-draft-Entangled Insights: A Feminist Reconceptualization of Insight[1]

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[1] **n.b.** the ideas in this document are works in progress

Context: This paper is a working draft that was originally produced between the summer of 2020 and spring of 2021. We've chosen to publish the document as a draft because it marks a significant milestone in how we as visualization researchers began to understand the benefits and complexities of using feminist theory in visualization research. That summer we read *Meeting the Universe Halfway* Barad [2007] and this paper is a result of discussing and theorizing Barad's theory of entanglements with the field of visualization's theorizing about insights. Since then, our thoughts have changed and it is likely some later draft of this paper will be quite different, but we provide this paper as an archive.

Introduction

Over twenty years ago Card, Mackinlay, & Shneiderman wrote: *"The purpose of visualization is insight, not pictures"* [Card et al., 1999, p.6]. Researchers have since quoted this statement in papers, talks, lectures, and books to motivate and explain that the scope of visualization research goes beyond putting pictures on screens. Pinning the goals of visualization on insight has also prompted a wealth of research that centers on insight generation. In addition to creating visualization tools that support insight generation, researchers have defined and characterized insight Chang et al. [2009], Plaisant et al. [2008], Saraiya et al. [2005], North [2006], Karer et al. [2021], Law et al. [2020], Yi et al. [2008], used it to establish the value of visualizations Van Wijk [2005], Stasko [2014], discussed and developed methods of evaluation Saraiya et al. [2005, 2006], Plaisant et al. [2008], designed insight management systems Chen et al. [2009b], Smuc et al. [2009], Gotz and Zhou [2008], and created taxonomies to characterize the relationship between insights and interaction He et al. [2020], Gotz and Zhou [2008], Yi et al. [2007].

Despite this bounty of research, insight remains an elusive and fuzzy concept. Visualization papers that characterize or evaluate insight offer a myriad of definitions with varying levels of specificity. Consistent across these definitions, however, is a value-laden characterization of insight that prioritizes insights into a domain over those about the data. This value system is at odds with the numerous visualization tools and systems that work to provide data insights, or with the knowledge that the community has amassed about perceptual and cognitive processes from well-defined, low-level tasks.

Because this value system emerges from a focus on the *what* of insight, rather than on *how* insights are produced, it becomes difficult for visualization researchers to understand with precision how the tools we design are making a difference in the world.

Using a lens of feminist theory, we identify fundamental problems with the visualization community's current conception of insight. We begin by asking: Who and what does work in the production of an insight? How, more precisely, is an insight produced? And what are the influences that lead to the production of an insight? When confronted with these questions, we find the current thinking around insight strained and incomplete. We observe that the lack of satisfying answers to these questions is the result of an understanding of insight as separate from its context, as seen through various attempts to measure, count, model, and predict insight. Scholars in the field of critical data studies argue that context is what gives meaning, and thus an insight cannot (and should not) be considered on its own. In reality, the context of a visual analysis session is a complex, dynamic entangling of influences that shifts and shapes the emergence of an insight. These influences include people, visualizations, data, processes, conventions, history, and power. We argue that the current conceptualization of insight as distinct from its context shrouds a more authentic description of how insights emerge.

From this perspective, we recharacterize insight and context as dynamic, relational, and inseparable. On the basis of this revised understanding, we move from the visualization community's current representational framing of insight and instead propose one that draws from the new materialist theories of feminist scholar Karen Barad. Barad's theories provide a model for reconfiguring the concepts currently used to describe insight — context, influence, production, and relevance — into the new materialist concepts of *entanglement*, *intra-action*, *emergence*, and *mattering*. From these concepts we redefine insight as emergent from an entanglement of intra-acting influences, the meaning of which comes to matter through the practice of visual analysis. We call this *entangled insight*. The conceptualization of entangled insight is meant to shift our thinking about insight and context away from being static, fixed, and delineable, and instead to thinking of both insight and context as lively, entangled, and teeming with possibility.

The primary contribution of this work is the conceptualization of entangled insight. We motivate this (re)conceptualization through a detailed discussion of the current thinking around insight and arguments as to its short-comings. We build our conceptualization of entangled insights so as to address these short-comings, ending with a proposal for a wholly new way to think about how insights come to be. Through a series of examples, we show how entangled insights are in many ways already visible and supported in visualization research and design, as well as how this new conceptualization exposes a wealth of opportunities for the community to rethink our methods and objectives. Because entangled insight involves a wholesale rethinking of the practice of visual analysis, it upends many of our current approaches to evaluating and designing tools. Thus, we conclude by pointing to the ethic-onto-epistemic implications of Barad's theories as a way to rework the theoretical underpinnings of visualization research. Throughout the paper we use footnotes (found in supplemental materials) to further entangle our main arguments with relevant side-discussions that speak to the social, historical, and political implications of this work. [2]

[2] A quick note on reading this paper: in the spirit of Barad, each section intentionally builds upon one another, fully entangling the prior sections. You the reader have the choice of what path you take and which sections you skip, but we provide a little guidance on how to do so.

- Insight is an overview of current research in the visualization community regarding insight. We unpack value-laden definitions and begin our discussion about how insights come to be.
- Context is an overview of the myriad of influences that contribute to the production of an insight in the visual analysis session. Jump straight to Context gives meaning for an unpacking of context and the troubles it brings.
- Entangled Insights is the heart of the paper. Please read it. If you want the high-level takeaways, jump to Definition of entangled insight.
- Entanglements in Visualization grounds our proposed concept of entangled insight in current visualization research.
- Conclusion concludes the work with an entangling of our work with ethical, ontological, and epistemological provocations.

Insight

In their recent paper Karer et al. [2021], Karer et al. state: "Although it is a common argument that the mission of visualization is to support its users in obtaining insight, there is no commonly accepted definition about what insight actually is." They make this argument based on the wealth of definitions for insight offered within the visualization literature. Saraiya et al. call insight "an individual observation about the data by the participant, a unit of discovery" Saraiya et al. [2005], while Plaisant et al. say it is "a nontrivial discovery about the data or a complex, deep, qualitative, unexpected, and relevant assertion" Plaisant et al. [2008]. More recently Karer et al. propose that an insight is "a step forward in the interpretation and analysis in the form of a change of the user's knowledge or understanding" Karer et al. [2021]; Chang et al. provide that it is "a moment of enlightenment, . . . an advance in knowledge, or a piece of information" Chang et al. [2009]; and Mathisen et al. state that "insights are pieces of information relevant to the analysis that can be characterized in manifold ways—complex, deep, qualitative, or even unexpected" Mathisen et al. [2019].

How is it possible to motivate insight as the goal of visual analysis without having a clear understanding of what it is? Stated acutely by Chris North, "insight seems to capture the intuitive notion of visualization's purpose. However, for the most part, the definition of insight remains fairly informal, making success [of visualizations] difficult to evaluate" North [2006]. The lack of a clear understanding of what insight is and how it is produced stymies not only our abilities to evaluate the success of visual analysis systems, but also our understanding of the work that visualizations (can) do in the production of new knowledge.

In this section we look more closely at these definitions and expose an inherent value system that cloaks a more authentic characterization of insight. We propose a new characterization – one based on the insight's relationship to data – and use this as a starting point to probe more deeply into how insights come to be.

The valuing of insights

Much of the literature that attempts to define insight does so from a desire to measure it. With insight as the stated goal of visualization Ragan et al. [2016], Yi et al. [2008], He et al. [2020], Karer et al. [2021], Chen et al. [2009a], Chang et al. [2009], Card et al. [1999], quantifying insight has emerged as a natural metric for evaluating the effectiveness of visual analysis tools.

In their foundational work on measuring insight, Saraiya et al. develop the insight-based methodology as an approach to evaluating a visual analysis tool based on its ability to spur insights Saraiya et al. [2005]. This method assigns a score to each insight generated during a visual analysis session, providing a way for tools to be assessed and compared in an empirical study. The score is based on the "domain value" of the insight: "the value, importance, or significance of the insight. Simple observations such as 'Gene A is high in experiment B' are fairly trivial, whereas more global observations of a biological pattern such as 'deletion of the viral NS1 gene causes a major change in genes relating to cytokine expression' are more valuable." Saraiya et al. [2005] Thus, "trivial insights" receive low scores, while insights that "confirm, deny, or create a hypothesis" earn high marks. In reflecting on this conceptualization of insight, North emphasizes that valuable insights go "beyond dry data analysis, to relevant domain impact" North [2006].

The development of the insight-based methodology brought the idea of evaluating insight to the forefront of other evaluation scenarios. Plaisant et al. incorporated insight evaluation into the judging protocol for the InfoVis contest of the late-aughts; reflecting on their experiences of judging the contest, they described the insights they evaluated as either "simple tasks" that are easy to judge precisely or "complex exploratory tasks" that are "more interesting" but also more difficult to evaluate Plaisant et al. [2008]. Stasko proposed a new metric for evaluating a visualization, including insight as one of the criteria Stasko [2014]. In justifying the use of an insight criteria, he states that visualizations should "go beyond just answering specific data-centered questions. Visualization should ideally provide broader, more holistic benefits to a person about a data set, giving a 'bigger picture' understanding of the data and spurring insights beyond specific data case values" Stasko [2014]. And more recently, He et al. build on the insight-based method in order to quantify the "quality" of an insight from a user's interactions with a visual analysis tool He et al. [2020]. Their scoring system gives high marks for insights that are unexpected, verifiably correct, deep, and express "domain value", and low marks for those that are just "simple" observations about the data.

Looking across these characterizations there is a clear valuing of some types of insights over others. The "simple", "trivial", "specific", "dry" insights about data are those that we devalue and rank below the "relevant", "complex", "interesting", "broad", "unexpected", "deep", "valuable" insights about a domain. This value system, however, is at odds with the large portion of visualization research that builds on familiar analysis tasks in order to produce straightforward insights about data. A wealth of knowledge now exists about how people perceive and make sense of visual encodings, developed through an abundance of empirical studies that rely on well-defined analysis tasks Elliott et al. [2021]. Standard approaches for designing visual analysis systems rely on data and task abstractions as a primary motivator for design requirements Sedlmair et al. [2012] and evaluation Munzner [2009]. And efforts to automate and capture parts of the visual analysis process through recommendations Vartak et al. [2015], Wongsuphasawat et al. [2016], auto-insights Law et al. [2020], Ding et al. [2019], and provenance Xu et al. [2020], Ragan et al. [2016] build algorithms around an understanding of common analysis tasks. Are these efforts misplaced? Is this research unimportant?

Of course not. And we doubt that insight researchers would say so either. All insights have value. Unpacking the value-laden characterizations of insight, however, reveals their connection to the *what* of insight: *what* is the focus of the insight? Is it about the data, or about the domain? Insight researchers have proposed *what*-characterizations that identify three types of insight: insight into the visualization, insight into the data, and insight into the domain Karer et al. [2021], Smuc et al. [2009]. But if all insights are equally valuable, maybe it no longer matters *what* the insight is about.

Other researchers have in fact argued that a focus on the *what* of insight doesn't help us better understand the underlying question: *how* insights are produced Yi et al. [2008], Sacha et al. [2014], He et al. [2020]. Understanding the *how* is arguably at the heart of designing visualizations that support the production of rich and varied insights. In their work on characterizing insight through examining the procedural aspects of insight generation, Yi et al. describe their shift to a focus on the *how*: "Inspired by research in sensemaking, we realized the importance of the procedural aspects in understanding insight.

Thus, rather than asking 'What is insight?' we instead focus on 'How do people gain insights?'" Yi et al. [2008].

In this work, we go beyond the question of how people gain insights, and instead question more fundamentally how an insight comes to be. We start with a recharacterization of insight based on the influence of the data involved in its production, which in turn points the way towards a more complex notion of insight as an entanglement of people, visualizations, data, processes, conventions, history, and power.

Data literal to data inspired

In their description of insight, Saraiya et al. provide examples of two different types Saraiya et al. [2005]. The first example – "Gene A is high in experiment B" – is qualified as a "fairly trivial" insight about the data, while the second example – "deletion of the viral NS1 gene causes a major change in genes relating to cytokine expression" – is a "more valuable" insight into the domain. But if we reject the valuation of these two insights, as well as the focus on the *what*, how else might we distinguish them?

We propose a characterization based on the role that data plays in the production of the insight. The first example – "Gene A is high in experiment B" – is tightly coupled with a feature in the data: the value of a specific data item in a specific subset of the data. In this *data literal* insight, a feature of the data is a clear and strong influencer of this insight. In contrast, the second example – "deletion of the viral NS1 gene causes a major change in genes relating to cytokine expression" – has a much less obvious data influence. It is a *data inspired* insight, emerging from the combination of the influence of the data with other influences such as domain knowledge and interactions with a visual analysis tool. This new characterization focuses on the role of data in the production of the insight; or more precisely, the (obvious) primacy of data in the influences that lead to an insight.

Insights, however, are not simply data literal or data inspired; there exist a whole spectrum of insights in between. We make the deliberate choice to use a spectrum for characterizing insights for several reasons. [3] Practically, it is hard to precisely define an insight as one type or the other. For example, at a quick glance "Gene A is high in experiment B" can be perceived as a data literal insight, yet upon closer examination, we can see more influences such as data literacy (how the reader understood that A was high), visual literacy (how the reader interpreted the visualization), and knowledge about Gene A and experiment B (what domain knowledge was necessary

[3] Politically, the choice of a spectrum rejects the binary logic that unduly circumscribes the varieties of life and embraces the wonderful messiness of the space in-between. Here we underscore that a rejection of binaries is also a rejection of fragmenting and othering, as expressed and further explained in the feminist literature (d'Ignazio and Klein [2016], Fausto-Sterling [2000], Grosz and Grosz [1994], Butler et al. [2004], Dourish and Bell [2011]).

to place Gene A in experiment B). These observations of influences begin to nudge this insight toward the more data inspired side of the spectrum.

Theoretically, the spectrum offers an opportunity to probe into what changes along this scale. Our community's current conception of insight identifies more and more things that influence insight generation as we move along the spectrum. That is, the more inspired an insight is, the more varied and complex the influences are that lead to its production. Traditionally, the source of these additional influences has been ascribed to *context*. According to this view, insights become more inspired as the context of a particular visual analysis session becomes more complex. In the next section we unpack the community's conception of context and the established influences that it contains. We use critiques of context to point out its limitations with how insights come to be, and argue for a radically different conceptualization where contexts are entangled with insights and insights with context.

Context

Here we review the visualization community's current conceptualization of context through a description of the many influences researchers implicate in the production of insight. We establish the argument that an insight is meaningless without this context by building on critiques of big data and ubiquitous computing. We then shift, exposing the inherent flaws of the idea of context for describing how insights occur, arguing for a move to a new, entangled conceptualization of insight.

Context of visual analysis

The visualization literature discusses various contextual influences that affect the production of insight. We distinguish between the comprehensive notion of context and the more specific influences that make up this context. Most pervasive of these contextual influences is that of data, which is central to all insights that are produced through visual analysis. As insights move from being data literal to data inspired, additional contextual influences become increasingly relevant. In this section we review the literature on these influences.

Data Influence

Visualizations are graphical representations of data, meant to facilitate analytical reasoning Ware [2019], Keim et al. [2008]. Thus, central to any insight gleaned through visual analysis is the influence of the data. People perceive data features such as patterns, outliers, clusters, correlations, and connections through visual cues. The influence of these features can result in data literal insights such as "there are three clusters of data items" or "node A is a hub in the graph." Insights that are influenced *solely* by the data can be automated and used as contextual building blocks for subsequent analysis Law et al. [2020]. Data influences also catalyze other influences, such as inspiring a user to bring their knowledge about the domain to reason about data features, or inspiring a designer to make explicit decisions in how to represent the data visually. Our discussions of other influences largely build on the fundamental influences of data.

User Influence

From domain knowledge to visual literacy and individual differences, the influence of the user [4] builds on perceived data features when interpreting information in the data Karer et al. [2021]. Based on a user's knowledge of the conditions in which the data were collected, they can interpret that the value of a specific data item means that "Gene A is high in experiment B." Or instead, domain knowledge about metabolic pathways builds on the same perceived data feature to produce a different insight: "deletion of the viral NS1 gene causes a major change in genes relating to cytokine expression." In scenarios like these, a user's physiological, cognitive, and cultural characteristics may also influence how they perceive data features from specific encoding decisions, such as the use of color Ware [2019], Liu et al. [2020], Winawer et al. [2007]. The countless sources of influence of the user combine in complex and unique ways.

[4] The term 'user' is not neutral. Don Norman emphasizes "[w]ords matter. Psychologists depersonalize the people they study by calling them 'subjects.' We depersonalize the people we study by calling them 'users.' Both terms are derogatory" Norman [2018]. Olia Lialina, in contrast, makes the argument that the term user is helpful because it counteracts an invisible computing system by serving as a reminder that computers and computer programs are constructed objects, distinct from the user Lialina [2012]. And finally, empirical studies have shown that the term user is more often associated with a man than a woman Bradley et al. [2015]. HCI research also disputes the semantics of user, pointing out that the term user is not historically homogeneous Baumer and Brubaker [2017], Bardzell and Bardzell [2015], is dynamically (re)defined in the material practices of use Brubaker and Hayes [2011], and that "a myopic focus on the user prevents [HCI scholars] from fully accounting for the diversity of interactions between humans and computers" Baumer and Brubaker [2017]. We debated and read and discussed whether we would use the word 'user' or some other term. Ultimately, we chose user, one for clarity and two because like Lialina, we want it to represent the constructed aspect of human computer interaction rather than concealing it.

Perception & Cognition A host of empirical studies reveal ways that a user's perceptual and cognitive traits influence their interpretation of a visualization. Vision science research establishes that physiological differences can lead to a variety of color blindness effects Ware [2019] or low- to no-vision abilities. A rich collection of studies shows individual differences based on personality traits and cognitive abilities lead to different task performance and usage patterns when interacting with a visualization Liu et al. [2020]. For example, a study comparing personality types correlates personality with different interaction patterns and number of insights generated, with introverts producing more Green and Fisher [2010]. Introverts also spend more time problem solving, perhaps giving them an advantage in generating insights from unfamiliar visualizations and datasets Ziemkiewicz et al. [2013]; this is similar to findings on the benefits of visual difficulties Hullman et al. [2011]. Other studies show that cognitive traits like spatial ability impact people's abilities to interpret a visualization in decision making contexts Conati and Maclaren [2008], Ottley et al. [2016]. Visual literacy also plays a role in the correct interpretation of standard graphs Maltese et al. [2015], even among people highly trained in statistical analysis Belia et al. [2005].

Bias & Beliefs Visualizations that show data that resonates personally with a user can evoke bias and pre-existing beliefs as another source of influence. In a series of lab studies, Kim et al. show that eliciting beliefs about data trends can affect someone's comprehension of a visualization Kim et al. [2017, 2018, 2019]. And in an interview study with participants in rural Pennsylvania, Peck et al. report on the influence of political leanings on the preference for, and trust in certain charts Peck et al. [2019]. The personal and political influence of users' beliefs was also evident when people interpreted COVID-19 charts published in the Financial Times. In a keynote address, John Burn-Murdoch described how readers interpreted these charts as either insights into the change of the growth rate of cases, or as a pro-government message that the pandemic was improvingBurn-Murdoch [2020].[5] A study by Lee et al. on the data and visualization practices of people who did not want to wear a mask during the COVID-19 pandemic, similarly showed how tapping into people's "lived-experience" was a powerful tool for coronavirus skeptics to fuel distrust in public health messaging Lee et al. [2021].

[5] In his keynote at BELIV 2020, John Burn-Murdoch of the Financial Times argued that visualizations are both personal and political Burn-Murdoch [2020] He recounted his team's experience in producing charts that tracked the COVID-19 outbreak, and specifically how readers' interpretations of the charts bifurcated when the team moved from showing COVID-19 cases with a linear scale to a log scale. Some readers appreciated how the log scale improved their interpretation of how the growth-rate of cases was changing as the pandemic progressed. But other readers' instead interpreted a higher level message in the charts: "People had pre-existing beliefs about the way, for example that the UK or US government was handling the virus was bad, and therefore they saw the chart implying that things were perhaps improving. But their pre-existing beliefs that 'no, things are bad, this is going badly' led them to react negatively to those charts and believe that the use of a log scale was problematic." The lived experience of these readers framed their reaction to the insights that emerged.

Domain Knowledge Domain knowledge – deep knowledge about a field of study – is recognized across the visualization literature as having an important influence on insight in professional settings Karer et al. [2021], Saraiya et al. [2005, 2006], North [2006], Federico et al. [2018], Chen et al. [2009a], Sacha et al. [2014], He et al. [2020], Sedlmair et al. [2012], Chang et al. [2009]. Discussions on the role of domain knowledge focus on its influence for data inspired insights that are "deeply embedded in the data domain, connecting the data to existing domain knowledge and giving it relevant meaning" North [2006]. Interviews with professionals reveal that exploratory data analysis is both "driven in reaction to the data, in a bottom-up fashion" and "motivated by knowledge of the domain or problem space" Alspaugh et al. [2019], implicating the ways that domain knowledge influences a user's interactions with a tool. Other studies show that the incorporation of domain knowledge into the analysis process produces a more diverse set of insights He et al. [2020], as well as insights that are not replicable by non-experts even when given access to the same views of the data Dou et al. [2009].

Data Knowledge The original work on insight-based evaluations, however, suggests the role of another facet of domain knowledge, namely knowledge of the data and the specific circumstances from which they were captured Saraiya et al. [2005, 2006]. In their initial study, Saraiya et al. were surprised that the varying levels of domain expertise of their participants did not have a strong influence on their resulting insights. They speculate this was because the participants were unfamiliar with the experimental context of the data, and thus "the data did not mean as much to them because, simply put, it was not their data" Saraiya et al. [2006]. More recent work with public health experts provides evidence that knowledge about data collection and processing impacts the ways that these experts interpret global health data McCurdy et al. [2019]; similar evidence exists for avalanche forecasters Nowak et al. [2020].

Personal Knowledge Familiarity with the source of the data influencing insight is echoed in personal informatics where "the data is personally important and relevant, as opposed to work-motivated" Pousman et al. [2007]. Studies show that participants bring a wealth of knowledge about their personal data to their analysis, which is not only critical in differentiating and interpreting interesting patterns in the data from everyday routine Tolmie et al. [2016], but also for providing personally relevant insights into their lives Moore et al. [2018]. Self-reflection is a "unique type of insight that is particularly relevant in the personal data context" as people bring their deep and intimate knowledge of their lived experiences to analysis of their personal data to "extract meaningful insights and make positive changes" Choe et al. [2015]. In circumstances where there is both overlap and differences in knowledge about the data, like doctor's and patient's discussions of self-tracked health data, the data can "ground and provide objectivity in clinic consultations and can foster collaboration by emphasizing both the medical expertise a provider contributes and the detailed experiential knowledge of a patient" Schroeder et al. [2019].

Interaction Influence Interaction has emerged as a specific subfield of interest within the visualization research community, with research looking at both the design of interaction techniques and their role in insight generation Dimara and Perin [2020]. Early theorizing focused on the need for interaction in handling increasingly large and complex datasets Dix and Ellis [1998], Shneiderman [2003], Yi et al. [2007], but moved to framing interaction as a means of amplifying human cognition Endert et al. [2012], Guo et al. [2016], Heer and Shneiderman [2012], Liu et al. [2020]. In their review of visualization literature on interaction, Dimara & Perin conclude that within the field of visualization, "interaction is conceptualized as a *dialogue* between a human user and the visualization system over a central object of interest: the data" Dimara and Perin [2020]. Researchers have sought to quantify, qualify, model, and predict the influence of user-driven interaction on analysis and insight through a variety of proposed methods Guo et al. [2016], Reda et al. [2014], Kang et al. [2009], He et al. [2020], Yi et al. [2008]. Studies show that increases in the number of actions a participant takes during a visual analysis session can push insights to be more data inspired and less data literal He et al. [2020], and also that knowledge of the domain of the data can change the types of actions a participant takes Ishack et al. [2015]. In a longitudinal study tracking the work of bioinformaticians, Saraiya et al. found that the "most exciting insights [were gained] after almost 1.5 months of data analysis and several months of 'learning' time with the software... It is clear that later analysis is influenced by findings from the earlier analysis" Saraiya et al. [2006].

Visualization (designer) Influence

Visualization designers make a host of decisions – both large and small – when creating a chart or tool Wood et al. [2019]. Some of these decisions include what to exclude, such as uncertainty for reasons of complexity and understandability Hullman [2020]; some include how to (re)design data representations in support of new analysis tasks Nielsen et al. [2009]; and others include scoping the problem that a visualization is meant to support Meyer and Dykes [2019]. These design decisions inevitably influence the interpretations people make. For example, an empirical study by Zacks et al. showed that participants interpreted the same data in different ways when viewing different visual representations Zacks and Tversky [1999]. Despite the common assumption, and design intention, that visualizations are windows onto the data, critics point out that "a visualisation is the result of numerous choices involving a range of people (those who want the visualisation to be made, those making it, and others in between)" as well as the "entanglement of power and practice" Kennedy et al. [2016]. Visualizations are not neutral Correll [2019], Dörk et al. [2013], Meyer and Dykes [2019], Drucker [2011], and are instead designed interfaces that determine the way data are used, providing "a procedural setting that shapes the roles and ways of knowing available to users" [Loukissas, 2019, p.128].

Convention Influence

In addressing the influence of conventions, Loukissas encourages us to "consider how interfaces are rooted in normative cultural assumptions about what data can and should do . . . . [because] data don't speak for themselves" [Loukissas, 2019, p.130]. Some visualization researchers have pushed against the normative goal of speed and efficiency for visual analysis systems through a series of studies, finding that there are information-retention benefits in slowing down the viewer through use of more complex encodings Hullman et al. [2011], Bradley et al. [2019] or more memorable charts Borkin et al. [2016]. Building on these studies, Bertini et al. question the visualization community's reliance on design guidelines that are grounded in the perceptual efficiency of visual channels, arguing that these guidelines "do not seem to capture important components of how people use, interpret, and learn from visualizations" Bertini et al. [2020]. Kennedy et al. argue further that "[visualization designers'] choices are constrained by the conventions that are available to them, conventions which do persuasive work" Kennedy et al. [2016], specifically calling out a variety of normative encoding conventions that work to imbue a visualization, and thus the underlying data, with a sense of objectivity. These conventions influence the multitude of decisions a visualization designer makes, and thus the ways of knowing available to a user; the trend in visualization recommendation systems that build on established channel rankings is just one poignant mark Wongsuphasawat et al. [2016, 2017], Mackinlay et al. [2007].

Context gives meaning

The set of influences described above can be understood as the *context* that brings meaning to any particular visual analysis session. Placed within the characterization proposed in Data literal to data inspired, it can be said that contextual influences beyond that of data increase in significance as the insights produced during visual analysis move from data literal to data inspired. By the same token, the significance of the context increases as the insights move from data literal to data inspired. What connects these two statements is the centrality of context to the process of meaning-making prompted by visual analysis. In this section we review the literature from the field of critical data studies that explores the centrality of context to making meaning from data.

For the past decade at least, scholars in the field of critical data studies have asserted that data cannot be considered out of context. Bowker Bowker [2008] and Gitelman Gitelman [2013] have memorably asserted that "raw data is an oxymoron." Offering a more theoretical version of that same argument, Drucker draws from the Latin origins of the word "data," meaning "given," in order to propose that "*data are capta*, taken not given, constructed as an interpretation of the phenomenal world, not inherent in it" Drucker [2011]. A corollary to the premise that data cannot be understood outside of context is that data require context in order to make meaning. In their critique of big data, boyd & Crawford describe how data analytics inherently strip data of their context in pursuit of an objective representation of the world, but that this move is an error: "taken out of context, data lose meaning and value" boyd and Crawford [2012]. Extending this further, Seaver provocatively reminds us that "taken out of context, *everything* loses its meaning" Seaver [2015].

In the case of visualization, what loses meaning when taken out of context is insight. What meaning does "Gene A is high in experiment B" have without the context of the data (data influence) and the domain (user influence)? What meaning does the "deletion of the viral NS1 gene causes a major change in genes relating to cytokine expression" have without the context of the experiment (user influence) and the analysis (interaction, visualization, and convention influences)? While we could quibble about the exact influences that contribute to these two insights, the point here is that influences contribute to the context of visual analysis, and that insight cannot be produced without them. Like data, insight without context is meaningless. We further propose that insight *requires* context for its meaning to become clear.

A corollary of the claim that insight requires context to have meaning is that acting on an insight without considering its context can result in significant error. This line of reasoning has also been explored in the field of critical data studies. D'Ignazio & Klein observe that the failure to consider data outside of its context can run the risk of "analytic misstep[s]" [D'Ignazio and Klein, 2020, p.159]. Seaver argues similarly that researchers run the risk of "mistaking their measures for phenomena of interest" if and when they examine their data apart from their context Seaver [2015]. Yet to accept the argument that data cannot, and should not be considered without their context "necessitates a significant shift in our expectations of digital data given that the digital was invented to be independent of any substrate" [Loukissas, 2019, p.53]. Loukissas is not alone in pointing out that our standard methods of data capture and storage lack the technical infrastructure to capture this context D'Ignazio and Klein [2020], Gurin [2014], Borgman [2016]. To this claim, we add that computational fields that work with data — including the visualization community — also lack the *conceptual* infrastructure to assimilate context.

The trouble with context

The visualization community's current conception of insight places it *within* a context Van Wijk [2005], Karer et al. [2021]. This context is considered to be composed of various contextual influences that can be captured, represented, and modeled. For example, provenance systems focus on user and interaction influence: they capture a user's interactions during an analysis session to support replication and communication of findings Gratzl et al. [2016], Stitz et al. [2019]. Visualization tools that include annotation mechanisms focus on data and user influence: they capture tacit knowledge about the data and domain McCurdy et al. [2019], Heer et al. [2009]. And visualization recommender systems focus on interaction and convention influence: they model design conventions within recommender algorithms that then offer the user choices Wongsuphasawat et al. [2016, 2017], Mackinlay et al. [2007].

The idea that context can be defined by a set of influences is a *representational* one. The implications of this formulation have been explored in the field of ubiquitous computing. According to Dourish: "As a representational problem, the central concern with context is with the questions, 'what is context and how can it be encoded?'" Dourish [2004]. He associates these questions with the positivist perspective that underlies much of computing research. This perspective is characterized by the belief that all phenomena in the world, however complex, can be captured, modeled, or otherwise empirically described. The representational view of context thus presumes several things: *context is information*, and thus can be known, encoded, and represented; *context is delineable and stable*, and thus the relevant contextual influences of an insight can be determined; *context and insight are separable*, and thus context describes an environment that is separate from an insight.

The critical data studies scholarship is again helpful in exposing the limits of this representational view: "Because there is no objective limit to what can be invoked as context, an exhaustive catalog of context is impossible. As a result, such an analysis inevitably involves choices about what counts and where the work of contextualization should cease" Seaver [2015]. Decisions about what counts are also foundational to visualization design. Visual analysis provenance systems capture some, but not all user interactions based upon a model of user intent; annotation mechanisms structure the ways that a user can externalize tacit knowledge; recommender systems use an internalized model of which visual encoding options are best in order to present (or not) a subset of available charts; and the uncountable number of decisions made in the design of every visualization. This is the reality of visualization design.

How might we better account for this reality? Drawing from Dourish's "interactional" framework Dourish [2004], we propose an alternative view of context and insight: *context and insight are dynamic, relational, and inseparable*. During visual analysis, a wide range of influences combine, compound, and themselves reconfigure in order to shape the production of an insight. Domain knowledge combines with perception; interactions with a tool compound over an analysis session; a designer's choice of visual representation reconfigures the kinds of data features that are salient. In other words, the production of insight is a process that changes and unfolds over time. Furthermore, influences are not simply relevant or not; relevance entails a continuous reconsideration of what matters as decisions are made, actions take place, and insights emerge. Because insight depends upon context, and because the context that informs any particular insight is always changing, it becomes impossible to separate them.

This view of the mutual constitution of insight and context requires a fundamentally different conceptualization of insight, one that captures its entangled, dynamic, and emergent nature. In the next section we adapt a concept from feminist science and technology studies (STS) – *entanglement* – in order to anchor this new way of thinking about the relationship between insight and context.

Entangled Insights

Here we get to the heart of our contribution: the reconfiguring of context and insight as an entanglement. We draw from the work of feminist theorist Karen Barad to shift from the notions of context, influence, production, and relevance to those of entanglement, intra-actions, emergence, and mattering. After a brief introduction to the history of Barad's theory of agential realism, we make our conceptual moves and introduce the new idea of *entangled insights*.

A genealogy of entanglement

Much of the inspiration for the field of critical data studies, as well as Dourish's work in ubiquitous computing, comes from science and technology studies (STS) and feminist STS in particular. Feminist STS is a field that brings together STS and feminist theory. Among the most widely known feminist STS theories is Haraway's highly influential formulation of all knowledge as situated Haraway [1988] – meaning that all knowledge reflects the particular conditions in which it is produced. Haraway's theories have prompted scholars from a wide range of disciplines – including visualization Correll

[2019], d'Ignazio and Klein [2016], Dörk et al. [2013] – to consider what those situated conditions might be, as well as how more precisely those conditions impact the production of knowledge Butler [2011], Suchman and Suchman [2007], Rosner [2020], de la Bellacasa [2017].

Meanwhile, the next generation of feminist STS scholars continued to engage with and elaborate Haraway's theories, resulting in a new area of inquiry, alternately described as *new materialism* or *feminist materialism*, that probes even more deeply into the nature of knowledge production, as well as the nature of the objects that we seek to know more about Barad [2007], Alaimo et al. [2008], Coole et al. [2010], Braidotti [2013]. Modeling their work on scientific research that challenges the assumptions embedded in Newtonian physics – namely, that material objects in the world exist as discrete entities, and act only when acted upon – these scholars draw from theories of quantum mechanics in order to question the distinctions among objects in the world, as well as among the objects which (or people who) act and the objects which (or people who) are acted upon.

Arguably the most prominent of the new materialist scholars is Karen Barad. Trained as a theoretical physicist, Barad turned to feminist STS as way to pursue the broader implications of the phenomenon that they encountered in their scientific work. In their landmark book, *Meeting the Universe Halfway: Quantum Physics and the Entanglement of Matter and Meaning* (2007), they use Niels Bohr's investigations of quantum physics as the point of departure for their own theorization of "the nature of nature" and of our role in making sense of it. Just as Bohr's experiments in particle physics demonstrated that there are no hard distinctions between matter and measurement, Barad's philosophical extension of that work – a worldview that they name *agential realism* – offers a framework for understanding how "human and nonhuman, material and discursive, and natural *and* cultural factors" are entangled with each other, in scientific practice as in the world [Barad, 2007, p.26]. In order to better describe this revised worldview, Barad also introduces a new conceptual vocabulary. Thus, the concept of *entanglement*, along with the related ideas of *intra-action, emergence, and mattering*, take the place of the set of ideas — such as embodiment and causality [6] — that have traditionally been used to explain the discrete relationships among people and objects in the world.[7]

[6] Barad calls out the set of concepts that her agential realism framework refigures: "The new philosophical framework that I propose entails a rethinking of fundamental concepts that support binary thinking, including the notions of matter, discourse, causality, agency, power, identity, embodiment, objectivity, space, and time." [Barad, 2007, p.26]

[7] Barad's theory of agential realism, and the ideas associated with new materialism more broadly, have been engaged widely across the humanities. The decade following the publication of Barad's key text saw thousands of applications and extensions of their work. Today, a new generation of scholars have taken up where Barad left off, enriching the ideas associated with new materialism with key concepts and conversations from queer theory, animal studies, environmental humanities, Black feminism, and Black studies (e.g.Prescod-Weinstein [2021], McKittrick [2021], Tsing [2015], Weston [2017], Frost [2016])

Conceptual shifts

Through the lens of Barad's theory of agential realism and their idea of entanglement, we rework the notion of insight. Our new conceptualization of *entangled insight* isn't "just any old kind of connection, interweaving, or enmeshment in a complicated situation" [Barad, 2007, p.160]. It is a theoretically precise reconfiguration of the traditional ideas that have been used to explain insight in the visualization community — context, influence, production, and relevance – into the new materialist concepts of *entanglement, intra-action, emergence, and mattering*. These conceptual shifts reflect our view, following Barad, that the nature and workings of visualization cannot be reduced to discrete parts or distinct processes, but instead are best understood in relation to each other, and are themselves always in flux. We map these contextual shifts as follows:

Context	→	Entanglement
Influences	→	Intra-actions
Production	→	Emergence
Relevance	→	Mattering

Throughout this section we note the ways in which visualization research already reflects this reframing, and suggest new possibilities and opportunities for the community that this reconceptualization enables.

Entanglement

The main concept that underpins the theory of agential realism is *entanglement*. With this term, Barad intends to describe a world in which object and observation, matter and meaning, are mutually constituted. Extending this line of thinking to visualization, we move from a conception of insight and context as separate entities to one that entangles them together – dropping the idea of context as a discrete entity unto itself. This formulation emphasizes the inseparable and interdependent nature of insight and context. Put another way: insight becomes meaningful only through context; and context becomes relevant only through an insight. Thus, the meaning of an insight and the relevance of its contextual influences are *entangled*.

In visualization, an entanglement consists of all possible influences and all possible outcomes of a visual analysis session. It is "teeming with the full set of possibilities of what may come to be"[Barad, 2007, p.354]. The nature of any particular entanglement cannot be defined in advance, nor can the influences or outcomes that give it form be separated from one another. The implication for visualization research is a critical one: the entanglement that characterizes a particular visual analysis session encompasses more influences than we can easily identify, observe, or capture. They go well beyond the influences we detail in Context of visual analysis.[8]. Rather than be overwhelmed by the magnitude of potential entanglements, we

[8] In describing the achievement by IBM nanotechnologists in 1990 of creating an image of the world's smallest logo built from individual atoms, Barad says: "The entangled set of practices that go into making these images include: STM microscopes and practices of microscopy, the history of microscopy, scientific and technological advances made possible by scanning tunneling microscopes, the quantum theory of tunneling, material sciences, IBM's corporate resources and research and development practices, scientific curiosity and imagination, scientific and cultural hopes for the manipulability of individual atoms, Feynman's dream of nanotechnologies, cultural iconography, capitalist modes of producing desires, advertising, the production and public recognition of corporate logos, the history of the atom, the assumption of metaphysical individualism, complex sets of visualizing and reading practices that make such images intelligible as pictures of words and things, and the intertwined histories of representationalism and scientific practices. And this is merely an abbreviated list..." [Barad, 2007, p.360]

should view the idea of entanglement as an invitation to re-imagine the role of visualizations as part of the relationships and dynamics that contribute to a particular insight.

Intra-actions

In order to understand the dynamic and relational nature of entanglement as it relates to insight, we must shift from an understanding of entanglement as consisting of influences to instead as consisting of *intra-actions*. Barad makes use of this term, as opposed to the more standard term *interaction*, as a way to emphasize within-ness as opposed to between-ness. In the case of visualization, the idea of intra-action accentuates how influences are co-constituted by each other – that is, they cannot and do not exist as independent entities prior to actions that bring them together. An influence, Barad might say, "is an enactment, not something that someone or something has" [Barad, 2007, p.178]. Thus, influences are emergent and dynamic intra-actions rather than a measurable set of features delineable as contextual properties.

Reconceived in this way, visual analysis can be viewed as an enactment of iterative changes to intra-actions: influences coming together in ways that combine, compound, and themselves reconfigure in order to shape the production of an insight. The idea of intra-action allows visualization researchers to consider how influences work together (or not). For example: a person using a visual analysis tool has an insight; that tool was designed by another person who made many design decisions; some of those decisions were influenced by visualization conventions; and those conventions were established by a system of power that values certain perspectives over others. It is only by considering influences in relation to each other at a specific moment – in this case, at the moment an insight emerges – that it becomes possible to identify and describe the relevant intra-actions, even as they remain entangled with each other.

Emergence

Insights are not produced as the result of a linear or finite process. Rather, they *emerge* from entanglements, which are themselves constituted by intra-actions. The shift from insight production to insight emergence affirms that the process is not required to be static, linear, or even complete. Insights can emerge from a visual analysis session that meanders; they only need to increase clarity rather than total knowledge; revision and reconsideration are welcome.

Visualization design is imbued with valuing and supporting emergence. The interactive, flexible, multifaceted tools we create are meant to support rich visual analysis, providing flexible, change-able, bespoke opportunities for intra-actions between people and data. Indeed, such tools already support the emergence of insight, and the possibilities for any particular insight to evolve. In other words, insights support the emergence of other insights, in a process that entangles what came before with what is happening now. Here we must remind ourselves that insights do not emerge from people alone, nor can they be separated from the environment of the analysis session or the affordances of the particular tool. Data and visualization, design and convention, not only intra-act, but also actively participate in the process of insight emergence. The converse is also true: data, visualization, design, and convention, all also accumulate meaning as they participate in the process of an insight's emergence.

Barad connects emergence with *discourse*, describing discursive practices as "the material conditions for making meaning" [Barad, 2007, p.335]. By focusing on discourse as the substrate from which meaning is made, Barad draws from the rich history of critical theory that implicates language with knowledge. In visualization, meaning is made through other practices – the practice of visual analysis or the practice of visualization design; we lean on *practice* rather than discourse in a nod towards the entangling of action and meaning through practice as proposed by Dourish Dourish [2004]. Practices are specific forms of engagement that make specific insights emerge. As practices develop, evolve, and deepen, so too do new entanglements and possibilities for intra-action. Crucially, practices are not restricted to those directed by people. Barad argues that, because reality does not depend on the prior existence of people, "the space of agency is not restricted to the possibilities for human action" [Barad, 2007, p.178]. Their arguments emphasize the entanglements of humans and non-humans, and the range of opportunities for meaningful intra-actions such that meaning can emerge.

Mattering

Coupled with the idea of emergence is the idea of *mattering*. Mattering encompasses both meaning and relevance, once again entangling the notions of relevant influences and meaningful insights. In order to arrive at their formulation of the term, Barad purposefully overloads matter in both its noun and verb meanings: "Matter is substance in its interactive becoming – not a thing but a doing, a congealing of agency" [Barad, 2007, p.336]. They ground this entangling of meanings in the wave-particle duality paradox of quantum physics that describes how a photon is observed as a wave under certain circumstances, and as a particle (matter) under others. It is through the choosing of a specific experimental apparatus that a photon becomes matter *and* comes to matter. In the context of visualization, it could be said that specific insights come to matter through specific intra-actions in a specific visual analysis session. These insights matter both in the sense that they have become present and palpable *and* meaningful through the session.

Definition of entangled insight

Here we bring together our conceptualizations of entanglement, intra-action, emergence, and mattering into the core contribution of this work: a reconfiguration of insight with the new concept of *entangled insight*. Our conceptualization of entangled insight relies on the following assertions:

- Entanglements are dynamic, relational, and inseparable.
- Influences intra-act within entanglements.
- A visual analysis session is characterized by entanglements (influences that intra-act).
- The practice of visual analysis engages these entanglements and intra-actions.
- Insights emerge from, and are entangled with, the practice of visual analysis.
- Through the practice of visual analysis, insights and intra-actions come to matter.

In summary:

> ENTANGLED INSIGHTS EMERGE FROM VISUAL ANALYSIS PRACTICES IN WHICH INTRA-ACTIONS COME TO MATTER.

We argue that entangled insights are a more authentic reflection of visual analysis, and one that captures the dynamic, relational, inseparable reality of insight emergence. Both data inspired *and* data literal insights are entangled; our conceptualization implies that the latter are entangled in much more complex ways than our community currently acknowledges. Entangled insights are already present throughout visualization research, and we walk through several examples of this in the next section. We also show how marking insight as entangled provides new opportunities to question how and what we are designing.

Entanglements in Visualization

Entangled insights are already visible in, and supported by visualization research, which we illustrate through three examples of entanglements: the entanglement of people through a provenance system that expands the possibilities for intra-actions; the entanglement of insights through an annotation mechanism that allows people to mark their intra-actions for others to see; and the entanglement of design knowledge in a visualization tool. We use these examples to provide evidence that entangled insights reflect the reality of visual analysis and design, but also that this (re)conceptualization opens new possibilities for research.

Expanding intra-actions through provenance

Reproducibility is an important goal of the scientific method, and one that visualization researchers have identified as an important challenge for interactive, visual analysis Ragan et al. [2016], Stitz et al. [2019], Mathisen et al. [2019]. Replication of a visual analysis session requires both capturing *and* communicating the process and results of a visual analysis session. Visualization research, however, has largely focused on these two requirements through separate threads of inquiry: the design of provenance systems Ragan et al. [2016], and storytelling with data Segel and Heer [2010]. Most provenance systems focus on capturing the analysis process, allowing the analyst to both engage with the analysis at hand, while also providing a meta-perspective of the sensemaking process Xu et al. [2020]; while most storytelling systems focus on the engagement of users through a curated history of the visual analysis process Gratzl et al. [2016]. But as Gratzl et al. note, there is a disconnect between the two parts of the reproducibility requirement: "existing storytelling tools focus on how to tell a story, but rarely base the story on provenance data" Gratzl et al. [2016].

To address this gap, Gratzl et al. design a model they call CLUE that brings together provenance capabilities with communication strategies. By implementing CLUE within a visual analysis tool, an analyst can explore their data, while CLUE captures a trail of their interactions. The analyst can then review the provenance data to craft a story that captures the important steps of getting to their results, which is bundled into an interactive artifact called a *vistory* for sharing with others. The authors describe the purpose of a vistory: "Vistories can be shared and encourage collaborative visual data analysis. Consumers can step through a story, but also switch to the exploration mode and interactively build upon the previous analysis to gain new insights" Gratzl et al. [2016].

Replication is inherently an act of entanglement that engages a person in the practices of someone else. A vistory provides the substrate for entanglement with a previous visual analysis session. It captures a trace of an analyst's intra-actions that mattered for a resulting insight, and then makes those intra-actions available to someone else. A vistory expands the possibilities for intra-actions by entangling someone in another's entangled insight; it is an invitation to revise and refine a finding. The entanglements that a vistory affords exemplifies the dynamic and collaborative nature of visual analysis (and of science more broadly). So, it is not *just* the affordances of provenance combined with storytelling that defines a vistory, but the possibilities it affords for entangling others with intra-actions and insights that came to matter.

A study by Dou et al., however, indicates that the user-tool interactions that provenance systems currently capture are not enough for replication. In their study Dou et al. show that non-experts could not fully recover all of the insights of financial experts from the interaction logs of the experts' visual analysis sessions Dou et al. [2009]. This is because the intra-actions that matter for any given insight are complex and multifaceted, and extend well beyond user-tool interactions. What other intra-actions could (and should) provenance systems capture? How do we identify and communicate a more complex entanglement of intra-actions?

Given the complexity of entangled insights, it is worth considering whether reproducibility of visual analysis is itself a productive goal. Is it possible to capture and communicate *every* intra-action that mattered? Work by Meyer & Dykes suggests a different approach, one based on supporting judgements about the plausibility of insights: "provide clear, open, and honest descriptions of analysis processes; release memos, design expositions, and other reflective documents; report on dead-ends and failures" Meyer and Dykes [2019]. Thinking about intra-actions instead of context – context being the more familiar user-tool interactions currently captured in provenance systems – we are presented with the opportunity for a richer, more authentic record of a visual analysis session. We expand these recommendations with other intra-actions that come to matter in a visualization analysis session: What experiential aspects of visual analysis are important for others to understand the work of an analyst? How do their experiences, beyond what is on the screen, affect how they do science, read a chart, discover an insight? By expanding our focus to include the procedural, embodied, tacit, emotional knowledges that are often embedded within interactions, visual analysis provenance tools have the capacity to entangle others in the *how* of knowledge rather than the what.

Marking intra-actions that matter with annotations

In writing about sensemaking, Heer et al. offer that "sensemaking is often a social process. People may disagree on how to interpret the data and may contribute contextual knowledge that deepens understanding" Heer et al. [2009]. To experiment with how visualizations can contribute to collaborative sensemaking, Heer et al. designed a website called *sense.us* that combines visualizations of US Census data with mechanisms for sharing insights about the data. Motivated by the awkwardness of referencing visual elements in mainly text-based discussion threads, they implemented a unidirectional bookmarking system where users can bookmark a visualization state that would take another user to that visual reference; or while exploring visualizations, if there were comments associated with the visualization state's current parameters, then associated comments would appear. This design decision was meant to facilitate "situated conversation[s]" about the visualization, because, as Heer et al. state: "for users to collaborate, they must be able to share what they are seeing to establish a common ground for conversation" Heer et al. [2009].

An interesting observation made by Heer et al. during their study of how people used sense.us, was that "[v]isual data analysis, historical knowledge, and personal anecdote all played a role in the sensemaking process, explicating various factors shaping the data" Heer et al. [2009]. This observation is reflected in an asynchronous exchange between two users of sense.us that is reported in their paper. One user linked to a view showing that the percentage of dentists in the labor force declined over time, while the percentage of dental technicians increased over the same time period increased. Another user engaged with this view and commented: "I wonder if school has become too expensive for people to think about dentistry, or at least their own practice when they can go to technical school for less?"

Sense.us entangles people and data across time and space, and it does so through mechanisms that allow people to mark the intra-actions and insights that matter, and to make those markings public. The commenting feature provides a mechanism for a user to externalize and communicate their insight, and the bookmarking feature allows a user to mark the view that led them to their insight. Taken together, the design decision to show the comments of users associated with specific states of the visualization is an act of displaying intra-actions that have mattered to users at different times and places. These features also turn insights into intra-actions: an insight that is captured from one person becomes an intra-action opportunity for another. The example we provide of the conversation between two users over dentistry jobs illustrates that the data analysis of the first user is revised and expanded by the second. This entanglement, in turn, then becomes the basis for other, future, possible insights to emerge. This interaction demonstrates that insights are not fixed pieces of information, rather they are emergent from the entanglement of intra-actions that matter.

Marking the insights and intra-actions that matter is an act that communicates a specific and entangled perspective. A core argument that underlies Barad's theories is that knowledge is objective and real, but entangled,[6] and it is by reading through diverse entanglements that we arrive at a rich, full, and objective view of the world. The commenting features of sense.us are one example that supports collecting and communicating varied and diverse entangled insights. But what are other ways to mark and capture insights and their intra-actions? How do we support marking intra-actions beyond annotations? How do we let others read through these insights? We speculate that visualization has an important role to play in addressing these questions.

[6] The entangled nature of knowledge that Barad argues for in her agential realism is built upon the earlier framing by Haraway of situated knowledges Haraway [1988].

Entangled artifacts from design study

Working with global health experts and Zika virus data, McCurdy et al. were set up for a classic design study: "there were data, there were clear domain tasks, and our collaborators were interested in exploring new approaches to visualization" McCurdy et al. [2019]. Like many design studies, it was through early, frequent interactions with their collaborators that the team was able to learn about the domain. They translated this learning into data and task abstractions that informed the design of their original prototype. Evaluation of the prototype was positive from multiple stakeholders.

When trying to deploy the prototype to their primary collaborators, however, the visualization team noticed a hesitancy by their collaborators to use the tool for their analysis work. In probing this hesitancy, they learned that while the visualization "was an effective reflection of the data, the data itself was not an accurate reflection of what the experts knew about the current status of the Zika outbreak." They engaged their collaborators through a variety of methods to understand the scope and scale of the problems with the data. What they learned informed the design of an annotation feature they implemented in their prototype to support externalization of the knowledge the experts had about the data discrepancies, as well as visual encodings of the annotations to support communication of that knowledge across the expert community.

Throughout the design study, McCurdy et al. learned many things about the domain, data, intuitions, and work practices of their collaborators. The things they learned – design insights – emerged through their practice of design study. This practice entangled a multitude of intra-actions with the emergence of numerous design insights, which ultimately became entangled with and within the resulting visualization artifact. Design study is a practice that purposefully seeks out opportunities for intra-actions, recognizing the more, the better Sedlmair et al. [2012], Meyer and Dykes [2019]. The results of design study are complex, dynamic entanglements of people, data, visualization, processes, conventions, history, power, and so much more. These entanglements are deeply embedded in the visualization artifacts that emerge.

Design researchers already embrace the entangled nature of artifacts, noting that "knowledge resides in [artifacts] themselves"Cross [1999]. These researchers recognize that design insights are not reducible to a set of measurements, facts, or statements, but acknowledge that "much of the value of [artifacts] as carriers of knowledge can be implicit or hidden" Stappers [2007]. The entangled nature of visualization artifacts leads to two crucial questions: How do we as designers come to understand the intra-actions that matter in the emergence of a visualization artifact? How do we communicate these intra-actions to others?

In response to the first question, Dumit proposes *implosion workshops* as a pedagogical tool to help students investigate the hidden genealogies of a particular object Dumit [2014]. What would an implosion workshop be for visualization designers? What are the hidden genealogies that matter in the emergence of a visualization? And more provocatively, what are the possible intra-actions yet to come that are entangled with a visualization that exists now? We point to engagements across different fields, where researchers and practitioners are interrogating the future possibilities of how their work may potentially cause physical, emotional, and societal harm spo, Gebru et al. [2018], Parvin and Pollock [2020], Hecht et al. [2018] as inspirations for helping us understand the future implications of our visualization designs.

As for the question on how to communicate the entanglements of visualization artifacts, we point to several lines of existing work in the visualization community that offer possibilities. One proposal is that of *literate visualization*, which is the act of crafting a narrative that justifies design choices to external audiences, with deliberate attention to articulating competing design decisions and forking paths Wood et al. [2019]. Another is *trrrace*, a conceptualization that supports tracing the emergence of a visualization artifact for the purposes of recording, reflecting, and reportingRogers et al. [2021]. Both of these ideas help to expose the practice of visualization design, and offer starting points about how to further expose the entangled intra-actions that make a visualization artifact matter.

Conclusion

In this paper we expose the limitations of the visualization community's current conception of insight. Through the lens of feminist theory, we point out the short-comings of our representationalist perspectives on context and insight, and argue that in reality, context and insight are dynamic, relational, and inseparable. Drawing from Karen Barad's theory of agential realism, we reconfigure the concepts currently used to describe insight – context, influence, production, and relevance – into the new materialist concepts of *entanglement, intra-action, emergence, and mattering*. We use these reconfigurations to offer a new conceptualization of insight, which we call *entangled insight*. Through a series of examples, we show how entangled insights are already visible and supported in visualization research, and that naming and understanding them as such opens new opportunities for research and design.

Entangled insights expose the complexity of how insights come to be. Our conceptualization states that the practice of visual analysis – and visualization design – engages intra-actions of influences, enabling insights that matter to emerge. Entangled insights place the focus on *how* insights emerge over *what* insights and their contextual influences are. These influences are inseparable from insight, and also meaningless without considering the intra-actions that entangle them. This new conceptualization invites us to reimagine the roles of people, visualizations, data, processes, conventions, history, and power as part of the relationships and dynamics that contribute to a particular insight. Embracing the idea of entangled insights, however, upends some of the most basic assumptions of visualization research.

Prior work on insight regards it as a distinct unit of discovery: static, delineable from context, and measurable. Our (traditional) visualization tools are designed to help users gain insights through interacting with data in a visual way. Our (traditional) evaluation methods judge how effective these tools are in getting a user from point A (no insight) to point B (insight), collecting additional points if multiple insights are produced, if those insights speak to a domain, or if those insights are unexpected. As we have illustrated in this paper, however, insights cannot be reduced to discrete units of information, nor are they simply waiting to be revealed. Furthermore, all insights have value, even as this value may change in response to a particular task, a particular user, a particular setting, or a particular time. Indeed, insights emerge from specific intra-actions and come to matter through the practice of visual analysis. These intra-actions are inseparable, relational, and dynamic; and so too, are insights.

But questions remain: How do we evaluate the efficacy of our tools if we cannot untangle and identify their effects on insight emergence? How do we probe into the nature of insight if we are hopelessly entangled in its emergence? From these questions, it would seem that an embrace of entangled insights fundamentally challenges how we conceive of visualization research and how we conduct it.

This supposition is true. To answer the questions posed above requires nothing less than a rethinking of our community's epistemological assumptions and values — that is, how we understand the nature of knowledge and the processes by which that knowledge is formed. Our field currently relies primarily on a positivist epistemology: the belief that all knowledge can be observed, quantified, or otherwise captured in the world. This belief system has led us to consider only representationalist approaches to visualization: those that seek to represent, encode, or otherwise model the more complex phenomenon that we encounter in the world. These approaches, however, are fundamentally at odds with the idea of entangled insights. But an expansion of our field's epistemological framework, in line with the expansion that Barad's theory of agential realism describes, can offer a wealth of new opportunities for us to rethink the process of visualization knowledge production. After all, Barad's agential realism isn't only composed of a bunch of concepts; together, they offer a framework for a revised understanding of the nature of knowledge and its production, the nature of the reality that knowledge seeks to describe, and the role of people (and other objects and entities) in it. Barad names this capacious frame an *ethic-onto-epistemology*, so as to indicate that questions about the nature and composition of reality (ontology) and the human role in it (ethics) are themselves entangled.

Fully comprehending the implications of an ethic-onto-epistemological framework for visualization research will never be complete. But we can begin this work by imagining some of the future possibilities for visualization research that might emerge from this worldview. Here are three such provocations:

On objectivity: Objectivity becomes redefined as engaging clearly and intentionally with entanglements and describing what matters, rather than relying on measurements or enumerating properties. Objectivity becomes an act of exercising knowledge and responsibility in order to understand how and why entanglements differ. The idea of entangled insights recognizes that insights can be objective, but it also necessitates discussions about how and why they matter. This leaves us with the recognition that it is no longer sufficient for us to count insights for objectivity to be achieved. Instead, we must push ourselves to engage with entanglements and ask: How might we develop additional practices – visual, procedural, descriptive, and more – that allow us to understand and describe these entanglements more fully?

ON ETHICS: Ethics becomes a fundamental part of visualization research, inseparable from questions about the nature of the knowledge, how that knowledge is formed, and who (or what) forms it. This arises from an understanding of entanglement as including all the influences that came before, and all the effects that come after. In other words, the past is entangled with the future. If this is so, we must necessarily consider the ethical implications of the tools that we build, as well as the prior influences that have brought us to this point. Furthermore, we must recognize our role as visualization researchers and designers as enabling (or disabling) intra-actions through our tools. These intra-actions have the potential to serve as inflection points, altering future impacts. How can we mitigate future harms and design for more just, equitable, and environmentally sustainable futures? How can we do so while also we recognizing that humans are only one set of influences among many?

ON CAUSALITY: Finally, we must recall causality. As visualization researchers, we continue to care about understanding the role that visualizations play in sparking insight; a causal relation. At first glance it may seem that an ethic-onto-epistemology does not support an inquiry into causal relations, since the distinctions between influencer and influenced, cause and effect are blurred. But it is more that the ideas of entanglement and intra-action require a new conceptualization of causality, one that considers how the power imbalances among influences affect the nature of specific entanglements as well as the intra-actions that constitute and connect them. What, then, are the systems, people, institutional biases, personal preferences, and other influences that intra-act during a visual analysis session? How can those be incorporated into a richer explanation of how insights emerge? How might entangled insights encompass additional practices and ways of knowing, those that simpler explanations about insight production cannot include? Can understanding visualizations as interventions into entanglements help us design tools more appropriate for the intended task? Can visualizations themselves intervene into the unequal power relations that characterize our field?

These are only some of the questions prompted by the idea of entangled insights proposed in this paper. We hope that these questions, and the idea of entangled insights that underlies them, will inspire future work that engages responsibly with the intra-actions that matter.

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