(12), 2306–2315.

- Böttinger, M., Kostis, H.-N., Velez-Rojas, M., Rheingans, P., & Ynnerman, A. (2020). Reflections on visualization for broad audiences. *Foundations of data visualization*, 297–305.
- Boy, J., Rensink, R. A., Bertini, E., & Fekete, J.-D. (2014). A principled way of assessing visualization literacy. *IEEE Transactions on Visualization and Computer Graphics*, 20(12), 1963–1972. doi: 10.1109/tvcg.2014.2346984
- Boyd, D., & Crawford, K. (2011). Six provocations for big data. In *A decade in internet time: Symposium on the dynamics of the internet and society*.
- Brehmer, M., & Munzner, T. (2013). A multi-level typology of abstract visualization tasks. *IEEE Transactions on Visualization and Computer Graphics*, 19(12), 2376–2385.
- Bressa, N., Louis, J., Willett, W., & Huron, S. (2024). Input visualization: Collecting and modifying data with visual representations. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–18).
- Brown, M., & Knopp, L. (2008). Queering the map: The productive tensions of colliding epistemologies. *Annals of the association of American Geographers*, 98(1), 40–58.
- Brusilovsky, P. (2008). Social information access: the other side of the social web. In *International conference on current trends in theory and practice of computer science* (pp. 5–22). doi: 10.1145/2382636.2382638
- Burns, A., Lee, C., Chawla, R., Peck, E., & Mahyar, N. (2023). Who do we mean when we talk about visualization novices? In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–16).
- Chen, M., Hauser, H., Rheingans, P., & Scheuermann, G. (2020). *Foundations of data visualization*. Springer International Publishing. Retrieved from <https://books.google.de/books?id=mFD2DwAAQBAJ>
- Chen, Y., Barlowe, S., & Yang, J. (2010). Click2annotate: Automated insight externalization with rich semantics. In *2010 IEEE Symposium on Visual Analytics Science and Technology* (pp. 155–162).
- Cheng, C., Barceló, J., Hartnett, A. S., Kubinec, R., & Messerschmidt, L. (2020). COVID-19 government response event dataset (corononet v. 1.0). *Nature human behaviour*, 4(7), 756–768.
- Choi, J., Oh, C., Kim, Y. S., & Kim, N. W. (n.d.). Vislab: Enabling visualization designers to gather empirically informed design feedback. In *Proceedings of the 2023 chi conference on human factors in computing systems* (pp. 1–18). ACM. doi: 10.1145/3544548.3581132
- Conlen, M., Kale, A., & Heer, J. (2019). Capture & analysis of active reading behaviors for interactive articles on the web. In *Computer graphics forum* (Vol. 38, pp. 687–698).
- Correll, M. (2019). Ethical dimensions of visualization research. In *Proceedings of the chi conference on human factors in computing systems* (p. 1–13). New York, NY, USA: Association for Computing Machinery. Retrieved from <https://doi.org/10.1145/3290605.3300418> doi: 10.1145/3290605.3300418

- Cotgreave, A. (n.d.). *After 12 months of covid-19 charts, what have we learnt?* <https://gravyanecdote.com/sweet-spot/after-12-months> (Retrieved 2024-03-07).
- Dalton, C. M., Taylor, L., & Thatcher, J. (2016). Critical data studies: A dialog on data and space. *Big Data & Society*, 3(1), 2053951716648346.
- Danis, C. M., Viegas, F. B., Wattenberg, M., & Kriss, J. (2008). Your place or mine? visualization as a community component. In *Proceedings of the chi conference on human factors in computing systems* (pp. 275–284).
- DataChat. (n.d.). <https://datachat.ai/>. (Accessed: 2023-05-31)
- Datawrapper. (n.d.-a). *New York City Department of Health: Datawrapper was the backbone of our COVID reporting*. Retrieved from <https://www.datawrapper.de/case-studies/nyc-health> (Accessed: 2024-06-01)
- Datawrapper. (n.d.-b). *River - a place to exchange relevant data, charts and maps*. Retrieved from <https://app.datawrapper.de/river> (Accessed: 2024-06-01)
- De Haan, Y., Kruikemeier, S., Lecheler, S., Smit, G., & Van der Nat, R. (2018). When does an infographic say more than a thousand words? audience evaluations of news visualizations. *Journalism Studies*, 19(9), 1293–1312.
- Die Zeit. (n.d.). *Leserumfrage: Wie denken sie über die EU?* Retrieved from <https://www.zeit.de/politik/ausland/2019-05/leserumfrage-europaeische-union-meinung-eu-nationalstaaten> (Accessed: 2024-06-01)
- Dieberger, A., Dourish, P., Höök, K., Resnick, P., & Wexelblat, A. (2000). Social navigation: techniques for building more usable systems. *interactions*, 7(6), 36–45.
- Diehl, A., Abdul-Rahman, A., El-Assady, M., Bach, B., Keim, D. A., & Chen, M. (2018). Visguides: A forum for discussing visualization guidelines. In *Eurovis (short papers)* (pp. 61–65).
- D'Ignazio, C. (2017). Creative data literacy: Bridging the gap between the data-haves and data-have nots. *Information Design Journal*, 23(1), 6–18.
- D'Ignazio, C., & Klein, L. F. (2020). *Data feminism*. MIT press.
- Dimara, E., & Perin, C. (2019). What is interaction for data visualization? *IEEE Transactions on Visualization and Computer Graphics*, 26(1), 119–129.
- Donath, J., Dragulescu, A., Zinman, A., Viégas, F., & Xiong, R. (2010). Data portraits. *Leonardo*, 43(4), 375–383.
- Dörk, M., Carpendale, S., & Williamson, C. (2011). The information flaneur: A fresh look at information seeking. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1215–1224).
- Dörk, M., Feng, P., Collins, C., & Carpendale, S. (2013). Critical infovis: exploring the politics of visualization. In *Proceedings of the chi conference on human factors in computing systems extended abstracts* (pp. 2189–2198).

- Dosono, B., Semaan, B., & Hemsley, J. (2017). Exploring aapi identity online: Political ideology as a factor affecting identity work on reddit. In *Proceedings of the chi conference on human factors in computing systems extended abstracts* (pp. 2528–2535).
- Drucker, J. (2012). Humanistic theory and digital scholarship. *Debates in the digital humanities*, 150, 85–95.
- Drucker, J. (2017). Non-representational approaches to modeling interpretation in a graphical environment. *Digital Scholarship in the Humanities*, 33(2), 248–263.
- Duggan, M., & Smith, A. (2013). 6% of online adults are reddit users. <https://www.pewresearch.org/internet/2013/07/03/6-of-online-adults-are-reddit-users>. (Accessed: 2024-06-01)
- D'Ignazio, C. (2015). What would feminist data visualization look like. *MIT Center for Civic Media*, 20.
- D'Ignazio, C., & Klein, L. F. (2016). Feminist data visualization. In *Workshop on visualization for the digital humanities (vis4dh), baltimore. ieee*.
- Elias, M., & Bezerianos, A. (2012). Annotating BI visualization dashboards: Needs & challenges. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1641–1650).
- Feng, M., Deng, C., Peck, E. M., & Harrison, L. (2016). Hindsight: Encouraging exploration through direct encoding of personal interaction history. *IEEE Transactions on Visualization and Computer Graphics*, 23(1), 351–360. doi: 10.1109/TVCG.2016.2599058
- Ge, L. W., Cui, Y., & Kay, M. (2023). Calvi: Critical thinking assessment for literacy in visualizations. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–18). doi: 10.1145/3544548.3581406
- Geertz, C. (2008). *Local knowledge: Further essays in interpretive anthropology*. Basic books.
- Gilbert, E. (2013). Widespread underprovision on reddit. In *Proceedings of the cscw conference on computer supported cooperative work* (pp. 803–808).
- Habermas, J. (1981). *Theorie des kommunikativen handelns* (1st ed.). Frankfurt am Main: Suhrkamp Verlag.
- Hall, P., Heath, C., & Coles-Kemp, L. (2015). Critical visualization: a case for rethinking how we visualize risk and security. *Journal of cybersecurity*, 1(1), 93–108.
- Halliday, J., Campbell, D., Walker, P., & Sample, I. (2020). England COVID cases error means 50,000 contacts may not have been traced. <https://www.theguardian.com/world/2020/oct/05/england-covid-cases-error-unknown-how-many-contacts-not-traced-says-minister>. (Accessed: 2024-06-10)
- Hansen, C., Hotz, I., & Ynnerman, A. (2020). Visualization in public spaces. *IEEE Computer Graphics and Applications*, 40(2), 16–17.

- Haraway, D. (1988). Situated knowledges: The science question in feminism and the privilege of partial perspective. *Feminist studies*, 14(3), 575–599.
- Harley, J. B. (1988). Silences and secrecy: the hidden agenda of cartography in early modern europe. *Imago mundi*, 40(1), 57–76.
- Harley, J. B. (2002). *The new nature of maps: essays in the history of cartography* (No. 2002). JHU Press.
- He, H. A., Walny, J., Thoma, S., Carpendale, S., & Willett, W. (2023). Enthusiastic and grounded, avoidant and cautious: Understanding public receptivity to data and visualizations. *IEEE Transactions on Visualization and Computer Graphics*. doi: 10.1109/tvcg.2023.3326917
- Heer, J., Bostock, M., & Ogievetsky, V. (2010). A tour through the visualization zoo. *Communications of the ACM*, 53(6), 59–67.
- Heer, J., & Shneiderman, B. (2012). Interactive dynamics for visual analysis: A taxonomy of tools that support the fluent and flexible use of visualizations. *Queue*, 10(2), 30–55.
- Heer, J., Viégas, F. B., & Wattenberg, M. (2007). Voyagers and voyeurs: supporting asynchronous collaborative information visualization. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1029–1038).
- Helen Kennedy, G. A., Rosemary Lucy Hill, & Allen, W. (2016). The work that visualisation conventions do. *Information, Communication & Society*, 19(6), 715–735. Retrieved from <https://doi.org/10.1080/1369118X.2016.1153126> doi: 10.1080/1369118X.2016.1153126
- Hengesbach, N. (2022). Undoing seamlessness: Exploring seams for critical visualization. In *Proceedings of the chi conference on human factors in computing systems extended abstracts* (pp. 1–7). doi: 10.1145/3491101.3519703
- Hill, W. C., Hollan, J. D., Wroblewski, D., & McCandless, T. (1992). Edit wear and read wear. In *Proceedings of the chi conference on human factors in computing systems* (pp. 3–9).
- Hinrichs, U., Schmidt, H., & Carpendale, S. (2008). Emdialog: Bringing information visualization into the museum. *IEEE Transactions on Visualization and Computer Graphics*, 14(6), 1181–1188.
- Hullman, J., & Diakopoulos, N. (2011). Visualization rhetoric: Framing effects in narrative visualization. *IEEE Transactions on Visualization and Computer Graphics*, 17(12), 2231–2240.
- Hullman, J., Diakopoulos, N., Momeni, E., & Adar, E. (2015). Content, context, and critique: Commenting on a data visualization blog. In *Proceedings of the cscw conference on computer supported cooperative work* (pp. 1170–1175).
- Hung, Y.-H., & Parsons, P. (2017). Assessing user engagement in information visualization. In *Proceedings of the chi conference on human factors in computing systems extended abstracts* (pp. 1708–1717).

- Huron, S., Isenberg, P., & Fekete, J. D. (2013). Polemictweet: Video annotation and analysis through tagged tweets. In *Ifip conference on human-computer interaction* (pp. 135–152).
- Huron, S., Nagel, T., Oehlberg, L., & Willett, W. (2022). *Making with data: Physical design and craft in a data-driven world*. CRC Press.
- Isenberg, P., Elmqvist, N., Scholtz, J., Cernea, D., Ma, K.-L., & Hagen, H. (2011). Collaborative visualization: Definition, challenges, and research agenda. *Information Visualization*, 10(4), 310–326.
- Jänicke, S., Franzini, G., Cheema, M. F., & Scheuermann, G. (2015). On close and distant reading in digital humanities: A survey and future challenges. *Eurographics Conference on Visualization (EuroVis) - STARs*, 83–103. doi: 10.2312/eurovisstar.20151113
- Kamvar, S. D., & Harris, J. (2011). We feel fine and searching the emotional web. In *Proceedings of the fourth acm international conference on web search and data mining* (pp. 117–126). ACM.
- Kauer, T., Bach, B., & Dörk, M. (2019). Participatory deep maps: Towards discursive user engagement with data visualizations. In *Cityvis: 2nd workshop on urban data at ieee vis*.
- Kauer, T., Dörk, M., Ridley, A. L., & Bach, B. (2021). The public life of data: Investigating reactions to visualizations on reddit. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–12).
- Kauer, T., Joglekar, S., Redi, M., Aiello, L. M., & Quercia, D. (2018). Mapping and visualizing deep-learning urban beautification. *IEEE Computer Graphics and Applications*, 38(5), 70–83.
- Keim, D., Andrienko, G., Fekete, J.-D., Görg, C., Kohlhammer, J., & Melançon, G. (2008). *Visual analytics: Definition, process, and challenges*. Springer.
- Kennedy, H. (2015, May). *The challenge of visualising qualitative data: Can a venn diagram help us to understand the place of sociocultural factors in engaging with visualisations?* <https://seeingdata.org/seeing-data-blog/the-challenge-of-visualising-qualitative-data-can-a-venn-diagram-help-us-to-understand-the-place-of-sociocultural-factors-in-engaging-with-visualisations/>. ([Accessed 19-04-2024])
- Kennedy, H., & Hill, R. L. (2018). The feeling of numbers: Emotions in everyday engagements with data and their visualisation. *Sociology*, 52(4), 830–848.
- Kennedy, H., Hill, R. L., Allen, W., & Kirk, A. (2016). Engaging with (big) data visualizations: Factors that affect engagement and resulting new definitions of effectiveness. *First Monday*, 21(11).
- Kilgo, D. K., Yoo, J. J., Sinta, V., Geise, S., Suran, M., & Johnson, T. J. (2016). Led it on reddit: An exploratory study examining opinion leadership on reddit. *First Monday*.

- Kim, N. W., Bylinskii, Z., Borkin, M. A., Gajos, K. Z., Oliva, A., Durand, F., & Pfister, H. (2017). Bubbleview: an interface for crowdsourcing image importance maps and tracking visual attention. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 24(5), 1–40. doi: 10.1145/3131275
- Kim, Y.-S., Henry Riche, N., Lee, B., Brehmer, M., Pahud, M., Hinckley, K., & Hullman, J. (2019). Inking your insights: Investigating digital externalization behaviors during data analysis. In *Proceedings of the acm international conference on interactive surfaces and spaces* (pp. 255–267).
- Kim, Y.-S., & Hullman, J. (2015). User-driven expectation visualization: Opportunities for personalized feedback. In *Electronic proceedings of the ieee vis 2015 workshop personal visualization: Exploring data in everyday life*.
- Kirby, E., Watson, A., Churchill, B., Robards, B., & LaRochelle, L. (2021). Queering the map: Stories of love, loss and (be) longing within a digital cartographic archive. *Media, Culture & Society*, 1043–1060.
- Kirk, A., Kommenda, N., & Gutiérrez, P. (2021). *Revealed: The data that shows how COVID bounced back after the uk's lockdowns*. <https://www.theguardian.com/world/ng-interactive/2021/mar/19/revealed-the-data-that-shows-how-covid-bounced-back-after-the-uks-lockdowns>. (Accessed: 2024-06-01)
- Kitchin, R., & Lauriault, T. (2014). Towards critical data studies: Charting and unpacking data assemblages and their work. *Geoweb and Big Data*.
- Kong, H.-K., Liu, Z., & Karahalios, K. (2018). Frames and slants in titles of visualizations on controversial topics. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–12).
- Kong, H.-K., Liu, Z., & Karahalios, K. (2019). Trust and recall of information across varying degrees of title-visualization misalignment. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–13).
- Lee, B., Choe, E. K., Isenberg, P., Marriott, K., & Stasko, J. (2020). Reaching broader audiences with data visualization. *IEEE Computer Graphics and Applications*, 40(2), 82–90.
- Lee, C., Yang, T., Inchoco, G. D., Jones, G. M., & Satyanarayan, A. (2021). Viral visualizations: How coronavirus skeptics use orthodox data practices to promote unorthodox science online. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–18).
- Lee, S., Kim, S.-H., & Kwon, B. C. (2016). Vlat: Development of a visualization literacy assessment test. *IEEE Transactions on Visualization and Computer Graphics*, 23(1), 551–560. doi: 10.1109/tvcg.2016.2598920
- Lin, H., Akbaba, D., Meyer, M., & Lex, A. (2022). Data hunches: Incorporating personal knowledge into visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 29(1), 504–514. doi: 10.1109/tvcg.2022.3209451

- Lisnic, M., Lex, A., & Kogan, M. (2024). "Yeah, this graph doesn't show that": Analysis of online engagement with misleading data visualizations. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–14).
- Losev, T., Raynor, J., Carpendale, S., & Tory, M. (2022). Embracing disciplinary diversity in visualization. *IEEE Computer Graphics and Applications*, 42(6), 64–71.
- Loukissas, Y. A. (2019). *All data are local: Thinking critically in a data-driven society*. MIT press.
- Loukissas, Y. A., & Ntabathia, J. M. (2021). Open data settings: A conceptual framework explored through the map room project. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 5(CSCW2), 1–24.
- Luther, K., Tolentino, J. L., Wu, W., Pavel, A., Bailey, B. P., Agrawala, M., & Dow, S. P. (2015). Structuring, aggregating, and evaluating crowdsourced design critique. In *Proceedings of the 18th acm conference on computer supported cooperative work & social computing* (pp. 473–485). doi: 10.1145/2675133.2675283
- Maharawal, M. M., & McElroy, E. (2018). The anti-eviction mapping project: Counter mapping and oral history toward bay area housing justice. *Annals of the American Association of Geographers*, 108(2), 380–389.
- Mahyar, N., Kim, S.-H., & Kwon, B. C. (2015). Towards a taxonomy for evaluating user engagement in information visualization. In *Workshop on personal visualization: Exploring everyday life* (Vol. 3, p. 2).
- Makulec, A. (2020). *Ten considerations before you create another chart about COVID-19*. <https://medium.com/nightingale/ten-considerations-before-you-create-another-chart-about-covid-19-27d3bd691be8>. (Accessed: 2024-06-01)
- Matejka, J., Grossman, T., & Fitzmaurice, G. (2013). Patina: Dynamic heatmaps for visualizing application usage. In *Proceedings of the chi conference on human factors in computing systems* (pp. 3227–3236). doi: 10.1145/2470654.2466442
- Mauri, M., Elli, T., Caviglia, G., Ubaldi, G., & Azzi, M. (2017). Rawgraphs: a visualisation platform to create open outputs. In *Proceedings of the 12th biannual conference on italian sigchi chapter* (pp. 1–5).
- Mayr, E., Federico, P., Miksch, S., Schreder, G., Smuc, M., & Windhager, F. (2016). Visualization of cultural heritage data for casual users. In *IEEE vis workshop on visualization for the digital humanities* (Vol. 1).
- McCurdy, N., Gerdes, J., & Meyer, M. (2019). A framework for externalizing implicit error using visualization. *IEEE Transactions on Visualization and Computer Graphics*, 25(1), 925–935. Retrieved from <http://bit.ly/IEFramework> doi: 10.1109/TVCG.2018.2864913
- McInnis, B. J., Sun, L., Shin, J., & Dow, S. P. (2020). Rare, but valuable: Understanding data-centered talk in news website comment sections. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 4(CSCW2), 1–27. doi: 10.1145/3415245

- Medvedev, A. N., Lambiotte, R., & Delvenne, J.-C. (2017). The anatomy of reddit: An overview of academic research. In *Dynamics on and of complex networks* (pp. 183–204).
- Moon, W. L. H. (1999). *Prairyerth:(a deep map)*. Houghton Mifflin Harcourt.
- Moore, J. (2017). Data visualization in support of executive decision making. *Interdisciplinary Journal of Information, Knowledge, and Management*, 12, 125.
- Morais, L., Jansen, Y., Andrade, N., & Dragicevic, P. (2021). Can anthropographics promote prosociality? a review and large-sample study. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–18).
- Moretti, F. (2013). *Distant reading*. Verso Books.
- Naps, T. L., Rößling, G., Almstrum, V., Dann, W., Fleischer, R., Hundhausen, C., . . . others (2002). Exploring the role of visualization and engagement in computer science education. In *Working group reports from iticse on innovation and technology in computer science education* (pp. 131–152).
- Nugroho, K., Carden, F., & Antlov, H. (2018). *Local knowledge matters*. Policy Press.
- Nussbaumer Knaflic, C. (2018). *88 annotated line graphs*. <https://www.storytellingwithdata.com/blog/2018/1/22/88-annotated-line-graphs>. (Accessed: 2024-06-01)
- NZZ. (2024). *Coronavirus in der Schweiz: Die wichtigsten Grafiken*. <https://www.nzz.ch/panorama/coronavirus-in-der-schweiz-die-wichtigsten-grafiken-ld.1542774>. (Accessed: 2024-06-01)
- Offenhuber, D. (2023). *Autographic design: The matter of data in a self-inscribing world*. MIT Press.
- OpenAI. (n.d.). *Chat/GPT*. <https://chat.openai.com/>. (Accessed: 2023-05-31)
- OpenRefine Team. (2024). *Openrefine*. <https://openrefine.org/>. (Accessed: 2024-06-01)
- Padilla, L. M., Creem-Regehr, S. H., Hegarty, M., & Stefanucci, J. K. (2018). Decision making with visualizations: A cognitive framework across disciplines. *Cognitive research: principles and implications*, 3, 1–25.
- Pandey, A. V., Manivannan, A., Nov, O., Satterthwaite, M., & Bertini, E. (2014). The persuasive power of data visualization. *IEEE Transactions on Visualization and Computer Graphics*, 20(12), 2211–2220.
- Pandey, A. V., Rall, K., Satterthwaite, M. L., Nov, O., & Bertini, E. (2015). How deceptive are deceptive visualizations? an empirical analysis of common distortion techniques. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1469–1478). doi: 10.1145/2702123.2702608
- Park, S., Bekemeier, B., Flaxman, A., & Schultz, M. (2022). Impact of data visualization on decision-making and its implications for public health practice: a systematic literature review. *Informatics for Health and Social Care*, 47(2), 175–193.

- Peck, E. M., Ayuso, S. E., & El-Etr, O. (2019). Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–12).
- Perer, A., & Shneiderman, B. (2008). Integrating statistics and visualization: case studies of gaining clarity during exploratory data analysis. In *Proceedings of the chi conference on human factors in computing systems* (pp. 265–274).
- Pirolli, P., & Card, S. (1999). Information foraging. *Psychological review*, 106(4), 643. doi: 10.1037/0033-295x.106.4.643
- Pousman, Z., Stasko, J., & Mateas, M. (2007). Casual information visualization: Depictions of data in everyday life. *IEEE Transactions on Visualization and Computer Graphics*, 13(6), 1145–1152.
- Reddit. (2024). *Introducing reddit's new offering for advertisers: Trending takeover*. <https://www.redditinc.com/blog/introducing-reddits-new-offering-for-advertisers-trending-takeover/>. (Accessed: 2024-06-01)
- Ren, D., Brehmer, M., Lee, B., Höllerer, T., & Choe, E. K. (2017). Chartaccent: Annotation for data-driven storytelling. In *2017 ieee pacific visualization symposium (pacificvis)* (pp. 230–239).
- Ren, D., Lee, B., & Brehmer, M. (2018). Charticulator: Interactive construction of bespoke chart layouts. *IEEE Transactions on Visualization and Computer Graphics*, 25(1), 789–799.
- Rettberg, J. W. (2020). Ways of knowing with data visualizations. *Data Visualization in Society*, 35–48.
- Reuters. (2023, February 1). ChatGPT sets record for fastest-growing user base - analyst note. *Reuters*. Retrieved from <https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/> (Accessed: 2023-05-31)
- Riche, N. H., Hurter, C., Diakopoulos, N., & Carpendale, S. (2018). *Data-driven storytelling*. CRC Press.
- Ritzer, G. (2014). Prosumption: Evolution, revolution, or eternal return of the same? *Journal of consumer culture*, 14(1), 3–24.
- Roberts, J. C. (2005). Exploratory visualization with multiple linked views. In *Exploring geovisualization* (pp. 159–180). Elsevier.
- Roberts, J. C. (2007). State of the art: Coordinated & multiple views in exploratory visualization. In *Fifth international conference on coordinated and multiple views in exploratory visualization (cmv 2007)* (pp. 61–71).
- Romat, H., Henry Riche, N., Hinckley, K., Lee, B., Appert, C., Pietriga, E., & Collins, C. (2019). Activeink: (th) inking with data. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–13).

- Satyanarayan, A., & Heer, J. (2014). Authoring narrative visualizations with Ellipsis. In *Computer graphics forum* (Vol. 33, pp. 361–370).
- Satyanarayan, A., Moritz, D., Wongsuphasawat, K., & Heer, J. (2016). Vega-lite: A grammar of interactive graphics. *IEEE Transactions on Visualization and Computer Graphics*, 23(1), 341–350.
- Scavenger AI. (n.d.). <https://scavenger-ai.com/>. (Accessed: 2023-05-31)
- Schuster, R., Koesten, L., Möller, T., & Gregory, K. (2023). Who is the audience? designing casual data visualizations for the 'general public'. *arXiv preprint arXiv:2310.01935*.
- Schwabish, J. (2020). *Elevate the debate: A multilayered approach to communicating your research*. Wiley. Retrieved from <https://books.google.de/books?id=hdzODwAAQBAJ>
- Segel, E., & Heer, J. (2010). Narrative visualization: Telling stories with data. *IEEE Transactions on Visualization and Computer Graphics*, 16(6), 1139–1148.
- Shu, X., Wu, A., Tang, J., Bach, B., Wu, Y., & Qu, H. (2020). What makes a data-gif understandable? *IEEE Transactions on Visualization and Computer Graphics*, 27(2), 1492–1502.
- Silver, N. (2012). *The signal and the noise: Why so many predictions fail-but some don't*. Penguin.
- Sprague, D., & Tory, M. (2012). Exploring how and why people use visualizations in casual contexts: Modeling user goals and regulated motivations. *Information Visualization*, 11(2), 106–123.
- Srinivasan, A., Drucker, S. M., Endert, A., & Stasko, J. (2018). Augmenting visualizations with interactive data facts to facilitate interpretation and communication. *IEEE Transactions on Visualization and Computer Graphics*, 25(1), 672–681.
- Strauss, A., & Corbin, J. (1994). Grounded theory methodology. *Handbook of qualitative research*, 17(1), 273–285.
- Tableau. (2024). *Data cleaning: Definition, benefits, and how-to*. <https://www.tableau.com/learn/articles/what-is-data-cleaning>. (Accessed: 2024-06-01)
- Talk to Data. (n.d.). *Talk to Data*. <https://talktodata.ai/>. (Accessed: 2023-05-31)
- Technologies, S. (n.d.). *Slack API*. Retrieved from <https://api.slack.com/automation/workflows> (Accessed: 2024-06-01)
- Thomas, J. J., & Cook, K. A. (2006). A visual analytics agenda. *IEEE Computer Graphics and Applications*, 26(1), 10–13.
- Thudt, A., Hinrichs, U., & Carpendale, S. (2012). The bohemian bookshelf: supporting serendipitous book discoveries through information visualization. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1461–1470).
- Valkanova, N., Jorda, S., Tomitsch, M., & Vande Moere, A. (2013). Reveal-it! the impact of a social visualization projection on public awareness and discourse. In *Proceedings of the chi conference on human factors in computing systems* (pp. 3461–3470).

- Valkanova, N., Walter, R., Vande Moere, A., & Müller, J. (2014). Myposition: sparking civic discourse by a public interactive poll visualization. In *Proceedings of the cscw conference on computer supported cooperative work* (pp. 1323–1332).
- Van Es, K., & Schäfer, M. T. (2017). *The datafied society. Studying culture through data*. Amsterdam University Press.
- Vanhulst, P., Evequoz, F., Tuor, R., & Lalanne, D. (2018). A descriptive attribute-based framework for annotations in data visualization. In *International joint conference on computer vision, imaging and computer graphics* (pp. 143–166).
- Vanhulst, P., Évéquoz, F., Tuor, R., & Lalanne, D. (2018). Designing a classification for user-authored annotations in data visualization. In *Visigrapp (3: Ivapp)* (pp. 85–96).
- Viégas, F. B., Wattenberg, M., McKeon, M., Van Ham, F., & Kriss, J. (2008). Harry potter and the meat-filled freezer: A case study of spontaneous usage of visualization tools. In *Proceedings of the 41st annual hawaii international conference on system sciences (hicc 2008)* (pp. 159–159).
- Viegas, F. B., Wattenberg, M., Van Ham, F., Kriss, J., & McKeon, M. (2007). Manyeyes: a site for visualization at internet scale. *IEEE Transactions on Visualization and Computer Graphics*, 13(6), 1121–1128.
- Visuo AI. (n.d.). <https://www.visuo.ai/>. (Accessed: 2023-05-31)
- Walny, J., Storteboom, S., Pusch, R., Hwang, S. M., Knudsen, S., Carpendale, S., & Willett, W. (2020). Pixelclipper: Supporting public engagement and conversation about visualizations. *IEEE Computer Graphics and Applications*, 40(2), 57–70.
- Wang, Z., Sundin, L., Murray-Rust, D., & Bach, B. (2020). Cheat sheets for data visualization techniques. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–13). doi: 10.1145/3313831.3376271
- Wang, Z., Wang, S., Farinella, M., Murray-Rust, D., Henry Riche, N., & Bach, B. (2019). Comparing effectiveness and engagement of data comics and infographics. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–12).
- Wattenberg, M. (2005). Baby names, visualization, and social data analysis. In *Ieee symposium on information visualization, 2005. infovis 2005*. (pp. 1–7).
- Wattenberg, M., & Kriss, J. (2006). Designing for social data analysis. *IEEE Transactions on Visualization and Computer Graphics*, 12(4), 549–557.
- Weiner, D., & Harris, T. (2003). Community-integrated GIS for land reform in south africa. *URISA journal*, 15(2), 61–73.
- Wexelblat, A., & Maes, P. (1999). Footprints: History-rich tools for information foraging. In *Proceedings of the chi conference on human factors in computing systems* (pp. 270–277). doi: 10.1145/302979.303060
- Wickham, H., Vaughan, D., & Girlich, M. (2024). *Tidy messy data*. <https://tidyr.tidyverse.org/>. (Accessed: 2024-06-01)

- Willett, W., Heer, J., & Agrawala, M. (2007). Scented widgets: Improving navigation cues with embedded visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 13(6), 1129–1136. doi: 10.1109/tvcg.2007.70589
- Willett, W., Heer, J., Hellerstein, J., & Agrawala, M. (2011). CommentSpace: structured support for collaborative visual analysis. In *Proceedings of the chi conference on human factors in computing systems* (pp. 3131–3140).
- Wong, P. C., & Thomas, J. (2004). Visual analytics. *IEEE Computer Graphics and Applications*, 24(05), 20–21.
- Wong, Y. L., Madhavan, K., & Elmqvist, N. (2018). Towards characterizing domain experts as a user group. In *Evaluation and beyond-methodological approaches for visualization (beliv)* (pp. 1–10).
- Wood, D., & Fels, J. (1992). *The power of maps*. Guilford Press.
- Xu, A., Huang, S. W., & Bailey, B. (2014). Voyant: Generating structured feedback on visual designs using a crowd of non-experts. In *Proceedings of the conference on computer supported cooperative work & social computing* (pp. 1433–1444). ACM. doi: 10.1145/2531602.2531604
- Yau, N. (n.d.). *Flowingdata*. <https://flowingdata.com/>. (Accessed: 2024-06-11)
- Yeh, E. T. (2016). How can experience of local residents be “knowledge”? Challenges in interdisciplinary climate change research. *Area*, 48(1), 34–40.
- Zhang, Y., Sun, Y., Padilla, L., Barua, S., Bertini, E., & Parker, A. G. (2021). Mapping the landscape of COVID-19 crisis visualizations. In *Proceedings of the chi conference on human factors in computing systems* (pp. 1–23).
- Zhao, Z., Marr, R., & Elmqvist, N. (2015). Data comics: Sequential art for data-driven storytelling. *tech. report*.