# AFF

Resolved: Predictive Policing is Unjust.

Value: Justice

Understanding Justice and defining it is difficult. Most people would say today’s debate requires some baseline definition of Justice. But this itself is futile. John Rawls and Plato use this method called Ideal Theory where some idea definition of justice is used to define right or wrong. I would argue that that’s counterproductive. I’ll be drawing from Naomi Zack’s understanding of Justice which, to borrow a quote from her website: what people in reality care about is not justice as an ideal, but injustice as a correctable ill. Essentially, viewing justice as correcting injustice is a way to move forward. The resolution isn’t about justice, but rather injustice, and because the resolution states that predictive policing is unjust. Today’s debate boils down to a framework that the neg must disprove completely that predictive policing is unjust. If *even one point* remains that makes predictive policing unjust, the Aff must win.

Value Criterion: Upholding American Ideals

Of course, in order to determine what is unjust and correct it, we need some understand of what is wrong, or unjust. Things that violate American rights like equality, privacy, and the fundamental right to be innocent until proven guilty should be considered wrong and unjust, and by upholding these values, correcting injustice, we would be upholding justice.

As for my definitions, I’ll be defining Predictive Policing as “any policing strategy or tactic that develops and uses information and advanced analysis to inform forward-thinking crime prevention.”

Now on to my contentions

Contention 1. Predictive Policing reinforces inequality

O’Neil 2017

The small city of Reading, Pennsylvania, has had a tough go of it in the postindustrial era. Nestled in the green hills fifty miles west of Philadelphia, Reading grew rich on railroads, steel, coal, and textiles. But in recent decades, with all of those industries in steep decline, the city has languished. By 2011, it had the highest poverty rate in the country, at 41.3 percent. (The following year, it was surpassed, if barely, by Detroit.) As the recession pummeled Reading’s economy following the 2008 market crash, tax revenues fell, which led to a cut of forty-five officers in the police department—despite persistent crime. [The] Reading police chief William Heim had to figure out how to get the same or better policing out of a smaller force. So in 2013 he invested in crime prediction software made by PredPol, a Big Data start-up based in Santa Cruz, California. The program processed historical crime data and calculated, hour by hour, where crimes were most likely to occur. The Reading policemen could view the program’s conclusions as a series of squares, each one just the size of two football fields. If they spent more time patrolling these squares, there was a good chance they would discourage crime. And sure enough, a year later, [the] Chief Heim announced that burglaries were down by 23 percent. Predictive programs like PredPol are all the rage in budget-strapped police departments across the country. Departments from Atlanta to Los falling crime rates. New York City uses a similar program, called CompStat. And Philadelphia police are using a local product called HunchLab that includes risk terrain analysis, which incorporates certain features, such as ATMs or convenience stores, that might attract crimes. Like those in the rest of the Big Data industry, the developers of crime prediction software are hurrying to incorporate any information that can boost the accuracy of their models. If you think about it, hot-spot predictors are similar to the shifting defensive models in baseball that we discussed earlier. Those systems look at the history of each player’s hits and then position fielders where the ball is most likely to travel. Crime prediction software carries out similar analysis, positioning cops where crimes appear most likely to occur. Both types of models optimize resources. But a number of the crime prediction models are more sophisticated, because they predict progressions that could lead to waves of crime. PredPol, for example, is based on seismic software: it looks at a crime in one area, incorporates it into historical patterns, and predicts when and where it might occur next. (One simple correlation it has found: if burglars hit your next-door neighbor’s house, batten down the hatches.) Predictive crime models like PredPol have their virtues. Unlike the crime-stoppers in Steven Spielberg’s dystopian movie Minority Report (and some ominous real-life initiatives, which we’ll get to shortly), the cops don’t track down people before they commit crimes. Jeffrey Brantingham, the UCLA anthropology professor who founded PredPol, stressed to me that the model is blind to race and ethnicity. And unlike other programs, including the recidivism risk models we discussed, which are used for sentencing guidelines, PredPol doesn’t focus on the individual. Instead, it targets geography. The key inputs are the type and location of each crime and when it occurred. That seems fair enough. And if cops spend more time in the high-risk zones, foiling burglars and car thieves, there’s good reason to believe that the community benefits. But most crimes aren’t as serious as burglary and grand theft auto, and that is where serious problems emerge. When police set up their PredPol system, they have a choice. They can focus exclusively on so-called Part 1 crimes. These are the violent crimes, including homicide, arson, and assault, which are usually reported to them. But they can also broaden the focus by including Part 2 crimes, including vagrancy, aggressive panhandling, and selling and consuming small quantities of drugs. Many of these “nuisance” crimes would go unrecorded if a cop weren’t there to see them.

These nuisance crimes are endemic to many impoverished neighborhoods. In some places police call them antisocial behavior, or ASB. Unfortunately, including them in the model threatens to skew the analysis. Once the nuisance data flows into a predictive model, more police are drawn into those neighborhoods, where they’re more likely to arrest more people. After all, even if their objective is to stop burglaries, murders, and rape, they’re bound to have slow periods. It’s the nature of patrolling. And if a patrolling cop sees a couple of kids who look no older than sixteen guzzling from a bottle in a brown bag, he stops them. These types of low-level crimes populate their models with more and more dots, and the models send the cops back to the same neighborhood. This creates a pernicious feedback loop. The policing itself spawns new data, which justifies more policing. And our prisons fill up with hundreds of thousands of people found guilty of victimless crimes. Most of them come from impoverished neighborhoods, and most are black or Hispanic. So even if a model is color blind, the result of it is anything but. In our largely segregated cities, geography is a highly effective proxy for race.

Contention 2. Predictive Policing violates Constitutionally Protected Civil Liberties

The Aclu. (2016)

A growing number of police departments across the United States are deploying new computer systems that use data in an attempt to automatically forecast where crime will happen or who will be involved. Today, these “predictive policing” tools are used primarily to further concentrate enforcement activities in communities that are already over-policed, rather than to meet human needs.

We believe that:

1. A lack of transparency about predictive policing systems prevents a meaningful, well-informed public debate. Whenever automated predictions are considered for policing, all stakeholders must understand what data is being used, what the system aims to predict, the design of the algorithm that creates the predictions, how predictions will be used in practice, and what relevant factors are not being measured or analyzed.

2. Predictive policing systems ignore community needs. Most predictive policing systems fielded today focus narrowly on the reported crime rate.

3. Predictive policing systems threaten to undermine the constitutional rights of individuals. The Fourth Amendment forbids police from stopping someone without reasonable suspicion — a specific, individualized determination that is more than just a hunch.

4. Predictive technologies are primarily being used to intensify enforcement, rather than to meet human needs. Social services interventions can help to address problems for at-risk individuals and communities before crimes occur

5. Police could use predictive tools to anticipate which officers might engage in misconduct, but most departments have not done so.

[signatories include]

American Civil Liberties Union  
Electronic Frontier Foundation  
NAACP

# 1AC

## Definitions

#### Predictive Policing Symposium

National Institute of Justice (2014) Overview of Predictive Policing | National Institute of Justice. Retrieved February 19, 2020, from https://nij.ojp.gov/topics/articles/overview-predictive-policing

NIJ convened two symposium to discuss predictive policing and its impact on crime and justice.

The first focused on the concept of predictive policing. The symposium introduced a working definition of predictive policing: “any policing strategy or tactic that develops and uses information and advanced analysis to inform forward-thinking crime prevention.”

The second symposium focused on how to make predictive policing available to all law enforcement agencies.

In proactive policing, law enforcement uses data and analyzes patterns to understand the nature of a problem. Officers devise strategies and tactics to prevent or mitigate future harm. They evaluate results and revise practices to improve policing. Departments may combine an array of data with street intelligence and crime analysis to produce better assessments about what might happen next if they take various actions.

What Is Predictive Policing?

Predictive policing tries to harness the power of information, geospatial technologies and evidence-based intervention models to reduce crime and improve public safety. This two-pronged approach — applying advanced analytics to various data sets, in conjunction with intervention models — can move law enforcement from reacting to crimes into the realm of predicting what and where something is likely to happen and deploying resources accordingly.

The predictive policing approach does not replace traditional policing. Instead, it enhances existing approaches such as problem-oriented policing, community policing, intelligence-led policing and hot spot policing.

Predictive policing leverages computer models — such as those used in the business industry to anticipate how market conditions or industry trends will evolve over time — for law enforcement purposes, namely anticipating likely crime events and informing actions to prevent crime. Predictions can focus on variables such as places, people, groups or incidents. Demographic trends, parolee populations and economic conditions may all affect crime rates in particular areas. Using models supported by prior crime and environmental data to inform different kinds of interventions can help police reduce the number of crime incidents.

Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations. With funding from NIJ, RAND Corporation developed this reference guide for law enforcement agencies interested in predictive policing. The guide assesses the most promising technical tools for making predictions as well as the most promising tactical approaches for acting on predictions.

## VALUE + VC

#### Injustice Theory

Naomi Zack, 2016, Applicative Justice, <https://philosophy.uoregon.edu/2016/03/17/applicative-justice-a-pragmatic-empirical-approach-to-racial-injustice-new-book-from-naomi-zack/>

Naomi Zack is a professor of philosophy at [Lehman College](https://en.wikipedia.org/wiki/Lehman_College), [City University of New York (CUNY)](https://en.wikipedia.org/wiki/City_University_of_New_York_(CUNY)), having formerly been a professor at the [University of Oregon](https://en.wikipedia.org/wiki/University_of_Oregon).[[2]](https://en.wikipedia.org/wiki/Naomi_Zack#cite_note-bio-2)[[3]](https://en.wikipedia.org/wiki/Naomi_Zack#cite_note-bio2-3) She is a prolific author, having published nine books and edited five anthologies in addition to a large number of papers and contributed chapters in collections

“Naomi Zack pioneers a new theory of justice starting from a correction of current injustices. While the present justice paradigm in political philosophy and related fields begins from John Rawls’s 1970 Theory of Justice, Zack insists that what people in reality care about is not justice as an ideal, but injustice as a correctable ill. For a way to describe real injustice and the society in which it occurs, Zack resurrect Arthur Bentley’s key insight that government and law (or political life) is a constant process of contending interest groups throughout society. Bentley’s main idea allows for a resolution of the contradiction between formal legal equality for U.S. minorities and post-civil rights practical inequality. Just law and unjust practice co-exist as a fact of political life. The correction of injustice in reality requires *applicative justice*, in a comparison between those who are treated unjustly with those who are treated justly, and the design of effective measures to equalize such treatment. Zack’s theory of applicative justice offers a revolutionary reorientation of society’s pursuit of justice, seeking to undo injustice in a practical and fully achievable way.”

### Value: Justice

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### Value Criterion: Upholding American Ideals

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## Contention 1. Predictive Policing reinforces inequality

#### Weapons of Math Destruction Chapter

O'NEIL, CATHY. *WEAPONS of MATH DESTRUCTION: How Big Data Increases Inequality and Threatens Democracy*. CROWN Publishing, 2017.

Cathy O’Neil has a PHD in mathematics from Harvard, worked as a quant on Wall Street, and worked in the math departments of MIT and Barnard. She wrote the book Weapon’s of Math Destruction in 2017.

The small city of Reading, Pennsylvania, has had a tough go of it in the postindustrial era. Nestled in the green hills fifty miles west of Philadelphia, Reading grew rich on railroads, steel, coal, and textiles. But in recent decades, with all of those industries in steep decline, the city has languished. By 2011, it had the highest poverty rate in the country, at 41.3 percent. (The following year, it was surpassed, if barely, by Detroit.) As the recession pummeled Reading’s economy following the 2008 market crash, tax revenues fell, which led to a cut of forty-five officers in the police department—despite persistent crime. [The] Reading police chief William Heim had to figure out how to get the same or better policing out of a smaller force. So in 2013 he invested in crime prediction software made by PredPol, a Big Data start-up based in Santa Cruz, California. The program processed historical crime data and calculated, hour by hour, where crimes were most likely to occur. The Reading policemen could view the program’s conclusions as a series of squares, each one just the size of two football fields. If they spent more time patrolling these squares, there was a good chance they would discourage crime. And sure enough, a year later, [the] Chief Heim announced that burglaries were down by 23 percent. Predictive programs like PredPol are all the rage in budget-strapped police departments across the country. Departments from Atlanta to Los falling crime rates. New York City uses a similar program, called CompStat. And Philadelphia police are using a local product called HunchLab that includes risk terrain analysis, which incorporates certain features, such as ATMs or convenience stores, that might attract crimes. Like those in the rest of the Big Data industry, the developers of crime prediction software are hurrying to incorporate any information that can boost the accuracy of their models. If you think about it, hot-spot predictors are similar to the shifting defensive models in baseball that we discussed earlier. Those systems look at the history of each player’s hits and then position fielders where the ball is most likely to travel. Crime prediction software carries out similar analysis, positioning cops where crimes appear most likely to occur. Both types of models optimize resources. But a number of the crime prediction models are more sophisticated, because they predict progressions that could lead to waves of crime. PredPol, for example, is based on seismic software: it looks at a crime in one area, incorporates it into historical patterns, and predicts when and where it might occur next. (One simple correlation it has found: if burglars hit your next-door neighbor’s house, batten down the hatches.) Predictive crime models like PredPol have their virtues. Unlike the crime-stoppers in Steven Spielberg’s dystopian movie Minority Report (and some ominous real-life initiatives, which we’ll get to shortly), the cops don’t track down people before they commit crimes. Jeffrey Brantingham, the UCLA anthropology professor who founded PredPol, stressed to me that the model is blind to race and ethnicity. And unlike other programs, including the recidivism risk models we discussed, which are used for sentencing guidelines, PredPol doesn’t focus on the individual. Instead, it targets geography. The key inputs are the type and location of each crime and when it occurred. That seems fair enough. And if cops spend more time in the high-risk zones, foiling burglars and car thieves, there’s good reason to believe that the community benefits. But most crimes aren’t as serious as burglary and grand theft auto, and that is where serious problems emerge. When police set up their PredPol system, they have a choice. They can focus exclusively on so-called Part 1 crimes. These are the violent crimes, including homicide, arson, and assault, which are usually reported to them. But they can also broaden the focus by including Part 2 crimes, including vagrancy, aggressive panhandling, and selling and consuming small quantities of drugs. Many of these “nuisance” crimes would go unrecorded if a cop weren’t there to see them.

These nuisance crimes are endemic to many impoverished neighborhoods. In some places police call them antisocial behavior, or ASB. Unfortunately, including them in the model threatens to skew the analysis. Once the nuisance data flows into a predictive model, more police are drawn into those neighborhoods, where they’re more likely to arrest more people. After all, even if their objective is to stop burglaries, murders, and rape, they’re bound to have slow periods. It’s the nature of patrolling. And if a patrolling cop sees a couple of kids who look no older than sixteen guzzling from a bottle in a brown bag, he stops them. These types of low-level crimes populate their models with more and more dots, and the models send the cops back to the same neighborhood. This creates a pernicious feedback loop. The policing itself spawns new data, which justifies more policing. And our prisons fill up with hundreds of thousands of people found guilty of victimless crimes. Most of them come from impoverished neighborhoods, and most are black or Hispanic. So even if a model is color blind, the result of it is anything but. In our largely segregated cities, geography is a highly effective proxy for race.

#### Dirty Data, Bad Policing (Conclusion)

Richardson, Rashida and Schultz, Jason and Crawford, Kate, Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice (February 13, 2019). 94 N.Y.U. L. REV. ONLINE 192 (2019). Available at SSRN: <https://ssrn.com/abstract=3333423>

Data is seen as an important tool for policymaking and governance because in its absence there is often too much reliance on subjective factors. The last twenty years have seen a widespread adoption of data driven practices, policies, and technologies in the public sector. Yet this increasing reliance on data to assess and make decisions about complicated social, economic, and political issues presents serious risks to fairness, equity, and justice, if greater scrutiny is not given to the practices underlying the creation, auditing, and maintenance of data. Our research demonstrates the risks and consequences associated with overreliance on unaccountable and potentially biased data to address sensitive issues like public safety. These case studies show that illegal police practices can significantly distort the data that is collected, and the risks that dirty data will still be used for law enforcement and other purposes. The failure to adequately interrogate and reform police data creation and collection practices elevates the risks of skewing predictive policing systems and creating lasting consequences that will permeate throughout the criminal justice system and society more widely. There may be a natural inclination to assume that predictive policing vendors can address the problems of dirty data identified in this study by removing known cases. But such mitigation methods are likely inadequate for a number of reasons. First, if there are few incentives and almost no requirements for police departments to self-monitor and reform practices or policies that create biased or dirty data, it is unlikely that police departments would identify these problems for a vendor to remove or otherwise address. Second, there is no current methodology or mechanism for identifying these problematic practices and policies in real-time; therefore, any system that includes recent or live data may be subject to additional undocumented biases. Third, as we have argued, a fundamental flaw of police data is that it does not capture all relevant crime information because of institutional policies or practices that ignore certain types of crimes or criminals, negative community relations that affect which crimes the police track, and corrupt or unethical practices that lead to the omission or manipulation of police records. There is no documented practice demonstrating meaningful ways for a vendor to adjust its system for what is unknown or not recorded. The absence of data is as significant as its creation, yet there is no technical “fix” for this. Instead, mitigation efforts should be focused on developing reliable mechanisms for assessing the harms inherent in the use of historical police data, as well as data generated after implementation of police data collection reforms, and backed by strong public transparency and accountability measures. The jurisdictions researched for this paper were limited to police departments that were subjects of publicized investigations and federal litigation. These case studies demonstrate the importance of independent government investigations and federal court litigation in uncovering unlawful and biased police practices that would otherwise persist without federal government intervention. Yet these crucial mechanisms for uncovering and addressing problematic police practices have been threatened with the parting acts of former U.S. Attorney General Jeff Sessions just before his unexpected forced resignation.145 Before he left office, he issued a Department of Justice policy memo significantly limiting the use of consent decrees by requiring top political appointees to sign off, limiting their scope and duration, and requiring department attorneys to provide evidence of additional violations beyond unconstitutional behavior.146 These limitations are significant and serious. The result may be that problematic police departments will remain unchecked, not because of lack of evidence of unconstitutional practices, but because the new standard of evidence is extremely high or because political leadership refuses to sign off. In light of these developments and the absence of incentives for self-scrutiny and reform, collective action for greater accountability, oversight, and redress is urgent. A broad coalition of stakeholders is needed to push public discourse on the drivers and consequences of dirty data, and to motivate government officials to act to ensure that principles of fairness, equity, and justice are reflected in government practices.

## Contention 2. Predictive Policing violates Constitutionally Protected Civil Liberties

#### Predictive Policing Today: A Shared Statement of Civil Rights Concerns

The Aclu. (2016) Statement of Concern About Predictive Policing by ACLU and 16 Civil Rights Privacy, Racial Justice, and Technology Organizations | American Civil Liberties Union. Retrieved February 24, 2020, from https://www.aclu.org/other/statement-concern-about-predictive-policing-aclu-and-16-civil-rights-privacy-racial-justice

On August 31, 2016, a coalition of 17 organizations issued the following statement about predictive policing tools used by law enforcement in the United States, pointing to the technology’s racial biases, lack of transparency, and other deep flaws that lead to injustice, particularly for people of color.

August 31, 2016

A growing number of police departments across the United States are deploying new computer systems that use data in an attempt to automatically forecast where crime will happen or who will be involved. Today, these “predictive policing” tools are used primarily to further concentrate enforcement activities in communities that are already over-policed, rather than to meet human needs.

The institution of American policing, into which these systems are being introduced, is profoundly flawed: it is systemically biased against communities of color and allows unconscionable abuses of police power. Predictive policing tools threaten to provide a misleading and undeserved imprimatur of impartiality for an institution that desperately needs fundamental change. Systems that are engineered to support the status quo have no place in American policing. The data driving predictive enforcement activities — such as the location and timing of previously reported crimes, or patterns of community- and officer-initiated 911 calls — is profoundly limited and biased.

Decades of criminology research have shown that crime reports and other statistics gathered by the police primarily document law enforcement’s response to the reports they receive and situations they encounter, rather than providing a consistent or complete record of all the crimes that occur. Vendors who sell and departments who embrace these new tools are failing to account for these realities, or to evaluate whether the data is so flawed that it cannot be relied upon at all. As a result, current systems reinforce bias and sanitize injustice.

Automated predictions based on such biased data — although they may seem objective or neutral — will further intensify unwarranted discrepancies in enforcement. Because of the complexity and secrecy of these tools, police and communities currently have limited capacity to assess the risks of biased data or faulty prediction systems.

Even within a broken criminal justice system, there are places where data can be a force for good: For example, data can identify people with mental illness for treatment rather than punishment, or provide early warning of harmful patterns of officer behavior. However, today, most “predictive policing” is not used for such constructive interventions. Instead, it concentrates existing law enforcement tactics, and will intensify stringent enforcement in communities of color that already face disproportionate law enforcement scrutiny.

We believe that:

1. A lack of transparency about predictive policing systems prevents a meaningful, well-informed public debate. Whenever automated predictions are considered for policing, all stakeholders must understand what data is being used, what the system aims to predict, the design of the algorithm that creates the predictions, how predictions will be used in practice, and what relevant factors are not being measured or analyzed. The natural tendency to rush to adopt new technologies should be resisted until a true understanding is reached as to their short and long term effects. Vendors must provide transparency, and the police and other users of these systems must fully and publicly inform public officials, civil society, community stakeholders, and the broader public on each of these points. Vendors must be subject to in-depth, independent, and ongoing scrutiny of their techniques, goals, and performance. Today, instead, many departments are rolling out these tools with little if any public input, and often, little if any disclosure. Vendors are shrouding their products in secrecy, and even seeking gag clauses or asking departments to pledge to spend officer time resisting relevant public records requests, as a precondition for trying out their products. These practices must stop. Claims of trade secrecy or business confidentiality must not be allowed to override the public’s interest in transparency. Transparency is necessary, but not by itself sufficient: A thorough and well-informed public debate, and rigorous, independent, expert assessment of the statistical validity and operational impact of any new system, are essential before any new system can be deployed at scale. Continuous assessment is vital so long as the system is in use.

2. Predictive policing systems ignore community needs. Most predictive policing systems fielded today focus narrowly on the reported crime rate. Other vital goals of policing, such as building community trust, eliminating the use of excessive force, and reducing other coercive tactics, are currently not measured and not accounted for by these systems. As a result, current systems are blind to their impact in these areas, and may do unnoticed harm. Policing should be equitable across racial and geographic lines. This requires measuring and tracking all uses of coercive authority and the demographics of the people involved.

3. Predictive policing systems threaten to undermine the constitutional rights of individuals. The Fourth Amendment forbids police from stopping someone without reasonable suspicion — a specific, individualized determination that is more than just a hunch. Computer-driven hunches are no exception to this rule, and a computer’s judgment is never a further reason (beyond the articulable facts that intelligibly caused that judgment) for a stop, search, or arrest. Similarly, predictive policing must not be allowed to erode rights of due process and equal protection. Systems that manufacture unexplained “threat” assessments have no valid place in constitutional policing.

4. Predictive technologies are primarily being used to intensify enforcement, rather than to meet human needs. Social services interventions can help to address problems for at-risk individuals and communities before crimes occur. Communities that invest in predictive technologies should consider whether and how these systems could be used to more effectively allocate social service resources, including educational opportunities, job training, and health services, taking into account the privacy interests of communities and the limits of available data. As the President’s Task Force on 21st Century Policing noted, “the justice system alone cannot solve many of the underlying conditions that give rise to crime. It will be through partnerships across sectors and at every level of government that we will find the effective and legitimate long-term solutions to ensuring public safety.”

5. Police could use predictive tools to anticipate which officers might engage in misconduct, but most departments have not done so. Early experiences from Chicago and elsewhere show that police misconduct follows consistent patterns, and that offering further training and support to officers who are at risk can help to avert problems. Police should be at least as eager to pilot new, data-driven approaches in the search for misconduct as they are in the search for crime, particularly given that interventions designed to reduce the chances of misconduct do not themselves pose risk to life and limb.

6. Predictive policing systems are failing to monitor their racial impact. Systems that are currently deployed, or are contemplated for future deployment, must each be publicly audited and monitored on an ongoing basis for their disparate impact on different communities the police department serves, with results broken out by race and by neighborhood. And those disparities must be addressed.

Signatories:

The Leadership Conference on Civil and Human Rights  
18 Million Rising  
American Civil Liberties Union  
Brennan Center for Justice  
Center for Democracy & Technology  
Center for Media Justice  
Color of Change  
Data & Society Research Institute  
Demand Progress  
Electronic Frontier Foundation  
Free Press  
Media Mobilizing Project  
NAACP  
National Hispanic Media Coalition  
Open MIC (Open Media and Information Companies Initiative)  
Open Technology Institute at New America  
Public Knowledge

#### Fast Company Report on Civil Rights and Predictive policing

[DJ Pangburn](https://www.fastcompany.com/user/dj-pangburn) (2019) Civil rights violations data causes bad predictive policing. Retrieved February 19, 2020, from https://www.fastcompany.com/90312369/how-dirty-data-from-civil-rights-violations-leads-to-bad-predictive-policing

In March 2015, the American Civil Liberties Union (ACLU) of Illinois published a [report](https://www.aclu-il.org/en/publications/2015-stop-and-frisk-report) on the Chicago Police Department’s (CPD) stop and frisk practices. After looking at records from 2012, 2013, and four months of contact card data from 2014, ACLU of Illinois concluded that many CPD stop and frisks were unlawful, and that black residents were disproportionately targeted. The report also noted deficiencies in CPD’s data and data collection practices, which were, alongside other practices and procedures, to be independently monitored as part of an August 2015 settlement agreement.

But the ACLU wasn’t alone in its findings about CPD data policies. A yearlong U.S. Department of Justice (DOJ) investigation into the fatal shooting of Laquan McDonald found a pattern of poor data collection to identify and address unlawful conduct, among other issues. All the while, CPD had been using its own predictive policing system, which has existed in some form since at least 2012. Funded by a DOJ grant and developed by the Illinois Institute of Technology, the Strategic Subject List (SSL) is an automated assessment tool that uses a number of data sets to analyze crime, as well as identify and rank individuals as at risk of becoming a victim or offender in a shooting or homicide. A 2017 Freedom of Information Act request revealed that the data set included 398,684 individuals, with much of the information having to do with arrests, not convictions–just one of many types of information that can warp SSL’s automated assessments.

Chicago, the report’s first case study, is of particular interest in the predictive policing debate. The city’s example is also included in a new [report](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3333423) published by AI Now–an interdisciplinary research center at New York University focused on the social implications of artificial intelligence–about “dirty data” from civil rights violations leading to bad predictive policing.

The report, published last week, investigates how 13 jurisdictions that had used, were using, or planned to implement predictive policing systems were feeding these systems data sullied by “unconstitutional and racially biased stops, searches, and arrests,” as well as excessive use of force and first amendment violations, among other issues. The jurisdictions, which included New Orleans; Maricopa County, Arizona; Milwaukee; and other cities, had all entered into notable consent decrees (settlements between two parties) with the Department of Justice, or some other federal court-monitored settlements for “corrupt, racially biased, or otherwise illegal policing practices.”

The automated tools used by public agencies to make decisions in criminal justice, healthcare, and education are often acquired and developed in the shadows. However, activists, lawyers, and lawmakers are working to [raise awareness](https://www.fastcompany.com/90292210/transparency-government-software-algorithms) about these algorithms, with a major effort currently under way in the state of Washington, where legislators are now debating an [algorithmic accountability bill](https://www.fastcompany.com/90302465/washington-introduces-landmark-algorithmic-accountability-laws) that would establish transparency guidelines. But one area in the debate that hasn’t received a great deal of attention is the “dirty data” used by predictive policing systems.

The report notes that police data can be biased in two distinct ways. First, police data reflects police practices and policies, and “if a group or geographic area is “disproportionately targeted for unjustified police contacts and actions, this group or area will be overrepresented in the data, in ways that often suggest greater criminality.” Another type of bias occurs when police departments and predictive policing systems tend to focus on “violent, street, property, and quality-of-life crimes,” while white-collar crimes–which some studies suggest occur with higher frequency than the aforementioned crimes–remain “comparatively under-investigated and overlooked in crime reporting.”

Rashida Richardson, director of policy research at AI Now, tells Fast Company that it was relatively easy to find public records of police misconduct in the targeted jurisdictions. However, information regarding police data sharing practices–what data and with which other jurisdictions it is shared, as well as information on predictive policing systems–were more difficult to find. Other instances existed where evidence was inconclusive about a direct link between policing practices and the data used in the predictive policing system.

“We didn’t have to do [Freedom of Information Act requests] or any formal public records requests,” says Richardson. “Part of the methodology was trying to rely on strictly what was already publicly available because the theory is that this is the type of information that the public should already have access to.”

“In some jurisdictions that have more recent consent decrees–those being Milwaukee, Baltimore, and Chicago–it’s a little bit harder because there is a lack of public information,” she adds. “A lot of the predictive policing pilots or use cases are often funded through federal dollars, so there were sometimes records through the DOJ that they provided a grant to the jurisdiction, but then no other documentation on the local level about how that money was used.”

Richardson says that HunchLab and PredPol are the two most common predictive policing systems of the 13 jurisdictions. IBM and Motorola also offer some type of predictive policing systems, while other jurisdictions develop their own in-house. It’s currently unknown how pervasive these automated systems are in the United States.

Richardson says that part of the reason for this is a lack of transparency around the acquisition and development of these technologies by jurisdictions. Many such systems are acquired or developed outside of the normal procurement process; that is, from federal or third-party grants from the likes of police organizations or nongovernment organizations with an interest in law enforcement. In New Orleans, for example, Palantir gave the [predictive policing] system as an in-kind gift to the police department.

“It didn’t go through the legislative process,” says Richardson. “It’s only due to some litigation and investigative journalism that we have some sort of a grasp about how common it is.”

For there to be unbiased predictive policing systems, Richardson says there must be reform of both policing and the criminal justice system. Otherwise, it will continue to be difficult to trust that information coming from what she calls a “broken system” can be implemented in a nondiscriminatory way.

“One day in the future, it may be possible to use this type of technology in a way that would not produce discriminatory outcomes,” says Richardson. “But the problem is that there are so many embedded problems within policing and, more broadly, within criminal justice that it would take a lot of fundamental changes, not only within data practices but also how these systems are implemented for there to be a fair outcome.”

## BLOCKS

### “It Stops Crime, which is good” “Crime Numbers Went Down” “Deterrence” [FIX]

O'NEIL, CATHY. *WEAPONS of MATH DESTRUCTION: How Big Data Increases Inequality and Threatens Democracy*. CROWN Publishing, 2017.

Cathy O’Neil has a PHD in mathematics from Harvard, worked as a quant on Wall Street, and worked in the math departments of MIT and Barnard. She wrote the book Weapon’s of Math Destruction in 2017.

O’Neil 2017

And in most jurisdictions, sadly, such a crime map would track poverty. The high number of arrests in those areas would do nothing but confirm the broadly shared thesis of society’s middle and upper classes: that poor people are responsible for their own shortcomings and commit most of a city’s crimes. But what if police looked for different kinds of crimes? That may sound counterintuitive, because most of us, including the police, view crime as a pyramid. Prioritizing the crimes at the top of the pyramid makes sense. Minimizing violent crime is and should be a central part of a police force’s mission. But how about crimes far removed from the boxes on the PredPol maps, the ones carried out by the rich? In the 2000s, the kings of finance threw themselves a lavish party. They lied, they bet billions against their own customers, they committed fraud and paid off rating agencies. Enormous crimes were committed there, and the result devastated the global economy for the best part of five years. Millions of people lost their homes, jobs, and health care. We have every reason to believe that more such crimes are occurring in finance right now. If we’ve learned anything, it’s that the driving goal of the finance world is to make a huge profit, the bigger the better, and that anything resembling self-regulation is worthless.

Just imagine if police enforced their zero-tolerance strategy in finance. They would arrest people for even the slightest go undercover for even the slightest infraction, whether it was chiseling investors on 401ks, providing misleading guidance, or committing petty frauds. Perhaps SWAT teams would descend on Greenwich, Connecticut. They’d go undercover in the taverns around Chicago’s Mercantile Exchange.

As O’Neil Later points out, the issue with this system is not just the arrests, but the feedback loop it creates. More arrests means more justification for allocating more resources to that area, which will in turn cause more arrests, which even neg scientific evidence says. This feedback loop is not changing the observed crime rate, just what police respond to.

### “We Can fix”

#### Dirty Data, Bad Policing (Abstract, full pdf in file share)

Richardson, Rashida and Schultz, Jason and Crawford, Kate, Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice (February 13, 2019). 94 N.Y.U. L. REV. ONLINE 192 (2019). Available at SSRN: <https://ssrn.com/abstract=3333423>

Law enforcement agencies are increasingly using predictive policing systems to forecast criminal activity and allocate police resources. Yet in numerous jurisdictions, these systems are built on data produced during documented periods of flawed, racially biased, and sometimes unlawful practices and policies (“dirty policing”). These policing practices and policies shape the environment and the methodology by which data is created, which raises the risk of creating inaccurate, skewed, or systemically biased data (“dirty data”). If predictive policing systems are informed by such data, they cannot escape the legacies of the unlawful or biased policing practices that they are built on. Nor do current claims by predictive policing vendors provide sufficient assurances that their systems adequately mitigate or segregate this data.

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Because Predictive Policing uses historical data, any ramification of bad policing practices alone wont be enough to fix predictive policing, the racist, historical data still exists and the past data will only reinforce racist ideals of policing.

### “No Science” [bad data + bad policing]

Richardson, Rashida and Schultz, Jason and Crawford, Kate, Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice (February 13, 2019). 94 N.Y.U. L. REV. ONLINE 192 (2019). Available at SSRN: <https://ssrn.com/abstract=3333423>

In our research, we analyze thirteen jurisdictions that have used or developed predictive policing tools while under government commission investigations or federal court monitored settlements, consent decrees, or memoranda of agreement stemming from corrupt, racially biased, or otherwise illegal policing practices. In particular, we examine the link between unlawful and biased police practices and the data available to train or implement these systems. We highlight three case studies: (1) Chicago, an example of where dirty data was ingested directly into the city’s predictive system; (2) New Orleans, an example where the extensive evidence of dirty policing practices and recent litigation suggests an extremely high risk that dirty data was or could be used in predictive policing; and (3) Maricopa County, where despite extensive evidence of dirty policing practices, a lack of public transparency about the details of various predictive policing systems restricts a proper assessment of the risks. The implications of these findings have widespread ramifications for predictive policing writ large. Deploying predictive policing systems in jurisdictions with extensive histories of unlawful police practices presents elevated risks that dirty data will lead to flawed or unlawful predictions, which in turn risk perpetuating additional harm via feedback loops throughout the criminal justice system. The use of predictive policing must be treated with high levels of caution and mechanisms for the public to know, assess, and reject such systems are imperative.

### “No Privacy issue” even so, civil liberties are hurt

Kathleen McKendrick . (2019) Artificial Intelligence Prediction and Counterterrorism | Chatham House. Retrieved March 02, 2020, from <https://www.chathamhouse.org/publication/artificial-intelligence-prediction-and-counterterrorism>

**Many academics have examined the way widespread digital surveillance could cause a ‘chilling effect’ on engagement with sensitive political issues or activities, dissenting opinion and critical thought, as individuals conform to perceived collective norms.121 The issue has been a concern of civil society groups, particularly following revelations (commonly referred to as the Snowden revelations) in 2013 about the scale of national surveillance programmes.122 Psychologists have observed that the mere perception of being watched – even one based on a simple trigger like a picture of a pair of human eyes – can lead to discernible changes in behaviour.123 While automated analysis might reduce privacy intrusion at the individual level, it also gives rise to the possibility that everybody might feel as if they are being watched at all times. Because of this, automated analysis could have higher costs to other rights, such as rights of expression and association, which would be felt most acutely when individual behavioural changes are aggregated at the societal level.**

# NEG

Resolved: Predictive Policing is Unjust.

My value for this debate is Quality of life, defined as the standard of health, comfort, and happiness experienced by an individual or group.

My Value Criterion for today’s debate is implementing cost-benefit analysis, by looking at the cost of predictive policing, and the benefit it serves, we can best improve the quality of life for all parties involved.

My definition for Predictive Policing, as defined by the National Institute of Justice is “any policing strategy or tactic that develops and uses information and advanced analysis to inform forward-thinking crime prevention.”

Contention 1. Predictive Policing has a wide range of possible applications

Pearsall 2010

Beck told participants that perhaps the greatest benefit to predictive policing is the discovery of new or previously unknown patterns and trends. Just as Walmart found increased demand for strawberry Pop-Tarts preceding major weather events, LAPD has found its own subtle patterns when examining data that have helped the department accurately anticipate and prevent crime.

Reducing Random Gunfire in Richmond. Every New Year's Eve, Richmond, Va., would experience an increase in random gunfire. Police began looking at data gathered over the years, and based on that information, they were able to anticipate the time, location and nature of future incidents. On New Year's Eve 2003, Richmond police placed officers at those locations to prevent crime and respond more rapidly. The result was a 47 percent decrease in random gunfire and a 246 percent increase in weapons seized. The department saved $15,000 in personnel costs.

Stuart Wolpert. (2015)

Can math help keep our streets safer? A new study by a UCLA-led team of scholars and law enforcement officials suggests the answer is yes. A mathematical model they devised to guide where the Los Angeles Police Department should deploy officers, led to substantially lower crime rates during a recent 21-month period.“Not only did the model predict twice as much crime as trained crime analysts predicted, but it also prevented twice as much crime,” said Jeffrey Brantingham, a UCLA professor of anthropology and senior author of the study. A paper about the work, which was also tested in Kent, England, was [published online today](http://amstat.tandfonline.com/doi/pdf/10.1080/01621459.2015.1077710) by the Journal of the American Statistical Association.Developed using six years of mathematical research and a decade of police crime data, the program predicts times and places that serious crimes will occur based on historical crime data in a given area. A key to its success, Brantingham said, is that the algorithm behind the model effectively “learns” over time. Based on those results, the researchers estimated that using the algorithm would save $9 million per year in Los Angeles, taking into account costs to victims, the courts and society. Brantingham said the mathematical model’s success rate could be improved even further as the researchers enhance the algorithm it uses.

Contention 2. Certain ideals of policing are unjust, not predictive policing itself

Essentially, Predictive Policing is an extension of policing, by reforming policing, and limiting how we use predictive policing, it becomes a tool of justice, rather than injustice.

O’Neil 2017

a successful policing initiative in Newark, New Jersey. Cops who walked the beat there, according to the program, were supposed to be highly tolerant. Their job was to adjust to the neighborhood’s own standards of order and to help uphold them. each policing approach, from broken windows to zero tolerance, represents a model. Just like my meal planning or the U.S. News Top College ranking, each crime-fighting model calls for certain input data, followed by a series of responses, and each is calibrated to achieve an objective.

Instead of simply trying to eradicate crimes, police should be attempting to build relationships in the neighborhood. This was one of the pillars of the original “broken-windows” study. The cops were on foot, talking to people, trying to help them uphold their own community standards. But that objective, in many cases, has been lost, steamrollered by models that equate arrests with safety. This isn’t the case everywhere. I recently visited Camden, New Jersey, which was the murder capital of the country in 2011. I found that the police department in Camden, rebuilt and placed under state control in 2012, had a dual mandate: lowering crime and engendering community trust. If building trust is the objective, an arrest may well become a last resort, not the first. This more empathetic approach could lead to warmer relations between the police and the policed, and fewer of the tragedies we’ve seen in recent years—the police killings of young black men and the riots that follow them. From a mathematical point of view, however, trust is hard to quantify. That’s a challenge for people building models. Sadly, it’s far simpler to keep counting arrests, to build models that assume we’re birds of a feather and treat us as such.

[Papachristos](https://sociology.yale.edu/people/andrew-papachristos) (2015)

It is no secret that most of the shooting victims in our cities are, or involve, young men who have had prior contact with the criminal justice system. But saving lives and lowering rates of gun violence require caring about these young people whom the justice system typically only views as “offenders.” Network analysis cannot predict who the next victim will be, but it produces better assessments of who might be in harm’s way and opens the door to intervention.

In this era of mass incarceration and hyper-surveillance of our most vulnerable communities, algorithms might help narrow the focus and reach of the justice system, leading to fewer and fairer contacts with citizens. But it cannot happen if police and prosecutors use data without oversight or accountability. We must not allow for-profit-companies, like [Palantir](https://www.nytimes.com/2014/06/01/business/unlocking-secrets-if-not-its-own-value.html) and [PredPol](https://bits.blogs.nytimes.com/2013/06/19/in-hot-pursuit-of-numbers-to-ward-off-crime/), to conceal their methods for data-driven policing behind proprietary rights.

# 1NC

## Definitions

#### Predictive Policing Symposium

National Institute of Justice (2014) Overview of Predictive Policing | National Institute of Justice. Retrieved February 19, 2020, from https://nij.ojp.gov/topics/articles/overview-predictive-policing

NIJ convened two symposium to discuss predictive policing and its impact on crime and justice.

The first focused on the concept of predictive policing. The symposium introduced a working definition of predictive policing: “any policing strategy or tactic that develops and uses information and advanced analysis to inform forward-thinking crime prevention.”

The second symposium focused on how to make predictive policing available to all law enforcement agencies.

In proactive policing, law enforcement uses data and analyzes patterns to understand the nature of a problem. Officers devise strategies and tactics to prevent or mitigate future harm. They evaluate results and revise practices to improve policing. Departments may combine an array of data with street intelligence and crime analysis to produce better assessments about what might happen next if they take various actions.

What Is Predictive Policing?

Predictive policing tries to harness the power of information, geospatial technologies and evidence-based intervention models to reduce crime and improve public safety. This two-pronged approach — applying advanced analytics to various data sets, in conjunction with intervention models — can move law enforcement from reacting to crimes into the realm of predicting what and where something is likely to happen and deploying resources accordingly.

The predictive policing approach does not replace traditional policing. Instead, it enhances existing approaches such as problem-oriented policing, community policing, intelligence-led policing and hot spot policing.

Predictive policing leverages computer models — such as those used in the business industry to anticipate how market conditions or industry trends will evolve over time — for law enforcement purposes, namely anticipating likely crime events and informing actions to prevent crime. Predictions can focus on variables such as places, people, groups or incidents. Demographic trends, parolee populations and economic conditions may all affect crime rates in particular areas. Using models supported by prior crime and environmental data to inform different kinds of interventions can help police reduce the number of crime incidents.

Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations. With funding from NIJ, RAND Corporation developed this reference guide for law enforcement agencies interested in predictive policing. The guide assesses the most promising technical tools for making predictions as well as the most promising tactical approaches for acting on predictions.

## VALUE + VC

### Value: Quality of Life

My value for this debate is Quality of life, defined as the standard of health, comfort, and happiness experienced by an individual or group.

### VC: Cost-Benefit

My Value Criterion for today’s debate is implementing cost-benefit analysis

## Contention 1. Predictive Policing has a wide range of possible applications

#### Predictive Policing useful

Beth Pearsall, "Predictive Policing: The Future of Law Enforcement?," June 22, 2010, nij.ojp.gov: https://nij.ojp.gov/topics/articles/predictive-policing-future-law-enforcement

For years, businesses have used data analysis to anticipate market conditions or industry trends and drive sales strategies.

Walmart, for example, learned through analysis that when a major weather event is in the forecast, demand for three items rises: duct tape, bottled water and strawberry Pop-Tarts. Armed with this information, stores in the affected areas can ensure their shelves are fully stocked to meet customer needs.

Police can use a similar data analysis to help make their work more efficient. The idea is being called "predictive policing," and some in the field believe it has the potential to transform law enforcement by enabling police to anticipate and prevent crime instead of simply responding to it.

In November 2009, the National Institute of Justice, in partnership with the Bureau of Justice Assistance and the Los Angeles Police Department, held a Predictive Policing Symposium to discuss this emerging idea and its impact on the future of policing. Researchers, law enforcement officers, crime analysts and scientists gathered in Los Angeles for three days to explore the policy implications, privacy issues and technology of predictive policing.

Predictive policing, in essence, is taking data from disparate sources, analyzing them and then using the results to anticipate, prevent and respond more effectively to future crime.

Predictive policing entails becoming less reactive. "The predictive vision moves law enforcement from focusing on what happened to focusing on what will happen and how to effectively deploy resources in front of crime, thereby changing outcomes," writes Charlie Beck, chief of the Los Angeles Police Department.[[1]](https://nij.ojp.gov/topics/articles/predictive-policing-future-law-enforcement#note1)

Beck told participants that perhaps the greatest benefit to predictive policing is the discovery of new or previously unknown patterns and trends. Just as Walmart found increased demand for strawberry Pop-Tarts preceding major weather events, LAPD has found its own subtle patterns when examining data that have helped the department accurately anticipate and prevent crime.

Predictive policing is not meant to replace tried-and-true police techniques, symposium speakers explained. Instead, it borrows from the principles of problem-oriented policing, community policing, evidence-based policing, intelligence-led policing and other proven policing models.

"This is a very important next step to move forward in the evolutionary process of our profession," said Bill Bratton, former LAPD chief and chairman of Altegrity Risk International. "We are building on the essential elements of all policing strategies for the greater good."

John Morgan, director of NIJ's Office of Science and Technology, added, "This is a framework to help us organize policing as an information-intensive business in an information age. Predictive policing is not meant to replace any other model of policing," he said. "Instead, it enables us to do these things better."

Moreover, doing them better remains critical given the current economic climate.

George Gascón, chief of police for the San Francisco Police Department, noted that predictive policing is the perfect tool to help departments become more efficient as budgets continue to be reduced. "With predictive policing, we have the tools to put cops at the right place at the right time or bring other services to impact crime, and we can do so with less," he said.

"There is no predictive policing in a box," explained Colleen McCue, president and CEO of MC2 Solutions, which provides professional services in predictive analytics. "Let the problem guide the solution," she advised.

Current analytic tools and techniques like hot spots, data mining, crime mapping, geospatial prediction and social network analysis can be applied to a broad range of criminal justice problems. For instance, they can be used to anticipate localized crime spikes, inform city and neighborhood planning and aid in police management decisions.

Here are two examples of predictive policing at work:

Reducing Random Gunfire in Richmond. Every New Year's Eve, Richmond, Va., would experience an increase in random gunfire. Police began looking at data gathered over the years, and based on that information, they were able to anticipate the time, location and nature of future incidents. On New Year's Eve 2003, Richmond police placed officers at those locations to prevent crime and respond more rapidly. The result was a 47 percent decrease in random gunfire and a 246 percent increase in weapons seized. The department saved $15,000 in personnel costs.

Connecting Burglaries and Code Violations in Arlington, Texas. The Arlington, Texas, Police Department used data on residential burglaries to identify hot spots and then compared these locations to areas with code violations. According to Chief Theron Bowman, officers found that every unit increase of physical decay resulted in almost six more residential burglaries in the city. Thus, neighborhoods with greater physical decay could expect greater increases in residential burglaries. Arlington subsequently developed a formula to help identify characteristics of these "fragile neighborhoods." The police department and other city agencies now work more efficiently in the neighborhoods to help prevent crime.

Some participants questioned whether predictive policing was, in fact, a new model. They argued that good crime analysts have been practicing predictive policing for more than 40 years.

"Are we doing anything new or innovative with this data or are we just doing it better and quicker?" asked Chief Tom Casady of the Lincoln, Neb., Police Department.

Casady argued that the idea is not new. "It is a coalescing of interrelated police strategies and tactics that were already around, like intelligence-led policing and problem solving. This just brings them all under the umbrella of predictive policing," he said. "What is new is the tremendous infusion of data," Casady added.

Referencing the Richmond example, he explained, "We knew there were shootings on New Year's Eve, and we knew where they were happening. So if we could pinpoint the time, we could put more police in those areas. This is pretty basic stuff," he said, "and we have been doing this for years." Casady said the real question the field should be asking is how to take this to a new level: How do we use information to stimulate different interventions?

Participants agreed that transparency and community involvement are important.

"Community trust is huge as we move down this path," Beck explained. "We need to be extremely transparent. As we advance this discussion of how law enforcement will use information and how we tie that information to officer deployment, all of these discussions must be open."

"The community must have confidence that law enforcement will handle information the right way," said Thomas O'Reilly, senior policy advisor at the Justice Department's Bureau of Justice Assistance. "As we move into predictive policing, nothing should be secret. We should engage privacy advocates and community leaders from the outset to explain the program and get their ideas and input to alleviate their concerns."

Sean Malinowski, a lieutenant with the LAPD, assured participants that predictive policing does not deny civil rights. "Police are not arresting people on the probability that they will commit a crime," he said. "Police still must have probable cause." In addition, predictive policing methods do not identify specific individuals; instead, they anticipate particular times and locations where crime is likely to occur.[[2]](https://nij.ojp.gov/topics/articles/predictive-policing-future-law-enforcement#note2)

Yet privacy and civil liberty issues are critically interrelated with predictive policing and must be addressed. "We have a solemn obligation and a strategic imperative for the success of predictive policing to put privacy, civil rights and civil liberties in the forefront from the outset," said Russell Porter, director of the State of Iowa Intelligence Fusion Center.

Participants stressed the importance of setting up a thorough privacy policy, training personnel to use it properly, enforcing accountability and continually refining the policy. Policies should also include what information can be shared with other agencies.

"Transparency, auditing and due diligence are critical to developing a process that is trustworthy, protects privacy and produces good outcomes," said Joan McNamara, a commander in the Los Angeles Police Department.

Bratton added, "If we do this right, if we do it constitutionally, collectively and transparently, we can lessen the concern. We can hear the concerns and move forward, all the while expanding and modifying and improving and continuing that path of discussion."

In the end, the success of predictive policing will all come down to how reliable it is, how different information sources are integrated and how all the data are analyzed.

"Police departments collect great data all the time," said Craig Uchida, president of Justice & Security Strategies Inc., a company that helps law enforcement agencies in evaluating and addressing program needs. "We just don't know how reliable, valid and clean it is. We need to oversee data collection to ensure the data are clean."

Along with watching quality, police departments also need to tap into the wealth of nontraditional data available locally, such as medical and code-compliance data.

"Predictive policing has another level outside the walls of the police department," Jim Bueermann, chief of police in the Redlands, Calif., Police Department, said. "It takes a holistic approach — how do we integrate health and school and land-use data?"

"Part of the challenge is understanding what all the available data are and then finding a way to fuse that data, bring the people who use that data together, and approach it from a holistic perspective," Bowman said. "It is just as important to understand what we don't know at the local level."

John Miller of the Office of the Director of National Intelligence suggested that the field also looks at "predictive perpetrating." "We must ask ourselves: What data sources have the bad guys pulled up? We are not the only ones looking at data," he warned.

"It is so important to bring these data warehouses and analytics together and to search and make them available so we can do our job," Beck said. Malinowski added, "Analyzing all of this data will give decision-makers better information to make better decisions."

"We have the ability to use information to save lives, and we need to use it constitutionally and consistently," Bratton said. "We are in a position to save lives, reduce injuries, improve safety … It doesn't get any better than that."

#### Reduced crime LA

Stuart Wolpert. (2015) Predictive policing substantially reduces crime in Los Angeles during months-long test | UCLA. Retrieved March 06, 2020, from https://newsroom.ucla.edu/releases/predictive-policing-substantially-reduces-crime-in-los-angeles-during-months-long-test

Can math help keep our streets safer?

A new study by a UCLA-led team of scholars and law enforcement officials suggests the answer is yes. A mathematical model they devised to guide where the Los Angeles Police Department should deploy officers, led to substantially lower crime rates during a recent 21-month period.

“Not only did the model predict twice as much crime as trained crime analysts predicted, but it also prevented twice as much crime,” said Jeffrey Brantingham, a UCLA professor of anthropology and senior author of the study. A paper about the work, which was also tested in Kent, England, was [published online today](http://amstat.tandfonline.com/doi/pdf/10.1080/01621459.2015.1077710) by the Journal of the American Statistical Association.

The model was so successful that the LAPD has adopted it for use in 14 of its 21 divisions, up from three in 2013.

Developed using six years of mathematical research and a decade of police crime data, the program predicts times and places that serious crimes will occur based on historical crime data in a given area. A key to its success, Brantingham said, is that the algorithm behind the model effectively “learns” over time.

“In much the same way that your video streaming service knows what movie you’re going to watch tomorrow, even if your tastes have changed, our algorithm is constantly evolving and adapting to new crime data,” he said.

Beginning in 2011, the researchers analyzed crime trends in the LAPD’s Southwest division and in two Kent divisions to determine whether their model could predict, in real time, when and where major crimes would occur. Their analysis in Los Angeles focused on burglaries, theft from cars and theft of cars. In Kent, they studied patterns for those crimes as well as violent crimes including assault and robbery.

The researchers tested the computer model by pitting it against professional crime analysts, seeing which could more accurately predict where crimes would occur. On each of 117 days in Los Angeles, they gave the human analysts a map of the entire police district and asked them to identify one precise location — only about half-a-block in size — where a crime would be most likely to occur within a specific 12-hour period. The algorithm was programmed to answer the same question. (In this phase of the experiment, police officers did not act on the model’s predictions.)

In Los Angeles, the mathematical model correctly predicted the locations of crimes on 4.7 percent of its forecasts, while the human analysts were correct just 2.1 percent of the time. In Kent’s two divisions, the model predicted 9.8 percent and 6.8 percent of the crimes; the analysts were correct 6.8 percent and 4 percent of the time. (Although those success rates might not appear to be dramatic, it’s important to note that the predictions were focused on minuscule target locations: The predicted hot spots represented less than 1 percent of Los Angeles’ land area, and an even smaller percentage of Kent.)

In the next phase of the study, police officers in each of three LAPD divisions — North Hollywood, Southwest and Foothill (in the northeastern San Fernando Valley) — were deployed to 20 half-block areas based on the predictions of either the model or the human analysts, on random days for between four and eight months. Neither the officers nor their commanders knew whether the assignments came from the computer or the professional analysts.

Officers were instructed to go to the specified areas, which were marked on maps as red boxes, to respond as they saw fit and to stay in the locations as long as they deemed necessary. Across the three divisions, the mathematical model produced 4.3 fewer crimes per week, a reduction of 7.4 percent, compared with the number of crimes that the police would have expected had officers not patrolled the “red box” areas. Crime was reduced when officers patrolled the areas selected by the human analysts as well, but only by two crimes per week in each division.

Based on those results, the researchers estimated that using the algorithm would save $9 million per year in Los Angeles, taking into account costs to victims, the courts and society.

Brantingham said the mathematical model’s success rate could be improved even further as the researchers enhance the algorithm it uses.

Based on its own test run, the Kent police now are rolling out the mathematical model to other divisions throughout the county.

“We have worked closely with counterparts in Los Angeles from the moment we became interested in predictive policing and the benefits it brings to keeping communities safe,” said Mark Johnson, head of analysis for the Kent police.

Brantingham thinks the mathematical model would be effective in cities worldwide. He is a co-founder of [PredPol](http://www.predpol.com/?gclid=CPCeituTqscCFUeBfgodVYQOHA), a company that markets predictive policing software to cities including Atlanta and Tacoma, Washington.

Brantingham also emphasized that the algorithm cannot replace police work; it’s intended to help police officers do their jobs better.

“Our directive to officers was to ‘get in the box’ and use their training and experience to police what they see,” said Cmdr. Sean Malinowski, the LAPD’s chief of staff.  “Flexibility in how to use predictions proved to be popular and has become a key part of how the LAPD deploys predictive policing today.”

Many social scientists have said human behavior and criminal behavior are too complex to be explained with a mathematical model, but Brantingham strongly disagrees.

“It’s not too complex,” he said. “We’re not trying to explain everything, but there are many aspects of human behavior that we can understand mathematically.”

Other co-authors are Andrea Bertozzi, UCLA professor of mathematics and director of applied mathematics; George Mohler, a former UCLA mathematics postdoctoral scholar; Martin B. Short, a former UCLA assistant adjunct professor of mathematics, who is currently an assistant professor at the Georgia Institute of Technology; and George Tita, an associate professor at UC Irvine.

The research was funded by the National Science Foundation (grant DMS-0968309), the Air Force Office of Scientific Research (grant FA9550-10-1-0569), Office of Naval Research (grants N000141010221 and N000141210838) and the Army Research Office (grants W911NF1010472 and W911NF1110332).

## Contention 2. Certain ideals of policing are unjust, not predictive policing itself

#### Weapons of Math Destruction Chapter

O'NEIL, CATHY. *WEAPONS of MATH DESTRUCTION: How Big Data Increases Inequality and Threatens Democracy*. CROWN Publishing, 2017.

Cathy O’Neil has a PHD in mathematics from Harvard, worked as a quant on Wall Street, and worked in the math departments of MIT and Barnard. She wrote the book Weapon’s of Math Destruction in 2017.

a successful policing initiative in Newark, New Jersey. Cops who walked the beat there, according to the program, were supposed to be highly tolerant. Their job was to adjust to the neighborhood’s own standards of order and to help uphold them. Standards varied from one part of the city to another. In one neighborhood, it might mean that drunks had to keep their bottles in bags and avoid major streets but that side streets were okay. Addicts could sit on stoops but not lie down. The idea was only to make sure the standards didn’t fall. The cops, in this scheme, were helping a neighborhood maintain its own order but not imposing their own. You might think I’m straying a bit from PredPol, mathematics, and WMDs. But each policing approach, from broken windows to zero tolerance, represents a model. Just like my meal planning or the U.S. News Top College ranking, each crime-fighting model calls for certain input data, followed by a series of responses, and each is calibrated to achieve an objective.

Instead of simply trying to eradicate crimes, police should be attempting to build relationships in the neighborhood. This was one of the pillars of the original “broken-windows” study. The cops were on foot, talking to people, trying to help them uphold their own community standards. But that objective, in many cases, has been lost, steamrollered by models that equate arrests with safety. This isn’t the case everywhere. I recently visited Camden, New Jersey, which was the murder capital of the country in 2011. I found that the police department in Camden, rebuilt and placed under state control in 2012, had a dual mandate: lowering crime and engendering community trust. If building trust is the objective, an arrest may well become a last resort, not the first. This more empathetic approach could lead to warmer relations between the police and the policed, and fewer of the tragedies we’ve seen in recent years—the police killings of young black men and the riots that follow them. From a mathematical point of view, however, trust is hard to quantify. That’s a challenge for people building models. Sadly, it’s far simpler to keep counting arrests, to build models that assume we’re birds of a feather and treat us as such. Innocent people surrounded by criminals get treated badly, and criminals surrounded by a law-abiding public get a pass. And because of the strong correlation between poverty and reported crime, the poor continue to get caught up in these digital dragnets. The rest of us barely have to think about them.

#### Can be good, requires regulation

[Andrew Papachristos](https://sociology.yale.edu/people/andrew-papachristos). (2015) Use of Data Can Stop Crime by Helping Potential Victims - NYTimes.com. Retrieved March 05, 2020, from <https://www.nytimes.com/roomfordebate/2015/11/18/can-predictive-policing-be-ethical-and-effective/use-of-data-can-stop-crime-by-helping-potential-victms>

[*Andrew Papachristos*](https://sociology.yale.edu/people/andrew-papachristos) *is an associate professor of sociology and public health, and the director of the Center for Research on Inequalities and the Life Course, at Yale University.*

Data analytics have been used to combat [cholera outbreaks](https://www.emeraldinsight.com/doi/abs/10.1016/S1057-6290%2802%2980027-4) and the [transmission of HIV](https://link.springer.com/article/10.1007/s10461-011-9959-1#/page-1). Why shouldn't we use similar systems of network science to address “outbreaks” of gun violence?

Patterns of gun violence share many of the hallmarks of infectious disease. For starters, victimization is usually highly concentrated within identifiable and relatively small social networks. In [one study](https://www.sciencedirect.com/science/article/pii/S0277953614000987), for example, my colleagues and I found that 70 percent of all gunshot injuries in Chicago between 2006 and 2012 occurred in networks that made up just 6 percent of the city’s population. This violence [spreads like an infection](https://link.springer.com/article/10.1007/s11524-012-9703-9) among individuals as they engage in risky behaviors.

It is no secret that most of the shooting victims in our cities are, or involve, young men who have had prior contact with the criminal justice system. But saving lives and lowering rates of gun violence require caring about these young people whom the justice system typically only views as “offenders.” Network analysis cannot predict who the next victim will be, but it produces better assessments of who might be in harm’s way and opens the door to intervention.

But interventions must be conducted with a victim-centered public health approach in mind — one based on risk assessment and observation, rather than prediction — that involves not just law enforcement, but social services and community members.

Police departments in [Chicago](https://onlinelibrary.wiley.com/doi/10.1111/1745-9133.12139/abstract), [Kansas City](https://www.kansascity.com/news/local/crime/article5304384.html), [Boston](https://link.springer.com/article/10.1007/s10940-013-9198-x), [New Orleans](https://onlinelibrary.wiley.com/doi/10.1111/1745-9133.12142/abstract) and [New Haven](https://isps.yale.edu/research/publications/isps15-024#.VkI_Da6rRp9) have all collaborated with communities to use network data for violence prevention efforts, and have seen significant declines in gun violence associated with these efforts. Some efforts entail cops and communities bringing those at highest risk not to a police station or jail — but to a park "rec" room or church basement where they are met with pizza and soda instead of handcuffs. Police and community members sit down at the same table with those at risk. The police warn of legal consequences; community and family members raise a moral and compassionate voice against gun violence; and service providers offer access to employment and health services.

This kind of community involvement is key to the fair and transparent use of data analytics by the police.

In this era of mass incarceration and hyper-surveillance of our most vulnerable communities, algorithms might help narrow the focus and reach of the justice system, leading to fewer and fairer contacts with citizens. But it cannot happen if police and prosecutors use data without oversight or accountability. We must not allow for-profit-companies, like [Palantir](https://www.nytimes.com/2014/06/01/business/unlocking-secrets-if-not-its-own-value.html) and [PredPol](https://bits.blogs.nytimes.com/2013/06/19/in-hot-pursuit-of-numbers-to-ward-off-crime/), to conceal their methods for data-driven policing behind proprietary rights. Life and liberty should have a greater value than a company’s bottom line.

An offender- and profit-based approach will only exacerbate an already punitive justice system, and incite fears of a Minority Report-style of policing.

## BLOCKS

### “Increases Bias”

Lindenwood University. (2019) Does Predictive Policing Lead to Biased Arrests? Results From a Randomized Controlled Trial: Statistics and Public Policy: Vol 5, No 1. Retrieved March 03, 2020, from <https://amstat.tandfonline.com/doi/full/10.1080/2330443X.2018.1438940#.Wqa2aIJG1yp>

Andrew P. **Wheeler. (2019)** [Allocating Police Resources While Limiting Racial Inequality](https://www.tandfonline.com/doi/abs/10.1080/07418825.2019.1630471). *Justice Quarterly* 0:0, pages 1-27.

5. Discussion and Conclusions

**The stated goal of the analyses presented above was to assess the degree to which arrest rates were impacted by the introduction of predictive policing in three divisions patrolled by the LAPD. Special attention was paid to arrest rates by the race-ethnicity of the individuals detained. Our null hypotheses were: (1) arrest of minority individuals did not differ between control and treatment conditions in test divisions; (2) arrest rates overall did not differ between control and treatment conditions in test divisions; (3) the rate of arrests per crime was unchanged across treatment and control conditions.**

The evidence presented does not allow us to reject null hypothesis (1). There is no significant difference in the arrest proportions of minority individuals between treatment and control conditions. We also cannot reject hypothesis (2) at the division level. Arrest rates overall are the same on control and treatment days within the test divisions as a whole. However, we do reject null hypothesis (2) at the box level. Arrests were higher overall in treatment prediction boxes. We therefore tested hypothesis (3) to see if the higher arrest rate in treatment boxes is explained by an overall higher crime rate in treatment boxes. We fail to reject the null hypothesis (3). Arrest rates per crime do not differ across treatment and control conditions.

Clearly, arrests are a common part of day-to-day police operations. The introduction of predictive policing did not increase arrests overall, though treatment prediction boxes did see significantly more arrests than control prediction boxes. The increase arrests in treatment prediction boxes are perhaps understandable given that algorithmic crime predictions are more accurate than those produced by existing best practice (Mohler et al. [2015](https://amstat.tandfonline.com/doi/full/10.1080/2330443X.2018.1438940)).

The present study has several important limitations. Arrests are an imperfect proxy for other types of police contacts including stops, searches and detentions short of arrest. It is possible that predictive policing induced increases in these other categories of police contacts, without a concomitant impact on arrests. For this to hold true, it would have to be the case that the rate of arrest actually declined as these other precursor contacts increased, leaving overall arrest numbers unchanged. This hypothetical downward adjustment in arrests would have to hold not only for the experimental deployment period overall, but also for randomly assigned treatment days. We do not have sufficient data to exclude such dynamics, but they seem improbable on the face of it.

Second, the analyses do not provide any guidance on whether arrests are themselves systemically biased. Such could be the case, for example, if black and Latino individuals experienced arrest at a rate disproportionate to their share of offending (Rosenfeld and Fornango [2014](https://amstat.tandfonline.com/doi/full/10.1080/2330443X.2018.1438940)). **The current study is only able to ascertain that arrest rates for black and Latino individuals were not impacted, positively or negatively, by using predictive policing.** Future research could seek to test whether the situational conditions surrounding arrests and final dispositions differ in the presence of predictive policing.

Finally, the results reported herein pertain for the narrowly-defined place-based predictive policing model used in the Los Angeles predictive policing experiment (Mohler et al. [2015](https://amstat.tandfonline.com/doi/full/10.1080/2330443X.2018.1438940)). This model focused on reported crime data for a limited set of crimes including burglary, car theft and burglary from vehicle and used only information on crime location and time. Predictions were made for small 500 × 500 foot boxes and changed every day. Under those conditions, we can conclude that predictive policing did not result in biased arrests. Whether the same outcomes would hold given changes in implementation is uncertain. If the exact same data types and methods are applied in a different location there may be reason to be optimistic. However, if the data types change, for example to focus on discretionary crimes or arrests, or if personal information is incorporated into predictions, then pessimism may be warranted. At the same time, we should ask whether police would be negligent if they had data or information that led to accurate forecasts of crime risk but failed to act on it for fear of potential bias (Ferguson [2017](https://amstat.tandfonline.com/doi/full/10.1080/2330443X.2018.1438940)). Continued empirical scrutiny along with careful policy development will be needed to guard against bias in predictive policing and ensure fairness in outcomes.

[Essentially, Bad Policing is still bad policing, but Predictive Policing did not affect the bias or arrest rates for minorities, it simply isn’t true that predictive policing increases bias.]

### “privacy issues”

#### due to data collection

Predpol (2020) Predictive Policing Technology | PredPol. Retrieved March 06, 2020, from https://www.predpol.com/technology/

**Incident Identifier** – For each crime, we need a unique identifier, such as docket number, incident ID or anything else used by the department to uniquely identify the crime.

**Crime or Event Type** – The violation code and/or crime description assigned to a particular incident type as used in your RMS.

**Location of Incident** – For best accuracy, latitude and longitude are desired. Your latitude and longitude must use the WGS 84 coordinate system. If latitude and longitude are not available, then the complete address of the incident is required. A complete address is Street Number, Street Name, City, State/Region.

**Timestamps with Start and End Date/Time for Incident** – We use these two fields because in some cases the exact date and time that the crime occurred is not known. For example, an auto theft may occur between midnight and 8 AM, or a burglary may occur over a weekend.PredPol calculates the incident occurrence time by taking the midpoint between beginning date/time and ending date/time. Incidents with a span of more than 72 hours between the beginning and ending date/time are excluded because it reduces the accuracy of our predictions.

**Record Modified Date/Time for Incident** – This is an optional field, but where possible we also request that you include a “record modified” date/time field to allow us to catch RMS records that may have changed (i.e. crime code has been reclassified).

The prediction software is not using personalized data, rather historical crime data, so privacy issues are non-existent

### Safety Outweighs Privacy

If predictive policing is able to stop non-victimless crimes, then we will have protected the rights of people, and small transgressions against privacy is necessary to protect people’s rights.

# FULL CARDS

#### Chatham House Paper [Privacy, no bias]

Kathleen McKendrick . (2019) Artificial Intelligence Prediction and Counterterrorism | Chatham House. Retrieved March 02, 2020, from <https://www.chathamhouse.org/publication/artificial-intelligence-prediction-and-counterterrorism>

Irrespective of how sophisticated AI becomes, or of how much data is made available, predicting involvement in terrorism, the incidence of attacks or vulnerability to radicalization with sufficient accuracy may prove to be beyond the bounds of possibility.

Methods would have to be proposed, tried and assessed in advance – and retired if sufficient predictive value was not obtainable. Many examples of machine learning AI that have been so successfully used in industry work by improving their predictive capabilities as they are used. To some extent, the benefits of machine learning-based approaches are linked to their ability to dynamically adapt to the system they are analysing, including adapting to changes to background data within that system. Imposing standards of validation before use, and incrementally updating models based on new data, rather than allowing them to dynamically adjust, may limit their utility. This limitation would arguably have to be accepted as a guarantor of fair use.

The requirement to develop and test models would also mean that historical datasets would have to be available for experimentation, constituting a compromise of data privacy with no immediate causal link to a legitimate aim.

This might be acceptable, but only if there was a reasonable chance that a useful predictive model could be developed. A decision about when and whether to accept experimentation of this form would be a prerequisite for concerted use of predictive AI for counterterrorism purposes.

The core problem of identifying terrorists or predicting terrorism in other ways cannot be solved by using computational methods alone. Coupled with some of the inherent technical limitations identified earlier, such as vulnerability to adversarial action and lack of contextual understanding, this places definitive limits on how AI should be used in predicting terrorism. Specifically, the results of any predictive system provide possibility, not proof, and careful attention should be given to where that system needs to supplement, rather than replace, existing methods.

The societal effects of mass surveillance

Proportionality, as discussed so far in this paper, has considered privacy intrusion at the individual level. However, the right to privacy at this level underpins other rights, such as those of freedom of expression and association, and has beneficial social effects.120

**Many academics have examined the way widespread digital surveillance could cause a ‘chilling effect’ on engagement with sensitive political issues or activities, dissenting opinion and critical thought, as individuals conform to perceived collective norms.121 The issue has been a concern of civil society groups, particularly following revelations (commonly referred to as the Snowden revelations) in 2013 about the scale of national surveillance programmes.122 Psychologists have observed that the mere perception of being watched – even one based on a simple trigger like a picture of a pair of human eyes – can lead to discernible changes in behaviour.123 While automated analysis might reduce privacy intrusion at the individual level, it also gives rise to the possibility that everybody might feel as if they are being watched at all times. Because of this, automated analysis could have higher costs to other rights, such as rights of expression and association, which would be felt most acutely when individual behavioural changes are aggregated at the societal level.**

Scepticism still exists as to the chilling effects of surveillance on online activity,124 although a number of studies have attempted to document these as an empirically observable phenomenon.125 Historical experience of the behaviour of citizens under totalitarian regimes provides compelling evidence of chilling effects, although it is impossible to disaggregate the impact of surveillance per se with that of other measures designed to induce fear and force changes in people’s behaviour. More recently, commentators have held up the continuance of political dissent and free speech after the 2013 revelations, and the increase in voluntary information sharing via social media, as evidence of the absence of meaningful chilling effects. Proponents of the chilling effect of surveillance acknowledge that it is not possible to anticipate exactly what the nature of that effect will be, or to measure it.126 It is also possible that the most drastic effects are not in response to government observation, but to the scrutiny of peers and competitors.127

Although it seems logical that the possibility of ubiquitous observation that advances in automation may soon offer could have chilling effects, whether or not they will do so is definitely speculative at this stage, and it is beyond the scope of this paper to try and project those effects. It will be incumbent on governments to pre-empt these possible impacts when they design suitable legal controls on surveillance activity. Addressing this future concern might require the development of models that assess the wider harms of individual privacy infringements based on their societal impact.128

Erosion of standards of proof

While dealing with evidentiary standards below the level of definite proof is already a characteristic of counterterrorism operations, concerns exist that ‘the growing availability of data might lead to an erosion of existing standards, rendering police and governmental interventions legitimate because the computer “said so”’.129 The potential offered by the ability to collect and use data may be coupled with a lower tolerance of risk and uncertainty at the societal level, which could lead to a greater focus on prevention – and even on pre-emption – than previously existed.130 In the extreme, some commentators worry that:

Crucial to banishing this spectre of ‘pre-crime’ is the recognition that the output of any predictive model always represents possibility rather than proof. Hence, interventions undertaken on the basis of predictive modelling must ultimately be based on a human decision made by someone who is sufficiently informed about the limits and capabilities of the model being used.

‘Functional creep’

There are precedents where measures have been adopted for the purposes of countering terrorism, and then appropriated for their general use in fighting crime. The New York City Police Department’s Domain Awareness System is one such. Integrating the feeds of 3,000 CCTV and ANPR cameras alongside other sensors, the system was originally installed – and is often touted – for its value in countering terrorism. However, an appraisal of its use indicates that there are very few examples where it has actually been used in this role.132

A hoard of data about the general public would be invaluable in identifying start points for criminal investigations, or even for directing any number of beneficial social interventions. The potential for ‘functional creep’ is massive, and requires safeguarding against. An appropriate measure might be that the dataset concerned was only used for interrogation by certain, pre-authorized models, rather than being available for directed specific queries by analysts. This could render the dataset easier to control, and could also give a level of transparency about how the data are used.

Study Finds Predictive Policing No More Racist Than Regular Policing. (2018) Retrieved March 02, 2020, from <https://gizmodo.com/study-finds-predictive-policing-no-more-racist-than-reg-1823733844>

Police agencies are increasingly using advanced technologies to fight crime, including biometrics, auditory detection, and even virtual reality. One of the most controversial tools is “predictive policing,” which has long been accused of reinforcing racial biases. But a team of researchers from Indiana University, UCLA, and Louisiana State University found the practice, and its effects on bias, is more complicated than that.

Predictive policing is a “[smart policing](https://gizmodo.com/black-data-is-the-reason-why-smart-policing-is-still-1819288923)” tool that trains an algorithm to [predict where crime](https://www.youtube.com/watch?v=YxvyeaL7NEM) will happen. For this study, the LAPD was given maps of “hot spot” areas to patrol. On “treatment” days, the hot spot areas were selected by an algorithm. On “control” days, they were selected by a human analyst. The researchers compared arrest rates on both treatment and control days, wanting to know if minorities were arrested more or less frequently on either day.

Why is this controversial? Because arrest data lacks nuance. A person could commit the same crime in two different places, but would only be arrested if there’s an officer there (or one who comes after responding to a 911 call.) As advocates argue, areas with more police presence will always have more arrests. So if officers are more suspicious of a neighborhood, it will have more arrests because there are more officers sent there. This dynamic isn’t reflected in the arrest data used to train algorithms; it simply shows where arrests happen and how often. Law enforcement agencies, however, say that officers are sent into areas based on crime levels, not racial suspicion.

But what the Indiana University researchers found neither proved nor disproved either assertion. The paper, [“Does Predictive Policing Lead to Biased Arrests? Results from A Randomized Control Trial?”](https://www.tandfonline.com/doi/full/10.1080/2330443X.2018.1438940) was published in the latest edition of Statistics and Public Policy.

**Researchers say minorities were not arrested at higher rates on algo-determined days than on analyst-determined days. The racial proportions of arrestees were the same on both “treatment” and “control” days. Taken as a whole, arrest rates for all races were the same on both “treatment” and “control” days overall.**

**Interestingly, when broken down to a geographic level, officers did arrest more people in specific “hot spot” areas determined by the algorithm than the “hot spots” determined by an analyst. But, the researchers assert that this is expected—the increase in arrests scales upward proportional to the increase in crime.**

**“The higher crime rate, and proportionally higher arrest rate, is what you would expect since the algorithm is designed to identify areas with high crime rates,” George Mohler, one of the study’s authors, told Physics.org.**

**Ultimately, the researchers found that predictive policing seemingly doesn’t increase bias. That does not mean policing, predictive or no, doesn’t have racial biases; simply that in this case, algorithms weren’t found to have caused any racial imbalances in arrests. From the results section:**

**The analyses do not provide any guidance on whether arrests are themselves systemically biased. Such could be the case, for example, if black and Latino individuals experienced arrest at a rate disproportionate to their share of offending. [...] The current study is only able to ascertain that arrest rates for black and Latino individuals were not impacted, positively or negatively, by using predictive policing. Future research could seek to test whether the situational conditions surrounding arrests and final dispositions differ in the presence of predictive policing.**

Predictive policing simply augments existing policing patterns. If there are biases, algorithms augment them as well, but they aren’t the originator. The researchers point out that the root causes of crime and racial bias are a different subject, though left unasked is an obvious question: Why augment policing while there are still pervasive, unaddressed biases?

That remains a debate for community leaders and law enforcement agencies. For now, Mohler hopes the study serves as a “framework” for auditing the racial impact of this practice.

“Every time you do one of these predictive policing deployments, departments should monitor the ethnic impact of these algorithms to check whether there is racial bias,” Mohler said. “I think the statistical methods we provide in this paper provide a framework to monitor that.”

#### Weapons of Math Destruction Chapter

O'NEIL, CATHY. *WEAPONS of MATH DESTRUCTION: How Big Data Increases Inequality and Threatens Democracy*. CROWN Publishing, 2017.

Cathy O’Neil has a PHD in mathematics from Harvard, worked as a quant on Wall Street, and worked in the math departments of MIT and Barnard. She wrote the book Weapon’s of Math Destruction in 2017.

The small city of Reading, Pennsylvania, has had a tough go of it in the postindustrial era. Nestled in the green hills fifty miles west of Philadelphia, Reading grew rich on railroads, steel, coal, and textiles. But in recent decades, with all of those industries in steep decline, the city has languished. By 2011, it had the highest poverty rate in the country, at 41.3 percent. (The following year, it was surpassed, if barely, by Detroit.) As the recession pummeled Reading’s economy following the 2008 market crash, tax revenues fell, which led to a cut of forty-five officers in the police department—despite persistent crime. Reading police chief William Heim had to figure out how to get the same or better policing out of a smaller force. So in 2013 he invested in crime prediction software made by PredPol, a Big Data start-up based in Santa Cruz, California. The program processed historical crime data and calculated, hour by hour, where crimes were most likely to occur. The Reading policemen could view the program’s conclusions as a series of squares, each one just the size of two football fields. If they spent more time patrolling these squares, there was a good chance they would discourage crime. And sure enough, a year later, [the] Chief Heim announced that burglaries were down by 23 percent. Predictive programs like PredPol are all the rage in budget-strapped police departments across the country. Departments from Atlanta to Los falling crime rates. New York City uses a similar program, called CompStat. And Philadelphia police are using a local product called HunchLab that includes risk terrain analysis, which incorporates certain features, such as ATMs or convenience stores, that might attract crimes. Like those in the rest of the Big Data industry, the developers of crime prediction software are hurrying to incorporate any information that can boost the accuracy of their models. If you think about it, hot-spot predictors are similar to the shifting defensive models in baseball that we discussed earlier. Those systems look at the history of each player’s hits and then position fielders where the ball is most likely to travel. Crime prediction software carries out similar analysis, positioning cops where crimes appear most likely to occur. Both types of models optimize resources. But a number of the crime prediction models are more sophisticated, because they predict progressions that could lead to waves of crime. PredPol, for example, is based on seismic software: it looks at a crime in one area, incorporates it into historical patterns, and predicts when and where it might occur next. (One simple correlation it has found: if burglars hit your next-door neighbor’s house, batten down the hatches.) Predictive crime models like PredPol have their virtues. Unlike the crime-stoppers in Steven Spielberg’s dystopian movie Minority Report (and some ominous real-life initiatives, which we’ll get to shortly), the cops don’t track down people before they commit crimes. Jeffrey Brantingham, the UCLA anthropology professor who founded PredPol, stressed to me that the model is blind to race and ethnicity. And unlike other programs, including the recidivism risk models we discussed, which are used for sentencing guidelines, PredPol doesn’t focus on the individual. Instead, it targets geography. The key inputs are the type and location of each crime and when it occurred. That seems fair enough. And if cops spend more time in the high-risk zones, foiling burglars and car thieves, there’s good reason to believe that the community benefits. But most crimes aren’t as serious as burglary and grand theft auto, and that is where serious problems emerge. When police set up their PredPol system, they have a choice. They can focus exclusively on so-called Part 1 crimes. These are the violent crimes, including homicide, arson, and assault, which are usually reported to them. But they can also broaden the focus by including Part 2 crimes, including vagrancy, aggressive panhandling, and selling and consuming small quantities of drugs. Many of these “nuisance” crimes would go unrecorded if a cop weren’t there to see them.

These nuisance crimes are endemic to many impoverished neighborhoods. In some places police call them antisocial behavior, or ASB. Unfortunately, including them in the model threatens to skew the analysis. Once the nuisance data flows into a predictive model, more police are drawn into those neighborhoods, where they’re more likely to arrest more people. After all, even if their objective is to stop burglaries, murders, and rape, they’re bound to have slow periods. It’s the nature of patrolling. And if a patrolling cop sees a couple of kids who look no older than sixteen guzzling from a bottle in a brown bag, he stops them. These types of low-level crimes populate their models with more and more dots, and the models send the cops back to the same neighborhood. This creates a pernicious feedback loop. The policing itself spawns new data, which justifies more policing. And our prisons fill up with hundreds of thousands of people found guilty of victimless crimes. Most of them come from impoverished neighborhoods, and most are black or Hispanic. So even if a model is color blind, the result of it is anything but. In our largely segregated cities, geography is a highly effective proxy for race. If the purpose of the models is to prevent serious crimes, you might ask why nuisance crimes are tracked at all. The answer is that the link between antisocial behavior and crime has been an article of faith since 1982, when a criminologist named George Kelling teamed up with a public policy expert, James Q. Wilson, to write a seminal article in the Atlantic Monthly on so-called broken-windows policing. The idea was that low-level crimes and misdemeanors created an atmosphere of disorder in a neighborhood. This scared law-abiding citizens away. The dark and empty streets they left behind were breeding grounds for serious crime. The antidote was for society to resist the spread of disorder. This included fixing broken windows, cleaning up graffiti-covered subway cars, and taking steps to discourage nuisance crimes. This thinking led in the 1990s to zero-tolerance campaigns, most famously in New York City. Cops would arrest kids for jumping the subway turnstiles. They’d apprehend people caught sharing a single joint and rumble them around the city in a paddy wagon for hours before eventually booking them. Some credited these energetic campaigns for dramatic falls in violent crimes. Others disagreed. The authors of the bestselling book Freakonomics went so far as to correlate the drop in crime to the legalization of abortion in the 1970s. And plenty of other theories also surfaced, ranging from the falling rates of crack cocaine addiction to the booming 1990s economy. In any case, the zero-tolerance movement gained broad support, and the criminal justice system sent millions of mostly young minority men to prison, many of them for minor offenses.

But zero tolerance actually had very little to do with Kelling and Wilson’s “broken-windows” thesis. Their case study focused on what appeared to be a successful policing initiative in Newark, New Jersey. Cops who walked the beat there, according to the program, were supposed to be highly tolerant. Their job was to adjust to the neighborhood’s own standards of order and to help uphold them. Standards varied from one part of the city to another. In one neighborhood, it might mean that drunks had to keep their bottles in bags and avoid major streets but that side streets were okay. Addicts could sit on stoops but not lie down. The idea was only to make sure the standards didn’t fall. The cops, in this scheme, were helping a neighborhood maintain its own order but not imposing their own. You might think I’m straying a bit from PredPol, mathematics, and WMDs. But each policing approach, from broken windows to zero tolerance, represents a model. Just like my meal planning or the U.S. News Top College ranking, each crime-fighting model calls for certain input data, followed by a series of responses, and each is calibrated to achieve an objective. It’s important to look at policing this way, because these mathematical models now dominate law enforcement. And some of them are WMDs. That said, we can understand why police departments would choose to include nuisance data. Raised on the orthodoxy of zero tolerance, many have little more reason to doubt the link between small crimes and big ones than the correlation between smoke and fire. When police in the British county of Kent tried out PredPol, in 2013, they incorporated nuisance crime data into their model. It seemed to work. They found that the PredPol squares were ten times as efficient as random patrolling and twice as precise as analysis delivered by police intelligence. And what type of crimes did the model best predict? Nuisance crimes. This makes all the sense in the world. A drunk will pee on the same wall, day in and day out, and a junkie will stretch out on the same park bench, while a car thief or a burglar will move about, working hard to anticipate the movements of police. Even as police chiefs stress the battle against violent crime, it would take remarkable restraint not to let loads of nuisance data flow into their predictive models. More data, it’s easy to believe, is better data. While a model focusing only on violent crimes might produce a sparse constellation on the screen, the inclusion of nuisance data would create a fuller and more vivid portrait of lawlessness in the city.

And in most jurisdictions, sadly, such a crime map would track poverty. The high number of arrests in those areas would do nothing but confirm the broadly shared thesis of society’s middle and upper classes: that poor people are responsible for their own shortcomings and commit most of a city’s crimes. But what if police looked for different kinds of crimes? That may sound counterintuitive, because most of us, including the police, view crime as a pyramid. At the top is homicide. It’s followed by rape and assault, which are more common, and then shoplifting, petty fraud, and even parking violations, which happen all the time. Prioritizing the crimes at the top of the pyramid makes sense. Minimizing violent crime, most would agree, is and should be a central part of a police force’s mission. But how about crimes far removed from the boxes on the PredPol maps, the ones carried out by the rich? In the 2000s, the kings of finance threw themselves a lavish party. They lied, they bet billions against their own customers, they committed fraud and paid off rating agencies. Enormous crimes were committed there, and the result devastated the global economy for the best part of five years. Millions of people lost their homes, jobs, and health care. We have every reason to believe that more such crimes are occurring in finance right now. If we’ve learned anything, it’s that the driving goal of the finance world is to make a huge profit, the bigger the better, and that anything resembling self-regulation is worthless. Thanks largely to the industry’s wealth and powerful lobbies, finance is underpoliced. Just imagine if police enforced their zero-tolerance strategy in finance. They would arrest people for even the slightest infraction, whether it was chiseling investors on 401ks, providing misleading guidance, or committing petty frauds. Perhaps SWAT teams would descend on Greenwich, Connecticut. They’d go undercover in the taverns around Chicago’s Mercantile Exchange. Not likely, of course. The cops don’t have the expertise for that kind of work. Everything about their jobs, from their training to their bullet-proof vests, is adapted to the mean streets. Clamping down on white-collar crime would require people with different tools and skills. The small and underfunded teams who handle that work, from the FBI to investigators at the Securities and Exchange Commission, have learned through the decades that bankers are virtually invulnerable. They spend heavily on our politicians, which always helps, and are also viewed as crucial to our economy. That protects them. If their banks go south, our economy could go with them. (The poor have no such argument.) So except for a couple their attention. Today they focus almost exclusively on the poor. That’s their heritage, and their mission, as they understand it. And now data scientists are stitching this status quo of the social order into models, like PredPol, that hold ever-greater sway over our lives. The result is that while PredPol delivers a perfectly useful and even high-minded software tool, it is also a do-it-yourself WMD. In this sense, PredPol, even with the best of intentions, empowers police departments to zero in on the poor, stopping more of them, arresting a portion of those, and sending a subgroup to prison. And the police chiefs, in many cases, if not most, think that they’re taking the only sensible route to combating crime. That’s where it is, they say, pointing to the highlighted ghetto on the map. And now they have cutting-edge technology (powered by Big Data) reinforcing their position there, while adding precision and “science” to the process. The result is that we criminalize poverty, believing all the while that our tools are not only scientific but fair.

One weekend in the spring of 2011, I attended a data “hackathon” in New York City. The goal of such events is to bring together hackers, nerds, mathematicians, and software geeks and to mobilize this brainpower to shine light on the digital systems that wield so much power in our lives. I was paired up with the New York Civil Liberties Union, and our job was to break out the data on one of the NYPD’s major anticrime policies, so-called stop, question, and frisk. Known simply as stop and frisk to most people, the practice had drastically increased in the data-driven age of CompStat. The police regarded stop and frisk as a filtering device for crime. The idea is simple. Police officers stop people who look suspicious to them. It could be the way they’re walking or dressed, or their tattoos. The police talk to them and size them up, often while they’re spread-eagled against a wall or the hood of a car. They ask for their ID, and they frisk them. Stop enough people, the thinking goes, and you’ll no doubt stop loads of petty crimes, and perhaps some big ones. The policy, implemented by Mayor Michael Bloomberg’s administration, had loads of public support. Over

the previous decade, the number of stops had risen by 600 percent, to nearly seven hundred thousand incidents. The great majority of those stopped were innocent. For them, these encounters were highly unpleasant, even infuriating. Yet many in the public associated the program with the sharp decline of crime in the city. New York, many felt, was safer. And statistics indicated as much. Homicides, which had reached 2,245 in 1990, were down to 515 (and would drop below 400 by 2014). Everyone knew that an outsized proportion of the people the police stopped were young, dark-skinned men. But how many did they stop? And how often did these encounters lead to arrests or stop crimes? While this information was technically public, much of it was stored in a database that was hard to access. The software didn’t work on our computers or flow into Excel spreadsheets. Our job at the hackathon was to break open that program and free the data so that we could all analyze the nature and effectiveness of the stop-and-frisk program. What we found, to no great surprise, was that an overwhelming majority of these encounters—about 85 percent—involved young African American or Latino men. In certain neighborhoods, many of them were stopped repeatedly. Only 0.1 percent, or one of one thousand stopped, was linked in any way to a violent crime. Yet this filter captured many others for lesser crimes, from drug possession to underage drinking, that might have otherwise gone undiscovered. Some of the targets, as you might expect, got angry, and a good number of those found themselves charged with resisting arrest. The NYCLU sued the Bloomberg administration, charging that the stop-and-frisk policy was racist. It was an example of uneven policing, one that pushed more minorities into the criminal justice system and into prison. Black men, they argued, were six times more likely to be incarcerated than white men and twenty-one times more likely to be killed by police, at least according to the available data (which is famously underreported). Stop and frisk isn’t exactly a WMD, because it relies on human judgment and is not formalized into an algorithm. But it is built upon a simple and destructive calculation. If police stop one thousand people in certain neighborhoods, they’ll uncover, on average, one significant suspect and lots of smaller ones. This isn’t so different from the long-shot calculations used by predatory advertisers or spammers. Even when the hit ratio is miniscule, if you give yourself enough chances you’ll reach your target. And that helps to explain why the program grew so and harassment suffered by thousands upon thousands of innocent people was justified. Weren’t they interested in stopping crime? Aspects of stop and frisk were similar to WMDs, though. For example, it had a nasty feedback loop. It ensnared thousands of black and Latino men, many of them for committing the petty crimes and misdemeanors that go on in college frats, unpunished, every Saturday night. But while the great majority of university students were free to sleep off their excesses, the victims of stop and frisk were booked, and some of them dispatched to the hell that is Rikers Island. What’s more, each arrest created new data, further justifying the policy. As stop and frisk grew, the venerable legal concept of probable cause was rendered virtually meaningless, because police were hunting not only people who might have already committed a crime but also those who might commit one in the future. Sometimes, no doubt, they accomplished this goal. By arresting a young man whose suspicious bulge turned out to be an unregistered gun, they might be saving the neighborhood from a murder or armed robbery, or even a series of them. Or maybe not. Whatever the case, there was a logic to stop and frisk, and many found it persuasive. But was the policy constitutional? In August of 2013, federal judge Shira A. Scheindlin ruled that it was not. She said officers routinely “stopped blacks and Hispanics who would not have been stopped if they were white.” Stop and frisk, she wrote, ran afoul of the Fourth Amendment, which protects against unreasonable searches and seizures by the government, and it also failed to provide the equal protection guaranteed by the Fourteenth Amendment. She called for broad reforms to the practice, including increased use of body cameras on patrolling policemen. This would help establish probable cause—or the lack of it—and remove some of the opacity from the stop-and-frisk model. But it would do nothing to address the issue of uneven policing. While looking at WMDs, we’re often faced with a choice between fairness and efficacy. Our legal traditions lean strongly toward fairness. The Constitution, for example, presumes innocence and is engineered to value it. From a modeler’s perspective, the presumption of innocence is a constraint, and the result is that some guilty people go free, especially those who can afford good lawyers. Even those found guilty have the right to appeal their verdict, which chews up time and resources. So the system sacrifices enormous efficiencies for the promise of fairness. The

Constitution’s implicit judgment is that freeing someone who may well have committed a crime, for lack of evidence, poses less of a danger to our society than jailing or executing an innocent person. WMDs, by contrast, tend to favor efficiency. By their very nature, they feed on data that can be measured and counted. But fairness is squishy and hard to quantify. It is a concept. And computers, for all of their advances in language and logic, still struggle mightily with concepts. They “understand” beauty only as a word associated with the Grand Canyon, ocean sunsets, and grooming tips in Vogue magazine. They try in vain to measure “friendship” by counting likes and connections on Facebook. And the concept of fairness utterly escapes them. Programmers don’t know how to code for it, and few of their bosses ask them to. So fairness isn’t calculated into WMDs. And the result is massive, industrial production of unfairness . If you think of a WMD as a factory, unfairness is the black stuff belching out of the smoke stacks. It’s an emission, a toxic one. The question is whether we as a society are willing to sacrifice a bit of efficiency in the interest of fairness. Should we handicap the models, leaving certain data out? It’s possible, for example, that adding gigabytes of data about antisocial behavior might help PredPol predict the mapping coordinates for serious crimes. But this comes at the cost of a nasty feedback loop. So I’d argue that we should discard the data. It’s a tough case to make, similar in many ways to the battles over wiretapping by the National Security Agency. Advocates of the snooping argue that it’s important for our safety. And those running our vast national security apparatus will keep pushing for more information to fulfill their mission. They’ll continue to encroach on people’s privacy until they get the message that they must find a way to do their job within the bounds of the Constitution. It might be harder, but it’s necessary. The other issue is equality. Would society be so willing to sacrifice the concept of probable cause if everyone had to endure the harassment and indignities of stop and frisk? Chicago police have their own stop-and-frisk program. In the name of fairness, what if they sent a bunch of patrollers into the city’s exclusive Gold Coast? Maybe they’d arrest joggers for jaywalking from the park across W. North Boulevard or crack down on poodle pooping along Lakeshore Drive. This heightened police presence would probably pick up more drunk drivers and perhaps uncover a few cases of insurance fraud, spousal abuse, or racketeering. Occasionally, just to give everyone a taste of the unvarnished experience, the cops might throw wealthy citizens on the trunks of their cruisers, wrench their calling them hateful names. In time, this focus on the Gold Coast would create data. It would describe an increase in crime there, which would draw even more police into the fray. This would no doubt lead to growing anger and confrontations. I picture a double parker talking back to police, refusing to get out of his Mercedes, and finding himself facing charges for resisting arrest. Yet another Gold Coast crime. This may sound less than serious. But a crucial part of justice is equality. And that means, among many other things, experiencing criminal justice equally. People who favor policies like stop and frisk should experience it themselves. Justice cannot just be something that one part of society inflicts upon the other. The noxious effects of uneven policing, whether from stop and frisk or predictive models like PredPol, do not end when the accused are arrested and booked in the criminal justice sys tem. Once there, many of them confront another WMD that I discussed in chapter 1 , the recidivism model used for sentencing guidelines. The biased data from uneven policing funnels right into this model. Judges then look to this supposedly scientific analysis, crystallized into a single risk score. And those who take this score seriously have reason to give longer sentences to prisoners who appear to pose a higher risk of committing other crimes. And why are nonwhite prisoners from poor neighborhoods more likely to commit crimes? According to the data inputs for the recidivism models, it’s because they’re more likely to be jobless, lack a high school diploma, and have had previous run-ins with the law. And their friends have, too. Another way of looking at the same data, though, is that these prisoners live in poor neighborhoods with terrible schools and scant opportunities. And they’re highly policed. So the chance that an ex-convict returning to that neighborhood will have another brush with the law is no doubt larger than that of a tax fraudster who is released into a leafy suburb. In this system, the poor and nonwhite are punished more for being who they are and living where they live. What’s more, for supposedly scientific systems, the recidivism models are logically flawed. The unquestioned assumption is that locking away “high-risk” prisoners for more time makes society safer. It is true, of course, that prisoners don’t commit crimes against society while behind bars. But is it possible that their time in prison has an effect on their behavior once they step out? Is there a chance that years in a brutal

environment surrounded by felons might make them more likely, and not less, to commit another crime? Such a finding would undermine the very basis of the recidivism sentencing guidelines. But prison systems, which are awash in data, do not carry out this highly important research. All too often they use data to justify the workings of the system but not to question or improve the system. Compare this attitude to the one found at Amazon.​com. The giant retailer, like the criminal justice system, is highly focused on a form of recidivism. But Amazon’s goal is the opposite. It wants people to come back again and again to buy. Its software system targets recidivism and encourages it. Now, if Amazon operated like the justice system, it would start by scoring shoppers as potential recidivists. Maybe more of them live in certain area codes or have college degrees. In this case, Amazon would market more to these people, perhaps offering them discounts, and if the marketing worked, those with high recidivist scores would come back to shop more. If viewed superficially, the results would appear to corroborate Amazon’s scoring system. But unlike the WMDs in criminal justice, Amazon does not settle for such glib correlations. The company runs a data laboratory. And if it wants to find out what drives shopping recidivism, it carries out research. Its data scientists don’t just study zip codes and education levels. They also inspect people’s experience within the Amazon ecosystem. They might start by looking at the patterns of all the people who shopped once or twice at Amazon and never returned. Did they have trouble at checkout? Did their packages arrive on time? Did a higher percentage of them post a bad review? The questions go on and on, because the future of the company hinges upon a system that learns continually, one that figures out what makes customers tick. If I had a chance to be a data scientist for the justice system, I would do my best to dig deeply to learn what goes on inside those prisons and what impact those experiences might have on prisoners’ behavior. I’d first look into solitary confinement. Hundreds of thousands of prisoners are kept for twenty-three hours a day in these prisons within prisons, most of them no bigger than a horse stall. Researchers have found that time in solitary produces deep feelings of hopelessness and despair. Could that have any impact on recidivism? That’s a test I’d love to run, but I’m not sure the data is even collected. How about rape? In Unfair: The New Science of Criminal Injustice , Adam Benforado writes that certain types of prisoners are targeted for the relevant data and expertise could work out, but prison systems have thus far been uninterested in cataloging the long-term effects of this abuse. A serious scientist would also search for positive signals from the prison experience. What’s the impact of more sunlight, more sports, better food, literacy training? Maybe these factors will improve convicts’ behavior after they go free. More likely, they’ll have varying impact. A serious justice system research program would delve into the effects of each of these elements, how they work together, and which people they’re most likely to help. The goal, if data were used constructively, would be to optimize prisons—much the way companies like Amazon optimize websites or supply chains—for the benefit of both the prisoners and society at large. But prisons have every incentive to avoid this data-driven approach. The PR risks are too great—no city wants to be the subject of a scathing report in the New York Times . And, of course, there’s big money riding on the overcrowded prison system. Privately run prisons, which house only 10 percent of the incarcerated population, are a $5 billion industry. Like airlines, the private prisons make profits only when running at high capacity. Too much poking and prodding might threaten that income source. So instead of analyzing prisons and optimizing them, we deal with them as black boxes. Prisoners go in and disappear from our view. Nastiness no doubt occurs, but behind thick walls. What goes on in there? Don’t ask. The current models stubbornly stick to the dubious and unquestioned hypothesis that more prison time for supposedly high-risk prisoners makes us safer. And if studies appear to upend that logic, they can be easily ignored. And this is precisely what happens. Consider a recidivism study by Michigan economics professor Michael Mueller-Smith. After studying 2.6 million criminal court records in Harris County, Texas, he concluded that the longer inmates in Harris County, Texas, spent locked up, the greater the chance that they would fail to find employment upon release, would require food stamps and other public assistance, and would commit further crimes. But to turn those conclusions into smart policy and better justice, politicians will have to take a stand on behalf of a feared minority that many (if not most) voters would much prefer to ignore. It’s a tough sell.

I would argue that the model that led police to Robert McDaniel’s door has the wrong objective. Instead of simply trying to eradicate crimes, police should be attempting to build relationships in the neighborhood. This was one of the pillars of the original “broken-windows” study. The cops were on foot, talking to people, trying to help them uphold their own community standards. But that objective, in many cases, has been lost, steamrollered by models that equate arrests with safety. This isn’t the case everywhere. I recently visited Camden, New Jersey, which was the murder capital of the country in 2011. I found that the police department in Camden, rebuilt and placed under state control in 2012, had a dual mandate: lowering crime and engendering community trust. If building trust is the objective, an arrest may well become a last resort, not the first. This more empathetic approach could lead to warmer relations between the police and the policed, and fewer of the tragedies we’ve seen in recent years—the police killings of young black men and the riots that follow them. From a mathematical point of view, however, trust is hard to quantify. That’s a challenge for people building models. Sadly, it’s far simpler to keep counting arrests, to build models that assume we’re birds of a feather and treat us as such. Innocent people surrounded by criminals get treated badly, and criminals surrounded by a law-abiding public get a pass. And because of the strong correlation between poverty and reported crime, the poor continue to get caught up in these digital dragnets. The rest of us barely have to think about them.

# Workshop

<https://ld.debateus.org/2019/06/21/resolved-predictive-policing-is-unjust/>

#### Can fight bias

Eric Siegel. (2018) How to Fight Bias with Predictive Policing - Scientific American Blog Network. Retrieved March 05, 2020, from https://blogs.scientificamerican.com/voices/how-to-fight-bias-with-predictive-policing/

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Law enforcement's use of predictive analytics recently came under fire again. Dartmouth researchers [made waves reporting](http://advances.sciencemag.org/content/4/1/eaao5580) that simple predictive models—as well as nonexpert humans—predict crime just as well as the leading proprietary analytics software. That the leading software achieves (only) human-level performance might not actually be a deadly blow, but a flurry of press from dozens of news outlets has quickly followed. In any case, even as this disclosure raises questions about one software tool’s credibility, a more enduring, inherent quandary continues to plague predictive policing.

Crime-predicting models are caught in a quagmire doomed to controversy because, on their own, they cannot realize racial equity. It’s an intrinsically unsolvable problem. It turns out that, although such models succeed in flagging (assigning higher probabilities to) both black and white defendants with equal precision, as a result of doing so they also falsely flag black defendants more often than white ones. In this article I cover this seemingly paradoxical predicament and show how predictive policing—more generally, big data in law enforcement—can be turned around to make the legal system fairer in this unfair world.

[Predictive policing](https://www.amazon.com/Rise-Big-Data-Policing-Surveillance/dp/1479892823) introduces a quantitative element to weighty law enforcement decisions made by humans, such as whether to investigate or detain, how long to sentence and whether to parole. When making such decisions, judges and officers take into consideration the calculated probability a suspect or defendant will be convicted for a crime in the future. Calculating predictive probabilities from data is the job of “predictive modeling” (aka machine learning) software. It automatically [establishes patterns by combing historical conviction records](http://www.newsweek.com/lets-not-be-too-hasty-shut-down-big-data-security-sweeps-399115), and in turn these patterns—together a predictive model—serve to calculate the probability for an individual whose future is as-yet unknown.

Although “colorblind,” crime-predicting models treat races differently from one another. The models don’t explicitly incorporate race—nor any protected class—into their calculations (although [religion has been a consideration](https://blogs.scientificamerican.com/observations/why-data-science-argues-against-a-muslim-ban/)). Despite this, black defendants are flagged as higher risk more often than white ones.

This disparity is a direct consequence of the racially imbalanced world in which we live. For example, a defendant's number of prior convictions is a standard input for predictive models, because defendants that have previously been convicted are more likely to re-offend (after release) than those who have not. Because more black defendants have prior convictions, this means predictive models flag (that is, assign higher probabilities to) black defendants more often than white ones. A black defendant isn't flagged by race, but is more likely to be flagged nonetheless.

Today's heated dispute, however, isn't about this higher rate of flagging—more specifically, it’s about a higher rate of falsely flagging. Predictive models incorrectly flag black defendants who will not re-offend more often than they do for white defendants. In what is the most widely cited piece on bias in predictive policing, [ProPublica reports](https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing) the nationally used COMPAS model (Correctional Offender Management Profiling for Alternative Sanctions) falsely flags white defendants at a rate of 23.5 percent and black defendants at 44.9 percent. In other words, black defendants who don’t deserve it are erroneously flagged almost twice as much as undeserving whites. To address this sort of disparity, researchers at Google propose an affirmative action–like policy whereby a disenfranchised group is held to a more lenient standard. (Their [interactive demo](https://research.google.com/bigpicture/attacking-discrimination-in-ml/) depicts the case of flagging for loan defaults rather than future crime, but the same concept applies.)

In opposition, advocates of COMPAS counter each flag is equally justified for both races. Responding to ProPublica, the creators of COMPAS point out that among those flagged as higher risk, [the portion falsely flagged is similar for black and white defendants](https://www.documentcloud.org/documents/2998391-ProPublica-Commentary-Final-070616.html): 37 and 41 percent, respectively. In other words, among defendants who are flagged, it is erroneous for white and black defendants equally often. [Others data scientists agree](https://medium.com/@AbeGong/ethics-for-powerful-algorithms-1-of-3-a060054efd84) this meets the standard to exonerate the model as unbiased.

It appears, however, each individual flag is racially equitable, but the overall rates of false flagging are not. Although they may seem to contradict one another, these two things both hold true:

—If you’re flagged, the chances it was deserved are equal, regardless of race.

—If you don’t deserve to be flagged, you’re more likely to be erroneously flagged if you’re black.

Who’s right? These two views counter each other, and yet each appears valid on its own. On one hand, all flags seem to be equally well deserved. For defendants who are assigned higher probabilities, the rate of subsequent prosecutions is the same for both white and black defendants. On the other hand, among defendants who won’t re-offend, black individuals face a higher risk of being falsely flagged. A more nuanced position claims that to settle the matter [we must agree on how fairness is defined](https://www.washingtonpost.com/news/monkey-cage/wp/2016/10/17/can-an-algorithm-be-racist-our-analysis-is-more-cautious-than-propublicas/).

But instead of crossing swords, the ultimate resolution would be to agree on measures to combat racial inequity. Debating whether the COMPAS model deserves the indictment “biased” distracts from the next course of action. Rather than only vetting a predictive model for whether it worsens racial injustice, let’s enhance predictive policing to actively help improve things. The key impetus to do so comes directly from the seeming paradox behind this dispute over “bias” that makes it so sticky to resolve. The oddity itself brings to light a normally hidden symptom of today's racial inequity: If predictive flags are designed so they indicate the same re-offense probability for both white and black defendants—that is, designed to be equally precise for both groups—then, given the higher overall rate of re-offense among black defendants, that group suffers a greater prevalence of false flags.

And what an astonishing inequity that is. For a defendant of any race, being flagged means enduring a substantial risk that the flag is false. This can result in additional years of incarceration, with no way of confirming whether it was warranted (because the jailed defendant loses the freedom to demonstrate a lack of future crimes). For the black population, enduring this risk more often than whites adds insult to injury: Not only are black people more likely to become defendants in the first place, black defendants are in turn more likely to be unjustly sentenced to additional years on the basis of a false prediction of future crime.

This inequity isn't new. Even before predictive models, the common practice of considering a suspect's conviction history would have contributed to the same kind of cyclic perpetuation for the African-American population. The difference now is that it's been explicitly quantified and widely publicized. Awareness rises and the impetus to act will grow.

Given this revelation, predictive policing is in an ideal position to respond and do something about it. An undertaking to integrate technology that supports decision-making across law enforcement, predictive policing has built the ideal platform on which new practices for racial equity may be systematically and widely deployed. It's an unprecedented opportunity for racial justice.

To that end, let’s educate and guide law enforcement decision makers on the observed inequity. Train judges, parole boards and officers to understand the pertinent caveats when they’re given the calculated probability a black suspect, defendant or convict will reoffend. In so doing, empower these decision makers to incorporate these considerations in whatever manner they deem fit—just as they already do with the predictive probabilities in the first place.

There are three crucial considerations to reflect on when working with re-offense probabilities:

First, via proxies, the defendant’s race has influenced the calculated probability you’re looking at. Although race is not a direct input into the formula, the COMPAS model may incorporate unchosen, involuntary factors that approximate race such as family background, neighborhood (“Is there much crime in your neighborhood?”); education level (only partially chosen); and [the behavior of family and friends](https://medium.com/@AbeGong/ethics-for-powerful-algorithms-2-of-3-5bf750ce4c54). [FICO](http://www.fico.com/independent/?CID=70180000001TxHT&utm_medium=WSJ_HomePage_Takeover&utm_campaign=FY18_Q1_NorAM_WSJ_Independent_Google_Adwords&utm_source=Google_Adwords&gclid=Cj0KCQiA_JTUBRD4ARIsAL7_VeUMe0nYa9-0OkAlsW_B1eJgxA3yTgB-h6oEiO5oTJ4TrQEibcxK5FcaAk4YEALw_wcB) credit scores [have been similarly criticized](https://arxiv.org/abs/1610.02413) for incorporating factors such as the “number of bank accounts kept, that could interact with culture—and hence race—in unfair ways.” Furthermore, the COMPAS model is sealed as a “black box,” so the ways in which it incorporates such factors is unknown to law enforcement, the defendant and the public. In fact, the model's creators [recently revealed](http://www.equivant.com/blog/official-response-to-science-advances) it only incorporates a selection of six of [the 137 factors collected](https://www.documentcloud.org/documents/2702103-Sample-Risk-Assessment-COMPAS-CORE.html), but which six remains a proprietary secret. However, [the founder of the company behind COMPAS has stated](https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing), if factors correlated with race, such as poverty and joblessness, “…are omitted from your risk assessment, accuracy goes down.”

Keeping the inner working proprietary in this way is like having an expert witness without allowing the defense to cross-examine. It’s like enforcing a public policy the details of which are confidential. There’s [a movement](https://www.wired.com/2017/04/courts-using-ai-sentence-criminals-must-stop-now/) to make such algorithms transparent in the name of accountability and due process, in part forwarded by [pertinent legislation in Wisconsin](https://www.nytimes.com/2016/08/01/opinion/make-algorithms-accountable.html?_r=1) and in [New York C](https://thecrimereport.org/2018/01/26/algorithms-and-justice-scrapping-the-black-box/)ity, although the U.S. Supreme Court declined to take on a pertinent case last year.

Second, The calculated probabilities disfavor black defendants due to biased ground truth. Conventional wisdom and anecdotal evidence support the presumption black individuals are investigated, arrested and therefore convicted more often than white individuals who have committed the same crime. As a result, the data analyzed to develop crime-predicting models includes more cases of white “false negatives” than black ones—criminals who got away with it. Because the prevalence of this is, by definition, not observed and not in the data, measures of model performance do not reveal the extent to which black defendants are unjustly flagged more often. After all, the model doesn’t predict crime per se; it predicts convictions—you don’t know what you don’t know. The problem of biased ground truth is frequently covered, such as by [The Washington Post](https://www.washingtonpost.com/opinions/big-data-may-be-reinforcing-racial-bias-in-the-criminal-justice-system/2017/02/10/d63de518-ee3a-11e6-9973-c5efb7ccfb0d_story.html) and by [data scientists](https://medium.com/@AbeGong/ethics-for-powerful-algorithms-2-of-3-5bf750ce4c54).

Third, The black population is ravaged by false flags. As a result of being flagged more often, undeserving black defendants and suspects are wrongly flagged almost twice as often as undeserving whites. Unlike the first two points above, this does not necessarily mean the flags themselves are unfairly influenced by race. Taking this systematic issue into consideration, however, contributes to the greater good. It is an opportunity to help compensate for past and present racial injustices and the cycles of disenfranchisement that ensue. This is where predictive policing can de-escalate such cyclic patterns rather than inadvertently magnify them. Just as we protect suspects by limiting the power to convict when evidence has been illegally obtained, we can choose to take protective measures on behalf of this disenfranchised group as well. This is a unique opportunity for law enforcement to be a part of the solution rather than a part of the problem.

If we make it so, predictive policing could turn out to be a sheep dressed in wolf's clothing. Unearthing inequity, it looks threatening—but it presents an unprecedented opportunity to implement new measures to fight social injustice. Crime-predicting models themselves must remain colorblind by design, but the manner in which we contextualize and apply them cannot remain so. Reintroducing race in this way is the only means to progress from merely screening predictive models for racial bias to intentionally designing predictive policing to actively advance racial justice.

#### The Pitfalls of Predictive Policing

Jessica Saunders. (2016) Chicago's Predictive Policing Program Isn't a Cure-All for Violent Crime | Civil Wars | US News. Retrieved March 06, 2020, from <https://www.usnews.com/opinion/articles/2016-10-07/chicagos-predictive-policing-program-isnt-a-cure-all-for-violent-crime>

Consider it the real-life "Minority Report": Chicago police say they're successfully using big data to predict who will get shot – and who will do the shooting. But life is more complicated than the movies. The statistics that police tout to say the program works mask the fact that society is a long way from being able to prevent crime, even if police have a strong idea who might be involved.

Chicago police assert that three out of four shooting victims in 2016 were on the department's secret "heat list" of more than 1,000 people. And 80 percent of those arrested in connection to shootings were on the list, they say, but there has been no independent verification. Yet if that were the case, why is 2016 on track to be the most violent year in Chicago's recorded history?

This question was put to test in a recent RAND Corporation study of the Chicago program, and the results are not encouraging.

No algorithm is likely to ever predict with absolute certainty the who-when-where of a crime. But researchers have made great progress at identifying who is at heightened risk for both criminal perpetration and victimization. By calculating how often a person has been arrested with someone who later became a homicide victim, Illinois Institute of Technology researchers have identified a small group of people who are up to 500 times more likely to be the victim of a gun-related homicide than the average Chicago resident.

Less is known about how to reduce gun violence for such a high-risk population. A 2009 study on gun violence in Chicago found that a popular intervention that brings offenders to "notification forums," which relay the enhanced punishment they will receive if they commit a crime, can reduce reincarceration by as much as 30 percent. (While reducing reincarceration and preventing homicide are two different things, this strategy is the closest to what Chicago is proposing to do with their list. They propose to have the police deliver customized letters to offenders containing their criminal history and the punishments they will receive if they reoffend, along with contact information for social services.)

Given those developments, it was exciting to have the opportunity to independently evaluate Chicago Police's predictive policing program. To make a long story short: It didn't work.

The Chicago Police identified 426 people as being at the highest risk for gun violence, with the intention of providing them with prevention services. In a city of over 2.7 million, that's a manageable number of people to focus on. However, the Chicago Police failed to provide any services or programming. Instead they increased surveillance and arrests – moves that did not result in any perceptible change in gun violence during the first year of the program, according to the RAND study.

The names of only three of the 405 homicide victims murdered between March 2013 and March 2014 were on the Chicago police's list, while 99 percent of the homicide victims were not. So even if the police knew how to prevent these murders, only three people would have been saved – and the other 402 would not have been. In a recent news release, Chicago police dismissed the conclusions of RAND's findings by saying the department has more than doubled the predictive accuracy of its list and is going to start providing better intervention programming. Even if those improvements are real, the drop in crime will be almost imperceptible.

Here's why: Consider the number of homicides that would be prevented if the list's accuracy has doubled over the 2013 pilot and the police actually deliver an intervention program that is 30 percent effective. That would prevent fewer than two murders per year, a drop of less than 1 percent in the city's overall homicide rate.

To achieve even a 5 percent drop in the city's homicide rate, enormous leaps in both prediction and intervention effectiveness are necessary. In fact, the list would have to be 10 times more accurate than it was in the 2013 pilot – and prevention efforts would need to be five times more effective than current estimates. And after all that improvement – here's how many lives would be saved: 21. In a city that reported 468 murders last year, that would be tremendous progress but hardly the definitive solution.

For significant drops in citywide homicide rates, monumental – not incremental – improvements in predictive policing are needed. Preventing even one killing is laudable. But neither the police nor the public should expect predictive policing alone to have a major impact on overall homicide rates anytime soon.