memo to readers: this is an extremely early, rough, draft of some ideas I'm trying to work out about the possibility of a kind of bottom-up data science rooted in the needs and capacities of oppressed communities. It isn't remotely ready for prime time, and I hadn't planned on posting it online for quite a while. (Its ultimate destination is to become a chapter in an edited volume which has, due to nobody's fault, become stalled—as such volumes often do.). However, I was motivated to post it by being made aware of a wonderful talk by Dan McQuillan entitled "Towards an Anti-Fascist AI,"[1] as well as a paper of his entitled "People's Councils for Ethical Machine Learning."[2] Needless to say, future iterations of this chapter will be engaging with McQuillan's work in some detail. But I post this draft now as a moment to participate in the ongoing conversation about the notion of placing control over machine learning in the hands of the oppressed—goals that McQuillan and I clearly share.

To the limited extent that this chapter presently has an

Abstract

it is that many current uses of data science/machine learning/artificial intelligence operate from a top-down standpoint, rooted in a standpoint of distrust, in which authoritative entities (governments, credit raters, etc.) use data for surveillance of subordinated groups. But these technologies also have the potential for bottom-up use, on behalf of and by the subordinated and the oppressed. In order to achieve this potential, a transdisciplinary research program encompassing the theory of trust and collective action as well as the techniques of distributed machine learning and transfer learning, should be initiated.

[1] http://danmcquillan.io/ai_and_antifascism.html
[2] http://research.gold.ac.uk/23040/

Critical Race Data Science and Epistemologies of Trust

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1. Introduction: Data Surveillance.

This chapter considers the distinctive harms of racialized data-surveillance (often known to scholars in the field of surveillance studies as "dataveillance") in the context of contemporary machine learning techniques, as well as potential subversive uses of those same techniques to pursue racial justice.

I use the term "data surveillance" in a relatively narrow sense. By "data surveillance," I mean the use of aggregate data about individuals to drive conscious authoritative human decisions about those or other individuals. For example, "predictive policing" is a quintessential case of data surveillance: individual human police officers make conscious decisions about individuals either directly or indirectly as a result of aggregate crime data. So is the use of credit scores in lending, insofar as loan officers make use of those scores to make decisions about whom to approve or reject. While the arguments in this chapter are meant to apply to all cases of authoritative data surveillance (other examples include public benefits investigation and control, anti-terror and anti-financial-fraud data predictive modeling), it focuses on the case of policing as the most salient (and well-studied) example.

This stipulative definition excludes automated uses of aggregate data, such as the business models of internet companies that use personal data to run algorithmic advertising markets, or automated rather than human-involved financial uses of individual data (such as automatically set insurance premiums or loan approval thresholds). I take no position on the appropriateness of the language of surveillance to describe these forms of automation, but they are not the subject of this essay, which focuses on the use of data to inform authoritative human decision. By limiting the definition of data surveillance in this chapter in that way, I aim to capture a distinct phenomenon by which contemporary developments in machine learning facilitates not merely new kinds of social control (which could be carried out algorithmically, with no human intervention), but also new kinds of human observation and judgment, and the associated belief-formation processes (including trust and distrust, the key focus of this chapter).

Authoritative data surveillance also has a second important feature: it can justify further surveillance, including further data surveillance. If the police identify geographic markers of crime or welfare officials identify behavioral markers of fraudulent claims, these data justify further police scrutiny of the areas or investigation of individuals displaying the behaviors in question—investigation that may generate additional data to feed back into the predictive process.

Those two features mark the limits of the scope of the first part of the chapter. The second part of the chapter describes a vision of data surveillance that is not authoritative, and may not even warrant the term "surveillance": the use of data and machine learning techniques on behalf of those subject to authority to enable political and legal action.[1]

A. And Race

There is a highly active scholarly conversation surrounding the racialized use of machine learning. The existing literature focuses on several key areas of concern, including:

- the perpetuation of racialized crime stigma through machine learning algorithms that convert preexisting social bias into racial predictors of crime (Lum and Isaac 2016, Joh 2016, Ferguson 2017, Selbst 2017);
- the inadequate training and validation of contemporary machine learning models on non-normative races, leading to systematic errors such as higher inaccuracies in the recognition of non-white faces (Buolamwini & Gebru 2018);
- the use of racial criteria to facilitate private market segmentation, sometimes for pernicious ends, as with the "dark posts" targeted at African-American voters during the 2016 American elections (Graham 2016);
- the use of machine learning to make more traditional tools of government surveillance more effective and more useful to target subordinated racial groups, such as the use of facial recognition technology to enhance camera surveillance, and its racialized use by China (Apps 2018); and
- more generally, the problem of and techniques to ameliorate "algorithmic bias," that is, the tendency of machine learning models to have a disparate effect when used to predict human judgments which are themselves rooted in circumstances arising out of white supremeacy–such as explicit or implicit biases of data sources or the simple lack of representation of non-normative racial (and gender, religious, etc.) groups in the organizations building those models (Kilbertus et. al. 2017, Hardt et. al. 2016, Barocas & Selbst 2016, Garcia 2016, among many others).

While the general account of this chapter will be relevant to all of these areas of concern, the focus will (for the first part) on the first as a case study of what I see as a distinctive dynamic surrounding the wrongs of racially biased data

[1] Scholars in surveillance studies sometimes use the term "sousveillance" to capture the idea of bottom-up observation (Mann & Ferenbook 2013). I avoid this term here because I do not mean to limit the scope of the discussion in the second part of this chapter to mere observation of the powerful by the powerless, but rather to all uses of machine learning techniques from the standpoint of subordinated groups, no matter whom the underlying data is about.

surveillance: the perpetuation and expansion of racialized distrust. The core claim of the first part of this chapter is that the use of machine learning by social authorities to make negative predictions in the context of preexisting racial stigma relies on and validates a dangerous kind of intergroup distrust which, as a normatively meaningful harm, is distinct from mere disparate effect.

The second part of this chapter then sketches the outline of what I call a critical race data science, which is rooted in the notion that bottom-up uses of machine learning controlled by and from the epistemic standpoint of subordinated groups, especially (but not only) subordinated racial groups, can be successful in view of the capacity of such tools to build on relationships of trust rooted in common experience and interests and that subordinated epistemic standpoint, and for that reason can reinforce democratic collective action on behalf of subordinated groups.

B. And Trust

By "trust" and "distrust," I mean nothing more than relative dispositions to believe that another person or group of people will behave as they ought, by one's own lights. On a bayesian model of reasoning, I come to trust a person when my subjective probability in their doing the set of things that they ought to do increases. Of critical importance, some forms of trust are central to democratic organization and political action—in particular, democratic forms of political organization that depend on the coordinated use of power (Gowder 2015b).

This chapter claims, in essence, that we can helpfully understand the relationship of data surveillance and race in terms of the *dynamics of trust*. When carried out under the control of hierarchically empowered racial groups and racialized institutions, data surveillance is rooted in cycles of distrust. It embeds preexisting distrust by hierarchically superordinated groups of subordinated groups into predictive models, and it exacerbates, or risks exacerbating, that distrust by reinforcing it; at the same time it exacerbates reciprocal distrust by members of subordinated groups against those deploying the surveillance—distrust in the collection of the data, in the shape the collection process allows it to take, and in its use. This distrust is rooted in the epistemology of inequality, which encourages the collection and use of data in the forms and for the purposes specified by hierarchically superordinated classes.

By contrast, a critical race data science is one that can be built on an egalitarian epistemology, where the shape of data corresponds to the shape of the knowledge of groups working to overcome hierarchy. Moreover, shared rather than conflictual interests among hierarchically subordinated groups can permit trust in the collection and use of such data within the group, and thus permit the use of such data to support increasing intragroup trust and collective action.

2. A Case Study: Predictive Policing and Distrust

The notion of "predictive policing" is that criminal activity can be predicted using machine learning techniques, allowing policing resources to be allocated to deter crime in advance of its occurrence (or potentially to narrow down the investigative scope of those resources after the fact). Predictive policing has been carried out on a geographic basis, with the creation of "heat maps" predicting likely crime areas, as well as on an individual basis with the creation of "heat lists" that predict those likely to be involved in violence (see Ferguson 2017 for a description of the state of the art).

In both cases, the academic literature has focused on the prospect of racial bias in the application of those techniques, particularly in the United States. The essential concern about bias can be stated simply (see Isaac 2018 for another summary): we know that race plays a causal role, independent of criminal behavior, in the extent to which individuals are subject to punitive action at all stages of the criminal justice system. We would expect, therefore, predictive policing models to overestimate the risk posed by individuals who are ascribed racial classifications subject to a stigma of criminality, as well as radicalized places subject to that stigma (on place-based racial criminal stigma, see Quillian & Pager 2001). Even the creator of a commercial predictive policing product acknowledges these risks (Brantingham 2018). And while some scholars have argued that there are racially egalitarian implications of policing technology as well, particularly in supplying officers with de-racialized information about criminality and for that reason reducing the use of biased subjective perceptions and explicit racial profiling (Capers 2017, pp. 1276-1283), in light of the work of scholars like Ferguson (2017) and Buolamwini & Gebru (2018), it seems unlikely that these hopes will be realized with the technology in its present form.

I argue that the race-based harms of predictive policing and other forms of authoritative data surveillance are best expressed in the language of distrust. These surveillance systems incorporate preexisting distrust, in the form of the increased propensity of members of superordinated races to suspect members of subordinated races of crimes or of other misconduct (welfare fraud, etc.). They then exacerbate that distrust, by creating in authorities an increased level of suspicion in the objects of prediction.

For example, place-based predictive policing inherently communicates an increased propensity to commit crime to people found in a specific geographic area, thus changing the priors (in bayesian terms) of a rational police officer as to the likelihood any individual she interacts with in that area is involved in crime—even if that police officer does not herself labor under any racially biased belief-formation processes. These beliefs, if translated into conduct (police searches, credit denials, welfare investigations), will confirm that distrust on an institutional level: to the extent data generated by that conduct feeds back into the predictive system at a higher rate than data generated from areas or individuals not targeted for special surveillance as the output of some algorithm, it is likely that disproportionately more signals will be discovered from the targeted areas or individuals.

Because of well-known human psychological features such as confirmation bias and cognitive dissonance reduction, it is also likely that this distrust will be confirmed on an individual basis. The police officer who is sent into a segregated neighborhood as the result of a place-based predictive policing algorithm is likely to start to make inappropriate generalizations, at least unconsciously and perhaps consciously, about the relationship between the personal characteristics of the individuals in the neighborhood (such as race) and the crimes that she observes.

I claim that this distrust spiral is a distinctive harm of radicalized data surveillance. Such distrust poisons intergroup relationships—making it difficult to coordinate political, social, and commercial relationships across racial group lines, in a way that is independent of the harms that also come from the simple fact of racially biased authoritative decision-making. Bias alone merely imposes a welfare cost on members of a victimized group; cyclic distrust imposes an additional *stigma cost* represented by the damage to the reputation of members of stigmatized groups, and the likelihood that members of non-stigmatized groups will be unwilling to relate in cooperative terms to members of stigmatized groups.

Worse, that stigma can leak into the incentives of the stigmatized groups. Kim and Loury (2018) illustrate this with a model of employment discrimination, according to which members of stigmatized racial groups, anticipating that employers will discriminate against them due to a perceived lack of human capital, may have a disincentive to invest in human capital (since it's disproportionately costly to overcome preexisting biases), thus reinforcing that perception and spiraling down into what they call a "low reputation trap." While their model is developed in terms of the employment market, we can apply it to other situations of what they call "statistical discrimination." If others are going to distrust you regardless of your behavior, what's the point of building trust?[2]

3. Critical Race Data Epistemology

We can imagine a better alternative, one that embeds the use of data both about subordinated racial groups, and about authorities in the interests of those over whom authority is exercised, in relationships of trust derived from the control of that data and the shaping of its collection in members of subordinated groups themselves.

One insight that we have learned from feminist and critical race approaches to the philosophy of science is that knowledge is not independent of social position (see discussion in Gowder 2015a). Our embededness in social groups and hierarchies

[2] Also see Loury's other work on racial stigma and the incentives of stigmatized groups (e.g. Bowles, Loury & Sethi 2014, Loury 2002 and many other papers).

frames the kinds of questions we can ask and the kinds of observations we can make.

But this principle applies not just to ordinary inferential science but also to machine learning, for the conceptual machinery that people use to make the observations that compose the data on which the training of models is carried out is itself influenced by social position.

At least two kinds of conceptual judgments must be made in the context of any machine learning model. The first is the *feature representation*—the machine learning analogue to the scientific question of the unit of observation. If we conceive of a machine learning problem in its most abstract form as a lot of linear algebra, this amounts to the question of what kinds of things are on the columns of the matrix. For example, in the context of a linear regression on structured data, what's on the right side of the equation? Even in modern deep learning approaches which have some capacity to learn their own feature representation from unstructured data, there must still be choices about how to segment the data in the first place—is the natural language processing project trained on words? Characters? Sentences?

The second is the formation of labels for supervised learning projects. The labeling of data to permit the use of supervised machine learning techniques requires the continual exercise of judgment, as anyone who has ever supervised a team of research assistants in building a dataset can attest. In the context of policing, for example, that judgment includes the choice to classify a particular behavior as criminal or non-criminal. It also includes the choice to have the labels (and thus the thing predicted) be, for example, observed criminality, as opposed to arrests, crime reporting, or some entirely different outcome that isn't directly related to law enforcement.

These judgments, as noted, are partially factors of social position and group-affiliation: the things that to a police department count as crime may to an ordinary member of the community count as ordinary social behavior. We saw this vividly in the aftermath of the killing of Michael Brown, where those of us with the good fortune not to live in St. Louis County learned that the white power structure of that county imposed expropriative regulations on a wide swathe of ordinary social behavior—requiring, for example, residents to pay a licensing fee to have a roommate—and then ruthlessly criminalized those (much more dominated by non-whites than those doing the criminalizing) who were unaware of the regulations or unable to comply with them (see discussion in Gowder 2016, pp. 193-4). The most astonishing statistic to come out of Ferguson, Missouri stands as a monument to differential police and community judgments of what count as crime: there were an estimated three warrants *per household* (Tabarrok 2014). It beggars the imagination to suppose that all of these arrest warrants represented things that the ordinary people of the community and members of subordinated classes understood as criminal behavior, as opposed to the endless duplication of crimes cooked up for ilicit purposes by bandit municipalities looking to profit from white supremacy. The point, for present purposes, is this: the enterprise of predicting a value-laden concept like crime is contingent on hierarchically-grounded choices about what kinds of "crimes" to look out for.

Moreover, there is strong reason to expect a systematic difference in the judgments of the powerful and the powerless about classification criteria related to their own power, for the powerful have strong psychological reasons to adopt judgments that validate their own hierarchically superior status. As Anderson (2016, 2015) vividly describes in the context of moral judgment, power and social hierarchy profoundly distort the reasoning process; in the context of data collection we should for that reason expect systematic status-quo justifying biases in the form and content of data collected by and for the purposes of the powerful.

This features of the institutional level also appear on a local level in terms of individual acts of data collection, which are themselves choices.[3] Put differently, the judgments of whether to take the actions that generate criminal justice metadata are socially contingent. If an individual police officer chooses to let someone off with a warning rather than subject them to the criminal justice system, this choice affects not only the fate of that individual but also the data generated from the interaction—and it is likely to be affected by race (Kochel et. al. 2011). Another example of the impact of this choice to record or not record data: Brucato (2015) points out that police have a tendency to turn on body cameras when those cameras capture things that the police want to be seen. Data collected by members of the community subject to authoritative data surveillance, rather than by authorities or hierarchically empowered groups, would be more likely to incorporate an egalitarian rather than an authority-favoring or hierarchy-favoring set of judgments about which observations to make and which to discard.

Furthermore, there is also strong reason to expect the powerful and the powerless to have systematically different available stores of information to carry out classification tasks. This point is aptly made in the context of police body cameras by Brucato (2015), who points out that body cameras inherently capture the visual perspective of the police. For example, they show the allegedly threatening movements of the policed citizen, and not the threatening movements of the officer which might be leading to the citizen's behavior. To see the world from the perspective of a police officer as opposed to the perspective of the one policed is to make selections about the scope of the questions that can be asked ("did the police officer have enough information to justify the use of violence," as opposed to "did the citizen have reason to fear the police and run away").

Similar phenomena apply to the more general case of the collection of data. One of the most familiar burdens of dealing with a bureaucracy is the incapacity of its forms to take account of one's individual situation, often because they were written from a hierarchically empowered perspective—in the most benign cases,

[3] As Joh (2016, pp. 30-1) points out, the acts leading to data collection in policing are themselves discretionary.

for example, from perspectives that assume that all names come in the form of native English speakers, but in more pernicious cases in the form of the absence of any way to communicate information that would allow a rational decision-maker to rule in favor of the bureaucratic petitioner. In effect, forms—and all other established data-collection procedures and customs—create an organizational epistemology that constrain the sorts of data that an institution of governance will collect. The only data that will be collected will be data that is useful to the powerful, in a form that suits their needs.

Even when efforts are made to collect data taking into account the perspective of hierarchically subordinated groups, the danger of doing so in terms of the concerns of superordinated groups is always present. For example, McCarthy and Rosenbaum (2015) describe a Chicago project called “RespectStat” that aims to track the citizen-perceived quality of civilian-police interactions. But while this information might be useful for the police department seeking to control its own officers, it is less clear how it is immediately actionable for subordinated communities.

More useful, for example, might be a community-based catalogue of the excuses used by police to hassle citizens. At least in some communities, a major driver of racialized police injustice is the abuse of penny-ante “crimes” to inflict constant police scrutiny on minority populations—this was, for example, the essential strategy of Giuliani’s implementation of “broken windows” policing in New York City, and, of course, St. Louis County. From the perspective of the victimized communities, rather than data on how police or impolite officers are, it may be more useful to have the capacity to observe and predict these hostile police practices—effectively to use data science to replicate the cognitions of police officers and discover what kinds of ridiculous charges they’re inventing, as well as, e.g., to learn where police are likely to appear in order to hassle citizens for walking in the road or selling loose cigarettes, so that the community can choose to respond to those abuses, either via the democratic process, via simply avoiding the predicted location and preferred categories of abused discretionary power of the officers, or via engaging in mass community resistance in order to prevent rather than in response to police misconduct.

I imagine, for example, the entire neighborhood showing up to a racist officer’s favorite harassment beat in order to engage in preemptive civil disobedience and provoke the inevitable confrontation en masse rather than on a one-to-one basis. This seems to me far more useful to as a roadmap to political action on behalf of subordinated communities than anything that can be generated by a police respect dataset representing something like the responses of survey respondents to items on a Likert scale. But to make any of these dreams realistically possible, the data collection process has to begin from the standpoint of the concerns and interests of the subordinated, not the technical demands of effective policing and other exercises of authority from the already-empowered.

A. Bottom-Up Trust

Another instance where perspective matters in the interpersonal relationship embedded in the collection of data. Virginia Eubanks (2018, p. 107) reports that there is wide variance in primarily African-American South Los Angeles in the scores on the instrument used by public services to prioritize the homeless for housing: local residents get substantially higher scores when measured by the local organization, not because the social workers elsewhere tell lies, but because the instrument asks extremely personal questions and the local workers are more inclined, if not more able, to build trust to get them answered. Another vivid illustration of the relationship between trust and racial hierarchy in terms of the provision of important life services is a recent working paper (Alsan 2018), which provides experimental evidence of increased use of preventative care services by African-American patients when treated by African-American doctors—and the authors plausible interpret their results to be partly mediated by increased trust in same-race doctors.

Consider, in this context, Ferguson's (2017) promotion of "bright data"—the idea that the data now used for predictive policing might instead be used by authorities to facilitate the provision not of violent force but social services like housing assistance and counseling. I confess to some skepticism about the efficacy of the notion: in the absence of trust by the community in the uses to which authorities will put these data, those authorities are unlikely to have access to accurate data even in terms of their own epistemological standpoints. Put intuitively, if you don't know whether information you give to some local bureaucrat will be misused to, for example, potentially subject you to police scrutiny, subject your child to removal or justify the revocation of welfare benefits it is unlikely that you will be fully forthcoming with information.

What Does Community-Based, Bottom-Up Data Science Look Like?

In addition to trust in the use of the data, community-based, bottom-up data surveillance could be organized to permit a kind of trust in the fidelity of the data from non-normative standpoints, rooted in the potential for trust in the judgments underlying the conceptual frameworks captured in the data. As discussed above, the kinds of things that seem like relevant data to those on the high side of relations of racial and institutional power are unlikely to be the same as what seem like relevant data to those below.

Thus, a more efficacious strategy to achieve something like Ferguson's bright data may be the creation of community-controlled data reservoirs in which ordinary citizens from subordinated groups decide what goes in. Moreover, such citizens should be empowered by bleeding-edge technology to decide the uses to which they are put. Even if data must be centralized for purposes of scale, it does not follow that the uses it is to be put must also be centralized.

Consider the following sketch of a design for community-controlled data science. Neighborhood organizations (advocacy organizations, churches, community groups, etc., as decided on by a democratic process within the neighborhood or possibly selected by individuals and operating together) organize their own local data centers, which democratically decide what data to collect and take over the collection and storage of all public data on individuals within the neighborhoods. In order to achieve the benefits of machine learning at scale, these data are shared with centralized learning algorithms, but only in a controlled fashion.

These kinds of security controls may be technically possible on the basis of recent research. "Data parallelism"—where the model is trained on multiple processors, each of which trains on its own data and shares weights between processors for the overall model" has been used for some time to handle large-scale machine learning problems (e.g. Krizhevsky 2014). The concern is that data could leak from these distributed nodes, subjecting it to centralization and capture by hierarchically empowered authorities. However, the needs of privacy-protected industries like health care have led to active research on ameliorating this risk, and there is at least some current research (Phong et. al. 2018, Mohassel & Zhang 2017) suggesting that security against data leaks is possible.[4]

In addition to secure training of models from widely disparate data, a community-controlled data science could also promote locally controlled use. To generate binary predictions (such as the risk of crime, homelessness, etc.) from a machine learning model, users typically must choose a probabilistic threshold that will trigger a positive prediction.[5] Typically, in industry, such a threshold is chosen in order to trade-off between false positives and false negatives, depending on the interests at stake in the use to which the data will be put. In the community-based model, a neighborhood itself can set its own threshold, and thus deliberate on the appropriate balance between proactive intervention and intrusiveness in light of its own experience with the accuracy of such models under local conditions as well as its degree of trust in the people who will conduct such interventions. In a neighborhood where there are few social services available and where interventions into potentially dangerous situations are likely to be made by outsiders or potentially violent police officers, for example, the local citizens may have good reason to choose a much more demanding threshold for predictive intervention; in a neighborhood where interventions are carried out by trusted local organizations who draw from local norms, the community may have reason to choose a less demanding threshold.

[4] The general strategy is to use what's known as "homomorphic encryption"—encryption that enables certain mathematical operations to be carried out on the encrypted data—to enable the training of models without exposing unnecessary information (Aslett et. al. 2015).

[5] By probabilistic threshold, I simply mean the probability that triggers action. Typically, machine learning classification algorithms generate estimated probabilities for each class label (like "about to become homeless" or "likely to be involved in violence in the next 90 days"—but humans have to decide how high an estimated probability warrants action—do we intervene when we think the likelihood is better than even? 90%? 99%

ii. Technical Challenges: a Research Agenda

One of the core problems of a critical race data science is that the capacities that make machine learning effective tend to be located in hierarchically empowered institutions operating on general populations. Partly, of course, this is simply because of the demands of technical fields in general—given the educational disparities in societies like the United States, it should be unsurprising that there is a "pipeline problem" contributing not only to the relative absence of voices of color in the machine-learning community, and hence disparities like the facial recognition bias described by Buolamwini & Gebru (2018). However, this disparity may also be due to a relative lack of short-term capacity to deploy such tools on behalf of communities of color.

It seems to me that this is also potentially built into the structure of machine learning itself. For the most part, the effectiveness of machine learning increases in the number of observations. This poses one relatively obvious problem: the collection of large datasets itself is expensive, and requires financial resources as well as widespread observational capacity, both of which tend to be concentrated in the powerful. It also poses one less obvious problem: numerical minorities simply may not have as many observations available. For example, according to the U.S. Census Bureau, the category "white alone" describes 91.1 percent of Iowa residents.[6] Iowa is also largely rural. Under such circumstances, there may be a tension between data science from a bottom-up epistemology and the physical demographics of race: there may not just be enough people of color in any given community to shape and collect data from the epistemology of racial subordination.[7]

This is not an insurmountable challenge, but a research agenda. In recent years, one of the most effective techniques in some fields of machine learning is known as "transfer learning." The basic idea is that sufficiently well-developed machine learning models trained on data from a general problem can be used for more specialized problems for which sufficient data are missing (Yosinski 2014). For example, in computer vision, deep learning models trained on the famous "ImageNet" dataset have been used quite effectively to identify image labels in novel contexts; similarly in natural language processing, pre-trained word vectors (numerical encodings of language relationships trained on large data sources such as English Wikipedia) have proven very useful to faciliate learning on novel linguistic corpoi.

Thus, I propose that machine learning researchers interested in promoting

[6] From U.S. Census Bureau "Quickfacts" at https://www.census.gov/quickfacts/ia

[7] At the same time, there is a dire need for such work: picking a single example, according to the ACLU, progressive Iowa City, the college town that houses the University of Iowa, pulls over drivers of color in traffic stops at almost double the population rate. See ACLU press release of November 30, 2017, Iowa Civil Rights Groups file Amicus Brief With Iowa Supreme Court on Racist Pretextual Stops, at https://www.aclu.org/news/iowa-civil-rights-groups-file-amicus-brief-iowa-supreme-court-racist-pretexual-stops. Yet it is difficult to believe that it would be practicable in the short-run to capture data rooted in the epistemology of people of color in Iowa City, simply because there aren't enough people of color in Iowa City to do it.

racial justice should explore the prospects of developing a transfer learning strategy to allow the training of models on facts of interest to minoritized communities (developed in conjunction with social scientific researchers, such as anthropologists and sociologists from, as well as studying, those communities) from large minoritized communities, that can be used in smaller and more scattered minoritized communities to inform local judgments.

B. *Data as Law, Community Data as Common Law, Data Science as Democratic Action*

Larry Lessig famously kicked off the subdiscipline of cyberlaw by recognizing that code is law—that behavior can be constrained by architecture, including the walls and bars of the code establishing the affordances of daily life. I would like to propose that data is also law, but for different reasons. Data is law because a legal proposition is at heart a mapping from facts to outcomes: Jane stabbed John, so she goes to jail for murder, there's a bicycle in the park, so someone has violated the law against vehicles in the park. But those facts are themselves mappings from sense-data to judgments about reality and are (like all observations—see Gowder 2015 again for discussion) theory-laden. When we develop more capacities for mapping sense-data to factual assertions, we have more capacity for making legal judgments. This is a point that Ferguson (2017, pp. 125-7) explores in different terms. A police officer with access to a predictive database makes different legally relevant judgments about the observations of people she sees on the street than does a police officer who does not—the classification of such a person as potentially threatening, or as a likely drug dealer, directly changes the legal justification for the actions of the police, by changing the things that the officer is warranted in believing. In that sense, the law is partly constituted by the background data.

But if this is true, then we can borrow an insight from Hayek (1978, ch. 5) about the rule of law. He argued that the common law was superior, in rule of law terms, to other sources of law, essentially because, by being rooted in community customs and judgments, it could more readily be conformed to those judgments, and hence more accessible to the general public. (For Hayek's purposes, that accessibility comes in the form of prediction; for mine—see Gowder 2016—this can be represented by the rule of law principle of publicity, requiring people to be able to make use of the law to constrain the powerful.) Likewise, I submit that community-rooted data—a kind of common [law] data, as opposed to the administrative [law] data imposed by distant bureaucrats—can more readily support the freedom and equality of the people in general, especially disadvantaged social groups.

We should understand a critical race data science rooted in bottom-up epistemologies of local communities to constitute a kind of pluralist conception of law, that could be used to directly feed legal contestation. For example, suppose that police data (whether ordinary observation or the product of predictive policing) is used to justify a warrant or arrest. Further on in the legal process, perhaps a defendant could make use of bottom-up data science to contest it—to show, using data collected by and in the interests of community members, that the officer had a history of pushing the boundaries of probable cause. More ambitiously still (and more in line with the idea of a critical race data science), suppose such data could be used to ground an argument that the underlying crime itself was so radically distant from community perceptions of antisocial behavior, and that those percpetions are so tied to racial disparity (such as with the harassment crimes in Ferguson, MO) that enforcement could constitute a due process or equal protection violation. This would amount to a demand that the courts recognize a kind of legal validity based in the behavior not of hierarcially superordinated officials but of subordinated community members–and a novel and transgressive version of H.L.A. Hart's famous claim that (his) legal positivism is a form of, or at least related to, "descriptive sociology."

4. Conclusion: Trust, Collective Action, Democracy

I submit that the ultimate payoff of this vision of a critical race data science is in an enhanced trust and capacity for collective action. One foundational principle of collective action is the importance of common knowledge (in a game theoretic sense), but this common knowledge is precisely what is so often targeted, particularly in efforts to suppress the political participation of subordinated groups. Consider, in this context, the efforts to suppress African-American electoral participation with hyper-targeted messaging in the 2016 U.S. Presidential election—a strategy that specifically depended on and attempted to promote the absence of common knowledge as to how shared interests among African-Americans as well as between African-Americans and other groups would best be realized.

While top-down authoritative data surveillance may have the capacity to establish greater control by those in power, bottom-up critical race data science may have the capacity to disrupt that control by providing a foundation for common knowledge about the activities of the powerful. Consider again the concept of transfer learning from subordinated epistemologies. If hierarchically subordinated racial groups in the United States can establish a shared model of police mistreatment, one that can be used to identify negative patterns as well as predict police action nationally, but on a local basis, it can enable a different kind of national political organizing: decentralized activist groups such as the Movement for Black Lives can, for example, collectively identify the worst departments, the effects of different strategies across jurisdictions, and the places to prioritize movement organizing, and can have a credible shared justification, in terms of values held by subordinated rather than superordinated groups, to take to local communities to facilitate their coordination with the national movement.

At its most optimistic, this is a vision for a kind of Afrofuturist democracy: one in which data collected by, from the epistemic standpoint of, and for the purposes of, subordinated groups, in a decentralized fashion based on technical advances permitting local security and trust in the context of aggregated machine learning, can be used to build distinctive kinds of knowledge. These distinctive kinds of knowledge can, in turn, be used to support transformative political action. Data and technology alone cannot achieve this, but if they can be used to contribute to the fight against white supremacy, research in this direction should be a high priority.

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