# Visualizing Uncertainty:

## *Developing an Experiential Language for Uncertainty in Data Journalism*

**Mac Hill**

Department of Graphic Design and Industrial Design,
College of Design, North Carolina State University
*9 May 2018*

Submitted in partial fulfillment for the degree of
Master of Graphic Design

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# Abstract

Data journalism has become a pervasive feature of mass media, with infographics and visualizations appearing online, in television coverage, and in print. While visualizations in mass media can render data accessible to the public, they can also give users a false sense of truth and certainty. Uncertainty, in the form of incomplete or imperfect data, exists in all information and visualizations; it can be introduced during collection, analysis, or even during the design process, but it is often left out of final information visualizations. Conveying the uncertainty involved in a data set provides users with a fuller picture and a more in-depth understanding of an issue.

Currently, there is not a robust, experiential visual language for conveying that uncertainty. While there are methods for visualizing uncertainty in scientific or statistical figures, these graphics are typically created for audiences familiar with the visual language of scientific data, making them inaccessible to non-expert audiences. This gap provides an opportunity for design methods and research to develop techniques for non-expert audiences. Drawing from design methods and frameworks, particularly explorations of visual form, in addition to statistical and scientific methods for conveying uncertainty, this investigation examines experiential techniques that data journalists can use to convey uncertainty in statistical and scientific information to a non-expert audience.

**Miles "Punkin Duster" Johnstone**
@johnstoneing

So I think we can all agree that the @UpshotNYT needle is the biggest winner tonight.

11:51 PM - Dec 12, 2017

♡ 115 18 people are talking about this

**Atrios**
@Atrios

oh needle I love you marry me

11:21 PM - Dec 12, 2017

♡ 125 15 people are talking about this


**Benjy Sarlin**
@BenjySarlin

Me 10 minutes ago: What's this NYT needle I've hard so much about

Me now

10:28 PM - Dec 12, 2017

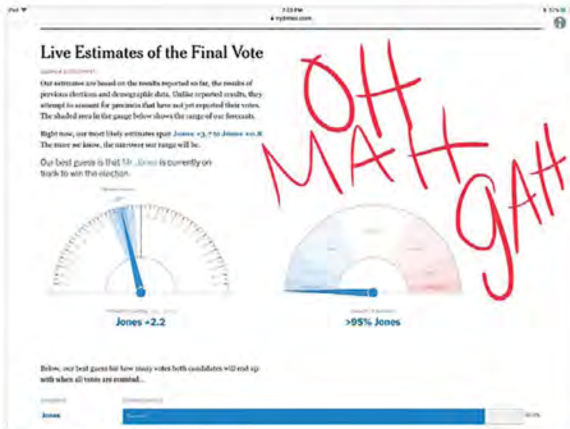
♡ 346 98 people are talking about this

**Trillmonger** 🌹
@KnifeOfDamocles

The New York Times election needle should win Time's Person of the Year in 2018.

1:11 AM - Dec 13, 2017

♡ 46 See Trillmonger 🌹's other Tweets




**Imani Gandy**
@AngryBlackLady

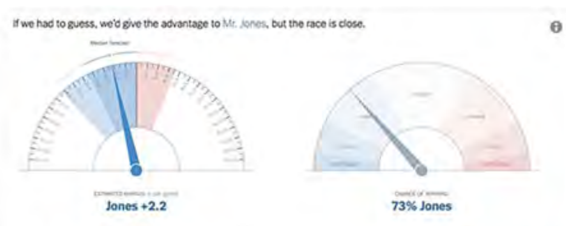
All hail the Needle.

For the greater good!

(The greater good!)

11:25 PM - Dec 12, 2017

♡ 405 87 people are talking about this




**Amee Vanderpool**
@girlsreallyrule

Here is the @nytimes race needle if you want to push this whole heart attack thing along...nytimes.com/elections/resu...

11:13 PM - Dec 12, 2017

♡ 97 42 people are talking about this

**Jon Favreau**
@jonfavs

I love/hate/love/hate that fucking NYT needle.

9:43 PM - Dec 12, 2017

♡ 10.6K 1,327 people are talking about this

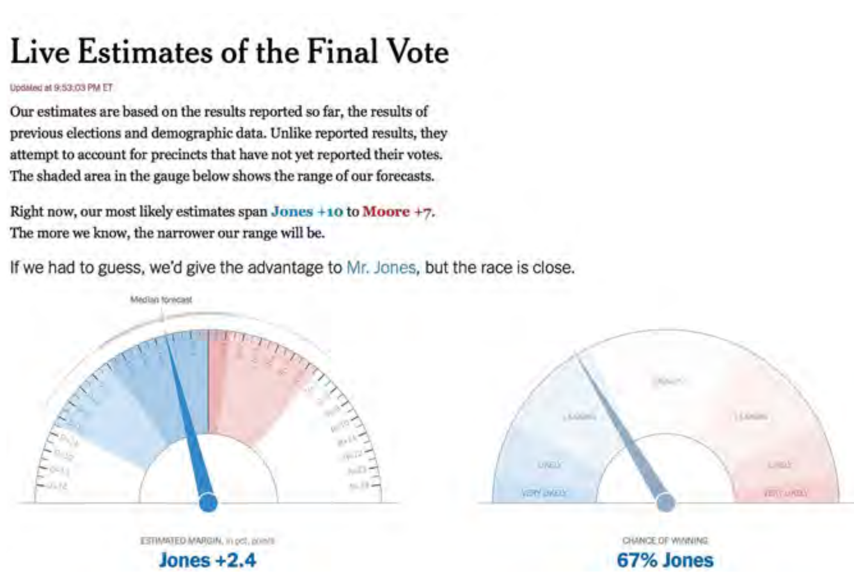
# Introduction

Mass media has embraced data journalism as the future of storytelling. *The New York Times* includes an entire section dedicated to visualizations, and Nate Silver's *FiveThirtyEight* attracts users with articles and visualizations based heavily in data storytelling. Infographics and visualizations appear online, in television coverage, and in print. In rendering data accessible to the public, visualizations often give users a false sense of truth and certainty. All information contains some form of uncertainty, or moments of incomplete or imperfect information. Any interaction or manipulation of data, be that collection or analysis, can introduce uncertainty, but it is often left out of final information visualizations. The creators of graphics can provide a fuller picture of information by conveying the uncertainty involved in their formation.

During the 2016 presidential election, *The New York Times*' election coverage incorporated two moving "needle" gauges to convey the uncertainty in their election forecasts (Figure 1). The needle, as The Times (Wartik, 2017) has taken to calling it, was an object of both "obsession and derision," sparking social media hashtags and a host of memes (Figure 2). The reaction to, and evolution of, the needle points to a desire among users and designers for more complete visualizations, ones that can convey moments of doubt alongside confidence.

Figure 1: **"The Needle"** (Below) *The New York Times'* needle interface for election results.

Figure 2: **Twitter Responses** (Opposite) Responses to *The New York Times'* Election Needle on Twitter.



The needle, and information visualizations in general, give users the opportunity to explore information quickly and on their terms. With the rise of big data, almost every aspect of modern life—shopping patterns, web searches, voter behavior—has become a data source. Nearly every aspect of modern life involves some form of data collection, to the point that missing data makes as much news as the data itself (Bach, 2018). The pervasiveness of big data provides unique opportunities for us to explore the world around us through numbers and statistics. Data and its collection, however, removes information from the original phenomenon that it represents and can be difficult for individuals without specific training or expertise to understand. This gap in understanding provides a unique problem space for designers to explore methods for making information accessible. This investigation looks at one particular problem space for understanding, uncertainty, but it points to further issues that arise from the pervasiveness of data and visualization, including the accessibility of scientific information and the necessity of visual literacy.

For designers, the accessibility of data and new forms of information provide a unique opportunity for storytelling and information design. Uncertainty, in particular, offers a particular challenge to those wishing to convey a complete picture of information. Currently there is not a robust, experiential visual language for conveying uncertainty. While there are methods for visualizing uncertainty in scientific or statistical figures, those graphics are typically created for audiences familiar with the visual language of scientific data, making them inaccessible to non-expert audiences. These graphics cannot be interpreted intuitively and require a great deal of background knowledge to make sense of their forms. Designers can employ user-centered design methods and research to expand visualization techniques to non-expert audiences. Using a human cognition framework, this investigation explores experiential techniques that data journalists can use to convey uncertainty in statistical and scientific information to a non-expert audience.

# Area of Investigation

## PROBLEM STATEMENT & JUSTIFICATION

Big data has become a pervasive part of our society. Almost every aspect of modern life—air quality, weather conditions, voter behavior, the performance of sports teams, and more—is statistically measured and forecast (Nguyen & Lugo-Ocando, 2016). Despite the prevalence of scientific and statistical data, the visual language that scientists and statisticians use to present information often requires an expert level of understanding to interpret, making the visuals that use this language inaccessible to the majority of the population (Grainger, Mao, & Buytaert, 2016). Furthermore, the software scientists and statisticians use also requires a level of user knowledge and produces static and inaccessible visualizations that exacerbate the gap between experts and non-experts. In many ways the news media has stepped in to bridge this divide. *Data journalism*, or storytelling through infographics and data analysis, has become a prevalent part of mass media, with infographics and visualizations appearing in print, online, and in television coverage (Bradshaw, n.d.). *The New York Times* has an entire section—*The Upshot*—devoted to the exploration of data as it relates to current events, and Nate Silver's *FiveThirtyEight* reaches upwards of 10 million unique users each month (Silver, 2017a). Visualizations produced for the mass media can give users a false sense of truth, especially when conveying predictive data, or data that forecasts future activity, such as that found in election projections or weather forecasts (Spiegelhalter, Pearson, & Short, 2011). Few visualizations show instances of doubt behind the quantities, giving infographics in news media an unwarranted authority. Uncertainty, however, exists in all data and subsequent visualizations, and can stem from all phases of data collection and presentation, including the nature of the information itself, the method of visualization, and the biases of the analyst (McInerny et al., 2014; MacEachren et al., 2012). All information contains elements of uncertainty, such as contradictory *data points* or *outliers* in a data set. For the purpose of this investigation, *uncertainty* is incomplete or imperfect knowledge arising from a variety of factors including: measurement precision, completeness, inferences, disagreement, and credibility (Skeels, Lee, Smith, & Robertson, 2010). Creators of information graphics, however, strive for completeness, and therefore leave out uncertainty, partially to make the information easy to digest quickly, and partially to feed the audience's desire for

**Data Journalism**
Storytelling through infographics and data analysis.

**Data point**
A piece of information.

**Outlier**
A data point on a graph or in a set of results that is very much bigger or smaller than the next nearest data point.

**Uncertainty**
Incomplete or imperfect knowledge.

Figure 3: **2016 Visualization** (Below) *FiveThirtyEight's* visualizations of the 2016 election relied on percentages to convey the uncertainty involved in the data.

certainty. Including representations of uncertainty in information visualizations provides a more robust picture of the data being conveyed. The presentation of data has an impact on its meaning to a user, and, consequently, on the user's ability to make decisions based on that data (Bond et al., 2007). Predictive data visualizations are used across news media and cover topics ranging from weather forecasts to election polling. In particular, these visualizations can have mundane impacts on daily life, for instance forgetting an umbrella on a rainy day, or they can impact major life decisions, like choosing to evacuate before a hurricane.

Recently, predictive visualizations in data journalism have become a standard part of national politics. Consider, for example, the pervasive role of statistical projections in the 2016 Presidential election. Users interpreted the visualizations and analysis presented by data journalists such as Nate Silver from *FiveThirtyEight* as showing Clinton with an insurmountable lead all the way up to November 6th, 2016, only to have Donald Trump win the Electoral College and the presidency (Figure 3). In his analysis of the journalism leading up to the election, Silver points to "a failure to appreciate uncertainty" (2017b). Throughout the campaign, the polls used to create *FiveThirtyEight*'s and other sites' visuals had "hallmarks of high uncertainty," yet the infographics and visualizations showed no sign and instead relied on percentages and odds that suggested Clinton's lead was inevitable, potentially impacting voter behavior (Silver, 2017b).


Part of the challenge for mass media infographics is the lack of a robust, experientially based visual language for conveying uncertainty in the data. This problem also exists in the scientific community where even the definition of uncertainty is debated (Skeels et al., 2010). Furthermore, non-experts do not always understand the techniques experts use. As a result of these challenges, journalists often leave uncertainty out of visualizations and simply incorporate it into the accompanying text or the caption, relying on the user to engage with the text and not just look at the graphic representation.

A design approach can help non-experts understand scientific or statistical data by visually translating what is happening behind the numbers. Traditionally, a tension exists between scientific visualizations and design aesthetics. In the scientific community, visualizations that are aesthetically sophisticated or especially engaging to lay audiences are often looked upon as untrustworthy (McInerny et al., 2014). Scientific and statistical figures are typically created for audiences familiar with the visual language of scientific data, which, in turn, provides an opportunity for graphic design methods and research to expand those techniques to non-expert audiences (Grainger et al., 2016). Visualizations in mass media are not, and should not be, simply pretty pictures that break up a text, but must be designed as tools for understanding complex relationships that exist behind the scenes, in the numbers, and upon which any given visualization is derived. Designers can and should incorporate a full range of techniques to convey the true nature of information to a user, regardless of knowledge level—especially when designers, who are operating in interactive and time-based media, possess a variety of tools capable of telling the story behind the data. An approach grounded in our understanding of human experience and perception can focus on the cognitive needs of non-experts by incorporating techniques familiar in communication design, such as the use of interaction, narrative, and animation, not traditionally employed in expert-oriented data visualization.

Developing techniques for conveying uncertainty to non-experts requires a broad understanding of the techniques experts in the scientific community use, as well as how a user cognitively interprets information visualizations. This knowledge can support designers' exploration of techniques for visualizing uncertainty, which will, in turn, result in the field's ability to pinpoint methods that can experientially convey uncertainty to non-expert audiences. It is also important to consider potential users when developing these techniques. A design approach can visually translate what is happening behind the numbers in a way non-experts can understand. Through a review of the literature, an examination of precedents, and several graphic studies, this investigation attempts to develop a design vocabulary for visualizing uncertainty to a non-expert audience.

## ASSUMPTIONS AND LIMITATIONS

### Assumptions

For the purposes of this investigation, I assume that users want an accurate understanding of the data they encounter in news media and that the uncertainty involved in a data set can add to that understanding. News media is defined as those elements of the media that focus on delivering news to the general public ("News media," n.d.). This investigation focuses on digital and interactive news formats, like those found on websites and apps. Furthermore, I assume these visualizations are part of a larger article or piece of journalism that provides greater context to the visualization. These visualizations convey information on one specific part of a larger phenomenon and provide a focused analysis of that moment for the user to explore, rather than an overarching explanation of the whole phenomenon. Limiting the scope of these visualizations allows for studies to highlight specific moments of uncertainty that could be incorporated into larger scale visualizations.

From the literature review, it is clear that information visualizations provide a real challenge to understanding for non-expert audiences, especially for users with limited visualization literacy. This study assumes a minimal visual literacy level and looks for experiential methods to overcome challenges to interpretation. However, some basic skills are assumed, such as the ability to interpret an x-y axis.

#### Limitations

To move forward with this investigation, it is important to make clear what this investigation is not. This investigation does not address three-dimensional methods for visualizing uncertainty. 3D visualization methods introduce new comprehension and literacy issues that are beyond the scope of this investigation and further complicate information visualization methods.

This research is not a definitive statement about the cognitive processes involved in interpreting information visualizations. It employs a human cognition framework for data visualization to relate visualizations to specific cognitive processes—which does not suggest that multiple processes are not involved in working with each visualization, nor that a single process is dominant. This human cognition framework simply provides a conceptual space within which to ground design investigations that also acknowledge cognitive processes.

Furthermore, while I have made every attempt to maintain the accuracy of the data used to create mini explorations and studies, I am not an expert in statistics. The studies in this investigation should be examined for their design and the experiential methods that convey uncertainty, rather than for statistical inaccuracies or mistakes.

# Literature Review

This research began with an in-depth inquiry into information visualizations, visual literacy, and the relationship between non-experts and forecasted information. This brief review of the literature points to overarching issues between information visualizations created for the mass media and the language of science and statistics. While visualization is a valuable cognitive tool, the visual language used by experts is often inaccessible to most of the public, and can provide flawed or even false insights.

## MEANING FROM VISUALIZATIONS

Designers create information visualizations to convey complicated information in a quick and efficient manner, however, the process of deriving meaning from visualizations is dependent on the user. When designers create information visualizations, they rely on the assumption that the user is able to interpret the patterns, trends, and correlations represented (Börner, Maltese, Balliet, & Heimlich, 2016). Meaning itself is not set by the graphic, but created in the mind of the user; as Chandler posits, meaning is a construction, with a user making sense of what is seen or heard (2004). Visual images themselves can be interpreted in many ways and depend on users understanding the system of symbols portrayed (Drucker, 2014; Davis, 2012). Peirce calls the consumption of signs in images, signification. Signification is a mental process where meaning resides in the mind of the user (Davis, 2012). Information visualizations themselves rely heavily on users to derive meaning from what they are shown. To create successful information visualizations, designers must consider the interpretative abilities of the end user and the significance of the visual images and symbols used to convey that information.

An image, however, does not exist in a vacuum. Peirce and other theorists assert that the context of an image can impact its interpretation (Davis, 2012). Chandler (2004) stated that the medium through which a visualization is conveyed can impact the message's meaning and effectiveness. It is difficult to separate an image from the technologies that produce it, as the image itself embodies the qualities of the media in which it exists (Drucker, 2014). With the production of meaning relying on the mind of the user, designers working on information visualizations must consider carefully the context, medium, and tools they use to create visualizations.

## INFORMATION VISUALIZATION AS COGNITIVE AID

Information visualizations rely on users' ability to interpret and make sense of abstraction to convey complicated entanglements of ideas with an economy of means, or through simple forms and representations (Cairo, 2014; Tufte, 2013). Adults encounter visuals in a wide variety of contexts including work and everyday life (Börner et al., 2016). These visualizations become cognitive aids that assist users in understanding issues and making decisions.

Visualizations act as cognitive tools by compressing complicated information into manageable pieces, such as signs and symbols, focusing on what is most important, and eliminating extraneous information (Ryan, 2016). This compression is a form of abstraction, like those Latour described as cascades of inscriptions (Roth & Tobin, 1997). Latour argues that in order to understand different phenomena, humans collect information in slightly abstracted forms, then create further abstractions to represent that information, thereby creating *cascades of inscriptions* (Roth & Tobin, 1977). These inscriptions act as cognitive aids for users to share and translate information, however, they also are removed from the phenomena they represent, which can obscure information or make it difficult for users to fully understand a phenomenon. Our interactions with these processes are a type of *external cognition*, which decreases the users' required cognitive effort and allows for the processing of more complex information (Scaife & Rogers, 1996). Abstracting information away from the initial phenomenon is part of human intelligence. Norman argues that humans abstract away irrelevant details in a way that creates new experiences, insights, and creations (1993). Abstraction provides a means for humans to better comprehend complicated phenomena and ideas, but designers must be aware of how visualizations obscure reality.

**Cascades of Inscriptions**

A series of representations of phenomena created by scientists and researchers.

Psychologists have demonstrated that the human brain has separate systems for interpreting verbal and nonverbal information. *Dual Coding Theory* (Paivio, 1991) posits that a nonverbal systems, which is governed by structural and spatial dimensions, is separate from a verbal system, which relies on sequential structures (Figure 4). The human ability to code the same stimulus, or piece of information, through two different channels (verbal and nonverbal) increases our ability to remember and process a piece of information (Paivio, 1991). Information visualizations can use both verbal and nonverbal channels to give users greater opportunities to process and remember the information presented.

**Dual Coding Theory**

Posits that the human brain has separate systems for interpreting verbal and nonverbal information

*Cognitive Load Theory* posits that some materials are difficult to understand and apply because they require processing several elements simultaneously. For example, 2 + 2 is easier for us to solve than 25670 + 235905 because it has fewer elements to process simultaneously. Cognitive load theory deals with the creation of schemas as a means of reducing the demands on short term memory and pull from long term memory (Moreno & Park, 2010). Non-experts may not have a schema for visualizations, which can increase cognitive load and interfere with the primary goal of interpreting the visualization. This

**Cognitive Load Theory**

Materials can be difficult to process because they require a lot of mental effort.

problem suggests that a simplified means of representation is important and that building off of users' existing schemas, or allowing for the development of new ones, can assist in interpreting information visualizations correctly.

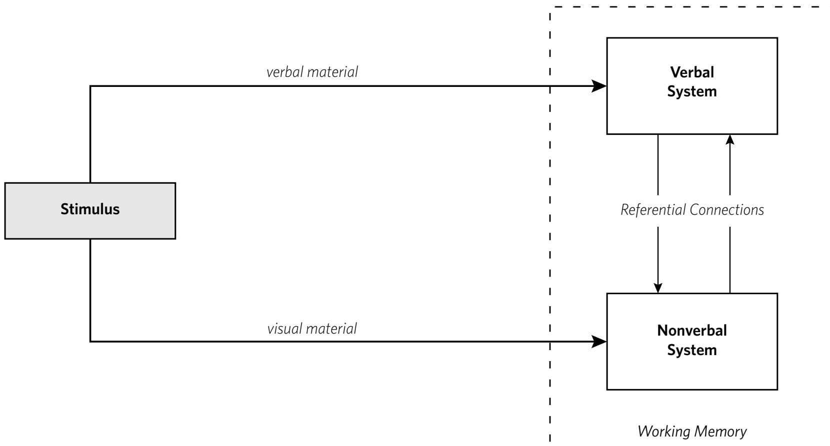



Figure 4: **Dual Coding Theory**
(Left) Information that uses both verbal and nonverbal channels provides greater opportunities to process information.

Other research on the efforts involved in information visualizations suggests that deriving meaning from visualizations involves numerous cognitive processes, including: attention, working memory, pattern recognition, encoding, long-term memory, and decision-making (Patterson et al., 2014). Patterson et al. developed a useful framework for influencing those processes in information visualizations, providing guidelines for designers to build off cognitive research and give users extended opportunities for gaining insights (2014).

Through information visualizations, designers have an opportunity to create powerful cognitive tools that lighten cognitive load and increase understanding. Designers, however, must consider psychological theories of cognition and memory when creating visualizations. Information visualizations are not art; rather, they are carefully engineered tools (Grainger et al., 2016).

## VISUALIZATION LITERACY

While information visualizations can be valuable cognitive aids, they often require a level of technical literacy many users do not have. Börner et al. (2016) define visualization literacy as "the ability to make meaning from and interpret patterns, trends, and correlations in visual representations of data" (p. 200). Studies of non-expert audiences point to strong empirical evidence that many users "cannot name or interpret data visualizations beyond very basic reference systems" (Börner et al., 2016, p. 210). This research suggests that technical names are unfamiliar to most people and the lack of a cohesive language behind visualizations makes it difficult for those without advanced levels of STEM education to understand many forms of visualization (Börner et al., 2016). Authors point out that the lack of a language for data and information visualization, a necessary component of human learning, makes it harder, if not impossible to learn or talk about visualizations. Other studies on non-expert audiences suggest that scientific visualizations remain broadly inaccessible because they emphasize static explanations of research that require specialist expertise to understand (McInerny et al., 2014). The literature and research on visualization literacy suggests that visualizations created for non-expert audiences must be easily discernible, rather than relying on complex visual languages and codes.

## VISUALIZATIONS IN DATA JOURNALISM

Information visualizations have become increasingly popular in mass media; however, the rise of data journalism has led to questions about its impact on journalistic ethics. Journalist and information designer Alberto Cairo (2014) posits that the "point of journalism is to increase understanding while minimizing harm" (p. 25). Researchers and information designers see data journalism as a way to increase understanding about complex issues quickly, with visualizations condensing information into visuals that can be digested in a matter of seconds (Ryan, 2016). The nature of data journalism and the methods used to create visualizations, however, may provide a skewed or flawed version of reality. Spiegelhalter et al. suggest that the processes used are often inherently biased, with statistical analysis and the angle of approach biasing the creation of the graphic itself; for example, showing death rates rather than survival rates (2011). Furthermore, users often do not question graphical representations, giving visuals a sense of authority that may not be warranted (Cairo, 2014; Schrager, 2014). This combination of inherent bias in methods and the air of authority given to visualizations has led journalist Allison Schrager to label data journalism "opinion journalism given more credibility" (2014). Overall, the quality of graphics depends on the quality of reporting and research, or the information being conveyed (Cairo, 2016). For information visualizations to provide a full and robust depiction of information, designers should include depictions of uncertainty rather than abstracting information to a point that uncertainty is removed.

## DESIRE FOR CERTAINTY

Information visualizations in mass media satisfy users' desire for certainty, in some ways at the expense of understanding. Psychologically, humans have a hard-wired preference for narrative or deterministic storytelling, which can lead to misinterpretation of visualizations and information (Ryan, 2016). Mass media and journalism cater to this desire for certainty to increase usership, which conflicts with the uncertain and inconsistent nature of reality (Cairo, 2016). Furthermore, users often do not question graphical representations (Cairo, 2014). In cartography, this phenomenon of accepting information presented in map form as true, simply because there is a graphic to explain the information, is called "cartohypnosis" (Boggs, 1947). When a user does not question the information presented, she is accepting the creator's conclusions as fact, which can be problematic considering the inherent biases of information visualization, like data exclusion and manipulation (Schrager, 2014). When designing for uncertainty, designers must make representations clear to combat users' tendency to misinterpret information in favor of certainty.

## THE PROBLEM WITH PROBABILITIES

Probabilities and frequencies are often used in information visualizations to convey uncertainty; however, research has shown that audiences struggle to understand their meaning or how to work with multiple probabilities. One study found that 25% of US participants given three different frequencies, specifically 1 in 100, 1 in 1000, and 1 in 10, could not determine which number represents the biggest risk of getting a disease (Spiegelhalter et al. 2011). Furthermore, audiences' pre-wired desire for determinism and certainty leads them to translate probabilistic information into fixed terms, making it difficult to properly interpret information, as demonstrated, for example, in a weather forecast that displays percentages and probabilities (Ryan, 2016). In the case of weather forecasts, people interpret a forecast of 90% chance of rain in multiple ways: it will rain for 90% of the day, 90% of an area will see rain, or 90% of users will see rain, when in actuality it is a percentage based on confidence and area that gives the percent chance that rain will occur in some part of the area (Ryan, 2016; Spiegelhalter 2011). This failure to understand and interpret basic frequencies provides an added challenge when representing uncertainty and can lead to flawed decision-making.

Graphical representations have been shown to aid users in interpreting probabilities. Spiegelhalter et al. (2011) point to pie charts and other visuals that provide parts-to-whole comparisons as easily interpretable visuals for probabilities. Other researchers however caution that the information being conveyed has to be complicated enough to warrant a visual (Wright, 2009), which suggests that information dealing with multiple probabilities or percentages could benefit from visualization, while simpler probabilities may not. Overall, the visualization and representation of probabilities provides a unique challenge, requiring information designers to consider both the complexity of the information and the visualization itself.

## EXPLORATORY RATHER THAN EXPLANATORY

Much of the literature surrounding information visualization emphasizes the need for interactive visualizations that users can explore, rather than static explanatory figures. McInerny et al. (2014) point out that "science is strongly biased towards 'explanatory' figures that summarize information rather than producing 'exploratory' knowledge interfaces where audiences can 'learn by doing'" (p. 153). Researchers suggest that interactive visualizations can engage users of different literacy levels and needs (McInerny et al., 2014; Wright, 2009). Interactive visualizations can act as cognitive tools, allowing users to explore at their own pace, and decide what pieces of information are valuable to their own needs (Grainger et al., 2016). Wright's research on users' interactions with interactive visualizations suggests that users need tools to limit or refine information to aid user understanding, much like a shopping interface (2009). Introducing uncertainty into visualization, by nature, suggests complicating the abstraction. Information designers working with representations of uncertainty must consider how to scaffold interactive visualizations so that introducing uncertainty does not overly complicate the interactions and impair usability. Interactive visualizations have a unique opportunity to engage a variety of users, but to function properly they must scaffold information to be usable by a variety of users with minimal guidance (Wright, 2009). Since the meaning of a visualization is created by the user, and not the visualization itself, designing visualizations as interactive interfaces gives users more opportunities and tools to derive meaningful information that fits their needs or interests.

## UNCERTAINTY AND DECISION MAKING

Information visualizations can be valuable decision-making tools, but leaving out uncertainty provides a skewed picture, reducing the value of visualizations for making informed decisions. When making decisions, the problem most people face is not access to information, but the ability to assimilate and interpret information in a timely manner (Wright, 2009). By visualizing information in a way that conveys uncertainty, users are empowered to make educated decisions. Presenting a range of possible outcomes can help decision-makers understand the inherent uncertainty of a scenario and aid in decision-making (Grainger et al., 2016). However, the presentation of a data set, as well as the underlying uncertainty, impacts the data's value for decision making (Bond et al., 2007). Information designers must convey a full picture in a manner that users can interpret and tailor to their own needs.

# Conceptual Framework

The framework for my investigation is based on types of uncertainty, cascades of inscriptions, external cognition, and Patterson et al.'s human cognition framework for information visualizations.

## TYPES OF UNCERTAINTY

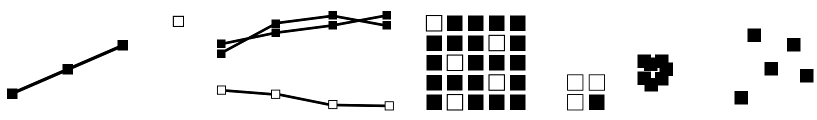



Figure 5: **Uncertainty Types** (Left) This investigation looks at inference, disagreement, completeness, and precision uncertainty, which come from the framework developed by Skeels et al. (2010).

As we collect data and convert into information through analysis and the creation of charts, tables, and graphs, uncertainty is introduced. Collection methods, analysis, and visualization techniques can all introduce uncertainty into information. Skeels et al. provide a definition and classification system for different types of uncertainty present in a data set (2010). The classification system covers multiple variations of uncertainty commonly found in scientific and statistical information. This investigation will focus specifically on four types of uncertainty (Figure 5):

**Inference:** Uncertainty arising from predictions and the meaning given to data.

**Disagreement:** Conflicts in data, whether from multiple measures, different data sets, or from multiple conclusions being drawn from the same data set.

**Completeness:** Uncertainty arising from concerns about sampling methods and generalizing to the population.

**Precision:** Any variation, imperfection or theoretical precision limitations in measurement techniques that produce quantitative data.

Skeels et al. include credibility as a type of uncertainty, meaning uncertainty arising from an information source that produces data in conflict with other data (2010). For this investigation, credibility falls within the other types of uncertainty. This classification system provides a framework for categorizing the visual techniques developed in this study based on the type of uncertainty being conveyed.

## CASCADES OF INSCRIPTIONS

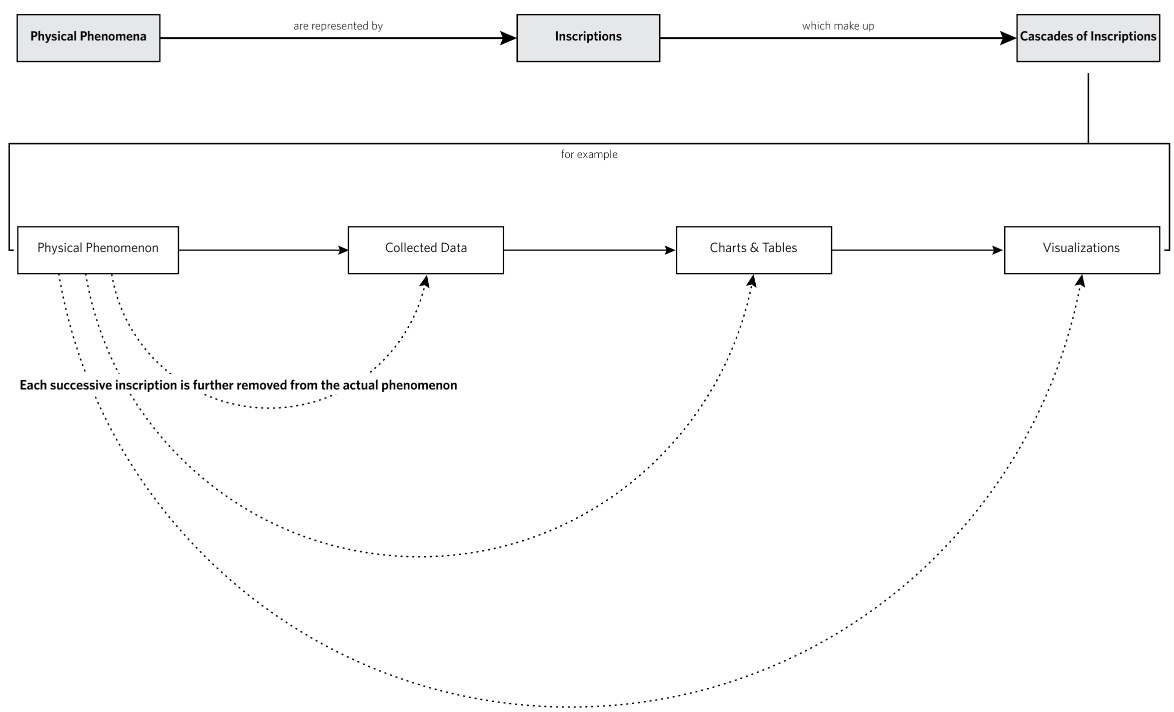



Figure 6: **Cascades of Inscriptions** (Above) Latour's theory describes the process of translating a physical phenomenon into abstract representations,

To make sense of the world around us, scientists, mathematicians, and researchers translate phenomena into inscriptions, such as collected data. Usually, these inscriptions are translated multiple times before a phenomenon is represented in an interpretable form, resulting in what Latour calls a cascade of inscriptions (Roth & Tobin, 1997). Cascades of inscriptions represent the relationship between an observed phenomenon and the mathematical and visual structures, as in information visualizations, that describe and represent the original phenomenon (Figure: 6).

This process of translation removes inscriptions from the phenomena they represent and can result in information gaps. For example, when physicists examine a rolling ball, they translate it's motion into numbers like velocity and acceleration, which are used in equations, then tables, and finally graphs and visualizations (Roth & Tobin, 1997). Each of these levels of abstraction is an individual inscription. Experts, such as scientists and researchers, have been exposed to the language and process of creating inscriptions and therefore no longer see the gaps between inscriptions and real world phenomenon. In contrast, non-experts can have trouble relating inscriptions back to the visual phenomenon they represent and can get lost in these gaps. Non-experts' lack of experience with cascades of inscriptions can impede their understanding of inscriptions, like information visualizations, and their ability to work with the information presented.

Uncertainty, which is introduced at all points of the inscription process, further complicates the matter. Visualizations often leave out uncertainty, further removing inscriptions from the phenomena they represent (Bond et al., 2007; Roth & Tobin, 1997). This omission makes it even more difficult for non-experts to understand scientific and mathematical information.

In this investigation, I use the idea of cascades of inscriptions as a framework for thinking about the different viewpoints of expert and non-expert users. Incorporating uncertainty into information visualizations is a means of moving these inscriptions closer to the phenomena they represent, providing non-experts with a more complete picture.

## EXTERNAL COGNITION

The relationship between a user's internal thinking processes and the external representations of the world around her is referred to as external cognition (Scaife & Rogers, 1996). External cognition explores the role played by external representations on our internal mental processes, providing a framework for how external aids, like information visualizations, can support a user's cognitive processing of information.

External cognition builds off of the idea that humans can devise external aids to extend human intelligence and enhance cognitive abilities (Norman, 1993). Norman (1993) argues that "the powers of cognition come from abstraction and representation," that humans have the unique ability to represent the world and the events that occur around them in new media and to abstract important details away from the irrelevant, and in doing so, we create new experiences through abstraction that are totally separate from the original phenomenon (p. 43). Information visualizations are themselves a new experience created through the abstraction of a natural phenomenon. Scaife and Rogers (1996) define three central characteristics of external cognition:

> **Computational Offloading:** The extent to which representations reduce the amount of cognitive effort required to solve equivalent problems (p. 188).
>
> **Re-representation:** The different external representations of the same phenomenon, which can make problem-solving easier or more difficult, and which can present variable perspectives or information (p. 189).

**Graphical Constraining:** The way graphical elements in a representation are able to constrain the kinds of inferences that can be made (p. 189).

These central characteristics provide a framework for understanding how information visualizations can aid in a user's cognitive processing.

A visualization that does not take into account a user's cognition is simply data, or unorganized and unprocessed facts that do not convey specific meaning. A user must be able to cognitively process a visualization to translate the data it represents into useful information that adds value to the understanding of a subject (Baškarada & Koronios, 2013). From information, a user is able to generate knowledge, or organized information, that can be used to aid decision making (Baškarada & Koronios, 2013). When creating information visualizations, designers cannot simply present information without consideration for the end user's ability to interpret the data presented; otherwise the visualization is simply a form of data that cannot be converted to information and knowledge.

## PATTERSON ET AL.'S HUMAN COGNITION FRAMEWORK FOR INFORMATION VISUALIZATIONS

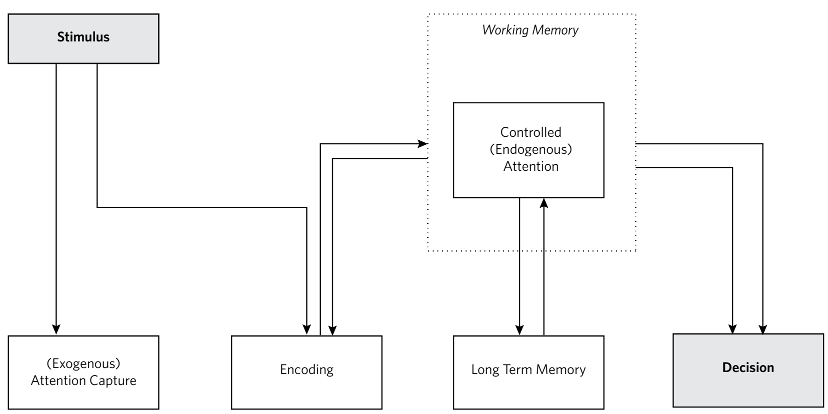



Figure 7: **Human Cognition Framework for Information Visualization** (Left) Patterson et al.'s framework focuses on a user's internal cognitive processes that engage with an information visualization.

Information visualizations have the potential to serve as powerful cognitive tools. Patterson et al. provide a design framework to influence different aspects of human cognition and as a means of inducing reasoning, insight, and understanding (2014). In contrast to the work on external cognition which focuses on the role of visualizations as tools, Patterson et al. examines the role of a user's cognitive processes during interactions with visualizations(Figure 7).

Patterson et al.'s framework involves six cognitive processes—attention, working memory, pattern recognition, encoding, long-term memory, and decision-making (2014). From these processes, Patterson et al. provide six leverage points to influence the cognitive powers of information visualizations. Patterson et al.'s (2014) proposed leverage points are :

**Capture exogenous attention:** Utilize noticeable cues to drive exogenous attention, alerting users to changes in or important attributes of a visualization (p. 47). *Exogenous attention* is the capturing of attention with triggering stimuli in the visual field, often in the periphery.(p. 42).

**Exogenous Attention**

The capturing of attention with triggering stimuli in the visual field.

**Guide endogenous attention:** Provide interaction options to assist *endogenous*, or active, attention and minimize distracting information (p. 48).

**Endogenous Attention**

Active attention

**Facilitate chunking:** Choose visualization parameters that provide strong grouping cues to facilitate the chunking of information, which will minimize the effects of working-memory, or the part of short-term memory that deals with immediate processing, which has severe capacity limitations (p. 48).

**Aid reasoning with mental models:** Organize information based on mental models in order to provide strong retrieval cues for knowledge structures in long-term memory and aid reasoning (p. 49).

**Aid analogical reasoning:** Structure information in order to provide strong retrieval cues for knowledge structures (mental models) to aid in analogical reasoning (p. 51).

**Encourage implicit learning:** Develop training regimens for learning about patterns within a visualization. Implicit learning implies "learning without being able to verbalize what has been learned" (p. 52).

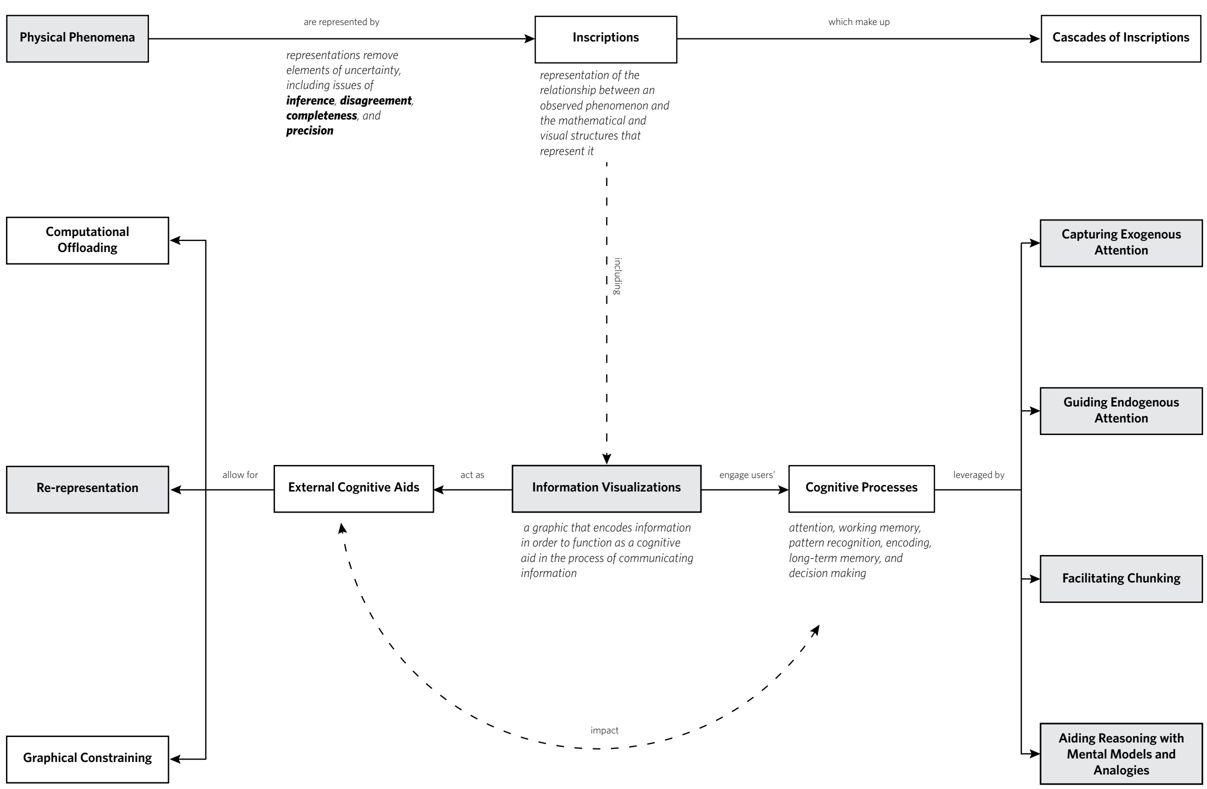
These leverage points provide a means of exploring different methods of visualizing uncertainty to engage a user's cognitive processes. The final leverage point, "encourage implicit learning," requires time and prolonged exposure to visualizations, so it would fall outside the scope of the studies created for this investigation. For the purposes of this investigation, "aid reasoning with mental models" and "aid analogical reasoning" have been combined into one point, aid reasoning with mental models and analogies. The two points both involve accessing a users' existing mental models in order to further understanding.

By aligning the human cognition framework for data visualization developed by Patterson et al. (2014) with the work of Scaife and Rogers (1996) on external cognition, the combined framework permits the development of techniques for visualizing uncertainty that consider both external representation and internal cognition processes.

## COMBINED CONCEPTUAL FRAMEWORK

Figure 8: **Conceptual Framework** (Below) The combined conceptual framework provides leverage points and reference points for the development of designed studies.

To represent a physical phenomenon, we create cascade of inscriptions, or abstracted representations, including information visualizations. Visualizations affect a user's mental processes through computational offloading, re-representation, and graphical constraining. Internally, cognitive processes, including attention, working memory, pattern recognition, encoding, long-term memory, and decision-making, are used to interpret and utilize information visualizations. The framework (Figure 8) includes six design concepts that can be used to leverage these cognitive processes when creating information visualizations (Patterson et al., 2014).



## CONCEPTUAL MATRIX

Studies for this project fall into a matrix based off of the conceptual framework (Table 1). Studies use one of four data sets that depict political, economic, and weather information.

| | Inference Uncertainty | Disagreement Uncertainty | Completeness Uncertainty | Precision Uncertainty |
|---|---|---|---|---|
| Capture Exogenous Attention | | | | |
| Guide Endogenous Attention | | | | |
| Facilitate Chunking | | | | |
| Aid Reasoning With Mental Models and Analogies | | | | |

Table 1: **Conceptual Matrix** (Above) The conceptual framework translated into a matrix for visual explorations.

## PRIMARY RESEARCH QUESTION

How can information visualizations commonly found in news media incorporate representations of uncertainty to facilitate non-expert decision making about current events?

## SUB-QUESTIONS

**Types of Uncertainty.** How can information visualizations convey inference, disagreement, completeness, and precision uncertainty beyond conventional visualization strategies?

**Capture Exogenous (Peripheral) Attention.** What visual qualities in information visualizations can serve to capture a user's exogenous attention in the conveyance of uncertainty?

**Guide Endogenous (Controlled) Attention.** What interactive qualities in information visualizations can serve to guide a user's endogenous attention in the conveyance of uncertainty?

**Facilitate Chunking.** How can chunking visual elements in an information visualization convey uncertainty?

**Aid Reasoning with Mental Models and Analogies.** How can designers leverage visual analogies and a user's existing mental models in information visualizations to convey uncertainty?

# Methodology

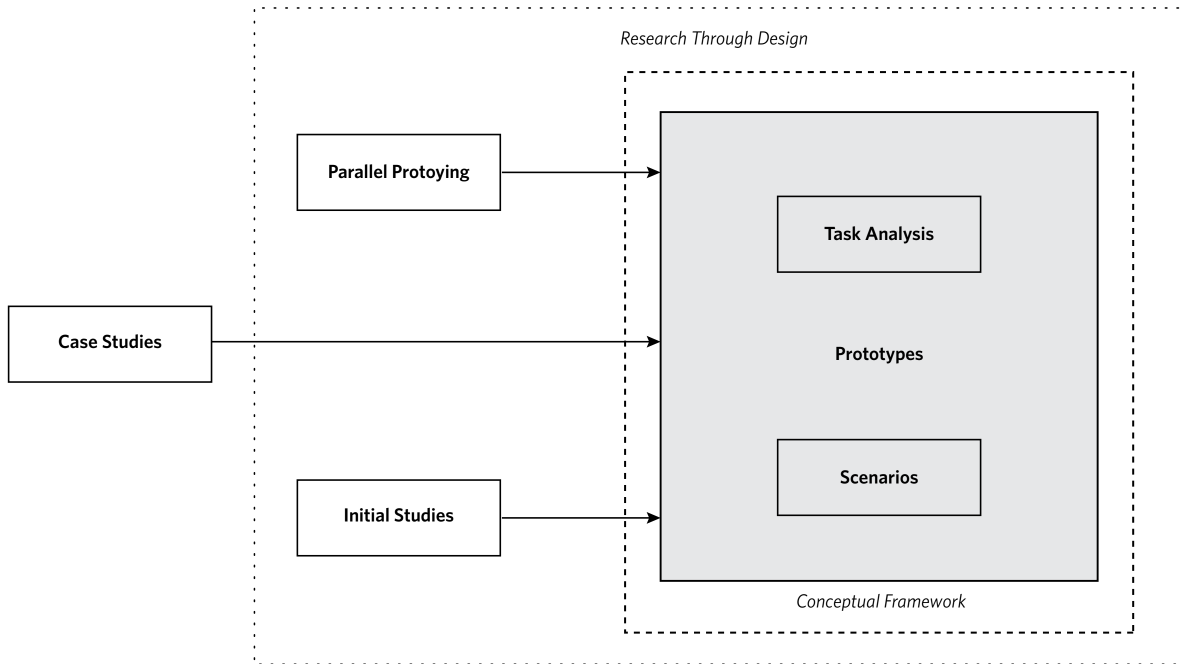



Figure 9: **Methodology**
(Above) The methodology for this investigation includes case studies, parallel prototyping, and research through design.

## DESIGN RESEARCH METHODS

The methodology (Figure 9) for this investigation employees a number of design-centric approaches, with the aim of developing a diverse set of experiential techniques for visualizing uncertainty.

### Case Studies

The investigation began by examining existing methods for visualizing uncertainty, which resulted in a set of small scale case studies. *Case studies* involve the investigation of single events or instances in context and help designers understand existing phenomena or designed solutions for comparison, information, or inspiration (Martin & Hanington, 2012).

**Case Studies**
Investigations of single events or designed instances in context.

### Research Through Design

The majority of my investigation involves the development of visual studies and prototypes as a means of research through design. According to Martin and

Hannington (2012). “[*R*]*esearch through design* recognizes the design process as a legitimate research activity” (p. 146). Research through design integrates theoretical and conceptual frameworks with the design process to ground explorations and studies. Through ideation, experimentation, and critical reflection, designers advance design scholarship and pose new questions about design issues. This research had three distinct phases: a study with a graduate graphic design studio, initial studies I created, and more in-depth final studies.

**Research Through Design**

Integrating theoretical and conceptual frameworks to ground design explorations and studies.

### Parallel Prototyping with a Graduate Level Graphic Design Studio

Building off of the information gleaned from case studies, I worked with a graduate level studio to develop studies exploring uncertainty. This exercise had several designers prototyping different methods in parallel to my own design explorations through parallel prototyping. Martin and Hannington define *parallel prototyping* as simultaneously exploring multiple design opportunities as a means of keeping designers from fixating on a design direction too early (2012). The process encourages divergent explorations and the exploration of multiple design elements.

**Parallel Prototyping**

Simultaneous design explorations by multiple designers.

### Initial Explorations and Studies

My initial studies involved rapid iteration and reflection, with the aim of familiarizing myself with the visual language and existing methods for visualizing uncertainty. For later studies, I designed within my combined conceptual framework as a means of grounding design interventions and user scenarios, task analysis, and prototyping as methods for developing design interventions.

#### *Scenarios*

Each of my studies is grounded in a scenario that explores a user’s interactions with the design intervention. *Scenarios* are narratives that explore the future use of an artifact or system from a user’s perspective and how that design integrates into the user’s life and activities (Martin & Hanington, 2012). Scenarios focus more on what technology enables than the details of the technology itself.

**Scenarios**

Narratives that explore the future use of an artifact or system from a user’s perspective.

#### *Task Analysis*

After developing scenarios for my studies, I completed a task analysis. A *task analysis* breaks down the elements of a user’s interactions with a system. It breaks the task down into distinct actions and categorizes those actions based on their relationship to the system and the user (Martin & Hanington, 2012).

**Task Analysis**

A break down of a user’s interactions with a system.

The scenarios and task analysis informed the creation of information graphics and artifacts to explore methods for visualizing uncertainty. These artifacts, or studies, provide an example of visual techniques. *Prototyping* is the creation of artifacts for developing and testing ideas (Martin & Hanington, 2012). Prototyping allows designers to test concepts and potential users. Prototyping allows for critical examination of ideas in context and is an integral part of research through design.

**Prototyping**
The creation of artifacts for developing and testing ideas.

## PRECEDENTS

Table 2: **Precedents Comparison** (Opposite) The table analyzes the different precedents explored in this investigation.

As part of my initial research, I sought to establish an understanding of the existing tools and methods used to represent uncertainty. These precedents come from statistical and scientific visualizations as well as methods used by major news outlets. Each visualization was evaluated based on the additional knowledge a user would need to interpret the graphic and the underlying information and the pros and cons of the overall strategy (Table 2).

### Box Plots

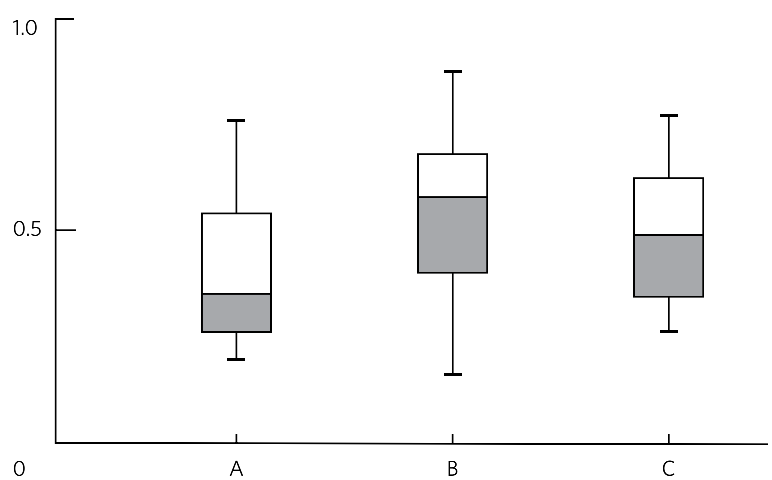



Figure 10: **Box Plot** (Right) Box plots convey the distribution of a data set, but require some statistical knowledge to interpret quickly, making them inaccessible to non-experts.

Box plots, or box and whisker plots (Figure 10), display the distribution of a data set through the data's quartiles, or four equal groups that divide the data based on a particular variable ("Quartile, adj. and n.," 2007). For example, the lower quartile is the lowest 25% of a data set while the upper quartile is the upper 25% of the data set (Agresti & Finlay, 2009). To really understand the

| Precedent | Definition | Additional Knowledge | Pros | Cons |
|---|---|---|---|---|
| **Box Plots**<br><br>("Box and Whisker Plots - Learn about this chart and its tools," n.d.)<br><br>(Agresti & Finlay, 2009) | Box with lines extending from it to display data distribution through its quartiles | Median, quartiles, minimum, maximum, and outliers | Simple visual strategy<br><br>With prior knowledge, it's easy to see uncertainty | Requires knowledge of statistical terms and ideas |
| **Violin Plots**<br><br>("Violin Plot - Learn about this chart and tools to create it," n.d.) | Combination of a box plot and a density plot to show the distribution of data. Contains a confidence interval, the median, and the interquartile range | Density, quartiles, interquartile range, median, and confidence interval | Adds more information than a box plot.<br><br>Visually interesting, density plot relates width to number of data points<br><br>Can make interesting comparisons between plots | Requires significant additional knowledge<br><br>More complicated than a box plot |
| **Error Plots**<br><br>(Krzywinski & Altman, 2012) | Bars used to show difference between two values. Often represent one standard deviation, standard error, or a confidence interval | Confidence interval, standard deviation, or standard error | Simple visual | Requires considerable prior knowledge to fully understand<br><br>Can mean many different things, making it even more complicated for non-experts |
| **Confidence Intervals**<br><br>(Agresti & Finlay, 2009) | An interval of numbers within which the parameter (point or value in question) is believed to fall. | Parameter, margin of error, confidence, limits | Conveys a substantial amount information | Requires statistical knowledge and understanding of the context |
| **Hurricane Cone of Uncertainty**<br><br>(Liu, Mirzargar, Kirby, Whitaker, & House, 2015) | Represents the probable track of the center of a tropical cyclone, and is formed by enclosing the area swept out by a set of circles along the forecast track. The size of each circle is set so that two thirds of historical official forecast errors over a 5-year sample fall within the circle | Must know that cone does not represent size, rather a representation of uncertainty | Simple visual that is now familiar to many people | Does not facilitate important time and location specific queries<br><br>False sense of certainty in and outside the cone<br><br>Issues with misinterpretation |
| ***The New York Times* Exit Polls Needle**<br><br>(Wartik, 2017) | Two needles, one showing the confidence of winning and one showing the margin. These were updated continuously based on new returns. The confidence needle ventured closer to 100% as the night wore on. | Basic understanding of elections or poll terminology (margin, confidence) | Simple and engaging graphic for users.<br><br>Uncertainty is captured by a moving needle that catches the user's exogenous attention.<br><br>Way to qualify the paper's predictions. | User cannot tailor the information and control the presentation<br><br>The metrics behind it are somewhat cloudy. |
| ***The Wall Street Journal* Economic Survey Graphics**<br><br>("Econ Forecast - The Wall Street Journal - WSJ.com," n.d.) | *The Wall Street Journal* uses solid bars to indicate the actual value of an economic indicator. For dates in the present, it uses red lines to indicate the average from their survey and lighter bars to show the range of the predictions. | It's not clear that the solid line is an average or how many participants there are in the survey from the graphic. The fainter lines do not appear to have a key or any obvious meaning | Provides for a quick read, if you are familiar with error bars, etc.<br><br>Depicts some of the uncertainty involved. | Requires familiarity with statistical diagrams or error bars.<br><br>Does not include a key. Geared towards those who work in finance or economics, rather than a non-expert audience. |

information presented by a box plot, a user needs to be familiar with numerous statistical concepts, including:

> **Mean:** The most commonly used measure of the center. The mean is the sum of the data points divided by the number of observations. Often called the average (Agresti & Finlay, 2009).
>
> **Median:** The data point that falls in the middle of an ordered data set (Agresti & Finlay, 2009).
>
> **Outlier**: An observation that falls well above or below the bulk of the data (Agresti & Finlay, 2009).

Box plots give a user more information than a single point graphed on an x-y axis. With a box plot a user can see a range of possibilities, rather than a single point, thereby representing a whole data set and some of the uncertainty involved. A box plot requires expert knowledge to understand how to interpret the visualization. Each part of the visualization is encoded with meaning that cannot be interpreted without prior knowledge of the visualization and its code — a user cannot intuitively interpret what the different points of the plot mean or the lines within the box. A user has to know that the box represents the inner two quartiles of a data set, while the extended whiskers mark the minimum and maximum points of a data set.

To an expert user, box plots are a visually simple way to display information. Someone with statistical knowledge can glean numerous insights about the spread or distribution of a data set from a box plot, but to someone who is unfamiliar with the statistical concepts involved, the visualization is unreadable and provides little insight into the information being presented, making it inaccessible to non-expert audiences.

### Violin Plots

Violin plots combine a box plot and a density plot (Figure 11). Density plots visualize the distribution, or the spread, of data over a period of time ("Density Plot - Learn about this chart and tools to create it," n.d.). Combining a box plot with a density plot shows the shape of the data as well as the quartile ranges and displays more information than a traditional box plot.

Violin plots, however, run into the same interpretation issues as a box plot. A user has to understand what the different parts of the visualization mean in order to interpret the visualization. The shape of the violin plot does add some intuitive elements, as a user can easily interpret wider bumps as larger than smaller ones, yet that comparison means little if a user does not understand the rest of the visualization or what it shows about the data.

Like box plots, violin plots rely on the user to understand the structure and statistical meaning of its parts, making the visualization strategy inaccessible.

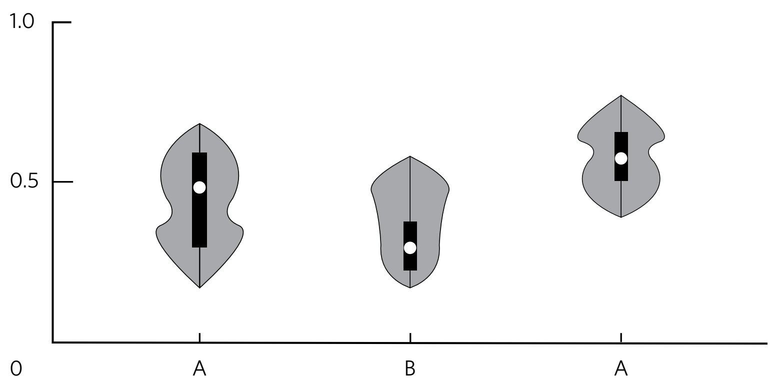



Figure 11: **Violin Plot** (Left) While the shape does provide some intuitive elements, the rest of the plot encodes statistical information that requires prior knowledge on the part of the user.

**Error Bars**

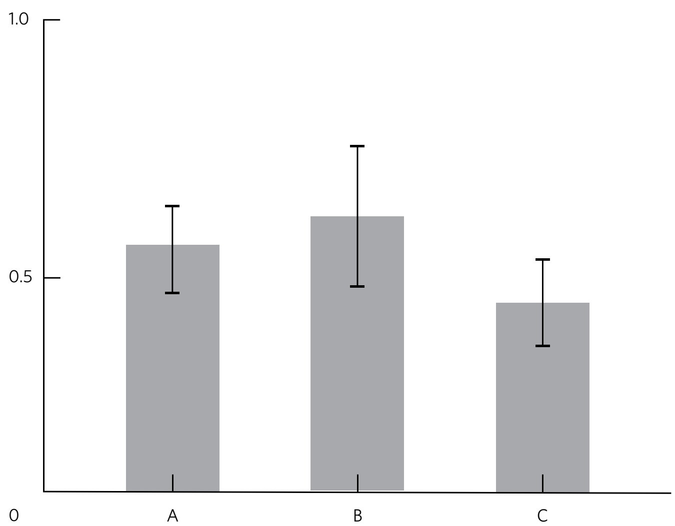



Figure 12: **Error Bars** (Left) Error bars can mean several different things, making them difficult for a non-expert to interpret.

Error bars (Figure 12) visualize the variability of information plotted on a graph (Krzywinski & Altman, 2012). They can be added to scatter plots, dot plots, bar charts, or line graphs to include a representation of the uncertainty to a visualization. Adding an error bar suggests that the data point or piece of information could vary from the point by the distance of the bar.
Error bars can display numerous statistical elements, including:

> **Standard Deviation:** Value that tells how varied data points are from the mean. A higher value means that the data is more spread out (Agresti & Finlay, 2009).

**Standard Error:** The standard deviation of a particular statistic across several samples (Agresti & Finlay, 2009). It provides a way to know how close a particular statistic from a particular sample is to the actual value for a whole group.

**Confidence Intervals:** An interval of numbers within which a particular statistic is believed to fall (Agresti & Finlay, 2009). For example, if I am looking for the percentage of voters who support Donald Trump, I would use a confidence interval to suggest that that value falls within a specified range of values based on my statistical analysis.

**Minimum and Maximum Values:** The highest and lowest values in a data set ("Error Bars" The Data Visualization Catalogue).

For an expert user, it may be easy to discern which statistical element an error bar represents, but for a non-expert user, even understanding the possible meanings is difficult. Standard deviation, standard error, confidence intervals, and minimum and maximum values are not easy concepts to understand, so while an error bar is incredibly simple, its meaning is difficult for non-experts to understand.

### Confidence Intervals

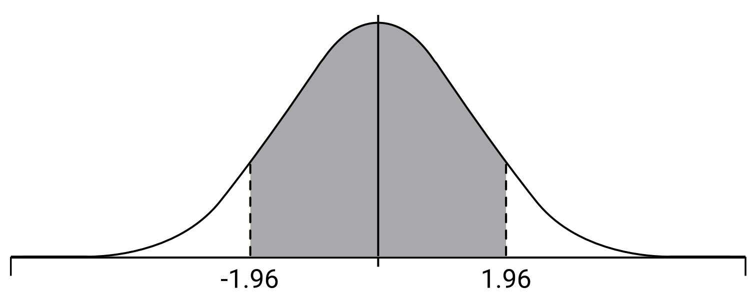



Figure 13: **Confidence Interval** (Right) Confidence intervals express uncertainty by giving a range of numbers within which a value might fall, but their abstracted structure is not intuitive or easy for non-experts to understand.

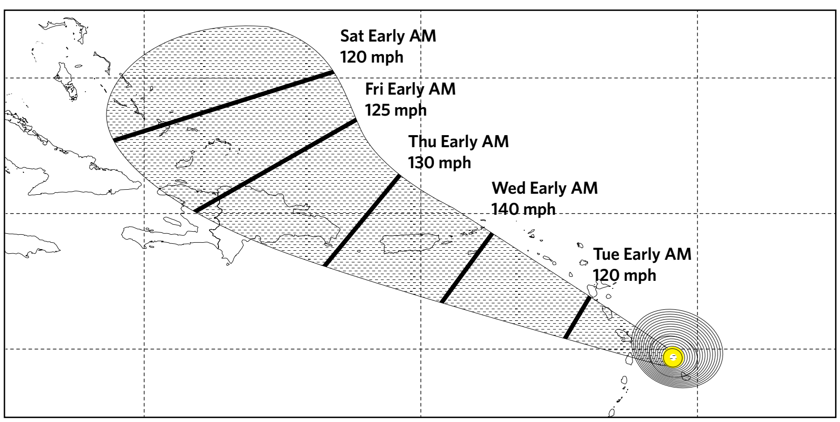
A confidence interval (Figure 13) gives a range of numbers within which a particular statistic or data point is believed to fall (Agresti and Finlay 110). Confidence intervals express uncertainty by reporting a range rather than one specific data point. It is a way of saying a piece of information could be this high or this low, but it builds off of statistical principles like margin of error, or how much an estimated value could differ from the actual value. For example, for a poll to have a four percent margin of error means that the number that comes from the poll's sample, e.g., how many people will vote for a particular candidate, will fall within four percentage points of the real value for the entire population.

While the margin of error is a powerful statistic, the way confidence intervals present that information make it difficult for a non-expert to understand. A user has to understand the meaning of the curve and the lines involved to interpret the curve and the different sections of the graph. Like box plots, violin plots, and error bars, without prior knowledge, confidence intervals are nearly impossible to interpret.

**Hurricane Cone of Uncertainty**

During hurricane season, newspapers, broadcast news, and websites often use visualizations that depict a cone of uncertainty to display the forecasted path of a storm (Figure 14). The cone of uncertainty represents the probable track of the center of a tropical storm. In these graphics, the farther in the future the predictions, the wider the displayed path, forming a cone shape. The width and size of the path are determined by the historical accuracy of forecasts. For example, with less accurate forecasts 10 days out, the visual 10 days out is much wider than 2 days out, thereby making the width of the cone the estimate of uncertainty for that prediction (Liu et al., 2015).

Figure 14: **Cone of Uncertainty** (Right) Uses an expanding cone to visualize the uncertainty in a projection.




The cone of uncertainty has become a pervasive way to visualize hurricane paths, however the graphics can be misleading and often fail to convey the uncertainty involved in weather forecasting. Liu et al. (2015) point out that the width of the cone is often misread as indicating an increase in the storm's size . This misinterpretation is understandable. The graphic shows a stagnant image, often with solid coloring that gives no indication of a change in confidence or certainty. Instead it appears the storm is going to grow larger as it moves over a specific path.

Furthermore, the design of the cone of uncertainty can provide a false sense of certainty for those inside and outside of the projected path. People who rely on the cone to make decisions about evacuating can misinterpret the confidence involved in the graphic, leading to poor decisions. People who live outside of the cone may interpret the graphic as meaning a hurricane will not affect them, when in reality a hurricane can have impact for miles beyond its path (Liu et al., 2015).

The cone of uncertainty attempts to visualize a complicated forecast that spans a time period in a single stagnant visualization. Incorporating a time based visualization could give a user understanding of the changing certainty of a projection over time. The visualization also does not facilitate important time and location specific queries. Instead of giving the user the ability to determine the likelihood that the storm will hit her area at a specific time, it shows a broad general overview that does little to facilitate individual decision making (Liu et al., 2015).

### *The New York Times'* Exit Polls Needle


Figure 15: **The Needle**
(Left) The needle interface uses a gauge metaphor to convey the uncertainty in live election numbers, providing the user with an experiential visualization.

*The New York Times* used a set of two moving needles to track the results of the 2016 presidential election and the Alabama Senate race. The representations were both incredibly popular and divisive. The needle made its debut during the 2016 Presidential Election and its inaccuracy led to much criticism and derision online (Wartik, 2017). During the Alabama Senate race, *The Times'* live results election page received more than 13 million page views, making it among their most-read pieces of 2017, and #NYTNeedle was trending on Twitter (Wartik, 2017). *The New York Times'* graphics department used the needle to visualize the uncertainty involved in an election and give users a more "visceral understanding" of the error involved in making election predictions (Wartik, 2017).

The needle interface is comprised of two displays (Figure 15); one that represents the estimated margin of victory for a candidate, and the other that represents the Times' confidence in their prediction, or the chance of a particular candidate winning. The margin display uses a swinging needle graphic to point to a particular point on a wheel, while the wheel itself is colored to indicate how confident that prediction is and within what range. Over the course of election night, the size of the range on the estimated margin needle display grew smaller, while the position on the chance of winning needle ventured closer to 100%. These graphics gave users an understanding of how confident pollsters were in their predictions and showed how that confidence changed as polls closed.

These graphics are incredibly popular in part because of their simplicity. The needle displays use simple language and can be quickly interpreted by someone without a great deal of background knowledge. Even if the estimated margin was beyond the understanding of a user, the "chance-of-winning" needle could provide a quick indication of the certainty or uncertainty involved in *The Times'* coverage.

The needle interface itself leveraged user's analogical reasoning, using metaphor to relate the uncertainty in an election to the fluctuating gauges on dashboards. Gauges, like speedometers and temperature indicators in cars, display fluctuating measurements over time. These gauges swing and move as a car moves, just as election predictions change as an evening progresses. Similarly, some gauges swing more than others, just as the margin of victory may fluctuate more than the chance of winning. The motion of the needle interface over time represents both the changing values and the uncertainty involved in the information presented. *The Times* takes this approach a step further, using a highlighted range on one of the gauges to indicate uncertainty, with the highlighted range growing smaller to indicate a decrease in uncertainty.

The dashboard gauge metaphor works well to display changes in certainty and confidence over time. However, the metaphor may not apply to data that is not changing as quickly, as the interface would be stagnant and less engaging to a user. Needles and gauges are also difficult when comparing two data sets. *The Times'* needle interface works because the data presented functions as an either/or, like a two sided continuum that the needle can swing between, if the data set had more possibilities or was not ordered linearly, the needle metaphor would be ineffective, as the motion suggests a relation between the data points.

Overall, *The New York Times'* election needle provides an easily understandable representation of uncertainty for a particular context. The visual itself does not draw on complicated statistical terms; instead the user is able to intuitively interpret the graphic's motion as uncertainty, exemplifying an experiential visualization. The interface provides enough labeling and information that a non-expert user can quickly interpret the information presented, relying only on observations. The needle interface suggests that metaphorical visualizations can be effective when applied to appropriate contexts.

#### ***Wall Street Journal's*** **Economic Survey Graphics**

*The Wall Street Journal* conducts a survey on major economic indicators and presents its data online for users through an interactive data visualization (Figure 16). This visualization uses gray bars to display the actual economic indicator, once it has been released by the government, and red lines to display the average of their survey's predictions. The red lines show the average prediction and then indicate any outliers with lighter bars. While the graphic provides a quick read, it is difficult to interpret the information as presented. It is not clear whether the solid lines are an average or some other measurement, or how many participating firms are making a particular prediction. The graphic attempts to suggest some of the uncertainty involved in their survey, but the result functions like a scatter plot combined with a bar graph, with the bars indicating known values and the lines indicating predictions. This approach suggests that the graphic is for a quick view, rather than in-depth exploration.

*The Wall Street Journal's* graphic may fall short at visualizing uncertainty, but it does give the user a great deal of control over the information she see. The graphic provides filters that allow a user to toggle between the actual values and estimates and determine how many predictions she wants to see. These filters give a user control and guide their endogenous attention, allowing a user to tailor the interface to her own needs, thereby drawing her in and personalizing the tool.

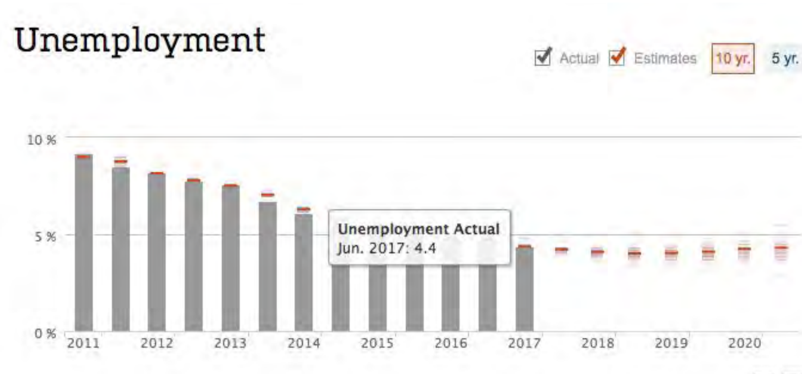



Figure 16: **Economic Survey Graphic** (Left) *The Wall Street Journal's* conveys the uncertainty in their survey by contrasting gray bars with red lines.

## VISUALIZING UNCERTAINTY IN A GRADUATE GRAPHIC DESIGN STUDIO

While completing my own research and design studies, a group of graduate students in a first year foundations Master of Graphic Design course, taught by Dr. Matthew Peterson at North Carolina State University, created their own studies on visualizing uncertainty. I had the opportunity to prepare the source material for Dr. Peterson's course and thus align it to this investigation. These designers prototyped data visualizations for news platforms that conveyed some form of uncertainty to a non-expert adult audience.

Each designer worked with one polling data set and visualization from a major news organization, specifically *FiveThirtyEight*, *The New York Times*, *The Washington Post*, and *CNN*. The data sets were:

President Trump's Popularity (*FiveThirtyEight*)

Projections for the Virginia Governor’s Race (*The New York Times*)

Poll on US Withdraw from Paris Climate Agreement (*The Washington Post*)

President Trump’s Approval Rating by Party (*CNN*)

The final visualizations used a variety of methods, including motion, interactivity, and variations on traditional visualizations, to convey uncertainty.

**Motion**

Several designers explored motion as a means of conveying uncertainty. For example, Matthew Norton, animated a data set’s margin of error so that a user can see all the possible outcomes suggested by the data. The visualization uses a simple part-to-whole graphic, but the parts grow and shrink over time to suggest a range (Figure 17). The motion draws the user in, attracting their

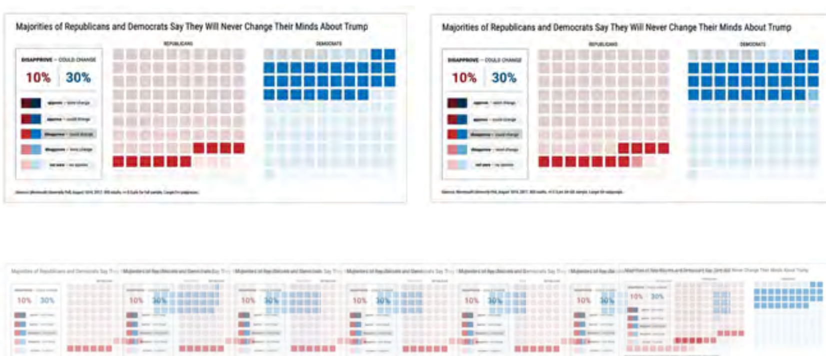



Figure 17: **Visualization by Matthew Norton** (Right) Based on President Trump’s Approval Rating by Party (*CNN*). The visualization shows the margin of error for the data set through a growing animation, storyboarded here.

See the animation at: https://college.design.ncsu.edu/thenfinally/hill/disapprove_cc_titles.gif

exogenous attention. By using colors associated with the two major U.S. political parties (red for Republican, blue for Democrat), the user can quickly associate the two blocks with the parties they represent. The coloring and layout also aid in chunking information together and drawing out the different categories of information.

While Norton’s visualization uses a growth motion to convey the margin of error, visualizations could use more random, or glitched, animations to suggest even more uncertainty in a data set. Less uniform animations would both draw in a user’s attention and work to metaphorically convey uncertainty.

Visualizations like Norton’s suggest that motion can convey uncertainty quickly. By incorporating animation into familiar layouts and forms, a designer can create visualizations of uncertainty that a user can easily interpret.

Norton’s studies suggest that specific statistical information, like margin of error, or specific types of uncertainty may lend themselves to simple animations more than others. A range of possibilities is a relatively easy concept for a user to understand, while uncertainty coming from a more abstract source, like inference or precision error, might be more difficult to convey quickly via animation. The studies also reinforce the importance of building off of a user's existing mental models. Maintaining traditional political color schemes made the visualizations easier to interpret and relate the information to a political race.

### Interactivity

Interactivity played a major role in many of the visualizations produced. Several designers used interactive filters and rollover features to convey uncertainty in data, drawing in the user's endogenous attention and adding more layers of information to otherwise traditional layouts.

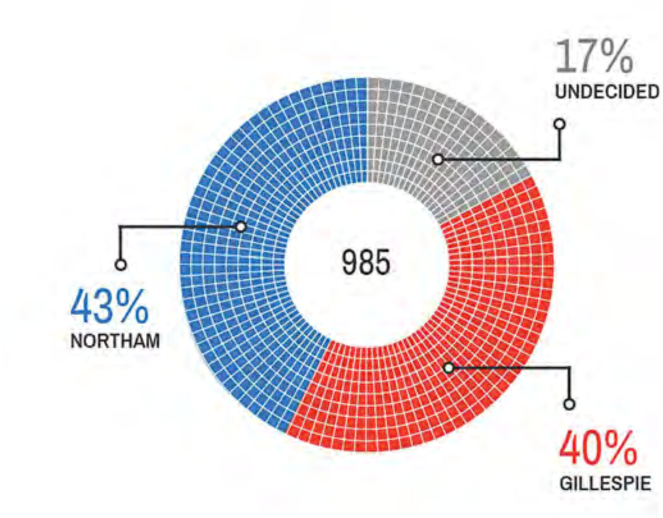


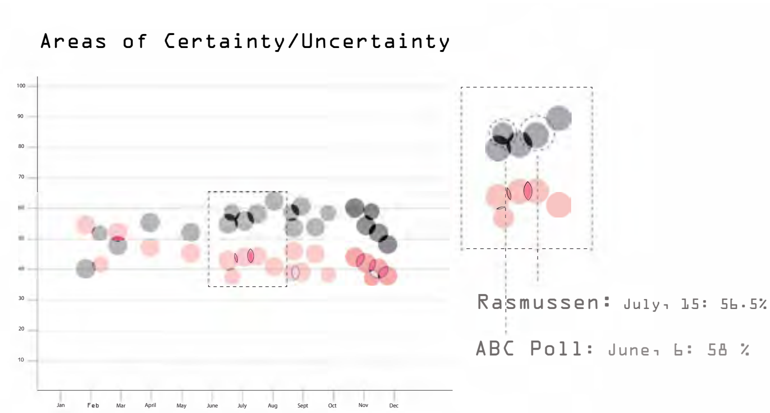

Figure 18: **Visualization by A. Anderson** (Right) Based on Projections for the Virginia Governor's Race (*The New York Times*). Anderson's visualization shows the weighting given to different respondents in the final poll numbers.

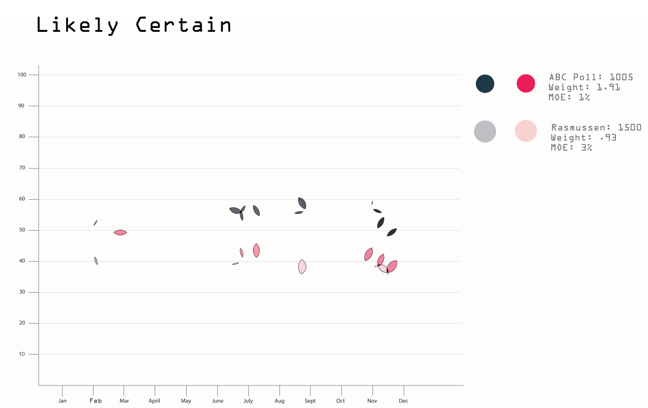
One designer divided donut chart based on the sample size to give users information about weighting in sampling (Figure 18). By providing information about the type of person polled, a user is given information about the statistical processes behind a polling projection, as well as the human side of the numbers. The circle, however, is not divided equally, as each section has a different area. Exaggerating the area differences could suggest the different weights given to individuals. The design itself sticks to a traditional political color scheme, making the light blue moments stand out more and drawing in a user's exogenous attention and chunking the different pieces of information together.

These visualization techniques could be pushed further, with the interactive feature including more of the process behind the projections with rollovers and filters that a user can explore on their own, or ignore.

### Variations on Traditional Visualization Formats

Many of the visualizations created for this project began with traditional visualization techniques, such as scatter plots, bar graphs, and pie charts. Several designers explored ways to convey uncertainty in data by modifying the traditional format visually, rather than by adding motion or interactivity.




Figures 19: **Visualization by K. Frohbose** (Left) Based on President Trump's Popularity Poll (*FiveThirtyEight*). The visualization conveys disagreement uncertainty by highlighting areas of overlap between two different polls on the same topic.

For example, Katie Frohbose started with a traditional scatter plot to display polling data from numerous sources and she then used opacity to darken areas of overlap, thereby calling out those areas as more certain than those with less consensus among polls (Figure 19).

This variation on a scatter plot gives the user a better sense of how to interact with conflicting data sets, or disagreement uncertainty. A non-expert user, however, may have trouble interpreting what these areas of overlap mean. Any user would need more visual cues and labels to fully understand what information is presented in these graphics. Furthermore, a designer would have to provide more labels and embedded cues to allow a user to fully interpret this variation of a scatter plot. These labels could be incorporated through interaction, which would attract a user's endogenous attention and allow individual exploration. The removal of non-overlapping areas could also be animated to convey the relationship between the two different charts, with the visualization highlighting certain moments and removing less certain pieces of information.

Visualizations like Frohbose's suggest that traditional structures could be modified visually and structurally to include representations of uncertainty. However, a designer must consider how a non-expert user would interpret those changes and provide visual cues to aid in understanding.

### Conclusions

Reflecting on the visualizations produced in this studio, I realized that representations of uncertainty need to build on a user's existing knowledge. As a user I found that the simpler or more subtle the intervention the easier it was to interpret the uncertain elements. The visualizations that maintained familiar color schemes were also easier to interpret than ones that totally redesigned the style of political visualizations.

## INITIAL EXPLORATIONS

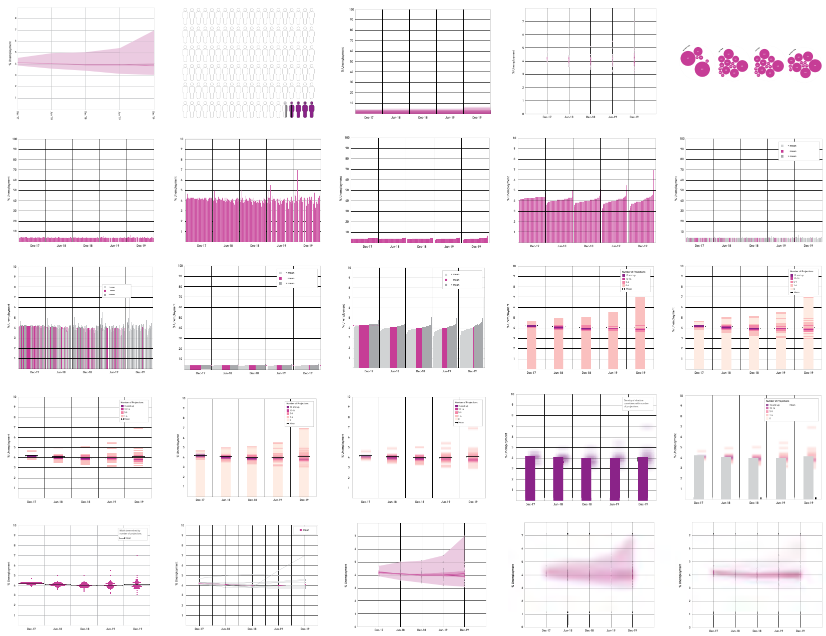


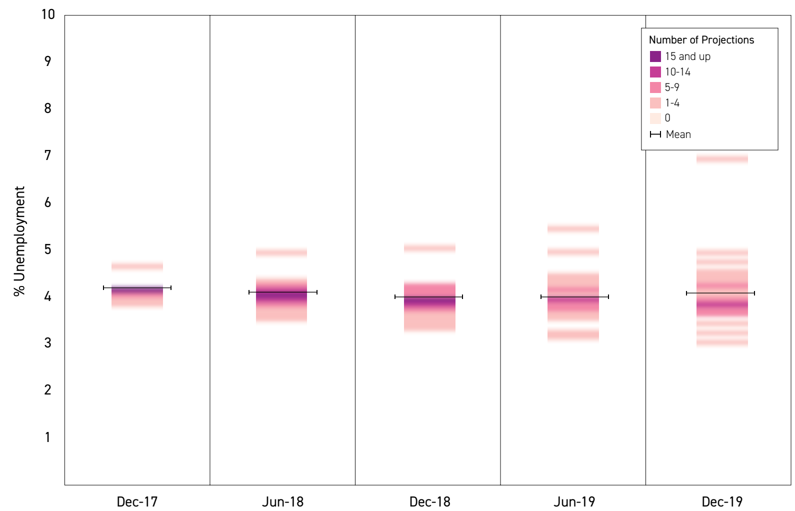
Figure 20: **Initial Studies** (Left) These studies focused on one data set and iterating through different possibilities for visualizing uncertainty.

In order to better understand the visual language of data visualization and its relationship with uncertainty, I began to iterate on different ways to visualize uncertainty in a single data set (Figure 20). These studies did not operate within my conceptual framework; instead, they were an exercise in iteration and reflection to prepare myself for future studies. I saw these studies as a way of getting the more obvious forms out of the way and a means of developing potential frameworks. In making quick, iterative studies, I saw the need for a framework that both grounded my work in user needs and pushed me to consider multiple types of interventions.

I began with unemployment data from *The Wall Street Journal's* monthly economic survey. The data set contained unemployment projections from 75 major firms, so I chose to focus on the disagreement uncertainty involved in visualizing projections from 75 different sources. My initial variations drew on existing visualization techniques, looking for ways that I could change the structure or layout of these visualizations to convey uncertainty. After iterating on several different visualization techniques, I focused on bar graphs and created iterations that modified bar graphs to include representations of uncertainty.

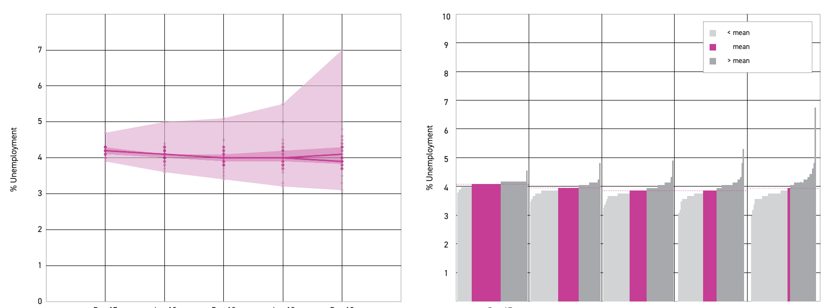
These visualizations, however, relied heavily on statistical elements like mean lines and quartile ranges to depict uncertainty, which might prove difficult for a non-expert to understand. I found that the simpler the visualization, the easier it was to discern elements of uncertainty. Visual techniques like blur added an element of uncertainty, but blur is difficult to quantify, so it limits the usability of the visualization (Figure 21).

Figure 21: **Blurred Bar Graph** (Right) The color scale shows the number of projections at each value. The blurr increases the user's feeling of uncertainty, but is difficult to quantify.




Reflecting on these visualizations, I found that displaying multiple data points rather than ranges or means gave a greater impression of uncertainty. These visualizations allow the user to see the contradictions or points of contention in a data set, and show how much consensus there is about a mean value, and how that consensus changes over time (Figure 22).

Figure 22: **Two Strategies** (Left) The visualization on the left uses quartile ranges to show the different projections, while the one on the right uses multiple bars, in ascending order, to show each projection.

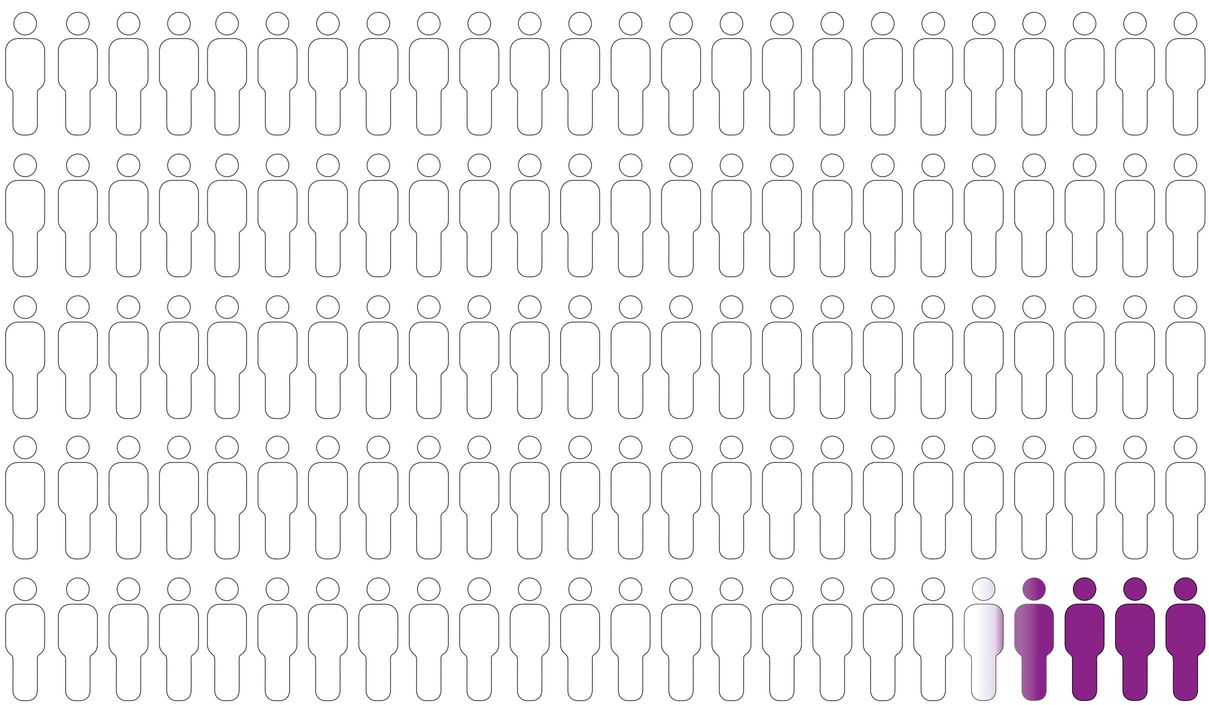



All of these initial studies are static graphics, with no interaction or motion. While creating them, I saw opportunities for interactive labels and tags or motion to increase the user's understanding of the uncertainty conveyed and make graphics easier to understand. For example, the graphic in figure 23 does not convey much more than a part to whole relationship as a static graphic, but if it was animated or interactive, a user could compare differences in each projection through actual parts-to-wholes, rather than percentages.

In reflecting on these initial studies and the work done in the graduate studio, I determined that interaction and motion will do more to depict uncertainty than totally new formats. Existing visualization structures are easier for a user to work with because users already have mental models for interpreting them. If uncertainty can be incorporated into these formats without drastically challenging existing mental models, users should have an easier time working with the visualizations.

Neither the visualizations created in the graduate studio nor my initial studies dealt with pictorial or metaphorical methods for visualization. Visualizations that draw on illustration more than statistical visual languages have the potential to draw on a user's analogical reasoning processes and depict uncertainty outside of traditional charts and graphs.

Figure 23: **Part-to-whole Visualization** (Below) If this visualization was one frame of an animation, it could convey the different projections as parts-to-wholes.



| | Inference Uncertainty | Disagreement Uncertainty | Completeness Uncertainty | Precision Uncertainty |
|---|---|---|---|---|
| **Capture Exogenous Attention** | Study 1A : Rising Water | Study 1B: Expert Projections | Study 1C: Bouncing Polls | Study 1D: Constant Motion |
| **Guide Endogenous Attention** | Study 2A: Taking Control | Study 2B: Hurricane Heat Map | Study 2C: Comparing Polls | Study 2D: Finding Agreement |
| **Facilitate Chunking** | Study 3A: A Bite Out of Unemployment | | | Study 3D: Blurring Bars |
| **Aid Reasoning With Mental Models and Analogies** | | Study 4B: Hurricane Dashbaord | Study 4C: Adding to the Scale | Study 4D: Taking the Temperature of the Electorate |

Table 3: **Studies Matrix**

# *Visual Explorations*

To explore methods for conveying uncertainty, I created a series of visual explorations, or studies, guided and constrained by my conceptual matrix. Each study set explores one of Patterson et al.'s leverage points for data visualizations, as well as the four types of uncertainty.

*The task analyses for these studies can be found in the appendix.*

## Study Set 1: Capture Exogenous Attention

In order to capture exogenous attention, Patterson et al. suggest designers use elements like color and texture to highlight specific elements, or motion to indicate a change in relationship between objects (2014). Building off of these leverage points, I created a series of studies that explored how capturing exogenous attention could be used to indicate uncertainty in a data set.

Study 1A: **Rising Water** (Inference)
Study 1B: **Expert Projections** (Disagreement)
Study 1C: **Bouncing Polls** (Completeness)
Study 1D: **Constant Motion** (Precision)

## *Scenario*

Alan moved from Colorado to Florida just in time for hurricane season. All of the news he sees is about Hurricane Irma and her path, which may or may not include his new home in the next week, though he's not really sure what all that means. Everyone he talks to has another opinion on the impending storm, and Alan isn't really sure what he should do.

Alan is looking at news articles about Hurricane Irma online when he comes across an article on the projected storm surge. It includes a graphic that shows a scale of storm surge and a moving water level, going from under five feet to twelve feet, just like the projection listed in the article (2–12 feet). The scale includes information about what each of those surge levels can mean. Alan realizes that the forecasters are making a rather wide prediction, but that roads in his area are going to be dangerous at either end of the projection. He starts thinking about evacuating, or at least stocking up on food and supplies, as he believes he will most likely be stuck in his house for some time. The graphic, in some ways, explains the conflicting advice he's been receiving from friends and neighbors—a lot of things could happen with the storm in the next few days.

## Study 1A: Rising Water *Inference Uncertainty*

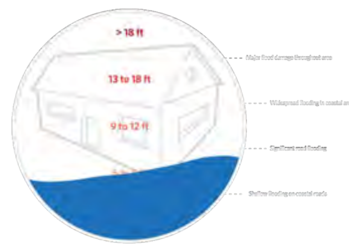
For inference uncertainty, I worked with information on Hurricane Irma's projected path and impact on Florida, specifically storm surge forecasts. Hurricanes push water on shore at levels far above regular tides, swallowing beaches and structures in storm surges that can cause devastating damage; however, the concept is often misunderstood (Andone, 2018).

I developed a scenario of someone new to a hurricane prone area who is not familiar with hurricane forecasts. My user is confused about what to do and what the forecasts he views mean to him personally.

The task analysis revealed moments of precision and inference that come from my user's interactions with the graphics. Exogenous attention, by definition, deals with a user's initial impressions, so the motion has to convey uncertainty through a quick initial impression, making the task of interpreting the graphic rather rapid.

To represent storm surge, and the inferences that accompany it, I wanted a scale that dealt with the impact of the surge itself. Including impact makes the scale more useful to non-experts and provides information for decision making. I was surprised and frustrated to find that most scales do not include storm surge, and those that do so use words like catastrophic, extreme, and extensive for the levels of the scale (Storm Surge Overview). How does someone differentiate between those three different levels? Is the scale supposed to make anyone who sees it terrified of anything above minimal? Reading more, I found that even minimal storm surge can destroy mobile homes and make roads impassable, which wouldn't sound like minimal damage to someone who lives in a mobile home (National Hurricane Center).

In creating these graphics, I used water as a visual metaphor for the uncertainty represented. The graphic uses a rising and lowering water level to represent the uncertainty in the projected storm surge and indicate the range of the prediction. My initial design incorporated a house in the scale as a means of further relating the graphic to storm surge and the damage that it causes (Figure 24). Including the house, however, changes the perception of the graphic. The water appears to be filling up the house, rather than more abstractly indicating uncertainty. The water and house combination pushes the graphic too close to the literal, rather than the metaphorical. Perceptually, it appears less uncertain and more like a space filling up with water. The use of moving water as a metaphor for the uncertainty involved in storm surge projections has the potential to confuse the user, since water is already involved. Removing the literal figures of houses and replacing it with the scale renders the graphic more metaphorical and less literal, giving it some power to convey uncertainty (Figure 25).

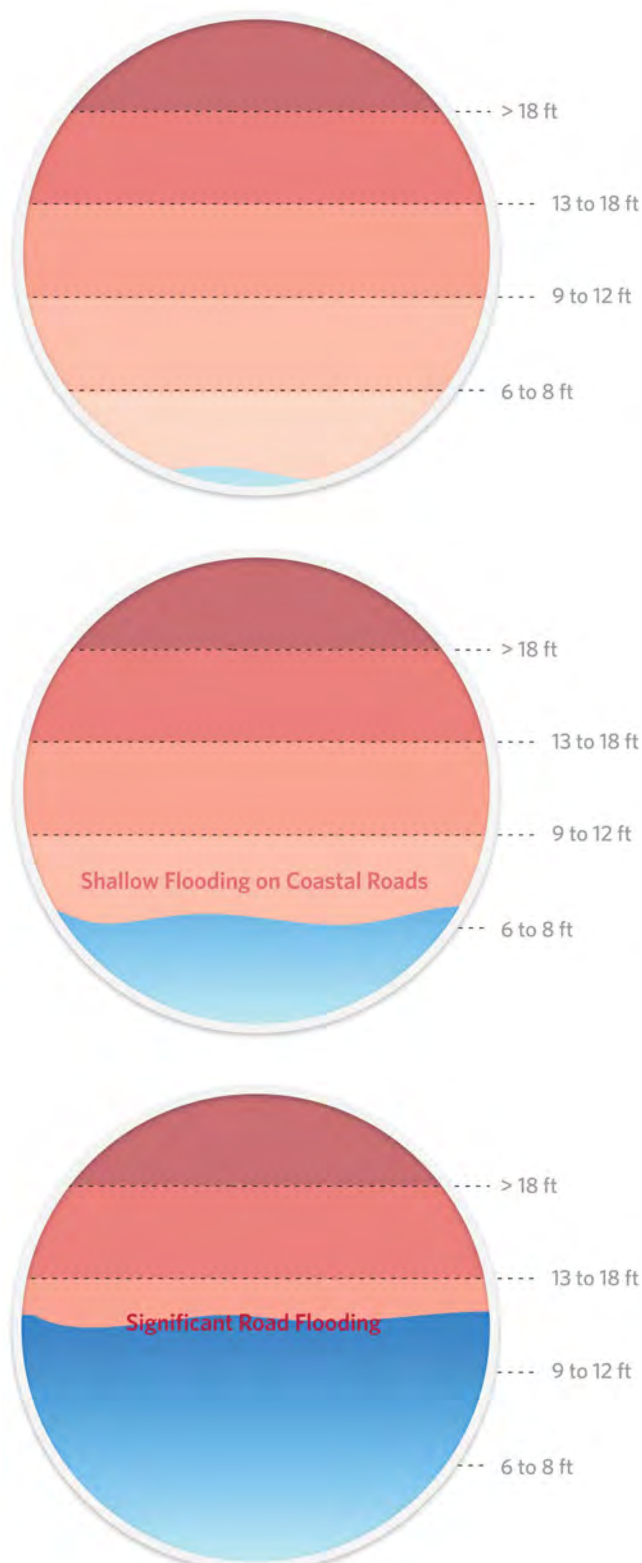



I also created a version of this graphic that includes a representation of Miami behind the scale (Figure 26). This graphic is similar to my first iteration, in that it is open to a very literal interpretation. Perhaps if the concept being conveyed was totally unrelated to water, the graphic would do more to convey the uncertainty involved.

Figure 24: **Rising Water Initial Iteration** (Above)
The initial design incorporated a house in the scale as a means of further relating the graphic to storm surge and the damage that it causes, however, the metaphor is so closely related to the subject that it could be misunderstood.

Figure 25: **Rising Water 1**
(Right) The second version of this graphic uses a perspective view of Miami and has similar issues to the initial house iteration.

See the animation at: https://college.design.ncsu.edu/thenfinally/hill/risingwater-1.gif



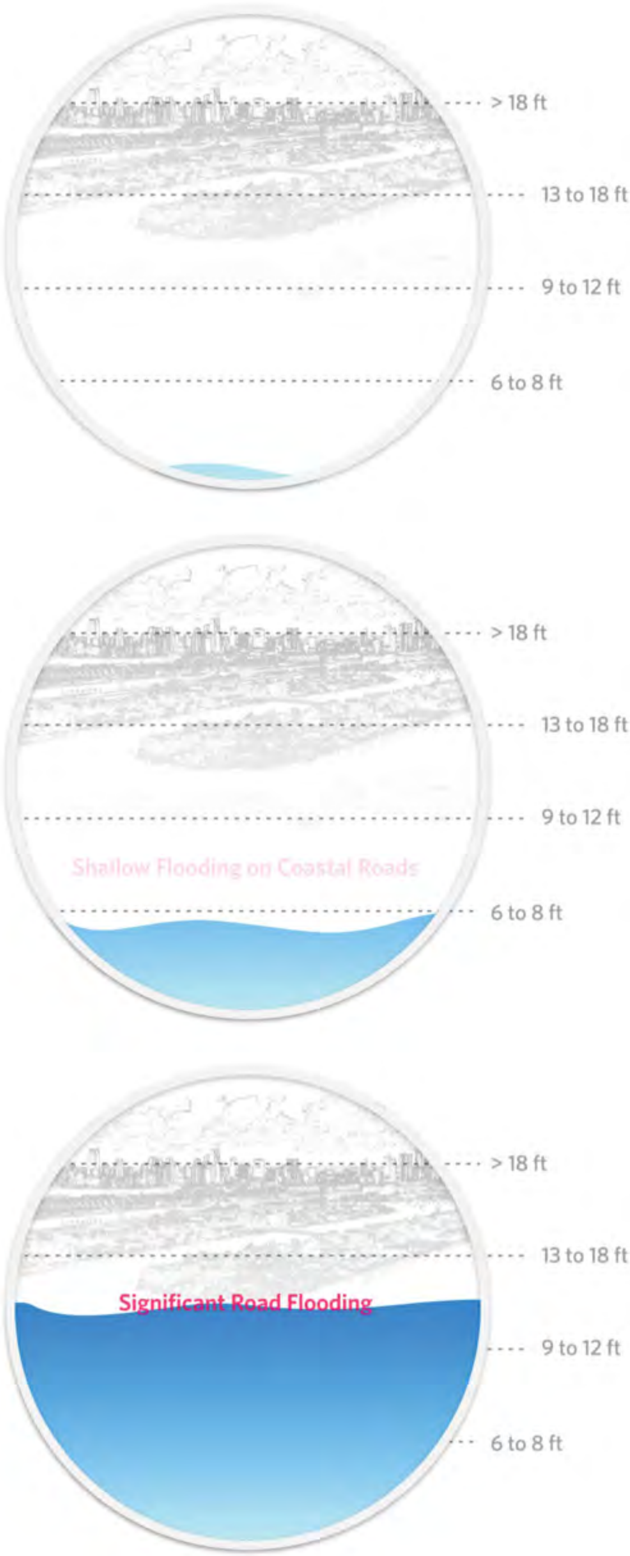



Figure 26: **Rising Water 2**
(Left) This iteration incorporates the Miami skyline with the rising water. It can also be seen as too literal or misinterpreted.

See the animation at: https://college.design.ncsu.edu/thenfinally/hill/risingwater-2.gif

## *Scenario*

Casey is about to finish graduate school and is looking for jobs. Lately, she's been wondering about what the economy and job market are like—she's been absent from the market for a couple years and doesn't really know what she's about to move into.

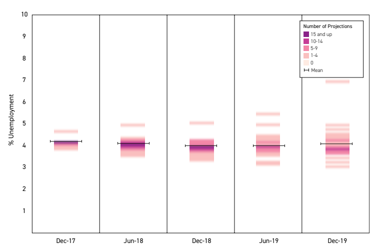
Casey checks out a business-oriented newspaper and sees a moving graphic of unemployment numbers. It includes the names of a bunch of different companies and a chart that looks something like a bar graph. Over time, the different names are highlighted and corresponding bars on the graph turn yellow. Casey watches it for a while, trying to interpret the meaning. She has to refer to the caption to understand that the yellow indicates each firm's unemployment projection. Once she has that knowledge, she notices that the projections are pretty varied, especially the further away the date is.

Casey still isn't sure what this means for her. She comes away from the graphic thinking that the economy is a tough thing to pin down, but doesn't really understand what a value like 4% unemployment means in her case—is that high or low? She realizes that she needs to do more research to really understand what's going on and what kind of job market she's facing.

## Study 1B: Expert Projections *Disagreement Uncertainty*

*The Wall Street Journal's* economic survey takes projections from 75 major US firms on economic topics like the unemployment rate. The conflict between these projections provides an opportunity to visualize disagreement among projections.

I built this study off of one of my initial studies, which used layers of transparent bars to indicate agreement or disagreement among projections (Figure 27). The visualization shows all of the different projections while maintaining a relatively simple structure.




I worked with a scenario and task analysis for a user, Casey, who has a personal interest in unemployment numbers. Working through Casey's task analysis, I found that while the data included disagreement uncertainty, it really did not relate to her life in a meaningful or important way. How does a percentage relate to an individual's job search? The data itself lacks meaningful context for a non-expert user. So, while the graphic may convey uncertainty, it falls short on really engaging with a non-expert user.

In developing the study, I animated each projection so that the visualization showed how projections stacked up on top of each other and changed the visualization's appearance. My initial study added data points one at a time on top of each other, with the organization name at the top (Figure 28). While the graphic shows the progression of projections, the nature of the motion I created suggests that they build on top of each other or have some time-based relationship, rather than having equal weight and no substantial relationships between projections.

For my second iteration, I started with the visualization fully formed, rather than animating its creation (Figure 29). This change eliminated the feeling of growth or progression and gave the motion from one projection to another a more random feel. I chose a bright yellow to highlight both the name of the organization making a projection and the projection itself. The yellow stands out sharply from the black and gray colors of the visualization and further draws in the user's exogenous attention.

In this study, each projection is given equal time in the animation. In a different scenario, where the projections are weighted or of varying credibility, the timing of the animation could be altered to give specific frames longer or shorter durations in the animation, using duration as a variable to create the visualization.

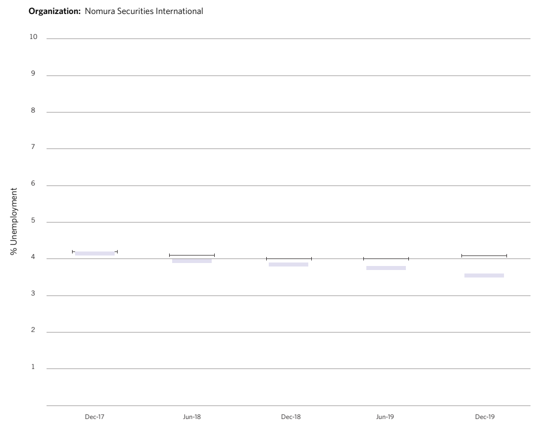
If this technique were to be used in a published visualization, a pause button or interactive features could be incorporated, allowing the user to control the timing and the information presented. These techniques would move beyond engaging exogenous attention and into other cognitive processes.

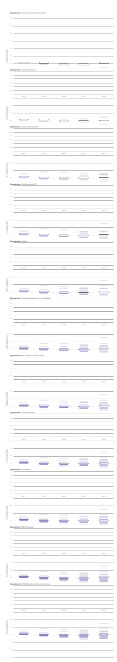
In creating visualizations for non-experts, designers must recognize the context and the relatability of data sets. A value like the unemployment rate is challenging for a non-expert to comprehend without some relatable context. Designers must also consider how different builds and sequencing can change the interpretation of motion. Objects slowly growing or building on top of each other may convey growth, rather than simply uncertainty. Overall, I believe that both context and the nature of motion are important to consider in any visualization, not just when conveying uncertainty.

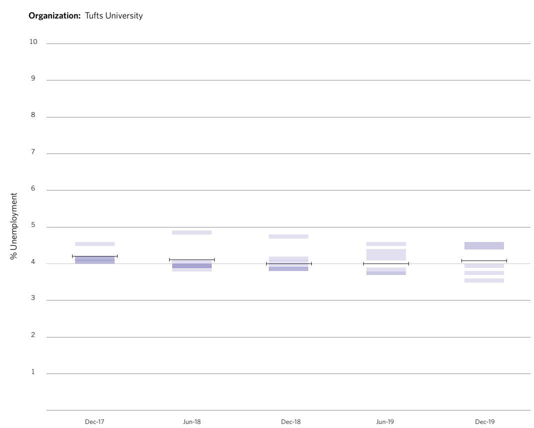
Figure 27: **Initial Study** (Above) This study was based off of an earlier iteration that used transparent layers to show different projections.

Figure 28: **Expert Projections**
(Right) The motion in this initial study suggested growth or an ordered relationship between elements, rather than disagreement.

See the animation at: https://college.design.ncsu.edu/thenfinally/hill/expertprojections-1.gif





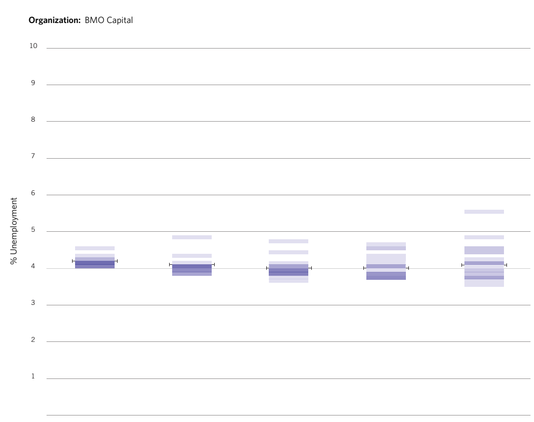
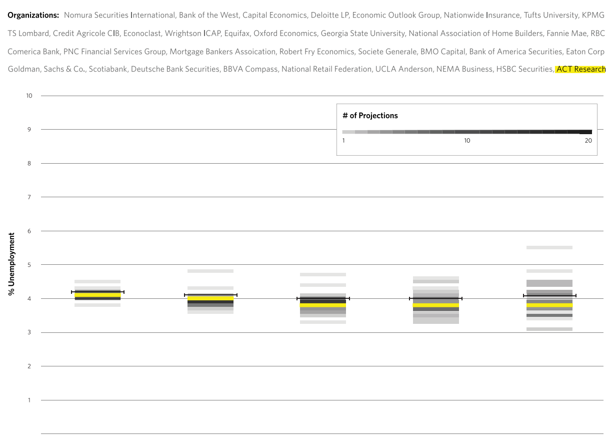
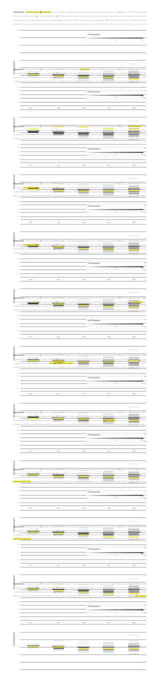
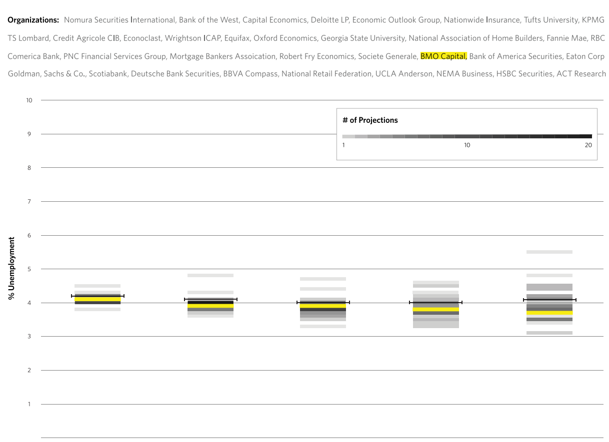




Figure 29: **Expert Projections 2**
(Left) The second iteration eliminated the feeling of growth by highlighting projectionss, rather than building in order.

See the animation at: https://college.design.ncsu.edu/thenfinally/hill/expertprojections-2.gif





## *Scenario*

Alison is in her early twenties and has just started living on her own. She has recently developed a budding interest in politics, something her parents rarely talked about and that she grew up mostly ignoring. This interest has her exploring new media sources and seeking information about the upcoming election. One afternoon, she sees an article on polls for the election. It includes a graphic of moving balls and counters for each candidate, as well as the total number of voters in the United States. Alison is struck by the relatively small size of the sample in comparison to how many people can vote.

She watches as the balls bounce around and move from candidate to candidate, with the counters changing by whole percentage points because one or two balls bounce across the screen. Alison realizes that the poll doesn't really reflect the entire population. She wonders what happens if a couple people in the poll lie, could it throw the whole prediction off? She reads through the rest of the article, which addresses implications of their projection, but considers it all very carefully. It's all conjecture, she realizes. She finishes the article feeling like polls aren't worth much. She decides that she can mostly ignore them. She should vote based on her opinions, not what the polls say.

## Study 1C: Bouncing Polls *Completeness Uncertainty*

Completeness uncertainty concerns the degree to which sampling represents a population. To convey completeness uncertainty through a user's exogenous attention, I worked with polls from the 2016 election. These polls make projections for who will win an election with hundreds of millions of voters based on relatively minuscule samples, generally around 1000 participants (Goldmacher, 2016).

My scenario describes Alison, a twenty-something with little political knowledge but a budding interest in the subject. Using the task analysis to walk through her interactions with the graphic reveals the power of motion and of contrasting the size of a poll with the overall size of a population.

The graphic represents the people sampled by a given poll (Figure 30). It begins with the first poll of the election cycle, which determines the color of each ball. The graphic then animates through the polls leading up to the election, showing changes in the poll projections, as well as time to the election. The balls stay their initial color, but reposition to indicate the changes that have been made over time as well as the progression of an election style.

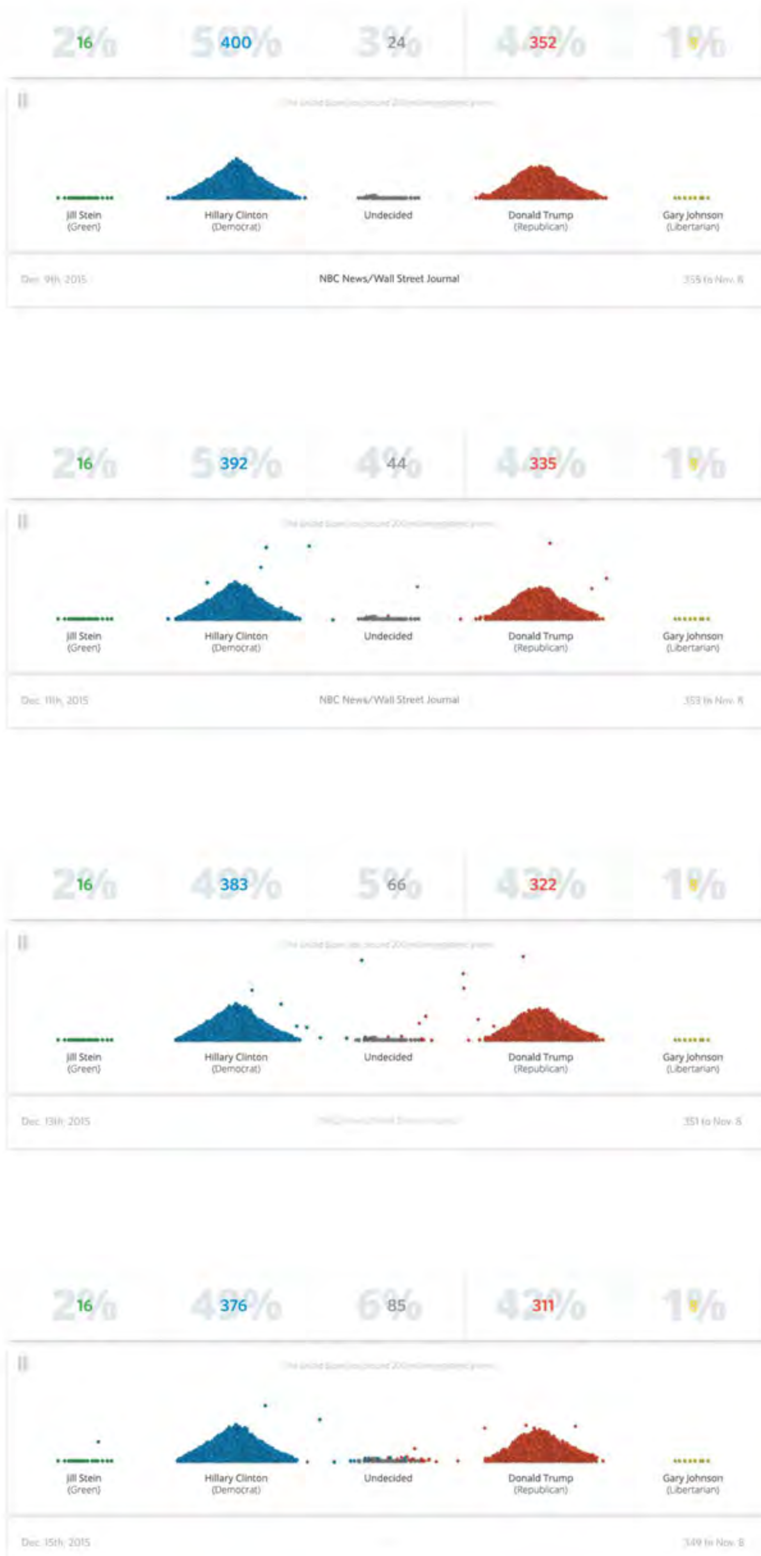
Throughout the whole animation, the user is reminded of the total possible number of voters, which contrasts with the degree to which a few changes in the sample can impact a polling projection.

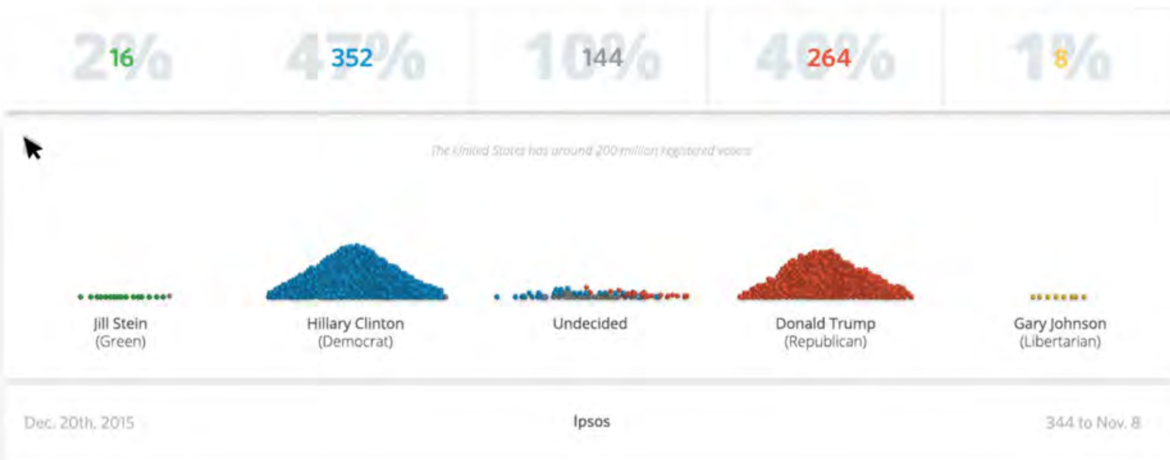
The graphic includes play and pause controls, allowing the user to pause on polling moments and explore the data through cursor rollovers. A user can see the pollster's grade or relevant details that impact the reliability of a poll, e.g., if the sample includes all voters, registered voters, or likely voters.

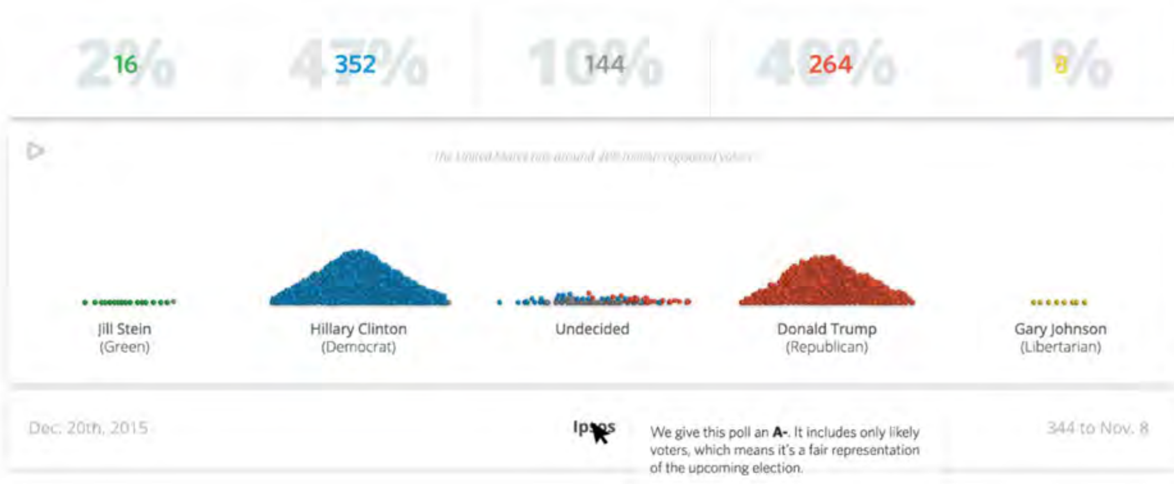
This graphic demonstrates how a simple and familiar motion can indicate uncertainty. Bouncing balls are a familiar metaphor for randomness and change, which when applied to polling numbers can convey uncertainty. Furthermore, relating the poll to the overall number increases the contrast between sample and population. Highlighting this gap in a poll graphic gives the user a better understanding of polls as an inference and a tool, rather than as all knowing forecasts.

Figure 30: **Bouncing Polls**
(Right) The graphic uses bouncing balls to represent the uncertainty involved in the relationship between a poll and the total population.

See the animation at:
https://college.design.ncsu.edu/thenfinally/hill/bouncing.gif





16
352
144
264
8
Jill Stein
(Green)
Hillary Clinton
(Democrat)
Undecided
Donald Trump
(Republican)
Gary Johnson
(Libertarian)
Dec. 20th, 2015
Ipsos
344 to Nov. 8


16
352
144
264
8
Jill Stein
(Green)
Hillary Clinton
(Democrat)
Undecided
Donald Trump
(Republican)
Gary Johnson
(Libertarian)
Dec. 20th, 2015
Ipsos
We give this poll an **A-**. It includes only likely voters, which means it's a fair representation of the upcoming election.
344 to Nov. 8

## *Scenario*

Irene likes to read political articles during breaks at work. One day she's drawn in by an animated graphic in an article about Trump's approval rating. The graphic's motion captures her attention. After examining it for a while, she notices that it consists of two moving lines that represent approval and disapproval. Both lines have a glowing background behind them.

Irene interprets the motion to suggest change and uncertainty. She realizes that the approval ratings fall in a range, rather than at a specific point. The changes give Irene the impression that the actual numbers aren't that precise. However, Irene isn't really able to make a stable interpretation of the graphic as a whole. Instead she comes away feeling like the numbers are constantly in motion and unsettled. She intuits that disapproval seems higher than approval, but she isn't sure by how much. The entire interaction makes her wonder how precise any of these things actually are.

## Study 1D: Constant Motion *Precision Uncertainty*

For my final exploration into capturing a user's exogenous attention, I created a graphic that pushes motion to an extreme and makes it difficult for the user to pick out one particular value or data point. The study visualizes data on President Trump's approval rating, which changes from day to day, but generally within a somewhat narrow range.

The scenario and task analysis follow a user who is interested in politics and used to viewing polls.

For this study, I decided to stay with a traditional line graph format and use motion to capture the user's exogenous attention and relate a feeling of uncertainty. This study was an exploration into the power of motion and how constant motion could push uncertainty and still convey information.

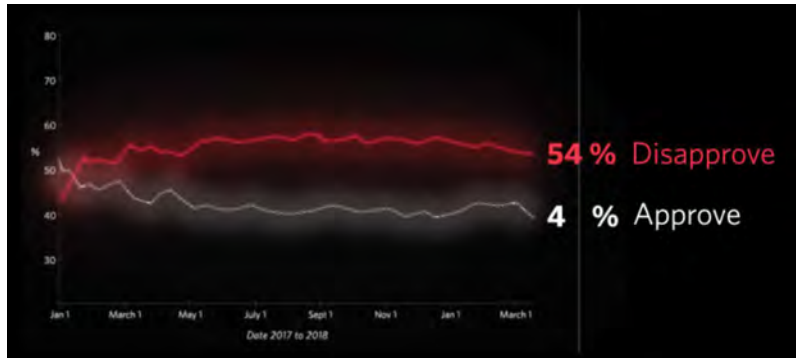
The final graphic displays two moving lines in a traditional line graph format, however, the lines animate and move within the calculated range of uncertainty and carry their labels with them (Figure 31). The constant motion makes it difficult for a user to properly read individual points or values. Instead, the user is forced to make generalized interpretations.

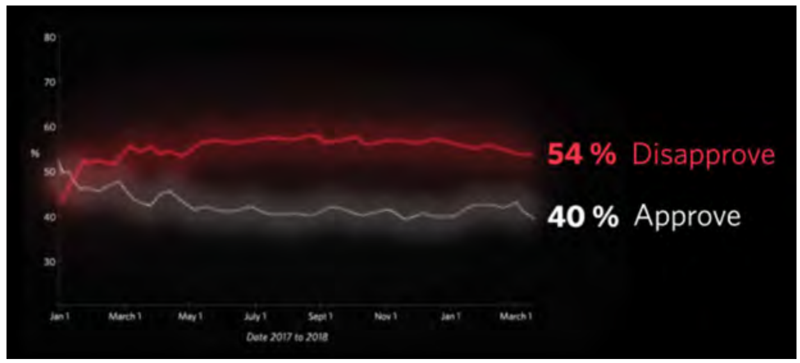
The animation also incorporates a glitch element that adds to the feeling of uncertainty. Every few frames a line scratches across the numbers, suggesting a glitch or change in the values and pushing the user's feeling of uncertainty.

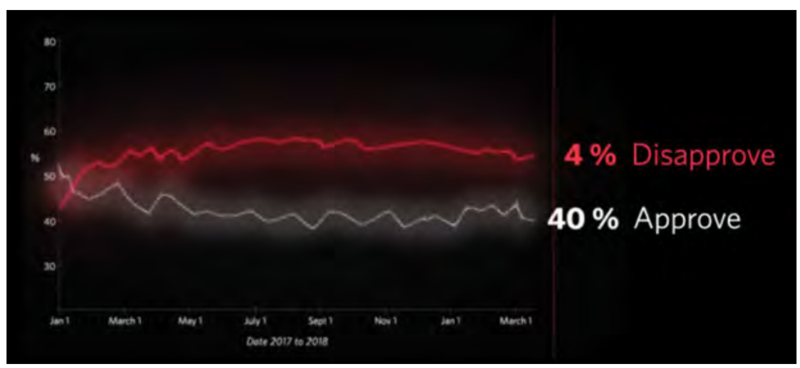
This kind of motion could be useful in representing imprecise or changing data. The motion forces generalized interpretations, rather than allowing a user to quantify specific values, leaving an impression of uncertainty, but also providing a rough forecast, which could prevent a user from feeling misled or misinformed.

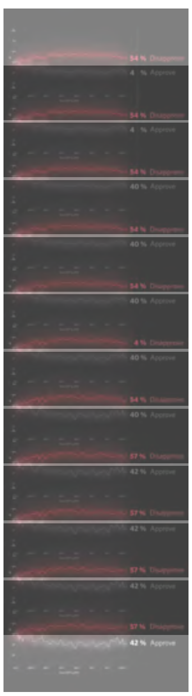
Figure 31: **Constant Motion**
(Right) The graphic explores how constant motion can impact a user's interpretations. It incorporates a glitch element as well as blur into a moving line graph.

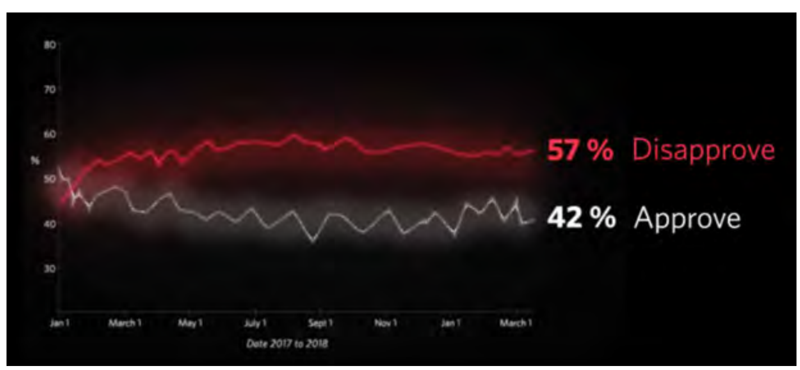
See the animation at: https://college.design.ncsu.edu/thenfinally/hill/motion.gif

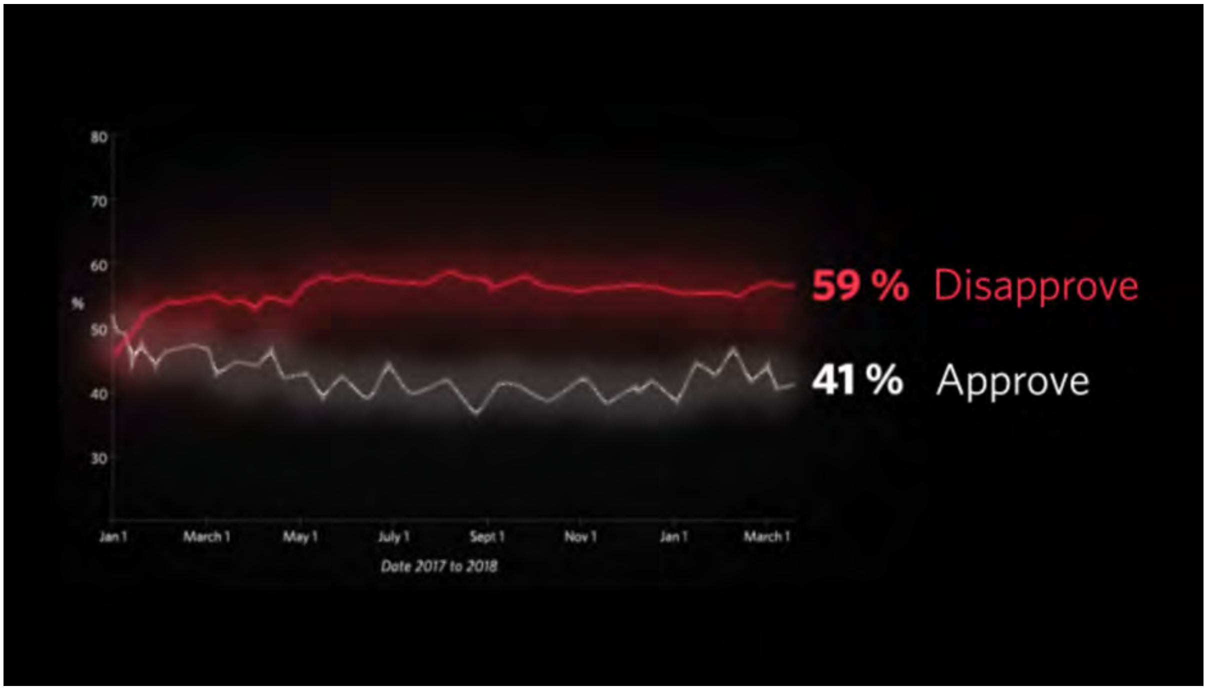


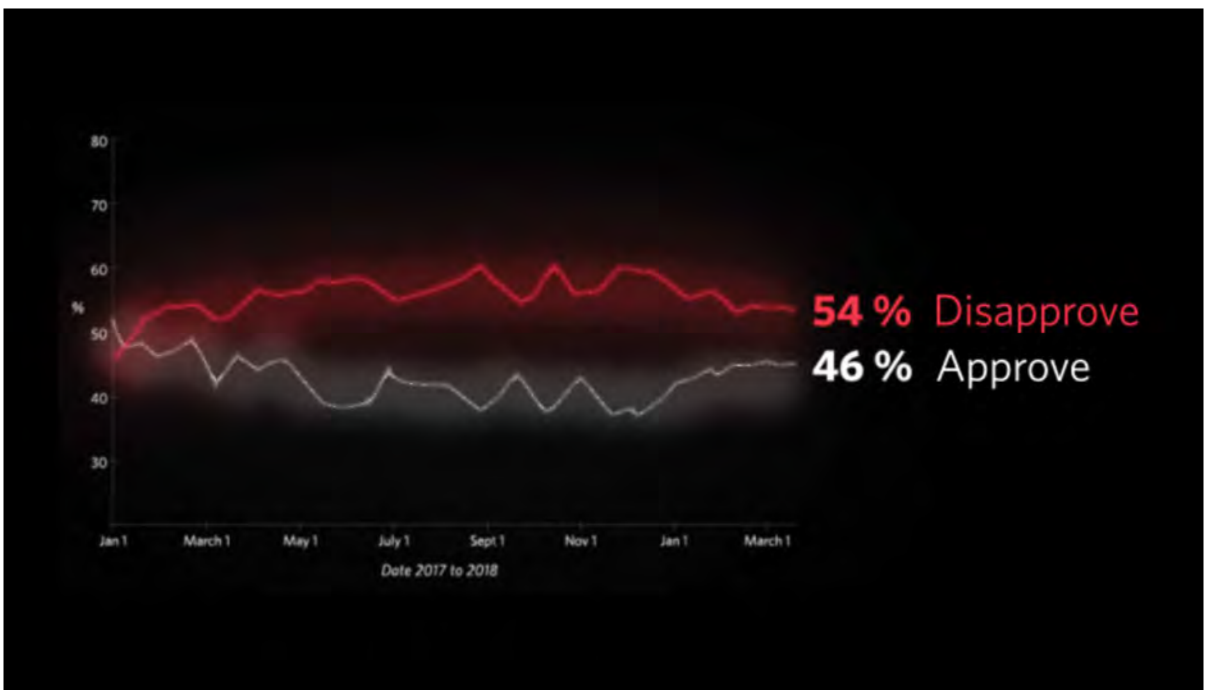






80
70
60
%
50
40
30
Jan 1
March 1
May 1
July 1
Sept 1
Nov 1
Jan 1
March 1
Date 2017 to 2018
59 % Disapprove
41 % Approve


80
70
60
%
50
40
30
Jan 1
March 1
May 1
July 1
Sept 1
Nov 1
Jan 1
March 1
Date 2017 to 2018
54 % Disapprove
46 % Approve

# Capturing Exogenous Attention *Outcomes*

### *Motion*

Simple motions can experientially convey uncertainty to a user. Graphic elements that move in familiar ways both capture a user's exogenous attention and metaphorically express uncertainty. For example, a back and forth motion suggests indecision, while the bouncing of numerous objects suggests randomness. Designers can also push the limits of motion and challenge a user's ability to latch onto concrete data points. Instead, constant motion forces a user to make broad generalizations.

While motion can be read intuitively, designers must consider the connotations involved in a specific animation or sequence. Objects growing or changing in a progression can suggest growth or an ordered relationship (See Study 1B, Figure 28), while the relationship between a moving object and its surroundings can suggest literal rather than metaphorical interpretations (see Study 1A, Figures 25 and 26).

### *Relatable Contexts*

In designing for a non-expert audience, designers must consider how a user will relate to the information being conveyed. Often times statistical measures are so abstracted from the initial phenomenon they represent that a non-expert user cannot relate to their meaning (see Study 1B). Designers must find opportunities to render information useful and relatable to a user.

## **Study Set 2: Guide Endogenous Attention**

Patterson et al. (2014) define exogenous attention as active attention and suggest providing interaction options that give a user control over an interface and minimize distracting information. To explore how endogenous attention could express uncertainty, I created four studies that explored how to convey different types of uncertainty through various interactions and interface options.

Study 2A: **Taking Control**(Inference)
Study 2B: **Hurricane Heat Map** (Disagreement)
Study 2C: **Comparing Polls** (Completeness)
Study 2D: **Finding Agreement** (Precision)

## *Scenario*

Anne's view of the world is shaped by the news she consumes. She tends to stick to the same sources and believes them without questioning. One afternoon, a colleague sends her a link to an article and graphic on President Trump's approval rating. Anne generally does not read news from this website, as it doesn't fit into her general world view, but she likes this colleague and skims the article. When she gets to the graphic, she's drawn in by the contrast of the text and the bright colors. The interactive features hold her attention and encourage her to explore the different steps taken to generate the articles numbers.

Interacting with the graph, Anne is able to track how the numerous polls involved in the article were analyzed and manipulated. She now understands that there's a great deal of manipulation behind the polls' numbers. She feels that the article's writers are being upfront about their inferences and work—something she appreciates. Seeing the work that goes into the numbers feels honest and open, as if the article is letting her in on a secret. It makes her wonder about the articles and polls she generally reads and question how much those are manipulated before they reach her. The interaction suggests to Anne that she should question what she reads in a more serious way, especially when it involves data.

## Study 2A: Taking Control *Inference Uncertainty*

My first study on guiding endogenous attention addressed presidential approval polls and inference uncertainty. Since inference uncertainty deals with the analysis and meaning given to data, I broke down the statistical analysis in order to calculate an overall approval and disapproval rate. My user scenario and task analysis follow a skeptical user who normally does not read or trust the source of the graphic.

In considering how an interface can expose the interpretations behind a data visualization, the visualization format should be familiar to a user. A familiar form allows a user to recognize changes quickly and does require lots of interpretation or attention. This study uses a line graph and scatter plot display and breaks down the process of analyzing poll numbers step by step (Figure 32).

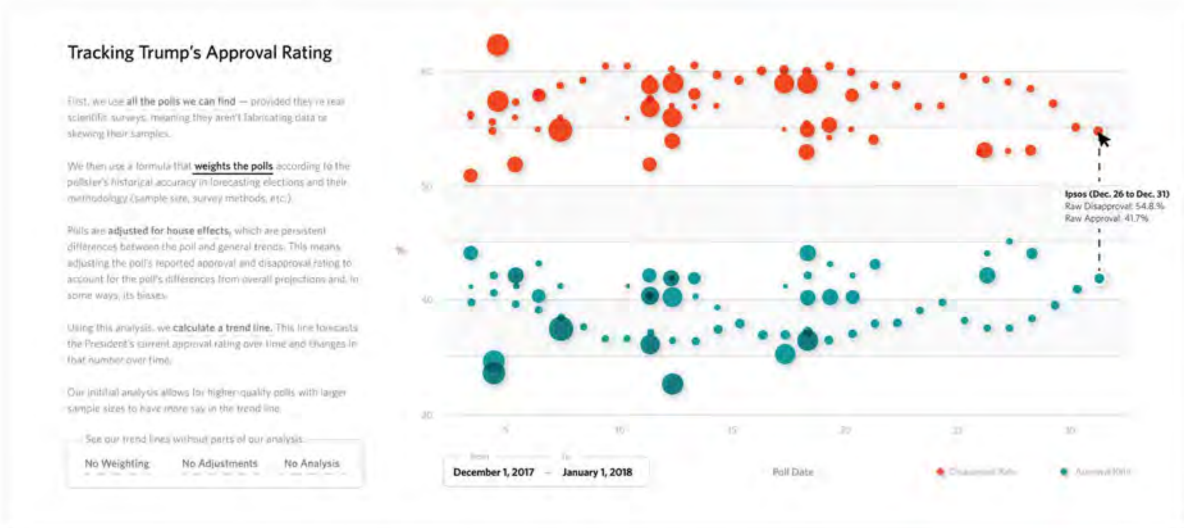
Next to the graphic is a description of the analytical process with interactive links. As the user reads through the paragraph, she can activate the links, changing the visualization to show how that piece of analysis changes the data.

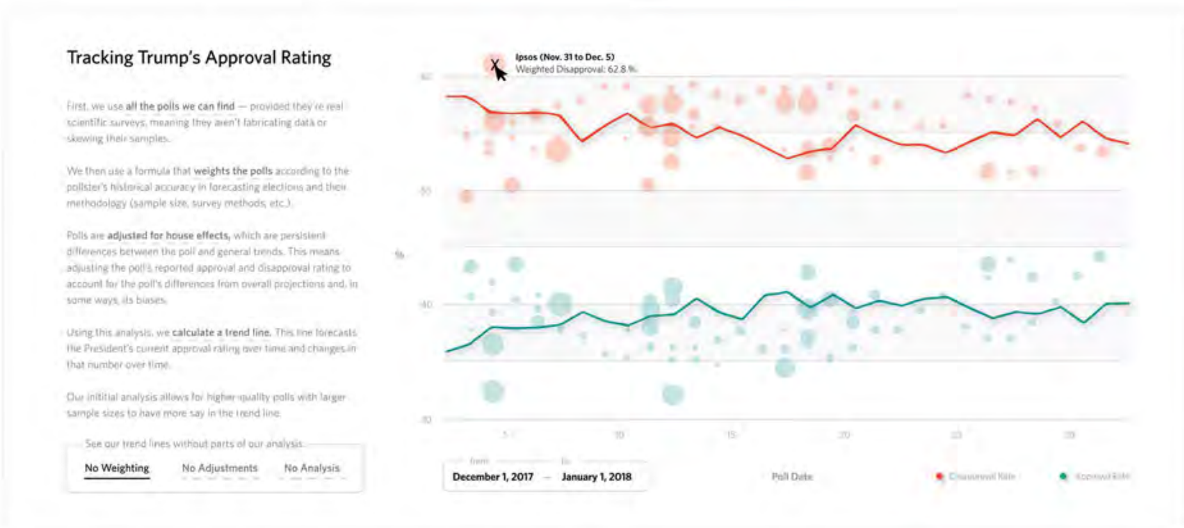
The user can also subtract data points from the trendline analysis by hovering over a data point and clicking to eliminate it. This feature gives the user even more power over the analysis, letting her tinker with the data to find patterns and make inferences at her own speed. This feature reignites the user's endogenous attention, but for it to really be appreciated, a user must dedicate a considerable amount of attention.

Giving the user control over analysis offers her insight into what is really going on with a forecast or graphic and conveys honesty and transparency. This study suggests that uncertainty and inferences can be conveyed by breaking down the analysis process and taking the user along for the inscription cascade, allowing her to see the process of translating rough data into a forecast.

Figure 32: **Taking Control**
(Right) In this study, the user controlls the analysis process and changes the graphic.

See the animation at: https://college.design.ncsu.edu/thenfinally/hill/takingcontrol.gif


Tracking Trump's Approval Rating
First, we use all the polls we can find — provided they're real scientific surveys, meaning they aren't fabricating data or skewing their samples.
We then use a formula that weights the polls according to the pollster's historical accuracy in forecasting elections and their methodology (sample size, survey methods, etc.).
Polls are adjusted for house effects, which are persistent differences between the poll and general trends. This means adjusting the poll's reported approval and disapproval rating to account for the poll's differences from overall projections and, in some ways, its biases.
Using this analysis, we calculate a trend line. This line forecasts the President's current approval rating over time and changes in that number over time.
Our initial analysis allows for higher-quality polls with larger sample sizes to have more say in the trend line.
See our trend lines without parts of our analysis
No Weighting
No Adjustments
No Analysis
Ipsos (Dec. 26 to Dec. 31)
Raw Disapproval: 54.8 %
Raw Approval: 41.7%
December 1, 2017
January 1, 2018
Poll Date


Tracking Trump's Approval Rating
First, we use all the polls we can find — provided they're real scientific surveys, meaning they aren't fabricating data or skewing their samples.
We then use a formula that weights the polls according to the pollster's historical accuracy in forecasting elections and their methodology (sample size, survey methods, etc.).
Polls are adjusted for house effects, which are persistent differences between the poll and general trends. This means adjusting the poll's reported approval and disapproval rating to account for the poll's differences from overall projections and, in some ways, its biases.
Using this analysis, we calculate a trend line. This line forecasts the President's current approval rating over time and changes in that number over time.
Our initial analysis allows for higher-quality polls with larger sample sizes to have more say in the trend line.
See our trend lines without parts of our analysis
No Weighting
No Adjustments
No Analysis
Ipsos (Nov. 31 to Dec. 5)
Weighted Disapproval: 62.8 %
December 1, 2017
January 1, 2018
Poll Date

## *Scenario*

Susan is supposed to visit Miami for work next week, but it seems like Hurricane Irma might change her plans. She's seeking out information about the hurricane when she finds a graphic on Irma's impact.

The graphic allows the user to customize the projections to a specific location. Susan enters Miami into the blank and the graphic changes, showing a row of colorful squares. The grid is broken down by dates along the left side and different projections across the top. Susan examines the color scale which ranges from no impact to catastrophic.

Susan plays with the graphic, using the interface options to reorganize the boxes and chunk together the colors. She switches from wind to storm surge projections and looks at specifc days. She realizes that a lot of the projections show severe impact on the days she's supposed to visit Miami. After playing with the graphic for a while, Susan decides to reschedule her trip.

## Study 2B: Hurricane Heat Map *Disagreement Uncertainty*

In dealing with disagreement uncertainty and Hurricane Path projections, a graphic must show conflicts in projections in a way that is relatable and immediately understandable. This study utilizes a user scenario that describes someone, Susan, planning for a trip to a potentially impacted area. The task analysis follows Susan through her interactions with the graphic and how it both guides her endogenous attention and chunks information in a way that facilitates interpretation.

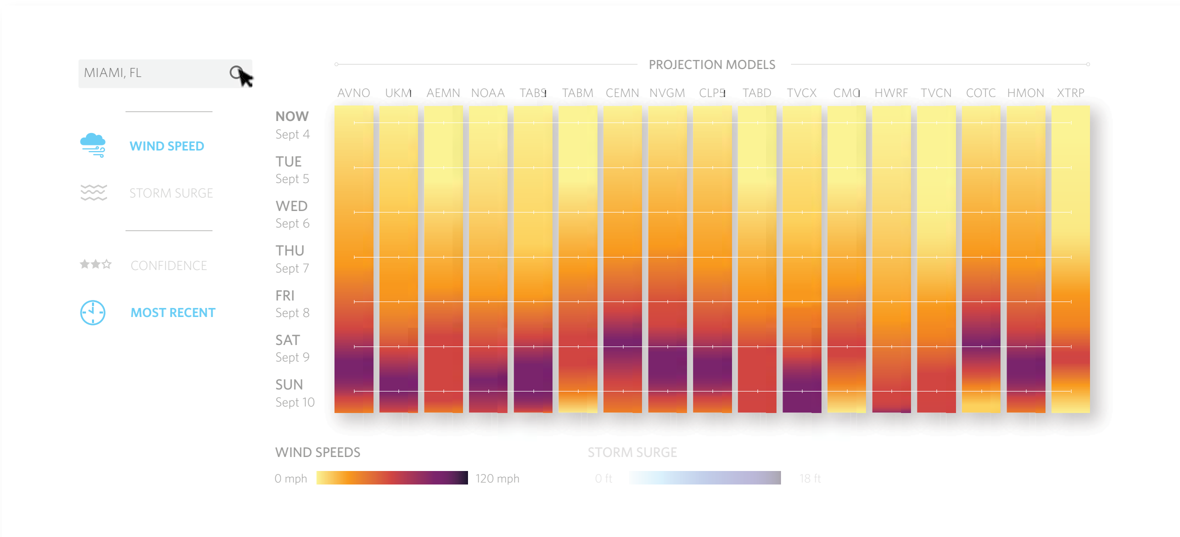
This study starts out by allowing the user to customize it to a specific location. The user enters a location to customize the interface to her needs. This feature gives the user control and allows her to tailor the focus of the graphic. The information is then laid out in a simple grid that the user can modify using the interface controls (Figure 33). The user can switch between different kinds of projections (wind speed and storm surge) and zoom in on specific dates to see a map view.

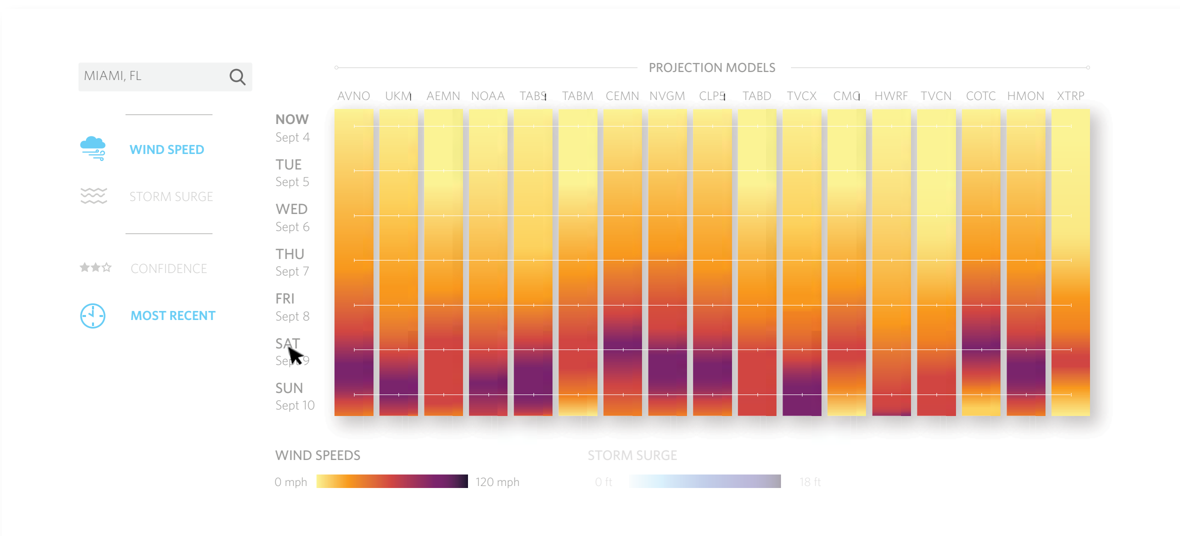
The different hurricane projection models are laid out in an eminently navigable manner, where a user can compare the projected impacts. After encountering a graphic like this for several storms, a user might intuit which models are more reliable, changing her relationship with the data.

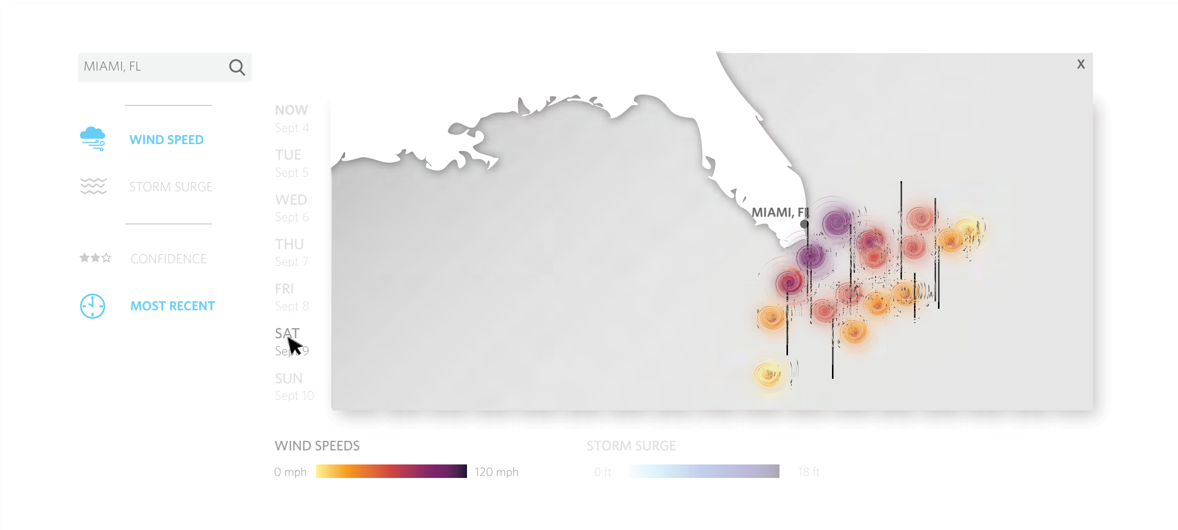
This study combined the strategies of guiding endogenous attention and facilitating chunking. By chunking together blocks, but giving the user control, the interface allows a user to make quick inferences and tailor the information to personal needs.

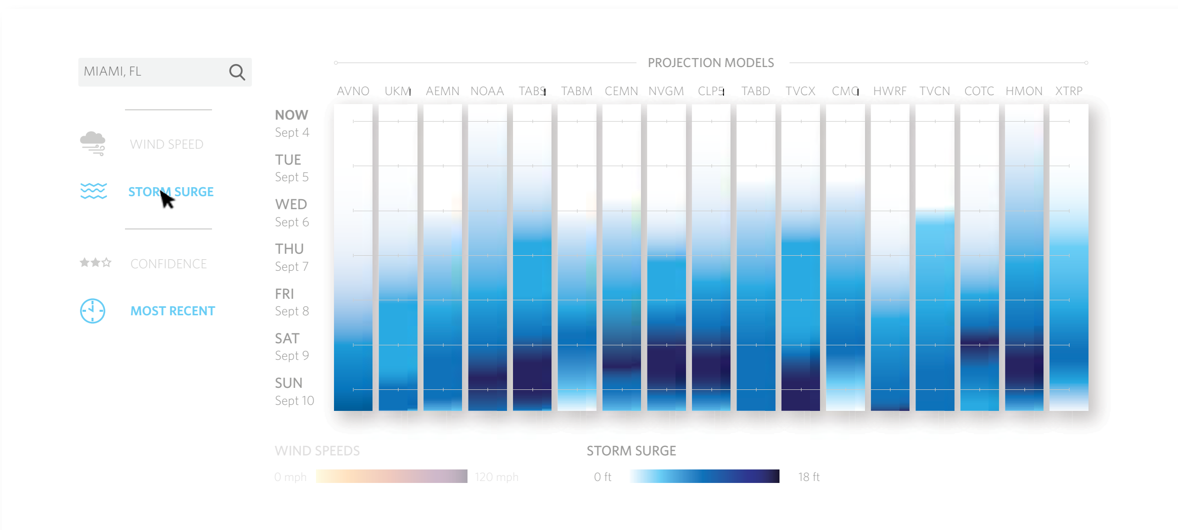
From this study, it is clear that many of Patterson et al.'s leverage points can be combined or coexist in a graphic. By combining the leverage points, a designer can engage more of a user's cognitive processes and strengthen the representations of uncertainty.

Figure 33: **Hurricane Heat Map**
(Right)This graphic combines a user's endogenous attention and the chunking of elements. The user can customize the interface and explore different layers of information.




MIAMI, FL
WIND SPEED
STORM SURGE
CONFIDENCE
MOST RECENT
NOW
Sept 4
TUE
Sept 5
WED
Sept 6
THU
Sept 7
FRI
Sept 8
SAT
SUN
Sept 10
MIAMI, FL
X
WIND SPEEDS
0 mph
120 mph
STORM SURGE
0 ft
18 ft


MIAMI, FL
WIND SPEED
STORM SURGE
CONFIDENCE
MOST RECENT
PROJECTION MODELS
AVNO UKM AEMN NOAA TABS TABM CEMN NVGM CLP5 TABD TVCX CMC HWRF TVCN COTC HMON XTRP
NOW
Sept 4
TUE
Sept 5
WED
Sept 6
THU
Sept 7
FRI
Sept 8
SAT
Sept 9
SUN
Sept 10
WIND SPEEDS
0 mph
120 mph
STORM SURGE
0 ft
18 ft

## *Scenario*

All of the news Claire sees has her feeling like the Presidential election is a done deal. Claire herself is only slightly active politically—she holds opinions but rarely acts on them, and does not really see a huge reason to vote if everyone already knows what is going to happen. One afternoon at work she is browsing her favorite news website and stumbles on an article about the election that draws from one specific poll. She scrolls through the article before stopping on an interactive visualization.

The visualization begins with a representation of the 200 million registered voters in the United States before zooming in to the tiny portion of the population that the poll sampled. The scale of the key changes dramatically to reflect the change in scale. The graphic then splits to show the proportion of the sample that supports each candidate. Claire moves the pieces of the sample around to compare sizes. She plays with comparing the different samples and then uses the key to zoom in and out, toggling from registered voters down to the sample size. The graphic also shows how this sample size compares to other top polls. After playing with the graphic for a minute or two, Claire realizes that all the election projections and articles she's been reading are based off of tiny samples. The graphic gives Claire the impression that no one really knows what is going to happen in the election. This uncertainty scares her and pushes her to actually vote.

## Study 2C: Comparing Polls *Completeness Uncertainty*

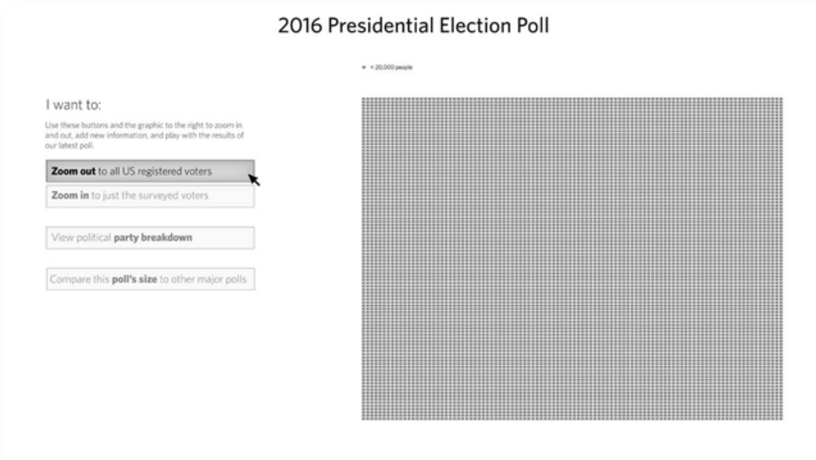
For the previous exploration on completeness uncertainty, I looked at capturing exogenous attention in a graphic about the 2016 Presidential election polls. I returned to that data set to explore how a similar graphic could convey completeness uncertainty by guiding a user's exogenous attention through an interactive graphic that a user can explore at her own pace.

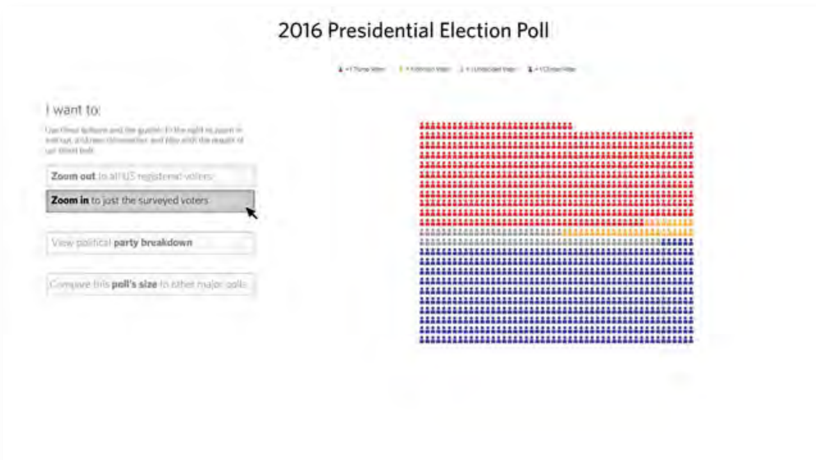
The study utilizes a user scenario and task analysis that shows how Claire, a semi-politically active individual, interacts with an interface that clusters users together by candidate.

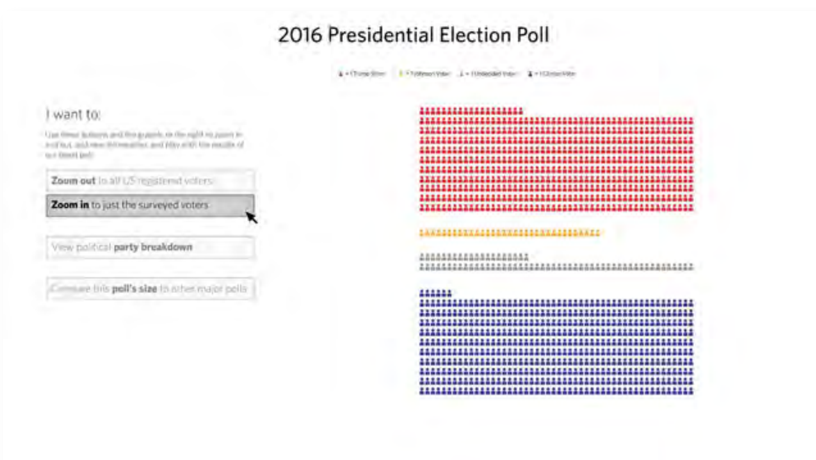
This study considered how allowing a user to explore the differences between a population and a sample conveys completeness uncertainty. Presenting the scale differences through animation, and then allowing the user to move things around and play with the pieces, exemplifies the minimal differences between sampled values (Figure 34). The user can see how a relatively small number of voters can drastically change the forecasted percentage.

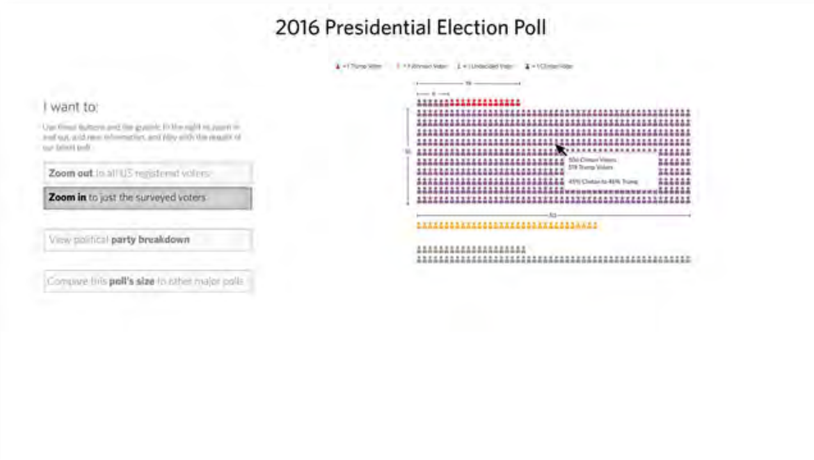
In this study, the user has control and can make inferences on her own. She is able to move pieces around and compare, drawing her own conclusions. While this approach leaves interpretations up to the user, it may not fully convey the magnitude of the uncertainty involved. The uncertainty exists mainly in the motion from population to sample. The part-to-whole comparison shows a user the drastic differences in scale and leads to questions about representativeness and inclusion. Should a user ignore that part or skip over it, she might miss the uncertainty. Breaking poll data down into individual participants, however, exposes how few people participate in a poll, which serves to convey uncertainty on its own.

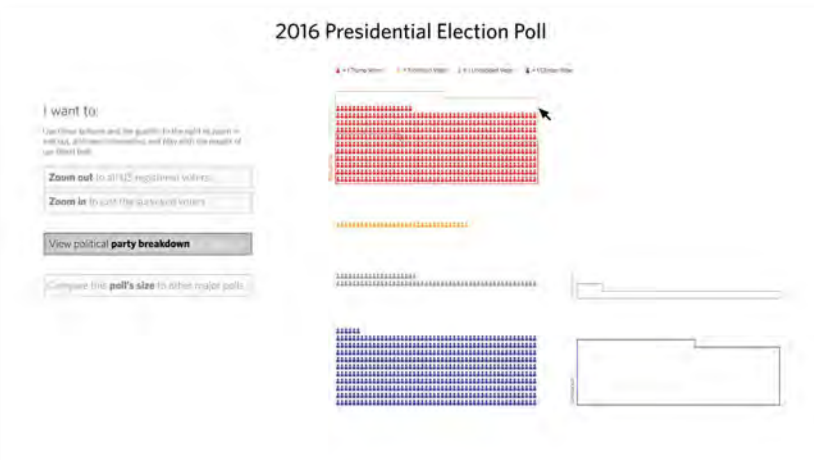
Figure 34: **Comparing Polls**
(Right) This study uses animations and interactions to show a population in comparison to a sample.

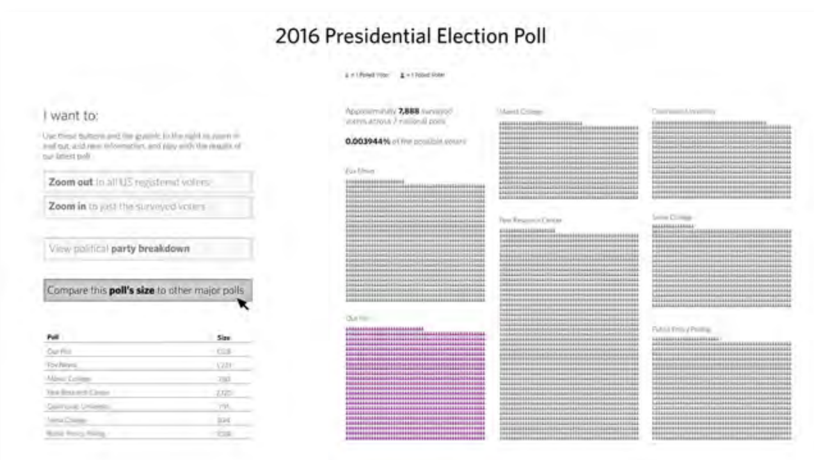



2016 Presidential Election Poll
I want to:
Zoom out to all US registered voters
Zoom in to just the surveyed voters
View political party breakdown
Compare this poll's size to other major polls


2016 Presidential Election Poll
I want to:
Zoom out to all US registered voters
Zoom in to just the surveyed voters
View political party breakdown
Compare this poll's size to other major polls


2016 Presidential Election Poll
I want to:
Zoom out to all US registered voters
Zoom in to just the surveyed voters
View political party breakdown
Compare this poll's size to other major polls

## *Scenario*

Chris is viewing political articles online when he comes across a graphic that explores President Trump's approval rating. The graphic resembles a scatter plot, but its data is chunked together in hexagons. In examining the color scales and format, Chris realizes that darker sections are moments of consensus. He follows the written cues on the graphic and rolls over different points. Chris then clicks and drags across the graphic, zooming in on a time frame. The graphic transitions to a traditional scatter plot, which Chris continues to explore.

After a while, Chris gains an understanding of the overall trend in approval numbers, but is also left wondering how precise the projections he sees are.

## Study 2D: Finding Agreement *Precision Uncertainty*

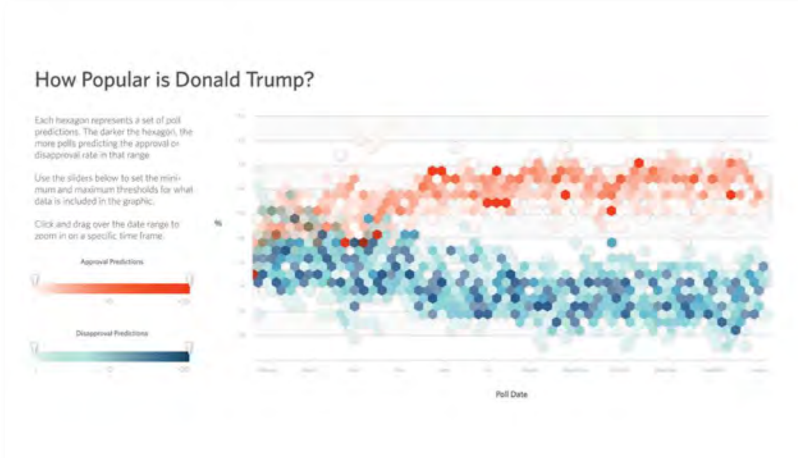
In working with precision uncertainty and endogenous attention, this study examines how a graphic can show moments of greater precision and guide a user through an altered version of a traditional format. The user scenario and task analysis follow Chris through interacting with the graphic and drawing his own conclusions.

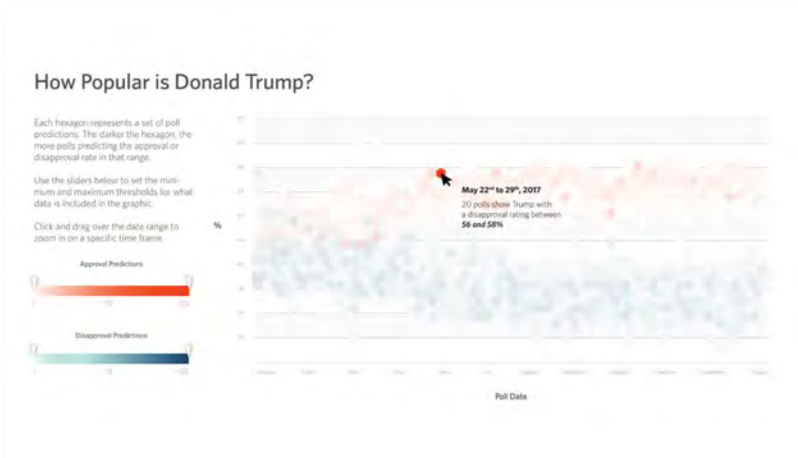
In this study, the graphic itself is fairly imprecise. Data points that relate to each other are chunked using a hexagonal grid. This format allows a user to see points of greater consensus in the data. This study combines several parts of my framework, including endogenous attention, chunking, precision, and disagreement uncertainties (Figure 35). The user can use sliders to control the precision of the graphic and eliminate sections of the visualization that portray moments of less agreement. These threshold values allow a user to explore the data at his own pace and set his own parameters for interacting with the data set.

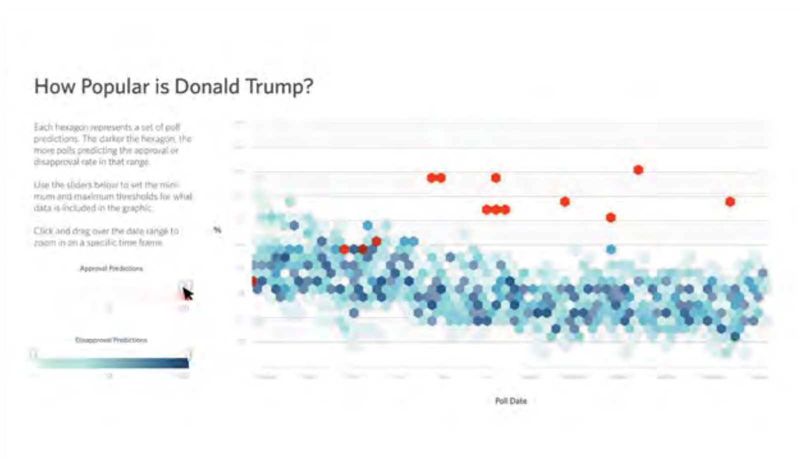
This study's interface uses rollovers to control information. When a user selects a specific data point, he is given more information about that cluster, staggering the flow of information. The user then has the power to select a range of data points by clicking and dragging. This allows him to zoom in on the information and find concrete data points, rather than the less precise range of values.

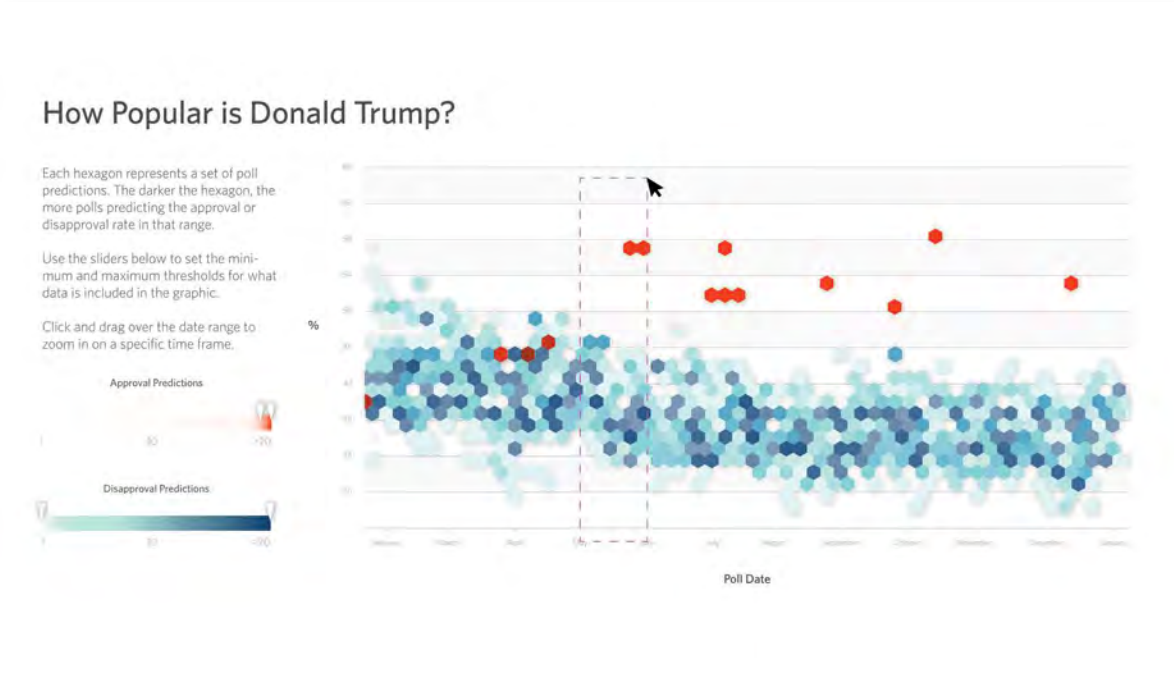
Again, this study demonstrates how combining different visual techniques can convey uncertainty and engage more of a user's cognitive processes. It also shows that multiple types of uncertainty exist and should be considered in every visualization.

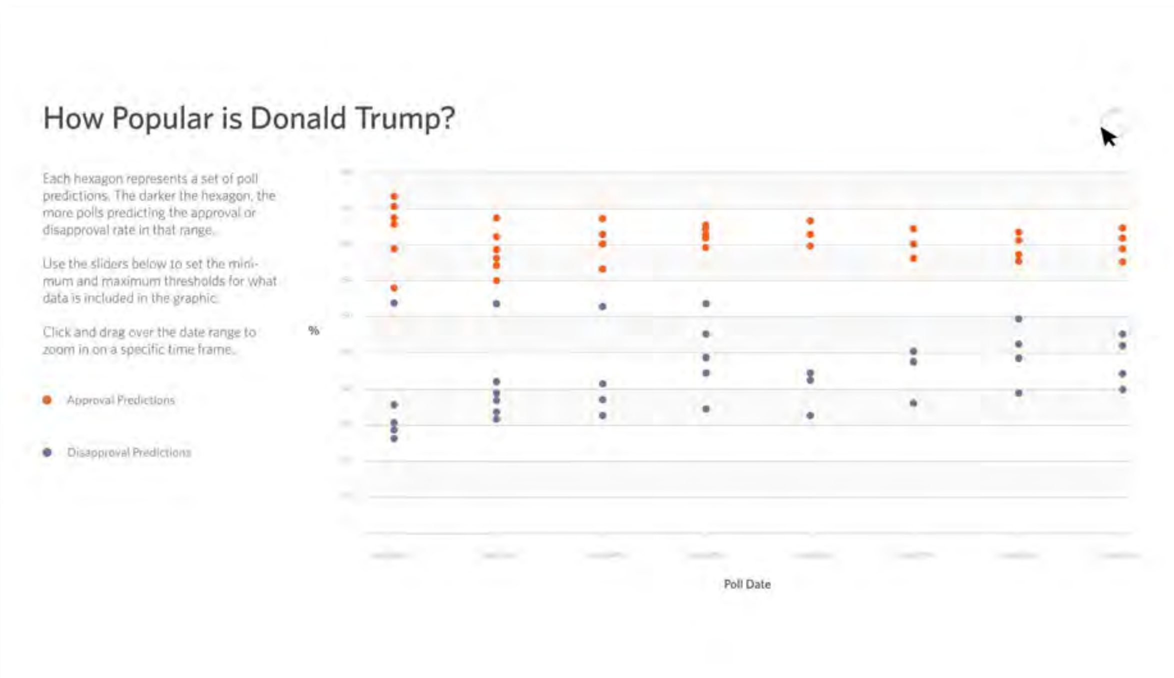
Figure 35: **Finding Agreement**
(Right) This visualization allows the user to set different thresholds for the data and explore the information through roll overs and zoom.




How Popular is Donald Trump?
Each hexagon represents a set of poll predictions. The darker the hexagon, the more polls predicting the approval or disapproval rate in that range.
Use the sliders below to set the minimum and maximum thresholds for what data is included in the graphic.
Click and drag over the date range to zoom in on a specific time frame.
Approval Predictions
Disapproval Predictions
%
Poll Date


How Popular is Donald Trump?
Each hexagon represents a set of poll predictions. The darker the hexagon, the more polls predicting the approval or disapproval rate in that range.
Use the sliders below to set the minimum and maximum thresholds for what data is included in the graphic.
Click and drag over the date range to zoom in on a specific time frame.
Approval Predictions
Disapproval Predictions
%
Poll Date

## Guide Endogenous Attention *Outcomes*

***User Control Over Analysis***

Giving a user control over the analysis behind a visualization brings a user closer to the initial phenomenon and allows for her to see changes and moments of inference. Breaking down the analysis process gives the user opportunities to question inferences made in the creation of a visualization, such as grading or weighting data points (See Study 2A). This strategy also allows a designer to scaffold information, making it easier to ignore information she does not understand, or to build off of initial insights with new information.

***Relatable Contexts***

Allowing a user to tailor the context of a visualization, such as determining the geographic focus of a visualization, gives the visualization a more relatable context and transforms it into a concrete tool (See Study 2B). Tailoring the information into a context that is relevant to the user engages the user's endogenous attention and makes the visualization more useful in general. Visualizations can do this by providing opportunities for a user to select specific locations, thresholds, and time frames. Giving a user the power to tailor information allows a user to make her own interpretations and find unique interpretations and moments of uncertainty. Designers, however, should consider how a graphic exists without those user inputs and if moments of uncertainty are not conveyed without customization.

***Using Part-to-Whole Representations to Convey Completeness Uncertainty***

Providing the opportunity for a user to compare a population size to a sample size pushes her to question the representativeness of that sample. Providing cues that force a user to make that comparison can experientially convey completeness uncertainty to a user. Part-to-whole arrangements can call out missing parts or convey drastic differences in scale and are easier for a non-expert to understand than percentages.

## Study Set 3: Facilitate Chunking

For my third study, I created visualizations that facilitated chunking, or provided strong grouping cues to make it easier for a user to see patterns and connections (Patterson et al., 2014). Chunking came up in several studies outside of this set, so previous visualizations that fall into other studies including studies 1C, 2B, 2C, and 2D.

Study 3A: **A Bite Out of Unemployment** (Inference)
Facilitating Chunking to Show Disagreement and Completeness Uncertainty
Study 3D: **Blurring Bars** (Precision)

## *Scenario*

David considers himself informed on current events. He likes to read the news during breaks at work. One day he reads an article about the current unemployment rate. The article includes an animated graphic that catches his attention. It's a quick animation that shows a set of blocks. It then shows the percent of that group that's unemployed, but it moves beyond that to show more groups that are excluded, for instance, the underemployed and discouraged. The graphic makes it easy for David to see part-to-whole comparisons and understand the completeness of the number, as well as the inferences being made by using the lower number. David is able to navigate through the graphic after the initial animation, comparing different values and finding his own meaning. He leaves the graph doubting the reality unemployment numbers, but also feeling more informed about the statistic.

## Study 3A: A Bite Out of Unemployment *Inference Uncertainty*

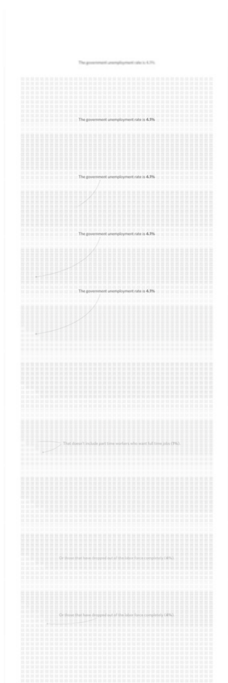
My previous studies with unemployment numbers were difficult for a user to relate to, as a result, I wanted to represent an aspect of the numbers that would be more relatable and contextualized for a non-expert user. This study focuses on who is and is not included in the unemployment numbers. The study utilized a user scenario and task analysis for a user, David, who is interested in current events but not really in touch with what unemployment numbers mean or show.

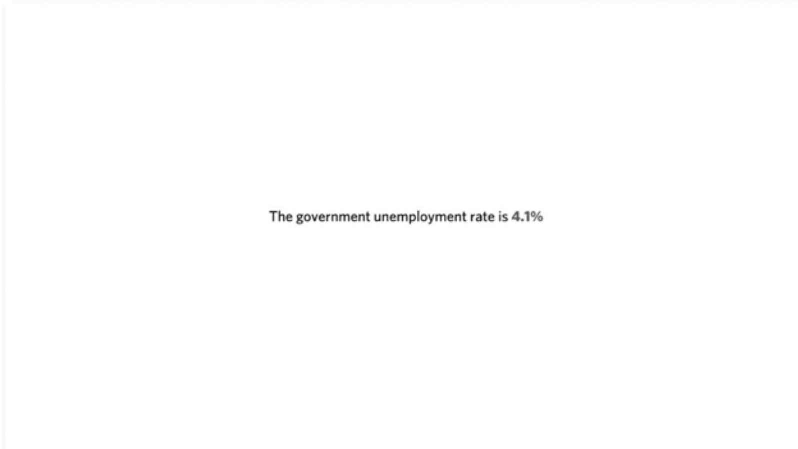
The graphic utilizes a simple part-to-whole comparison to show how adding different demographic groups to the unemployment statistic can impact the overall rate (Figure 36). The animation takes a user through the inferences the analysts made in examining the data, a technique similar to the design of Study 2A, where the user controls the visualizations as she reads the creator's inferences. Showing the changes the creators of visualizations make by adding, changing, or excluding data helps to convey to a user the impact of statistical decisions that can bias a visualization or introduce uncertainty.

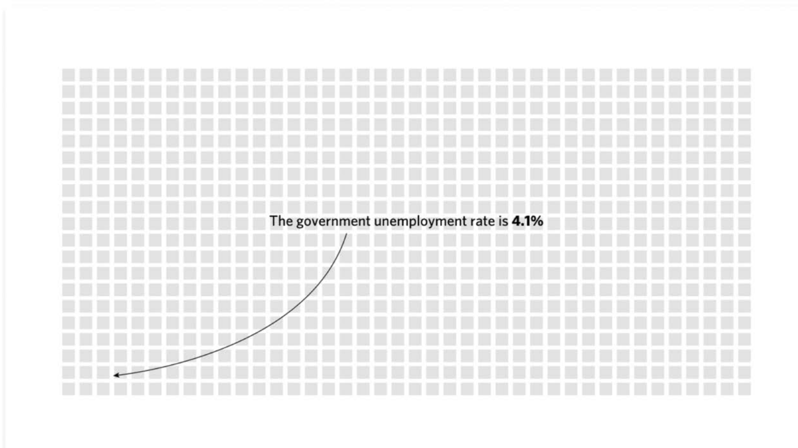
This visualization is an extremely pared down version of chunking. More complex visualizations could show different chunks and their impact in a similar part-to-whole comparison with varying colors or by highlighting parts through animation. The visualization could also incorporate more user controls, allowing the user to compare chunk sizes or change the size of the whole to see how scale impacts the data.

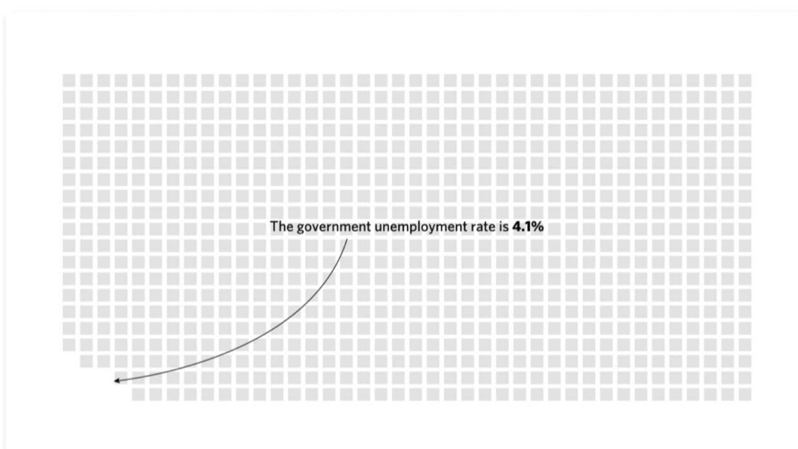
Figure 36: **A Bite out of Unemployment** (Right) This visualization walks the user through the inferences made in calculating the unemployment rate., specifically which demographics are included.

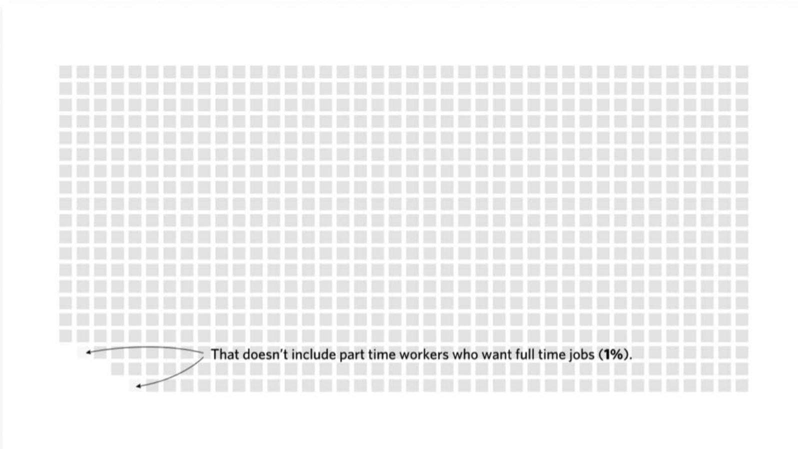
See the animation at: https://college.design.ncsu.edu/thenfinally/hill/biteunemployment.gif

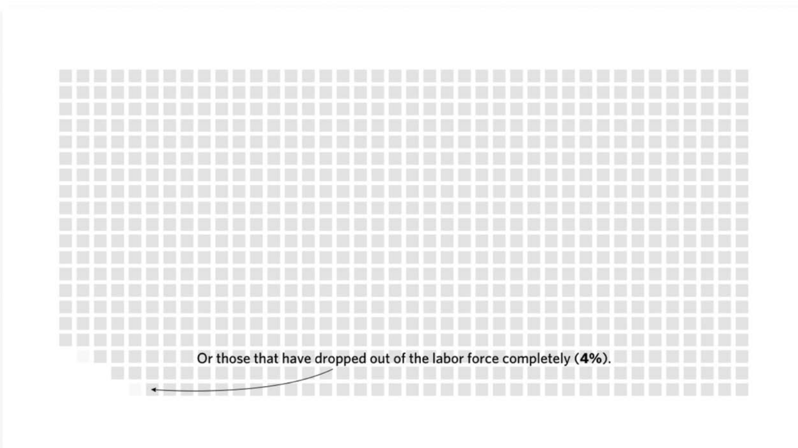


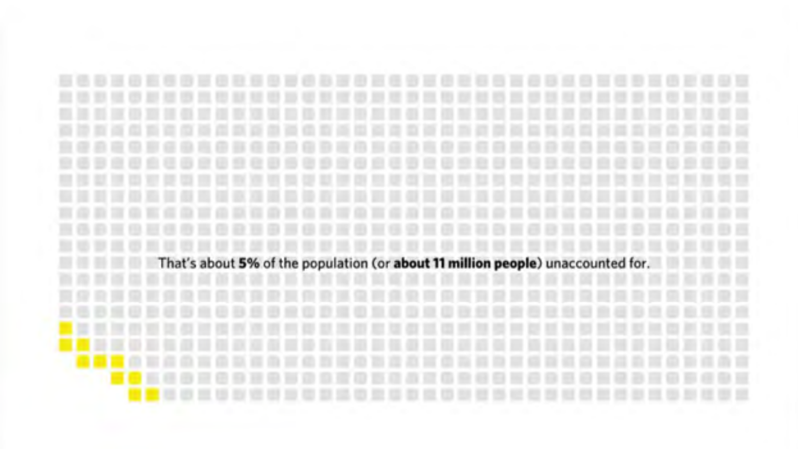


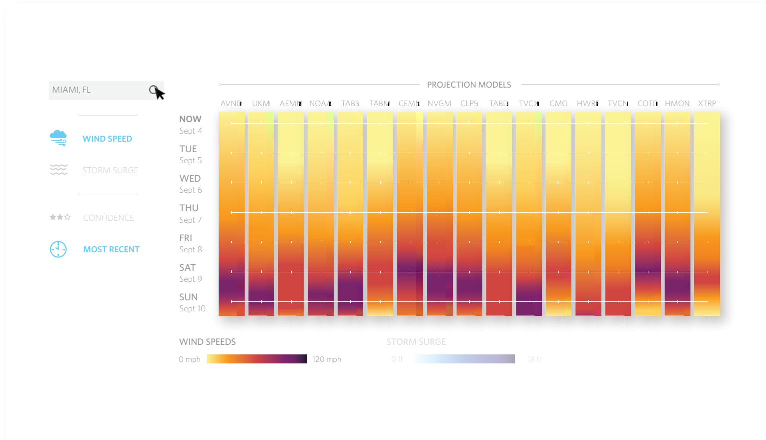

That doesn't include part time workers who want full time jobs (**1%**).


Or those that have dropped out of the labor force completely (**4%**).


That's about **5%** of the population (or **about 11 million people**) unaccounted for.

# Facilitate Chunking *Disagreement and Completeness Uncertainty*

Several studies from other sections of this investigation chunk elements together to convey disagreement and completeness uncertainty. In studies 2B and 2D, chunked elements reveal conflicts in data sets and information (Figures 37 and 38), while in studies 1C and 2C, the studies use chunking to show part-to-whole comparisons and convey sampling issues (Figures 39 and 40). These studies all group elements by color, allowing a user to easily spot moments of importance or conflict.



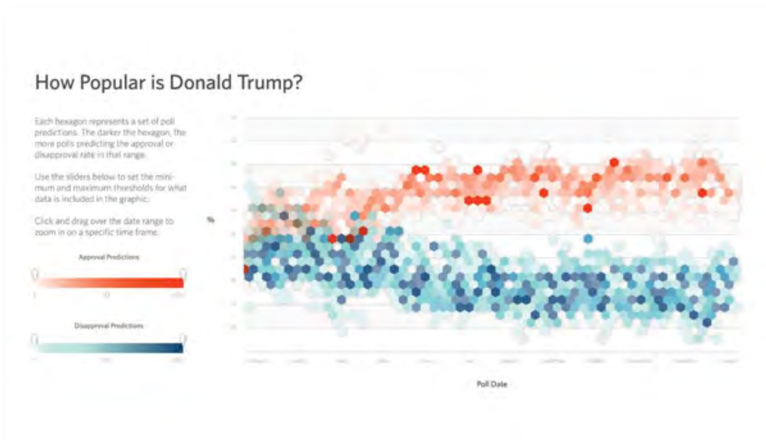
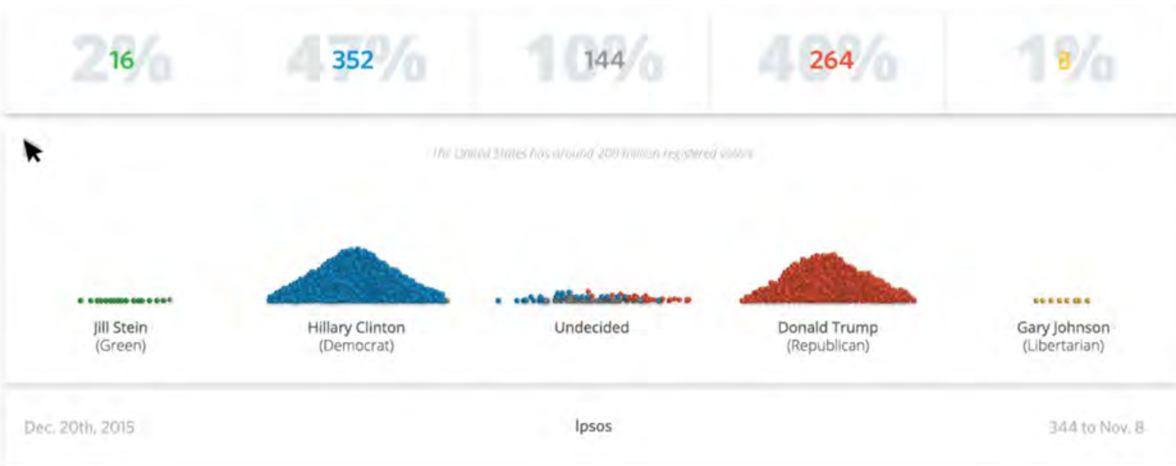



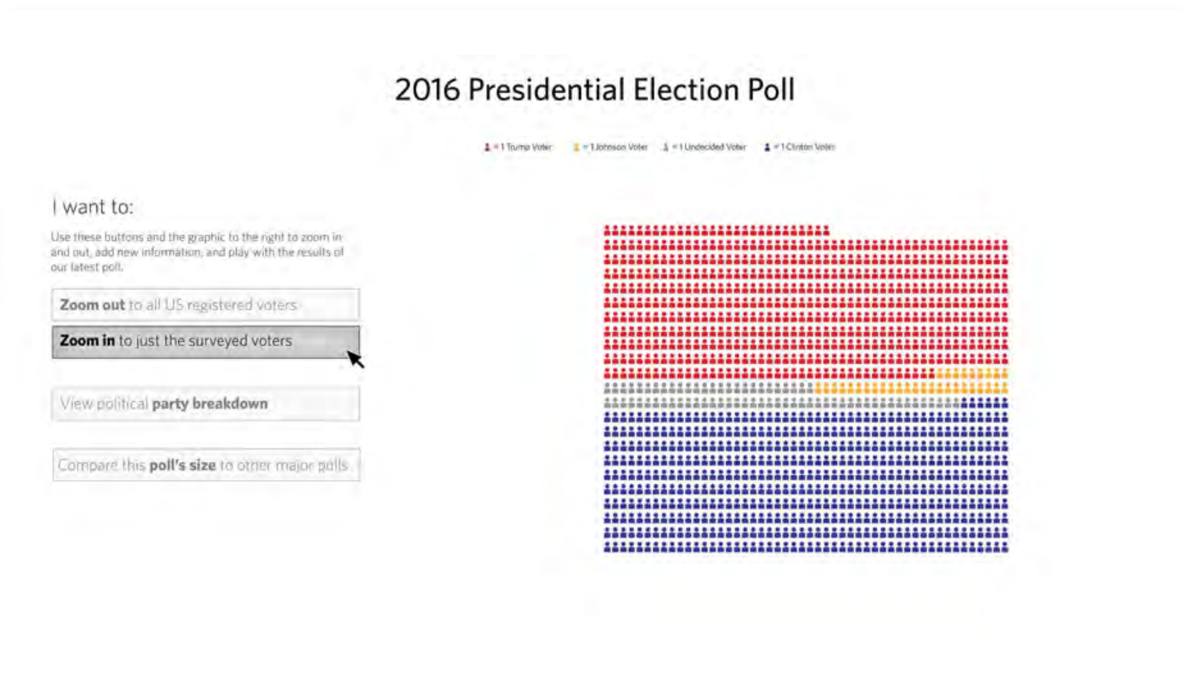

Figure 37: **Hurricane Heat Map** (Above) This study chunks information to show disagreement uncertainty in hurricane models.

Figure 38: **Finding Agreement** (Right) This study chunks elements to show precision uncertainty.

Figure 39: **Bouncing Polls** (Opposite Top) This study chunks information to show sampling issues.

Figure 40: **Comparing Polls** (Opposite Bottom) This study allows a user to play with chunked elements to convey sampling issues.


16
352
144
264
8
The United States has around 200 million registered voters
Jill Stein
(Green)
Hillary Clinton
(Democrat)
Undecided
Donald Trump
(Republican)
Gary Johnson
(Libertarian)
Dec. 20th, 2015
Ipsos
344 to Nov. 8


2016 Presidential Election Poll
= 1 Trump Voter
= 1 Johnson Voter
= 1 Undecided Voter
= 1 Clinton Voter
I want to:
Use these buttons and the graphic to the right to zoom in and out, add new information, and play with the results of our latest poll.
Zoom out to all US registered voters
Zoom in to just the surveyed voters
View political party breakdown
Compare this poll's size to other major polls

## *Scenario*

Sarah is browsing through the day's news when she sees an article about the unemployment rate. She's not much for economics, but the headline draws her in and she skims through. As she's reading, she's attracted to a brightly colored graphic. The left side of the graphic where the current unemployment number sits is clear and crisp, but as the graphic gets further away from the present, the bars become blurred. The contrast and change allows Sarah to quickly relate that blur to a fuzziness about the actual number. The average, which is black, contrasts sharply from the range in yellow, allowing Sarah to mentally chunk the items together and interpret the graph quickly. She interprets it as the author or creator being careful; they don't know what's going to happen in a year or two, so why make a firm prediction just to be wrong?

## Study 3D: Blurring Bars *Precision Uncertainty*

Previous explorations with chunking considered how grouping elements by color allows a user to spot inconsistencies and missing pieces. For this final study, I explored how blurring elements that are otherwise identical can lead a user to interpret elements as uncertain. This study works with *The Wall Street Journal's* economic survey on unemployment numbers, as well as a scenario and task analysis of someone quickly skimming the graphic in a longer article.

The graphic in this study shows the average estimate from the survey, as well as the range of the estimates. The further out a projection is from the current date, the more blurred the graphic element. This is reinforced by the growing size of the estimate range over time. The color of the elements allows a user to chunk them together and compare size and positioning, while the changes in blur suggest changes in the certainty of the data. In this case, blur is interpreted metaphorically, with the user unable to make a concrete and firm interpretation of the specific value and relating that to uncertainty (Figure 41).

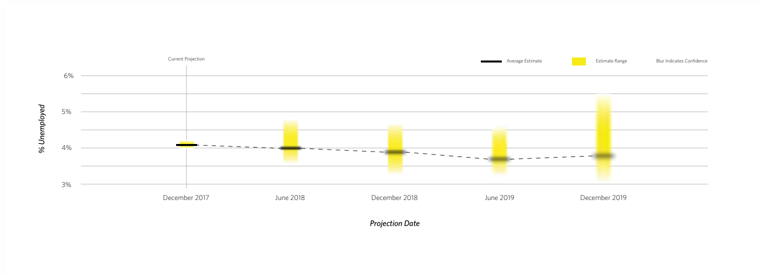



Figure 41: **Blurring Bars** (Above) This study uses blur to contrast more solid elements and convey uncertainty through the differences.

# Facilitate Chunking *Outcomes*

### *Using Part-to-Whole Comparisons*

Grouping elements together provides the opportunity to convey uncertainty through contrasting or missing elements. It also allows a user to make generalized interpretations based on part-to-whole comparisons, much in the way a percentage value works. Allowing the user to reach a generalization on her own, however, means she is aware of the size of the other part and that there is the possibility of other outcomes.

### *Blur*

In visualizations, blur makes it difficult for a user to quantify a value or give specific meaning to an element. It allows a user to make generalized interpretations, rather than come away with concrete values. Blur can be used with similar elements to suggest that one value is more certain than another, or to make a single element stand out in contrast.

Blur acts as a kind of metaphor for uncertainty: elements are literally fuzzy and challenge a user's ability to quantify data points. By blurring objects, a designer implies that an object, and what it represents, is not solid or fully formed. The metaphor is strongest when blurred elements are presented with sharp or solid ones, making the blur noticeable and providing contrast. In using it, designers must be comfortable with giving users a generalized, rather than specific, impression of the data. Too much blur could potentially give a graphic an untrustworthy or timid feeling, something a designer should keep in mind.

Pairing blur with an element like time (see study 3D) gives it a concrete value to fix on and allows a user to see changes in uncertainty over time (or any other value), telling more of a story about the data and its reliability.

## **Study Set 4: Mental Models and Analogies**

Our mental models and analogies can be powerful tools in reasoning through new situations or complicated information. We organize information based on mental models, which allow us to access long-term memory and aid reasoning (Patterson et al., 2014). Structuring visualizations through analogies allows us to access these mental models and reason with complex information (Patterson et al., 2014). Metaphor and analogy provide powerful tools for designers to convey complex ideas in simplistic terms. Previous studies on motion and blur have touched on metaphor and how it experientially conveys uncertainty, but this section deals with broader metaphors that can drive the entire structure of a data visualization.

Using Mental Models and Analogies to Reveal Inference Uncertainty
Study 4B: **Hurricane Dashboard** (Disagreement)
Study 4C: **Adding to the Scale** (Completeness)
Study 4D: **Taking the Temperature of the Electorate** (Precision)

# Mental Models and Analogies: *Inference Uncertainty*

Other studies in this investigation utilize analogies to convey inference uncertainty. Study 1A uses a water metaphor to convey the different inferences surrounding storm surge projections (Figure 42). Many studies rely heavily on motion, in the case of study 1A a wave-like motion, to convey different possibilities. Motion itself acts as a kind of metaphor for uncertainty, with different motions suggesting different meanings. A wave suggests motion between two points or rising and falling.

Other motions, like the random bouncing motion in Study 1C can be used to relate inference when combined with a specific data set or structure, for example, objects could bounce from one idea to another to convey uncertainty about an inference in a simulation or other visualization (Figure 43). Designers must consider the intricate details of a motion when creating a visualization as inappropriate motions can lead to misinterpretation and false conclusions.

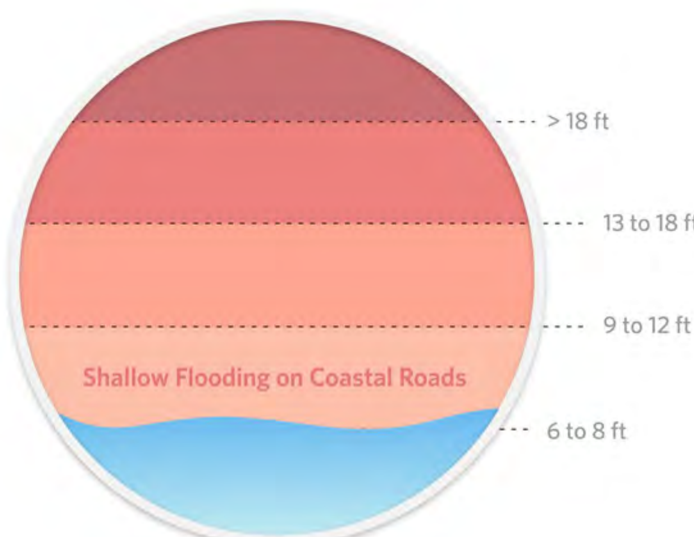
Blur can also be used to relate inference uncertainty, with objects relating dubious inferences or less certainty blurred more than more certainty data points, like the progressive blur in Study 3D (Figure 44).

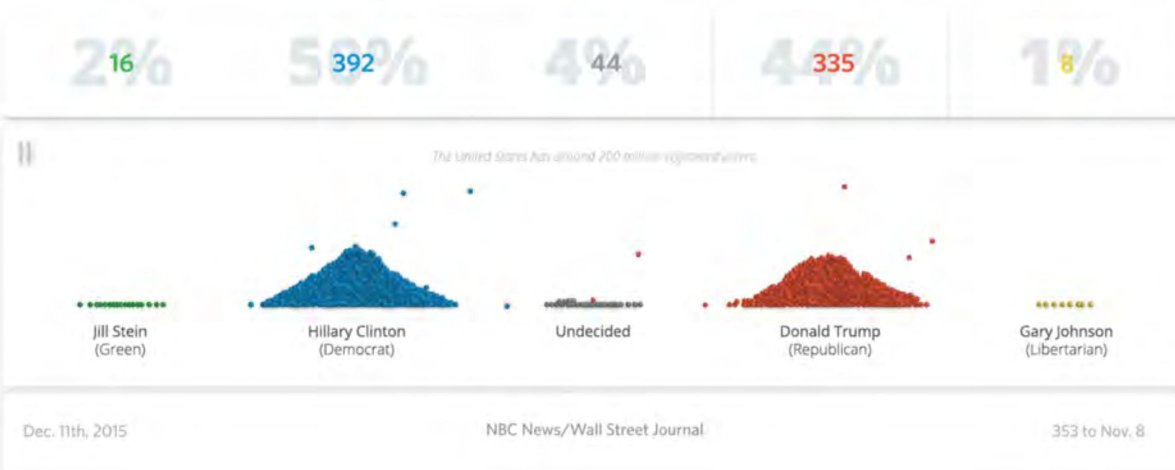
My design explorations suggest that designers can use analogies to develop new visualization structures that convey inferences.

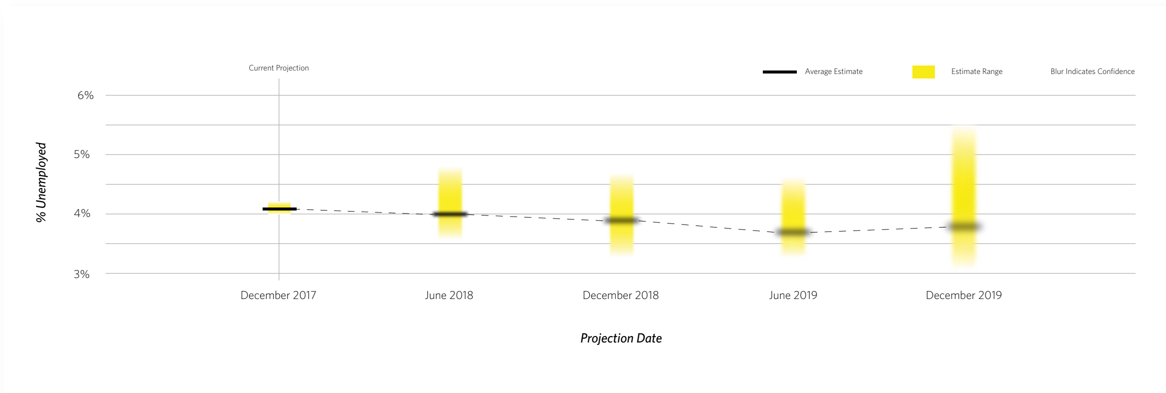
Figure 42: **Rising Water** (Below) The wave motion in this study could be used to metaphorically convey inference uncertainty.

Figure 43: **Bouncing Polls** (Opposite Top) The bouncing motion from this study could be used to convey inference uncertainty..

Figure 44: **Blurring Bars** (Opposite Bottom) Blur can function as a metaphor for uncertainty and be used to convey inference uncertainty.




16
392
44
335
8
Jill Stein
(Green)
Hillary Clinton
(Democrat)
Undecided
Donald Trump
(Republican)
Gary Johnson
(Libertarian)
Dec. 11th, 2015
NBC News/Wall Street Journal
353 to Nov. 8


Current Projection
Average Estimate
Estimate Range
Blur Indicates Confidence
6%
5%
4%
3%
% Unemployed
December 2017
June 2018
December 2018
June 2019
December 2019
Projection Date

## *Scenario*

Ben is supposed to go to Miami next week for work, unfortunately, it looks like Hurricane Irma will be visiting then too. Ben's not sure what's going to happen with the hurricane, so he's seeking out information from online news sources.

One website includes a graphic that looks like a car dashboard. Ben stops and examines the graphic. It includes a spinning hurricane, a couple of gauges, and a search bar. As Ben enters in his information (location, date, etc.), the dashboard comes alive and the gauges move, giving him information about the hurricane's path.

Ben examines the interface and sees that it includes a time bar. He slides the bar closer to when he'll be in Miami and a transparent version of the hurricane splits into multiple hurricanes that slide along the paths. The spinners on the left go wild, all moving away from calm towards stronger winds.

Ben clicks on one of the little hurricanes that doesn't directly hit Miami. The other paths and hurricanes fade out, but the spinners stay near dangerous wind speeds. Ben continues to play with the different paths, watching their impact on the spinners and their relationship to Miami. After a while, Ben becomes convinced that regardless of the directness of the hit Miami receives, he doesn't want to be anywhere near South Florida.

## Study 4B: Hurricane Dashboard *Disagreement Uncertainty*

*The New York Times* uses a needle gauge to convey uncertainty in polling projections. For my initial study into metaphor, I pushed that metaphor further, building a whole dashboard to convey disagreement uncertainty in hurricane path projections. The dashboard metaphor is so pervasive that almost every interface includes some sort of dashboard. Users encounter real and metaphorical dashboards every day, making them powerful tools for conveying complex information.

For this study, I worked with a scenario and task analysis that describes a user trying to make a decision about traveling to a hurricane prone area. The user, Ben, is familiar with the dashboard metaphor, making the interface easy for him to use and interpret (Figure 45).

In this hurricane forecast, the user is interested in how the storm will impact him. Designers can tailor these visualizations to a specific user by including customization options, like location searches and time sliders. This gives the user the power to favor impacts that are relevant to them. For this study, the spinners give a user a sense of the impact, but also of confidence. The wind speed spinner shows impact, and as the dial lingers on areas of greater damage, the top of the scale lights up, capturing the user's exogenous attention.

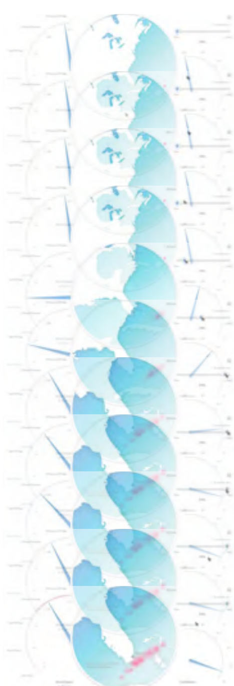
In designing visualizations with metaphors, designers can incorporate other leverage points, like exogenous and endogenous attention, to further facilitate cognitive processing.

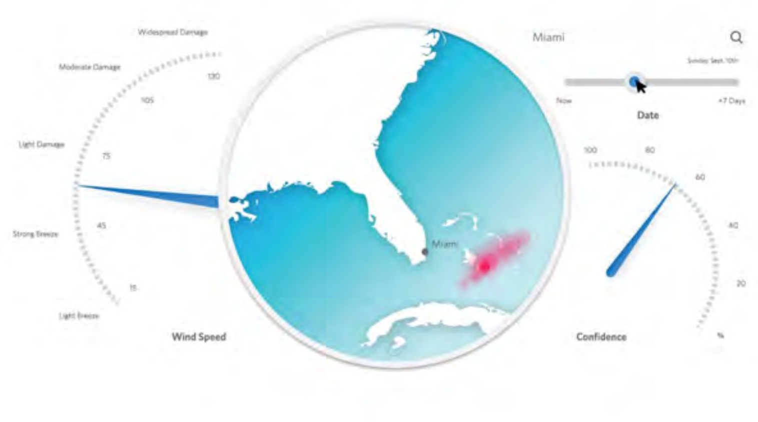
The dashboard metaphor has become so ubiquitous because of its simplicity and relatability. We read dashboards to gain information at a given moment, so users expect motion and responsiveness. Dashboards can incorporate numerous ideas at once because users are familiar with reading them and are not challenged by the structure. These qualities make dashboards a useful metaphor for conveying uncertainty, especially in complex situations, and demonstrate the benefit of metaphors being familiar and relatable.

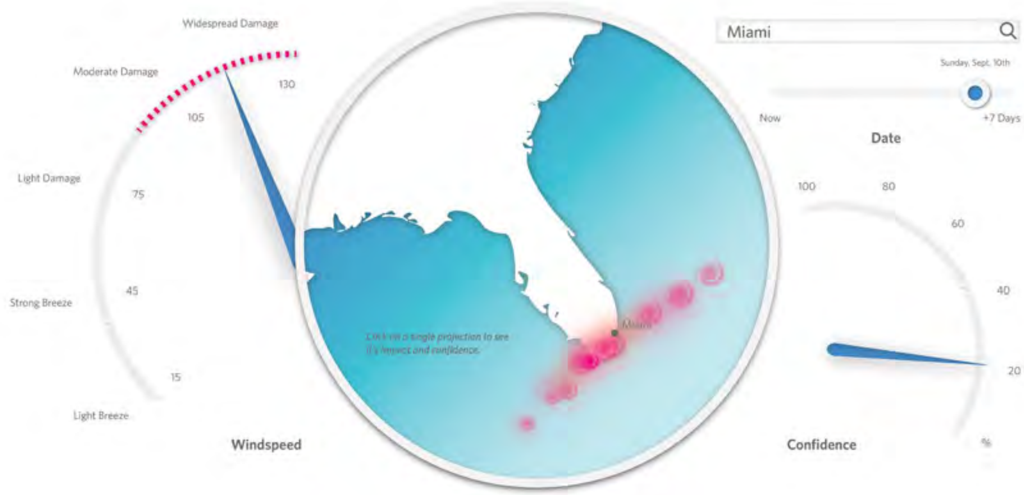
Furthermore, the motion of the gauges acts as a metaphor separate from the dashboard itself. As I discussed with previous studies, an oscillating motion conveys indecision and makes it difficult for a user to select a specific value. This creates an experiential feeling of uncertainty. Large scale structural metaphors, like dashboards, can combine various analogies in one visualization, furthering reinforcing elements that convey uncertainty.

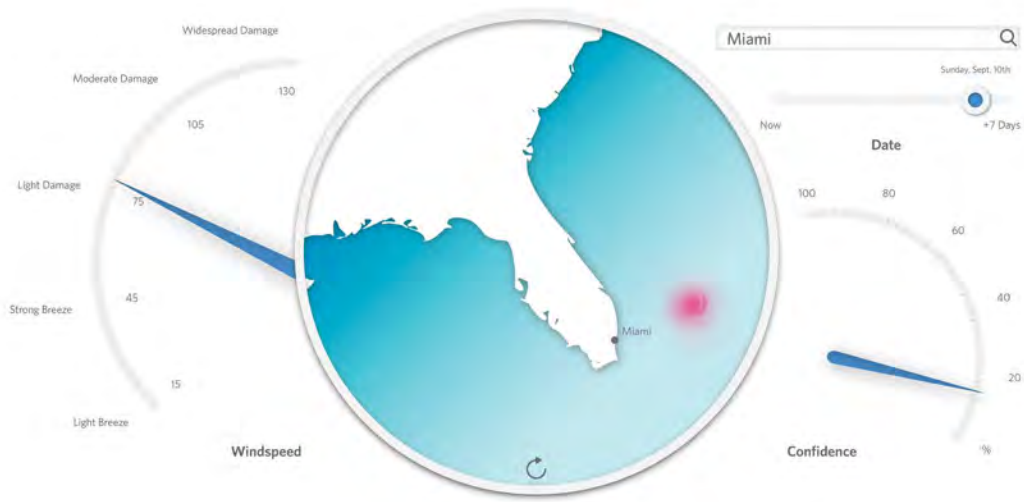
Figure 45: **Hurricane Dashboard** (Right) The visualization uses a familiar dashboard structure and movement to convey disagreement uncertainty.

See the animation at: https://college.design.ncsu.edu/thenfinally/hill/dashboard.gif


Widespread Damage
Moderate Damage
130
105
Light Damage
75
45
Strong Breeze
15
Light Breeze
Windspeed
Miami
Sunday, Sept. 10th
Now
+7 Days
Date
100
80
60
40
20
%
Confidence


Widespread Damage
Moderate Damage
130
105
Light Damage
75
45
Strong Breeze
15
Light Breeze
Windspeed
Miami
Sunday, Sept. 10th
Now
+7 Days
Date
100
80
60
40
20
%
Confidence
Miami

## *Scenario*

Lately, Audrey has been hearing how great the US economy is doing. She's bombarded with messages about low unemployment and a booming stock market, but this doesn't reflect her life or that of those around her. She's been working part time for months because she can't find a full-time job. She doesn't understand why everything she hears about jobs and unemployment is so positive, when that doesn't reflect her reality. One day, Audrey is torturing herself by reading an article on the unemployment rate on a news website. She's really just skimming over the discussion when she comes to a strange graphic. In the middle of the article is what looks like a scale. To the right are three people with brief descriptions of each person's situation and to the left is a traditional kitchen scale with a large dial. Audrey clicks on the first person presented, she's described as jobless and actively looking for a new job. When Audrey clicks, the woman moves onto the scale and the dial hovers around 4%. The caption on the scale reports that this demographic is the only one the government uses. Audrey then clicks on the next person, who is described as underemployed, or working part time because they can't find a full-time position. When this person is added to the scale, the arrow jumps and hovers around 8%.

Audrey is shocked. She realizes she's been left out of the numbers and information she's seen on unemployment. Audrey feels that politicians and those around her have been misrepresenting the economy and failing to represent her.

## Study 4C: Adding to the Scale *Completeness Uncertainty*

In working with unemployment numbers and a metaphorical display, I used a scenario and task analysis for a user, Audrey, who is confused by unemployment numbers . She is unable to see herself or her situation in the numbers.

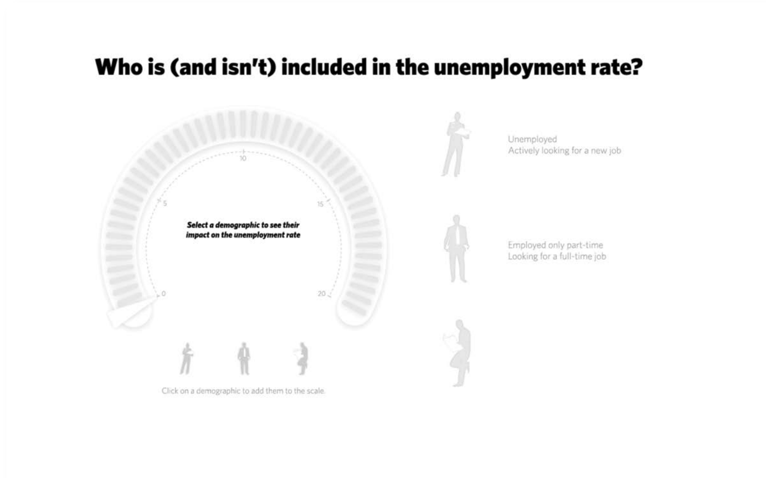
Audrey's situation calls for a representation that highlights the human factor of the numbers. This exploration uses a scale to convey the weight of different demographic groups. The needle on the scale operates experientially. Logic dictates that adding more to a scale increases the weight. The visualization uses this knowledge to convey how making the unemployment rate represent more demographics increases the statistic (Figure 46). The metaphor also works in reverse: removing people from the scale decreases the unemployment value shown.

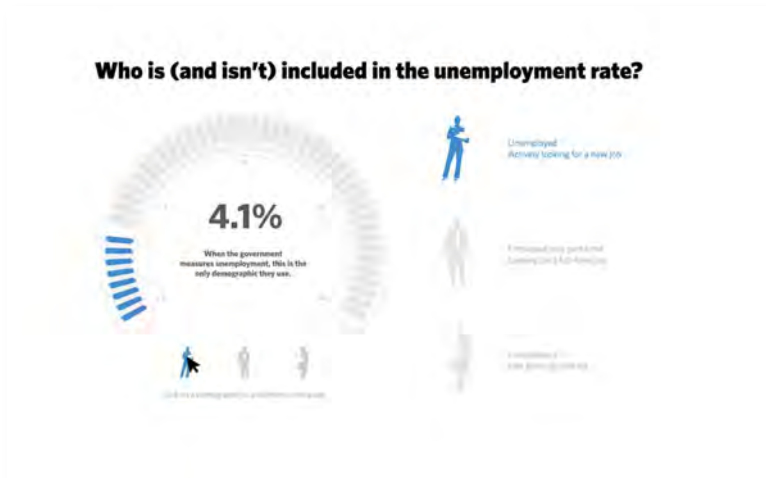
The scale metaphor brings the visualization closer to the phenomenon. In this case, the visualization deals with adding and subtracting demographic groups from a statistic, just as adding items or people to a scale can increase the value shown. Unlike Study 1A where the metaphor is so close to the information being represented that it makes it too easy for a user to interpret the graphic literally, this type of metaphorical representation is abstracted enough to allow a user to make inferences about the actual statistic without being distracted by literal interpretations. This suggests that metaphorical structures that mimic tools or other forms of measurement could be useful ways to convey uncertainty.

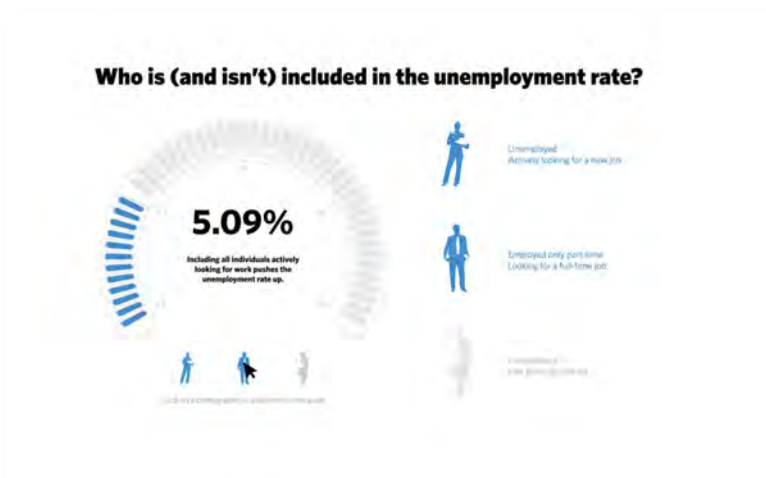
The scale metaphor works in much the same way as the dashboard or needle metaphor. The metaphor is familiar, allowing a user to intuit the structure and focus on the information being visualized. Designers could use a similar technique to explain how an increase in sample size can change values in political polling situations.

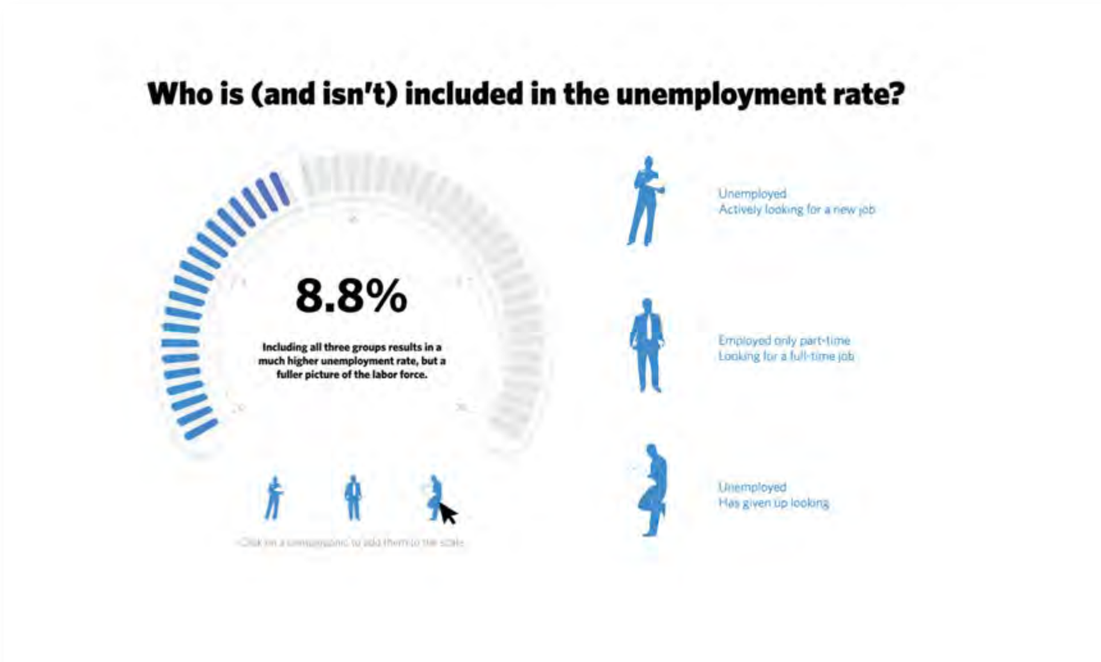
Figure 46: **Adding to the Scale**
(Right) This visualization uses a scale to convey completeness uncertainty surrounding unemployment rates.

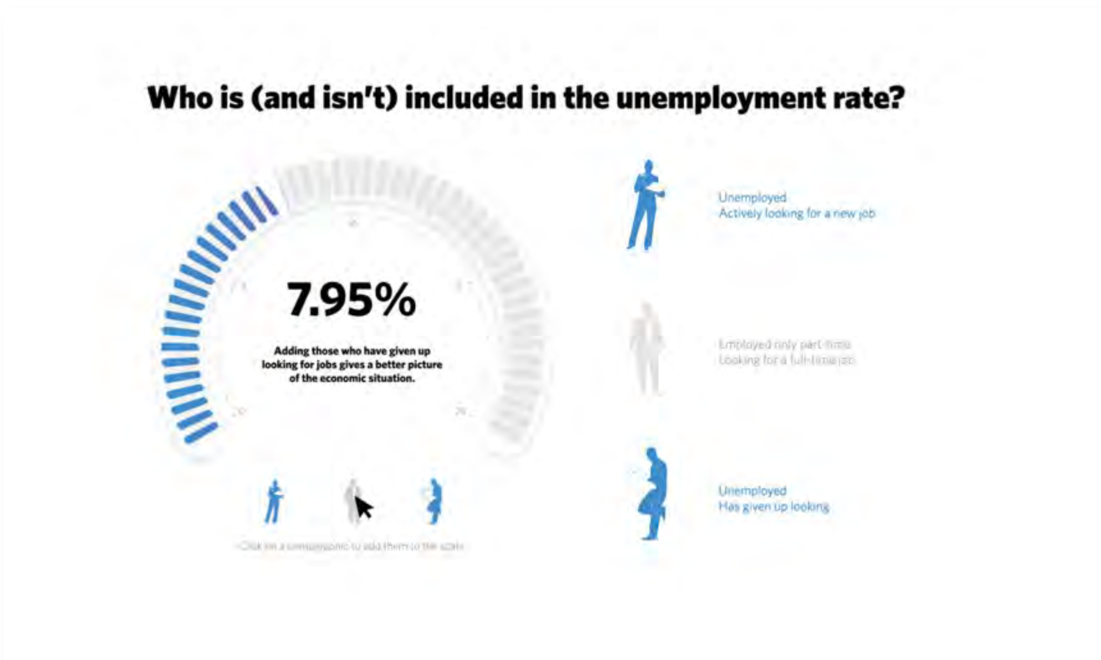
See the animation at: https://college.design.ncsu.edu/thenfinally/hill/scale.gif





Who is (and isn't) included in the unemployment rate?
8.8%
Including all three groups results in a much higher unemployment rate, but a fuller picture of the labor force.
Unemployed
Actively looking for a new job
Employed only part-time
Looking for a full-time job
Unemployed
Has given up looking


Who is (and isn't) included in the unemployment rate?
7.95%
Adding those who have given up looking for jobs gives a better picture of the economic situation.
Unemployed
Actively looking for a new job
Employed only part-time
Looking for a full-time job
Unemployed
Has given up looking

## *Scenario*

Arthur is nervous about the upcoming election and has been reading every projection he can find. One of his favorite sites includes a moving graphic entitled "Taking the Temperature of the Popular Vote." The graphic consists of five thermometers with changing readings, displaying changes in voter sentiment as well as the current leader. Arthur obsesses over it, watching as Trump and Clinton slip in and out of the lead. The graphic makes Arthur incredibly nervous, especially the motion. Sometimes Clinton has a large lead, sometimes she's narrowly behind Trump. Arthur can't settle on a single idea of the election; he only comes away with a general sense, which adds to his anxiety. His uncertainty makes Arthur determined to vote and inspires him to annoy his friends about voting.

## Study 4D: Taking the Temperature of the Electorate *Precision Uncertainty*

My final study on mental models and analogies uses the 2016 Presidential election polls data set as well as a user scenario and task analysis for Arthur, who is already nervous about the election.

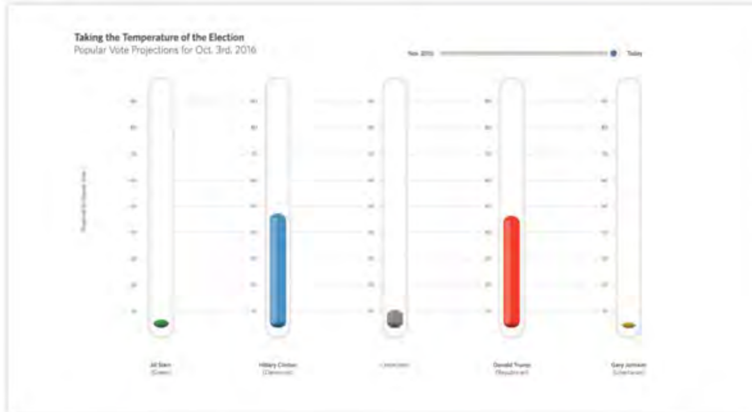
The study uses thermometers as a metaphorical structure for a political visualization (Figure 47). Each candidate has their own thermometer which moves back and forth, relating the different polling projections. Like other oscillating motions, it conveys uncertainty and makes it difficult for a user to settle on a specific value. Since several thermometers are aligned, it conveys a sense of competition and acts as a kind of race. While the thermometer metaphor builds on the colloquial sense of the “temperature” of a situation, thermometers are usually isolated, so the “competitive race” between multiple thermometers is unexpected and could be problematic for that reason

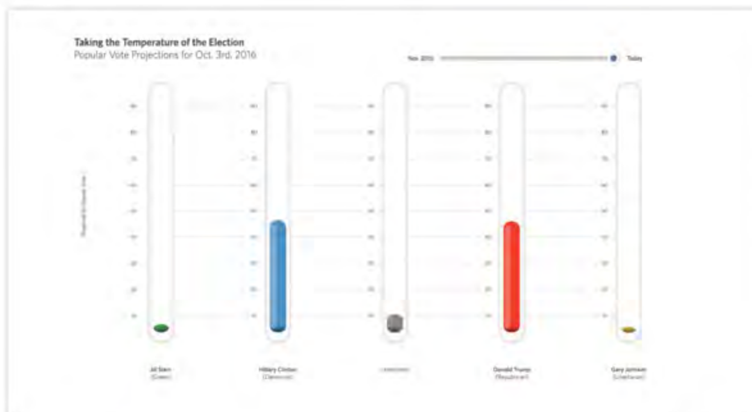
The thermometers function like bar graphs, a structure most users will understand. A user can easily compare multiple bars at once and easily see who has a lead according to the polls. The movement and thermometer metaphor add uncertainty to that familiar structure, allowing the user to see changes and suggest imprecision.

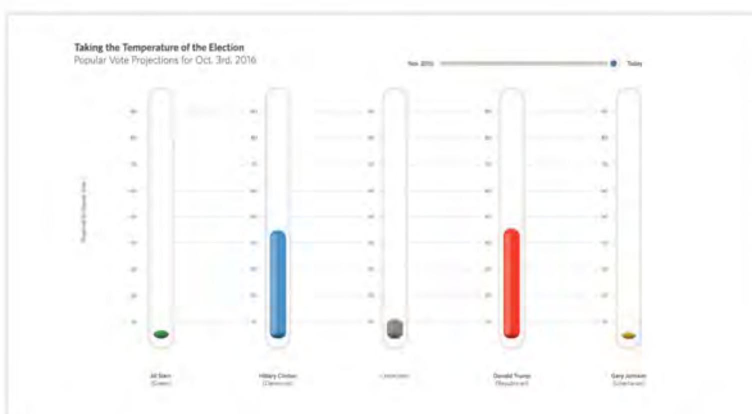
The thermometer metaphor is simple enough for most users to understand intuitively, allowing it to include a set of motions and still be interpreted rather quickly. Other simple tools or gauges, like levels, rulers, scales that indicate measurements could also provide metaphorical structures for intuitive visualizations.

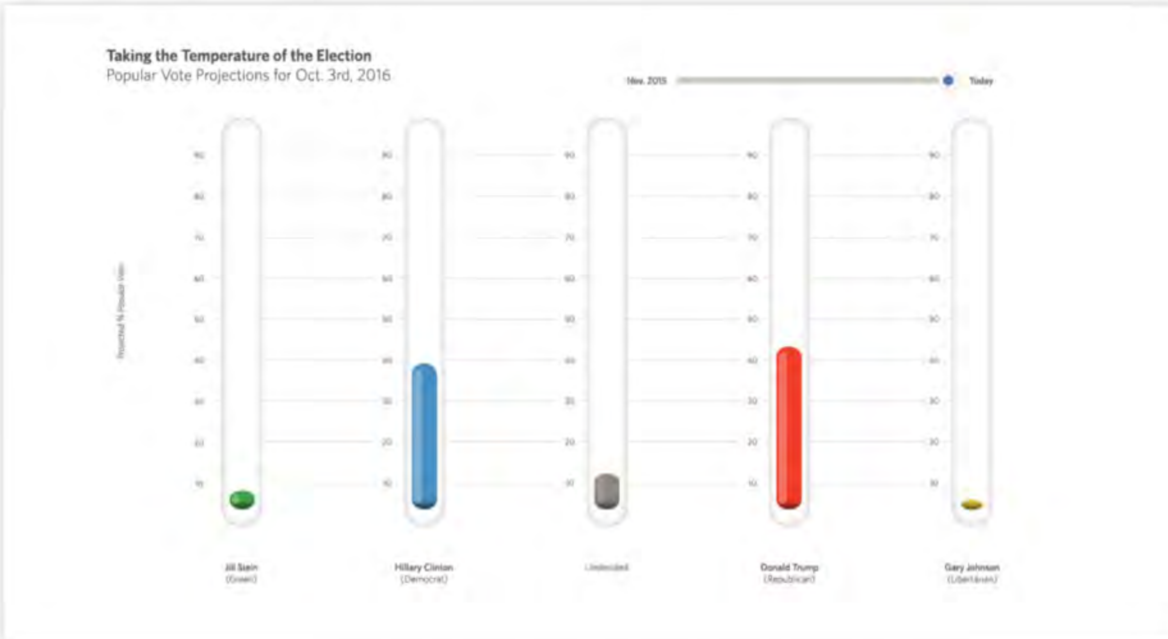
Figure 47: **Taking the Temperature of the Electorate** (Right) This visualization uses thermometers to convey issues of precision in election forecasts.

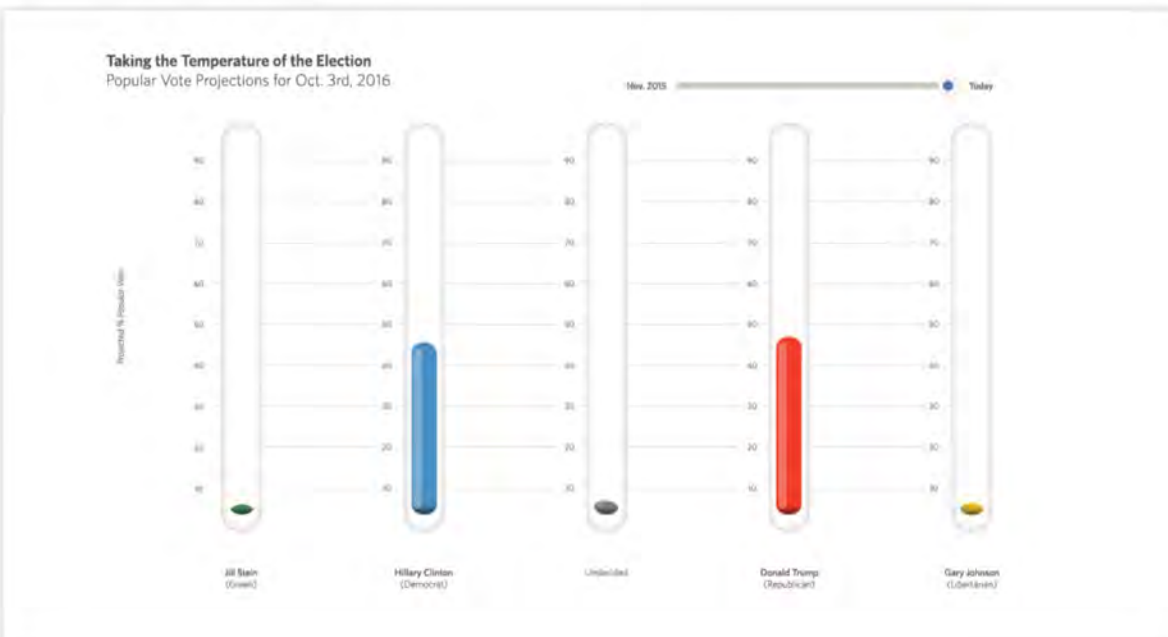
See the animation at: https://college.design.ncsu.edu/thenfinally/hill/temperature.gif




Taking the Temperature of the Election
Popular Vote Projections for Oct. 3rd, 2016
Jill Stein
(Green)
Hillary Clinton
(Democrat)
Undecided
Donald Trump
(Republican)
Gary Johnson
(Libertarian)


Taking the Temperature of the Election
Popular Vote Projections for Oct. 3rd, 2016
Jill Stein
(Green)
Hillary Clinton
(Democrat)
Undecided
Donald Trump
(Republican)
Gary Johnson
(Libertarian)

# Mental Models and Analogies *Outcomes*

***Relatable Contexts and Metaphors***

In information visualizations, metaphors have to be familiar so that a user can interpret them quickly and not get distracted. Dashboards and tool structures work well, as user are accustomed to reading them for information.

***Motion***

Motion itself acts as a metaphor for uncertainty. Designers should consider the connotations of different kinds of motion and how they can add to feelings of uncertainty, rather than distract a user. Oscillation suggests indecision, while a sequence of builds or an expanding object can suggest growth.

# Principles

The studies developed for this investigation point to several experiential techniques designers can use to convey uncertainty in information visualizations. The emergent principles described here represent the most compelling and translatable techniques derived from the studies. These principles can lead to techniques not realized in this investigation. Designers can use these principles to develop more techniques for visualizing uncertainty or a toolkit for visualizing uncertainty in specific contexts through specific motions, metaphors, and visual elements.

### MOTION CAN FUNCTION AS A METAPHOR FOR UNCERTAINTY.

Designers can use simple motions to convey uncertainty to a user. Motion functions as a type of metaphor, for instance, a back and forth motion is analogous to indecision. Designers should consider the connotations of different motions and whether the motion relates uncertainty, or is open to other interpretations (for example, expanding elements can suggest growth rather than change). Visualizations can also push the limits of interpretation by challenging a user's ability to latch onto concrete data points and force a user to make broad generalizations.

*See study set 1 and studies 4B and 4D.*

### BLUR CAN ACT AS A STATIC VISUAL METAPHOR FOR UNCERTAINTY.

Blur makes it difficult for a user to quantify a value or give specific meaning to an element. Designers can use blur to force generalized interpretations or in contrast to similar, more defined elements to suggest that one value is more certain than another. In visualizations, blur functions as a metaphor for uncertainty. Elements are literally fuzzy and challenge a user's ability to quantify information. Too much blur could give a graphic an untrustworthy or indecisive feeling.

Designers can pair blur with an element, such as time, to show changes in the certainty of information over time. This suggests a reason or justification for the uncertainty and provides a narrative about the reliability of the data for the user.

*See studies 3D and 4B.*

### FAMILIAR CONTEXTS AND METAPHORS MAKE DATA RELATABLE.

Designers must consider how a user will relate to the data or information being conveyed. Providing a relatable context makes visualizations more useful and easier for a user to employ existing knowledge structures when interpreting visual elements. Allowing a user to tailor content to their particular situation, for example, by dictating a location for a weather-related map, is one method for making the context relatable to a user. A tailored visualization acts as a concrete and specific tool for the user, rather than just an abstract resource.

Furthermore, when designers use metaphors to relate complex information, these metaphors have to be familiar enough that a user can interpret them quickly without getting distracted. Dashboards and simple tool structures, like scales, work well, as users are already used to reading them for information.

*See study sets 2 and 4.*

### USER CONTROL IN THE ANALYSIS PROCESS BRINGS THE USER CLOSER TO THE REPRESENTED PHENOMENON.

Allowing a user to control the stages or components of analysis brings the user closer to the initial phenomenon and makes changes in the data and moments of inference clearer. This strategy allows a designer to scaffold information, making it easier to understand and build off of initial insights with new information. For instance, designers can use sliders that tailor how much or how little information is seen, step-by-step walk-throughs of data analysis, or rollovers to give a user control over the analysis involved in a visualization.

*See studies 2A and 2D.*

### VISUAL PART-TO-WHOLE COMPARISONS CONVEY ISSUES IN SCALE AND CAN MAKE MISSING ELEMENTS MORE OBVIOUS.

Designers can group elements together to show contrasting or missing elements. Such grouping allows a user to make generalized interpretations and develop part-to-whole comparisons, much in the way a percentage value works.

Conveying completeness uncertainty depends on a user's ability to perceive issues with the sample as compared to the overall population. Parts-to-whole comparisons can provide opportunities for a user to compare a population size to a sample size. When working with large populations, this comparison can push a user to question the representativeness of the sample. Designers can use parts-to-whole arrangements to call out missing parts or convey drastic differences in scale that are easier for a non-expert to understand than percentages.

*See study set 3.*

# Discussion

The primary research question behind this study asked "How can information visualizations commonly found in news media incorporate representations of uncertainty to facilitate non-expert decision making about current events?" After exploring the topic through extensive research, I found that experientially based visualizations can convey the uncertainty involved in complex information to non-expert users. Including this uncertainty through familiar contexts, metaphors, and structures gives users a fuller picture of information and empowers a user to make well-informed decisions. Beyond the initial research question, this research looked at a rich problem space that provides a number of opportunities for further design investigation.

## INFORMATION VISUALIZATION AS A PROBLEM SPACE

Generally speaking, information visualization provides a rich problem space in which designers can make a meaningful impact through user centered thinking and creative explorations. This investigation focused on data journalism, but information visualizations occur in a variety of different contexts, providing myriad opportunities for designers to explore means of conveying uncertainty, as well as information in general, to a non-expert audience. Designers working with information visualizations have a unique opportunity to work in an inherently interdisciplinary problem space, as visualizations exist across a variety of different subject matters, including the source subject of the information, some form of statistical analysis, and the design of the display.

In this investigation, I benefited from the input of several subject matter experts, including consultants from statistics and atmospheric sciences. These conversations focused on translating complex information into simplified graphics in a way that still accurately relayed the scientific information. While I had the benefit of speaking with experts one-on-one, graphical displays must relay information in a straightforward way with little discussion. I worked to translate these conversations into meaningful graphics that answered the questions a non-expert would have, just as I myself had questions in these conversations. Designers working with experts can provide a unique perspective on information, playing both the role of translator and often that of non-expert. Developing experientially sound visualizations requires collaboration between subject matter experts and designers, making it an inherently interdisciplinary problem space.

## TESTING

Moving forward, this work could benefit from usability testing that examines interpretation of the principles I have outlined through my investigation. User testing could approach these principles from a credibility angle, e.g., how do design interventions like motion impact the credibility of an overall graphic. Testing could also examine a user's confidence in the presented information, using a Likert scale or survey.

Testing these principles could also explore Berlo, Lemert, & Mertz's work done on source credibility, specifically the multi-dimensional aspect of credibility (1969). Berlo et al. present credibility, or the trustworthiness of information and specifically the trustworthiness of an information source, as multi-dimensional, with several factors impacting a user's impression of a source's credibility, including safety, qualification, and dynamism (1969). These scales provide a unique opportunity to examine how different design interventions translate into dimensions of credibility and impact a user's interpretation of uncertainty. These dimensions could be translated into a more tailored concept that examines dimensions of uncertainty, for example, the safety dimension of Berlo et al.'s scale includes honest/dishonest, which could be used in testing conveyances of uncertainty.

Fully testing these principles would require breaking down visualizations into constituent parts, examining individual interventions. For example, in Study 4B (figure XX, pg. XXX) the individual gauges and motions could be broken separated and examined through individual survey or scale questions. Isolating individual interventions would allow for the testing of specific principles and their impact.

## THE ISSUE OF UNCERTAINTY

Conveying uncertainty has become an especially relevant topic in visualization circles. The popularity and discussion surrounding *The New York Times'* needle graphics shows how challenging and popular depictions of uncertainty can be, especially when a wide range of users can interpret their meaning experientially.

Future investigations on uncertainty can move into tangential issues, such as creative and information biases. Designers can use similar user-centered design methods to explore how visualizations can convey biases in their creation or in information in general. Furthermore, designers can address issues like "false balance" presentations, meaning the tendency of journalism to present scientific issues as under debate when there is none (Dixon, McKeever, Holton, Clarke, & Eosco, 2015). Journalists often fail to place competing views in an appropriate context, for example, the two sides of the debate over a possible link between vaccines and autism are often given equal weight, despite overwhelming scientific evidence that no link exists between the two (Dixon et al., 2015). Research shows that presenting this information in a visual form that shows the weight-of-evidence on either side has a strong impact on interpretation and personal beliefs (Dixon et al., 2015). A simple graphic showing the radical differences in support each side has can impact a user's interpretation of the information.

As designers negotiate these methods, they must take pains to make users less likely to draw conclusions that disregard the science behind the visualizations. These methods encourage users to question the analysis and information behind a visualization. They must, however, walk a fine line between leading a user to question the information and driving a user disregard the information completely. The techniques have the potential drawback of making a user question the authority of a publication, an impact that designers must carefully consider when including uncertainty in visualizations.

## FUTURE EXPLORATIONS IN VISUALIZING INFORMATION FOR NON-EXPERTS

The framework laid out in this investigation, especially the translated work of Patterson et al., provides a unique and useful structure for exploring information visualizations in a variety of contexts. Information visualizations provide a unique opportunity to convey complex information to non-expert users, but the creators of these visualizations must consider the accessibility of their visualization techniques. Designers can expand on the leverage points presented by Patterson et al. by exploring tools familiar to designers, such as developing narrative structures. Research shows that users retain and process information best when it is presented in a narrative format (Goodman et al., 2017). Narrative is a familiar tool in the designer's handbook, one that can be used to translate complex information into a format that non-experts can understand. Designers exploring information visualizations, as well as uncertainty, can build off of this research to explore how the overall narrative of a story can impact the accessibility of information and a visualization's ability to convey uncertainty.

Designers can play an integral role in making information accessible in a variety of contexts. For example, scientific papers rely heavily on subject specific visualizations that act as a form of jargon, rendering most of the information they convey inaccessible to those outside the field of study. Current research looks at revolutionizing the structure of scientific papers and developing the "paper" of the future, which includes interactive information visualizations (Goodman et al., 2017). Designers can play a unique role in research like this, examining the structure and usability of these interactive visualizations, as well as their accessibility to non-experts.

## CONCLUSIONS

The topics of uncertainty and information visualization both provide a great deal of design and design research opportunities. The emergent principles presented here provide methods for experientially conveying uncertainty to non-experts. These principles can lead to techniques not realized in this investigation and suggest there are numerous opportunities for design exploration within this problem space.

Furthermore, the current demand for information visualizations, especially those that appeal to a wide audience, makes research into the subject especially timely. Designers have a unique opportunity to bring design techniques like narrative and metaphor into new contexts, expanding the range of forms and methods for conveying information. Furthermore, both uncertainty and information visualization have the potential to segue into numerous subject areas beyond the scope of this investigation, such as public health and education. In a way, this problem space is representative of the future of design; it is an inherently interdisciplinary subject matter that requires designers to collaborate with researchers from a variety of fields.

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# Appendices

## DEFINITION OF TERMS

**Cascades of Inscriptions:** A series of representations of phenomena created by scientists and researchers (Roth and Tobin, 1977).

**Case Studies:** Investigations of single events or designed instances in context (Martin & Hanington, 2012).

**Cognitive Load Theory:** Some materials are difficult to understand and apply because they require a great deal of cognitive processing (Moreno & Park, 2010).

**Completeness:** uncertainty arising from concerns about sampling methods and generalizing to the population.

**Computational Offloading:** The extent to which representations reduce the amount of cognitive effort required to solve equivalent problems (Scaife & Rogers, 1996).

**Cone of Uncertainty:** Representation of the probable track of the center of a tropical storm. The width of the cone indicates the uncertainty involved in the prediction (Liu et al., 2015).

**Confidence Intervals:** An interval of numbers within which a particular statistic is believed to fall (Agresti & Finlay, 2009).

**Credibility:** Uncertainty arising from an information source that produces data in conflict with other data, has produced unreliable data in the past, or is otherwise suspect for some reason.

**Data Journalism:** Storytelling through infographics and data analysis (Bradshaw, n.d.).

**Data point:** A piece of information ("data, n.," 2017).

**Data:** Related items of (chiefly numerical) information considered collectively, typically obtained by scientific work and used for reference, analysis, or calculation ("Data, N.").

**Disagreement:** conflicts in data, whether from multiple measures, different data sets, or from multiple conclusions being drawn from the same data set.

**Dual Coding Theory:** Posits that the human brain has separate systems for interpreting verbal and nonverbal information (Paivio, 1991).

**Endogenous Attention:** Active attention (Patterson et al., 2014)

**Exogenous Attention:** The capturing of attention with triggering stimuli in the visual field (Patterson et al., 2014).

**Graphical Constraining:** The way graphical elements in a representation are able to constrain the kinds of inferences that can be made (Scaife & Rogers, 1996).

**Inferences:** uncertainty arising from predictions and the meaning given to data.

**Information visualization:** A graphic that encodes information in order to function as a cognitive aid in the process of communicating information (Cairo, 2016, p. 5).

**Information:** The communication or reception of knowledge or intelligence ("Information, N.").

**Interactive:** a visualization that responds to a user's input ("Interactive, Adj.").

**Margin of Error:** How much an estimated value could differ from the actual value (Agresti & Finlay, 2009).

**Mean:** The most commonly used measure of the center. The mean is the sum of the observations divided by the number of observations. Often called the average (Agresti & Finlay, 2009).

**Median:** The observation that falls in the middle of an ordered data set (Agresti & Finlay, 2009).

**Minimum and Maximum Values:** The highest and lowest values in a data set ordered by value ("Error Bars" The Data Visualization Catalogue).

**News Media:** Communication outlets that focus on delivering news to the general public (Science Daily).

**Non-expert:** audiences that are unfamiliar with the graphical representations or statistical analysis that make up data visualizations (Grainger et al., 2016).

**Outlier:** An observation that falls well above or below the bulk of the data (Agresti & Finlay, 2009).

**Parallel Prototyping:** Simultaneous design explorations by multiple designers (Martin & Hanington, 2012).

**Precision:** any variation, imperfection or theoretical precision limitations in measurement techniques that produce quantitative data.

**Predictive Data:** projections extracted from patterns in data that are used to forecast trends or behaviors.

**Prototyping:** The creation of artifacts for developing and testing ideas (Martin & Hanington, 2012).

**Quartiles:** Four equal groups that divide the data based on a particular variable. ("Quartile, adj and n.").

**Re-representation:** The different external representations of the same phenomenon, which can make problem-solving easier or more difficult, and which can present variable perspectives or information (Scaife & Rogers, 1996).

**Research Through Design:** Integrating theoretical and conceptual frameworks to ground design explorations and studies (Martin & Hanington, 2012).

**Scenarios:** Narratives that explore the future use of an artifact or system from a user's perspective (Martin & Hanington, 2012).

**Standard Deviation:** Value that tells how spread out data points are from the mean. A higher standard deviation means that the data is more spread out (Agresti & Finlay, 2009).

**Standard Error:** The standard deviation of a particular statistic across several samples (Agresti & Finlay, 2009). It provides a way to know how close a particular statistic from a particular sample is to the actual value for a whole group.

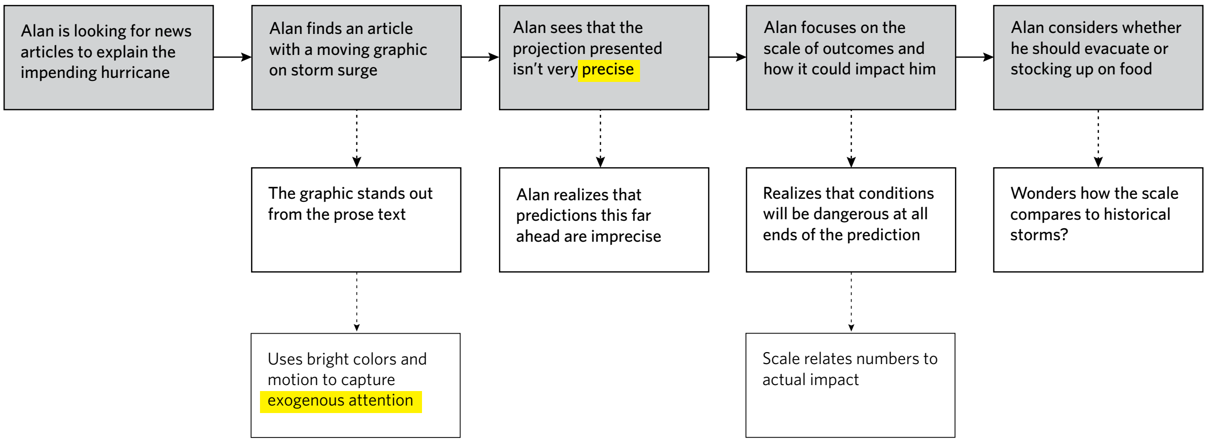
**Task Analysis:** A break down of a user's interactions with a system (Martin & Hanington, 2012).

**Time:** The interval separating successive events or actions, or the period during which an action, condition, or state continues ("Time, n., Int., and Conj.").

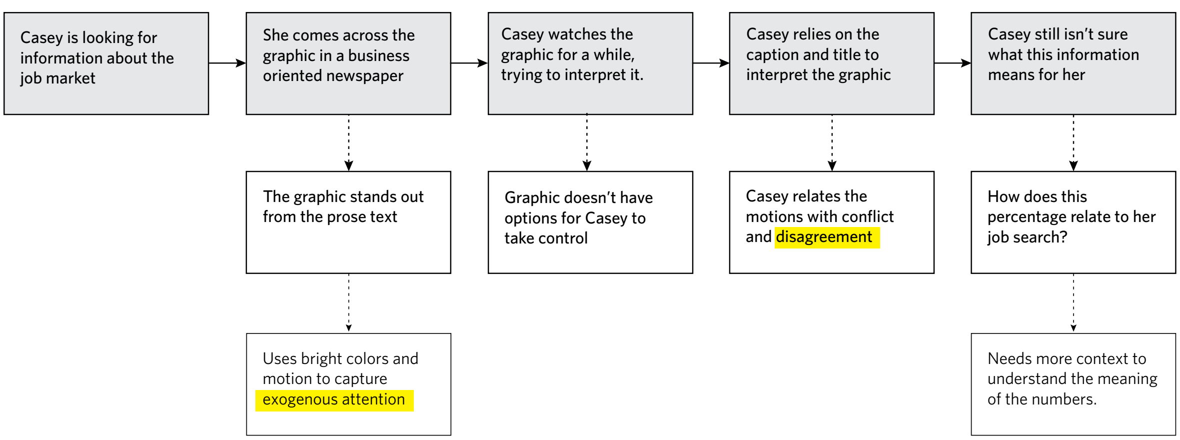
**Uncertainty:** Incomplete or imperfect knowledge arising from a variety of factors including: measurement precision, completeness, inferences, disagreement, and credibility (Skeels et al., 2010).

**Visualization Literacy:** The ability to make meaning from and interpret patterns, trends, and correlations in visual representations of data. (Börner et al., 2016).

# TASK ANALYSES




**Study 1A Task Analysis**

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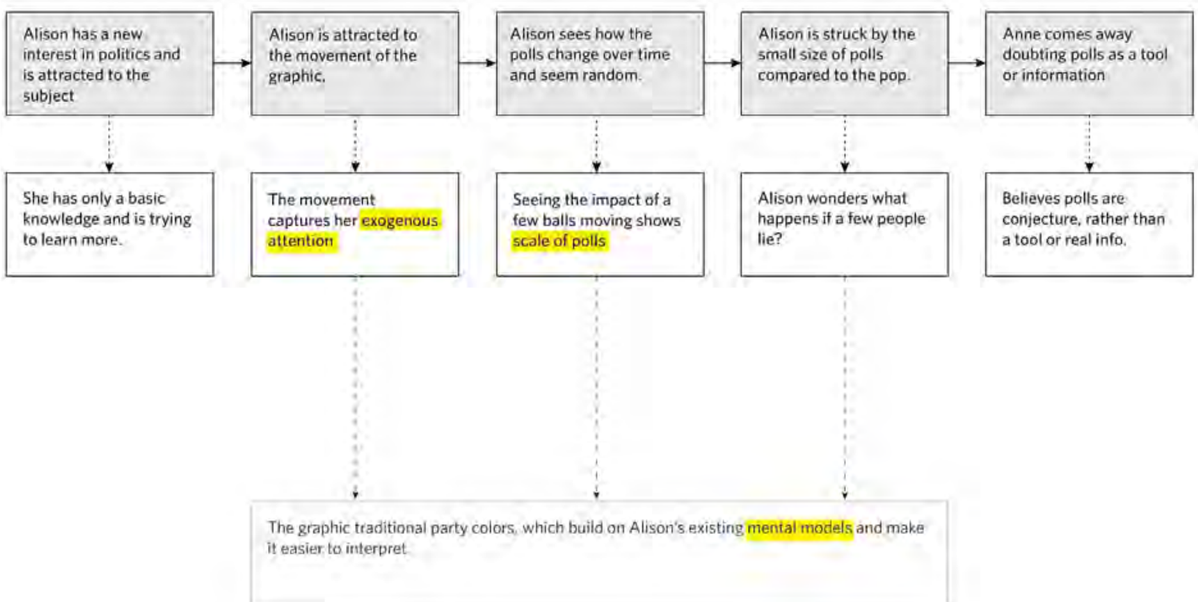


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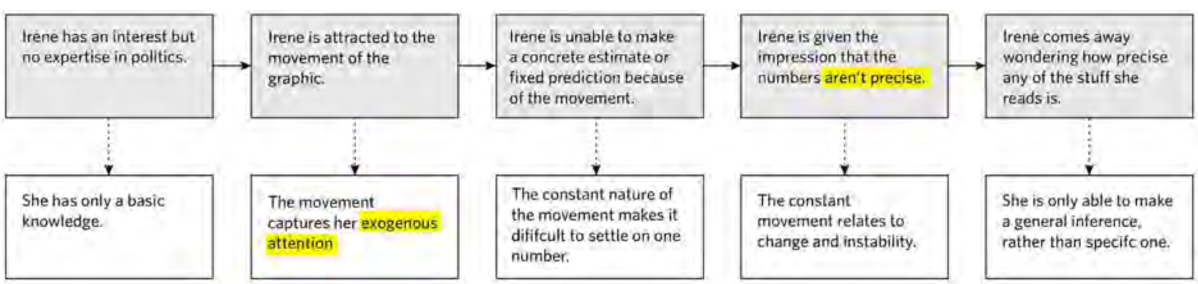


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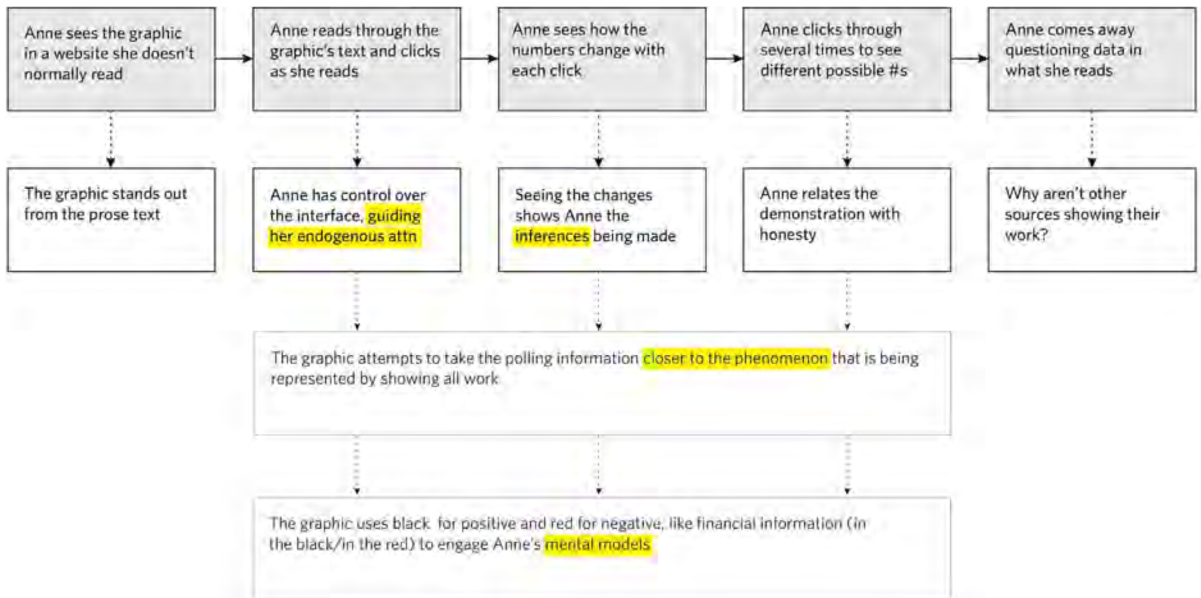


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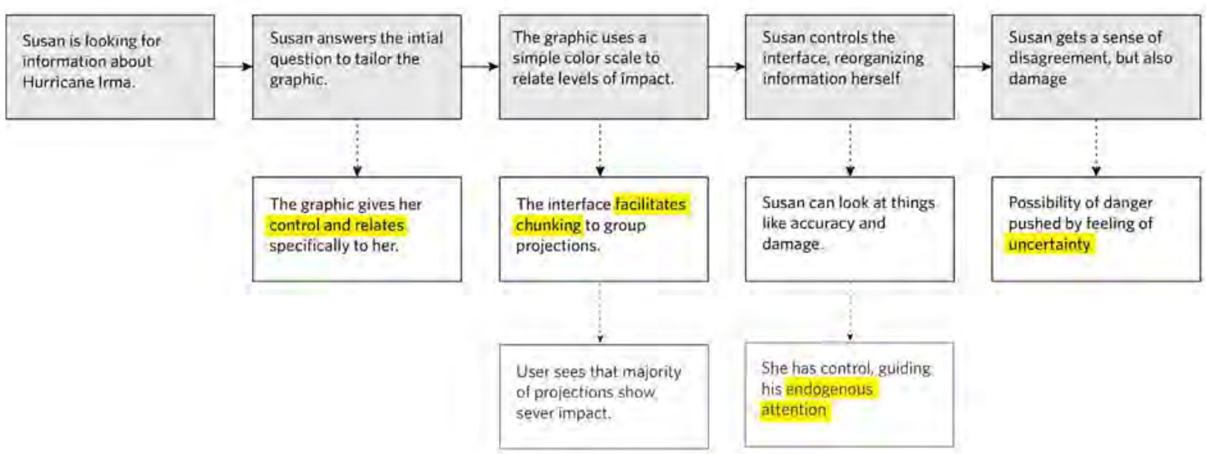


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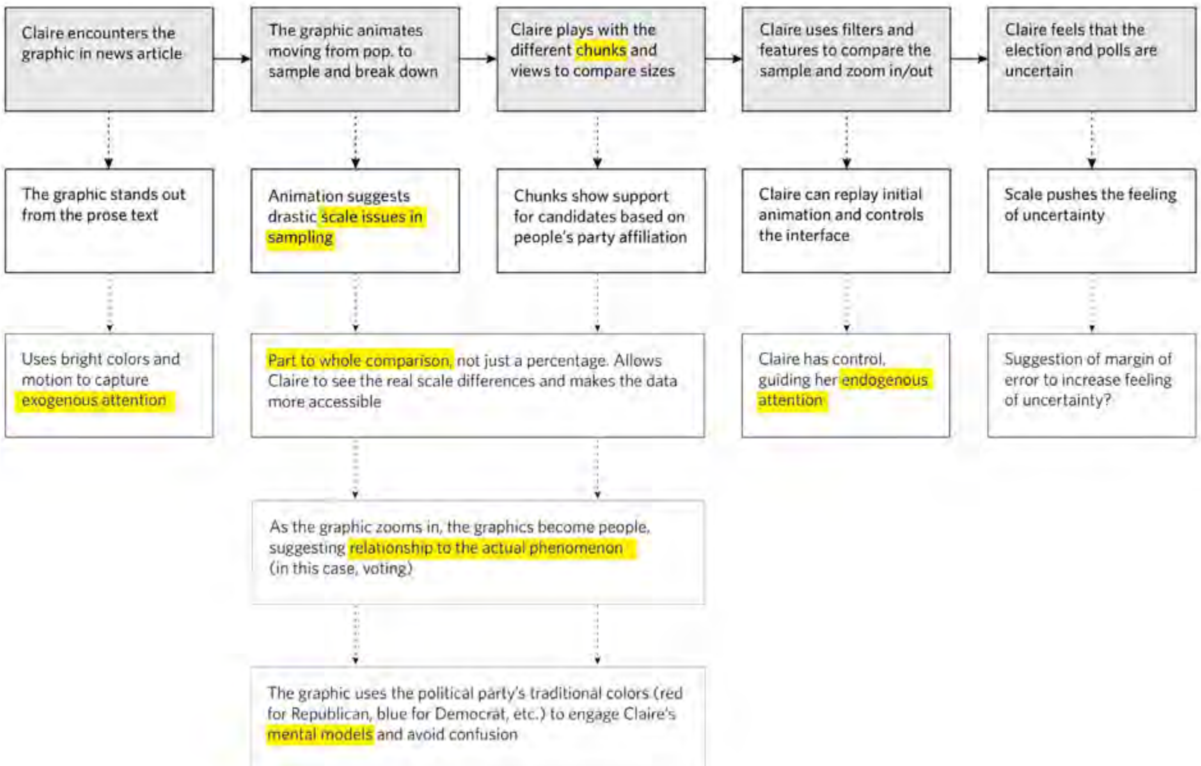


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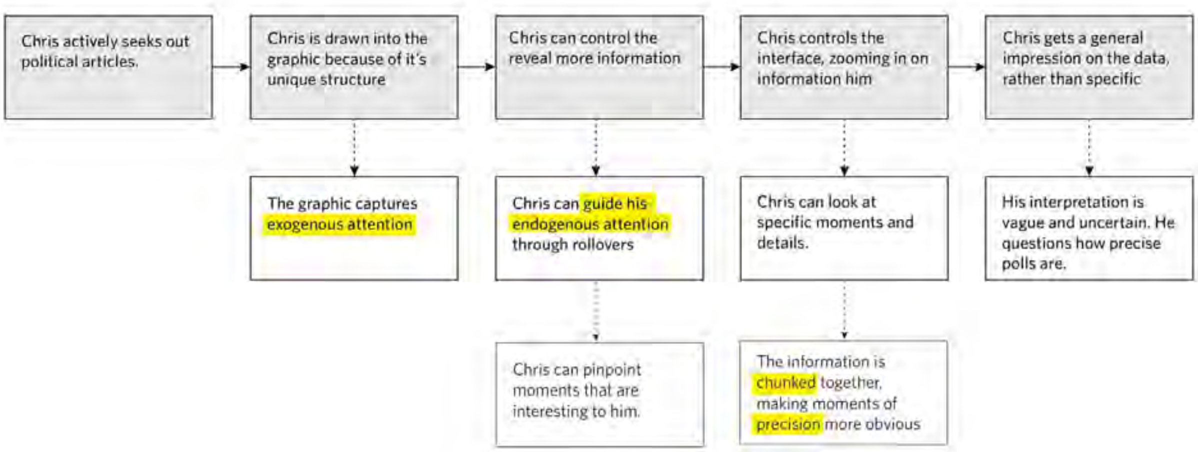


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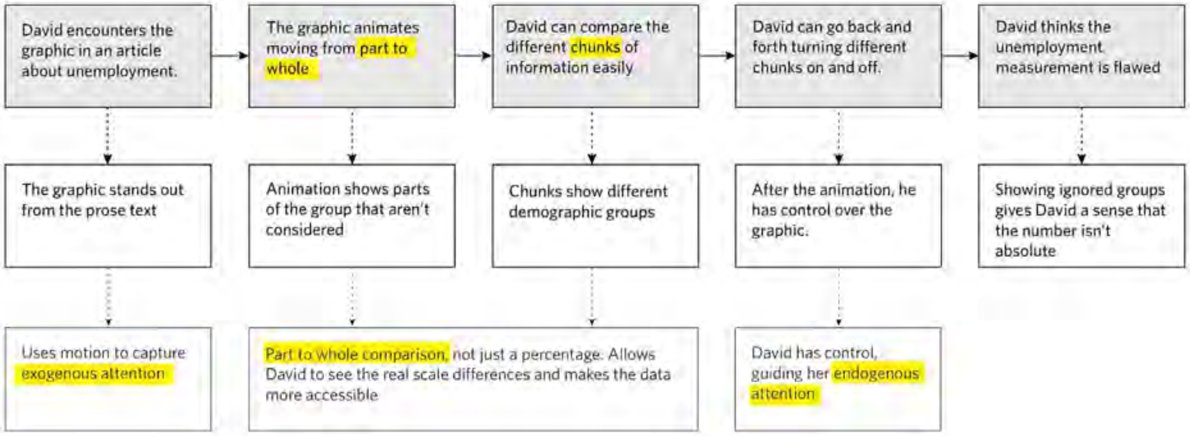


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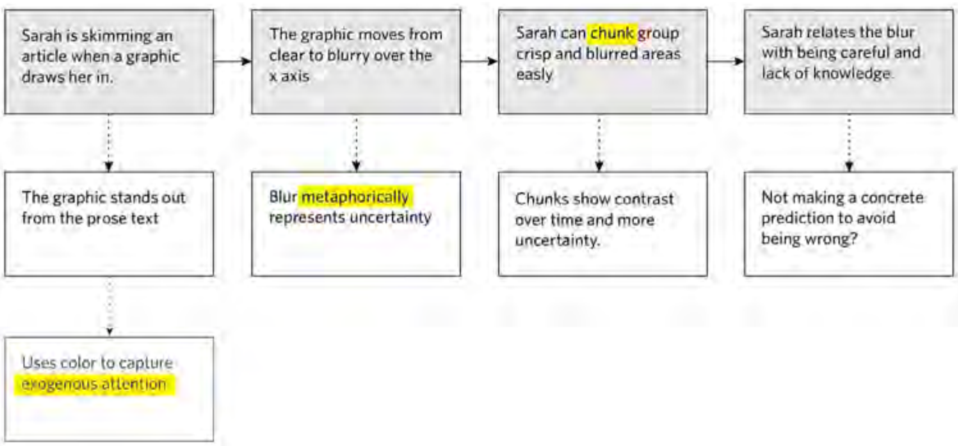


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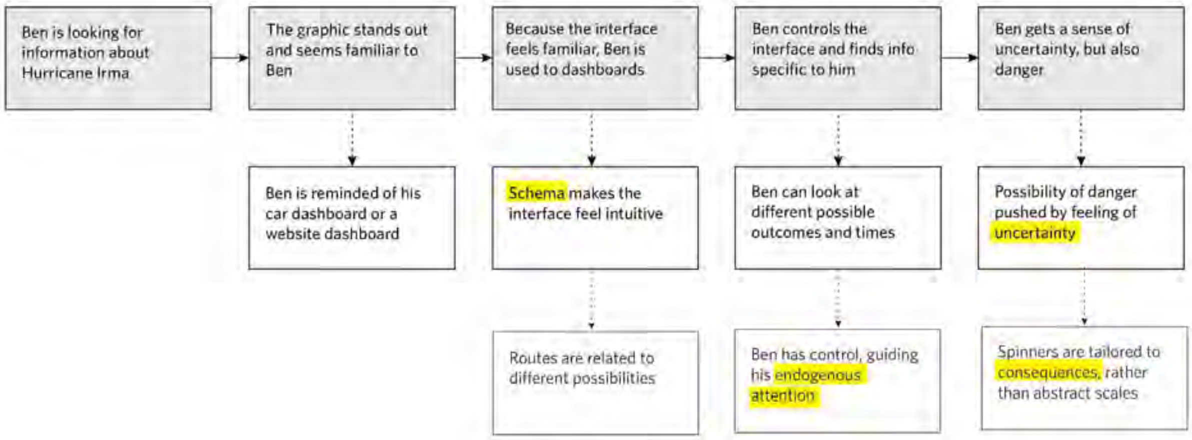


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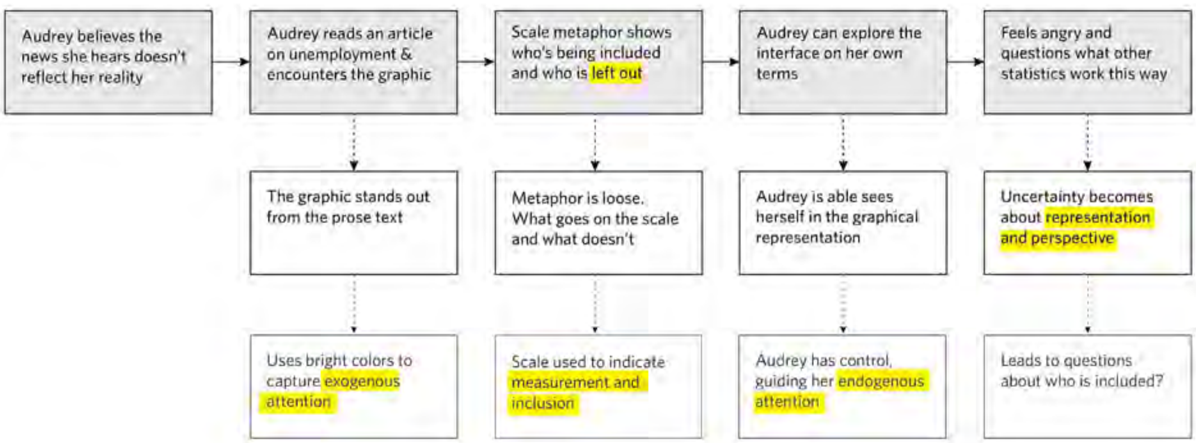


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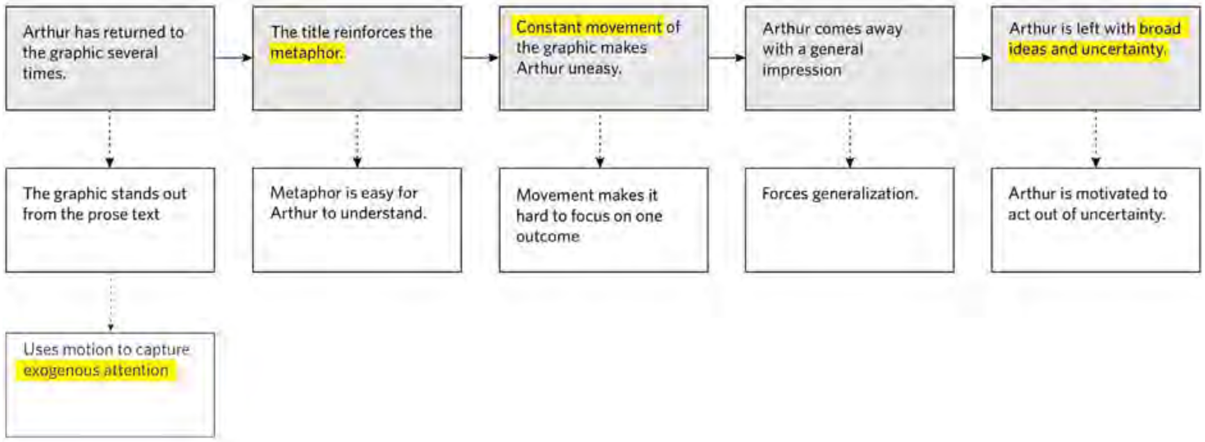


## Study 4D Task Analysis

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