Predictive Policing

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Introduction[1]

Predictive policing refers to the use of analytical techniques by law enforcement to make statistical predictions about potential criminal activity.[2] Predictive policing can involve either predicting events (i.e., forecasting when and where crimes are likely to occur) or people (i.e., individuals likely to be victims or perpetrators of crimes). Instead of relying on an officer's 'hunch' about an area, "predictive policing uses the power of 'big data' to isolate patterns."[3] A 2013 RAND report offers a taxonomy of predictive methods, identifying four categories of predictive policing:

- Methods for predicting crimes
- Methods for predicting offenders
- Methods for predicting perpetrators' identities
- Methods for predicting victims[4]

This primer offers an overview of what is currently known about predictive policing and highlights unanswered questions about the implications of predictive policing.

Context

Predictive policing is emblematic of a broader trend towards data-driven decision-making in a wide range of fields. Within criminal justice, actuarial methods have long been an important component of managing risk.[5] In the 1920s, Ernest Burgess of the Chicago School of sociology created the first parole prediction instrument, in which he calculated probability estimates of reoffending. Although actuarial methods have existed in criminal justice for almost a century, predictive analytics have only become systematically incorporated into law enforcement practices over the past two decades. [6]

Statistically informed policing (also referred to as intelligence-led, or data-driven policing) gained traction in the 1990s. Then-New York City transit police officer Jack Maple created a crime mapping system that was later adopted by William Bratton, then-Chief of the New York City Transit Police and later Chief of the New York City Police Department. CompStat (short for computer statistics), as the approach came to be called, is now implemented as a managerial practice in police departments across the world to identify crime patterns and hotspots, quantify and incentivize police activity, and direct police resources.

The shift towards predictive policing occurred in the late 2000s. In the face of low crime rates, departments were facing pressure to push crime rates even lower. Following the logic that the 'low-hanging fruit had already been taken' (i.e., the easy crimes had already been intercepted or prevented), law enforcement needed a means by which to further reduce crime rates. Coupled with pressure to allocate resources more efficiently in light of tight budgets, in 2008, Bratton, who had moved on to become the Chief of the Los Angeles Police Department, began working with federal agencies to assess the viability of a more predictive approach to policing.

Predictive Policing in Theory

Predictive policing draws from canonical theories of crime that focus on criminal events, crime-prone locations, and criminal opportunities. The basic underlying assumption of predictive policing is that crime is not randomly distributed across people or places. Rather, patterns of crime are a "function of environmental factors that create vulnerabilities for victims and spaces at certain times."[7] Opportunity theory, for example, suggests that offenders systematically select targets that offer high reward with low effort and risk. According to routine activities theory, daily activities result in the convergence of the following three elements in time and space: motivated offenders (i.e., potential criminals), suitable targets (e.g., electronics in a house), and an absence of capable guardians (e.g., residents working outside of the house). Another term used in policing discourse is 'soft targets' – originally a military term to refer to unarmored or undefended targets, it is now used in policing to denote unprotected individuals, objects, or places that may be easily victimized for crime.

The root causes of crime vary. Therefore, it is important to consider the different underlying assumptions informing different predictive models. For example, Another participant who had been working with criminal justice organizations to increase access to data on traffic stops, found that models predicting violent crime sometimes identify people, rather than places, as their outcomes.

Predictive Policing in Practice

The most common form of predictive policing is location-based prediction, which takes retrospective crime data and applies it prospectively to determine deployment.[8] For example, consider a particular block where houses are broken into frequently at night. Based on near-repeat theory – which suggests once a crime occurs in a particular location, it is more likely to happen again in that area – it is logical to infer that houses may continue to be burglarized unless there is some sort of police intervention. Data demonstrates that offenders focus on familiar areas. The police intervention, in this instance, could simply be deploying an officer to patrol the area to prevent future break-ins. Police presence may deter individuals from committing crimes, or may displace the crimes to another area (in the process of which some attrition may occur, leading to reduced crime).

Another form of predictive policing is person-based. In such systems, law enforcement may predict individuals or groups most likely to be involved in crimes, either as victims or offenders. Person-based predictive policing could involve social network analysis or regression models using risk factors.[9] One of the civil liberties questions that arises is: what are the implications of the police modeling risk for individuals who have no criminal record? For example, as the White House report on Big Data documents, "In response to an epidemic of gang-related murders, the city of Chicago conducted a pilot that shifts the focus of predictive policing from geographical factors to identity. By drawing on police and other data and applying social network analysis, the Chicago police department assembled a list of roughly 400 individuals identified by certain factors as likely to be involved in violent crime. As a result, police have a heightened awareness of particular individuals that might reflect factors beyond charges and convictions that are part of the public record."[10]

Once individuals are identified as high risk, police interventions could range from patrolling the areas where individuals reside to more aggressive interventions – such as talking to identified individuals or their family members.

Whether location or individual based, there are four key stages in the practice of predictive policing:[11]

In the first stage, data is collected. These data can range from basic crime data (i.e., when and where historical crimes occurred), to more complex environmental data such as seasonality, neighborhood composition, or risk factors (e.g., vacant lots, parks, ATMs). The second stage involves data analysis, which yields predictions about future crime. When deciding what predictive method to use, law enforcement needs to consider both the type of crime they want to target and their department's resources.

The third stage in the predictive cycle is police intervention. Usually police intervention involves distributing crime forecasts to commanders who use them to make decisions about where to deploy officers in the field. Patrol officers are also sometimes given reports at briefings to inform them where to go while on shift. During uncommitted time (i.e., when they are not responding to calls for service), patrol officers focus their time and resources to surveilling the people and places models suggest are likely to be involved in future crime. It is important to note that the very act of predictive policing creates new data as well. For example, police describe how they 'enter and clear predictive boxes,' and they enter their status in the computer terminal in their car to notify dispatch and keep records for future analysis.[12]

The fourth stage, target response, highlights that this predictive policing cycle, or, 'battle rhythm' as some law enforcement officials have called it, grows increasingly complex over time. Law enforcement needs to account for individuals' responses to police intervention. As mentioned earlier, the intervention could serve as a deterrent, preventing crime from occurring, or could lead to the displacement of crime to a different area.

Rhetoric

There is considerable hype in media and policy circles about predictive policing. TIME Magazine named predictive policing as one of the 50 best inventions in 2011. With its emphasis on 'big data' analytics, predictive policing is touted as a means to improve both efficiency and equity.

In terms of efficiency, advocates of predictive policing say it can more accurately predict future crimes than humans can.[13] One possible explanation for this is that humans overestimate meaningful patterns.[14] Traditional crime analysts may possess exaggerated perceptions of crime patterns and consequently overreact by directing a disproportionately high amount of police resources to an area. Additionally, police departments face resource constraints, so predictive policing's ability to 'do more with less' can be appealing from a budgetary perspective.

Champions of predictive policing argue it can serve as a technical solution to problems of discrimination and information sharing. For example, advocates suggest it can reduce problematic biases in police practices along lines of race, class, and neighborhood. Moreover, as one FBI report explains, instead of relying on officer intuition, predictive policing relies on data, which can "standardize information across shifts and experience levels" ultimately "eliminating the concern about adequate information sharing."[15] It is important to avoid false binaries such as "intuition-driven" versus "data-driven" policing, because in practice, neither approach exists in isolation from the other; each informs the other in consequential ways.

Just as people are excited about predictive policing, there are anxieties that have bubbled to the surface since its implementation. Fears stem from civil rights groups, researchers, the communities that are being policed, and law enforcement themselves. Civil rights advocates suggest predictive policing will be used to profile and harass people who have not committed any crime, and that it can do so under the patina of objectivity.

Researchers suggest that new analytic techniques may, to a certain extent, reproduce conventional police practices, but under the guise of data science. Mirroring debates occurring over discriminatory lending,[16] some of the variables included in predictive models may simply be a proxy for race or other protected categories.

Individuals in law enforcement argue predictive models should not substitute experience, 'street smarts,' and officer intuition. It is worth noting that law enforcement is not uniform in their opinion of predictive policing. Rather, there are divisions, with some officers viewing it as another useful tool in their toolbox, others viewing it as an entrenchment of managerial control, and others still viewing it as a subversion of their experiential knowledge.[17]

Some (but not all) concerns are driven by misconceptions. The major pervasive misconception is the Minority Report myth. Minority Report, a book and subsequent film that depicts a dystopian world in which individuals are arrested for crimes "precogs" foresee them committing in the future, is relentlessly invoked in discourse around predictive policing. This is a misleading characterization of predictive policing that distracts from the important issues at hand relevant to having a productive conversation about the promises and perils of predictive policing moving forward. Predictive policing is not akin to a crystal ball. It does not foretell the future. Rather, when used correctly, it can give police officers probabilistic information about where to go and who to police. Much of the time, predictive models serve to confirm police intuitions. However, they may also be able to dispel officers' individual perceptions of crime or crime rates that may be inaccurate or outdated. The implications of predictive policing techniques have much more to do with the bureaucratic processes that surround the technology than the technology itself. The same tools can be used to redress existing inequities or amplify them.

Actors

There are a variety of relevant actors involved in predictive policing, including local, state and federal governments and agencies, predictive platform designers, vendors, researchers, and consultants.

Most predictive policing pilot projects in local police departments are made possible by injections of federal funding. For example, in 2011, the Los Angeles Police Department received a three million dollar grant from the U.S. Department of Justice (DOJ) to conduct a multiyear analysis of predictive policing. In 2015, the Miami Police Department received $600,000 to do the same. Smaller cities tend to take up predictive tools after pilots are run in larger departments. Some of the cities that are currently using predictive policing include: Chicago, IL, Memphis, TX, Los Angeles, CA, Santa Cruz, CA, Minneapolis, MN, Palm Beach, FL, Dallas, TX, Vancouver (British Columbia, Canada), Charlotte-Mecklenburg, NC, Nashville, TN, Glendale, AZ, East Orange, NJ, Baltimore, MD, New York City, NY, Philadelphia, PA, Miami, FL, New Castle, DE, Lincoln, NE, and Montevideo, MN.

One of the biggest predictive policing vendors is PredPol. Researchers Jeff Brantingham and George Mohler, currently at the University of California Los Angeles and Santa Clara University, respectively, suggested it was possible to predict certain crimes much like it was possible to forecast the distribution of earthquake aftershocks. They co-founded PredPol, now headed by Larry Samuels. Informed by predictive techniques used in research on counterinsurgency operations, PredPol is run on a cloud-based SaaS platform and uses three types of data in its proprietary algorithm – place, type, and time of crime. It includes three years of data, weighting the more recent data more heavily. The algorithm generates 500 by 500 square foot predictive boxes on maps, indicating areas where particular crimes are most likely to occur. PredPol is currently used in almost 60 departments, the largest of which are the Los Angeles Police Department and the Atlanta Police Department.

Another software is Hunchlab, designed by the GIS firm Azavea. Robert Cheetham, a former crime analyst for Philadelphia Police Department is the President and CEO. Hunchlab's statistical models account for the interaction of social, behavioral and physical risk factors. Hunchlab is currently used by the Philadelphia Police Department and the Miami Police Department. In 2015, the New York City Police Department announced their plans to begin testing Hunchlab software.[18]

A key contrast between PredPol and Hunchlab is their analytic strategy. Informed by near-repeat theory, PredPol has a parsimonious model, only using historical crime data. Whereas Hunchlab also uses near-repeats, it also uses risk-terrain modeling[19] which involves a much wider range of variables, such as seasonality, collective efficacy (the willingness of individuals to intervene), school calendars, and environmental risk factors. An interesting conflict and break in the predictive policing narrative is that advocates of PredPol preempt some of the criticism leveled at Hunchlab, namely for including too many factors that could be considered discriminatory in their models. Individuals at PredPol are careful to emphasize their software does not predict who commits crimes, but rather focuses on what types of crimes are predicted to occur where and when.

So, how is predictive policing different from conventional hot spot policing? There are three main differences. First, although preliminary data suggests they actually yield substantively similar predictions, hot spot policing uses density maps. In other words, hot spot policing involves simply plotting crimes in order to visualize a geographic distribution of crime, and subsequently deploying officers to the "hottest areas." Although the predictive boxes generated by algorithms often overlay conventional hot spots, predictive boxes are much smaller than hot spots and sometimes generate boxes that do not match up with conventional hot spots. A second important difference is that predictive algorithms are highly opaque, a phenomenon referred to as "algorithmic secrecy."[20] Simply stated, police officers understand how heat maps are generated, but the algorithmic process by which predictive boxes are generated is invisible and difficult to interpret. Finally, whereas hotspot policing is retrospective in its analytic approach, predictive policing is prospective. Hotspot policing directly maps where crimes occurred in the past, but predictive policing could predict crime will occur in a location that there has not been a crime before. The exact ways in which this would happen are often shielded by the proprietary nature of predictive policing algorithms.

Understanding the actors and agencies involved in funding and adopting predictive policing efforts is helpful as we transition into the next section on open questions about the practice. Knowing the institutional architecture of predictive policing is integral to knowing where the points of leverage are and understanding where and how research, measurement, and assessment can occur.

Open Civil Rights Questions

There are a number of open questions that are pertinent to address as predictive policing is implemented. These systems have been designed based on research using existing data yet, as these systems mature, new data will influence the algorithms in profound ways and policing decisions will be driven by the information provided by these algorithms. This raises numerous questions about efficacy and societal implications.

How and where does biased data shape these systems?

Establishing causal inference (i.e., being able to directly test whether predictive policing causes a decrease in crime) is difficult. In terms of research design, assessments of predictive policing usually involve longitudinal studies examining crime rates before and after predictive policing. Simply because crime goes down after predictive policing is implemented does not necessarily mean predictive policing caused the drop in crime. Predictive policing is not randomly distributed and other forces – such as broader crime trends, selection bias in terms of which divisions are most likely to adopt predictive policing (e.g., they may also be the most likely to have proactive officers regardless of whether they use formal predictive methods or not) – may also explain the drop in crime.

- How do decisions by law enforcement affect the validity of the data? What can be done to correct biases in the data?

- How does the implementation of predictive policing affect the data that these techniques rely on?

- Who can meaningfully assess the algorithms that are being implemented and what kind of algorithmic oversight is appropriate?

- How does missing or biased data shape the predictions that these systems make?

Ongoing assessment of these systems will be critical, but is by no means guaranteed. We need to ask what kinds of structures are necessary for evaluating the efficacy of predictive policing. One possibility is to run randomized control trials (RCTs) across divisions. Such trials need to be evaluated by researchers independent from the department, the designers of the strategy, and the vendors. For example, we should not simply rely on assessments of a policing initiative by the consulting firm that designed the strategy, which is currently the case in some departments.

How do different policing tools perform, relative to each other and relative to earlier methods?

Although we know about comparative accuracy of crime prediction in patrol (e.g., we have data on the predictive power of algorithms vs. analysts), we do not know how platforms measure up against one another (e.g., Hunchlab vs. PredPol). Moreover, even less is known about the application of predictive models in investigations.

- Are there more cases cleared by arrest when detectives employ predictive analytics?

- How do law enforcement officers treat the information they receive from each system?

- Do they solve cases faster?

- Are fewer people wrongfully ensnared in criminal justice system?

- Do officers trust the information they provide?

- What bureaucratic dynamics influence how officers incorporate the information they receive into their policing practices?

It is also important to consider not only how efficacious a predictive technique is, but also how transparent it is. As mentioned above, algorithms tend to be relatively inscrutable for police officers, and research suggests that simple heuristics may be almost as effective as advanced computational methods. For example, stop heuristics with simple scoring rules may have comparable accuracy to fuller statistical models.[21] Models that are easier to understand can improve police buy-in and can be less expensive, making it possible for smaller departments with fewer financial resources to adopt the approach.

How can Fourth Amendment protections be preserved in the context of these new tools?

The way law enforcement uses predictive analytics challenges the traditional paradigm of Fourth Amendment law because predictive information may be used to justify stops under the existing Fourth Amendment precedent.[22][23] In a 2015 law review article, Ferguson asks whether a stop can "be predicted on the aggregation of specific and individualized, but otherwise noncriminal, factors."[24] He argues that otherwise noncriminal factors "might create a predictive composite that satisfied the reasonable suspicion standard."[25] In other words, predictive analytics may effectively make it easier to meet the reasonable suspicion standard in practice, thus justifying more police stops. Ferguson suggests that if the police use big data to reach the threshold of reasonable suspicion, the courts "should require a higher level of detail and correlation using the insights and capabilities of big data."[26]

- In the context of predictive policing, should we raise the standard of reasonable suspicion?
- Should being a high risk individual be grounds for police surveillance (with or without a warrant)?
- How will all the new forms of data being generated through predictive policing be used? What will be admissible under the exclusionary rule?

How will predictive policing affect the overall dynamic between police and the communities they serve?

We must also consider questions about the implications of predictive policing in terms of civil rights and social inequality.

- To what extent does predictive policing create self-fulfilling statistical prophecies?
- Does it improve or erode police-civilian relations?
- What kind of hit rate (i.e., the percentage of stops in which an officer makes an arrest or issues a summons) constitutes defensible public policy?

- How can we measure bias in predictive models?

As Barocas and Selbst argue, discrimination may be an artifact of the data collection and analysis process itself. Even with the best intentions, algorithmic decision-making can lead to discriminatory practices and outcomes.[27] Algorithmic decision procedures can "reproduce existing patterns of discrimination, inherit the prejudice of prior decision makers, or simply reflect the widespread biases that persist in society. It can even have the perverse result of exacerbating existing inequalities by suggesting that historically disadvantaged groups actually deserve less favorable treatment."[28] Each of the steps in data analysis can create "possibilities for a final result that has a disproportionately adverse impact on protected classes, whether by specifying the problem to be solved in ways that affect classes differently, failing to recognize or address statistical biases, reproducing past prejudice, or considering an insufficiently rich set of factors."[29] Simply stated, we need to ask whether predictive policing reduces police discretion (and to what extent we want to reduce it in the first place), and whether it serves to exacerbate or remedy existing inequalities in police practices.

Finally, returning to an age-old question in policing literature: to what extent is the crime rate a function of enforcement practices? More generally, to what extent is what we "know" about crime conditional on how we know it? We need revisit these questions in the context of predictive policing, because the 'raw' data inputted into predictive models is in fact not 'raw' at all, but rather fundamentally social.

Having answers to these types of questions will help us determine to what extent predictive policing is defensible public policy, and what the best practices of predictive policing are. It is an anachronism to think that the police can (or should) stop using data or predictive models. Consequently, we need to design and implement models with these questions in mind.

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1 We are very grateful for the strong contributions and insights made by David Robinson, Harlan Yu, Corrine Yu, Patrick Davison, and Angie Waller in the research and production of this primer.

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