
BOOK REVIEW

DIGITIZING THE CARCERAL STATE

AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR. By Virginia Eubanks. New York, N.Y.: St. Martin's Press. 2018. Pp. 260. \$26.99.

*Reviewed by Dorothy E. Roberts**

Many life-changing interactions between individuals and state agents in the United States today are determined by a computer-generated score.¹ Government agencies at the local, state, and federal levels increasingly make automated decisions based on vast collections of digitized information about individuals and mathematical algorithms that both catalogue their past behavior and assess their risk of engaging in future conduct.² Big data, predictive analytics, and automated decisionmaking are used in every major type of state system, including law enforcement, national security, public assistance, health care, education, and child welfare.³ The federal government has pumped billions of

* George A. Weiss University Professor of Law & Sociology, Raymond Pace and Sadie Tanner Mossell Alexander Professor of Civil Rights, Professor of Africana Studies, University of Pennsylvania. Penn Law student Rachel Baker Mann provided excellent research assistance for this Review.

¹ See, e.g., CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION 3–14 (2016) (explaining that computer-generated scores inform decisions about teacher evaluation, criminal sentencing, and consumer finance); FILIPPO A. RASO ET AL., BERKMAN KLEIN CTR., ARTIFICIAL INTELLIGENCE & HUMAN RIGHTS: OPPORTUNITIES & RISKS (2018), <https://ssrn.com/abstract=3259344> [<https://perma.cc/V446-C6JS>] (discussing how artificial intelligence affects human rights in the contexts of criminal justice, credit scores, health care, human resources, and education).

² See generally BERNARD E. HARCOURT, AGAINST PREDICTION (2007); VIKTOR MAYER-SCHÖNBERGER & KENNETH CUKIER, BIG DATA (2013); O'NEIL, *supra* note 1; FRANK PASQUALE, THE BLACK BOX SOCIETY (2015).

³ See O'NEIL, *supra* note 1, at 134–40 (discussing models that score public school teachers' performance); Bill Cope & Mary Kalantzis, *Big Data Comes to School: Implications for Learning, Assessment, and Research*, 2 AERA OPEN 1 (2016), <https://journals.sagepub.com/doi/abs/10.1177/2332858416641907> [<https://perma.cc/YA8G-WAW3>]; Kevin Miller, *Total Surveillance, Big Data, and Predictive Crime Technology: Privacy's Perfect Storm*, 19 J. TECH. L. & POL'Y 105, 107 (2014) (describing “total surveillance, big data analytics, and actuarial trends in policing” as a “triple threat” to privacy); Nicolas Terry, *Navigating the Incoherence of Big Data Reform Proposals*, 43 J.L. MED. & ETHICS (SUPPLEMENT) 44, 44 (2015) (“The health care industry will be a large customer of big data while predictive analytics already underlie important health care and public health initiatives.”); Damien Van Puyvelde et al., *Beyond the Buzzword: Big Data and National Security Decision-Making*, 93 INT'L AFF. 1397, 1398 (2017) (“In the US intelligence community big data has become institutionalized”); Press Release, White House, Office of the Press Sec'y, Fact Sheet: First Ever White House Foster Care & Technology Hackathon (May 26, 2016), <https://obamawhitehouse.archives.gov/the-press-office/2016/05/26/fact-sheet-first-ever-white-house-foster-care-technology-hackathon> [<https://perma.cc/23M2-W2UA>] (listing a number of measures the

dollars not only into its own data reservoirs, but also into state and local efforts to digitize government operations.⁴

Government officials claim their expanding use of big data will improve the accuracy, efficiency, and neutrality of their decisions.⁵ But big data has been met by a tremendous chorus of alarm. These concerns have centered paradoxically on claims that there is both too little and too much automation. On one hand, some scholars and advocates have criticized the “digital divide” created by the unequal distribution of access to technological innovations.⁶ In this view, inequality in big data stems from the lack of opportunities socially disadvantaged groups have to share in its benefits. Alternatively, some experts argue that digitized tools can increase equality in access to public resources. For example, adopting online platform technologies that move away from a face-to-face model for handling legal disputes may enhance access to justice by giving more people opportunities to interact with government agencies such as state courts⁷ and to utilize government assistance such as legal services.⁸

On the other hand, numerous commentators have pointed to the dangers of state overreliance on big data. These dissenters warn that the mushrooming technological surveillance of citizens threatens to invade individuals’ privacy and erode government accountability at an unprecedented scale.⁹ According to this view, citizens should demand more regulation to protect their personal data and subject automated decisionmaking to greater public scrutiny.¹⁰ The European Union, for example, recently enacted a new data privacy law “designed to give individuals the right to control their own information.”¹¹

Obama Administration implemented “to increase the use of technology and improve outcomes in the foster care system”).

⁴ See Sara Friedman, *State Data Officers Offer Feedback on Federal Data Strategy*, GCN (July 31, 2018), <https://gcn.com/articles/2018/07/31/state-cdo-federal-data-strategy.aspx> [<https://perma.cc/E8H2-QRFJ>].

⁵ See Press Release, White House, *supra* note 3 (announcing a convening hosted by the White House, the U.S. Department of Health and Human Services, and Think of Us to “discuss ways to improve our foster care system through the use of technology”); see also William M. Grove et al., *Clinical Versus Mechanical Prediction: A Meta-Analysis*, 12 PSYCHOL. ASSESSMENT 19, 19 (2000) (finding that mechanical predictions of human health and behavior “were about 10% more accurate than clinical predictions”). *But see* Miller, *supra* note 3, at 118–22 (discussing the technological and methodological limitations of predictive systems).

⁶ Jan A.G.M. van Dijk, *Digital Divide Research, Achievements and Shortcomings*, 34 POETICS 221, 221–22 (2006).

⁷ J.J. Prescott, *Improving Access to Justice in State Courts with Platform Technology*, 70 VAND. L. REV. 1993, 1996–99 (2017).

⁸ James E. Cabral et al., *Using Technology to Enhance Access to Justice*, 26 HARV. J.L. & TECH. 241, 246 (2012).

⁹ See sources cited *supra* note 2.

¹⁰ See O’NEIL, *supra* note 1, at 213–14.

¹¹ Jacob Weisberg, *The Digital Poorhouse*, N.Y. REV. BOOKS (June 7, 2018), <https://www.nybooks.com/articles/2018/06/07/algorithms-digital-poorhouse/> [<https://perma.cc/HY8X-FSE7>] (describing the European Union’s General Data Protection Regulation).

While important, these concerns about access to and protection from big data fail to capture a critical aspect of automation's danger to society. Government digitization is not inherently or universally beneficial or harmful. Rather, the outcomes of big data depend on the particular ideologies, aims, and methods that govern its use. In the United States today, government digitization targets marginalized groups for tracking and containment in order to exclude them from full democratic participation. The key features of the technological transformation of government decisionmaking — big data, automation, and prediction — mark a new form of managing populations that reinforces existing social hierarchies. Without attending to the ways the new state technologies implement an unjust social order, proposed reforms that focus on making them more accurate, visible, or widespread will make oppression operate more efficiently and appear more benign.

Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor by political scientist Virginia Eubanks significantly advances our understanding of the threat to social equality posed by government use of big data by examining how it functions in public assistance programs. Based on in-depth investigations of three systems, she describes how their eligibility determinations, which are based on computerized risk assessments, constitute a modern system for regulating poor and working-class people. Eubanks systematically explores the automated eligibility system the state of Indiana adopted for its welfare services (pp. 39–83), the electronic registry of unhoused people living in Los Angeles's Skid Row (pp. 84–126), and the statistical model used in Allegheny County, Pennsylvania, that is an adaptation of a model developed by researchers in New Zealand to score families according to 132 variables that predict future cases of child maltreatment (pp. 127–73). Each program illustrates a different aspect of high-tech shadow mechanisms for regulating the poor: they divert poor people from public resources (Indiana); classify and criminalize them (Los Angeles); and punish them based on predictions of their future behavior (Allegheny County) (pp. 179–82). Eubanks's analysis extends beyond concerns about data privacy and access to data to unveil "the new digital infrastructure of poverty relief" constructed with high-tech monitoring tools (p. 11). Eubanks argues that government agencies are using computer technologies to "target, track, and punish" poor people in ways that divert attention from the need for social change and erode democracy for everyone (p. 178). Thus, *Automating Inequality* expands the literature criticizing how government use of big data reflects existing social inequalities to show how big data helps agencies structure state programs to create new punitive and antidemocratic modes of social control.

Eubanks's investigation of digitized public welfare programs refutes dominant perspectives that view the growth of big data as both a positive and a negative development. First, Eubanks shows that agencies'

reliance on computer software to generate risk scores doesn't make decisionmaking more objective (pp. 142, 153). The algorithms the agencies use build biases into decisionmaking processes, shielding agency determinations even more from government accountability (pp. 79, 167). Second, Eubanks finds that high-tech tools don't radically improve state agencies' ability to address poverty (pp. 197–200). Rather, she concludes that technological innovations reconstitute the nineteenth-century poorhouse as a modern day “digital poorhouse” (p. 12). The contemporary system is undergirded with the same ideologies that blame poor people for their disadvantaged social position but upgraded with the ability to monitor and punish them more efficiently (pp. 12, 17). Today's digital revolution is but the latest in a history of innovations in poverty management. “[T]he new regime of data analytics is more evolution than revolution,” Eubanks writes. “It is simply an expansion and continuation of moralistic and punitive poverty management strategies that have been with us since the 1820s” (p. 37).

Finally, Eubanks's analysis reveals that proposals to bridge the “digital divide” by assuring greater inclusion in technological progress badly miss the mark. “I found that poor and working-class women in my hometown of Troy, New York, were not ‘technology poor,’ as other scholars and policy-makers assumed,” observes Eubanks. “Data-based systems were ubiquitous in their lives . . .” (p. 8). Big data critics who decry a universal invasion of the public's privacy make a similar mistake by failing to attend to the way state surveillance concentrates on poor people with an intensity unknown to middle-class and wealthy Americans. To tackle the government's expanding reliance on automated analytics, we must understand it in terms of the particular ways it is structured to reinforce unjust hierarchies of power.

Eubanks's astute interpretation of big data analytics as poverty management provides critical yet partial insight into modern day state oppression. *Automating Inequality* shines a needed spotlight on government assistance programs the public is more likely to view as benevolent than as punitive. The key aspects Eubanks highlights — big data collection, automated decisionmaking, and predictive analytics — also characterize expanding high-tech approaches to criminal justice.¹² Taking account of both civil and criminal state surveillance systems reveals a coherent carceral form of governance that extends far beyond prisons to deal with problems caused by structural inequalities by punishing the very people suffering most from them (p. 177). In addition, all of the oppressive features Eubanks describes result from racism as much as disdain for poor people. Computerized risk assessments and determinations regulate people on the basis of race as well as economic status:

¹² See *infra* Part II, pp. 1707–21.

“Though these new systems have the most destructive and deadly effects in low-income communities of color, they impact poor and working-class people across the color line” (p. 12).¹³ Her central insight, that digital systems are structured to maintain an unjust class order, applies equally to the systems’ reinforcement of white supremacy.

In this Review, I expand Eubanks’s focus on state welfare programs to include a broader range of systems, with particular attention to the criminal justice system, and Eubanks’s focus on poverty management to include white supremacy. This more comprehensive analysis illuminates how computerized prediction is fundamental to the ideology, methods, and impact of the modern mode of social control in the United States — the digitized carceral state. My analysis of the role big data, automation, and prediction play in carceral governance proceeds as follows. Part I provides a holistic portrait of the carceral state, which extends beyond prisons to encompass multiple institutions that are supposed to serve people’s needs. This punitive regime includes criminal law enforcement, education, and health care, as well as the poverty-relief and child-protection systems Eubanks describes. By examining the way the prison, foster care, and welfare systems operate together to punish black mothers in particular, I show the importance of attending to racism, along with sexism and classism, in understanding the proliferation of carceral responses to social inequality. Part II explores how automated decisionmaking works to implement carceral governance. Despite claims that computerized prediction is objective, its databases and algorithms build in unequal social structures and ideologies that create new modes of state surveillance and control in marginalized communities. Adding to Eubanks’s focus on poverty management, I argue that racism is central to the carceral state’s reliance on prediction and embedded in predictive policing. Part III concludes by advocating for an abolitionist approach to contesting the digitized carceral state. While agreeing with Eubanks’s call to dismantle the digital poorhouse rather than reform it, I argue that acknowledging racism’s crucial role in carceral governance accentuates the need for explicitly antiracist strategies to build a viable movement for change.

I. THE CARCERAL STATE: BEYOND PRISONS AND POVERTY MANAGEMENT

The automated system of poverty management described in *Automating Inequality* is part of a broader trend in punitive governance.

¹³ See SAFIYA NOBLE, *ALGORITHMS OF OPPRESSION* 80–104 (2018) (discussing how allegedly neutral search engines like Google discriminate against African Americans); *see also* RUHA BENJAMIN, *RACE AFTER TECHNOLOGY* (forthcoming 2019) (discussing multiple ways in which emerging technologies encode white supremacy).

In recent decades, U.S. policies have drastically cut social programs and transferred their services to the private realm of market, family, and individual while promoting the free-market conditions conducive to capital accumulation.¹⁴ At the same time federal, state, and local governments were dismantling the social safety net, they dramatically expanded their coercive functions, including increasing incarceration at unprecedented rates.¹⁵ The regime of state privatization, a critical part of neoliberalism, entails the simultaneous intensification of brutal state intervention in the very communities most devastated by the evisceration of public resources.¹⁶

A growing body of scholarship documents that this punitive regime extends far beyond prisons.¹⁷ By exposing this trend in poverty relief programs, *Automating Inequality* contributes to this literature and details an important part of a larger carceral regime. All institutions in the United States increasingly address social inequality by punishing the communities that are most marginalized by it.¹⁸ Systems that ostensibly exist to serve people's needs — health care, education, and public housing, as well as public assistance and child welfare — have become behavior modification programs that regulate the people who rely on them,¹⁹ and these systems resort to a variety of punitive measures to enforce compliance. In addition, state and federal civil laws, such as landlord-tenant and banking codes, assist private market actors to impose harsh penalties on members of these same communities.²⁰ Mirroring the two sides of neoliberalism, computerized tools help state agencies

¹⁴ See DAVID HARVEY, A BRIEF HISTORY OF NEOLIBERALISM 5–38 (2005).

¹⁵ See MICHELLE ALEXANDER, THE NEW JIM CROW 58–94 (2010).

¹⁶ See HENRY A. GIROUX, THE TERROR OF NEOLIBERALISM 54–80 (2004); LOÏC WACQUANT, PUNISHING THE POOR 195–208 (2009); see also RUTH WILSON GILMORE, GOLDEN GULAG 88 (2007) (linking California's prison expansion to surpluses of labor, land, and financial capital).

¹⁷ See, e.g., KAARYN S. GUSTAFSON, CHEATING WELFARE 44–46 (2011); MONIQUE W. MORRIS, PUSHOUT: THE CRIMINALIZATION OF BLACK GIRLS IN SCHOOLS 135–69 (2015); JOE SOSS ET AL., DISCIPLINING THE POOR 138–40 (2011); WACQUANT, *supra* note 16, at 108–09.

¹⁸ See SOSS ET AL., *supra* note 17; WACQUANT, *supra* note 16, at 3.

¹⁹ See KHIARA M. BRIDGES, REPRODUCING RACE 23–24, 147–52 (2011); MORRIS, *supra* note 17, at 4–5; ANNA MARIE SMITH, WELFARE REFORM AND SEXUAL REGULATION 2–3 (2007); Priscilla A. Ocen, *The New Racially Restrictive Covenant: Race, Welfare, and the Policing of Black Women in Subsidized Housing*, 59 UCLA L. REV. 1540, 1565–68 (2012).

²⁰ See MATTHEW DESMOND, EVICTED 305–08 (2016) (arguing that housing-market exploitation “relies on government support,” *id.* at 307); Ocen, *supra* note 19, at 1568–81 (discussing how police officers and public officials enforce private citizens' discriminatory complaints against black women in publicly subsidized housing); Aaron Glantz & Emmanuel Martinez, *Modern-Day Redlining: How Banks Block People of Color from Homeownership*, CHI. TRIB. (Feb. 17, 2018, 2:30 PM), <https://www.chicagotribune.com/business/ct-biz-modern-day-redlining-20180215-story.html> [https://perma.cc/AJ8B-83YJ]. Private corporations' increasing use of big data, which is outside the scope of this article, is also the subject of scholarly concern. See, e.g., O'NEIL, *supra* note 1; PASQUALE, *supra* note 2.

both exclude people from public resources and target them for surveillance and punishment. State policing and violence not only occur in poverty management outside the criminal justice system (pp. 214–15), but also are entangled with criminal law enforcement to form a cohesive punitive apparatus.

A defining feature of government agencies' carceral approach is the imposition of punishment as part of providing needed state support. People who rely on Medicaid, Temporary Assistance for Needy Families, and child protective services are denied privacy rights and must permit otherwise unconstitutional state intrusions into their lives justified by the theory that they waived their rights as a condition of receiving benefits.²¹ Welfare receipt comes with intense surveillance by government agents — including home inspections and behavioral requirements.²² Under the Personal Responsibility and Work Opportunity Reconciliation Act of 1996,²³ “welfare ceased being an entitlement and became instead a behavior modification program to control the sexual and reproductive decisions of cash poor mothers.”²⁴ Supported by stereotypes of black “Welfare Queens,” Congress sought to deter recipients' childbearing and pressure them to get married as solutions to female poverty.²⁵

Soon after the welfare safety net was abandoned in 1996, Congress passed the Adoption and Safe Families Act²⁶ (ASFA), which stressed the role of adoption as a way to curb the rise of foster care. “Like welfare restructuring, ASFA was promoted by the racially explicit vilification of black mothers.”²⁷ ASFA proponents called upon states to “free” black children for adoption by speeding up termination of their mothers' rights.²⁸ At the same time, Congress appropriated diminishing funds for family preservation and reunification while spending increasing amounts on foster care and adoption assistance.²⁹ These 1990s reforms

²¹ See KHIARA M. BRIDGES, *THE POVERTY OF PRIVACY RIGHTS* 65–68, 73, 85–86 (2017); Dorothy E. Roberts, *Welfare and the Problem of Black Citizenship*, 105 *YALE L.J.* 1563, 1576–84 (1996) (book review).

²² See Roberts, *supra* note 21, at 1576–84.

²³ Pub. L. No. 104-193, 110 Stat. 2105 (codified as amended in scattered sections of U.S. Code).

²⁴ DOROTHY E. ROBERTS, *KILLING THE BLACK BODY*, at xvi (2d ed. 2017); see also GUSTAFSON, *supra* note 17, at 44–46; GWENDOLYN MINK, *WELFARE'S END* 7–8, 30–31, 50–51, 61, 133–39 (1998); SMITH, *supra* note 19, at 18, 89, 93–94, 116–19.

²⁵ ANGE-MARIE HANCOCK, *THE POLITICS OF DISGUST* 12–14 (2004).

²⁶ Pub. L. No. 105-89, 111 Stat. 2115 (1997) (codified as amended in scattered sections of 42 U.S.C.).

²⁷ Dorothy E. Roberts, *Critical Race Feminism*, in *RESEARCH HANDBOOK ON FEMINIST JURISPRUDENCE* 112, 122 (Robin West & Cynthia Grant Bowman eds., 2019) [hereinafter Roberts, *Critical Race*]; see also DOROTHY ROBERTS, *SHATTERED BONDS: THE COLOR OF CHILD WELFARE* 167–68 (2002) [hereinafter ROBERTS, *SHATTERED BONDS*].

²⁸ See ROBERTS, *SHATTERED BONDS*, *supra* note 27, at 109, 167.

²⁹ See EMILIE STOLTZFUS, *CONG. RESEARCH SERV.*, R43458, *CHILD WELFARE: AN OVERVIEW OF FEDERAL PROGRAMS AND THEIR CURRENT FUNDING* 1, 5–6, 13 (2017), <https://fas.org/sgp/crs/misc/R43458.pdf> [<https://perma.cc/F7YR-XJYR>].

were neoliberal measures that replaced public aid for struggling families with reliance on low-wage work, marriage, and adoptive parents to meet families' needs.

As Eubanks observes, “[p]oor and working-class families feel forced to trade their rights to privacy, protection from unreasonable searches, and due process for a chance at the resources and services they need to keep their children safe” (p. 158). The child welfare system exerts a particularly onerous penalty for parents to receive state resources to care for their children. For many parents involved in the system, the price of accessing resources from child welfare agencies is relinquishing custody of their children (p. 161).³⁰ Social workers have at their disposal an assortment of assistance mechanisms for families, including cash payments, food stamps, furniture, parent counseling, and drug treatment services; but most of this assistance is available only to parents whose children have been placed in foster care.³¹ Eubanks found that the Allegheny County parents she interviewed had “deeply mixed feelings” about the agency’s punitive approach: “While they describe frightening, frustrating experiences, they are also grateful for the support and resources they received” (p. 152).

I discovered the same reaction in my 2006 study of attitudes about the Department of Children and Family Services (DCFS) in Woodlawn, a predominantly black neighborhood in Chicago with an extremely high rate of child welfare agency involvement.³² I called this reaction the paradox of neighborhood involvement: “Although respondents criticized the agency’s damage to neighborhood relationships, they nevertheless recognized neighborhood reliance on DCFS to meet the material needs of its struggling families.”³³ Thus, most of the women I interviewed called for more agency involvement in Woodlawn to gain access to needed resources, but with “less disruption of family relationships.”³⁴

Another central aspect of the widening carceral web is the entanglement of public welfare services with the criminal justice system. Poverty programs not only seem like criminal law enforcement; they also operate as pathways to prison. Police officers are increasingly the first

³⁰ Dorothy E. Roberts, *Kinship Care and the Price of State Support for Children*, 76 CHI.-KENT L. REV. 1619, 1621, 1628 (2001); Dorothy E. Roberts, *The Racial Geography of Child Welfare: Toward a New Research Paradigm*, 87 CHILD WELFARE 125, 145–46 (2008) [hereinafter Roberts, *Racial Geography*].

³¹ See *State-by-State Data*, CASEY FAM. PROGRAMS (May 16, 2018), <https://www.casey.org/state-data/> [<https://perma.cc/8BEN-WBE2>] (“Most states currently use the bulk of the \$7.3 billion in dedicated federal child welfare funding only for services related to foster care.”).

³² Roberts, *Racial Geography*, *supra* note 30, at 126–28.

³³ *Id.* at 141.

³⁴ *Id.* at 145.

responders to crises caused by social needs.³⁵ As Eubanks notes, “[t]here is a long history of social services and the police collaborating to criminalize the poor in the United States” (p. 116). One of the homeless people she interviewed in Los Angeles, Gary Boatwright, who at age sixty-four had lived on and off the street for ten years, had regular run-ins with law enforcement (pp. 98–100). “In five years, he racked up 25 separate tickets for crimes associated with homelessness: unlawfully entering or remaining in a park, failure to leave land as ordered by a peace officer, storage of personal property in public places, jaywalking, littering, and unauthorized removal of a shopping cart, among others” (pp. 100–01). The reason for this regular involvement with law enforcement is that many of the basic conditions of being homeless are also prohibited as crimes (p. 117).

Receipt of welfare benefits is also increasingly criminalized. Public assistance offices are patrolled by security guards and staff frequently call police to settle disagreements with recipients.³⁶ In December 2018, a guard ordered Jazmine Headley, age twenty-three, to move from the floor of a New York City public-benefits office where she sat down with her one-year-old son after waiting hours to find out why her child-care benefits had been stopped.³⁷ When she refused, police were called to arrest her. A video shows two officers restraining Headley while two guards yank the screaming toddler from her arms. Headley was charged with resisting arrest and child endangerment and spent several days locked in a Rikers Island cell, for this and other unrelated charges, before attorneys were able to get the charges dropped.³⁸

Welfare clients are not only treated like criminals; they are also prosecuted for crimes they might commit in relation to the receipt of public assistance, such as welfare fraud.³⁹ Welfare fraud allegations can

³⁵ See Debanjan Roychoudhury, *On Second Sight, Surveillance and the Black Planet: Notes on a New Framework*, in *THE NEW BLACK SOCIOLOGISTS* 210, 212 (Marcus Anthony Hunter ed., 2018) (citing Amy E. Lerman & Vesla M. Weaver, *Staying Out of Sight? Concentrated Policing and Local Political Action*, 651 *ANNALS AM. ACAD. POL. & SOC. SCI.* 202 (2014)) (“Police contact is the most consistent form of interaction with the state in many [black] communities.”); Zusha Elinson, *When Mental-Health Experts, Not Police, Are the First Responders*, *WALL ST. J.* (Nov. 24, 2018, 10:00 AM), <https://www.wsj.com/articles/when-mental-health-experts-not-police-are-the-first-responders-1543071600> [<https://perma.cc/9CQC-JYJZ>] (noting that in most American cities, police typically respond to mental health crises involving poor and unhoused people).

³⁶ See Ashley Southall & Nikita Stewart, *They Grabbed Her Baby and Arrested Her. Now Jazmine Headley Is Speaking Out.*, *N.Y. TIMES* (Dec. 16, 2018), <https://nyti.ms/2Gkwx29> [<https://perma.cc/9AD4-69FW>] (“Since January 2017, law enforcement agencies have been called to food-stamp offices across the city 2,212 times . . .”).

³⁷ See *id.*

³⁸ See Ben Mathis-Lilley, *Charges Dropped Against Mother from Viral Arrest Video, but She’s Still in Jail (UPDATE: She’s Been Ordered Released)*, *SLATE* (Dec. 11, 2018, 2:43 PM), <https://slate.com/news-and-politics/2018/12/jazmine-headley-charges-dropped-rikers.html> [<https://perma.cc/7EJG-X5D9>].

³⁹ GUSTAFSON, *supra* note 17, at 63–70.

lead not only to civil penalties, but also to felony charges and prison sentences.⁴⁰ Welfare and law enforcement agencies routinely share client records without any judicial process.⁴¹ Eubanks compares the Los Angeles coordinated entry project's transfer of the homeless population records to police as a sting operation that often triggers the arrest and incarceration of unhoused people (pp. 116–17). Similarly, child protective services and police officers forcibly remove children from their homes,⁴² police officers report child maltreatment discovered while investigating crimes,⁴³ and child neglect, which is confused with effects of poverty,⁴⁴ can be the basis of criminal charges.

The carceral state extends beyond the public assistance programs Eubanks discusses. Public schools, too, are now common sites for police surveillance, arrest, and detention of children.⁴⁵ The school-to-prison pipeline is a well-documented pathway in the expanding carceral state that is especially perilous for black children.⁴⁶ The results of a recent survey showed that the probability of a school's using a variety of security measures (including metal detectors, school police and security guards, locked gates, and "random sweeps") was two to eighteen times higher for schools with a student body made up of a majority of people of color than for schools where white children made up more than eighty percent of the student body.⁴⁷ Children attending these heavily policed schools are often arrested for minor misbehaviors like "pushing other students . . . or disobeying a teacher."⁴⁸ The carceral state also runs a

⁴⁰ *Id.*; see also Dorothy E. Roberts, *Prison, Foster Care, and the Systemic Punishment of Black Mothers*, 59 UCLA L. REV. 1474, 1480 (2012).

⁴¹ Kaaryn Gustafson, *The Criminalization of Poverty*, 99 J. CRIM. L. & CRIMINOLOGY 643, 669 (2009).

⁴² See TINA LEE, CATCHING A CASE 79–83, 118–21 (2016); Paul Chill, *Burden of Proof Begone: The Pernicious Effect of Emergency Removal in Child Protective Proceedings*, 41 FAM. CT. REV. 457, 457 (2003).

⁴³ See Katie Wedell, *Ohio Is Only State Where Police Are Not Required to Report Child Abuse*, DAYTON DAILY NEWS (Nov. 15, 2017), <https://www.ajc.com/news/national/ohio-only-state-where-police-are-not-required-report-child-abuse/61ftfl7jU8k1NdqKtIisCI/> [<https://perma.cc/XAB8-WKRV>].

⁴⁴ See LEE, *supra* note 42, at 9–10, 107; ROBERTS, SHATTERED BONDS, *supra* note 27, at 33–39.

⁴⁵ See MORRIS, *supra* note 17, at 66–83; CARLA SHEDD, UNEQUAL CITY 80–119 (2015) (describing the "school disciplinary superstructure," *id.* at 108, that implements a "universal carceral apparatus," *id.* at 84, at predominantly black public high schools in Chicago).

⁴⁶ See, e.g., NANCY A. HEITZEG, THE SCHOOL-TO-PRISON PIPELINE 35–36 (2016); Libby Nelson & Dara Lind, *The School to Prison Pipeline, Explained*, JUST. POL'Y INST. (Feb. 24, 2015), <http://www.justicepolicy.org/news/8775> [<https://perma.cc/D6GF-9T7Y>]; NAACP LEGAL DEF. & EDUC. FUND, INC., DISMANTLING THE SCHOOL-TO-PRISON PIPELINE, https://www.naacpldf.org/wp-content/uploads/Dismantling_the_School_to_Prison_Pipeline__Criminal_Justice_.pdf [<https://perma.cc/366J-TGML>].

⁴⁷ See Jason P. Nance, *Student Surveillance, Racial Inequalities, and Implicit Racial Bias*, 66 EMORY L.J. 765, 810–11 (2017); see also Melinda D. Anderson, *When School Feels Like Prison*, THE ATLANTIC (Sept. 12, 2016), <https://www.theatlantic.com/education/archive/2016/09/when-school-feels-like-prison/499556/> [<https://perma.cc/5GTT-PGLV>].

⁴⁸ NAACP LEGAL DEF. & EDUC. FUND, INC., *supra* note 46.

foster-care-to-prison pipeline: children living in or aging out of foster care are at high risk of incarceration in juvenile detention and adult prisons because of vulnerabilities created by foster care itself.⁴⁹ For example, child welfare authorities frequently have foster children arrested when they run away or break disciplinary rules.⁵⁰

Even the health care system belongs to the carceral state. Law enforcement treats the health problem of drug addiction as a criminal offense. Supported in the 1980s and 1990s by pregnant-crack-addict and crack-baby myths, prosecutors charged hundreds of black women with fetal crimes and child protection agents removed thousands of black newborns from their mothers' care.⁵¹ For many cash-poor Americans, the only place to get mental health care is behind bars. Jails and prisons are some of the largest state providers of mental health care in the United States.⁵² Hospital emergency room staff frequently deny services to poor patients, especially poor patients of color, and turn them over to the police because they suspect the patients of drug seeking or other criminal behavior.⁵³ In December 2015, police officers forcibly removed Barbara Dawson, age fifty-seven, from a Florida hospital⁵⁴ and tried to shove her in a police car while she insisted that she could not breathe.⁵⁵ A short time later, Ms. Dawson died from a blood clot in her lung.⁵⁶ In

⁴⁹ See Melissa Jonson-Reid & Richard P. Barth, *From Placement to Prison: The Path to Adolescent Incarceration from Child Welfare Supervised Foster or Group Care*, 22 CHILD. & YOUTH SERVS. REV. 493, 499–504 (2000); Rachel Anspach, *The Foster Care to Prison Pipeline: What It Is and How It Works*, TEEN VOGUE (May 25, 2018), <https://www.teenvogue.com/story/the-foster-care-to-prison-pipeline-what-it-is-and-how-it-works> [<https://perma.cc/WT9Q-THCA>].

⁵⁰ See, e.g., Ali Watkins, *She Ran Away from Foster Care. She Ended Up in Handcuffs and Leg Irons.*, N.Y. TIMES (Dec. 6, 2018), <https://nyti.ms/2zVuVqf> [<https://perma.cc/BK3U-9GM3>].

⁵¹ DOROTHY E. ROBERTS, KILLING THE BLACK BODY 150–62 (1999).

⁵² See, e.g., Matt Ford, *America's Largest Mental Hospital Is a Jail*, THE ATLANTIC (June 8, 2015), <https://www.theatlantic.com/politics/archive/2015/06/americas-largest-mental-hospital-is-a-jail/395012/> [<https://perma.cc/95PA-GBG4>] (reporting on the country's history of deinstitutionalization and incarceration of the mentally ill); see also Jason Schnittker et al., *Incarceration and the Health of the African American Community*, 8 DU BOIS REV. 133, 135 (2011) (discussing evidence that “incarceration negatively impacts health” and “any positive short-term effects of incarceration are likely outweighed by its long-term negative effects”).

⁵³ See Armando Lara-Millán, *Public Emergency Room Overcrowding in the Era of Mass Imprisonment*, 79 AM. SOC. REV. 866, 873–77 (2014).

⁵⁴ Shamar Walters & Jacquellena Carrero, *Barbara Dawson, Florida Woman, Dies After Being Removed from Hospital*, NBC NEWS (Dec. 23, 2015, 9:00 PM), <https://www.nbcnews.com/news/us-news/barbara-dawson-florida-woman-dies-after-being-removed-hospital-n485186> [<https://perma.cc/QAS7-XRN8>].

⁵⁵ Christine Hauser, *Recordings Add Detail in Death of Woman Forced from Florida Hospital*, N.Y. TIMES (Jan. 7, 2016), <https://nyti.ms/1mJlJMb> [<https://perma.cc/N68X-4CPG>]; Alicia Turner, *Barbara Dawson Case: An Inside Look at Calhoun-Liberty Hospital*, WCTV (May 16, 2016, 1:14 PM), <https://www.wctv.tv/home/headlines/Attorneys-Plan-Release-of-Dash-Cam-Footage-in-Dawson-Case-364268291.html> [<https://perma.cc/97US-Q2MF>].

⁵⁶ Jessica Eggert, *Florida Woman Barbara Dawson Dies After Police Removed Her from Hospital in Handcuffs*, MIC (Dec. 23, 2015), <https://mic.com/articles/131190/florida-woman-barbara>

short, multiple state systems purportedly designed to serve human needs, along with prisons, operate as mutually supporting aspects of carceral governance.

Adding the intersections of racism and sexism to Eubanks's focus on poverty is also critical to understanding the carceral regime. I have argued elsewhere that the prison, foster care, and welfare systems operate together to punish black mothers in particular, and that this systemic intersection in black mothers' lives is crucial to the carceral state's proliferation.⁵⁷ Cash-poor and low-income black mothers are disproportionately involved in all of these systems and are subjected to the harshest supervision.⁵⁸ Indeed, we can see black mothers at the epicenter of a multi-institutional apparatus of surveillance, social control, and punitive regulation. In response to growing black female involvement, these systems have cut back on supportive family services while intensifying their punitive role.⁵⁹ Open segregation in welfare services and public aid schemes prior to the civil rights movement meant that most black families could not participate.⁶⁰ These systems have become more punitive since the 1970s as black mothers demanded their rights to government entitlements and made up increasing shares of the recipients — and as the black female prison population rose exponentially.⁶¹ Welfare benefits became stingier and burdened with sexual and reproductive regulations, work requirements, and racialized stigma.⁶² By 2000, when black children made up the largest group in foster care, “the number of children receiving child welfare services [in their homes] ha[d] declined dramatically, while the foster care population ha[d] skyrocketed.”⁶³ This led state and federal governments to spend more of their child welfare budgets on punitive out-of-home services, rather than on less disruptive

dawson-dies-after-police-removed-her-from-hospital-in-handcuffs#.xdegTtAkW [https://perma.cc/HR23-8CYY].

⁵⁷ See ROBERTS, SHATTERED BONDS, *supra* note 27, at 200–01; Dorothy Roberts, *Complicating the Triangle of Race, Class and State: The Insights of Black Feminists*, 37 ETHNIC & RACIAL STUD. 1776, 1778–80 (2014); Roberts, *supra* note 40, at 1492; see also BETH E. RICHIE, ARRESTED JUSTICE 112–18 (2012); ANDREA J. RITCHE, INVISIBLE NO MORE 165–82 (2017); Kimberlé W. Crenshaw, *From Private Violence to Mass Incarceration: Thinking Intersectionally About Women, Race, and Social Control*, 59 UCLA L. REV. 1418, 1426–27 (2012).

⁵⁸ See Roberts, *supra* note 40, at 1476–77, 1486–87.

⁵⁹ *Id.* at 1485.

⁶⁰ See ROBERTS, SHATTERED BONDS, *supra* note 27, at 7; JILL QUADAGNO, THE COLOR OF WELFARE 19–20 (1996); Roberts, *supra* note 40, at 1483.

⁶¹ ROBERTS, SHATTERED BONDS, *supra* note 27, at 14–16; *Facts About the Over-Incarceration of Women in the United States*, ACLU, <https://www.aclu.org/other/facts-about-over-incarceration-women-united-states> [https://perma.cc/8G9L-MT7A].

⁶² ROBERTS, SHATTERED BONDS, *supra* note 27, at 14–16.

⁶³ *Id.* at 15; see also U.S. DEP'T OF HEALTH & HUMAN SERVS., THE AFCARS REPORT (2006), <https://www.acf.hhs.gov/sites/default/files/cb/afcarsreport12.pdf> [https://perma.cc/7ZH2-S24Y] (finding that, in the 2000 fiscal year, 39% of children in foster care were black, 38% were white, 15% were Hispanic, and 1% were Asian).

in-home services.⁶⁴ The choice to fund punitive rather than supportive programs has led to pervasive law enforcement, public assistance, and child welfare surveillance in poor, black communities. At the same time, appeals to longstanding stereotypes of black procreative pathology and maternal irresponsibility generated public support for these political choices.⁶⁵

II. BUILT-IN INEQUALITY

Placing the public welfare programs Eubanks examines in the context of the carceral state widens the inquiry into the way big data functions to serve punitive government ends. How does digitization work to implement more effectively a carceral approach to governance? One of Eubanks's chief insights about automated decisionmaking is that it is not the objective process the government claims it to be. Criticizing computerized scores for being erroneous or biased also fails to grasp the way they are *structured* to promote the carceral regime. "Technologies of poverty management are not neutral," Eubanks writes (p. 9). "They are shaped by our nation's fear of economic insecurity and hatred of the poor; they in turn shape the politics and experience of poverty" (p. 9). Politics shapes the carceral state's use of computerized tools in two main ways: (1) unequal political structures are built into the data collected and the algorithms that interpret that data; and (2) state agencies then use the results according to a predetermined philosophy to punish instead of support marginalized communities. Taking racism and white supremacy into account is critical to understanding the ideologies and structures that govern the digitized carceral state.

A. *More than Bias: Big Data's Social and Ideological Structure*

In her devastating exposé of big data's dangers, *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*, data scientist Cathy O'Neil writes that "[m]odels are opinions embedded in mathematics."⁶⁶ Contrary to the claim that computerized algorithms are more objective than human decisionmakers, O'Neil points out that the algorithms reflect the judgments of the programmers who create them. Eubanks's investigation of the technological tools used by poverty programs shows that they contain more than the accumulation of biased human opinions. Rather, the unequal structure of institutions is coded into algorithms. Not only does Allegheny County's risk assessment model include only parents who receive public assistance, but also

⁶⁴ ROBERTS, SHATTERED BONDS, *supra* note 27, at 15; Roberts, *supra* note 40, at 1484.

⁶⁵ See, e.g., THE SENTENCING PROJECT, RACE AND PUNISHMENT: RACIAL PERCEPTIONS OF CRIME AND SUPPORT FOR PUNITIVE POLICIES 7–12 (2014); Roberts, *supra* note 40, at 1492.

⁶⁶ O'NEIL, *supra* note 1, at 21.

the staff of every organization those parents accessed for help with their parenting is made up of mandated reporters (pp. 158, 160).

As critical race scholars have noted, racism is systemic, structural, and institutionalized.⁶⁷ Centuries of discriminatory laws, policies, and practices designed to privilege white people and disadvantage people of color have resulted in institutions that produce unequal outcomes even apart from the prejudiced decisions of individual state agents. Residential segregation, for example, structures the lives of most black people to make them more vulnerable to profiling by police,⁶⁸ environmental toxins,⁶⁹ inferior schools,⁷⁰ and inadequate housing.⁷¹ Computerized risk assessments are based on data taken from a social context that has already been shaped by hierarchies of race, class, and gender. Predictive algorithms package this unequal social structure into a score that necessarily reflects individuals' privileged or disadvantaged positions. The aphorism "garbage in, garbage out" captures an important aspect of data collection but doesn't capture the nature of built-in structural bias. Inequality in, inequality out is more apt.

At times, Eubanks casts the problem with automated prediction as producing erroneous determinations. She opens the chapter on Allegheny County's risk assessment tool with a comparison of scores for children from two different families that appear wrong to her. "In these cases, the model does not seem to meet a commonsense standard for providing information useful enough to guide call screeners' decision-making" (p. 142). What's more, because the standards for child maltreatment are notoriously ambiguous, the system doesn't generate accurate enough results. "A model's predictive ability is compromised when outcome variables are subjective" (p. 146). But, as Eubanks recognizes elsewhere, the problem with computerized risk assessments is not that they produce the wrong score. The problem is they are used to aid a fundamentally wrong approach to families' needs.

⁶⁷ See, e.g., EDUARDO BONILLA-SILVA, *RACISM WITHOUT RACISTS* 8 (2003) ("Whereas for most whites racism is prejudice, for most people of color racism is systemic or institutionalized."); MICHAEL OMI & HOWARD WINANT, *RACIAL FORMATION IN THE UNITED STATES* 137 (3d ed. 2015) ("What we call racial projects have interacted over half a millennium to build up the *social structures* of race and racism.").

⁶⁸ See Albert J. Meehan & Michael C. Ponder, *Race and Place: The Ecology of Racial Profiling African American Motorists*, 19 JUST. Q. 399, 400-01 (2002). See generally PAUL BUTLER, *CHOKEHOLD* (2017).

⁶⁹ See Myron Orfield, *Segregation and Environmental Justice*, 7 MINN. J.L. SCI. & TECH. 147, 152 (2005).

⁷⁰ See EVE L. EWING, *GHOSTS IN THE SCHOOLYARD* 17-27 (2018); NOLIWE ROOKS, *CUTTING SCHOOL* 20 (2017); Erika K. Wilson, *The New School Segregation*, 102 CORNELL L. REV. 139, 155-56 (2016).

⁷¹ See RICHARD ROTHSTEIN, *THE COLOR OF LAW* 17-18 (2018); Emily Rosenbaum, *Racial/Ethnic Differences in Home Ownership and Housing Quality*, 1991, 43 SOC. PROBS. 403, 417 (1996).

Eubanks shows that Allegheny County's software model, the Allegheny Family Screening Tool (AFST), was structured to be biased against poor families. Like U.S. child welfare policy generally, "[t]he AFST sees the use of public services as a risk to children. A quarter of the predictive variables in the AFST are direct measures of poverty . . ." (p. 156).⁷² Because "[t]he data set it utilizes contains only information about families who access public services," she notes, "it may be missing key factors that influence abuse and neglect" (p. 146). She goes on to explain: "Because variables describing [non-public services parents'] behavior have not been defined or included in the regression, crucial pieces of the child maltreatment puzzle might be omitted from the AFST" (p. 147). Eubanks correctly notes that child protective services fail to acknowledge the risky behaviors of wealthier families. But the problem with the AFST is not missing data. The problem is that it is structured to pull poor families into its carceral supervision. The system's aim isn't to understand and address children's needs; its aim is to regulate poor families. Wealthy families' maltreatment isn't missed; it's irrelevant.⁷³

These assumptions directed at poor families exclusively governed the underlying philosophies and aims of the other welfare programs Eubanks studied — to monitor, accuse, and exclude. "In a system dedicated [instead] to supporting poor and working-class people's self-determination," the same high-tech tools could "guarantee that [poor and working-class people] attain all the benefits they are entitled to by law" by affording "more precise measuring and tracking, better sharing of information, and increased visibility of targeted populations" (pp. 81–82). Instead, data collection, automation, and predictive analytics facilitate the carceral mission to deal with social inequality by punishing the communities marginalized by it.

B. Automation Is Antidemocratic

A corollary to the argument that automated decisionmaking is less biased is the argument that it is more transparent. Big data proponents point out not only that human actors are swayed by their prejudices but also that those prejudices aren't discernable.⁷⁴ While acknowledging

⁷² See also Dorothy Roberts & Lisa Sangoi, *Black Families Matter: How the Child Welfare System Punishes Poor Families of Color*, THE APPEAL (Mar. 26, 2018), <https://theappeal.org/black-families-matter-how-the-child-welfare-system-punishes-poor-families-of-color-33ad20e2882e/> [<https://perma.cc/U6A2-VP94>].

⁷³ See Carole Jenny et al., *Analysis of Missed Cases of Abusive Head Trauma*, 282 JAMA 621, 623 (1999) (finding doctors missed abusive head trauma significantly more often in white children than in children of color).

⁷⁴ See Anna Maria Barry-Jester et al., *The New Science of Sentencing: Should Prison Sentences Be Based on Crimes that Haven't Been Committed Yet?*, MARSHALL PROJECT (Aug. 4, 2015), <https://www.themarshallproject.org/2015/08/04/the-new-science-of-sentencing> [<https://perma.cc/F3JQ-Y54Q>] (providing a quotation from Adam Gelb, director of the public safety performance

the longstanding bias in child welfare and public assistance decisionmaking, Eubanks compellingly refutes this claim by arguing that automated decisionmaking leaves less room for democratic participation. “The widespread use of these systems impacts the quality of democracy for us all,” she writes (p. 12). Eubanks reminds us that removing human discretion from sentencing only compounded racial disparities in the criminal justice system (pp. 80–81). “Tough on crime” laws that established mandatory minimum sentences tying judges’ hands helped to fuel the astronomical rise in prison rates. A 2000 report concludes: “Minorities fare much worse under mandatory sentencing laws and guidelines than they did under a system favoring judicial discretion. By depriving judges of the ultimate authority to impose just sentences, mandatory sentencing laws and guidelines put sentencing on auto-pilot” (p. 81).⁷⁵

Automated state systems erode democracy in part because they operate as a “black box” of secret surveillance, data collection, and algorithms hidden from the public.⁷⁶ Because the inputs into big data technologies aren’t transparent, their operations aren’t subject to public scrutiny and their outputs evade government accountability.⁷⁷ As Eubanks puts it, automated decisionmaking constitutes “a thousand invisible human choices . . . under a cloak of evidence-based objectivity and infallibility” (p. 168). Many government entities purchase software and hire private tech companies to program computers and provide other technical guidance. The ability of government agents to inform the public about automated decisionmaking is severely limited by the agents’ own lack of technological expertise.⁷⁸

Moreover, private companies’ technologies are typically proprietary trade secrets and safeguarded from disclosure by intellectual property law.⁷⁹ Besides this enforced lack of transparency, the computer’s decisionmaking process is shrouded in deeper layers of obscurity arising

project at the Pew Charitable Trusts, stating that “[a]nything that’s on paper is more transparent than the system we had in the past. . . . There was no transparency, and decisions could be based on just about any bias or prejudice”).

⁷⁵ The author quotes LEADERSHIP CONFERENCE ON CIVIL RIGHTS, JUSTICE ON TRIAL 22 (2000), <http://www.protectcivilrights.org/pdf/reports/justice.pdf> [<https://perma.cc/7DEL-LLH2>].

⁷⁶ See Miller, *supra* note 3, at 136–37.

⁷⁷ David ROBINSON & HARLAN YU, CIVIL RIGHTS, BIG DATA, AND OUR ALGORITHMIC FUTURE 20 (2014); Elizabeth E. Joh, *The New Surveillance Discretion: Automated Suspicion, Big Data, and Policing*, 10 HARV. L. & POL’Y REV. 15, 40–42 (2016).

⁷⁸ Andrew Guthrie Ferguson, *Illuminating Black Data Policing*, 15 OHIO ST. J. CRIM. L. 503, 510 (2018).

⁷⁹ See Elizabeth E. Joh, *The Undue Influence of Surveillance Technology Companies on Policing*, 92 N.Y.U. L. REV. ONLINE 101, 119–20 (2017); Mitch Smith, *In Wisconsin, a Backlash Against Using Data to Foretell Defendants’ Futures*, N.Y. TIMES (June 22, 2016), <https://nyti.ms/28Q3x1K> [<https://perma.cc/JN6B-3LLU>].

from the way machine learning and artificial intelligence work.⁸⁰ In the latest big data models, computers are programmed with artificial intelligence to continuously “learn from past data without human input,”⁸¹ so it may be impossible to untangle the self-taught process by disclosing the original programmer’s instructions.⁸² Even the experts who designed the models may not be able to explain the scores they generate. As Jacob Weisberg notes: “If machines are learning on their own, human accountability becomes trickier to ascribe.”⁸³ Technology companies whose tools are used by customers in discriminatory ways tend to attribute the problem to a technical glitch rather than an ethical failure.⁸⁴

Eubanks also turns on its head the claim that machines are fairer than human decisionmakers because they are more objective. Digitized systems are antidemocratic, Eubanks argues, *because* they remove human discretion. She points to substituting online applications for face-to-face interactions, electronic communications for in-person social work, and automatic investigations based on computer-generated risk scores for screening based on intake workers’ professional judgments (pp. 47, 62, 142). Recognizing that state agents’ determinations have been marked by racism, sexism, and hatred for poor people, Eubanks nevertheless finds them more open to challenge than automated forms of inequality. She explains: “I find the philosophy that sees human beings as unknowable black boxes and machines as transparent deeply troubling. It seems to me a worldview that surrenders any attempt at empathy and forecloses the possibility of ethical development. . . . [It is] an admission that we have abandoned a social commitment to try to understand each other . . . [and] the potential for connection and community” (p. 168). Parents involved with child protective services told Eubanks “they’d rather have an imperfect person making decisions about their families than a flawless computer. ‘You can teach people how you want to be treated’ . . .” (pp. 166–67).

As I discussed above, anti-black racism poses an especially daunting obstacle to such appeals to our common humanity, an obstacle Eubanks may underestimate. The vilification and scapegoating of black mothers have served to foster support among poor and working class white people for punitive policies that damage their own economic well-being. Yet Eubanks is correct that human biases can be exposed, resisted, and

⁸⁰ Ferguson, *supra* note 78, at 509.

⁸¹ *Id.* at 509.

⁸² *Id.* at 512. *But see* Elaine Angelino et al., *Learning Certifiably Optimal Rule Lists for Categorical Data*, 18 J. MACHINE LEARNING RES. 1, 6–29, 46–47 (2018) (presenting an algorithm that produces rule lists that are comparable in accuracy to the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) proprietary risk prediction tool but are completely interpretable).

⁸³ Weisberg, *supra* note 11.

⁸⁴ *See, e.g.*, Mary Hodder, *Why Amazon Didn’t Just Have a Glitch*, TECHCRUNCH (Apr. 14, 2009), <https://techcrunch.com/2009/04/14/guest-post-why-amazon-didnt-just-have-a-glitch/> [<https://perma.cc/DN7B-86HY>].

potentially transformed, whereas computer algorithms cement biases into automated systems. The digitized carceral state “concentrates administrative power in the hands of a small elite” who have control over the algorithms, squelching opportunities for appeals to justice, mass resistance, and social change (p. 200).

C. Racism, Prediction, and the Carceral State

Prediction is a defining feature of the carceral state. Automated risk assessments are not only a way to make government decisionmaking more effective; they also reflect and implement a carceral approach to social problems. Algorithms that predict future conduct reinforce the state’s control over marginalized populations by legitimizing punishment without the need to prove individual culpability. Moreover, predictive models that rely on data structured by existing racial inequality predetermine a future that corresponds to the past racial order. Prediction is also fundamental to white supremacy because it both helps to obscure structural racism and is essential to the very concept of race. Understanding the importance of prediction to digitizing the carceral state further accentuates the centrality of racism in this modern form of governance.

New predictive models employed by government agencies are actuarial rather than clinical.⁸⁵ Modern criminal justice, public assistance, and foster care systems are not predicting risk based on subjective opinions of experts about individuals’ propensities. Rather, they rely on actuarial methods that look for “statistical correlations between group traits and group criminal offending rates,” as well as other salient behaviors.⁸⁶ Eubanks makes a similar distinction between prior forms of surveillance and today’s high-tech monitoring of poor people. In the past, state agents identified risky individuals who needed to be watched. “In contrast, in new data-based surveillance, the *target often emerges from the data*. The targeting comes after the data collection, not before” (p. 122). State agencies’ ability to apply sophisticated analytical tools to massive amounts of data collected through sweeping surveillance has radically transformed the very nature of prediction.⁸⁷

Reliance on this actuarial form of big data analysis is critical to the expansion of the carceral regime. Under a carceral approach, the state’s aim is to control populations rather than to adjudicate individual guilt or innocence, to manage social inequalities rather than to aid those who are suffering from them.⁸⁸ Risk assessment has been detached from the

⁸⁵ HARCOURT, *supra* note 2, at 77–107; Miller, *supra* note 3, at 114.

⁸⁶ Miller, *supra* note 3, at 114 (quoting HARCOURT, *supra* note 2, at 18).

⁸⁷ *See id.*

⁸⁸ *See* ISSA KOHLER-HAUSMANN, MISDEMEANORLAND 4–5 (2018).

“bounds set by moral concerns about culpability” to match the carceral state’s objective to maintain the unequal social order through surveillance, regulation, and punishment.⁸⁹ Computerized predictions identify people for government agencies to regulate from the moment of birth, without any regard to their actual responsibility for causing social harm. It is their devalued status in the political hierarchy that makes them threats to the carceral state and subject to its control.⁹⁰ Police gang databases have included toddlers.⁹¹ A California county has instituted a probation program that monitors children identified to be “pre-delinquent.”⁹² A 2011 paper concluded “a prenatal maltreatment-predicting algorithm was theoretically possible: ‘A risk assessment tool that could be used on the day of birth to identify those children at greatest risk of maltreatment holds great value’” (p. 137).⁹³

As discussed above, all of these predictive tools are structured to target poor communities of color. Moreover, their forecasts of the future are based on data that were produced by existing racial discrimination in systems such as policing, housing, education, health care, and public assistance. The future predicted by today’s algorithms, therefore, is predetermined to correspond to past racial inequality.⁹⁴ Thus, prediction becomes a way for the carceral state to foreclose visions of a more humane future.

Although big data and predictive algorithms facilitate the carceral state’s mission in new ways, prediction has long been one of racism’s central features. Race itself is a form of state categorization that ranks

⁸⁹ Jennifer L. Skeem & Christopher T. Lowenkamp, *Risk, Race, and Recidivism: Predictive Bias and Disparate Impact*, 54 CRIMINOLOGY 680, 682–83 (2016) (“Risk assessment should never be used to sentence offenders to more time than they morally deserve.” *Id.* at 683.); see also John Monahan & Jennifer L. Skeem, *Risk Redux: The Resurgence of Risk Assessment in Criminal Sanctioning*, 26 FED. SENT’G REP. 158, 158 (2014).

⁹⁰ See OSCAR H. GANDY, JR., *THE PANOPTIC SORT* 29–33 (1993) (discussing theories of class consciousness).

⁹¹ *Beware of Gangster Babies: Calif. Database Slammed*, CBS NEWS (Aug. 15, 2016, 9:31 AM), <https://www.cbsnews.com/news/california-gang-database-slammed-listing-babies-privacy-concerns/> [<https://perma.cc/L3MP-SFK8>].

⁹² Carimah Townes, *California County Law Enforcement Puts Kids on Probation for Bad Grades*, THE APPEAL (July 10, 2018), <https://theappeal.org/california-county-law-enforcement-puts-kids-on-probation-for-bad-grades/> [<https://perma.cc/U2JV-KV5L>].

⁹³ The author quotes Emily Putnam-Hornstein & Barbara Needell, *Predictors of Child Protective Service Contact Between Birth and Age Five: An Examination of California’s 2002 Birth Cohort*, 33 CHILD. & YOUTH SERVS. REV. 2400, 2406 (2011).

⁹⁴ See WENDY HUI KYONG CHUN, PROGRAMMED VISIONS 9 (2013) (noting computer software creates “programmable visions that extrapolate the future — or, more precisely, a future — based on the past”).

people by supposedly innate traits that are claimed to predict their behavior and character.⁹⁵ Prominent stereotypes about black people portray them as prone to crime, welfare dependence, poor health, and low intelligence. Today's computerized predictive policing reincarnates in high-tech garb "vague loitering and vagrancy laws [that historically gave] license to police officers to arrest people purely on the basis of race-based suspicion," categorically identifying black people as lawless apart from their criminal conduct.⁹⁶

It is telling that, as Eubanks notes, "[e]ugenics created the first database of the poor" (p. 22). Based on the belief that socially relevant traits are inherited, American eugenicists catalogued socioeconomic classes and races according to predictions of their social value.⁹⁷ These predictions were the basis of repressive social policies such as incarceration, compelled sterilization, and immigration exclusions of people considered to have defective heredity. In its 1927 decision *Buck v. Bell*,⁹⁸ the U.S. Supreme Court upheld Virginia's mandatory sterilization law by approving eugenic predictive decisionmaking.⁹⁹ Justice Holmes explained the state's interest in preemptively sterilizing people based on scientific risk assessments: "It is better for all the world, if instead of waiting to execute degenerate offspring for crime, or to let them starve for their imbecility, society can prevent those who are manifestly unfit from continuing their kind."¹⁰⁰ Eugenicists like Justice Holmes legitimized state violence against marginalized populations by predicting their inevitably worthless futures based on their alleged biological inheritances from past generations. Both eugenics and computerized predictive analytics rationalize continuing structural inequality by conflating forecasting the future with replicating the past.¹⁰¹ Thus, the predictive model that animates the contemporary carceral state has deep roots in U.S. oppressive ideologies supported by mainstream science.

The digitized carceral state is also fueled by current trends in genetic science. I have documented elsewhere how genomic scientists are re-

⁹⁵ DOROTHY ROBERTS, *FATAL INVENTION* 3–25 (2011); see also BENJAMIN, *supra* note 13 (describing race as a technology of white supremacy).

⁹⁶ See Dorothy E. Roberts, *Foreword: Race, Vagueness, and the Social Meaning of Order-Maintenance Policing*, 89 J. CRIM. L. & CRIMINOLOGY 775, 788–89 (1999); see also SIMONE BROWNE, *DARK MATTERS* (2015) (discussing the history of state surveillance of black people in the United States).

⁹⁷ See, e.g., DANIEL J. KEVLES, *IN THE NAME OF EUGENICS* 82–83 (4th prtg. 2001); ALEXANDRA STERN, *EUGENIC NATION* (2005); see also RICHARD J. HERRNSTEIN & CHARLES MURRAY, *THE BELL CURVE* (1994) (arguing that race and class inequalities stem from immutable differences in inherited cognitive ability measured by IQ).

⁹⁸ 274 U.S. 200 (1927).

⁹⁹ *Id.* at 207.

¹⁰⁰ *Id.*

¹⁰¹ Cf. CHUN, *supra* note 94, at 101–31 (comparing the history of software to the history of genetics).

inventing race as a biological category using giant DNA databases and statistical estimates of gene frequencies that differ among geographic populations.¹⁰² In contrast to Enlightenment racial typologists who classified people into natural kinds based on outward physical features, modern-day racial scientists use computer software to infer a racial population structure from genotype data based on statistical probabilities. For example, some researchers use a popular software program called Structure to divide DNA databases sampled globally into clusters of genetic similarity. The program allocates the individuals whose DNA was sampled into a specific number of clusters, which are predetermined by the researcher, based on algorithms that maximize the chances that the individuals' genotypes will match.¹⁰³ Although receiving less attention from critics, the genetic science of race is run by big data and predictive analytics. Like other computerized tools, high-tech genomic classification is not as objective as scientists claim. Every aspect of the project — collecting the DNA samples, selecting the number of clusters, creating the algorithms, mapping the predicted clusters onto common conceptions of race — is determined by researchers' subjective, socially influenced decisions.¹⁰⁴

Moreover, scientists increasingly advocate that government agencies use genetic predictions to solve social problems. An emerging field of social genomics involving collaborations of social scientists and biologists investigates genetic contributions to social behaviors such as educational attainment, gang membership, and voting patterns.¹⁰⁵ Adding genetics to scientific understandings of social inequality radically affects state responses to marginalized groups because it allows the political status of individuals to be predicted and explained by their innate traits. The authors of a 2016 study, for example, claimed its findings marked “a turning point in the social and behavioral sciences because” they “make[] it possible to predict educational achievement for individuals directly from their DNA.”¹⁰⁶ The authors proposed that “polygenic scores may soon become a useful tool for early prediction and prevention of educational problems.”¹⁰⁷ Although proponents argue sociogenomic predictions can be used to reduce inequities in education, health, and income,¹⁰⁸ it is far more likely that they will reinforce existing social

¹⁰² See ROBERTS, *supra* note 95, at 57–80.

¹⁰³ *Id.* at 59.

¹⁰⁴ See Ann Morning, *Does Genomics Challenge the Social Construction of Race?*, 32 SOC. THEORY 189 (2014).

¹⁰⁵ See CATHERINE BLISS, *SOCIAL BY NATURE* 2–5, 41–42 (2018).

¹⁰⁶ S. Selzam et al., *Predicting Educational Achievement from DNA*, 22 MOLECULAR PSYCHIATRY 267, 271 (2017).

¹⁰⁷ *Id.*

¹⁰⁸ See, e.g., Kathryn Paige Harden, *Why Progressives Should Embrace the Genetics of Education*, N.Y. TIMES (July 24, 2018), <https://nyti.ms/2JRgQvO> [<https://perma.cc/AM7P-QSY2>].

hierarchies and target those who are predicted to be the least socially valuable for extra surveillance.¹⁰⁹

D. *How Racism Is Built into Predictive Policing*

Nowhere is big data's structural bias more apparent than in predictive policing. The expansion of automated technologies in public assistance programs described in *Automating Inequality* has been accompanied by a similar technological revolution in the criminal justice system.¹¹⁰ Law enforcement agencies nationwide collect and store vast amounts of data about past crimes, analyze these data using mathematical algorithms to predict future criminal activity, and incorporate these forecasts in their strategies for policing individuals, groups, and neighborhoods.¹¹¹ Judges use big data predictive analytics to inform their decisions about pretrial detention, bail, sentencing, and parole.¹¹² Automated risk assessments help to determine whether or not defendants go to prison, what type of facility they are assigned to, how long they are incarcerated, and the conditions of their release.¹¹³ The digital poorhouse is mirrored in the digital prison.

Police departments in numerous cities across the nation are using computer algorithms to identify geographic areas and individuals at high risk for crime.¹¹⁴ In 2009, the National Institute of Justice spurred this technological transformation by offering millions of dollars in grants to police departments to develop predictive programs.¹¹⁵ The Chicago Police Department (CPD) was awarded more than \$2 million to test implementation of its "heat list," which uses CPD's crime database and predictive analytics to identify residents who are most likely to be involved in violent crime, either as perpetrators or victims, before an offense occurs.¹¹⁶ The heat list ranks residents according to a numerical

¹⁰⁹ See Dorothy Roberts, *Can Research on the Genetics of Intelligence Be "Socially Neutral"?*, 45 HASTINGS CTR. REP. (SPECIAL ISSUE) S50 (2015).

¹¹⁰ See, e.g., DANIELLE KEHL ET AL., BERKMAN KLEIN CTR. FOR INTERNET & SOC'Y, ALGORITHMS IN THE CRIMINAL JUSTICE SYSTEM: ASSESSING THE USE OF RISK ASSESSMENTS IN SENTENCING (2017); WALTER L. PERRY ET AL., RAND CORP., PREDICTIVE POLICING: THE ROLE OF CRIME FORECASTING IN LAW ENFORCEMENT OPERATIONS (2013).

¹¹¹ See, e.g., ANDREW GUTHRIE FERGUSON, THE RISE OF BIG DATA POLICING (2017); Sarah Brayne, *Big Data Surveillance: The Case of Policing*, 82 AM. SOC. REV. 977 (2017); Andrew Guthrie Ferguson, *Big Data and Predictive Reasonable Suspicion*, 163 U. PA. L. REV. 327 (2015); Ferguson, *supra* note 78.

¹¹² See, e.g., Ric Simmons, *Big Data and Procedural Justice: Legitimizing Algorithms in the Criminal Justice System*, 15 OHIO ST. J. CRIM. L. 573 (2018); Jason Tashea, *Calculating Crime*, 103 A.B.A. J. 54 (2017); Barry-Jester et al., *supra* note 74.

¹¹³ See, e.g., Barry-Jester et al., *supra* note 74.

¹¹⁴ See Ferguson, *supra* note 78, at 505–06; Miller, *supra* note 3, at 117–18.

¹¹⁵ Matt Stroud, *The Minority Report: Chicago's New Police Computer Predicts Crimes, but Is It Racist?*, THE VERGE (Feb. 19, 2014, 9:31 AM), <https://www.theverge.com/2014/2/19/5419854/the-minority-report-this-computer-predicts-crime-but-is-it-racist> [https://perma.cc/239V-FTGD].

¹¹⁶ See *id.*

risk score that allows police to take steps to prevent future violence and to know the riskiness of individuals they happen to stop — a “virtual most wanted list.”¹¹⁷ Residents living in high-crime neighborhoods in Chicago might experience a personal visit from police officers who warn them that they should avoid committing a crime because the department is watching them.¹¹⁸

Similarly, the Memphis police department’s Blue CRUSH program applies IBM predictive-analytics software to data on past crimes to identify “hot spots” where officers are directed to conduct sweeps and show a heightened presence to deter future criminal activity.¹¹⁹ A number of police departments have collected secret gang databases that list residents likely to be gang members.¹²⁰ Police departments are also monitoring social media online to collect data for investigating and identifying criminal activity and to collect evidence in criminal cases.¹²¹ In 2014, the New York Police Department (NYPD) arrested 103 alleged gang members residing in a Harlem public housing project after monitoring their social media communications for four years.¹²² Numerous law enforcement agencies also use facial recognition software in solving crimes.¹²³

In addition, federal and state law enforcement agencies are amassing giant databases of DNA seized from people who are convicted — and in some states merely arrested — for crimes.¹²⁴ This form of genetic surveillance treats people as permanent suspects by indefinitely storing their profiles as potential matches to DNA collected at future crime scenes.

¹¹⁷ Ferguson, *supra* note 78, at 505–06, 520.

¹¹⁸ See Stroud, *supra* note 115.

¹¹⁹ Miller, *supra* note 3, at 117. See generally Anthony A. Braga, *Hot Spots Policing and Crime Prevention: A Systematic Review of Randomized Controlled Trials*, 1 J. EXPERIMENTAL CRIMINOLOGY 317, 318–20 (2005); *Real-Time Crime Forecasting Challenge*, NAT’L INST. OF JUST. (July 31, 2017), <https://www.nij.gov/funding/Pages/fy16-crime-forecasting-challenge-document.aspx> [<https://perma.cc/MF7N-BQU6>].

¹²⁰ See Aaron Harvey, *The List that Can Take Your Life*, HUFFINGTON POST (Sept. 27, 2016), https://www.huffingtonpost.com/entry/the-list-that-can-take-you-life_us_57eae82ce4b07f20daaofd51 [<https://perma.cc/M3ZD-G8FE>].

¹²¹ See Desmond Upton Patton et al., *Stop and Frisk Online: Theorizing Everyday Racism in Digital Policing in the Use of Social Media for Identification of Criminal Conduct and Associations*, 3 SOC. MEDIA & SOC’Y 1, 2–3 (2017).

¹²² *Id.* at 1.

¹²³ CLARE GARVIE ET AL., CTR. ON PRIVACY & TECH. AT GEORGETOWN LAW, *THE PERPETUAL LINE-UP: UNREGULATED POLICE FACE RECOGNITION IN AMERICA* (2016), <https://www.perpetuallineup.org/sites/default/files/2016-12/The%20Perpetual%20Line-Up%20-%20Center%20on%20Privacy%20and%20Technology%20at%20Georgetown%20Law%20-%20121616.pdf> [<https://perma.cc/9FXG-42KQ>].

¹²⁴ See ROBERTS, *supra* note 95, at 264–86; Erin Murphy, *Databases, Doctrine & Constitutional Criminal Procedure*, 37 FORDHAM URB. L.J. 803, 807–09 (2010).

Some scholars and policymakers argue that computerized risk assessments can reduce racial bias in policing and sentencing decisions and even help to end mass incarceration.¹²⁵ Analyses of these predictive technologies, however, reveal that they disproportionately identify African Americans as likely to commit crimes in the future. An examination of the NYPD gang database, for example, showed that only approximately one-quarter of the individuals identified as potential gang members were white.¹²⁶ A comprehensive investigation of police department facial recognition by the Center on Privacy and Technology at Georgetown Law found that the databases likely contain a disproportionate number of images of black people and that the software may be especially inaccurate in recognizing black people's faces.¹²⁷ Experts also estimate that DNA databases contain profiles from a disproportionate number of African Americans.¹²⁸ With astronomical arrest rates in many black neighborhoods, DNA collection by police officers could create a comprehensive database of urban black men. After examining risk scores assigned by the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) to more than 7000 people arrested in Broward County, Florida, ProPublica reported that the tool falsely labeled black defendants as future criminals at almost twice the rate as white defendants and mislabeled white defendants as low risk more often than it did black defendants.¹²⁹

Scholars have pointed out that the variables included in predictive tools can function as “prox[ies] for race” even when race is omitted from

¹²⁵ See, e.g., Simmons, *supra* note 112, at 577–78 (“It is arguably easier to remove race based criteria from a computer algorithm than from a decision made by an individual actor, since algorithms could theoretically be programmed to discount any factors which have been tainted by prior racial discrimination.” *Id.* at 577.); Skeem & Lowenkamp, *supra* note 89, at 705–06; Bhagwan Chowdhry et al., *How Big Data Can Make Us Less Racist*, ZÓCALO PUB. SQUARE (Apr. 28, 2016), <http://www.zocalopublicsquare.org/2016/04/28/how-big-data-can-make-us-less-racist/ideas/nexus/> [<https://perma.cc/8KV6-C2BB>]; Shaila Dewan, *Judges Replacing Conjecture with Formula for Bail*, N.Y. TIMES (June 26, 2015), <https://nyti.ms/1BRYP5E> [<https://perma.cc/K3WX-8RLH>].

¹²⁶ See Nick Pinto, *NYPD Disputes Gang Database Numbers — But Its Math Doesn't Add Up*, THE INTERCEPT (June 14, 2018, 2:51 PM), <https://theintercept.com/2018/06/14/nypd-gang-database-city-council-dermot-shea/> [<https://perma.cc/3EF4-BPKM>].

¹²⁷ GARVIE ET AL., *supra* note 123.

¹²⁸ See ROBERTS, *supra* note 95, at 277–78.

¹²⁹ Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/2LSQ-URH7>]; see also *State v. Loomis*, 881 N.W.2d 749, 753 (Wis. 2016) (denying defendant's claim that use of COMPAS in sentencing violated his due process rights); Tashea, *supra* note 112, at 56.

the algorithms.¹³⁰ Neighborhood, marital history, educational attainment, employment status, and criminal history can combine to target black people even when race is not a variable.¹³¹

This racial identification does not result from accidental correlation or from deliberate animus on the part of programmers. The factors they program into risk assessments disproportionately apply to black Americans because white supremacy has structured the factors that way. Employment discrimination, residential segregation, unequal public school funding, and racial profiling by police shape the social universe from which the raw data are drawn and the algorithms are constructed, generating higher risk scores for black people.

Crime data collection reflects discriminatory policing. Numerous studies demonstrate that police engage in rampant racial profiling throughout the nation.¹³² Because of residential segregation, police routinely bias data collection against black residents by patrolling their neighborhoods with far greater intensity than white neighborhoods.¹³³ In New York City, for example, police stop black residents and arrest them for marijuana possession at far higher rates than white residents, despite roughly the same rates of marijuana use.¹³⁴ The database used to determine the characteristics of New York City residents who illegally possess marijuana and to develop the algorithm to predict future offenders, therefore, will produce outputs that are just as racist as the policing that created it.¹³⁵ Just like police who racially profile communities, surveillance technologies such as video cameras and audio sensors placed primarily in black neighborhoods amass a biased database that skews the variables later used to predict crime.¹³⁶ If police officers mostly patrol black neighborhoods, much of the digital footage their body cameras upload to data warehouses will include the movements of black people.¹³⁷

¹³⁰ See, e.g., Bernard E. Harcourt, *Risk as a Proxy for Race: The Dangers of Risk Assessment*, 27 FED. SENT'G REP. 237, 237 (2015); Sonja B. Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 819, 838 (2014).

¹³¹ See HARCOURT, *supra* note 2, at 237; O'NEIL, *supra* note 1, at 97; Kelly Hannah-Moffat, *Actuarial Sentencing: An "Unsettled" Proposition*, 30 JUST. Q. 270, 279–84 (2013); Starr, *supra* note 130, at 838–39.

¹³² See, e.g., BUTLER, *supra* note 68, at 190–94.

¹³³ See DAVID ROBINSON & LOGAN KOEPKE, UPTURN, STUCK IN A PATTERN: EARLY EVIDENCE ON "PREDICTIVE POLICING" AND CIVIL RIGHTS 5–7 (2016), https://www.upturn.org/static/reports/2016/stuck-in-a-pattern/files/Upturn_-_Stuck_In_a_Pattern_v.1.01.pdf [<https://perma.cc/4UH6-MKHK>].

¹³⁴ Benjamin Mueller et al., *Surest Way to Face Marijuana Charges in New York: Be Black or Hispanic*, N.Y. TIMES (May 13, 2018), <https://nyti.ms/2IdyUUX> [<https://perma.cc/K6Y9-YXRZ>].

¹³⁵ See O'NEIL, *supra* note 1, at 91–95.

¹³⁶ See Ferguson, *supra* note 78, at 513–14; Elizabeth E. Joh, *Feeding the Machine: Policing, Crime Data, & Algorithms*, 26 WM. & MARY BILL RTS. J. 287, 289 (2017) (noting that police "generate the information that big data programs rely upon").

¹³⁷ See Ferguson, *supra* note 78, at 506–07, 514.

Or take another data point used in forecasting violent crime — an individual’s social networks.¹³⁸ Because black people are under law enforcement supervision at such high rates, it is almost impossible for any black person living in America — especially those living in predominantly black neighborhoods — to have a social network free of connections to crime.¹³⁹ The high odds of involvement in the criminal justice system makes it likely black individuals will have offenders among their social relationships, even if they are not offenders themselves.

Risk assessment models that import institutionally biased data become a “self-fulfilling feedback loop”¹⁴⁰ where the prediction ensures future detection. When a predictive model identifies a trait or place based on structurally biased data or programming, the profiled trait or place garners heightened police attention. The police are then more likely to find crime associated with the trait or located in the area. Not only does this unjustly target individuals who have these traits or live in these areas, but the new data recorded from these biased encounters “then feed into the predictive policing algorithm on subsequent days, generating increasingly biased predictions.”¹⁴¹ These successes in crime detection appear to the machine and to policymakers to confirm the prediction.¹⁴² Indeed, the prediction can only be verified by reproducing the biases built into it and generating more discriminatory arrests. There is no room in the model to respond to the prediction by ending the racial profiling that produced it. Because predictive models are evaluated by their success rates in finding crime without regard to their discriminatory social impact, the models seem to work well.¹⁴³ Eubanks found a similar feedback loop in Allegheny County’s child maltreatment risk assessment: “A family scored as high risk by the AFST will undergo more scrutiny than other families. . . . If [a parent in that family] loses her children, the risk model can claim another successful prediction” (p.

¹³⁸ See, e.g., Whet Moser, *The Small Social Networks at the Heart of Chicago Violence*, CHI. MAG. (Dec. 9, 2013), <https://www.chicagomag.com/city-life/December-2013/The-Small-Social-Networks-at-the-Heart-of-Chicago-Violence> [<https://perma.cc/L97B-6CD6>].

¹³⁹ See Ferguson, *supra* note 78, at 513–15. On the relationship between social networks, geography, and crime, see Andrew V. Papachristos, David M. Hureau & Anthony A. Braga, *The Corner and the Crew: The Influence of Geography and Social Networks on Gang Violence*, 78 AM. SOC. REV. 417 (2013). Such sociological theories of how social networks produce crime have influenced predictive models. My argument is not about crime production but rather racially biased crime detection that skews social networks toward predicting black people’s involvement in future crime.

¹⁴⁰ Ferguson, *supra* note 78, at 516; see also O’NEIL, *supra* note 1, at 27; William S. Isaac, *Hope, Hype, and Fear: The Promise and Potential Pitfalls of Artificial Intelligence in Criminal Justice*, 15 OHIO ST. J. CRIM. L. 543, 550 (2018).

¹⁴¹ Isaac, *supra* note 140, at 550 (citing Kristian Lum & William Isaac, *To Predict and Serve?*, SIGNIFICANCE MAG., Oct. 2016, at 19) (describing the “ratchet effect” from newly recorded crimes).

¹⁴² Miller, *supra* note 3, at 124–25; see also Isaac, *supra* note 140, at 548.

¹⁴³ Miller, *supra* note 3, at 125.

169). Thus, the original selection bias arising from structural inequities generates observation bias which produces confirmation bias.¹⁴⁴ All this built-in bias subjects black people to being criminalized — not caught for committing crimes but predicted to commit crimes in the future.

III. REFORMING BIG DATA OR ABOLISHING THE CARCERAL STATE?

A structural analysis of big data's role in fostering the carceral state shapes both the diagnosis of the problem big data poses for society and the prescription to fix it. Concerns about technological flaws in the government's predictive tools have resulted in proposals to correct either the technological models or the way state agencies deploy them.¹⁴⁵ However, recognizing that state agencies use predictive tools for punitive purposes to reinforce unjust political arrangements suggests the need for a more radical approach to digitizing the carceral state.

A. *The Potential and Limits of Due Process*

Many big data reformers have focused on illuminating big data's "black box" so its hidden biases can be exposed and eliminated.¹⁴⁶ A technological approach seeks to make the algorithms themselves more transparent. For example, a team of computer scientists sought to determine whether there was a more accurate and more transparent model than the COMPAS software.¹⁴⁷ They introduced a special algorithm, called Certifiably Optimal Rule ListS (CORELS), that provides the optimal solution using rule lists that are approximately as accurate as COMPAS.¹⁴⁸

¹⁴⁴ See Isaac, *supra* note 140, at 550–51 (noting that the feedback mechanism in predictive policing algorithms is "selection bias meets confirmation bias," *id.* at 551). *But see* ROBINSON & KOEPKE, *supra* note 133, at 7 ("[O]ur research surfaced few rigorous analyses of predictive policing systems' claims of efficacy, accuracy, or crime reduction.").

¹⁴⁵ See, e.g., Terry, *supra* note 3, at 44–45 (discussing five federal reports proposing increased regulation of big data to protect consumer privacy); Moritz Hardt, Eric Price & Nathan Srebro, Equality of Opportunity in Supervised Learning 2–3 (Oct. 11, 2016) (unpublished manuscript), <https://arxiv.org/pdf/1610.02413.pdf> [<https://perma.cc/2ZPC-7G3G>] (discussing approaches to removing discrimination from machine learning); John Podesta, *Findings of the Big Data and Privacy Working Group Review*, WHITE HOUSE: BLOG (May 1, 2014, 1:15 PM), <https://obamawhitehouse.archives.gov/blog/2014/05/01/findings-big-data-and-privacy-working-group-review> [<https://perma.cc/L9QD-UKZP>].

¹⁴⁶ See, e.g., EXEC. OFFICE OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 21 (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf [<https://perma.cc/N56T-D3EL>]; Simmons, *supra* note 112, at 579 ("Proponents of big data algorithms may want to impose a transparency requirement in order to increase the trustworthiness of their system.").

¹⁴⁷ Angelino et al., *supra* note 82, at 2; see also Skeem & Lowenkamp, *supra* note 89, at 706 ("[R]isk assessment instruments *can* be free of predictive bias and *can* be associated with small mean score differences by race.").

¹⁴⁸ Angelino et al., *supra* note 82, at 2.

Another approach is to increase transparency by applying updated standards of technological due process that give individuals subject to automated adjudication “the right to inspect, correct, and dispute” the bases for agency decisions.¹⁴⁹ At a minimum, due process requires notice that provides “audit trails” of the inputs, codes, and rules used at each algorithmic decision point so affected individuals may seek meaningful administrative review of the process.¹⁵⁰ In addition, government agencies should be accountable to the public by instituting their own oversight of their use of big data as well as making their algorithms public to facilitate auditing and research by independent experts in the field.¹⁵¹ In 2017, the New York City Council passed an algorithmic accountability bill, the first of its kind in the country, establishing a task force to examine how city agencies use algorithms, in an effort to make them more transparent and less biased.¹⁵²

Attempting to eliminate biases from the algorithms, however, is an incomplete remedy because unequal structures are built into the data that state systems collect and the objectives they pursue. Some government decisions simply should not be automated at all because automation itself makes adjudication undemocratic. Professor Danielle Citron argues that certain types of decisionmaking require human discretion that can’t be codified and delegated to a computer without violating citizens’ due process rights.¹⁵³

Other policymakers argue that automated risk assessment can limit carceral governance by identifying people who are less prone to engage in harmful behavior and therefore can be subjected to lower levels of surveillance. Police departments, criminal courts, and child protective services all use predictive analytics to sort people into groups requiring more or less state intervention. By using an algorithm developed by the Laura and John Arnold Foundation, judges have been able to release low-risk defendants before trial without setting prohibitive bail amounts.¹⁵⁴ Courts across the nation divert certain drug offenders from

¹⁴⁹ Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 20 (2014); see also *Perdue v. Gargano*, 964 N.E.2d 825, 828–29 (Ind. 2012) (discussing due process challenge brought against Indiana’s Family and Social Services Administration).

¹⁵⁰ Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1277, 1305 (2008); Miller, *supra* note 3, at 138–39; see also *About*, AUDITING ALGORITHMS: ADDING ACCOUNTABILITY TO AUTOMATED AUTHORITY, http://auditingalgorithms.science/?page_id=89 [<https://perma.cc/U5L3-28PX>] (describing a “research design” aimed at “diagnosing the unwanted consequences of algorithmic systems”).

¹⁵¹ See KEHL ET AL., *supra* note 110, at 133–37.

¹⁵² Lauren Kirchner, *Machine Bias: New York City Moves to Create Accountability for Algorithms*, PROPUBLICA (Dec. 18, 2017, 12:08 PM), <https://www.propublica.org/article/new-york-city-moves-to-create-accountability-for-algorithms> [<https://perma.cc/Q5WT-686V>].

¹⁵³ Citron, *supra* note 150, at 1304–05.

¹⁵⁴ Dewan, *supra* note 125.

prison to drug treatment and other supervisory programs.¹⁵⁵ Child welfare departments in a number of states have adopted differential response programs that provide in-home services to parents rated at low risk of maltreating their children while reserving more coercive surveillance and foster care for parents rated at high risk of maltreating their children.¹⁵⁶

Yet these dual track systems based on risk assessments can have precisely the opposite effect, sweeping into the carceral net low-risk individuals who previously would not have been on the government's punitive radar at all. Struggling parents who are targeted by automated models become subject to agency monitoring and therefore more vulnerable to losing custody of their children even though they are unlikely to harm them. Criminal justice diversion programs often lead to longer entanglements with the criminal courts than would a prison sentence and entail extremely intrusive regulation of defendants' behavior with the constant threat of being sent to prison for minor infractions. Electronic monitoring of low-risk defendants extends surveillance outside prison walls into people's homes and everyday lives.

California's recent bail reform legislation provides a telling illustration. In August 2018, California became the first state in the nation to eliminate the system of cash bail for defendants charged with nonviolent crimes, which unjustly based pretrial detention on the ability to afford bail.¹⁵⁷ The state legislature replaced the bail system with algorithmic tools that can score individuals according to their likelihood to be rearrested or fail to appear in court if released.¹⁵⁸ Key advocates of abolishing cash bail pulled their support for the law because of concerns that the bill's predictive model would worsen discrimination against black defendants.¹⁵⁹ As Ivette Alé, an organizer with Californians United for a Responsible Budget (CURB), put it, "[w]e are replacing

¹⁵⁵ See Barry-Jester et al., *supra* note 74 (discussing various states that use risk assessments to determine sentencing and probation decisions).

¹⁵⁶ See NAT'L QUALITY IMPROVEMENT CTR. ON DIFFERENTIAL RESPONSE IN CHILD PROTECTIVE SERVS., DIFFERENTIAL RESPONSE APPROACH IN CHILD PROTECTIVE SERVICES: AN ANALYSIS OF STATE LEGISLATIVE PROVISIONS, <http://www.ucdenver.edu/academics/colleges/medicalschooll/departments/pediatrics/subs/can/DR/qicdr/General%20Resources/General%20Resources/docs/differential-response.pdf> [<https://perma.cc/LK2M-TCDQ>].

¹⁵⁷ Sophia Bollag, *New Law to Make California First State to End Bail*, ASSOCIATED PRESS (Aug. 28, 2018), <https://www.apnews.com/02cd9e0b507244d6bb773e285057a7fb> [<https://perma.cc/VXN9-DTL2>].

¹⁵⁸ S.B. 10, 2018 Leg., Reg. Sess. (Cal. 2018) (enacted) (codified at CAL. GOV'T CODE § 27771 and scattered sections of CAL. PENAL CODE).

¹⁵⁹ See Sam Levin, *Imprisoned by Algorithms: The Dark Side of California Ending Cash Bail*, THE GUARDIAN (Sept. 7, 2018, 10:09 AM), <https://www.theguardian.com/us-news/2018/sep/07/imprisoned-by-algorithms-the-dark-side-of-california-ending-cash-bail> [<https://perma.cc/5LPF-CGFX>]; see also Megan Stevenson, *Assessing Risk Assessment in Action*, 103 MINN. L. REV. 303 (2018) (finding Kentucky's pretrial risk assessment resulted in only a small increase in pretrial release, which appeared to benefit white defendants more than black defendants).

money bail with an even more harmful system of profiling.”¹⁶⁰ Without changing the fundamental philosophy of the carceral state — and instead punishing people marginalized by the current unjust social order — California’s statistical tools threaten to expand rather than curtail its reach.

B. Rationalizing Political Failure

Another reason why reforming risk assessments is insufficient to rein in the carceral state is that the predictive approach itself promotes public support for punitive governance. Eubanks argues compellingly that digitizing government programs serves to rationalize the nation’s failure to address poverty. Big data not only facilitates policing people in place of meeting their needs, it also makes this unjust substitution seem fair, objective, and ethical. Eubanks situates the rise of automated decisionmaking in the current political moment when the white professional middle class is desperate to preserve its status in the face of expanding wealth, growing economic inequality, and increasing demographic diversity (p. 184). After the civil rights–era victories and rejection of blatantly discriminatory practices, maintaining the unequal social order required a class-neutral, colorblind ideology (p. 191).¹⁶¹ Computer-generated risk scores appear to provide apolitical solutions to problems caused by unjust political hierarchies. “The classism and racism of elites are math-washed, neutralized by technological mystification and data-based hocus pocus,” writes Eubanks (p. 192). Ruling by algorithm makes carceral policies seem scientific, accurate, precise, and unbiased. Moreover, it permits the public to deny the need to dismantle oppressive systems and radically change state and societal approaches to social inequalities. Thus, automatic decisionmaking furthers a “public policy fixat[ion] on attributing blame for poverty rather than remedying its effects or abolishing its causes” (p. 176).

C. Toward Abolishing the Digitized Carceral State

Recognizing that the digital poorhouse functions to reinforce inequality, Eubanks proposes to dismantle it (pp. 201–17). Her recommendations don’t focus on reforming risk assessments. They begin instead with the 1968 Southern Christian Leadership Conference (SCLC) demands for an economic and social Bill of Rights (p. 208). In a letter to President Johnson and Congress, Dr. Martin Luther King, Jr., and fellow SCLC members set forth six fundamental rights required for all Americans to experience the promises of U.S. democracy: rights to a decent job, minimum income, decent housing, adequate education, democratic participation, and health care (p. 208). Eubanks suggests that

¹⁶⁰ Levin, *supra* note 159.

¹⁶¹ See also BONILLA-SILVA, *supra* note 67, at 1–4.

the universal basic income might be a first step to weaken the allure of the digital poorhouse and expose it as “an overly elaborate technological infrastructure that wastes time, resources, and human potential” (p. 211). In other words, the way to stop big data’s threat to society is not to improve big data. It is to work toward changing the unjust structures that big data supports.

Extending Eubanks’s insights to the wider digitized carceral state, the need for an abolitionist approach that centers on antiracism becomes even clearer.¹⁶² First, improving risk assessment procedures within multiple interlocking systems designed to exclude black people from social, economic, and political participation threatens to obscure these procedures’ antidemocratic functions and make them operate more efficiently. The only way to address the digitized carceral state is to dismantle its social institutions that enforce a racial caste system and reconstitute them in radically new forms.

Second, centering racism’s role in the digitized carceral state emphasizes the need to directly contest racism and white supremacy to build a viable coalition to dismantle it. The racism embedded in predictive analytics highlights how federal, state, and local governments have been willing to impose security measures on people of color to secure white people’s liberty.¹⁶³ A majority of white Americans acquiesce in or support the criminalizing and antidemocratic effects of automated decisionmaking because they comport with racist ideologies about black people that have long propped up the unequal U.S. racial order. As I have noted elsewhere, white Americans “are willing to tolerate intolerable amounts of state violence against black people because their white racial privilege protects them from experiencing this violence themselves and because they see this violence as necessary to protect their own privileged racial status.”¹⁶⁴ Just as “[w]e manage the individual poor in order to escape our shared responsibility for eradicating poverty” (p. 13), the carceral state criminalizes whole black communities so whites can escape their responsibility to end structural racism. Many of the white people trapped in the digital poorhouse support the very policies that trap them there in order to keep black people bound in intersecting carceral systems.

Regulating black women’s bodies acts as the linchpin that binds not only disciplinary welfare, criminal justice, and child protection policies directed at marginalized communities but also disciplinary policies that

¹⁶² See Dorothy E. Roberts, *Democratizing Criminal Law as an Abolitionist Project*, 111 NW. U. L. REV. 1597, 1604–07 (2017).

¹⁶³ Roberts, *supra* note 96, at 827–36.

¹⁶⁴ Roberts, *supra* note 162, at 1606. See generally CAROL ANDERSON, *WHITE RAGE* (2016); DERRICK BELL, *FACES AT THE BOTTOM OF THE WELL* (1993); IAN HANEY LÓPEZ, *DOG WHISTLE POLITICS* (2014).

keep socially privileged people from seeing the need for social change. “For example, portraying state agencies’ placement of Black children in foster care as necessary to protect them from their deprived or incompetent mothers creates a barrier between these mothers and middle-class white mothers who would benefit from government provision of high-quality child care for all families.”¹⁶⁵ In this way, the carceral state, aided by supposedly race-neutral predictions of child maltreatment, secures public support for inadequate market-based forms of child care along with punitive surveillance of parents instead of a unified movement for generous state support for families.

This lack of unity not only means that an abolitionist movement should include the universal economic rights that Eubanks proposes, but also requires an explicitly antiracist mission that contests the white supremacist ideologies that support punitive governance and the stranglehold on black communities. To the extent that Eubanks appeals directly to the data scientists about their technology designs, she offers a “gut check” that relates to the tools’ social impact rather than efficiency: “Does the tool increase the self-determination and agency of the poor? Would the tool be tolerated if it was targeted at non-poor people?” (p. 212).¹⁶⁶ These questions should be extended to include race, gender, disability, and other political categories that mark people disadvantaged by the digitized carceral state.

With an abolitionist vision, people can employ technology in novel ways to facilitate social change.¹⁶⁷ Social justice movements like Black Lives Matter, Say Her Name, and Survived and Punished have organized, publicized, and raised money for their efforts using social media platforms, including Facebook, Instagram, and Twitter.¹⁶⁸ Organizations use electronic tools to collect and circulate data that document rising inequalities and state violence in order to end them.¹⁶⁹ Ordinary

¹⁶⁵ Roberts, *Critical Race*, *supra* note 27, at 122.

¹⁶⁶ Eubanks also proposes a more detailed “Hippocratic Oath for the data scientists, systems engineers, hackers, and administrative officials of the new millennium” (pp. 212–13).

¹⁶⁷ See BENJAMIN, *supra* note 13 (exploring ways technologies can be used to contest racism); LISA NAKAMURA, *DIGITIZING RACE* (2007) (arguing that people of color use visual culture on the internet to articulate their own racial identities and politics).

¹⁶⁸ See, e.g., Monica Anderson et al., *Activism in the Social Media Age*, PEW RES. CTR. (July 11, 2018), <http://www.pewinternet.org/2018/07/11/activism-in-the-social-media-age/> [<https://perma.cc/KQA9-NFA2>]; see also PAOLO GERBAUDO, *TWEETS AND THE STREETS* (2012) (analyzing the rise of social media and the global emergence of new forms of protest); John T. Jost et al., *How Social Media Facilitates Political Protest: Information, Motivation, and Social Networks*, 39 *ADVANCES POL. PSYCH.* 85 (2018) (examining how social media platforms facilitate protest movements in the United States, Spain, Turkey, and Ukraine). White supremacists are also using online platforms to organize and promote their views. See JESSIE DANIELS, *CYBER RACISM* 3–4 (2009).

¹⁶⁹ See, e.g., MAPPING POLICE VIOLENCE, <https://mappingpoliceviolence.org> [<https://perma.cc/P8Q4-SLL7>] (using big data to document, measure, and display information about police violence and its victims); *About Data for Black Lives*, DATA FOR BLACK LIVES, <http://d4bl.org/about.html>

residents monitor the actions of police officers in their neighborhoods and capture incidences of brutality on their cell phones.¹⁷⁰ Indeed, the same predictive analytics used by the carceral state to reproduce unequal structures can be used by abolitionists to identify and excavate the sites where inequality has been institutionally embedded. If supposedly objective algorithms produce discriminatory outcomes, audit trails can help to pinpoint where structural changes need to take place.¹⁷¹ While reforming big data is inadequate to stop the digitized carceral state, abolitionists can include technologies among their tools to dismantle it.

Abolishing the carceral state requires more than placing the same technologies in different hands. I have argued that big data, predictive analytics, and automated decisionmaking function in particular ways to reinforce an unjust, unequal, and antidemocratic political order. Abolitionists must envision a radically different relationship between technology and politics, one that facilitates justice, equality, and democracy. We might begin to sketch out the contours of an abolitionist approach by opposing the chief aspects of carceral data collection, prediction, and automation and replacing them with emancipatory features.

A fundamental innovation for abolitionists must be to end prediction as a way of foreclosing social change by collapsing the future into past inequality. Abolitionist forecasting technologies must facilitate envisioning a future that doesn't replicate the past. Communication theorist Professor Wendy Chun proposes the concept of "hypo-models" to engage with the risk of inexperienceable future conditions, such as climate change.¹⁷² Rejecting dominant scientific models whose predictions can only be verified when past political problems are reproduced, Chun calls for models that "address uncertainty as enabling rather than disabling" and "treat the nonexact coincidence between scientific predictions and observed reality as the promise, rather than the end, of science and of politics."¹⁷³ Hypo-models, Chun suggests, should be used to change hu-

[<https://perma.cc/35N6-QNSP>] ("Data for Black Lives is a group of activists, organizers, and mathematicians committed to the mission of using data science to create concrete and measurable change in the lives of Black people.")

¹⁷⁰ Farhad Manjoo & Mike Isaac, *Phone Cameras and Apps Help Speed Calls for Police Reform*, N.Y. TIMES (Apr. 8, 2015), <https://nyti.ms/1FjocRG> [<https://perma.cc/RRJ2-2URB>].

¹⁷¹ See Aaron M. Bornstein, *Are Algorithms Building the New Infrastructure of Racism?*, NAUTILUS (Dec. 21, 2017), <http://nautil.us/issue/55/trust/are-algorithms-building-the-new-infrastructure-of-racism> [<https://perma.cc/XR6R-FY5R>] ("One of the great benefits of the big data age is that the logic of our decisions can be formally analyzed, and numerically picked apart, in ways that were previously impossible.")

¹⁷² Wendy Hui Kyong Chun, *On Hypo-Real Models or Global Climate Change: A Challenge for the Humanities*, 41 CRIT. INQUIRY 675 (2015).

¹⁷³ *Id.* at 678–79.

man behavior rather than preempt it and “produce the improbable rather than the probable.”¹⁷⁴ She asks, “how are we to consider the relations between correlation and the future, not to shut down the future — to shape it into what is most statistically probable — but to deal with invisible forces that we cannot entirely know, but need nonetheless to change?”¹⁷⁵ Thus, we can use climate change forecasts to envision and work toward a better future guided by environmental justice rather than to predict an inevitable future devastated by global warming.

Similarly, abolitionists can design technological models that facilitate engagement with the risks produced by current unequal social structures in new ways. These tools could motivate changes in human behavior rather than make automated decisions predetermined by structural inequality and bias. Instead of using predictive tools to identify risky populations to be managed without regard to individual culpability, we could use them to identify and support individuals who are at risk of suffering because of institutionalized group discrimination. Instead of protecting the power of privileged elites to determine the inputs of automated decisions, we could put in place democratic frameworks that allow the public, especially people from the most marginalized communities, to participate in technology development and management. By contesting the digitized carceral state, abolitionists invite the potential for human beings to reject technological reproduction of past injustice and to use technology to help create a more humane future reality.

¹⁷⁴ *Id.* at 697.

¹⁷⁵ *Id.*