ANNUAL REVIEWS

Annual Review of Sociology

The Society of Algorithms

Jenna Burrell and Marion Fourcade

School of Information and Department of Sociology, University of California, Berkeley, California 94720, USA; email: jburrell@berkeley.edu, fourcade@berkeley.edu

Annu. Rev. Sociol. 2021. 47:213–37

First published as a Review in Advance on May 27, 2021

The *Annual Review of Sociology* is online at soc.annualreviews.org

https://doi.org/10.1146/annurev-soc-090820-020800

Keywords

algorithms, artificial intelligence, automation, social class, inequality

Abstract

The pairing of massive data sets with processes—or algorithms—written in computer code to sort through, organize, extract, or mine them has made inroads in almost every major social institution. This article proposes a reading of the scholarly literature concerned with the social implications of this transformation. First, we discuss the rise of a new occupational class, which we call the coding elite. This group has consolidated power through their technical control over the digital means of production and by extracting labor from a newly marginalized or unpaid workforce, the cybertariat. Second, we show that the implementation of techniques of mathematical optimization across domains as varied as education, medicine, credit and finance, and criminal justice has intensified the dominance of actuarial logics of decision-making, potentially transforming pathways to social reproduction and mobility but also generating a pushback by those so governed. Third, we explore how the same pervasive algorithmic intermediation in digital communication is transforming the way people interact, associate, and think. We conclude by cautioning against the wildest promises of artificial intelligence but acknowledging the increasingly tight coupling between algorithmic processes, social structures, and subjectivities.

> The algorithm has taken on a particularly mythical role in our technology-obsessed era, one that has allowed it wear the garb of divinity. Concepts like "algorithm" have become sloppy shorthands, slang terms for the act of mistaking multipart complex systems for simple, singular ones.
>
> —Ian Bogost (2015)

THE HACKER ETHIC AND THE SPIRIT OF SILICON VALLEY

In the 1940s, the rolling hills of the Santa Clara Valley, between San Jose and San Francisco, were best known for their prune orchards and open grazing fields. In spite of being an early pioneer in electronics, Stanford University—"the sentimental folly of a nineteenth century robber baron and his wife"—was still called "the farm" (O'Mara 2019, p. 29). Its radical transformation from pastoral ivory tower to global economic powerhouse originates in a campaign of vast government investment at the beginning of the Cold War. Riding the lofty language of science as "the endless frontier" (Bush 1945), hard cash from the Department of Defense started pouring into universities, eventually reaching the West Coast.

The marriage with government, however, was not an easy one. The Vietnam War and the rise of the 1960s counterculture made military sponsorship (and the militarization of technological innovations) increasingly objectionable to the rising class of engineers and computer scientists that populated the area. Eager to proclaim their autonomy, they professed their belief in the free circulation of information, in the political superiority of community, and in an ethos of gift-giving and reciprocity (Barbrook 1998, Fourcade & Kluttz 2020, Rheingold 1993, Turner 2006). As one technological revolution after another rolled in (semiconductors, personal computers, the Internet, biotechnology, social media, etc.), the myth of a timeless Silicon Valley culture began to crystallize. In Palo Alto, major firms were born in garages and basements. No one wore a tie. Executives were college dropouts. Corporate hierarchies were flat. The engineers celebrated these values—and themselves—through spectacular cultural forms, such as Burning Man (Chen 2009, Turner 2009). But their irreverent ethics and associated anarcho-libertarian politics fulfilled an ideological function, too, helping erase the history of federal government involvement and propelling the myth that the business successes of the sector's pioneers were entirely their own (Barbrook & Cameron 1996). Despite talk about community and reciprocal exchange, tech leaders and the rank and file alike maintained fervent beliefs in individualism, competition, and survival of the fittest.

The bursting of the dot-com bubble in March 2000 initiated a critical transition. Silicon Valley was at a crossroads. Firms associated with the Internet—then a relatively new invention—struggled to demonstrate long-term profitability. Start-ups that managed to survive the economic bust, such as Google, were still offering their services for free, with no obvious strategy of monetization. This changed with the incidental discovery of what Zuboff (2019) calls the "behavioral surplus"—logged digital traces that people leave behind as they wander around and inhabit the web. Suddenly, unprofitable lines of business in search, chat, social interaction, and the like could be repurposed toward exploitation by advertisers—and they were. Companies started pairing the incidental data exhaust they were generating with new algorithmic techniques of machine learning to predict human behavior. Ad-supported platforms, often open and nominally free, began to displace the old model of expensive boxed software. Now anyone, it seemed, could make an app, and anyone could afford to use it. Independent developers could reap huge profits, and some did.

The flip side of this democratization of access and development was the intensification of user surveillance and manipulation. Caginess about user privacy or consumer welfare now stood in the way of the business. Generating revenue increasingly turned on trickery. To capture the attention of users, developers employed addictive techniques pioneered in the gambling industry (Hwang 2020, Schüll 2012, Vaidhyanathan 2018). Belying their own exalted celebration of openness, freedom, and social connection, firms were now focused on generating ever more data from more people and artfully manipulating them to secure desired outcomes: a scroll; a click; or better, a purchase. What made the development of this "instrumentarian power" (Zuboff 2019, p. 8) possible was the cooptation of existing law to serve the needs of informational capitalism (Cohen 2019, Kapczynski 2020, Pasquale 2015, Pistor 2019). First, tech firms defined the personal data that were produced through cookies and trackers as abundant and free for the taking. They harvested them through platform protocols and seemingly benign boilerplate contracts that framed the process as a mutually beneficial exchange.[1] Second, they jealously protected their data bounty through legal performances of ownership involving patents and arguments about trade secrecy. Once marked with all the "indicia of legal privilege" (Cohen 2019, p. 64), the data that supposedly lay within individuals or in the public commons were effectively appropriated and recoded as private capital or assets (Birch & Muniesa 2020, Pistor 2019, Sadowski 2020), as if in a modern process of enclosure or colonization (Couldry & Mejias 2019).

Out of these unprecedented ownership claims over the means of digital production, a new system of class relations could now arise. This article analyzes the social divisions associated with the ascendancy of the tech industry and the reorganization of social processes through algorithms[2] —sets of instructions written as code and run on computers. In the next section, The Rise of the Coding Elite and the Pre-Automation of Everyone Else, we argue that the core divide in digital capitalism opposes what we call the coding elite, who hold and control the data and software, and the cybertariat, who must produce, refine, and work the data that feed or train the algorithms, sometimes to the point of automating their own jobs and making themselves redundant. We also show that claims of technical and economic efficiency, as well as fairness, are an important component of the coding elite's societal power. Next, in the section titled Actuarialism and Its Discontents, we discuss the broader effects of the diffusion of algorithmic methods across a range of occupational jurisdictions, including retail, transportation, insurance, social work, medicine, banking, police, and the judicial system. We analyze the promise, but also the pitfalls, of the generalization of algorithmic tools across social institutions and consider its implications for social class-making and inequality. In the section titled Classifiers and Their Discontents, we show that algorithmic processes also structure how people come to know and associate with one another, and how technical mediations intersect with the perception and production of self and community. Finally, we ponder predictions about the likely future paths of this technological trajectory, positing two possible directions. One leads back to an embodied but now algorithmically augmented cyborg self. The other leads to a parallel disembodied society where our data selves interact with institutional minders, with consequences that are ambiguous and indirectly felt.

THE RISE OF THE CODING ELITE AND THE PRE-AUTOMATION OF EVERYONE ELSE

But let us not get ahead of ourselves and return, instead, to the significance of the rapid acceleration of the "world's technological capacity to store, communicate, and compute information" in the

[1] Cohen (2019, pp. 54–58) refers to this as the creation of the "biopolitical public domain": "The willingness to accept at least some kinds of cookies became an increasingly necessary precondition for transacting online and participating in online communities. . . . Consent to data extraction [was] sublimated into the coded environment" (also see Citron 2007, Nissenbaum 2009, Radin 2013).

[2] The concept of the algorithm originated in the ninth century. In principal, an algorithm is independent of the machine that executes its instructions. Today, algorithms are an essential component of all computer software. People increasingly experience and are affected by algorithms as more of our interactions with firms, institutions, and each other are mediated (directly or indirectly) by computers.

early 2000s (Hilbert & López 2011). The institutionalization of a "data imperative" (Fourcade & Healy 2017) across organizations of all types was game-changing, not only for the tech industry but for capitalism in general. Business magazines proclaimed that data were "the new oil." Now every small company and every public or nonprofit corporation could get into the action and try to mine their own. Anyone with the ability to code could set up a website, build an app, or write software with that purpose in mind. Any web page could be filled with trackers—and analytics was the way to monetize it all.

After the dot-com boom and bust, the phoenix of Silicon Valley rose from its own ashes. A new mode of production, powered by big data and analytics, was surging. The belief that they, too, were about to ride a unicorn kept hopeful computer scientists and engineers flowing into the Bay Area. Rising incomes sent property values soaring, emptying one neighborhood after another of its working-class life but leaving behind scores of homeless encampments (Herring 2014, Walker 2018). The politics of the place remained firmly Californian: progressive in principle, but "not in my backyard" in practice (Dougherty 2020, Eliasoph 1998). While Silicon Valley engineers joined fringe movements preoccupied with radical life extension and other transhumanist pursuits; eliminated time-wasting activities by eating meal substitutes (Thompson 2020); or, like their Gilded Age predecessors, set up ambitious new philanthropies (Giridharadas 2018), more and more people went hungry and slept in the streets of San Jose and San Francisco. The coronavirus disease 2019 (COVID-19) pandemic, far from precipitating the inevitable reckoning, may have instead further emboldened the claims of tech "solutionists" (Morozov 2013) and created new kinds of inequalities, around digital education for example.

The copresence of extreme urban wealth and poverty is the most visible feature of the new economy upon which the algorithmic society is built. In a classic (Marxist) manner, this distinction pits, at its most extreme, the owners of capital (primarily the venture capitalists, the company founders, and the tech employees, many of whom are also paid in stock) against those who toil for them (the service workers, subcontractors, and day laborers who bear the brunt—and none of the benefits—of rising costs of living). As of 2018, San Mateo County was the most unequal county in California, with the top 1% making 49.1 times more than the bottom 99% (Sommelier & Price 2018). The San Francisco Bay Area as a whole was home to one of the fastest growing income gaps in the country: Between 1980 and 2018, incomes for families in the 90th percentile increased by 60%, while incomes at the 50th percentile (median) and 10th percentile grew by 24% and 20%, respectively (Bohn & Thorman 2020). Black and Latinx people were also overrepresented at lower income levels and in lower rungs of the tech industry labor force. In 2016, 78% of employees at major tech firms were White or Asian. Only 30% were female (Tomaskovic-Devey & Han 2018). Other hubs of digital capitalism (like Seattle, home of Amazon and Microsoft) had similar profiles and experienced similar evolutions.

The Coding Elite: Power at Scale

Karl Marx famously saw relations of production, and the ideological formations they give rise to, as intimately linked to the development of technology. He stated the point clearly in a famous passage of *The Poverty of Philosophy*:

> Social relations are closely bound up with productive forces. In acquiring new productive forces men change their mode of production; and in changing their mode of production, in changing the way of earning their living, they change all their social relations. *The hand-mill gives you society with the feudal lord; the steam-mill, society with the industrial capitalist.* The same men who establish their social relations in conformity with the material productivity produce also principles, ideas, and categories in conformity with their social relations. (Marx 1920, p. 119, emphasis added)

Today's equivalent technology is the software system fueled by data and algorithmic ingenuity. It gives us the society with the software capitalist.

A new elite occupies the upper echelons of the digitized society—a class or proto-class that, in a self-conscious nod to Mills (2000), we call the coding elite. The coding elite is a nebula of software developers, tech CEOs, investors, and computer science and engineering professors, among others, often circulating effortlessly between these influential roles. At universities around the country, and even more at Stanford University, the wall between the academy and the tech industry is often thin (O'Mara 2019). Professors circulate between their own start-ups, key positions in large firms, government-sponsored research labs, and classrooms. Most valued in this world are those people who touch and understand computer code. Most powerful are those who own the code and can employ others to deploy it as they see fit.

Mastery of computational techniques bestows special kinds of powers. These powers are at once cultural, political, and economic. On the cultural side, the coding elite dwells in the trustworthy world of numbers (Espeland & Stevens 1998, Golumbia 2009, Porter 1996). Because their formalisms are mathematically provable, the techniques appear universal and removed from the messy world of human politics (Agre 1997, Forsythe & Hess 2001, Ribes et al. 2019). The coding elite advances computation as the key to unlocking breakthroughs in practically every discipline (Hofman et al. 2017), including sociology (Watts 2014); to transforming every domain of government action (Fourcade & Gordon 2020, O'Reilly 2010); and generally to solving most problems facing human society (Morozov 2013). But only the initiated can penetrate their cryptic language (Burrell 2016), craft solutions to thorny problems through it, and improve their social status in the process.

On the political side, the coding elite dwells in the powerful world of control. In a narrow sense, the interpretive work that computer scientists must perform in order to translate social norms and legal rules from human language into computer code inevitably introduces distortions and simplifications (Citron 2007). But in a broader sense, "code is law" (Lessig 2000). Code governs, which means two things. First, code makes the world legible (Scott 1999, Uliasz 2020). It speaks for people and objects by reconstructing them into machine-readable entities that can be acted upon (Amoore 2013, 2020; Cheney-Lippold 2017; Johns 2021). Second, code enforces. It admits and excludes, separates and allocates in much the same way that law does. But whereas the law as specified on paper must be enforced by a separate body (generally human and therefore able to exercise discretion), code both specifies the rules and (once compiled and run) automates them.

On the material side, the coding elite dwells in the profitable world of money. For venture capitalists, what is most compelling about the products of digital tech sector firms is how well they scale. For instance, Facebook to date has more than 2.6 billion users worldwide, all voluntarily producing the platform's core content. As Morozov (2015) puts it, "the more people on Facebook, the more valuable it becomes. . . . It's the same for search engines: the more people are using Google, the better it becomes, because every search is in some sense a tinkering and improvement in the service." The first advantage is known as network effects. The second is a direct consequence of the way machine learning works: It is fueled by automated feedback loops, devouring new data continuously and incrementally improving predictive accuracy (or at least claiming to do so) and thus market possibilities.

The long history of information technology is a more or less continuous drive to refine control—control over labor, control over the vagaries of materials and markets—that finds its roots in the industrial revolution (Beniger 1989, Braverman 1974). Burris (1989, 1993) argues that this immanent tendency has made the class of experts tasked with technical control more and more autonomous from their bureaucratic masters. This is especially true of computerized forms of control, which tend to favor a flattening of social hierarchies, a polarization of organizations between expert and nonexpert sectors, and a convergence between technical and managerial functions. As Burris (1989, p. 11) puts it, "demonstrated expertise and credential certification tend to replace rank authority as the basic source of legitimate power."

The coding elite offers the next iteration of this process. Their power resides almost wholly in their control of technique as opposed to the institutional processes of professionalization that once defined occupational jurisdiction (Eyal 2013). Notably dismissive of credentialing, the coding elite broadly embodies the idea that craft proves its value through concrete application. They gain power through "the sheer capacity to accomplish [a] task better and faster" (Eyal 2013, p. 869). When necessary, they also rely on the allure of "prophecy, spectacle and promise" (Pardo-Guerra 2019) embedded in technical demonstrations (Rosental 2013). In the words of Komisar (2000, p. 93; also Thrift 2000), "it's the romance, not the finance, that makes the business worth pursuing." A cultural circuit made of management gurus, specialized magazines, and tech evangelists (tasked with spreading belief in a particular technology and building a loyal following) further helps organize this myth-making and consolidate power into the hands of those able to implement and understand code and the institutions and individuals who fund them.

In its quest for market expansion, the tech industry increasingly carves away at and lays claim to tasks that once were protected as the proper domain of professional judgement in every occupation from business management, medicine, and the criminal justice system to national defense, education, and social welfare. Deeply entrenched jurisdictions and human institutions are nothing but transient compromises awaiting the automation of their most routine tasks and sometimes their entire work domain. And no profession, no matter how prestigious or how high the barriers to entry, is exempt from having its judgment subject to a second (algorithmic) opinion, if not wholly supplanted by it. Legitimacy has been displaced from the professional to the coder-king—and, increasingly, to the algorithm.

In their challenge to professional jurisdictions, the coding elite leverages arguments that draw on behavioral economics or social psychology, often relying on formal comparisons between human decision-makers and algorithmic tools, but in tests designed to favor the technical. Engineers call upon a burgeoning literature, some of it popularized by the trade press and mainstream media, showing that even professionals at the highest levels of prestige prove fallible on tests of objectivity or optimal decision-making (i.e., Ariely 2010, Kahneman 2013, Rachlinski & Wistrich 2017, Watts 2011, Volokh 2019). To these failures they oppose the indefatigable consistency of machines. Compared to physicians, "algorithms need no sleep, and their vigilance is the same at 2am as at 9am" (Obermeyer & Emanuel 2016, p. 1218). In their eyes, the very existence of mountainous quantities of data (in some cases specifically generated to train machine learning algorithms) renders human decision-makers inadequate (Obermeyer & Lee 2017); rather, people should use algorithms to reform their own conscious practices of reasoning (Christian & Griffiths 2016). The overarching ideology at work here is "the notion that human mentation is frail and flawed, leading to irrational choices that fail to adequately consider the wider structures of alternatives" (Zuboff 2019, p. 343). However, lurking beneath code's promise to tame the human tendency to be "unpredictable, recalcitrant, and otherwise irrational" (Andrejevic 2020, p. 2) are powerful economic incentives to better predict—or direct—behavior so people can produce more data or see more ads; provide for people's desires before they even register, so as to nudge them toward new purchases; or gain a foothold in perennially underfunded public agencies eager to speed up, streamline, and automate processes; replace customer service; or overcome work backlogs.

Cybertarians of the World, Disunited

The consolidation of power in the hands of the coding elite also comes into view through their distinctive methods of extracting labor from workers in both new and old jobs. If industrial capitalism concealed labor's existence through the fetishism of commodities, digital capitalism intentionally conceals it through the fetish of artificial intelligence (AI) and feigned automation. The smooth functioning of on-demand apps, search engines, mapping sites, social media websites, and even autonomous vehicles and many other products all depend on the collective intelligence of armies of humans performing ghost work (Gray & Suri 2019; also see Gillespie 2018, Roberts 2019). This is because most algorithmic systems cannot function adequately without content being carefully prepared for processing, without outcomes being checked and corrected for flaws, or without humans completing the so-called last-mile jobs. The work of matching drivers to ride requests on ridesharing apps, scoring web pages for quality, correcting digital maps, tagging and annotating videos, double-checking virtual assistants' responses, correcting biases, and moderating social media postings[3] all demands, to this day, a multitude of real humans in the loop. What stands beneath the fetish of AI is a global digital assembly line of silent, invisible men and women, often laboring in precarious conditions, many in postcolonies of the Global South. A new class of workers stands opposite the coding elite: the cybertariat.

The existence of this labor force yoked into the day-to-day operations of algorithmic systems is a liability for small start-ups and large firms alike. This is because their valuations and profit projections rest on the feasibility of automating as fully as possible any and all of the tasks performed by their systems. For instance, the ridesharing platform Uber invested massively in developing automated vehicles in recognition of the threat of labor regulation that might force them to pay drivers a more livable wage. Revealingly, however, the company pulled back from this plan shortly after California voters approved industry-sponsored Proposition 22, which classified app-based drivers as contractors rather than employees (who could have pressured the company for benefits and higher wages). Sometimes the enrollment of humans is viewed as a temporary fix, but as programmers struggle with the computational limits of what can be automated, the temporary may become permanent (Shestakofsky 2017). The platformization of work is on the rise in every sector and throughout the organizational hierarchy, allowing firms to shift uncertainty onto an externalized labor force. No one is invulnerable: Technology also penetrates and deskills management roles, such as taxi dispatch or shift scheduling (e.g., Brynjolfsson & McAfee 2014, Ford 2015).

It is important to understand that these reorganizations and innovations do not simply aim to digitize traditionally analog tasks or to outsource them to a cheaper and globally distributed workforce. Rather, they are also native and essential to the very operation of digital capitalism. Just as the production of industrial goods led to the making of the proletariat, so the production of digital goods (algorithms and AI) has created the "cybertariat" (Huws 2014) that performs "a continuum of unpaid, micropaid and poorly paid human tasks" (Casilli 2017, pp. 3934–35; see also Ettlinger 2016). However, differences with the industrial proletariat described by Marx and others are stark. The proletariat was physically copresent, densely packed in factories. Digital warehouses and click farms sometimes have these qualities, but increasingly less so. As crowdsourcing platforms take over, members of this digital precariat are more and more individualized and isolated from one another. In fact, their working conditions resemble more the old proto-industrial putting-out system, or piecework, by which laborers are supplied materials that they transform at home. For cybertarians, too, the lines between work and domesticity have blurred. The fragmentation of the digital workforce, its algocratic (rather than bureaucratic) management (Aneesh 2009), and the

[3]While user-generated content moderation has an automated element, armies of human moderators also verify content if flagged and expunge it if it violates the organization's policies or copyright law, among other tasks.

disaggregation of work projects into microtasks makes collective action and solidarity difficult (Irani & Silberman 2013, Gray & Suri 2019).

For Marx and Engels, what kept the proletariat miserable was the ever-present competition from other workers (the industrial reserve army) and that from technology itself. For the cybertariat, both threats have been fully endogenized. First, digital companies' investments in scaling up a workforce via a platform and disaggregating its work into myriads of microtasks are also designed to support that workforce's autonomous replacement, a process Vertesi and coauthors (2020) call "pre-automation" (see also Casilli & Posada 2019). In other words, platforms are simultaneously using their own precarious cyber workers both to perform the tasks that cannot be easily automated and to use the data they produce to automate them (Shestakofsky 2017). These workers labor on platforms and within systems promoted as artificially intelligent. Their contributions are intentionally obscured, and the hope of many who buy their services is that the need for such human computation can eventually be eliminated altogether (Gray & Suri 2019). Second, platforms also magnify the competition among workers, by allowing certain occupations (e.g., teachers, cultural performers) to scale up their reach dramatically, possibly minimizing manpower needs and allowing a winner-take-all logic to take hold. Third, platformized workforces, whether on- or offline, are typically managed algorithmically themselves, so as to be optimized in real time for market conditions, service quality, physical distance or compensation (Kellogg et al. 2020). The resulting precarity in the experience of work—in the form of uncertain jobs, irregular schedules, suffocating surveillance, constant high-stakes reviews, and unstable wages—(Dubal 2017, Duffy 2020, Gregg 2018, Kalleberg & Vallas 2018, Levy & Barocas 2018, Rosenblat 2019, Schor 2020) leads to a host of social pathologies, including negative health outcomes (Schneider & Harknett 2019). In addition, workers may experience algorithmic cruelty in the form of sudden reversals of fortune caused by changing algorithmic rules or the crossing of a perilous threshold (Gray & Suri 2019). Many gig workers or content providers, for example, experience being suddenly cut off from platforms that were their primary source of income for a dip in their rating or worked hours. Importantly, this forced flexibility of labor is also buttressed by the industry's firm opposition to labor regulations (such as California's Assembly Bill 5)[4] that propose to treat platform workers as employees rather than independent contractors.

Finally, the boundaries of the cybertariat do not stop at the cheap, platformized workforce. One of the distinguishing features of digital capitalism is its reliance on free labor. Much of the relevant work of classification and identification is in fact performed by unpaid platform users and microtaskers. As defined by Ekbia & Nardi (2017), this process of "heteromation" includes generating content, crowd-puzzling over problems, providing feedback, or just being tracked. Tesla drivers train the company's autonomous driving algorithms every time they drive, as do we all when completing a captcha "I am not a robot" test to enter a website. In that sense, nearly everyone belongs to the cybertariat. Historian Yuval Harari (2017, p. 276) writes that "if Marx came back to life today, he would probably urge his few remaining disciples to devote less time to reading *Das Kapital* and more time to studying the Internet and the human genome." A modern Marx would have remarked that in the twenty-first century, the real value, to capital, of a human being is located less and less in their labor power and physical body and increasingly in something much more intimate, perhaps closer to their species' being: the millions of bits of information about who they are, deep

[4]Ridesharing and app-based delivery companies poured more than $200 million into a successful campaign to convince voters to pass California Proposition 22, which created a specific exemption for their workers from Assembly Bill 5.

down, and how they relate to one another. He would have identified new forms of surplus value generation in the unpaid clickwork that billions of digital users do as they go about their online lives (Huws 2014, Zuboff 2019). And he would have wanted to specify the class antagonisms and associated ideological struggles that are specific to this mode of accumulation.

What about the possibilities for collective mobilization and solidarity? It may be more difficult for the cybertariat to resist the extraction of their labor by undertaking shop-floor organizing, as did the proletarians of the past. The material basis of their work situation precludes it. Resistance is actively underway nonetheless, for example, in online forums organized off-site. Coders allied to cyber workers' rights also play a role, creating tools to aid cybertarians in information sharing and self-organizing. The ingenious Turkopticon, for example, is a web browser plugin that overlays features on the Amazon Mechanical Turk platform, helping workers who do pay-per-task clickwork to avoid poor quality jobs, delayed payment, and outright wage theft (Irani & Silberman 2013). The companion Dynamo platform supports workers in collective organizing around these issues (Salehi et al. 2015). Finally, the foot-dragging and work-to-rule strategies of the past reemerge in the gaming of workplace algorithms (Kellogg et al. 2020). These and other forms of algoactivism work through, against, and outside of profit-making algorithmic systems.

Traditional forms of organizing are emerging as well, including labor union formation and efforts to realize worker protection legislation. The fair scheduling movement, to give one example, seeks to regulate and limit the use of shift allocation software that has exacerbated workers' precarity and reinstate control over their time outside of work. In Los Angeles, drivers for ridesharing companies have formed Rideshare Drivers United, which is now growing its membership in California and opening chapters in other parts of the United States. Finally, worker-owned platforms have emerged as an alternative to the predominant corporate platforms. Existing co-ops offer stock photo collections, bartering and babysitting swaps, and streaming music services (Scholz & Schneider 2016). This movement for platform cooperativism seeks to link together high-tech co-ops across occupations and industries into a consortium, or a kind of co-op of co-ops.

ACTUARIALISM AND ITS DISCONTENTS

The coding elite's expansive domain relevance claims have transformed organizational processes in another fundamental way: by advancing a logic of governance grounded in technical efficiency and mechanical objectivity (Porter 1996). To be sure, governance through numbers is not new and precedes the advent of computers by centuries. Algorithmic modes of thinking (for example, via decision tree–type structures) have long proliferated in the criminal justice system, finance and insurance, labor management, and education (Bouk 2015, Gandy 1993, Harcourt 2007, Lauer 2017). What is new is the use of behavioral trace data, including the things we do on devices and also things captured about us by devices in our environment, and the growing reliance on computing power to process these data.

The sheer abundance of data of many varied kinds has allowed certain classes of algorithms already in existence to become much more powerful. Additionally, a new class of algorithms (deep learning, an evolution of neural network models) exploits this abundance by drawing direct inferences from the data. While it is not quite apt to suggest that these algorithms program themselves, they do self-optimize in ways that outpace human understanding. Although these techniques have a long history going back to the 1950s, they really took off in the 1980s, when applications started being implemented in finance (MacKenzie 2018). Today's learning algorithms are embedded in social media feeds, in workplace surveillance systems, in smart cities, at ports and borders, and in modern warfare (e.g., Amoore 2013, Green 2019, Russell 2019, Suchman 2020). One important consequence is that many models commonly used to predict people's actions can now be dynamically updated as new data come in, allowing for continuous adjustments to be made through cybernetic feedback loops. These techniques have magnified the cultural power of what Golumbia (2009) calls computationalism, or the belief that computers can and must underwrite fundamental processes of social organization and resource allocation.

The previous section showed how the coding elite consolidate power by framing human reasoning as inadequate, even the expert decision-making of high-status professionals. In the coding elite's judgment, machine reasoning is not only faster and technically superior but also more equitable and fairer. The notion that a mechanistic, impersonal process is superior to one rooted in the discretion of individuals is also not an invention of the computer age. Over a century ago, Max Weber discussed the rise of the expert functionary who follows "calculable rules" and decides "without regard for persons" (Weber 1978, p. 975). Bureaucratic administration, he noted, has displaced administration by lords who could be "moved by personal sympathy and favor, by grace and gratitude." By contrast, anyone subject to a bureaucratic process receives the same impartial consideration. In fact, bureaucracy is more perfectly developed the more it is dehumanized. And it goes hand in hand with the capitalist market economy, which demands that the "official business of public administration be discharged precisely, unambiguously, continuously, and with as much speed as possible" (Weber 1978, p. 974).

The incorporation of historical data about social groups into the rule-driven processes of bureaucracy has allowed for more precise risk assessments about unknown individuals. This actuarialism was elevated to a noble purpose linked to progressive ideas about providing more equitable access to social institutions and improving the life chances of the excluded. In domains such as credit and insurance, for instance, inclusion often took the form of aggressive market expansion, driving the search for information on previously unseen populations. As customer pools grew and lending operations became more arms' length, statistics were brought in as a way to both standardize decision-making criteria and better manage uncertainty. A national trust infrastructure was built through the generalization of credit reporting and the quantitative evaluation of risk, making it easier for lenders to work with unknown borrowers (Guseva & Rona-Tas 2001, Lauer 2017, Marron 2009). Meanwhile, the availability of increasingly varied data made it possible to expand the range of variables that were deemed relevant to the determination of risk, fueling a movement away from group assessment of risk and, increasingly, toward its individualization (Harcourt 2007, Lauer 2017).

The changing political landscape was another important factor driving the appeal of actuarial approaches across a wide range of institutions. A new wave of antidiscrimination legislation in the 1970s had made reliance on human judgment increasingly problematic. Evidence had accumulated that both private and public decision-makers were routinely giving into vague intuitions, personal prejudices, and arbitrary opinions. These decisions were deemed unfair in the sense that they were often skewed against low-status groups, or were simply inconsistent. Historical accounts of the rise of actuarial techniques thus emphasize progressive efforts to both demand accountability from institutions and redress histories of bias, favoritism, and exclusion. The mechanics of modern algorithms offered promises of transparency and of equal, dispassionate treatment—behind the veil of ignorance—without making distinctions based on prohibited demographic characteristics such as race or gender (Krippner 2017, Lauer 2017, Simon 1988). For instance, the COMPSTAT system for tracking and mapping crime developed by the New York City Police Department in this era was pitched as a way to reduce discriminatory policing practices by making policing decisions more objective and data driven (Didier 2013). Similarly, the Los Angeles Police Department adopted predictive tools as a response to a grave crisis of legitimacy and accountability (Brayne 2020, p. 138).

By seemingly eliminating human arbitrariness, the new regime of algorithmic classification lends itself to an argument for procedural fairness. However, it may not satisfy other social definitions of fairness. Scholars are now reckoning with the fact that algorithmic systems may both reproduce certain group inequalities and create new social hierarchies (Barocas & Selbst 2016, Benjamin 2019, Eubanks 2017, Fourcade & Healy 2013, Gandy 1993, Noble 2018, O'Neill 2016). The mechanisms by which an algorithm—particularly a machine learning algorithm, which operates by detecting patterns in data and generalizing from those patterns to novel cases—produces inequality are different from the ways a rule-bound institution or an intuitive human decision-maker does so. Finally, because algorithmic decisions depend on massively multi-dimensional, complex, and often proprietary models, they are also more opaque and harder to challenge (Burrell 2016, Pasquale 2015).

Algorithmic Inequalities

In a Weberian analytical frame, what ultimately shapes the making of classes (or class situations) is the way that assets and opportunities are socially distributed within and across a range of institutional domains. Wherever computational algorithms distribute rewards, opportunities, or punishments, they have the capacity to alter the life chances of individuals (Fourcade & Healy 2013). Algorithmic mechanisms do this work of allocation explicitly and rationally, and through their capacity to scale efficiently, they also increase the number of sites where it might take place. By doing so, however, they implicitly rework the process of social class-making. Unlike traditional mechanisms of gatekeeping rooted in bright lines of inclusion versus exclusion (e.g., those who can obtain credit versus those excluded from it), new algorithmic mechanisms produce a sliding scale of classification situations with a much more fine-grained differentiation of positions (Fourcade & Healy 2013). For instance, desirable borrowers with favorable assessments of credit risk enjoy generous credit contracts, undesirable borrowers face deeply usurious ones, and those situated in between receive a panoply of more or less favorable offers (Cottom 2017, Poon 2009). Instead of complete exclusion, digitality may thus facilitate various forms of predatory inclusion. As these often exact an unequal burden on ethno-racial minorities, familiar processes of racial capitalism are being reinvented for the digital era (Cottom 2020).

Algorithmic allocations are envisioned in theory to be perfectly accurate and fair, but they fall short in practice in several ways. A key problem is that coders and model builders rarely question the quality of the input data they use (Broussard 2018, O'Neill 2016), although the problem of data quality in model-building is starting to be addressed (see Gebru et al. 2018). Many training data sets were produced without much attention to the representativeness of different groups or the quality of annotations obtained from users or from workers hired through crowdsourcing platforms. For instance, data sets widely used to train facial recognition systems contributed to the propagation of errors and prejudices throughout the field (Hanna et al. 2020, Noble 2018). Likewise, policing data are notoriously skewed, yet they are commonly used in data models for predictive policing as though they were a transparent window into criminal behavior. They are not. Sociologists have long known that police reports are likely to reflect institutional self-presentations that depart systematically from reality (Bittner & Garfinkel 1984) or individual and collective strategies to work around bureaucratic benchmarks and metrics (Lande & Mangels 2017). Specific technical requirements of machine learning systems may compound these problems further. For instance, the need for large data sets to improve predictive power has created an incentive to include low-level crimes (like drinking in public or loitering) in training data sets. The result, as O'Neill (2016) notes, is models that form risk predictions based on precisely those minor transgressions that are likely to be an artifact of policing practices rather than assessments of criminality.

A key premise that justifies an actuarial logic in decision-making is "the belief that patterns observed in the past provide useful information about activities and events that may take place in the future" (Gandy 2016, p. 9). But in human matters, predicting the future on the basis of the past threatens to reify and reproduce existing inequalities of treatment by institutions. Because people's visibility to data collection engines is socially organized, digital coding becomes a new conduit for the familiar operations of the race, gender, and class structures (Benjamin 2019). Thus, the overpolicing of communities of color, combined with institutionalized practices of racial profiling, produces crime data sets skewed to severely overrepresent these groups (Jefferson 2020). The automation of social services eligibility criminalizes the most vulnerable families and diverts them from the benefits to which they are entitled (Eubanks 2017). Conversely, algorithms trained on mostly White or mostly male data sets might not see the dominated groups at all. A machine learning–based algorithm reviewing job applicants famously picked up on Amazon's pattern of disproportionately hiring men and gave low scores to applications containing signals that indicated the candidate was a woman.

Other pitfalls of predictive systems have to do with poor conception or misapplication. While the use of algorithms is justified by claims that it makes decision-making more impersonal, the objective functions built into these systems often reflect other goals, particularly institutional cost optimization and risk minimization. For example, a medical risk assessment model programmed to optimize healthcare spending underestimates the severity of the condition of Black patients, who on average utilize fewer healthcare resources, leading to worse health outcomes (Obermeyer et al. 2019).[5] Notably, the processes through which machine learning models are dynamically refined can also produce a damaging feedback loop (O'Neill 2016). For instance, predicted high-crime areas or high-risk individuals will receive more police attention, leading to more arrests and, in turn, still more scrutiny. Harcourt (2007) names this reinforcing cycle of scrutiny the ratcheting effect. Similarly, higher rates of predicted credit defaults cause lending conditions to be much less favorable on average for Black borrowers, likely causing more defaults. Furthermore, disproportionate entanglement in the criminal justice system and a poor credit record both have other social costs, including barriers to employment, education, or housing, all of them resulting in further financial harm (Alexander 2012). This turboperformativity of predictive analytics (Rona-Tas 2017) creates a self-fulfilling prophecy, reproducing historical disadvantage and structural inequality even in the absence of any discriminatory intent.

Finally, these forms of disadvantage may be harder to contest politically. Because they are channeled through the measurement of individual, rather than group, behavior, they are perceived to be fair. And because they are embodied in mathematical formulas, they are "promoted and perceived as more objective or progressive than the discriminatory systems of a previous era" (Benjamin 2019, p. 5) and may thus be harder to see and to challenge (Burrell 2016). But as Harcourt (2007) points out, reducing justice (and punishment) to a computational model is fundamentally problematic. The prediction of future criminality overdetermines decision-making above other considerations such as deterrence, intent, and magnitude of harm. This amounts to an "epistemic distortion" of criminal justice (Harcourt 2007, p. 22).

Fairness may be the most hotly debated topic in machine learning today, which often leads to complex arguments about which statistical criterion best fits the situation: false negatives versus false positives, or demographic parity versus predictive rate parity (Weinberger 2019, Narayanan

[5] Institutionally, the critique of the use of machine learning to manage human affairs has led to the formation of the Artificial Intelligence Caucus in the US Congress and the creation of the Fairness, Accountability, and Transparency conference series.

2019). Some critics reject outright the claim that mathematical objectivity is inherently better at guarding against social inequities than human judgement, however subjective the latter may be. Eubanks (2017, p. 168) insists on the fundamental role of empathy in the delivery of social services: "the assumption that human decision-making is opaque and inaccessible is an admission that we have abandoned a social commitment to try to understand each other." Echoing this sentiment (and turning Max Weber on his head), Pasquale (2019) concludes that a rule of persons is better able to guarantee legal due process than a rule of machines.

The Algorithmic Dominion

Inclusion into some identification database has long been a prerequisite of modern citizenship (Koopman 2019; Lyon 2009, 2015), but digitality has magnified the ambition to eliminate fraud and also tailor the terms and benefits of citizenship in ever more fine-grained ways (Fourcade 2021). This trend is global: Informational modernization can look eerily familiar and, at the same time, strikingly different across political and historical contexts. In India, Aadhaar, an integrated identification system that stores fingerprint and iris scans along with demographic data for each citizen, was originally publicized as a tool for graft elimination and the efficient delivery of welfare services. It has swiftly become required for interactions with both public and private institutions, anchoring an emergent mass surveillance infrastructure (Rao & Nair 2019). In South Africa, the postapartheid government similarly sought to implement a nationwide biometric identification system to improve the uniformity of social welfare grant disbursement. In typical Weberian fashion, the government claims that the system's universalism and standardization guarantee equal treatment (Donovan 2015). Despite the country's history of oppressive information infrastructures, most notoriously its passbook system, this new citizen database was embraced by postapartheid leaders.[6]

In China, both municipalities and the central government have partnered with private sector firms to develop social credit systems oriented to improving the financial behavior and civic-mindedness of individuals and organizations (Ahmed 2019, Liu 2019, Ohlberg et al. 2017). By linking algorithmically produced social credit scores to tangible outcomes (conveniences and perks, public praising or shaming), these systems foster rule compliance (e.g., using crosswalks to cross the street) and obedience to social expectations (e.g., taking care of one's parents, doing volunteer work). While Western commentators have often interpreted the development of social credit through the lens of China's political authoritarianism, it is useful to remember that private data infrastructures elsewhere can feel similarly oppressive and inescapable. O'Neill (2016) describes, for example, how a job applicant was shut out of work in a sizeable portion of the American retail industry when he failed a hiring prescreening test designed by a software company with contracts throughout the sector. Other data systems operate ubiquitously across national borders. Euro-centric assumptions built in to cybersecurity tools that automate the identification of fraud, for example, have become a ubiquitous part of the global infrastructure (Jonas & Burrell 2019).

In these examples, fair allocation is not the only issue. The inability of those so forcefully governed to shape the terms of the algorithmic dominion, or to evade the rule of the code, raises fundamental questions about democracy and human autonomy (Amoore 2020, Aneesh 2009). The coding elite frames its approach as universal and domain nonspecific (Ribes et al. 2019). But

[6]The passbook system as a race-based total classification system was critical in the enforcement of the apartheid government's policies (Bowker & Star 1999).

reliance on a unitary logic to shape outcomes across institutions has the potential to trap people into self-reinforcing cycles of exclusion across the whole range of their social existence—including jobs, credit, education, housing, and social rights (Fourcade & Healy 2013, Rona-Tas 2017). Varying decision logics, by comparison, create openings and opportunities for those whose data profiles register them as unpredictable or unpromising candidates in some particularly salient domain (such as personal finance).[7] This is perhaps why regulators in the United States are wary about letting car insurers use credit scores to predict accident risk and why employers similarly tread carefully around credit reporting data, looking for the human story behind bad numbers (Kiviat 2019a,b).

Being ruled—or overruled—by an insensate and affectless system seems to violate some fundamental notion of human dignity and autonomy. Echoing these sentiments, the European Union's General Data Protection Regulation instituted a right to an explanation that requires a human review of algorithmic decisions (Jones 2017). Similarly, a burgeoning ethnographic literature suggests that people quietly resist the authority of algorithms in their working lives. Important legal victories have been won against "algorithmic bosses" in the United States. In the United Kingdom, protests erupted over the use of machine learning to determine student placements in the 2020 university admissions cycle, and London borough councils went back on their "use of computer algorithms in helping to make decisions on benefit claims and other welfare issues" (Marsh 2020). These examples of popular resistance dovetail with the extensive ethnographic evidence showing that professionals outfitted with algorithmic tools also routinely express skepticism and override or ignore them in their day-to-day work (Brayne 2017, 2020; Christin 2017, 2020; O'Neill 2016).[8]

Finally, algorithmic systems and their advocates run the risk of propelling the dangerous superstition, once denounced by von Hayek (1989), that only what is measurable is important. Framing a society's normative or legal truths according to the technical capabilities of algorithmic systems may blind us to nonmeasurable but essential processes (Agamben 2014), cause us to focus on the wrong outcomes, or generate social costs that are not worth the payoff (Crawford 2021, Espeland & Sauder 2016). In particular, the single-minded focus on predictive accuracy on narrow tasks, circumscribed by the data that are available and what can be submitted to classification, curtails what political or ethical claims can be articulated. As Gandy (2016, p. 8) remarks, in the digital society, "concern about risk has come to replace our interest in discovering the essence of the good life with an attempt to identify and control those things that threaten to put it out of reach." A proper critique must thus begin with the recognition that algorithms are ethico-political entities that generate their own "ideas of goodness, transgression and what society ought to be" (Amoore 2020, p. 7). In other words, algorithms are transforming the very nature of our moral intuitions—that is, the very nature of our relations to self and others—and what it means to exist in the social world. The next section examines this shifting terrain.

CLASSIFIERS AND THEIR DISCONTENTS

Expert systems, whether human or mechanical, always place demands on laymen who interact with them: People must make themselves legible or the system will not recognize them, they have to

[7]However, this strategy would not eliminate structural disadvantage altogether since poor performance is likely to be correlated across domains for reasons that sociologists understand all too well (Sampson 2016).
[8]Salganik et al. (2020) show that machine learning algorithms—trained on a very rich longitudinal dataset—perform no better at predicting child harm than a simple linear regression model using just a handful of variables.

follow rules when interacting with it, and their ability to question decisions is often limited. In traditional bureaucracies, the final arbiter of these processes is almost always a human being (Weber 1978). But as technology becomes increasingly autonomous and human processors and decision-makers recede into the background, even these steps may become guided by machines (Ellul 1967). Andrejevic (2020) suggests that, by forcing people to preprocess themselves—to standardize and fragment messages, ideas, identities and interactions so as to be machine readable—computers operate a form of social deskilling. Instead of making machines augment human intelligence, the coding elite reorganizes social activities to make humans support the operation of computers. It is thus humans who are, in a certain sense, automated.

What does it mean, concretely, for human life to be condensed into packs of bits, for the flow of experience to be filtered through algorithms that perform a classifying function? We are used to thinking that the classification situations implemented through contemporary algorithmic classifiers only matter at certain key moments—for example, when allowing a credit check in order to apply for a loan. But the digital infrastructure operates in increasingly totalizing, continuous, and dynamic ways. Not only do digital data traces allow for intrusive probing by institutions far afield from the data's original collection site (e.g., credit data matter to landlords and to prospective romantic partners, and police departments are hungry for social media data), but they also enable the guiding or control of behavior through reactive, cybernetic feedback loops that operate in real time. The more one interacts with digital systems, the more the course of one's personal and social life becomes dependent on algorithmic operations and choices. This is true not only for the kinds of big decisions mentioned above but also for mundane, moment-by-moment actions: For instance, each online click potentially reveals some underlying tendency or signals a departure from a previous baseline. As new data flow in, categories and classifications get dynamically readjusted, and so do the actions that computing systems take on the basis of those categories. This has important implications for how people ultimately perceive themselves and for how social identities are formed.

The Modulation of Identities

In today's systems of data extraction and analysis, properties of the individual are often inferred from behavioral traces. Each flesh and blood, embodied person has a "data double" made of these traces—a surveillant assemblage whose components, "circulate in a host of different centers of calculation" (Haggerty & Ericson 2000, p. 611). These "tranches" of individual behavior have acquired the liquidity of financial products and can be traded and shared for predictive profiling (Cohen 2019, p. 67). Even those aspects of identity once thought fixed or almost unchanging—gender, race, citizenship, nationality—become readable in this virtualized way. For instance, patterns of web browsing and other digital activities can be mined to determine whether one is likely to be a woman or a man. But these assessments (another set of algorithmically derived classification situations) are always flexible and provisional, depending on data flowing in and on the particular combination of classifiers. Consequently, the algorithmic inference of gender identity may change at any moment. Technology, then, builds on and feeds into a broader cultural shift by which gender identity may be increasingly experienced as multiple and fluid rather than binary and stable.

Building on Deleuze, Cheney-Lippold (2017) notes that algorithmic identities have the quality of modulation; that is, the attributes derived from behavioral traces are continually subject to change and revision. The modularity of what Deleuze (1992) calls control supplants the rigidity of discipline, which cast each subject in the same mold—the assembly line worker, the manager, the housewife. Inferences made about us are often fed back to us as visualizations, assessments, scores, or recommendations and, in turn, reconfigure how we understand ourselves in real time. Even discrepancies—for instance, between biological age and algorithmic age or between gender self-identification and algorithmic gender—may come to be taken not as amusing mistakes by an imperfect technical system but as external, objective, and constantly fluctuating signals informing us of who we really are. They may even help tighten subjective associations with the measured types through self-reinforcing feedback processes (by serving certain kinds of ads or returning certain search results).

While algorithms can make intimately lived truths external and modulatory, shifting "the sense by which we take our bearings in the world" (Arendt 2006, p. 252), they are unlikely to fundamentally transform how major structural formations, such as gender or race, operate in the world, as we discussed in the section titled Actuarialism and Its Discontents. Instead, the power of measurable types may be strongest when deployed to legitimize creative expression and self-experimentation (around sexuality, for instance; see Hawgood 2020) or to reform institutional categorization systems. For instance, the Snowden disclosures revealed that the US government, via the National Security Agency, had sought to infer citizenship from digital traces, including language (other than English) used in communication, nationality of communication partners, and web browsing history as input data. This strategy was to provide legal cover for warrantless collection and inspection of digital communications, something allowable for noncitizens whose data pass through US networks but illegal for citizens by the Fourth Amendment of the US Constitution, which prohibits unreasonable search and seizure.[9] With the help of data-hungry algorithms, citizenship was reframed from a binary, institutional category to a continuum of behavior (Cheney-Lippold 2016).

As algorithmic classifiers loop back toward us, they prompt us to question what we know about ourselves and how we know it (Amoore 2020, Andrejevic 2020, Brubaker 2020, Hong 2016, Neff & Nafus 2016). The notion that we will discover some ultimate self-truth may be misplaced, however: What we may observe, instead, are bewildering movements up and down some self-tracking scale, or multiple de- and reconstructions of ourselves, varying across time and across platforms.[10] Harcourt (2015, p. 253) describes our increasingly digitized lives as a "mirrored glass pavilion," a space where we self-consciously construct a depiction of who we are, "[for] the gaze of others and, of course, our own." But we have little control over the parameters of our self-depictions: The desire to expose and be exposed has been sublimated into the technical environment, and the metrics, calculators, and visualization tools that presumably tell our personal truth are not of our own making. However inaccurate, daily step counts, menstrual cycles, heart rate, emotional states, social networks, and spending patterns are reflected back to us, to institutional others (e.g., doctors, insurance companies, welfare agencies), and to the world as undeniable evidence of who we are over and above subjective self-assessment or the old techniques of analog self-presentation (Stark 2018). Thanks to algorithmic tools, we may now feel compelled to incessantly search for and discover ourselves in measurable biological or social indicators that we must manage in a hyper-rationalized, dynamic, and continuous fashion (Schüll 2016). Monitoring and investigating our sleep patterns, eating habits, and social relations this way is slowly becoming second nature. What may sometimes feel like playful self-diagnosis is really no play at all, however—rather, it is

[9]According to the scheme, a legal citizen whose algorithmic foreignness measure crossed the 51% threshold of confidence could be treated as foreign and thus denied the Fourth Amendment protection of privacy.

[10]This is also true in the biological domain, where companies such as 23andMe offer quick genetic assessments that include ethnic and regional origin. Nelson (2016) discusses how people accommodate these externalized representations into their lives and self-understanding, and Fourcade (2020) provides a general presentation of "ordinalization."

a permanently self-probing condition, powered by incessant feedback loops between human and machine (Fourcade & Johns 2020).

The coding elite nudge us to surrender our subjectivity to systems that, they profess, know us better than we know ourselves. But algorithms are nothing but partial representations, sliced-up-and-put-back-together versions of ourselves. Some versions, predictably, are better than others. When algorithms are disturbingly wrong in their assessments (rather than spookily accurate), the process can be especially oppressive (Broussard 2018). And as we have seen, problems of misidentification, when they occur, are not randomly distributed across the population. Facial recognition systems repeatedly fail to recognize faces with dark skin tones and disproportionately misgender Black women (Buolamwini & Gebru 2018). Search engine results return prejudiced representations, adversely affecting women and members of minority groups (Cottom 2017, Noble 2018, Sweeney 2013). Historically dominated groups are disproportionately on the receiving end of a new form of symbolic violence that operates at the interface between humans and machines. For them, the mirrored glass pavilion is more like a glass cage—full of ignorance, disregard, and misclassification, insisting on a "truth about the racial body and one's identity (or identities) despite [one's] claims" (Browne 2015, p. 110). More fundamentally, this mechanization exacerbates the denial of subjectivity already effected by a racialized status hierarchy and its attendant inequalities.

Moral Economy of the Algorithmic Interface

Much of the vast digital infrastructure mediating online interactions is oriented to generating revenue through advertising and requires human eyeballs and click-throughs to sustain its operations. Digital firms meticulously program sociality so as to yield maximum economic benefit (Bucher 2018).[11] Firms obsessively track time spent on a given site by users, euphemized as "engagement," which they depend upon to generate personal data and maximize advertising exposure. Site visitors are put to work preprocessing the data entering the digital pipeline. Tags, such as buttons, emojis, labels, hashtags, authentication and other forms of user-directed actions, help categorize the messiness of the social world so that it is rendered machine-readable all the way down (Fourcade & Healy 2017). But they also create new affordances that take a life of their own, fueling social dynamics that are native to the digital environment.[12]

The persistence facilitated by platforms like Facebook extends relationships over time that might otherwise have dwindled, and the associative properties of algorithms, combined with the platforms' suggestive power, enables relationships to emerge that would never have existed otherwise. Strategic prompts to connect with people on the platform, passive updates sent as notifications, and addictive designs capitalizing on social recognition and approval foster social anxiety, compulsive habits, and competitive dispositions (Bishop 2018, Fourcade & Johns 2020). Not participating may guarantee a certain kind freedom, but it may also mean social isolation. Participating a lot may lead to fame and fortune (Stuart 2020) but also excruciating overexposure (Cottom 2017). Platforms generally find it profitable to exploit viral content and other forms of emergent sociality [that is, unless they interpret it as gaming the algorithm, in which case it must be controlled or eliminated (Ziewitz 2019)].

[11]For instance, when the YouTube recommendation algorithm began to reward longer videos, the duration of videos uploaded by platform users grew.

[12]The broad literature on these issues in media studies and communication, where computer-mediated communication is a core subfield, is reviewed by Gillespie et al. (2014) and Hancock et al. (2020).

Through these psychological and economic techniques, Twitter, Facebook, YouTube, Instagram, Reddit, and a handful of other digital platforms run by even fewer companies[13] have built themselves into a de facto global public sphere with near-monopoly power over the social distribution of attention. With the majority of people now receiving their information from social media, anyone seeking exposure or pursuing activist goals must master this new landscape (Tufekci 2017). Public debate, knowledge circulation, affirmative pursuits, and reportage have all become intimately dependent upon social media intermediaries and their secretive algorithms. But the sheer abundance of information, which people are supposed to parse through on their own, "often provoke[s] paranoid and otherwise speculative forms of public knowledge and participation" (Hong 2020, p. 8). Established actors have been displaced by skilled or well-funded activist upstarts, coordinated online mobs, and clickbait producers. The spirits of collective mobilization and counter-mobilization are easily overwhelmed in the unequal struggle over the means of digital production (Schradie 2019). It is instead the old demons of conspiracy, belief, and gossip that have ascended from their graves, called to the surface by rapacious algorithmic spells.

From the Algorithmic Society to the Society of Algorithms

The endgame of the coding elite, the ultimate goal of their professional project, like the algorithms they build, remains opaque. This may simply reflect a lack of consensus; their members diverge from one another, sometimes considerably, in the futuristic dreams they espouse. The most ambitious vision, held by many computer scientists, is that the algorithmic society is simply a prelude to the advent of a new social species, a general AI that will replicate or exceed the intelligence of humans and perhaps escape their control (Bostrom 2014, Harari 2017, Russell 2019, Tegmark 2017). Moore's law specifies that computer power tends to grow exponentially. If we accept the premise that the measure of intelligence and the capacity to develop it further are rooted in processing power, then this law marks a clear trajectory.

AI's trajectory in society, however, is not simply a question of whether humanity will benefit or not but, rather, who will benefit. A new division of learning opposes the knowers against the known (Zuboff 2019); those who make AI work face those who make AI work for themselves. Unlike the mass of those surveilled, those misrepresented and alienated, the data capitalists may be able to correct, control, or improve their personal data representation; to buy themselves entirely out of surveillance regimes; or to benefit from AI in new ways. Recent discussions and concrete investments in developing neural implants, smart prostheses, and data-intensive genetic engineering have revived old cyborg fantasies, unleashing possibilities pondered by Haraway (1990) and others. If such a world came to pass, the members of the coding elite would be best positioned not only to increase their material power by claiming ownership over new kinds of data outputs (e.g., neuro-informational), but also to literally deploy new technologies to augment their own minds and bodies (Harari 2017).

For now, dominant industry talk promises a gentler, more acceptable, less biased kind of AI, compliant with best practices and ethically infused (Crawford & Calo 2016). But for all the great chatter about equity and value alignment (Gabriel 2020), the established technological trajectory has remained secure: Venture capital offices and start-up firms continue to roll out a world of ubiquitous computing, located in everything from human bodies and mundane objects to city

[13] People fed up with site policies, misinformation, or the political influence of Facebook corporation may turn to a seemingly kinder community on Instagram, only to realize that this platform is also owned by Facebook. Facebook also owns WhatsApp, Google owns YouTube, and so on.

infrastructures and other large works of engineering. Algorithms will continue to capitalize on the transformation of persons into disembodied data streams. And as this parallel dataverse becomes second nature, actual flesh and blood people may learn to apprehend each other (and themselves) as eminently malleable algorithmic constructs that they must carefully, continuously, cater to.

For years now, many have proclaimed that the end of Moore's law is imminent.[14] Humanity is still a considerable distance from developing human-like general AI and is yet further from superintelligence, according to those technical experts best positioned to bring about such a scenario.[15] It would be a mistake to uncritically embrace the fever dreams of the coding elite's most fervent boosters, to treat computing "theologically rather than scientifically or culturally" (Bogost 2015). In that respect, sociology offers a useful reality check. Ethnographers who observe digital technology in action have brilliantly tackled the unglamorous everyday realities of algorithms. They have documented considerable resistance to algorithmic systems, frequent errors and breakdowns, and variations in meaning and effect, both across and within societies (Brayne 2020, Christin 2020, Rafalow 2020). We can both reject magical thinking about machine intelligence and acknowledge the enormous economic, political, and cultural power of the tech industry to transform the world we live in. Beyond futurism and hype, existing AI is actually quite mundane.[16] It is designed by the coding elite, sustained by the cybertariat, fueled by personal data extracted by (mainly) large digital firms, frequently optimized for profit maximization, and supported by a contingent set of legal institutions that authorize (at the time of this writing) continuous data flows into corporate as well as state servers. Like prior control innovations, AI surveils, sorts, parses, assembles, and automates. And like prior forms of social surveillance and discipline, it weighs differently and more prejudicially on poor and minority populations. Far from being purely mechanistic, it is deeply, inescapably human.

DISCLOSURE STATEMENT

The first author has received research gift funding from Google Corporation within the past three years. The authors are not aware of any additional affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

The authors thank Gil Eyal, Katy Habr, Shreeharsh Kelkar, Arvind Karunakaran, Aaron Mendon-Plasek, Frank Pasquale, Kiran Samuel, David Stark, Anne Washington, Elizabeth Watkins, Amy Weissenberg, and an anonymous ARS reviewer for stimulating comments and suggestions.

LITERATURE CITED

Agamben G. 2014. What is a destituent power? *Environ. Plan. D* 32:65–74

---

[14]Even Moore's law is arguably under human direction. Intel, a software company cofounded by Gordon Moore (of Moore's law), set product development timelines for microprocessor designers according to this so-called law.

[15]In a 2015 survey of 352 attendees of two major technical conferences on machine learning and neural networks, respondents gave a 50% chance of general AI occurring within the next 45 years and only a 10% chance of it occurring in the next 10 (Grace et al. 2018).

[16]Suchman (2007) discusses how assumptions of human–machine equivalency are baked into the language of AI research. Elish & boyd (2018) and Campolo & Crawford (2020) discuss the way discourses of magic and enchantment are deployed to leverage the opacity of these systems and further depict AI as superhuman.

Agre P. 1997. Toward a critical technical practice: lessons learned in trying to reform AI. In *Social Science, Technical Systems, and Cooperative Work: Beyond the Great Divide*, ed. GC Bowker, SL Star, W Turner, L Gasser, pp. 131–157. Mahwah, NJ: Lawrence Erlbaum Assoc. Inc.

Ahmed S. 2019. The messy truth about social credit. *Logic Magazine*, May 1. **https://logicmag.io/china/the-messy-truth-about-social-credit/**

Alexander M. 2012. *The New Jim Crow: Mass Incarceration in the Age of Colorblindness*. New York: New Press

Amoore L. 2013. *The Politics of Possibility: Risk and Security Beyond Probability*. Durham, NC: Duke Univ. Press

Amoore L. 2020. *Cloud Ethics: Algorithms and the Attributes of Ourselves and Others*. Durham, NC: Duke Univ. Press

Andrejevic M. 2020. *Automated Media*. New York: Routledge

Aneesh A. 2009. Global labor: algocratic modes of organization. *Sociol. Theory* 27(4):347–70

Arendt H. 2006. *Between Past and Future: Eight Exercises in Political Thought*. New York: Penguin Books

Ariely D. 2010. *Predictably Irrational: The Hidden Forces That Shape Our Decisions*. New York: Harper Perennial

Barbrook R. 1998. The hi-tech gift economy. *First Monday* 3(12). **https://doi.org/10.5210/fm.v3i12.631**

Barbrook R, Cameron A. 1996. The California ideology. *Sci. Cult.* 6(1):44–72

Barocas S, Selbst AD. 2016. Big data's disparate impact. *Calif. Law Rev.* 104(3):671–732

Beniger J. 1989. *The Control Revolution: Technological and Economic Origins of the Information Society*. Cambridge, MA: Harvard Univ. Press

Benjamin R. 2019. *Race After Technology: Abolitionist Tools for the New Jim Code*. Cambridge, UK: Polity

Birch K, Muniesa F. 2020. *Assetization*. Cambridge, MA: MIT Press

Bishop S. 2018. Anxiety, panic and self-optimization: inequalities and the YouTube algorithm. *Convergence* 24(1):69–84

Bittner E, Garfinkel H. 1984. "Good" organizational reasons for "bad" clinic records. In *Studies in Ethnomethodology*. Cambridge, UK: Polity

Bogost I. 2015. The cathedral of computation. *The Atlantic*, Jan. 15. **https://www.theatlantic.com/technology/archive/2015/01/the-cathedral-of-computation/384300/**

Bohn S, Thorman T. 2020. Income inequality in California. *Public Policy Institute of California/Just the Facts Blog*, January. **https://www.ppic.org/publication/income-inequality-in-california/**

Bostrom N. 2014. *Superintelligence: Paths, Dangers, Strategies*. Oxford, UK: Oxford Univ. Press. 1st ed.

Bouk D. 2015. *How Our Days Became Numbered: Risk and the Rise of the Statistical Individual*. Chicago: Univ. Chicago Press

Bowker GC, Star SL. 1999. *Sorting Things Out: Classification and Its Consequences*. Cambridge, MA: MIT Press

Braverman H. 1974. *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. New York: Mon. Rev.

Brayne S. 2017. Big data surveillance: the case of policing. *Am. Sociol. Rev.* 82(5):977–1008

Brayne S. 2020. *Predict and Surveil: Data, Discretion, and the Future of Policing*. Oxford, UK: Oxford Univ. Press

Broussard M. 2018. *Artificial Unintelligence: How Computers Misunderstand the World*. Cambridge, MA: MIT Press

Browne S. 2015. *Dark Matters: On the Surveillance of Blackness*. Durham, NC: Duke Univ. Press

Brubaker R. 2020. Digital hyperconnectivity and the self. *Theory Soc.* 49(5):771–801

Brynjolfsson E, McAfee A. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton

Bucher T. 2018. *If...Then: Algorithmic Power and Politics*. Oxford, UK: Oxford Univ. Press

Buolamwini J, Gebru T. 2018. Gender shades: intersectional accuracy disparities in commercial gender classification. *Proc. Mach. Learn. Res.* 81:77–91

Burrell J. 2016. How the machine 'thinks': understanding opacity in machine learning algorithms. *Big Data Soc.* 3(1). **https://doi.org/10.1177/2053951715622512**

Burris B. 1989. Technocratic organization and control. *Organ. Stud.* 10(1):1–22

Burris B. 1993. *Technocracy at Work*. Albany, NY: SUNY Press

Bush V. 1945. *Science, the endless frontier.* Rep., Off. Sci. Res. Dev., Washington, DC

Campolo A, Crawford K. 2020. Enchanted determinism: power without responsibility in artificial intelligence. *Engaging Sci. Technol. Soc.* 6:1–19

Casilli, AA. 2017. Digital labor studies go global: toward a digital decolonial turn. *Int. J. Commun.* 11:3934–54
Casilli AA, Posada J. 2019. The platformization of labor and society. In *Society and the Internet: How Networks of Information and Communication Are Changing Our Lives*, ed. M Graham, WH Dutton, pp. 293–306. Oxford, UK: Oxford Univ. Press
Chen K. 2009. *Enabling Creative Chaos: The Organization Behind the Burning Man Event*. Chicago: Univ. Chicago Press
Cheney-Lippold J. 2016. Jus algoritmi: how the National Security Agency remade citizenship. *Int. J. Commun.* 10:1721–42
Cheney-Lippold J. 2017. *We Are Data: Algorithms and The Making of Our Digital Selves*. New York: NYU Press
Christian B, Griffiths T. 2016. *Algorithms to Live By: The Computer Science of Human Decisions*. New York: Holt
Christin A. 2017. Algorithms in practice: comparing web journalism and criminal justice. *Big Data Soc.* 4(2):1–14
Christin A. 2020. *Metrics at Work: Journalism and the Contested Meaning of Algorithms*. Princeton, NJ: Princeton Univ. Press
Citron DK. 2007. Technological due process. *Wash. Univ. Law Rev.* 85(6):1249–314
Cohen J. 2019. *Between Truth and Power: The Legal Constructions of Informational Capitalism*. Oxford, UK: Oxford Univ. Press
Cottom TM. 2017. Black cyberfeminism: ways forward for intersectionality and digital sociology. In *Digital Sociologies*, ed. J Daniels, K Gregory, TM Cottom, pp. 211–31. Bristol, UK: Bristol Univ. Press
Cottom TM. 2020. Where platform capitalism and racial capitalism meet: the sociology of race and racism in the digital society. *Sociol. Race Ethn.* 6(4):441–49
Couldry N, Mejias U. 2019. *The Costs of Connection: How Data Is Colonizing Human Life and Appropriating It for Capitalism*. Stanford, CA: Stanford Univ. Press
Crawford K. 2021. *Atlas of AI*. New Haven, CT: Yale Univ. Press
Crawford K, Calo R. 2016. There is a blind spot in AI research. *Nat. News* 538(7625):311–13
Deleuze G. 1992. Postscript on the societies of control. *October* 59:3–7
Didier E. 2013. From sensors to sentinel: pressure and depression in crime statistics. *Limn*, June 15. **https://limn.it/articles/from-sensors-to-sentinel-pressure-and-depression-in-crime-statistics/**
Donovan KP. 2015. The biometric imaginary: bureaucratic technopolitics in post-apartheid welfare. *J. S. Afr. Stud.* 41(4):815–33
Dougherty C. 2020. *Golden Gates: Fighting for Housing in America*. New York: Penguin
Dubal VB. 2017. The drive to precarity: a political history of work, regulation, & labor advocacy in San Francisco's taxi & Uber economics. *Berkeley J. Employ. Labor Law* 38(1):73–136
Duffy B. 2020. Algorithmic precarity in cultural work. *Comm. Public* 5(3–4):103–7
Ekbia HR, Nardi BA. 2017. *Heteromation, and Other Stories of Computing and Capitalism*. Cambridge, MA: MIT Press
Eliasoph N. 1998. *Avoiding Politics: How Americans Produce Apathy in Everyday Life*. Cambridge, UK: Cambridge Univ. Press
Elish MC, boyd d. 2018. Situating methods in the magic of Big Data and AI. *Commun. Monogr.* 85(1):57–80
Ellul J. 1967. *The Technological Society*. New York: Random House
Espeland WN, Sauder M. 2016. *Engines of Anxiety: Academic Rankings, Reputation, and Accountability*. New York: Russell Sage Found.
Espeland WN, Stevens ML. 1998. Commensuration as a social process. *Annu. Rev. Sociol.* 24:313–43
Ettlinger N. 2016. The governance of crowdsourcing: rationalities of the new exploitation. *Environ. Plan. A* 48(11):2162–80
Eubanks V. 2017. *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. New York: St. Martin's
Eyal G. 2013. For a sociology of expertise: the social origins of the autism epidemic. *Am. J. Sociol.* 118(4):863–907
Ford M. 2015. *Rise of the Robots: Technology and the Threat of a Jobless Future*. New York: Basic
Forsythe D, Hess DJ. 2001. *Studying Those Who Study Us: An Anthropologist in the World of Artificial Intelligence*. Stanford, CA: Stanford Univ. Press

Fourcade M. 2021. Ordinal citizenship. *Br. J. Sociol.* 72:154–73

Fourcade M, Gordon J. 2020. Learning like a state: statecraft in the digital age. *J. Law Political Econ.* 1:78–108

Fourcade M, Healy K. 2013. Classification situations: life-chances in the neoliberal era. *Account. Organ. Soc.* 38(8):559–72

Fourcade M, Healy K. 2017. Seeing like a market. *Socioecon. Rev.* 15(1):9–29

Fourcade M, Johns F. 2020. Loops, links and ladders: the recursivity of social and machine learning. *Theory Soc*. 49:803–32

Fourcade M, Kluttz DN. 2020. A Maussian bargain: accumulation by gift in the digital economy. *Big Data Soc*. 7(1). **https://doi.org/10.1177/2053951719897092**

Gabriel I. 2020. Artificial intelligence, values and alignment. arXiv:2001.09768 [cs]

Gandy OH. 1993. *The Panoptic Sort: A Political Economy Of Personal Information*. Boulder, CO: Westview

Gandy OH. 2016. *Coming to Terms with Chance: Engaging Rational Discrimination and Cumulative Disadvantage*. New York: Routledge

Gebru T, Morgenstern J, Vecchione B, Vaughan JW, Wallach H, et al. 2018. Datasheets for datasets. arXiv:1803.09010 [cs.DB]

Gillespie T. 2018. *Custodians of the Internet: Platforms, Content Moderation, and the Hidden Decisions That Shape Social Media*. New Haven, CT: Yale Univ. Press

Gillespie T, Boczkowski PJ, Foot KA, eds. 2014. *Media Technologies: Essays on Communication, Materiality, and Society*. Cambridge, MA: MIT Press

Giridharadas A. 2018. *Winners Take All: The Elite Charade of Changing the World*. New York: Knopf

Golumbia D. 2009. *The Cultural Logic of Computation*. Cambridge, MA: Harvard Univ. Press

Grace K, Salvatier J, Dafoe A, Zhang B, Evans O. 2018. When will AI exceed human performance? Evidence from AI experts. arXiv:1705.08807 [cs]

Gray M, Suri S. 2019. *Ghost Work: How to Stop Silicon Valley from Building a New Global Underclass*. Boston: Houghton Mifflin Harcourt

Green B. 2019. *The Smart Enough City: Putting Technology in Its Place to Reclaim Our Urban Future*. Cambridge, MA: MIT Press

Gregg M. 2018. *Counterproductive: Time Management in the Knowledge Economy*. Durham, NC: Duke Univ. Press

Guseva A, Rona-Tas A. 2001. Uncertainty, risk, and trust: Russian and American credit card markets compared. *Am. Sociol. Rev.* 66(5):623–46

Haggerty K, Ericson R. 2000. The surveillant assemblage. *Br. J. Sociol.* 51(4):605–22

Hancock JT, Naaman M, Levy K. 2020. AI-mediated communication: definition, research agenda, and ethical considerations. *J. Comput. Mediated Commun.* 25(1):89–100

Hanna A, Denton E, Amironesei R, Smart A, Nicole H. 2020. Lines of sight. *Logic Magazine*, Dec. 20. **https://logicmag.io/commons/lines-of-sight/**

Harari YN. 2017. *Homo Deus: A Brief History of Tomorrow*. New York: Harper

Haraway D. 1990. *Simians, Cyborgs, and Women: The Reinvention of Nature*. New York: Routledge

Harcourt BE. 2007. *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age*. Chicago: Univ. Chicago Press

Harcourt BE. 2015. *Exposed: Desire and Disobedience in the Digital Age*. Cambridge, MA: Harvard Univ. Press

Hawgood A. 2020. Everyone is gay on TikTok. *The New York Times*, Oct. 24. **https://www.nytimes.com/2020/10/24/style/tiktok-gay-homiesexuals.html**

Herring C. 2014. The new logics of homeless seclusion: homeless encampments in America's West Coast cities. *City Community* 13(4):285–309

Hilbert M, López P. 2011. The world's technological capacity to store, communicate, and compute information. *Science* 332(6025):60–65

Hofman JM, Sharma A, Watts DJ. 2017. Prediction and explanation in social systems. *Science* 355(6324):486–88

Hong S. 2016. Data's intimacy: machinic sensibility and the quantified self. *Communication +1*. 5:3

Hong S. 2020. *Technologies of Speculation: The Limits of Knowledge in a Data-Driven Society*. New York: NYU Press

Huws U. 2014. *Labor in the Global Digital Economy: The Cybertariat Comes of Age*. New York: NYU Press

Hwang T. 2020. *Subprime Attention Crisis: Advertising and the Time Bomb at the Heart of the Internet*. New York: Farrar, Straus and Giroux

Irani LC, Silberman MS. 2013. Turkopticon: interrupting worker invisibility in Amazon Mechanical Turk. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 611–20. New York: ACM

Jefferson B. 2020. *Digitize and Punish: Racial Criminalization in the Digital Age*. Minneapolis: Univ. Minn. Press

Johns F. 2021. Governance by data. *Annu. Rev. Law Soc. Sci.* 17:In press

Jonas A, Burrell J. 2019. Friction, snake oil, and weird countries: cybersecurity systems could deepen global inequality through regional blocking. *Big Data Soc*. 6(1). **https://doi.org/10.1177/2053951719835238**

Jones ML. 2017. The right to a human in the loop: political constructions of computer automation and personhood. *Soc. Stud. Sci.* 47(2):216–39

Kahneman D. 2013. *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux

Kalleberg AL, Vallas SP. 2018. Probing precarious work: theory, research, and politics. In *Research in the Sociology of Work*, Vol. 31, ed. S Vallas, pp. 1–30. Bingley, UK: Emerald

Kapczynski A. 2020. The law of informational capitalism. *Yale Law J.* (129):1460–515

Kellogg KC, Valentine MA, Christin A. 2020. Algorithms at work: the new contested terrain of control. *ANNALS* 14(1):366–410

Kiviat B. 2019a. The art of deciding with data: evidence from how employers translate credit reports into hiring decisions. *Socioecon. Rev.* 17(2):283–309

Kiviat B. 2019b. The moral limits of predictive practices: the case of credit-based insurance scores. *Am. Sociol. Rev.* 84(6):1134–58

Komisar R. 2000. *The Monk and the Riddle: The Education of a Silicon Valley Entrepreneur*. Boston: Harv. Bus. Sch. Press

Koopman C. 2019. *How We Became Our Data: A Genealogy of the Informational Person*. Chicago: Univ. Chicago Press

Krippner GR. 2017. Democracy of credit: ownership and the politics of credit access in late twentieth-century America. *Am. J. Sociol.* 123(1):1–47

Lande B, Mangels L. 2017. The value of the arrest: the symbolic economy of policing. *Eur. J. Sociol.* 58(1):73–112

Lauer J. 2017. *Creditworthy: A History of Consumer Surveillance and Financial Identity in America*. New York: Columbia Univ. Press

Lessig L. 2000. *Code: And Other Laws of Cyberspace*. New York: Basic

Levy K, Barocas S. 2018. Refractive surveillance: monitoring customers to manage workers. *Int. J. Commun.* 12:1166–88

Liu C. 2019. Multiple social credit systems in China. *Eur. Econ. Sociol. Newsl.* 21(1):22–32

Lyon D. 2009. *Identifying Citizens: ID Cards as Surveillance*. Cambridge, UK: Polity

Lyon D. 2015. *Surveillance After Snowden*. New York: Wiley

MacKenzie D. 2018. 'Making', 'taking' and the material political economy of algorithmic trading. *Econ. Soc.* 47(4):501–23

Marron D. 2009. *Consumer Credit in the United States: A Sociological Perspective from the 19th Century to the Present*. New York: Palgrave Macmillan

Marsh S. 2020. Councils scrapping use of algorithms in benefit and welfare decisions. *The Guardian*, Aug. 24. **https://www.theguardian.com/society/2020/aug/24/councils-scrapping-algorithms-benefit-welfare-decisions-concerns-bias**

Marx K. 1920. *The Poverty of Philosophy*. Chicago: Charles H. Kerr

Mills CW. 2000. *The Power Elite.* Oxford, UK: Oxford Univ. Press

Morozov E. 2013. *To Save Everything, Click Here: The Folly of Technological Solutionism*. New York: PublicAffairs

Morozov E. 2015. Socialize the data centres! *New Left Review*, Jan./Feb. **https://newleftreview.org/issues/ii91/articles/evgeny-morozov-socialize-the-data-centres**

Narayanan A. 2019. 21 fairness definitions and their politics. In *Fairness and Machine Learning*, ed. S Barocas, M Hardt, A Narayanan. **https://fairmlbook.org/**

Neff G, Nafus D. 2016. *Self-Tracking*. Cambridge, MA: MIT Press

Nelson A. 2016. *The Social Life of DNA: Race, Reparations, and Reconciliation After the Genome*. Boston: Beacon

Nissenbaum H. 2009. *Privacy in Context: Technology, Policy, and the Integrity of Social Life*. Stanford, CA: Stanford Law

Noble SU. 2018. *Algorithms of Oppression: How Search Engines Reinforce Racism*. New York: NYU Press

Obermeyer Z, Emanuel EJ. 2016. Predicting the future—big data, machine learning, and clinical medicine. *N. Engl. J. Med.* 375(13):1216–19

Obermeyer Z, Lee TH. 2017. Lost in thought—the limits of the human mind and the future of medicine. *N. Engl. J. Med.* 377(13):1209–11

Obermeyer Z, Powers B, Vogeli C, Mullainathan S. 2019. Dissecting racial bias in an algorithm used to manage the health of populations. *Science* 366(6464):447–53

Ohlberg M, Ahmed S, Lang B. 2017. Central planning, local experiments: the complex implementation of China's social credit system. *Merics China Monitor*, Dec. 12. **https://merics.org/en/report/central-planning-local-experiments**

O'Mara M. 2019. *The Code: Silicon Valley and the Remaking of America*. New York: Penguin

O'Neill C. 2016. *Weapons of Math Destruction*. New York: Crown

O'Reilly T. 2010. Government as a platform. In *Open Government: Collaboration, Transparency, And Participation In Practice*, ed. D Lathrop, L Ruma, pp. 11–40. Sebastopol, CA: O'Reilly

Pardo-Guerra JP. 2019. *Automating Finance: Infrastructures, Engineers, and the Making of Electronic Markets*. Cambridge, UK: Cambridge Univ. Press

Pasquale F. 2015. *The Black Box Society*. Cambridge, MA: Harvard Univ. Press

Pasquale F. 2019. A rule of persons, not machines: the limits of legal automation. *George Wash. Law Rev.* 87(1):1–55

Pistor K. 2019. *The Code of Capital: How the Law Creates Wealth and Inequality*. Princeton, NJ: Princeton Univ. Press

Poon M. 2009. From new deal institutions to capital markets: commercial consumer risk scores and the making of subprime mortgage finance. *Account. Organ. Soc.* 34(5):654–74

Porter TM. 1996. *Trust in Numbers*. Princeton, NJ: Princeton Univ. Press

Rachlinski JJ, Wistrich AJ. 2017. Judging the judiciary by the numbers: empirical research on judges. *Annu. Rev. Law Soc. Sci.* 13:203–29

Radin MJ. 2013. *Boilerplate: The Fine Print, Vanishing Rights, and the Rule of Law*. Princeton, NJ: Princeton Univ. Press

Rafalow MH. 2020. *Digital Divisions: How Schools Create Inequality in the Tech Era*. Chicago: Univ. Chicago Press

Rao U, Nair V. 2019. Aadhaar: governing with biometrics. *South Asia J. South Asian Stud.* 42(3):469–81

Rheingold H. 1993. *The Virtual Community: Homesteading on the Electronic Frontier*. Reading, MA: Addison-Wesley

Ribes D, Hoffman AS, Slota SC, Bowker GC. 2019. The logic of domains. *Soc. Stud. Sci.* 49(3):281–309

Roberts ST. 2019. *Behind the Screen: Content Moderation in the Shadows of Social Media*. New Haven, CT: Yale Univ. Press

Rona-Tas A. 2017. The off-label use of consumer credit ratings. *Historical Soc. Res.* 42:52–76

Rosenblat A. 2019. *Uberland: How Algorithms Are Rewriting the Rules of Work*. Berkeley: Univ. Calif. Press

Rosental C. 2013. Toward a sociology of public demonstrations. *Sociol. Theory* 31(4):343–65

Russell S. 2019. *Human Compatible: Artificial Intelligence and the Problem of Control*. New York: Viking

Sadowski J. 2020. *Too Smart: How Digital Capitalism Is Extracting Data, Controlling Our Lives, and Taking Over the World*. Cambridge, MA: MIT Press

Salehi N, Irani LC, Bernstein MS, Alkhatib A, Ogbe E, et al. 2015. We are dynamo: overcoming stalling and friction in collective action for crowd workers. In *CHI '15: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pp. 1621–30. New York: ACM

Salganik MJ, Lundberg I, Kindel AT, Ahearn CE, Al-Ghoneim K, et al. 2020. Measuring the predictability of life outcomes with a scientific mass collaboration. *PNAS* 117(15):8398

Sampson RJ. 2016. The characterological imperative: on Heckman, Humphries, and Kautz's *The Myth of Achievement Tests: The GED and the Role of Character in American Life*. *J. Econ. Lit.* 54(2):493–513

Schneider D, Harknett K. 2019. Consequences of routine work-schedule instability for worker health and well-being. *Am. Sociol. Rev.* 84(1):82–114

Scholz T, Schneider N, eds. 2016. *Ours to Hack and to Own: The Rise of Platform Cooperativism, a New Vision for the Future of Work and a Fairer Internet*. New York: OR Books

Schor J. 2020. *After the Gig: How the Sharing Economy Got Hijacked and How to Win It Back*. Berkeley: Univ. Calif. Press

Schradie J. 2019. *The Revolution that Wasn't: How Digital Activism Favors Conservatives*. Cambridge, MA: Harvard Univ. Press

Schüll N. 2012. *Addiction by Design: Machine Gambling in Las Vegas*. Princeton, NJ: Princeton Univ. Press

Schüll N. 2016. Data for life: wearable technology and the design of self-care. *BioSocieties* 11(3):317–33

Scott JC. 1999. *Seeing Like a State: How Certain Schemes to Improve the Human Condition Have Failed*. New Haven, CT: Yale Univ. Press

Shestakofsky B. 2017. Working algorithms: software automation and the future of work. *Work Occup*. 44(4):376–423

Simon J. 1988. The ideological effects of actuarial practices. *Law Soc. Rev*. 22(4):771–800

Sommelier E, Price M. 2018. *The new gilded age: income inequality in the U.S. by state, metropolitan area, and county*. Rep., Econ. Policy Inst., Washington, DC. **https://www.epi.org/publication/the-new-gilded-age-income-inequality-in-the-u-s-by-state-metropolitan-area-and-county/**

Stark L. 2018. Algorithmic psychometrics and the scalable subject. *Soc. Stud. Sci*. 48(2):204–31

Stuart F. 2020. *Ballad of the Bullet: Gangs, Drill Music, and the Power of Online Infamy*. Princeton, NJ: Princeton Univ. Press

Suchman L. 2020. Algorithmic warfare and the reinvention of accuracy. *Crit. Stud. Secur.* 8:175–87

Suchman LA. 2007. *Human-Machine Reconfigurations*. Cambridge, UK: Cambridge Univ. Press

Sweeney L. 2013. Discrimination in online ad delivery. *ACM Queue* 11(3):1–19

Tegmark M. 2017. *Life 3.0: Being Human in the Age of Artificial Intelligence*. New York: Knopf

Thompson C. 2020. *Coders: The Making of a New Tribe and the Remaking of the World*. New York: Penguin

Thrift N. 2000. "It's the romance, not the finance, that makes the business worth pursuing": disclosing a new market culture. *Econ. Soc*. 30(4):412–32

Tomaskovic-Devey D, Han J. 2018. *Is Silicon Valley tech diversity possible now?* Cent. Employ. Equity, Univ. Mass., Amherst, MA

Tufekci Z. 2017. *Twitter and Tear Gas: The Power and Fragility of Networked Protest*. New Haven, CT: Yale Univ. Press

Turner F. 2006. *From Counterculture to Cyberculture: Stewart Brand, the Whole Earth Network, and the Rise of Digital Utopianism*. Chicago: Univ. Chicago Press

Turner F. 2009. Burning Man at Google: a cultural infrastructure for new media production. *New Media Soc*. 11(1–2):73–94

Uliasz R. 2020. Seeing like an algorithm: operative images and emergent subjects. *AI Soc*. **https://doi.org/10.1007/s00146-020-01067-y**

Vaidhyanathan S. 2018. *Antisocial Media: How Facebook Disconnects Us and Undermines Democracy*. Oxford, UK: Oxford Univ. Press

Vertesi J, Goldstein A, Enriquez D, Liu L, Miller K. 2020. Pre-automation: labor in the era of platform monopolies. *Sociologica* 14(3):167–93

Volokh E. 2019. Chief Justice Robots. *Duke Law J*. 68(6):1135–92

von Hayek FA. 1989. The pretence of knowledge. *Am. Econ. Rev*. 79(6):3–7

Walker RA. 2018. *Pictures of a Gone City: Tech and the Dark Side of Prosperity in the San Francisco Bay Area*. Oakland, CA: PM

Watts DJ. 2011. *Everything Is Obvious: How Common Sense Fails Us*. New York: Crown Bus.

Watts DJ. 2014. Common sense and sociological explanations. *Am. J. Sociol*. 120(2):313–51

Weber M. 1978. *Economy and Society: An Outline of Interpretive Sociology*. Berkeley: Univ. Calif. Press

Weinberger D. 2019. How machine learning pushes us to define fairness. *Harvard Business Review*, Nov. 6. **https://hbr.org/2019/11/how-machine-learning-pushes-us-to-define-fairness**

Ziewitz M. 2019. Rethinking gaming: the ethical work of optimization in web search engines. *Soc. Stud. Sci*. 49(5):707–31

Zuboff S. 2019. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. New York: PublicAffairs