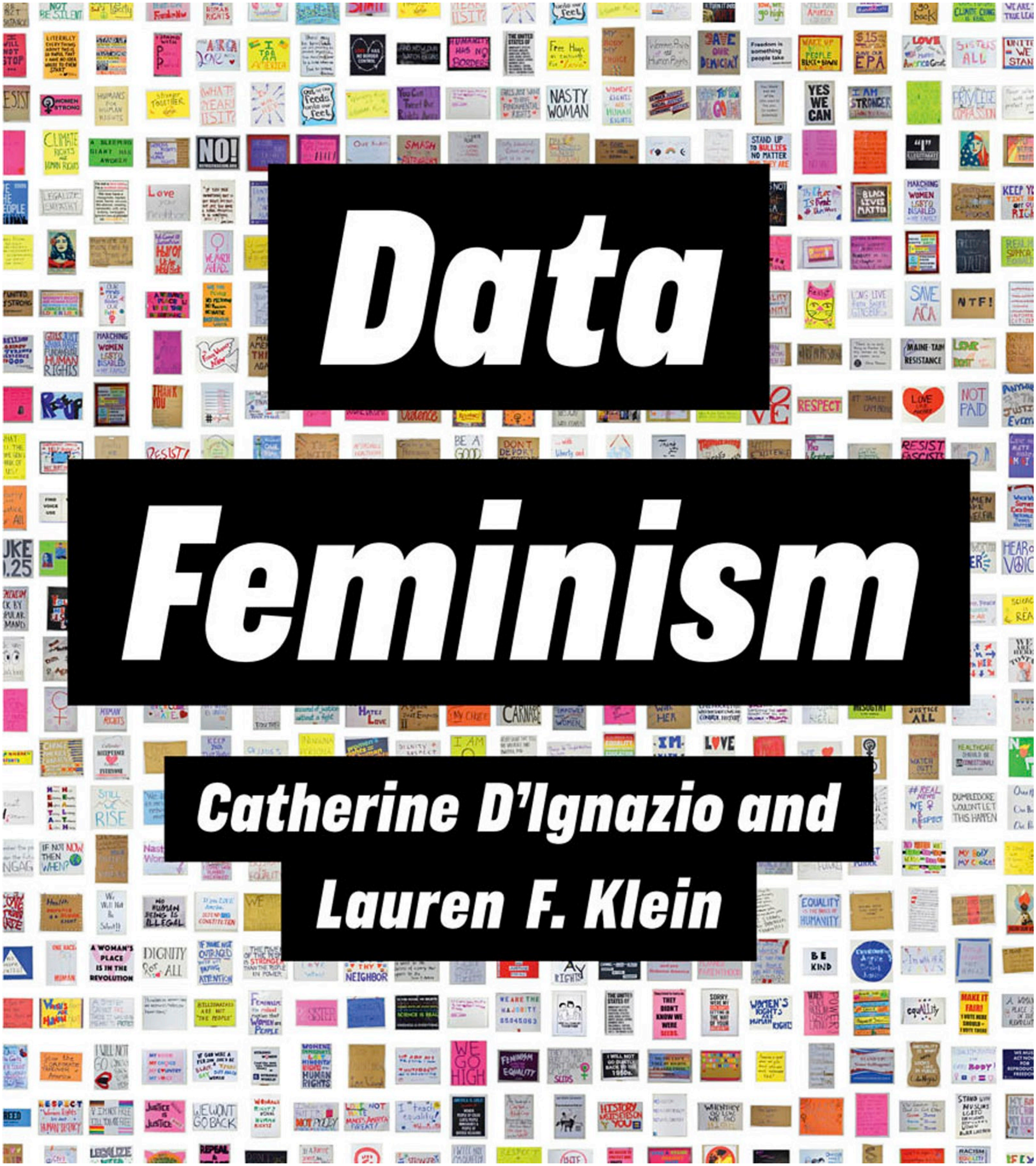

Data Feminism

Catherine D'Ignazio and Lauren F. Klein

about maternal harm.[40] Artists are inviting participants to perform ecological maps and using AI for making intergenerational family memoirs (figure 0.3a).[41]

All these projects are *data science*. Many people think of data as numbers alone, but data can also consist of words or stories, colors or sounds, or any type of information that is systematically collected, organized, and analyzed (figures 0.3b, 0.3c).[42] The *science* in data science simply implies a commitment to systematic methods of observation and experiment. Throughout this book, we deliberately place diverse data science examples alongside each other. They come from individuals and small groups, and from across academic, artistic, nonprofit, journalistic, community-based, and for-profit organizations. This is due to our belief in a capacious definition of data science, one that seeks to include rather than exclude and does not erect barriers based on formal credentials, professional affiliation, size of data, complexity of technical methods, or other external markers of expertise. Such markers, after all, have long been used to prevent women from fully engaging in any number of professional fields, even as those fields—which include data science and computer science, among many others—were largely built on the knowledge that women were required to teach themselves.[43] An attempt to push back against this gendered history is foundational to data feminism, too.

Throughout its own history, feminism has consistently had to work to convince the world that it is relevant to people of all genders. We make the same argument: that data feminism is for everybody. (And here we borrow a line from bell hooks.)[44] You will notice that the examples we use are not only about women, nor are they created only by women. That's because *data feminism isn't only about women*. It takes more than one gender to have gender inequality and more than one gender to work toward justice. Likewise, *data feminism isn't only for women*. Men, nonbinary, and genderqueer people are proud to call themselves feminists and use feminist thought in their work. Moreover, *data feminism isn't only about gender*. Intersectional feminists have keyed us into how race, class, sexuality, ability, age, religion, geography, and more are factors that together influence each person's experience and opportunities in the world. Finally, *data feminism is about power—about who has it and who doesn't*. Intersectional feminism examines unequal power. And in our contemporary world, data is power too. Because the power of data is wielded unjustly, it must be challenged and changed.

Data Feminism in Action

Data is a double-edged sword. In a very real sense, data have been used as a weapon by those in power to consolidate their control—over places and things, as well as

Figure 0.3
We define data science expansively in this book—here are three examples. (a) *Not the Only One* by Stephanie Dinkins (2017), is a sculpture that features a Black family through the use of artificial intelligence. The AI is trained and taught by the underrepresented voices of Black and brown individuals in the tech sector. (b) Researcher Margaret Mitchell and colleagues, in "Seeing through the Human Reporting Bias" (2016), have worked on systems to infer what is *not said* in human speech for the purposes of image classification. For example, people say "green bananas" but not "yellow bananas" because yellow is implied as the default color of the banana. Similarly, people say "woman doctor" but do not say "man doctor," so it is the words that are *not spoken* that encode the bias. (c) A gender analysis of Hollywood film dialogue, "Film Dialogue from 2,000 Screenplays Broken Down by Gender and Age," by Hanah Anderson and Matt Daniels, created for The Pudding, a data journalism start-up (2017).

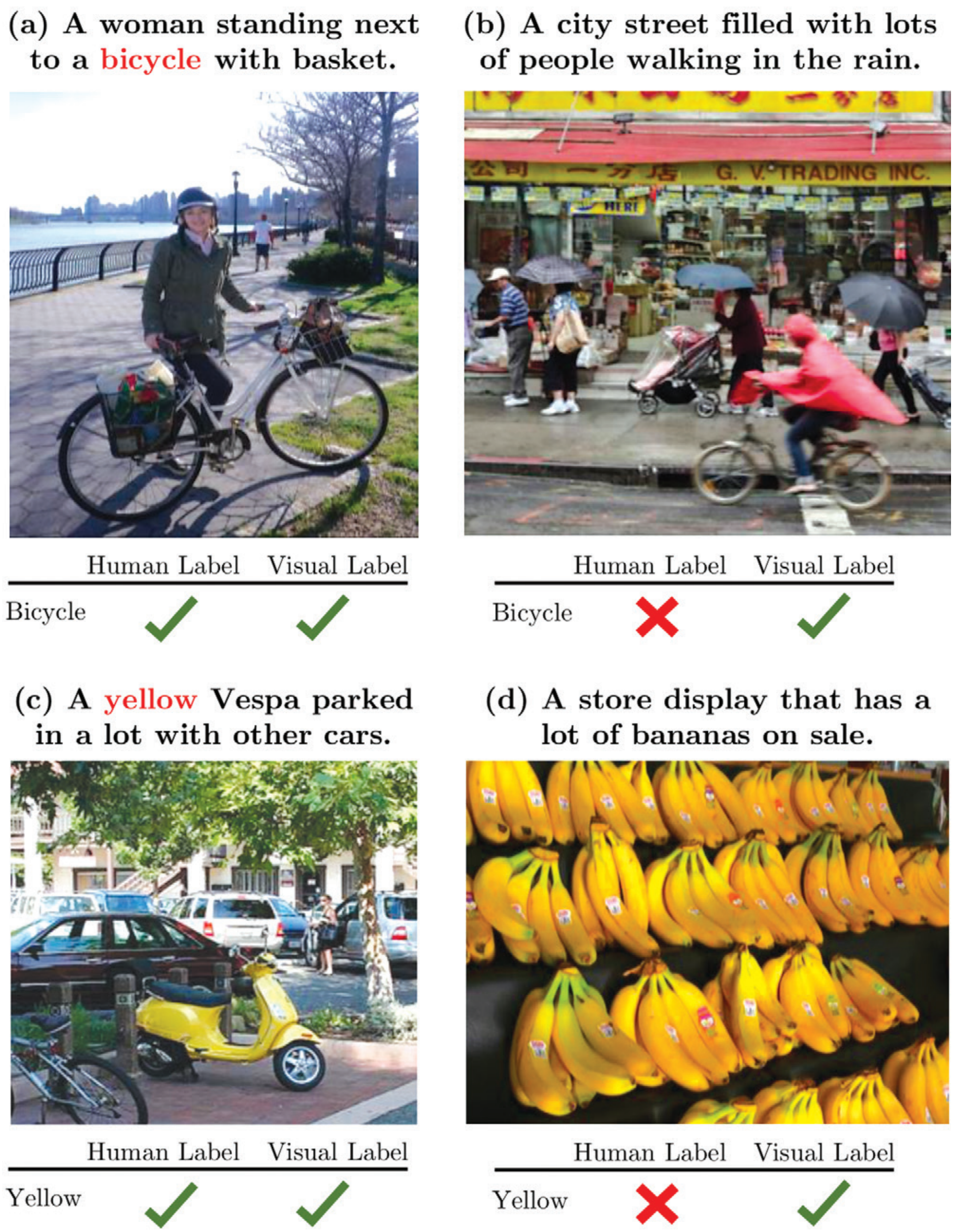

Figure 0.3 (continued)

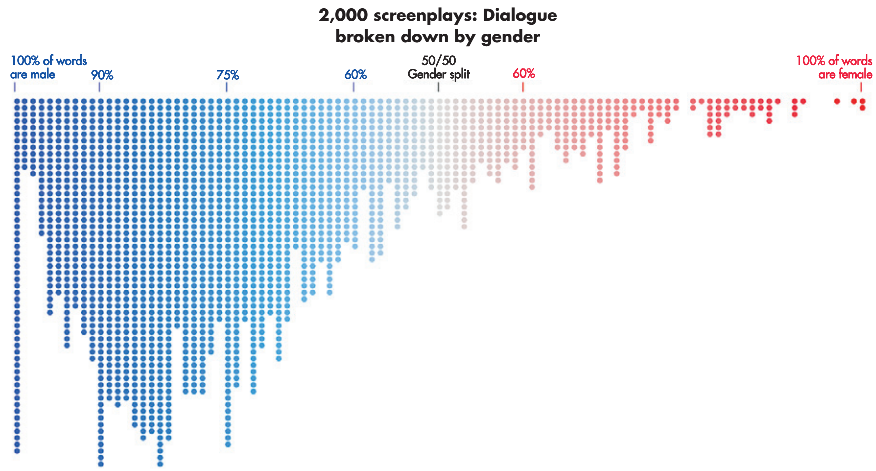

Figure 0.3 (continued)

people. Indeed, a central goal of this book is to show how governments and corporations have long employed data and statistics as management techniques to preserve an unequal status quo. Working with data from a feminist perspective requires knowing and acknowledging this history. To frame the trouble with data in another way: it's not a coincidence that the institution that employed Christine Darden and enabled her professional rise is the same that wielded the results of her data analysis to assert the technological superiority of the United States over its communist adversaries and to plant an American flag on the moon. But this flawed history does not mean ceding control of the future to the powers of the past. Data are part of the problem, to be sure. But they are also part of the solution. Another central goal of this book is to show how the power of data can be wielded back.

To guide us in this work, we have developed seven core principles. Individually and together, these principles emerge from the foundation of intersectional feminist thought. Each of the following chapters is structured around a single principle. The seven principles of data feminism are as follows:

1. **Examine power.** Data feminism begins by analyzing how power operates in the world.
2. **Challenge power.** Data feminism commits to challenging unequal power structures and working toward justice.

3. **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.
4. **Rethink binaries and hierarchies.** Data feminism requires us to challenge the gender binary, along with other systems of counting and classification that perpetuate oppression.
5. **Embrace pluralism.** Data feminism insists that the most complete knowledge comes from synthesizing multiple perspectives, with priority given to local, Indigenous, and experiential ways of knowing.
6. **Consider context.** Data feminism asserts that data are not neutral or objective. They are the products of unequal social relations, and this context is essential for conducting accurate, ethical analysis.
7. **Make labor visible.** The work of data science, like all work in the world, is the work of many hands. Data feminism makes this labor visible so that it can be recognized and valued.

Each of the following chapters takes up one of these principles, drawing upon examples from the field of data science, expansively defined, to show how that principle can be put into action. Along the way, we introduce key feminist concepts like the matrix of domination (Patricia Hill Collins; see chapter 1), situated knowledge (Donna Haraway; see chapter 3), and emotional labor (Arlie Hochschild; see chapter 8), as well as some of our own ideas about what data feminism looks like in theory and practice. To this end, we introduce you to people at the cutting edge of data and justice. These include engineers and software developers, activists and community organizers, data journalists, artists, and scholars. This range of people, and the range of projects they have helped to create, is our way of answering the question: What makes a project feminist? As will become clear, a project may be feminist in *content*, in that it challenges power by choice of subject matter; in *form*, in that it challenges power by shifting the aesthetic and/or sensory registers of data communication; and/or in *process*, in that it challenges power by building participatory, inclusive processes of knowledge production. What unites this broad scope of data-based work is a commitment to action and a desire to remake the world.

Arrianna Planey, quoting Robert M. Young, states, "A racist society will give you a racist science."[47] We cannot filter out the downstream effects of sexism and racism without also addressing their root cause.

Data Science for Whom?

One of the downstream effects of the privilege hazard—the risks incurred when people from dominant groups create most of our data products—is not only that datasets are biased or unrepresentative, but that they never get collected at all. Mimi Onuoha—an artist, designer, and educator—has long been asking *who questions* about data science. Her project, *The Library of Missing Datasets* (figure 1.4), is a list of datasets that one might expect to already exist in the world, because they help to address pressing social issues, but that in reality have never been created. The project exists as a website and as an art object. The latter consists of a file cabinet filled with folders labeled

Figure 1.4
The Library of Missing Datasets, by Mimi Onuoha (2016) is a list of datasets that are not collected because of bias, lack of social and political will, and structural disregard. Courtesy of Mimi Onuoha. Photo by Brandon Schulman.

with phrases like: “People excluded from public housing because of criminal records,” “Mobility for older adults with physical disabilities or cognitive impairments,” and “Total number of local and state police departments using stingray phone trackers (IMSI-catchers).” Visitors can tab through the folders and remove any particular folder of interest, only to reveal that it is empty. They all are. The datasets that should be there are “missing.”

By compiling a list of the datasets that are missing from our “otherwise data-saturated” world, Onuoha explains, “we find cultural and colloquial hints of what is deemed important” and what is not. “Spots that we’ve left blank reveal our hidden social biases and indifferences,” she continues. And by calling attention to these datasets as “missing,” she also calls attention to how the matrix of domination encodes these “social biases and indifferences” across all levels of society.[48] Along similar lines, foundations like Data2X and books like *Invisible Women* have advanced the idea of a systematic “gender data gap” due to the fact that the majority of research data in scientific studies is based around men’s bodies. The downstream effects of the gender data gap range from annoying—cell phones slightly too large for women’s hands, for example—to fatal. Until recently, crash test dummies were designed in the size and shape of men, an oversight that meant that women had a 47 percent higher chance of car injury than men.[49]

The *who question* in this case is: Who benefits from data science and who is overlooked? Examining those gaps can sometimes mean calling out missing datasets, as Onuoha does; characterizing them, as *Invisible Women* does; and advocating for filling them, as Data2X does. At other times, it can mean collecting the missing data yourself. Lacking comprehensive data about women who die in childbirth, for example, ProPublica decided to resort to crowdsourcing to learn the names of the estimated seven hundred to nine hundred US women who died in 2016.[50] As of 2019, they’ve identified only 140. Or, for another example: in 1998, youth living in Roxbury—a neighborhood known as “the heart of Black culture in Boston”[51]—were sick and tired of inhaling polluted air. They led a march demanding clean air and better data collection, which led to the creation of the AirBeat community monitoring project.[52]

2 Collect, Analyze, Imagine, Teach

Principle: Challenge Power

Data feminism commits to challenging unequal power structures and working toward justice.

In 1971, the Detroit Geographic Expedition and Institute (DGEI) released a provocative map, *Where Commuters Run Over Black Children on the Pointes-Downtown Track*. The map (figure 2.1) uses sharp black dots to illustrate the places in the community where the children were killed. On one single street corner, there were six Black children killed by white drivers over the course of six months. On the map, the dots blot out that entire block.

The people who lived along the deadly route had long recognized the magnitude of the problem, as well as its profound impact on the lives of their friends and neighbors. But gathering data in support of this truth turned out to be a major challenge. No one was keeping detailed records of these deaths, nor was anyone making even more basic information about what had happened publicly available. "We couldn't get that information," explains Gwendolyn Warren, the Detroit-based organizer who headed the unlikely collaboration: an alliance between Black young adults from the surrounding neighborhoods and a group led by white male academic geographers from nearby universities.[1] Through the collaboration, the youth learned cutting-edge mapping techniques and, guided by Warren, leveraged their local knowledge in order to produce a series of comprehensive reports, covering topics such as the social and economic inequities among neighborhood children and proposals for new, more racially equitable school district boundaries.

Compare the DGEI map with another map of Detroit made thirty years earlier, *Residential Security Map* (figure 2.2). Both maps use straightforward cartographic techniques: an aerial view, legends and keys, and shading. But the similarities end there. The maps differ in terms of visual style, of course. But more profound is how they diverge in terms of the worldviews of their makers and the communities they seek to support. The latter map was made by the Detroit Board of Commerce, which consisted

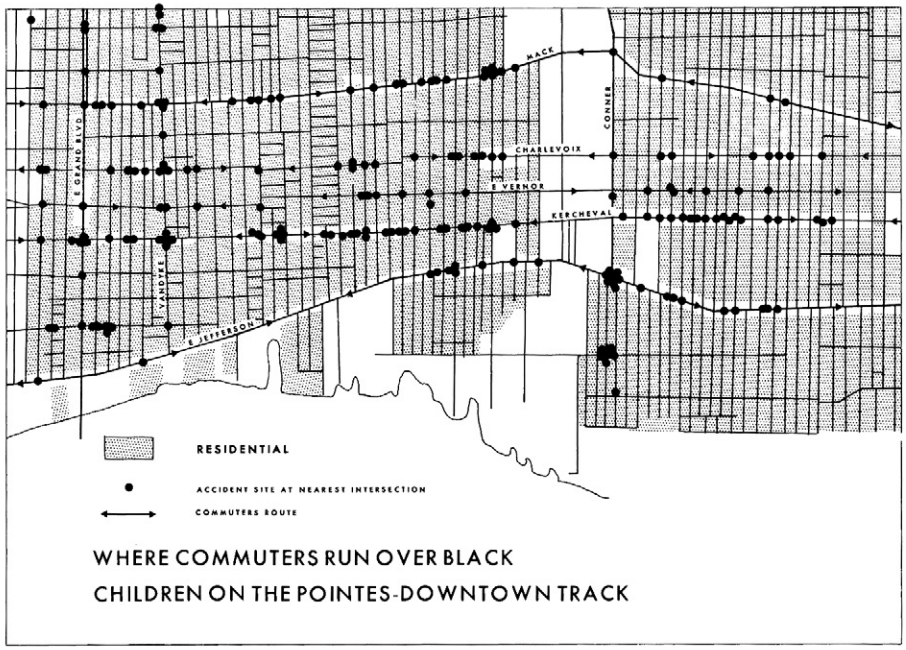

Figure 2.1

Where Commuters Run Over Black Children on the Pointes-Downtown Track (1971) is one image from a report, "Field Notes No. 3: The Geography of Children" which documented the racial inequities of Detroit children. The map was created by Gwendolyn Warren, the administrative director of the Detroit Geographic Expedition and Institute (DGEI), in a collaboration between Black young adults in Detroit and white academic geographers that lasted from 1968–1971. The group worked together to map aspects of the urban environment related to children and education. Warren also worked to set up a free school at which young adults could take college classes in geography for credit. Courtesy of Gwendolyn Warren and the Detroit Geographical Expedition and Institute.

of only white men, in collaboration with the Federal Home Loan Bank Board, which consisted mostly of white men. Far from emancipatory, this map was one of the earliest instances of the practice of *redlining*, a term used to describe how banks rated the risk of granting loans to potential homeowners on the basis of neighborhood demographics (specifically race and ethnicity), rather than individual creditworthiness.

Redlining gets its name because the practice first involved drawing literal red lines on a map. (Sometimes the areas were shaded red instead, as in the map in figure 2.2.) All of Detroit's Black neighborhoods fall into red areas on this map because housing discrimination and other forms of structural oppression predated the practice.[2] But denying home loans to the people who lived in these neighborhoods reinforced those

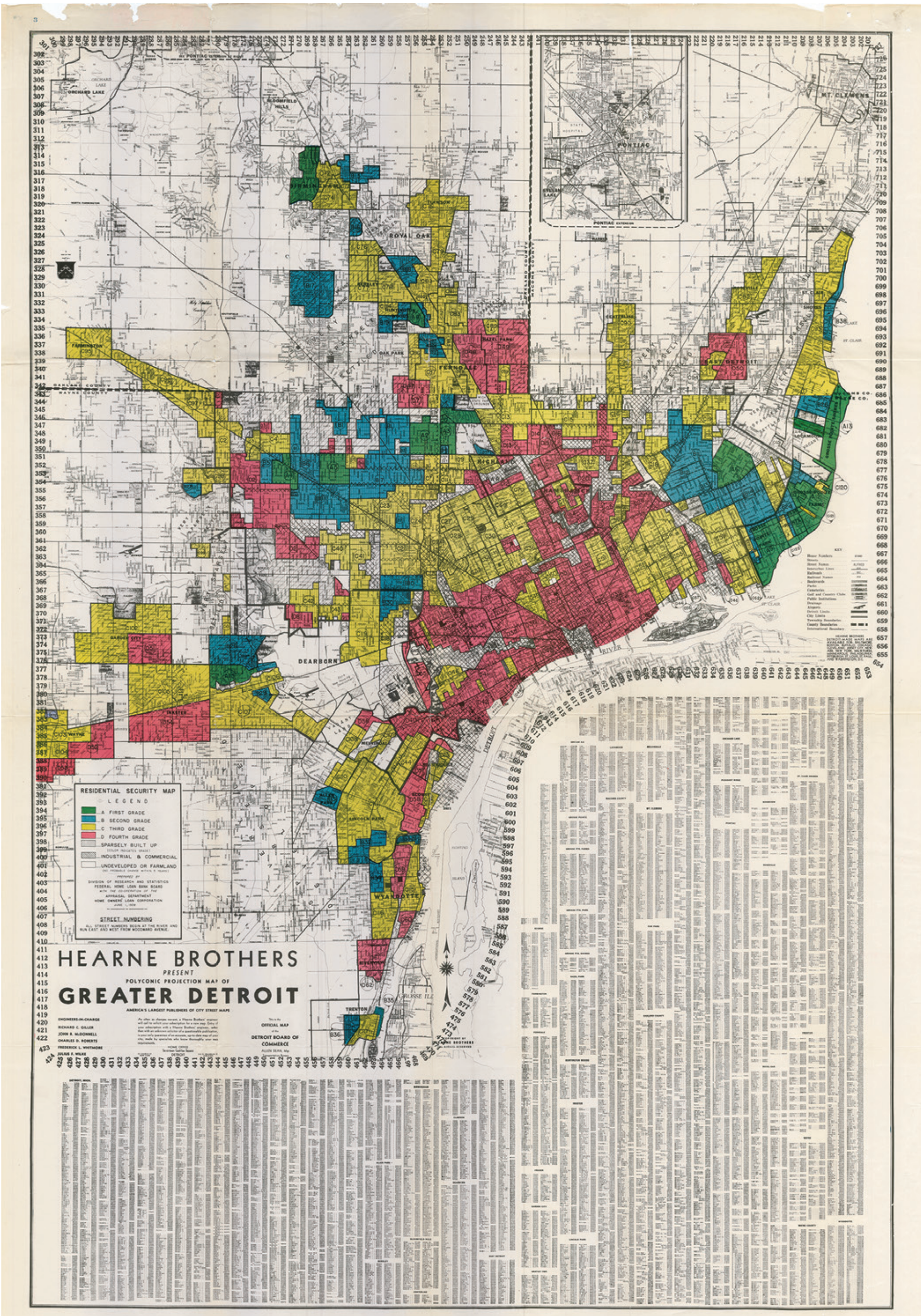

Figure 2.2
Residential Security Map, a redlining map of Detroit published in 1939. Created as a collaboration between the (all white and male) Detroit Chamber of Commerce and the (majority white and male) Federal Home Loan Bank Board, the red colors signify neighborhoods that these institutions deemed red neighborhoods, at "high risk" for bank loans. Courtesy of Robert K. Nelson, LaDale Winling, Richard Marciano, Nathan Connolly, et al., *Mapping Inequality: Redlining in New Deal America*.

existing inequalities and, as decades of research have shown, were directly responsible for making them worse.[3]

Early twentieth-century redlining maps had an aura very similar to the "big data" approaches of today. These high-tech, scalable "solutions" were deployed across the nation, and they were one method among many that worked to ensure that wealth remained attached to the racial category of whiteness.[4] At the same time that these maps were being made, the insurance industry, for example, was implementing similar data-driven methods for granting (or denying) policies to customers based on their demographics. Zoning laws that were explicitly based on race had already been declared unconstitutional; but within neighborhoods, so-called covenants were nearly as exclusionary and completely legal.[5] This is a phenomenon that political philosopher Cedric Robinson famously termed *racial capitalism*, and it continues into the present in the form of algorithmically generated credit scores that are consistently biased and in the consolidation of "the 1 percent" through the tax code, to give only two examples of many.[6] What's more, the benefits of whiteness accrue: "Whiteness retains its value as a 'consolation prize,'" civil rights scholar Cheryl Harris explains. "It does not mean that all whites will win, but simply that they will not lose."[7]

Who makes maps and who gets mapped? The redlining map is one that secures the power of its makers: the white men on the Detroit Board of Commerce, their families, and their communities. This particular redlining map is even called *Residential Security Map*. But the title reflects more than a desire to secure property values. Rather, it reveals a broader desire to protect and preserve home ownership as a method of accumulating wealth, and therefore status and power, that was available to white people only. In far too many cases, data-driven "solutions" are still deployed in similar ways: in support of the interests of the people and institutions in positions of power, whose worldviews and value systems differ vastly from those of the communities whose data the systems rely upon.[8]

The DGEI map, by contrast, challenges this unequal distribution of data and power. It does so in three key ways. First, in the face of missing data, DGEI compiled its own counterdata. Warren describes how she developed relationships with "political people in order to use them as a means of getting information from the police department in order to find out exactly what time, where, how and who killed [each] child."[9] Second, the DGEI map plotted the data they collected with the deliberate aim of quantifying structural oppression. They intentionally and explicitly focused on the problems of "death, hunger, pain, sorrow and frustration in children," as they explain in the report.[10] Finally, the DGEI map was made by young Black people who lived in the community, under the leadership of a Black woman who was an organizer in the community, with support provided by the academic geographers.[11] The identities of these makers matter, their proximity to the subject matter matters, the terms of their collaboration matter, and the leadership of the project matters.[12]

For these reasons, the DGEI provides a model of the second principle of data feminism: *challenge power*. Challenging power requires mobilizing data science to push back against existing and unequal power structures and to work toward more just and equitable futures. As we will discuss in this chapter, the goal of challenging power is closely linked to the act of examining power, the first principle of data feminism. In fact, the first step of challenging power is to examine that power. But the next step—and the reason we have chosen to dedicate two principles to the topic of power—is to take action against an unjust status quo.

Taking action can itself take many forms, and in this chapter we offer four starting points: (1) *Collect:* Compiling counterdata—in the face of missing data or institutional neglect—offers a powerful starting point as we see in the example of the DGEI, or in María Salguero's femicide maps discussed in chapter 1. (2) *Analyze:* Challenging power often requires demonstrating inequitable outcomes across groups, and new computational methods are being developed to audit opaque algorithms and hold institutions accountable. (3) *Imagine:* We cannot *only* focus on inequitable outcomes, because then we will never get to the root cause of injustice. In order to truly dismantle power, we have to imagine our end point not as "fairness," but as co-liberation. (4) *Teach:* The identities of data scientists matter, so how might we engage and empower newcomers to the field in order to shift the demographics and cultivate the next generation of data feminists?

Analyze and Expose Oppression

One can make a direct comparison between yesterday's redlining maps and today's risk assessment algorithms. The latter are used in many cities in the United States today to inform judgments about the length of a particular prison sentence, the amount of bail that should be set, and even whether bail should be set in the first place. The "risk" in their name has to do with the likelihood of a person detained by the police committing a future crime. Risk assessment algorithms produce scores that influence whether a person is sent to jail or set free, effectively altering the course of their life.

But risk assessment algorithms, like redlining maps, are neither neutral nor objective. In 2016, Julia Angwin led a team at ProPublica to investigate one of the most widely used risk assessment algorithms in the United States, created by the company Northpointe (now Equivant).[13] Her team found that white defendants are more often mislabeled as low risk than Black defendants and, conversely, that Black defendants are mislabeled as high risk more often than white defendants.[14] Digging further into the process, the journalists uncovered a 137-question worksheet that each detainee is required to fill out (figure 2.3). The detainee's answers feed into the software, in which they are compared with other data to determine that person's risk score. Although the questionnaire does not ask directly about race, it asks questions that, given the structural inequalities embedded in US culture, serve as proxies for race. These include questions like whether you were raised by a single mother, whether you have ever been suspended from school, or whether you have friends or family that have been arrested. In the United States, each of those questions is linked to a set of larger social, cultural, and political—and, more often than not, racial—realities. For instance, it has been demonstrated that 67 percent of Black kids grow up in single-parent households,

The next few questions are about the family or caretakers that mainly raised you when growing up.

31. Which of the following best describes who principally raised you?
☐ Both Natural Parents
☐ Natural Mother Only
☐ Natural Father Only
☐ Relative(s)
☐ Adoptive Parent(s)
☐ Foster Parent(s)
☑ Other arrangement

32. If you lived with both parents and they later separated, how old were you at the time?
☑ Less than 5 ☐ 5 to 10 ☐ 11 to 14 ☐ 15 or older ☐ Does Not Apply

33. Was your father (or father figure who principally raised you) ever arrested, that you know of?
☑ No ☐ Yes

34. Was your mother (or mother figure who principally raised you) ever arrested, that you know of?
☑ No ☐ Yes

35. Were your brothers or sisters ever arrested, that you know of?
☐ No ☑ Yes

36. Was your wife/husband/partner ever arrested, that you know of?
☑ No ☐ Yes

37. Did a parent or parent figure who raised you ever have a drug or alcohol problem?
☑ No ☐ Yes

38. Was one of your parents (or parent figure who raised you) ever sent to jail or prison?
☑ No ☐ Yes

Figure 2.3
Equivant's risk assessment algorithm is called Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) and is derived from a defendant's answers to a 137-question survey about their upbringing, personality, family, and friends, including many questions that can be considered proxies for race, such as whether they were raised by a single mother. Note that evidence of family criminality would not be admissible evidence in a court case for a crime committed by an individual, but here it is used as a factor in making important decisions about a person's freedom. Courtesy of Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner for ProPublica, 2016.

whereas only 25 percent of white kids do.[15] Similarly, studies have shown that Black kids are punished more harshly than are white kids for the same minor infractions, starting as early as preschool.[16] So, though the algorithm's creators claim that they do not consider race, race is embedded into the data they are choosing to employ. What's more, they are using that information to further disadvantage Black people, whether because of an erroneous belief in the objectivity of their data, or because they remain unmoved by the evidence of how racism is operating through their technology.

Sociologist Ruha Benjamin has a term for these situations: the *New Jim Code*—where software code and a false sense of objectivity come together to contain and control the lives of Black people, and of other people of color.[17] In this regard, the redlining map and the Equivant risk assessment algorithm share some additional similarities. Both use aggregated data about *social groups* to make decisions about *individuals*: Should we grant a loan to this person? What's the risk that this person will reoffend? Furthermore, both use past data to predict future behavior—and to constrain it. In both cases, the past data in question (like segregated housing patterns or single parentage) are *products* of structurally unequal conditions. These unequal conditions are true across large social groups, and yet the technology uses those data as *predictive elements* that will influence one person's future. Surya Mattu, a former ProPublica reporter who worked on the story, makes this point directly: "Equivant didn't account for the fact that African Americans are more likely to be arrested by the police regardless of whether they committed a crime or not. The system makes an assumption that if you have been arrested you are probably at higher risk."[18] This is one of the challenges of using data about people as an input into a system: the data are never "raw." Data are always the product of unequal social relations—relations affected by centuries of history. As computer scientist Ben Green states, "Although most people talk about machine learning's ability to predict the future, what it really does is predict the past."[19] Effectively such "predictive" software reinforces existing demographic divisions, amplifying the social inequities that have limited certain groups for generations. The danger of the New Jim Code is that these findings are actively promoted as objective, and they track individuals and groups through their lives and limit their future potential.

But machine learning algorithms don't just predict the past; they also reflect current social inequities. A less well-known finding from the ProPublica investigation of Equivant, for example, is that it also surfaced significantly different treatment of women by the algorithm. Due to a range of factors, women tend to recidivate—to commit new crimes—less than men do. That means the risk scale for women "is such that somebody with a high risk score that's a woman is generally about the level of a medium risk score for a man. So, it's actually really shocking that judges are looking at these and thinking that high risk means the same thing for a man and a woman when it doesn't," explains lead reporter Julia Angwin.[20]

Angwin decided to focus the story on race in part because of the prior work of criminologists such as Kristy Holtfreter, which had already highlighted some of these gender differentials.[21] But there was another factor at play in her editorial decision: workplace sexism faced by women reporters like Angwin herself. Angwin explains how she had always been wary of working on stories about women and gender because she wanted to avoid becoming pigeonholed as a reporter who *only* worked on stories about women and gender. But, she explains, "one of the things I woke up to during the #MeToo movement was how many decisions like that I had made over the years"—an internalized form of oppression that had discouraged her from covering those important issues. In early 2018, when we conducted this interview, Angwin was hiring for her own data journalism startup, the Markup, founded with a goal of using data-driven methods to investigate the differential harms and benefits of new technologies on society. She was encouraged to see how many job candidates of all genders were pitching stories on issues relating to gender inequality. "In the era of data and AI, the challenge is that accountability is hard to prove and hard to trace," she explains. "The challenge for journalism is to try to make as concrete as possible those linkages when we can so we can show the world what the harms are."

Angwin is pointing out a tricky issue that is unlikely to go away. The field of journalism has long prided itself on "speaking truth to power." But today, the location of that power has shifted from people and corporations to the datasets and models that they create and employ. These datasets and models require new methods of interrogation, particularly when they—like Equivant's—are proprietary. How does one report on a *black box*, as these harmful algorithms are sometimes described?[22] Much like the situation encountered by Gwendolyn Warren when she looked into the data on the Detroit children's deaths, or like María Salguero when she started logging femicides in Mexico, ProPublica found no existing studies that examined whether the risk scores were racially biased, or existing datasets they could use to point them to answers. To write the risk assessment story, ProPublica had to assemble a dataset of their own. The researchers looked at ten thousand criminal defendants from a single county in Florida and compared their recidivism risk scores with people who actually reoffended in a two-year period. After doing some initial exploratory analysis, they created their own regression model that considered race, age, criminal history, future recidivism, charge degree, and gender. They found that age, race, and gender were the strongest predictors of who received a high risk score—with Black defendants 77 percent more likely than white ones to receive a higher violent recidivism score. Their analysis also included creating models to test the overall accuracy of the COMPAS model over time and an investigation of errors to see if there were racial differences in the distribution of false positives and false negatives. As it turns out, there were: the system was more likely to predict that white people would not commit additional crimes if released, when they actually did recidivate.[23]

Angwin and her coauthors used data science to challenge data science. By collecting missing data and reverse-engineering the algorithm that was judging each defendant's risk, they were able to prove systemic racial bias. This analysis method is called *auditing algorithms* and it is being increasingly used in journalism and in academic research in order show how the harms and benefits of automated systems are differentially distributed. Computational journalism researcher Nicholas Diakopoulos has proposed that work like this become formalized into an algorithm accountability beat, which would help to make the practice more widespread.[24] He and computer scientist Sorelle Friedler have asserted that algorithms need to be held "publicly accountable" for their consequences, and the press is one place where this accounting can take place.[25] By providing proof of how racism and sexism, among other oppressions, create unequal outcomes across social groups, analyzing data is a powerful strategy for challenging power and working toward justice.

The Pitfalls of Proof

Let's pause here for a feminist *who question*, as we introduced in chapter 1. Who is it, exactly, that needs to be shown the harms of such differentials of power? And what kind of proof do they require to believe that oppression is real? Women who experience instances of sexism, as Angwin did in her workplace, already know the harms of that oppressive behavior. The young adults whom Gwendolyn Warren worked with in Detroit already knew intimately that the white commuters were killing their Black neighbors and friends. They had no need to prove to their own communities that structural racism was a factor in these deaths. Rather, their goal in partnering with the DGEI was to prove the structural nature of the problem to those in positions of power. Those dominant groups and institutions were the ones that, by privileging their own social, political, and economic interests, bore much of the responsibility for the problem; and they also, because of the phenomenon we have described as a privilege hazard, were unlikely to see that such problem existed in the first place. The theory of change that motivates these efforts to use data as evidence, or "proof," is that by being made aware of the extent of the problem, those in power will be prompted to take action.

These kinds of data-driven revelations can certainly be compelling. When the analysis appears in a high-profile newspaper or blog or TV show (in other words: a place white enough and male enough to be considered mainstream), it can indeed prompt people in power to act. The ProPublica story on risk assessment algorithms, for example, prompted a New York City council member to propose an algorithmic accountability bill. Enacted in 2018, the bill became the first legal measure to tackle algorithmic discrimination in the United States and led to the creation of a task force focused on "equity and fairness" in city algorithms.[26] Should the city implement some of the task force's recommendations, it would influence the work of software vendors, as well as legislation in other cities. This path of influence—from community problem to gathering proof to informed reporting to policy change—represents the best aspirations of speaking truth to power.[27]

While analyzing and exposing oppression in order to hold institutions accountable can be extremely useful, its efficacy comes with two caveats. Proof can just as easily become part of an endless loop if not accompanied by other tools of community engagement, political organizing, and protest. Any data-based evidence can be minimized because it is not "big" enough, not "clean" enough, or not "newsworthy" enough to justify a meaningful response from institutions that have a vested interest in maintaining the status quo.[28] As we saw in chapter 1, María Salguero's data on femicides was augmented by government commissions, reports from international agencies, and rulings of international courts. But none of those data-gathering efforts have been enough to prompt comprehensive action.

Another feminist *who question*: On whom is the burden of proof is placed? In 2015, communications researcher Candice Lanius wrote a widely shared blog post, "Fact Check: Your Demand for Statistical Proof is Racist," in which she summarizes the ample research on how those in positions of power accept anecdotal evidence from those like themselves, but demand endless statistics from minoritized groups.[29] In those cases, she argues convincingly, more data will never be enough.

Proof can also unwittingly compound the harmful narratives—whether sexist or racist or ableist or otherwise oppressive—that are already circulating in the culture, inadvertently contributing to what are known as *deficit narratives*. These narratives reduce a group or culture to its "problems," rather than portraying it with the strengths, creativity, and agency that people from those cultures possess. For example, in their book *Indigenous Statistics*, Maggie Walter and Chris Anderson describe how statistics used by settler colonial groups to describe Indigenous populations have mainly functioned as "documentation of difference, deficit, and dysfunction."[30] This can occur even when the creators have good intentions—for example, as Kimberly Seals Allers notes (see chapter 1), a great deal of the media reporting on Black maternal mortality data falls into the deficit narrative category. It portrays Black women as victims and fails to amplify the efforts of the Black women who have been working on the issue for decades.

This goes for gender data as well. "What little data we collect about women tends to be either about their experience of violence or reproductive health," explains Nina Rabinovitch Blecker, who directs communications for Data2X, a nonprofit aimed at improving the quality of data related to gender in a global context.[31] The current data encourage additional deficit narratives—in which women are relentlessly and reductively portrayed as victims of violent crimes like murder, rape, or intimate partner violence. These narratives imply that the subjects of the data have no agency and need "saving" from governments, international institutions, or concerned citizens. As one step to counteract that, Blecker chose to publish an example from Uruguay that didn't focus on violence, but rather on quantifying women's unseen contributions to the economy.[32]

So, though collecting counterdata and analyzing data to provide proof of oppression remain worthy goals, it is equally important to remain aware of how the subjects of oppression are portrayed. Working with communities directly, which we talk more about in chapter 5, is the surest remedy to these harms. Indigenous researcher Maggie Walter explains that ownership of the process is key in order to stop the propagation of deficit narratives: "We [Indigenous people] must have real power in how statistics about us are done—where, when and how."[33] Key too is a sustained attention to the ways in which communities themselves are already addressing the issues. These actions are often more creative, more effective, and more culturally grounded than the actions that any outside organization would take.

Envision Equity, Imagine Co-liberation

As the examples discussed thus far in this book clearly demonstrate, one of the most dangerous outcomes of the tools of data and data science being consolidated in the hands of dominant groups is that these groups are able to obscure their politics and their goals behind their technologies. Benjamin, whose book *Race after Technology: Abolitionist Tools for the New Jim Code* (mentioned earlier), describes this phenomenon as the "imagined objectivity of data and technology" because data-driven systems like redlining and risk assessment algorithms are not really objective at all.[34] Her concept of *imagined objectivity* emphasizes the role that cultural assumptions and personal preconceptions play in upholding this false belief: one imagines (wrongly) that datasets and algorithms are less partial and less discriminatory than people and thus more "objective."[35] But as we discuss in chapter 1, these data products seem objective only because the perspectives of those who produce them—elite, white men and the institutions they control—pass for the default. Assumptions about objectivity are becoming a major focus in data science and related fields as algorithm after algorithm is revealed to be sexist, racist, or otherwise flawed. What can the people who design these computational systems do to avoid these pitfalls? And what can everyone else do to help them and hold them accountable?

The quest for answers to these questions has prompted the development of a new area of research known as *data ethics*. It represents a growing interdisciplinary effort—both critical and computational—to ensure that the ethical issues brought about by our increasing reliance on data-driven systems are identified and addressed. Thus far, the major trend has been to emphasize the issue of "bias," and the values of "fairness, accountability, and transparency" in mitigating its effects.[36] This is a promising development, especially for technical fields that have not historically foregrounded ethical issues, and as funding mechanisms for research on data and ethics proliferate.[37] However, as Benjamin's concept of imagined objectivity helps to show, addressing bias in a dataset is a tiny technological Band-Aid for a much larger problem. Even the values mentioned here, which seek to address instances of bias in data-driven systems, are themselves non-neutral, as they locate the source of the bias in individual people and specific design decisions. So how might we develop a practice that results in data-driven systems that challenge power at its source?

The following chart (table 2.1) introduces an alternate set of orienting concepts for the field: these are the six ideals that we believe should guide data ethics work. These

Table 2.1
From data ethics to data justice

Concepts That Secure Power Because they locate the source of the problem in individuals or technical systems	**Concepts That Challenge Power** Because they acknowledge structural power differentials and work toward dismantling them
Ethics	Justice
Bias	Oppression
Fairness	Equity
Accountability	Co-liberation
Transparency	Reflexivity
Understanding algorithms	Understanding history, culture, and context

concepts all have legacies in intersectional feminist activism, collective organizing, and critical thought, and they are unabashedly explicit in how they work toward justice.

In the left-hand column, we list some of the major concepts that are currently circulating in conversations about the uses of data and algorithms in public (and private) life. These are a step forward, but they do not go far enough. On the right-hand side, we list adjacent concepts that emerge from a grounding in intersectional feminist activism and critical thought. The gap between these two columns represents a fundamental difference in view of why injustice arises and how it operates in the world. The concepts on the left are based on the assumption that injustice arises as a result of flawed individuals or small groups ("bad apples," "racist cops," "brogrammers") or flawed technical systems ("the algorithm/dataset did it"). Although flawed individuals and flawed systems certainly exist, they are not the root cause of the problems that occur again and again in data and algorithms.

What is the root cause? If you've read chapter 1, you know the answer: the matrix of domination, the matrix of domination, and the matrix of domination. The concepts on the left may do good work, but they ultimately keep the roots of the problem in place. In other words, they maintain the current structure of power, even if they don't intend to, because they let the matrix of domination off the hook. They direct data scientists' attention toward seeking technological fixes. Sometimes those fixes are necessary and important. But as technology scholars Julia Powles and Helen Nissenbaum assert, "Bias is real, but it's also a captivating diversion."[38] There is a more fundamental problem that must also be addressed: we do not all arrive in the present with equal power or privilege. Hundreds of years of history and politics and culture have brought us to the present moment. This is a reality of our lives as well as our data. A broader focus on *data justice*, rather than *data ethics* alone, can help to ensure that past inequities are not distilled into black-boxed algorithms that, like the redlining maps of the twentieth century, determine the course of people's lives in the twenty-first.

In proposing this chart, we are not suggesting that ethics have no place in data science, that bias in datasets should not be addressed, or that issues of transparency should go ignored.[39] Rather, the main point is that the concepts on the left are inadequate *on their own* to account for the root causes of structural oppression. By not taking root causes into account, they limit the range of responses possible to challenge power and work toward justice. In contrast, the concepts on the right start from the basic feminist belief that oppression is real, historic, ongoing, and worth dismantling.