Article

CONVERGENCE

Convergence: The International Journal of Research into New Media Technologies
1–17

DOI: 10.1177/1354856520933838
journals.sagepub.com/home/con
SAGE

Predictable policing: New technology, old bias, and future resistance in big data surveillance

Xerxes Minocher
University of Wisconsin–Madison, USA

Caelyn Randall
University of Wisconsin–Madison, USA

Abstract
Within this article, we explore the rise of predictive policing in the United States as a form of big data surveillance. Bringing together literature from communication, criminology, and science and technology studies, we use a case study of Milwaukee, Wisconsin, USA to outline that predictive policing, rather than being a novel development, is in fact part of a much larger, historical network of power and control. By examining the mechanics of these policing practices: the data inputs, behavioral outputs, as well as the key controllers of these systems, and the individuals who influenced their adoption, we show that predictive policing as a form of big data surveillance is a sociotechnical system that is wholly human-constructed, biases and all. Identifying these elements of the surveillance network then allows us to turn our attention to the resistive practices of communities who historically and presently live under surveillance – pointing to the types of actions and imaginaries required to combat the myth and allure that swirls around the rhetoric of big data surveillance today.

Keywords
Big data, broken windows, critical race, local-historical, predictive policing, resistance, sociotechnical systems, surveillance

As stories of misbehaving algorithms continue to surface in news media, academic articles, and the popular press, there is growing public awareness of the socially constructed nature of software and the increasing pervasiveness of big data surveillance. The titles of popular books and articles on the

Corresponding author:
Xerxes Minocher, University of Wisconsin–Madison, 5137 Vilas Hall, 821 University Avenue, Madison, WI 53706, USA.
Email: minocher@wisc.edu

topic such as *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy* (O'Neil, 2016), 'The Dystopia We Signed Up For' (Manning, 2017), and *How Big Data is Automating Inequality* (Eubanks, 2018) all help build a myth of big data surveillance as a new, nearly cataclysmic threat to public well-being. But surveillance, especially as an apparatus of state governance, has long been used for the social control of marginalized communities (Browne, 2015). While big data surveillance may represent a new, 21st-century partnership between private companies and the US intelligence community, it is still guided by a preexisting and long-standing ideology of monitoring and controlling.

Within communication and technology studies, the influence and effects of big data surveillance are beginning to be explored. Alongside the broader questions and concerns that come with such a sociotechnical phenomenon (boyd and Crawford, 2012), the initial surveys and approaches to big data are largely theoretical explorations: responses to news coverage and debates (Karppi, 2018), reflections enacting the philosophical positions of Deleuze/Guattarian notions of desire and Foucauldian views of power (Ettlinger, 2018), and even ontopolitical considerations of surveillant assemblages (Mantello, 2016). While these conceptual works indicate the manifold positions research on big data can take and the range of implications that can be considered, empirical works have begun to take a focused view to big data. It is with a more focused lens that questions of big data can be considered in relation to professional sport (Hutchins, 2016), or queried as effects of networking data in crowdsourced surveillance (Lally, 2017).

Within the sphere of criminology, policing, and surveillance studies, the questioning of big data surveillance has a richer history in studies of predictive policing. Theoretical studies here have outlined how our neoliberal moral economy influences the governance of populations through metadata (Sanders and Sheptycki, 2017), as well as the complexity and nuances of enacting criminological theory in a big data-driven system (Chan and Bennett Moses, 2016). Empirical works illustrate organizational and situated perspectives such as the difficulties in evaluating claims of effectiveness about predictive policing programs (Bennett Moses and Chan, 2018), the challenges police officers face in adapting to these new technological systems (Sanders and Hannem, 2012), and even the 'dirty data' inputs to predictive policing systems (Richardson et al., 2019). While attentive to the emergence of technologically enabled policing practices, these papers overlook the work being done by local community groups to resist and challenge the racialized effects of such practices.

In this article, we bring together these strands of literature alongside a local-historical approach informed by critical race theory. We first introduce big data surveillance and predictive policing to a communications audience, problematizing the effects of these systems, before presenting a 'local-historical' case-study approach that is critical of both the technology involved in predictive policing as well as the racialized practice of policing itself. This methodological approach allows us to extend the rich and extensive work being done in criminology and surveillance studies by including discussions of resistive practices currently occurring in local communities of color which are most burdened by these policing and surveillance practices. Doing so allows us to reflect on local and historical practices of both surveillance and resistance in communities of color and how they are appearing today.

In the next section, we establish our case study of predictive policing in Milwaukee, Wisconsin, USA, to highlight the practices and dangers of predictive policing as a form of big data surveillance. We then unpack how the mythology of 'predictive policing' as a new technical phenomenon obscures its presence as only one component of many in a larger, long-standing system of sociopolitical power and control. We show that policing in the United States has always been 'predictive' and driven by individuals and their personal ideologies, further problematizing today's modern mythology. We close with an analysis of proposed resistant practices to predictive policing forms of big data surveillance, highlighting the local community practices which are currently underrepresented in academic study, but provide great potential and opportunity for conceptualizing resistance to predictive policing practices.

Intelligence partnerships and predictive policing

In the simplest terms, big data surveillance refers to a large amount of information – personal data such as online purchases, social media activity, and cellphone activity – being collected and aggregated into 'data warehouses' where mathematical models (algorithms) analyze all known information in order to identify potential threats and trends. As used elsewhere, big data here refer to the sheer volume, velocity, and variety of data which necessitate specific technological and analytic methods for transforming information into intelligence (De Mauro et al., 2016). While big data collections are used as key intelligence products, when data are collected into these large aggregate forms, the absence of sociohistorical and geographic context in a sense 'flattens' the data, replacing 'distinct regional features with a singular, level topology' (Jackson, 2014: 311). This characteristic of big data surveillance obviates local histories, peoples, and experiences in order to render a particular perspective for controllers and users of these big data-driven systems. This rendering of communities by institutions and actors of power who may hold different worldviews and values of the communities under surveillance is then further used to obscure political agendas behind a veil of objectivity and technology (D'Ignazio and Klein, 2020). Current usage of big data-driven systems in policing and surveillance has yet to engage with the biases or omissions that emerge within these data sets (Richardson et al., 2019; Sanders and Hannem, 2012), while key assumptions about big data collections incite the fervor of system controllers and mass media without proper scrutiny (Bennett Moses and Chan, 2018). In sum, while there may be a large amount of information available with big data, the absence of context implicates a certain absence of meaning as well (Welles, 2014).

In order to work against these characteristics of big data surveillance, we illustrate how a local-historical approach can extend our understanding of big data surveillance and subsequent imaginations of resistance with a case study of the Intelligence Fusion Center (IFC) in Milwaukee, Wisconsin, USA. The IFC, a joint effort between the US Department of Homeland Security and the Milwaukee Police Department (PD), is the primary intelligence center in the US Midwest, linking local police to federal groups, sharing information, technology, and data management practices across agencies. This linkage between federal surveillance organizations and local PDs facilitates the integration of policing strategies and tactics alongside nation-wide data collection and profiling practices, all undergirded by a corporate profit structure that rewards companies that provide tech-solutions to these organizations and their information analysis needs (Stop LAPD Spying Coalition, 2018).

Since 2007, the Milwaukee IFC began using a 'predictive policing' platform: a system created by private companies, designed to 'anticipate' and 'predict' where crime will occur (PoliceOne, 2017). Predictive policing techniques in the United States trace their history to similar tactics used by the American military in foreign and domestic wars. First supported by military-funded university research on statistics during the 2003 Iraq insurgency, the use of historical crime data to predict future crime patterns is now used across the country to track and surveil individuals in order to 'predict' crime (Stop LAPD Spying Coalition, 2018).

Predictive policing works through the combination of algorithms and big data. Predictive policing algorithms churn through 'big data' collections of historical police information such as previous crime reports and police calls, alongside collected demographic information and known personal connections, in order to identify trends and 'predict' future crimes. While the logic that underlies these types of algorithms often remains the proprietary property of the private companies that provide such services (Amoore and Piotukh, 2015; Ferguson, 2017), close attention to the implementation of 'predictive' algorithms already reveals troubling trends. An investigation on the use of a predictive algorithm in US court systems revealed a bias against people of color, with White criminals receiving lower 'recidivism scores' for similar or more severe crimes (Angwin et al., 2016), while similar patterns of bias appear even in hiring algorithms that companies use to screen potential job candidates for interviews (Mann and O'Neil, 2016). Specifically with regard to the use of predictive policing algorithms, advocacy groups were among the first to raise the alarm call – groups like the American Civil Liberties Union (ACLU), the National Association for the Advancement of Colored People (NAACP), as well as local community groups like the Stop LAPD Spying Coalition recognize that this 'new' development is simply one more step in the long march of surveillance and monitoring of marginalized groups.

The hallmark of predictive policing is crime mapping. Maps highlight which areas are most likely to see criminal activity, and this information is used to direct officer attention to those areas. By converting massive amounts of data comprised of historical crime reports, social media activity, as well as video and audio surveillance into maps, PDs have access to what they call 'actionable intelligence' in real time. Whereas traditional policing relies upon officer intuition and judgment – which requires a temporal and spatial proximity to the scene – proponents of predictive policing claim that it is not bound by the same kind of situational constraints (Griffith, 2015; Jefferson, 2018).

Predictive policing maps work by shading different 'beats' with colors based on their potential for criminal activity at points of time, usually represented as a scale from green (low criminal potential) to red (high criminal potential). These colors attempt to make data meaningful by using common sense cultural associations (green means 'good' or 'go' and red means 'bad' or 'stop'), and in so doing, translate the complex geographic space of different beats into single-dimension places defined by their criminal potentiality. The predictive maps work to bind beats to their histories, containing and essentializing the space, rendering the area stuck in time, unable to be seen as anything more than a seedbed of criminality or a safe zone (Ferguson, 2017). Based upon past criminal activity as well as patterns identified by an algorithm, criminal potentiality is aggregated into very specific predictions of the type of crime to occur, and the type of person likely to commit it.

It is argued that officer judgment is enhanced when the identification of areas rife with criminal potential is facilitated through the technological insight of big data, promoting the idea that a technical solution neutralizes bias by providing some type of objective visual representation of local communities (Griffith, 2015). This is an important justification for predictive policing since officer judgment has consistently been identified as a problem in discourse on police violence (Greengard, 2012; Griffith, 2015). But, because the criminalization of Black and Brown communities is at the heart of the historical data that fuels predictive policing, the 'judgment' that emerges from predictive policing systems does not seem to meaningfully differ from the office judgment upon which traditional policing styles depend (Richardson et al., 2019; Sanders and Hannem, 2012). There is also, perhaps, an important distinction to make between the collection of metadata and the collection of personally identifying data. References to the data that undergird predictive policing usually refer to the collection of metadata. Metadata is 'data about data', and as such describes the relationship between large quantities of data. Yet, by identifying patterns, metadata can also reveal sensitive personal information. For example, as Ferguson notes, by connecting 'the dots of social networks and locations of people suspected of criminal activities', metadata can quite easily provide access to personal data and identification of individuals (as cited in Kift and Nissenbaum, 2016: 114).

In Milwaukee, the IFC's use of predictive policing results in troubling outputs. Between 2007 and 2015, traffic and pedestrian stops in Milwaukee tripled, from 66,000 to 196,000, nearly half of which were conducted without reasonable suspicion. Unsurprisingly, Black people were six times more likely to be stopped by Milwaukee PD than White people, even after all other variables were accounted for, and were 20% less likely to be found with drugs on them (Choudhury, 2018). Even with these initial numbers, it is apparent that the application of technical solutions in policing practices is increasing the burden of living as a person of color in Milwaukee. A lawsuit filed by the ACLU against the city of Milwaukee, the Fire and Police Commission, and Milwaukee Police Chief outlines how Milwaukee PD employs a stop-and-frisk approach that includes 'blanketing certain geographic areas in which residents are predominantly people of color with "saturation patrols" by MPD officers, who conduct high-volume, suspicionless stops and frisks throughout the area' (Collins et al. v. The City of Milwaukee et al., 2017: 2).

The language of 'blanketing certain geographic areas' should certainly evoke concern when we consider how the crime mapping outputs of predictive policing practices will concentrate attention to particular areas and communities within a city. As the ACLU notes, 'Though implemented citywide, the MPD's [stop-and-frisk] program has been largely concentrated in neighborhoods of color' (Collins et al. v. The City of Milwaukee et al., 2017: 3). It is, of course, not possible to determine exactly what caused the dramatic increase in traffic and pedestrian stops in Milwaukee, but significantly, between 2006 and 2008, the arrival of a new police chief wanting to use data-driven policing practices in Milwaukee PD preceded the IFC partnership that shares data between federal and local police agencies, and entities all over the country. Through predictive policing software, in Milwaukee and throughout the United States, an individual's 'reasonable expectation to privacy' continues to erode in the name of public safety – with the result that people of color are increasingly being stopped under 'reasonable suspicion' for being in the same place at the same time that a software's geographic output suggested crime might occur (Hu, 2017).

The data from Milwaukee PD indicate that their predictive policing system did nothing to minimize or limit surveillance and over-policing of already marginalized communities (in fact, quite the opposite). However, investigating what biases lies in these algorithmic systems is first concealed by the private companies which develop them, claiming intellectual property rights (Wexler, 2018), while a further layer of obscuring tint is added by the Milwaukee PD's limited sharing of its own output data.[1] Our local-historical analysis of Milwaukee below will show the ideological and personal forces that preceded the use of the current predictive policing system, and how it is predicated on a theory of 'broken windows' policing. It is this ideological understanding of deviance, crime, and how to respond to it that guides how the controllers of these systems perpetuate their own practice of monitoring and surveillance, all while distancing themselves from the fact that they are the very same individuals who determine what these big data surveillance systems should identify as pertinent information, and what should be included or excluded.

Algorithms are not processing information based on their own criteria of what is a 'good' output, nor are these collections of big data emerging by themselves. At the start of each of these technical practices (producing algorithms, collecting data), there is human intervention and decision-making to determine what constitutes a meaningful output (Chan and Bennett Moses, 2016; Richardson et al., 2019; Sanders and Hannem, 2012). We should consider not only the influence of the algorithms within these predictive policing systems but also take careful note of the power structures and collections of big data that fuel and allow these algorithms to trace their predictive trends.

Collections of data, structures of control

Because it relies on historical crime data, predictive policing often directs law enforcement to police the same communities that have historically been subject to over-policing, creating a confirmation feedback loop (Richardson et al., 2019). While the neat and careful presentation of numbers such as a 'recidivism score' or 'likelihood to commit crime map' appeals to a quaint notion of objectivity (Porter, 1996), such outputs obscure the arrangements of power that undergird sociotechnical dynamics and perpetuate a racial bias which has very real effects on the lived experiences of individuals within communities of color.

Beyond the obvious racial bias embedded within policing practices (Ferguson, 2017; Lum and Isaac, 2016), police crime data are notoriously misleading and incomplete in terms of what is reported. Predictive policing is fueled by historical crime data that are generated from racially biased, and in some cases, illegal policing practices (e.g. planting drugs or falsifying records: Richardson et al., 2019). Public presentations of police crime data are even further misleading and incomplete in terms of what is reported as police officers frequently manipulate crime reports in order to produce desirable crime statistics (Ruderman, 2012), and PDs have touted 'record-low' crime rates, without mentioning that rates of homicides, rapes, and robberies increase during the same time period (Bialik, 2016). There is also the question of what is not reported: most startlingly, PDs do not need to report how many people their officers have killed every year to any central agency. One database held by the FBI that is supposed to track police-involved killings has been described as 'almost comically incomplete and unreliable' as it only tracks those killings that PDs deem 'justifiable', relies on voluntary submission of killings, and does not collect detailed information regarding the circumstances of each incident (Neyfakh, 2015).[2] At the forefront of our questioning about predictive policing programs are the lives of those affected by these predictive sociotechnical systems. However, in order to interrogate such systems, it is also necessary to recognize that the controllers of these systems – the PDs and federal agencies which provide the data that is then used to predict crime – are motivated by their own power interests and ideologies. These factors make it virtually impossible to separate 'good data' from 'bad data' (Richardson et al., 2019) as it exists within current matrices of domination (D'Ignazio and Klein, 2020).

If the historical crime data that fuel predictive policing are generated from traditional policing practices that were/are racially biased, then the problem of predictive policing is not just the technological or predictive element but also *policing itself.* While scholars interested in predictive policing have and continue to draw attention to the data and technology that facilitates predictive policing and its dangerous effects, a consequence of framing big data surveillance as a technological problem is that it often situates expert intervention as the only viable solution. As a result of this framing, ongoing community/grassroots efforts to resist these systems are erased from scholarly consideration and discussion. However, these perspectives are valuable as the resistive possibilities generated from such positions would necessarily exceed the domain of technological and scholarly experts. Put another way, some of the most knowledgeable people on police bias and resistance are the Black and Brown communities who have overwhelmingly experienced such practices throughout their lives (Collins, 1990).

In their analysis of ‘dirty data’, Richardson et al. (2019) appear to offer one potential interruption of the aforementioned trend in that they underscore that predictive policing is predicated on racially biased data and sometimes unlawful policing practices. However, while they acknowledge that it is virtually impossible to separate ‘good data’ from ‘bad data’, they conclude their analysis of predictive policing in eight US cities with a call for ‘an empowered an independent authority’ to oversee PD policies and collections of data (2019: 224). While their analysis draws attention to the ‘dirty data’ problems of predictive policing, they continue to overlook ways to assert control against such practices outside existing systems of oppression and control. Given that predictive policing in the United States is only one aspect of a larger network of structural and systemic racism, it is unclear how one more regulative authority would stop the effects we see, especially since interventions from the Department of Justice are not enough to change police behavior (Richardson et al., 2019), and the nation’s Supreme Court ‘tells officers that they can shoot first and think later, and it tells the public that palpably unreasonable conduct [shooting a civilian without warning] will go unpunished’ (Kisela v. Hughes, 2018, dissent, p. 15).

In order to more holistically respond to the problem of predictive policing, one would need to offer a more extensive historical analysis while underscoring how the specific communities that are subjected to predictive policing practices have developed resistive responses that occur outside the structures of systemic racism (e.g. D’Ignazio and Klein, 2020). Such an approach represents a significant challenge because the sociopolitical networks of power that underlie predictive policing practices today remain hidden behind layers of privacy and false objectivity. However, a shift in the locus of analysis to the local and historic specifics that underlie the production of crime data can refocus our attention on the forces and dynamics that produce, circulate, and perpetuate these systems of control, rather than simply the data itself. By taking a local-historical approach, we recognize that technical predictive policing systems are complex, heterogeneous, human-made assemblages of control that are constituted by and connected to existing sociopolitical networks of power (Eubanks, 2018; Jasanoff, 2006).

Let us first review the history of policing practices in the United States, and Milwaukee in particular, showing that modern policing has always been ‘predictive’, before linking this to questions of how to challenge and resist the biases endemic to such a system. In doing so, we illustrate how a local-historical approach can reveal the actors and power interests that influence the development of a surveillance network as well as the logic that underlies such a system.

Policing practices, then and now

> Being black in Milwaukee means having the constant specter of police haunting your life . . . Black and Latino people are magnets for police harassment in this city. Police abuse of people of color here isn’t imagination. It’s reality. This has been true for a long time. From 1967 to 2017, not much has changed. (Jarrett English, youth organizer, ACLU Wisconsin)

In the United States, 21st-century policing has always been predictive. Looking back at the history of policing in America, we can see that today’s policing practices are the outgrowth of an older ‘public safety’ paradigm known as ‘order maintenance policing’. While the US government first proposed (unsuccessfully) the construction of a National Data Center in 1967 (Bodenner, 2015), the theory of order maintenance policing, or ‘broken windows’ policing as it is better known, derives from a ‘non-data-based and significantly anecdotally derived hypothesis’ first published in a 1982 Atlantic Monthly article, arguing that ‘correcting visible signs of disorder will reduce serious crimes’ (Oberman and Johnson, 2016: 936). George Kelling and James Wilson (1982), in making their argument for broken windows policing, suggested that ‘Social psychologists and police officers tend to agree that if a window in a building is broken and is left unrepaired, all the rest of the windows will soon be broken’. Kelling and Wilson go on to imagine the slippery slope that appears once signs of ‘disorder’ are left unaddressed:

> We suggest that ‘untended’ behavior also leads to the breakdown of community controls. A stable neighborhood of families who care for their homes, mind each other’s children, and confidently frown on unwanted intruders can change, in a few years or even a few months, to an inhospitable and frightening jungle. A piece of property is abandoned, weeds grow up, a window is smashed. Adults stop scolding rowdy children; the children, emboldened, become more rowdy. Families move out, unattached adults move in. Teenagers gather in front of the corner store. The merchant asks them to move; they refuse. Fights occur. Litter accumulates. People start drinking in front of the grocery; in time, an inebriate slumps to the sidewalk and is allowed to sleep it off. Pedestrians are approached by panhandlers.

As has been noted elsewhere, this theory of broken windows policing enacts an odd perspective of public safety, assuming that ‘physical decay begets the moral kind’, while ‘appearances must be maintained for civility to cohere’ (Bellafante, 2014). In effect, the results of implementing broken windows policing is a higher volume of non-felony, ‘quality-of-life arrests’ (Oberman and Johnson, 2016). ‘Quality of life’ arrests are a term for non-violent offences such as drug usage, prostitution, or homelessness. In New York City where Kelling previously consulted, quality of life arrests were often used to collect homeless people and bus them out of the city, while in Milwaukee, similar tactics to collect those with outstanding warrants were used ‘When a major convention took place in town and city government wanted the downtown area to look spiffy’ (Kelling, 2015: 182).

While the theory of broken windows policing may have been interpreted to mean that local PDs should engage in the rebuilding and repair of connections in communities when ‘visible signs of disorder’ emerge, in practice it has manifested as a logic that presumes that these are areas that must be surveilled and policed, with minor offenders displaced in order keep safe an imagined population that would deteriorate at the slightest sign of disorder. Even further, broken windows policing suggests major crimes can be prevented by aggressively pursuing minor offences. As Kelling and Wilson (1982) contend, ‘The unchecked panhandler is, in effect, the first broken window’.

It is upon this challenging logic of broken windows policing that today’s predictive policing practices draw upon. The belief that crime can be predicted by tracking visible signs of disorder is now embedded within algorithms that churn through big data collections, identifying trends and ‘predicting’ crime, all the while assuming the key foci are minor offenders, the ‘unchecked panhandlers’ within our local communities.

In 2006, the Milwaukee PD hired Kelling, a Milwaukee native himself and self-described ‘Consultant for solving problems’, to assess local police operations and make changes to ‘impact crime itself’. It is through this partnership that Milwaukee turned to predictive policing algorithms and a ‘predictive’ paradigm of policing.

Predictive policing in Milwaukee

Upon first arriving to Milwaukee PD, Kelling noted a handful of key issues. Top among these was the department's lack of 'urgency for addressing Milwaukee's crime problems' and what Kelling identified as 'The absence of an effective technological capacity for collecting, storing, and facilitating analysis of data on local crime and problems' (2015: 40–41).

Kelling's review of Milwaukee PD's quarterly evaluations revealed a focus on metrics such as response time, control of overtime, and similar administrative concerns, with an overall lack of established goals or metrics for reducing crime. The result of these institutional practices according to Kelling was that 'it would be hard to decipher the real *business* of the MPD' (2015: 39, emphasis added). For Kelling, of course, the real 'business' of police work is the aggressive pursuit and punishment of non-felony, quality of life crimes: capturing and removing the 'broken windows' of local communities before they can lead to the inevitable moral decay he first identified in 1982. Secondly, there was the lack of adequate 'technological capacity'. In order to facilitate Milwaukee PD's shift to its new 'business', it required an upgrade to its information systems, needing some type of system that would aggregate large amounts of data and allow for predictive trends to be calculate through these big data sets.

Kelling's solution to these problems was to identify and recruit 'the best chief of police possible' (2015: 44). Though Milwaukee PD already had a final list of 16 candidates, Kelling outlines how he reached out to encourage Edward Flynn to apply for the position since Flynn's ideology of 'community policing' aligned with Kelling's broken windows theory approach. Though it is unclear just how much influence Kelling had on the selection process, on January 7, 2008, Milwaukee named its newest Chief of Police: Kelling's preferred and outside candidate Edward Flynn. Taking leadership of the Milwaukee PD in January, 2009, Flynn arrived with the explicit mission of implementing 'community-based, problem-oriented, data-driven policing' (Kelling, 2015: 148). In order to achieve his goals, Flynn wanted to develop a sense of 'urgency' regarding Milwaukee's crime problem, and he did so by unifying the PD around a crime prevention strategy predicated on the marriage of broken windows theory and technological development. It is at this time that the partnership between Milwaukee PD and Homeland Security began with the IFC, and predictive policing practices began to emerge in the city. Flynn's tenure as Milwaukee's Chief of Police until the announcement of his retirement in early 2018 has been credited as 'modernizing the agency, introducing new technologies and raising the profile of the department in national policing circles' (Luthern, 2018).

Milwaukee PD's preferred predictive policing program is the data management program known as Information Builders. According to Information Builders' client profile for the Milwaukee County Sheriff's Office, the exigence for the adoption of this new program was a need to generate more information, without having to spend more time inputting data (Information Builders Milwaukee Case Study (IBMCS), 2014). One of the most striking features of Information Builders literature is its banality. Even the name of the company, particularly, when compared to other policing software like PredPol sounds jarringly neutral. One of the more important differences between Information Builders and other predictive policing software like PredPol is that Information Builders was founded in 1975 as a software company for business analytics (also dubbed 'business intelligence'). They provide software analytics for businesses ranging from 'education and not-for-profit, financial services, government, healthcare, insurance, manufacturing, retail, transportation and logistics, travel, and hospitality and entertainment' (IBMCS, 2014). PDs, thus, make up a small portion of their overall clientele and their website and literature reflects that. The background is white with blue lettering, appearing clean and fresh. As the name suggests, Information Builders aims to 'operationalize' data into usable information – it 'builds' information data.

In what is a particularly alarming project, 'Achieving a Single View of the Citizen with Information Management', Information Builders proposes the

> consolidation, cleansing, and synchronization of individuals and entities so that workers at every level – from executives to managers and front-line workers – have accurate and reliable views of each person or entity. This allows actionable insights on the people, programs, and departments that they operate. (IBMCS, 2014)

This process involves bringing together data from a diverse range of government and private entities, including the departments of education, homeland security, housing, human and health services, immigration, licensing agencies, corrections, public health, public safety and courts, tax and treasury, social security, and the DMV (IBMCS, 2014). Because Information Builders is a private company, they are under no legal obligation to share the nature of their algorithms with the public. However, their project of 'achieving a single view of the citizen' suggests that it may not just be criminal records and observable data (such as the weather) that are coded into their predictive policing software, but other information including property taxes and public housing that would make poor communities vulnerable to surveillance.

Information Builders' program for PDs, Law Enforcement Analytics (LEA), is just one of the components that make up their public safety software, but it is the foundation on which the other programs operate. The primary selling point of the program is its capacity to uncover 'critical patterns, trends, relationships, and variables that can be indicators of future crime activity' (Information Builders Law Enforcement Fact Sheet, 2013). By finding correlations between previously unseen or unnoticed stimuli like weather reports, time of day and month, special events, and more, LEA is marketed as a pattern finding genius. According to Information Builders, through LEA, patterns are operationalized as intelligence information that allow PDs to anticipate 'threats' rather than 'simply reacting to crimes that occur' (Information Builders, 2018).

Information Builders' LEA is premised on two primary assumptions: that there is always a threat to public safety, and that crime can be predicted and therefore controlled. For example, on the Predictive Policing Fact Sheet, they write, 'By uncovering the critical patterns, trends, relationships, and variables that can be indicators of future crime activity, police departments can proactively recognize – and react to – threats and risks to public safety before they take place' (Information Builders, 2018). LEA literature emphasizes 'Prolific criminals' and 'criminal associates' as potential threats, as well as activities and locations where there is likely to be 'criminal activity', and estimations of 'who is most likely to participate in criminal behavior'. In the Information Builders literature that is available to the public, they do not indicate who is most likely to participate in criminal behavior, though they reference people who many would agree are indeed 'threats', such as 'sex offenders' and 'criminals' released from jail (Information Builders, 2018). The invocation of common sense logic that suggests that sex offenders need to be monitored, and that people who have been in jail are necessarily public safety threats, elides the way in which being legally and socially marked as a criminal is itself the product of structural violence that targets people of color.

Consider, for example, that in Milwaukee, over half of all Black men in their 30s and half of all Black men in their 40s have been or are currently incarcerated (Pawasarat and Quinn, 2013). In general, Wisconsin incarcerates a higher percentage of Black men – 12.8% – than any other state in the country, and at a rate twice the US average of 6.7% (Pawasarat and Quinn, 2013). It is not merely the case that people of color, and Black individuals specifically, are disproportionately represented in arrest rates and incarceration statistics; they are actively criminalized.

As noted earlier, the rise of technological systems to coordinate and direct policing attention also suggests a network of connections and power that links flows of data and prediction in complex, regional contexts. At the time predictive policing technology was implemented in Milwaukee, pedestrian and traffic stops of people of color jumped, and Police Chief Flynn claimed that crime in the city had decreased (Milwaukee PD, 2018). The point of stop and frisk behavior in general is not about fighting crime, 'it is about *suppressing* crime through constant surveillance, intelligence gathering, searching, questioning, and frisking' (Correia and Wall, 2018). This is, of course, the quotidian refrain for policing and security agencies: suspending the civil liberties of some people is necessary in order to keep the 'public' safe (a public which apparently does not include some people). It is also the familiar language of broken windows theory: aggressively pursuing individuals committing 'quality of life' offences decreases the potential build-up of insecurity from leaving 'unchecked panhandlers' alone.

To be sure, it is virtually impossible to tell if predictive policing software affects crime because the data gathered and information generated by these systems is usually considered to be the intellectual property of the software company. The relative lack of independent and rigorous assessments – both in terms of the accuracy of the software used as well as comparisons between traditional and predictive policing – makes it difficult to assess the effectiveness of predictive policing systems in terms of crime reduction and fair treatment (Bennett Moses and Chan, 2018). Still, the traffic stop numbers offered in the lawsuit filed by the ACLU against the Milwaukee PD are compelling: predictive policing does not appear to be making things 'better' for people of color, and may even be making things worse. While most studies offering support for predictive policing come from the companies that create the solutions themselves (e.g. Edwards, 2016), studies conducted independently by the RAND corporation raise significant questions about their efficacy (Hunt et al., 2014; Saunders et al., 2016). In the race toward new technological solutions through predictive software, PDs continue to move away from supporting their local communities of color and toward criminalizing them further.

This is not to suggest that a return to traditional policing is desirable, even if it were possible. Rather, this suggests that far from making the work of policing 'objective', as many proponents argue, predictive policing continues to target to people of color as criminals. Now utilized in hundreds (if not thousands) of PDs around the country (and all over the world), predictive policing is undoubtedly the way of the future.

Resisting predictive policing

While police office bias has received widespread criticism over the last decade, supporters of predictive policing measures claim that it offers a more impartial approach to reducing crime. While these programs purport to be impersonal and 'objective', they rely on people to create the computer algorithms that undergird systems like Information Builders, to interpret the data, and to report crime. Because these systems are predicated on past and present crime reports, biases that have informed policing practices in the past like the surveillance of Black and Brown communities and the criminalization of 'victimless crimes' (e.g. loitering, prostitution, homelessness) are encoded into the predictive metrics. These programs are, of course, neither impersonal nor objective, though they clearly gain public credibility through being discursively framed as impartial and scientific. The maps produced from Information Builders function like one-way mirrors, marking criminogenic zones of exception visible only to police officers. This new kind of specialized targeting gains legitimacy because it targets *spaces* rather than specific groups of people based on race and other factors.

We have suggested that what has changed over the last few decades is not so much the ends of policing, but rather the means by which these practices are operationalized, amounting to what Kade Crockford of the ACLU has called a 'tech-washing' of historically racist policing (Burrington, 2015). Surveillance technologies are not neutral, and the ways in which they are used reflect both social and cultural factors (Amicelle et al., 2015; Marx, 2002). This is why it is vital to understand not just the digital and material network that underlies predictive policing but also the historical discourses that have helped to shape it.

It is tempting to despair about the seemingly diminished space of resistance created by technological surveillance, but both scholars and members of surveilled communities have forwarded possible modes of resistance. Scholarly approaches generally focus on using other collections of big data (Ettlinger, 2018) or new technological developments such as hacktivism to challenge the authority of big data surveillance practices (Cardullo, 2015; Kubitschko, 2015), while others looks to enact further regulative and normative responses (Richardson et al., 2019). However, from the perspective of those experiencing the constant surveillance that policing and its 'newest' predictive iteration presents, these approaches have two primary limitations. First, as we identified above, these practices of resistance leave the underlying power structure that aims to maintain the status quo intact, challenging the technology in use but not the practice and effects of policing itself. And second: while the approaches have merit, their presumption of digital literacy, technological access, and technical ability limits its potential for use by most surveilled communities (D'Ignazio and Klein, 2020). But, if policing has in some sense always been predictive insofar as Black and Brown communities are more policed because of stereotypes that link people of color to criminality, then we can look to the resistive practices that these communities have developed to survive centuries of 'predictive' surveillance and violence.

What is needed is an approach to resistance that is accessible for surveilled communities while also sensitive to the local-historical context that predictive policing technology is embedded within. While the scholarly literature recognizes that surveillance technologies, like all other technologies, are socially constructed and influenced by resistive acts (Amicelle et al., 2015; Marx, 2002), specific examples of community-based action remain absent from the discussion thus far. The focus on technical solutions and calls for further regulative authority obscures the important work already being done by communities of color and perpetuates a deficit-model of thinking which paints these communities as unable to enact their own forms of resistance. Here we look to communities themselves for vernacular, nuanced approaches to resisting policing in local contexts, recognizing that big data surveillance is an extension of a power structure they have long grappled with.

The community approach sidesteps limitations of the technical approach by focusing on what is already available in local contexts: social bonds, community groups, and even creative imaginaries for harm accountability. Community resistance, in addressing big data surveillance and the system of power from which big data surveillance emerges, provides new access points, opportunities for resistance, and challenges us to imagine and enact new futures, rather than reinforcing the status quo.

In Milwaukee, there is the recent campaign #liberateMKE started by African American Roundtable (AART), a coalition of leaders serving the African American community in

Milwaukee. The goal of #liberateMKE is to gain public support to divest US$25 million dollars from the city's budget funding the Milwaukee PD (currently, US$311 million dollars – 46% of the city's budget – goes to MPD) and divert it to programs that address poverty and violence, such as those that support jobs, public health, and housing. The organizers of #liberateMKE determined where to divert the money through a community-wide survey where residents could indicate which programs the funds should support (LiberateMKE, 2019).

A central component of gaining public support for #liberateMKE was AART's information session on the history of the Milwaukee PD. By providing this history, campaign organizers aimed to situate the call for divestment as a response to historical and ongoing discrimination and oppression. In this way, the local-historical is crucial to the exigency of the disinvestment from police. #liberateMKE is not calling for the elimination of predictive policing technology, or for better discernment and oversight of the historical crime data that fuels predictive policing. Rather, in calling for disinvestment from MPD and reinvestment in the community, they signal the importance of material infrastructure and human relationships in moving away from systems of surveillance.

Schenwar and Ludwig (2018) write that resolving to not call the police is a crucial part of reducing anti-black violence that forces us to have constructive conversations with neighbors about our mutual and individual needs. They argue that

> Talking with our neighbors about taking responsibility for keeping our communities safe and happy helps us learn from each other and establish trust: the first steps toward building relationships that are strong enough to confront more complicated problems, such as bullying or domestic violence. (Schenwar and Ludwig, 2018: 149)

Ironically, these practices take on an interpretation diametrically opposed to what Kelling and Wilson suggested in their theory of 'broken windows': rather than policing and punishing those who break windows, these community solutions move toward broken windows as opportunities to repair and restore after harm has occurred within local contexts.

Central to these resistive practices is the development of networks and social ties that provide a robust alternative to calling the police. Consider the Oakland Power Projects (OPP) whose focus is to build

> the capacity for Oakland residents to reject police and policing as the default response to harm and to highlight or create alternatives that actually work by identifying current harms, amplifying existing resources, and developing new practices that do not rely on policing solutions. (Schenwar and Bernd, 2018: 152)

Currently, members of the OPP are even undergoing medical training and workshops so that they can provide emergency healthcare to each other (Schenwar and Bernd, 2018). By developing a robust network of individuals and local grassroots organizations including the Ella Baker Center and Stop the Injunctions Coalition who are committed to policing alternatives, and drawing on the resistive networks established by groups like the Black Panther Party which originated in Oakland, Oakland residents are building a vital alternative to calling the police. Such a network also reduces the input of information into the predictive policing data collection, thus disrupting the flow of information into these data-driven surveillance systems.

Resistance toward these seemingly untouchable big data edifices emerges when we first recognize the opacity, incompleteness, and representations of surveillance assemblages are in fact part of a much longer, storied history. Recognizing this, resistance then becomes a question of localized, community-based support and solidarity. Alongside the focus on technical approaches of resistance to big data surveillance, we should include the sensitized and contextualized community approach that attunes us to the actors, networks of power, and biases that underlie all that we see in predictive policing today.

Conclusion

In our analysis of predictive policing as a form of big data surveillance, we have examined and challenged the myth of this practice as a new danger to public well-being, instead showing that is merely one more step in a much longer, storied ideology of monitoring and control. By exploring the presence of the biases, power interests, and the results of predictive policing practices in Milwaukee, WI through a 'local-historical' approach, we can begin to glimpse the networks of power that underlies this sociotechnical assemblage. Predictive policing, and big data surveillance, is not new: it is simply an extension of what has been long-practiced. In this way, we argue, resistance too does not need to be novel. Rather it needs to draw on the local and lived knowledge of communities who have, and continue to, exist under intensive surveillance and monitoring. By looking to their resistive practices and imaginative approaches to creating a framework outside those that support traditional power structures, we can identify new approaches for conceptualizing resistance to predictive policing practices which involve harm accountability without the use of existing policing structures. As attention continues to focus on predictive policing, big data surveillance, and the racialized effects of these sociotechnical systems on communities of color, we should look to the same communities to understand how they are fighting back and asserting their own claims to a safe community.

ORCID iD

Xerxes Minocher https://orcid.org/0000-0002-2501-2265

Notes

1. The public-facing Milwaukee PD website which is supposed to share maps similar to those being produced for law enforcement officers by their predictive policing systems has been unavailable for at least the better part of 2018–present since the authors first began focusing on this context. Much of our understanding of the maps has come from examining the marketing materials of the company that supports Milwaukee PD, as well as seeing the output of similar systems such as 'PredPol', a predictive policing platform launched in several cities across the United States. In contrast to the Information Builders system used by Milwaukee PD, PredPol has been more transparent with its algorithmic logic.
2. Exemplifying the journalist watchdog role, both the Washington Post & The Guardian maintain databases tracking the number of people shot and killed by police in the United States. At the time of writing this article, 678 people have been shot and killed by police in 2019.

References

Amicelle A, Aradau C, and Jeandesboz J (2015) Questioning security devices: Performativity, resistance, politics. *Security Dialogue* 46(4): 293–306.

Amoore L and Piotukh V (2015) Life beyond big data: Governing with little analytics. *Economy and Society* 44(3): 341–366.

Angwin J, Larson J, Mattu S, et al. (2016) Machine bias. *ProPublica*, 23 May.

Bellafante G (2014, November 27) In New York Public Housing, Policing Broken Lights. Available at: https://www.nytimes.com/2014/11/30/nyregion/in-new-york-public-housing-policing-broken-lights.html?rref=collection/byline/ginia-bellafante (accessed 10 July 2018).

Bennett Moses L and Chan J (2018) Algorithmic prediction in policing: Assumptions, evaluation, and accountability. *Policing and Society* 28(7): 806–822.

Bialik C (2016, January 08) How to make sense of conflicting, confusing and misleading crime statistics. Available at: https://fivethirtyeight.com/features/how-to-make-sense-of-conflicting-confusing-and-misleading-crime-statistics/ (accessed 9 May 2019).

Bodenner C (2015, October 14) Paranoia, half a century ago. Available at: https://www.theatlantic.com/notes/2015/10/paranoia-in-1967/409396/ (accessed 15 September 2019).

boyd d and Crawford K (2012) Critical questions for big data. *Information, Communication and Society* 15(5): 662–679.

Browne S (2015) *Dark Matters: On the Surveillance of Blackness.* Duke University Press.

Burrington I (2015, June 29) What Amazon taught the cops. Available at: https://www.thenation.com/article/what-amazon-taught-cops/ (accessed 11 August 2018).

Cardullo P (2015) Hacking multitude' and big data: some insights from the Turkish 'digital Coup. *Big Data & Society* 2(1): 2053951715580599.

Chan J and Bennett Moses L (2016) Is big data challenging criminology? *Theoretical criminology* 20(1): 21–39.

Choudhury N (2018) New data reveals Milwaukee police stops are about race and ethnicity. ACLU. Available at: https://www.aclu.org/blog/criminal-law-reform/reforming-police-practices/new-data-reveals-milwaukee-police-stops-are (accessed 15 June 2018).

Collins et al. v. The City of Milwaukee et al., 81 (United States District Court Eastern District of Wisconsin Milwaukee Division, February 22, 2017).

Collins PH (1990) Black feminist thought in the matrix of domination. *Black Feminist Thought: Knowledge, Consciousness, and the Politics of Empowerment* 138: 221–238.

Correia D and Wall T (2018) *Police: A Field Guide*. Brooklyn, NY: Verso.

De Mauro A, Greco M, and Grimaldi M (2016) A formal definition of big data based on its essential features. *Library Review* 65(3): 122–135.

D'Ignazio C and Klein L (2020) *Chapter one: The power chapter*. MIT Press Open. Available at: https://bookbook.pubpub.org/pub/7ruegkt6?version=279195a6-9900-4d74-96ff-5d1e5849f8ab.

Edwards E (2016, August 31) Predictive policing software is more accurate at predicting policing than predicting crime. Available at: https://www.aclu.org/blog/criminal-law-reform/reforming-police-practices/predictive-policing-software-more-accurate (accessed 12 May 2018).

Eubanks V (2018) *Automating Inequality: How High-Tech Tools Profile, Police and Punish the Poor*. New York: St. Martin's Press.

Ettlinger N (2018) Algorithmic affordances for productive resistance. *Big Data and Society* 5(1): 205395171877139.

Ferguson AG (2017) *The Rise of Big Data Policing: Surveillance, Race, and the Future of Law Enforcement*. New York: New York University Press.

Greengard S (2012) Policing the future. *Society* 55(3): 19–21.

Griffith D (2015) Predictive policing: Seeing the future. Available at: http://www.policemag.com/channel/technology/articles/2015/06/predictive-policing-seeing-the-future.aspx (accessed 12 May 2018).

Hu M (2017) Orwell's 1984 and a Fourth Amendment Cybersurveillance Nonintrusion Test. *Washington Law Review* 92: 1819–1904.

Hunt P, Jessica S, and John S (2014) *Hollywood, Evaluation of the Shreveport Predictive Policing Experiment*. Santa Monica, CA: RAND Corporation.

Hutchins B (2016) Tales of the digital sublime: Tracing the relationship between big data and professional sport. *Convergence: The International Journal of Research into New Media Technologies* 22(5): 494–509.

Information Builders (2013) *Law Enforcement Analytics*. Available at: https://www.informationbuilders.com/sites/default/files/pdf/factsheets/fs_lea_wf_2013.pdf (accessed 12 May 2018).

Information Builders (2014) *Information Builders Milwaukee Case Study*. Available at: https://www.informationbuilders.com/sites/default/files/pdf/applications/cs_milwaukee_county_sheriffs_office_business_intelligence_integration_webfocus_iway_2014.pdf (accessed 12 May 2018).

Information Builders (2018) *Predictive Policing*. Available at: https://www.informationbuilders.com/sites/default/files/201801/fs_predictive_policing_webfocus_rstat_0.pdf (accessed 12 May 2018).

Jackson RC (2014) Locating Oklahoma: Critical regionalism and transrhetorical analysis in the composition classroom. *College Composition and Communication* 66(2): 301–326.

Jasanoff S (2006) Biotechnology and empire: The global power of seeds and science. *Osiris*. 21: 273–292.

Jefferson BJ (2018) Predictable policing: Predictive crime mapping and geographies of policing and race. *Annals of the American Association of Geographers* 108(1): 1–16.

Karppi T (2018) 'The computer said so': On the ethics, effectiveness, and cultural techniques of predictive policing. *Social Media + Society* 4(2): 205630511876829.

Kelling GL (2015) *Policing in Milwaukee: A Strategic History*. Milwaukee: Marquette University Press.

Kelling G and Wilson J (1982, March 04) Broken Windows. Available at: https://www.theatlantic.com/magazine/archive/1982/03/broken-windows/304465/ (accessed 13 December 2018).

Kift P and Nissenbaum H (2016) Metadata in context-an ontological and normative analysis of the NSA's bulk telephony metadata collection program. *ISJLP* 13: 333.

Kisela v. Hughes 17-467 (Supreme Court of the United States, April 2, 2018).

Kubitschko S (2015) Hackers' media practices: Demonstrating and articulating expertise as interlocking arrangements. *Convergence* 21(3): 388–402.

Lally N (2017) Crowdsourced surveillance and networked data. *Security Dialogue* 48(1): 63–77.

LiberateMKE (2019) Available at: https://www.liberatemke.com/ (accessed 15 December 2018).

Lum K and Isaac W (2016) To predict and serve? *Significance* 13(5): 14–19.

Luthern A (2018, February 16). 'A lifetime in policing': Chief Ed Flynn retires having radically changed the Milwaukee Police Department. Available at: https://www.jsonline.com/story/news/crime/2018/02/16/lifetime-policing-milwaukee-police-chief-ed-flynn-retires-leaves/334878002/ (accessed 13 December 2018).

Mann G and O'Neil C (2016, February 22) Hiring algorithms are not neutral. Available at: https://hbr.org/2016/12/hiring-algorithms-are-not-neutral (accessed 13 December 2018).

Manning C (2017, September 13) Chelsea Manning: The dystopia we signed up for. Available at: https://www.nytimes.com/2017/09/13/opinion/chelsea-manning-big-data-dystopia.html (accessed 15 October 2018).

Mantello P (2016) The machine that ate bad people: The ontopolitics of the precrime assemblage. *Big Data and Society* 3(2): 205395171668253.

Marx GT (2002) What's new about the 'new surveillance'? Classifying for change and continuity. *Surveillance and Society* 1: 9–29.

Milwaukee Police Department (2018) Chief Edward A. Flynn's 10 Year Retrospective. Milwaukee Independent. Available at: http://www.milwaukeeindependent.com/wp-content/uploads/2018/01/ChiefFlynn10YearRetrospective.pdf (accessed 13 December 2018).

Neyfakh L (2015, October 15) The FBI has data on police violence. It's just disastrously incomplete and unreliable. Available at: https://slate.com/news-and-politics/2015/10/police-violence-eric-garner-tamir-rice-oscar-grant-all-left-out-of-fbi-s-database-of-officer-involved-killings-the-guardian-reports.html (accessed 13 December 2018).

Oberman J and Johnson K (2016) Broken windows: Restoring social order or damaging and depleting New York's poor communities of color. *Cardozo Law Review* 37(3): 931–954.

O'Neil C (2016) *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. New York, NY: Crown Books.

Pawasarat J and Quinn LM (2013) Wisconsin's mass incarceration of African American males: Workforce challenges for 2013. ETI Publications.

PoliceOne (2017, June 2) How one sheriff's office uses integrated data management to gain actionable intelligence. Available at: http://www.prophoenix.com/blog-mkecasestudy/ (accessed 13 December 2018).
Porter TM (1996) *Trust in Numbers: The Pursuit of Objectivity in Science and Public Life*. Princeton: Princeton University Press.
Richardson R, Schultz J, and Crawford K (2019) Dirty data, bad predictions: How civil rights violations impact police data, predictive policing systems, and justice. *New York University Law Review Online*, Forthcoming.
Ruderman W (2012, June 28) New York Police Department manipulates crime reports, study finds. Available at: https://www.nytimes.com/2012/06/29/nyregion/new-york-police-department-manipulates-crime-reports-study-finds.html (accessed 13 December 2018).
Sanders CB and Hannem S (2012) Policing "the risky": Technology and surveillance in everyday patrol work. *Canadian Review of Sociology/Revue Canadienne de Sociologie* 49(4): 389–410.
Sanders CB and Sheptycki J (2017) Policing, crime and 'big data' Towards a critique of the moral economy of stochastic governance. *Crime, Law and Social Change* 68(1–2): 1–15.
Saunders J, Hunt P, and Hollywood JS (2016) Predictions put into practice: A quasi-experimental evaluation of Chicago's predictive policing pilot. *J Exp Criminol* 12(3): 347–371.
Schenwar M and Bernd C (2018) Community groups work to provide emergency medical alternatives, separate from police. In Macaré J and Price AY (eds) *Who Do You Serve, Who Do You Protect?: Police Violence and Resistance in the United States*. Chicago, IL: Haymarket Books, pp. 151–161.
Schenwar M and Ludwig M (2018) A New Year's resolution: Don't call the police. In: Macaré J and Price AY (eds) *Who Do You Serve, Who Do You Protect?: Police Violence and Resistance in the United States*. Chicago, IL: Haymarket Books, pp. 147–151.
Stop LAPD Spying Coalition (2018) Available at: https://stoplapdspying.org/ (accessed 13 December 2018).
Welles BF (2014) On minorities and outliers: The case for making big data small. *Big Data and Society* 1(1): 205395171454061.
Wexler R (2018) Life, liberty, and trade secrets: Intellectual property in the criminal justice system. *Stanford Law Review* 70: 1343.

Author biographies

Xerxes Minocher studies the construction of cultural relationships with technology. They are a PhD student in Mass Communications at the School of Journalism and Mass Communication, University of Wisconsin-Madison, with a focus in Science and Technology studies.

Caelyn Randall is a doctoral candidate in the Department of Communication Arts at the University of Wisconsin-Madison. Their research focuses on the rhetoric of disability and the construction of spatio-temporality in public discourse.