THE USE OF PREDICTIVE ANALYTICS IN POLICING BULLETIN

As part of the Bureau of Justice Assistance (BJA)-funded initiative *Using Analytics to Improve Officer Safety*, CNA's Center for Justice Research and Innovation produced this bulletin as a companion document to an issue brief that provides an in-depth look into the use of predictive analytics in policing. Visit CNA's Officer Safety and Wellness page to learn more about this initiative.

Predictive analytics in policing "is a data-driven approach to characterizing crime patterns across time and space and leveraging this knowledge for the prevention of crime and disorder."[1] Its use has evolved in the last several decades as a promising method to reduce and prevent crime. This bulletin provides information for law enforcement agencies and their stakeholders (e.g., crime analysts, policy makers, and researchers) interested in learning more about the role of predictive analytics in police operations.

PREDICTIVE ANALYTICS IN POLICING

HOT SPOT DETECTION

According to Selbst (2017),[2] hot spot detection involves mapping crime locations to pinpoint geographically defined clusters of crime, known as "hot spots." Hot spot detection moves agencies away from geographic-based patrols or deployments and toward incident-based patrols or deployments, allocating an agency's resources to areas that most need or most request them.

The Philadelphia predictive policing experiment increased uniformed and, separately, unmarked patrol in three 500 by 500 feet high-crime grids for each of the 20 police districts that were identified based on risk-based computerized mapping. Results indicated a statistically significant 23 percent reduction in street violent crime incidents.[3]

RISK TERRAIN MODELING

Risk terrain modeling (RTM) starts with identifying "all factors that are related to a particular outcome for which risk is being assessed" and then "assigns a value signifying the presence, absence or intensity of each factor at every place throughout a given geography."[4] Each factor is represented by a separate map of the same geography, and the maps are combined to create the risk terrain map.

The Indio, California, Police Department developed a computer model that predicts, by census block group, where burglaries are likely to occur within the City of Indio. The model incorporated an RTM approach that included data on socioeconomic characteristics of the block group, probation data, data on school absences, truancy arrests, and historical truancy rates. The model showed a strong relationship between historical truancy rates and current burglary rates.[5]

IDENTIFYING PREVENTION OPPORTUNITIES

Identifying prevention opportunities involves focusing resources on places and individuals that have been historically involved as drivers of crime. In some applications, a scoring method is created based on a number of factors including criminal history, address, and social media use.[6]

Through funding from the BJA Smart Policing Initiative (SPI) program, Cambridge, Everett, and Somerville, Massachusetts, collaborated on the Regional Analytics for the Safety of Our Residents (RASOR) effort. RASOR implemented person-based predictive policing methods as an innovative method of identifying individuals for intervention using focused deterrence. The social harm score was effective in identifying high-risk individuals, though the evaluation of the focused deterrence effort returned mixed results.[7]

Bureau of Justice Assistance
U.S. Department of Justice

VALOR OFFICER SAFETY AND WELLNESS INITIATIVE
BUREAU OF JUSTICE ASSISTANCE

MACHINE LEARNING PROCESSES AND ITS BENEFITS

The goal of machine learning is "to develop methods that can automatically detect patterns in data, and then to use the uncovered patterns to predict future data or other outcomes of interest."[8] In the context of policing, past crime data are analyzed using a machine-learning algorithm to detect patterns and relationships that conventional predictive analytics cannot uncover. Then, the data pertaining to the uncovered patterns are further analyzed to improve predictions. Machine learning offers a number of helpful capabilities:

PATTERN IDENTIFICATION

Based on identified patterns and relationships, machine-learning algorithms continuously adapt and can discover additional patterns.[9] In policing, identified patterns might inform an agency about the times of day when a particular neighborhood is more likely to experience a specific type of crime.

DATA COMPLEXITY

Because human behavior and neighborhoods, among other characteristics that influence crime, are dynamic, machine-learning algorithms can better examine complex criminological data than linear and more conventional techniques.[10]

ACCURACY

Accuracy is critical for the field of policing, and machine learning has been argued to be more accurate than conventional predictive models. Researchers argue that machine-learning algorithms provide greater forecasting accuracy for more complex data, such as criminological data, than more conventional models.[11]

CONSIDERATIONS AND LIMITATIONS OF PREDICTIVE ANALYTICS

GOALS AND FEASIBILITY

Agencies should consider the crime problem or intelligence gap they will address using predictive analytics. Certain predictive analytics techniques are more appropriate for particular problems.

- **Regression analysis** can be used to identify areas at increased risk of crime and identify variables that are positively associated with increased risk.
- **Hot spot detection** can be used to identify areas with increased concentration of crime.
- **Risk terrain modeling** can be used to identify areas at increased risk of crime based on environmental factors that increase vulnerability for specific locations.
- **Identifying prevention opportunities** can help focus resources on areas and individuals at increased risk of possibly being involved in criminal activity.
- **Machine-learning algorithms** can identify areas at increased risk of crime.

A law enforcement agency's ability to conduct these analyses will depend heavily on its willingness, ability, and capacity to use predictive analytics properly or to adopt predictive analytics software. Being understaffed, lacking crime analysts, or having limited time for in-service training can further complicate the adoption of new analytical methods or software.

TECHNICAL SKILLSETS

The predictive analytics techniques described in this brief all require **technical skills**, such as statistical analysis skills, statistical programing language skills, and data management skills. These capabilities may be fulfilled by agency personnel (e.g., crime analyst) or by outside providers such as research partners or vendors. Different techniques also require increasingly sophisticated skills and advanced training.

BIAS

One of the primary criticisms of predictive analytics is that it can **perpetuate historical biases** when using biased data.[12] Existing biases in resource allocation and police enforcement will inherently be reflected in any analysis based on those data. For example, if police have allocated more resources in one neighborhood and thus have made more arrests in that neighborhood, then analyses may unfairly predict that crime is more likely to occur in that neighborhood.

BLACK BOX OF MACHINE LEARNING

Many researchers and critics consider machine-learning algorithms to be "black boxes" because identifying the particular factors that led a machine-learning model to a final decision can be nearly impossible.[13] This **lack of transparency** obscures how decisions are made and makes it difficult to challenge a decision.[14] The black box nature of machine-learning algorithms has led to concerns about due process and the civil rights of individuals involved in the criminal justice system and other vulnerable populations.[15] Addressing the lack of transparency, Babuta and colleagues (2018) recommend that machine-learning models should not be the sole source of decision-making; instead, agencies should use them in conjunction with officer discretion.

PRIVATIZED SOFTWARE

Because law enforcement agencies are sometimes the clients, they are not fully aware of how the software provider uses predictive analytics or how certain algorithms make decisions.[16] When working with private companies, agencies have to sign contracts that may include nondisclosure agreements.[17] As a result, agencies are unable to share crucial information with the public, which **decreases transparency** and perpetuates the idea of the black box.

AS THE FIELD OF POLICING HAS EVOLVED, SO HAVE THE CAPABILITIES AND COMPLEXITIES OF PREDICTIVE ANALYTICS.

Machine learning is emerging within the field as a superior option for forecasting crime and other phenomena. The use of predictive analytics has empowered agencies to take more proactive approaches to crime reduction, rather than conventional reactive approaches, such as rapid responses to 9-1-1 calls. Researchers argue that machine learning is better suited for the complex nature of criminological data and that machine learning's ability to incorporate costs (i.e., consequences) improves the accuracy of prediction. However, the decision to allocate resources (e.g., staff, money) toward predictive analytics strategies and software should be well informed. The proper use of predictive analytics to reduce and prevent crime requires careful planning and training.

ABOUT CNA

CNA is a nonprofit research and analysis organization dedicated to the safety and security of the nation. It operates the Institute for Public Research — which serves civilian government agencies — and the Center for Naval Analyses, the Department of the Navy's federally funded research and development center (FFRDC). CNA is dedicated to developing actionable solutions to complex problems of national importance. With nearly 700 scientists, analysts and professional staff, CNA takes a real-world approach to gathering data, working side-by-side with operators and decision-makers around the world. CNA's research portfolio includes global security and great power competition, homeland security, emergency management, criminal justice, public health, data management, systems analysis, naval operations and fleet and operational readiness.

For more information please contact:
Ben Carleton, Deputy Project Director | CARLETONB@cna.org
Dr. Brittany Cunningham, Project Director | CUNNINGHAMB@cna.org

ENDNOTES

1. Fitzpatrick, D. J., Gorr, W. L., & Neill, D. B. (2019). Keeping score: Predictive analytics in policing. *Annual Review of Criminology*, 2(1),473–491.
2. Selbst, A. D. (2017). Disparate impact in big data policing. *Ga. L. Rev.*, 52, 109–195.
3. Ratcliffe, J. H., Taylor, R. B., Askey, A. P., Thomas, K., Grasso, J., Bethel, K. J., Fisher, R., & Koehnlein, J. (2021). The Philadelphia predictive policing experiment. *Journal of Experimental Criminology*, 17(1): 15–41.
4. Caplan, J. M., Kennedy, L. W., & Miller, J. (2011). Risk terrain modeling: Brokering criminological theory and GIS methods for crime forecasting. *Justice Quarterly*, 28(2), 360–381.
5. Parker, R. N., & Martinez, E. (2014). *Indio, California Smart Policing Initiative: Reducing burglaries through predictive policing and community engagement*. Washington, DC: Bureau of Justice Assistance.
6. Joh, E. E. (2017). Feeding the machine: Policing, crime data, & algorithms. *Wm. & Mary Bill Rts. J.*, 26(1), 287–302.; Selbst, 2017.
7. Uchida, C. D., Swatt, M., Davis, J. S., Connor, C., Shutinya, M., Phillips, W., & Wagner, D. (2016). *The RASOR'S Edge: Focused deterrence in Cambridge, Everett, and Somerville.* Rockville, MD: Justice & Security Strategies, Inc.
8. Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*. Cambridge, MA: MIT Press.
9. Berk, R. A., & Bleich, J. (2013). Statistical procedures for forecasting criminal behavior: A comparative assessment. *Criminology & Pub. Pol'y*, 12(3), 513–544.; Lum, K., & Isaac, W. (2016). To predict and serve? *Significance*, 13(5), 14–19.
10. Brennan, T., & Oliver, W. L. (2013). The emergence of machine learning techniques in criminology: Implications of complexity in our data and in research questions. *Criminology & Pub. Pol'y*, 12, 551–562.
11. Berk & Bleich, 2013.
12. Babuta, A., Oswald, M., & Rinik, C. (2018). *Machine learning algorithms and police decision-making: Legal, ethical and regulatory challenges*. London, UK: Royal United Services Institute.; Brayne, S. (2017). Big data surveillance: The case of policing. *American Sociological Review*, 82(5), 977–1008.; Cino, J. G. (2017). Deploying the secret police: The use of algorithms in the criminal justice system. Ga. St. UL Rev., 34, 1073–1102.; Fitzpatrick et al., 2019; Joh, 2017; Perry, W. L., McInnis, B., Price C. C., Smith, S. C., & Hollywood J. S. (2013). *Predictive policing: The role of crime forecasting in law enforcement operations*. San Monica, CA: RAND Corporation.; Selbst, 2017; Shapiro, A. (2019). Predictive policing for reform? Indeterminacy and intervention in big data policing. *Surveillance & Society*, 17(3/4), 456–472.
13. Babuta et al., 2018; Brennan & Oliver, 2013.
14. Babuta et al., 2018; Brennan & Oliver, 2013; Joh, 2017.
15. Babuta et al. 2018; Kutnowski, M. (2017). The ethical dangers and merits of predictive policing. *Journal of Community Safety and Well-being, 2*(1), 13–17.; Perry et al., 2013; Selbst, 2017;
16. Cino, 2017; Joh, 2017.
17. Garrett, B. L. (2018). Evidence-informed criminal justice. *Geo. Wash. L. Rev., 86*, 1490–1524.

This work was performed under BJA-2018-DP-BX-K015. This project was supported by Cooperative Agreement Number BJA-2018-DP-BX-K015 awarded by the Bureau of Justice Assista, U.S. Department of Justice. The opinions contained herein are those of the author(s) and do not necessarily represent the official position or policies of the U.S. Department of Justice. References to specific agencies, companies, products, or services should not be considered an endorsement by the author(s) or the U.S. Department of Justice. Rather, the references are illustrations to supplement discussion of the issues.

IIM-2021-U-030293