

3 On Rational, Scientific, Objective Viewpoints from Mythical, Imaginary, Impossible Standpoints

Principle: Elevate Emotion and Embodiment

Data feminism teaches us to value multiple forms of knowledge, including the knowledge that comes from people as living, feeling bodies in the world.

In 2012, twenty kindergarten children and six adults were shot and killed at an elementary school in Sandy Hook, Connecticut. In the wake of this unconscionable tragedy, and of the additional acts of gun violence that followed, the design firm Periscopic began a new project: to visualize all the gun deaths that took place in the United States over the course of a calendar year. Although there is no shortage of prior work on the subject in the form of bar charts or line graphs, Periscopic, a company with the tagline “Do good with data,” took a different approach.

When you load the project’s webpage, you first see a single orange line that arcs up from the x-axis on the left-hand side of the screen. Then, the color abruptly changes to white. A small dot drops down, and you see the phrase, “Alexander Lipkins, killed at 29” (figure 3.1a). The line continues to arc up across the screen and then down, coming back to rest on the x-axis, where a second phrase appears: “Could have lived to be 93.” Then, a second line appears—the arc of another life. The animation speeds up and the arcs multiply. A counter at the top right displays how many years of life have been “stolen” from these victims of gun violence. After several excruciating minutes, the visualization completes its count for the year: 11,419 people killed, totaling 502,025 stolen years (figure 3.1b).

The visualization uses demographic data and rigorous statistical methods to arrive at these numbers, as is explained in the methods section on the site. But what makes Periscopic’s visualization so very different from a more conventional bar chart of similar information, such as “The Era of ‘Active Shooters’” from the *Washington Post* (figure 3.2)? The projects share the proposition that gun deaths present a serious threat. But unlike the *Washington Post* bar chart, Periscopic’s work is framed around an emotion:

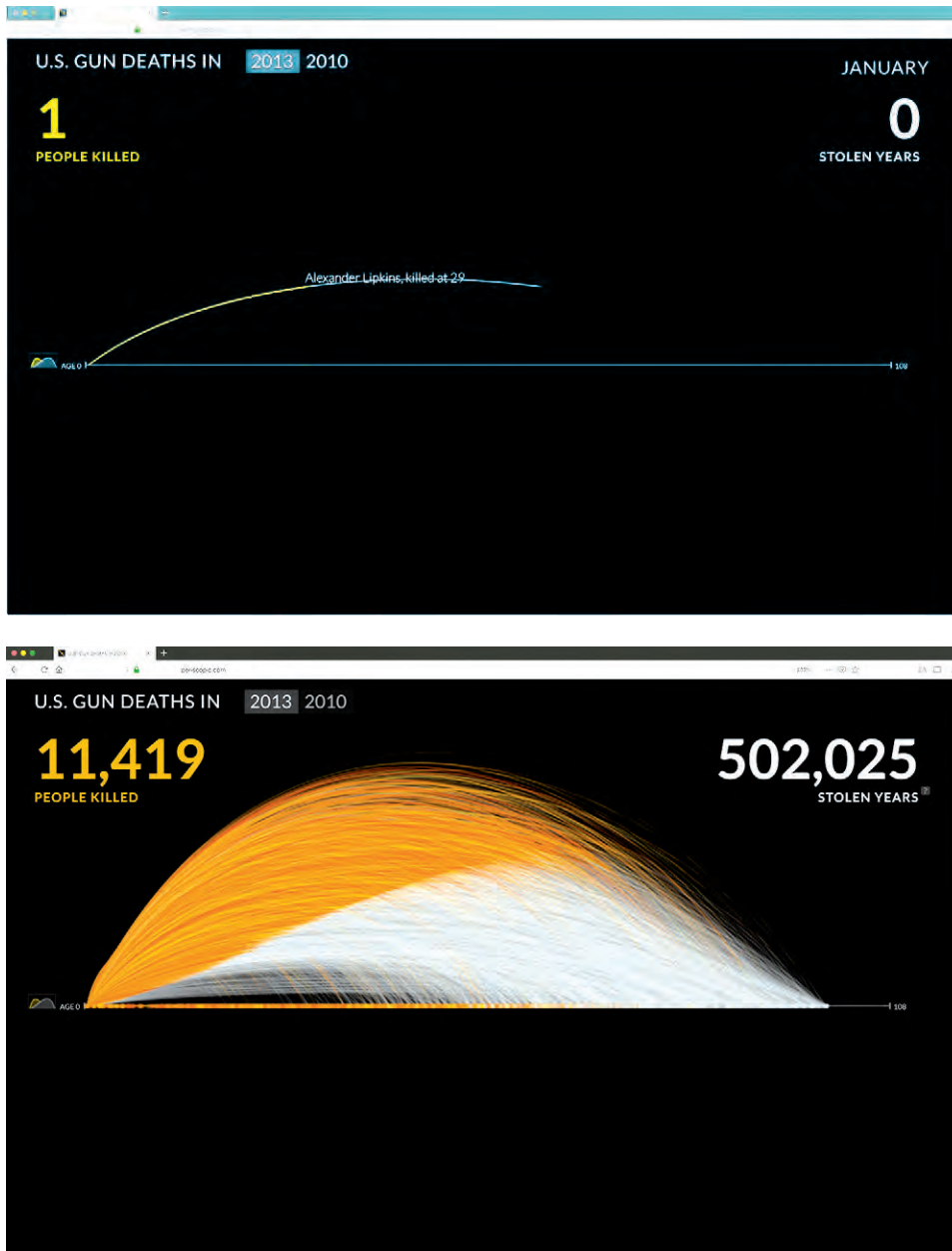


Figure 3.1

An animated visualization of the “stolen years” of people killed by guns in the United States in 2013. The first image (a) shows the beginning state of the animation and the second image (b) shows the end state. Images by Perisopic.

The era of “active shooters”

Number of active shooter incidents annually

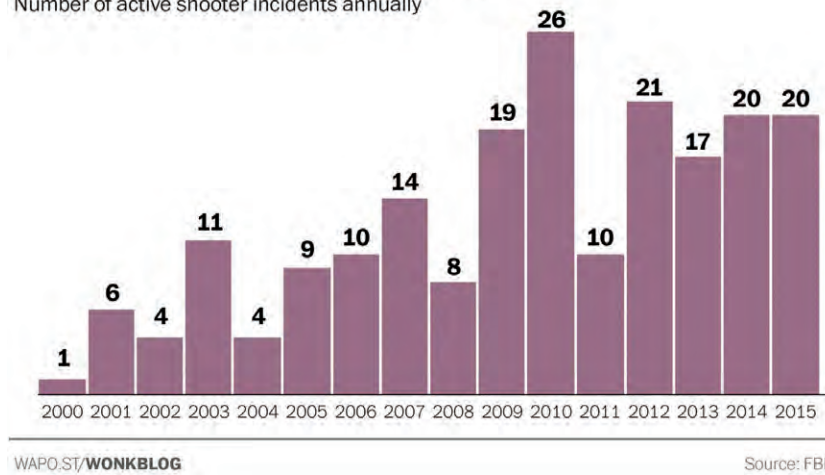


Figure 3.2

A bar chart of the number of “active shooter” incidents in the United States between 2000 and 2015. Images by Christopher Ingraham for the *Washington Post*.

loss. People are dying; their remaining time on earth has been stolen from them. These people have names and ages. They have parents and partners and children who suffer from that loss as well.

This message was clearly received, as was the project overall. It was featured in *Wired* magazine, and even won an Information is Beautiful award. But it also caused some stewing on the part of the visualization community. Alberto Cairo, the author of the visualization book *The Truthful Art*, expressed his concerns about the use of emotion and persuasion in the project: “Is it clear to a general audience that what they see is the work of professionals who actively shape data to support a cause, and not the product of automated processes?”¹ At root for Cairo was the question of how detached and “neutral” a visualization should be. He wondered, Should a visualization be designed to evoke emotion?

The received wisdom in technical communication circles is, emphatically, “No.” In the recent book *A Unified Theory of Information Design*, authors Nicole Amare and Alan Manning state: “The plain style normally recommended for technical visuals is directed toward a deliberately neutral emotional field, a blank page in effect, upon which viewers are more free to choose their own response to the information.”² Here, plainness is equated with the absence of design and thus greater freedom on the part

of the viewer to interpret the results for themselves. Things like colors and icons work only to stir up emotions and cloud the viewer's rational mind.

They're not the first ones to posit this belief. In the field of data communication, any kind of ornament has long been viewed as suspect. Why? As historian of science Theodore Porter puts it, "Quantification is a technology of distance."³ And distance, he explains, is closely related to objectivity because it puts literal space between people and the knowledge they produce. This desire for separation is what underlies the nineteenth-century statistician Karl Pearson's exhortation, echoed in Cairo's comments about the Periscope visualization, for people to set aside their "own feelings and emotions" when performing statistical work.⁴ The more plain, the more neutral; the more neutral, the more objective; and the more objective, the more true—or so this line of reasoning goes. At a data visualization master class in 2013, workshop leaders from the *Guardian* newspaper held up spreadsheet data—spreadsheet data!—as an ideal for the communication of quantitative data, calling it: "Clarity without persuasion."⁵

But persuasion is everywhere, even in spreadsheets, and—as feminist philosopher Donna Haraway would likely argue—especially in spreadsheets. In the 1980s, Haraway was among the first to connect the seeming neutrality and objectivity of data and their visual display to the ideas about distance that we've just discussed. She described data visualization, in particular, as "the god trick of seeing everything from nowhere." The view from nowhere—from a distance, from up above, like a god—may be data visualization's most signature feature. It's also the most ethically complicated to navigate for the ways in which it masks the people, the methods, the questions, and the messiness that lies behind clean lines and geometric shapes. Haraway calls it the *god trick*: it's a trick because it makes the viewer *believe* that they can see everything, all at once, from an imaginary and impossible standpoint. But it's also a trick because what appears to be everything, and what appears to be neutral, is always what she terms a *partial perspective*. And in most cases of seemingly "neutral" visualizations, this perspective is the one of the dominant, default group. Think back to the presumption of whiteness as default that we discussed in the introduction, or—for an example of an actual visualization—to the redlining map discussed in chapter 2. This is a good example of the god trick at work.⁶

The god trick and its underlying assumptions about neutrality and truth are baked into today's best practices for data visualization. This is largely due to the influence of one man: the renowned statistical graphics expert Edward Tufte. Back in the 1980s, Tufte invented a metric for measuring the amount of superfluous information included in a chart. He called it the *data-ink ratio*.⁷ In his view, a visualization designer should strive to use ink to display data alone. Any ink devoted to something other than

the data themselves—such as background color, iconography, or embellishment—is a suspect and intruder to the graphic. Visual minimalism, according to this logic, appeals to reason first. As police officer Joe Friday says to every woman character on the American TV series *Dragnet*, “Just the facts, ma’am.” Decorative elements, on the other hand, are associated with messy feelings—or, worse, represent stealthy (and, according to Tufte, unscientific) attempts at emotional persuasion. Data visualization has even been named as “the unempathetic art” by designer Mushon Zer-Aviv because of its emphatic rejection of emotion.⁸

The logic that sets up this false binary between emotion and reason is gendered, of course, because the belief that women are more emotional than men (and, by contrast, that men are more reasoned than women) is one of the most persistent stereotypes across many Western cultures. Indeed, psychologists have called it a *master stereotype* and puzzled over how it endures even when certain emotions—even extreme ones, like anger and pride—are simultaneously associated with men.⁹ A central focus of feminist scholarship has been to challenge false binaries like this one between reason and emotion and to point out how they establish hierarchies as well. (We discuss this more in chapter 4.) For now, the important thing to note is how false binaries work to benefit a single one of Haraway’s partial perspectives: that of the group already at the top—elite white men.

How can we let go of this binary logic? Two additional questions help challenge this reductive way of thinking and the oppressive hierarchies that it supports. First, is visual minimalism really more neutral? And second, how might activating emotion—leveraging, rather than resisting, emotion in data visualization—help us learn, remember, and communicate with data? Exploring these questions helps get us closer to the third principle of data feminism: *embrace emotion and embodiment*.

Visualization as Rhetoric

Information visualization has diverse origins. Its history is often traced from the explosion of European men mapping their colonial conquests in the late fifteenth and early sixteenth centuries, through the development of new visual typologies like the timeline and the bar chart in the seventeenth and eighteenth centuries, to the adoption of those forms by powerful nations as they amassed increasing amounts of data on the populations they sought to control. But feminist scholars are increasingly challenging this simple narrative of progress, as well as its cast of characters, which is predominantly white and male. Whitney Battle-Baptiste and Britt Rusert recently published a new edition of the visualization work of W. E. B. Du Bois, the renowned Black sociologist

and civil rights activist, who created his “data portraits” of African American life for the 1900 Paris Exposition. Laura Bliss, in a blog post that went viral, called attention to the “narrative maps” of Shanawdithit, a member of the Beothuk (Newfoundland) tribe, which she created around 1829 at the urging of a visiting anthropologist. And Lauren, one of the authors of this book, created a website that reanimates the historical charts of Elizabeth Palmer Peabody, the nineteenth-century editor and educator, who used visualization in her teaching (figure 3.3).¹⁰

Each of these early visualization designers understood how their images could function rhetorically. But in more recent history, many of data visualization’s theorists and practitioners have come from technical disciplines aligned with engineering and computer science and have not been trained in that most fundamental of Western communication theories. In his ancient Greek treatise, Aristotle defines *rhetoric* as “the faculty of observing in any given case the available means of persuasion.”¹¹ But rhetoric isn’t only found in political speeches made by men dressed in tunics with wreaths on their heads.¹² Any communicating object that reflects choices about the selection and representation of reality is a rhetorical object. Whether or not it is rhetorical (it always is) has nothing to do with whether or not it is *true* (it may or may not be).

The question of rhetoric matters because “a rhetorical dimension is present in every design,” says visualization researcher Jessica Hullman.¹³ This includes visualizations that do not deliberately intend to persuade people of a certain message. It *especially and definitively* includes those so-called neutral visualizations that do not appear to have an editorial hand. In fact, those might even be the most perniciously persuasive visualizations of all!

Editorial choices become most apparent when compared with alternative choices. For example, in his book *The Curious Journalist’s Guide to Data*, journalist Jonathan Stray discusses a data story from the *New York Times* about the September 2012 jobs report.¹⁴ The *New York Times* created two graphics from the report: one framed from the perspective of Democrats (the party in power at the time; figure 3.4a) and one framed from the perspective of Republicans (figure 3.4b).

Either of these graphics, considered in isolation, appears to be neutral and factual. The data are presented with standard methods (line chart and area chart respectively) and conventional positionings (time on the x-axis, rates expressed as percentages on the y-axis, title placed above the graphic). There is a high data-ink ratio in both cases and very little in the way of ornamentation. But the graphics have significant editorial differences. The Democrats’ graphic emphasizes that unemployment is decreasing—in its title, the addition of the thick blue arrow pointing downward, and the annotation “Friday’s drop was larger than expected.” Whereas the Republicans’ graphic highlights

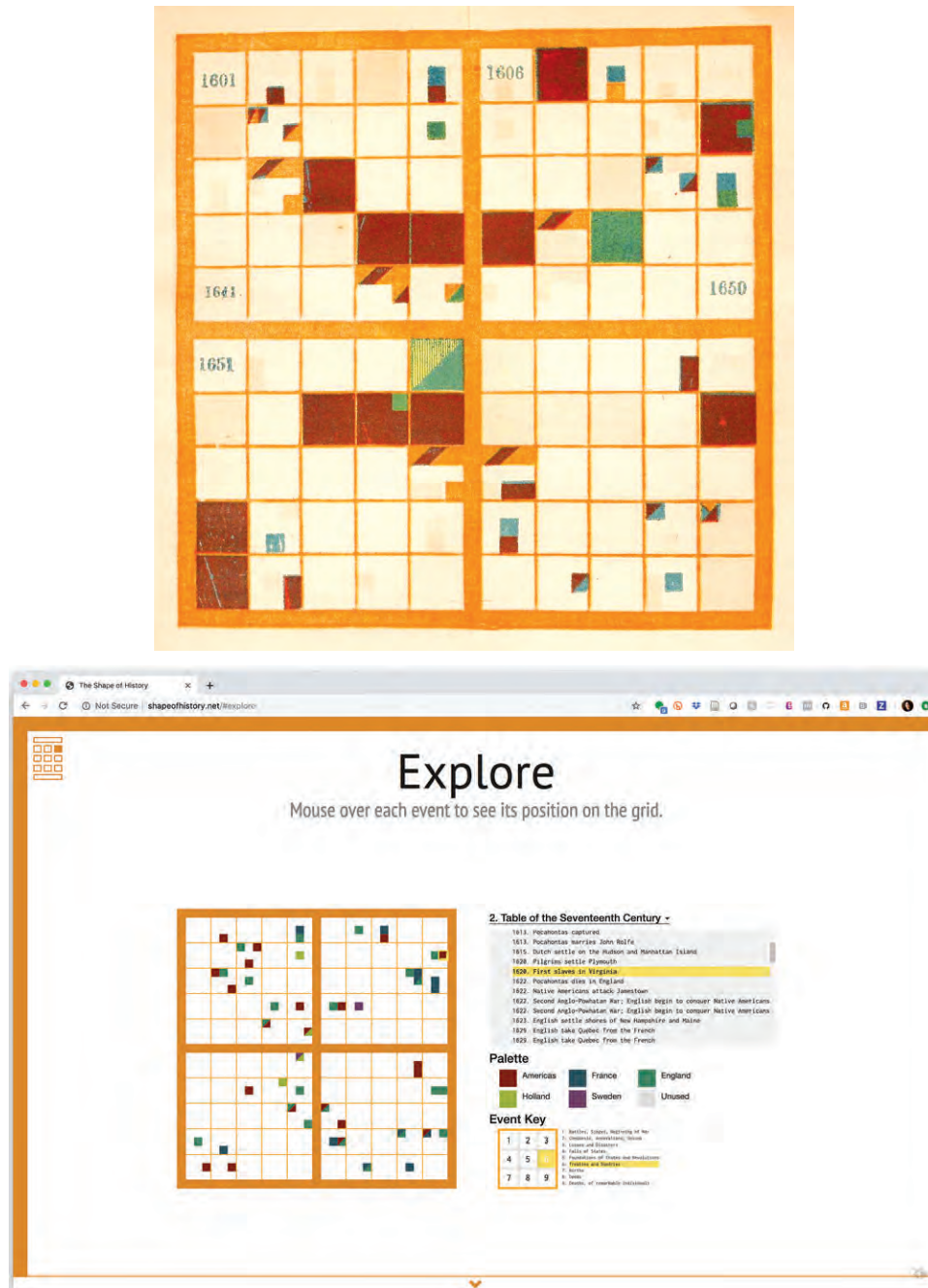


Figure 3.3

(a) Elizabeth Palmer Peabody's chart of "Significant Events of the 17th Century United States" (1865). (b) Peabody's chart recreated in digital form by Lauren's Digital Humanities Lab (2017). (c) A rendering of Peabody's chart reimaged as an interactive quilt by Lauren's Digital Humanities Lab (2019). Images by (a) Elizabeth Palmer Peabody, *A Chronological History of the United States* (1856), (b) the Georgia Tech Digital Humanities Lab, and (c) Courtney Allen for the Georgia Tech Digital Humanities Lab.



Figure 3.3 (continued)

the fact that unemployment has been steadily high for the past three years—through the use of the “8 percent unemployment” reference line, the choice to use an area chart instead of a line, and, of course, the title of the graphic.¹⁵ So neither graphic is neutral, but both graphics are factual. As Jonathan Stray says, “The constraints of truth leave a very wide space for interpretation.”¹⁶ When visualizing data, the only certifiable fact is that it’s impossible to avoid interpretation (unless you simply republish the September jobs report as your visualization, but then it wouldn’t be a visualization).

Fields very close to visualization, like cartography, have long seen their work as ideological. But discussions of rhetoric, editorial choices, and power have been far less

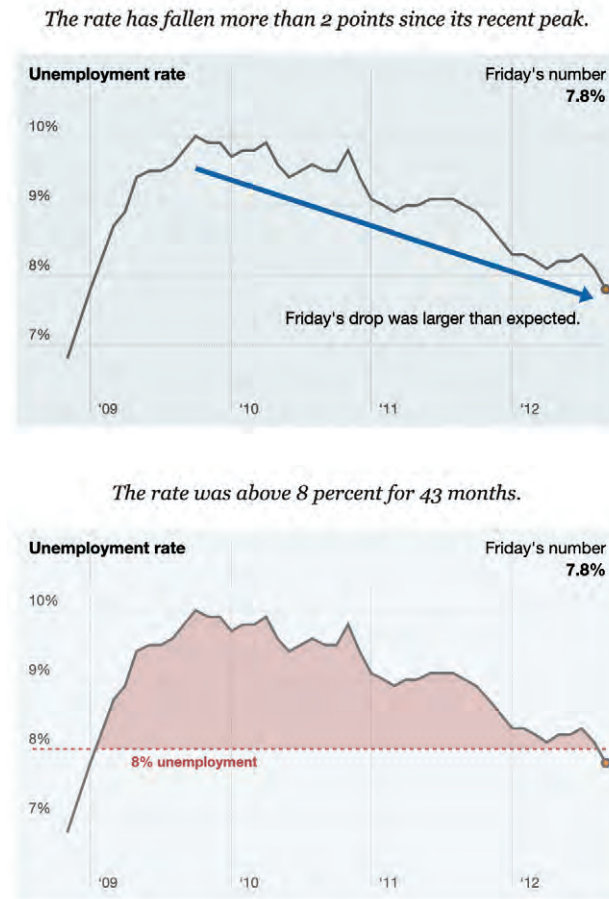


Figure 3.4

A data visualization of the September 2012 jobs report from the perspective of Democrats (a) and Republicans (b). The *New York Times* data team shows how simple editorial changes lead to large differences in framing and interpretation. As data journalist Jonathan Stray remarks on these graphics, “The constraints of truth leave a very wide space for interpretation.” Images by Mike Bostock, Shan Carter, Amanda Cox, and Kevin Quealy, for the *New York Times*, as cited in *The Curious Journalist's Guide to Data* by Jonathan Stray.

frequent in the field of data visualization. In 2011, Hullman and coauthor Nicholas Diakopoulos wrote an influential paper reasserting the importance of rhetoric for the data visualization community.¹⁷ Their main argument was that visualizing data involves editorial choices: some things are necessarily highlighted, while others are necessarily obscured. When designers make these choices, they carry along with them *framing effects*, which is to say they have an impact on how people interpret the graphics and what they take away from them.

For example, it is standard practice to cite the source of one's data. This functions on a practical level—so that readers may go out and download the data themselves. But this choice also functions as what Hullman and Diakopoulos call *provenance rhetoric* designed to signal the transparency and trustworthiness of the presentation source to end users. Establishing trust between the designers and their audience in turn increases the likelihood that viewers will believe what they see.

Other aspects of data visualization also work to displace viewers' attention from editorial choices to reinforce a graphic's perceived neutrality and "truthiness." After doing a sociological analysis, Helen Kennedy and coauthors determined that four conventions of data visualization reinforce people's perceptions of its factual basis: (1) two-dimensional viewpoints, (2) clean layouts, (3) geometric shapes and lines, and (4) the inclusion of data sources at the bottom.¹⁸ These conventions contribute to the perception of data visualization as objective, scientific, and neutral. Both unemployment graphics from the *New York Times* employ these conventions: the image space is two-dimensional and abstract; the layout is "clean," meaning minimal and lacking embellishment beyond what is necessary to communicate the data; the lines representing employment rates vary smoothly and faithfully against a geometrically gridded background; and the source of the data is noted at the bottom. Either the Democrat or the Republican graphic would have been entirely plausible as a *New York Times* visualization, and very few of us would have thought to question the graphic's framing of the data.

So if plain, "unemotional" visualizations are not neutral, but are actually extremely persuasive, then what does this mean for the concept of neutrality in general? Scientists and journalists are just some of the people who get nervous and defensive when questions about neutrality and objectivity come up. Auditors and accountants get nervous, too. They often assume that the only alternative to objectivity is a retreat into complete relativism and a world in which alternative facts reign and everyone gets a gold medal for having an opinion. But there are other options.

Rather than valorizing the neutrality ideal and trying to expunge all human traces from a data product because of their bias, feminist philosophers have proposed a goal

of more complete knowledge. Donna Haraway's idea of the god trick comes from a larger argument about the importance of developing *feminist objectivity*. It's not just data visualization but all forms of knowledge that are *situated*, she explains, meaning that they are produced by specific people in specific circumstances—cultural, historical, and geographic.¹⁹ Feminist objectivity is a tool that can account for the situated nature of knowledge and can bring together multiple—what she terms *partial*—perspectives. Sandra Harding, who developed her ideas alongside Haraway, proposes a concept of *strong objectivity*. This form of objectivity works toward more inclusive knowledge production by centering the perspectives—or *standpoints*—of groups that are otherwise excluded from knowledge-making processes.²⁰ This has come to be known as *standpoint theory*. To supplement these ideas, Linda Alcoff has introduced the idea of *positionality*, a concept that emphasizes how individuals come to knowledge-making processes from multiple positions, each determined by culture and context.²¹ All of these ideas offer alternatives to the quest for a universal objectivity—which is, of course, an unattainable goal.

The belief that universal objectivity should be our goal is harmful because it's always only partially put into practice. This flawed belief is what provoked renowned cardiologist Dr. Nieca Goldberg to title her book *Women Are Not Small Men* because she found that heart disease in women unfolds in a fundamentally different way than in men.²² The vast majority of scientific studies—not just of heart disease, but of most medical conditions—are conducted on men, with women viewed as varying from this “norm” only by their smaller size.²³ The key to fixing this problem is to acknowledge that all science, and indeed all work in the world, is undertaken by individuals. Each person occupies a particular perspective, as Haraway might say; a particular standpoint, as Harding might say; or a particular set of positionalities, as Alcoff might say. And all would agree that research by only men and about only men cannot be universalized to make knowledge claims about all other people in the world.

Disclosing your subject position(s) is an important feminist strategy for being transparent about the limits of your—or anyone's—knowledge claims. Thus, for example, we (the authors) included statements about our own positionalities in the introduction in order to disclose the gender, race/ethnicity, class, ability, education, and other subject positions that informed the writing of this book. Rather than viewing these positionalities as threats or as influences that might have biased our work, we embraced them as offering a set of valuable perspectives that could *frame* our work. This is an approach that we would like to see others embrace as well. Each person's intersecting subject positions are unique, and when applied to data science, they can generate creative and wholly new research questions.

Data Visceralization

This embrace of multiple perspectives and positionalities helps to rebalance the hierarchy of reason over emotion in data visualization.²⁴ How? Since the early 2000s, there has been an explosion of research about *affect*—the term that academics use to refer to emotions and other subjective feelings—from fields as diverse as neuroscience, geography, and philosophy. (We discuss affect further in chapter 7.) This work challenges the thinking that casts emotion out as irrational and illegitimate, even as it undeniably influences the social, political, and scientific processes of the world. Evelyn Fox Keller, a physicist turned philosopher, famously employed the Nobel Prize-winning research of geneticist Barbara McClintock to show how even the most profound of scientific discoveries are generated from a combination of experiment and insight, reason and emotion.²⁵

Once we embrace the idea of leveraging emotion in data visualization, we can truly appreciate what sets Periscopic’s “US Gun Deaths” graphic apart from the *Washington Post* graphic or from any number of other gun death charts that have appeared in newspapers and policy documents. The *Washington Post* graphic, for example, represents death counts as blue ticks on a generic bar chart. If we didn’t read the caption, we wouldn’t know whether we were counting gun deaths in the United States or haystacks in Kansas or exports from Malaysia or any other statistic. In contrast, the Periscopic visualization leads with loss, grief, and mourning—primarily through its rhetorical emphasis on counting “stolen years.” This draws the attention of viewers to “what could have been.” The counting is reinforced by the visual language for representing the “stolen years” as grey lines, appropriate for numbers that are rigorously determined but not technically facts because they come from a statistical model. The visualization also uses animation and pacing to help us first appreciate the scale of one life, and then compound that scale 11,419-fold. The magnitude of the loss, especially when viewed in aggregate and over time, makes a statement of profound truth revealed to us through our own emotions. It is important to note that emotion and visual minimalism are not incompatible here; the Periscopic visualization shows us how emotion can be leveraged alongside visual minimalism for maximal effect.

Skilled data artists and designers know these things already, or at least intuit them. Like the Periscopic team, others are pushing the boundaries of what affective and embodied data visualization could look like. In 2010, Kelly Dobson founded the Data Visceralization research group at the Rhode Island School of Design (RISD) Digital + Media graduate program. The goal for this group was not to visualize data but to *visceralize* it. Visual things are for the eyes, but visceralizations are representations of data

that the whole body can experience, emotionally as well as physically—data that “we see, hear, feel, breathe and even ingest,” writes media theorist Luke Stark.²⁶

The reasons for visceralizing data have to do with more than simply creative experimentation. First, humans are not two eyeballs attached by stalks to a brain computer. We are embodied, multisensory beings with cultures and memories and appetites.²⁷ Second, people with visual disabilities need a way to access the data encoded in charts and dashboards as well. According to the World Health Organization, 253 million people globally live with some form of visual impairment, on the spectrum from limited vision to complete blindness.²⁸ For reasons of accessibility, Aimi Hamraie, the director of the Mapping Access project at Vanderbilt University, advocates for a form of data visceralization, although not in those exact terms: “Rather than relying entirely on visual representations of data,” they explain, “digital-accessibility apps could expand access by incorporating ‘deep mapping,’ or collecting and surfacing information in multiple sensory formats.”²⁹

At the moment, however, examples of objects and events that make use of multiple sensory formats are more likely to be found in the context of research labs and galleries and museums. For example, in *A Sort of Joy (Thousands of Exhausted Things)*, the theater troupe Elevator Repair Service joined forces with the data visualization firm the Office of Creative Research to script a live performance based on metadata about the artworks held by New York’s Museum of Modern Art (MoMA).³⁰ With 123,951 works in its collection, MoMA’s metadata consists of the names of artists, the titles of artworks, their media formats, and their time periods. But how does an artwork make it into the museum collection to begin with? Major art museums and their collection policies have long been the focus of feminist critique because the question of whose work gets collected translates into the question of whose work is counted in the annals of history.³¹ As you might guess, this history has mostly consisted of a parade of white male European “masters,” as the Guerrilla Girls project pictured in figure 3.5 reminds us.

In 1989, the Guerrilla Girls, an anonymous collective of women artists, published an infographic: *Do Women Have to Be Naked to Get into the Met. Museum?* The graphic makes a data-driven argument by comparing the gender statistics of artists collected by another New York museum, the Metropolitan Museum of Art (the Met) to the gender statistics of the subjects and models in the artworks. It was designed to be displayed on a billboard, but it was rejected by the sign company because it “wasn’t clear enough.”³² If you ask us, it’s pretty clear: the Met readily collects paintings in which women are the (naked) subjects but it collects very few artworks created by women artists themselves.



Figure 3.5

Do Women Have to Be Naked to Get into the Met. Museum? An infographic (of a sort) created by the Guerrilla Girls in 1989, intended to be displayed on a bus billboard. Courtesy of the Guerrilla Girls.

After being thwarted by the sign company, the Guerrilla Girls then paid for the infographic to be printed on posters displayed throughout the New York City bus system, until the Metropolitan Transportation Authority (MTA) cancelled the contract, stating that the figure seemed to have more than a fan in her hand. It is *definitely* more than a fan, but this deliberate understatement reveals the MTA's discomfort with this provocative, activist image.³³

A Sort of Joy deploys wholly different tactics to similar ends. The performance starts with a group of white men standing in a circle in the center of the room. They face out toward the audience, which surrounds them. The men are dressed like stereotypical museum visitors: collared shirts, slacks, and so on. Each wears headphones and holds an iPad on which the names of artists in the collection scroll by. "John," the men say together. We see the iPads scrolling through all the names of the artists in the MoMA collection whose first name is John: John Baldessari, John Cage, John Lennon, John Waters, and so on. Three female performers, also wearing headphones and carrying iPads with scrolling names, pace around the circle of men. "Robert," the men say together, and the names scroll through the Roberts alphabetically. The women are silent and keep walking. "David," the men say together. It soon becomes apparent that the artists are sorted by first name, and then ordered by which first name has the most works in the collection. Thus, the Johns and Roberts and Davids come first, because they have the most works in the collection. But Marys have fewer works, and Mohameds and Mariás are barely in the register. Several minutes later, after the men say "Michael,"

“James,” “George,” “Hans,” “Thomas,” “Walter,” “Edward,” “Yan,” “Joseph,” “Martin,” “Mark,” “José,” “Louis,” “Frank,” “Otto,” “Max,” “Steven,” “Jack,” “Henry,” “Henri,” “Alfred,” “Alexander,” “Carl,” “Andre,” “Harry,” “Roger,” and “Pierre,” “Mary” finally gets her due, spoken by the female performers, the first sound they’ve made.

For audience members, the experience is slightly confusing at first. Why are the men in a circle? Why do they randomly speak someone’s name? And why are those women walking around so intently? But “Mary” becomes a kind of aha moment, highlighting the highly gendered nature of the collection—exactly the same kind of experience of insight that data visualization is so good at producing, according to researcher Martin Wattenberg.³⁴ From that point on, audience members start to listen differently, eagerly awaiting the next female name. It takes more than three minutes for “Mary” to be spoken, and the next female name, “Joan,” doesn’t come for a full minute longer. “Barbara” follows immediately after that, and then the men return to reading: “Werner,” “Tony,” “Marcel,” “Jonathan.”

From a data analysis perspective, *A Sort of Joy* consists of simple operations: counting and grouping. A bar chart or a tree map of first names could easily have represented the same results. But presenting the dataset as a time-based experience makes the audience wait and listen and experience. It also runs counter to the mantra in information visualization expressed by researcher Ben Shneiderman in the mid-1990s: “Overview first, zoom and filter, then details-on-demand.”³⁵ In this data performance, we do not see the overview first. We hear and see and experience each datapoint one at a time and only slowly construct a sense of the whole. The different gender expressions, body movements, and verbal tones of the performers draw our collective attention to the issue of gender in the MoMA collection. We start to anticipate when the next woman’s name will arise. We *feel* the gender differential, rather than *see* it.

This feeling is affect. It comprises the emotions that arise when experiencing the performance, as well as the physiological reactions to the sounds and movements made by the performers, as well as the desires and drives that result—even if that drive is to walk into another room because the performance is disconcerting or just plain long.

Data visceralizations that leverage affect aren’t limited to major art institutions. Catherine and artist Andi Sutton led walking tours of the future coastline of Boston based on sea level rise.³⁶ Interactive artist Mikhail Mansion made a leaning, bobbing chair that animatronically shifts based on real-time shifts in river currents.³⁷ Nonprofit organizations in Tanzania staged a design competition for data-driven clothing that incorporated statistics about gender inequality and closed the project with a fashion runway show.³⁸ Artist Teri Rueb stages “sound encounters” between the geologic layers of a landscape and the human body that is affected by them.³⁹ Simon Elvins drew a

giant paper map of pirate radio stations in London that you can actually listen to.⁴⁰ A robot designed by Annina Rust decorates real pies with pie charts about gender equality, and then visitors eat them.⁴¹

These projects may seem to be speaking to another part of brain (or belly) than your standard histograms or network maps, but there is something to be learned from the opportunities opened up by visceralizing data. Deliberately embracing emotions like wonder, confusion, humor, and solidarity enables a valuable form of data maximalism, one that allows for multisensory entry points, greater accessibility, and a range of learning types.

Visceralizing Uncertainty

Scientific researchers are now proving by experiment what designers and artists have known through practice: activating emotion, leveraging embodiment, and creating novel presentation forms help people grasp and learn more from data-driven arguments, as well as remember them more fully.⁴² As it turns out, visceralizing data may help designers solve one particularly pernicious problem in the visualization community: how to represent uncertainty in a medium that's become rhetorically synonymous with the truth. To this end, designers have created a huge array of charts and techniques for quantifying and representing uncertainty. These include box plots, violin plots (figure 3.6), gradient plots, and confidence intervals.⁴³ Unfortunately, however, people are terrible at recognizing uncertainty in data visualizations, even when they're explicitly told that something is uncertain. This remains true even for some researchers who use data themselves!⁴⁴

For example, let's consider the Total Electoral Votes graphic displayed as part of the *New York Times* live online coverage of the 2016 presidential election (figure 3.7). The blue and red lines represent the *New York Times's* best guess at the outcomes over the course of election night and into the following day. The gradient areas show the degree of uncertainty that surrounded those guesses, with the darker inner area showing electoral vote outcomes that came up 25 percent to 75 percent of the time, and the lighter outer areas showing outcomes that came up 75 percent to 95 percent and 5 percent to 25 percent of the time, respectively. If you look closely at the far left of the graphic, which represents election night (everything prior to the 12:00 a.m. axis label), the outcome of Trump winning and Clinton losing easily falls within the 5 to 25 percent likelihood range.

Although many election postmortems pronounced the 2016 election the Great Failure of Data and Statistics, because most simulations and other statistical models

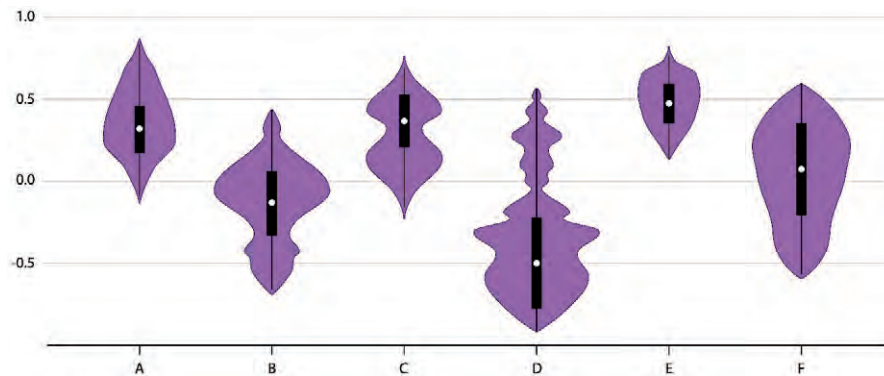


Figure 3.6

What is the best way to communicate uncertainty in a medium that looks so certain? Designers have created diverse chart forms to try to solve this problem. Depicted here are five violin plots; each shows the distribution of data along with their probability density (the purple part). You could also think of this form as a beautiful purple vagina, as the comic *xkcd* has observed; see <https://www.xkcd.com/1967/>. Images from the Data Visualisation Catalogue.

Total Electoral Votes

The estimates below include an estimate of uncertainty. We expect the uncertainty around these estimates to narrow, especially after races are called.

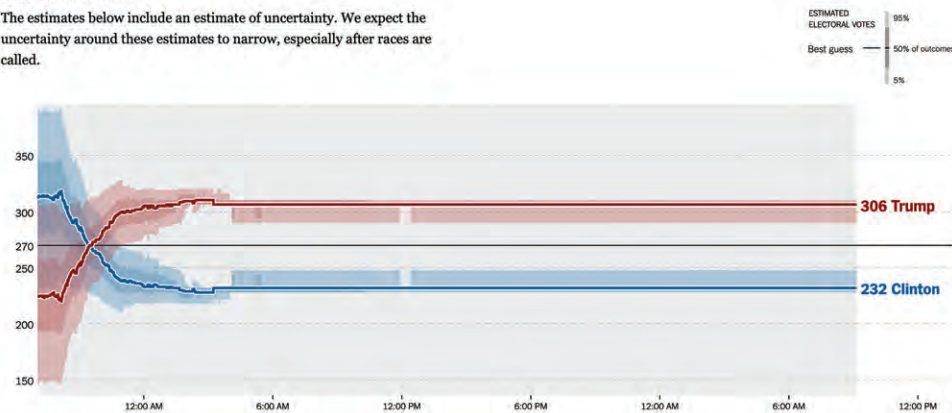


Figure 3.7

A 2016 chart from the *New York Times* that uses opacity—darker and lighter shades of blue and red—to indicate uncertainty. Images by Gregor Aisch, Nate Cohn, Amanda Cox, Josh Katz, Adam Pearce, and Kevin Quealy for the *New York Times*.

suggested that Clinton would win, most forecasts did include the possibility of a Trump victory. The underlying problem was not the failure of data but the difficulties of depicting uncertainty in visual form. People are just not sufficiently trained to recognize uncertainty in graphics such as this. Rather than interpreting the gradient bands as probabilities (e.g., Trump had a 20 percent chance of winning at 6 p.m.), people may interpret them as votes (e.g., Trump had 20 percent of the vote at 6 p.m.). Or they may ignore the gradient bands altogether and look only at the lines. Or they see Clinton on top and assume she is winning. This is called *heuristics* in psychology literature—using mental shortcuts to make judgments—and it happens all the time when people are asked to assess probabilities.⁴⁵ A large part of the problem is that visualization conventions reinforce these misjudgments. The graphics look so certain, even when they are trying their very hardest to visually illustrate *uncertainty*!

Jessica Hullman, whose work on rhetoric we've already mentioned, offers one solution to this problem. Instead of creating fixed plots as in the *New York Times* example that represents uncertainty in aggregate or static form, Hullman advocates for rendering experiences of uncertainty.⁴⁶ In other words, *leverage emotion and affect* so that people experience uncertainty perceptually. Or, to invoke a common refrain from rhetorical training and design schools, “show, don't tell.” Rather than *telling* people that they are looking at uncertainty while employing a certain-looking graphic style—which creates conditions ripe for those pesky heuristics to intervene—make them *feel* the uncertainty.

We can see a good example of showing uncertainty in action on the same *New York Times* live election coverage webpage. At the top of the page was a gauge (figure 3.8) that showed the *New York Times*'s real-time prediction of who was likely to win the race, with a gradient of categories that ranged from medium blue (“Very Likely” that Clinton would win) to medium red (“Very Likely” that Trump would win). But the needle did not stay in one place. It *jittered* between the twenty-fifth and seventy-fifth percentiles, showing the range of outcomes that the *New York Times* was then predicting, based on simulations using the most recent data. At the beginning of the day, the range of motion was fairly wide but still only showed the needle on the Hillary Clinton side. As the night went on, its range narrowed, and the center moved closer and closer to the red side of the gauge. By 9 p.m., the needle jittered just a little, and on the Trump side only.

A number of *New York Times* readers were aggressive in their dislike of the jitter, calling it “irresponsible” and “unethical” and “the most stressful thing I've ever looked at online and I've seen a lot of stressful shit.”⁴⁷ In response, Gregor Aisch, one of the designers of the gauge, defended it, explaining that “we thought (and still think!) this

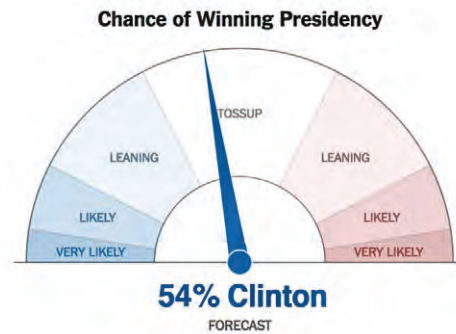


Figure 3.8

The controversial “jittering” election gauge featured in the *New York Times* coverage of the 2016 presidential election. Images by Gregor Aisch, Nate Cohn, Amanda Cox, Josh Katz, Adam Pearce, and Kevin Quealy for the *New York Times*.

movement actually helped demonstrate the uncertainty around our forecast, conveying the relative precision of our estimates.”⁴⁸ So was this “unethical” design, or the sophisticated communication of uncertainty?

Building off of Hullman’s work, we’d say that the answer is the latter. The jittering election gauge was actually exhibiting current best practices for communicating uncertainty. It gave people the perceptual, intuitive, *visceral*, and *emotional* experience of uncertainty to reinforce the quantitative depiction of uncertainty. The fact that it unsettled so much of the *New York Times* readership probably had less to do with the ethics of the visualization and more to do with the outcome of the election. So score one for emotion in the task of representing uncertainty.

Don’t Never Do a God Trick

So does this mean that all election graphics should jitter? Or that data visceralizations are categorically superior to visual graphics? Or that a data visualization framed around emotion is always the “better” choice for the design task at hand? Or that designers should never use the god trick to present a view from above?

The answer to these questions may surprise you: definitively no! If there is any single rule in design, it’s that context is queen. A design choice made in one context or for one audience does not translate to other contexts or audiences. Simply stated: it is never a good idea to say “never” in design. We delve deeper into the importance of context when working with data in chapter 6.

Let's take the god trick as an example. Even though the god trick can do harm—for example, in the form of those racist, objective-looking redlining maps from chapter 2—there are also good reasons to use the god trick as a form of recuperation, contestation, or empowerment. As renowned data visualization designer Fernanda Viégas says, “The kind of overview that data visualization provides is one of the superpowers I treasure the most.”⁴⁹

It is this “superpower”—the aerial view from no body—that we see put into practice in the map *Coming Home to Indigenous Place Names in Canada* (figure 3.9a). Margaret Pearce, a cartographer and member of the Citizen Potawatomi Nation, spent fifteen months collecting Indigenous place names from First Nations, Métis, and Inuit peoples. The map depicts the land that is known in a contemporary Anglo-Western context as Canada, but without any of the common colonial orientation points, like the boundaries of the provinces or the locations of major cities like Ottawa, Montréal, and Nova Scotia. For example, you can see in figure 3.9b that places like Kinooamaagewaabi-kaang (“Teaching rocks”) and Odawa (“Traders”) and Kazabazua gajibajiwana (“River runs under”) fill the area usually described as Toronto. As the publisher's description states, “The names are ancient and recent, both in and outside of time, and they express and assert the Indigenous presence across the Canadian landscape in Indigenous languages.”⁵⁰

Coming Home to Indigenous Place Names in Canada leverages the authority of the god's-eye view to challenge the colonizer's view, to advocate for a “reseeing” of the land under terms of engagement that recognize Indigenous sovereignty and respect Indigenous homelands. The extent of geographic territory included and the sheer number of names asserts the Indigenous presence as major, originary, and ongoing. This is by design. Pearce intentionally created the map with the same paper size, fold, scale, and projection as the map published by Natural Resources Canada, the country's geographic authority.⁵¹ By replicating these design features, *Coming Home* proposes an alternative yet equally authoritative conception of national identity.⁵²

There is actually another twist on top of its intentionally authoritative view: the map does *not* reveal everything.⁵³ As the cartographer, Pearce proceeded with the Indigenous methodologies of respect, responsibility, and reciprocity.⁵⁴ What this meant in practice was caring for each name as Indigenous cultural property—securing the permissions for each name and respecting when communities did not want to share English translations of the name. She is definitive about the fact that the names are not data: “The place names aren't datasets. The place names are cultural property being shared with the map that come from people.” Protecting that cultural property also meant protecting the exact geographic location of each site from being shared with outsiders. This is where the scale of the god trick has protective effects: because it is generalized, at

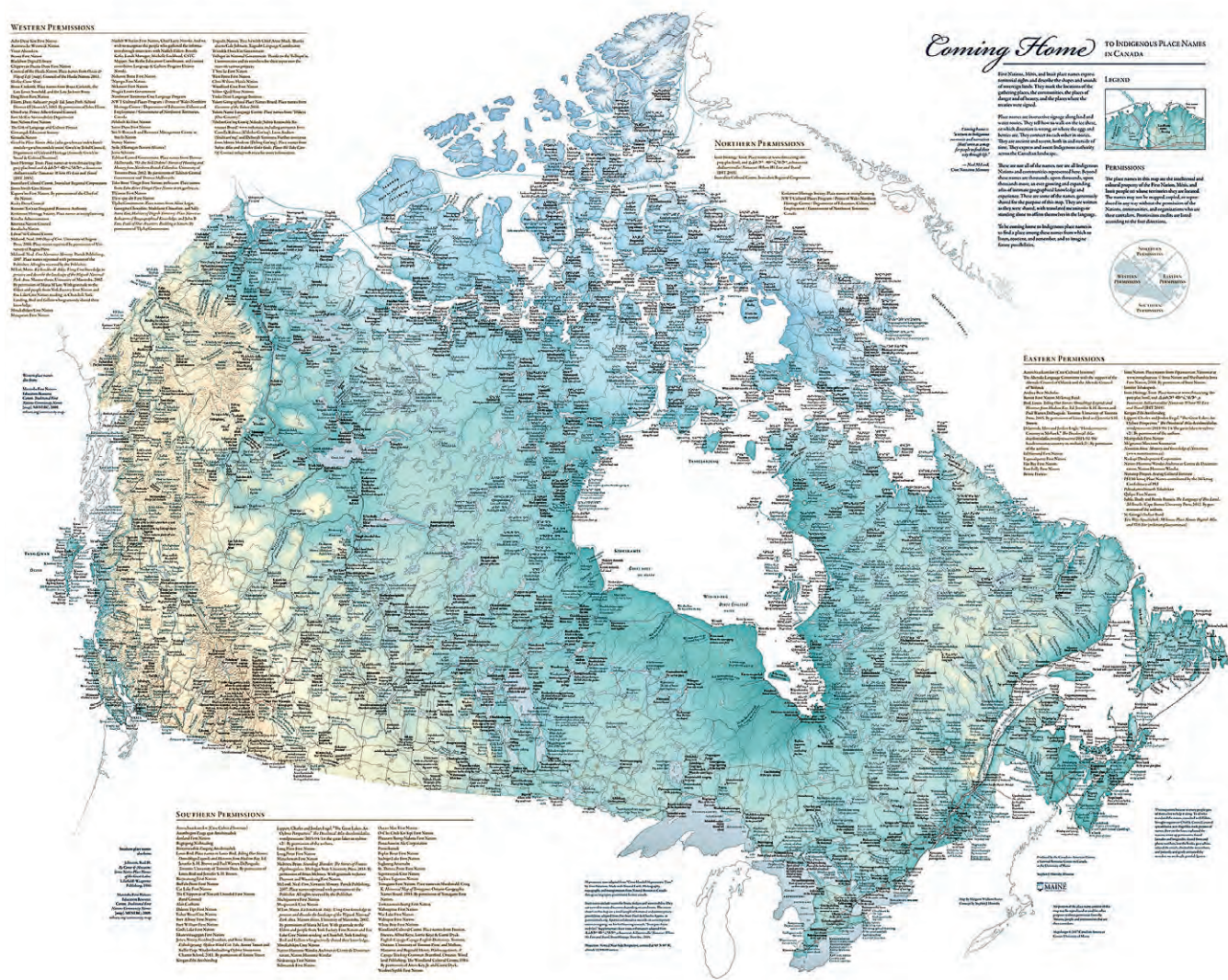


Figure 3.9

Overview and detail view of *Coming Home to Indigenous Place Names in Canada* (2017). (a) The map depicts First Nations, Métis, and Inuit place names collected from many tribes and nations across what is today more commonly called Canada. (b) The detail view depicts Indigenous names from the area around Toronto. Map by Margaret W. Pearce; map design copyright 2017 Canadian-American Center, University of Maine.



Figure 3.9 (continued)

Place names in this detail image shared by permission of the following:

Alan Corbiere.

Hiio Delaronde and Jordan Engel, "Haudenosaunee Country in Mohawk," *The Decolonial Atlas*, decolonialatlas.wordpress.com/2015/02/04/haudenosaunee-country-in-mohawk-2/, by permission of the authors.

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Kitigan Zibi Anishinabeg.

Brian McInnes, *Sounding Thunder: The Stories of Francis Pegahmagabow* (East Lansing: Michigan State University Press, 2016), by permission of Brian McInnes, with gratitude to James Dumont and Wasauksing First Nation.

Woodland Cultural Centre, place names from Frances Froman, Alfred Keye, Lottie Keye, and Carrie Dyck, *English-Cayuga/Cayuga-English Dictionary* (Toronto, Ontario: University of Toronto Press); and Marianne Mithun and Reginald Henry, *Wadewayestanih. A Cayuga Teaching Grammar* (Brantford, Ontario: Woodland Publishing, The Woodland Cultural Centre, 1984), by permission of Amos Key Jr. and Carrie Dyck.

1:5,000,000, it serves to communicate general location without pinpointing exact location. In this case, the god trick communicates Indigenous authority while preserving Indigenous autonomy.

Although the map has been published and the project is ostensibly finished, Pearce's commitment to and care for the Indigenous names continues. Each time the map is reproduced, such as in the detail image in figure 3.9b, Pearce writes to the communities to whom the names belong, explains the proposed context of the names, and requests permission for the names to be reproduced in that context. You can see these permissions as they were granted in the caption for the figure. Pearce proceeds with sensitivity to her own positionalities, as well as the depth of meaning of each particular place, its name, and the community. Place names are "relations," she says. "And they're not my relations, it's not my territory. ... They co-exist as relations that are incorporated into the community." Cartography, then, becomes not a straightforward representation of "what is" in some absolute sense. Rather, *Coming Home* is a map of relations, conversations, and shared investments across difference in the landscape.

Elevate Emotion and Embodiment

The third principle of data feminism, and the theme of this chapter, is to *elevate emotion and embodiment*. As we have shown, these are crucial if often undervalued tools in the data communication toolbox. They help avoid inadvertently conveying the view from no body: the view from an imaginary and impossible standpoint that does not and cannot exist.

How has the whole picture, the overview, or the god trick come to be seen as rational and objective at all? How did the field of data visualization arrive at a set of conventions that prioritize rationality, devalue emotion, and completely ignore the nonseeing organs in the human body? Who is excluded when only vision is included?

Any knowledge community inevitably places certain things at the center and casts others out, in the same way that male bodies are almost always taken as the norm in scientific studies while female bodies are viewed as deviations, or that abled bodies are almost always taken as primary design cases while disabled bodies require a design retrofit. Feminist human-computer interaction (HCI) scholar Shaowen Bardzell asserts designers should look first to those at the margins: the people pushed to the margins in any particular design context demonstrate who and what the system is trying to exclude.⁵⁵ Subsequent work in HCI insists that designers then work to "demarginalize the 'margins' by recognizing intersections that exist, and engaging solidarity to navigate towards equity and inclusion."⁵⁶

In the case of data visualization, what is excluded is emotion and affect, embodiment and expression, embellishment and decoration. These are the aspects of human experience associated with women, and thus devalued by the logic of our master stereotype. But Periscope's gun violence visualization shows how visual minimalism can coexist with emotion for maximum impact. Works like *A Sort of Joy* demonstrate that data communication can be visceral—an experience for the whole body. And *Coming Home to Indigenous Place Names in Canada* establishes that the god trick itself can be used to simultaneously engender emotion and challenge injustice.

Rather than making universal rules and ratios (think: data-ink) that exclude some aspects of human experience in favor of others, our time is better spent working toward a more holistic and more inclusive ideal. All design fields, including visualization and data communication, are fields of possibility. Black feminist sociologist Patricia Hill Collins describes an ideal knowledge situation as one in which “neither ethics nor emotions are subordinated to reason.”⁵⁷ Rebalancing emotion and reason opens up the data communication toolbox and allows us to focus on what truly matters in a design process: honoring context, architecting attention, and taking action to defy stereotypes and reimagine the world.⁵⁸

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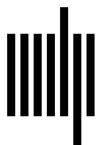
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