Handle with Care: Lessons for Data Science from Black Female Scholars

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The contribution of Black female scholars to our understanding of data and their limits of representation hint at a more empathetic vision for data science that we should all learn from.

There’s no such thing as flattening stereotypes—only flattening stereotypes. The strong Black woman, the math genius Asian. It is an inherent insult to crush full and complex human beings into the one or two dimensions one chooses to see.

Yet this is the entire goal of data science. On the Internet, the world is flat. For reality to be computable, it must lose dimensions. The definition of dynamic, complicated objects—including humans, especially humans—collapses into inputs for operations and analysis.

In her book Race After Technology, Ruha Benjamin often weaves back to this theme of stereotypes, referring to its fitting historical definition as “an image perpetuated without change.”1 Stereotypes are meant to be something static and universal, in a way we know we as humans are not. They persist for months, years, decades, and centuries, enduring and concrete in the way we expect our data to be. Perhaps a reflection of something real and natural but ultimately built as a limited sketch designed by an individual, organization, or society in their attempt to compress and capture. Stereotypes are the consequence of alert or unconscious pattern recognition over long or short histories, personal anecdotes, or systemic habits that feed into our modern judgements. This is the unnamed “intuition” that may cause a teacher to dismiss a minority student, give an employer their instant “feeling” of a lack of “cultural fit,” or prompt a premature move to cross to the other side of the street as a Black man approaches.

The way we decide to see people of color in the real world shapes their impressions in our constructed online space. In her book Algorithms of Oppression, Safiya Noble highlights how a Google Image search for “black girls” directs to pornographic photos, reminiscent of the over-sexualized imagery of the Black Jezebel Whore in US media.2 She discusses how Harvard Professor Latanya Sweeney’s discovery of the association of African American names with online advertisements for criminal record checks is in line with long-standing assumptions of Blackness and criminality. She explores a case in which a search for “unprofessional hairstyles” directs to images of afros on Black women, while “professional hairstyles” only feature the images of white models, reinforcing notions of professionalism born from decades of employment discrimination.

The nature of these embedded stereotypes reveals the default lens through which our data are defined. From diagrams in medical textbooks to glamour shots in magazines, it is uncomfortably clear to many people of color that our default depiction of “human” in all but the most unfavorable contexts is white. Joy Buolamwini of the Algorithmic Justice League (https://www.ajl.org/) often speaks to the prevalence of “paie male” datasets and the “undersampled majority” to highlight how this unbearable imbalance of perspective filters into our datasets. Up to 77.4% of the subjects in a mainstream face dataset are male, and up to 94.6% are lighter skinned,3 leading to commercial products that are dysfunctional and dangerous for darker-skinned individuals.4,5 Similarly, over 80% of the images in the major datasets of the computer vision field are sourced in the West,6 mainly the US and UK, and as a result, many object recognition models are ineffective on images of any different cultural context.7 Abeba Birhane also discusses how, although there is a clear opportunity to collect data on crop disease in the cassava plant or information on gender equality in Ethiopia, Western agendas often override those needs, imposing their own priorities of enabling operational expansion into the Global South.8

As Yeshimabeit Milner of Data for Black Lives (https://d4bl.org/) says, “The Google search bar is a false oracle, a dead end for seeking truth.”9 Google will often fill in the blanks for us of exactly which perceptions will be embedded in its results, repeating stereotypes of Black people as “loud,” “athletic,” “ghetto,” or “poor” and Black women specifically as “lazy,” “sassy,” and “angry.”10 What these results echo are nothing but inherited fables crystallized in data and presented as fact. The challenge arrives when we trust those stories, choosing to allow those data to become consequential in the real world, feeding into algorithms or consulted in impactful decision-making—when this automated stereotyping becomes leveraged to tangibly interfere with Black lives. Yeshimabeit brings up the example of the record-keeping practices of the slave trade and how, by keeping a tally of certain physical features categorizing these humans as they would cattle, these records would reinforce the slave’s status as property. Rashida Richardson and Amba Kak present how modern-day gang databases do the same, noting that “judgments on who and what to include in gang databases reflect a historic pattern of over policing Black, Latinx, and other racial and ethnic minority communities.”11 They mention that Black and Latinx young people make up 99% of NYPD’s gang database and, in London, 78% of the Metropolitan Police’s Gang Matrix database—even though this...
demographic only makes up 27% of youth violence.

For a long time, practical convenience for data collection was the unspoken rule in data science—the data we can easily access and manipulate, the data that are there, the data that fit the narrative of the person who wishes to use them. This is what guided our decision-making regarding the data we use. What these women are saying is that practicality is not enough to encompass all that we need to consider—there is something neglected in a blind chase for efficiency and performance. There is inherent subjectivity to this work, and empirical analysis alone is insufficient in making data science effective. Timnit Gebru in several papers actually calls for caution in the current practice through which we collect our data, record their logics, and report on the performance of the models we build on top. What she and others are advocating for is a slowness data scientists are not accustomed to, a carefulness that many technologists are not taught.

In the moment of silence at a Data for Black Lives Movement Pulse Check (https://d4bl.org/reports.html) or Abeba’s plea for “genuine care for the welfare of the marginalized,” I can tell that there’s something in the data that these Black women see—they see pulsing hearts, like their own, tragically twisted into caricatures that oversimplify and devalue. They understand that although we call out to “Alexa,” “Siri,” “Cortana,” and “Watson,” it is the data points that have names, not the AI systems. These marked imprints and tabled structures can capture the highlights of existence—a birth, a college degree, a vote—and the worst—a felony, a debt, a preexisting condition. What is captured and by whom is what will make all the difference in how the story of that data point will go.

What these Black women taught me is that people are no less deserving of care when represented by a data point than at any other point in their lives. Humans are no less fragile and their experiences no less meaningful when housed in digital identities or bookmarked into a spreadsheet than if they were to stand right in front of me. Data are most beautiful when they are alive—when they grow, compound, and evolve. When predictions are wrong and the limits of the image become clear. Jasmine McNealy goes so far as to propose the analogy of data ecosystems over economies. Yeshimabebit writes, “I knew this…would be about something more than data, more than algorithms, but about people, about asserting life.” Abeba simply states this as fact: “Data are people.” Meredith Broussard echoes this and adds, “this is true of all data.” Whether about humans, by humans, or for humans, data are our socially constructed interface with the computational world. And for that reason alone, we must pay close attention, because the data that we handle are human fates, not footnotes—frames that can change the entire picture as consequential representations of real people enduring real life.

If these Black women seem overly critical, it is because their consciousness and attention to the life in the data simplifies for them the negotiation between lived experience and a higher accuracy score. As Black women, we write obituaries to explain what the death certificate didn’t say. We see most clearly the imposed contradictions, because of the divergence between the reality we know and what we see emphasized and represented in the data. But, most importantly, we know the lives impacted will always be worth more. This knowledge is most apparent from where we stand, at a viewpoint often erased and initially unconsidered.

I celebrate the vision of these Black women for the future of data science. To say “cite Black women” does not mean to plow through a post hoc checklist of names to search for and add after your paper is already written and your experiments completed. It doesn’t mean tokenism. This is not a gift you are giving, but one you must receive. Engage in the radical vision for what this field could be
and how data work. Allow this literature to redefine perspectives. Join in our hope for a new direction—one that protects rather than exploits, and fills out rather than flattens.

WEB RESOURCES
Algorithmic Justice League, https://www.ajl.org/
Data for Black Lives, https://d4bl.org/

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About the author
Inioluwa Deborah Raji is an incoming Mozilla fellow interested in topics of algorithmic auditing and evaluation. She has worked closely with the Algorithmic Justice League initiative on several award-winning projects to highlight cases of bias in computer vision. She has also worked with Google’s Ethical AI team and been a research fellow at the Partnership on AI and AI Now Institute at New York University working on various projects to operationalize ethical considerations in machine learning engineering practice.