Spring 2024

Predictive Policing

Emily Musgrove

Emily Musgrove

12/14/23

CS-477-A

Predictive Policing

In this paper, I will discuss the ethics of machine learning and artificial intelligence by those involved in criminal justice systems. Currently, machine learning and artificial intelligence are still somewhat new to the world of law enforcement, however, they appear to be rapidly gaining traction for their usefulness in a variety of manners. In 2018, the International Criminal Police Organization (INTERPOL) and the United Nations Interregional Crime and Justice Research Institute (UNICRI) held their first Global Meeting on the Opportunities and Risks of Artificial Intelligence and Robotics for Law Enforcement. At that conference, individuals from national police and government agencies from across the world came together to share their views on AI. Overall, it appears that AI is viewed in high regard internationally and there is extensive research being conducted on how to use it for a variety of purposes within law enforcement. The article detailing the conversations held at the conference listed 26 ways, in various stages of development, that law enforcement agencies are attempting to use AI (Artificial Intelligence and Robotics for Law Enforcement, pp.7-8). Those uses fall into four categories, prediction & analysis, communication, recognition, and exploration (Artificial Intelligence and Robotics for Law Enforcement, p.4). However, of those 26 suggestions, only 2 have been approved for use. Those are crime anticipation, which attempts to predict the times and places that crime is likely to occur, and the identification of legally privileged information (Artificial Intelligence and Robotics for Law Enforcement, p.8), both of which fall into the prediction and analysis category (Artificial Intelligence and Robotics for Law Enforcement, pp.8-9). While this makes artificial intelligence incredibly useful to law enforcement, it's ability to predict and reduce crime is highly dependent on the data placed into it and the capability of law enforcement to properly act on it. In this paper, I will examine how technically useful machine learning-based predictive policing is, the ethical conundrums that come with its practical uses, and how to mitigate the risks of its use.

Prior to the introduction of machine learning, predictive policing was done using algorithms designed using mathematical formulas that attempted to predict crime and human behavior. Predictive policing expands on crime forecasting because "rather than assuming continuity of current crime patterns and hot spots, predictive policing explicitly models change over time, often relying on evidence of statistically broader geographical impact of a single crime event" (Bennett Moses and Chan, p.808). It analyzes that data using various combinations of the three epistemologies of predictive policing, mathematical social science, social physics, and machine learning (Hälterlein, p. 2). The mathematical social science epistemology attempts to collect information on the behaviors of criminals through empirical, such as by interviewing past offenders, or theoretical, such as by examining the rational choice and routine activities theories promoted by sociologists, means (Hälterlein, p. 3). There are two main forms of this epistemology in predictive policing, the boost hypothesis and risk terrain modeling. The boost hypothesis is derived from the concept of near repeat crimes, which suggests that there is a "statistical observation that certain types of crime (property crime in particular) often occur at places close to each other within a short period of time" (Hälterlein, p. 4). The concept also suggests that “once a particular location has been subject to a crime, it is statistically more likely that that location and the close environs will be subject to additional, similar crime events during a brief time frame after the initial crime” (Ferguson, p. 277). Similarly, risk terrain modeling suggests that “the risk of crime in places that share criminogenic attributes is higher than other places as these locations attract offenders (or more likely concentrate them in close locations) and are conducive to allowing certain events to occur” (Caplan et al., p. 377). These theories support the idea that spatial and temporal closeness to the occurrence of a similar crime can be a determining factor in the likelihood of the crime occurring again and the time and area in which it will occur. Additionally, the social physics epistemology suggests that the same algorithms that are used to predict physical processes can be reused to predict human behavior. Social physics was “[just as] matter as comprised of atoms and molecules that are moving randomly but can be described by mathematical laws, a scientific endeavor emerged that sees societies as comprised of individuals that are characterized by randomness and idiosyncrasy but are predictable on the collective scale through statistical analysis” (Hälterlein, p. 5). These epistemologies are influential in the last, and most relevant, epistemology of machine learning, which is used to create algorithms that will continuously improve their efficiency and accuracy by learning from the data that it is fed.

Unlike previous methods of predictive policing, machine learning can allow an individual to choose to use specific parameters or have the parameters decided for them depending on their intentions for the model. The process of parametrization allows an individual to choose the type of regression analysis that would be best for their specific algorithm. Hälterlein states that “non-parametric regression analysis might be an option, if it is not predetermined which independent variable(s) are good predictor(s) for a dependent variable and the ML-task is to determine the best predictor based on a given data sample or to adjust the form of a function in order to capture unusual or unexpected features of the data" (Hälterlein, p. 6). Therefore, machine learning does not necessarily require the scientists to individualize the algorithm in the same way that other forms of predictive policing might require. Additionally, machine learning is more beneficial because it allows for more data to be analyzed without determining the variables being examined beforehand, which also allows for the exploration of variables outside of those presented by previous theories or empirical data. Additionally, unlike in the previous forms of predictive policing, machine learning allows law enforcement to use the best traits of all previous predictive policing epistemologies. Many major machine learning-based predictive policing systems utilize elements of social physics in their machine learning. Social physics is the most frequently used in tandem with machine learning-based predictive policing systems, with most major systems using some variation of it. PredPol utilizes a model developed for use in studying seismic activity in their system, and both PredPol and the Chicago Police Department's "heat-list" use models previously used to study infectious disease spread (Hälterlein, p.5). Overall, machine learning use in predictive policing has made it so that predictive policing is more accessible than ever. The paper produced by those in charge of the Global Meeting on the Opportunities and Risks of Artificial Intelligence and Robotics for Law Enforcement, the creation of AI for use in law enforcement can be broken down into four distinct steps, "finding the right initiatives. . . labeling the data. . . launching the solution. . . [and] updating the model". (Global Meeting on the Opportunities and Risks of Artificial Intelligence and Robotics for Law Enforcement, pp. 16-18). After the first three steps are properly performed, artificial intelligence-based systems are able to improve their accuracy and efficiency so long as the data is continuously updated. However, the accuracy and efficiency of AI will only increase if it is trained on unbiased data and it's results are implemented correctly by law enforcement. In these ways, this form of predictive policing tends to suffer from a variety of key ethical issues.

Most ethical dilemmas in predictive policing tend to come as a result of the use of biased data, improper police responses to the results, or inaccurate understandings of the implications of said results. This discussion will center around the predictive policing software PredPol, which has been widely used by U.S. police departments, the Northpointe system used by police in the state of New York, and the unknown predictive policing software used by the Chicago Police Department. The primary ethical concern that police forces using these software programs tend to face is the problem of a biased data set. AI is only as good as the data it uses, so if the data placed into it is biased by certain characteristics it too will emulate those biases. Often the data placed into these algorithms comes from prior arrests, which is concerning when considering that police arrests tend to be highly biased by social characteristics such as race, income, age, gender, etc. In fact, when analyzing the arrest data from Oakland and comparing it to a synthetic population of the same area, which used data from the 2011 National Survey on Drug Use and Health to properly represent the demographic distribution of drug use, it was found that “drug arrests in the police database appear concentrated in neighborhoods around West Oakland (1) and International Boulevard (2), two areas with largely non-white and low-income populations. These neighborhoods experience about two hundred times more drug-related arrests than areas outside of these clusters” (Lum and Issac, para. 18). This shows that the police arrest data used to train predictive policing systems is highly likely to be racially or economically biased in ways that would negatively impact the quality of the system's results. PredPol does claim that it “uses ONLY 3 data points – crime type, crime location, and crime date/time – to create its predictions. No personally identifiable information is ever used. No demographic, ethnic, or socio-economic information is ever used. This eliminates the possibility for privacy or civil rights violations seen with other intelligence-led policing models" (PredPol, para. 1). However, while such systems refrain from using explicitly biasing information, they do use other data that could imply that information. The Chicago Police Department's system uses geographical data, which was later changed to just include the census tract and community of arrest, in its data (Dumke and Main, para.27). This data could imply demographic information about an individual, such as race, because factors such as race and income often impact where an individual may live. This is supported by Brown University's Diversity and Disparities Project which uses an index of dissimilarity to rank the distribution of racial and ethnic groups in American cities. It quantifies anything with a value of 60 or over is considered an example of extreme segregation between census tracts (Logan and Stults, p.16). Out of 200 cities, 24.5% have extreme segregation between Black and White people with Chicago being the highest with a rating of 80. For the same cities, segregation is moderately better between Hispanic and White people, with only 6% having extreme segregation between the two groups. However, Chicago ranked among the most highly segregated with a rating of 60.8 (*Segregation City Sorting 2020*). This means that in order for White and Black people and White and Hispanic people to be evenly distributed in Chicago's census tracts, 80% of either Black or White people and 60.8% of either White or Hispanic people would need to move. Sociology's "routine activities" theory suggests that individuals are most likely to commit crimes during and as a result of their everyday lives. Therefore, since individuals are frequently residentially segregated in major cities and they tend to commit crimes around where they live, the census tract and community of an individual's arrest could imply some of their demographic information. In fact, it does appear that these systems are racially biased. For the Northpointe system, "Black defendants were still 77 percent more likely to be pegged as at higher risk of committing a future violent crime and 45 percent more likely to be predicted to commit a future crime of any kind [even when accounting for potential differences in age, gender, criminal history, and recidivism]" (Angwin et al., para. 16). In all of the predictive policing systems examined, there are significant ethical concerns with the variables used to calculate geographic "hot spots" or individualized risk assessments, which can have long-lasting negative consequences for individuals considered high risk or who live in predicted crime "hot spots". Another major ethical concern comes from how police officers respond to the results, primarily in the case of risk assessments.

The Chicago Police Department's Strategic Subject List (SSL), which predicts an individual's risk of being either a gun violence victim or shooter, is an excellent example of how these programs suffer from poor implementation of the results of AI models. Beat officers, who would be interacting with those on the Strategic Subject List, were often not taught how to approach or help those on the SSL. In fact, "In less than one in five (18.7 %) presentations, there was both a discussion and executive guidance, which consisted of: (1) allow beat officers to take the lead in contacting SSL subjects, (2) consider using fugitive location and district intelligence teams to locate SSL subjects, and/or (3) change the focus from arresting SSL subjects for minor offenses (for which they would be immediately released) to finding ways to detain SSL subjects over the long term. There was no evidence of executive follow-up on these recommendations at the meetings. . . Overall, the observations and interview respondents indicate there was no practical direction about what to do with individuals on the SSL, little executive or administrative attention paid to the pilot, and little to no follow-up with district commanders" (Saunders et al., page. 10). This lack of direction or even understanding of how the SSL works results in many police officers viewing the SSL as merely a list of future killer, rather than potential killers or victims. Matt Stroud, a writer for *The Verge*, was told by a commander in the police force that "If you end up on that list, there's a reason you're there," (Stroud, para. 43). This lack of understanding of how these predictive policing systems work or how to use the results can result in police potentially behaving more violently or aggressively to these individuals because they automatically perceive them as threats. These risk assessments could be potentially harmful even beyond interactions with the police, since "they are used to inform decisions about who can be set free at every stage of the criminal justice system, from assigning bond amounts — as is the case in Fort Lauderdale — to even more fundamental decisions about defendants' freedom. In Arizona, Colorado, Delaware, Kentucky, Louisiana, Oklahoma, Virginia, Washington, and Wisconsin, the results of such assessments are given to judges during criminal sentencing." (Angwin et al., para. 8). This could mean that an individual with a high risk assessment score could be denied bail, receive a higher sentence for a crime, etc. because of their score. Ultimately, these predictive policing systems are useful, but their potential biases and negative consequences are not studied enough to justify their use. There are several key ways for the creators and users of these machines to mitigate the ethical issues of these predictive policing systems before they can justify their use in the judicial system.

In order to decrease the risks of the use of artificial intelligence in predictive policing systems, the creators of such systems must increase the transparency of their models and the users of these systems should increase their knowledge of the systems, plan for how to help the areas or individuals who are deemed high risk or "hot spots" outside of just targeting and arresting them. Individuals at the Global Meeting on the Opportunities and Risks of Artificial Intelligence and Robotics for Law Enforcement conference gave a multitude of suggestions on how to mitigate the risks of AI use in law enforcement, including, "Law enforcement needs for

AI and robotics should be identified, structured, categorized and shared to facilitate development of future projects. . . New or ongoing AI and robotics initiatives should be identified and mapped, with law enforcement agencies in Member States being informed. . . . The acceptable legal and ethical boundaries for data collection & analysis for and by law enforcement should be clarified. . . . Opportunities and techniques for addressing privacy and accountability issues using AI should be investigated. . . . Greater awareness of AI and robotics issues should be developed in law enforcement agencies through improved education and information exchange. . . . Relations between law enforcement, academia, industry partners and civil society should be encouraged and fostered" (pp. 23-24). These suggestions could deeply benefit all involved. The companies who produce these systems would be able to sell their products, the police forces would be able to use a system that makes their jobs fundamentally easier, and citizens would have advanced safety from both criminals and the police. In addition, it is also important to regularly assess the accuracy of the AI and analyze whether or not the results are biased. When New York began using Northpointe in 2010 they did not run a statistical evaluation of its accuracy nor its bias, and when they did run an evaluation 2 years later, they did not account for race as a bias (Angwin et al., para 50-51). Running such an evaluation would have allowed them to analyze the bias and accuracy of the algorithm and determine if the potential benefits that a program with those features would allow for would outweigh the potential harms. While these suggestions are currently things to consider when making predictive policing software programs, there is certainly the question of whether or not it should be used at all.

Currently, there are too many flaws in the decision-making of these AI models and too many ethical issues in the interpretation and execution of their results to justify their use in policing. It is possible that if serious and significant changes were made, this technology could be ethically used in the police force. However, currently, these models are using biased data and output results given to undertrained officers who are implementing them in dubiously ethical ways that do more harm to those they are supposed to protect. Ultimately, these systems are emulating the same biases that have existed in policing for decades. Yet, in switching the decision-making process from humans to an algorithm, the public perception of the system is viewed as not being possible of bias and therefore it's results are often not examined or critiqued as much as human decisions. Although, while they are not capable of personal opinions that is even more dangerous because they will unquestioningly emulate the biases of their data. Whether or not humans can be unbiased enough to create sufficiently large quantities of unbiased data on which to train these models and then train other humans how to interpret and act on the results in an unbiased manner is debatable. However, should that ever be possible, I would not want to discount the significant positive impacts that properly used predictive policing could achieve. If used properly, this technology could significantly reduce crime rates and protect both people and property, but its current capabilities can only do more harm than good to the individuals and communities it is supposed to help protect. While we can hope and work towards ethical and safe AI models to implement predictive policing, we should also recognize the harms that come from using an undertested and underdeveloped technology to make decisions on individual's lives and safety.

References

Angwin, Julia, et al. “Machine Bias.” *ProPublica*, 23 May 2016, www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

Artificial Intelligence and Robotics for Law Enforcement, United Nations Interregional Crime and Justice Research Institute (UNICRI), 2019, unicri.it/sites/default/files/2019-11/Artificial%20Intelligence%20and%20Robotics%20for%20Law%20Enforcement.pdf.

Bennett Moses, Lyria, and Janet Chan. “Algorithmic Prediction in Policing: Assumptions, Evaluation, and Accountability.” *Policing and Society*, vol. 28, no. 7, 8 Nov. 2016, pp. 806–822, doi:10.1080/10439463.2016.1253695.

Caplan, Joel M., et al. “Risk Terrain Modeling: Brokering Criminological Theory and GIS Methods for Crime Forecasting.” *Justice Quarterly*, vol. 28, no. 2, 2011, pp. 360–381, doi:10.1080/07418825.2010.486037.

Dumke, Mick, and Frank Main. “A Look inside the Watch List Chicago Police Fought to Keep Secret.” *Chicago Sun-Times*, 18 May 2017, chicago.suntimes.com/2017/5/18/18386116/a-look-inside-the-watch-list-chicago-police-fought-to-keep-secret.

Ferguson, Andrew G. “Predictive Policing and Reasonable Suspicion.” *Emory Law Journal*, vol. 62, no. 2, scholarlycommons.law.emory.edu/cgi/viewcontent.cgi?article=1251&context=elj.

"How Predpol Works: Predictive Policing." *PredPol*, 15 May 2018, predpol.com/how-predictive-policing-works#:~:text=PredPol%20uses%20ONLY%203%20data%20points%20%E2%80%93%20crime,and%20crime%20date%2Ftime%20%E2%80%93%20to%20create%20its%20predictions. Accessed 15 Dec. 2023.

Hälterlein, Jens. "Epistemologies of Predictive Policing: Mathematical Social Science, Social Physics and Machine Learning." *Big Data & Society*, vol. 8, no. 1, 2021, doi:10.1177/20539517211003118.

Logan, John R., and Brian J. Stults. "Metropolitan Segregation: No Breakthrough in Sight." *Brown University*, 12 Aug. 2021, s4.ad.brown.edu/Projects/Diversity/Data/Report/report08122021.pdf.

Lum, Kristian, and William Isaac. "To Predict and Serve?" *Significance*, vol. 13, no. 5, 2016, pp. 14–19, doi:10.1111/j.1740-9713.2016.00960.x.

Saunders, Jessica, et al. "Predictions Put into Practice: A Quasi-Experimental Evaluation of Chicago's Predictive Policing Pilot." *Journal of Experimental Criminology*, vol. 12, no. 3, 12 Aug. 2016, pp. 347–371, doi:10.1007/s11292-016-9272-0.

"Segregation City Sorting 2020." *Brown University*, 2020, s4.ad.brown.edu/projects/diversity/SegCitySorting2020/Default.aspx.

Stroud, Matt. "Heat Listed." *The Verge*, 24 May 2021, www.theverge.com/c/22444020/chicago-pd-predictive-policing-heat-list.