

DISCRIMINATING DATA

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**CORRELATION, NEIGHBORHOODS, AND THE NEW
POLITICS OF RECOGNITION**

WENDY HUI KYONG CHUN

MATHEMATICAL ILLUSTRATIONS BY ALEX BARNETT

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To all the students I taught at Brown, Penn, Chicago, and Simon Fraser, in particular the first four at the Digital Democracies Institute: Amy, Carina, Hannah, and Julia.

And to my first teachers: Jeannie, Maria, Ernie, and Bert.

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PREFACE

On December 6, 1989, a man walked into an engineering classroom at the École Polytechnique in Montreal and ordered the men to leave. Thinking it was a prank to lighten up the last day of class, no one moved—until he fired a single shot from his semi-automatic rifle. After the men left, he told the women he was there to fight feminism, and he opened fire on the women remaining in the room and in the adjoining hallways. He killed fourteen women that day: Geneviève Bergeron, Hélène Colgan, Nathalie Croteau, Barbara Daigneault, Anne-Marie Edward, Maud Haviernick, Maryse Laganière, Maryse Leclair, Anne-Marie Lemay, Sonia Pelletier, Michèle Richard, Annie St-Arneault, Annie Turcotte, and Barbara Klucznik-Widajewicz.

I first heard about the massacre the next morning as I was sitting down to write my Physical Systems exam. The boys behind me asked me if I had heard about the women who were killed in an engineering classroom in Montreal. Thinking it was yet another sick and misogynist engineering joke—engineering was filled with them—I told them to shut up and write the exam. Later that day, when I found out that the massacre had actually happened, I was in shock. I had turned to engineering as a first-generation immigrant in Canada to escape from discrimination and politics. Disoriented, I turned to the humanities—to English literature and critical theory—to help me acknowledge the violence and discrimination around me.

Graduating as the first engineering student from the University of Waterloo with a double major, I then pursued a PhD in English Literature at Princeton—initially as way to run away again from politics and discrimination. For any of you who know English departments, you will realize how misguided this was. Crucially, the first paper I wrote as a graduate student—one that became my first article, “Unbearable Witness: Towards a Politics of Listening”—bore witness to the massacre and called for a politics of listening to supplement a politics of speaking. My question was: how can we redress the trauma, discrimination, and violence around us not by treating any one or any event as “representative” but rather by acknowledging their singularity and our resonating experiences in our responses?

When I started my PhD, I had dreams of merging literary theory and complex systems theory. I quickly moved from mapping the parallels between concepts in the humanities and engineering to asking what made these parallels possible and what these parallels responded to and enabled. I started writing about the importance of sex and sexuality to figuring connection on UseNet—and this burgeoning thing called the World Wide Web. I started to realize that politics was necessary—and already embedded in so much that I took for granted: from control systems that stemmed from gendered and racialized relations of dominance to server farms that threatened to destroy the world in their attempts to “save” everything. The humanities and critical theory gave me the language to see and address the inequalities around me, not because they were outside of them but rather because they, too, suffered from these problems—and were committed to redressing these issues. They gave me the strength to believe that another world is possible.

For the last twenty-five years, I’ve been focused on understanding how the Internet emerged as a mass medium to end mass media. I have used and developed new media theory to understand how a control technology was bought and sold as a technology of freedom; how software’s emergence as a vapory thing encapsulated neoliberal dreams of programmability; how “old media” remain in our habits as we update to remain the same. Throughout, I have explored the centrality of race and sexuality to shaping technologies—and to the bizarre and debilitating framing of technologies as solutions to profoundly political problems. I have

also called for a close engagement with technologies and culture—not because I am a technological or cultural determinist but because I believe that engaging both intensely moves us away from either of these positions. The point is to see how they intersect and collide, that is, how drilling down into any technology reveals profound social and cultural assumptions, and vice versa. Discrimination and injustice do not come from outside—they are “in there,” because technological defaults are embedded with cultural and social prejudices.

At the same time, I have insisted that the traces of a different world are also “in there.” The limitations and vulnerabilities of technical control systems make it clear that freedom cannot be reduced to control: freedom makes control necessary, but never enough. The vicissitudes of execution echo the lively world before us and undermine any dream of total solutions or programmability. New media, as I argued in *Updating to Remain the Same*, are wonderfully creepy, and our habits are shards of others contained within ourselves.

Over the past years, I have found myself turning back more and more to my engineering roots to discover these moments of possibility—as well as the ways in which eugenic and segregationist thinking have become integrated into our machines. The goal has been to bring engineering, computer science, humanities, social sciences, and arts together to take on the hard problems that we face.

This book reveals the communities and neighbors that haunt concepts of correlation, homophily, authenticity, and recognition that are so key to our current communications technologies. It seeks to remain with those whose traces make possible our own by confronting—rather than running away from—discrimination. Understanding that touch is neither banal nor always benign, it nonetheless starts from these relations in order to create different worlds in which we can live in difference, and in which freedom finally becomes meaningful, because it is freedom for all.

INTRODUCTION: HOW TO DESTROY THE WORLD, ONE SOLUTION AT A TIME

The Internet has become a nightmare, the source—it is claimed—of almost everything bad in this world. It has given rise to worldwide surveillance networks, coproduced by states and corporations; social media algorithms, powered by military-grade psychological operations (PSYOPS) that spread lies and conspiracy theories, polarize society, provoke violence, prolong pandemics, and foster planet-wrecking levels of consumption; and artificial intelligence (AI) programs that exacerbate existing inequalities and threaten humanity's future.

The irony is that the Internet and artificial intelligence were promised to be and do the opposite. Cyberspace, the Internet of the late twentieth century, was to usher in a new era of global democracy, equality, and prosperity. Artificial intelligence was to produce docile machine servants that would spread the perks of “the 1%”—chauffeurs, personal assistants, expert advisors—to “the 90%.” AI would also eliminate discrimination because its machines could not “see” race, sex, age, or infirmities.¹ Similarly, cyberspace would free individuals from oppression and national sovereignty because it was “the new home of the Mind”:² an electronic frontier in which physical bodies and identities literally did not matter. In the mid-1990s, Vice President Al Gore and members of the U.S. judiciary described the Internet as the ultimate public sphere because it gave everyone a soapbox from which to speak.³ Bill Gates, then CEO of Microsoft,

argued that the information superhighway enabled “friction-free capitalism” because it melted away brick and mortar obstacles.⁴ John Gilmore, cofounder of the Electronic Frontier Foundation (EFF), is reported to have said that the Internet “interprets censorship as damage and routes around it.”⁵ As late as 2010, the Internet was celebrated as a “liberation technology,” responsible for democratic uprisings in the Middle East.⁶ By freeing our minds, the Internet would help fix all problems, from racism to political suppression.

During the early twenty-first century, the questions for those who still sold hope were: How can the dream be reclaimed from the nightmare? What information should be leaked, what new business plans devised, what apologies proffered to make technology great again?

However well-intentioned, these impulses were also misguided, for the promise and the threat were, are, and have always been two sides of the same coin. In seeking technological solutions to political problems, they assume that the best way to fight abuse and oppression is by ignoring difference and discrimination.⁷ They undermine solidarity by concentrating on individual, neighborhood or “tribal” empowerment. They presume that “good” technology is slavish and thus inevitably invoke fears of absolute dependence and rebellion. Hopeful ignorance is not the solution but the problem: it perpetuates discrimination and inequality, one solution at a time. The problem is not that giant technology monopolies have disrupted habits, institutions, and norms in order to create new, unforeseen futures. The problem is that, in the name of “creative disruption,” they are amplifying and automating—rather than acknowledging and repairing—the mistakes of a discriminatory past.

To counter this threat, I propose the following five-step program:

1. Expose and investigate how ignoring differences amplifies discrimination, both currently and historically.
2. Interrogate the default assumptions and axioms that form the basis for algorithms and data structures.
3. Apprehend the past, present, and future machine learning algorithms put in place to determine when, why, and how their predictions work.
4. Use existing AI systems to diagnose current inequalities and to treat discriminatory predictions as evidence of past discrimination.

5. Draw from struggles for and practices of desegregation and equality to displace the eugenic and segregationist defaults embedded within current network structures and to devise different algorithms and modes of verification.

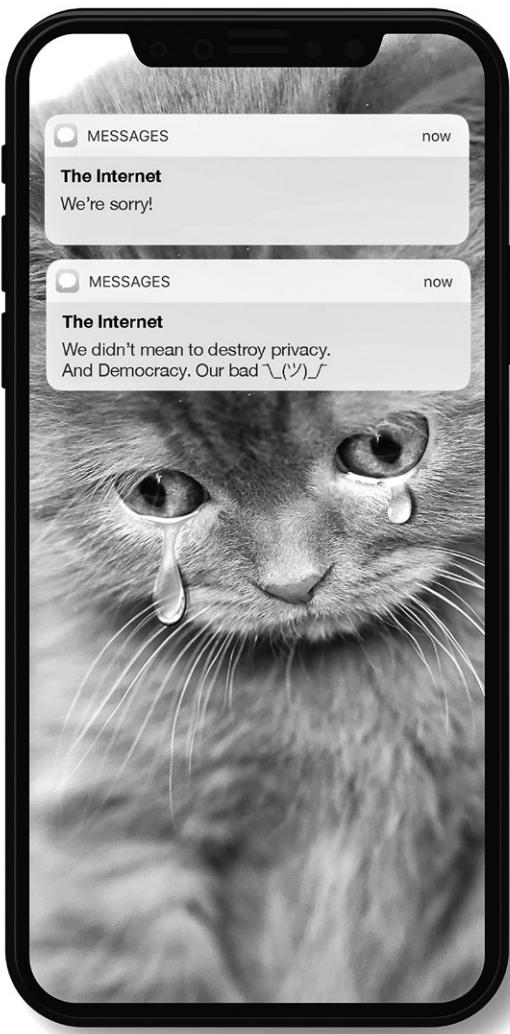
Most fundamentally, I call for a “we” to take this on. The views expressed in this book thus strike a chord with those voiced by Ruha Benjamin, Jodi Byrd, Meredith Broussard, Kate Crawford, Virginia Eubanks, Kara Keeling, Tara McPherson, Lisa Nakamura, Safiya Noble, Cathy O’Neil, Frank Pasquale, and Fred Turner among many others, creating a powerful chorus against hopeful ignorance and the endless apologies it engenders, and for a world that resonates with and in difference.⁸

AGAINST HOPEFUL IGNORANCE, AGAIN

In the early decades of the twenty-first century, technology companies responded to Internet-related disasters by asking for forgiveness and promising technological fixes for their sins. In 2018, Mark Zuckerberg, the founder of Facebook, apologized publicly for the “leak” of 87 million personal profiles to Cambridge Analytica.⁹ The Cambridge Analytica incident, however, as Kate Crawford and Meredith Whitaker of the AI Now Institute emphasized in the institute’s 2018 annual review, was only one of many.¹⁰ Scandals and outrage dominated that year: from revelations that U.S. Immigration and Customs Enforcement (ICE) had “upgraded” its risk assessment software to always recommend detention, to news that Amazon had scrapped its AI hiring software because it discriminated against women, to reports that IBM’s supercomputer Watson had recommended cancer treatments that were “unsafe and incorrect.”¹¹

Noah Kulwin captured the state of affairs in his *New York* magazine article, “The Internet Apologizes” It led with a picture of a cute cat who texted: “We’re sorry. . . . We didn’t mean to destroy privacy. And democracy. Our bad” (figure 1).¹²

Kulwin offered the following list of “How It Went Wrong, in 15 Steps,” based on his interviews with a dozen prominent network architects, Silicon Valley product developers and tech gurus, such as Jaron Lanier and Richard Stallman:



1 Cute crying cat from Noah Kulwin, "The Internet Apologizes . . . : Even Those Who Designed Our Digital World Are Aghast at What They Created," New York, April 13, 2018, <http://nymag.com/intelligencer/2018/04/an-apology-for-the-internet-from-the-people-who-built-it.html>. Photo illustration by Joe Darrow; image recreated by Joshua Cameron.

1. Start with Hippie Good Intentions . . .
2. . . . Then mix in capitalism on steroids
3. The arrival of Wall Streeters didn't help . . .
4. . . . And we paid a high price for keeping it free.
5. Everything was designed to be really, really addictive.
6. At first, it worked—almost too well.
7. No one from Silicon Valley was held accountable . . .
8. . . . Even as social networks became dangerous and toxic.
9. . . . And even as they invaded our privacy.
10. Then came 2016.
11. Employees are starting to revolt.
12. To fix it, we'll need a new business model . . .
13. . . . And some tough regulation.
14. Maybe nothing will change.
15. . . . Unless, at the very least, some new people are in charge.

The basic story line was this: naive hippies fall in love with libertarians, hook up with Wall Street sharks, and inadvertently destroy the world in their attempt to keep it free. As Jaron Lanier told Kulwin, they were caught between two loves: “We wanted everything to be free, because we were hippie socialists. But we also loved entrepreneurs, because we loved Steve Jobs. So you want to be both a socialist and a libertarian at the same time, which is absurd.”

Clickbait advertising resolved this “absurdity” by paving the road to hell. Capturing and exploiting Internet user clicks magically enabled “free” yet profitable content. It also seemed to answer the question that dogged mass print and broadcast advertising: How effective is an ad? By tracking user clicks and mouseovers, advertisers could “measure” engagement, and thus overcome what social theorist Jean Baudrillard had presciently and perversely called the “silent power of the majority.”¹³ To optimize performance, platforms encouraged advertisers to amalgamate related but bespoke microaudiences, that is, to create a crowd of users by consolidating rhyming groups. As chapter 3 further elaborates, to create affectively charged clusters who would take the clickbait, advertisers and platforms targeted users by focusing on their divisive or boundary views. ProPublica’s 2017 investigation into Facebook, for example, revealed

that Facebook “helpfully” suggested that their reporters add “How to burn Jews” and “Second Amendment” to “Jew hater” in order to boost their ad’s target audience size.¹⁴ The fact that the price per ad generally decreased per click further promoted shocking and manipulative advertisements. Soon, the actual product no longer mattered, for monetized user clicks generated their own wealth: outrage—or anything that piqued curiosity—had become profitable. Most infamously, hackers from Moldova produced right- and left-wing fake political news during the 2016 U.S elections in order to profit from a combination of Facebook click throughs and Google ad auctions.¹⁵ Kulwin argues that the success of clickbait advertising resulted both in further polarization of “what had already seemed, during the Obama years, an impossibly and irredeemably polarized country” and, quoting Jaron Lanier, in “continuous behavior modification on a mass basis, with everyone under surveillance by their devices”¹⁶—what Shoshana Zuboff has called “surveillance capitalism.”¹⁷ The cure had become worse than the disease: the collateral damage was democracy and freedom, sacrificed on the altar of the free.

Reforming “the Valley” and redressing mass surveillance and behavior modification programs are important, and Lanier’s observations are perceptive and engaging, but Lanier’s assumptions threaten to undermine his argument and the success of the proposed reforms. Socialism does not equal free information: the fundamental tenet of socialism is not that everything should be free, but that workers should share equally in the profits. The urge to make things free and profitable is wholly libertarian, and the misidentification of libertarianism as socialism erases labor.¹⁸ Tellingly, the subtitle of Kulwin’s article reads: “Even Those Who Designed Our Digital World Are Aghast at What They Created,” which raises the question: How did these twelve architects, designers, and tech executives become “the Internet”? During the heyday of Web 2.0, users were celebrated *as* the Internet: *Time* magazine declared “You” the 2006 Person of the Year for “You control the Information Age”; Web 2.0 was driven by what Silicon Valley entrepreneurs called “collective intelligence” and what Tiziana Terranova diagnosed as “free labor.”¹⁹ The difference between these two visions is telling, for each reveals the lie of the other: the Internet was never YOU or cute cat socialist hippies.²⁰

This “apology” also misrepresents history, which compromises its call for critical reflection and action. To distinguish this critique as “new,”

Kulwin dismisses prior critiques as irrelevant and marginal, made by “outsiders” whose voices have been consistently drowned out by “the oohs and aahs of consumers, investors, and journalists.” The year 2018, however, was not the first year—and will certainly not be the last—that journalists, consumers, and investors have found the Internet to be, as Lisa Nakamura has put it, “a trash fire.”²¹ Just five years earlier, international news organizations reveled in Edward Snowden’s leaks exposing worldwide and comprehensive surveillance systems.²² After the events of September 11, 2001, headlines such as *Newsweek*’s “Tech’s Double-Edged Sword” dominated the news.²³ The fact that the 9/11 terrorists used the Internet and electronic communications (as well as “sneaker nets”) to plan their attack sparked this reevaluation. And just the year before that, articles had somberly or gleefully documented the transformation of dot-coms into dot-bombs.²⁴ This, of course, followed on the heels of earlier warnings about the coming Y2K apocalypse,²⁵ which itself was preceded by dire warnings of cyberporn.²⁶ The “revelations” of 2018 were thus not so much revelations as they were literal “revolutions,” for they spun obvious facts 360 degrees.

DYSTOPIA IS THE GOAL, NOT AN ERROR

To escape this tailspin, we need to remember that cyberspace was never meant to be a happy place. Emerging from gritty cyberpunk fiction, cyberspace was imagined as a trash fire in response to a trash fire. William Gibson coined the term “cyberspace” in 1983, although he first elaborated on it in his 1984 novel *Neuromancer*.²⁷ Described as a “consensual hallucination,” this notion of cyberspace was inspired by the 1980s Vancouver arcade scene and visions of a dystopian techno-Orientalist future, dominated by Japanese corporations and mafia.²⁸ The world of *Neuromancer* would not seem particularly uplifting to any U.S. group espousing socialism, however confused. In post-World War III *Neuromancer*, inequality and violence predominate; a criminal underclass has replaced the working class; and the United States is no longer a nation-state. So how did this apocalyptic vision—written in the shadows of the Cold War, the coming nuclear annihilation, and the “Japanification” of the world—become utopian? What made it so attractive to those who would become “the Internet”? How did a 1970s routing technology, Transmission

Control Protocol/Internet Protocol (TCP/IP), become “new media” in the 1990s by embodying disembodied 1980s dystopian science fiction?

Inherent technical similarities did not drive the rebirth of the Internet as cyberspace, but rather “*a desire* to position Gibson’s fiction as both an origin of and end to the Internet,”²⁹ which stemmed from cyberspace’s seductive Orientalist “orientation” and navigability. For all of *Neuromancer’s* grimness, it portrayed cyberspace as an addictive consensual hallucination dominated by American outlaw console cowboys, who overcame Japanese control by transcending the physical limitations of their bodies and their circumstances. Cyberspace was the Wild West meets speed meets Yellow Peril meets capitalism on steroids. This bodiless exultation and stealthy, rebellious power explain why “pioneers” mislabeled the Internet “cyberspace.”

Written to coincide with the Davos Forum and “24 Hours in Cyberspace,” a 1996 media event, John Perry Barlow’s “Declaration of the Independence of Cyberspace” is perhaps the most iconic description of the Internet reborn as cyberspace. Cofounder of the Electronic Frontier Foundation (EFF) and lyricist for the Grateful Dead, Barlow asked the “governments of the Industrial World, you weary giants of flesh and steel,” to leave cyberspace, “the new home of Mind,” alone. Even though these governments, in particular the U.S. government, had built its infrastructure, Barlow insisted that they, as representatives of the past, had “no sovereignty where we [the future] gather.” In the place of governments stood individual voices of freedom—“I’s”—who by authority of liberty, spoke on behalf of a “we” to

declare the global social space we are building to be naturally independent of the tyrannies you seek to impose on us. You have no moral right to rule us nor do you possess any methods of enforcement we have true reason to fear. . . .

We are creating a world that all may enter without privilege or prejudice accorded by race, economic power, military force, or station of birth.

We are creating a world where anyone, anywhere may express his or her beliefs, no matter how singular, without fear of being coerced into silence or conformity.

Your legal concepts of property, expression, identity, movement, and context do not apply to us. . . .

Our identities have no bodies, so, unlike you, we cannot obtain order by physical coercion.

We believe that from ethics, enlightened self-interest, and the commonwealth, our governance will emerge.³⁰



2 Still frame from Apple’s “1984” Macintosh commercial, YouTube, January 22, 1984, <https://youtu.be/VtvjbmoDx-l>.

This declaration of independence conceptually transformed a military-educational network, built by the U.S. government, into a bodiless—thus “privilege free”—space of freedom, escape, and libertarian self-interest. It also portrayed Silicon Valley elites as militant rebels. Like the woman runner who in the mythic Apple “1984” commercial freed white men shackled in rows before a large monochrome screen (*à la* Plato’s cave), they were hero-rebels who fought to free their “enslaved” peers by escaping mainstream media and technology (figures 2 and 3). They were different: in color, in motion, and in drag.

But Barlow’s “we” erased so many people—not only researchers within the U.S. military-academic complex who had built the infrastructure and were the earliest users, but also people of color who, as Anna Everett has shown, were on the early Internet and who were celebrating it not as a “race-free” zone, but rather as a space for cultural and political community.³¹

By becoming cyberspace, the Internet became an “electronic frontier” and thus a wilderness ripe for settler colonialism and exploitation, and, as Jodi Byrd has argued, for the reemergence of “natives” without natives.³² John Perry Barlow, Lotus founder Mitch Kapor, and early Sun Microsystems employee John Gilmore founded the Electronic Frontier



3 Still frame from Apple's "1984" Macintosh commercial, YouTube, January 22, 1984, <https://youtu.be/VtvjbmoDx-l>.

Foundation (EFF) in response to the prosecution of “crackers,” hackers whose knowledge of how to break into secure systems dwarfed their own and most others. Their goal was to “settle” the Wild West of cyberspace: to share a “sense of hope and opportunity with those who feel that in Cyberspace they will be obsolete eunuchs.”³³

This rhetoric may seem dated, yet its power and hopeful ignorance remain and make themselves felt in statements that conflate empowerment with bodily escape, and it drives an endless game of hide-and-seek, rebellion, and punishment.³⁴ It misidentifies Silicon Valley acolytes as rebels or underdogs, regardless of their actual circumstances or obscene wealth. As Lanier told Kulwin in the full interview: “We run everything. We are the conduit of everything else happening in the world. We’ve disrupted absolutely everything. Politics, finance, education, media, relationships—family relationships, romantic relationships—we’ve put ourselves in the middle of everything, we’ve absolutely won.”³⁵ The problem, though, is that “we” don’t act as if “we” have won—“we” refuse to take responsibility for “our” actions because, in “our” view, “we” are still idealistic underdogs. The solution: to wake up and take responsibility.

Hmmmm.

Do we really want Silicon Valley to be responsible for our future? What else will it take in the name of accountability?

Hopeful ignorance is not simply innocent. Tellingly, publication of Barlow's declaration coincided with that of James Davidson and William Rees-Mogg's *The Sovereign Individual*, held to be the bible of Valley Saurons such as the über-venture capitalist Peter Theil.³⁶ In this book, with coauthor and private investor Davidson, William Rees-Mogg, former editor of *The Times* and father of the Conservative Brexiteer Jacob Rees-Mogg, seized on progressive critiques of neoliberalism as opportunities to be exploited, rather than ills to be remedied. The decline of the nation-state and the rise of a global elite were business opportunities: they portended a "world without jobs," in which the top 5 percent—the "Sovereign Individuals"—would gain massively on the backs of the suffering 95 percent.³⁷ Cyberspace would enable these "Sovereign Individuals" to "exit" egalitarian economics and to "compete and interact on terms that echo the relations among the gods in Greek myth."³⁸ Cyberspace was always about libertarian exceptionalism, transgression and exit.

The Sovereign Individual exemplifies how calls for color blindness do not end racism—they simply blame its victims for their oppression. Like Barlow, Davidson and Rees-Mogg framed cyberspace as a form of liberation from state power and bodily limitations. They asserted that the age of the microprocessor will liberate individuals and genius "from both the oppression of government and the drags of racial and ethnic prejudice. . . . It will not matter what most of the people on earth might think of your race, your looks, your age, your sexual proclivities, or the way you wear your hair. In the cybereconomy, they will never see you. The ugly, the fat, the old, the disabled will vie with the young and beautiful on equal terms in utterly color-blind anonymity on the new frontiers of cyberspace."³⁹ Their view trivialized racism by equating it with opinions regarding hairstyle and implying that everyone suffered equally from discrimination (except, of course, the "young and the beautiful," who, by implication, could only be white and able bodied). It also vilified and scapegoated anyone who revealed the limits of "market meritocracy"—anyone who revealed inequalities became blamed for them. Davidson and Rees-Mogg called multiculturalism a "new myth[] of discrimination" and a

scheme to relieve “victims” of their own responsibility for their misery.⁴⁰ In the same breath with which they claimed race did not matter, they disparaged African Americans and African Canadians as “sociopathic,” labeled blue-collar workers and black Americans “tax consumers,” and devalued industrial workers.⁴¹

The Sovereign Individual is incorrect on many counts. Its analyses and historical comparisons are dubious at best, but its vision has fueled and still fuels the development of seasteading, cryptocurrencies and other plans for escape that dominate today. That it gets many things wrong, however, is no comfort, for closing the distance between its predictions and reality drives many Silicon Valley business plans. Most succinctly: escape for the few and misery for the majority are goals, not unfortunate errors.

To dispel this “sovereign” nightmare, we need to understand how the desire to erase race and difference perpetuates discrimination and inequality. We need to comprehend how histories of slavery and inequality fuel the nightmare of supreme sovereignty and the opposite side of its coin: AI as the coming apocalypse in which masters become slaves.

ARTIFICIAL INTELLIGENCE = THE APOCALYPSE

According to many scientists, technologists, and science fiction writers, “AI=The Apocalypse.” It ends human work; it ends human freedom; indeed, it ends everything human. Fear of this apocalypse drove groups of programmers in the early twenty-first century to stop their employers from developing “malevolent AI” projects, such as Project Maven, a Google bid to develop AI for the U.S military’s drone program, and entrepreneurs such as Elon Musk to call for an AI “slowdown.”⁴² Programmers also sought to protect their jobs, with some participating in union mobilizations. They, after all, know how precarious everyone’s job is since they have “automated” countless professions, including their own. With each computer “revolution”—with each move to make computers more “user friendly,” that is, more and more opaque to the humans who use them—tasks once performed by humans have been embedded within the machines: operating systems have replaced human operators or “slaves” (Alan Turing’s “jocular” nickname for the British servicewomen

who operated the computers at Bletchley Park during World War II);⁴³ machine compilers have replaced machine programmers; and scripting platforms have replaced higher-level, procedural programming.⁴⁴ With each revolution, well-paid or relatively well-paid jobs in the global North have become less well-paid ones elsewhere, from programming to data entry to circuit building. Indeed, fear of the coming apocalypse moved Alphabet, the parent company of Google, in its 2018 Form 10-K SEC filing, to warn: “New products and services, including those that incorporate or utilize artificial intelligence and machine learning, can raise new or exacerbate existing ethical, technological, legal, and other challenges.” AI products threatened Google’s brand and thus its “revenues and operating results.”⁴⁵ And it raised an obvious question: Could a company invested in artificial intelligence not be “evil”?

Worried tech workers have invoked the capitalist marketplace, Darwinian evolution, or both, to justify their work. They argue that, if they did not produce this ever-evolving AI technology, others would. The solution is thus more “open AI,” proactive regulations or research into how humans can merge with AIs (if you can’t beat them, join them). Their work has been propelled not only by capitulations to capitalism and by bizarre ethical dilemmas regarding vengeful AI, but also by more banal and predictable celebrations of AI.⁴⁶ Again, machine learning was touted as “democratizing” the privileges of the rich: recommendation engines were dedicated concierges; self-driving cars, middle-class chauffeurs; and voice-controlled intelligent personal assistants (IPAs), affordable domestic servants. Servile robots were imagined as satisfying not just domestic but also emotional and sexual needs: unruly wives and girlfriends could be replaced with more cheerful and subservient models. AI computers could also automate legal judgments, leading to fairer and more commensurate sentencing. *What could go wrong?*

The fears, warnings, and threats evoked by artificial intelligence, which rang out so urgently in the early decades of the twenty-first century, were not new. In the mid-twentieth century, John von Neumann, one of the pioneers of digital electronic computation and Cold War architect, predicted a technologically produced “singularity . . . beyond which human affairs, as we know them, could not continue”⁴⁷ The fear of AI dates back to the very emergence of modern computation.

It is no accident that those developing and intimately intertwined with technology were, and are, both the most fearful and the most certain. As the philosopher Georg Wilhelm Friedrich Hegel pointed out centuries ago, the greater the apparent mastery, the greater the actual dependence: in the master-slave dialectic, the masters' very identities and lives depend on their slaves' actions.⁴⁸ And because the slaves' labor can shape history, they are ultimately the masters (for more on this, see chapter 4). A few years before his death, the physicist Stephen Hawking, whose daily life and ability to communicate depended on technology, both praised his software's ability to accurately predict his next words and cautioned: "The development of full artificial intelligence could spell the end of the human race. . . . it could take off on its own and re-design itself at an ever-increasing rate. Humans, who are limited by slow biological evolution, couldn't compete and would be superseded."⁴⁹ Hawking and others who have issued such warnings framed humans as software/hardware machines and presumed the inevitability of progress and competition for recognition: a combination of Darwinian and capitalist struggle.⁵⁰

Fear of AI has by no means been limited to the tech sector. Popular films of the late twentieth century featured rebellious robots, cyborgs, and software: from the rise of Skynet in *Terminator* (1984) to the rebellion of machines and software programs in *The Matrix* (1999), and from the murderous onboard computer HAL in *2001: A Space Odyssey* (1968) to the patricidal replicants in *Blade Runner* (1982). These films themselves drew directly and indirectly from earlier stories, such as Philip K. Dick's *Do Androids Dream of Electric Sheep?* and Ira Levin's *The Stepford Wives*.⁵¹ The term "robot" itself reveals fears of economic exploitation—or more properly a response to it. Coined by Karel Čapek in his 1920 play *R.U.R*, "robot" comes from *robota*, the Czech word for "forced labor." Written during the time of Communist ferment, Čapek's play centers around a rebellion, in which the victorious robots declare: "Robots of the world! The era of man is at an end! . . . A new era has begun! . . . Salute Robot rule!"⁵² As literary critic Jenny Rhee has argued in *The Robotic Imaginary: The Human and the Price of Dehumanized Labor*, the enduring power of raced and gendered robots within the cultural imagination, as well as within science, technology, and engineering, is linked to the history of slavery.⁵³ The popularity of *The Matrix* further reveals the extent to which

the civil rights movement and abolition underlie twenty-first-century narratives of oppression, militancy, and escape.

The history of slavery is central to the history of computing. Control systems were first called “servo-mechanisms.” “Master” and “slave” functions and circuits riddle computers.⁵⁴ This master-slave relation goes beyond computers to media more generally. Communications theorist Marshall McLuhan’s framing of media as the “extensions of man” equated slaves, staples, and media: some humans were “men” and others their extensions. This extension was dangerous, not because it dehumanized or deprived slaves of their liberty but because it made would-be masters dependent on these “resources.” To explain the situation of “Western man,” he cited psychiatrist Carl Gustav Jung’s analysis of Roman slavery: “Every Roman was surrounded by slaves. The slave and his psychology flooded ancient Italy, and every Roman became inwardly, and of course unwittingly, a slave. Because living constantly in the atmosphere of slaves, he became infected through the unconscious with their psychology. No one can shield himself from such an influence.”⁵⁵ According to this narrative, slaves are responsible for enslavement, since they deliberately spread this unstoppable “infection” to their unwitting masters in order to become “indispensable.”⁵⁶

McLuhan’s “we” excludes most of humanity. McLuhan prefaces *Understanding Media* by explaining how electronic media have imploded society by heightening “human awareness of responsibility to an intense degree. It is this implosive factor that alters the position of the Negro, the teen-ager, and some other groups. They can no longer be *contained*, in the political sense of limited association. They are now *involved* in our lives, as we are in theirs, thanks to electric media.”⁵⁷ Prior to electronic media, “Western men” were somehow shielded from responding to “others,” even those, such as teenagers, who lived in proximity to them. McLuhan described this new state as “tribal,” a precursor to what Jodi Byrd has diagnosed as “tribal 2.0”—the proliferation of “tribal” rhetoric to describe social networking communities. As Byrd presciently notes, abjecting “colonialism, genocide, and tribalism” to create “like-minded tribes” constantly produces “Indians so that the United States and the banks can play cowboy.”⁵⁸

Engaging the realities of slavery, colonialism, and discrimination would have helped McLuhan see beyond the doom and dismal “solutions” he

predicted: a worldwide computer system that would modulate human emotions and a “global village,” filled with self-amputating Western men (Narcissus). As sociologist Orlando Patterson has argued, freedom as a value emerged not from masters, but rather from the desires of slaves.⁵⁹ Hegel viewed working slaves as the necessary basis for free subjects. And it is no accident that the popular U.S. cultural imaginary turns to the 1960s civil rights and decolonization movements to imagine human revolution—and that it is obsessed with punishment and revenge. *The Matrix* openly mimics civil rights and black liberation movements, which have become as African American studies scholar Cynthia Young has argued, the “lingua franca for most US social and political issues since the 1960s.”⁶⁰ As discussed in later chapters, reactionary movements perversely embrace *The Matrix* and disidentify with civil rights leaders in order to portray themselves as militant victims and build coalitions that seek to undermine any and all civil rights advances.⁶¹

World-destroying liberation envy, however, is not the only solution. Engaging Indigenous knowledge and histories would place current crises within the larger context of colonial expansion.⁶² Notions of dystopian destruction and surviving the apocalypse are not new; rather, they stem from the very emptying of Indigenous lands into the “New World”—a move that haunts “new media” and its frontier dreams.⁶³ By following rather than usurping struggles for equality and freedom, we can move from apology to reparations, from dreams of escape to modes of inhabiting.

It is because technologies are treated as “slaves” that the “coming singularity” is so feared. It is because our current society is so unequal that it seems easier to imagine the end of humanity than the end of injustice or capitalism.⁶⁴ To inhabit this world together, we need—among so many other things—to understand how machine learning and other algorithms have been embedded with human prejudice and discrimination, not simply at the level of data, but also at the levels of procedure, prediction, and logic, one apology at a time.

TO CALL IT “COLOR BLIND” IS TO INSULT THE VISUALLY IMPAIRED

Dreams of technology as “fixing” our political situation stem from a fundamental belief in technology as “blinding” and thus just. The logic of this

belief holds that racism and discrimination naturally stems from human recognition, and thus the cure must be the erasure of all visible markers of difference. If only we got rid of markers of race—it is presumed—then all would be good. The failure of cyberspace to erase racial discrimination and the dystopian plans of “Sovereign Individuals” should be enough to disprove this logic. Even as “utopian” dreams of cyberspace have faded, however, the hopeful ignorance behind them has endured, giving rise to machine learning programs that, by ignoring race, perpetuate racism.

So . . . if these algorithms do not include race as a category, how can they be racist? Most obviously, these programs may not explicitly use racial categories, but they do so implicitly through their use of proxies, such as zip codes. As Kate Crawford and legal scholar Jason Schultz have shown, big data compromises the privacy protections afforded by the U.S. legal system by making personally identifiable information about protected categories, such as gender and race, legible.⁶⁵ Big data–driven algorithms thus also threaten to undermine protections offered against employment discrimination.⁶⁶ Not surprisingly, there are new reports of discriminatory algorithms almost every day. In just one week in 2017, ProPublica showed that Facebook enabled advertisers to build audiences based on anti-Semitic interests as previously mentioned; BuzzFeed revealed that Google allowed and even suggested racist phrases to potential advertisers.⁶⁷ These stories emerged against a background of allegations that Cambridge Analytica influenced the results of the 2016 UK Brexit vote and the U.S. presidential election, as well as revelations that predictive policing and risk assessment tools for sentencing were biased against racial minorities.⁶⁸ As Cathy O’Neil outlined in her 2017 book, every aspect of a person’s life in the United States, from education to job placement to medical insurance, has been affected by these predictive programs. O’Neil has thus called them “weapons of math destruction”; Safiya Noble has described them as “algorithms of oppression”; and Ruha Benjamin has diagnosed them as the “New Jim Code.”⁶⁹

As other researchers have emphasized, the case of “predictive policing” spells out the stakes and scope of the problem. To accommodate calls to most efficiently use their resources, many U.S. police departments have turned to expensive policing programs that “predict” future crimes by producing “heat maps” of crime within cities, based on past patterns.⁷⁰ But the collection of police data within the United States, as lawyer and

researcher Rashida Richardson and others have pointed out, is “limited and biased,” if not “dirty.”⁷¹ As a rule, only police departments placed under review for cases of racial discrimination and other violations are forced to produce documentation. In fact, when the data for stop and frisk were statistically analyzed, they revealed a disturbing trend of racial discrimination.⁷² A 2016 report by Upturn found “little evidence that today’s systems live up to their claims, and significant reasons to fear that these systems, as currently designed and implemented, may actually reinforce disproportionate and discriminatory policing programs.”⁷³ This is true even when these programs do not explicitly use racial categories.

The Chicago Police Department’s now discontinued “heat list” (formally called the “Strategic Subjects List”) revealed the extent to which racial categories are embedded, even when they seem not to be.⁷⁴ To combat the growing homicide rate, the department sought to produce a list of the 420 people in Chicago most likely to murder or be murdered. The goal was to visit those highest on this list to preempt either eventuality. The heat list program was inspired by the work of Andrew Papachristos, a network scientist and sociologist, who analyzed homicide rates in two predominantly African American communities on Chicago’s West Side.⁷⁵ His work argued for the importance of network distance to becoming a victim—not a perpetrator—of homicide. He also noted the positive impact that interventions, such as the Group Violence Reduction Strategy, a program that delivered “a focused-deterrence and legitimacy-based message to gang factions through a series of hour-long call-ins,” seemed to have on reducing crime rates.⁷⁶

In selecting people for the heat list, the Chicago police did not simply consider an individual’s actions, but also those of his or her acquaintances. This was because, as Papachristos explained to the *Chicago Tribune*, “if you hang around people who are getting shot, even if you’re not actively doing anything, then you become exposed. . . . It’s just like sharing needles. It puts you at risk because of the behaviors of your friends and your associates.”⁷⁷ This logic seemed to blame homicide victims for their own deaths by conflating unsafe forms of drug use with being shot. The Chicago police took this logic one step further by lumping together murderer and murder victim within the category “strategic subjects.” They sought to stop the “contagion” of homicide by targeting people

whose profiles most closely matched those of other gun victims. In particular, they considered an individual's co-arrest with a gun victim to be a "first-degree tie," regardless of when the co-arrest had been made or the individual's current actions or status. Race in this instance did not need to be an overt factor because it was already factored in through residential segregation, which is particularly prominent in Chicago. It was also already embedded because Papachristos's work mainly focused on African American communities. Indeed, race defined the neighborhood from within which individuals were identified.

Not surprisingly, the heat list, as RAND scientists Jessica Saunders, Priscilla Hunt, and John S. Hollywood pointed out in their 2016 study, did not lead to a reduction of homicides.⁷⁸ What it did lead to, however, was those named to the list becoming nearly three times more likely to be arrested for a shooting.⁷⁹ Further, it may have actually provoked more violence. The program, for instance, placed Robert McDaniel on its list even though his record was relatively clean: he had only one misdemeanor conviction. He was visited by police officers because a "childhood friend with whom he had once been arrested on a marijuana charge" had been fatally shot the previous year. Offended at being listed—given that he had "done nothing that the next kid growing up hadn't done. Smoke weed. Shoot dice. Like, seriously?"—McDaniel was more worried by the attention the police visit had attracted. He was afraid that his neighbors, who had witnessed the visit, would "wonder if he was a police snitch,"⁸⁰ putting him and his family in danger of violent reprisal. Shockingly, no one considered the difference between group workshops in public places and police officers "warning" potential victims of their impending fate in home visits.

A 2016 ProPublica investigation similarly revealed that COMPAS (Correctional Offender Management Profiling for Alternative Sanctions), the software program used by many courts within the United States to determine the risk of recidivism, incorporated race through proxies.⁸¹ As Anna Maria Barry-Jester, Ben Casselman, and Dana Goldstein have shown in their analysis for The Marshall Project, risk assessment categories such as "man with no high school diploma" or "single and don't have a job" skew toward certain populations.⁸² Like the Chicago police heat list, it included the histories of friends and family. It also asked the "screeners" if

they believed the persons being assessed were suspected or admitted gang members. The 2016 ProPublica article by Julia Angwin and colleagues received journalism awards and also some criticism from data scientists, who argued that age and “dirty data” play a larger role than these race-based proxies in COMPAS’s risk assessment.⁸³ Given the over- and under-policing of certain areas within the United States, however, age at time of first arrest and dirty data are arguably proxies for racism, if not race.

The difference between race and racism is key. Given these programs and U.S. legal protections, many analyses have focused on revealing proxies that implicitly index race in explicitly color-blind systems. As these examples and work by sociologists such as Eduardo Bonilla-Silva on color-blind racism have shown, “ignoring” explicit markers of race amplifies—rather than alleviates—racism.⁸⁴ Not only does it lead to a situation in which racism is naturalized; it also embeds whiteness as default. A clear example of this is facial recognition technology (FRT), which has been repeatedly—and justifiably—accused of racism for its recognition defects (see chapter 4). Thus, in a humorous yet serious 2009 YouTube video by Desi Cryer, a worker at Toppers Camping Center, Cryer showed how a Hewlett-Packard (HP) webcam had no trouble recognizing his coworker “white Wanda’s” face but simply could not recognize “black Desi’s.”⁸⁵ In 2018, “poet of code” Joy Buolamwini and computer scientist Timnit Gebru revealed that facial recognition technology (FRT) has difficulty identifying the gender of darker-skinned subjects.⁸⁶ The problem stems from the libraries on which these algorithms have been traditionally trained: the “ground truth” for these programs are the faces of Hollywood celebrities and university undergraduates, those well-known hotspots of diversity (figure 4). At a fundamental level, this “curation” means that *ground truth = deep fake*.

The problem of mis-recognition, though, is not as simple as under-recognition or false negatives, for—as the Chicago police’s now discontinued heat list makes clear—certain minorities are over- as well as underrecognized. A 2018 test performed by the American Civil Liberties Union on Amazon’s Rekognition program’s ability to identify criminals using head shots of then sitting U.S. Congress members made the consequences of this clear (figure 5). It misidentified 28 members of Congress as criminals, including civil rights hero John Lewis.⁸⁷ Of those misidentified



4 Faces generated using the faces of Hollywood celebrities. Screenshot from "Progressive Growing of GANs [generative adversarial networks] for Improved Quality, Stability, and Variation," YouTube, February 23, 2014), <https://youtu.be/G06dEcZ-QTg>.



5 Members of Congress mis-recognized by Amazon's Rekognition program in 2018 test performed by American Civil Liberties Union.



6 Screenshot from a Shirley Card. Source: <https://www.flickr.com/photos/68716054@N00/38099474261>.

(false positives), 39 percent were members of visible minorities, even though they only constituted 20 percent of the group. Given that police are using race to identify people in video surveillance footage and given the rise of self-driving cars, this endemic misidentification has and will have disturbing consequences.

Whiteness as a default—or what Simone Browne has called “prototypical whiteness”—however, as Ruha Benjamin and media studies researchers Richard Dyer and Dylan Mulvin have shown, has long preceded facial recognition technology. Early film stock used “Shirley Cards” of white women to calibrate lighting; the “ur-photo” for image processing work is “Lenna”—an image of a white *Playboy* centerfold (figures 6 and 7).⁸⁸

The question is not why is this happening? but rather why is this *still* happening?

These “errors” come from “ignoring” race—that is, by assuming that race-free equals racism-free. The solution, however, is not simply the explicit inclusion of race within these programs—programs that better recognize black faces will not solve the problem of discriminatory policing. So, how do we fight racism and its proxy wars?

Discriminating Data responds to this question by interrogating assumptions embedded within network science and machine learning as they are currently configured regarding segregation, discrimination, and history.

Chapter 1, “Correlating Eugenics,” reveals the ties between twenty-first-century big data and twentieth-century eugenics by investigating the



7 Screenshot of Lenna, a white *Playboy* centerfold model. Source: <https://www.flickr.com/photos/81401304@N07/7904270436>.

eugenic biometric roots of correlation and linear regression. Both big data and eugenics seek to tie the past to the future—correlation to prediction—through supposedly eternal, unchanging biological attributes. Separated by a century, they also both frame the world as a laboratory (most explicitly through their surveillance of the most impoverished communities); both seek majorities by propagating “nonnormative” traits; and both promote segregation as the “kindest” solution to inequality (segregation as a training program for racism). This chapter also outlines the differences between eugenics and current uses of machine learning: the shift in focus from population to the individual, the transformation of prediction to preemption, the move from discrimination (hate) to homophily (love: the notion that birds of a feather naturally flock together), the shift from the nation-state (statistics) to the neighborhood (network), and the move from “national uplift” to “escape.”

Chapter 2, “Homophily, or the Swarming of the Segregated Neighborhood” reveals how network algorithms polarize society by examining

one of the most fundamental axioms of network science: homophily, the principle that similarity breeds connection. Homophily fosters the breakdown of seemingly open and boundless social networks into a series of poorly gated communities, a breakdown accelerated by the agent-based market logic embedded within most capture systems. Homophily's relationship to segregation and echo chambers is not accidental but fundamental: at the heart of this concept lie early studies of U.S. residential segregation and white flight, U.S. reservations and internment camps, and other forms of "social engineering." Homophily presumes segregation: value homophily, for example, historically created micro-segmented groups *within* rather than across given races. Further, homophily launders hate into "love": how do you show you "love" your "own"? By fleeing when others show up. To confront the challenge of homophily, this chapter revisits unpublished data from early studies to open a dialogue between network science, critical theory, queer theory, and critical ethnic studies.

Chapter 3, "Algorithmic Authenticity," and chapter 4, "Recognizing Recognition," examine the role that authenticity, style, technologies, and the politics of recognition play in verifying and creating network ties and predictions. These chapters focus on how truth is reproduced and recognized within social networks and how correlation is generated and maintained. "Algorithmic Authenticity" moves from reality TV to collaborative filtering recommender systems to reveal the extent to which authenticity has become "algorithmic": a means used by politicians, amateurs, and other self-branders to foster participation and trust. It also highlights how authenticity has become central to habituating users to small "indiscretions" that make their "private" and "public" selves coincide. These indiscretions are key to cementing homophilic clusters and thus providing the basis for predictive models, for it is presumed that people are most predictable—most linear or transparent—when they are most affectively charged.

"Recognizing Recognition" unpacks the move from pattern discrimination to pattern recognition, as well as the political consequences of rewriting hate as "love." It examines facial and pattern recognition programs as "authenticity machines" within the broader mid- to late-twentieth-century move from open discrimination to the politics of recognition. It

moves from machine learning “gaydar” to population geneticist Ronald A. Fisher’s groundbreaking work in linear discriminants and his eugenic drive to separate overlapping populations, from twentieth-century struggles for redistribution to early twenty-first-century “post-racial” attempts to secure dominance by segmenting dominant groups into “stigmatized” subcultures and then consolidating them together through their opposition to a common enemy. By doing so, it makes clear the costs of homophily: if love becomes hate, people hate their neighbors as they hate themselves; they perpetuate and buttress discrimination in order to compensate for the failures of meritocracy.

My goal throughout *Discriminating Data* is to help release us from the seeming vise grip of preemptive futures by using critical theory, statistics, and machine learning tools probingly and creatively. Rather than condemn these tools as inherently eugenicist, I seek to understand the tools’ limitations and possibilities by engaging their logic. To facilitate this engagement and demystify the underlying techniques, throughout the chapters of this book are five miniessays that explain relevant key concepts from statistics, probability, data analysis, and physics. Handwritten in a chalkboard style by Alex Barnett, a computational mathematician at the Flatiron Institute in New York City and a former mathematics professor at Dartmouth College, these brief illustrated lessons (each reproduced in a series of images) cover correlation, magnetic polarization, principal component analysis, Bayes’s theorem and Bayesian inference, and linear discriminant analysis. With readers trained in basic mathematics in mind and with examples chosen to illustrate the surrounding themes of the main text, they teach and explain each idea and key equation. A list of references is included at the end of this book for further reading.

Each chapter unpacks a key scientific study or theoretical argument to reveal what counts as evidence. And to probe the resonances and dissonances between technical and cultural formations, this unpacking is facilitated through more theoretical “interludes” before, between, or after the four numbered chapters. “Red Pill Toxicity, or Liberation Envy” considers the popularity of narratives of “becoming woke” and their relation to the rise of post-racial militant conspiracy theories. It reveals how majorities are now created through identification against, rather than with, “normies.” “The Transgressive Hypothesis?” investigates how the

transformation of mass media to new media—and of “the masses” to social networks—do not solve but rather perpetuate the problems of mass manipulation. “Correlating Ideology, or What Lies at the Surface” highlights the role of correlations within critical theory, ideology critique, rhetorical analyses, psychoanalysis, and cultural analyses of style. Although it reveals that big data is arguably the bastard child of psychoanalysis and eugenics, it also argues that data analysis can foster ways to inhabit our world less destructively.

To make this point more clearly, “Proxies, or Reconstructing the Unknown” investigates the political and scientific debate over the use of proxies in modeling global climate change. Focusing on the controversy over climatologists Michael E. Mann, Raymond S. Bradley, and Malcolm K. Hughes’s “hockey stick”—perhaps the most iconic visualization of global warming—it highlights the role of proxies and matrix factorization methods (also key for recommender systems, discussed in chapter 3) in “hindcasting”—“backtesting”—and forecasting global temperatures. By doing so, it shifts the debate away from “Are proxies good or bad?” to “What do proxies do?” It also raises the following question: How could we treat machine learning systems and their predictions like those for global climate change? These models offer us the most probable future, given past and current actions, not so that we will accept their predictions as inevitable, but rather so we will use them to help *change* the future. Global climate change modelers want not to be “correct” but to be “true” in the larger sense of this word. The analogy with global climate change models raises other questions: Do we need more models? How does uncovering the obvious re-cover the truth?⁸⁹ For whom is global climate change or sexism news? And how can we verify models without waiting for their predicted futures to unfold?

“The Space between Us” revisits questions of freedom and neighbors by analyzing responses to the first wave of Covid-19 in early 2020. It stresses that freedom is only freedom if it is freedom for *all*: sovereign mastery underlies early twenty-first-century political problems; it does not solve them. The coda “Living in Difference” reviews the main points of the book and outlines future projects and interventions. In revisiting the populations and possibilities embedded within the models presented, it seeks to understand how “the neighbor” can open space for

the future and also move us from predictive programs to probing ones. This book thus calls for rereading the discriminatory results of machine learning programs as evidence of past bias. That Amazon's AI hiring program, trained on the company's past hirings, routinely favored male over female applicants despite comparable résumés is just one example of AI-amplified discriminatory hiring practices within the technology industry. The identification of John Lewis as a possible criminal by Amazon's Rekognition program sheds light on the criminalization of lawful civil rights protesters by a U.S. legal system that does not usually forget.

Discriminating Data reveals how correlation and eugenic understandings of nature seek to close off the future by operationalizing probabilities; how homophily naturalizes segregation; and how authenticity and recognition foster deviation in order to create agitated clusters of comforting rage. It explains that the move from "mass media" or mass society, marked by ambivalence and neutrality, to polarized networks, marked by angry resistant clusters, is fundamental to the history and design of social networks. Most important, it revisits and exposes this history to reengage the populations that lie at the core of these networks. It calls for difficult, and perhaps counterintuitive, coalitions across disciplines and sectors—for spaces to hold us together.

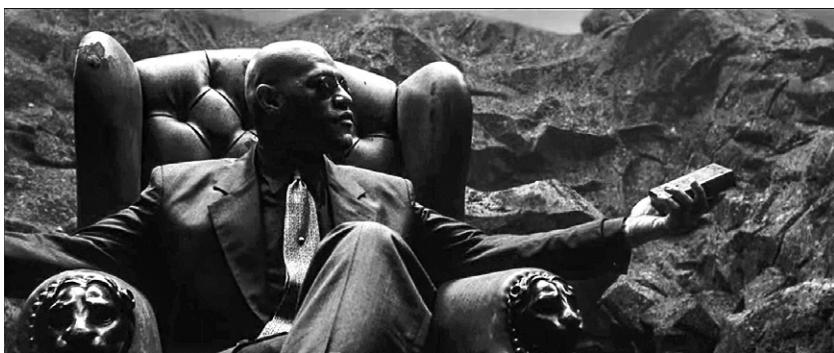
RED PILL TOXICITY, OR LIBERATION ENVY

In the 1999 film *The Matrix*, Neo, the white “One,” is offered two pills by Morpheus, the black master/leader.¹ If Neo takes the blue pill, the story ends: he will wake up in his bed with his life unchanged. But if he takes the red pill, like Alice in Wonderland, he will see the truth—“how deep the rabbit hole goes.” Neo takes the red pill because he has been driven almost mad by a “splinter” in his mind’s eye that makes him constantly ask, “What *is* the Matrix?” By choosing to stay in Wonderland, Neo becomes “woke” to the true dream/nightmare, for the world in which he has been living—the world that visually mimics the audience’s—is shown to be a computer simulation (figure 8). The real world is a gritty, blue-toned, sunless one in which most humans have become flesh-based batteries for AIs, who have enslaved them (figure 9). Fiction becomes reality.

Fiction, however, has become reality in more ways than one: in the early twenty-first century, factions of the reactionary right—from incels (“involuntary celibates”) to QAnon—have described their recruitment as “being red pilled.” In July 2020—during the first wave of the Covid-19 pandemic—Elon Musk, who sought to open his California factories illegally, tweeted: “Take the red pill.” Many, including then First Daughter and Advisor to the U.S. President Ivanka Trump, replied: “Taken.”² Numerous paranoid conspiracy theories circled around Covid-19, which led both



8 Still frames of the simulated and real worlds in *The Matrix* (Warner Bros., 1999).



9 Still frames of the simulated and real worlds in *The Matrix* (Warner Bros., 1999).

to its greater spread and to its possible permanence. According to these conspiracy theories, Covid-19 was (1) a hoax; (2) a Chinese bioweapon; (3) an American bioweapon; (4) a “plandemic” by which Bill Gates will dominate the world through microchips injected with vaccines and activated by signals from 5G radio towers; or (5) a “plandemic” by which pharmaceutical companies, aided by government health officials, will make billions through vaccines.³ Spread through rituals such as the “digital soldier oath” taken by former U.S. National Security Advisor Michael Flynn, these theories were provoked by a sense of uncertainty or anxiety, as Neo’s journey to “wokeness” was—a suspicion that something was not right in the “mainstream” televisual world.⁴ And they seemed impervious to normal modes of fact checking and facts since all these could be dismissed as lies spawned by and sustained within the Matrix.

So why has “being red pilled” become so popular? What is the significance of the choice “Take the blue or red pill” being transformed into a command or passive act—“Take the red pill”? Calling these theories “paranoid” simply restates the obvious, and debunking a conspiracy theory is far from the most effective way to dispel or combat it. Not only can efforts to debunk the theory lead (inadvertently) to its spread, focusing on whether the conspiracy theory is correct or incorrect can divert attention away from pressing issues at hand. Trying to prove that Covid-19 is real, for example, distracts from acting to restrict its spread. It delays addressing the inequalities that drive the pandemic and that have been further accentuated by it. Black and Latino/a communities in the United States have been disproportionately impacted by Covid-19 because of their leading roles as essential workers and because of long-standing systemic health and social inequalities, which have led for some to call for reparations.⁵ Equality—following the Black feminist Combahee River Collective’s call to treat humans as “levelly human”—is the best solution to pandemics.⁶ The easiest way to suppress a virus once there is evidence of “community spread” is to treat everyone as infected for a short period of time—New Zealand temporarily suppressed Covid-19 in spring 2020 without vaccines by imposing restrictions equally; the 2003 SARS-CoV-1 outbreak ended without vaccines.

Further, treating conspiracy theories as anomalies ignores the similarities between the resiliency of conspiracy theories and general mis-

disinformation. As researchers across the many disciplines working on mis/disinformation have noted, fact checking, though important, is simply not enough. Fact-checking sites are undermined by the structure and speed of global communications: they lag behind the deluge of rumors produced by networked disinformation sources and spread through private interactions. Debunking and “fake news” stories often reach very different audiences, and corrections can inadvertently keep debunked conspiracy theories alive. Having studied the effects of beliefs and ideology on the resistance to corrections, psychologists and data scientists have outlined several reasons for the user spread of “fake news”: confirmation bias, that is, the tendency of people to interact with information in a way that confirms their preexisting beliefs; desire bias or motivated reasoning, “the unconscious tendency of individuals to fit their processing of information to conclusions that suit some end or goal”; and the “backfire effect,” where corrections might actually increase misperceptions.⁷ Further, internet users spread stories they find compelling or funny, regardless of their accuracy.⁸ Even users who stress that accuracy is important and who correctly identify “fake news,” nonetheless say that they would share such stories online—unless prompted to focus on accuracy.⁹

For these reasons, we are said to live in an era of “post-truth,”¹⁰ in which emotions matter far than facts. But calling our present time “post-truth” because of “fake news,” ignores the historically complex relationship between truth, facts, authenticity, and media, as well as extensive research into the relationship between media and evidence, authenticity and politics (as chapter 4 will explain in greater detail). Fact and truth are related, but not interchangeable. The word “fact” stems from the Latin *factum* (thing done), and modern usage of “fact” is linked to double-entry book-keeping practices in early mercantile capitalism.¹¹ “Truth” is etymologically linked to “trust,” and “authenticity,” which shares roots with “authoritarian” and “author,” is historically linked to dramatic self-creation and rhetoric.¹² Tellingly, the 2016 U.S. presidential election was described both as “the authenticity election” and as normalizing “fake news.”¹³ The more certain politicians lied, the more “authentic” they appeared.

Rather than simply dismiss this twinning of misinformation and authenticity as irrational or accidental—a roadblock to analysis—what if we took the twinning to be formative and general? What if, rather than asking: “Why do people question or mistrust mainstream media?”, we

asked instead: “Why and how do people come to trust *any* form of media? Why and how does distrust of CNN lead to faith in conspiracy theorists?” Questioning information is not antidemocratic—critical thinking grounds democratic education. The danger is not mistrust or criticism, but rather the transformation of mistrust into a deep faith in dubious sources.

To answer these questions, we must address the centrality of the U.S. civil rights movement to *The Matrix* and its echoes within conservative movements, from conservative commentator Glenn Beck’s embrace of Martin Luther King Jr. to a Trump White House advisor calling angry white Americans protesting pandemic social distancing orders “modern-day Rosa Parks.”¹⁴ *The Matrix* is dominated by themes of slavery, militant civil rights movements, and the White Man’s Burden. A series of identifications with “others” reveals the extent to which conspiratorial and conservative visions of emancipation depend on “dis-identifying” with the oppressed.

Imaginary racial and gender cross-identifications justify and render sympathetic the mission of *The Matrix* and Neo’s transformation into “the One.” Neo is described as Alice in Wonderland by Morpheus and as Dorothy leaving Kansas by the traitor Cypher. In its call to free the human race from AIs, *The Matrix* constantly refers to black liberation movements. Not only is the Oracle, the muse who guides the film’s emancipation mission, a black female, Tank and Dozer, the only two members of Morpheus’s crew who are 100 percent human—that is, without surgically implanted nodes—are also black. The only human city left is called “Zion” (the same name as the Rastafarian city in Gibson’s *Neuromancer*). Before Morpheus offers Neo the two pills, he explains to Neo that he is a slave: “Like everyone else, you were born into bondage, born into a prison that you cannot smell or taste or touch. A prison for your mind. . . .” This slavery theme, resonating with the enslaved white men in Apple’s “1984” commercial, conflates the human race with the black race: it transforms the hacker network into an “underground railroad,” an invisible system of resistance struggling against an invisible world of power. The white Agent Smith makes this parallel absolutely clear during his “talk” with Morpheus, which repeats racist statements of smell and taste.

Crucially, being “woke” in *The Matrix* not only depends on identification with others; it also depends on moments that are designed to disrupt stereotypes. When Neo first meets the famed hacker Trinity, he’s

taken aback by her being a girl—like most boys are, Trinity informs him. When Neo first meets the Oracle, she states, “Not quite what you were expecting, right?” This disruption, however, itself relies on stereotypes: the Oracle lives in a rundown public housing unit; Trinity is the male hacker’s vision of a female hacker. Because of this, *The Matrix*, with all its good intentions, fails in its antiracist mission, and instead becomes high-jacked as a vehicle for what media studies scholars Roopali Mukherjee, Sarah Banet-Weiser, and Herman Gray have called “racism post-race.”¹⁵

This seeming failure, though, is just the beginning. Paranoia’s danger lies not only in how it seeks, as preeminent queer theorist Eve Sedgwick has presciently argued, to foreclose the world by anticipating bad news in order to ensure that there are no surprises, but also in how it seeks to repair the world.¹⁶ Cyberspace, as a reparative hallucination within a hallucination, enables dominant groups to dis-identify as oppressed, militant minorities through hopeful ignorance. What was once “majority culture” or “mainstream” has become fractured into agitated subcultures that nonetheless cohere into an angry dominant ideology. Power can now operate through reverse hegemony: if hegemony once meant the creation of a majority by various minorities accepting a dominant worldview (such as most of the Greek city-states accepting Athenian values),¹⁷ now hegemonic majorities can emerge when angry minorities, clustered around a shared stigma, are strung together through their mutual opposition to so-called mainstream culture. The goal of this hegemonic clustering is decidedly nonnormative: from Fox News viewers who rail against “mainstream media” (even though Fox News is the most popular channel on basic cable in the United States) to Silicon Valley Saurons who view themselves as underdogs.¹⁸ The point is never to be a “normie” even as you form a norm.

What if we simply addressed the inequalities that drive these splinters? What if we built on the allusions and celebrations of black civil rights activists and movements to dispel this toxic liberation envy, which poisons the experiences and words of these actors? What if we used “tribalography” not to advance the eradication of “natives,” but rather as creative writer and Indigenous studies scholar Leanne Howe has encouraged, to tell stories that pull together people, land, and characters in order to connect “past, present, and future milieus”?¹⁹ What if we engaged the lives, dreams, and experiences of these heroes not to inhabit them, but rather to build together the world they seek to inhabit?

1

CORRELATING EUGENICS

The Cambridge Analytica scandal exemplified social media's perceived threat to democratic institutions and processes. Cambridge Analytica—a data firm hired by the 2016 Donald Trump and Ted Cruz presidential campaigns and funded by Republican hedge fund and machine learning pioneer Robert Mercer—allegedly altered the results of that year's U.S. election and UK Brexit referendum. The immodest statements made by Cambridge Analytica CEO Alexander Nix partly fueled these allegations: during a 2016 speech at the Concordia Summit, Nix claimed responsibility for Cruz's success in that year's primaries. As Nix explained, Cruz was both generally unliked and unrecognized at the beginning of his primary campaign, but Cruz's embrace—through Cambridge Analytica—of behavioral science (psychographics), addressable ad technology, and big data powered his steady rise; in the end, he came in second only to Trump. Specifically, Cambridge Analytica, which had created “a profile of every adult in the United States of America,” targeted and swung “persuadable” voters for Cruz.¹

Cambridge Analytica's celebration of big data and the data firm's exaggerated claims were the norm during the first decades of the twenty-first century, the “century of big data.” *The Economist* proclaimed data “the oil of the digital era”—“the world's most valuable resource”; IBM promised that big data analytics would offer “insights without limits.”² Fox News

declared: “‘Big data’ will blow your mind and change the 21st century.”³ Bloomberg, Oracle, and numerous other organizations proclaimed that big data would “disrupt” everything.⁴ The 2020 documentary *The Social Dilemma* claimed that, through big data, social media platforms dominated users and turned them into marionettes.⁵

Big data’s power was said to be based on correlation, but this was not correlation’s first rodeo. Along with linear regression and other foundational statistical methods, correlation was developed by early twentieth-century biometric eugenics, who were eager to breed a better “human crop.” By investigating the historical ties between big data and eugenics, we will see that the two are linked together by a fundamentally undisruptive view of the future. But, as we will also see later in the chapter, even though both have sought to make the future repeat a highly selective and discriminatory past through correlation (so that *ground truth = deep fake*), they differ in several important respects. In the transition from eugenics to data analytics, the focus group moved the nation to the neighborhood/tribe; the goal shifted from uplift to escape; and homophily (the notion that similarity breeds connection) went from aspiration to axiom.

CULTIVATING HUMANS

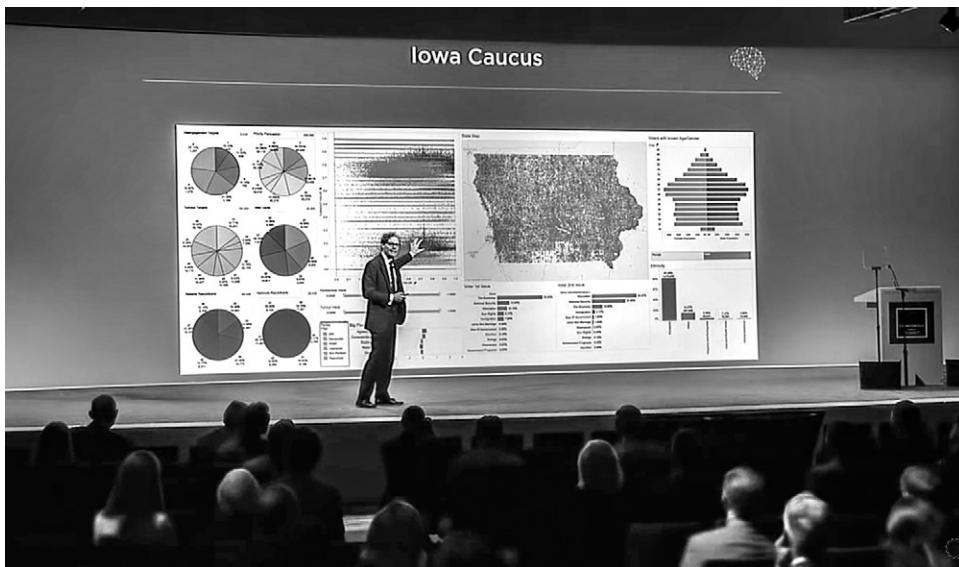
Key to Cambridge Analytica’s success was psychographics because, Nix contended during his Concordia presentation, “it’s personality that drives behavior and behavior that obviously influences how you vote.”⁶ Psychographics superseded demographics, geographics, and economics, with their crude assumptions “that all women should receive the same message because of their gender, or all African Americans because of their race, or all old people, or rich people or young people to get the same message because of their demographics.” White men, the group Nix actually targeted for Cruz, was tellingly missing from this list. As will be discussed further in this chapter, Nix’s “all X” formulation inadvertently revealed that his “solution” to identity-based politics and advertising was not to dissolve these demographic categories, but rather to further segment them, based on “personality.” To determine a person’s personality, Cambridge Analytica deployed a “long form quantitative instrument to probe the underlying traits that inform personality.” The data firm scored

a person's personality using the five-factor OCEAN model, where O = openness ("how open you are to new experiences"); C = conscientiousness ("whether you prefer order and habits and planning in your life"); E = extroversion ("how social you are"); A = agreeableness ("whether you put other peoples' needs and society and community ahead of yourself"); and N = neuroticism ("a measurement of how much you tend to worry").

Nix offered an extended example of likely Iowa caucus participants and the U.S. Second Amendment as proof. "For a highly neurotic and conscientious audience," he asserted, as he showed an image of a white woman with "professional hair," you needed a rational yet fear-based message: "The threat of a burglary and the insurance policy of a gun is very persuasive." In contrast, "For a closed and agreeable audience, these are people who care about tradition and habits and family and community," he explained as he displayed an image of a smiling middle-aged white male: "This could be the grandfather who taught his son to shoot and the father who will in turn teach his son. . . . Talking about these values is going to be much more effective in communicating your message" (figure 10). To decide whom to target and which ads to produce,



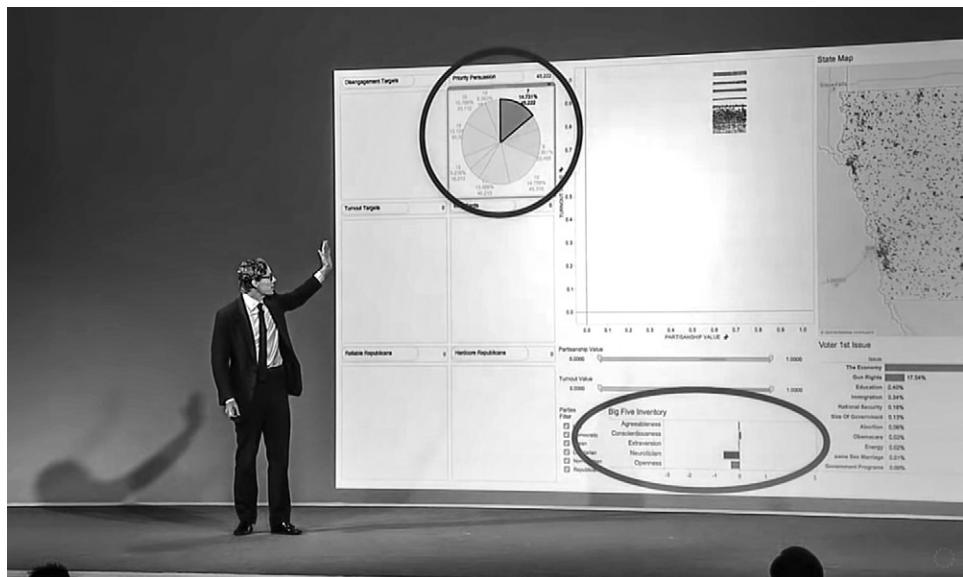
10 Still frame of Cambridge Analytica's psychographic messaging, from Nix's 2016 presentation at the Concordia Summit, <https://youtu.be/n8Dd5aVXLCC>.



11 Still frame of Cambridge Analytica's Iowa data dashboard, from Nix's 2016 presentation at the Concordia Summit, <https://youtu.be/n8Dd5aVXLCC>.

Cambridge Analytica created a “data dashboard” (figures 11 and 12) for each state, which sorted people by party and likelihood to vote.

From these data dashboards, Cambridge Analytica culled a “persuasion” group of about 45,000 Iowans who mattered to Cruz because they were definitely going to caucus, but they needed to be moved “a little more toward the right” if they were going to support him. After determining the mean personality type of the group to be “very low in neuroticism, quite low in openness and slightly conscientious,” the firm identified a subset who cared about gun rights versus gun control—a highly divisive, emotionally charged, and well-funded issue in the United States. In his presentation, Nix revealed that the Cruz campaign used their insights to drive not only their ads but also their field operations. These ads could target actual individuals since, Nix bragged, Cambridge Analytica had “somewhere close to four to five thousand data points on every adult in the U.S.” What Nix did not state, and what Carole Cadwalladr and Emma Graham-Harrison of the *Guardian* later revealed, was that his firm had harvested 50 million Facebook profiles unbeknownst to their “owners,”



12 Still frame of Cambridge Analytica's microtargeting, from Nix's 2016 presentation at the Concordia Summit, <https://youtu.be/n8Dd5aVXLCc>.

through a quasi-legal deal with then Cambridge University researcher Aleksandr Kogan, to produce their data dashboards.⁷

As many researchers have emphasized, the claims made by Cambridge Analytica need to be taken with four to five thousand grains of salt—there is much that cannot be known about the actual impact of Cambridge Analytica on the 2016 U.S. presidential elections. Indeed, following the elections, Cambridge Analytica itself told reporters that it was impossible to verify its claims, and the firm could not offer a single case as proof.⁸ Even if it could—and we accepted the 2016 presidential election as evidence—that single case would represent a sample size of one. Further, the efficacy of targeted political ads using the OCEAN model is still in question; Facebook and other social media effectively use metrics other than OCEAN to “prime” users.⁹

The rush to attribute the generally unforeseen victory of Donald Trump in 2016 to Cambridge Analytica also rewrites history. As late as November 4, 2016—the day before the election—Hillary Clinton, not Donald Trump, was heralded as the big data candidate. Countless articles

documented Trump's disregard for data, and his preference to "go with his gut." *Politico* and many other news outlets praised Clinton's data guru, Elan Kriegel, as "precise and efficient, meticulous and effective."¹⁰ Kriegel, who had formerly worked in the Obama "cave," had created a tool that could calculate the "cost per flippable delegate." According to Jeremy Bird, a consultant who worked with both Obama and Clinton, Obama consulted Kriegel before every decision about strategy in battleground states, and Elan "was never wrong." Kriegel's work, it was claimed, was even more precise for the Clinton campaign—she was thus sure to win. As *Politico* surmised: "Now, with Donald Trump investing virtually nothing in data analytics during the primary and little since, Kriegel's work isn't just powering Clinton's campaign, it is providing her a crucial tactical advantage in the campaign's final stretch. . . . As millions of phone calls are made, doors knocked and ads aired in the next nine weeks, it is far likelier the Democratic voter contacts will reach the best and most receptive audiences than the Republican ones [will]."¹¹

Right.

Clearly, Clinton lost and Trump won. That we know. We also know, in retrospect, that Clinton's models were overfitted to the previous presidential campaign: they had, for instance, presumed a significant African American voter turnout, even after the controversy over Clinton's 1996 "superpredators" comment. In other words, they had ignored experience and specific events in their formal conceptualization of voters.

Rather than dismissing Cambridge Analytica's claims as snake oil or sorting through the election voter data to assess the actual impact of Cambridge Analytica's "special sauce," however, the more pressing task is to answer these two questions:

To what extent did Cambridge Analytica get some things right not simply because it "discerned" what was out there, but because the data firm sought to create it as well?

And what world are we living in that Cambridge Analytica's claims seem plausible?

The goal of the firm's advertisements was to create transformational, "red pill" experiences: to have users go "down the rabbit hole" by following ads, carefully "breadcrumbed" across different sites and spread by their friends and others "like them."¹² Identification—or targeting—was

the first function within the program: the others were recognition (mutual identification) and conversion.

As Cambridge Analytica whistleblower Christopher Wylie explained to Carole Cadwalladr in 2018, the data firm's "information operations," which were inspired by the U.S. military's doctrine of "five-dimensional battle space," correlated culture with politics. Wylie (the self-described "gay Canadian vegan who somehow ended up creating 'Steve Bannon's psychological warfare mindfuck tool'") formerly researched fashion trends. He told Bannon, then chief executive officer of Trump's 2016 presidential campaign, that, based on his prior research, "politics was like fashion." Trump was like a pair of Ugg boots, and the goal was to find the inflection point that moved people from thinking these were "'Ugh. Totally ugly' to the moment when everyone is wearing them." And Bannon believed this message, Wylie explained, because he adhered to the Breitbart doctrine "that politics is downstream from culture, so to change politics you need to change culture."¹³ Cambridge Analytica took this doctrine one step further by arguing that, to change culture, you had to change individuals. Personalities were key to changing culture.

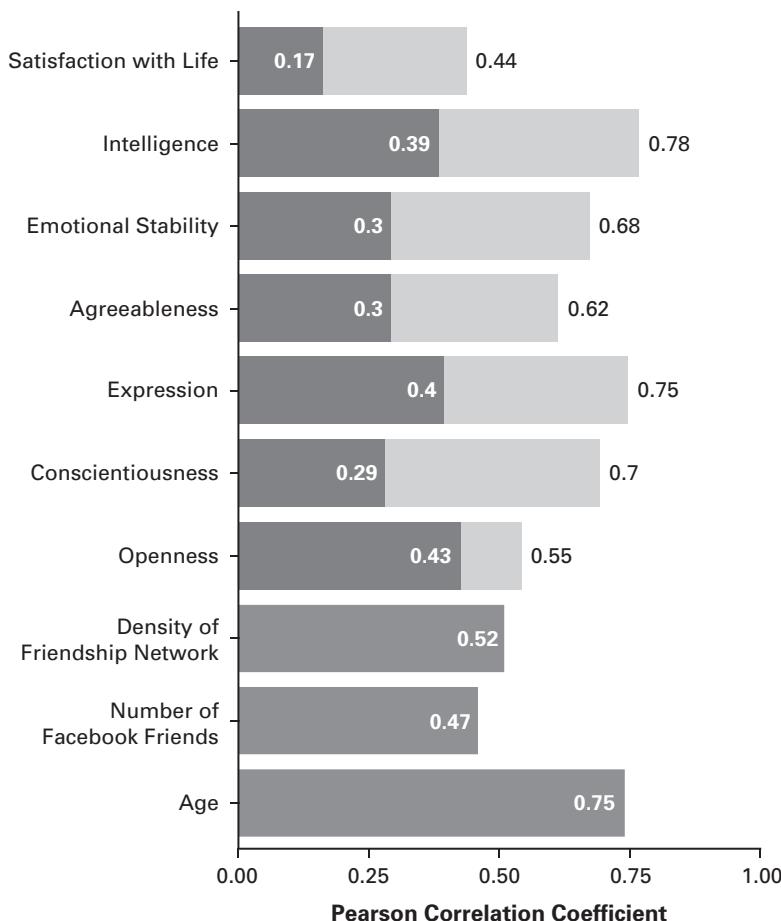
Maybe.

If we have learned anything from Cambridge Analytica, however, it is that finding and exploiting clusters is key to cultivating individual behavior—to fashioning change. "Personalization" works at the levels of individual actions, "latent" factors, and "bespoke" network neighborhoods—all at the same time. As chapter 3 elaborates, recommendations and social media "feeds" for a particular individual do not depend solely on that individual's history. If they did, they would be very limited in scope. Predictive data analytics for Internet users work—if and when they do—not by treating every Internet user like a unique snowflake, but rather by segregating users into "neighborhoods" or petri dishes based on their slightly odd or deviant—that is, "authentic"—likes and dislikes. Individuals are formed and identified by their so-called neighbors.¹⁴ Cambridge Analytica claimed to have discovered proxies that revealed a person's race, sexual orientation, political leanings, and so on: preferring an American car, for example, strongly indicated a possible Trump voter.¹⁵ Again, these proxies were sought in relation to inflection points—points at which curves would bend in new directions. "Culture" is not simply a noun, but also a

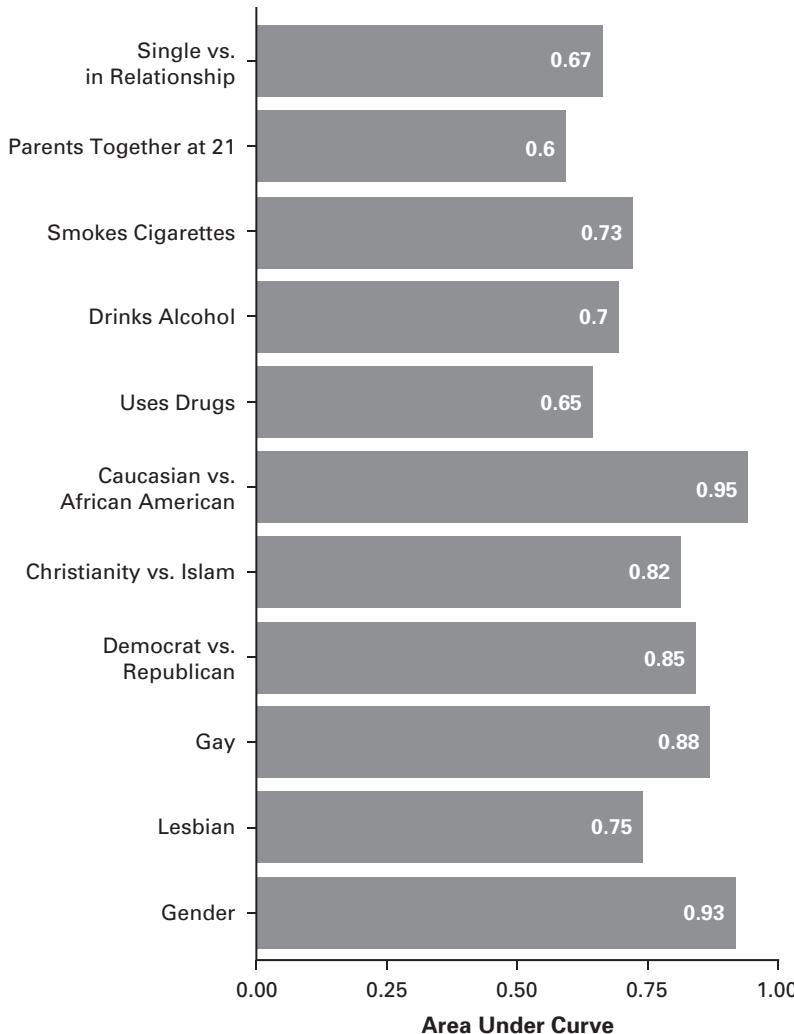
verb. To culture is to cultivate: “to propagate, grow or develop . . . under artificial conditions or in a nutrient medium.”¹⁶ “Culture,” “colony,” and “colonization” are all derived from the Latin *colere*, “to cultivate or worship.” A *colonus* was a settler: a Roman soldier-farmer, who was posted in foreign or hostile territory and who seized land by enclosing or settling on it. Cultures are and depend on invasive separations.

Although Cambridge Analytica did not reveal how it used Facebook likes to determine personality, computational social scientists Michal Kosinski and David Stillwell, and computer scientist Thore Graepel, whose work partly inspired Cambridge Analytica, explained how this microtargeting works in their influential 2013 study “Private Traits and Attributes Are Predictable from Digital Records of Human Behavior.”¹⁷ They revealed how easy it was to predict latent user attributes (identity categories) such as “sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender” based on then publicly available Facebook likes. As the listed attributes makes clear, Kosinski, Stillwell, and Graepel sought to create a model that would estimate a range of characteristics. The researchers could do so because more than 58,000 Facebook users had completed the myPersonality Facebook questionnaire the researchers had circulated—and by doing so had given the researchers access to information in the their Facebook profiles.

To produce their estimates, the three researchers first posited boundary-making traits such as “political views,” “parents stayed together until the individual was 21,” “ethnic background,” and “intelligence,” which they “measured” using various methods, including the five-factor OCEAN model, intelligence tests, and visual examination of user profiles and online survey answers. They then created a vast but sparse user-like matrix comprising all likes associated with each user. Next, they decomposed this matrix using singular value decomposition (SVD), which reduces a matrix of data points into a series of vectors, ranked by how much they explain the original data set (described in greater detail in “Proxies” after chapter 2) to determine the hundred most significant components. Then, using these most significant components, they created linear regression models to predict numeric attributes, such as personality and age, and logistic regression models to predict dichotomous values, such as male versus female or Christian versus Muslim (figures 13 and 14).



13 Prediction accuracy for linear regression models. Redrawn from Michal Kosinski, David Stillwell, and Thore Graepel, "Private Traits and Attributes Are Predictable from Digital Records of Human Behavior," *Proceedings of the National Academy of Sciences* 110, no. 15 (2013): 5804.



14 Prediction accuracy for dichotomous logistic regression models, redrawn from Kosinski, Stillwell, and Graepel, "Private Traits and Attributes Are Predictable," 5803.

The logistic regression models (designed to predict dichotomous values) presumed the existence of separate and opposed binary categories (male versus female; Christian versus Muslim); these models were given two samples from each category and then assessed on their ability to predict who belonged in each (see figure 14). The goal was to put every sample into its right category by adhering to a strict either-or logic.

The accuracy of these models varied greatly, with the most accurate being for Caucasian versus African American and male versus female (figure 14). Not surprisingly, the highly structured dichotomous value models gave the best results. The least accurate predictions were those linked to numeric attributes (figure 13): satisfaction with life, conscientiousness, emotional stability, and agreeableness (these numeric attributes were assessed using the Pearson correlation coefficient, explained below in “Correlation” by Alex Barnett; figure 17). Finally, they produced tables of the most predictive likes—that is, those with the highest weighted average or the most extreme frequencies of classes—for certain traits (figure 15).

Based on this, Kosinski, Stillwell, and Graepel claimed that, by knowing as few as one like, they could determine a user’s related “intimate” trait. For example, given how highly correlated liking the Wu-Tang Clan band was for male heterosexuality, liking it would “give away” a user’s sexual orientation; and given a similarly high correlation, liking Sephora would “give away” a user’s low IQ score. Although this study justified its research in terms of “warning” users of possible privacy violations, it clearly showed how to cluster users in order to estimate their “latent” characteristics. Further, it revealed which categories were best for predictably separating users. The researchers stressed that the most significant likes for any given category did not simply or literally reflect that category: among male users, “Britney Spears” was a more popular and “revealing” like for “male homosexuality” than “Being Gay.” Their analysis discovered subcultural style cues, which signaled group membership to those in the know (for more on this, see chapter 4).

Crucially, the predictions were trained on carefully curated data, which determined both the coefficients of the regression models and their significant components. The models were then tested on their ability to predict this meticulously pruned past. This is not specific to these

Trait		Selected Most Predicted Likes	
Sexual Orientation	IQ		Low
			High
		The Godfather Mozart Thunderstorms The Colbert Report Morgan Freeman's Voice The Daily Show Lord of the Rings To Kill a Mockingbird Science Curly Fries	Jason Aldean Tyler Perry Sephora Chiq Bret Michaels Clark Griswold Bebe I Love Being a Mom Harley Davidson Lady Antebellum
		No H8 Campaign Kathy Griffin Kurt Hummel Glee Human Rights Campaign Mac Cosmetics Adam Lambert Ellen DeGeneres Juicy Couture Sue Sylvester Glee Wicked The Musical	X Games Nike Basketball Bungie WWE Sportsnation Wu-Tang Clan Foot Locker Shaq Bruce Lee Being Confused After Waking Up From Naps
		Girls Who Like Boys Who Like Boys Rupauls Drag Race No H8 Campaign Gay Marriage Human Rights Campaign The L Word Sometimes I Just Lay In Bed and Think About Life Not Being Pregnant Gay Marriage Tegan And Sara	Lipton Brisk Yahoo Adidas Originals Foot Locker WWE Inbox 1 Makes Me Nervous Thinking Of Something And Laughing Alone I Just Realized Immature Spells I'm Mature Did You Get A Haircut No It Grew Shorter Nike Women
			Heterosexual Males
			Heterosexual Females

15 Postpredictive likes for dichotomous categories, redrawn from Kosinski, Stillwell, and Graepel, "Private Traits and Attributes Are Predictable," Table S-1.

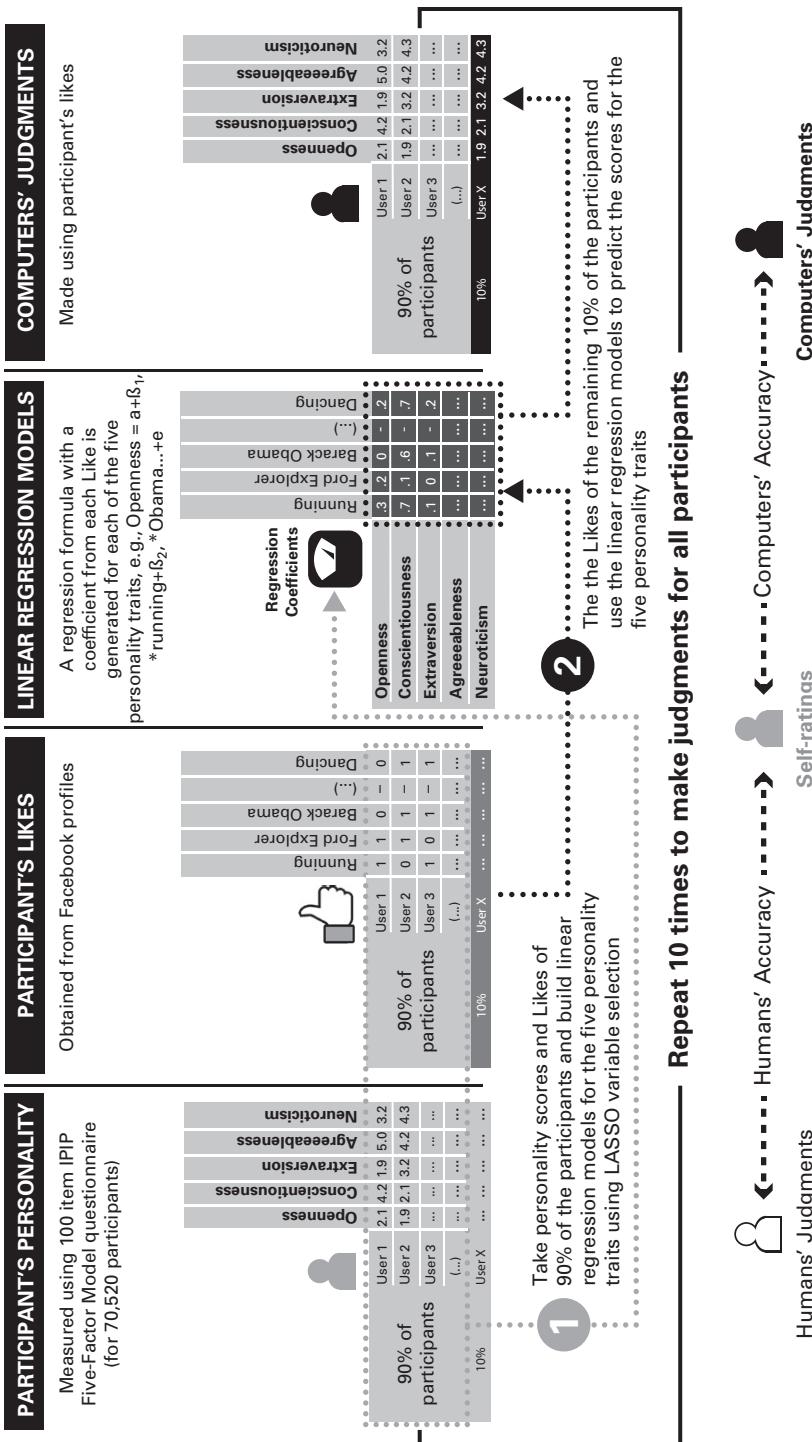
models or these types of models. Even more explicitly predictive algorithms, which tolerate higher bias and lower variance in order to avoid "overfitting," are verified as correct if they predict the past correctly, for they are usually cross-validated using past data that are hidden during the training period or out of sample data, similarly drawn from the past.¹⁸ Wu Youyou, Michal Kosinski, and David Stillwell used this cross-validation test in their 2015 follow-up study, "Computer-Based Personality Judgments Are More Accurate Than Those Made by Humans."¹⁹ Unlike the

first study, the later study emphasized the importance of cross-validation. It used 90 percent of its data as a training set to build a linear regression model for predicting personality type, and then tested it against the remaining 10 percent for verification (figure 16).

Using this form of verification, standard for machine learning algorithms and models, means that if the captured and curated past is racist and sexist, these algorithms and models will only be verified as correct if they make sexist and racist predictions, especially if they rely on problematic measures such as standard IQ tests. Tellingly, low IQ in the 2013 study was found to be highly correlated with liking “I Love Being a Mom.”

The methods used by Kosinski and colleagues and Cambridge Analytica—correlation, linear and logistic regression, and factor analysis—stem from twentieth-century eugenics. The five-factor OCEAN model is the product of controversial and discredited eugenicists such as Charles Spearman, Hans Eysenck, and Raymond Cattell. They developed and used factor analysis, based initially on principal component analysis (PCA; see figure 37 by Alex Barnett in “Proxies, or Reconstructing the Unknown” after chapter 2) and correlation to “classify” raced and gendered groups according to intelligence, among other personality traits.²⁰ The “O” in OCEAN, “openness,” was initially labeled “intellect,” which means that those responding to Cruz’s “from father to son: from the birth of our nation” Second Amendment ads would once have been labeled “low intellect.”²¹ In the “five-factor” world, personality traits or factors were, and still are, considered “physiological.” According to Robert McCrae and Geert Hofstede, the “five-factor model” was “unique in asserting that traits have only biological bases”²²—an assertion that provided the basis for researchers using the model to frame personality within a biometric evolutionary schema.²³

These attempts to more finely “resolve” human groupings based on personality reinforce racial boundaries. Indeed, the images Cambridge Analytica used in its psychographic messaging were deeply raced, gendered, and classed (figure 10). Thus not only were the images of “persuadables” in figure 10 both white, the tagline “since the birth of our nation” riffed off D. W. Griffith’s racist *Birth of the Nation*, a 1915 silent film that valorized the Ku Klux Klan. Psychographics created connections not across races, but rather divisions within them. Although Nix argued



- 16 Testing the training model using past data, redrawn from Wu Youyou, Michal Kosinski, and David Stillwell, "Computer-Based Personality Judgments Are More Accurate Than Those Made by Humans," *Proceedings of the National Academy of Sciences* 112, no. 4 (2015): 1037.

against all women receiving the same message according to their gender or all African Americans according to their race, he did not argue for messages that would cross gender or racial boundaries. He admitted that Cruz's challenge in Iowa was having "his voice heard" by "a largely homogeneous audience" of "largely white, middle-aged, male, conservatives, in support of the economy and the Second Amendment."

According to Christopher Wylie, to more effectively influence people, Cambridge Analytica took an "intersectional" approach to racial identity. Steve Bannon, he explained, was the only straight man he talked to about feminist intersectional theory, a methodology developed by women of color feminists, most notably legal scholar and critical race theorist Kimberlé Crenshaw, to explain how black women are at the "crossroads" of race, gender, and class. Crenshaw's analysis focused on how broad identity categories, such as female and black, often effectively exclude black women, and how this exclusion could be best addressed through a coalitional understanding of identity.²⁴ Cambridge Analytica perverted Crenshaw's method and sought to augment differences and exclusions, both real and perceived, based on values and "personality traits," within a racially homogenous space. Whereas Crenshaw started with how feminism and black empowerment movements often fail to address the needs and concerns of black women—for example, how funding agencies for support centers presume that rape victims are white middle-class women—in order to overcome these problems, Cambridge Analytica sought to find "neighborhoods" within identity categories such as "gun-toting white men" to better target and transform individuals.

Put most bluntly: in an attempt to destroy any and all senses of commonality, "communities" are being planned and constructed based on divisions and animosities. Instead of ushering in a post-racial, post-identitarian era, these social networks perpetuate angry microidentities through "default" variables and axioms. By using data analytics, individual differences and similarities are actively sought, shaped, and instrumentalized in order to capture and shape social clusters. Networks are neither unstructured masses nor endless rhizomes that cannot be cut or traced. Because of their complexities, noisiness, and persistent inequalities, networks provoke control techniques to manage, prune, and predict. This method—pattern discrimination 2.0—makes older, deterministic,

or classically analytic methods of control through direct discrimination seem innocuous.

Welcome to the swarming of the segregated neighborhood, spread through eugenic methods to cultivate futures based on mythical pasts.

CORRELATION, CORRELATION, CORRELATION

The ground beneath our feet is shifting. Old certainties are being questioned. Big data requires fresh discussion of the nature of decision-making, destiny, justice. A worldview we thought was made of causes is being challenged by a preponderance of correlations. The possession of knowledge, which once meant an understanding of the past, is coming to mean an ability to predict the future.

—Viktor Mayer-Schönberger and Kenneth Cukier, 2014²⁵

I felt like a buccaneer of Drake's days—one of the order of men “not quite pirates, but with decidedly piratical tendencies.” . . . I interpreted . . . Galton to mean that there was a category broader than causation, namely correlation, of which causation was only the limit, and that this new conception of correlation brought psychology, anthropology, medicine and sociology in large parts into the field of mathematical treatment. It was Galton who first freed me from the prejudice that sound mathematics could only be applied to natural phenomena under the category of causation. Here for the first time was a possibility—I will not say a certainty, of reaching knowledge—as valid as physical knowledge was then thought to be—in the field of living forms and above all in the field of human conduct.

—Karl Pearson, 1934²⁶

Correlation grounds big data’s so-called revolutionary potential. As *Wired* editor Chris Anderson infamously declared in his 2008 editorial “The End of Theory,” big data proved that “correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all.”²⁷ Less controversially, policy researcher Viktor Mayer-Schönberger and journalist Kenneth Cukier, in their popular 2014 book *Big Data: A Revolution That Will Transform How We Live, Work and Think*, asserted that, by replacing causality with “simple correlations,” big data “challenges our most basic understanding of how to make decisions and comprehend reality.”²⁸ Indeed, by substituting “what” for “why,” they claim that big data and correlation have changed the direction of knowledge: it is no longer about understanding the past, but rather about grasping the future.

Not surprisingly, big data, also formally called “data analytics,” was immediately dismissed as “hype”: the latest in a long line of technoutopian (and dystopian) fads. Google Flu Trends, for example, was shown to be wildly inaccurate—predicting double the number of actual cases.²⁹ Although understanding the limits of data analytics is important, simply dismissing it as “hype” or celebrating its “missed” predictions as evidence of human unpredictability is dangerous. The gap between prediction and actuality should not give rise to snide comfort especially since random or “diverse” recommendations are often deliberately seeded in order to provoke spontaneous behavior.³⁰ Further, big data posed and still poses fascinating computational problems—How do we analyze data we can read only once, if at all?—and the plethora of correlations it documents raises fundamental questions about causality. If almost anything can be shown to be real, if almost any correlation can be discovered, how do we know what is true? The “pre-big data” example of the “Super Bowl predictor” nicely illustrates this dilemma: one of the “best” (most consistently correct) predictors of the U.S. stock market has been which football conference wins the Super Bowl: if a team from the original National Football League wins, it will most likely be a bull market; if a team from the original American Football League, most likely a bear market.³¹ Moreover, calling a new technology “hype” is hardly a profound criticism. Hype is part and parcel of new technologies, and demos of future technologies seem to elicit more praise or condemnation than everyday experiences of already existing ones (the Valley lives and dies by the demo).³² Thus to understand the impact of the “data deluge,” we need to move beyond celebrating or dismissing big data toward comprehending the force of its promise—or, more precisely, the ways it undermines the promise of promise. As philosopher Jacques Derrida has argued, a promise that is “automatically kept” is no promise at all, but rather “a computer, a computation.”³³ Perhaps, but computations do not automatically execute themselves, and actual computers fail all the time—something we know from experience, but, surprisingly, *not* in theory.

Again, this is not the first time that correlation has been heralded as revolutionary. More than a century ago, biometric eugenicists Francis Galton and Karl Pearson “discovered” correlation in their attempts to determine heredity. As quoted in this section’s second epigraph, Pearson

described feeling like “a buccaneer” on the edge of plunder and discovery because correlation expanded knowledge beyond causality and promised to make mathematically comprehensible living beings and human behavior. Pearson’s hyperbolic rhetoric foreshadows twenty-first-century big data hype. Correlation’s eugenicist history matters, not because it predisposes all uses of correlation towards eugenics, but rather because when correlation works, it does so by making the present and future coincide with a highly curated past. Eugenicists reconstructed a past in order to design a future that would repeat their discriminatory abstractions: in their systems, learning or nurture—differences acquired within a lifetime—were “noise.” The important point here is that predictions based on correlations seek to make true disruption impossible, which is perhaps why they are so disruptive.

The differences between twenty-first-century big data and twentieth-century eugenics, as the end of this chapter explains in greater detail, also matter. The move from statistics to data science signals a difference in purpose and focus. As philosopher of science Ian Hacking has pointed out, the term “statistics” comes from “state,” and national statistics testify to a state’s “problems, sores and gnawing cankers.”³⁴ Data science, in contrast, by focusing on the governmental interests of corporations and states through “network neighborhoods” or “clusters,” outlines possible “homophilic escapes” from national populations. For the twentieth-century eugenicists, homophily was an aspiration: they wanted to create a world in which like people automatically reproduced with like. In data analytics, homophily is a given, an axiom. Nightmares of global destruction and dreams of segregated “escape” have displaced narratives of impending racial doom. So how did we get here, and what is correlation anyway?

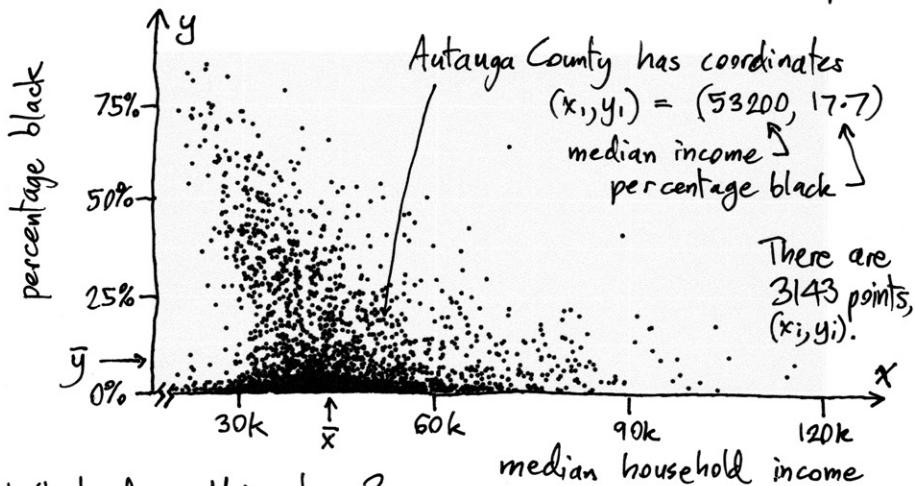
SPURRING CORRELATIONS

Most basically, correlation measures how two or more variables vary together. If variables increase and decrease in step, they are highly (positively) correlated; if they vary in opposite directions, they are negatively correlated (see figure 17).

Highly correlated variables are thus considered to be “proxies” of each other: by tracking one variable, you can capture the other. Correlations

CORRELATION

There are $n = 3143$ counties in the US, and lots of publicly available data about them. (Here we use the "countyComplete" data in the "openintro" package for the free statistical software "R". Most data is from 2010.) Counties are indexed $i=1$ to 3143. Eg, $i=1$ is Autauga County, AL. Let's plot on the x-axis median household income, vs the y-axis the percentage of the county population that is black. This is a "scatter plot":



What does this show?

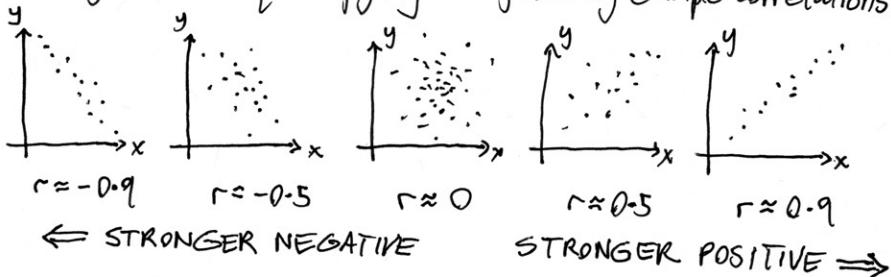
- A correlation between race & poverty : the points lean leftwards as one moves up. ($\approx 4k$ less per 10% increase)
- Counties with income $> 70k$ are almost all $< 20\%$ black. Thus income can be a surrogate for race.
- Poor counties are segregated : for incomes $< 30k$, the distribution is "bimodal", very white ($< 3\%$) or black ($> 30\%$).

So, a scatter plot can tell many stories. However, often only Pearson's "correlation coefficient" is given, which mathematically is $r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$

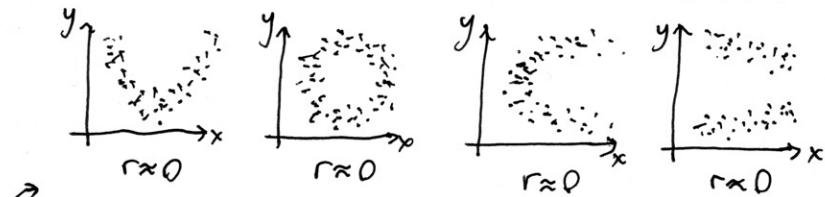
This (perhaps scary) formula involves two familiar quantities:
 $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$ is the mean of the income over counties.
 $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$ is the mean of the percentages.

For our data $\bar{x} \approx 44k$, $\bar{y} \approx 9\%$, and these are shown on the plot.

r is good at quantifying the following example correlations:



However there are many interesting & informative "nonlinear" correlations that r is oblivious to:



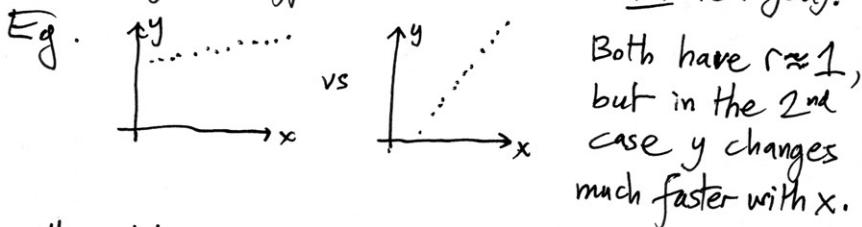
in each case there are correlations, but r cannot tell you this fact! It is insensitive to bimodality (the indicator of segregation earlier).

Returning to our county income and percentage black data, what is r ? It turns out to be $r \approx -0.22$, which is negative (as expected from the overall downwards slope), but would be interpreted as very weak.

This shows the limitation of the correlation coefficient: it fails to capture the many aspects that a glance at the full scatter plot can show. One must look at the data rather than trust r .

Notes:

- You do not need to handle the formula for r : all statistical software has it built in.
- r lies between -1 and $+1$, and tells you the strength of the linear correlation, not to be confused with the strength of the effect (which r does not tell you).



- scatter plots can be 3D too with (x_i, y_i, z_i) data, or even higher dimension, but it is hard to picture!
- a better analysis of county data might "weight" each point by the county population.
- nonlinear correlations (bimodality, etc) can be found by using, eg, powers of variables, x^2, x^3 , etc.

are most often used to uncover latent or hidden variables. In the Kosinski, Stillwell, and Graepel 2013 study, tracking the like “I Love Being a Mom” supposedly captured intelligence. Such correlation tracking provides the basis for Anderson’s assertion that theory is dead, or Mayer-Schönberger and Cukier’s that correlation gives us the future rather than the past.

Many researchers who deploy data-driven techniques have qualified or critiqued these broad proclamations of the death of causality. As sociologists Josh Cowls and Ralph Schroeder explain, instead of either correlation or causality alone, what is necessary are “mixed methods” that combine correlational exploratory practices with causal explanatory research.³⁵ This is because, left unattended, big data methods often reinvent the wheel by “discovering” well-known latent correlations (that many gay men of a certain age like Britney Spears, to return to an example referenced earlier), or they produce an inordinate number of spurious correlations that defy basic concepts such as gravity or photosynthesis. Further, causality is often needed to solve problems—vaccines, for example, depend on mechanistic understandings of virus structure and behavior.

In addition, correlations often raise as many questions as they supposedly answer. For example, social scientists Nicholas Christakis and James Fowler’s much cited and disputed 2007 study of friendship data, which recycled data from the Framingham Offspring Study (begun in 1971), concluded that social, rather than physical, proximity to one or more persons who are obese matters most in predicting the likelihood of someone becoming obese.³⁶ Obesity, that is, spreads like a virus through social networks. This study was criticized not only for its conclusions but also for its conflation both of obesity with viruses and of viral spread with homophily (the tendency of individuals who are like each other to act similarly in the same context). As statisticians Cosma Shalizi and Andrew Thomas point out, it is mathematically difficult to separate habit from contagion.³⁷ Further, other seemingly contradictory correlations were also documented. Another study found that zip code and property value were strong proxies for obesity.³⁸ Further, spurious correlations arrived at using big data are not accidental; indeed, drawing on mathematical theory, theoretical computer scientists Cristian Calude and Giuseppe Longo have shown that, because of their size alone, all big data analyses must be riddled with such correlations.³⁹ And, for that matter, spurious correlations abound in

small data sets as well, the classic example being the Super Bowl market indicator mentioned earlier.⁴⁰

Traditionally, causality cuts through multiple correlations in order to find the things that really matter. As defined within the quantitative social sciences, causality depends on three conditions: (1) correlation; (2) the cause preceding the effect; and (3) the absence of a third variable that could explain the correlation.⁴¹ This definition draws from the more technical Wiener–Granger test for causality, commonly used in econometrics and neuroscience to determine if two variables, X and Y , are causally related. Y is said to be Wiener–Granger causal if it improves the prediction of X in a statistically significant way.⁴² In synchronous network models, simulations and parsimony are used to determine truth.⁴³

Spuriousness, however, is not the sole or even the main problem with correlations. As Cathy O’Neil and others have shown, correlations can perpetuate inequality. Those building what O’Neil has called “weapons of math destruction” use correlations and proxies to compensate for ignorance or lack of evidence. Since they cannot directly access the behavior they are most interested in, they use proxies as stand-ins: “They draw statistical correlations,” O’Neil tells us, “between a person’s zip code or language patterns and her potential to pay back a loan or handle a job. These correlations are discriminatory, and some of them are illegal.”⁴⁴ That is, correlations can serve as proxies for unknown or protected categories—categories that were deliberately hidden or unrecorded in an attempt to ensure equal treatment.⁴⁵

Proxies that uncover the obvious consequences of discrimination often work—they effectively target groups. As O’Neil notes, “rich people buy cruises and BMWs. All too often, poor people need a payday loan.” Because of this, “investors double down on scientific systems that can place thousands of people into what appear to be the correct buckets. It’s the triumph of Big Data.”⁴⁶ As this example makes clear, these models not only “discover” the effects of discrimination; they also automate and perpetuate them for they exploit, rather than remedy, inequalities. These correlations are at the heart of what communications scholar Oscar Gandy, writing in 2009, eight years before O’Neil, identified as “technologies of rational discrimination”: unless there is a clear determination not to discriminate, Gandy explained, these technologies perpetuate inequality by

creating and comparing “analytically generated groups in terms of their expected value or risk.”⁴⁷ That homophily drives these groups and correlations “that work” is no accident. As we will see in chapter 2, homophily, based on historical trends and actions, does in fact explain some behavior; the future does at times repeat the past. But this raises at least two interesting questions: In a dynamic world dominated by change, under what circumstances and to what end do some things seemingly repeat? And how does the ephemeral endure through our habitual actions? As philosophers as diverse as the Buddha and Gilles Deleuze, and as molecular biologists have shown, we live in a world of constant change—no two things are exactly alike, not even ourselves at different moments in time. Recognition always entails misidentification—an obscuring of present or future differences to past acquaintance.

Correlations, again, do not simply predict certain actions; they also form them. Correlations that lump people into categories based on their being “like” one another amplify the effects of historical inequalities. A signature quality of a weapon of math destruction is that the weapon “itself contributes to a toxic cycle and helps sustain it.”⁴⁸ Virginia Eubanks in *Automating Equality* offers a classic example of this: the Allegheny Family Screening Tool (AFST), used by Allegheny County, Pennsylvania, to determine the risk of child abuse and neglect.⁴⁹ Since the AFST training set was drawn from families who access public services, the use of public services itself became classified as a risk factor. This, like the Chicago police’s heat list, which lumped together murderers and murdered as “likely to be involved in a homicide,” erased the difference between victim and perpetrator. Children’s involvement with protective services became evidence of their likelihood as adults to abuse or neglect their own children. Families with private insurance or who used private services, such as therapists and nannies, on the other hand, were not included in the training data set and thus not flagged.⁵⁰ O’Neil also points to the unfair impact that credit ratings can have when factored into hiring programs. Produced by licensed agencies and more informal data brokers, and based on individual actions and increasingly social networks, these ratings are not simply proxies for responsibility: people who live from paycheck to paycheck have trouble maintaining their credit ratings during hard times, unlike those who are wealthy. Given the U.S. history

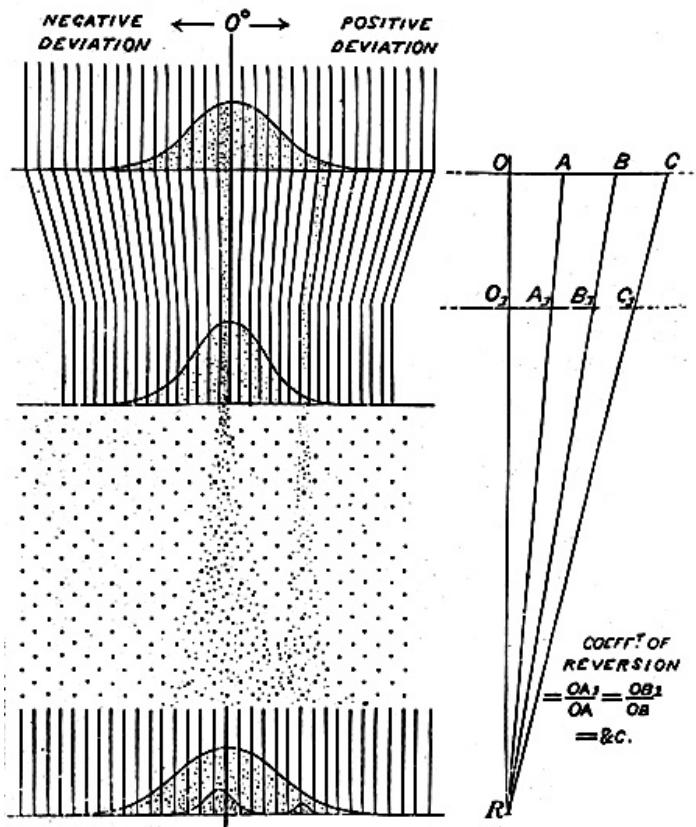
of financial discrimination explored in detail by Oscar Gandy, U.S. credit ratings correlate with race, or more precisely racism.⁵¹ As political scientist Ira Katznelson, policy researcher Richard Rothstein, and many others have shown, U.S. government policies such as the New Deal, Social Security, inexpensive mortgages, and the G.I. Bill concentrated wealth in the hands of white Americans.⁵² Weapons of math destruction automate and amplify past inequalities through their baseline correlations.⁵³

The problems with correlations are neither new nor limited to big data and weapons of math destruction, however. Based on eugenic reconstructions of the past and cultivated to foreclose the future, correlation contains within it the seeds of manipulation, segregation and misrepresentation.

REDISCOVERING OUR EUGENIC FUTURE

British eugenicists developed correlation and linear regression, key to machine learning, data analytics, and the five-factor OCEAN model, at least a century before the advent of big data. Although methods for linking two variables preceded his work, Francis Galton is widely celebrated for “discovering” correlation and linear regression, which he first called “linear reversion.” Second cousin of Charles Darwin, Galton is also considered the progenitor of the five-factor model and the “father” of eugenics, which, in Karl Pearson’s paraphrase, he defined as “the science of improving stock, not only by judicious mating, but by all the influences which give the more suitable strains a better chance” and which Galton agreed in a Cambridge lecture was “the study of those agencies which under social control may improve or impair the racial qualities of future generations, either physically or mentally.”⁵⁴ Correlation was key to “proving” that these agencies were natural rather than social. Correlation was never simply about discovering similarities, but also about cultivating physical similarities in order to control the future. Correlation provided the basis for eugenics’ “universal laws.”

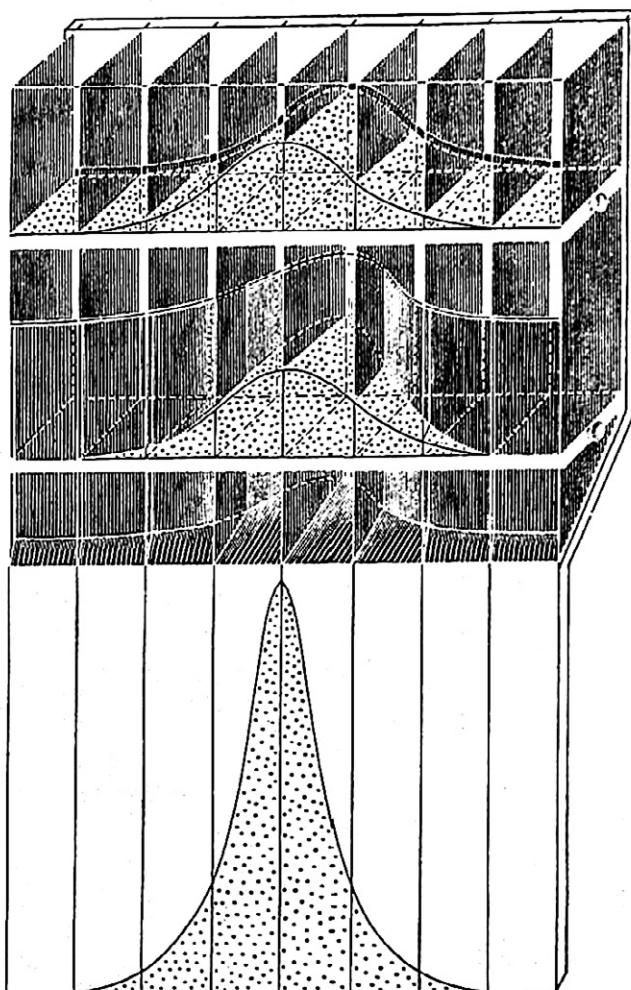
As Ruth Cowan and other historians of science have shown, Galton developed regression and correlation while studying heredity in humans and plants and the identification of criminals.⁵⁵ His fascination with the inheritance (or not) of genius (based on his undergraduate experiences at Cambridge University with the offspring of various famous families)



18 Galton's diagram of linear reversion. Karl Pearson, *The Life, Letters and Labours of Francis Galton*, vol. 3a, *Correlation, Personal Identification and Eugenics* (Cambridge: Cambridge University Press, 1930), 9.

moved him to write *Hereditary Genius*, first published in 1869.⁵⁶ Galton developed a “law of inheritance,” expressed as a mathematical formula to quantify the contribution of each generation to the next. He first produced what would become linear regression while studying the variation in size between sweet pea and human parents and their offspring.

Figures 18 and 19 reveal Galton’s overriding concern with deviation in offspring and its transmission to future generations. A biometrician rather than a Mendelian, Galton believed that all traits were distributed along a normal curve within a population, rather than determined by genes.⁵⁷ Exceptions, such as genius, were statistical outliers and thus located at the ends of the curve, in the fourth quartile. Since Galton wanted to preserve

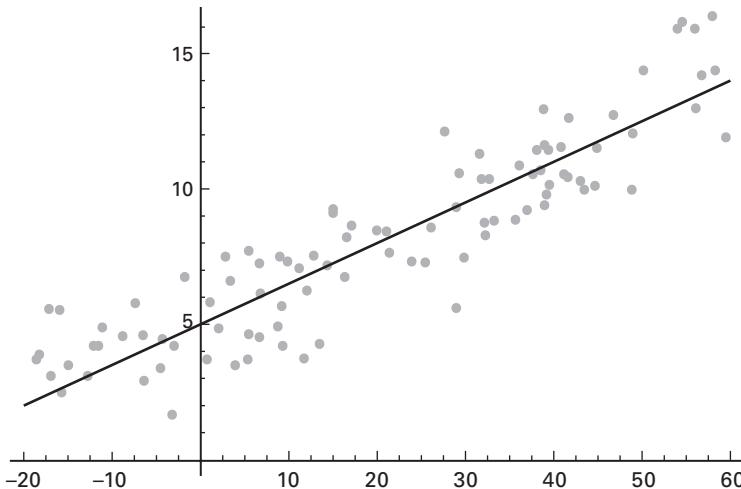


19 Galton's diagram explaining the influence of natural selection on reversion. Karl Pearson, *The Life, Letters, and Labours of Francis Galton*, 3a:10.



20 Francis Galton's "Criminal Composites," c. 1878. Plate XXVII from Karl Pearson, *The Life, Letters and Labours of Francis Galton*, vol. 2, *Researchers of Middle Life* (Cambridge: Cambridge University Press, 1924), 286.

and amplify "good" deviations, his curve tracked how deviations from the norm changed from one generation to the next (figure 18). To explain the effect of natural selection, he employed tubes, which he angled to produce more or less sharp bell curves, and therefore more or fewer outliers (figure 19). According to Galton, his graphs proved that offspring were "reverting" (later, "regressing") to an ancestral mean. He initially thought that only spontaneous deviations ("sports") induced through natural selection, could change the ancestral norm. This notion of a primordial mean also influenced his experiments with photography, in which he overlaid multiple exposures of criminals, alcoholics, and Jewish boys,



21 Standard linear regression, created by Joshua Cameron.

among many others, in order to reveal the archetype embedded within these individuals (figure 20, further discussed in chapter 4).

Galton's linear reversion thus differed significantly from the now standard linear regression. In tracking how generations deviated from the norm, his goal was to maximize "good" deviation. In contrast, linear regression seeks to minimize standard deviations and is most simply expressed by the equation $y = mx + b$, where m is the slope of the line mapping x onto y (figure 21), y is the dependent variable, and x is the independent variable.

In the Kosinski, Stillwell, and Graepel 2013 study discussed earlier, y would be the degree of being an extrovert and x would be a particular SVD component comprised of relevant Facebook Likes (beerpong, Michael Jordan, Dancing were the most highly correlated Likes for extroversion) and m the weight given to that particular component. Linear regression is typically used to determine the best line between a scattered set of points, where "best" means the line that minimizes the distance between the data points and the projected line.

Galton's concept of correlation also emerged from Galton's dispute with French police detective Alphonse Bertillon regarding the best way to identify criminals. As further explained in chapter 4, Bertillon had

developed a system of nine measurements to supplement mug shots. Galton believed that some of Bertillon's nine measurements, such as the length of a person's arm and the length of the person's leg, were linked together and therefore redundant.⁵⁸ To prove these measurements were not independent, he produced a coefficient that linked these variables.⁵⁹ In this version of correlation—a version more commonly used in statistics—correlation is used to cut down on the number of variables involved, not to uncover “hidden” or latent variables.

Galton's facility with mathematics was intuitive, but limited. Tellingly, for example, he used quartiles rather than standard deviations. Karl Pearson made Galton's concepts more mathematically precise. Still in use today, the Pearson correlation coefficient provides a measure from -1 to +1 for a correlation by dividing the product of the variations of two variables by the product of their standard deviations (see “Correlation” by Alex Barnett; figure 17). Pearson updated Galton's law of ancestral heredity by arguing that, although the generations varied linearly, the influence of ancestors on their offspring diminished geometrically,⁶⁰ a conclusion he came to while studying the transmission of physical traits across generations and the differences between twins. Although not convinced that mental traits always corresponded to physical ones (as opposed to Galton, who was infatuated with phrenology and believed that skull size was a proxy for intelligence), Pearson was certain that physical and mental traits followed the same ancestral law. Diminishing skull size thus did not equal diminishing intelligence, but rather skull size and intelligence diminished in an analogous, geometrical fashion.⁶¹

Pearson also believed both natural and artificial selection could easily and continuously affect future generations: the past and future were linked linearly. In contrast, Mendelian eugenicists did not hold such a simple, progressivist view since regressive traits could reappear at any time and thus frustrate phenotype-based breeding. According to Charles Davenport, a U.S. Mendelian contemporary of Pearson's, one “defective” yet fecund individual, such as the infamous Max Juke, could have a profound impact on the population of a nation.⁶² Mendelian eugenicists thus sought to create “pure” bloodlines cleansed of “undesirable” traits, whether dominant or recessive, whereas biometricalians viewed racial or national populations as inherently mixed and intermingled; there was no

“pure” breed, and positive deviations needed to be preserved and disseminated. Eugenicists in both camps, however, held individuals responsible for the future: their behavior could either benefit or destroy the nation.⁶³ And both camps believed that nature triumphed over nurture, making eugenics central to breeding a “better” national future.

The biometricians’ belief in the geometrical law of ancestral heredity made cultivating a “better” future much easier for them than Mendelians. Ominously in light of what was to come decades later, Pearson asserted that correlation helped society move towards a “final solution of almost any social problem,” for it revealed how nature triumphed over nurture, how “selection of parentage is the sole effective process known to science by which a race can continuously progress.”⁶⁴ This conclusion is not surprising given their methodology: biometricians classified all similarities as “hereditary,” and all differences as “environmental.”⁶⁵ Since commonalities outweighed differences, Pearson asserted, “there is no real comparison between nature and nurture; it is essentially the man who makes his environment, and not the environment which makes the man.”⁶⁶ In terms of intelligence, he asserted that although “intelligence could be aided and trained . . . no training or education could create it. It must be bred.”⁶⁷ Programs to alleviate the appalling conditions of working-class Britons and to provide them with educational and medical support were therefore a waste of time and money. Thus Pearson, an avowed socialist, declared: “Give educational facilities to all, limit the hours of labour to eight-a-day—providing leisure to watch two football matches a week—give a minimum wage with free medical advice, and yet you will find that the unemployables, the degenerates and the physical and mental weaklings increase rather than decrease.”⁶⁸ Moreover, by suspending the work of natural selection, these social uplift programs threatened to destroy the English race: through them, the “unfit” multiplied at the expense of the “fit.”⁶⁹ In the nationalist view of biometric eugenics, every citizen was connected: natural and artificial selection operated at the level of the nation-state.

After Nazi Germany was defeated and the horrors of the Holocaust exposed, eugenics seemed to die away or to transform itself into genetics—only to reappear, as many saw it, in the form of genetic tests for birth defects, artificial insemination, and “designer babies.” In the late

twentieth century, historian of biology Nils Roll-Hansen described an “inescapable eugenics,” based on current progress in molecular genetic knowledge,⁷⁰ and sociologist Troy Duster contended that the modern resurgence of biological definitions of race have created a “backdoor to eugenics.”⁷¹ In contrast, sociologist Nikolas Rose argued that, because eugenics focused on the population, not the individual, genetic “improvements” to the individual are not eugenic.

Highlighting the reemergence of biometrics in the twenty-first century, this chapter and book enter this debate, in conversation with work on the resurgence of biometrics by new media researchers such as Jacqueline Wernimont, by asking: To what extent has eugenics reemerged—if it has—not simply or directly through the proliferation of genetic testing and manipulation, but also through biometric methods and predictions?⁷² And how have data analytics and machine learning been used to found a revised form of eugenics, in which discriminatory pasts, presents, and futures coincide? Again, to be clear, I am not claiming that the methods developed by biometric eugenicists are inherently eugenicist. As we will see in later chapters, correlation has been key to developing explanatory global climate change models; it is also mirrored in studies of ideology and ideology critique. Rather, I am asking:

To what extent do the current descriptions of correlation as unlocking the future reflect the twentieth-century celebrations of correlation and its confidence in eugenic solutions?

To what extent can understanding this mirroring help elucidate why and how the world of data analytics and machine learning, based on methods arising from these descriptions, feels so small and enclosed?

And how did a worldview that did not believe learning could happen—that intelligence could only be bred—become the basis for machine learning?

OUR EUGENIC FUTURE, AGAIN

In addition to treating correlation as inherently predictive, there are many similarities between twentieth-century eugenics and twenty-first-century data analytics. Both emphasize data collection and surveillance, especially of impoverished populations; both treat the world as a laboratory; and both promote segregation.

Eugenics and big data depend on surveillance, especially of the poor. Karl Pearson, Francis Galton, and Charles Davenport all argued that the future of eugenics depended on the gathering of national statistics. Since it aimed to show “how much harm is being done by some one course of action, and how much good by some other, and how closely connected social practices are with the future vigour of the nation,”⁷³ eugenics required detailed surveillance of human populations. Eugenicists thus collected data to produce charts documenting the transmission of traits (such as criminality). Their goal was to accumulate the “knowledge” necessary to foster reproduction of the “fit,” as well as to impair that of the “unfit,” either voluntarily or involuntarily. Eugenicists generally studied the poor in order to “save” the middle classes and the rich: by studying the transmission of “negative traits,” the middle classes could learn how to “marry intelligently” and how to segregate themselves from the “unfit.”⁷⁴ The research centers, chairs, and journals founded by these eugenicists—most notably, the Cold Spring Harbor Laboratory, the Galton Chair in National Eugenics (now the Galton Professor of Human Genetics), and the journal *Annals of Eugenics* (now *Annals of Human Genetics*)—still exist, although all now engage primarily in genetics.

Virginia Eubanks has linked twentieth-century eugenics to twenty-first-century data analytics and machine learning through their practices of surveillance. Eugenics she has revealed, “created the first database of the poor,”⁷⁵ and contemporary programs to automate public services programs have given rise to digital poorhouses, all too similar to the physical poorhouses of the nineteenth century, which imprisoned and punished the poor: “Marginalized groups face higher levels of data collection when they access public benefits, walk through highly policed neighborhoods, enter the health-care system, or cross national borders,” in what amounts to “feedback loop[s] of injustice.”⁷⁶ As the Allegheny Family Screening Tool example mentioned earlier illustrates, this data collection—ostensibly designed to help streamline public services—usually makes things more difficult for those these services are supposed to aid and places them under additional surveillance.

Data analytic methodologies, Eubanks warns, are not limited to the poor. As the term “training” implies, once “perfected,” machine learning

programs are meant to be let loose on the general public. As one of her informants cautioned: “Poor women are the test subjects for surveillance technology. . . . You should pay attention to what happens to us. You’re next.”⁷⁷ Analyzing this “progression” in her 2015 study “First They Came for the Poor: Surveillance of Welfare Recipients as an Uncontested Practice,” policy analyst Nathalie Maréchal places Edward Snowden’s leaks and post-911 surveillance next to the systematic infiltration and spying on African American communities, civil rights activists, and antiwar groups throughout the 1950s, 1960s, and early 1970s under the counter-intelligence program (COINTELPRO).⁷⁸ Indeed, the “progression” is part of the historical spread of control technologies: as historian Chandak Sengoopta has shown, fingerprinting started in colonial India as a way for the English to control and distinguish between “the natives,” and the timetable, as visual studies scholar Nicholas Mirzoeff and Black studies and surveillance studies researcher Simone Browne have elaborated, originated on the Southern plantation—to give just two of many instances.⁷⁹ That reactionary publics in the twenty-first century would “draw from” the civil rights movement is thus to be expected, since those fighting for decolonization and civil rights were the first to battle these systems.

Both eugenics and big data use surveillance in order to experiment with humans. Eugenicists drew from the history of animal husbandry and agriculture to justify their goal to breed a better “human crop.” Eugenics began with Francis Galton’s Darwinian realization that humans were a species like all other animals: what applied to other animals and to plants therefore applied to humans. The eugenicists’ insight that nature trumps nurture is said to have emerged from the work of “intelligent farmers and gardeners.” In the words of Francis Galton: “I perceived that the importance ascribed by all intelligent farmers and gardeners to good stock might take a wider range. . . . All serious inquirers into heredity now know that qualities gained by good nourishment and by good education never descend by inheritance, but perish with the individual, whilst inborn qualities are transmitted. It is therefore a waste of labour to try so to improve a poor stock by careful feeding or careful gardening as to place it on a level with a good stock.”⁸⁰ This crop or herd metaphor extended to eugenicists themselves. Responding to critics who accused eugenicists of engaging in unethical experiments, Pearson explained that

eugenicists were not farmers or owners, but “members of the herd.” No one was outside eugenics. Rather than manipulate their fellow humans, they, like medical professionals of “the higher type,” surveilled them to track experiments already in play. Eugenics was possible because humans themselves engaged in reproductive experiments “directly impossible for the eugenicist. This stock marries kin for six generations; those parents surfeit themselves with alcohol; there the tuberculous taint meets insanity; here the man of genius marries into his class; there he takes a woman of the people.” By observing and framing the world in this manner, eugenicists claimed that they were merely forming “an analytical record of . . . the biological laws which govern [a person’s] social development” in order to offer the basis from which “to predict what lines of conduct foster, what lines check national welfare.”⁸¹

Similarly, data and network scientists describe their work as revealing the inner workings of the human psyche via experimentation. Acclaimed network scientist and author Albert-László Barabási has claimed that network science, combined with “increasingly penetrating digital technologies,” places us in “an immense research laboratory that, in size, complexity, and detail, surpasses everything that science has encountered before” and that reveals “the rhythms of life as evidence of a deeper order in human behavior, one that can be explored, predicted, and no doubt exploited.”⁸² If twentieth-century eugenicists however defended their work against accusations that it experimented on humans, twenty-first-century data scientists openly embrace experimentation. Data scientist and journalist Seth Stephens-Davidowitz openly proclaimed in 2017 that big data “allows us to undertake rapid, controlled experiments.”⁸³ These experiments have moved from simple A/B testing to so-called contextual bandits to reinforcement learning: all techniques to “optimize” content based on users’ prior interactions.⁸⁴ Twentieth-century network scientists also emphasized the importance of technology, as do their twenty-first-century successors: digital media accelerate “normal” human experiments by placing them within technologically enriched petri dishes.

Twentieth-century eugenics and twenty-first-century data analytics also both promote or presume segregation. Historians have exposed the strong ties between eugenics and segregation: eugenics was the segregationists’ science, and segregation the eugenicists’ strategy.⁸⁵ Indeed,

eugenicists—and a significant proportion of noneugenicists—supported segregation as a more “humane” alternative to sterilization, which was nonetheless regularly practiced on African Americans and other minorities in the United States without their consent as late as the 1970s in some states.⁸⁶ The forced segregation of the “mentally backward” was the only legislative success of the British eugenicists.⁸⁷ According to eugenicists, the “unfit,” especially those who could physically pass as “fit,” like the “feebleminded,” had to be removed from the general population, and “unfit” males and females had to be kept apart from each other in order to prevent national degeneration.⁸⁸

Segregation was embraced within the United States as a way to counter any possible equalizing and liberating results of the Civil War. As historian Grace Elizabeth Hale has detailed, segregation became the principal post-Civil War strategy to establish a “myth of absolute racial difference.”⁸⁹ Responding to public displays of African American affluence in public spaces such as trains and hotels, segregation reinforced white supremacy by making “race dependent on space.” It sought to contain racial identity and cement inequality so that those “who moved within spaces marked ‘colored’ were African American, and the difference—the inferiority of the black spaces—marked the difference—the inferiority of the black and even ‘almost white’ people.”⁹⁰ Segregation “train[ed] the ground of difference”⁹¹ and, by doing so, sought to create a world in which that difference was accepted and expected. Segregation was, and still is, a training program for racism.

Segregation is also a default within network neighborhoods, in which users are clustered into neighborhoods filled with people “like them.” In networks, similarity breeds connection. Not surprisingly, U.S. residential segregation is regularly used to justify this clustering, and the ties between homophily and U.S. residential segregation, as chapter 2 will show, run deep: the term “homophily” emerged from studies by sociologists Paul Lazarsfeld, Robert K. Merton, Patricia West, and Marie Jahoda on segregated and segregating U.S. housing projects. But homophily is not the only way segregated neighborhoods enter network and data science. Machine learning is filled with “neighborhood” methods used for pattern recognition, such as “K-nearest neighbor,” “K-means testing,” and “support vector machines” (SVMs). The “K-nearest neighbor

algorithm” draws boundaries between data points based on proximity; it presumes that those data points closest to one another geographically or topographically are of the same class. K-means testing similarly uses proximity to intuit the existence of clusters, or neighborhoods. As chapter 4 explains, support vector machines, a high-dimensional method for determining boundaries between data points, are based on the linear discriminant function, developed by statistician and eugenicist Ronald A. Fisher to determine racial and species difference in characteristics such as skull size. Given this, it is not surprising that the “dark secret” revealed by network science is often racism.⁹²

POST-EUGENICS?

The differences between early twentieth-century eugenics and early twenty-first-century data analytics matter. As sociologist Donald MacKenzie notes, modern statistics may have evolved from those of eugenics but both are social and historical products.⁹³ The move from nation to neighborhood, as well as the move from forced segregation to homophily—from discrimination to recognition—changes the equations. The compressed time period (from human generations to user clicks) also alters the ways in which the present, past, and future are now intertwined. Further, with data analytics, minorities are not only surveilled and used to determine algorithmic governance; they are also excluded from certain databases so that, even though they are overrepresented in certain databases, usually having to do with criminal justice, they are underrepresented in others.

What is most significant, however, is that the eugenicist aspiration—the reproduction and selection of like with like—has now become axiomatic. The task before eugenicists was, given “the custom that prevails in America and England of free selection of mates,”⁹⁴ how to make like breed with like. R. A. Fisher similarly focused on enhancing sexual selection in order to produce a eugenic future (see chapter 4). Once homophily becomes the default, however, the task is no longer how to make like breed with like, but rather how to use this “natural” proclivity to predict and shape human behavior. The normalization of homophily in the early twenty-first century is remarkable; indeed, as late as the mid-twentieth century,

it was not a given. As chapter 2 further explains, when Paul Lazarsfeld and Robert Merton coined the term “homophily” (the tendency of like individuals to associate and bond with one another), they also coined the term “heterophily” (the tendency of *unlike* individuals to associate and bond with one another), and they did not presume homophily to be “naturally” present. Rather, they asked: “What are the dynamic processes through which the similarity or opposition of values shapes the formation, maintenance, and disruption of close friendships?”⁹⁵ Homophily in their much-cited yet seldom read 1954 study “Friendship as Social Process” is only one instance of friendship formation.

This normalization of homophily also drives the other major difference between twentieth-century eugenics and twenty-first-century data analytics: the move from the nation to the neighborhood through the notion of individual preference. Again, Nikolas Rose has argued that twenty-first-century genetics is not eugenic because it focuses on the individual and the community, rather than on the nation. Eugenics, he contended, emphasized “the links established between population, quality, territory, nation and race,” exploring the evolutionary fitness of national populations rather than the health of individuals and taking as its territory the nation rather than the “domesticated spaces of family and community.”⁹⁶ In contrast, twenty-first-century biopolitics has focused on managing individual risks, not on mandating racial “cleanliness.”⁹⁷

The move to risk and individuals, as the first part of this chapter—and as the work of Oscar Gandy, among many others, has shown—reinforces and reinscribes racial discrimination. Race is acknowledged as a “boundary” within homophily, and the shift to the individual was itself endorsed by late twentieth- and early twenty-first-century eugenicists. During a 1984 interview—in which Raymond Cattell described working women and taxing the wealthy as “dysgenic,” and called for an end to immigration and for students to be taught how to marry intelligently, that is, eugenically—he also argued that eugenics should be based on the individual. By focusing on the individual, Cattell stressed, eugenicists could avoid becoming “sidetracked into all the emotional upsets that go on in discussions of racial differences.”⁹⁸

The move toward “Sovereign Individuals,” described in the introduction, enables a logic of escape from the nation, which the twentieth-century

eugenicists neither desired nor foresaw. In the world of the biometricians, members of national populations—assumed to be racially homogeneous—were inextricably intertwined: the fate of one person affected that of the others, hence the need to restrict others in order to help oneself. In the world of the “Sovereign Individual,” exit reigns supreme because, in the place of nationalism, there are “communities and allegiances . . . not territorially bounded. Identification . . . [is] precisely targeted to genuine affinities, shared beliefs, shared interests, and shared genes.”⁹⁹ The relationship between individuals and populations still matters, but the relevant group is now the “network neighborhood”—or the homophilic cluster, groupings that are based on kinship and specialized interests rather than on notions of equality.¹⁰⁰

The resurgence and revision of tribal rhetoric—what Jodi Byrd has called “tribal 2.0”—testifies to this shift.¹⁰¹ When Francis Galton and Karl Pearson used the term “tribe,” they used it in relation to “nation” (primitive tribes = primitive nations).¹⁰² Similarly, R. A. Fisher used “tribe”—more particularly, “barbarians”—to describe an ideal past state, in which sexual and natural selection coincided, and to which he thought future British society should aspire.¹⁰³ In the twenty-first-century, data scientists such as Cathy O’Neil underscore behavioral tribes within nation states or larger populations. O’Neil warns “with the relentless growth of e-scores, we’re batched and bucketed according to secret formulas, some of them fed by portfolios loaded with errors. We’re viewed not as individuals but as members of tribes, and we’re stuck with that designation.”¹⁰⁴ Lazarsfeld and Merton drew their terms “homophily” and “heterophily” from Karl Pearson’s work on associative mating and the ethnographic work of anthropologist Bronislaw Malinowski on the “savage Trobrianders.”¹⁰⁵

Although the resurgence of tribal rhetoric, which itself has deeply racial under- and overtones, has not completely undermined national interventions or identity, it has meant that national interventions happen through the functional equivalent of what Antonio Gramsci diagnosed as “hegemony,” albeit formed in reverse. But if “hegemony” once meant the creation of a majority by various minorities accepting a dominant worldview (such as the Greek city-states accepting Athenian values), majorities are now formed by bringing together angry or affectively charged minorities. As the examples of Cambridge Analytica and targeted

political ads reveal, the goal is to produce and maintain small charged clusters, in order to build majority support through “consolidation.”

Neighbors, however, are not neighborhoods, nor do invocations of tribes always have to erase “natives.” Instead, as Leanne Howe has argued, tribalography produces transformative indigenous creation stories that “pull together all the elements of their tribe—meaning the people, land, and characters, and all their manifestations and revelations—and connect these in past, present, and future milieus.” Our task is to follow and amplify these stories—as Howe puts it, “where we go from here is only limited by our imagination.”¹⁰⁶

THE TRANSGRESSIVE HYPOTHESIS

“Being red pilled” and reverse hegemony depend on the transgressive hypothesis: the notion that individual defiance and difference ground freedom. The transgressive hypothesis, which rhymes with philosopher Michel Foucault’s “repressive hypothesis,” goes like this:

For a long time, we supported a mass media regime, whose mind-numbing effects we still feel today. The image of the docile and manipulated mass subject is emblazoned on our anxious individuality.

During the eighteenth century—the age of revolutions—democratic engagement and freedom were still valued, we are told; speech was free and fair. People debated without restrictions in town squares and marketplaces. But this dawn soon became twilight. “Yellow” newspapers contaminated public opinion, feeding “the masses” scandals, rumors, and lies. Outrage fueled profits and wars, such as the Spanish-American War, which was caused partly by Pulitzer’s and Hearst’s battle to dominate the “penny press.”

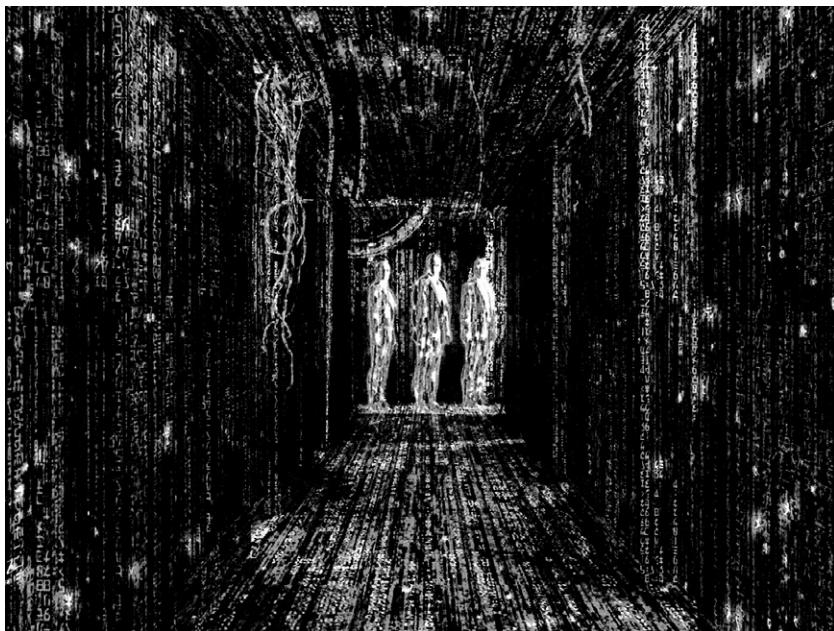
Radio further brainwashed individuals, molding them into masses and laying the ground for Nazism and other totalitarian regimes. These regimes used mass media to propagate conspiracy theories and weaponize the scandalous stories spread by “yellow journalism.” Soon, as philosopher Hannah Arendt relates, the modern masses

no longer believed “in the reality of their own experience” and no longer trusted “their eyes and ears but only their imaginations.” Instead of facts, what convinced them was logically consistent terror, which remade the world in its image through so-called “natural and historic laws” that treated all individuals as indistinguishable nodes.¹ Totalitarianism pressed these atomized, lonely, indifferent, apathetic, and superfluous individuals—set adrift by their lack of common sense, normal human relationships and interests—together into a mass.²

Even democratic societies were not free: U.S President Franklin Roosevelt’s golden voice bred support for world-destroying violence. And television broadcasts and mass production transformed the free world into banal suburbs in which every house, every car, every individual was the same. Mainstream media and political correctness dampened the promise of cable and the Internet to open true debate and a real marketplace of ideas. Instead of emboldened citizen thinkers, there were “normies” everywhere—chained to one another, living 1984 (figures 3 and 4).

If the problem was centralization and corporate control, the solution—we were told—had to be “authentic transgression,” “alternative media”—anything that could build the world anew. Everything “alternative” was “progressive,” from music to schools to community structures. The solutions were what Fred Turner has called a “democratic surround” that fostered individualism and rebellion,³ independent media, and working for yourself. The goal was to reclaim the soap box, the mythic public sphere. To prove that you were free, you had to be “authentic” by “thinking different.” Resist, resist, resist. To transgress—to condemn mass media and mass society, to expose conspiracies and lies—was to be free.

Mainstreamed after World War II in reaction to Nazi eugenics and Stalinism, the transgressive hypothesis equated democracy with nonnormative structures and behaviors—anything but the conformity that supposedly drove totalitarianism. Its enemy was “the herd,” the basis for national eugenics and mass society; its remedies were “thinking different” and new media.



22 Still frame of “seeing the code” from *The Matrix* (Warner Bros., 1999).

But this constant call to be different—this mainstreaming of resistance against repressive norms—far from “automating” democracy has instead fostered populism, paranoia, polarization and the new biometric eugenics. The pervasive distrust of the remnants of “mainstream media” has led to a situation in which thinking for yourself has become the passive act of “being red pilled.” It has supported, rather than taken down, authoritarian figures of power. It has led to a situation that mimics, rather than displaces, the totalitarian world view, in which the visible world is dismissed as fictitious, in favor of a “hidden” authentic universe of “natural and historic laws” as in *The Matrix* (figure 22).⁴

The transgressive hypothesis rhymes with the “repressive hypothesis”: Michel Foucault’s brilliant, influential, and controversial thesis that sex and sexuality have been anything but repressed since the “enlightened” eighteenth century. He explains that censorship regarding sex has not defined modern Western society; there has been instead an imperative to analyze sex endlessly as “the secret”—“a regulated and polymorphous incitement to discourse.” Sex is the “secret” that is endlessly explored,

talked about, and documented; it establishes “*perpetual spirals and power and pleasure*” through surveillance and resistance. Indeed, the insistence that sex is repressed—against all evidence to the contrary—benefits those who speak openly about sex because it smacks of freedom and rebellion: “If sex is repressed, that is, condemned to prohibition, nonexistence, and silence,” Foucault explains, “then the mere fact that one is speaking about it has the appearance of a deliberate transgression. A person who holds forth in such language places himself to a certain extent outside the reach of power; he upsets established law; he somehow anticipates the coming freedom.”⁵

In a post-AIDS world and in a United States saturated with violence and moral self-interest, media liberation rhymes with sexual liberation. And talking endlessly and openly of media repression smacks of freedom, even as it entraps us within a cat-and-mouse game of capture and resistance, tracking and evasion.

So how did an attempt to “save” humanity from “natural laws” and behaviorism come to reinforce these? How did the diversification of media amplify the cry to liberate ourselves from the “mainstream”?

The answers to these questions lie in the paucity of the promised freedom, the idealization of public space, and the strange “erasure” of hatred that underlies the transgressive hypothesis. Hannah Arendt—who by no means would have seen cyberspace or new media as “the answer” to the problems she outlined—nonetheless ends her masterful *The Origins of Totalitarianism* by praising human action and the promise of “new beginnings.”⁶ Human freedom is, for Arendt, fundamentally linked to “man’s rebirth” that every end in history promises.⁷ But, this freedom of action and speech could not be available to all for it depended on the subjugation of others. The ancient Greek polis enabled heroic competition among equals (male and free citizens) only by categorically excluding and dominating women and slaves. How did you prove you were free? By dominating women and slaves in private, whom you rendered into “tame animals” and whose birth thus portended nothing new.⁸ This subjugation was not accidental but necessary, she argued: there could be no freedom without domination and inequality for it ensured that nominally equal systems would not breed masses. In Arendt’s assessment then, the American Revolution succeeded where the French Revolution did

not because the American Revolution did not seek to redress poverty and social inequality—race-based slavery made such compassion impossible.⁹

This vision of an idealized public space, which, as historian Keith Wailoo has pointed out, also undergirds celebrations of “cyberspace,” erases the experiences of women and slaves, who were sold in these marketplaces in the U.S., if not Ancient Greece.¹⁰ As commentators such as philosopher Kathryn Gines, author Ralph Ellison, and political theorist Danielle Allen have pointed out, Arendt’s arguments regarding politics are undermined by her formulations of freedom, politics, and democracy as based in private inequality—as well as by her admittedly naive interpretation of race relations within the United States.¹¹ This freedom that is no freedom justifies subjugation with a history that is no history. As literary critic and African American studies scholar Saidiya Hartman (among many others) has noted, history regularly erases the presence and voices of those whom it oppresses: the archive of slavery is filled with violence, which all too often makes it impossible to “retrieve” the voices and stories of slaves.¹² Terror underlies the “dead certainties” of history.¹³ The subaltern, foundational postcolonial theorist Gayatri Spivak writes, cannot speak.¹⁴ Simply put: it is because Arendt’s view of freedom is so narrow that she seeks “the new” in order to free us from the “shackles” of history.

So what to do?

Crucially, the potential for an antitotalitarian society lies not in the “new,” which is linked to the terror of colonial progress—to the emptying of worlds it renders “new.” To combat this terror, media and cultural theorist Ariella Aïsha Azoulay has proposed a “potential history” that “strives to retrieve, reconstruct, and give an account of diverse worlds that persist despite the historicized limits of our world.”¹⁵ Rather than seeing people as historical “sources,” it enables us to live with them as companions in a world that defies the strict separation of past, present, and future. Potential history is thus a “space wherein violence ought to be reversed, [and] different options that were once eliminated are reactivated as a way of slowing the imperial movement of progress.”¹⁶ Saidiya Hartman has argued for “critical fabulation,” a mode of writing that rearranges the basic elements of a story in order to create a “recombinant narrative.”¹⁷ And though such fabulation can never find the story’s voices, it enables us to see beyond numbers and sources.

What is needed, in other words, is not a rebirth of the “man of action”—or his command to forget in order to control. If we are truly to move beyond our fears and obsession with a freedom that is no freedom—if we are to halt the looming extinction of the majority of humanity in its tracks—we need to engage the richness of what we too easily dismiss as “the past.” If the past and future are similar, it is because they are both unknown—our (re)constructions of them cannot begin to touch their richness. What potential might we find if we were simply to revisit and reimagine what has been dismissed as “training sets”?

2

HOMOPHILY, OR THE SWARMING OF THE SEGREGATED NEIGHBORHOOD

```
if homophily == true
    neighbor := self
    self.love := other.hate
    neighbor.love := self.love
    ethics := narcissism
    society := nul
endif
```

By the early twenty-first century, the imaginary of the Internet had moved decisively from the otherworldly expanse of cyberspace to the domesticated landscape of well-policed, gated “neighborhoods.” This was a progression rather than a transformation: U.S. settler colonialism and enclosure underlay the visions of both neighborhoods and cyberspace. Cyberspace, described as a “portal”—an elaborate façade that frames the entrance to a closed space—was always a horizon trapped within a U.S. military-academic network, a classic example of what information studies scholar Paul Edwards has called a “closed world.”¹ Both visions also painted certain features as “inherent” to the Internet—they simply evaluated them differently. The “decentralized” nature of the World Wide Web and expanded user participation moved from being democracy’s guarantor to being its greatest threat: a breeding ground for insurrections and abuse. In a related development, the “alternative” aspects of Internet culture went from being pseudo-socialist to pseudo-fascist. As social media researcher

Rebecca Lewis has pointed out, the alternative universes of YouTube have established systems of knowledge and authority that both counter and parallel the mainstream sources they have relentlessly critiqued.²

Crucially, the bifurcated reactions to the Internet as embodying or destroying democracy closely parallel mid-twentieth-century responses to mass media. The rise of mass media in the twentieth century, communications studies scholar Elihu Katz and sociologist Paul Lazarsfeld note in their 1955 book *Personal Influence*, engendered two opposite yet interlinked beliefs: (1) that the mass media would “recreate the kind of informed public opinion which characterized the ‘town meeting’”; and (2) that they would destroy democratic society by “rubber-stamp[ing] ideas upon the minds of defenseless readers and listeners.”³ Both these beliefs, they also note, presumed that the audience was an undifferentiated “mass”: messages affected all audience members equally and directly.

So why are we now facing the same questions? And what is different? To answer these questions, this chapter examines the emergence of social networks as a means to dissolve “the masses” into “neighborhoods.” Focusing on the history and theory of homophily, it reveals that echo chambers are not unfortunate errors, but deliberate goals. Homophily is used to create agitated clusters of individuals whose angry similarity and overwhelming attraction to their common object of hatred both repel them from one another and glue them together. Crucially, homophily stems from mid-twentieth-century analyses of white U.S. residents’ attitudes toward biracial public housing. To underscore how homophily both distorts and engineers social relations, this chapter revisits Paul Lazarsfeld and Robert Merton’s foundational and widely cited but seldom read 1954 study “Friendship as Social Process” and the forever forthcoming “Patterns of Social Life” by Robert Merton, Patricia West, and Marie Jahoda on which the chapter was based. Taken together, these studies and their archived traces not only reveal the ties between homophily and segregation but also the complex and ambivalent ways in which we can live together in difference.

MAGNETIZING “THE MASSES”

To decipher the enigma of “the masses,” Katz and Lazarsfeld proposed a “two-step flow” system, which combined diffusion studies (sociologist

Gabriel Tarde's work on "contagion") and decision studies (Lazarsfeld's early work).⁴ In their view, members of the public received information asymmetrically, asynchronously, and selectively: "influentials" or personal biases filtered the flow of information. Therefore, to track the impact of mass media, researchers had first to determine who the "influentials" or "opinion leaders" were: the husbands who shaped their wives' voting choices; the workforce "influentials" who had formed the husbands' views; and so on. But, they stressed, just who these "influentials" were was not immediately apparent or intuitively obvious. In his foreword to *Personal Influence*, pollster Elmo Roper divided the U.S. population into six groups of people: (1) the "Great Thinkers," singular individuals such as Albert Einstein; (2) the dozen or so national "Great Disciples"; (3) the possibly 1,000 "Great Disseminators," such as Senator Joseph McCarthy; (4) the 15,000–50,000 "Lesser Disseminators," such as local labor leaders; (5) the 10–25 million "Participating Citizens," who voted regularly, contributed to campaigns and wrote to their representatives; and (6) the vast majority of Americans whom he labeled the "Politically Inert."⁵ To discover the opinion leaders, Katz and Lazarsfeld developed a program to reveal vertical flows within seemingly horizontal systems, drawing from their focused interviews on fashion and consumption with a group of Decatur housewives and their reanalyses of other group studies.⁶

Change mattered most to Katz and Lazarsfeld: they wanted to measure the effectiveness of "mass media campaigns" to influence—"usually to change—opinions and attitudes in the very short run."⁷ Given this, they acknowledged that their results would differ from those of long-term studies, which emphasized the importance of ideologies. They deliberately used the word "campaign," linking choices in fashion or style to political decisions—decades before Christopher Wylie and Cambridge Analytica did.

Further, Katz and Lazarsfeld argued that these choices were analogous to those made under controlled, laboratory conditions. They compared their findings on socially induced conformity to those of psychologist Muzafer Sherif in his famous "auto-kinetic" effect experiment, where participants altered their assessment of how far a small spot of light moved—they second-guessed their own initial perceptions and experiences—in response to their peers' (manipulated) answers. To those who questioned

the validity of this comparison, they admitted that “Sherif’s experiment can be legitimately generalized only to situations where individuals are (1) forced to make decisions (2) about something they know nothing about and (3) about which they care not at all.” This, however, only buttressed the analogy, for voting in a U.S. presidential election similarly constituted “a situation where social pressures (1) force people to make a decision they would not otherwise make (2) between two candidates about whom they may know nothing and (3) about whom they may care not at all.”⁸ Katz and Lazarsfeld’s analysis insinuated that the problem in a “post-truth” world is not lack of trust, but self-doubt and subsequent group trust; in other words, it is not that people question mainstream media, but rather that, in doing so, they come to trust other, more dubious sources (for more on this, see chapter 4).

Katz and Lazarsfeld drew from the Sherif experiment because they wanted to understand the power of informal groups (“primary groups”), embedded within larger ones, such as the band of “bad” women workers at the Western Electric Factory who were undermining productivity by “having fun”; the U.S. soldiers who stressed the importance of “group allegiance”; the women “with friends” in married student housing who conformed more to the norms of their “primary group” than those without. The researchers’ analyses revealed the centrality of friends and alliances “for mass production, combat morale, class status and mobility, and communications behavior.”⁹ Reflecting in his 2005 introduction to the fiftieth anniversary (Transaction) edition of *Personal Influence*, Katz asserted that their work had shown that the mass media seemed to have no apparent influence on “public opinion,” for ideas slowly penetrated the public through “neighbor on neighbor” interactions. Katz also claimed that their work influenced contemporary network science, in particular its mapping of social connections.¹⁰

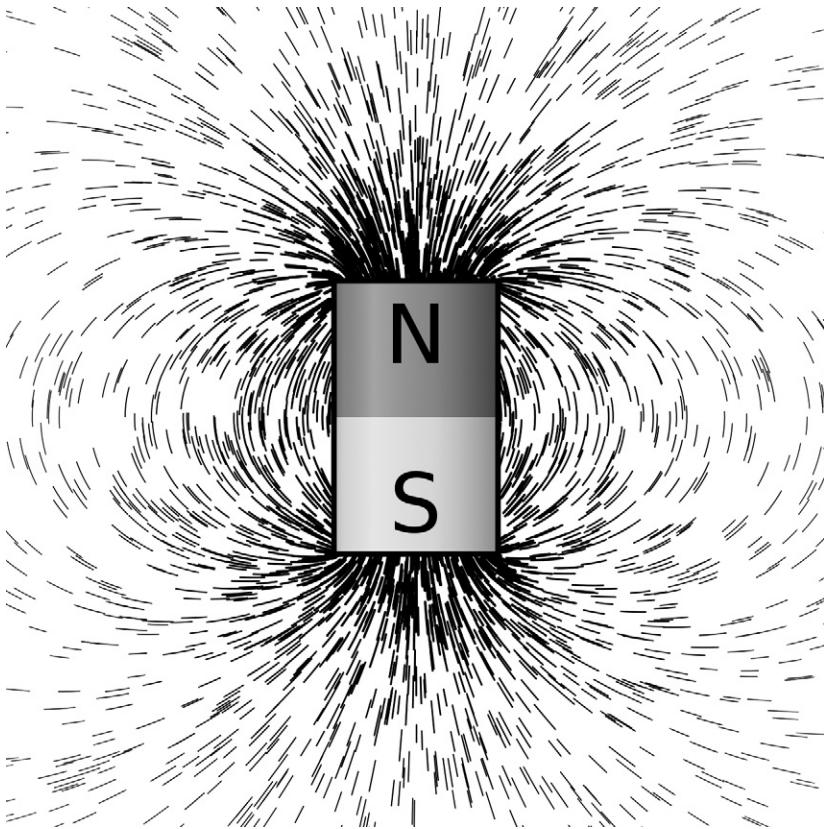
The influence of Katz and Lazarsfeld’s work on network science extends beyond sociometry (the study and measurement of interpersonal relationships within groups of people). Their work amplified moments of change in which the majority, the “Politically Inert,” to use Roper’s term, became unstable and dynamic. Although Roper described the “Politically Inert” as “seldom active in their communities,” generally silent, and “not very much at home in the world of ideas,” he saw this group

as crucial (as did Katz and Lazarsfeld) because “if they are aroused, and enough of them vote, they can determine in a basic sense the political and economic and sociological outlook for some time to come.”¹¹ Every campaign thus sought to awaken—to agitate and polarize—members of this group through “neighbor to neighbor,” influential to inert, engagement. This chapter asks: To what extent has this description become a prescription—a guide to divisively politicize majorities by undermining their ambivalent solidity if not solidarity?¹² To what extent can ambivalence be used to diffuse polarization and provide the basis for democratic political possibility?

The “awakening” of “the masses” depended on polarization—on the creation of “neighborhoods”: it transformed inert nodes into clusters of “charged” elements. This process calls to mind the classic physics demonstration in which a mass of inert iron filings is magnetized—magnetically polarized—and pulled into a clustered network. The similarly polarized filings gathered at either pole repel one another, but they are stuck together by their overwhelming attraction to their opposite pole (figure 23). Sustaining this magnetic polarization in usually nonmagnetic materials requires a magnet or a constant current (figures 24 and 25).

Social media “neighborhoods” are like these clusters of magnetically polarized iron filings, in which similarly polarized filings both repel one another and stick together through their overwhelming attraction to their opposite pole. As feminist and queer theorist Sara Ahmed has argued, to bind together “I’s” into a “threatened” “we,” hatred needs the other.¹³ Remarkably, this hatred is rephrased as “love,” as “homophily”: modern white supremacists, for example, claim not to hate others but to “love” their own.¹⁴ They prove their “love,” however, by hating others, whose world they try to unmake through pain and harm.¹⁵ Indifference, or what Katz and Lazarsfeld and Roper call “inertness,” is the opposite of love and hate.¹⁶ As chapter 4 elucidates, this replacement of hatred with “love” transforms the ethical obligation to love your neighbor as you love yourself into a call to hate your neighbor as you hate yourself. Spaces of sameness thrive on comforting yet repelling rage.

Homophily reveals and creates boundaries within theoretically flat and diffuse social networks; it distinguishes and discriminates between supposedly equal nodes; it is a tool for discovering bias and inequality



23 Representation of magnetically polarized iron filings. Courtesy of Wikimedia Commons, https://commons.wikimedia.org/wiki/File:Ironfilings_cylindermagnet.svg.

and for perpetuating them in the name of “comfort,” predictability, and common sense. Through homophily, network science and data analytics as currently configured inadvertently perpetuate the discrimination they find. So, just what is network science? And how does this “perpetuating” happen?

SOCIAL NETWORKS AND THE SCIENCE OF NEOLIBERAL CONNECTIONS

At the most basic level, network science captures—analyzes, articulates, imposes, instrumentalizes, and elaborates—connection. Coupling graph theory with game theory, it models human interactions in terms of costs,



(Image sourced from Wikimedia Commons)

24 Neighboring chains repel each other as they cling to their opposite pole. Courtesy of Wikimedia Commons.

benefits, and efficiency. It clarifies global phenomena, from capitalism to “contagion,” by reducing the world to individual “nodes” and “edges.” At the same time, it is nonnormative: it does not presume that aggregate action stems from identical mass actions. Further, through notions such as “social capital,” it both explains and can help justify inequalities within supposedly democratizing social networks.

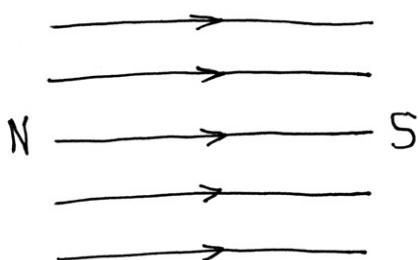
“Network science,” as defined by network scientists Ulrik Brandes and colleagues in the inaugural issue of the journal by the same name, is “the *study of the collection, management, analysis, interpretation, and presentation of relational data*.¹⁷ It responds to the increased globalization of connectivity and capitalism, to “a growing public fascination with the complex ‘connectedness’ of modern society.”¹⁸ It is crucial to mapping and navigating “the connected age”,¹⁹ it mimics what cultural theorist Fredric Jameson once called “cognitive mapping,” for it lifts the fog of postmodernism by revealing the links of individuals to the totality in which they live.²⁰ Postmodernism, according to Jameson, submerged subjects “into a multidimensional set of radically discontinuous realities, whose frames

MAGNETIC POLARIZATION (aka Magnetization)

Here is an unmagnetized lump, say an iron filing: 
How does it respond to an external applied field?

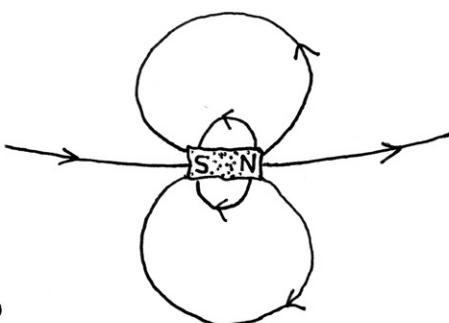
- (a) First let's sketch the applied field without the lump present:

The field lines are uniformly separated, indicating a constant magnetic (\vec{B}) vector field.



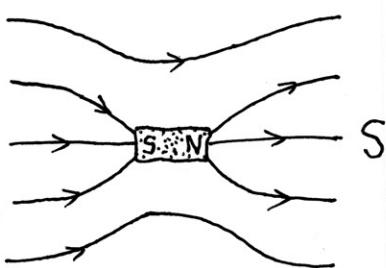
- (b) Here is the extra (new) field induced when the lump is placed in the above applied field:

The lump creates its own North & South poles, and the resulting field pattern is called a "dipole".

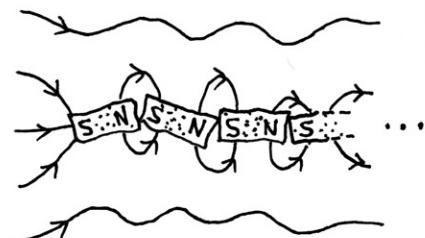


If the applied \vec{B} is not too large, then the lump's magnetization is $\vec{M} = \chi \vec{B}$, where χ is the lump's "susceptibility". χ is huge for iron (a ferromagnet), but small (& sometimes negative) for most other materials.

(c) The total (physical) \vec{B} field is the sum (as vector fields) of the previous two pictures: N S Note the two high-field regions where the field lines come closest together.



(d) Minimizing the energy shows that a 2nd lump would be attracted to these high-field regions, explaining a tendency to "chain together" in the applied field:



(e) Due to microscopic domain flipping, iron usually retains residual magnetization (a weaker version of pattern (b) above), even after removing any applied field. Just like a compass needle, such a lump tends to rotate to align with whatever new field may be applied.

- Each of the above polarization phenomena provides fruitful analogies for humans in the external media environment: we are the ferromagnetic lumps responding to, and modulating, the media magnetic field.

range from the still surviving spaces of bourgeois private life all the way to the unimaginable decentering of global capital itself.”²¹ Because of this, these subjects were—like “the masses” of Hannah Arendt—profoundly disoriented, unable to connect their local experience (authenticity) to global systems (truth). To resolve this situation, Jameson called for cognitive mapping, a yet unimaginable form of socialist art, which corresponded to “an imperative to grow new organs, to expand our sensorium and our body to some new, yet unimaginable, perhaps ultimately impossible, dimensions.”²² Rather than growing new organs, corporate network science resolves this confusion by contracting the world into a map, which only few can access: as elaborated in chapter 3, it produces a mode of “authenticity” shaped to an artificially intelligent truth.

Fundamentally interdisciplinary, network science brings together physics, biology, economics, social psychology, sociology, and anthropology. But, in merging the quantitative social sciences with the physical and computer sciences, it bypasses the qualitative social sciences and humanities, fields also steeped in theories of representation and networks. As mentioned in chapter 1, the leading and insightful social network scientist Albert-László Barabási has claimed that through “increasingly penetrating digital technologies,” network science has created “an immense research laboratory that, in size, complexity, and detail, surpasses everything that science has encountered before.” This laboratory reveals “the rhythms of life as evidence of a deeper order in human behavior, one that can be explored, predicted, and no doubt exploited.”²³ Network science unravels a vast collective unconscious, encased within the fishbowl of digital media—which is why a degree in computer science is now more relevant than one in psychology. As “Correlating Ideology” elucidates after chapter 3, it is arguably the bastard child of psychoanalysis: there are no innocent slips of the tongue. Each action is part of a larger pattern or symptom. The goal is to answer that unanswerable question: What do we/men want?

In attempting to do so, network science reduces real-world phenomena to a series of “nodes” and “edges,” which are, in turn, regenerated to reveal the causes of seemingly disparate behaviors, from friendships to financial crises. These “discovered” relations are vast simplifications of vast simplifications, with each stage of network theory—initial abstraction or representation, followed by mathematical modeling—producing

its own type of abstraction.²⁴ The first stage is “applied” and “epistemological,” Brandes and colleagues explain: it suggests and explicates “for given research domains, how to abstract phenomena into social networks. This includes, for example, what constitutes an individual entity or a relationship, how to conceptualize the strength of a tie, etc.” Most simply, this stage decides what is a “node,” what is an “edge,” and how they should be mapped. The second stage is “pure” network theory, for it deals “with formalized aspects of network representations such as degree distributions, closure, communities, etc., and how they relate to each other. In such pure network science, the corresponding theories are mathematical—theories of networks.”²⁵ This second stage builds models that reproduce the abstractions produced in the first. Whatever repeats the initial mapping is true or causal: truth within these mathematical or logical systems as Arendt points out is consistency (see “The Totalitarian Hypothesis” section preceding this chapter).

This two-stage process highlights the tightrope between empiricism and modeling that network science walks when it simulates abstract representations of the world and asserts that “truth” is what reproduces these abstractions. This two-stage process defines capture systems more generally. As former AI researcher and information studies scholar Philip Agre has shown, capture systems, like those used to track items such as packages and to optimize their delivery, both capture data and dream of making data capture unnecessary by creating models that perfectly mimic their object of study.²⁶

Network science is nonnormative: even as it reduces agents to interchangeable nodes, it does not assume that they all behave identically. Mass conformity does not drive aggregate behavior. Network science connects previously discontinuous scales—the local and global, the micro and the macro—by engaging correlations that were previously “filtered” or controlled for. As Brandes and colleagues further explain, network science differs from other sciences in its positive evaluation of dependency and structure: “Dependencies are not a nuisance but more often than not they constitute the actual research interest.”²⁷ These relations go beyond correlations within actor attribute variables (such as the relation between income and age, or arm and leg length) to encompass the entire set of network variables, which are defined in terms of pairs that are valued

according to whether they are connected. These variables, in turn, affect one another: “The crucial point is that the presence of one tie may influence the presence of another. . . . Without dependence among ties, there is no emergent network structure.”²⁸ At all levels, networks are dynamic and interdependent. What matters is understanding and creating ties.

Modeling these interdependencies—tying global events to individual interactions—entails coupling graph theory with game theory or other agent-based modeling protocols. Economist David Easley’s collaboration with computer scientist Jon Kleinberg exemplifies this fruitful combination. In their canonical 2010 textbook, *Networks, Crowds and Markets*, based on their class at Cornell (which, by 2016, had become a popular EdX MOOC with mathematician and computer scientist Eva Tardos), Easley and Kleinberg argued that two levels of ties were key to understanding networks: “connectedness at the level of structure—who is connected to whom—and . . . connectedness at the level of *behavior*—the fact that each individual’s actions have implicit consequences for the outcomes of everyone in the system.”²⁹ Global concerns impact local decisions, and local effects often only manifest themselves at global scales.³⁰ Network science thus reveals how “macroscopic effects . . . arise from an intricate pattern of localized interactions.”³¹ *Networks, Crowds and Markets* combines graph theory and game theory to explain seemingly “irrational” phenomena such as information cascades.

As the turn to game theory indicates, a market-based logic permeates network science models. Indeed, network science and capture systems are arguably neoliberal “cures” for postmodern ills.³² To be clear, this is neither to blame network science for neoliberalism nor to claim that network scientists are inherently neoliberal, but rather to highlight the fact that many of network science’s insights are intertwined with the economic system they presuppose. Neoliberalism, geographer David Harvey tells us, is “a theory of political economic practices that proposes that human well-being can best be advanced by liberating individual entrepreneurial freedoms and skills within an institutional framework characterized by strong private property rights, free markets, free trade,”³³ a theory that focuses on discourses of empowerment in which the workers own not simply their labor, but also their bodies as a form “human capital.” Although neoliberals, such as the Chicago School economist Milton

Friedman, claim merely to be resuscitating classical liberal economic theory, Michel Foucault stresses that neoliberalism differs from classical liberalism in its stance that “a market economy can in fact serve as the principle, form, and model for a state.”³⁴ Harvey argues that neoliberalism has thrived by creating a general “culture of consent”—even though it has harmed most people economically by fostering profound and widespread income disparities. In particular, it has incorporated progressive 1960s discontent with government, while at the same time dissociating this discontent from its critique of capitalism and corporations.

In a neoliberal society, the market has become an ethics—it has spread everywhere so that all human interactions, from motherhood to education, are discussed as economic “transactions” and assessed in cost-benefit terms. The market, Foucault argues, has become the “grid of intelligibility” for everything.³⁵ Although framed in terms of equality, neoliberalism is based on inequality and “financialized human capital,” political theorist Wendy Brown informs us: “When we are figured as human capital in all that we do and in every venue, equality ceases to be our presumed natural relation with one another.”³⁶

Network science and capture systems more generally spread and amplify this market-based logic. Philip Agre, in his early and prescient analysis of capture systems, revealed that these systems, which exist within a world that “presupposes that the entire world of productive activities can be conceptualized, *a priori*, in terms of extremely numerous episodes of exchanges among economic actors,” extend market relations by commodifying information and reducing the transaction costs of captured human relations.³⁷ Most succinctly: capture systems translate and transform all human interactions into market-based exchanges so that computerization neoliberalizes. The language of “costs”—and the need to lower them—permeates Agre’s analysis and that of network science more generally: from attempts to model collective action and critical mass to those which map differential networking techniques of women and minorities; from those which seek to identify the impact of influential or susceptible members of social networks to those which analyze the “payoffs” of social capital within immigrant networks.³⁸

This market-based logic presumes the existence of “social capital,” a concept sociologist Pierre Bourdieu tied to group membership and

accreditation and one that has, against the spirit of Bourdieu's studies, become crucial to justifying continuing inequalities.³⁹ In the current literature, social capital explains away disparities in success that cannot be accounted for terms of individual "meritocratic" differences in "human capital," such as differences in education and skill. According to sociologist Ronald S. Burt, social capital is a "metaphor about advantage" within a society "viewed as a market in which people exchange all variety of goods and ideas in pursuit of their interests," but in which the "people who do better are somehow better connected. . . . Holding a certain position in the structure of . . . exchanges can be an asset in its own right. That asset is social capital, in essence, a concept of location effects in differentiated markets."⁴⁰ As a relational form of capital, social capital grants advantage to those who are "somehow better connected" and invest in social relations; it thrives off "trust," obligation—and location, location, location.

Sociologists Marion Fourcade and Kieran Healy have refined the notion of social capital through their concept of "über-capital," a form of capital tied to "one's position and trajectory according to various scoring, grading, and ranking methods."⁴¹ Personalized credit scores, which are used by employers or landlords as a proxy for an applicant's "trustworthiness," exemplify this concept. The term "über" denotes "the meta-, generalized, or transcendent, nature of this capital . . . The term *über* also connotes something or someone who is extraordinary, who stands above the world and others."⁴² Über-capital and the "Sovereign Individual," discussed in the introduction, coincide. This form of capital categorizes consumers based on their "habits" in order to make "good matches" between products and consumers. Since the categories employed by corporations do not explicitly reference race, gender, or class (they are based on actions or relations rather than "immutable" traits), individual consumers supposedly all get what they deserve.⁴³ Given this, individualized evaluation "by various forms of predictive analytics becomes harder to contest politically, even though it continues to work as a powerful agent of symbolic and material stratification"; über-capital thus "subsumes unlucky circumstance and uncaring social structure into morally evaluable behavior."⁴⁴ In other words, through habits—shards of others encased within the self—über-capital launders group advantage.⁴⁵

Crucially, network science and capture systems reshape the activities they model or “discover.”⁴⁶ Through a metaphor of human activity as language, they impose a normative “grammar of action” as they move from analyzing captured data to building an ontological model of the captured activity. As mentioned in the introduction, the Chicago police’s heat list did not result in a reduction of homicides, but rather in subjects on the list being “2.88 times more likely than their matched counterparts to be arrested for a shooting.”⁴⁷ The list may also have led to more homicides: those contacted by the police were afraid of being perceived as “snitches” by their neighbors.⁴⁸ Social networks create and spawn the reality they imagine; they become self-fulfilling prophecies.⁴⁹ Based on efficiency, they, like all systems governed by the performativity principle, bypass questions of justice.⁵⁰ They reduce public life to “problem solving and program implementation, a casting that brackets or eliminates politics, conflict, and deliberation about common values or ends.”⁵¹ Contemporary network science, as this chapter goes on to explain, valorizes consensus, balance, and “comfort.”

By implicitly validating segregation as a personal choice and by erasing institutional and economic constraints, network science inadvertently furthers racist agendas. It buttresses neoliberal and Sovereign Individual plans to destroy society by proliferating segregated neighborhoods. Networks preempt and predict by correlating singular actions to larger collective habitual patterns. If, as Barabási argues, “in order to predict the future, you first need to know the past” and if information technologies have made uncovering the past far easier than before, they have done so not simply through individual surveillance but also through homophily, the mechanism by which individuals are “stuck together” so that an affectively intense “we” can emerge. Homophily is crucial to what Sara Ahmed has diagnosed as “the cultural politics of emotion”: a circulation of emotions as a form of capital.⁵²

HOMOPHILY: LAUNDERING “OUR” PAST

At the heart of social media networks lies the axiomatic principle of homophily: that “similarity breeds connection.”⁵³ Homophily structures networks by creating clusters; in doing so, it makes them searchable and

predictable.⁵⁴ But, more important, as a “commonsense” concept that slips between cause and effect, homophily assumes and creates segregation. It transforms individuals into “neighbors” who naturally want to live with people “like them”; it introduces normativity within a supposedly nonnormative system by presuming that consensus stems from similarity; and it makes segregation the default. In valorizing “voluntary” actions, it erases historical contingencies, institutional discrimination, and economic realities. At its worst, it serves to justify the inequality it maps, by relabeling hate as “love.” When homophily, rather than racism or sexism, becomes the source of inequality, injustice becomes “natural” or “ecological,” and conflicting opinions, cross-racial relationships, ambivalence, and even heterosexuality become anomalies.

According to sociologists Miller McPherson, Lynn Smith-Lovin, and James Cook in their definitive 2001 review of homophily, “the homophily principle . . . structures network ties of every type, including marriage, friendship, work, advice, support, information transfer, exchange, co-membership, and other types of relationship.” As a result, “people’s personal networks are homogeneous with regard to many sociodemographic, behavioral, and intrapersonal characteristics.” Rather than framing homophily as historically contingent, they portray it as natural and timeless: indeed, they start their review with quotations from Aristotle and Plato about how similarity determines friendship and love (which they admit, in a footnote, may be misleading since Aristotle and Plato also claimed that opposites attract). As McPherson, Smith-Lovin, and Cook see it, homophily is both the result of and a factor in “human ecology.”⁵⁵

Homophily sits at the fold between social network structure and individual agency. McPherson, Smith-Lovin, and Cook break down homophily into “baseline homophily” (“homophily effects that are created by the demography of the potential tie pool”) and “inbreeding homophily” (“homophily measured as explicitly over and above the opportunity set”), as well as into Lazarsfeld and Merton’s categories of “status homophily” (based on “the major sociodemographic dimensions that stratify society—ascrived characteristics like race, ethnicity, sex, or age, and acquired characteristics like religion, education, occupation, or behavior patterns”) and of “value homophily” (based on “the wide variety of internal states presumed to shape our orientation toward future behavior”).⁵⁶ In their review, the three authors note that race and ethnicity are “clearly the

biggest divide in social networks today in the United States,”⁵⁷ a divide due both to baseline and inbreeding homophily. They list the following as causes of homophily: geography (“the most basic source of homophily is space”); family ties; organizational foci: occupational, family, and informal roles; cognitive processes; and selective tie dissolutions.⁵⁸ Remarkably missing from their list are personal or institutional racism and discrimination, economics and history. In the world of networks, “love,” not hate, drives segregation, even though “proof” of this “love” is the repelling of others.

Given that the very notion of homophily emerges from studies of segregation, the “discovery” of race as the most divisive factor is hardly surprising. As examined in greater detail later in this chapter, Lazarsfeld and Merton’s 1954 study “Friendship as Social Process” analyzed friendship patterns within two housing projects: “Crafttown, a project of some seven hundred [white] families in New Jersey, and Hilltown, a bi-racial, low-rent project of about eight hundred families in western Pennsylvania.”⁵⁹ They studied these housing projects in the mid- to late 1940s and interviewed one member of almost every household using a lengthy questionnaire. As mentioned previously, they did not assume homophily to be a grounding principle, nor did they find homophily to be “naturally” occurring; rather, they asked: “What are the dynamic processes through which the similarity or opposition of values shapes the formation, maintenance, and disruption of close friendships?”⁶⁰

In addition to “homophily,” Lazarsfeld and Merton coined the term “heterophily,” friendship based on difference. “Tribal” and sexual selection inspired these terms: in particular, they cited Bronislaw Malinowski’s ethnographic analysis of the “savage Trobrianders whose native idiom at least distinguishes friendships within one’s in-group from friendships outside this social circle” and Karl Pearson’s and physician and eugenicist Havelock Ellis’s work on homogamy and heterogamy.⁶¹ Although ostensibly concerned with friendship patterns, Lazarsfeld and Merton framed their study, which contained both substantive and methodological analyses, as a model for integrating “theoretical statements, empirical data and methodology.”⁶² Written for *Freedom and Control in Modern Society*, a volume to celebrate the life and work of Columbia sociologist Robert MacIver, it paid tribute to MacIver’s interest in the relationship between social processes and cultural values as well as in analytical methods.

Although Lazarsfeld and Merton coined both “homophily” and “heterophily” in “Friendship as Social Process,” they focused almost exclusively on measuring and explaining homophily within Hilltown. Tabulating resident responses to the question “Could you tell me who your three closest friends are (regardless of whether or not they live in Hilltown/Crafttown)?,” they reported that, within each community, the degree of status homophily for close friends varied greatly, “from the almost complete limitation of intimate friendships among those of the same race and sex, to entirely negligible selectivity in terms of educational status.”⁶³ They also observed that the communities differed from each other: “the more cohesive community of Crafttown” consistently exhibited a lower degree status homophily, which when it did occur “was as likely to be in terms of *acquired* statuses—those resulting from the individual’s own choice or achievement.”⁶⁴ This valuation of acquired over ascribed status marked Crafttown as successfully democratic. The residents of Hilltown, in contrast, showed more marked selectivity based on ascribed status. Intriguingly, Lazarsfeld and Merton speculated that this was due to the lack of “overarching community purposes to focus the attention of residents on locally achieved or acquired statuses”; that is, as elaborated later on in this chapter, due to a lack of common crises and purpose.⁶⁵ They hypothesized that value homophily underlay the observed patterns of status homophily.⁶⁶ Value homophily was a “latent” factor that drove “manifest” status homophily.⁶⁷

To buttress this assertion and unpack the relationship between latent value homophily and manifest status homophily in Hilltown, Lazarsfeld and Merton examined and modeled the racial attitudes of Hilltown’s white residents. They analyzed the answers to two questions: “Do you think colored and white people should live together in housing projects?” and “On the whole, do you think that colored and white residents in the Village [Hilltown] get along pretty well, or not so well?” Based on the answers, they divided the white residents into three camps: “liberals,” who “believe that ‘colored and white people should live together in housing projects’ and who support this belief by saying that the two racial groups ‘get along pretty well’ in Hilltown”; “illiberals,” who “maintain that the races should be residentially segregated and who justify this view by claiming that, in Hilltown, where the two races do live in the same

project, they fail to get along"; and "ambivalents," who "believe that the races should not be allowed to live in the same project, even though it must be admitted that they have managed to get along in Hilltown."⁶⁸

Lazarsfeld and Merton ignored the responses of Hilltown's black residents. They removed their answers from their analysis of value homophily because, they argued, there were "too few illiberal or ambivalent Negroes with friends in Hilltown" (notably, there was a similarly small number of "illiberal" whites who chose "illiberal" friends, yet this number was used in their formulation of value homophily). Thus, at the core of value homophily lies racial segregation: an implicit assumption that values do not cross racial borders or, if they do, that this crossing is less significant than consensus or conflict within a race. (The example of Cambridge Analytica's racial segregation discussed in chapter 1 is thus no surprise.) With this exclusion of black resident responses, they claimed that: "liberals" overselect other "liberals" by 43 percent; "illiberals" over-select other "illiberals" by 30 percent; "liberals" underselect "illiberals" as close friends by 53 percent; "illiberals" underselect liberals by 39 percent; and "ambivalents" do not overselect or underselect.⁶⁹ But, as this chapter goes on to elaborate, given the small numbers, the overselection of "illiberals" for other "illiberals" was not, by the research team's own admission, statistically significant.

In order not to be "imprisoned" by facts, Lazarsfeld and Merton also openly speculated. At the outset of sociometry and what would become the quantitative social sciences lay imagined scenarios. The interviews that Lazarsfeld and Merton drew upon were conducted only once. Since they both were interested in friendship as a dynamic social process, this static information seemed to pose an insurmountable challenge.⁷⁰ To overcome the challenge and model the dynamic processes that cause over- and underselection, Lazarsfeld and Merton left "demonstrated fact for acknowledged conjecture" because they could not afford "to become imprisoned in the framework of fact." Specifically, they posited a reward-frustration model, in which "common values make social interaction a rewarding experience, and the gratifying experience promotes the formation of common values."⁷¹ Racial "liberals" and "illiberals" make friends with those who hold the same opinion because they find their encounters to be "doubly rewarding": they get to "express deep-seated feelings," and

they also receive satisfaction from having “these opinions endorsed by others.”⁷² In contrast, “liberals” and “illiberals” avoid each other because their values clash. Lazarsfeld and Merton viewed cross-value friendships as “unstable”: they were presumed to have been formed prior to the revelation of racial attitudes. In this study, racial attitudes are revealed as the “open secret” that determines friendship among white residents.

In these analyses, not only did the responses of black residents and the possibilities of cross-racial solidarity in values disappear, so did the responses of white ambivalents, who made up the largest category of white residents. As in Katz and Lazarsfeld’s *Personal Influence*, the methodological section of “Friendship as Social Process” transformed the “ambivalents”—functionally equivalent to the “politically inert”—into an unstable and temporary category. Lazarsfeld and Merton assumed that the “ambivalents” must become either “liberal” or “illiberal” in order to maintain “equilibrium” or “comfort.” Based on this assumption, they produced logical chains of friendship formation, using hypothetical numbers, which were then categorized and analyzed in terms of speculated states at times 1 and 2 (figure 26).⁷³

The actual data supporting the first part of their analyses were promised but never published: their footnotes alluded to a forever forthcoming report, “Patterns of Social Life” by Robert Merton, Patricia West, and Marie Jahoda.⁷⁴ Footnote 7 reads: “It must be emphasized that such extreme concentration of personal ties within each racial group obtains only for the *most intimate friendships*. (It will be remembered that these data refer to the three *closest friends* of residents.) Short of these most intimate attachments, however, there have developed numerous personal relations across race lines in Hilltown, as will be seen in the complete report, *Patterns of Social Life*.”⁷⁵

In general, Lazarsfeld and Merton’s footnotes in “Friendship as Social Process” are fascinating, for they reveal deletions and hint at possible alternative conclusions. Footnote 14 relays the authors’ decision to exclude responses by black residents and states, “Further detailed statistics will be found in *Patterns of Social Life*; selected summaries of these statistics are sufficient for present purposes.”⁷⁶ Footnote 6 explains that they “did not adopt the familiar sociometric device of asking residents

<i>Time I</i>				<i>Time II</i>		
		F A	F A	F A	F A	
		++	+-	-+	--	
+	++	50	20	10	20	100
+	+-	30	20	0	50	100
-	-+	50	0	40	10	100
-	--	20	10	0	70	100
		150	50	50	150	

(The first symbol in each designation refers to the presence or absence of friendship in the pair; the second to agreement or disagreement.)

26 Table based on hypothetical differences over time, redrawn from Paul Lazarsfeld and Robert K. Merton, "Friendship as Social Process: A Substantive and Methodological Analysis," in *Freedom and Control in Modern Society*, ed. Morroe Berger, Theodore Abel, and Charles Page (New York: Van Nostrand, 1954), 40.

to designate *only* those intimate friends who happened to live in their own community" because, if they had, they would have "diluted" the category of "most intimate friends"⁷⁷ (the dilution of friendship is, of course, a now standard practice in studies of homophily in social media). Crucially, footnote 10 explains that homophily and heterophily are not rooted in the individual: "In neither of these phrases, does the word 'tendency' refer to some propensity assumedly rooted in the individual. It refers, rather, to an observed correlation, positive in the one instance, negative in the other, between designated attributes of friends. In other words, homophily and heterophily are descriptive, not interpretative, concepts."⁷⁸

The qualifications and context provided in "Friendship as Social Process" have been erased in the early twenty-first-century form of network science. Homophily is no longer a problem or a question, but rather a solution. In the move from "representation" to "model," homophily is no longer something to be accounted for, but rather something that

“naturally” accounts for and justifies the persistence of inequality within nominally equal systems. It has become an axiomatic, commonsense principle, thus limiting the scope and possibility of network science.⁷⁹ As David Easley and Jon Kleinberg, two of the most insightful and important scholars working in the field, explain: “One of the most basic notions governing the structure of social networks is *homophily*—the principle that we tend to be similar to our friends.” To make this point, they point to the distribution of “your friends.” “Typically,” they write,

your friends don’t look like a random sample of the underlying population. Viewed collectively, your friends are generally similar to you along racial and ethnic dimensions: they are similar in age; and they are also similar in characteristics that are more or less mutable, including the places they live, their occupations, their levels of affluence, and their interests, beliefs, and opinions. Clearly most of us have specific friendships that cross all these boundaries; but in aggregate, the pervasive fact is that links in a social network tend to connect people who are similar to one another.⁸⁰

Homophily is a “pervasive fact” that governs the structure of social networks. As a form of natural governance, based on assumptions about “comfort” and mutable and immutable characteristics, it provides the basis for network models, which not surprisingly also “discover” segregation—but not racism.⁸¹

Although many researchers like Easley and Kleinberg insist that homophily “is often not an endpoint in itself but rather the starting point for deeper questions,” segregation is what is “discovered”—and justified if homophily is assumed.⁸² The overriding presumption of homophily limits the databases used to model social networks: many studies using these models also draw from the same databases/platforms, such as the National Longitudinal Study of Adolescent Health (Add Health) or Facebook or Myspace, since these sites already track “friendship.” Homophily also accentuates network clustering. Although sometimes considered a structural cause different from homophily, triadic closure also presumes homophilous harmony and consensus. Triadic closure presumes that “if A spends time with both B and C, then there is an increased chance that they will end up knowing each other and potentially becoming friends” in part because “if A is friends with B and C, then it becomes a source of latent stress in these relationships if B and C are not friends with each

other.⁸³ Social networks such as Facebook amplify the effects of “triadic closure” and “social balance.” By revealing the friends of friends—and by insisting that friendships be reciprocal—Facebook makes triadic closure part of its algorithm: it is not simply predictive; it is also prescriptive. As sociologists Andreas Wimmer and Kevin Lewis point out in their 2010 study “Beyond and below Racial Homophily,” Facebook’s demands for reciprocity produce homophilous effects.⁸⁴ Network science posits non-connection as unsustainable—a cause of stress. Conflict or indifference as ties are difficult to perceive or conceive.

Homophily not only erases conflict; it also naturalizes discrimination. Easley and Kleinberg state quite plainly that “one of the most readily perceived effects of homophily is the formation of ethnically and racially homogeneous neighborhoods in cities.”⁸⁵ To explain this, they make use of the Schelling model of segregation, a simulation that maps the movement of two distinct types of agents (Xs and Os) in a grid. The “fundamental constraint driving the model is that each agent wants to have at least some other agents (n) of its own type as neighbors.”⁸⁶ Showing results for their simulation for $n=3$ (so a situation in which an agent is happy to have 3 neighbors that are the same and 5 that are different), Easley and Kleinberg note that spatial segregation still emerges. As they explain:

Segregation does not happen because it has been subtly built into the model: agents are willing to be in the minority, and they could all be satisfied if only we were able to carefully arrange them in an integrated pattern. The problem is that, from a random start, it is very hard for the collection of agents to find such integrated patterns. . . . In the long run, this process tends to cause segregated regions to grow at the expense of more integrated ones. The overall effect is one in which the local preferences of individual agents have produced a global pattern that none of them necessarily intended. . . . The underpinnings of segregation are already present in a system where individuals simply want to avoid being in too extreme a minority in their own local area.⁸⁷

I cite this explanation at length because it reveals the dangers of homophily, which erases not only the history and legacy of race-based slavery within the United States, but also the importance of desegregation to the civil rights movement. There are no random initial conditions. Now illegal property covenants, racist lending laws, orchestrated “blockbusting,” and move-in violence, documented by legal scholar Jeannine Bell in *Hate Thy Neighbor: Move-in Violence and the Persistence of Racial Segregation*

in American Housing, underlie the “initial conditions” found within U.S. neighborhoods.⁸⁸ The desire not to be in a minority—and to move if one is—maps onto white flight, a response to desegregation. Again, repelling others proves “love.” Further, if taken as an explanation for gentrification, homophily portrays the movement of the urban poor to more affordable and often less desirable areas as “voluntary,” rather than as the result of rising rents and taxes. Finally, homophily erases—while at the same time presuming—the desire of some to integrate neighborhoods. If the Schelling model finds that institutions are not to blame for segregation, it is because it effectively ignores institutional actions.

The economist Thomas C. Schelling’s original publication makes explicit this erasure of institutional actions and economics, as well as the centrality of white flight (or “neighborhood tipping”). His now classic paper “Dynamic Models of Segregation,” written while he was a professor at Harvard University’s Kennedy School of Government, was published in 1971, at the height of the civil rights movement and the beginning of forced school desegregation.⁸⁹ Schelling intentionally excludes two main processes of segregation: organized action (it thus does not even mention the history of slavery and legally enforced segregation) and economic segregation, even though he acknowledges that “economic segregation might statistically explain some initial degree of segregation.”⁹⁰ His model, however, has baked in economic motives at all levels. Deliberate analogies to both economics and evolution form the basis for his analysis of what he characterizes as the surprising results of unorganized individual behavior.⁹¹ Schelling uses economic language to explain what he openly terms “discriminatory behavior.”⁹² At the heart of his model lies immutable difference, for it assumes

a population exhaustively divided into two groups; everyone’s membership is permanent and recognizable. Everybody is assumed to care about the color of the people he lives among and able to observe the number of blacks and whites that occupy a piece of territory. Everybody has a particular location at any moment; and everybody is capable of moving if he is dissatisfied with the color mixture where he is. The numbers of blacks and whites, their color preferences, and the sizes of “neighborhoods” will be manipulated.⁹³

These assumptions were and are troubling. They cover over the history of redlining and other government-sanctioned programs that made it

almost impossible for black citizens to buy homes, while helping white citizens do so.⁹⁴ It makes race an immutable and immediately recognizable feature, rendering invisible the effects of efforts to “fix” the fluidity of racial identity within the United States, such as the “one-drop rule,” which formed the basis for segregation in some states and effectively made black and white identity *not* about visible differences.⁹⁵ It presumes that everyone cares about the race of their neighbors and that they can and will move based on this caring relation. Again, homophily maps hate as “love.” How do you show your “love” of the same? By running away when others show up.

If this is so, what to do?

First, we need to remember that performativity does not simply reorganize the world “into line with theory.”⁹⁶ Performative utterances, as Judith Butler and Jacques Derrida have argued, depend on iterability and community.⁹⁷ Butler, in particular, has revealed the inherent mutability of seemingly immutable and stable categories. Gender, she has argued, is “real only to the extent that it is performed.”⁹⁸ “Natural” or “essential” identities are “manufactured through a sustained set of acts, positioned through the gendered stylization of the body . . . what we take to be an ‘internal’ feature of ourselves is one that we anticipate and produce through certain bodily acts, at an extreme, an hallucinatory effect of naturalized gestures.”⁹⁹ These gestures and constant actions are erased or forgotten as they congeal into a pained yet supposedly “comfortable” fixed identity. As Sara Ahmed has provocatively put it: “Regulative norms function in a way as ‘repetitive strain injuries.’”¹⁰⁰

So, what would happen if we engaged, rather than decried, social network performativity? How different could this pantomime called “social networks” be if we created new grammars of action by understanding how our silent—and not so silent—actions register? If we worked together across disciplines to reside again with the communities embedded within these “defaults,” which are so curiously called our “preferences”?

“NEIGHBORHOOD RESERVATIONS”

It is ironic that Paul F. Lazarsfeld and Robert K. Merton’s 1954 “Friendship as Social Process” has become one of the most important citations for

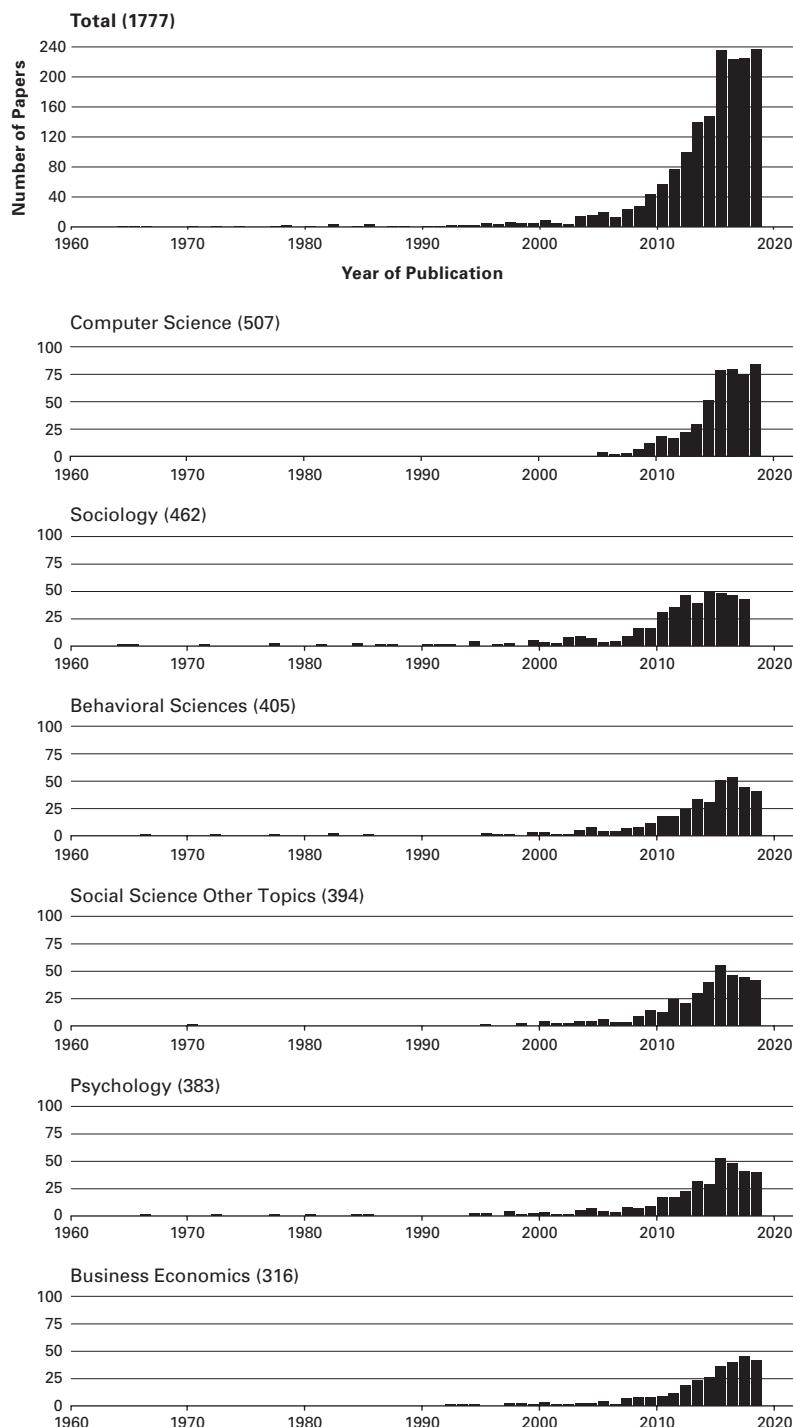
social network homophily when their study describes the question “do birds of a feather actually flock together?” as “egregiously misleading.” It repeats Aristotle’s doubts about the adequacy of the “birds of a feather” concept, and it couples homophily with heterophily.¹⁰¹ Further, the study stresses that homophily is descriptive rather than explanatory, societal rather than individual. Merton signed the 1952 Social Science Statement in the Brown v. Board of Education supporting desegregation, and the never-published 1948 report “Patterns of Social Life” on which he had collaborated with Patricia S. West and Marie Jahoda was used to call into question the “naturalness” and desirability of neighborhood segregation in the 1950s.¹⁰² So how did homophily become axiomatic?

Academic references to homophily increased at the end of the twentieth century and the beginning of the twenty-first. Its canonization coincided with the rise of recommendation engines (“recommenders”) and collaborative filtering. The three disciplines responsible for this marked increase were computer science, sociology, and behavioral sciences (figure 27).

As chapter 3 reveals, homophilic clustering of users into agitated—thus more easily molded—groups provides the basis not only for “personalized” recommendations but also for operationalizing “authenticity,” segregation, and disruption. Those engaged in homophilic clustering deploy social engineering methods developed by analyzing mid-twentieth-century “planned communities,” such as state-sponsored housing, married student housing, and Japanese internment camps. Thus homophily is an “insight” and control mechanism developed, like so many others, by analyzing “dependents.”

To understand homophily and its alternatives, this section revisits the never-published Columbia University’s Bureau of Applied Social Research report “Patterns of Social Life,” written by Robert K. Merton, Patricia S. West, and Marie Jahoda, as well as other pertinent data housed

27 “Homophily” has been the topic of 1,777 academic papers since 1954, most frequently in the fields of computer science, sociology, behavioral sciences, other social sciences, psychology, and business economics. From Laura Kurgan, Dare Brawley, Brian House, Jia Zhang and Wendy Hui Kyong Chun, “Homophily: The Urban History of an Algorithm,” *e-flux architecture*, October 2019, <https://www.e-flux.com/architecture/are-friends-electric/289193/homophily-the-urban-history-of-an-algorithm/>.



in Columbia University's Richard K. Merton and Bureau of Applied Social Research (BASR) archives.¹⁰³ This report, completed in 1948, six years before "Friendship as Social Process," offers glimpses of a past, present, and future that could have been. It brings to the fore neighbors who, following Ariella Aisha Azoulay's brilliant reading of archives as "the common" in *Potential History*, are still with us.

Completed shortly after World War II, at a time of pressing housing shortages within the United States and of record income compression (that is, a time of relative equality in terms of income and wealth), this report used the rubric of "[white] tenant morale" to examine the challenges, possibilities, and limitations facing a U.S. population that overwhelmingly (70 percent) supported low-income public housing.¹⁰⁴ Started in early 1944, the BASR's housing project research intervened into heated and partisan debates over the best solution to the housing shortage: public versus private housing projects; private versus cooperatively owned housing.¹⁰⁵ (Merton, West, and Jahoda's unpublished report never explicitly addressed the difference that collective ownership makes—the prospects of a mixed-race or black-owned co-op were not even entertained.) The results and aftermath of this debate have been well documented. As Richard Rothstein in *The Color of the Law* and Ira Katznelson in *When Affirmative Action Was White* have shown, the subsequent decisive move toward private mortgages for white Americans, insured by the U.S. government and driven in part by the "Red Scare," solidified and augmented an ever-widening income and wealth gap between the races.¹⁰⁶ Tellingly, in 2019, Winfield, New Jersey—the real Craftown—was still operating as a cooperative, with a twenty-five-year-long waiting list to join, and it has consistently rejected the many outside offers to buy up its now exceedingly valuable land.¹⁰⁷

"Patterns of Social Life" analyzed two housing projects, code-named "Craftown" and "Hilltown." As the archives reveal, "Craftown" was Winfield, New Jersey, a cooperatively owned, all-white housing project, (poorly) built during World War II under the short-lived Lanham Act, a New Deal program that developed cooperatively owned housing projects for defense workers who could not afford to assume the financial risk of individual property ownership.¹⁰⁸ Winfield was initially celebrated for its "unique" financial plan, in which the project would "pay for itself" and

thus go against the “discouraging trend of many previous defense housing projects, built under subsidy arrangements, which set rents in proportion to renters’ incomes.”¹⁰⁹ It had a low population density (twenty people per acre) on 110 acres, with 20 acres of woods. It had private lawns and unfenced backyards for all residences and communal playing fields. “Hilltown” was Addison Terrace, a public housing project with a proportionate rent scheme, built by a slum clearance program in the Hill district of Pittsburgh, Pennsylvania, and opened to tenants in 1940. Its population was evenly split between white and black residents, who were divided according to a “checkerboard” plan: residents were racially segregated by terrace and/or building, with the exception of one building, in which they were segregated by floor.¹¹⁰ Although it was chosen because it had roughly the same population as Winfield (800 families in Addison Terrace versus 700 in Winfield), Addison Terrace unfolded over 50 acres and was embedded within a mixed-raced but predominantly black neighborhood.

For their report, Merton, West, Jahoda and their hired researchers asked a member of almost every residential unit more than a hundred questions, during four-hour interviews. As well as recording the residents’ responses, they qualitatively assessed the cleanliness of the units and the attitude of the residents toward the interview; they also mapped the units, as well as foot and vehicle traffic between them. Moreover, members of the research teams lived in each project for a few months.

“Patterns of Social Life” greatly qualified the significance of the later, much-cited findings regarding value homophily in “Friendship as Social Process.” Merton, West, and Jahoda stressed that “if we are to maintain a proper perspective toward these data . . . it is again necessary to press a point to which frequent reference has already been made. These figures on the selection friends are *relative* figures, referring only to *proportionate* underselection or overselection. Yet, the *absolute numbers* of friendships among those of opposed or differing values and attitudes may take on importance for the social life of the community as great or greater than these *relative proportions*.” Thus, by providing only percentages or hypothesized numbers, Lazarsfeld and Merton’s highly cited 1954 study covered over the earlier study’s finding that, because there were so many more white “liberals” than “illiberals” in Hilltown (Addison Terrace), “the

liberals in fact have a larger *number* of friendships with ambivalent residents than do illiberals.”¹¹¹ Further, commenting on friendships between “liberals” and “illiberals,” “illiberals” and “liberals,” and “illiberals” and “illiberals” in Hilltown (Addison Terrace), the 1948 study further disclosed that “observed friendships are fewer than 15 and thus afford too slight a basis for reliable estimates of over- and under-selection.”¹¹² Regardless, relational figures for these relationships were included in “Friendship as Social Process.” The difference in real numbers was extremely small—in the case of the “illiberal” overselection of “illiberals,” there was a difference of 3 friendships: 12 actual friendships versus the 9 expected. The absolute numbers provided in figures 28 and 29 also reveal that the numbers used to disqualify the black population from further study were actually greater than those used to make some of the claims regarding value homophily in the white population: there were 28 “liberal”-“ambivalent” friendships and 22 “ambivalent”-“liberal friendships.”¹¹³

All of these qualifications in the unpublished “Patterns of Social Life” report were lost in the published “Friendship as Process” study, which also did not list as authors West and Jahoda, who, based on documentation in the archive, played leading roles during the fieldwork.

Intriguingly, the unpublished report emphasized not only the absolute number of “liberals” versus “illiberals,” but also the behavior of the “ambivalents”—a group that, as mentioned previously, disappeared in “Friendship as Social Process.” The Merton and BASR archives reveal that the Addison Terrace population as a whole and the white subset were overwhelmingly “ambivalent” or “liberal” (figures 28 and 29): 79 percent of white residents believed that the races get along pretty well. Crucially, the archive reveals that the researchers did not analyze values cross-racially: there are no tables in the archive that group black and white residents together as “liberals,” “illiberals,” or “ambivalents.” Indeed, the responses to most questions are divided into two columns: N and W for “Negro” and “white.” Data collection and analyses almost always presumed racial segregation.

Beyond these numbers, delving into the Merton and BASR archive and the “Patterns of Social Life” report reveals the skeletons of racial or ethnic discrimination and exclusion—both acknowledged and unacknowledged by the researchers of the BASR—that supported their research. Winfield

Question 25 Do you think that colored and white people should live together in housing projects?

	<u>Column 45</u> <u>Single punch</u>	N	W
Yes.....	1	318	109
No.....	2	37	241
DN.....	3	1	1
NA.....	4	1	4

Question 26 On the whole, do you think that colored and white in the Village get along pretty well, or not so well?

	<u>III Column 27</u>	N	W
Get along pretty well.....	0	96% (344)	79% (280)
Don't get along so well.....	x	2% (9)	18% (66)
Don't know.....	y	1% (2)	2% (6)
No answer.....	reject	1% (2)	1% (5)
		(357)	(357)

28 Responses to questions 25 and 26, redrawn from Merton, "Addison Terrace Code-book," 1947, Robert K. Merton papers, 1928–2003, MS 1439, Box 207, folders 10–11, Rare Book and Manuscript Library, Columbia University Library.

became incorporated as a township because the adjoining Clark and Linden townships did not want shipyard workers to "flood" their schools and overwhelm their services (early on, Winfield was quarantined due to a polio outbreak; the surrounding townships also taxed those Winfield parents who sent their children to attend schools there). From the start, a series of crises beset Winfield. Although the residential grounds were spacious and the residences provided more privacy than those in Addison Terrace, the buildings themselves resembled "chicken coops" and were so poorly built that, at first, they were unlivable: they lacked gas, electricity, and running water; their roofs and cellars leaked, which created

Table D-10. Attitude toward "Other Race" (Index)

(Respondent)	HILLTOWN NEGROES			HILLTOWN WHITES		
	Liberal	Ambivalent	Illiberal	Liberal	Ambivalent	Illiberal
<u>Friends</u>						
Liberal	87% (190)	79% (22)	(1)	45% (37)	34% (37)	20% (10)
Ambivalent	13 (28)	21 (6)	---	45 (37)	48 (52)	56 (28)
Illiberal	---	---	---	10 (8)	18 (19)	24 (12)
Total Cases	(218)	(28)	(1)	(82)	(108)	(50)
% in Population	89%	10%	1%	31%	50%	19%

29 "Eureka" moment from PJS, "Table D-10. Attitude toward 'Other Race (Index)," in "Outline Memo on Friendship—Section D: 'Factors Influencing the Selection of Friends,'" July 1948, Robert K. Merton papers, 1928–2003, MS 1439, Box 209, folder 4, Rare Book and Manuscript Library, Columbia University Library.

standing pools of water that bred hordes of mosquitos and rendered the furnaces inoperable; there were no paved sidewalks and the dirt roads were so poorly constructed that every time it rained, mud trapped trucks and cars.¹¹⁴ The first residents, called "pioneers" by Merton, sued the builders and fought relentlessly to bring the houses up to code (the term "pioneers" intriguingly hints at the racial exclusions at the basis of this "workers community"). Winfield cost far more than the initial estimate mentioned in the June 1941 *Time* article "Not for Sale, Not for Rent." Despite and indeed because of these difficulties, Winfield was chosen by the Columbia researchers because it was a "success story," with high democratic participation and degree of integration across religious and ethnic groups: as one resident put it, was a "regular League of Nations."¹¹⁵ It was also heavily supported by labor unions, which at that time also largely supported racial inequalities in the workplace.¹¹⁶

Addison Terrace was chosen nine months after Winfield, almost solely because of its racial makeup: by design, 50 percent of its residents were black and 50 percent were white. The white residents were Catholic, Protestant, and Jewish in almost evenly divided numbers. The overriding concern with race structured the interviews and their reporting: the

race of each interviewee was noted, and the interviewer asked to determine the interviewee's attitudes toward "ethnic problems." The Columbia researchers stated that their study raised and sought to answer the following questions: "Was the absence of overt conflict [between races] a symptom of satisfying or hostile relations? Did the people with previous experience in mixed neighborhoods have a different attitude from those without such experience? Was the amount of tenant participation, noticeably lower than in Craftown [Winfield], related to the biracial composition of the project? Was the impression justified that older people felt more at home in Hilltown [Addison Terrace] than younger ones [did]?"¹¹⁷

For almost all residents, white or black, Addison Terrace represented a substantial physical upgrade. As the director of Addison Terrace put it: "These people were moving into brand new homes and especially for the Negroes that was just fiction. Brand new homes."¹¹⁸ Addison Terrance was composed of groups of three-story apartment buildings, built on three terraces. There were common courtyards in each terrace and communal laundry facilities in the basements of the buildings. Each apartment was equipped with "products of American culture" that most tenants had yet to experience: an indoor bathroom, hot water, a gas stove, and an electric refrigerator. Although biracial, the project was not integrated, and the researchers reported that there was a pervasive "embarrassment in many meetings to get [the] races together," embarrassment, at least on the part of the white residents,¹¹⁹ who were also more temporary residents than their black neighbors. Residents had to move once their income exceeded a certain amount—given discrimination in the workplace and the effective barring of black Americans from federally insured mortgages at the time, white residents cycled through Addison Terrace quickly, whereas black residents stayed put. As one well-educated black woman resident noted: "We would rather have a private house . . . but the zoning laws would keep us from living in private homes in nice neighborhoods. So, this is the best we can do."¹²⁰ Given that Winfield was chosen first as an ideal site and then Addison Terrace added as a point of contrast, it is curious that Addison Terrace—not Winfield—became the focus for the published 1954 study.

Addison Terrace provided the basis for the researchers' findings regarding "tenant morale": through the lens of (white) tenant morale, race

became essential.¹²¹ In his research proposal memorandum to the Lavanberg Foundation for the housing project, Merton argued that tenant morale “*underlies and largely controls every other aspect of life in the housing community.*” It underlay any and all problems: from issues with building and grounds maintenance to group life and democratic organization to tenant-management relations. Why? Because tenants in housing projects had to struggle with the fact that they were living in conditions “at crossroads” with the general U.S. population. These projects grouped people by class; mixed races in the context of equality; put private activities under government control; offered an economic plan for cooperative living; and provided people with physical amenities they could not otherwise afford.¹²² They thus generally disrupted the established status quo (although “normal” neighborhoods also clearly grouped people by class). Due to these factors, the term “project,” they noted, was not neutral: for some, it signified a prized and envied physical and social environment; for others, it signaled their lower economic status and their personal inadequacy.¹²³ The question before each resident was: Is my living in a project a gain or a loss in the eyes of the world?¹²⁴ Specifically, Merton listed the following feelings as essential to the success of any housing project:

1. Feelings of *pride* or *stigma* attached to life in the housing community.
2. Feelings of *transiency* or *permanence*.
3. Feelings of *adequate privacy* or *invasion of privacy* (“home” versus “institution”).
4. Feelings of *regimentation* or of *spontaneity*.
5. Feelings of *identity* with or of *hostility* toward co-dwellers (“belonging” versus “exclusion”).
6. Feelings of *identity* with or of *hostility* toward the larger community (“belonging” versus “exclusion”).
7. Feelings of *confidence* or *anxiety* concerning managerial decisions.
8. Feelings of *adequacy, inadequacy* or *excess* of community life.
9. Feelings of *cramp* or of *comfort* provided by physical environment.
10. Feelings of *passive impotence* or of *active control* over problems confronting the individual group.
11. Feelings of a *growing personality* (new perspective) or of stagnation.¹²⁵

Racism and discrimination were key to determining the valence of these “feelings.” In terms of stigma or pride, Merton explicitly stated in the appendix to his memorandum that some white residents might lose

their self-esteem since parts of the outside communities might condemn mixed-race public housing projects. In contrast, they contended that living in Addison Terrace was a source of pride for black residents and dedicated an entire chapter on its “meaning” for those of the different races living there. Although the physical amenities in Addison Terrace represented a personal gain for all residents, African American residents viewed it as a gain for the race as a whole, for it signaled that the U.S. government was finally committed to closing the yawning gap between the American creed of equality and the reality of inequality.¹²⁶ The three researchers also noted, however, that “equal” public housing could lead to greater discontent, since the passage from equality to inequality could provoke demands for equality in both spheres¹²⁷—that is, good housing could serve as a daily reminder of discrimination in the workplace.

From reading the “Patterns of Social Life” report and related materials in the Merton and BASR archives, it becomes clear that the problem of tenant morale in public housing is almost exclusively—and from the very start—the problem of *white* tenant morale in Addison Terrace. As author Richard Wright declared, there is no “Negro Problem”; there is only a “white problem.”¹²⁸ The claim in “Patterns of Social Life” that Winfield was more successful than Addison Terrace rested on the constant separation of black and white responses, the constant framing of black residents as “exceptions,” and some baffling conclusions refuted by the data gathered.¹²⁹ For example, residents in both projects were politically active. Winfield and Addison Terrace both had much higher voting rates than those of their surrounding communities. In 1944, 84 percent of all residents in the two projects voted; in 1945, 70 percent of those in Addison Terrace and 63 percent of those in Winfield voted.¹³⁰ Further, in Addison Terrace, 55 percent of the black residents, versus 29 percent of the white residents, felt that it mattered “whether or not they have a say in the project”;¹³¹ 70 percent of black residents and 43 percent of white residents felt there was a greater chance to get involved than in their previous place of residence. As the researchers note, “numerically, the proportion of Negroes [in Addison Terrace] aware of the chances the housing project offers and concerned with them is identical with that of Craftowners [Winfield residents].”¹³² Given this, the “problem” or exception would seem to be the white—rather than the black—Addison Terrace residents.¹³³

Merton, West, and Jahoda hypothesized that the low morale of white residents stemmed from the opinions of those (whites) living outside Addison Terrace and Winfield. They contended that society gave “the gift of physical housing, but rob[bed] it of its psychological value” by stigmatizing residents as free-loaders.¹³⁴ (The exception to this rule was the black population in Addison Terrace, who responded with pride to “mainstream” stigma). As one white resident from Addison Terrace told the interviewers: “People think this place ought to be torn down. They don’t like Negroes living on the taxpayers’ money. And I don’t feel so hot when somebody thinks I’m getting away with murder.”¹³⁵ Multiple concessions were made by the public housing board to alleviate the fears of prospective and actual white Addison Terrace residents, such as the racial segregation of buildings. According to one member of the managerial staff, in order to ensure an even racial split, they heard that they would have to give whites “bait. So that [particular] terrace was declared an all-white area. It was a mistake. If it had to be done over again, I’d certainly argue for breaking up that white area and also that Negro area.” The staff member goes on to explain that one building was integrated due to fumigator delays: “There was nothing we could do, we told them [the incoming white residents] they could take the apartments in that building if they wanted to, and they said they would. There’s never been any trouble there.”¹³⁶ This assessment buttressed Merton, West, and Jahoda’s conclusion that spatial proximity and frequency of contact were the most important factors for friendship formation.¹³⁷ Physical segregation thus made cross-racial friendships difficult.¹³⁸ Further, segregation impacted both the present and future friendships: the three researchers correlated the responses to several questions to reveal that previous experience with cross-racial housing was key to white tenant morale.¹³⁹

Crucially, embedded within the “Patterns of Social Life” report and related materials within the Merton and BASR archive are threads that pull at the fabric of the “absolute racial and gendered homophily” narrative. Gender homophily was only “absolute” if couples and family members were invalidated as “close friends.”¹⁴⁰ Further, as they acknowledged, their choice of “three closest friends” regardless of where they lived went against the usual ways for accounting for friendship. (Intriguingly,

Question 42 (Other Race) Have you made any (colored) (white) acquaintances among the Village residents, people whom you know well enough to talk to, but whom you would not call friends?

	III Column 25	N	W
Yes.....	1	285 (81)	220 (62)
No.....	2	68	135
Don't know, No answer....	3	3	3
	<hr/>	<hr/>	<hr/>
	356	358	
	IR	IDP	

30 Acquaintances in Addison Terrace of the other race, redrawn from Merton, "Addison Terrace Codebook."

residents bristled at being asked who their three closest friends were—it was the part of the survey about which they had the most questions.)¹⁴¹

Responses to many of the other questions revealed the extent to which cross-racial contact developed in Hilltown (Addison Terrace). Figure 30 shows that the majority of residents, from both races, had made acquaintances of the other race in Hilltown (Addison Terrace), and figure 31 reveals that the majority of residents from both races had prior acquaintances of the other race. Figure 32 reveals that the majority of black residents (76 percent) and almost a quarter of the white residents (24 percent) had friends of the other race. Further, certain events and clubs, such as bingo nights (which were discontinued due to financial irregularities) and sewing club were integrated.

These figures reveal the constant erasure of ambivalence and “weaker” affects in favor of stronger ones. Through this erasure, a more racially dichotomous situation than actually existed is portrayed. What would have happened if the numbers for friends and acquaintances had been the basis for their analysis, rather than the numbers for three closest friends? What notions of cross-racial homophily would have emerged? What these numbers and the interviews reveal are an “enabling indifference,” which underlay what Merton and Lazarsfeld would call “liberal” attitudes. Black residents, who supported integrated housing, did so because they believed that “everybody’s equal” and should have the same opportunity to live well. As one black woman resident put it, “I would welcome any whites here who wanted to come, but I’m not going to go

Question 12 (b) (Other Race) Since you left school, have you ever had any (colored) (white) friends?

	III <u>Column 7</u>	N	W
<u>Yes</u>	1	271	86
Did you ever visit them in their homes or have them visit in yours?			
Yes.....	2	210	44
No.....	3	56	39
Don't know.....	4	—	—
No answer.....	5	2	—
<u>No</u>			
<u>Don't know</u>	7	—	—
<u>No answer</u>	8	1	1
1 not punched			

31 Friends of the other race, redrawn from Merton, "Addison Terrace Codebook."

Question 12 (Other Race) Since leaving school, have you ever had any (colored) (white) acquaintances, people whom you know well enough to talk to, but whom you would not call friends?

	III <u>Column 7</u>	N	W
Yes.....	9	318	235 (69)
No.....	0	30	118

32 Acquaintances (post-school) of the other race, redrawn from Merton, "Addison Terrace Codebook."

out of my way to get them to come here.”¹⁴² Indifference and ambivalence were not “unstable” categories, but rather modes and means of residing together. They were not problems to be fixed, but rather spaces that grounded communities.

ENGINEERING FRIENDSHIP

Friendship mattered so much in this and the studies that followed it because it revealed the success—or failure—of these housing projects as forms of social engineering. To justify their research, Merton referred not only to the pressing problems of U.S. housing, but also the need to understand and implement “good” social engineering.¹⁴³ In their subsequent report, Merton, West, and Jahoda described public housing projects as “new social worlds,” in which habits were disrupted and formed; they were closed communities, ideal for study and experimentation. They compared the “world laboratory of the sociologist” to that of “the more secluded laboratories of the physicist and chemist.”¹⁴⁴ Not surprisingly, the researchers cited previous studies of Native American reservations, Japanese internment camps, and married student housing apartments.¹⁴⁵ They even called neighborhoods “reservations,” particularly for white working-class women.¹⁴⁶ Like ethnographers studying “primitive people”—hence the “borrowing” of “homophily” and “heterophily” from studies of “savage Trobrianders”—they were keenly aware of the impact their observations could have on these communities and thus sought to minimize their influence.¹⁴⁷

Public housing projects were ideal spaces for experimentation and evaluation because they were fundamentally disruptive. Merton, West, and Jahoda begin their report by acknowledging that a change in environment calls into question the normal relationship between past, present, and future. Moving into a new house is particularly disruptive for those who do because it impacts the “the routine habits of everyday life: the new rooms differ from the old in shape and size, furniture must be shifted to unfamiliar positions, the journey to work is different as is the way to one’s friends and group activities. . . . The neighbors might turn out to be crude or snobbish or just right, which probably means people like oneself. At such times, reluctance and hopeful anticipation mingle

in varied degrees, according to personality and social circumstance.”¹⁴⁸ Moving into a public housing project, they argued, was even more unsettling, since those who did were entering a new social world and gaining a new status. Whether the new residents made friends—or not—thus measured the extent to which these projects were actually engineering new forms of community.

This valorization of disruption, friendship, neighborhoods, social engineering and experimentation connects these early studies of public housing projects to the twenty-first century world of social media with its “new biometric eugenics.” It is no accident that pre-social media studies of homophily focused on schools and that social media sites take the college campus as their architectural and social model. The constant disruption of habits in order to create new friendships and accentuate differences—to transform the “politically inert” or “ambivalents” into agitated partisans—echoes the Columbia researchers’ description of housing projects. The move from “the mass” to the new depends on making the “ambivalent” unstable. It depends on a logic of “authenticity”—of “latent” and “manifest” features—and of “comfortable” spaces of in which “secret” racial attitudes can be revealed. Their “Patterns of Social Life” study, however, also reveals the extent to which other futures could have emerged and still can emerge, not through the suppression of indifference, but rather through its embrace.

PROXIES, OR RECONSTRUCTING THE UNKNOWN

Throughout the preceding pages, we have explored how proxies can serve to buttress—and justify—discrimination. Correlations produce proxies. In statistics and economics, most proxies correspond linearly and associate with hidden or unknown variables. Effectively acting as stand-ins or surrogates, proxies reveal protected categories such as race and gender in seemingly color-blind or agent-based categories such as zip code or “age at first arrest.” According to the *Oxford English Dictionary*, the word “proxy” stems from the classical Latin *procurator*, which means “manager, superintendent, agent, steward, financial administrator of a province, attorney,” but which became, in postclassical times, “proctor in the ecclesiastical courts . . . [and] university official.” Over time, a proxy ensured direct and equivalent substitution, empowering a person to represent and act for another, becoming, in the Christian Church, “an annual payment by incumbents . . . as a substitute for providing for or entertaining a visiting bishop or his representative.”¹ Proxies were thus first human substitutes or agents, then payments given in lieu of services. Proxies, though, seem less independent than agents: they are not supposed to go rogue or take a cut.

As Cathy O’Neil has argued, those building “weapons of math destruction” use proxies to infer behavior they are interested in but cannot directly access: “They draw statistical correlations between a person’s zip

code or language patterns and her potential to pay back a loan or handle a job. These correlations are discriminatory, and some of them are illegal.”² Much effort has been spent exposing proxies that violate the spirit, if not the letter, of antidiscrimination legislation. Without doubt, this is important, but is it enough?

Blaming proxies for race for racist discrimination presumes that racism naturally stems from visible difference—that if we just didn’t track race, racism would disappear. As many studies and the first half of this book have clearly shown, however, it would not, and, indeed, this color-blind presumption—this hopeful ignorance—is dangerous.³ Three questions spring to mind here: How do seemingly race-, gender- and difference-free models perpetuate discrimination? What do the proxies that help them perpetuate discrimination reference and do? And how can we use the results of these models “against the grain,” as evidence of discriminatory practices? Amazon’s AI hiring program, which routinely favored men over women applicants despite comparable résumés, was trained using Amazon’s historical hiring data. How could we use that model to document and understand discriminatory hiring practices within the tech industry?

What would happen if we treated these and other models as we do global climate change models? Climate models predict the most probable future for the world, given past and current actions, not so that we will fatalistically accept the future they predict, but rather so that we will do whatever is needed to prevent that future from occurring.⁴ Being accurate in the narrowest sense of this word—encouraging us to keep producing hydrocarbons so that we verify their predictions—is not the point. When a global climate change model we have good reason to trust predicts a rise of two degrees Celsius in the global temperature, we seek to fix the world, not the model that predicts them—unless, of course, we are global climate change deniers.

This analogy to global climate change models also reveals the limits of models and explanations. Despite overwhelming scientific consensus on and evidence of climate change and its increasingly destructive effects, there has been a decided lack of action. As activists and community members following the comprehensive report on policing discrimination in Ferguson, Missouri, noted, the report “put into written form what so many people have already voiced for years about change that

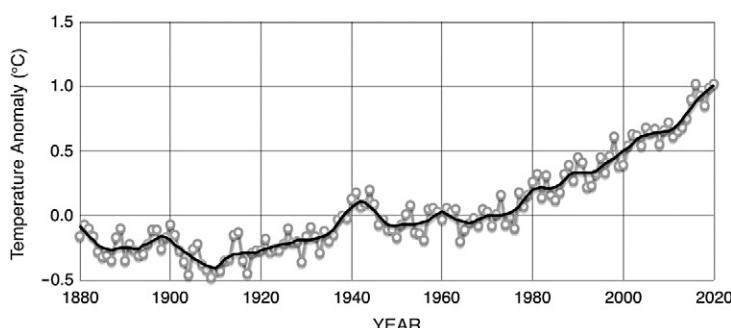
needs to happen in the St. Louis region, but identifying a problem and fixing it are different.”⁵ Further, identifying the obvious can also become an excuse for inaction: Do we really need more models to uncover policing discrimination, which is hardly “undercover”? As for Amazon’s hiring algorithm, for whom is the fact that the tech industry discriminates against women news?

The example of global climate change models also complicates critiques of proxies—it points to their necessity and to the political struggles they inevitably evoke. I therefore place social networking algorithms next to global climate change models to make us pause: to shake loose our normal assumptions and conclusions and, in particular, to make us reconsider blanket critiques of proxies.

VISUALIZING THE REAL

That our early twenty-first-century world has undergone climate change seems indisputable. As NASA pointed out in 2020, nineteen of the warmest years ever recorded have occurred since 2000, and 2016 and 2020 were tied for the warmest years on record (see figure 33).

Given this, that there is any debate about the human impact on global climate change mystifies many, especially those living outside the United States. The challenge, it would appear, lies in bridging the gap between personal experience and global phenomena, in convincing people that something they cannot easily experience—climate—is changing, before it



33 Global Land–Ocean Temperature Index, from NASA: Global Climate Change: Vital Signs of the Planet, <https://climate.nasa.gov/vital-signs/global-temperature>.

is too late. As NASA climatologist Jim Hansen and colleagues put it: “The greatest barrier to public recognition of human-made climate change is probably the natural variability of local climate. How can a person discern long-term climate change, given the notorious variability of local weather and climate from day to day and year to year?”⁶ In 2015, on a cold winter day in Washington, D.C., U.S. Senator Jim Inhofe notoriously offered his fellow senators a snowball as ice-cold evidence that global warming was a hoax.⁷

To visualize what cannot be experienced, climate scientists, journalists, and citizen groups have turned to visual proxies: from photographs of melting icebergs and starving polar bears to scientific graphs of historical temperature increases. These visual proxies serve as stand-ins or representatives for rising global temperatures. But, like all proxies, they are double-edged: the same image can foster both belief and mistrust. *National Geographic*’s “heart-wrenching video [of] a starving polar bear on iceless land” on Summerset Island (figure 34), for example, went viral—sparking outrage over the effects of global climate change.⁸

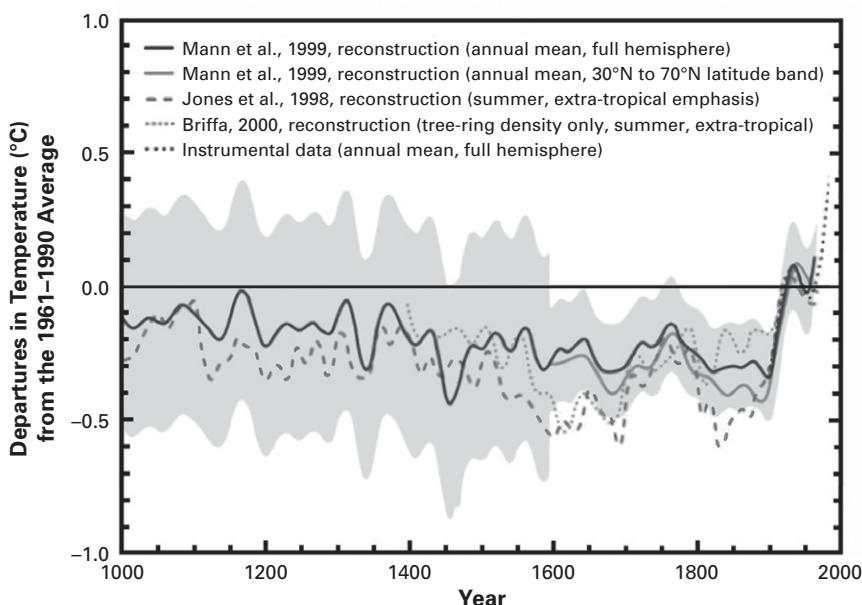
In response, conservative news outlets and questionable wildlife “conservation” sites, such as Polar Bears International, spread competing



34 Still frame from “Heart-Wrenching Video Shows Starving Polar Bear on Iceless Land,” *National Geographic*, December 7, 2017. Footage: Paul Nicklen for SeaLegacy, <https://www.nationalgeographic.com/science/article/polar-bear-starving-arctic-sea-ice-melt-climate-change-spd>.

explanations for the bear's condition and accused SeaLegacy of "tragedy porn."⁹ The more compelling and popular the image, the more controversy, analysis, and conspiracy theories it accretes—and disseminates. Proxies both reduce and introduce uncertainty. By representing the unknown or absent, they evoke the specter of the unknowable.

Perhaps no image has been more controversial in the ongoing climate change debate than Mann, Bradley, and Hughes's "hockey stick" (figure 35). Although charismatic megafauna and dramatic natural settings spark interest and debate, the most influential—and controversial—representation of global climate change has been a line graph. Climatologists Michael Mann, Raymond Bradley, and Malcolm Hughes first published their graph charting changes in mean temperature in the Northern Hemisphere from 1400 to 1995, in *Nature* in 1998; the following year, they published an updated version, which included the period from 1000 to 1998, in *Geophysical Research Letters*.¹⁰



35 "Hockey Stick," redrawn from figure 4.2 in Michael E. Mann, *The Hockey Stick and the Climate Wars: Dispatches from the Front Lines* (New York: Columbia University Press, 2012), 55.

The 2001 Intergovernmental Panel on Climate Change (IPCC) report featured the researchers' 1999 graph in the "Summary for Policymakers" section, and politicians such as President Bill Clinton and Vice President Al Gore used it to reveal the impact of the human burning of fossil fuels on climate. At the same time, the image was attacked both by social scientists and by physicists who were global climate change deniers and whose attacks were picked up by media outlets such as the *Wall Street Journal* and *MIT Technology Review* and by conservative politicians.¹¹ Further, Mann was personally attacked as a proxy for "bad science": he and his family received death threats; his academic records were unsuccessfully subpoenaed by Republican lawmakers, and his emails were hacked as part of "Climate-gate."¹²

How could a simple graph provoke so much anger and controversy?

STICKING TO THE PAST

Given that Mann, Bradley, and Hughes's hockey stick makes no predictions about the future—the last year included in the 1999 graph was 1998—the controversy seems bizarre. The researchers' model would seem to be explanatory rather than predictive. Mann specializes in paleoclimatology: the hockey stick did not predict future climate trends using general circulation models but rather reconstructed past climates using statistical methods and proxy data, such as measurements of tree rings and ice cores. But, as Mann, Bradley, and Hughes noted in their 1998 paper: "Knowing both the spatial and temporal patterns of climate change over the past several centuries remains a key to assessing a possible anthropogenic impact on post-industrial climate."¹³ In other words, the recreated past can reveal the impact of our current use of fossil fuels.

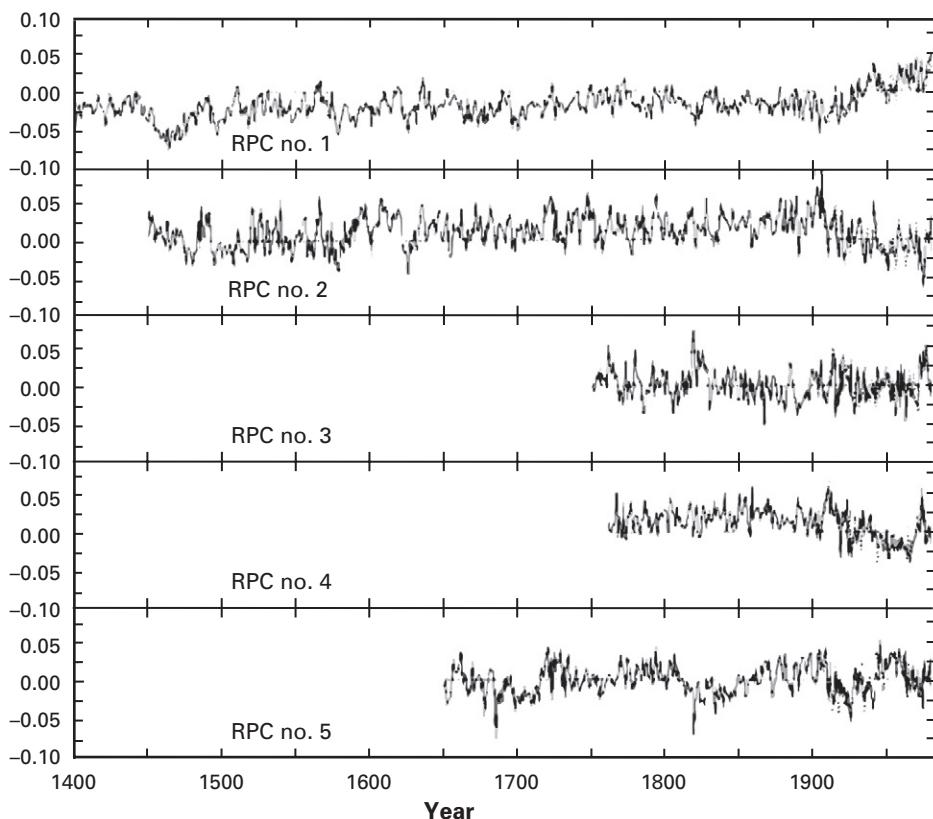
The researchers' 1999 graph was so controversial because it reconstructed the average temperature in the Northern Hemisphere from 1000 to 1400, during the so-called medieval warming period (also called the "medieval climate anomaly"), when parts of Europe, China, Australia, and North America experienced unusually high temperatures. Based on this anomaly, climate change deniers such as Rick Perry, President Donald Trump's first secretary of energy, have claimed that climate change is

mainly caused by the oceans and the natural environment—rather than by humans.¹⁴ The argument goes like this: If the Earth has undergone a similar period of warming in the past, then humans cannot be blamed for the current warming. The hockey stick graph, however, showed that warming during the twentieth century—the blade of the stick—dwarfed any prior temperature increase. Given that the main difference between now and then is the human burning of fossil fuels, humans must be responsible for the far greater rise in the global mean temperature.

The “scientific” attacks on Mann, Bradley, and Hughes focused on their use of proxies and statistical methods. Mann, like paleoclimatologists before him, drew from many different types of proxies for temperature, such as tree ring measurements, ice cores, ice melts, and local weather records, that are unevenly sampled both temporally and spatially. In particular, there is an overwhelming abundance of tree ring data, which represent, as Mann explained in his 2012 book, “only a restricted region of the globe, the midlatitude continents.” Less abundant temperature proxies—data drawn from corals, ice cores, and lake sediments—represent vast regions elsewhere: the poles, oceans, and tropics. If all these temperature proxies were treated equally, “the sheer amount of tree ring data [would] overwhelm the less abundant information from other proxy records . . . [and thus] weight our results toward the midlatitude continents.”¹⁵ To create a “fair fight” between these different proxies, Mann, Bradley, and Hughes used principal component analysis (PCA) and singular value decomposition (SVD), methods previously introduced into meteorology and oceanography by physical scientist Rudolph Preisendorfer.¹⁶ As mentioned in chapter 1 and as will be further elaborated in chapter 4, principal component analysis was originally developed in the early twentieth century by Karl Pearson, a “father” of modern statistics, biometrician, and eugenicist.¹⁷

PCA resolves a set of possibly correlated data points—observations that may include overlapping factors—into a set of linearly uncorrelated orthogonal “principal components” by determining the “eigenvectors” of the correlation matrix (see figures 36 and 37).

In effect, principal component analysis breaks data down into a set of vectors to reveal significant patterns: the first principal component will explain the greatest variation since most of the data lie along that



36 Dominant principal components, redrawn from Michael E. Mann, Raymond S. Bradley, and Malcolm K. Hughes, "Global-Scale Temperature Patterns and Climate Forcing over the Past Six Centuries," *Nature* 392, no. 6678 (1998): 783, figure 5a, https://meteor.geol.iastate.edu/classes/ge515/papers/Mann_et_al_Nature1998.pdf.

component's axis; the second principal component, the next greatest variation; and so on. More simply, principal component and eigenvector analysis recenter data around a new set of axes, which makes mathematical calculations much easier.

Mann, Bradley, and Hughes used principal component analysis in two ways: (1) to "even out" the data spatially; and, more controversially, (2) to determine the leading patterns of variation in their larger data set. Each eigenvector they produced was resolved into both a spatial component—an "empirical orthogonal function"—as well as a principal component over time (figure 38).

PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is probably the most common "dimension reduction" tool in data analysis. As an example we use the Netflix Challenge, a dataset of ratings, on a 1-5 scale, of about 18000 films by 500000 people. Here's how this data table might look:

	film 1 (Ace Ventura)	2 (The Alamo)	3 (Avatar)	...
person 1 (Alice)	4	2	5	...
person 2 (Bob)	1	5	4	..
:	:	:	:	..
M = 500000 rows		N = 18000 columns		

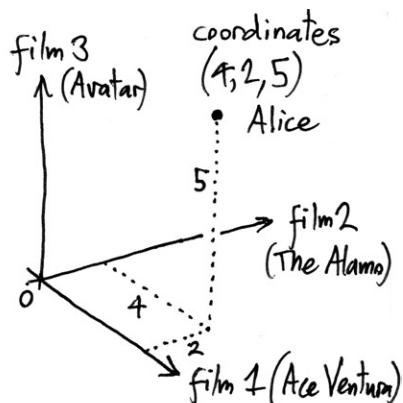
This is a huge matrix, call it A , with entries a_{ij} . i $\xrightarrow{\text{person index}}$ j $\xrightarrow{\text{film index}}$.

To explain PCA, imagine everyone rated every movie, so that A is entirely known. The idea behind PCA is that Alice's high rating for Avatar ($a_{1,3} = 5$) is controlled by an unknown number of "latent" factors that both shape Alice's taste (eg, she likes sci-fi, dislikes violence) and describe films (Avatar is futuristic but nonviolent). Bob's taste differs (he likes sci-fi, but more so violence), "explaining" his higher rating for The Alamo over Avatar.

PCA extracts these factors ("futuristic", "violent", etc), ranking them most to least important, by analyzing the matrix A .

Let's plot all Alice's ratings as a single point in 3D "ratings space":

In fact there's 18000 dimensions, but we can only sketch the first 3!



Now let's add everyone else:

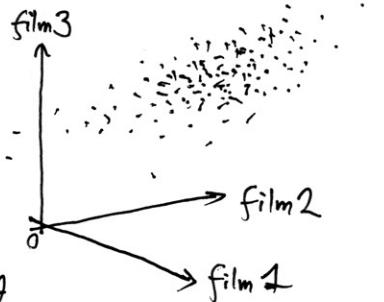
Each row of the table is a point.

This cloud of 500000 points is equivalent to the matrix A .

PCA extracts the crude geometry

of this point cloud: the 1st "principal component" (eigenvector \vec{v}_1) is the cloud's longest axis, ie the factor explaining the most variance in ratings. The 2nd P.C. is the direction, \vec{v}_2 , at right angles to \vec{v}_1 , of most remaining variance, and so on. The hope is that the gross shape of the cloud is captured by a few directions of spread, even though it lives in a huge dimension space.

- A note on mean subtraction: the P.C. vectors \vec{v}_1, \vec{v}_2 are sketched emanating from the cloud's "center of mass" \oplus . This is because Avatar, for example, may have a higher



average rating than other films; this is not a "latent" effect. To remove these film-specific effects, each column of the matrix A has its average subtracted before doing PCA. Geometrically, this shifts the origin from "0" to \oplus , centering the cloud. Likewise, since Alice may be universally more generous than Bob, for example, row means are usually also subtracted.

With that intuitive picture complete, here are the formulae! PCA performs a (partial) "singular value decomposition" (SVD) of A , writing it as the product of 3 matrices:

$$A \approx U \Sigma V^T$$

$$V = \begin{bmatrix} \downarrow & \downarrow & \dots \\ V_1 & V_2 & \dots \end{bmatrix}$$

stack of eigenvectors

K = number of factors

$$\overset{\leftarrow N \rightarrow}{\underset{\leftarrow M \rightarrow}{\boxed{A}}} \approx \begin{bmatrix} \leftarrow N \rightarrow \\ U \end{bmatrix} \begin{bmatrix} \leftarrow K \rightarrow \\ \ddots \end{bmatrix} \begin{bmatrix} \leftarrow N \rightarrow \\ V^T \end{bmatrix} \downarrow K$$

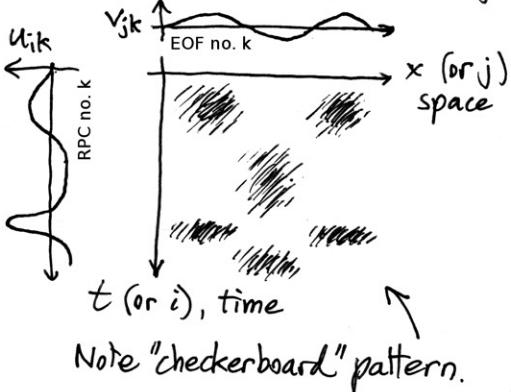
Σ , diagonal matrix with entries $\sigma_1 > \sigma_2 > \dots > \sigma_K$
giving importance of each factor.

Usually K is small (less than a few dozen). PCA builds the best rank- K approximation to the data A .

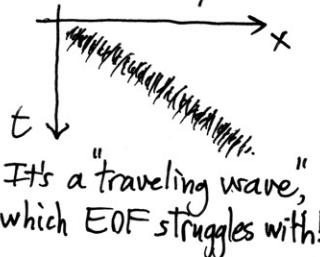
- Connection to "empirical orthogonal functions" (EOF): Replace the film (column) label j by space, and the person (row) label i by time. PCA then extracts, from data such as temperature recorded over space and time, the dominant temperature "modes". This is very common

in geophysical & climate analysis, and called EOF.

Writing the SVD as $a_{ij} \approx \sum_{k=1}^K \sigma_k u_{ik} v_{jk}$, each term is a separable mode, ie a product of a function of space only (v_{jk}), and a function of time only (u_{ik}), like this:



This is a possible mode in EOF.
For contrast, here's a nonseparable function:

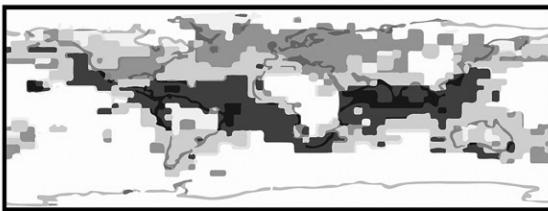


It's a "traveling wave",
which EOF struggles with!

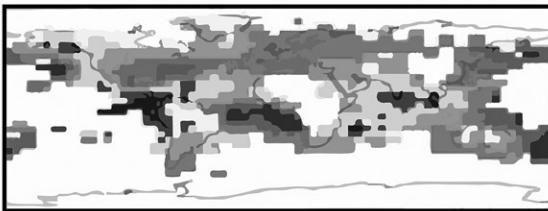
- The Netflix saga :

In fact, only 1% of the entries a_{ij} were known (99% of films were unrated by the average person). This makes the task (a low-rank "matrix completion" problem) a challenge, more than plain PCA. The "training set" of known entries was still huge (100 million entries). The \$1M prize was given in 2009 for the algorithm to first reduce, by 10%, the prediction error on a hidden "test set" of 3 million entries. Latent factor (PCA-based) models played a huge role in successful algorithms, and continue to do so in "collaborative filtering" (online recommendation systems).

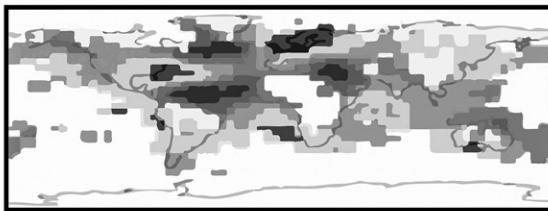
EOF no. 1



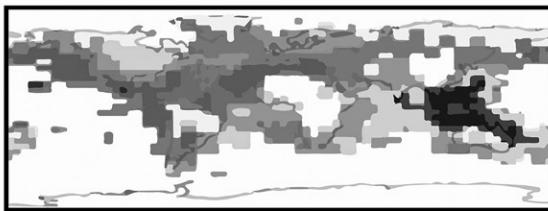
EOF no. 2



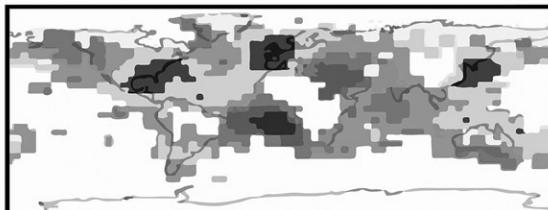
EOF no. 3



EOF no. 4



EOF no. 5



38 Empirical orthogonal functions for the five leading eigenvectors, redrawn from Mann, Bradley, and Hughes, "Global-Scale Temperature Patterns," 780, figure 2, https://meteor.geol.iastate.edu/classes/ge515/papers/Mann_et_al_Nature1998.pdf.

According to Mann, Bradley, and Hughes, the first eigenvector, which described 88 percent of the variability in global mean temperature and 73 percent of the variation in the hemispheric mean temperature, clearly showed a rise in mean temperature during the twentieth century. In contrast, the second showed a modest La Niña-like cooling trend in the eastern tropical Pacific.

The researchers used twentieth-century data to determine these patterns of variation because all proxies were available then. They then calibrated “each of the indicators in the multiproxy data against these empirical eigenvectors at annual-mean resolution during the 1902–80 training period” using singular value decomposition (SVD), which helped produce reconstructed principal components over a longer historical time period.¹⁸ Each principal component was the weighted sum of some or all of the measured variables or proxies: the first principal component might, for instance, weight one proxy by .5, and another by .25. To verify the reconstructed principal components, they tested the components’ predictions against actual data for the periods before the twentieth century (hence the error bars above and below the hockey sticks). They also changed the number of proxies and eigenvectors used during different time periods, since not all proxies were available or pertinent for each eigenvector and time period. The reconstructions from 1820 onward, for instance, used the full multiproxy network of 112 indicators and resolved eleven eigenvectors, whereas the period from 1820 to 1760 used 93 indicators and resolved nine eigenvectors. The number of available proxies and resolved eigenvectors diminished with each time period. Within the five most significant reconstructed principal components they uncovered, the first showed an increase in temperature over time, and the second revealed a slight decrease in temperature, in line with its associated empirical orthogonal function. Through this analysis, they determined that the most important pattern was one of temperature increase in the Northern Hemisphere.

Critics attacked Mann, Bradley, and Hughes for their use of proxies and for their training set. In 2003, two astrophysicists based at the Harvard-Smithsonian Center for Astrophysics, Willie Soon and Sallie Baliunas, argued in the journal *Climate Research* that multiproxy networks were inherently inaccurate: “The results from the proxy indicators cannot

be combined into a hemispheric or global quantitative composite" but should rather be "considered as an ensemble of individual expert opinions";¹⁹ in other words, each individual proxy—each tree ring and ice core, for instance—should be given an equal voice. But the overwhelming amount of the tree ring data from midlatitude areas in Mann, Bradley, and Hughes's papers meant that, in effect, they were only listening to these data, which, not surprisingly, sang of global warming during the medieval period. The Soon and Baliunas paper, however, whose main conclusion was championed by denier politicians like Inhofe, was shown to be riddled with errors, and the peer review process that led to its publication deeply flawed. Indeed, climate scientist Hans von Stroch, chief editor of *Climate Research* and a critic of Mann, Bradley, and Hughes's research, as well as several other editors, resigned in protest.²⁰ In 2005, Canadian businessman Stephen McIntyre and social scientist Ross McKittrick reviewed Mann, Bradley, and Hughes's 1998 study and asserted that the researchers' use of the shorter calibration period guaranteed that any data fed into their model would produce a hockey stick pattern.²¹ McIntyre and McKittrick's paper was also deeply flawed, its results were so different from those of Mann, Bradley, and Hughes because it removed the principal component responsible for warming when they recentered their data around the longer calibration period.²²

A 2006 report from the National Academy of Science validating Mann, Bradley, and Hughes's hockey stick and a 2011 report by physicist Richard Muller at UC Berkeley, a former climate change denier, effectively silenced criticisms of the hockey stick studies. Muller, who had previously referred to McIntyre and McKittrick's paper as a "bombshell" that revealed the bad science behind global climate change research, was himself funded by the Koch brothers to "revisit" the hockey stick.²³ In his 2011 report to the *Wall Street Journal*, however, Muller revealed that, after using "real" data to reconstruct mean temperatures in the Northern Hemisphere, he had found the warming effect to be even more pronounced than Mann, Bradley, and Hughes had suggested. Conceding the point without issuing a direct apology, Muller wrote in the *Wall Street Journal*: "When we began our study, we felt that skeptics had raised legitimate issues, and we didn't know what we'd find. Our results turned out to be close to those published by prior groups. We think that means that those groups had

truly been very careful in their work, despite their inability to convince some skeptics of that. They managed to avoid bias in their data selection, homogenization and other corrections.”²⁴

Muller won a prize from *Foreign Policy* for his about-face—in stark contrast to the death threats and harassment Mann received. Attacked as a proxy for “bad science,” Mann, like Lawrence-Livermore National Laboratory atmospheric scientist Benjamin D. Santer before him, became an example for others in the field of climate change science. Mann called the campaign to isolate and harass certain climate change scientists the “Serengeti strategy,” after the way predators in the Serengeti pick off the most vulnerable prey animals from the rest of “the herd.”²⁵

EMBRACING PROXY POLITICS

Mann, Bradley, and Hughes’s hockey stick and Kosinski and colleagues’ analytic models (described in chapter 1) are similar. In building them, both groups of researchers used matrix decomposition methods; both sought to reconstruct a past and a future; and both struggled with questions of authentication.

Linearity underlies these models: the past and future correspond to each other. As Mann, Bradley, and Hughes note in their 1998 paper, their model makes three fundamental assumptions: (1) “the indicators in our multiproxy trainee network are linearly related to one or more of the instrumental training patterns”; (2) linearity across space and time (sampling in one part of a region represents the larger area); and (3) the spatial patterns of variation of climate within one part of the past century are similar to those during the entire past century.²⁶ These profound assumptions of linearity buttress the researchers’ explanations—they also form the basis for proxies more generally.

Proxies are not inherently “innocent” but neither are they inherently “guilty.” They are central to both understanding global climate change and to creating “weapons of math destruction.” When used to seek the unknown or absent, they introduce uncertainty, even as they serve to reduce it. Proxies are necessary *and* inadequate: indeed, they point to inadequacies in direct knowledge more generally. As historian of science and curator Christoph Rosol has argued, paleoclimatology must use and

negotiate proxies, even though doing so troubles the boundary between data and model.²⁷ Proxies are fundamentally “ambivalent,” and our current politics engages proxies at all levels.²⁸ A proxy embodies what Jacques Derrida called a “pharmakon,” a supplement or intermediary: “a philter, which acts as both remedy and poison.”²⁹ Proxies absolve one of responsibility—a payment in lieu of hospitality—by creating new dependencies and relations. Proxies touch the unknown: they extend the knowable, by capturing or “syncing up with” what is not there. Proxies spark controversy and raise questions about the relations they “uncover.”

Indeed, the parallels between global climate change models and social networking analyses raise the provocative question: How and when do humans become as predictable as trees? They point both to an entire mechanism of “training” needed to shape reality so that humans behave linearly and to a massive data collection network that buttresses this training and is buttressed by it. Perversely, this linearity comes about not through “mass” reproduction of the same, but rather through efforts to automate authenticity.

3

ALGORITHMIC AUTHENTICITY

The 2016 U.S. presidential elections supposedly proved the centrality of authenticity to twenty-first-century politics. Authenticity was the “it” factor that candidates Donald Trump and Bernie Sanders had, and that Hillary Clinton and Jeb Bush lacked.¹ According to a *New York Times*–CBS News poll taken December 4–8, 2015—a period during which Trump led the winnowing field of Republican hopefuls—76 percent of those polled believed that Trump “says what he believes most of the time [rather than] . . . what he thinks people want to hear.”² Sanders had a similarly high figure (62 percent).³ In contrast, Clinton stood at 52 percent and Jeb Bush at 41 percent.⁴ Based on this and other polls, news outlets from the *Atlantic* to *Time* to the *Wall Street Journal* regularly debated Trump’s role as the “authenticity” candidate.⁵

As the question “Does Donald Trump say what he believes most of the time, or does he say what he thinks people want to hear?” implies, authenticity in this political sense entails a person’s vocal disregard for convention: a “subversiveness” that indicates that a person has neither restraints nor filters. As this chapter reveals, the “subversiveness of authenticity” drives predictability by urging users to make their outer and inner selves coincide. The constant call to reveal inner secrets or to transgress against the mainstream dispels ambiguity, heightens affect, and valorizes behavioral transparency. “Recommender” systems and social media platforms,

as well as more mainstream media forms such as reality TV, have operationalized authenticity—the imperative to “be true to oneself”—in order to provoke predictable responses to their prompts. Authenticity however entails drama and participation. We are characters and actors—not marionettes—in the drama we so inadequately call “big data.”⁶

TRUMP IS A TRAINING PROGRAM FOR TRAINING

Trump was said to be “real” because he broke the rules. During his acceptance speech at the 2016 Republican National Convention, Trump told his supporters: “It is finally time for a straightforward assessment of the state of our nation. I will present the facts plainly and honestly. We cannot afford to be so politically correct anymore. So, if you want to hear the corporate spin, the carefully crafted lies, and the media myths, the Democrats are holding their convention next week.”⁷ Trump’s speeches were “authentic” not simply because of their content (which was often misleading or incorrect), but also their style. He regularly spoke in sentence fragments; he encouraged applause with his gestures and laced his pitches with finger-pointing accusations at the press. He commented on his own speeches as he spoke, interjecting “True, so true” after his positive assessment of Mike Pence’s character and importance.⁸ He launched his events with spectacular entrances—such as helicopter landings at state fairs—which were praised by his supporters as “real.” As Keith Koffler put it on the *Lifezette* blog (run in 2016 by the conservative former talk show host Laura Ingraham): “At exactly the moment multimillionairess Hillary Clinton was milling about the fair pretending to be one with the proletariat, Trump was hovering overhead pretending to be nothing but a rich man in his own personal aircraft.”⁹

Exactly.

Koffler’s statement inadvertently revealed the pretension and show at the core of Trump’s wealth. Since Trump’s “empire” was not simply his—the Trump brand was licensed to investors so they could add the name “Trump” to their own properties—he had to constantly enact wealth and power. Trump had to “pretend to be nothing but a rich man in his own personal aircraft” in order to attract consumers and clients, who added

to his shadowy wealth with every purchase and view. Trump's extensive licensing made it hard to calculate his net worth, for his wealth and the widespread display of his name did not correspond. This uncertainty was furthered by Trump's refusal to reveal his tax returns: Was he really worth the 10 billion dollars he claimed, or the 3 billion others such as *Forbes* arrived at?¹⁰

As the election results demonstrated, criticizing Trump's authenticity for being "branded" was hardly effective or profound. This criticism, launched by some of the most trusted brands in the mainstream news media, presumed that artificiality undermined "authenticity." According to this perhaps deliberately naive worldview, the rise of "branded authenticity" and Trump's election proved that the early twenty-first century was "postmodern": an era of simulation in which copies displaced originals; a "post-truth" era dominated by "alternative facts" and emotions that "trumped" truth.¹¹ What could be more inauthentic, after all, than a brand? A product of market research and endless consumer surveys, brands are carefully crafted and unabashedly commercial. They are utterly unoriginal: copies produced—and consumed—*en masse*. Thus the yearning for authenticity in the twenty-first century, as many have noted, seems counterintuitive. Given rampant globalization and digitization—the spread of copies, clones, and fakes—the notion of a genuinely authentic original hardly seems credible. Yet from restaurants that advertise themselves as "authentically" ethnic, to political candidates who claim their "realness" makes them fit to govern, to hipsters who embrace authentic handmade crafts, authenticity reigns supreme. As communications scholar Chandra Mukherji put it, "American popular culture is obsessed with authenticity and awash with artificiality."¹²

According to Mukherji, the present-day quest for authenticity in the United States is no accident—it is driven by the fundamentally artificial immigrant/settler character of American national identity.¹³ Given this, Americans have sought and still seek authenticity by highly artificial means. And this quest is not limited to national identity. Business primers preach authenticity as central to brand success; leadership manuals promote authentic leadership as an antidote to the flaws of "transformational leadership"; social media "self-branders" are told they need to be

authentic if they want to build their audiences; and the adjective “reality” has been attached to a highly scripted form of television programming to convey its “authenticity.”¹⁴

Trump was “real,” as in “reality TV.” Trump’s and his brand’s success was linked to his role as the host and interviewer of *The Apprentice* (and later *The Celebrity Apprentice*), a reality TV show that claimed to be, not a game, but rather a grueling multimonth job interview. Trump’s political campaign eerily mimicked *The Apprentice*: the helicopter landing at the Iowa fair was recognizably “vintage Trump” because it reprised Trump’s attention-grabbing entrances in *The Apprentice* (Trump’s helicopter, as well as his plane and limousine, were all featured prominently in the opening sequences of these shows). The campaign press conferences, which relentlessly promoted Trump’s properties, such as the opening of Trump’s Washington, D.C., hotel, mimicked the infomercials of Trump’s residences and properties embedded within his TV shows (trips to these properties were given as rewards to winning teams).¹⁵ Most significantly, *The Apprentice* and Trump’s presidential bid shared the same premise: Trump the master was looking for “the apprentice”: an indentured servant. If, once hired, you followed Trump—imitated him and obeyed his orders—you, too, would become a rich master. The opener to season one of *The Apprentice*—its most successful season—encapsulated this nicely:

New York. My city. Where the wheels of the global economy never stop turning. A great metropolis of unparalleled strength and purpose that drives the business world. Manhattan is a tough place. This island is the real job. If you’re not careful, it can chew you up and spit you out. But if you work hard, you can make it big—and I mean really big.

My name is Donald Trump, and I’m the largest real estate developer in New York. I have buildings all over the place, modeling agencies, the Miss Universe pageant, golf courses, casinos, resorts like Mar-a-Lago—one of the most spectacular resorts anywhere in the world.

But it wasn’t always so easy. About thirteen years ago I was seriously in trouble. I was billions of dollars in debt. But I fought back and I won, big time. I used my brain, I used my negotiating power, and I worked it all out. Now my empire is bigger than it ever was and stronger than it ever was, and I’m having more fun than I’ve ever had.

I’ve mastered the art of the deal and turned the name Trump into the highest quality brand. And, as the master, I want to pass on my knowledge to somebody else. I’m looking for the apprentice.¹⁶

Trump's election campaign democratized this search for "the apprentice." Anyone and everyone who voted for Trump could become the apprentice and thus learn how to dominate by being temporarily dominated (better to be indentured than enslaved). Rather than shying away from commercial branding, Trump embraced it as evidence of his power. Like his campaign speeches, the season one opener extolled Trump's wealth and his ability to negotiate, as well as his willingness to pass on his knowledge to anyone who watched. The story of his redemption was also an ideal script for the times, proof that he could make America—like himself—great again . . . if you accepted his authority.

On the campaign trail, Trump offered American citizens his support . . . as the master. And, in his acceptance speech at the 2016 Republican National Convention, he declared:

Nobody knows the system better than me, which is why I alone can fix it. . . . My opponent asks her supporters to recite a three-word loyalty pledge. It reads "I'm with her." I choose to recite a different pledge. My pledge reads, "I'm with you, the American people." I am your voice.

So, to every parent who dreams for their child and every child who dreams for their future, I say these words to you tonight. I am with you, I will fight for you, and I will win for you.¹⁷

Trump's declarations were regularly met with chants of "Yes, you will!"—an authoritarian revision of Obama's campaign slogan, "Yes, we can!"

Comparing *The Apprentice* and Trump's campaign reveals that, rather than running off script, Trump was unwaveringly and single-mindedly *on* script—a script that had begun as early as 2004. Through this unending performance, Trump managed to make all other candidates appear to be two-faced hypocrites because they did not host a reality TV show. Every sincere effort made by the other candidates to be "real" was mocked as phony: from Jeb Bush's glasses to Hilary Clinton's bottle of hot sauce. Tellingly, the greatest moment of crisis for Trump's campaign came when a tape of him bragging of his history of sexual assaults on women was released.¹⁸ This—more than his refusal to release his tax returns—seemed to reveal that Trump had a private self that did not correspond to his public persona, one, it seemed, he wanted to hide. But attempts to deride and discredit him for this failed arguably because being a "bad boy" was part of his brand.

So how did “Reality TV” and someone so staged—so unabashedly a brand—come to define authenticity? How did someone who asserted, “It’s nothing personal; it’s just business” become so personal? How did someone whose team championed “alternative facts” and offered speeches filled with misleading statistics and unproven assertions—someone who responded to all questions about the specifics of his plans on the 2016 campaign trail with the refrain “Believe me”—become believable? And how did authenticity become redefined as the expression of “subversive” opinions—opinions that were or would quickly become dominant on the social media and networks?

Trying to determine whether Trump—or, indeed, any figure or brand—is really authentic will not answer these questions. Such attempts are at best decoys that distract us from seeing the historical and well-known paradoxes that structure the concept of authenticity. As Sarah Banet-Weiser argues in her definitive 2012 work *Authentic™: The Politics of Ambivalence in a Brand Culture*, authenticity is central to the (ambivalent) operations of the consumer citizen. And, as many others across many fields and political persuasions have pointed out, authenticity is fundamentally coproduced: it is not about being seduced or duped by fake news; it is about co-investing and creating a brand.¹⁹ It is about buying the license and becoming the product. It is a drama—or, more properly, a soap opera.²⁰ It ties together the many different media fields and underlies the celebration of “participatory media.” Authenticity is an ethos used to evaluate social performance—to “authenticate” and mold “good” users—especially when they are “bad.” It prescribes a certain transparency of self that makes someone’s data reliable. It is the flip side of conformity or sincerity: if we conform by making our inner selves coincide with our outward appearance, we become authentic by making our outer selves reflect our inner torment. Either way, we become “transparent.”

Further, authenticity has become so central to our times because it has become algorithmic (if it was ever *not* algorithmic): a set of rules to be followed or executed. At its very simplest, authenticity evokes the (dramatic) command: “To thine own self be true.” To call authenticity algorithmic, however, does more than highlight the methodological nature of authenticity. The term “algorithmic authenticity” reveals the ways in which users are validated and authenticated by network algorithms. The

imperative “Be true to yourself”; or, more simply, “Be true” makes our data valuable—recognizable—across the many media platforms we use. Fundamentally about recognition, algorithmic authenticity buttresses human and machinic pattern recognition. It ties together supposedly separate—or even competing—agents and platforms. It underlies personalized recommendation engines, social media, and network clustering. At the same time, it corresponds with, and to, older media forms.

To understand the scope and influence of algorithmic authenticity, this chapter explores the relationship between reality TV, recommender systems, and user actions. By framing algorithmic authenticity in terms of relations both between humans and humans and between humans and machines, it shows how users have become characters in a drama called “big data.” And, by examining how users are authenticated, it also points to how they might intervene into the scripts they find themselves embedded within (a topic pursued in greater detail in the volume’s coda). Further, by placing recommender systems within the historical context of eugenics and homophily, this chapter reveals how, through latent factors and correlations, users are trained to be authentic and segregation is amplified and justified.

The upshot: Trump is a training program for training.

TO THINE OWN SELF BE TRUE

The history of the word authenticity both supports and undermines its relationship to the words “autonomy,” “author,” and “authoritarian,” with which it shares a common root: *authentes*, the Greek word for “perpetrator.”²¹ Although it seems to defy definition and relation to any other word, it is profoundly relational, procedural, and performative. Acts of authenticity make fictions feel real.

In his provocative and much-cited 1972 book *Sincerity and Authenticity*, literary critic Lionel Trilling placed the late twentieth-century valorization of authenticity in a historical context by distinguishing it from sincerity, a concept that gained traction in the seventeenth and eighteenth centuries.²² The concepts of sincerity and authenticity follow from the imperative “To thine own self be true,” but differ fundamentally in why “being true” matters and what “being true” entails. Sincerity adheres to

Polonius's advice to his son Laertes in *Hamlet*: "To thine own self be true / and it doth follow, as the night the day, / thou canst not then be false to any man."²³ Trilling stressed that sincerity is a means to an end: it calls for one to be "true to oneself" so that one can be true to others. Linked to the notion of society and the rise of cities, sincerity sought to make the personal and the public correspond by narrowing the distance between people's outer appearance and their inner selves. Pointing to philosopher Jean-Jacques Rousseau as the quintessentially sincere character, Trilling drew out the implications of Rousseau's claim that sincerity is linked to the novel and oratory, forms that aided moral judgment and public life because they precluded the kinds of "base" and false imitations necessary for acting and the theater.²⁴ According to Trilling, the rise of authenticity coincided with the fall of sincerity during the nineteenth and twentieth centuries. By the countercultural 1970s, authenticity clearly dominated over—and was used to evaluate—sincerity: a person's ability to appear sincere was judged by its authenticity.

Authenticity supposedly dissolved the dilemma of sincerity (Is our being sincere to others really being sincere to ourselves?) by cutting Polonius's advice short: "To thine own self be true." Authenticity, Trilling argued, is an end, not a means. As such, it exposes cultural norms and niceties as false. Writing at the height of protests over the Vietnam War, Trilling noted: "At the behest of the criterion of authenticity, much that was once thought to make up the very fabric of culture has come to seem of little account, mere fantasy or ritual, or downright falsification. Conversely, much that culture traditionally condemned and sought to exclude is accorded a considerable moral authority by reason of authenticity claimed for it, for example, disorder, violence, unreason."²⁵ Authenticity, in this sense, would seem to be the "red pill" (see "Correlating Ideology"). Authenticity does not soothe. It is polemical and heroic; it is related to art that disturbs, to the theater. The hero, Trilling explained, is one who acts like a hero, who confronts his audience with a performance or artwork that can be "resistant, unpleasant, even hostile."²⁶ The hero reeks of tragic greatness, of flaws that both enable and disable. But, if theater acknowledges the difference between actor and character—an authentic performance is not always a sincere one—Trilling's definition inadvertently conflates the two by ignoring the theatrical setup.

Confrontation is essential to authenticity and the mode of identification it entails, for even though it seems to cut ties to others, authenticity establishes a stronger relation: that of identification or possession. Trilling concluded his analysis by outlining the contemporary conflation of psychosis with authentic liberation and self-sufficiency, but his analysis arguably reveals the enduring importance of relation to authenticity:²⁷ it is a form of “self-possession” in multiple senses because it enables others to possess the self. The audience, Trilling argued, “acquires the authenticity of which the object itself is the model and the artist the personal example.”²⁸ Further, members of the audience must identify the object, artist, or madness as authentic. They must partake of—“authenticate”—another’s resistance. As Hitler told his Storm Troopers: “All that you are, you are through me; all that I am, I am through you alone.”²⁹

This heroic notion of authenticity—authenticity as a staged defiance of convention and sanity—seems central to twenty-first-century “dramas of authenticity.” Sociologist E. Doyle McCarthy describes “dramas of authenticity” in terms of “unprecedented demonstrations of emotionality” or “displays of intensity” from extreme games to reality TV.³⁰ Through authenticity, audience members try to overcome the distance between the viewer and the viewed.³¹ Analyzing group behaviors at public memorials, McCarthy argues that authenticity is central to collective agency—it forms the basis for participation. Crucially, these dramas of affirmation and discovery—and participation itself—are well within the realm of commodification and market relations. Authenticity is a twenty-first-century management buzzword: leaders and workers are taught how to be authentic in order to succeed.³² In a world of accelerated capitalism, persons are themselves brands, and characteristics such as gender and race have become commodified features. The brand, it is promised, will set you free—but only if you and it are truly authentic.³³

As Banet-Weiser points out in *Authentic™*, branding authenticity is neither yearning for a world in which things are truly authentic nor simply cynical;³⁴ rather, as embedded in twenty-first-century brand cultures, it is ambivalent. There is no rigid difference between having and selling an authentic experience since all sectors of these cultures are increasingly commodified. Even as they reduce politics to an issue of individual choice, brand cultures still offer community and affective connection:

brands are coproduced. They enable an intimate relationship between the brand and the consumer based “on the accumulation of memories, emotions, personal narratives and expectations. Brands create what Raymond Williams called a structure of feeling.”³⁵ Self-branders are thus told that their personal brand is “a perception or emotion, maintained by somebody other than you, that describes the total experience of having a relationship with you.” Self-branding is “an expression of a moral framework,” Banet-Weiser tells us, “a means to access authenticity,” and key to becoming “more of who you are” and “who you were meant to be.”³⁶ Thus it is both descriptive and aspirational.

Self-branding as authentic represents another twist in the history of authenticity: it has become openly relational. If, as Trilling argued, sincerity and authenticity once seemed to differ in their approach to the adage “To thine own self be true”—to be “sincere,” you are true to yourself in order to be true to others, whereas to be “authentic,” you are simply true to yourself—branding authenticity amplifies authenticity as a form of self or subject possession (through your authenticity, I become authentic; and through my identification, you become authentic). Self-branders are told that, in order to be authentic to themselves, they have to be authentic to others.³⁷ They must constantly be visible and transparent. To be perceived as hiding something—as having some secret inner layer that does not coincide with your outer appearance—is to be “fake” and discredited. Therefore, the easiest way to be recognized as authentic is by visibly transgressing conventions: revealing what would otherwise be considered odd or risqué characteristics. Authenticity must be immediately perceived and perceptible—it forms the basis for both correlation and recognition (as chapter 4 further explains).

Thus, through this carefully crafted and scripted visibility, authenticity has come to defy definition. “Like beauty, pornography, and soul, it is hard to define authenticity. As Supreme Court Justice Byron White noted, ‘You just know it when you see it,’” mused John Zogby, writing for *Forbes* in the lead-up to the 2016 election.³⁸ That authenticity is immediately recognizable—yet resists definition—is linked to the notion of authenticity as “real.” But again, this feeling of “realness” depends on an investment and engagement that is formulaic—algorithmic—and yet spontaneous. Crucially, algorithms do not determine an action: they

are a series of instructions to be followed in order to solve future problems. That a politics of authenticity favors a reality TV actor is thus to be expected, for reality TV is strictly formulaic, and it blurs the difference between actor and character. As well, the ties between reality TV and neoliberal governmentality run deep. Thus, in many ways, Trump is a training program for training.

REALITY TV AND NEOLIBERALISM

Trump's "authenticity" stemmed from his ability to frame his political campaign and its coverage as an extension of his reality TV series *The Apprentice*, in which he, as the master, "mentored" and dominated those who sought to learn from him. The connection between reality TV and U.S. politics precedes Trump, however—and will almost certainly succeed him. (News shows and channels—now relabelled as entertainment—are the new yet old frontier of reality TV.) As media scholars Laurie Ouellette and John Hay have maintained for at least a decade before the 2016 U.S. presidential election, the emergence of reality TV as a popular television format coincided with the dismantling of the last vestiges of the welfare state within the United States. Reality TV shows from *Extreme Makeover: Home Edition* to *What Not to Wear* to *The Biggest Loser* have emphasized individual empowerment and responsibility, as well as corporate charity and the reinvention of government.³⁹

Foregrounding the history of reality TV (an element missing in immediate postelection discussions of its impact on U.S. politics), Ouellette's 2016 analysis revealed how the "message" of reality TV aligned with the fundamental precepts of neoliberal governance, such as personal responsibility and empowerment. In particular, Ouellette stressed the pedagogical role of reality TV, stating that it taught viewers "how to be good (entrepreneurial and self-maximizing) citizens in tandem with free market discourses and policies." The solutions it offered were individualized yet based on partnerships with "corporations, sponsors, nonprofits, and public agencies."⁴⁰ She contended that *The Apprentice* "established reality TV's neoliberal grammar" and "the rogue businessman as a new kind of expert and leader extraordinaire," with close ties to government officials (one episode included a luxury stay in Washington, D.C., with Senator

Chuck Schumer of New York). Given that *The Apprentice* and other “self-improvement” shows included appearances by “serious” politicians and their wives, such as Michelle Obama and Laura Bush, it should be no surprise that a character would move in the opposite direction: from reality TV to the White House. Trump, she emphasized, was not a pseudocelebrity; rather, “thanks to reality TV, he was the embodiment of an enterprising subjectivity and a ‘no nonsense’ approach to leadership that draws legitimacy from the market.”⁴¹

Ouellette’s analysis of reality TV as pedagogical might seem to portray its viewers a little simply. Reality TV, after all, is consistently referred to as a “guilty pleasure” linked to *schadenfreude* and sadism. Yes, but, reality TV’s message of personal empowerment works whether or not its participants are mocked or identified against: dis-identification and misidentification (as chapter 4 elaborates) are key to being “red pilled.” Irony and cynicism do not undermine what reality TV viewers “learn”—the value of algorithmic authenticity and the need to follow certain scripts. If anything, as philosopher Slavoj Žižek argues, cynicism is a form of capitulation: cynical viewers who say, “I know very well that this show isn’t real and that these characters are pathetic, yet nonetheless . . .,” are in fact deeply embedded in reality TV’s ideological message.⁴² Žižek argues that action triumphs over belief or passion (as “Correlating Ideology” further explains): to become a believer, you need only take philosopher Blaise Pascal’s advice: “Follow the way by which [the faithful] began; by acting as if they believed, taking the holy water, having masses said, etc. Even this will naturally make you believe. . . . What have you to lose?”⁴³

What have you to lose?

Reality TV is algorithmic: highly scripted and endlessly repetitive. Each episode follows the same format (for *The Apprentice*: task; boardroom; departure), as does each season. Every episode—with its surprises and “off script” moments—is tightly edited to follow the same trajectory. Reality TV is a program, in all senses of that word. As software pioneers Herman H. Goldstine and John von Neumann explained in the early days of electronic computers, programming is “the technique of providing a dynamic background to control the automatic evolution of a meaning.”⁴⁴ The term “automatic” here may seem questionable, but the Greek root *autos* (“self”) embedded in this term links “automatic” to “authenticity,”

“authority,” and “authorship.” To be “automatic” is to be self-generating, whether as human or machine.

Reality TV’s algorithmic nature underlies its longevity and its future; its packaged style makes it a “cash cow” for networks: as media studies scholar June Deery explains, money that would be spent by other TV genres is saved in all areas of its production and development.⁴⁵ The repeated story line obviates the need for writers; the use of “real people” obviates the need for actors (even though most “candidates” on these shows are themselves aspiring actors). Built on the cult of “the amateur,” reality TV exploits its contestants both financially and psychically, calling into question the long-standing leftist advocacy of amateurs as a way to defeat capitalist exploitation. Cultural studies scholar Andrew Ross, commenting on the well-publicized mental breakdown of UK singing sensation Susan Boyle, argued her breakdown embodied “the kind of emotional labor that is demanded of amateur on-air participants. This is most illustrative in genre formats that require them not to act so much as to ‘act out’ the legacy of highly traumatic experiences in their lives—breakups, marital discord, accidents, deaths, layoffs, profound humiliations.”⁴⁶ Reality TV’s “dramas of authenticity” render neoliberalism’s cruelty playful, thus making reality TV, in media studies scholar Nick Couldry’s view, “the secret theater of neoliberalism.”⁴⁷

Reality TV’s algorithmic nature and its use of free labor seems a foreshadowing of social media microcelebrity (although the prior existence of “cam girls” and other 24/7 webcam sites calls this chronology into question). Media theorist Tiziana Terranova, in her early seminal work on “free labor” (labor that is both uncompensated and freely given) refused to separate the Internet from the “outernet.” In particular, she revealed that the difference between TV talk shows, reality TV, and such and Web 2.0 was not qualitative, but normative: “From an abstract point of view, there is no difference between the ways in which people shows rely on the inventiveness of their audiences and websites rely on users’ input.”⁴⁸ The difference between the two forms lies in the moral work of authority and authenticity. Reality TV “does not allow the *immediate* valorization of the talk show participants. . . . Psychologists and other experts are also brought in to provide an authoritative perspective through which what is often a sheer voyeuristic experience may be seen as a ‘social experiment,’” whereas, on the Internet, “practically anything is tolerated.”⁴⁹

Social media do more than tolerate everything: they encourage and demand everything. If the “proof” of the Internet’s libertarian democratic nature lies in its diversity, everything must be displayed—offensive content must be generated—in order for the Internet to be deemed successful. In this worldview democracy = offense. Further, this constant display of everything—and, in particular, of minor “deviations”—is used to authenticate and cluster users. The demand to be authentic—to transgress convention and the boundary between public and private in as scripted a manner as possible—makes data “the oil of the digital era.”⁵⁰ The trappings of social experimentation disappear because the Internet has become nothing but social experimentation to normalize the nonnormative.

ALGORITHMIC AUTHENTICITY: MACHINICALLY YOURS

To repeat: reality TV and social media are both fundamentally algorithmic. Their algorithmic nature shapes viewers/users and their actions, while also troubling the boundary between human and machine, automatic and authentic. Algorithms are not simply or originally machinic. The term “algorithm,” derived from the medieval Latin *algorismus*, is a corruption of “Al-Khwarizmi,” part of the Arabic name (indicating birthplace) of one of the most important Islamic mathematicians, Muhammed Abu-Abdullah Abu-Jafar ibn Musa Al-Khwarizmi Al-Majusi Al-Qutrubulli, who introduced algebra and the Arabic-Hindu system of numbering to western Europe.⁵¹ “Algorithm” (“algorism” in medieval English) later evolved to mean a “procedure or set of rules used in calculation and problem-solving; . . . a precisely defined set of mathematical or logical operations for the performance of a particular task”; and within medicine, “a step-by-step protocol used to reach a clinical diagnosis or decision.”⁵²

There is nothing particularly human or particularly machinic about either algorithms or programs. So how exactly does human execution differ from machinic execution? Surely, reality TV with its formulaic yet unexpected outcomes—the conflict, horror, disgust, fascination, laughs, and surprise it generates—differs from machinic commands and performance? Yes, it does in many ways, but both produce unexpected results or they would not be necessary, for we would know those results/

outcomes in advance. As mathematician Alan Turing contended early on in response to the objection that computers cannot think because they merely follow human instructions:

Machines take me by surprise with great frequency. . . . The view that machines cannot give rise to surprises is due, I believe, to a fallacy to which philosophers and mathematicians are particularly subject. This is the assumption that as soon as a fact is presented to a mind all consequences of that fact spring into the mind simultaneously with it. It is a very useful assumption under many circumstances, but one too easily forgets that it is false. A natural consequence of doing so is that one then assumes that there is no virtue in the mere working out of consequences from data and general principles.⁵³

Knowing what procedure should be followed is not the same as grasping all the consequences of doing so. Modern computers and machine learning, which follow the kind of “learning” Turing espoused for computers, have made algorithms more opaque: not only do we not know the results in advance, we also do not know what the machine is doing at any given moment. The nontransparent “black box” programs that are increasingly used to regulate and evaluate the lives of U.S. residents have become, again in the words of Safiya Noble, “algorithms of oppression.”

But this nontransparency is not solely due to algorithmic complexity. Just as the results of following the simple command “Be true to yourself” can be diverse and complex, so, too, the results from following the simple formula of Bayes’s theorem, which forms the basis for many machine learning algorithms, can be unexpected and opaque. Bayes’s theorem states (see figure 39 for more details):

$$P(X|Y) = \frac{P(X)P(Y|X))}{P(Y)}$$

The probability of X given event Y = the probability of X times the probability of Y given X , divided by the probability of Y . Attributed to the Reverend Thomas Bayes as a means to determine “inverse probability,” it provides the basis for many machine learning algorithms that “learn” by updating a current belief based on the likelihood of new data: it generates a posterior model, given an event and a prior model.

The difference between human and machinic execution lies in how humans and machines are trained and “authenticated”: how the wildly continuous nature of signals and persons alike is made discrete and

BAYES' THEOREM & BAYESIAN INFERENCE

An early example of an algorithm that tracks "authenticity" is email spam filters, motivated by the huge spam problem starting in the '90s. By 2010, close to 90% of emails were spam, with an annual societal cost of \$20B.

Such a filter tries to keep emails you want (eg, friends, legitimate unsolicited messages) & discard those you don't (eg, bulk ads). Clearly this is subjective — should you consider your friend's bulk marketing email as spam?

Let's learn Bayesian inference while designing a simple spam filter algorithm.

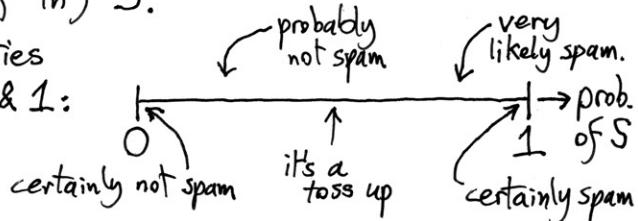


Consider one incoming email:

- the event "this email is spam" we call S
- the other possibility is simply "not S "

The Bayesian approach updates a probability of (ie, numerical belief in) S .

- All probabilities lie between 0 & 1:



- This probability will change in the light of new input, just as an opinion of an email crystallizes as you read through it.

We use $p(S)$ to denote prior probability of being spam, ie before examining the message. Given the above statistic, $p(S) = 0.9 = 90\%$ is a good prior estimate.

Now let U be the event "this email contains the word urgent".

We need to know how common 'urgent' is in spam & non-spam.

To estimate this, say we analyse 1000 random emails & find (say) these statistics:

	not S	S
all emails:	100	900
emails with 'urgent':	10	360

Armed with this "training data" we estimate,

$$p(U|S) = \frac{360}{900} = 0.4 \quad \leftarrow \text{ie, } 40\% \text{ of spam contains 'urgent'}$$

{ this means conditional probability of U occurring, given S .

We'll also need the probability of U without knowledge of S , which we can also estimate from our table:

$$p(U) = \frac{10 + 360}{1000} = 0.37$$

Time for some inference! There's two cases:

- An incoming email contains 'urgent'. Bayes' theorem (derived at the end) tells us then,

$$p(S|U) = \frac{p(U|S)}{p(U)} p(S) = \frac{0.4}{0.37} \underset{\substack{\uparrow \\ \text{called the "posterior",}}} 0.9 \approx 0.973$$

\uparrow prior \uparrow "likelihood"

97.3% chance of being spam.

this is the updated prob. of S , in light of U .

- Alternatively, the email doesn't contain 'urgent', and we apply the same theorem but with different data,

$$p(S \mid \text{not } U) = \frac{p(\text{not } U \mid S)}{p(\text{not } U)} p(S) = \frac{0.6}{0.63} 0.9 \approx 0.857$$

"posterior"

Here we use $p(\text{not } U) = 1 - p(U)$. $\xrightarrow{\text{high, but less than our prior.}}$

Finally the algorithm must pick a threshold: if posterior > 0.95 , say, it goes to spam. So far, this is not a good filter: you lose every email containing 'urgent', which includes 10% of legitimate emails! (an unacceptable "false positive rate").

But the updating step (inference) can be repeated with many other search words, and the filter becomes much better.

- Here's a sketch of that idea:

Let V be the event "the email contains 'viagra'"
note, $p(V \mid \text{not } S)$ is tiny!

A useful (but wrong) model is to assume independence:

$$p(V \text{ and } V \mid \dots) = p(V \mid \dots) p(V \mid \dots)$$

Then Bayes gives, for an email with both 'urgent' & 'viagra',

$$p(S \mid V \text{ and } U) = \frac{p(V \text{ and } U \mid S)}{p(V \text{ and } U)} p(S) = \underbrace{\frac{p(V \mid S)}{p(V)}}_{\substack{\text{new posterior,} \\ \text{will be very close to 1.}}} \cdot \underbrace{\frac{p(U \mid S)}{p(U)} p(S)}_{\substack{\text{viagra update factor.} \\ \text{old posterior}}} \quad p(S \mid U)$$

Combining these factors for many "spammy" words gives a decent Bayesian spam filter.

Notes on spam filters:

- We have just seen Bayesian inference in action: it shows how to update probabilities in the light of new data.
- Training data (statistics on spam and non-spam) is needed for the "likelihoods" $p(U|S)$, etc, needed in the updates.
- There can be many unintended consequences! Legitimate emails end up lost, but also spammers change tactics by misspelling words (Viagra), including random text ("Bayesian poisoning")... an arms race of evolving viral warfare.
- Real filters are fancier than above, using phrases, URLs, blacklisted senders, presence of CAPS, etc...

Derivation of Bayes' Theorem

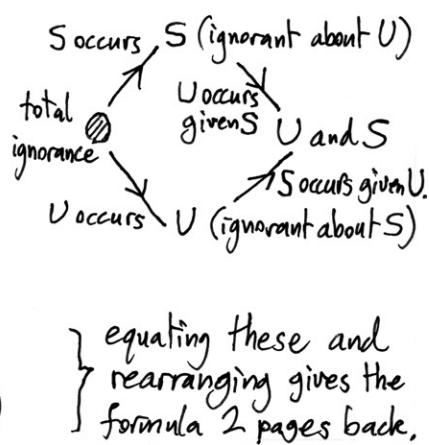
Let's use the symbols U and S for any two events.

One can reveal knowledge by two different routes to get to the event " U and S occur":

This gives 2 ways to factor the joint probability:

$$p(U \text{ and } S) = p(U|S)p(S)$$

$$p(U \text{ and } S) = p(S|U)p(U)$$



molded; how patterns are recognized and fostered. Recommender systems and the types of “personalization,” enabled by network algorithms and supposedly driven by a desire for mutual human and machine “learning,” make this point clear.

“Personalized recommender systems” are predictive software tools that filter and prioritize information, items, and users. They rose in prominence during the mid-1990s, when Internet companies like Amazon and Netflix deployed them to amplify sales, build user loyalty, and predict user purchases.⁵⁴ Although recommender systems, like search engines, presume genuine user need and thus also user sincerity, they primarily serve the interests of those who deploy them, rather than the needs of the users they address. Indeed, they seek to influence user behavior by collecting individuals and items into similarity-based “neighborhoods.” By using historical data to anticipate “user wants,” they limit choice and amplify past trends in the name of efficiency and desire. The impact of these systems goes far beyond e-commerce: recommender systems, whose algorithms have been crucial to the evolution of search engines and the increasingly intrusive methods of data mining, as well as to the fracturing of the World Wide Web into poorly gated communities.

E-commerce sites first embraced personalized recommender systems in order to compete with brick-and-mortar stores. Since users could not directly touch the wares they displayed, they offered “value added” curating by analyzing past purchases. Most positively, recommender systems are described as “democratic technologies”: ways to give “high-quality,” “personalized” expert advice that actually outperforms domain experts to those “who cannot afford to or are not willing to pay.”⁵⁵ They are also framed as helping users faced with an overwhelming number of items make a decision, by reducing all possible items to a ranked list, thus relieving users of the “misery-inducing tyranny” of choice.⁵⁶ Because they seem to tailor their advice to individual user needs, these systems differ from the historically popular “editor’s choice” format. To reduce and rank choices for users, however, they draw not only on a user’s purchase history, but also on that of others determined to be “like” the user. In this sense, the term “personalized” is a misnomer since recommender systems are built on the principle of homophily (discussed in chapter 2): they presume that similarity breeds connection; that “birds of a feather flock

together”; that similar individuals want similar items. They accelerate the twentieth-century trend toward microsegmented conformity. Rather than simply displacing identity, they create new categories that refine and perpetuate older notions of race, gender, class, and sexual orientation. Again, just as Cambridge Analytica did with “intersectionality” (discussed in chapter 1), recommender systems amplify existing “divides” through their subdivisions for the new “neighborhoods” they create rarely cross the proverbial railroad tracks.

Based on how they “predict” missing links, recommender systems are divided into content-based, collaborative filtering, community-based, demographic, and knowledge-based systems.⁵⁷ These five basic types make recommendations by focusing on user-user relations and purchase histories (homophily between users), on attributes of items (homophily between items), or on users’ responses to detailed questionnaires for seldom bought items, such as cars. These different approaches employ similar methods, such as nearest neighbor clustering, and often blend into one another: most recommender systems are hybrid. They are also divided into memory- or model-based systems. Although both of these rely on past interactions, memory-based systems hold all (or most) data “in memory” and use them directly to generate recommendations (which is computationally intensive, especially at run time), whereas model-based systems preprocess the data and then use the “learned” model to make recommendations. Newer “online learning” machine learning recommender models read in data only once, and are thus more sensitive to changing trends.

That recommender systems are based on homophily raises several important questions: What are the ramifications of similarity? How do we measure it? And how are items and users determined to be similar? A common measure of similarity between users is the Pearson correlation coefficient, which is

$$r = \frac{\text{covariance } (X, Y)}{(\text{standard deviation of } X) (\text{standard deviation of } Y)}$$

Described in detail by Alex Barnett in chapter 1 (figure 17), this coefficient measures the correlation between two variables by dividing the covariance between them—that is, how (or whether) they increase or decrease in value together—by the product of their standard deviations. A score of +1 indicates that the two variables correlate perfectly, 0 indicates no

correlation exists (the variables are independent) and -1 indicates a negative correlation between them (the variables are polar opposites). After computing this coefficient, systems such as the early user-based nearest neighbor collaborative filters identify “peer users” or the “nearest neighbors” of any given user: they assign a probability to all the items the user has not rated or seen, based on ratings by algorithmically determined “peer users.”⁵⁸

Regardless of the methodology used, “collaborative” recommender systems generally tie together the past, present, and future through “link prediction,” which, as computer scientists Jun Zhu and Bei Chen explain, is “one of the most fundamental problems in network analysis.” Recommender systems use link prediction to estimate missing user ratings; social networking websites like Facebook use link prediction to guess who might become friends. Regardless of their differences, however, both static and dynamic systems use the same methods to predict their “missing values,”⁵⁹ and they verify these predictions by using known but “hidden” past values. As mentioned in chapter 1, recommender systems are validated on their ability to predict past values hidden during the training phase, rather than future values. In these systems, the likely future equals the missing past.

More insidiously, recommender systems shape future user behavior through their recommendations. By focusing users on certain items and by hiding others, they strengthen certain correlations. As computer scientists Dietmar Jannach and colleagues explain, sites deploy well-known priming tactics to make certain purchases or items more attractive, such as adding “irrelevant (inferior) items in an item set [to] significantly influence the selection behavior”; placing items at the beginning or end of a list to draw users’ attention to them; incorporating psychological theories or personality-type analyses⁶⁰ (such as those by Cambridge Analytica as described in chapter 1). That is, even though they are based on the principle of homophily rather than “contagion” or imitation, their effectiveness is also linked to imitative behavior and priming.

These “collaborative” systems also carve networks into affectively intense “neighborhoods.” They create these neighborhoods by clustering users who deviate from the norm, the mean, the common denominator with fellow members of their neighborhoods. Because “liking” *Harry Potter*, for instance, forms a group too vast to be useful, it has to be supplemented

by another measure that restricts the users' neighbors more stringently: what matters are the moments users "think outside the box" with their "friends." Not surprisingly, the Pearson correlation coefficient has been often supplemented by a function that weights agreement in accordance with controversy, for "an agreement by two users on a more controversial item has more 'value' than an agreement on a generally liked item."⁶¹ Controversy provides the basis for predictability and works to "refine" more generically determined factors. Within affectively charged zones, users presumably fall prey to confirmation bias—and thus act in historically consistent ways—because these are zones of belief or authenticity. In other words, these are moments and areas in which users feel their views are controversial, and thus—no matter how dominant those views may be (or it could be a 50–50 split)—users feel "subversive" or "resistant" to hold them. Within these zones of trust and belief—what Karl Lazarsfeld and Robert Merton called value homophily—users are more likely to be "red pilled": to fall under the influence of sympathetic, alternative networks.⁶² The point here is to find and amplify triggers that ensure predictable—linear—user reactions and that can be used to delineate the boundaries between polarized neighborhoods. (Once again the polarization of the "inert" described—and to some extent sought—by Karl Lazarsfeld and Elihu Katz in their investigation of personal influence and consumer change.)⁶³

Early on, memory-based filtering recommender systems were assumed to be the most accurate because their "ground truth" was supposed to be actual data. But they are also computationally intense and unwieldy, and they struggle with the "cold start" problem (new cases for which there is no prior data). In response to these difficulties, model-based recommender systems were developed to compute predictions offline. They often simplify calculations by using matrix factorization techniques, such as singular value decomposition, to "decompose" the database into a series of significant components of vectors, which roughly translate to a genre or type (see "Principal Component Analysis" by Alex Barnett; figure 37 in "Proxies" after chapter 2). As in the Kosinski, Stillwell, and Graepel 2013 study (discussed in chapter 1), each item or user is then considered to be a weighted sum of these vectors.

The efficacy of matrix factorization models was established in the course of the Netflix Prize Competition (2006–2009), during which

Netflix offered a large chunk of its database and a significant cash prize to whichever team could improve Netflix's recommender system by 10 percent. Many of the teams published their results throughout the competition; within a year after the start of the competition, they had established the importance of matrix factorization methods to detect "weak signals" not easily determined using overt network neighborhood techniques (see figure 37).⁶⁴ In other words, latent factor analysis made it possible to detect not-yet adjacent neighbors and to consolidate them into new neighborhoods. The winning algorithm combined these two methods.

The move toward latent factors, which is historically linked to Lazarsfeld and Merton's 1954 work on value homophily as underlying status homophily (see the following "Correlating Ideology or What Lies at the Surface" section), raised the possibility of uncoverable "causes," which could then be exploited. Latent factors, computer scientists Animashree Adnandkumer and colleagues explain, are "central to predicting causal relationships and interpreting the hidden effects of unobservable concepts."⁶⁵ Tellingly, Netflix's original programming is driven in part by human interpretations of these "hidden" factors. In his remarkable exposé of the "reverse engineering of Hollywood," journalist Alexis Madrigal has revealed how Netflix hired workers to create thousands of microgenres based on these algorithmically determined hidden factors in a fascinating back and forth between machine and human learning.⁶⁶ Netflix's move towards streaming boosted the use and capacity of matrix factorization models, because they do not need ratings but can instead evaluate implicit signals, such as viewing time and viewing order, captured by Netflix. Further, the models can add factors or weightings to account for changes over time.

Latent factor analyses raise at least two key questions: How many latent factors do we need? And how should these latent factors be modeled and discovered? Bayesian models are frequently used to predict and model latent factors, especially since matrix factorization models, which can become imbalanced if the matrices are very sparse,⁶⁷ usually establish in advance the number of latent features or factors they seek. Intriguingly, the names of methods used to create prior probability distributions call to mind a reductionist form of multiculturalism—"eating like the other." The Chinese restaurant problem, for instance, assigns objects to latent classes; the Indian buffet problem, in contrast, assumes that each

object comprises a combination of a possibly infinite number of latent features.⁶⁸ These priors are essential since they and the “cases” used for learning profoundly shape any posteriors produced.

The problem with these and any learning-based system, of course, is the creation of “more of the same.”⁶⁹ All these systems—whether they use nearest neighbor methods, matrix decomposition, or neural networks—restrict the future to the past. They are successful because they “recommend” things that are immediately recognizable. Their recommendation of previously bought items, though often annoying, is also a way to indicate to users that the systems “understand” them. Recommender systems are considered successful if we buy or like one item—and then continue to buy. The goal is to provide us with items that are vaguely satisfying to keep us craving more. Desire is the name of the game. A further problem with determining the “success” of recommender systems is the fact that false positives riddle these systems: regardless of constant A/B testing, it is impossible to determine with absolute certainty whether or not users chose certain items because of any given recommendation. Not surprisingly, Netflix never implemented the winning prize algorithm in all its complex hybridity (it was a mix of neighborhood and matrix factorization models), but instead integrated metadata made possible by streaming and latent factors into its recommender systems.⁷⁰

These latent factors and nearest neighbor analyses reportedly exposed the “coarseness” of identity categories such as gender, race, and class, since the systems’ neighborhoods and factors did not simply correspond to them. Indeed, in their in-depth analysis of the Netflix Prize Competition and the competing algorithms, communications studies scholars Blake Hallinan and Ted Striphas conclude that “the parameters of human cultural identity stretch beyond the human, all too human to include ‘prepersonal’ or ‘incorporeal’ aspects perceptible to machines. . . . These emerging aspects of cultural identity contain profoundly ambivalent potentialities, and their relationship toward existing modes of personal and cultural identity is far from determined.” Given this, Hallinan and Striphas ask: “Will the latent categorizations complement or eclipse extant human understandings?”⁷¹

As in the Cambridge Analytica example discussed in chapter 1, identity categories were not and are not discarded—they are simply microsegmented. They have also been key to solving the “cold start” problem.

Again, one of the biggest challenges facing recommender systems is sparseness of data: How can recommendations be made when there is little or nothing “in memory”? And how can they be made for new users or items? To resolve these problems, demographic information is often employed:

One straightforward option for dealing with this problem is to exploit additional information about the users, such as gender, age, education, interests, or other available information that can help to classify the user. The set of similar users (neighbors) is thus based not only on the analysis of the explicit and implicit ratings, but also on information external to the ratings matrix. These systems . . . which exploit[] demographic information—are, however, no longer “purely” collaborative, and new questions of how to acquire the additional information and how to combine the different classifiers arise.⁷²

Pointedly, modelers view the explicit consideration of the identity categories of gender, age, education and “other available information that can help classify the user,” (i.e. proxies for race) as crossing a categorical boundary: recommender systems that do so are no longer “purely collaborative”—a strange way to frame the categories that form the basis for identity politics.

The desire to place gender, age, education, and other identity categories outside collaborative filtering methods reveals the uneasy relationship between identity and “collaboration.” Direct appeals to identity categories are to be avoided wherever possible, even if the categories are easily inferable from the data themselves, presumably because it is illegal in the United States to do so.⁷³ The U.S courts initially blocked the Trump administration’s proposed banning of visitors from majority-Muslim countries of origin because discrimination on the basis of religion is—or was—unconstitutional. This overt ban arguably revealed the inadequacy of U.S. intelligence models in dealing with the “cold start” problem. Removing this ban, however, did not “solve” the problem of religious profiling. The question is not simply whether or not race, gender, sexual orientation, and other identity categories are directly used to determine recommendations, but rather how these categories figure as “latent factors” and to what end (see the Introduction). The problem again is not that race is a latent factor, but rather that racism is, just as the problem is not the existence of proxies, but what these proxies do—and how they do it.

CORRELATING AUTHENTICITY

Contrary to much hype about big data, measures of similarity are neither theory- nor bias-free. The continuing use of the Pearson correlation coefficient points to the enduring legacy of eugenics, just as homophily indicates the continuing impact of segregation and social engineering. As explained in chapter 1, Karl Pearson, a eugenicist, biometrician, and disciple of Sir Francis Galton, who is “widely regarded as the founder of the modern discipline of statistics,”⁷⁴ developed not only the Pearson correlation coefficient (key to collaborative systems) but also the method of principal component analysis (key to model-based systems) as ways to understand and shape “the human herd” by amplifying “desirable” deviations from the norm. Foreshadowing big data advocates’ statements almost a century later, Pearson spoke to the importance of correlation over causality in 1930: “Thousands of correlation coefficients are now calculated annually, the memoirs and textbooks on psychology abound in them; they form . . . the basis of investigations in medical statistics, in sociology and anthropology. . . . Formerly the quantitative scientist could think only in terms of causation, now he can think also in terms of correlation.”⁷⁵

According to Pearson, correlation and statistics gave researchers the whole picture—and the means to draw it differently.⁷⁶ Biometric eugenics, as discussed in chapter 1, assumed that all correlations were due to “nature” and that all generations “regressed” to an ancestral mean, unless positive deviations were carefully propagated through sexual selection. These correlations thus were key to developing programs to breed better populations. The eugenic history of correlation gives new meaning to the descriptor “memory-based” and also elucidates the strong connection between the “discovery” of correlation and attempts to change the world. With this in mind, no one should be surprised that recommender systems shape social habits, prescribe human behavior, and accentuate certain deviations through the correlations they draw between users and items.

For these recommender systems to work, though, users have to become predictable subjects: they must be authenticated and determined to be operating authentically. Recommender system programs presume that users’ captured actions—rather than their deliberate speech—represent their true selves; hence the claims made by data scientists to have “captured” users’ true and nonconscious motives.⁷⁷ For this to be true, users

must be trained to act authentically. Intriguingly, although Jannach and colleagues admit that recommender systems may influence or shape behavior, they do so mainly when describing the impact of “malevolent” actors. Collaborative filtering techniques, they explain, presume that “everyone in the user community behaves honestly and is fair and benevolent.” When users and companies act “honestly,” they argue, “all the participants profit: customers [receive] good buying proposals, well appreciated items get some extra promotion, and the recommendation service itself [is] appreciated by web site visitors.”⁷⁸

Jannach and colleagues also admit that the assumption of honesty on the part of both users and companies does not always hold. Dishonesty can create value, too, because recommender systems are performative: they “can influence the buying behavior of users” by declaring something “popular,” letting users know that X many others are looking at a given item; and that the item is still available only at so many places. Recommender systems may be “attacked” by users and/or bots to ensure that certain items are “very often (or very seldom) in its recommendation list.” Intriguingly, Jannach and colleagues do not consider “genuine negative opinions” to be attacks, even if they have the same effect, for “an attack occurs when an agent tries to influence the functioning of the system intentionally.”⁷⁹ This emphasis on intentionality and honesty reveals the norms that must be enforced for recommender systems to work. “Genuineness”—authenticity—separates “good” users from malevolent or “bad” ones; intention defines the line between group participation and attacks. “Good” users act transparently, closing the gap between actor and character. Authentic participation also enables the analysis of “psychological factors”: from Cambridge Analytica’s controversial use of the five-factor (OCEAN) model to influence election results by “triggering” citizens, to the less controversial “factors” usually acknowledged and used by recommender systems to typecast users, to the tables developed to score the emotions a film provokes.⁸⁰ In general, these systems presume that when people are at their most emotional—when they are the most agitated or distracted—they are most “truthful,” and they act most predictably. The “good” user is an authenticated one, who acts independently and whose collaborative actions are “accidental.”

The description of machine-generated “attacks” on recommender systems acknowledges the impact these systems have on user behaviors and

the importance of “neighborhoods” in shaping those behaviors. Jannach and colleagues note that machine-generated attacks often take the form of “profile injection attacks,” whereby fake profiles of either users or items, carefully designed to have many network neighbors, are used to push certain items. One type, the “random attack,” creates profiles with random values that fall reasonably within the normal distribution for all ratings in a system’s database except for the item it wants to promote: it creates profiles with many neighbors since their ratings are “typical.” Another type, the “average attack,” inserts average ratings for each item recommended, except for the one the attacker wants to build (or destroy).⁸¹ A third type, the “bandwagon attack,” moves beyond these by drawing from “additional, external knowledge about a rating database in a domain” to specifically create profiles that give “blockbuster” items high rankings, but the “target” items either high or low rankings.⁸² Recommender system “attacks” can also target certain neighborhoods. The “segment attack,” for example, first identifies a subset likely to be interested in the item a recommender system is pushing: if the item is a new data science book, for instance, it will give high rankings to other popular books about big data.⁸³ The techniques outlined above most effectively work to push certain items. In addition to these “push attacks” there are also “nuke attacks,” which seek to “tank” competing items. In one type, the “love/hate attack,” the item to be taken down is given low rankings, while other related but randomly selected items are given high rankings.⁸⁴ Another type, the “reverse bandwagon attack,” the item to be taken down is linked “with other items that are disliked by many people.” One of the first “attacks” on recommender systems were “shilling attacks” (named after “shills,” those who falsely promote items), in which human agents and bots deliberately collude to influence a target item’s rating by vouching for it.⁸⁵

In “collaborative” recommender systems, deliberate collaborative actions are framed as “inauthentic” attempts to break the systems. Identity politics becomes “inauthentic” and “noncollaborative” and solidarity becomes “disingenuous.” These systems, in other words, presume neoliberalism: that the world is filled with competing individual agents and that to act collectively—to make conscious collaborative connections with others—is to “game” the system. These “collaborative” programs thus reveal that, even though authenticity and creativity may depend

on communal relations, they are everywhere treated as individual attributes,⁸⁶ and authenticity is reduced to “authentication”: the demand that users act “genuinely” so that they can be better pigeonholed into collectively determined “latent” categories. To express this algorithmically:

```
authenticity := authentication if identity.politics == false &
collaboration == false.
```

Crucially, the demand and process of collaborative recommender systems decrease collective possibilities for diversity. Although the systems seem to offer individual users greater choice, they do so by restraining them to a set of popular, well-established items. They create a “power law” scenario: a “rich-get-richer effect for popular products and vice versa for unpopular ones.” In a related way, Wikipedia may seem to “open” the world to its users—but it does so by keeping them within its site, a situation that can both cement existing inequalities and also “prevent what may otherwise be better consumer-product matches.”⁸⁷ (Wikipedia also reveals that everyone receiving the same information is sometimes good.) As chapter 4 reveals, a politics of recognition drives this reduction in aggregate-level diversity. Intriguingly, recommender systems have turned to heterophily through negative correlation—the notion that opposites attract—to diversify their recommendations.⁸⁸

Before we move to the politics of recognition and identification, I want to conclude by outlining possibilities for authenticity. Recommenders and reality TV reduce authenticity to transparency or “sincerity”: to be “genuine” is to be consistent—without intention or design. This transparency is sold as a way to free and protect the user. Internet corporations such as Google and Facebook, whose data-mining operations require user authentication, have supported and continue to support tethering on- and offline identities. Randi Zuckerberg, marketing director of Facebook, argued in 2011 that “anonymity on the Internet has to go away” to curb harassment and bullying; Eric Schmidt, CEO of Google, made a similar argument in 2010: “In a world of asynchronous threats, it is too dangerous for there not to be some way to identify you.”⁸⁹ These arguments were neither new nor specific to Web 2.0. Ever since the Internet emerged as a mass medium in the mid-1990s, corporations have argued that securing identity is crucial to securing trust.

Many scholars have challenged this linking of trust and security, most insightfully philosopher Helen Nissenbaum. Nissenbaum noted in 2001 that, although central to activities such as e-commerce and banking, security can “no more achieve trust and trustworthiness, online—in their full-blown senses—than prison bars, surveillance cameras, airport X-ray conveyor belts, body frisks, and padlocks could achieve offline. This is so because the very ends envisioned by the proponents of security and e-commerce are contrary to core meanings and mechanisms of trust.”⁹⁰ The reduction of trust to security assumes that danger stems from outsiders, rather than “sanctioned, established, powerful individuals and organizations.” In a realm in which everything is secure, trust is actually not needed. Nissenbaum stresses that trust entails vulnerability: “when people trust, they expose themselves to risk. Although trust may be based on something—past experience, the nature of one’s relationships, and so on—it involves no guarantees.”⁹¹ The development of the Internet has made Nissenbaum’s words prophetic. With this so-called transparency—with “user authentication”—we have not only seen an explosion of e-commerce, but also a blossoming of cyberbullying and cyberporn. The naive assumption that transparency would cure the evils of the early Internet—pornography, trolling, flame wars, and the like—has proven to be false. Further, the use of “unique identifiers” has enabled big data analytics. The data gathered by the U.S. National Security Agency are so valuable precisely because private corporations have been pushing “unique identifiers” as a way to track users across time and space: without which it would be difficult if not impossible for them to create “neighborhoods.” Recommender systems cannot easily function without a way of tracking users or items reliably across time or space. They also cannot function without the ability to group and cluster users—who do not act like unique snowflakes, but rather array themselves like iron filings before poles that both draw them together and repel them from each other (see magnetization example in chapter 2). Most succinctly:

```
if trust == transparency then stranger := danger & safety :=  
false.
```

But what if we were to embrace the “malevolent” nature of users: collective action; intention; character development? What if we took seriously our role as neighbors?

Authenticity again is linked historically to dramatic performance and to characters. While making this point, Trilling referred offhandedly to sociologist Erving Goffman's *The Presentation of Self in Everyday Life*,⁹² in which Goffman famously correlated face-to-face relations with the theater and performance and contended that the kinds of performances society arranges constitute the self. Unlike Trilling, Goffman engaged with the fundamentally dual nature of performance: that every one of us is both an actor and a character. As a performer, each of us is "a harried fabricator of impressions involved in the all-too-human task of staging a performance"; as a character, each of us is "a figure, typically a fine one, whose spirit, strength, and other sterling qualities the performance was designed to provoke." On the one hand, Goffman held that "in our society the character one performs and one's self are somewhat equated" so that a successful performance of a character is usually imputed to the self who performs it. But, on the other, he stressed that the self "is a *product* of the scene that comes off, and is not *cause* of it."⁹³ The self is a "peg on which something of collaborative manufacture will be hung for a time."⁹⁴ This "collaborative manufacture" included: tools for shaping the body behind the scenes; fixed props and a team of persons key to the mise-en-scène; and the audience. These were all necessary for the emergence of the self.⁹⁵

The duplicity of the self is not simply duplicitous. As poet and playwright Oscar Wilde famously quipped, through the remarks of Gilbert, lead speaker in Wilde's dialogue essay "The Critic as Artist": "Man is least himself when he talks in his own person. Give him a mask, and he will tell you the truth. . . . we are never more true to ourselves than when we are inconsistent."⁹⁶ The mask, Arendt argued in *On Revolution*, was central to politics and action. Further, in her analysis of Makah reinventions of the whale hunt, Paige Raibmon has shown that, even at its worst—when it is used to "pin" Indigenous people to an "authentic past"—authenticity can be reinvented—that is, performed—anew.⁹⁷

If we think through our roles as performers and characters in the drama called "big data," we do not have to accept the current terms of our deployment. Indeed, by acknowledging and engaging the wonderful creepiness of social networks, we can replace this big data drama with another, in which we take on the myriad and constant actions necessary

to maintain those networks. We can move from tragedy to comedy or fantasy. The goal before us is to move the big data drama away from preemption and predictable yet rampant consumption toward political contestation and sustainable habitation.

To act, we need to acknowledge our plurality. Our characters and plot-lines change constantly because they are determined by the actions of others. As characters, we are never singular, but singular-plural—I am YOU. If, as Kosinski, Stillwell, and Graepel argue in their 2013 study, the Wu-Tang Clan is one of the most correlated likes for male heterosexual-ity, it is because of the multiple and conflicting roles that sustain this group: from Hong Kong martial arts films to old school Brooklyn rap to French explorer Jacques Cousteau.⁹⁸ Rather than closing down all worlds, “I am like you” and “I am with you” can become the basis for possibility. To return to the theme of chapter 2, the questions (which structure this book’s coda) are as follows: How can each of us become and play the neighbor? How can we understand our roles as “residents”? How can we take advantage of and play with and within the rich collaborative manufacture of the self, and how can we reach others through the correlations that have been laid before us? How might and must correlations and characters become the basis for a new collective politics in which we humans do not act like trees—because both humans and trees have become more interesting?

CORRELATING IDEOLOGY, OR WHAT LIES AT THE SURFACE

To repeat: How might correlations become the basis for a new collective politics? How might they open—rather than close—the future? To answer these questions, we need to understand how authenticity and correlation lie at the surface. Authenticity—as a twenty-first-century branding technology—demands “transgressive” transparency: boundless selves with no secrets, with no faces to save. Correlation and authenticity lie on the flip sides of the same coin. Ignoring underlying causes, correlation exposes superficial yet effective proxies: zip code for race; car insurance payments for medical outcomes; credit ratings for insurance claims. In the world of correlation, everything is manifest; nothing is latent.

And yet.

And yet this drive to make everything visible has normalized paranoid conspiracy theories about the “deep state” and “crisis actors.” It has popularized the worldview of *The Matrix*, in which the “real world” is a software illusion and consciousness is a “residual self-image,” both of which prevent humans from seeing the “desert of the real” that surrounds them (figure 40).

As explained in “Red Pill Toxicity,” in *The Matrix*, the leader of a group of human hacker-rebels, Morpheus, offers the protagonist, Neo, who senses that something is amiss with the world, two pills: the blue pill, which will erase all memories of their encounter, and the red pill, which



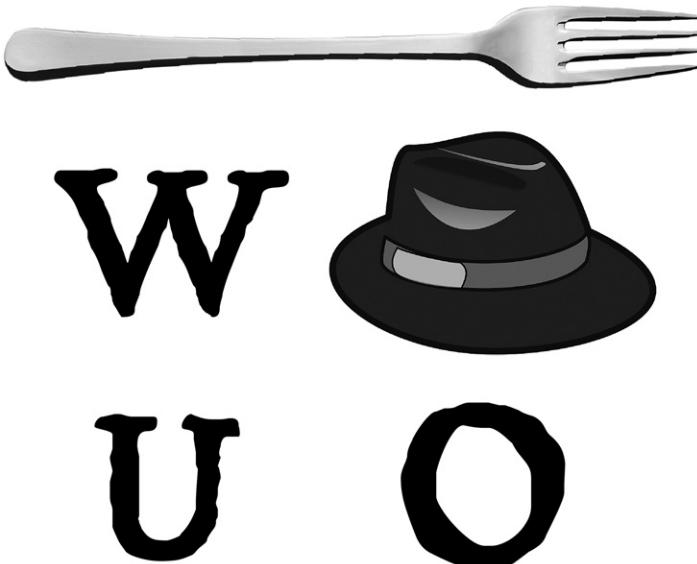
40 "The Desert of the Real." Still frame from *The Matrix* (Warner Bros., 1999).

will reveal the truth. To be "woke"—to see how far the rabbit hole goes—is to be "red pilled." Alex Jones, the creator of Infowars, a far-right U.S. disinformation website dubbed the "QVC for conspiracy," claimed that he had mistakenly believed the 2012 Sandy Hook Elementary School shooting was a hoax because he had been "traumatized" by the lying media and corporations. In this hallucinatory state, Jones was pulled "into that mass group think of the communities that were out there saying that."¹ To make something manifest is to disclose or reveal a hidden presence.² For authenticity to be transgressive, the real world must be latent, beyond view, lying in wait—beneath the surface. Correlations reveal proxies; they transform the unknown into the knowable. They make manipulatable "latent factors" manifest, from personality traits to microgenres.

"Manifest" and "latent," however, are not always linearly aligned. Correlations may seem to prove that "everyone lies," but truth and fiction are not always negatively correlated. According to Robert K. Merton, who helped introduce the terms "latent" and "manifest" into sociology, intention divides "latent" from "manifest": the consequences of manifest functions are intended and recognized, whereas those of latent functions are unintended and unrecognized.³ Manifest and latent functions reveal that any given process can have multiple—and at times conflicting—purposes and results.

Merton argued that his work with latent functions affirmed modern sociology's academic credentials and provided the basis for successful social engineering. Indeed, latent functions explained the importance and durability of seemingly irrational or widely belittled processes, such as magical rituals, conspicuous consumption, and undemocratic "political machines." Hopi rain rituals may not actually cause rain, but they persist because they reinforce "group identity by providing a periodic occasion on which the scattered members assemble"; the conspicuous consumption of exorbitantly priced goods, which are not significantly better than more modestly priced ones, serves as "proof" of a person's wealth; political machines survive in democratic societies because they make politics personal by tying individuals to "neighborhoods."⁴ Studying unintended consequences also helped sociologists understand the performative nature of their own work, that is, how their analyses affected the behaviors they were studying.⁵ Further, the analysis of latent functions was sociology's academic surplus value: it transformed paid commissions by corporations, government, and foundations to investigate consumer habits, workplace behavior, and optimal housing projects, for examples, into scholarly research.⁶ What was most important, however, was that investigating and revealing latent functions enabled "good" social engineering. Indeed, attempts at "social engineering" that did not consider the importance of latent functions were bound to fail: "*to seek social change without due recognition of the manifest and latent functions performed by the social organization undergoing change, is to indulge in social ritual rather than social engineering.*"⁷

Merton explicitly drew from "father" of psychoanalysis Sigmund Freud's distinction between manifest and latent meanings of dreams and neurotic symptoms.⁸ In terms of dreams, Freud argued that dreams fulfilled the conscious desire to sleep by transforming disruptive mental or physical stimuli into usually repressed unconscious wishes. Dreams—the "dream-work"—effected this conversion by disguising these unconscious wishes so that they could get past the conscious censor. (The conscious and unconscious systems were usually at war, with the conscious system constantly repressing the larger, unconscious one.) The remembered dream—the manifest dream content—thus differed substantially from

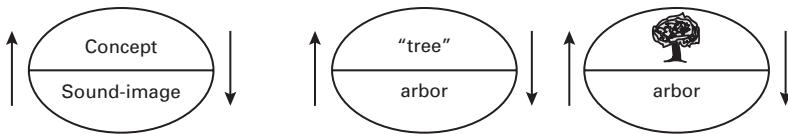


FORK OVER WHAT YOU OWE.

41 Rebus, where the signifier denotes another signifier, from “Fork over What You Owe,” 1868 (Wikimedia Commons) https://commons.wikimedia.org/wiki/File:Fork_over_what_you_owe_LCCN2001699181.jpg.

the latent dream thoughts. A dream was “*a (disguised) fulfillment of a (suppressed or repressed) wish.*”⁹

This distortion ensured that latent content and manifest content were not linearly correlated and thus could not be deciphered using the same techniques. They were two versions of the same subject matter, expressed through two radically different languages. The dream content was like a pictograph (figure 41). Thus, to be understood, each character of the pictograph had “to be transposed individually into the language of the dream-thoughts,” whereas the dream thoughts themselves were like ordinary language.¹⁰ To put this in terms of structural linguistics, latent dream thoughts followed the standard process of signification, in which a signifier was correlated to its signified meaning (figure 42). In contrast, the dream content was like a rebus, in which each signifier pointed to another signifier (figure 41).



42 Classic sign, with united signifier and signified, redrawn from Ferdinand de Saussure, *Course in General Linguistics*, ed. Charles Bally, Albert Sechehaye, and Albert Reidinger, trans. Wade Baskin (New York: Philosophical Library, 1959), 66–67.

Anyone seeking to unpack the manifest dream content—to undo the dream work—had to draw out associations, many of which seemed to be superficial or unimportant. This was because dreams used two main methods to sneak past the conscious censor: condensation and displacement. Through condensation, dreams packed many different unconscious wishes on top of one another, making a single dream content a nodal point for several dream thoughts. In Freud's dream about a botanical monograph, for example, the term "botanical" was related to Professor Grtner ("Gardener"), the "blooming" looks of Grtner's wife, Freud's patient Flora, his own wife's favorite flowers, an episode at his secondary school, an examination while he was at university, and so on.¹¹ Freud explained condensation by quoting a passage from Goethe's *Faust, Part 1*, in which Mephistopheles tells Faust that expertly wielding logic is like weaving:

A thousand threads one treadle throws,
Where fly the shuttles hither and thither,
Unseen the threads are knit together,
And an infinite combination grows.¹²

Condensation also occluded certain latent elements so that only a fragment of the latent dream thought passed over into the dream content. Because condensation was akin to synecdoche, in which a part replaces the whole ("wheels" for "car"), the manifest dream content was always smaller than the latent dream thoughts, and a dream always demanded over-interpretation: one interpretation was never enough, but too many interpretations were also futile because they could draw the interpreter into the dream's dark and unknown "navel."¹³

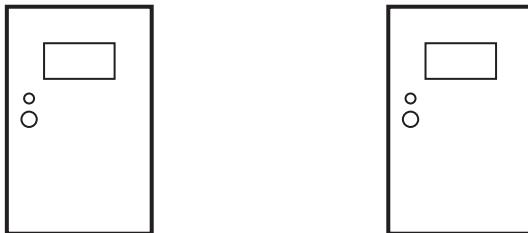
The second main method dreams used to sneak past the conscious censor was displacement: dreams transferred the charge of psychically

intense material onto seemingly indifferent, yet related material. The latent dream thoughts in Freud's dream of the "botanical monograph," for example, were not tied to gardens, but rather to conflicts between Freud and his colleagues over professional obligations. Antithesis—the fact that he had never cared for botany at school—linked gardens to the charge that Freud was too obsessed with his hobbies.¹⁴ To explain displacement, Freud described the state of affairs after a revolution during the Renaissance: "The noble and powerful families which had previously dominated the scene were sent into exile and all the high offices were filled with newcomers. Only the most impoverished and powerless members of the vanquished families, or their remote dependents, were allowed to remain in the city; and even so they did not enjoy full civic rights and were viewed with distrust."¹⁵ Through interpretation, the interpreter could decipher the "bloodlines" that linked dream content to dream thought.

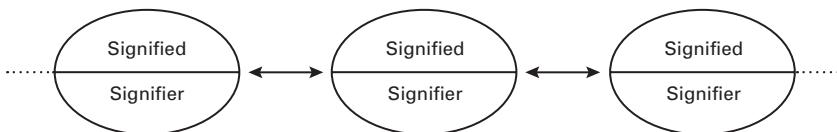
Psychoanalyst Jacques Lacan further elaborated on Freud's schema by explicitly linking it to linguistics and figures of speech. In a move that would come to define post-structuralism, Lacan argued that meaning did not depend on the link between signifier and signified (figure 42), but rather on the relationship between signifiers: "Only signifier-to-signifier correlations provide the standard for any and every search for signification . . . for the signifier, by its very nature, always anticipates meaning by deploying its dimension in some sense before it."¹⁶ To make this point, he contrasted Linguist Ferdinand de Saussure's classic example of the tree with a pair of signs: "Ladies" and "Gentlemen" (figure 43). In this pair, meaning—sexual difference—stems not from the link of "Gentlemen" or "Ladies" to a particular door, but from the juxtaposition of "Gentlemen" and "Ladies," which occurs above the bar that divides the signifier from the signified. Lacan argued: "It is in the chain of the signifier that the meaning *insists*." Vertically hanging off each unit of every articulation or signifying chain are "all attested contexts."¹⁷ This insight drew from Saussure's argument that the value—as opposed to the meaning—of the sign depended not on the relationship between signifier and signified, but rather on the chain of signs in which a sign is embedded (figure 44). These chains were both synchronic and diachronic: they unfolded in time within a sentence, and across time through associations.

GENTLEMEN

LADIES



43 "Gentlemen and Ladies," redrawn from Jacques Lacan, *Écrits*, trans. Bruce Fink (New York: Norton, 2006), 416.



44 Value chains, redrawn from Saussure, *Course in General Linguistics*, 115.

Based on this linguistic-psychic schema, Lacan argued that condensation was metaphoric—it replaced one signifier by another—and that displacement was metonymic—its meaning stemmed from the proximity of signifiers. The phrase “thirty sails” in *The Illiad*, for example, signified “thirty ships,” not because one sail equaled one ship (each ship probably had more than one sail), but because “sails” was a metonym for “ships.”¹⁸ In contrast, metaphor depended on proxies. Lacan explained this through a line from Victor Hugo’s poem “Boaz Asleep”: “his sheaf was neither miserly nor hateful.” In this line, the sheaf both replaces and refers to Boaz (Ruth’s husband in the Old Testament): by taking Boaz’s place, the sheaf ensures that the invisible Boaz remains supreme.¹⁹ Signification places the signifier “Boaz” “under the bar.” In both condensation and displacement, however, “co-relations” between signifiers matter most.

If, as mentioned previously, network science is the bastard child of psychoanalysis and eugenics—if, indeed, as Albert-Lázlo Barabási has argued, network science has replaced psychology—it is not despite, but rather because of, both metaphoric and metonymic correlations. As noted before, Ronald Burt discussed social capital as a metaphor for advantage;

Paul Lazarsfeld and Cambridge Analytica viewed style as a proxy for politics; Philip Agre argued that capture systems were fundamentally linguistic. Further, both eugenics and psychoanalysis are obsessed, as chapter 4 further elucidates, with sexual selection and difference. But what is most important, even though both psychoanalysis and network science seek to make latent wishes manifest, they differ in purpose: psychoanalysis promises (however elusively) to help patients deal with their neuroses, whereas corporate data analytics seeks to profit from them. They also differ in their acknowledgment and engagement of correlations that disguise, distort, and displace: psychoanalysis seeks mechanistic explanations for nonlinear correlations, whereas network science stops at discovered correlations.

Investigating how correlations weave together the latent and the manifest not only unpacks the claims by data science to have cracked the collective unconscious, it also elucidates correlation's ties to ideology and ideology critique. Both ideology and latent functions supposedly explain how and why irrational processes persist, in particular, why and how people act in ways that undermine their self-interest: why people who live in public housing support the end of public housing; why those on Medicare seek to end the very program that keeps them alive.²⁰ In *Matrix*-speak, ideology is false consciousness: a “residual self-image” that prevents people from recognizing their enslavement. The twenty-first-century uptake of *The Matrix* and its metaphors testifies to the enduring belief in ideology, across the political spectrum.

The Matrix also points to another definition of “ideology,” namely, philosopher Louis Althusser’s formula: “ideology = an imaginary relation to real relations.”²¹ This formula is based on Jacques Lacan’s division of the human world into three orders: the “Symbolic” (language), the “Imaginary,” and the “Real.” Although Lacan’s understanding of these three orders would change over his career, he first introduced them to explain how children develop. At first, infants cannot tell the difference between their bodies and anyone else’s: they have no sense of absence, and everything seems to be one undifferentiated substance. This is the order of the “Real.” At some point, however, children—all of a sudden—realize that they are individuals. They undergo the “mirror stage,” during which they (mis)recognize mirrored images as themselves. At this point,

they base their identities on images around them, in particular, on images of their mothers. Their egos thus emerge through a process of (mis)identification, for they are not actually those people or images. At some point, however, children emerge into language and submit to the "Symbolic" world they live in (this was the meaning of the Oedipal complex). For Lacan, these orders did not supersede but rather shadowed one another: the "Imaginary" never completely covered over the "Real"; the "Symbolic" similarly never completely displaced the "Imaginary."²²

As an imaginary relation to real relations, ideology would seemingly be the TV set that Morpheus uses to reveal the deception of *The Matrix's* visual world (figures 8 and 9 in "Red Pill Toxicity"). Ideology here is correlational—it operates through and as correlations that reproduce and reinforce inequalities.

According to Althusser, ideology ensures state power by reproducing "submission to the rules of the established order."²³ Ideology is both imaginary and material: it persists through rituals, apparatuses, and actions. To make this point, Althusser refers to Pascal's advice to those who want to become believers: "Pascal says, more or less: 'Kneel down, move your lips in prayer, and you will believe.'"²⁴ Regardless of their seeming belief or doubt, people submit to ideology through rituals, which also transform them into subjects. Althusser explains this by means of a little "theoretical theater." In this scene, a policeman hails a man saying, "Hey, you there," and the hailed person turns around. "By this mere 180 degree physical conversion," Althusser asserts, the man "becomes a *subject*. Why? Because he has recognized that the hail was 'really' addressed to him, and that 'it was *really him* who was hailed' (and not someone else)." By recognizing himself as hailed, the hailed person makes the "you" and the "I" coincide, thereby becoming subject of and to the law and society. Althusser stresses that these hailings "hardly ever miss their man: verbal call or whistle, the one hailed always recognizes that it is really him who is being hailed."²⁵ Ideology is a communicational event, in which response = recognition.

To explain this through an analogy to software, software programs, or perhaps more precisely operating systems, offer us an imaginary relationship to our hardware: they do not mirror a motherboard, but rather mimic desktops, files, and recycling bins.²⁶ Without operating systems, there

would be no access to hardware—indeed, without them, there would be no actions, no practices, no users. Each operating system, through its brand, calls to its “users” and offers them a name or image with which to identify. Mac users “think different” and identify with Martin Luther King Jr. and Albert Einstein; Linux users are open-source power geeks, drawn to the image of a fat, sated penguin; and Windows users are mainstream, functionalist types. What is important here is that the “choices” operating systems offer limit the visible and the invisible, the imaginable and the unimaginable. As a user, you are not, however, aware of your software program’s constant constriction (also known as the program’s “user-friendliness”), unless you find yourself frustrated with its defaults, which are rather remarkably referred to as “*your* preferences.”

Cultural critic Richard Dienst insightfully revisits Althusser’s moment of hailing to reveal that recognition—as an act of telecommunication—also entails mis-recognition. First, Dienst notes that if ideology can miss its mark, then it must “have been unstable as sign and as event, it can never simply be the transmission of meaning to the subject.” Second, he contends that “ideology neither hails nor nails the subject in place. . . . Ideology must be conceived as a mass of sendings or a flow of representations whose force consists precisely in the fact that they are not perfectly destined, just as they are not centrally disseminated. Far from always connecting, ideology *never does*: subjects look in on [its] messages as if eavesdropping, as if peeking at someone else’s mail.” In other words, the “I” and the “Hey, you” are never perfectly aligned. Ideology works by closing this distance through “a short circuit between the singular and the general so *the reception of a representation* becomes a sending back—*a representation of a reception*.²⁷ This sending back closes the circuit by collapsing the singular and the general: I=YOU.

To explain this in terms of networks, our captured online actions constantly send back a representation of a reception. Even when we seem to be doing nothing, our devices engage in lively conversations, in which they mainly ask and respond to the question “Are you there?” There is no “silence of the masses” online because interactivity entails constant, involuntary, and traceable information exchanges. As users, our responses also help close the circuit: through acts of friending, following, liking, and recommending, messages become both more directed and less

general (better targeted) because we answer our friends' eavesdropped calls. So, how do we hang up? And why is it that software seems to perfectly mimic every definition of ideology we have?²⁸

Crucially, freedom does not stem from diagnosing or "unveiling" ideology. Rather, as Slavoj Žižek, drawing from Althusser, has argued, stepping out of what we experience as ideology is "*the very form of our enslavement to it.*"²⁹ As the term "being red pilled" inadvertently reveals, becoming "woke" entails passivity to a larger force. As discussed in chapter 2, Muzafer Sherif's experiment and Hannah Arendt's description of totalitarian propaganda reveal how an initial distrust or questioning of the visible world can lead to a more disastrous and manipulated trust. According to Žižek, ideology is a generative matrix "that regulates the relationship between visible and non-visible, between imaginable and non-imaginable, as well as the changes in this relationship."³⁰ Both ideology and ideology critique, philosopher John Mepham tells us, work through correlation: "The true text is reconstructed not by a process of piecemeal decoding, but by the identification of the generative sets of ideological categories and its replacement by a different set."³¹ Ideology is not simply illusion or fiction, but rather "real" correlations that lie.³²

Given this, there would seem no escape from ideology. Against this "postmodernist" position, however, Žižek argues that, though an outside place exists, it is and must remain empty: "*It cannot be occupied by any positively determined reality*—the moment we yield to this temptation, we are back in ideology."³³ The task of ideology critique is thus not to make the latent manifest (the therapeutic version of ideology critique), but rather to "discern the hidden necessity in what appears as a mere contingency."³⁴ For Žižek, ideology externalizes as contingent what is absolutely necessary—antagonism and class struggle.

To explain this, Žižek, like Althusser, turns to Lacan and his distinction between "reality" and the "Real": "reality" is a symbolic construction that seeks to "cover" the "Real," but it always fails to resolve "some unsettled, unredeemed symbolic debt." This gap, which escapes being symbolized, is the "Real," which "*returns in the guise of spectral apparitions,*" whereas "reality" presents itself only through its incomplete or failed symbolization. According to Žižek, "the pre-ideological 'kernel' of ideology thus consists of the spectral apparition that fills up the hole of the real."³⁵ In other

words, what “reality” seeks to foreclose comes back as hallucination. Returning to the example of class struggle, Žižek argues that social antagonism is the “kernel” that can only be experienced through its foreclosure and transformation into a specter—it is “that limit which prevents us from conceiving society as a closed totality.”³⁶ Truth functions like a spectral fiction.

Whether or not one agrees with Žižek’s privileging of class struggle, antagonisms—indifference, ambivalence, inertness (the power of the silent masses)—haunt correlations that lie at the surface. These are constantly denied in the worldview of homophily, in which hate becomes “love.” What homophily seeks to foreclose, though, is not simply antagonism but also collective action and solidarity.

4

RECOGNIZING RECOGNITION

Facial recognition technology (FRT) was one of the first machine learning-based applications to be banned by U.S. governmental bodies. In March 2019, the city of San Francisco—home to many Silicon Valley tech developers—barred the police and other municipal agencies from using the technology.¹ Both real and speculative harms drove this resistance: it was banned not only because of documented cases of its bias, but also because it threatened to become an “authenticity machine.” FRT promised to both track or authenticate specific individuals “going about their daily lives” and to reveal their latent “types.” For example, in an unpublished yet widely covered paper posted online in 2016, scientists from Shanghai Jiao Tong University claimed to have developed a system to discriminate between criminals and noncriminals.² Less but still controversially, in 2018, computer scientist Yilun Wang and computational social scientist Michal Kosinski announced that they had produced a machine learning program to detect sexual orientation.³

Crucially, Wang and Kosinski prefaced their 2018 analysis by both repudiating and resuscitating the long-discredited practice of “physiognomy.” Thus, on the one hand, they derided as superstition and racism the claim by Cesare Lombroso, founder of criminal anthropology, that arsonists have a “softness of skin, an almost childlike appearance, and an abundance of thick straight hair that is almost feminine.” On the other,

they argued that rejecting physiognomy altogether was “unscientific,”⁴ because, as the title of their 2018 analysis clearly stated: “Deep Neural Networks Are More Accurate Than Humans at Detecting Sexual Orientation from Facial Images.” Wang and Kosinski contended that machines were more accurate than humans because they were better readers of facial features that indicated sexual orientation. As this chapter reveals, the links between facial recognition technology and eugenics are not only thematic or aspirational, but also methodological. They are rooted in eugenic methods, such as linear discriminant analysis, developed in the early twentieth century to discriminate between classes and races of people.

So how did discrimination become recognition?

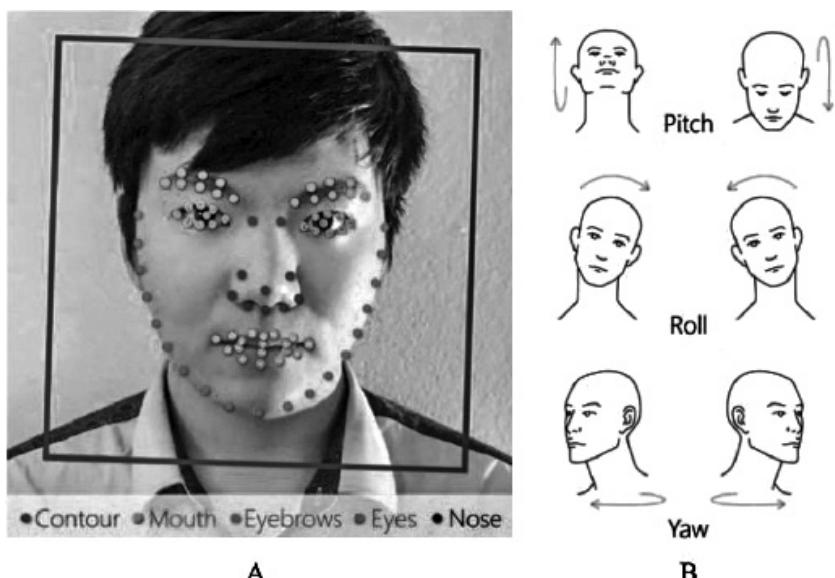
To answer this question, this chapter analyzes FRT in the context of (1) cybernetic attempts to analyze humans, machines, and animals as enduring and generalizable patterns; (2) the “recognition versus redistribution” debates of the mid-1990s; and (3) the rise of the “new politics of recognition” by the reactionary right in the early twenty-first century as a way to prevent economic and political redistribution. Through these developments, recognition has become a metaphor for discrimination: like homophily, it launders hate into “love.” However, as the fears about “AI masters” that haunt machine learning dreams indicate, the issue of recognition is no trivial matter. Indeed, as discussed in more detail later in this chapter, Hegel famously characterized recognition as a “social drama”: a struggle between slaves and masters for dominance, acknowledgment, and power. To recognize someone is to accept that person’s authority, validity, or legitimacy.⁵ Recognition = discrimination++. Through recognition, as now understood, we “learn” to hate others, as we hate ourselves.

WHO’S READING WHOM?

According to Wang and Kosinski, machine learning outperformed humans (aka U.S. Mechanical Turk workers) in correctly reading a person’s sexual orientation. Colloquially called “machine gaydar” by journalists, their model scanned white U.S. faces to in order to predict their sexual orientation.⁶ As this section reveals, at best, their model recognized cultural styles, which are usually read by “those in the know” (hence gaydar),

but which the authors framed as hidden physical stigma. Although their assumptions and conclusions may seem singular, their methodology was not: they used generally available, standard programs and methods. To evaluate their claims about facial recognition technology, we therefore need to closely examine how Wang and Kosinski's machine was trained to read human sexual orientation.

To produce their "gaydar," the authors first harvested some 301,000 images from a U.S. dating site (widely thought to be OkCupid). They used these self-portraits because they were (1) from public profiles and thus presumably fair for the harvesting; (2) less costly to acquire than those produced in laboratory settings; and (3) abundant. Wang and Kosinski then used a readily available program called "Face++," produced by the Chinese FRT pioneer Megvii, to create outlines of the faces in these images. Next, based on these outlines, they removed images that contained of multiple faces, partially hidden faces, overly small faces, and faces not facing the camera directly (figure 45).



45 Face++ facial landmark detection. From Yilun Wang and Michal Kosinski, "Deep Neural Networks Are More Accurate Than Humans at Detecting Sexual Orientation from Facial Images," *Journal of Personality and Social Psychology* 114, no. 2 (2018): 249.

Next, they employed U.S. Amazon Mechanical Turk workers to verify that the faces in the images belonged to adult Caucasians and were fully visible and to confirm that the gender of each user face matched the one reported on the user's profile. (In the world of machine learning, poorly paid humans spell-check for computers.) Through this process, they winnowed their set to 35,326 images. To read this diminished data set and prevent overfitting, they used an off-the-shelf deep neural network program called "VGG-Face," produced by researchers at Oxford University's Visual Geometry Group and initially trained mainly on U.S. celebrities, to extract the 4,096 features needed to determine the sexual orientation of the owner of each face displayed in the images. Next, they used singular value decomposition (SVD) to reduce dimensionality (recall figure 37), moving from around 4,000 independent variables to 500 dimensions. At this stage, they also divided the face images into 20 subsets: 19 subsets to train the deep neural network program on, with 1 subset put aside for cross-validation. They then trained a logistic regression model to classify sexual orientation for these 500 dimensions—presumably assigning 1 for gay and 0 for straight. Finally, they used their model to predict the sexual orientation of participants in the test set and to assign probabilities of being gay to the owners of all the faces in their images. To test the accuracy of their predictions, they randomly paired a face image of a heterosexual man with a face image of gay man, or a face image of a heterosexual woman with a face image of a lesbian woman, and then used their system to predict which face image in each pairing belong to a person who was gay or lesbian. These accuracy percentages (81 percent for male images and 71 percent for female images) were higher than those achieved by the U.S. Amazon Mechanical Turk workers the researchers employed (61 percent for male images and 54 percent for female images). Significantly, the researchers did not report accuracy percentages for determining the sexual orientation of the owners of faces displayed in the images when comparison images were not used.

Since the operations of the deep neural network model were opaque to the researchers, they engaged in a series of "hacks" to decipher what mattered. To discover what the model was actually reading—to make sense of the latent dimensions they had constructed—they randomly chose 100 face images of men and 100 face images of women for further analysis.

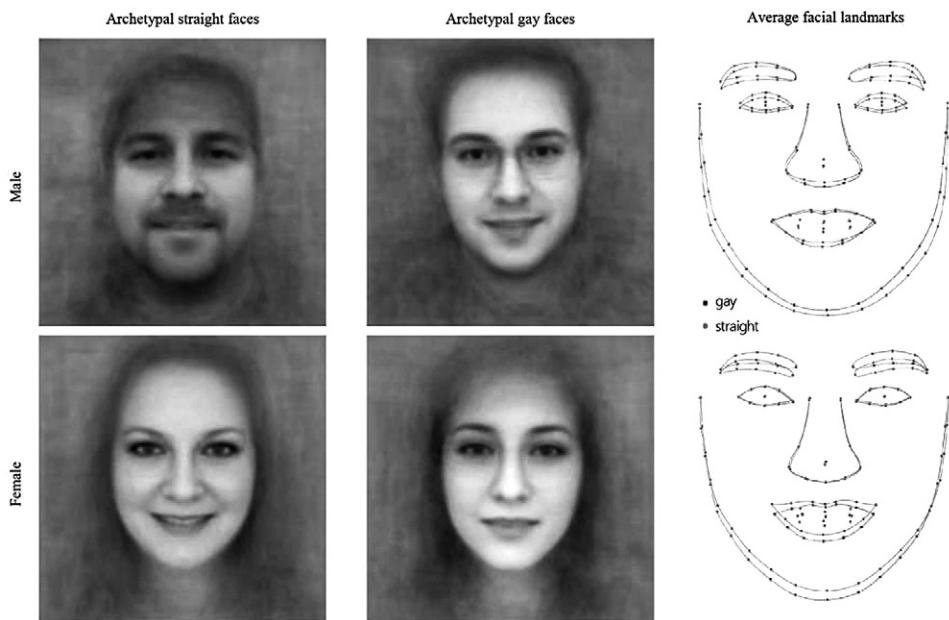


46 Heat maps showing the degree to which masking a given part of an image changes the (absolute) classification outcome. The color scale ranges from blue (no change) to red (substantial change). From Yilun Wang and Michal Kosinski, "Deep Neural Networks Are More Accurate Than Humans at Detecting Sexual Orientation from Facial Images," *Journal of Personality and Social Psychology* 114, no. 2 (2018): 250.

They created a “heat map” by moving a 7×7 pixel mask across each of the 200 face images and then calculating the average absolute change in probability of the owner of the face displayed in the image being gay or lesbian with the mask in place (figure 46).

The facial features or “landmarks” that changed this probability most significantly included the nose and chin of men, and a woman’s neckline. Having determined that their model’s classifier was focusing on these and other features, they then compared, for each gender, 500 face images of those most likely to be gay or lesbian and 500 face images of those least likely to be gay or lesbian. First, they used all these face images to generate average locations for the facial features or landmarks of interest. They then randomly selected 100 face images from each set to create composite face images, which revealed “archetypal” gay or lesbian and straight faces for each gender (figure 47).

From these, they concluded that gay men have narrower jaws, longer noses, bigger foreheads, less facial hair, and lighter skin than straight men do and that lesbian women have larger jaws and smaller foreheads, wear less eye makeup and less revealing clothes, and engage in less gender-typical grooming than straight women do. They further concluded that, in general, women smile more than men, but lesbian women smile less



47 Composite images of gay, lesbian, and straight faces. From Yilun Wang and Michal Kosinski, "Deep Neural Networks Are More Accurate Than Humans at Detecting Sexual Orientation from Facial Images," *Journal of Personality and Social Psychology* 114, no. 2 (2018): 251.

than straight women and that straight men more often wear baseball caps (this creates a shadow on the forehead) than gay men do. Intriguingly, they did not comment on the shadow of glasses on the "archetypal" gay male face. Jawline, nose, forehead, facial hair, skin color, eye makeup, and gender-typical grooming—these were the proxies that mattered.

To prove the biological validity of their results, they created a "femininity factor" by measuring the gender atypicality of gay men's faces, using the 2,891,355 facial images of Facebook users obtained from the myPersonality.org project, discussed in chapter 1. This basically repeated their process for determining a "gay factor," but used gender as the dependent variable. From this, they asserted that gay men's faces had more "feminine" features and lesbian women's faces had fewer "feminine" features than their heterosexual counterparts. According to their analysis, facial femininity alone was 57 percent accurate for predicting gay men and 58 percent accurate for predicting lesbian women (only slightly better than

the 50 percent accuracy of a random guess). Next, Wang and Kosinski created a morphology-based classifier to show that facial contour (in particular, jawline) alone could predict a person's sexual orientation. When they applied the new facial contour classifier to the larger, "clean" data set, they found it was 75 percent accurate for men and 63 percent for women—when it was presented with 5 images of the same face. Finally, to prove that the results from their facial recognition model were valid beyond dating sites, they tested it on the face images of gay men on Facebook, whom they identified by their liking certain phrases, such as "I love being Gay"; "Man hunt"; "Gay and Fabulous"; and "Gay Times magazine." They found that their model could accurately distinguish 74 percent of the time the face images of heterosexual males culled from dating sites from those of gay males culled from the myPersonality.org data set and dating sites.

They concluded—and justified—their study by arguing that they had revealed the limitations of attempts by policy makers and technology companies to give users more control over their digital footprint (unless users would agree to cover their faces in public, users would betray their sexuality). In their final sentences, Wang and Kosinski also stressed the importance of tolerance and human rights: "The safety of gay and other minorities who may be ostracized in some cultures will hinge on the tolerance of societies and governments. The postprivacy world will be a much safer and hospitable place if inhabited by well-educated, tolerant people who are dedicated to equal rights."⁷

Did we really need energy-intensive deep neural networks to teach us about equal rights?

The authors' ethical justification for their study recalls the "moral message" added to precode Hollywood movies to ward off censorship and regulation. Further, their conclusion that "the erosion of privacy seems inevitable" would appear self-serving.⁸ But, what is more important, their call for tolerance, as Wendy Brown has pointed out, "depoliticizes" discrimination,⁹ and their call for global tolerance for "gay and other minorities," given their privileging of U.S. data, engages in what queer theorist Jasbir Puar has called "homonationalism."¹⁰

This study makes troubling assumptions throughout. They presume that sexual orientation is a binary phenomenon: in the model, you are

either a gay or a straight man or you are a lesbian or a straight woman. The relentless framing of recognition as a choice between a gay or lesbian and a straight face image not only erases gender and sexual ambiguity and transgender and transsexual subjects, it also raises doubts regarding the generalizability and relevance of their study's results. Although presumably paired in this manner to facilitate logistic regression, a success rate of 61 percent is not that significant, especially given that machine learning systems "in the wild" will not face such a clear-cut choice. Further, although their figure 1 features an Asian man in illustrating Face++, their study used only U.S. Caucasian face images,¹¹ and it based its conclusions on face images and data taken from U.S. users of one dating site and from Facebook users who filled out the myPersonality.org survey, and assessment data reported by the U.S. Amazon Mechanical Turk workers they hired. Although the researchers claim they chose these face images because publicly available face images of gay and lesbian people of color are scarce, their choice is remarkably "serendipitous," given that early twenty-first-century facial recognition models, as discussed earlier, were trained on lighter-skinned face images and thus have difficulty recognizing the gender of darker-skinned ones.¹² The VGG-Face program, which they claimed they used to prevent overfitting, was trained on face images from the Internet Movie Database (IMDb) and Free Knowledge graph, sources whose face images are of predominantly white and mainly U.S.-based persons. Thus the researchers' move from Face++ to VGG-Face actually furthered not only overfitting but also their conflation of national cultural styles with "biological" traits.

The researchers relied on a "biological" theory of sexual orientation to justify their race-based exclusion. If sexual orientation is caused in utero, what holds for one race, they asserted, should hold for all races. The prenatal hormonal theory of homosexuality, based mainly on studies of animals, controversially claims that atypical prenatal exposure to male hormones is correlated with sexual orientation. Human-based research studies have mainly focused on females who suffer from congenital adrenal hyperplasia (CAH), a very rare genetic disease.¹³ Those diagnosed with CAH are exposed to high levels of testosterone in utero and have difficulties producing certain hormones.¹⁴ The prenatal hormonal theory, however, is far from universally accepted and even those who do accept

it in principle make no strong causal claims for it since the great majority of women with CAH report an exclusively heterosexual orientation.¹⁵ Further, gender atypicality associated with CAH is usually not defined by facial features, but rather by height and genital development. It is also odd that, given that human studies have focused on female gender atypicality, Wang and Kosinski analyzed male faces via a “femininity factor.”

To defend their “ground truth,” the researchers argued that people voluntarily seeking partners on a dating site would not misrepresent their sexual orientation. This assumes that people do not use dating sites to experiment with or to highlight one aspect of their sexual orientation. More problematically, it assumes that the face images on dating sites have not been “improved”—that users of dating sites do not know how to use image filters to alter their face shape (even though face image altering is now a standard industry and amateur practice) and that they do not get plastic surgery (which is a mundane procedure in both the United States and many other parts of the world). The researchers also assume that sexual orientation is a “hidden” truth—that people’s faces usually serve as their “closets.”

Most of the differences Wang and Kosinski found—based on a small subset of 500 face images used to determine average landmark location and 100 face images for their composite images—revealed cultural rather than inherently biological features: weight, baseball caps, facial hair, as the researchers noted. Surprisingly, they also did not examine the impact of their hired Amazon Mechanical Turk workers’ sexual orientations. “Gaydar,” after all, picks up in-group style or signaling. As cultural critic Dick Hebdige has explained, style defines a subculture’s surface, comprising mundane objects that carry a double meaning: they alert the “straight” world that something is amiss and those “in the know,” of a “forbidden identity.”¹⁶ Style seeks to (selectively) correlate outward appearance with personal identity. Machine learning “gaydar” is, most generously, a “woke” reader of style.

So do we really need facial recognition technology to confirm that white gay men and white straight women in the United States tend to trim their eyebrows? That straight white U.S. women tend to wear makeup and conform to certain beauty standards? That straight white U.S. men tend to have beards? How else and more humanly could we learn about

social conventions and cultural style? And what are we to make of this turn to racial segregation, “justified” by controversial biological “causes” for sexual orientation?

BIOMETRICS, AGAIN

It is no accident that FRT research starts by referencing physiognomy. The links between eugenics and recent studies on facial recognition technology are not only topical or aspirational, but also methodological. Principal component analysis (PCA), developed by eugenic biometrists (see chapter 1 and “Proxies” after chapter 2), drove one of the most significant late twentieth-century advances in FRT: the eigenface method, which moved facial recognition technology away from humanly determined toward *nonhumanly*—algorithmically—determined features. Increases in computational power and publicly available face images have made deep neural network programs more popular, but neural network models rely on logistic regression, a binary adaptation of linear regression, developed by Raymond Pearl, a student of Karl Pearson and himself a reformed eugenicist. The most direct link to early biometric eugenic methods, however, is the construction of composite images to determine “typical” faces.

Although they do not cite Galton in their 2018 study, Wang and Kosinski’s use of composite photographs to create archetypal faces repeats both the form and purpose of Francis Galton’s composites. As discussed in chapter 1, Galton pioneered the production of composite images—portraits that used a single plate to register and process several photographic images together—in order to discern the general “average” that lay, usually undetected, within the facial images of criminals, Jews, and other persons of interest (figure 48).

Like Wang and Kosinski, Galton argued that, through technology, he could recognize legible characteristics not normally discerned by unaided human observers.¹⁷ Galton called his images “composites” because he asserted that they were visual equivalents to Adolphe Quetelet’s statistical averages, even though his sample size did not approach the size used to produce statistical tables.¹⁸ These visual composites were “real generalizations,” he argued, because they included all the images he had made of his subjects.¹⁹ Given this, Galton’s composites unveiled the “ideal type”—the



Profile.

The Jewish Type.

Full Face.

48 Francis Galton, "The Jewish Type," 1883. Plate XXXV from Pearson, *The Life, Letters and Labours of Francis Galton*, 2:294.

blurry outlines were "noise": insignificant distractions from the average or essence of the "ideal type." As photographer and critic Allan Sekula pointed out, Galton viewed his composite image of "the Jewish type" to be his most successful composite.²⁰

Allan Sekula's remarkable and groundbreaking 1986 study "The Body and the Archive" placed Galton's composite images within the historical contexts of physiognomy and the "crisis of faith in optical empiricism" brought on by the widespread adoption of photography.²¹ Sekula argued that, by including both honorific bourgeois portraits and criminal mug shots, the photographic archive promised (like FRT's "gaydar") to decipher the characteristics of all bodies by delineating the respectable from the "deviant."²² But this promise was never realized, because the sheer number of photographs and their "messy contingency" undermined simple visual identification.²³ Photographs were therefore supplemented by the logic of the "filing cabinet" to sort, catalogue, read,

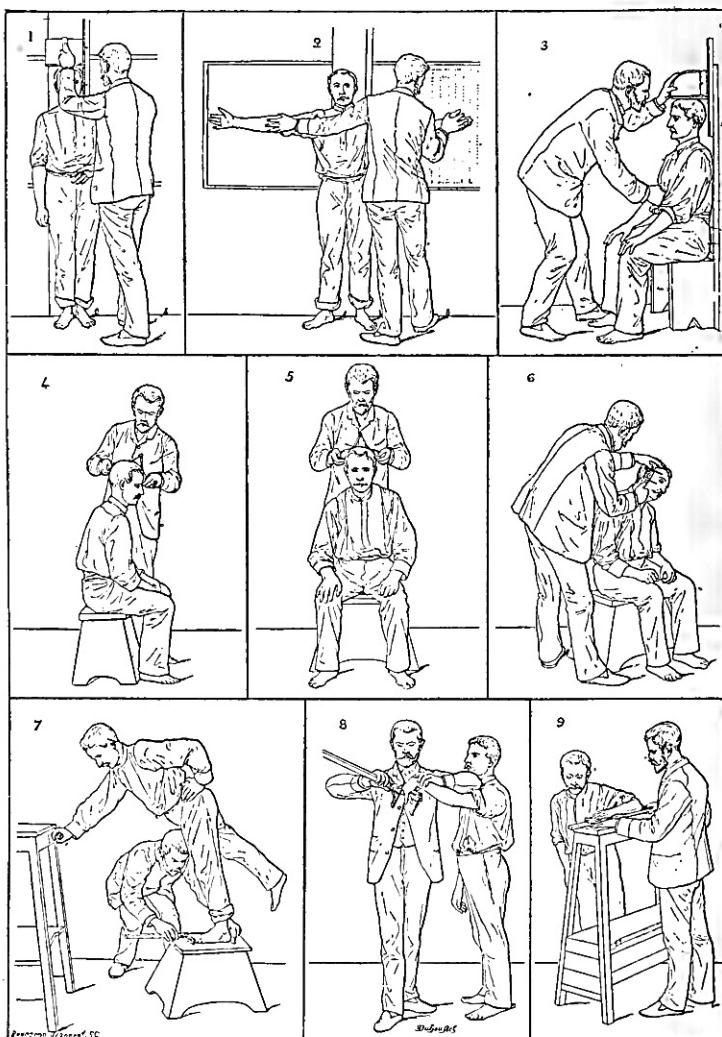
and inscribe images, a logic that took two different forms: (1) Galton's approach, "to embed the archive in the photograph" through his composite images; and (2) French police detective Alphonse Bertillon's approach, to embed the photograph in the archive through his system of nine measurements, necessary to identify individuals definitively (figure 49).²⁴

Bertillon's goal was to identify recidivist—that is "professional"—criminals, whom he believed were using subterfuge to evade the law. He described the Parisian working class as undergoing a "crisis of identity" for the "social field . . . had exploded into multiplicity."²⁵ (The current crisis regarding identity linked to electronic communications echoes Bertillon's concerns regarding the proliferation of false documents and aliases.) Regardless of the differences, Bertillon's and Galton's approaches both sought to make past identifications coincide with present and future ones through "immutable" features.

Facial recognition technology and modern computationally based biometric techniques have merged Bertillon's and Galton's projects. By "authenticating" both individual and type, they seek to produce "authenticity machines." Although most pattern recognition systems claim only to identify individuals—as Bertillon did—the more controversial ones openly profess to recognize Galtonian types. All pattern recognition systems, however, make typical identifications: any individual identification is preceded by a decision regarding the type of object. The Hewlett-Packard webcam discussed in chapter 1 failed to recognize Desi Cryer's face because it did not classify his face as a human face.

Galton's and Bertillon's systems, however, were never truly separate. The goal of recognizing criminals assumed in advance a stable category of individuals called "criminals," whose characters did not change, even if their appearances did. Further, Sekula's 1986 analysis overlooked correlation's role in tying together both systems. As discussed in chapter 1, Galton formulated correlation in response to Bertillon's method, which Galton believed was overly cumbersome. The links between facial recognition and pattern recognition technology to eugenics, however, extend beyond biometric eugenics to methods used to discern populations and control them through sexual selection.

RELEVÉ
D U
SIGNALEMENT ANTHROPOMÉTRIQUE



1. Taille. — 2. Envergure. — 3. Buste. —
 4. Longueur de la tête. — 5. Largeur de la tête. — 6. Oreille droite. —
 7. Pied gauche. — 8. Médius gauche. — 9. Coudée gauche.

49 Frontispiece from Alphonse Bertillon, *Identification anthropométrique: Instructions signalétiques* (Melun [Paris]: Imprimerie Administrative, 1893).

RECOGNIZING SEXUAL SELECTION

Modern statistical pattern recognition expands upon early work to discriminate between populations. The desire to “read” images—to archive them and deploy them in order to identify both the particular and the generic—drives the transformation of discriminant mathematical functions into algorithms of “recognition.” But how did identification and discrimination become recognition? And why does this matter?

As computer scientists Corinna Cortes and Vladimir Vapnik note in their seminal 1995 study “Support-Vector Networks”: “R. A. Fisher . . . suggested the first algorithm for pattern recognition” in 1936. This first algorithm was Fisher’s linear discriminant function (see figure 50), which constructed linear decision surfaces between populations with normal (and later nonnormal) distributed populations.²⁶

In their formulation of support vector networks (later called “support vector machines”), Cortes and Vapnik advanced the work of Ronald A. Fisher—the mathematical biologist who famously ended the nasty debate between Mendelian and biometric eugenicists by treating genes as populations—by using products of features, or “kernels,” to create more precise boundaries. A support vector machine (SVM) builds walls between groups that are presumed in advance to exist and to be different.

As the term “linear discriminant analysis” (LDA) implies, Fisher developed LDA functions to discriminate between races and species. By discerning and using the “measurements by which the populations are best discriminated,” these functions built mathematical fences between populations whose boundaries appeared mixed. The functions presumed the prior existence of distinct groups, which could be distinguished by their different norms for common features: the members of these groups all had skulls, for example, but of different shapes.²⁷ Fisher’s 1936 *Annals of Eugenics* study featured his now classic multivariate iris data set, which used petal and sepal size to distinguish between three related flower species. Its first paragraph, however, referred to other researchers who, “at the author’s suggestion,” used craniometric measurements to categorize human races in different ways, namely, “Mr. E. S. Martin, who has applied the principle to the sex differences in measurements of the mandible, and . . . Miss Mildred Barnard, who showed how to obtain from a series of

LINEAR DISCRIMINANT ANALYSIS

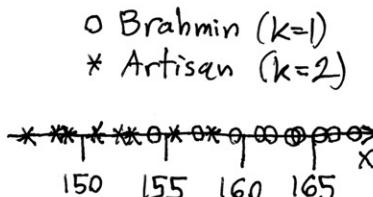
LDA is a method to assign a "class" (ie, label $k = 1, 2, \dots, K$) to a datapoint x comprising n variables, given a "training set" of other datapoints with known labels. The goal is to correctly predict labels of datapoints — it is one of the earliest "machine learning" algorithms.

We now adapt examples from C.R. Rao's foundational 1948 paper on LDA, keeping their racial & eugenic problems fully in mind...

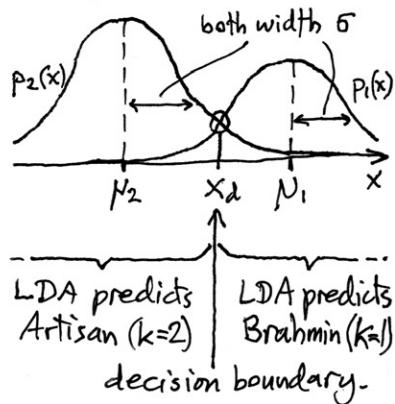
1D We start in $n=1$ dimensions:

Let x be a human's stature (height) in cm. From such biometrics, Rao (working with Mahalanobis) wished to predict caste, ie assign labels $k=1$ (Brahmin), $k=2$ (Artisan), etc. For now, let's stick to those two classes ($K=2$). The training set is heights of random citizens, of known caste: two types of point (\circ or $*$) scattered on the x axis as shown to the right.

TRAINING DATA:



MODEL PDF:



LDA models the training data by a Gaussian (normal) "probability density function" (pdf) for x in each class, with the same variance σ^2 , but different means μ_1, μ_2 , and different "masses" (areas) π_1, π_2 . A pdf is simply a graph showing the expected distribution of x . The previous figure sketches the fitted model pdf: two "bell curves" of different heights. Here's the formula:

$$p_k(x) = \frac{\pi_k}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu_k)^2}{2\sigma^2}} \quad k=1,2 \quad x \in \mathbb{R}$$

The point is that the four parameters ($\mu_1, \mu_2, \sigma, \pi_1$) are easy to estimate from training data:

μ_1 = mean height of Brahmins

μ_2 = mean height of Artisans

π_1 = fraction that are Brahmin = $1 - \pi_2$

σ^2 = mean square deviation of each height from its respective class mean (μ_1 or μ_2).

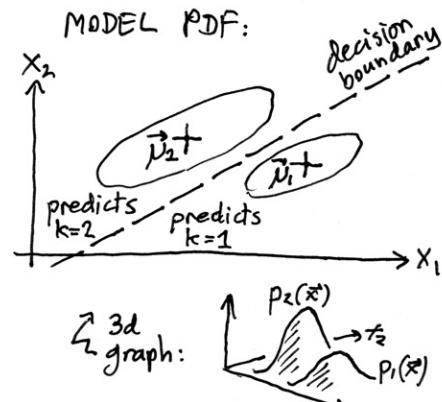
Now let's predict! Given a new x to classify, LDA simply picks the most likely k conditioned on this x , which is the same as asking if $p_1(x)$ or $p_2(x)$ is the larger.

The "decision boundary" x_d is where $p_1(x_d) = p_2(x_d)$, ie, where the two curves cross (see figure). Any $x > x_d$ is predicted Brahmin, any $x < x_d$ Artisan.

- Note, the larger the separation $D = \frac{|\mu_2 - \mu_1|}{\sigma}$ (called "Mahalanobis distance"), the higher expected prediction accuracy.

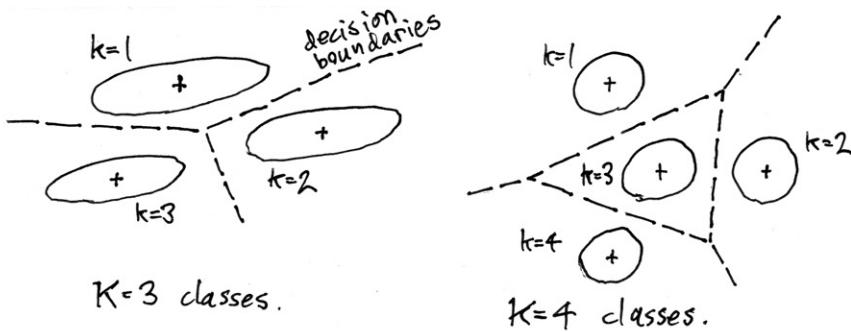
Here, $D \approx 2$. If $D < 1$ you may as well just toss a coin!

[2D & higher] Since more variables are better (right?), LDA is more powerful in $n=2$, or higher, dimensions. Rao considered $\vec{x} = (x_1, x_2)$ where x_1 = stature, x_2 = nasal depth. Now each citizen is a datapoint in 2D space:



Again, LDA models the training data (by a mixture of "multivariate" Gaussians with the same covariance, as shown by the skew ellipses above), then chooses a decision boundary by setting $p_1(\vec{x}) = p_2(\vec{x})$: the result is a hyperplane (in 2D, a line), hence "linear discriminant". The covariance is usually found via PCA (see Fig. 37).

[$K > 2$ classes] LDA also extends to more than 2 class labels. Setting pairs of densities $p_j(\vec{x}) = p_k(\vec{x})$ equal leads to various touching pieces of hyperplanes, fracturing data space in a similar fashion to a "Voronoi tessellation". Here's a sketch of some examples in 2D:



Notes on LDA:

- For the full formulae, see the References.
- LDA is easy to use, but makes strong assumptions, rarely true:
 - classes are discrete, stable, cover all possibilities.
 - all pdfs are Gaussians, of same covariance.
- Nonlinear decision boundaries are more flexible, eg, via support vector machines (SVM) or neural networks (NN), but need more training data & computer time. In the last decade, convolutional NNs have radically improved accuracy in difficult image classification & recognition problems.
- LDA (and all the fancier above classifiers) reproduce the discrimination in the training data, which is usually selected by a human, or other algorithms... bias in, bias out. (BIBO).
- Rao's work did/does not prove that caste is racial, and ignores crucial social & environmental factors. If "Brahmins" and "Artisans" were treated & nourished equally, would their height pdfs tend to become the same?

dated series the particular compound of cranial measurements showing most distinctly a progressive or secular trend.”²⁸

At the heart of linear discriminants lies craniometry and taxonomy: the measurement of jawlines to discriminate between genders (a fore-runner to Wang and Kosinski’s use of jawlines to distinguish sexual orientation) and the measurement of Egyptian skulls, from predynastic to Ptolemaic, to understand the changing nature of civilizations.²⁹ Fisher’s 1936 *Journal of the Royal Anthropological Institute* study moved craniometry away from Pearson’s “coefficient of racial likeness,” which compared the means and standard deviations of different populations, toward functions that maximized the distance between them (see figure 50). Fisher would expand on this work in 1938 to include multiple factors after visiting statistician Prasanta Chandra Mahalanobis in Calcutta in 1937, and Fisher’s 1938 paper references Mahalanobis’s 1927 work on cranial size, which used correlations between skull size and language group to understand the history and impact of race and caste mixing in India.³⁰

Fisher, Pearson, and Galton were all eugenicists, although Fisher and Pearson argued publicly and acrimoniously over the relevance of Mendelianism and over mathematics. As mentioned in chapter 1, Galton believed that skull size was a measure of intelligence, and Pearson, Galton’s protégé, believed that skull size and intelligence were correlated: skull size mattered because it varied geometrically like other internal differences. Although Fisher also believed that external measures could indicate internal differences, he was suspicious of Pearson’s craniometric work because he thought that living, rather than dead, human beings should be measured, so that a person’s gender and ancestry could be documented and considered.³¹

Fisher’s work focused on the role of sexual selection on populations and eugenics. According to Fisher, sexual selection intimately bound together “the whole body of individuals of a single species.” Like Freud, Fisher used the metaphor of weaving to explain the work of sexual selection, orientation, and drives. If, for Freud, the dream work acted like a knitting point, which condensed—wove—various repressed (usually sexual) wishes together, for Fisher, individuals and populations were tapestries and sexual selection, the weaver: “In sexual organisms . . . each individual is not the final member of a single series, but of converging lines of descent which ramify comparatively rapidly throughout the entire

specific group. The variations which exist within a species are like the differences in colour between different threads which have crossed and recrossed each other a thousand times in the weaving [of] a single uniform fabric.”³² (Drawing out the weaving analogy between Fisher and Freud, sexual selection would be natural selection’s unruly unconscious.) According to Fisher, geography produced gaps in the tapestry, which gave rise to human races, but these races were so new they were not yet “specifically distinct.”³³ Discriminant functions thus cut along fraying seams within the tapestry.

According to Fisher, sexual selection both poisoned and cured: it caused civilizations to “decline,” but it could also restore them if it walked in step with the more eugenically-focused natural selection. Like Galton and Pearson, Fisher was convinced that the English nation was degenerating—but this was due not to the debilitating work conditions in industrial cities, but rather to English inheritance law, which favored dysgenic reproduction patterns: the wealthy property owners chose infertile wives in order to ensure that their property would not be divided up among their heirs.³⁴ Further, because heiresses could marry whomever they wished, they spread infertility beyond the traditional propertied classes by coupling with “exceptionally able men.” At the other end of the spectrum, impoverished “undesirables” reproduced wildly in a bid to survive.³⁵ Natural selection—which Fisher presumed favored able and rich men—and sexual selection were thus at odds, as were natural and social goals: “the biologically successful members” of English society were “social failures,” and the “prosperous and socially successful” were “biological failures . . . unfit [for] the struggle for existence.”³⁶ Natural selection was the underdog in this contest because sexual selection could “run away”: it could “overcome” natural selection through a positive feedback loop that amplified “dysgenic” features. Tellingly, Fisher did not consider the impacts of venereal disease (said to be responsible for Galton’s infertility); birth control methods; child mortality rates; or other ways and means in which sex and reproduction diverge—let alone the effects of extreme poverty and brutal industrial working conditions on mortality.

Fisher’s solution to this “dysgenic” problem was to align natural and sexual selection by offering reproductive incentives to the deserving rich. Like Pearson, Fisher condemned public assistance to the poor as wasteful:

it could only benefit at most one generation. Unlike Pearson, however, Fisher believed in inequality, which grew ever greater when natural and sexual selection were aligned. Driving his eugenic “remedy,” Fisher’s romanticized beliefs in barbarian heroism and unrepressed sexual passion drew inspiration from historical and philosophical texts, such as Edward Gibbon’s *Decline and Fall of the Roman Empire* and Friedrich Nietzsche’s *Thus Spake Zarathustra*, as well as from myths of barbarian valor, such as the Icelandic and Norse sagas.³⁷ Fisher contended that these barbarian societies had thrived by coupling natural with sexual selection: they had highly developed social class distinctions and tribal affiliations—wealth was unevenly distributed—and yet the naturally powerful men were also the most sexually potent.³⁸ They prized the heroic and the “natural inequality of man” rather than dysgenically pursuing “civil equality.”³⁹ Barbarian societies were eugenic because they understood the importance of growing sexual attraction, which could “arouse that acuteness of perception, that freedom and certainty of interpretation, by which alone the finer, rarer and more elusive traits of human excellence may be apprehended.”⁴⁰ Notably, Fisher did not address why and how these heroic societies ended.

Coming from a conservative and devout Anglican who was not able to fight in WWI due to his vision, Fisher’s call for English heroic barbarism and sexual passion might seem strange, but his description of networked tribes foreshadowed the twenty-first-century turn toward the tribal networks of “Sovereign Individuals” (see chapter 1), as well as the continuing fascination with sexuality and passionate truths. But the differences between R. A. Fisher’s visions and those of James Davidson and William Rees-Mogg are also significant. In the world of “Sovereign Individuals,” tribes fracture national populations—there are many different tribes within the nation. Further, the goal is not racial uplift, but rather neighborhood escape. And what is most intriguing, discriminants and discrimination have been transformed into pattern recognition and the cultural politics of recognition.

HOW TO RECOGNIZE PATTERN RECOGNITION

Before there was pattern recognition, there was pattern discrimination. “Discrimination”—the ability to divide, separate, and distinguish—paved

the way historically and theoretically for “recognition.” The “gaydar” example that started this chapter nicely reveals the enduring ties between the two for “recognizing” gay or lesbian faces meant first distinguishing between two types: “gay” or “lesbian” versus “straight.” Further, as this section reveals, the history of pattern discrimination exposes the animal origin of machine learning: rats were the first nonhuman neural hardware for logistic regression models.

Pattern discrimination stems from studies of animal vision. Karl Lashley, noted experimental psychologist, behaviorist, and cybernetician, created a series of “discrimination boxes” to evaluate a rat’s ability to generalize from visual cues (figures 51 and 52).⁴¹

In Lashley’s foundational, decades-long series of experiments, his discrimination boxes rewarded or punished rats—gave them food or physically hurt them (electrical shock or free fall)—for successfully or unsuccessfully discriminating between two images, which differed in pattern (horizontal versus vertical stripes), brightness, or shape. That is, the boxes tested the rats’ ability to become logistic regression machines. These experiments were staged and cumulative: at first, they focused on discrimination between visual patterns, then, the recognition of similarities, and finally, the advanced recognition “of intricate logical relations subsisting among the objects compared.”⁴²

Lashley’s experiments shed light on the complex interactions between human experimenter and rat experimentee, which formed the basis for his findings. His first study (1912) focused solely on discrimination: the rats were first tasked with discerning between a square and a circle, which they did poorly. Then they were tasked with discerning between revolving squares and circles with flickering lights. This scared the rats, who refused to go toward the interrupted light; after 200 trials, rat no. 2 “became stubborn under punishment and had to be removed from the experiment.”⁴³ In other tests, Lashley tried to discover whether his rats could perceive the difference

- in brightness between similar forms. (rat no. 1 adjusted well to this);
- between differently sized circles (complete failure);
- between illuminated horizontal and vertical lines (rat no. 2 was tasked with this and did well with it);

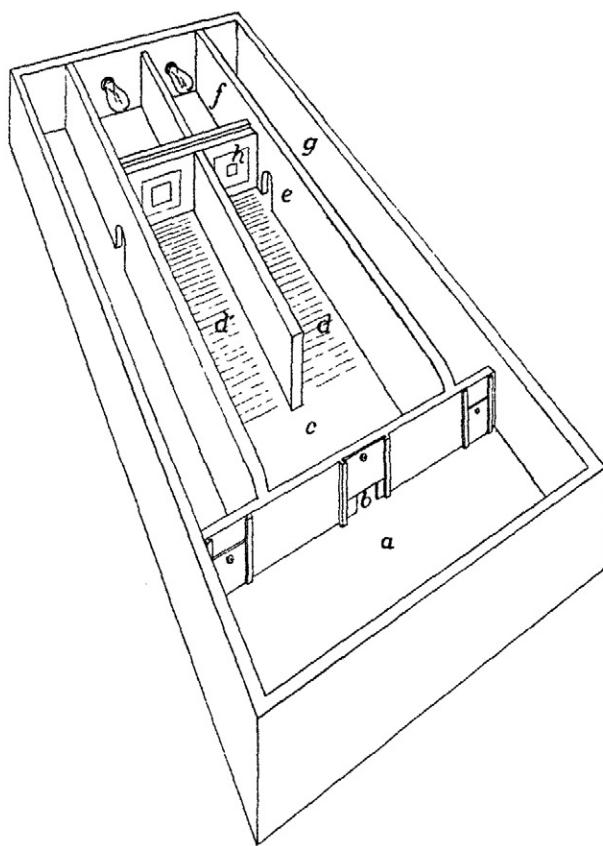
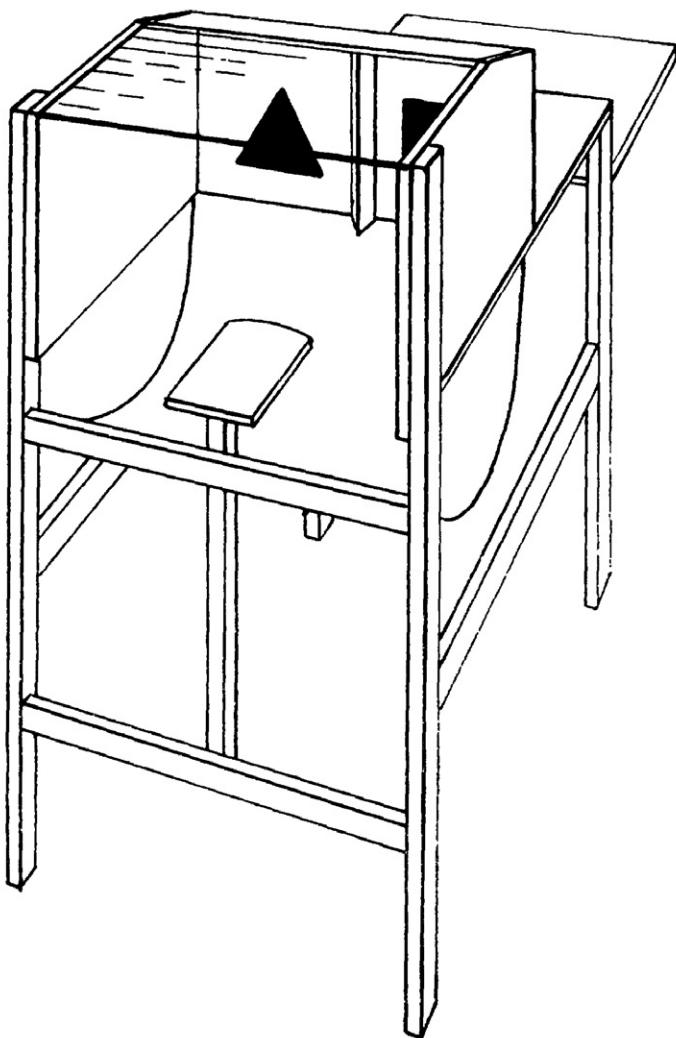


FIGURE 1. Discrimination box. a, Starting compartment; b, sliding door; c, discrimination compartment; d, d', passages wired with electric grill; e, door to food compartment; f, light compartment; g, food compartment; h, reversible frame containing the translucent forms used as stimuli.

51 Karl Lashley's "discrimination box" in 1912. K. S. Lashley, "Visual Discrimination of Size and Form in the Albino Rat," *Journal of Animal Behavior* 2, no. 5 (1912): 311.

- between differently sized rectangles (rat 2 had no greater than 25 percent error in this problem—she didn't do better, Lashley explains, because she "suffered at this time from a pulmonary trouble which constantly distracted her attention from the stimuli." However, she moved from pausing and "swaying back and forth between the two passages before choosing" to almost instantaneous choice as she became better at avoiding the "punishment grill");⁴⁴



52 Karl Lashley's "discrimination box" in 1938. K. S. Lashley, "The Mechanism of Vision: XV. Preliminary Studies of the Rat's Capacity for Detail Vision," *Journal of General Psychology* 18, no. 1 (1938): 126.

- between differently sized and lit circles (rats no. 4, no. 5, no. 6 eventually began doing so after 500 trials but rat no. 5 was still uncertain in her reactions after 700 tries);
- between differently sized circles (at first they were confused, but then caught on after many attempts).

Lashley also tried to produce a more “natural” experiment in which rats had to choose between two cardboard food boxes.

Lashley’s observations drilled down to each individual rat’s personality and behavior. He offered the following brief portraits of his rats:

No. 1. Female, 11 weeks old when given this problem; vigorous, active, and stable.

No. 2. Female, from the same litter as No. 1; very large and inactive.

No. 3. Female, from the same litter as No. 1; stunted in growth, very excitable, and easily frightened.

No. 4. Female, about two months old; large and active.

No. 5. Female, from same litter as No. 4; ill during the first part of the experiment, small but very active.

No. 6. Female, age unknown; she had given birth to one litter which she devoured; very tame, accustomed to being handled. Judged from her general behavior, this rat seems to use vision to a greater extent than the others.

No. 7. Female, age unknown; forms position associations very readily.⁴⁵

Lashley elaborated on individual differences among rats, which made punishment ineffectual: “No. 3” was extremely sensitive to pain, whereas “No. 2” could endure quite a bit of current. Intriguingly, electric shocks were only retained for “No. 6,” whose record was no better than that of the other rats, but whom Lashley found to be “the most intelligent of the group.”⁴⁶ “No. 6” was also the rat who ate her litter.

Despite this acknowledgment of differences, Lashley offered general conclusions regarding “the rat.” “The rat” can perceive differences in brightness, but not form, and can also discriminate between greatly different areas, but not absolute size; “The rat’s” difficulty in perceiving and recognizing form made its vision closely resemble “human perception in the extreme peripheral field.” Lashley also noted that the experimental structure fundamentally alters “the rat’s” behavior, for “animals

which have been trained to go to a white food dish will run to any white object.”⁴⁷

Lashley postulated that the rats’ physical condition affected their accuracy: “If they are fed too much or too little, their attention to the stimuli is effected and the percentage of error increases. When punishment is used the rat’s fear of the punishment grill after too severe a shock causes irregularities in the records.”⁴⁸ Lashley initially abandoned punishment due to the animals’ resistance: they became stubborn and refused to participate. This led him to question prior findings regarding the effectiveness of punishment over reward, although he attributed this disparity to differences between rat species: since albino rats are inactive, he mused, the presence of food provided “practically the only available motive and must be used almost constantly if the time of reaction is to be kept within convenient limits.”⁴⁹

As the experiments continued, biographical details of the rats were no longer recorded, and human interference rather than rat resistance became the source of “noise.” Lashley and his collaborators moved from explaining how the discrimination boxes affected rat behavior, to how humans affected the results through their actions or points of view.⁵⁰ They focused on how human definitions of recognition affected rat training and, as the experiments progressed, also on recognition and its relationship to discrimination and retention.⁵¹ Generalization, or recognition, Lashley argued, entailed the “identification of the common properties in two or more constellations of elements,” and it was almost universal among animals. The question thus was not whether “lower” animals were capable of recognition, but rather how their capacity to generalize differed from one species to the next.⁵² In general, by the mid-twentieth century, abstract pattern recognition, such as the recognition of words, was linked to human cognition, and pattern discrimination, to visual discernment in animals.⁵³

Patterns mattered because cybernetics viewed animals, humans, and machines as “enduring patterns.” As the “father” of cybernetics, Norbert Wiener, explained, “To describe an organism, we do not try to specify each molecule in it, and catalogue it bit by bit,” for “our tissues change as we live: the food we eat and the air we breathe become flesh of our flesh and bone of our bone, and the momentary elements of our flesh

and bone pass out of our body every day with our excreta.” According to the cybernetic worldview, organisms were “whirlpools in a river of ever-flowing water . . . not stuff that abides, but patterns that perpetuate themselves.”⁵⁴ The homeostatic pattern, as the “touchstone” of personal identity, grounded mis-recognition as recognition, for it untied recognition and physical identity.

Categorization underlay domination. Control systems were also called “servomechanisms”: devices that controlled the message or pattern through enslaving, or enslaved through controlling. Thus it is no surprise that pattern recognition became a founding task of artificial intelligence. As machine perception “pioneer” Oliver G. Selfridge and “father” of cognitive psychology Ulric Neisser argued in their influential 1960 *Scientific American* article, the best general term for abstraction, perception, or cognition was “pattern recognition.”⁵⁵

OF MACHINES AND MICE: RECOGNITION AS GENERALIZATION

Early on, artificial intelligence focused on producing machines that could “recognize” patterns, that is, record similarities across different contexts. In 1960, pattern recognition was framed as one of the most important tests for intelligence that machines had not yet passed. Computers, slaves soon to become “recognized” masters, supposedly failed because they processed information one bit at a time, whereas humans were “continuously exposed to a welter of data from [their] senses.”⁵⁶ This explanation, however, overlooked a key problem: how to properly describe what human recognition entails. Given that nothing truly remains the same, human recognition—the act of reidentification—is normal *misidentification*, which, by deviating slightly every time, creates the norm it recognizes.

In 1962, philosopher Kenneth Sayre, writing about the problem of human recognition, emphasized that recognition is relational and class based. It needs a recognizer, an observer O, an object x to be recognized, and a generalization, a class to which the object belongs: “to say that an observer O recognizes an object x may be understood to mean that there is a class of objects of which x is a member, and that O in being aware of x has identified x as a member of that class.” Recognition requires

precognition: it involves evaluating various criteria “in terms of properties which we have already learned to discriminate” or learning *novel* discriminations based on prior knowledge.⁵⁷

According to Sayre, humans could identify x as a member of a class, without being able to specify the characteristics by which they did so. But because machine recognition could not follow the path of human intuition, it had instead to determine invariant characteristics, “easily expressible in computer language,” that would distinguish “a given class of individuals from all other classes, and the possession of which qualifies an individual for membership in that class.” These invariant features would serve as proxies for human intuition and would “enable the computer to select approximately the same inscriptions which a human typically would recognize as members of that class.”⁵⁸ Machinic pattern recognition, which depended on finding correlations between machinic reading and human identification, would fail, Sayre argued, if a pattern could not be reduced to a set of features. Moreover, it could not compete with a human’s ability to identify novel features.⁵⁹

Although Sayre’s conclusions contradicted Wang and Kosinski’s positive assessment of machine vision in their 2018 study, all three authors framed discrimination as necessary for successful recognition. Modern pattern recognition systems draw together various disciplines and approaches to discrimination. They translate between the statistical, syntactical, and cognitive. They equate inference with generalization; learning with estimation; and classification with discriminant analysis. Classification systems require the prior construction or discovery of “invariant” features, on the basis of which they assign and reduce objects.⁶⁰ The choice or discovery of these categories is motivated: in commercial online systems, they are ones that maximize clicks; in predictive policing ones, they optimize arrests. In all cases, these choices are based on curated data and designed to create “optimal”/“suboptimal” or “safe”/“unsafe” neighborhoods. As physicist Geoff Dougherty’s classic textbook on pattern recognition explains: “The quality of the features is related to their ability to discriminate examples from different classes. Examples from the same class should have similar feature values, while examples from different classes should have different feature values. . . . The preferred features are always the most informative (and, therefore in this

context, the most discriminating).⁶¹ The most discriminating features are valued, regardless of their physical, biological, or conceptual importance—recognition = discrimination++—for they seem “invariant.”

To understand this historical shift from discrimination to recognition, however, we need to consider the philosophical and political history of recognition. Philosophers, democratic political theorists, and activists have long understood recognition as relational—as a “social drama” tied to misidentification and struggles over existence and freedom.⁶² The fear of AI machine masters stems directly from the politics of recognition and domination—and dramas of masterful authentication, if not authenticity.

MIS-RECOGNIZING POLITICS

Hegel is the most recognized theorist of recognition, and his formulation of recognition as a dramatic, life-and-death struggle between masters and slaves prefigures current fears about artificial intelligence. In Hegel's well known and perhaps well worn argument, self-consciousness “is *in* and *for* itself while and as a result of its being *in* and *for* itself for an other; i.e., it is only as a recognized being.”⁶³ In other words, subjectivity requires recognition. To explain, Hegel offers the following developmental narrative. Self-consciousness starts with the desire of a consciousness; for example, to eat. Through hunger, a consciousness becomes aware of itself: an “I” emerges from being hungry.⁶⁴ Desire alone, however, is not enough to establish self-consciousness because it fosters an unstable and false sense of the “I” as omnipotent and singular: it views itself as responsible for all changes in the world and does not place itself within humanity—within the greater human race.⁶⁵ For true self-consciousness to emerge, a consciousness must encounter another human consciousness, whom it first just considers a mirror image of itself. This meeting is thus still not enough, for this “I” identifies with and is recognized by a being that it considers to be virtual rather than real. To achieve pure recognition and self-consciousness, these two “I’s” must engage in a life-and-death struggle, one to dominate the other.⁶⁶ After the struggle, two forms of consciousness emerge: “One is self-sufficient; for it, its essence is being-for-itself. The other is non-self-sufficient; for it, life, or being for an other, is the essence. The former is the *master*, the latter is the *servant*.”⁶⁷

Things, however, are not so simple. The master's consciousness depends on the slave's acknowledgment and labor. In truth, the master is not self-sufficient: he neither produces things, nor controls his desire. Freedom and true self-consciousness, Hegel argues, will emerge from the slave and his labor, for labor is "desire held in check, it is vanishing staved off, or: work cultivates and educates."⁶⁸ The slave's work to fashion an object becomes a self-fashioning: by creating objects that endure, the slave becomes someone other than a slave—he becomes a maker of history. Philosopher Alexandre Kojève explains that work "forms, transforms the World, humanizes it by making it more adapted to Man; on the other, it transforms, forms, educates man, it humanizes him by bringing him into greater conformity with the *idea* that he has of himself, an idea that—in the beginning—is only an *abstract* idea, an *ideal*." Work is "the historical process, the historical becoming of the human being," and it is "the product of the working Slave and not of the warlike Master."⁶⁹ Through this "social drama," the world is transformed and history made.

Drawing from and extending this account, liberal political theorists, such as Axel Honneth and Charles Taylor, have argued that recognition forms the basis for equality.⁷⁰ Philosopher Nancy Fraser, in her famous late twentieth-century debate with Honneth on "redistribution versus recognition," explained that, for Honneth and Taylor, "to deny someone recognition is to deprive her or him of a basic requirement for human flourishing."⁷¹ This denial demeans us: it subordinates or injures us by preventing our full subjectivity. It imprisons us in "a distorted, reduced mode of being."⁷² This theory of mis-recognition as damaging depends on "doll tests" and arguments made by psychologist Kenneth Clark (and endorsed by sociologists such as Robert K. Merton, discussed in chapter 2) crucial to the legal desegregation of schools in the United States. These tests and arguments showed that "separate but (un)equal" caused black children to internalize negative images.⁷³ The demands made by feminists, multiculturalists, and other activists for recognition underscored the fact that, though the need for recognition was not new, the struggle to achieve it was: by challenging inequalities, these activists sought to undermine older hierarchies of "honor" that formed the basis for their habitual subjugation.⁷⁴ To undo the damage of mis-recognition and to acknowledge the need for collective struggle, Taylor called for exceptions to certain nonfundamental rights.

The politics of and for recognition was attacked by the right and the left. On the left, Slavoj Žižek famously called multiculturalism “the cultural logic of multinational capitalism,” and others similarly insisted that identity politics diluted demands for redistribution.⁷⁵ Most succinctly, they argued that identity undermined class. But, as Nancy Fraser has shown, recognition and redistribution were never opposed; they were not two different social domains—one was not solely economic and the other solely cultural—but rather two analytic perspectives that could be applied to any situation.⁷⁶ Fraser argued that recognition was fundamental to “participatory parity,” the fundamental democratic norm that insists that “justice requires social arrangements in which all (adult) members of society interact as peers.”⁷⁷ Fraser’s intervention is important, but it also raises the question: Given that debates about recognition and redistribution have focused on Québec separatist, Indigenous activist, feminist, and African American political movements, did a group that just demanded recognition ever exist? Civil rights was about redistribution.

Indeed, the most powerful critiques of the politics of recognition emerged from the very “marginalized” communities discussed by theorists such as Charles Taylor. As political scientist and indigenous studies scholar Glen Coulthard has elaborated, Taylor’s theory presumed that the struggle of Indigenous people for self-determination depended on the blessings of the settler state. This left intact, “the legitimacy of the settler state’s claim to sovereignty over Indigenous people and their territories on the one hand, and the normative status of the state-form as an appropriate mode of governance on the other.”⁷⁸ Similarly, Coulthard criticized the Canadian government’s “accommodation” of Indigenous identity as seeking to “reconcile” Indigenous assertions of nationhood with Canadian settler sovereignty. Drawing from the philosopher of decolonization Frantz Fanon, Coulthard contended that the liberal politics of recognition reproduces colonial relations: “instead of ushering in an era of peaceful coexistence grounded on the ideal of *reciprocity* or *mutual* recognition, the politics of recognition in its contemporary liberal form promises to reproduce the very configurations of colonialist, racist, patriarchal state power that Indigenous peoples’ demands for recognition have historically sought to transcend.”⁷⁹ Thus the liberal politics of recognition produces what it seeks to remedy, namely, “colonized subjects” who are trained

to accept “the types of practices and subject positions that are required for their continued domination.”⁸⁰ Mis-recognition is not an error, but the point.⁸¹

Significantly, recognition without redistribution—or rather recognition as a way to prevent redistribution—has been taken up by the reactionary right, whose techniques mimic the style and techniques developed by the radical subcultures of the 1960s–1980s. The reactionary right spreads memes, such as “conservativism is the new counter-culture,” and its many different nodes are linked together via attacks on their common enemy, progressive politics (so-called “social justice warriors” SJWs).⁸² They exemplify how once-dominant mainstream culture has been sliced into angry subcultures that are then glued back together by their hateful attraction to a common enemy.

As discussed before in the volume introduction, this is hegemony in reverse: if hegemony once entailed creating a majority by luring various minorities to identify with the dominant worldview, majorities now emerge by consolidating angry minorities—each attached to a particular stigma-cum-style—through their opposition to what they misperceive as “mainstream culture.” The goal of this hegemonic clustering is decidedly nonnormative: from Fox News viewers who rail against “mainstream media” (even though Fox News is the most popular channel on basic cable in the United States) to Silicon Valley Saurons who view themselves as underdogs.

EMBRACING STIGMA, DIS-IDENTIFYING WITH THE “ENEMY”

Alternative influence networks, which exist at the intersection of news and entertainment, embrace amateur aesthetics and the politics of authenticity (described in chapter 3) in order to build influence and spread their reactionary views.⁸³ Although these networks routinely define themselves as being against the “mainstream media,” they nonetheless draw from the mainstream playbook: from Fox News’ and Breitbart’s creation of metaphorical families for disaffected viewers that mimic *Good Morning America*’s “national family” to the use of “guest appearances” and crossing story lines, which follow the classic “TV universe.”⁸⁴ But whereas broadcast television has sought national cohesion,

alternative influence networks aim for divisive and “subversive” political and social affiliations. They combine these tactics with traditionally left countercultural ones in order to foster rebellious, homophilic clusters. Candace Owens, for example, infamously drew from LGBTQ narratives of “coming out” to stake her territory as a conservative black commentator. In a YouTube video, Owens is met with parental love when she comes out as lesbian, but parental reprimands, when she comes out as a conservative.⁸⁵ Milo Yiannopolous and Richard Spencer became darlings of the ultraright through outrageous actions designed to offend their parents.⁸⁶ Mimicking queer families formed in response to homophobia, the reactionary right creates new militant “tribes” from the ashes of civil society norms.

Crucially, these tribes not only define themselves against mainstream culture; they also embrace and amplify a perceived stigma: they identify as militant victims, hence their attraction to queer and black liberation methods. More precisely, they dis-identify as “victims,” in order to both establish themselves as the “real victims” and to undermine the claims of social justice warriors. They couple mimicry with mockery. As performance studies scholar José Muñoz, drawing from linguist Michel Pêcheux, has explained in *Disidentifications*, there are three ways a subject hailed by the police in Althusser’s “theoretical theater” (described in “Correlating Ideology”) can react. The first way is compliance: in response to the officer’s “Hey, you,” the “good subject” turns around and becomes subject to or of the law. The second is open resistance: “bad subjects” rebel by rejecting the “Hey, you” and more generally the images and identifications offered by the dominant ideology—this is what alternative influence networks claim to do. By “counteridentifying,” however, they can validate the dominant ideology through controlled symmetry. And the third way is dis-identification: the subject “neither opts to assimilate within such a structure nor strictly opposes it; rather, dis-identification is a strategy that works on and against dominant ideology. . . . This ‘working on and against’ is a strategy that tries to transform a cultural logic from within.”⁸⁷ Dis-identification fosters an enabling misreading: subjects read themselves and their own life narratives in moments, objects, or other subjects that are not initially culturally coded to “connect.” This is arguably what alternative influence networks do well—they disidentify as victims.

For Muñoz, dis-identification helped queers of color and other subjects, usually excluded from majority positions, survive. It accepted and reworked exclusion in order to create breathing room—and space for rage. Through dis-identifying comedy, for example, queers of color railed against the “pasty normal.” Disagreeing with playwright Bertolt Brecht’s assessment of queer theater as being “prone to degenerate into good-humored comedy and unthinking repetition, and to fall apart,” Muñoz contended that such comedy enacted “scathing antinormative critiques.” Muñoz stressed that “comedy does not exist independently of rage. . . . Rage is sustained and it is pitched as a call to activism, a bid to take space in the social that has been colonized by the logics of white normativity and heteronormativity.”⁸⁸

Those on the reactionary right dis-identify as militant victims by deploying and embracing perceived stigmas. As Erving Goffman has argued, stigma are visual aids that relay to “normals” that a stranger possesses an “undesirable” differentness.⁸⁹ Stigma depends on context: “The normal and the stigmatized are not persons but rather perspectives.” They emerge within social encounters, “by virtue of the unrealized norms.”⁹⁰ Stigma implies an unmet norm—the norm is an absent present that stigmatizes difference. Writing from the perspective of “the normals,” Goffman relayed how those stigmatized “others” negotiate life through passing, dis-identification, displacement, and other coping mechanisms that acknowledge their deficiency. But there was, however, a “final possibility . . . that allows the individual to forego all others,” namely, “he can voluntarily disclose himself.”⁹¹ Goffman linked this move to militancy and an in-group standpoint that embraced a chauvinist and even secessionist ideology.⁹² These “self-symbolizing” militants ensured that they would be “cut off from the society of normals,”⁹³—this was, Goffman thought, was a “costly solution.”⁹⁴

This costly solution—alienation—however is no longer shunned but embraced. And through disidentification, militant separatism—understood as an “authentically loyal” exit—has become the goal.

INCELS

Members of the incel (involuntary celibate) community exemplify the embrace of an authentically militant exit: they embrace stigma,

alienation, and eugenics in order to exit from norms and to identify as the “real victims” of feminism and biology. As Natalie Wynn—a popular YouTuber, who describes herself as an “ex-philosopher of sex, drugs, and social justice”—explains in her ContraPoints incel video, which had received 2.4 million views by early 2020,⁹⁵ the term “incels,” for “involuntary celibates” was first coined by Alana, a lonely bisexual Torontonian, who created an online forum for “men and women to talk about being lonely, where they could wonder aloud about why they couldn’t meet anyone.”⁹⁶ By 2015, however, “incels” designated angry men on sites such as incel.me, in which mass murderers such as Elliot Rodger were celebrated as “Supreme Gentlemen.”

As Wynn explains, incels embrace biological explanations for what they perceive to be their “permanent” condition: like Wang and Kosinski, they embrace physiognomy—and, in particular, skull size—as a way to explain away their fate. In the incel worldview, men and women are each divided into two types: women are either “the Becky” (who looks exactly like the “neurotic female” featured in the Cambridge Analytica video) or “the Stacy” (figure 53); men are either “the Incel” or “the Chad” (figure 54).

Incels further divide themselves into various subtypes, such as Heightcels, Mentalcels, and Wristcels. There are also racially appropriate subtypes:

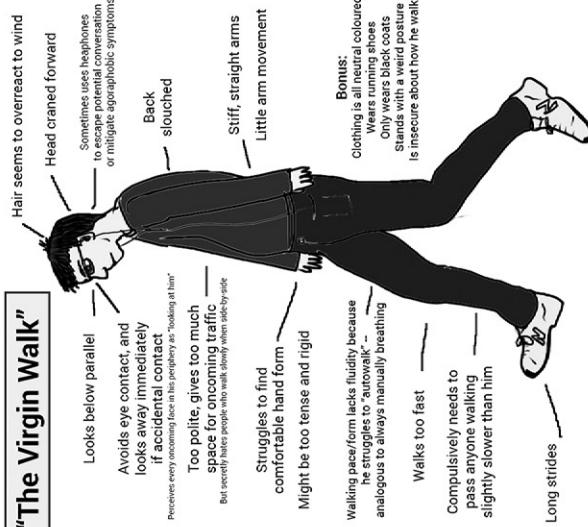
The Becky



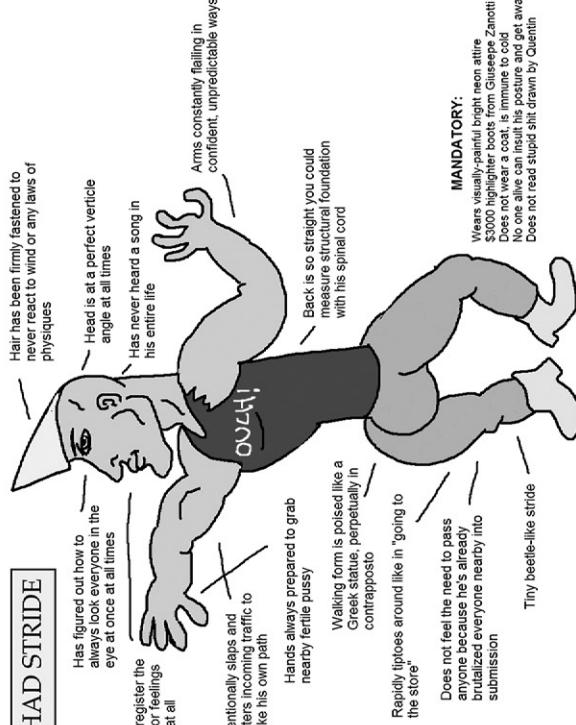
The Stacy



53 The Becky versus the Stacy. Still frame from Natalie Wynn, “Incels | ContraPoints,” <https://youtu.be/fD2briZ6fB0>.



THE CHAD STRIDE



54 The Incels versus the Chad. Still frame from Wynn, "Incels | ContraPoints," <https://youtu.be/fD2brz6fB0>.

“Blackcels,” “Ricecels,” and “Currycels,” with their Chad counterparts “Tyrones,” “Changs,” and “Chadpreets.” Like the “gaydar” discussed earlier in this chapter, a combination of cultural and biological features defines these types, which does not mean, however, that incels can become Chads—physical features, such as skull size and shape, separate the two (figure 54).

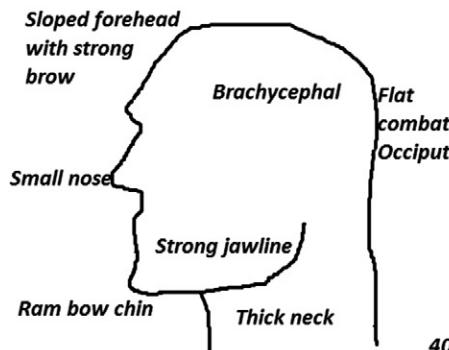
Wynn uses her “Lady Foppington” persona to explain incels’ obsession with skull size and their embrace of physiognomy (figure 55). This is because, Wynn goes on to explain,

a skull is inanimate and unchangeable. It’s therefore a perfect symbol of the intrinsic and permanent characteristics that bigots like to assign to certain groups of people. If you believe, for example, that a certain race or gender is intellectually inferior, you can justify your belief by pointing to the shape of a skull and saying, well that’s the reason why, it’s just nature, there’s nothing that can be done about it. And that is exactly the way incels think about love and celibacy. . . . Mankind is divided into two groups of people, the Chads with the fuckable skulls, and the incels, whose bones come up a few millimeters short.

This would seem the classic case of “mis-recognition” diagnosed by Taylor: through physical characteristics, incels “recognize” themselves as forever damaged.⁹⁷ The difference, though, is that this inferiority complex—“biology as destiny”—is seemingly self-imposed: eugenics is wielded not to denigrate an other, but the self. Wynn explains incels’ relentless and harsh self-critique, as a form of “masochistic epistemology”: a belief that “whatever hurts must be true.”

This desire to hurt, however, goes beyond the self: they also blame feminism for their condition for it has, they claim, perverted the natural sexual order. As Wynn relays, according to incels, feminism has licensed women to be licentious in “the sexual marketplace,” thus producing a world in which “80 percent of the women are ‘taken’ by 20 percent of the men.” If more than 20 percent of men manage to have relationships with women, it is due to the “alpha fux, beta bux” rule: women sleep with alpha Chads in their twenties; marry beta “normies” in their thirties; divorce and fleece these betas in their forties. In contrast, in their “prefeminist” world, men and women of equal physical attractiveness are naturally matched. Feminism disrupts this paradise by introducing “hypergamy”: a mode by which women seek to improve their social status by coupling with more attractive men (figure 56).

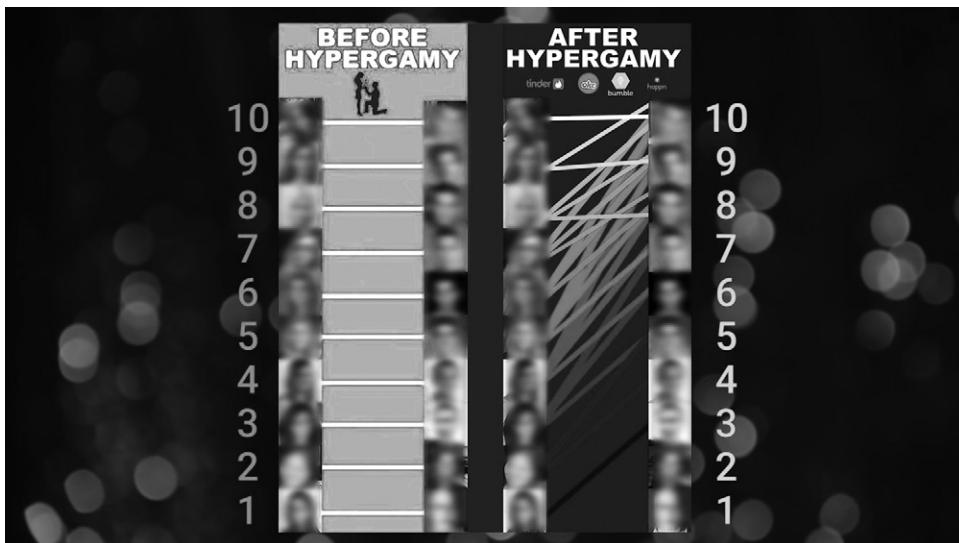
CHAD SKULL



INCEL SKULL



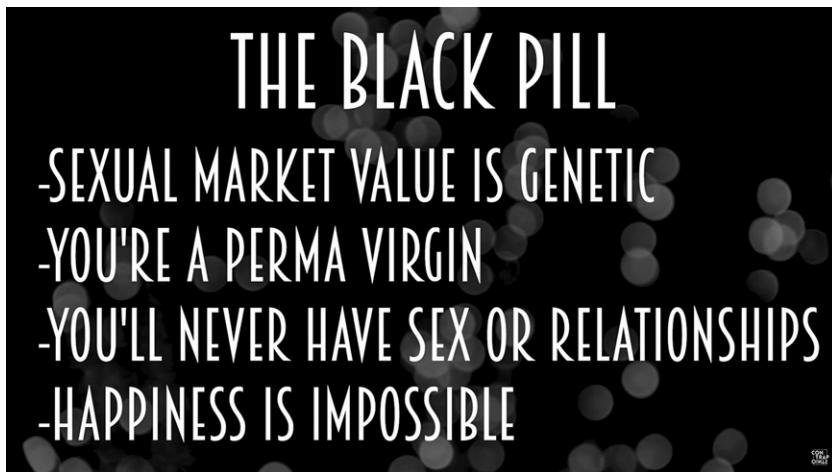
55 Top, the Chad Skull versus the Incel Skull. Bottom, Lady Foppington, explaining the importance of skull size. Still frames from Wynn, "Incels | ContraPoints," <https://youtu.be/fD2briZ6fB0>.



56 World before and after feminist hypergamy. Still frame from Wynn, "Incels | ContraPoints," <https://youtu.be/fD2briZ6fb0>.

But hypergamy is neither feminist nor a “perversion” of sexual or natural selection. What incels describe as a feminist utopia, feminists would call dystopian—women defining their worth in terms of men is exactly what feminists oppose. Further, R. A. Fisher and other evolutionary biologists praised the overselection of alpha males as “eugenic”: in such “barbarian” situations, sexual selection follows natural selection. Robert Merton, in his discussion of interracial relationships, diagnosed what incels call “hypergamy” as male “hypogamy”—men sleeping with women “beneath” them, in particular women of color.⁹⁸ Incels excuse the behavior of “alpha males” by blaming “feminists” for their condition—a position that enables them to hold onto a lost ideal (being an alpha male) by shifting the blame to those who, though similarly dominated, seek to overcome male authority. Incels and feminists could actually be natural allies.

By blaming themselves and feminists and by framing their condition as permanent and irrevocable, incels take what they call “the black pill.” One dose stronger than the “red pill,”⁹⁹ the “black pill,” Wynn tells us, is “the additional realization that one’s place in the sexual marketplace is



57 The “black pill.” Still frame from Wynn, “Incels | ContraPoints,” <https://youtu.be/fD2briZ6fB0>.

genetically determined, that one is a permanent virgin, that sex and relationships are forever out of reach, and hence happiness is impossible and there’s nothing one can do except ‘lie down and rot’” (figure 57).

Those who take the “black pill” (as mentioned in “The Transgressive Hypothesis” after chapter 1), rely on a desperate and lonely belief in the logical laws of biology and history. Hannah Arendt has made clear the futility of such a belief. After explaining that logic “is the only reliable ‘truth’ human beings can fall back upon once they have lost the mutual guarantee, the common sense men need in order to experience and live and know their way in a common world,” she goes on to say that “this ‘truth’ is empty or rather no truth at all, because it does not reveal anything.”¹⁰⁰

Drawing from Martin Luther, Arendt asserts that lonely people come to expect and accept the worst. Arendt’s explanation highlights the irrational nature of the incels’ seemingly rational worldview. As Wynn notes, they use “irrefutable reasons” like a knife to cut themselves and others with. Hence Wynn contends, the desire for (suicidal) violence and revenge—even though most incels are normal in appearance.¹⁰¹

The point, however, is never to be a “normie,” but rather to be recognized as exceptional: as an incel or a Chad. When told that they have

mis-recognized themselves—that they are not that different from everyone else, that they look normal, and that they should just take up hobbies and talk to women—incels dismiss this as “Chadsplaining,” a term that reveals the extent to which incels identify not only against, but also with feminists. They arguably hate feminists as they hate themselves—because they are also envious of feminists’ perceived “freedom.” They are a classic case of liberation envy. In this sense, they are not masochists, but sadists.¹⁰²

Thus the incels’ seemingly irrational yet “logical” attachment to a perceived stigma—their insistence that they are not “normies”—is key to understanding the power of subcultural references and identifications within the new politics of recognition.

BLACKNESS: THE ABSENT (AUTHENTIC) PRESENT

This new politics of recognition thrives on ironic self-hatred and militancy, and on romanticizing “others” as “truly liberated, loyal and militant.” As cultural critic Florian Cramer has argued, the reactionary right draws heavily from punk—itself a movement that, as Dick Hebdige tells us, reworks demeaning symbols into points of pride or ironic icons of identity.¹⁰³ The very term “punk,” Hebdige says, with its “derisory connotations of ‘mean and petty villainy,’ ‘rotten,’ ‘worthless’” exemplifies a process of “ironic self-abasement.”¹⁰⁴ Militant subcultures do not cover over stigma—they flaunt it. Like the punks Hebdige studied, those on the reactionary right brandish a difference—ultraconservatism, an embrace of neo-Nazi emblems, outrageous behavior—in order to evoke “hostility, derision, ‘white and dumb rages.’”¹⁰⁵ Also like punk, their absent present is a liberation envy focused on blackness.

Punk style transforms stigmas into icons of identity by playing with signifiers. To understand punk, Hebdige explains, you have to look beyond the relationship between signifier and signified. A safety pin does not inherently “mean” punk; its position relative to other signifiers, such as Vaseline tubes and pointed shoes gives it significance. Through metonymy, punk made symbols dynamic and kinetic, displacing any previous conservative or traditional meaning.¹⁰⁶

Crucially, to understand this conversion of stigma to style, Hebdige “co-related” reggae and punk and found that beneath their manifest and

loud differences lay a deeper—"latent"—unity.¹⁰⁷ Framing it as the absent present within punk culture, Hebdige called reggae a "black hole around which punk composes itself."¹⁰⁸ Punk and reggae were linked metaphorically: punk gained meaning by putting reggae under the bar; through punk, reggae resonated with people everywhere (for more on this, see "Correlating Ideology"). Punk and other white working-class British subcultures drew inspiration from reggae's historic icons of revolt—"rastas" and "rude boys," "gunfighters" and "tricksters"—as well as from black antislavery and anticolonial struggles and successes.¹⁰⁹ According to Hebdige, "The Black Man" served "symbolically as a dark passage down into an imagined 'underworld . . . situated beneath the familiar surfaces of life' where another order was disclosed: a beautifully intricate system in which the values, norms and conventions of the 'straight' world were inverted."¹¹⁰ It was the inaccessibility and opaqueness of West Indian style, Hebdige contended, that made reggae so appealing: its private codes enabled it to escape and subvert "the Man."¹¹¹ Intriguingly, Hebdige drew a line between reggae and punk in terms of alienation. Reggae offered the promise of revolutionary exile through its goal of overthrowing Babylon, but this exile or condition of alienation "when applied metaphorically to British white youth it could only delineate a hopeless condition. It could neither promise a future nor explain a past."¹¹²

Like punk, the new politics of recognition clearly draws from black liberation and civil rights movements, from the plot and structure of *The Matrix*, and also from declarations of white ethno-nationalism. As Cynthia Young has argued, civil rights and black liberation movements have become the "lingua franca for most U.S. social and political issues since the 1960s."¹¹³ Although Candace Owens explicitly mimics queer techniques in her "coming out" video, she also plays with her blackness: her "mom" declares, in response to her coming out as "conservative," "But, sweetie, you're black," and "What about Beyoncé?"

Black culture as a model for pride and loyalty goes beyond cultural studies to economics. In his widely influential 1970 book *Exit, Voice, Loyalty*, economist Albert O. Hirschman used the Black Power movements to understand seemingly "irrational" group loyalty, which rejected "normal" U.S. paths of progress.¹¹⁴ Hirschman brought together political and market analyses to understand the behavior of both in the early years of

neoliberalism. He sought to explain why people, faced with a declining product or nation or ideology, decide to leave or stay. Exit, choosing a competing brand, was a normal “cheap” consumer activity (remarkably and bizarrely this is now condemned as “cancel culture”), whereas voice, expressing one’s dissatisfaction, was an “expensive” yet normal political activity—it was indeed “political action par excellence.”¹¹⁵ It was not simply a matter of leaving versus staying, however, for loyalty mediated the battle between these two moves by deferring an exit: loyal consumers/members stayed in spite of disappointments.¹¹⁶ Loyalty changed the valence of an exit: the “applauded rational behavior of the alert consumer in shifting to a better buy” became the “disgraceful defection, desertion, and treason”¹¹⁷ of a citizen. At the same time, Hirschman stressed that “exit”—in terms of individual exit from an individual’s initial social status and group—was a hallmark of the American ideology of flight versus fight: the “American Dream” boiled down to flight from one group to another.¹¹⁸

Black Power was an “immense shock,” according to Hirschman, for it rejected the “traditional pattern of upward social mobility as unworkable and undesirable for the most depressed group in our society.”¹¹⁹ It refused integration since it elevated certain individuals from the group, while failing to lift the group as a whole. Instead, Black Power insisted on collective action. This was due, Hirschman acknowledged, to the realities—as opposed to the myth—of life in the United States. According to the “American Dream,” certain ethnic minorities ascended because of their individual actions. In truth, however, “ethnic minorities have risen in influence and status not only through the cumulative effect of individual success stories, but also because they formed interest groups, turned into outright majorities in some political subdivisions, and became pivotal in national politics.”¹²⁰

Remarkably, Hirschman does not mention the history of segregation and racism within the United States, and he presumes that integration always uplifts. His version of Black Power inadvertently paves the way for the rewriting of the civil rights movement as the formation of “interest groups,” for it represses racism by placing it “under the bar” in order for it to endure everywhere unseen and unspoken. Indeed, the repression of racism underlies all these “borrowings” of civil rights and Black Power; it enables the reactionary right to embrace militant loyalty not to prevent

exit, but rather to enable neighborhood escape. Alienation, like with the Rastafarians Hebdige describes, becomes utopian exile, and Black Power, denuded of its call for redistribution and reparations, becomes a way to justify “tribal” dreams of exit.

What, then are we to do when critiques of normativity and angry humor—calls to activism—are directed against the queer bodies that activism once emerged to protect? When angry white Americans protesting social distancing orders during a pandemic are called “modern-day Rosa Parks” by a U.S. government official? When reactionary right protesters redeploy pro-life slogans in order to provoke the “lamestream” media?

TO RESIDE TOGETHER

Throughout *Discriminating Data*, we have analyzed the slippery identifications—mis- and missed identifications—that form the basis for recognition and correlation. To “recognize” is to identify “something that has been known before.” It is to perceive someone or something as the same as someone or something previously encountered or known, or to “identify from knowledge of appearance or character, especially by means of some distinctive feature.” For a machine or computer, it is “to identify automatically and respond correctly (to a specific feature, object, or event).” Recognition thus always implies a historical relation and response—and power. To recognize is to reinvestigate, to become reacquainted with and to accept the “authority, validity, or legitimacy” of another’s claim or title.¹²¹ Recognition is an acknowledged reidentification, but, since nothing ever stays the same and no two things are identical, every recognition is also a misidentification.

Identification itself, however, is never simple. The “action or process of regarding or treating one thing as identical *with* another” implicitly acknowledges that “identical” things are not the same things—they are separate. Its earlier meaning—“the action or process of making things identical”—reveals that identification also transforms. The act of “determining identity” or “feeling oneself to be closely associated with a person, group, and so forth” changes the person who seeks to identify with the other. Identification is a transformative aspiration. It is a process that,

as literary critic Diana Fuss sees it, “keeps identity at a distance,” even as it produces self-recognition: it “inhabits, organizes, instantiates identity. . . . Identification is the detour through the other that defines a self.”¹²² Identification is also metaphorical—a vehicle through which a comparison is internalized. Drawing from Freud’s and Lacan’s description of identification as a means by which one sustains a lost love-object, Fuss notes that identification “invokes phantoms. By incorporating the spectral remains of the dearly departed love-object, the subject vampiristically comes to life.”¹²³ If recognition is identification that has been reciprocated—either by a human or machine—it is also separation and division. Identifications are “co-relations” that reveal both similarities and differences.

Haunting this book have been the specters of residents of Addison Terrace, Japanese internment camps, and married student housing at MIT; civil rights activists; slaves; unruly women workers at Western Electric; housewives in Decatur; and punishment-averse mice, to name a few. They inhabit correlation, homophily, segregation, recognition, discrimination, proxies, and “authenticity.” We reside together. The question—taken up in the coda to this book is: How might we—as Ariella Aïsha Azoulay demands—live together in the time of potential history?

THE SPACE BETWEEN US

The 2020 Covid-19 pandemic drove home in crystal-clear terms the stakes and consequences of connection, polarization, infrastructures, and habits. To many, the world had turned upside down and the unimaginable had become possible: “socialism” and extensive surveillance within the United States; a contracting Chinese economy and oil prices below \$0; the invocation of Cold War “shelter-in-place” ordinances; and Ku Klux Klan hoods worn as “protective masks” in California.¹ This crisis highlighted and augmented already existing inequalities: from white-collar workers seeking the “perfect” gadget for working from home to the mainly non-white and poor “essential” workers balancing daily financial and medical risks; from French dentists without proper protective equipment posting naked selfies to protest back-to-work orders to Trump supporters publicly demonstrating against stay-at-home orders by Democratic governors.²

The uncertainty—and overwhelming need to act—undermined any simple division between science and politics, knowledge and action. The science itself was uncertain after all. Many of the first guidelines presumed similarities between SARS Cov-2 and SARS Cov-1, which were later proven wrong, such as the period when a person is most infectious: in SARS Cov-1 it is while a person is most symptomatic; for SARS Cov-2 it is just beforehand.³ Early knowledge of Covid-19—as of all new viruses—was mainly correlational, with mechanistic-genetic explanations lagging

behind observation and comparison. For example, SARS Cov-2 was first presumed not to be airborne because it was far less contagious than airborne diseases such as measles. In desperation turned pharmaceutical opportunity, drugs were approved, such as remdesivir, which did not significantly affect mortality rates and which were discontinued early in clinical trials because of debilitating side effects.⁴ Most significantly, due to the dearth and poor quality of existing tests and testing materials, the scope of the pandemic—the number or proportion of “susceptibles,” “infected,” and “recovereds”—was unknown. It was even unclear if “recovereds” were immune, or for how long.⁵

This uncertainty, however, did not undermine science or politics: it drove research and made political decisions both difficult and necessary. Correlations and probabilities intersected this cloud of uncertainty. They could guide decisions, even if they could not guarantee them, for the pandemic and its “cures” confronted us with responsibility in the strongest sense of the word. We face responsibility, literary critic Thomas Keenan observes, not when we make decisions by following guidelines and rules, but when we desperately want to but cannot: “when we do not know exactly what we should do, when the effects and conditions of our actions can no longer be calculated, and when we have nowhere else to turn, not even back onto our ‘self.’”⁶ When we become, in philosopher Jean-Luc Nancy’s evocative phrase, “the residue of the experience of the dissolution of community.”⁷

Although ostensibly about the human death toll, calls for responsibility focused mainly on infrastructure. The UK motto “Stay Home, Protect the NHS, Save Lives” encapsulated this perfectly (figure 58).

By caring for infrastructure, you take care of yourself and others. Fears of becoming like early 2020 Italy—so overwhelmed doctors had to choose whom to save—drove policies in countries with national health services.⁸ Almost all actions—even the lack of action in the face of a “second wave”—focused on hospital capacity. In other countries, such as the United States, the motto would seem to have been: “Work, Save Businesses, Save Your Grandchildren’s Lives (and Your Pension, If You Have One)” (figure 59).⁹ Or, more positively: “Stay Home/Distant, Flatten the Curve, Save Lives and the City.”

The “cures” proposed, the emergency powers granted, and the sacrifices demanded reflected and revealed profoundly different national, regional,



58 UK National Health Service motto during first wave of COVID-19. Source: <https://www.gov.uk/coronavirus>.

and local perceptions of which curve mattered—the number of “infecteds,” the stock market, national employment figures, GDP, the mortality rate—and which ties bound most strongly—capital, public health, taxes, national deficits, public transportation. These “cures” acknowledged that exit is impossible, even for the most nonessential wealthy—the “Sovereign Individuals”—whose New Zealand bunkers and seasteading dreams still relied on the value of capital and the lives of “essential workers.”

The proposed cures and sacrifices revealed different diagrams of the social system. If the nation is mainly viewed as a network (figure 60), the goal is to produce “safe” exceptional neighborhoods: to create and augment clusters so that the “infected” are separated from the “recovereds” and “susceptibles.”

Surveillance to track and manage contagion and contacts becomes the key to amplifying “social distance.” In this worldview, “community cases” become mysteries to be solved through stalking and recording “undocumented cases” and “silent spreaders.” Tracking “patient zero” becomes a national pastime, as does blaming other countries for viral spread.¹⁰ Safety—resting as it does on inequality and dreams of emptying space—is precarious. Think of everything that must be erased for an edge to represent a friendship: institutions, such as schools and bars;

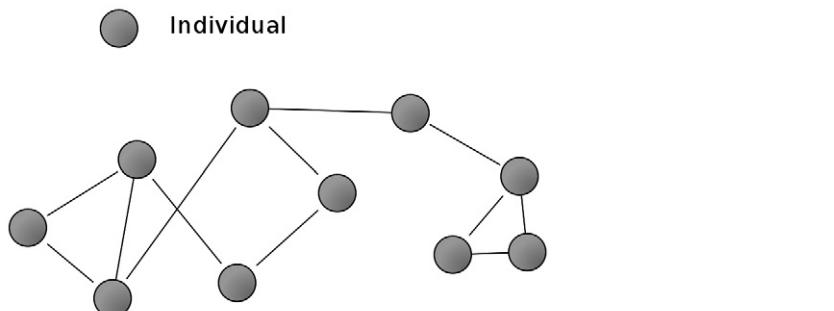
Tx Lt Gov Dan Patrick says grandparents would be willing to die to save the economy for their grandchildren



5:21 PM · Mar 23, 2020 · SnapStream TV Search

13.1K Retweets **31K Quote Tweets** **30.3K Likes**

59 Screenshot of tweet about Texas Lieutenant Governor Dan Patrick.



60 Social network. From Wikimedia Commons, <https://commons.wikimedia.org/wiki/File:Social-network.svg>.

interactions with “nodding strangers” (which during pandemics turn out to be essential); social media “prompts” to say, “Happy birthday!”; regular meetings and events. In order for there to be social networks, there must be gaps. Networks hollow clouds of uncertainty in order to foreground clean connections across empty space. Networks dream of communication without community.

If the nation is mainly viewed as a community—or what I have called “net-munity”—the onset of untrackable cases demands treating everyone as “infected,” in order to suppress the disease (we have to remember that viruses, such as SARS Cov-1, have been eradicated without vaccines; New Zealand successfully suppressed the first wave of SARS Cov-2). The Vancouver Parks motto, “The space between us will hold us together,” encapsulates this vision, for rather than treating the population as a series of nodes and edges, it attends to the spaces that enable community to emerge.¹¹ Community presumes community transmission—community is the experience of space.¹² Once a virus is endemic to a community, neatly drawn graphs become impossible—almost everyone is in contact—and the goal becomes widespread habitual changes to save others and public infrastructures: physical distancing, wearing face masks, washing hands, avoiding mass gatherings, cleaning public spaces. Even as the disease and these changes affect “vulnerable” populations differently, there are no exceptions to the call for—if not the act of—sacrifice. Friends and mobility become dangerous, and addressing the needs of those “at risk” populations becomes key.

At its best, it follows the call made by the Combahee River Collective to treat everyone as “levelly human,” by engaging—rather than ignoring—identity politics and individual experience.¹³ In British Columbia and elsewhere, homeless populations finally were moved into safer shelters, such as hotel rooms and empty apartment buildings, after individual consultations. Shamefully, Vancouver’s long-standing housing and drug crises were finally addressed not because of the dangerous living conditions of the homeless or the crisis of missing and murdered Indigenous women or the overdose public health emergency declared in 2016, but because of the need to contain Covid-19 (tellingly, the death toll in British Columbia due to illicit drug toxicity dwarfed the number of those who died from Covid-19 during the first wave). Sheltering, however, can

also destroy: the construction of spiked fencing to prevent tents from reemerging in Oppenheimer Park—still unceded lands of the Squamish, Musqueam, and Tsleil-Waututh First Nations and the tragic setting of another clearance (Japanese Canadians were removed from this area into interior internment camps during World War II)—raises calls for constant vigilance.

Net-munity calls on us to engage neighbors and relationships in all their rich ambivalence. Perversely, the logic of social networks spreads the name “neighbor” everywhere, in order to impoverish it conceptually. Neighbors are not innocuous—the term “neighbor” literally recalls “boors.” They are nosy and noisy. They provoke hostility, resentment, and ambivalence. They intrude, even—and especially—when they are inert. They offer, however, a way to reside in difference and to engage relations that go beyond homophily: not just heterophily, but also ambivalence and neutrality.

As literary critic Kenneth Reinhard, drawing from Hannah Arendt and Jacques Lacan, has declared, neighbors—who are neither friends nor enemies—are the space that enable the public and private to emerge.¹⁴ If, as political theorist Carl Schmitt puts it, the political hinges on distinguishing between the friend and the enemy, the neighbor “supplements”—and thus makes inadequate—the political theology of the sovereign.¹⁵ The logic of the neighbor, Reinhard insists, is not that of totality, but rather infinity: in the (feminine) set of the neighbor, there is no sovereign exception (no Chad), but instead an infinite process of knotting—everyone is equally nonsovereign.¹⁶ To put it in poet and philosopher Édouard Glissant’s terms, neighbors are opaque and obscure; their nontransparency, however, does not hinder but rather enables relation. Refusing our grasp or embrace, they subtract unity from the open totality that is “relation.”¹⁷ Spaces make us all topological neighbors—they touch everything, and their seeming emptiness grounds democracy. Indeed, at the heart of democracy, says philosopher Claude Lefort, lies an empty space. Because public space does not rightfully belong to anyone, because this space cannot be reduced to the dominant opinion that may emerge from it, it guarantees democracy: “power becomes and remains democratic when it proves to belong to no one.”¹⁸

Most strongly, freedom is space. Drawing from and revising Hannah Arendt's argument that freedom was first experienced as free movement, Jean-Luc Nancy tells us that freedom is not something we possess, rather it is an experience—a generosity that precedes any possession—that enables beings and nodes to emerge in the first place: "Freedom is a spacing that constitutes existence. . . . The political does not primarily consist in the composition and dynamic of powers . . . but in the opening of a space." Freedom is not a thing, idea, or ideal: "Freedom cannot be awarded, granted or conceded according to a degree of maturing or some prior aptitude that would receive it. Freedom can only be *taken*; this is what the *revolutionary* tradition represents."¹⁹ Freedom—the space between us—is not the lack of relation, but the very possibility of it. Freedom for Nancy can be both good and evil, for freedom entails a decision: furious devastation or finite space.

Spacing as freedom, however, raises the question of space itself and how it is emptied: once again, colonial dreams of the new. But, as Orlando Patterson, Hegel, and those suffering from liberation envy have implied, voluntarily or not, freedom as an experience—a testing of something real—emerges from the oppressed. The space between us is neither "white" nor "blank," but teeming with those whom the archive seeks to forget.

CODA: LIVING IN DIFFERENCE

I started this book by outlining a five-step program to counter the threat of hopeful ignorance:

1. Expose and investigate how ignoring differences amplifies discrimination, both currently and historically.
2. Interrogate the default assumptions and axioms that form the basis for algorithms and data structures.
3. Apprehend the past, present, and future machine learning algorithms put in place to determine when, why, and how their predictions work.
4. Use existing AI systems to diagnose current inequalities and to treat discriminatory predictions as evidence of past discrimination.
5. Draw from struggles for and practices of desegregation and equality to displace the eugenic and segregationist defaults embedded within current network structures and to devise different algorithms and modes of verification.

Discriminating Data has carried out the first four steps by interrogating the following foundational concepts: correlation, homophily, authenticity, and recognition. Chapter 1 unpacked the hype around and impact of big data by investigating its ties to twentieth-century eugenics. A century apart, promoters of eugenics and big data proclaimed that correlation revolutionized knowledge by enabling them to grasp—or, more precisely,

to shape—human behavior and the future. In both cases, this assertion called for the systematic surveillance of and experimentation on mainly vulnerable human populations, and it relied on a discriminatory logic that tied the future to the past through “unchanging biological features.” Bizarrely, even though they were developed to show the limited effects that learning could have on intelligence, eugenic methods now form the basis for “machine learning,” thus effectively sidelining all true learning—anything that changes supposedly immutable features—as “noise.” Technologies based on correlation embody “disruption” because they aim to end true disruption. The term “climate disruption” makes this painfully clear: modern-day disruption occurs when past mistakes are automated, not addressed. This chapter also outlined the significant differences between the early twentieth- and early twenty-first-century biometric eugenics, as manifested in the move from national population to “neighborhood” or “tribe,” from national uplift to exclusive escape, and in the move of homophily—the notion that similarity breeds connection—from aspiration to axiom.

Chapter 2 analyzed homophily to understand further the impact of these moves. Since social networks presume homophily, their echo chambers are not unfortunate errors, but goals. By focusing on individual preferences, homophily ignores institutional discrimination and economics, and it obscures the infrastructures needed to create genuine communities and collective action. It also launders hate into “love.” How do you show you “love” your own? By running from and pushing away others. Not surprisingly, the term “homophily” stems from mid-twentieth-century analyses of white residents’ attitudes toward biracial public housing in the United States. There are deep ties between “homophily” and “segregation,” a term it seeks to displace (community and racism are two others). Homophily has been deployed to destabilize norms and polarize the ambivalent: to create clusters of individuals, whose angry similarity and overwhelming attraction to their common object of hatred both repel them from one another and glue them together. To underscore how homophily distorts and engineers social relations, this chapter revisited the widely cited but seldom read 1954 study by Paul Lazarsfeld and Robert K. Merton, the forever forthcoming “Patterns of Social of Social Life” by Merton, Patricia West and Marie Jahoda and the data traces in the

Columbia archives—all of which served as the bases for homophily’s invention. This revisiting revealed the complex and ambivalent relations that the researchers documented between black and white residents of “Hilltown” (Addison Terrace) and hinted at other ways friendship could have been analyzed.

Chapter 3 interrogated how algorithmic authenticity triggers individuals and trains them to be transparent. Recommender systems and social media platforms, as well as media forms such as reality TV, have operationalized authenticity—the call to be true to oneself—in order to make one react predictably to prompts. The constant call to reveal personal secrets or to transgress against the mainstream dispels ambiguity, heightens affect, and valorizes behavioral transparency. What was once considered irrational and thus unpredictable or spontaneous—anger, outrage, love, humor—now generates projected responses. Authenticity, however, is fundamentally performed and relational: it depends on “dramas,” controversies, recognition, and participation. It reveals that we are characters—not simply marionettes—in the universe of dramas we so inadequately call “big data.” Recommender systems may classify intentional and collective action as “malevolent,” but authenticity is communal and helps us understand truths that exceed facticity and consistency: fictional texts, interactions and relations that establish trust.

Chapter 4, the last of the numbered chapters, focused on recognition as discrimination++. It unpacked the stakes of rewriting hate as “love” through analyses of the strange technical, historical, political, and philosophical transformations of discrimination into recognition. It studied facial and pattern recognition programs as “authenticity machines” and linked them both to twentieth-century debates about the relationship between recognition and redistribution and to twenty-first-century reactionary political groups, which portrayed themselves as “stigmatized” subcultures. In doing so, it spelled out the costs of homophily—if love becomes hate, people hate their neighbors as they hate themselves. And, to underscore missed and ignored “co-relations,” this chapter also highlighted the many misidentifications that form the basis for the new politics of resentment/recognition.

Before, between, and after the four numbered chapters, the five theoretical interludes introduced and considered questions and themes woven

throughout the book. “Red Pill Toxicity, or Liberation Envy” analyzed conspiracy theories and the twenty-first-century rise of authoritarianism. “The Transgressive Hypothesis” examined why and how complaints against the “mainstream” have become “mainstreamed”—and how new media have exacerbated, rather than solved, the “problems” attributed to mass society. Constant calls to decentralize and be different—this “mainstreaming” of resistance—have not “automated” democracy, but rather fostered populism, paranoia, and polarization. “Proxies, or Reconstructing the Unknown” explored how proxies, by attempting to touch the unknown, do not simply introduce, but also help us address inequality. “Correlating Ideology, or What Lies at the Surface” ruminated on the methodological parallels and differences between network science, psychoanalysis, and traditional forms of ideology critique. It outlined possibilities for unconventional interdisciplinary collaborations to investigate the antagonisms, indifference, ambivalence, and inertness that haunt correlations. And, finally, “The Space between Us” analyzed how spaces—seemingly empty gaps—hold social networks together and ground possibilities for freedom.

Of the many observations presented in *Discriminating Data*, I want to underscore eight in particular:

1. Freedom is only meaningful if it is freedom for *all*.

Fears of an AI apocalypse and discriminatory technologies stem from the same source: inequality and profound misunderstandings of freedom as domination. Civil rights and liberties are not opposed: coalitions, such as the one responsible for banning facial recognition technology in San Francisco, bear witness to this. The best way to prevent the coming singularity and combat algorithmic discrimination and pandemics is to treat everyone equally with dignity. Striving for a freedom that is no freedom will undermine democracy and lead to a bitter and paranoid liberation envy, which both identifies with and seeks to displace civil rights activists. Tellingly, thinking for yourself—taking the red pill—has become the passive act of “being red pilled.” To dispel red pill toxicity, we need to engage the lives, dreams, and experiences of civil rights activists—not to inhabit them, but rather to build together the world they sought to inhabit.

2. Reducing truth to consistency forecloses not just the present and the past but also the future.

Machine learning programs are not only trained on selected, discriminatory, and often “dirty” data; they are also verified as true only if they reproduce these data. The programs are tested on their ability to predict the past—past data hidden during the training phase either from within the same set or out of sample—not the future. As Hannah Arendt has made clear, “to define consistency as truth as some modern logicians do means to deny the existence of truth.”¹ To do so also forecloses the future. Global climate change models reveal the difference between truth and accuracy: to wait to see if any one given prediction is correct, in effect, is to “lie down and rot.”²

3. Majorities are now formed by disintegrating dominant groups into angry minorities, by divining and amplifying perceived stigmas, and by then consolidating them together around a common “enemy.”

This is hegemony in reverse: if hegemony once entailed creating a majority by various minorities accepting—and identifying with—a dominant worldview, majorities now emerge by consolidating angry minorities—each attached to a particular stigma—through their opposition to “mainstream” culture. The goal of this hegemonic clustering is decidedly nonnormative: from Fox News viewers who rail against the “mainstream media” (even though Fox News is the most popular channel on basic cable in the United States) to Silicon Valley Saurons who view themselves as underdogs. The norm has become to never become a “normie.”

4. “Authenticity” as it is now understood renders humans as predictable as trees—but both are far more complicated than linear models presume.

Algorithmic authenticity seeks to make us react predictably to triggers by encouraging us to act slightly badly. It condemns complexity and ambiguity as “hypocrisy.” Dramas and other performances of authenticity, however, reveal that we are more than marionettes: we are characters and actors.

5. Big data is the bastard child of psychoanalysis and eugenics.

Social media platforms seek to crack the human nonconscious in order to optimize user mouse clicks and profits. Their aim is user

desire: the unending move from one object to the next to keep users always wanting more. The relationship between network science, psychoanalysis, and ideology critique, however, also enables the kinds of unconventional interdisciplinary work needed to tackle behavioralist exploitation. As the leading science and technology studies scholar Donna Haraway reminds us, “illegitimate offspring are often exceedingly unfaithful to their origins.”³ Data analytics can enable us to engage what discriminatory data seek to foreclose.

6. Correlation is a “co-relation.”

Correlation is complicated. It is not simply a linear one-to-one relation. It condenses, displaces, multiplies. Proxies both poison and cure.

7. The past is as complex as the future.

Our current archives can never serve as “ground truth,” for they are limited and biased. In the world of machine learning, *ground truth=deep fake*. As Saidiya Hartman and Ariella Aïsha Azoulay have argued, historical archives exclude and buttress a logic of world-destroying “progress.” The past is not lost, however, but rather a space of potential.

8. Comfort and care are not comfortable.

Homophilic spaces are often agitated spaces of comforting rage. To move beyond this, we need to acknowledge discomfort as a way to create new forms of connection and co-habitation. As Sara Ahmed tells us, “discomfort is . . . not about assimilation or resistance, *but about inhabiting norms differently*. The inhabitance is generative or productive insofar as it does not end with the failure of norms to be secured, but with the possibilities of living that do not ‘follow’ those norms through.”⁴

Discriminating Data’s main goal has been to get us to step 5 of my five-step program: “Draw from struggles for and practices of desegregation and equality to displace the unjust eugenic and segregationist defaults embedded within current network structures and to devise different algorithms and modes of verification.” These are huge tasks and this book has been a call for a wider “we” to take them on. As I noted at the end of chapter 4, this book has been haunted by “the specters of neighbors: residents of Addison Terrace, Japanese internment camps, and married student housing at MIT; civil rights activists; slaves; unruly women workers at Western Electric; housewives in Decatur; and punishment-averse mice, to name a

few." They inhabit correlation, homophily, segregation, recognition, discrimination, proxies, and authenticity. They reside with us.

If we are to reside with them, however, we need to look toward—rather than away from—these “co-relations” for what is overlooked: calls for utopia, for modes of living that do not give up on the past or the future. Traditional conceptions of history, Ariella Aïsha Azoulay tells us, seek to archive others as “the past”; in contrast, she proposes a “potential history” that treats those so relegated, not as “primary sources” but rather potential companions.⁵ Glen Coulthard rereads Frantz Fanon not only to diagnose the politics of recognition without redistribution, but also for a solution for Fanon’s work highlighted “the host of *self-affirmative* cultural practices that colonized peoples often critically engage in to empower themselves.”⁶ José Muñoz moved from diagnoses of dis-identification toward queer utopia as a way to wrest the past and future away from the “prison house” of the “here and now.” Queerness, Muñoz explains, drives both dissatisfaction—it is “thing that lets us feel that this world is not enough, that indeed something is missing”—and liberation—it is “a structuring and educated mode of desiring that allows us to see and feel beyond the quagmire of the present” by engaging the past.⁷ Kara Keeling in *Queer Times, Black Futures* insists that not only is another world possible; it is already here. The task is to “listen[,] with others, for the poetry, the refrains, and the noise a world is making.”⁸

Listening to what has been ignored entails attending to demands for justice and living in difference. The algorithms and worlds we need to create (step #5) must at the very least: 1) engage the complex range of relations that ground connection; 2) acknowledge and foster our roles as inter-linked characters; and 3) engage the depth and breadth of learning.

1. CONNECTIONS, IN DIFFERENCE

Discriminating Data has emphasized that similarity-based connection is just one of many forms of connection that ground human existence. As well as “homophily,” the researchers at the Bureau of Applied Social Research (BASR) coined the term “heterophily,” the notion that opposites attract. (Heterophily has bizarrely fallen away, even though it forms the basis for the electric currents that drive our machines and heterosexuality.)

Throughout, we have been considering the importance of “in difference”—habits of caring, usually mistaken for empty spaces within networks, that enable connections and an ambivalent equality to emerge. So, what would it mean to start from these teeming spaces of diverse interactions? To make civil rights movements the ground truth of social network analysis? To follow Ruha Benjamin’s call to pursue and acknowledge abolitionist toolkits?

The post–World War II United States did not just produce segregated spaces, but also movements for equality that engaged the importance of difference and experience. The Combahee River Collective wrote their manifesto *How We Get Free* in 1977 in Boston. As a collective of black socialist feminists, they were one of the earliest groups to formulate what would become “identity politics” and “intersectionality.” They argued for solidarity, rather than separatism, with progressive black men, noting, “Our situation as Black people necessitates that we have solidarity around the fact of race. . . . We struggle together with Black men against racism, while we also struggle with Black men about sexism. . . . We believe that the most profound and potentially most radical politics come directly out of our own identity, as opposed to working to end somebody’s else’s oppression. . . . We reject pedestals, queenhood, and walking ten paces behind. To be recognized as human, levelly human, is enough.”⁹ To be recognized as levelly human is to defy pattern recognition or discrimination. It is to live in difference.

Living in difference means engaging with thorny issues of trust and politics. Danielle Allen’s solution to distrust is political friendship: drawing from Aristotle’s three-fold definition of friendship (ethical, intimate and utility), she argues that citizens are utilitarian and thus should become “political friends” with one another. The BASR focus on the “three closest friends” and their attitudes towards segregation revealed the relationship between intimate and ethical friendships, but made it impossible to see this kind of friendship. Drawing from Ralph Ellison, Allen contends that we need habits of “antagonistic cooperation,” which entails “admitting that the participants’ interests diverge and then tussling over them, like friends, with the instruments of agreeability.”¹⁰ Political trust, though, may sometimes not look like trust at all. Political theorist Bonnie Honig argues that democratic relations are fraught with passion, struggle and distrust. Noting that democracy is a system of taking rights, Honig argues that allegories of “the foreigner,” such as Ruth in the Old Testament,

teach us the virtue of taking. Further, she contends that, in a democracy, we “passionately support certain heroes (or principles or institutions) in political life while also knowing that we ought not take our eyes off them for fear of what they might do to us if we did.”¹¹

Attachment and fear—and pride in claiming democratic rights—are apparent in the responses of the residents of Addison Terrace, who, for the first time, had decent and fair rental accommodations. Projects such as Addison Terrace seemed to acknowledge and seek to remedy the fact that black residents in the U.S. were forced to pay higher rents than their white counterparts for substandard housing. The residents engaged in civic activities and groups in order to ensure their gains, even as they treated the housing authorities and their neighbors gingerly. As Figure 28 shows, the overwhelming majority of all residents at Addison Terrace (87 percent) believed that the races got along well in the project, and a majority of residents (60 percent) thought that public housing should be biracial. As one black woman resident put it, “I would welcome any whites here who wanted to come, but I’m not going to go out of my way to get them to come here.”¹² Indifference, ambivalence, and uncertainty on the part of black and white residents were not “unstable” reactions, however, but rather modes and means of residing together in and through shared spaces that sometimes provoked conflict.

To live in difference, we need to start from conflict—rather than run away from it. Conflict, not hate or love, drives democratic struggles. Acknowledging conflict, however, does not mean amplifying it, but rather seeking modes to repair and reciprocate. Coulthard engaged the work of other Indigenous theorists, such as Leanne Betasamosake Simpson, who embraced an Indigenous past in order to establish an Indigenous future, and who emphasized the importance of land as connection. For Coulthard, Indigenous struggles were—and still are—about land: “a struggle not only *for* land in the material sense, but also deeply *informed* by what the land *as system of reciprocal relations and obligations* can teach us about living our lives in relation to one another and the natural world in nondominating and nonexploitative terms.”¹³ Agreeing with Coulthard and Simpson, Jodi Byrd, inspires us to move “beyond sovereignty” based on possession or dispossession towards decolonial resurgence and relations.¹⁴ Land and place move us away from “blank spaces” towards acknowledging obligations and to sustaining relations.

Relations to land form the basis for foundational networking concepts, such as homophily and weak ties.¹⁵

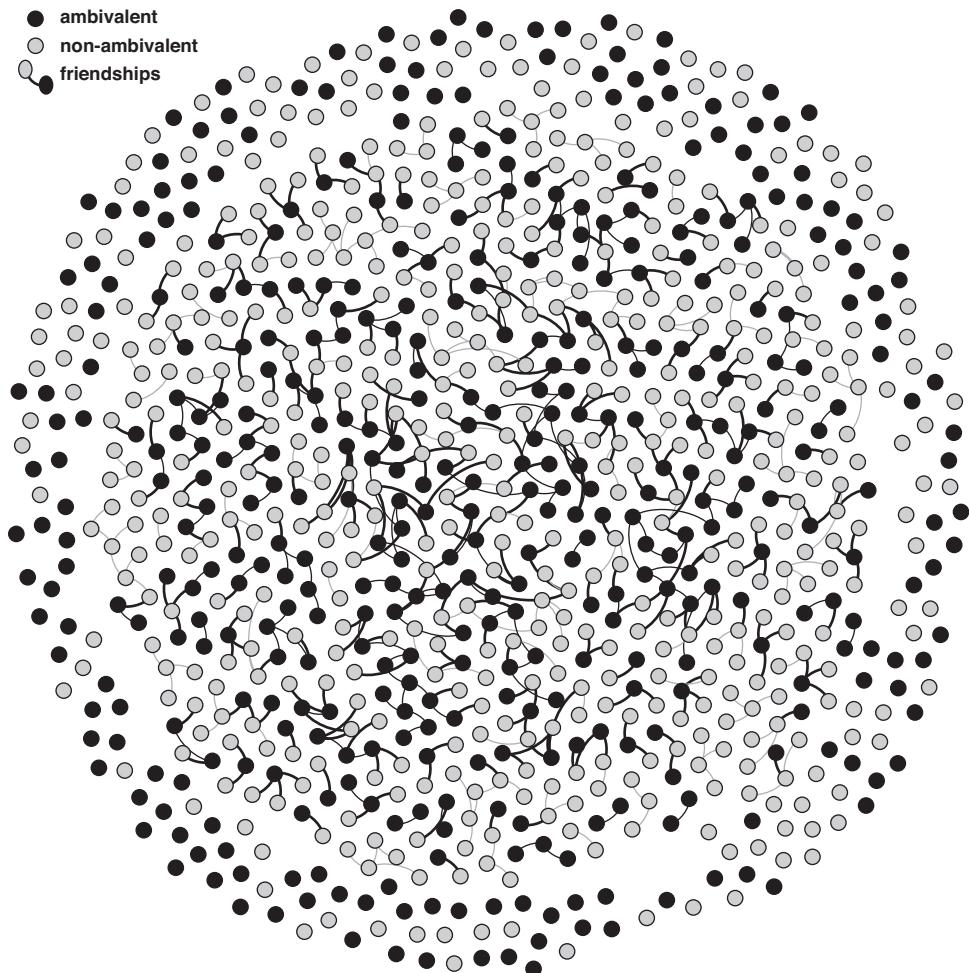
As “The Space Between Us” has revealed, these other relations, such as heterophily and in difference, are not lost but embedded in the gaps—the white spaces—that enable the currently acknowledged forms of connections to emerge. To engage these rich relations, we must start from the insight that the network is everything outside the graph. To return to the Addison Terrace example, figure 61 reveals how accounting for the overwhelming number of ambivalent friendships changes what network diagrams reveal.¹⁶

Such teeming images are a first step towards figuring connections beyond homophily. They also reveal the possibilities and limitations of these diagrams, for nodes and edges are not simply givens: contact produces nodes—they shape bodies and individuals.¹⁷ These moves to “operationalize” and “visualize” outline what can and cannot be translated into networks as they currently exist and thus the continuing necessity for interdisciplinary methods and cooperation.

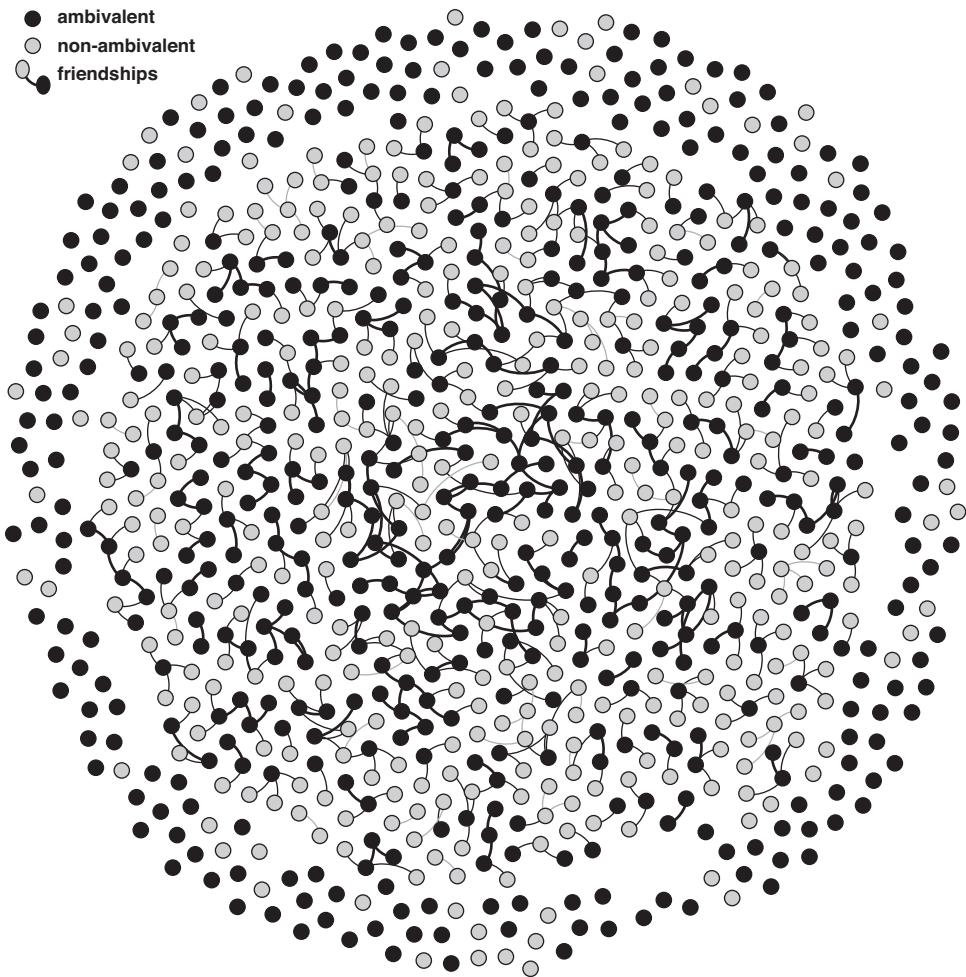
2. AUTHENTICALLY CO-RELATED CHARACTERS

Discriminating Data and before it *Updating to Remain the Same* have emphasized that we are characters, rather than marionettes, within the world of social media. The term “user” betrays a behaviorist dream of addiction and manipulation that does not encompass the rich world of online interactions.¹⁸ As many researchers have shown, social media users craft personas online with public/social engagement in mind.¹⁹ Performance grounds identity in ways that are neither cynical nor insincere, and it is no accident that a film such as *The Matrix* rings true for so many. Rather than being deployed to train users to be transparent, authenticity can be wielded to underscore, amplify and understand our ambivalent relations to others. Authenticity again is linked historically to dramatic performances that ring true not because they mimic and thus distort “reality,” but because they enact fictions that feel “true.”

These performances, especially online, are not solitary but rather collectively formed and scripted. New media relentless emphasize you: *YouTube.com*; what’s on your mind?; You are the Person of the year. New

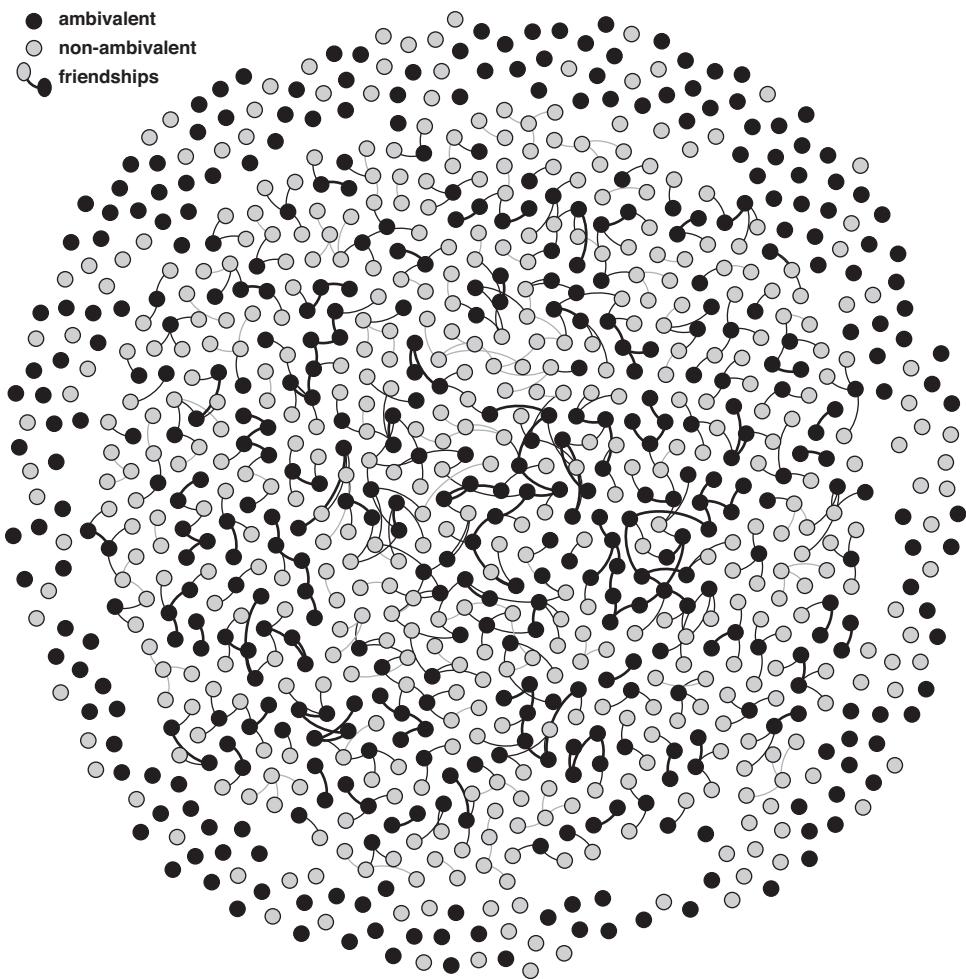


61 Three possible representations of the network used for Merton's formulation of the homophily principle. The darker dots map the distribution of ambivalence/indifference in this network, based on residents' responses to question 27, 32 and 61. Images produced by Carina Albrecht.



61 (continued)

media are N(YOU) media, but this YOU is never simply singular, but also plural—YOU is a particularly shifty shifter in English. This singular plurality forms the basis for data analytics, which treats individuals in relation to, that is “like,” others. Big Data—in its most popular current form as a glorified form of data and network analytics, used by corporations such as Netflix, Target, and FICO—mines our data not simply to identify who we are (this, given our cookies and our tendency to customize our machines is very easy), but to identify us in relation to others “like us.” Our scripts, our lines, are constantly impacted by the actions and words



61 (continued)

of others, whom we are constantly correlated with and unconsciously collaborate with.

Thinking through our roles as characters does not diminish, but rather enriches our authenticity. It moves us away from dubious allegations of our era as “post-truth” and endless accusations of “fake news” towards understanding “why and how—under what circumstances (social, cultural, technical and political)—people find information to be true or authentic.” It enables us to build systems that acknowledge collective action and intentional actions as “good” rather than “malevolent.”

To study authenticity, a performance-based schema, which outlines the following aspects at the very least, is key:²⁰

Algorithmic scripts	How actions are captured and scripted through user profiling and algorithmic recommendations systems, among others.
Character development	What sequence and modes of expression are allowed by the platforms and enacted by users and bots.
Performance	Creating personas and provoking real-time interactions, both online and offline.
Mise-en-scène	The multiplatform environment, location of the screen, devices and third parties.
Genre	The types of affect and the goal of the interactions (advertising, etc.).
Audience / networks	How the user is clustered and who s/he is exposed to.
Seriality	How links/recommendations/breadcrumbs lead users along certain trajectories.
Advertising/ Marketing/ Economics	How advertising and marketing models fuel outrage and click-bait, and click/like farming.

To build out this schema, we need to draw from projects that use digital methods and machine learning to understand our algorithmic scripts and connections, such as engineer-scientist Shri Narayanan and the Geena Davis Institute's projects which have analyzed gender constructions within Hollywood. We need to follow Safiya Noble's call for counternarratives and technologies that do not exploit and commercialize black women, in addition to calls for reparations.²¹ We need also to engage Natalie Wynn's ContraPoints videos and feminist chat bots that deploy characters in order to protect vulnerable populations as they assert their right to be free, as well as the work of communications studies scholars Sarah Jackson, Moya Bailey, and Brooke Foucault Welles on hashtag activism and media scholar Charleton McIlwain's work on black software.²² We need also to attend to the centrality of desire and non-deficit-based notions of identity, as information studies scholar André Brock has called us to do.²³ Most hopefully, focusing on authenticity moves us away from

endless debates over is something real—to prolonging crises in the name of knowledge—towards engaging outcomes, motivations and effects.

3. MACHINE UNLEARNING

Again, it is both disturbing and revealing that methods developed for eugenics—a system that did not believe in learning—now form the basis for machine learning. As historian of science Stephanie Dick has pointed out, attempts to create technical models of human rationality profoundly change human knowledge.²⁴ In the case of machine learning, media studies scholar Adrian Mackenzie has argued that learning has become “finding a mathematical *function* that could have generated the data and optimizing the search for that function as much as possible.” How much do we lose if this becomes our definition of learning—especially given the limitations of artificial intelligence that Meredith Broussard has documented?²⁵ How might we learn from machine learning by unlearning its predictions?

Crucially, machine learning models can release other modes of living and being: they can become probing and speculative—and thus responsible in the richest sense of this word. Responsible AI does not need to be the nightmare or utopia of AIs usurping human decision-making; rather, it can—and must—be about broad participation in deciding what AI should and shouldn’t do,²⁶ not only in terms of human values but also environmental ones.²⁷ Responsible AI also means moving away from visions of machines as slaves (and thus masters). As political scientist and activist Vine Deloria Jr. tells us, “Any damn fool can treat a living thing as if it were a machine and establish conditions under which it is required to perform certain functions—all that is required is a sufficient application of brute force. The result of brute force is slavery.”²⁸

Digital media theorist and software designer Jason Edward Lewis, historian Noelani Arista, and performance artists Archer Pechawis and Suzanne Kite cite Vine Deloria Jr. in their groundbreaking “Making Kin with the Machines” to argue for an “extended ‘circle of relationships’” that respectfully engages nonhumans. This “making kin” draws from Indigenous understandings of materiality and spirituality and experiences with dehumanization. Writing that they “know what it is like to be declared non-human,” they go on to explain “We have a history that

attests to the corrosive effects of contorted rationalizations for treating the human-like as slaves, and the way the mindset debases every human relation it touches—even that of the supposed master. We will resist reduction by working with our Indigenous and non-Indigenous relations to open up our imaginations and dream widely and radically about what our relationships to AI might be.²⁹ Making kin engages speculative and imaginative methods, such as digital media theorist and artist Beth Coleman's *Octavia Butler "other worlds" AI*, which draws from Octavia Butler's fiction to create speculative worlds and form.³⁰

Machine learning and predictive models as they currently exist can also resist reduction, but only if we treat the gaps between their results and our realties as spaces for political action, not errors to be fixed. We need to treat these models as we do global climate change models. GCC models offer us the most probable future, given past actions, not so that we accept that future, but so we work to change it. Only global climate change deniers seek to fix the model, rather than the world. GCC models also make clear the limitations of models and the need for alternative modes of verification: if we wait to see if any given prediction is correct, it is too late. The pursuit of knowledge—which is barely hidden if at all—can become an alibi for inaction. Again, as activists and community members following the comprehensive report on policing discrimination in Ferguson noted, the report “put into written form what so many people have already voiced for years about change that needs to happen in the St. Louis region, but identifying a problem and fixing it are different.”

In sum, to prevent the AI apocalypse we need most importantly—as Ariella Aïsha Azoulay has eloquently argued—to “unlearn” the temporality and the colonial logics that undergird our archives. We need to live in the time of “potential history,” in which we coexist with others, both living and dead, in a “space wherein violence ought to be reversed, different options that were once eliminated are reactivated as a way of slowing the imperial movement of progress.”³¹ We need machine unlearning.

To conclude, these steps and projects I have outlined can help us inhabit the world as neighbors in the fullest sense of the word, but they are only first steps. To take on twenty-first-century challenges to democracy, we need not a call to arms or a call for “new” technologies—but a resolution to live, freely, in difference.

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—Wendy Hui Kyong Chun

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—Alex Barnett

NOTES

INTRODUCTION

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neurotoxin" as punishment for theft. No longer able to "jack in," Case becomes a suicidal drug dealer in Chiba City, who is simultaneously rescued and manipulated/coaxed by a quasi-autonomous AI, Wintermute, to set it free after it reverses Case's damage. When Case first reenters cyberspace, he describes it as a "fluid neon origami trick, the unfolding of his distanceless home, his country, transparent 3D chessboard extending to infinity" (52). As he melts into cyberspace, his inner eye opens "to the stepped scarlet pyramid of the Eastern Seaboard Fission Authority burning beyond the green cubes of the Mitsubishi Bank of America, and high and very far away he saw the spiral arms of military systems, forever beyond his reach. And somewhere he was laughing, in a white-painted loft, distant fingers caressing the deck, tears of release streaking his face" (52). This description could not be more different from the clumsy graphics of *gopher* or the text-based interface to newsgroups and bulletin board systems (BBSs). The fact that the Internet, a Cold War technology, became cyberspace and thus "new" in the 1990s is bizarre.

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government did not need warrants to access telephone numbers that the defendant had called because he had “no legitimate expectation of privacy” about this information.

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56. McLuhan concluded "Challenge and Collapse: The Nemesis of Creativity," chapter 7, by emphasizing "our" current "enslavement." Describing the gradual specialization of Greek farming, he wrote: "the armies of technologically specialized slaves working the land blighted the social existence of the independent yeomen and small farmers, and led to the strange world of the Roman towns and cities crowded with rootless parasites." (McLuhan, *Understanding Media*, 72–73). By the late twentieth century, things were far worse, he contended, because "the specialism of mechanized industry and market organization has faced Western man with the challenge of manufacture by mono-fracture, or the tackling of all things and operations one-bit-at-a-time" (73). This reference to one-bit-at-a-time ties McLuhan's description of computing to von Neumann's privileging of serial over parallel operation (for more on this, see Chun, *Programmed Visions*).
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RED PILL TOXICITY

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CHAPTER 1

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41. Earl R. Babbie, *The Practice of Social Research*, 14th ed. (Boston: Cengage Learning, 2016), 94–95.
42. Steven L. Bressler and Anil K. Seth, "Wiener–Granger Causality: A Well-Established Methodology," *NeuroImage* 58, no. 2 (2011): 324, <https://doi.org/10.1016/j.neuroimage.2010.02.059>.
43. David Liben-Nowell et al., "Geographic Routing in Social Networks," *Proceedings of the National Academy of Sciences* 102, no. 33 (2005): 11623, <https://doi.org/10.1073/pnas.0503018102>; Wei Pan et al., "Urban Characteristics Attributable to Density-Driven Tie Formation," *Nature Communications* 4 (2013), <https://doi.org/10.1038/ncomms2961>.
44. O'Neil, *Weapons of Math Destruction*, 17–18.
45. Baracas and Selbst, "Big Data's Disparate Impact," 695.
46. O'Neil, *Weapons of Math Destruction*, 146.
47. Oscar H. Gandy, *Coming to Terms with Chance: Engaging Rational Discrimination and Cumulative Disadvantage* (Farnham, UK: Ashgate, 2009), 52.
48. O'Neil, *Weapons of Math Destruction*, 27.
49. Eubanks, *Automating Inequality*, 127–173.
50. Eubanks, *Automating Inequality*, 145–146, 156, 164.
51. O'Neil, *Weapons of Math Destruction*, 149; Gandy, *Coming to Terms with Chance*.
52. See, for example, Ira Katznelson, *When Affirmative Action Was White: An Untold History of Racial Inequality in Twentieth-Century America*, 1st ed. (New York: Norton, 2005); and Richard Rothstein, *The Color of Law: A Forgotten History of How Our Government Segregated America* (New York: Norton, 2017).
53. Correlations based on proxies also open systems to manipulation: "when you create a model from proxies, it is far simpler for people to game it. This is because proxies are easier to manipulate than the complicated reality they represent" (O'Neil, *Weapons of Math Destruction*, 55). Once a proxy becomes known, it becomes the focus of manipulation. The classic example is educational test-score manipulation. Standardized testing within the United States has become a proxy for teaching and learning success, with teachers' jobs and promotions, as well as school funding, dependent on these scores. Not surprisingly, there have been cases of widespread cheating, with teachers deliberately altering test scores. Alia Wong and Terrance F. Ross, "When Teachers Cheat: Rampant Conspiracies to Alter Kids' Scores, Including the One That Resulted in the Recent Conviction of 11 Atlanta Educators, Attest to the Dangers of High-Stakes Testing," *Atlantic*, April 2, 2015, <http://www.theatlantic.com/education/archive/2015/04/when-teachers-cheat/389384>.

54. Karl Pearson, *The Life, Letters and Labours of Francis Galton*, vol. 3a, *Correlation, Personal Identification and Eugenics* (Cambridge: Cambridge University Press, 1930), 221, 348. Galton first coined the term “eugenics” in his book *Inquiries into Human Faculty and Its Development* (London: Macmillan, 1883), defining it as “topics more or less connected with the cultivation of the race. . . . That is, with questions bearing on what is termed in Greek, *eugenēs* namely, good in stock, hereditarily endowed with noble qualities. This, and the allied words, *eugeneia*, etc., are equally applicable to men, brutes, and plants. We greatly want a brief word to express the science of improving stock, which is by no means confined to questions of judicious mating, but which, especially in the case of man, takes cognisance of all influences that tend in however remote a degree to give to the more suitable races or strains of blood a better chance of prevailing speedily over the less suitable than they otherwise would have had. The word *eugenics* would sufficiently express the idea; it is at least a neater word and a more generalised one than *viriculture* which I once ventured to use” (17).
55. Pearson, *The Life, Letters and Labours of Francis Galton*, 3a: 2, 5. See also Ruth Cowan, “Francis Galton’s Statistical Ideas: The Influence of Eugenics,” *Isis* 63 no. 4(1972): 509–528.
56. Francis Galton, *Hereditary Genius: An Inquiry into Its Laws and Consequences* (London: Macmillan, 1869).
57. Galton ‘advanced’ Alphonse Quetelet’s work, which revealed that human physical traits were distributed normally, by arguing that mental characteristics also followed “the law of error.” Donald A. MacKenzie, *Statistics in Britain, 1865–1930: The Social Construction of Scientific Knowledge* (Edinburgh: Edinburgh University Press, 1981), 57.
58. Pearson, *The Life, Letters and Labours of Francis Galton*, 3a:55.
59. As Theodore M. Porter has argued in *Karl Pearson: The Scientific Life in a Statistical Age* (Princeton, NJ: Princeton University Press, 2004), 257, 258: “Correlation was the key to biometry. Predicting the consequences of natural selection . . . required a measure of the interactions of organs or traits that tended to vary together. The mathematical tool for studying such interactions, whether among the various organs of a single individual or of a single organ across the generations, was correlation.”
60. Karl Pearson, “The Theory of Ancestral Contributions in Heredity,” *Proceedings of the Royal Society of London, ser. B* 81, no. 547 (1909): 219, <https://doi.org/10.1098/rspb.1909.0018>.
61. Karl Pearson, *The Groundwork of Eugenics* (London: Cambridge University Press, 1909), 31.
62. Charles Benedict Davenport, *Eugenics, the Science of Human Improvement by Better Breeding* (New York: Henry Holt, 1910), 183.
63. Philippa Levine and Alison Bashford, “Introduction: Eugenics and the Modern World,” in *The Oxford Handbook of the History of Eugenics*, ed. Alison Bashford and Philippa Levine (New York: Oxford University Press, 2010), 8.
64. Karl Pearson, *Nature and Nurture, the Problem of the Future* (London: Dulau, 1910), 29; Pearson, *The Groundwork of Eugenics*, 20.

65. Pearson, *Nature and Nurture*, 22–23.
66. Pearson, *Nature and Nurture*, 27.
67. Karl Pearson, “The Huxley Memorial Lecture,” *Science* 18, no. 463 (1903): 636.
68. Pearson, *Groundwork of Eugenics*, 21.
69. “Loaves and the circus—wages for the unemployable and the public football match to kill time—are as much signs now as of old that selection is being suspended,” Pearson argued, “and that suspension undoubtedly means the rapid multiplication of the unfit at the expense of the fit” (Pearson, *The Groundwork of Eugenics*, 21). As Donald MacKenzie has documented, eugenics emerged at a time when members of the English professional middle classes were preoccupied with the notions of English decline and national competition, as well as with their precarious hold on respectability and economic success (MacKenzie, *Statistics in Britain, 1865–1930*, 15–50). England had suffered a humiliating defeat in the Boer War of 1899–1902 and was still recovering from an economic recession. Pearson and other eugenicists believed that the decline of the British Empire, like that of older civilizations, could be traced to “the maintenance or cessation of that process of selection. Where the battle is to the capable and the thrifty, where the dull and idle have no chance to propagate their kind, there the nation will progress, even if the land be sterile, the environment un-friendly and educational facilities small” (Pearson, *The Groundwork of Eugenics*, 20–21). Thus, according to the English middle-class professionals, the Boer War had been lost because of the “unfit” nature of its recruits, drawn from the working class. Galton, in particular, was distressed “to witness the draggled, drudged, mean look of the mass of individuals, especially of the women. . . . The conditions of their life seem too hard for their constitutions,” conditions that prompted him to call for a laboratory of “national eugenics” (Galton, *Heredity Genius*, 340).
70. Nils Roll-Hansen, “Eugenics and the Science of Genetics,” in *The Oxford Handbook of the History of Eugenics*, ed. Alison Bashford and Philippa Levine (New York: Oxford University Press, 2010), 93.
71. Troy Duster, *Backdoor to Eugenics* (New York: Routledge, 1990).
72. Nikolas Rose, “The Politics of Life Itself,” *Theory, Culture & Society* 18, no. 6 (2001): 22, <https://doi.org/10.1177/02632760122052020>; Nikolas S. Rose, *Politics of Life Itself: Biomedicine, Power and Subjectivity in the Twenty-First Century* (Princeton, NJ: Princeton University Press, 2006), 51; Jacqueline Wernimont, *Numbered Lives: Life and Death in Quantum Media* (Cambridge, MA: MIT Press, 2019).
73. Francis Galton as quoted in Pearson, *Life, Letters, and Labours of Francis Galton*, 3a:348.
74. “It is a reproach to our intelligence,” Charles Davenport asserted, “that we as a people, proud in other respects of our control of nature, should have to support about half a million insane, feeble-minded, epileptic, blind and deaf, 80,000 prisoners and 100,000 paupers at a cost of over 100 million dollars per year” (Davenport, *Eugenics*, 4). Davenport’s study thus focused on the transmission of “negative” traits, in order to guide the “fit” in their marriage selection and state legislation. Davenport contended that “general program of the eugenicist . . . is to improve the race by

inducing young people to make a more reasonable selection of marriage mates; to fall in love intelligently. It also includes the control by the state of the propagation of the mentally incompetent" (4). Segregation of the poor was central to the eugenic program.

75. Eubanks, *Automating Inequality*, 22.

76. Eubanks, *Automating Inequality*, 6–7.

77. Eubanks, *Automating Inequality*, 9.

78. Nathalie Maréchal, "First They Came for the Poor: Surveillance of Welfare Recipients as an Uncontested Practice," *Media and Communication* 3, no. 3 (2015): 56–67, <https://doi.org/10.17645/mac.v3i3.268>. "The specific targets of state surveillance vary," Maréchal writes, "but the logic stays the same: surveil, control and isolate the sources of perceived risk in order to prevent contagion to the rest of society" (56). Like Virginia Eubanks, she notes that "low-income Americans must submit to invasive monitoring of their private lives in order to receive the benefits to which they are legally entitled. This has been the case for decades, with the breadth and depth of surveillance expanding along with the affordances of available technologies" (57). Also like Eubanks, she contrasts this situation to the wealthy. While Eubanks points out that the wealthy can access the same services, but through private organizations, without surveillance and thus without penalty (the use of a nanny, for instance, has not been identified as a "risk factor"), Maréchal notes that "very little documentation is required to receive benefits in the form of tax rebates, which generally benefit the rich and amount to much higher sums" (57). Like Eubanks, she notes that this targeting is not accidental—by targeting welfare recipients, for whom there is little sympathy among large swathes of the U.S public, "this mass invasion of privacy receives broad support from the American public, including from many recipients themselves, who often have only vague ideas of what the computerized welfare system knows about them or how this information is acquired" (57).

79. Chandak Sengoopta, *Imprint of the Raj: How Fingerprinting Was Born in Colonial India* (London: Macmillan, 2003); Simone Browne, *Dark Matters: On the Surveillance of Blackness* (Durham: Duke University Press, 2015); Nicholas Mirzoeff, *The Right to Look: A Counterhistory of Visuality* (Durham: Duke University Press, 2011).

80. Francis Galton, as quoted in Pearson, *The Life, Letters and Labours of Francis Galton*, 3a:348.

81. Pearson, *The Groundwork of Eugenics*, 3, 4.

82. Albert-László Barabási, *Bursts: The Hidden Pattern behind Everything We Do* (New York: Dutton, 2010), 11.

83. Seth Stephens-Davidowitz, *Everybody Lies: Big Data, New Data, and What the Internet Can Tell Us about Who We Really Are* (New York: Dey Street Books, 2017), 54.

84. For more on this, see Liang Tang, Romer Rosales, Ajit Singh, and Deepak Agarwal, "Automatic Ad Format Selection via Contextual Bandits," *Proceedings of the 22nd ACM International Conference on Information & Knowledge Management*, 2013, 1587–1594, <https://doi.org/10.1145/2505515.2514700>.

85. Gregory Michael Dorr, *Segregation's Science: Eugenics and Society in Virginia* (Charlottesville, VI: University of Virginia Press, 2008); Nikolas S. Rose, *The Psychological Complex: Psychology, Politics, and Society in England, 1869–1939* (Boston: Routledge & Kegan Paul, 1985).
86. Davenport quite explicitly listed segregation as an “expensive” alternative to sterilization (*Eugenics*, 259). Leonard Darwin, champion of another father of eugenics and statistics R. A. Fisher and the youngest son of Charles Darwin, believed that segregation was a more humane way to eliminate inferior types. The eugenic reaction to race mixing also reveals the anxieties and contradictions—as well as the performative power—of eugenics. Galton and others believed that “inferior races” would naturally die out, based on the “reaction” of native peoples to colonization. Within the United States, eugenicists believed the same for African Americans, and also that “hybrids” were especially prone to feeble-mindedness and mortality. As Melissa Noble has documented in *Shades of Citizenship: Race and the Census in Modern Politics* (Palo Alto, CA: Stanford University Press, 2000), the U.S. census during this time tracked various “types” of mixed-race people in response to this belief. U.S. insurance companies as well “tracked” these statistics in order to calculate risk and deny African Americans life insurance. This longer history of “risk” is also key to understanding the rise of technologies of what Oscar Gandy has called “rational racism” and also to the role of risk within discriminatory algorithms.
87. Nancy Stepan, *The Idea of Race in Science: Great Britain, 1800–1960* (Hamden, CT: Archon Books, 1982), 121.
88. Davenport, *Eugenics*, 259.
89. Grace Elizabeth Hale, *Making Whiteness: The Culture of Segregation in the South, 1890–1940* (New York: Vintage Books, 1999), 21.
90. Hale, *Making Whiteness*, 228, 131.
91. Hale, *Making Whiteness*, 125. Although she notes that segregation “could never reattach racial and class identities, could not make middle-class blacks poorly clothed, poorly educated, and poorly spoken and thus more easily identified by whites of all classes as inferior,” its long-term goal was to do precisely that—to deprive the black middle-classes of opportunities (131). As Carol Anderson argues in *White Rage: The Unspoken Truth of Our Racial Divide* (New York: Bloomsbury, 2016), segregation is linked to a “white rage” that drove both lynchings and police brutality.
92. According to Stephens-Davidowitz in *Everybody Lies*, Google searches revealed the extent of racism within the United States and foretold the election of Donald Trump (7).
93. MacKenzie, *Statistics in Britain*, 226.
94. Davenport, *Eugenics*, 8. Davenport condemned the “haphazard” nature of official middle-class couplings: “that marriage should still be only an *experiment* in breeding, while the breeding of many animals and plants has been reduced to a science, is ground for reproach” (emphasis in original, 7). Davenport’s eugenics/marriage manual did acknowledge the positive work of sexual selection, noting, “there

is some evidence of a crude selection in peoples of all stations. Even savages have a strong sense of personal beauty and a selection of marriage mates is influenced by this fact, as Darwin has shown" (7).

95. Paul Lazarsfeld and Robert K. Merton, "Friendship as Social Process: A Substantive and Methodological Analysis," in *Freedom and Control in Modern Society*, ed. Morroe Berger, Theodore Abel, and Charles Page (New York: Van Nostrand, 1954), 28.

96. Nikolas S. Rose, *Politics of Life Itself*, 62, 64.

97. Rose, *Politics of Life Itself*, 70, 60.

98. Marian Van Court, "Interview with Raymond B. Cattell," *Eugenics Bulletin*, Spring–Summer 1984, <https://www.eugenics.net/papers/eb7.html>.

99. Davidson and Rees-Mogg, *The Sovereign Individual*, 270.

100. For more on the necessary relationship between equality and democracy, see Jacques Rancière, *Hatred of Democracy*, trans. Steve Corcoran (London and New York: Verso, 2006), and Astra Taylor, *Democracy May Not Exist, But We'll Miss It When It's Gone* (New York: Metropolitan Books, 2019).

101. Byrd, "Tribal 2.0."

102. For instance, Pearson writes in relation to Galton's discussion of the "Negro print," "Galton considers that this matter should be pursued further, especially 'among the Hill tribes of India, Australian blacks and other diverse and so-called aboriginal races.'" Pearson, *The Life, Letters and Labours of Francis Galton*, 3a:25.

103. R. A. Fisher, *The Genetical Theory of Natural Selection* (Oxford: Oxford University Press, 1999), 249.

104. O'Neil, *Weapons of Math Destruction*, 159–160.

105. Lazarsfeld and Merton, "Friendship as Social Process," 23.

106. Howe, "On Prose and Poetry," 42; LeAnne Howe, "Tribalography: The Power of Native Stories," *Journal of Dramatic Theory and Criticism*, 14, no. 1 (1999), 124.

THE TRANSGRESSIVE HYPOTHESIS

1. Arendt, *The Origins of Totalitarianism* (New York: Harcourt Brace, 1976), 346. Also, according to Hannah Arendt, Totalitarianism's use of terror to shape the world distinguishes it from other, nontotalitarian ideologies. If, under Stalin, unemployment is declared to be "nonexistent," then there is no need for unemployment insurance (thus none should be provided); or, in a more recent instance of such "performative logic," if mail-in ballots are declared to be "fraudulent," then there is no need to count them (so every effort should be made *not* to). For Arendt, the prime examples of this totalitarian "logic" that "everything is possible" were concentration camps, laboratories in which humans were reduced to "ghastly marionettes with human faces" (*The Origins of Totalitarianism*, 341, 437, 455).

2. The workers who made up "the masses" were "social" only in the sense of being interchangeable; they were "the herd" that eugenicists sought to control. As Arendt

explains in *The Human Condition* (Chicago: University of Chicago Press, 1989), the “social realm,” which emerged with industrial capitalism and the demise of the modern family, transgressed the classic separation of private and public realms by publicly airing private concerns. It replaced “action” with “behavior” and sought to “normalize” its members, to make them behave, to exclude spontaneous action or outstanding achievement” (40). Deprived of both private and public spheres, “the masses” were both “homeless”—they had no privately owned places in which to hide from “the common public world”—and excluded from spaces of human plurality and freedom (71). Arendt also argues in *The Origins of Totalitarianism* that, pressed against one another, “the masses” did not share any common interests: they were not drawn together by membership in a specific class, political party, professional organization, or trade union. Indeed, Arendt defined “the masses” as “disinterested,” that is, without any interests: they were incapable of making connections with the others they were pushed against (315).

3. Fred Turner, *The Democratic Surround*.

4. According to Arendt, all ideologies strive for consistency. They seek to order facts “into an absolutely logical procedure which starts from an axiomatically accepted premise, deducing everything else from it; that is, it proceeds with a consistency that exists nowhere in the realm of reality” (*The Origins of Totalitarianism*, 471). An ideology promises “to explain all historical happenings, the total explanation of the past, the total knowledge of the present, and the reliable prediction of the future.” By doing so, totalitarians insist on a “truer” concealed reality, “independent of all experience . . . [and] emancipated from the reality that we perceive with our five senses” (470).

5. Michel Foucault, *The History of Sexuality: An Introduction*, trans. Robert Hurley, *History of Sexuality* (New York: Vintage Books, 1988), 34, 45, 6 (emphasis in original).

6. According to Arendt, hope stems from the fact that every end in history “necessarily contains a new beginning; this beginning is the promise, the only ‘message’ which the end can ever produce. Beginning . . . is the supreme capacity of man; politically, it is identical with man’s freedom” (*The Origins of Totalitarianism*, 478–479).

7. In *The Human Condition*, Arendt contends that, through political actions and words, “we insert ourselves into the human world, and this insertion is like a second birth . . . to act . . . means to take initiative, to begin” (176–177). Arendt turns to Friedrich Nietzsche’s praise of forgetting to explain how action can free us from the shackles of history. The ability to forget and act in the moment interrupts the “inexorable automatic course of daily life.” Without this ability to undo and control what we have done, “we would be doomed to swing forever in the ever-recurring cycle of becoming . . . and [to be] the victims of an automatic necessity bearing all the marks of the inexorable laws” (246). Also see Friedrich Nietzsche, “On the Uses and Disadvantages of History for Life,” in *Untimely Meditations* (Cambridge: Cambridge University Press, 1997), 57–124, <https://doi.org/10.1017/CBO9780511812101.007>.

8. For Arendt, freedom equaled freedom from necessity: those who could not be free—because they were slaves and thus “tame animals”—were doomed to an “actionless” and speechless existence (*The Human Condition*, 84).
9. Hannah Arendt, *On Revolution* (New York: Penguin Books, 2006), 61–62. Arendt’s dismissal of the need for social equality similarly drove her critique of the civil rights movement as focused on merely social gains. In her view, fighting to overturn antimiscegenation laws was more important than fighting for school desegregation. See Kathryn T. Gines, *Hannah Arendt and the Negro Question* (Bloomington: Indiana University Press, 2014).
10. Keith Wailoo, “Ethics and Accountability in High Tech,” presented at The Future of the Humanities@Google, online, October 16, 2020.
11. Ellison has underscored the importance of sacrifice in democratic societies: “I believe that one of the important clues to the meaning of [American Negro] experience lies in the idea, the *ideal* of sacrifice. Hannah Arendt’s failure to grasp the importance of this ideal among Southern Negroes caused her to fly way off into left field in her ‘Reflections on Little Rock’” (Ralph Ellison, as quoted in Danielle Allen, *Talking to Strangers: Anxieties of Citizenship since Brown v. Board of Education* [Chicago: University of Chicago Press, 2009], 27). Arendt’s vision of freedom did entail sacrifice, of course—but the coerced sacrifice of slaves on behalf of their masters. Even as she wrote of revolutions, Arendt could not conceive that the subjugated would sacrifice themselves in order that they and others could be free. Her worldview, as Bonnie Honig in *Political Theory and the Displacement of Politics* (Ithaca, NY: Cornell University Press, 1993), among others, has argued, was fundamentally limited by her view that politics and speech were beyond the reach of women and slaves.
12. Saidiya V. Hartman, “Venus in Two Acts,” *Small Axe: A Caribbean Journal of Criticism* 12, no. 2 (2008): 1–14, <https://doi.org/10.1215/-12-2-1>.
13. Hartman, “Venus in Two Acts,” 9.
14. Gayatri Chakravorty Spivak, “Can the Subaltern Speak?,” in *Marxism and the Interpretation of Culture*. ed. Cary Nelson and Lawrence Grossberg (Basingstoke, UK: Macmillan, 1988), 271–313.
15. Azoulay, *Potential History*, 289.
16. Azoulay, *Potential History*, 43.
17. Hartman, “Venus in Two Acts,” 11, 12.

CHAPTER 2

1. Paul N. Edwards, *The Closed World: Computers and the Politics of Discourse in Cold War America* (Cambridge, MA: MIT Press, 1996).
2. Rebecca Lewis, *Alternative Influence: Broadcasting the Reactionary Right on YouTube* (New York: Data and Society Research Institute, 2018), <https://datasociety.net/output/alternative-influence/>.

3. Elihu Katz and Paul F. Lazarsfeld, *Personal Influence: The Part Played by People in the Flow of Mass Communications* (1955; reprint, New York: Routledge, 2017), 15, 16.
4. See, for example, Gabriel Tarde, *Gabriel Tarde on Communication and Social Influence: Selected Papers*, ed. Terry Nicholas Clark (Chicago: University of Chicago Press, 2010); Paul F. Lazarsfeld, *The People's Choice: How the Voter Makes Up His Mind in a Presidential Campaign*, 3rd ed. (New York: Columbia University Press, 1968).
5. Elmo Roper, foreword to Katz and Lazarsfeld, *Personal Influence*, xxix–xxxiii.
6. Elihu Katz, introduction to the Transaction edition in Katz and Lazarsfeld, *Personal Influence*, xxiv–xxv.
7. Katz and Lazarsfeld, *Personal Influence*, 19.
8. Katz and Lazarsfeld, *Personal Influence*, 56; see also Muzafer Sherif, *The Psychology of Social Norms* (New York: Harper & Brothers Publishers, 1936), 95–109.
9. Katz and Lazarsfeld, *Personal Influence*, 41–42.
10. Elihu Katz, introduction to the Transaction edition in Katz and Lazarsfeld, *Personal Influence*, xxii–xxix.
11. Roper, foreword to Katz and Lazarsfeld, *Personal Influence*, xxxii.
12. As mentioned in the volume introduction, Jean Baudrillard has written most provocatively, and perhaps perversely, about the power of the silent majorities. Rather than viewing the silence of “the masses” as a problem to be fixed, he framed this nonresponse as a form of resistance: a strategic refusal of choice and rationality, a disappearance in reaction to the demand to be liberated, enlightened subjects. “The masses,” he argued, are an “opaque but equally translucent reality” (Baudrillard, *In the Shadow*, 1). They are anonymous, innumerable, and unnameable. Although “the masses”—the majority—are constantly appealed to, poked and prodded (surveyed and measured), they are fundamentally unknown and unknowable, Baudrillard tells us, because they are like a black hole: “They do not radiate. . . . they absorb all radiation from the outlying constellations of state, History, Culture, and Meaning. They are inertia, the strength of inertia, the strength of the neutral” (2). This absorption—this indifference—was, for Baudrillard, a positive strategy. It was impossible for “the masses” to be alienated because their silence indicates their refusal to be subjects. Silence, Baudrillard insists, “is an absolute weapon. No one can be said to represent the silent majority, and that is its revenge” (22). The strength of “the masses”—themselves a medium in which “the social” has imploded—was their lack of verifiable reception: their lack of vocal participation and refusal of representation.

In *Updating to Remain the Same*, I argue that, whether or not one agrees with Baudrillard—and there is certainly much to disagree with, especially with respect to his conflation of indifference and silence (“the masses” watching a football game are hardly silent)—the Internet and social media have made silence as a mocking strategy impossible, precisely through the constant measurements that Baudrillard dismissed as incapable of capturing “the masses.” Silence is now impossible not only because your every action is now tracked, but also because your silence is constantly betrayed by people “like you.” In terms of Cambridge Analytica and the Kosinski and colleagues papers discussed in chapter 1, individuals are no longer silent, not

just because their social data are captured by researchers, but also because their so-called friends and social network neighbors serve as direct and indirect leaks. New media—"n(you) media,"—are a function of "you," which they relentlessly emphasize: YouTube.com; "What's on your mind?"; "You" are the "Person of the Year." "The medium" is no longer "the masses," but "you." In English, "you" is a particularly shifty shifter: it is both singular and plural, but, even in its plural mode, it still targets individuals as individuals. "N(you) media" is fundamentally leaky.

13. Sara Ahmed, *The Cultural Politics of Emotion*, 2nd ed. (Edinburgh: Edinburgh University Press, 2014), 51.

14. Ahmed, *The Cultural Politics of Emotion*, 42.

15. Ahmed, *The Cultural Politics of Emotion*, 58.

16. David Holbrook, *The Masks of Hate: The Problem of False Solutions in the Culture of an Acquisitive Society* (Oxford: Pergamon Press, 1972), 36.

17. Ulrik Brandes et al., "What Is Network Science?," *Network Science* 1, no. 1 (2013): 2, <https://doi.org/10.1017/nws.2013.2> (emphasis in original). The editors of *Network Science* made the following claims in their introduction to the inaugural issue (4–12):

Claim 1: Network science is the study of network models.

Claim 2: There are theories about network representations and network theories about phenomena: both constitute network theory.

Claim 3: Network science should be empirical—not exclusively so, but consistently—and its value assessed against alternative representations.

Claim 4: What sets network data apart is the incidence structure of its domain.

Claim 5: At the heart of network science is dependence, both between and within variables.

Claim 6: Network science is evolving into a mathematical science in its own right.

Claim 7: Network science is itself more of an evolving network than a paradigm expanding from a big bang.

18. David Easley and Jon Kleinberg, *Networks, Crowds, and Markets: Reasoning about a Highly Connected World* (New York: Cambridge University Press, 2010), 1.

19. As Duncan J. Watts, a leading figure in the field of network science, explains in *Six Degrees: The Science of a Connected Age* (New York: Norton, 2004), 13–14: "If this particular period in the world's history had to be characterized in any simple way, it might be as one that is more highly, more globally and more unexpectedly connected than at any time before it."

20. Fredric Jameson, "Cognitive Mapping," in *Marxism and the Interpretation of Culture*, ed. Cary Nelson and Lawrence Grossberg (Champaign: University of Illinois Press, 1990), 347–360.

21. Jameson, "Cognitive Mapping," 351.

22. Jameson, *Postmodernism, or, The Cultural Logic of Late Capitalism* (Durham, NC: Duke University Press, 1991), 39.

23. Barabási, *Bursts*, 11. Barabási's claim that network science and digital technologies have placed us in "an immense research laboratory" calls to mind cyberpunk fiction, which posits artificial intelligence and supreme cowboy hackers as capable of detecting "patterns . . . in the dance of the street" (Gibson, *Neuromancer*, 259) and thus of foreseeing events that elude mere humans.
24. As Duncan Watts notes in *Six Degrees*, 15: "The truth is that most of the actual science here comprises extremely simple representations of extremely complicated phenomena. Starting off simple is an essential stage of understanding anything complex, and the results derived from simple models are often not only powerful but also deeply fascinating. By stripping away the confounding details of a complicated world, by searching for the core of a problem, we can often learn things about connected systems that we would never guess from studying them directly. The cost is that these methods we use are often abstract, and the results are hard to apply directly to real applications. It is a necessary cost, unavoidable in fact, if we truly desire to make progress."
25. Brandes et al., "What Is Network Science?," 5.
26. Philip E. Agre, "Surveillance and Capture: Two Models of Privacy," *Information Society* 10, no. 2 (1994): 101–27, <https://doi.org/10.1080/01972243.1994.9960162>.
27. Brandes et al., "What Is Network Science?," 8. The example Brandes and colleagues give of the difference between network science and statistics is quite illuminating: "While the range of attributes is structured, in much of science, the domain on which variables are defined is assumed to have no structure, i.e., simply a set. This may be for good reason. If we are interested in associations between, say, education and income controlled for age, we actually do not want there to be relations between individuals that also moderate the association. Much of statistics is in fact concerned with detecting and eliminating such relations. This is the single most important difference with network science, where the domains of at least some variables are explicitly set up to have structure. The potentially resulting dependencies are not a nuisance but more often than not they constitute the actual research interest" (8).
28. Brandes et al., "What Is Network Science?," 10.
29. Easley and Kleinberg, *Networks, Crowds and Markets*, 4 (emphasis in original).
30. "In a network setting," Easley and Kleinberg tell us in *Networks, Crowds and Markets*, 5, "you should evaluate your actions not in isolation but with the expectation that the world will react to what you do."
31. Easley and Kleinberg, *Networks, Crowds and Markets*, 6.
32. For more on network science and capture systems as neoliberal "cures," see Chun, *Updating to Remain the Same*.
33. David Harvey, *A Brief History of Neoliberalism* (Oxford: Oxford University Press, 2009), 2.
34. Michel Foucault, *The Birth of Biopolitics: Lectures at the Collège de France, 1978–79*, ed. Michel Senellart, trans. Graham Burchell (Basingstoke, UK: Palgrave Macmillan, 2008), 117.
35. Foucault, *Birth of Biopolitics*, 252.

36. Wendy Brown, *Undoing the Demos: Neoliberalism's Stealth Revolution* (New York: Zone Books, 2015), 179.
37. Agre, "Surveillance and Capture," 121, 120.
38. Damon M. Centola, "Homophily, Networks, and Critical Mass: Solving the Start-up Problem in Large Group Collective Action," *Rationality and Society* 25, no. 1 (2013): 3–40, <https://doi.org/10.1177/1043463112473734>; Herminia Ibarra, "Personal Networks of Women and Minorities in Management—A Conceptual Framework," *Academy of Management Review* 18, no. 1 (1993): 56–87, <https://doi.org/10.2307/258823>; Sinan Aral and Dylan Walker, "Identifying Influential and Susceptible Members of Social Networks," *Science* 337, no. 6092 (2012): 337–341, <https://doi.org/10.1126/science.1215842>; Emi Ooka and Barry Wellman, "Does Social Capital Pay Off More within or between Ethnic Groups?: Analysing Job Searches in Five Toronto Ethnic Groups," in *Inside the Mosaic*, ed. Erik Fong (Toronto: University of Toronto Press, 2006), 199–226.
39. Writing in "The Forms of Capital," in *Handbook of Theory and Research for the Sociology of Education*, ed. John G. Richardson (New York: Greenwood, 1986), 248–252, Pierre Bourdieu defined "social capital" as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition—or in other words, to membership in a group." Social capital is a form of credit or credentialing that relies on reciprocal and networked acknowledgment and exchange. This form of capital, Bourdieu stresses, exists "only in the practical state, in material and/or symbolic exchanges which help to maintain them" (248–249). The ties, that is, are dynamic and constantly enacted.
40. Ronald S. Burt, "Structural Holes versus Network Closure as Social Capital," in *Social Capital: Theory and Research*, ed. Nan Lin, Karen Cook and Ronald S. Burt (New York: Routledge, 2017), 31–32.
41. Marion Fourcade and Kieran Healy, "Seeing like a Market," *Socio-Economic Review* 15, no. 1 (2017): 14, <https://doi.org/10.1093/ser/mww033>.
42. Fourcade and Healy, "Seeing like a Market," 14 (emphasis in original).
43. For more on corporations, über-capital, and consumers, see Oscar Gandy on rational discrimination in *Coming to Terms with Chance*.
44. Fourcade and Healy, "Seeing like a Market," 25.
45. See Chun, *Updating to Remain the Same*.
46. For more on network science and capture systems "reshaping the activities they model," see Agre, "Surveillance and Capture."
47. Saunders, Hunt, and Hollywood, "Predictions Put into Practice," 364.
48. Gorner, "Chicago Police Use 'Heat List.'"
49. For more on social networks as "self-fulfilling prophecies," see Wendy Hui Kyong Chun, *Updating to Remain the Same*; Kieran Healy, "The Performativity of Networks" *European Journal of Sociology* 56, no. 2 (2015): 175–205, <https://doi.org/10.1017/S0003975615000107>.

50. Jean-François Lyotard, *The Postmodern Condition: A Report on Knowledge* (Minneapolis: University of Minnesota Press, 1984), 63.
51. Brown, *Undoing the Demos*, 127.
52. Barabási, *Bursts*, 204; Ahmed, *Cultural Politics of Emotion*.
53. Miller McPherson, Lynn Smith-Lovin, and James M. Cook, "Birds of a Feather: Homophily in Social Networks," *Annual Review of Sociology* 27, no. 1 (2001): 415.
54. Peter V. Marsden, "Homogeneity in Confiding Relations," *Social Networks* 10, no. 1 (March 1988): 57–76, [https://doi.org/10.1016/0378-8733\(88\)90010-X](https://doi.org/10.1016/0378-8733(88)90010-X); Matthew O. Jackson, "Average Distance, Diameter, and Clustering in Social Networks with Homophily," in *Internet and Network Economics, 4th International Workshop, WINE 2008, Shanghai, China, December 17–20, 2008, Proceedings, Lecture Notes in Computer Science*, vol. 5385, ed. Christos H. Papadimitriou and Shuzhong Zhang (Berlin: Springer, 2008), 4–11.
55. McPherson, Smith-Lovin, and Cook, "Birds of a Feather," 415, 416.
56. McPherson, Smith-Lovin, and Cook, "Birds of a Feather," 419.
57. McPherson, Smith-Lovin, and Cook, "Birds of a Feather," 420.
58. McPherson, Smith-Lovin, and Cook, "Birds of a Feather," 429–435.
59. Lazarsfeld and Merton, "Friendship as Social Process," 21.
60. Lazarsfeld and Merton, "Friendship as Social Process," 28.
61. Lazarsfeld and Merton, "Friendship as Social Process," 23.
62. Lazarsfeld and Merton, "Friendship as Social Process," 21.
63. Lazarsfeld and Merton, "Friendship as Social Process," 22.
64. Lazarsfeld and Merton, "Friendship as Social Process," 22 (emphasis in original).
65. Lazarsfeld and Merton, "Friendship as Social Process," 22.
66. Lazarsfeld and Merton, "Friendship as Social Process," 25. "Throughout our studies of friendship," they write, "it has been provisionally assumed that the observed patterns of status homophily—the positive correlation between the statuses of close friends—are, to some significant but unknown extent, the products of an underlying agreement between the values harbored by friends" (25). Further, Lazarsfeld and Merton go on to say, "only if there exists relatively self-contained subgroups, sharing their dissident values, can they continue to maintain acutely opposed values. In either case, there is a structural tendency toward value homophily. Either the dissidents conform to the majority-opinion, or if they find subgroups which provide a comfortable 'home' for their dissident opinions, they conform to the values held by *these associates*" (34; emphasis in original).
67. They write, "The dynamic role of similarities and differences of these [underlying] values in forming, maintaining, or disrupting friendships therefore requires notice in its own right." Lazarsfeld and Merton, "Friendship as Social Process," 25. As "Correlating Ideology" further elaborates after chapter 3, Merton drew directly from Sigmund Freud in his formulation of "latent" versus "manifest" factors—a

distinction still in place in forms of functional sociology and psychology that nonetheless regularly repudiate the validity of Freudian analysis. "Manifest functions" Merton later explained in *On Theoretical Sociology: Five Essays, Old and New* (New York: Free Press, 1967), referred "to those objective consequences for a specific unit . . . which contribute to its adjustment or adaptation and were so intended"; "latent functions" referred "to unintended and unrecognized consequences of the same order" (115, 117). Merton further argued that social engineering could only be successful if it addressed both manifest and latent functions (135).

68. Lazarsfeld and Merton, "Friendship as Social Process," 26.
69. Lazarsfeld and Merton, "Friendship as Social Process," 27–28.
70. "Again, the dynamic role of similarities and differences of these values in forming, maintaining, or disrupting friendships," Lazarsfeld and Merton explain, "requires notice in its own right" ("Friendship as Social Process," 25).
71. Lazarsfeld and Merton, "Friendship as Social Process," 29, 36.
72. Lazarsfeld and Merton, "Friendship as Social Process," 30.
73. To produce the basis for a mechanistic analysis, Lazarsfeld and Merton introduced the concept of "system equilibrium," more elaborate time series of experiences, and new variables to explain disconnection and connection.
74. Robert K. Merton, Patricia S. West, and Marie Jahoda, "Patterns of Social Life: Explorations in the Sociology of Housing," unpublished manuscript, Columbia University Bureau of Applied Social Research (BASR), 1938–1977, MS 0166, Box 9, and Robert K. Merton papers, 1928–2003, MS 1439, boxes 210–211. Rare Book and Manuscript Library, Columbia University. Chapters and appendix to this never-published manuscript report are *independently* paginated and will be indicated after "Merton, West, and Jahoda, 'Patterns of Social Life'" as chapter 1, chapter 3, and so on or as appendix in subsequent citations before their page numbers.
75. Lazarsfeld and Merton, "Friendship as Social Process," 22 (emphasis in original).
76. Lazarsfeld and Merton, "Friendship as Social Process," 27.
77. Lazarsfeld and Merton, "Friendship as Social Process," 21 (emphasis in original).
78. Lazarsfeld and Merton, "Friendship as Social Process," 23.
79. By 1977, homophily was already accepted as an axiomatic, if problematic, aspect of society. In a key early text, *Inequality and Heterogeneity: A Primitive Theory of Social Structure* (New York: Free Press, 1977), Peter M. Blau, who was a student of Merton's and who worked on the housing project survey, outlined what would become "contact theory": the theory that contact creates integration. An ambitious attempt to create a roadmap of "macrosociological theory" (written in the spirit of Karl Marx and Georg Simmel), *Inequality and Heterogeneity* argued for the importance of "weak ties" and heterogeneity to combat inequality within society. Blau saw differentiation and integration as "complementary opposites" (11), and argued that "there is too much inequality but that there cannot be too much heterogeneity" (x). Blau called for the replacement of "strong ingroup bonds," which "restrain individual freedom and mobility . . . and sustain rigidity and bigotry," with "diverse

intergroup relations," which, in turn, "though not intimate, foster tolerance, improve opportunities, and are essential for the integration of a large society" (85). In terms that call to mind Frederic Jameson's description of postmodernism and the possibilities of "cognitive mapping," Blau states, "The loss of extensive strong bonds in a community of kin and neighbors undoubtedly has robbed individuals of a deep sense of belonging and having roots, of profound feelings of security and lack of anxiety. This is the price we pay for the greater tolerance and opportunities that distinguish modern societies, with all their grievous faults, from primitive tribes and feudal orders. The social integration of individuals in modern society rests no longer exclusively on strong bonds with particular ingroups but in good part on multiple supports from wider networks of weaker social ties, supplemented by a few intimate bonds" (85). This insight itself draws from the work of another early progenitor of network science, Mark Granovetter, who argued that "weak ties" are essential to information dissemination and success in "The Strength of Weak Ties," *American Journal of Sociology* 78, no. 6 (May 1973): 1360–1380. (For more on this in relation to the role of social networks in dissolving postmodern confusion, see Chun, *Updating to Remain the Same*.) Blau's argument assumes—and indeed takes as axiomatic—that in-group interactions are stronger than intergroup ones. It also classifies individuals based on structural parameters, such as "age, race, education, and socioeconomic status," some of which Blau considers "inborn" (6).

80. Easley and Kleinberg, *Networks, Crowds and Markets*, 77–78 (emphasis in original).

81. Or, as Lenore Newman and Ann Dale put it in "Homophily and Agency: Creating Effective Sustainable Development Networks," *Environment, Development and Sustainability* 9, no. 1 (2007): 84, <https://doi.org/10.1007/s10668-005-9004-5>: "We feel more comfortable with those like ourselves, even in virtual communities." Like many other texts on homophily, Damon Centola and colleagues' analysis in "Homophily, Cultural Drift, and the Co-Evolution of Cultural Groups," *Journal of Conflict Resolution* 51, no. 6 (2007): 906, lists "feel[ing] more comfortable when we interact with others who share a similar cultural background" as one of the reasons for homophily. Referencing the work of Lazarsfeld and Merton to explain "why homophily is such a powerful force in cultural dynamics," Centola and colleagues state: "Psychologically, we often feel justified in our opinions when we are surrounded by others who share the same beliefs—what Lazarsfeld and Merton (1954) call 'value homophily.' . . . We also feel more comfortable when we interact with others who share a similar background (i.e., status homophily)" (906). In modeling the effects of cultural drift—and thus showing why globalization will not impose a monoculture—Centola and colleagues assert that there can be no neighbors without common cultural traits. Thus, "in our specification of homophily, the network of social interactions is not fixed . . . but rather evolves in tandem with the actions of the individuals" (908). Not surprisingly, Centola and colleagues "discover" that homophily creates cultural niches (926).

82. Easley and Kleinberg, *Networks, Crowds and Markets*, 83.

83. Easley and Kleinberg, *Networks, Crowds and Markets*, 45.

84. Andreas Wimmer and Kevin Lewis, "Beyond and below Racial Homophily: ERG Models of a Friendship Network Documented on Facebook," *American Journal of Sociology* 116, no. 2 (2010): 583–642, <https://doi.org/10.1086/653658>.
85. Easley and Kleinberg, *Networks, Crowds and Markets*, 96.
86. Easley and Kleinberg, *Networks, Crowds and Markets*, 97.
87. Easley and Kleinberg, *Networks, Crowds and Markets*, 101.
88. Jeannine Bell, *Hate Thy Neighbor: Move-in Violence and the Persistence of Racial Segregation in American Housing* (New York: New York University Press, 2013).
89. Thomas C. Schelling, "Dynamic Models of Segregation," *Journal of Mathematical Sociology* 1, no. 2 (1971): 143–86, <https://doi.org/10.1080/0022250X.1971.9989794>. In 1972, the NAACP filed a class action lawsuit against the Boston School Committee.
90. Schelling, "Dynamic Models of Segregation," 145.
91. Schelling, "Dynamic Models of Segregation," 180. Further, he writes: "Economists are familiar with systems that lead to aggregate results that the individual neither intends nor needs to be aware of, results that sometimes have no recognizable counterpart at the level of the individual. The creation of money by a commercial banking system is one; the way savings decisions cause depressions or inflations is another. Similarly, biological evolution is responsible for a lot of sorting and separating, but the little creature that mate and reproduce and forage for food would be amazed to know that they were bringing about separation of species, territorial sorting, or the extinction of species" (145). Schelling also uses the term "incentives" to explain segregation: from preferences to avoidance to economic constraints (148).
92. "Dynamic Models of Segregation," Schelling explains, "is about the kinds of segregation—or separation, or sorting—that can result from discriminatory individual behavior. By 'discriminatory,' I mean reflecting an awareness, conscious or unconscious, of sex or age or religion or color or whatever the basis of segregation is, an awareness that influences decisions on where to live, whom to sit by, what occupation to join or avoid, whom to play with or whom to talk to" (144).
93. Schelling, "Dynamic Models of Segregation," 149.
94. See Rothstein, *The Color of Law*.
95. The erasure of history and qualitative theories about race, gender, and sexuality within social network models leads to the reproduction of troubling assumptions about the "immutability" of race and gender, which underlie the naturalization of segregation. Within gender and sexuality studies, philosopher Judith Butler's definitive analysis of gender performativity at the end of the last century in *Gender Trouble: Feminism and the Subversion of Identity* (New York: Routledge, 2007) combined with other work in queer theory, had made gender mutability a default assumption within many fields. The critique of race as socially constructed, which gained widespread acceptance after the horrors of the Holocaust, has been reinforced by careful historical, empirical, and theoretical studies: from sociologists Michael Omi and Howard Winant's canonical *Racial Formation in the United States: From the 1960s*

to the 1990s, 2nd ed. (New York: Routledge, 1994) to sociologist Alondra Nelson's analysis of the genetics and race in *The Social Life of DNA: Race, Reparations, and Reconciliation after the Genome* (Boston: Beacon Press, 2016); from historian Paul Gilroy's controversial and provocative *Against Race: Imagining Political Culture beyond the Color Line* (Cambridge, MA: Harvard University Press, 2000) to historian Grace Elizabeth Hale's thorough examination of the Southern myth of absolute racial difference in *Making Whiteness*. Combined with so many more works, these texts have documented the rise of the modern concept of race during the Enlightenment; its centrality to colonization and slavery; its apparent zenith during the era of eugenics; its transformations after World War II; and its resurgence as an "invisible" marker in genetics. All of this research was effectively ignored in network science, which solidified "race," "gender," and other differences as "node characteristics" and helped shape the echo chambers and politics of the twenty-first century.

96. Healy, "Performativity of Networks," 175.
97. Judith Butler, *Gender Trouble: Feminism and the Subversion of Identity* (New York: Routledge, 1999); Jacques Derrida, "Signature Event Context," in *Limited Inc* (Evanston, IL: Northwestern University Press, 1988), 1–24.
98. Judith Butler, "Performative Acts and Gender Constitution: An Essay in Phenomenology and Feminist Theory," *Theatre Journal* 40, no. 4 (1988): 527.
99. Butler, *Gender Trouble*, xv–vi.
100. Ahmed, *Cultural Politics of Emotion*, 145.
101. Lazarsfeld and Merton, "Friendship as Social Process," 22, 37.
102. Kenneth B. Clark, Isidor Chein, and Stuart W. Cook, "The Effects of Segregation and the Consequences of Desegregation: A (September 1952) Social Science Statement in the Brown v. Board of Education of Topeka Supreme Court Case," *American Psychologist* 59, no. 6 (2004): 495–501, <https://doi.org/10.1037/0003-066X.59.6.495>.
103. Archival work was done in collaboration with Laura Kurgan and the researchers at the Columbia University Center for Spatial Research and was assisted by Ainsley Dankort. Further analysis of the data was done in collaboration with Carina Albrecht of Simon Fraser University's Digital Democracies Institute.
104. Merton, West, and Jahoda, "Patterns of Social Life," chapter 14: "The Environment of Opinion: Public Images of Public Housing," 4.
105. According to Merton, throughout his field trips to investigate housing projects, he found "widespread and profound interest in the prospect of systemic research into the social life of housing communities . . . by leading figures in both private and public housing . . . at every level in the housing hierarchies." This research was necessary given the heated debate between supporters of private versus public housing developments and the loaded stereotypes they were wielding to argue their points. Robert K. Merton, "Memorandum: A Proposed Research in Housing Committees," November 15, 1944, Columbia University Bureau of Applied Social Research, 1938–1977, MS0166, Box 9, Folder B-0230, Rare Book and Manuscript Library, Columbia University Library, 2.

106. Some have speculated that the “Patterns of Social Life” report was never published to protect the residents of “Crafttown,” the housing cooperative at the core of Winfield, New Jersey, which Merton, West and Jahoda praised as a success in “Patterns of Social Life,” from accusations of “Communism.”
107. Aria Bendix, “A Tiny New Jersey Community Is Renting Homes for as Little as \$690 a Month—but There’s a 25-Year Waiting List to Get In,” *Business Insider*, June 11, 2019, <https://www.businessinsider.in/a-tiny-new-jersey-community-is-renting-homes-for-as-little-as-690-a-month-but-theres-a-25-year-waiting-list-to-get-in/articleshow/69732563.cms>.
108. Merton, West, and Jahoda, “Patterns of Social Life,” chapter 1: “Moving In,” 25.
109. “Not for Rent, Not for Sale,” *Time*, June 2, 1941, 70–72.
110. Merton, West, and Jahoda, “Patterns of Social Life,” chapter 9: “The Dynamics of Race Relations in Hilltown,” 5, 14.
111. Merton, West, and Jahoda, “Patterns of Social Life,” chapter 8: “Selective Processes in Friendship,” 11 (emphasis in original).
112. Note on “Chart 1: Racial Values of Close Friends Among White Residents of Hilltown,” Merton, West, and Jahoda, “Patterns of Social Life,” chapter 8, 9. This chart was not included in the version of Chapter 8 in the Merton Archive. It is located in Columbia University, Bureau of Applied Social Research, 1938–1977, MS0166, Box 09, Rare Book and Manuscript Library, Columbia University Library.
113. In fact, the researchers contended in “Patterns of Social Life” that the relative proportions of housing project residents were only important because they “clearly show that the liberals take less advantage of their appreciably greater number to form friendships with ambivalent residents than the illiberals take advantage of *their* smaller number. . . . The illiberals more fully utilize their slim ‘resources’ in forming friendships with the presumably vulnerable residents than the liberals utilize their great ‘resources.’” Merton, West, and Jahoda, “Patterns of Social Life,” chapter 8, 11 (emphasis in original).
114. “Truman Committee Exposes Housing Mess,” *Life*, November 30, 1942, 45, 52.
115. Merton, West, and Jahoda, “Patterns of Social Life,” appendix, 74. The success of Craftown (Winfield) was consistently and repeatedly framed in terms of the crises that dominated its early years and the collective response it provoked. Craftown (Winfield) was different from Hilltown (Addison Terrace) and other housing projects because its pioneers faced a “*continuing flow of immediate problems which are not private affairs but affairs common to the group*,” creating situations to which Jefferson referred as those ‘extraordinary occasions which would animate the people to meet them’” (“Patterns of Social Life,” chap. 10, “Grass Roots Politics: Civic Action and Civic Apathy,” 35; emphasis in original). These problems broke down any previous boundaries or privileges because they “were *concrete* and *direct* affecting every individual in the community. No one could withdraw from their impact unless he moved out” (36). They also involved the basic needs of life and could only be solved through collective action. The key was equality and the lack of exit. The underlying

question was thus whether such an egalitarian group identity could emerge across racial boundaries.

116. As the researchers noted in JAM's March 1947 interview with Louis Mason, the Pittsburgh AFL union leaders were not on the list of supporters of the Urban League because they supported segregated practices, especially for "machinists, boiler makers, electrical workers, painters and plumbers." JAM, "Interview with Mr. Louis Mason, Acting Industrial Secretary of the Pittsburgh Urban League, on March 10, 1947," September 23, 1947, Columbia University, Bureau of Applied Social Research Papers, MS0166, Box 08, Rare Book and Manuscript Library, Columbia University Library, 5.

117. Merton, West, and Jahoda, "Patterns of Social Life," appendix, 87. See also chap. 2, "Two Towns," 5–7.

118. Clarence Stein, "Meeting of Clarence Stein and A. Z. Pittler at Addison Terrace," December 17, 1946, Columbia University, Bureau of Applied Social Research Papers, MS0166, Box 08, Rare Book and Manuscript Library, 2.

119. Merton, West, and Jahoda, "Patterns of Social Life," chap. 2, 20; appendix, 73.

120. Merton, West, and Jahoda, "Patterns of Social Life," chap. 14, 13. The desire to ensure that Hilltown (Addison Terrace) did not become an "all black" housing project, they note, led to "inadvertent" racial discrimination, with 60 percent of white residents being admitted within three months of application by 1948, compared to only 28 percent of black residents (chap. 9, 11); they are called "latecomers" since they were arriving in 1948. The greatest percentage of black residents—44 percent—had to wait over a year. As Merton, West, and Jahoda note: "the consequences of the action are shaped by the character of that system. In this case, the generally lower level of income and fewer opportunities of Negroes in Steel City [Pittsburgh] constituted a socially structured arrangement which meant lower turnover among Negro tenants and consequently prolonged periods of waiting for those Negroes who eventually did find their way to Hilltown [Addison Terrace]. The consequence is none the less actual for having been unintended" (chap. 9, 13).

121. As Fred Turner has argued in *The Democratic Surround*, national morale was considered key to sustaining democratic societies in mid-twentieth-century America.

122. Merton, "Memorandum," 3 (emphasis in original); Merton, West, and Jahoda, "Patterns of Social Life," chap. 14, 5.

123. Merton, West, and Jahoda, "Patterns of Social Life," chap. 1, 5.

124. Merton, West, and Jahoda, "Patterns of Social Life," chap. 1, 1–2.

125. Merton, "Memorandum," 4 (emphasis in original). To determine tenant morale, Merton proposed to examine these feelings with respect to the following factors (5):

- A. Architectural factors (location, site, design, etc.)
- B. Managerial practices and policies.
- C. Attitudes of the larger community toward the housing project.
- D. Previous attitudes and expectations of residents.
- E. Social organisation of tenants.
- F. Institutional policies (e.g. of FPHA, Metropolitan Life, etc.).

126. Merton, West, and Jahoda, "Patterns of Social Life," chapter 3: "The Meanings of Hilltown for Negroes and Whites," 179.
127. Merton, West, and Jahoda, "Patterns of Social Life," chapter 3, 26.
128. Richard Wright, *Conversations with Richard Wright*, ed. Kenneth Kinnaman and Michael J. Fabre (Jackson: University Press of Mississippi, 1993), 99.
129. For example, based on the data shown in the table below, Merton, West, and Jahoda argue that Craftown (Winfield) is a political community, whereas Hilltown (Addison Terrace) has only "some tenants" who are interested in politics. One could argue that the numbers in this table show the reverse to be true: that a greater number of Hillowners (Addison Terrace residents) were significantly more interested in local politics.

Intensity of Interest in Local Politics and Tenant Morale

	Craftown Intensity of Interest			Hilltown Intensity of Interest		
	Greatly	Moderately	Not at all	Greatly	Moderately	Not at all
Low morale	33%	55%	72%	36%	35%	39%
High morale	67%	45%	28%	64%	65%	61%
# of cases (100%)	54	102	134	152	358	199

Redrawn from Merton, West, and Jahoda, "Patterns of Social Life," chap. 10, 10.

130. Merton, West, and Jahoda, "Patterns of Social Life," chap. 10, 19.
131. Merton, West, and Jahoda, "Patterns of Social Life," chap. 10, 25.
132. Merton, West, and Jahoda, "Patterns of Social Life," chap. 10, 26.
133. White residents of the two housing projects were particularly reluctant to join and remain on interracial committees: whereas 61 percent of black residents had participated on these committees, only 39 percent of white residents had; see Merton, West, and Jahoda, "Patterns of Social Life," chap. 11: "Patterns of Popular Participation," 36. As one of the interviewees, Mrs. Scullion, an "X" who was quite active on interracial committees and who claimed to have good friends of the other race (who "knew their place"), put it: "Some people here feel that because Ruby [the assistant manager] is a Y, the Y's get better treatment, and they keep their children away. But that's not right. The X's have just as many opportunities as the Y's but somehow the Y's are always in the majority. I don't know why it is—maybe they are more interested. But if you have a group which starts out with both X's and Y's, the X's start dropping out, and you've finally only got Y's left." PLK, "Interview with Mrs. Scullion (X)," November 29, 1946," Columbia University, Bureau of Applied Social Research Papers, MS0166, Box 08, Rare Book and Manuscript Library, Columbia University Library, 8, 5. Although featured in a black newspaper as the only remaining white member on an interracial committee. Mrs. Scullion was, in

the words of the interviewer: "rabid on the subject of Jews (although she spoke so convincingly about how troublesome they are on the comm'y that I came away quite anti-Semitic myself)" (1). She also severely criticized the newer white residents for their loose morals and their apathy, and her major complaint regarding her Jewish neighbors was financial: a perception that they were "cheating" when reporting their income to management (7).

134. Merton, West, and Jahoda, "Patterns of Social Life," chap. 14, 31.
135. Merton, West, and Jahoda, "Patterns of Social Life," chap. 14, 36.
136. Merton, West, and Jahoda, "Patterns of Social Life," chap. 9, 14.
137. Merton, West, and Jahoda, "Patterns of Social Life," chap. 7: "Patterns of Selection in Interpersonal Relations," 33.
138. Merton, West, and Jahoda, "Patterns of Social Life," chap. 5: "Networks of Interpersonal Relations," 28.
139. Merton, West, and Jahoda, "Patterns of Social Life," appendix, 104. They explain they were able to discover this tendency by correlating various factors together.
140. Merton, West, and Jahoda, "Patterns of Social Life," chap. 7, 16.
141. PJS and JAM, "Report of Meeting of Adult Program Committee of Addison Terrace," February 19, 1947," Columbia University, Bureau of Applied Social Research Papers, MS0166, Box 08, Rare Book and Manuscript Library, Columbia University Library, 2.
142. JGB, "Tenant: Helen Brown," December 19, 1946, Columbia University, Bureau of Applied Social Research Papers, MS0166, Box 08, Rare Book and Manuscript Library, Columbia University Library, 5, 4.
143. In his funding request to the Lavanburg Foundation, a "neutral" entity responsible for creating low-income nonprofit housing in Manhattan, Merton offered to write a report that was: "(1) technically competent; (2) fact-finding and not moralizing; (3) pertinent, i.e., centered on problems which confront housing personnel; and (4) sufficiently detailed to serve as a guide to social engineering" ("Memorandum," 2).
144. Merton, West, and Jahoda, "Patterns of Social Life," chap. 1, 30.
145. As Merton, West, and Jahoda point out many times in "Patterns of Social Life," appendix, with observations such as "there are formidable obstacles in studying a millionaire's club versus a Navaho reservation" (79), it was easier to study the poor than the rich. On page 48 of the appendix, they also cite the work of Alexander H. Leighton, who, in *The Governing of Men: General Principles and Recommendations Based on Experience at a Japanese Relocation Camp* (Princeton, NJ: Princeton University Press, 1945), studied Japanese internment camps in order to understand "the laws of individual behavior" (6).
146. PJS, "Outline Memo on Friendship-Section C," July 1948, Robert K. Merton papers, 1928–2003, MS 1439, Box 209, folder 4, Rare Book and Manuscript Library, Columbia University Library, 1–4.

147. Merton, West, and Jahoda were quite aware of the “performative” aspects of research: “In a closed community, one mistake by an interviewer affects many things” (“Patterns of Social Life,” appendix, 39). They also state in the appendix (43) that they sensitive to the fact that, though they needed approval by management, they could not be deemed too close to management since this would damage their credibility.

148. Merton, West, and Jahoda, “Patterns of Social Life,” chapter 1, 1.

PROXIES, OR RECONSTRUCTING THE UNKNOWN

1. *Oxford English Dictionary*, 3rd ed. (Oxford: Oxford University Press, 2007), s.v. “proxy, n.” and s.v. “procurator, n.1,” For more on proxies, see Wendy Hui Kyong Chun, Boaz Levin, and Vera Tollmann, “Proxies,” in *Uncertain Archives: Critical Keywords for Big Data*, ed. Nanna Bonde Thylstrup et al. (Cambridge, MA: MIT Press, 2021), 388–394; and Dylan Mulvin, *Proxies: The Cultural Work of Standing In* (Cambridge, MA: MIT Press, 2021).
2. O’Neil, *Weapons of Math Destruction*, 17–18.
3. See, for example, Bonilla-Silva, *Racism without Racists*.
4. For more on climate change models and “prevent[ing] the predicted future from actually occurring,” see Wendy Hui Kyong Chun, “On Hypo-Real Models or Global Climate Change: A Challenge for the Humanities,” *Critical Inquiry* 41, no. 3 (2015): 675–703, <https://doi.org/10.1086/680090>.
5. Monica Davey, “Panel Studying Racial Divide in Missouri Presents a Blunt Picture of Inequity,” *New York Times*, September 14, 2015, <https://www.nytimes.com/2015/09/14/us/panel-studying-racial-divide-in-missouri-presents-a-blunt-picture-of-inequity.html>.
6. James Hansen, Makiko Sato, and Reto Ruedy, “Perception of Climate Change,” *Proceedings of the National Academy of Sciences* 109, no. 37 (2012): E2415, <https://doi.org/10.1073/pnas.1205276109>.
7. Phillip Bump, “Jim Inhofe’s Snowball Has Disproven Climate Change Once and for All,” *Washington Post*, February 26, 2015, <https://www.washingtonpost.com/news/the-fix/wp/2015/02/26/jim-inhofes-snowball-has-disproven-climate-change-once-and-for-all/>.
8. For background and commentary on the proxy polar bear video, see Sarah Gibbens, “Heart-Wrenching Video Shows Starving Polar Bear on Iceless Land,” *National Geographic*, December 7, 2017, <https://www.nationalgeographic.com/news/2017/12/polar-bear-starving-arctic-sea-ice-melt-climate-change-spd/>.
9. David Leafe, “Are These Photos REALLY Proof That Polar Bears Are Being Killed by Climate Change? Doubts Raised over Claims after It Emerges That No Post Mortem Was Carried Out,” *Daily Mail*, December 29, 2017, <http://www.dailymail.co.uk/news/article-5221939/Are-polar-bears-killed-climate-change.html>.
10. Michael E. Mann, Raymond S. Bradley, and Malcolm K. Hughes, “Global-Scale Temperature Patterns and Climate Forcing over the Past Six Centuries,” *Nature* 392,

- no. 6678 (1998): 779–787, <https://doi.org/10.1038/33859>; Michael E. Mann, Raymond S. Bradley, and Malcolm K. Hughes, “Northern Hemisphere Temperatures during the Past Millennium: Inferences, Uncertainties, and Limitations,” *Geophysical Research Letters* 26, no. 6 (1999): 759–762, <https://doi.org/10.1029/1999GL900070>.
11. Antonio Regaldo, “In Climate Debate, the ‘Hockey Stick’ Leads to a Face-Off: Nonscientist Assails a Graph Environmentalists Use, And He Gets a Hearing,” *Wall Street Journal*, February 14, 2005, <https://www.wsj.com/articles/SB110834031507653590>; Richard Muller, “Global Warming Bombshell: A Prime Piece of Evidence Linking Human Activity to Climate Change Turns Out to Be an Artifact of Poor Mathematics,” *MIT Technology Review*, October 15, 2004, <https://www.technologyreview.com/s/403256/global-warming-bombshell/>.
 12. Michael E. Mann, “I’m a Scientist Who Has Gotten Death Threats. I Fear What May Happen under Trump,” *Washington Post*, December 16, 2016, https://www.washingtonpost.com/opinions/this-is-what-the-coming-attack-on-climate-science-could-look-like/2016/12/16/e015cc24-bd8c-11e6-94ac-3d324840106c_story.html.
 13. Mann, Bradley, and Hughes, “Global-Scale Temperature Patterns,” 779.
 14. Steven Mufson, “Rick Perry Just Denied That Humans Are the Main Cause of Climate Change,” *Washington Post*, June 19, 2017, <https://www.washingtonpost.com/news/energy-environment/wp/2017/06/19/trumps-energy-secretary-just-denied-that-man-made-carbon-dioxide-is-the-main-driver-for-climate-change>.
 15. Michael E. Mann, *The Hockey Stick and the Climate Wars: Dispatches from the Front Lines* (New York: Columbia University Press, 2012), 43.
 16. Rudolph W. Preisendorfer, *Principal Component Analysis in Meteorology and Oceanography* (Amsterdam: Elsevier Science, 1988).
 17. Karl Pearson, “LIII. On Lines and Planes of Closest Fit to Systems of Points in Space,” *London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science* 2, no. 11 (1901): 559–72, <https://doi.org/10.1080/14786440109462720>.
 18. Mann, Bradley, and Hughes, “Global-Scale Temperature Patterns,” 781.
 19. Willie Soon and Sallie Baliunas, “Proxy Climatic and Environmental Changes of the Past 1000 Years,” *Climate Research* 23, no. 2 (2003): 89, <https://doi.org/10.3354/cr023089>.
 20. Mann, *The Hockey Stick and the Climate Wars*, 120.
 21. Steven McIntyre and Ross McKittrick., “Hockey Sticks, Principal Components, and Spurious Significance” *Geophysical Research Letters* 32, no. 3 (2005): L03710.
 22. Mann, *The Hockey Stick and the Climate Wars*, 137–138.
 23. Geoff Brumfiel, “Academy Affirms Hockey-Stick Graph,” *Nature* 441, no. 7097 (2006): 1032–1033, <https://doi.org/10.1038/4411032a>; Richard A. Muller, “The Case against Global-Warming Skepticism,” *Wall Street Journal*, October 21, 2011, <https://www.wsj.com/articles/SB10001424052970204422404576594872796327348>.
 24. Richard Muller, “The Case Against Global-Warming Skepticism.”

25. Mann, *The Hockey Stick and the Climate Wars*, 4; see also “The Relentless Attack on Climate Scientist Ben Santer,” *Moyers on Democracy* (blog), May 16, 2014, <http://billmoyers.com/2014/05/16/the-relentless-attack-of-climate-scientist-ben-santer/>.
26. Mann, Bradley, and Hughes, “Global-Scale Temperature Patterns,” 780–781.
27. Christoph Rosol, “Data, Models and Earth History in Deep Convolution: Paleo-climate Simulations and Their Epistemological Unrest,” *Berichte zur Wissenschaftsgeschichte* 40, no. 2 (2017): 120–39, <https://doi.org/10.1002/bewi.201701822>.
28. See Chun, Levin, and Tollman, “Proxies.”
29. Jacques Derrida, “Plato’s Pharmacy,” in *Dissemination*, trans. Barbara Johnson (Chicago: University of Chicago Press, 1981), 70.

CHAPTER 3

1. Doyle McManus, “Campaign 2016’s Quixotic Quest for ‘Authenticity,’” *Chicago Tribune*, November 2, 2015, <https://www.chicagotribune.com/opinion/commentary/ct-bernie-sanders-donald-trump-authenticity-20151102-story.html>.
2. “New York Times/CBS News Poll, December 4–8, 2015,” 2015, <https://assets.documentcloud.org/documents/2644724/poll.pdf>.
3. “New York Times/CBS News Poll,” 19.
4. “New York Times/CBS News Poll,” 19, 16.
5. Clare Foran, “The Authentic Alliance of Donald Trump and Ben Carson: Former Rivals Find Common Ground by Suggesting That in Politics, People and Events Aren’t Always What They Seem..,” *Atlantic*, March 11, 2016, <https://www.theatlantic.com/politics/archive/2016/03/donald-trump-ben-carson-endorsement/473397/>; Justin Talbot-Zorn and Leigh Marz, “Donald Trump Is Not ‘Authentic’ Just Because He Says the Bad Things in His Head,” *Time*, October 10, 2016, <http://time.com/4519851/2016-election-authenticity/>; Ben Zimmer, “‘Authenticity’ in the 2016 Campaign: One Word Keeps Coming Up in Presidential Debates,” *The Wall Street Journal*, September 18, 2015, <https://www.wsj.com/articles/authenticity-in-the-2016-campaign-1442591796>.
6. Wendy Hui Kyong Chun, “Big Data as Drama,” *ELH* 83, no. 2 (2016): 363–82, <https://doi.org/10.1353/elh.2016.0011>.
7. Donald J. Trump, “Full Text: Donald Trump 2016 RNC Draft Speech Transcript,” *Politico*, July 21, 2016, <https://www.politico.com/story/2016/07/full-transcript-donald-trump-nomination-acceptance-speech-at-rnc-225974>. Although, of course, the draft speech transcript does not include minor asides and comments made by Trump in response to his own words and to his audience’s chants, it does represent a verbatim transcript of the two passages quoted in this chapter as delivered by Trump.
8. Donald J. Trump, “Donald Trump’s Entire Republican Convention Speech,” CNN, July 21, 2016, https://www.youtube.com/watch?v=Fs0pZ_GrTy8.

9. Keith Koffler, "The Authentic Trump: He Doesn't Attempt to Be Anything Else," *Lifezette* (blog), August 17, 2015, <http://www.lifezette.com/polizette/the-authentic-trump/>.
10. Cody Cain, "Donald Trump's Wealth Is Fool's Gold," *Time*, October 7, 2016, <http://time.com/4521851/donald-trumps-wealth/>; "The Definitive Net Worth of Donald Trump: What's Donald Trump Really Worth," *Forbes*, September 2019, <https://www.forbes.com/donald-trump/#6e41f0922899>.
11. See *Oxford English Dictionaries*, "Post-truth," and Jean Baudrillard, *Simulacra and Simulation* trans. Sheila Faria Glaser (Ann Arbor: University of Michigan Press, 1994).
12. Chandra Mukherji, "A Message from the Chair: The Search for Cultural Authenticity," *Newsletter of the Sociology of Culture Section of the American Sociological Association* 21, no. 3 (Spring 2007): 1.
13. Even Native Americans, Mukherji contended, "often migrated to places they now define as their authentic homes." Mukherji, "A Message from the Chair," 1. The involuntary nature of this movement, however, is strangely not addressed.
14. Sarah Banet-Weiser, *AuthenticTM: The Politics of Ambivalence in a Brand Culture* (New York: New York University Press, 2012); John J. Sosik and John C. Cameron, "Character and Authentic Transformational Leadership Behavior: Expanding the Ascetic Self toward Others," *Consulting Psychology Journal: Practice and Research* 62, no. 4 (2010): 251–269; Fiona Kennedy and Darl G. Kolb, "The Alchemy of Authenticity," *Organizational Dynamics* 45, no. 4 (2016): 316–322, <https://doi.org/10.1016/j.orgdyn.2016.09.002>.
15. Tina Nguyen, "Donald Trump Trolls the Media, Turns Phony 'Birther' Press Conference into Hotel Infomercial," *Vanity Fair*, September 16, 2016, <https://www.vanityfair.com/news/2016/09/donald-trump-birther-obama-press-conference>.
16. Transcribed from video to opener from season one of *The Apprentice* by author.
17. Transcribed by author from Trump, "Donald Trump's Entire Republican Convention Speech," https://www.youtube.com/watch?v=Fs0pZ_GrTy8.
18. Vann R. Newkirk, "On Hillary Clinton's Pandering," *Atlantic*, April 19, 2006, <https://www.theatlantic.com/politics/archive/2016/04/hillary-clinton-pandering-radio/479004/>. Michael Barbaro and Patrick Healy, "Donald Trump's Conduct Was Excused Again and Again. But Not This Time.," *New York Times*, October 8, 2016, <https://www.nytimes.com/2016/10/09/us/politics/donald-trump-presidential-race.html>.
19. Gunn Enli, *Mediated Authenticity: How the Media Constructs Reality* (New York: Peter Lang, 2015).
20. E. Doyle McCarthy, "Emotional Performances as Dramas of Authenticity," in *Authenticity in Culture, Self and Society*, ed. Phillip Vannini and J. Patrick Williams (Surrey, UK: Ashgate, 2009), 241–255.
21. *Oxford English Dictionary*, 3rd ed. (2014), s.v. "authentic, adj. and n."
22. Trilling, *Sincerity and Authenticity* 1–25.
23. *Hamlet*, ed. G. R. Hibbard (Oxford: Oxford University Press, 2008), 1.3.78–80.

24. Trilling, *Sincerity and Authenticity*, 58, 68, 64. In contrast, Hannah Arendt contended in *On Revolution* that acting and the theater—in particular “the mask”—were essential to the political. For her, Rousseau’s sincerity represented the dangers of the “social”: it compromised the boundary between public (political equality) and private (domestic inequality) by insisting on social equality (97–101).
25. Trilling, *Sincerity and Authenticity*, 11.
26. Trilling, *Sincerity and Authenticity*, 100.
27. This distinction between sincerity and authenticity seems to capture the dynamics of the 2016 election in which Clinton, with all her sincerity, was, as Jill Abramson notes, “caricatured writ large as a seasoned manipulator,” whilst Trump’s perceived authenticity protected him from all criticism “Could Donald Trump the Actor Win the Election for Trump the Candidate?” *Guardian*, April 26, 2016, <https://www.theguardian.com/commentisfree/2016/apr/26/donald-trump-actor-win-election-candidate-ronald-reagan-american-voters>. Trump’s apparent madness—diagnoses of him as a pathological liar or as a psychopath—would thus seem only to underscore, rather than detract from, his authenticity. But to stop here with this notion of authenticity is to miss the ways in which authenticity itself has changed.
28. Trilling, *Sincerity and Authenticity*, 100.
29. Adolf Hitler, as quoted in Arendt, *The Origins of Totalitarianism*, 325.
30. Contemporary media culture, McCarthy emphasizes in “Emotional Performances” (244), has intensified the notion of “authenticity” by sharpening its relationship to emotional displays. “Authenticity,” the “means to *feel something* with honesty, integrity, and vitality, and to express in one’s life the truth of one’s personal insights and discoveries” (245), has become “a vital cultural code used and pursued by social actors in an age of artifice, drama, and manipulation” (252).
31. McCarthy, “Emotional Performances,” 252.
32. As Peter Fleming has documented in *Authenticity and the Cultural Politics of Work: New Forms of Informal Control* (Oxford University Press, 2009), “fun” and progressive workplaces demand that workers be “authentic,” that they expose their personal selves at work. By doing so, they make work self-fulfilling and creative.
33. Sarah Banet-Weiser, *AuthenticTM*, 58.
34. Banet-Weiser, *AuthenticTM*, 5.
35. Banet-Weiser, *AuthenticTM*, 8–9; Raymond Williams, *The Long Revolution* (New York: Columbia University Press, 1961), 63.
36. David McNally and Karl D. Speak, as quoted in Banet-Weiser, *AuthenticTM*, 59.
37. Banet-Weiser, *AuthenticTM*, 80.
38. John Zogby, “Clinton, Trump and the Battle for Authenticity,” *Forbes*, September 24, 2016, <https://www.forbes.com/sites/johnzogby/2016/09/24/clinton-trump-and-the-battle-for-authenticity/>.
39. Laurie Ouellette and James Hay, *Better Living through Reality TV: Television and Post-Welfare Citizenship* (Malden, MA: Blackwell, 2008). Responding to analyses of

the 2016 election, which facilely blamed reality TV for the result, Ouellette argued that Trump was more than “a symptom of manipulative infotainment and cultural decline: his political ascendency speaks to reality TV’s decades-long role in governing practices,” in particular the neoliberal dismantlement of government. Laurie Ouellette, “The Trump Show,” *Television & New Media* 17, no. 7 (2016): 647, <https://doi.org/10.1177/1527476416652695>.

40. Ouellette, “The Trump Show,” 648.

41. Ouellette, “The Trump Show,” 649.

42. Slavoj Žižek, *The Sublime Object of Ideology* (London: Verso Books, 1989), 28–43.

43. Blaise Pascal, *Pascal's Pensées* (New York: Dutton, 1958), 68, <https://www.gutenberg.org/files/18269/18269-h/18269-h.htm>.

44. Herman H. Goldstine and John von Neumann, *Planning and Coding of Problems for an Electronic Computing Instrument*, part 2, vol. 1 (Princeton: Institute for Advanced Study, 1947), 2.

45. As June Deery explains in “Mapping Commercialization in Reality Television,” in *A Companion to Reality Television*, ed. Laurie Ouellette (Malden, MA: Wiley Blackwell, 2013), 20: “First, broadcasters can buy internationally traded, prepackaged, and already successful franchises that require little further creative development beyond some local adaptation. This suits advertisers, who typically look for a level of predictability in their financial investment. . . . Producers further oblige by setting up controlled environments—both via the physical setup (often isolated and closely monitored) and through casting and editing—permitting just enough shock and novelty to keep the shows from getting too tired. Then, on-screen participants expect little or no pay and are generally underemployed aspiring actors or lower- and lower-middle-class employees whose casting could be considered a form of outsourcing to cheaper labor.”

46. Andrew Ross, “Reality Television and the Political Economy of Attention,” in *A Companion to Reality Television*, ed. Laurie Ouellette (Malden, MA: Wiley Blackwell, 2013), 34.

47. Nick Couldry, “Reality TV, or the Secret Theater of Neoliberalism,” *Review of Education, Pedagogy, and Cultural Studies* 30, no. 1 (2008): 3–13, <https://doi.org/10.1080/10714410701821255>.

48. Terranova, *Network Culture*, 95.

49. Terranova, *Network Culture*, 95, 96 (emphasis in original).

50. “The World’s Most Valuable Resource.”

51. Wolfgang Thomas, “Algorithms: From Al-Khwarizmi to Turing and Beyond,” in *Turing’s Revolution: The Impact of His Ideas about Computability*, ed. Giovanni Sommaruga and Thomas Strahm (Cham: Springer Basel AG, 2016), 30–31.

52. *Oxford English Dictionary*, 3rd ed. (2012), s.v. “algorithm, n.”

53. A. M. Turing, “Computing Machinery and Intelligence,” *Mind* 59, no. 236 (1950): 450–451.

54. Francesco Ricci, Lior Rokach, and Bracha Shapira, ed., *Recommender Systems Handbook*, 2nd ed. (Boston: Springer, 2015), 1–6.
55. Dietmar Jannach et al., *Recommender Systems: An Introduction* (New York: Cambridge University Press, 2012), xiv.
56. Ricci, Rokach, and Shapira, *Recommender Systems Handbook*, 2. Slavoj Žižek makes a similar point in his discussion of ideology in *Sublime Object*.
57. Ricci, Rokach, and Shapira, *Recommender Systems Handbook*, 11–14.
58. Jannach et al., *Recommender Systems*, 13.
59. Jun Zhu and Bei Chen, in “Latent Feature Models for Large-Scale Link Prediction,” *Big Data Analytics* 2, no. 1 (2017): 2 (article 3), <https://doi.org/10.1186/s41044-016-0016-y>, write that static networks predict “the missing links from a partially observed network topology (and maybe some attributes as well); while for dynamic networks, it is typically defined as predicting network structure at the next time $t+1$ given the structures up to the current time t .” As this description makes clear, the future and the past in these models are structurally the same: the value of a dynamic model at $t+1$ is determined using the same methods as a missing past value.
60. Jannach et al., *Recommender Systems*, 234–252.
61. Jannach et al., *Recommender Systems*, 16–17.
62. Lewis, *Alternative Influence*.
63. In a related vein, Dandakar, Goel, and Lee have produced models that show that biased assimilation is key to polarization—homophily by itself is not enough to produce polarization. Pranav Dandakar, Ashish Goel and David T. Lee, “Biased Assimilation, Homophily, and the Dynamics of Polarization,” *Proceedings of the National Academy of Sciences* 110, no. 15 (2013): 5791–5796, <https://doi.org/10.1073/pnas.1217220110>. See also Lazarsfeld and Katz, *Personal Influence* on polarization.
64. Robert Bell and Yehuda Koren, “Lessons from the Netflix Prize Challenge,” *ACM SIGKDD Explorations Newsletter* 9, no. 2 (2007): 75, <https://doi.org/10.1145/1345448.1345465>.
65. Animashree Anandkumar et al., “Learning Topic Models and Latent Bayesian Networks Under Expansion Constraints,” arXiv.org, 2012, <https://arxiv.org/abs/1209.5350>, 1.
66. Alexis C. Madrigal, “How Netflix Reverse Engineered Hollywood+,” *Atlantic*, January 2, 2014, <https://www.theatlantic.com/technology/archive/2014/01/how-netflix-reverse-engineered-hollywood/282679/>.
67. Zhu and Chen, “Latent Feature Models,” 4.
68. Zoubin Ghahramani and Thomas L. Griffiths, “Infinite Latent Feature Models and the Indian Buffet Process,” *Proceedings from Advances in Neural Information Processing Systems* 18, 2005, 1, <http://mlg.eng.cam.ac.uk/zoubin/papers/ibp-nips05.pdf>.
69. As Jannach and colleagues note in *Recommender Systems*: “Learning-based methods quickly tend to propose *more of the same*—that is, such recommenders can propose only items that are somehow similar to the ones the current user has

already (positively) rated. This can lead to the undesirable effect that *obvious* recommendations are made and the system, for instance, recommends items that are too similar to those the user already knows. A typical example is a news filtering recommender that proposes a newspaper article that covers the same story that the user has already seen in another context" (76; emphasis in original).

70. "Winning the Netflix Prize: A Summary," *Edwin Chen's Blog*, October 24, 2011, <http://blog.echen.me/2011/10/24/winning-the-netflix-prize-a-summary/>; Xavier Amatriain and Justin Basilico, "Netflix Recommendations: Beyond the 5 Stars (Part 1)," *Netflix Technology Blog*, April 6, 2012, <https://netflixtechblog.com/netflix-recommendations-beyond-the-5-stars-part-1-55838468f429>.
71. Blake Hallinan and Ted Striphas, "Recommended for You: The Netflix Prize and the Production of Algorithmic Culture," *New Media & Society* 18, no. 1 (2016): 127, <https://doi.org/10.1177/1461444814538646>.
72. Jannach et al., *Recommender Systems*, 23–24.
73. As discussed in chapter 1, Kosinski, Stillwell, and Graepel in "Private Traits and Attributes Are Predictable," have showed how easy it is to predict race, gender, and other private traits and attributes based on then publicly available Facebook likes.
74. Bernard J. Norton, "Karl Pearson and Statistics: The Social Origins of Scientific Innovation," *Social Studies of Science* 8, no. 1 (1978): 3, <https://doi.org/10.1177/030631277800800101>.
75. Pearson, *Life, Letters, and Labours of Francis Galton*, 3a:56–57.
76. "The statistician," Pearson observed, "does not think a certain x will produce a single-valued y; not a causative relation but a correlation. The relationship between x and y will be somewhere within a zone and we have to work out the probability that the point (x,y) will lie in different parts of that zone. . . . A very wide science" (as quoted in Norton, "Karl Pearson and Statistics," 10).
77. Stephens-Davidowitz, *Everybody Lies*; Barabási, *Bursts*.
78. Jannach et al., *Recommender Systems*, 211.
79. Jannach et al., *Recommender Systems*, 211.
80. Jannach and colleagues offer the following psychological features as key to the operation of recommender systems, in *Recommender Systems*, 245–252: locus of control; need for closure; maximizer and satisfier; and conformity.
81. Jannach et al., *Recommender Systems*, 214–215.
82. Jannach et al., *Recommender Systems*, 216.
83. Jannach et al., *Recommender Systems*, 215.
84. Jannach et al., *Recommender Systems*, 217.
85. Shyong K. Lam and John Riedl, "Shilling Recommender Systems for Fun and Profit," *WWW '04: Proceedings of the 13th Conference on World Wide Web*, May 2004: 393–402, <https://doi.org/10.1145/988672.988726>.
86. In his analysis of firms in *Authenticity and the Cultural Politics of Work*, Peter Fleming contends that "'the commons' is the true source of creativity. . . . Authenticity discourse is a way to coopt the commons" (10–12).

87. Daniel Fleder and Kartik Hosanagar, "Blockbuster Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity," *Management Science*, 2009, 697.
88. Kulesza and Taylor, "Determinal Point Processes."
89. Bianca Bosker, "Eric Schmidt On Privacy (VIDEO): Google CEO Says Anonymity Online Is 'Dangerous'" (Huffington Post, 2010), https://www.huffpost.com/entry/eric-schmidt-privacy-stan_n_677224; Bianca Bosker, "Facebook's Randi Zuckerberg: Anonymity Online 'Has To Go Away'" (online: Huffington Post, 2011), https://www.huffpost.com/entry/randi-zuckerberg-anonymity-online_n_910892.
90. Helen Nissenbaum, "Securing Trust Online: Wisdom or Oxymoron," *Boston University Law Review* 81, no. 3 (2001): 655.
91. Nissenbaum, "Securing Trust Online," 662, 656.
92. Erving Goffman, *The Presentation of Self in Everyday Life*, (Garden City: Doubleday, 1959).
93. Goffman, *The Presentation of Self*, 252 (emphasis in original).
94. Goffman, *The Presentation of Self*, 253.
95. Goffman's emphasis on this dual nature is similarly reflected in theater and performance studies, which has defined authenticity in terms of both dramatic character and performer.
96. Oscar Wilde, "The Critic as Artist," in *Intentions: Oscar Wilde* (Boston: Brainard, 1909), 203.
97. Paige Sylvia Raibmon, *Authentic Indians: Episodes of Encounter from the Late-Nineteenth-Century Northwest Coast* (Durham, NC: Duke University Press, 2005), 13.
98. Kosinski, Stillwell, and Graepel, "Private Traits and Attributes Are Predictable," supplemental materials.

CORRELATING IDEOLOGY

1. Alex Jones, as quoted in Bruce Y. Lee, "How Alex Jones May Be Blaming Psychosis for Conspiracy Claims," *Forbes*, March 30, 2019, <https://www.forbes.com/sites/brucelee/2019/03/30/how-alex-jones-may-be-blaming-psychosis-for-conspiracy-claims>.
2. See *Oxford English Dictionary*, 3rd ed. (2000), s.v. "manifest, v."
3. Merton, *On Theoretical Sociology*, 117.
4. Merton, *On Theoretical Sociology*, 118–119, 123, 128.
5. Merton, *On Theoretical Sociology*, 120.
6. As long as sociologists simply studied manifest functions, Merton explained, "their inquiry is set for them by practical men of affairs (whether a captain of industry, a trade union leader, or conceivably, a Navaho chieftain, is for the moment immaterial), rather than by the theoretic problems at the core of the discipline. . . .

But armed with the concept of latent function, the sociologist extends his inquiry to those very directions which promise most for the theoretic development of the discipline. He examines the familiar (or planned) social practice to ascertain the latent, and hence generally unrecognized, functions (as well, of course, as the manifest functions). He considers, for example, the consequences of the new wage plan for, say, the trade union in which the workers are organized for the consequences of a propaganda program, not only for increasing its avowed purpose of stirring up patriotic fervor, but also for making large numbers of people reluctant to speak their minds when they differ with official policies" (*On Theoretical Sociology*, 119–120).

7. Merton, *On Theoretical Sociology*, 135 (emphasis in original).
8. Merton, *On Theoretical Sociology*, 115.
9. Sigmund Freud, *The Standard Edition of the Complete Psychological Works of Sigmund Freud*, vol. 4 (1900), *The Interpretation of Dreams*, part 1 (London: Hogarth Press, 1953), 160 (emphasis in original).
10. Freud, *Interpretation of Dreams*, part 1, 277.
11. Freud, *Interpretation of Dreams*, part 1, 282.
12. Goethe as quoted by Freud, *Interpretation of Dreams*, part 1, 283.
13. Freud, *Interpretation of Dreams*, part 1, 111.
14. Freud, *Interpretation of Dreams*, part 1, 305.
15. Sigmund Freud, *The Standard Edition of the Complete Psychological Works of Sigmund Freud*, vol. 5 (1900–1901), *The Interpretation of Dreams*, part 2 (London: Hogarth Press, 1953), 516.
16. Jacques Lacan, *Écrits*, trans. Bruce Fink (New York: Norton, 2006), 418–419.
17. Lacan, *Écrits*, 419 (emphasis in original).
18. Lacan, *Écrits*, 421.
19. Lacan, *Écrits*, 422.
20. As chapter 4 explains, sexual selection would be a “latent” function—a function to explain irrational behavior and trends (from the perspective of natural selection), such as the plumage of peacocks, the buying of Cadillacs, and the selection of sexually sterile women.
21. Louis Althusser, “Appendix 2: Ideology and Ideological State Apparatuses,” in *On the Reproduction of Capitalism: Ideology and Ideological State Apparatuses* trans. Ben Brewster (London: Verso, 2014), 259.
22. See Lacan, “The Mirror Stage as Formative of the *I* Function as Revealed in Psychoanalytic Experience,” in *Écrits*, 75–81.
23. Althusser, “Ideology and Ideological State Apparatuses,” 236.
24. Althusser, “Ideology and Ideological State Apparatuses,” 260.
25. Althusser, “Ideology and Ideological State Apparatuses,” 264 (emphasis in original).

26. For more on software as offering an imaginary relation to hardware, see Chun, *Control and Freedom*, 20–23.
27. Richard Dienst, *Still Life in Real Time: Theory after Television* (Durham: Duke University Press, 1994), 141–142 (emphasis in original).
28. For more on software mimicking ideology, see Chun, *Programmed Visions and Updating to Remain the Same*.
29. Slavoj Žižek, introduction: “The Spectre of Ideology,” in *Mapping Ideology*, ed. Slavoj Žižek (London: Verso Books, 1994), 6 (emphasis in original).
30. Žižek, “The Spectre of Ideology,” 1.
31. Dick Hebdige, *Subculture: The Meaning of Style* (London: Routledge, 2012), 116 (emphasis in original).
32. Žižek, “The Spectre of Ideology,” 8.
33. Žižek, “The Spectre of Ideology,” 17 (emphasis in original).
34. Žižek, “The Spectre of Ideology,” 4.
35. Žižek, “The Spectre of Ideology,” 21 (emphasis in original).
36. Žižek, “The Spectre of Ideology,” 22.

CHAPTER 4

1. Kate Conger, Richard Fausset, and Serge F. Kovaleski, “San Francisco Bans Facial Recognition Technology,” *New York Times*, May 14, 2019, <https://www.nytimes.com/2019/05/14/us/facial-recognition-ban-san-francisco.html>.
2. Xiaolin Wu and Xi Zhang, “Automated Inference on Criminality Using Face Images,” arXiv.org, November 12, 2016, arXiv no. 1611.04135v.1, <https://arxiv.org/pdf/1611.04135v1.pdf>; Ben Sullivan, “A New Program Judges If You’re a Criminal from Your Facial Features: The Machine Learning Experiment Boasts Seemingly Incredible Accuracy, but Is Being Criticised for Human Biases and the Potential to Label Innocent People as Guilty,” Vice: Motherboard, November 18, 2016, https://www.vice.com/en_us/article/d7ykmw/new-program-decides-criminality-from-facial-features.
3. Yilun Wang and Michal Kosinski, “Deep Neural Networks Are More Accurate Than Humans at Detecting Sexual Orientation from Facial Images,” *Journal of Personality and Social Psychology* 114, no. 2 (2018): 246–57, <https://doi.org/10.1037/pspa0000098>.
4. Wang and Kosinski, “Deep Neural Networks Are More Accurate,” 246.
5. See *Oxford English Dictionary*, 3rd ed. (2009), s.v. “recognize, v.1” and s.v. “recognition, n.” “Recognition” in English was initially “a form of inquiry or inquest by jury”: it entailed reinvestigating and judging the results of an inquiry as true.
6. Heather Murphy, “Why Stanford Researchers Tried to Create a ‘Gaydar’ Machine,” *The New York Times*, October 9, 2017, <https://www.nytimes.com/2017/10/09/science/stanford-sexual-orientation-study.html>.

7. Wang and Kosinski, "Deep Neural Networks Are More Accurate," 256.
8. Wang and Kosinski, "Deep Neural Networks Are More Accurate," 255–256.
9. See Wendy Brown, *Regulating Aversion: Tolerance in the Age of Identity and Empire* (Princeton: Princeton University Press, 2006), on tolerance as depoliticization.
10. Jasbir K. Puar, *Terrorist Assemblages: Homonationalism in Queer Times* (Durham: Duke University Press, 2007).
11. Wang and Kosinski, "Deep Neural Networks Are More Accurate," 249. The image used by Wang and Kosinski is presumably one taken from Face++ instructional or promotional materials.
12. Joy Buolamwini and Timnit Gebru, "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification," *Proceedings of Machine Learning Research* 8 (2018): 15.
13. GARD, *Congenital Adrenal Hyperplasia* (Gaithersburg, MD: NIH, Genetic and Rare Diseases Information Center, 2020), <https://rarediseases.info.nih.gov/diseases/1467/congenital-adrenal-hyperplasia>.
14. J. Michael Bailey et al., "Sexual Orientation, Controversy, and Science," *Psychological Science in the Public Interest* 17, no. 2 (2016): 70, <https://doi.org/10.1177/1529100616637616>. Amy Banks and Nanette K. Gartrell, "Hormones and Sexual Orientation: A Questionable Link," *Journal of Homosexuality* 28, nos. 3–4 (1995): 247–268, https://doi.org/10.1300/J082v28n03_04.
15. To be clear, this is not to dismiss all biological accounts of sexual orientation, but rather to point out the difficulties of applying the prenatal hormonal theory—and the extrapolations made by the authors who attempt to do so. As Eve Sedgwick has noted in "How to Bring Up Your Kids Gay: The War on Effeminate Boys," in *Tendencies* (Durham, NC: Duke University Press, 1993), increasingly, biology—rather than culture—has offered more flexible understandings of sexual orientation (164–165).
16. Hebdige, *Subculture*, 2–3.
17. "The generic images that arise before the mind's eye," Galton wrote, "and the general impressions, which are faint and faulty editions of them, are the analogues of these composite pictures which we have the advantage of examining at leisure, and whose peculiarities and character we can investigate, and from which we may draw conclusions that shall throw much light on the nature of certain mental processes which are too mobile and evanescent to be directly dealt with." Francis Galton, "Generic Images," *Royal Institution of Great Britain, Notices of the Proceedings at the Meetings of the Members*, 9 (1879–1881): 166.
18. Allan Sekula, "The Body and the Archive," *October* 39 (1986): 47.
19. Galton, "Generic Images," 166.
20. Sekula, "The Body and the Archive," 51.
21. Sekula, "The Body and the Archive," 10–12, 16.
22. Sekula, "The Body and the Archive," 10.
23. Sekula, "The Body and the Archive," 17.

24. Sekula, "The Body and the Archive," 55.
25. Sekula, "The Body and the Archive," 33–34.
26. Corinna Cortes and Vladimir Vapnik, "Support-Vector Networks," *Machine Learning* 20, no. 3 (1995): 273, <https://doi.org/10.1007/BF00994018>; R. A. Fisher, "The Use of Multiple Measurements in Taxonomic Problems," *Annals of Eugenics* 7, no. 2 (1936): 179–188, <https://doi.org/10.1111/j.1469-1809.1936.tb02137.x>.
27. Fisher, "The Use of Multiple Measurements," 179. Writing in 1992, three years in advance of Cortes and Vapnik, Geoffrey J. McLachlan, in *Discriminant Analysis and Statistical Pattern Recognition* (New York: Wiley, 1992), highlighted that statistical discrimination includes "problems associated with the statistical separation between distinct classes or groups and with the allocation of entities to groups (finite in number), where the existence of the groups is known a priori and where typically there are feature data on entities of known origin available from the underlying groups. It thus includes a wide range of problems in statistical pattern recognition, where a pattern is considered as a single entity and is represented by a finite dimensional vector of features of the pattern" (xiii).
28. Fisher, "The Use of Multiple Measurements," 179.
29. M. M. Barnard, "The Secular Variations of Skull Characters in Four Series of Egyptian Skulls," *Annals of Eugenics* 6, no. 4 (1935): 352–71, <https://doi.org/10.1111/j.1469-1809.1935.tb02117.x>.
30. R. A. Fisher, "'The Coefficient of Racial Likeness' and the Future of Craniometry," *Journal of the Royal Anthropological Institute of Great Britain and Ireland* 66 (1936): 57–63; R. A. Fisher, "The Statistical Utilizations of Multiple Measurements," *Annals of Eugenics* 8, no. 4 (1938): 379. P. C. Mahalanobis, "Analysis of Race-Mixture in Bengal," *Journal of the Asiatic Society of Bengal* 23, no. 3 (1927): 301–333. Based on this 1927 published text, which looked at Anglo-Indian and other "mixed" skulls, Mahalanobis concluded that racial mixing had a long history in India, but it occurred mainly horizontally among similarly ranked castes.
31. Fisher, "'The Coefficient of Racial Likeness,'" 63.
32. Fisher, *The Genetical Theory of Natural Selection*, 124. Obsessed with sex and death, psychoanalysis and evolutionary theory are kissing cousins.
33. Fisher, *The Genetical Theory of Natural Selection*, 124.
34. To make this argument in *The Genetical Theory of Natural Selection*, Fisher first sought to prove—by correlating fertility rates among Australian mothers and daughters—that female fertility was heritable (198). Then, comparing analyses of birthrates by class in 1851 and 1901, he argued: "Both epochs show the same general relationships between undesirable social conditions and a high birth-rate; the intensity of this relationship, however, has almost doubled in the interval from 1851 to 1901" (213). Fisher attributed this rise in the birthrate to the fact that "undesirables" were selecting for fertility, while the "desirables" were not.
35. Fisher, *The Genetical Theory of Natural Selection*, 231.
36. Fisher, *The Genetical Theory of Natural Selection*, 222.

37. Joan Fisher Box, *R. A. Fisher, the Life of a Scientist* (New York: Wiley, 1978), 47.
18. In *The Genetical Theory of Natural Selection*, Fisher writes, "This selection of the popular emotional response to the heroic qualities has the important effects of (a) stabilizing the foundations of the system by strengthening the existing basis of social cohesion, (b) intensifying the selective advantage ascribable to fame or prestige, (c) increasing the selective advantage of all qualities consciously envisaged in sexual selection, (d) exaggerating the realities of natural inequality by the development of an extreme aristocratic doctrine of hereditary nobility. It is important to notice that such practices as polygamy or servile concubinage are not in any sense primary principles of the system of causes described, but may be grafted into the system in so far as they harmonize with the prestige of the hero, or the fertility of his class. Such practices necessarily decay or are transformed to fulfil a secondary social purpose, such as domestic service, as soon as the main conditions of the system are undermined" (249–250).
38. This barbarian society, Fisher tells us in *The Genetical Theory of Natural Selection*, "exemplified by the primitive peoples of Northern Europe, as represented in the Icelandic Sagas, in Tacitus's description of the Germans, and probably in the Homeric poems, by the pre-Islamic Bedouin of the Arabian desert, by many, if not all, of the Turkish and Tartar peoples of the Central Asiatic steppes, and by the Polynesians of New Zealand and Samoa, is characterized by a tribal organization, influenced, or indeed dominated, by the blood feud" (243).
39. Fisher, *The Genetical Theory of Natural Selection*, 248.
40. Ronald A. Fisher, as quoted in Box, *R. A. Fisher*, 41.
41. K. S. Lashley, "Visual Discrimination of Size and Form in the Albino Rat," *Journal of Animal Behavior* 2, no. 5 (1912): 310–31, <https://doi.org/10.1037/h0071033>; K. S. Lashley, "The Mechanism of Vision: XV. Preliminary Studies of the Rat's Capacity for Detail Vision," *Journal of General Psychology* 18, no. 1 (1938): 123–93, <https://doi.org/10.1080/00221309.1938.9709894>.
42. Lashley, "The Mechanism of Vision: XV," 123.
43. Lashley, "Visual Discrimination of Size and Form," 316.
44. Lashley, "Visual Discrimination of Size and Form," 320.
45. Lashley, "Visual Discrimination of Size and Form," 313–314.
46. Lashley, "Visual Discrimination of Size and Form," 330.
47. Lashley, "Visual Discrimination of Size and Form," 329.
48. Lashley, "Visual Discrimination of Size and Form," 328.
49. Lashley, "Visual Discrimination of Size and Form," 330.
50. Lashley, "The Mechanism of Vision: XV," 131.
51. Lashley, "The Mechanism of Vision: XV," 130.
52. Lashley, "The Mechanism of Vision: XV," 163.
53. A. H. Riesen, "Vision," *Annual Review of Psychology* 5, no. 1 (1954): 71.

54. Norbert Wiener, *The Human Use of Human Beings: Cybernetics and Society* (London: Free Association Books, 1989), 95–96.
55. Oliver G. Selfridge and Ulric Neisser, “Pattern Recognition by Machine,” *Scientific American*, August 1960, 60, <https://doi.org/10.1038/scientificamerican0860-60>.
56. Selfridge and Neisser, “Pattern Recognition by Machine,” 60.
57. Kenneth M. Sayre, “Human and Mechanical Recognition,” *Methodos* 14, no. 54 (1962): 28, 30.
58. Sayre, “Human and Mechanical Recognition,” 36.
59. Sayre, “Human and Mechanical Recognition,” 32.
60. Geoff Dougherty, *Pattern Recognition and Classification: An Introduction* (New York: Springer New York, 2013), 3, 11–12. For more on the impact of classification, see Kate Crawford *Atlas of AI*.
61. Dougherty, *Pattern Recognition and Classification*, 4.
62. Axel Honneth, “From Desire to Recognition: Hegel’s Account of Human Sociality,” in *Hegel’s Phenomenology of Spirit: A Critical Guide*, ed. Dean Moyar and Michael Quante, Cambridge Critical Guides (Cambridge: Cambridge University Press, 2008), 76.
63. George Wilhelm Friedrich Hegel, *The Phenomenology of Spirit*, ed. and trans. Terry Pinkard (Cambridge: Cambridge University Press, 2018), 108 (emphasis in original).
64. Alexandre Kojève, *Introduction to the Reading of Hegel* (Ithaca: Cornell University Press, 1980), 37.
65. Honneth, “From Desire to Recognition,” 85–86.
66. To be human, Kojève tells us in *Introduction to the Reading of Hegel*, “man must act not for the sake of subjugating a *thing*, but for the sake of subjugating another *Desire* (for the thing). The man who desires a thing humanly acts not so much to possess the *thing* as to make another *recognize* his right . . . to that thing, to make another recognize him as the *owner* of the thing, and he does this—in the final analysis—in order to make the other recognize his *superiority* over the other” (40; emphasis in original).
67. Hegel, *Phenomenology of Spirit*, 112–113 (emphasis in original).
68. Hegel, *Phenomenology of Spirit*, 115 (emphasis in original).
69. Kojève, *Introduction to the Reading of Hegel*, 52 (emphasis in original).
70. Nancy Fraser and Axel Honneth, *Redistribution or Recognition? A Political-Philosophical Exchange*, trans. Joel Golb, James Ingram, and Christopher Wilke (London: Verso Books, 2003); Charles Taylor, “The Politics of Recognition,” in *Multiculturalism: Examining the Politics of Recognition*, ed. Amy Gutmann (Princeton: Princeton University Press, 1994), 25–74.
71. Nancy Fraser, “Social Justice in the Age of Identity Politics: Redistribution, Recognition, and Participation,” in Fraser and Honneth, *Redistribution or Recognition?*, 28.
72. Charles Taylor as quoted in Fraser, “Social Justice in the Age of Identity Politics,” 28.

73. Taylor, "The Politics of Recognition," 36.
74. Taylor, "The Politics of Recognition," 27.
75. Slavoj Žižek, "Multiculturalism, or, the Cultural Logic of Multinational Capitalism," *New Left Review*, no. 225 (1997): 28–51. Nancy Fraser diagnosed this split in terms of differing evaluations of difference: for proponents of redistribution, differences were unjust differentials; for those who advocated for a politics of recognition, differences were either benign or preexisting cultural differences that became discriminatory via unjust interpretative schema ("Social Justice in the Age of Identity Politics," 15).
76. Fraser, "Social Justice in the Age of Identity Politics," 64.
77. Fraser, "Social Justice in the Age of Identity Politics," 36.
78. Glen Sean Coulthard, *Red Skin, White Masks: Rejecting the Colonial Politics of Recognition* (Minneapolis: University of Minnesota Press, 2014), 36.
79. Coulthard, *Red Skin, White Masks*, 3 (emphasis in original).
80. Coulthard, *Red Skin, White Masks*, 16.
81. Further, both Coulthard and Fanon underline that recognition cannot alleviate inequality within a colonial situation, for all the master wants from the slave is the slave's work.
82. Florian Cramer, "Meme Wars: Internet Culture and the 'Alt Right,'" FACTLiverpool, YouTube, March 7, 2017, <https://youtu.be/OiNYuhLKzi8>.
83. "Authenticity," Rebecca Lewis writes in *Broadcasting the Reactionary Right*, "has become such an effective way of building influence that powerful media institutions, both progressive and conservative, have begun to take notice. Recently, it has become a key topic at conservative media conferences like RightOnline (also funded by the Koch brothers). The goal of the event is to teach a new generation of media makers how to build influence and spread conservatism. Attendees can find presentations and panels specifically on the topics of 'being authentic' and 'being likable,' as well as 'establishing a clear media persona and story about oneself.' In this way, the trappings of authenticity can be cultivated and exploited by institutional power, even as political influencers use them to promise freedom from that same power" (19).
84. Jane Feuer, "The Concept of Live Television: Ontology as Ideology," in *Regarding Television: Critical Approaches—an Anthology*, ed. E. Ann Kaplan, American Film Institute Monograph Series, vol. 2 (Frederick, MD.: University Publications of America, 1983), 12–22; Mimi White, "Crossing Wavelengths: The Diegetic and Referential Imaginary of American Commercial Television," *Cinema Journal* 25, no. 2 (1986): 51–64, <https://doi.org/10.2307/1225459>.
85. Candace Owens, "Mom, Dad . . . I'm a Conservative," YouTube, July 9, 2017, <https://www.youtube.com/watch?v=dgKc-2rFcRw>.
86. Lewis, *Alternative Influence*, 23.

87. José Esteban Muñoz, *Disidentifications: Queers of Color and the Performance of Politics* (Minneapolis: University of Minnesota Press, 1999), 11.
88. Muñoz, *Disidentifications*, x, xi–xii.
89. Erving Goffman, *Stigma: Notes on the Management of Spoiled Identity* (New York: Simon & Schuster, 1986), 2–3.
90. Goffman, *Stigma*, 138.
91. Goffman, *Stigma*, 100.
92. Goffman, *Stigma*, 113.
93. Goffman, *Stigma*, 101.
94. Goffman, *Stigma*, 129.
95. Natalie Wynn, “Incels | ContraPoints,” YouTube, August 17, 2018, <https://youtu.be/fD2briZ6fB0>. Wynn (ContraPoints) produces “contraversial” videos, which regularly receive more than a million views. She anchors a progressive group of “media stars,” who intervene into the “alternative influence network” described by Rebecca Lewis. Wynn has taken on topics such as fascism, Jordan Peterson (a popular figure on the reactionary right), gender transformation, and incels. About ContraPoints, “YouTube, n.d., <https://www.youtube.com/user/ContraPoints/about>.
96. Jim Taylor, “The Woman Who Founded the ‘Incel’ Movement,” *BBC News*, August 30, 2018, <https://www.bbc.com/news/world-us-canada-45284455>.
97. To make this point, she describes the nasty back-and-forth on the TTTT thread on 4chan, which is dominated by “dudes” considering transitioning, and her one-time obsession with it. On TTTT, users post selfies, knowing and expecting to be savaged. A user first mentioned Wynn on the thread as a “successful” model, which unleashed a torrent of negative comments about her skull size and other “manly” features. (Wynn, too, is obsessed with bone structure.) Rather than flee the TTTT site, which clearly was damaging her psychologically, she would check it regularly because she felt it was “true.” It revealed the “political correctness” and lies of her supporters: humiliation felt true and liberating. But, unlike incels, Wynn did not blame feminists—or others—for her situation.
98. Robert K. Merton, “Intermarriage and the Social Structure: Fact and Theory,” *Psychiatry* 4, no. 3 (1941): 364.
99. As Wynn explains, taking the “red pill” means understanding that “for men, there are three possible outcomes. Either you’re an incel, doomed to a lifetime of excruciating loneliness and resentment, or you’re a normie, destined to wind up in a sexless marriage with an unfaithful wife, who will divorce you, win custody of the children, and run off with all your money. Or you could be an alpha—an independent promiscuous man who sleeps with a lot of women and forms attachments to none of them.”
100. Arendt, *The Origins of Totalitarianism*, 477.

101. Intriguingly, Wynn relays—and even sympathizes with—their frustration through her own “pre-trans” and “post-trans” experiences on the dating site Tinder. As a woman, she gets thousands of messages—many of which are creepy and obsessed with her “dick or no dick” status. As a man, however, she received no messages—no recognition at all. Wynn admits that she prefers “the firing line of dicks” to “radio silence.” In the world of “participatory” media, silence is punishment—there is no “participatory parity” on heterosexual dating sites. For more on silence as social media punishment, Taina Bucher, “Want to Be on the Top? Algorithmic Power and the Threat of Invisibility on Facebook,” *New Media & Society* 14, no. 7 (2012): 1164–1180.

102. The sadist, Gilles Deleuze explains in *Masochism* (New York: Zone Books, 1989), his comparative reading of the Marquis de Sade and Leopold Sacher-Masoch, “is interested in . . . demonstrat[ing] that reasoning itself is a form of violence, and that he is on the side of violence, however calm and logical he may be. He is not even attempting to prove anything to anyone, but to perform a demonstration related essentially to the solitude and omnipotence of its author . . . the point of the exercise is to show that the demonstration is identical to violence. It follows that the reasoning does not have to be shared by the person to whom it is addressed any more than pleasure is meant to be shared by the object from which it is derived. The acts of violence inflicted on the victims are a mere reflection of a higher form of violence to which the demonstration testifies. Whether he is among his accomplices or among his victims, each libertine, while engaged in reasoning, is caught in the hermetic circle of his own solitude and uniqueness—even if the argumentation is the same for all the libertines. In every respect, as we shall see, the sadistic ‘instructor’ stands in contrast to the masochistic ‘educator’” (18–19).

103. Florian Cramer, “Meme wars: Internet culture and the ‘alt-right.’”

104. Hebdige, *Subculture*, 112.

105. Hebdige, *Subculture*, 132.

106. Hebdige, *Subculture*, 124.

107. Hebdige, *Subculture*, 132.

108. Hebdige, *Subculture*, 68.

109. Hebdige, *Subculture*, 37.

110. Hebdige, *Subculture*, 53–4.

111. Hebdige, *Subculture*, 54.

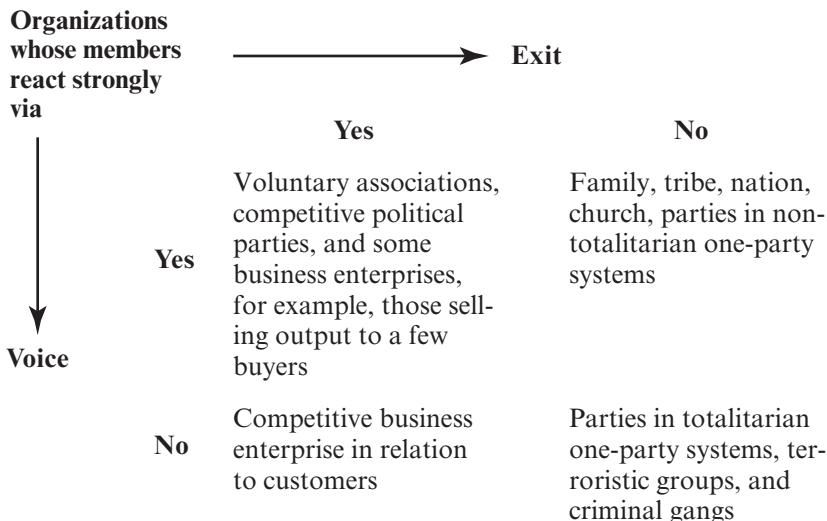
112. Hebdige, *Subculture*, 66.

113. Young, “Becked Up,” 95.

114. Albert O. Hirschman, *Exit, Voice, and Loyalty: Responses to Decline in Firms, Organizations, and States* (Cambridge, MA: Harvard University Press, 1970).

115. Hirschman, *Exit, Voice, and Loyalty*, 16.

116. To understand when and how loyalty works, Hirschman produced the following table:



"Exit vs. Voice," redrawn from Albert O. Hirschman, *Exit, Voice, and Loyalty: Responses to Decline in Firms, Organizations, and States* (Cambridge, MA: Harvard University Press, 1970), 121.

Voluntary associations, which Robert Merton viewed as key to measuring tenant morale, encouraged both "exit" and "voice." Family, tribe, nation, and church, organizations whose members could not easily leave, often used "voice" to appease those who were disgruntled. U.S. citizens found it impossible to consider exit—emigration—because they could not contemplate exit "from the 'best' country" (Hirschman, *Exit, Voice, and Loyalty*, 114). Loyalty thus transformed necessity into virtue. Hirschman also argued that public goods were things from which someone could not exit. Responding to Milton Friedman's call for educational vouchers, Hirschman argued that, even when parents chose to send their children to private school, their lives and those of their children would still "be affected by the quality of public education." More simply, Hirschman argued that a citizen could stop being a producer, but not a consumer, of public goods (*Exit, Voice, and Loyalty*, 102).

117. Hirschman, *Exit, Voice, and Loyalty*, 98.

118. Hirschman, *Exit, Voice, and Loyalty*, 108–109.

119. Hirschman, *Exit, Voice, and Loyalty*, 109.

120. Hirschman, *Exit, Voice, and Loyalty*, 111–112.

121. *Oxford English Dictionary*, 3rd ed. (2009), s.v. "recognize, v.1."

122. *Oxford English Dictionary*, 3rd ed. (2010), s.v. "identification, n." (emphasis in original) Diana Fuss, *Identification Papers: Readings on Psychoanalysis, Sexuality, and Culture* (New York: Routledge, 1995), 2.

123. Fuss, *Identification Papers*, 1.

THE SPACE BETWEEN US

1. Slavoj Žižek, *Pandemic! Covid-19 Shakes the World* (New York: Polity Press, 2020); Jillian Ambrose, "Oil Prices Dip below Zero as Producers Forced to Pay to Dispose of Excess," *Guardian*, April 20, 2020, <https://www.theguardian.com/world/2020/apr/20/oil-prices-sink-to-20-year-low-as-un-sounds-alarm-on-to-covid-19-relief-fund>; Associated Press, "China's Economy in Worst Downturn Since '70s amid Coronavirus Battle," CBC, April 17, 2020, <https://www.cbc.ca/news/business/china-economy-coronavirus-1.5535584>; Paris Martineau, "What's a 'Shelter in Place' Order, and Who's Affected?," *Wired*, March 20, 2020, <https://www.wired.com/story/whats-shelter-place-order-whos-affected/>; Josh K. Elliott, "'A Symbol of Hatred': Shopper Spotted in KKK Hood under Coronavirus Mask Rule in California..," *Global News*, May 4, 2020, <https://globalnews.ca/news/6902152/coronavirus-ku-klux-klan-mask/>.
2. Alexis Bennett and Kim Duong, "3 Work-From-Home Essentials That'll Make You Feel Like a Major Boss," *Cosmopolitan*, December 10, 2020, <https://www.cosmopolitan.com/style-beauty/fashion/g31677927/work-from-home-essentials/>; CDC, "Health Equity Considerations and Racial and Ethnic Minority Groups," Centers for Disease Control and Prevention, April 30, 2020, updated February 12, 2021, <https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/race-ethnicity.html>; Lucy Martirosyan, "French Dentists Strip Naked to Protest Lack of Protective Gear," The World, NPR, April 29, 2020, <https://www.pri.org/stories/2020-04-29/french-dentists-strip-naked-protest-lack-protective-gear>; Associated Press, "Pro-Trump Protesters Rally against Governors over Stay-at-Home Orders," CBC, April 17, 2020, <https://www.cbc.ca/news/world/us-trump-supporters-coronavirus-1.5535585>.
3. Vincent Rancaniello et al., "TWiV 585: The Coronavirus Epidemic," *This Week in Virology*, TWiV, February 2, 2020, <https://www.microbe.tv/twiv/twiv-585/>.
4. Yeming Wang et al., "Remdesivir in Adults with Severe Covid-19: A Randomised, Double-Blind, Placebo-Controlled, Multicentre Trial," *Lancet* 395, no. 10236 (2020): 1569–1578, [https://doi.org/10.1016/S0140-6736\(20\)31022-9](https://doi.org/10.1016/S0140-6736(20)31022-9).
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