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Predictive Policing as a New Tool for Law Enforcement? Recent Developments and Challenges

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Abstract Decision-making processes are increasingly based on intelligence gained from 'big data', i.e., extensive but complex datasets. This evolution of analyzing complex data using methods aimed at prediction is also emerging within the field of quantitative criminology. In the context of crime analysis, the large amount of crime data available can be considered an example of big data, which could inform us about current and upcoming crime trends and patterns. A recent development in the analysis of this kind of data is predictive policing, which uses advanced statistical methods to make the most of these data to gain useable new insights and information, allowing police services to predict and anticipate future crime events. This article presents the results of a literature review, supplemented with key informant interviews, to give insight into what predictive policing is, how it can be used and implemented to anticipate crime, and what is known about its effectiveness. It also gives an overview of the currently known applications of predictive policing and their main characteristics.

Keywords Predictive policing · Predictive analysis · Big data · Crime statistics · Crime mapping · Crime patterns

Introduction

Big data and the use of predictive analysis to analyze these data have become important practices in many disciplines (see, e.g., Siegel 2013 for an overview of the current applications of predictive analytics). Recently, it was stated that the use of big data will have an important impact on the social sciences and humanities in general (Kitchin 2014a) and criminology in particular (Chan and Moses 2015). Big data refers to datasets that are generally extremely large in volume, are collected near or in real time, link different sources or levels of information

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together, and which contain diverse variables that are detailed and tend to be exhaustive in scope (Kitchin 2014b). In other words, these are complex datasets, consisting of tens of thousands of cases and hundreds of variables, or even more, depending on the specific application. Although these characteristics make the analysis of big data time consuming and complicated, it also offers new sources of knowledge and intelligence, informing us about upcoming patterns and trends of that which we are trying to predict. The application of advanced statistical methods to obtain this intelligence from big data is commonly referred to as predictive analysis. When used to predict future crimes based on the available historical crime data, it is often referred to as 'predictive policing'. The main aim of predictive policing is to anticipate future events by learning from the available historical data using advanced statistical analysis.

Although the number of applications of predictive policing keeps increasing, critical examinations and evaluations are limited at this time (Moses and Chan 2016). In particular, not much is known about the current applications (especially those used in Europe) and their effectiveness, their technical requirements, working conditions, and what their use could mean for the technological innovation of criminal policy and research. Therefore, this study aims to provide an overview of the current state-of-the-art regarding predictive policing, focusing specifically on current applications of predictive policing in law enforcement.

Research Questions and Methods

The current study wishes to address the following questions regarding predictive policing and its applications: (1) What is predictive policing?; (2) how does predictive policing work?; (3) what can we learn from currently used applications of predictive policing?; and (4) what should we consider in evaluating its effectiveness? To answer these questions, a literature review was conducted, supplemented with key informant interviews. The literature review aimed to define predictive policing and to describe how it functions, its advantages and disadvantages, and what is known concerning its effectiveness. The literature review focused on main reference works and reviews of predictive policing and gray literature (e.g., manuals, internal reports, and white papers) concerning the existing predictive policing applications. Key informant interviews (N = 3) were conducted with experts and developers of three main predictive analysis applications for police services. Specifically, informants involved in the development and implementation of CAS (Crime Anticipation System) (Netherlands, March 3, 2015), PredPol (US, November 25, 2014), and Hunchlab (US, February 2, 2017) were interviewed. In addition to the interviews, we received a demonstration of the predictive policing software used in their respective police departments. The following cities were visited: Los Angeles (US), where PredPol is used (November 25, 2014); Amsterdam (Netherlands), where CAS (Crime Anticipation System) is used (March 3, 2015); and Miami (US), where Hunchlab is supposed to be used in a short time (February 2, 2017). The main aim of the key informant interviews was to gain additional information not available in the current predictive policing literature about the current existing applications of predictive policing and their practical implementation.

In the remainder of this article the functioning of predictive policing, the types of crime for which it is used and its data requirements are discussed first. Next, an overview of the currently existing applications of predictive policing is given, with their main characteristics. Finally, we discuss the main factors to consider in determining the effectiveness of predictive policing.

What is Predictive Policing?

At this time, there are several concrete criminological applications of predictive analysis, which is the statistical analysis of large amounts of historical data and serve to anticipate new crime events or phenomena. Perry et al. (2013) distinguish three main objectives of predictive analysis in criminological applications: (1) predicting perpetrators, (2) predicting victims, and (3) predicting when and where there is a higher risk of new crime events.

The first category consists of, for example, the prediction of recidivism (Berk et al. 2009) or the identification of possible perpetrators based on their background and the characteristics of certain crimes. In these cases, predictive analysis complements other methods such as (geographic) profiling. The second category is aimed at, for example, predicting which people are at risk of becoming a victim of a certain crime based on the known victims' data or the risk of the escalating of domestic or gang violence (Ratcliffe and Rengert 2008). The objective of the third category is to predict future crimes as precise as possible in time and space and use that information to proactively guide police patrol routes or the locations of police controls. Although the term 'predictive policing' is sometimes used to refer to all three categories, it is increasingly used to denote specifically the latter category. In that sense, predictive policing can be defined as: "*the use of historical data to create a spatiotemporal forecast of areas of criminality or crime hot spots that will be the basis for police resource allocation decisions with the expectation that having officers at the proposed place and time will deter or detect criminal activity*" (Ratcliffe 2014, p. 4).

The main purpose of predictive policing is to generate crime predictions in order to anticipate emerging crime trends and patterns, and to use the generated predictions to inform crime prevention strategies (Bachner 2013; McCue 2015; Perry et al. 2013, Moses and Chan 2016). The ultimate long-term aim of predictive policing is to make a significant contribution to the prevention of crime. As a policy strategy, predictive policing can thus be situated within the scope of intelligence-led policing (ILP). The main objective of ILP is to apply crime data analysis to objectively inform policy, policing strategies, and tactical operations in order to reduce and prevent crime emphasizing the proactive use of police resources, in contrast to reactive crime response strategies (Ratcliffe 2016).

The potential to predict crime follows from the empirical observation that crime does not happen randomly, but tends to be concentrated in time and space in so-called crime hotspots. Routine activity theory (Cohen and Felson 1979) and crime pattern theory (Brantingham 2010) both place an emphasis on the convergence in time and place of offender and victim (with the absence of a capable guardian), and, following rational choice theory (Cornish and Clarke 1987), also emphasize the bounded rationality of the offender. Therefore, there are contextual factors and patterns influencing crime opportunity that can be identified (Brantingham 2013; Eck and Weisburd 2015; Kinney et al. 2008). These indicators can be identified and serve to predict potential perpetrators, victims or locations at risk. However, predictive analysis is not suited to explain crime phenomena or as a replacement for sustained structural prevention. In that regard, predictive policing needs to be considered as a complementary technique to more traditional quantitative methods.

Hotspot analysis can be considered the main precursor to predictive policing. The general principle of hotspot analysis is that crime events are mapped to find high concentrations of crime during a certain time period. However, for the purposes of predicting crime this technique is considered retrospective, in the sense that patterns from the past are merely extrapolated to the present. To counter this problem, prospective hotspot analysis was proposed by Bowers et al. (2004; see also Bowers & Shane 2005; Johnson & Bowers 2004a, 2004b). In prospective hotspot analysis, hotspots are formed not by the areas with the highest concentration of crime, but by the aggregation of risk zones surrounding each incident. These risk zones are temporary, making the hotspots more dynamic. Another related development is risk terrain modeling (RTM) (Caplan and Kennedy 2010). Using a geographic information system (GIS), a risk map is created of locations sensitive to high crime rates, based (only) on their spatial properties and the interactions of those properties. Both prospective hotspot analysis and RTM result in a heat map charting the risk of crime for each area. There is a clear need for prospective methods that focus on prediction, ideally also incorporating both the space and time dimensions, to obtain a more dynamic picture of future crime trends (Groff and La Vigne 2002; Gorr and Olligschlaeger 2002; Ratcliffe 2010). Predictive policing can thus be considered a step forward in the crime mapping evolution because of its specific focus on spatio-temporal predictions of crime, thus enabling a more accurate estimation of future crime patterns.

How Does Predictive Policing Work?

Predictive policing is characterized mainly by the use of increasingly complex statistical methods such as machine learning models (see infra), and by the use of micro geographic levels of analysis, in practice generally a raster grid consisting of equally sized grid cells. The micro geographic level is considered to be more suitable and accurate as it better reflects the existing variability at that level of both crime and socioeconomic variables and provides more predictable crime patterns compared to higher geographic units of analysis such as census tracts, neighborhoods or districts (Weisburd et al. 2012). From a practical point of view, the micro geographic level also allows us to present the analysis results on a more detailed geographic level.

Building a Predictive Model

Technically, three phases can be distinguished in the use of predictive policing: (1) data collection and preparation, (2) modeling, and (3) mapping (see Fig. 1).

The first phase is to collect and clean the data. Next, the data is linked to a grid map of the area where it is used with the help of geocoding. The grid cells thus become the smallest unit of analysis, a risk percentage will eventually be calculated for each grid cell. In the second phase, the data are analyzed by a statistical model. This process can be divided into two steps: (1) the training step and (2) the prediction step. When training, the statistical model learns the relevant patterns in the available historical data: it links the values of relevant indicators to the risk of a new crime event. In the prediction step the actual predictions are made for a certain time frame (e.g., the next day, next week, etc.) by outputting a risk percentage for each grid cell based on the current values of the indicators. Finally, in the third phase the prediction results from the second phase are mapped. Taking into account the available police operational capacity there is often a selection of the highest risk areas, based on a certain critical threshold value. These zones are then mapped out, usually color-coded by risk value and/or crime type. Additional information, such as calls to emergency services, can also be displayed on these same maps.

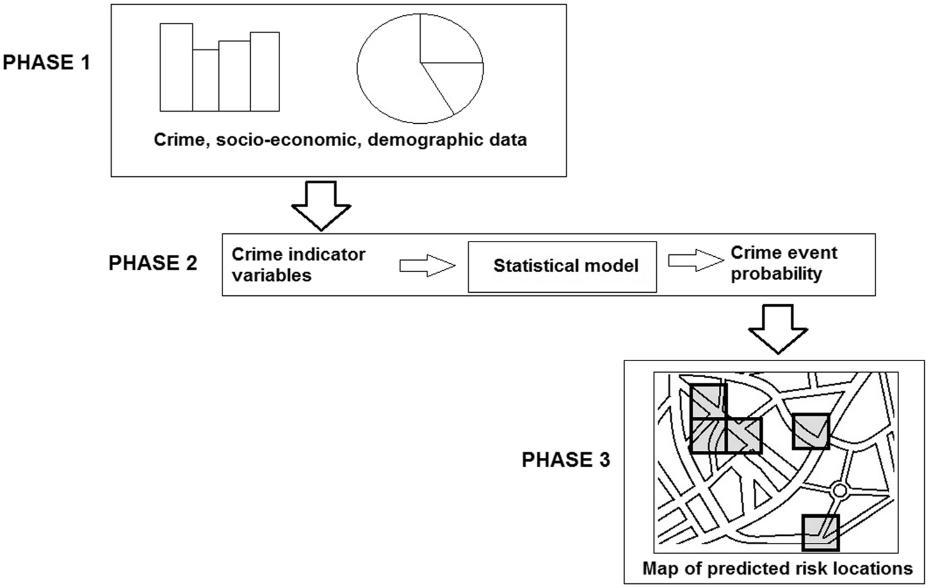

Fig. 1 Flow chart of predictive analysis

Types of Crime for Which Predictive Policing is Used

In principle, predictive policing can be applied to any crime type where (1) strong indicators for the risk of a crime event are known and (2) data regarding these indicators can be collected beforehand. The following type of crimes are consistently mentioned in the literature and in the field as suitable for predictive policing: home burglary, theft, and mugging. In general property crimes where victim and perpetrator are strangers to each other, are considered most suitable. Predictive policing seems to be less effective for drug crimes and relational violence (Bachner 2013; Hollywood et al. 2012; Perry et al. 2013). Ideally, the following conditions need to be met: high willingness by victims to report victimization and correct registration by the police (both ensure that the available data reflects as reliably as possible the true crime rates); relative high frequency (there needs to be enough data for the model to be able to link the relevant indicators with the risk of new crime events); time and place of the crimes need to be determined as precise as possible (preferably using geocoding and (short) time intervals).

If these conditions are not met, this has an impact on the quality of the model and therefore also impacts the accuracy and preciseness of the crime risk predictions. There are however no real standard threshold values making crime data unsuitable for the use of predictive policing. Generally, possible data collection problems within a police department are first analyzed to consequently establish qualitative thresholds relative to the desired accuracy and preciseness of the risk predictions. In the case of databases with a large amount of data coming from different sources, this is even more an important focus. Therefore, a data collection and quality evaluation strategy is needed. It can of course not be ruled out that there are still data quality problems which cannot be solved easily or timely. In that case a strategy should be developed to deal with these problems. One common example is lack of an exact location of crime events, e.g., only the street name. Data quality is important to ensure adequate prediction performance, as the use of predictive policing depends on historical data. Additionally, as a large amount of data is necessary it could be more challenging for smaller cities, or even impossible for rural areas, to use predictive policing, as in absolute numbers specific types of crime are extremely rare in rural areas. However, this assertion has not yet been formally tested.

Data Requirements

When collecting data, it is important to consider which variables to include. Three variables are always needed: time, place, and type of crime. Often these three standard variables are complemented with a range of other relevant indicators. The most suitable and relevant indicators can be determined based on the literature, existing applications, exploratory data analysis or variable selection when building the statistical model. In general, the following groups of variables can be distinguished: (1) crime history variables (time since the last crime event, number of crime events last month/last six months/last year, number of crime events in neighboring grid cells, number of calls to emergency services, etc.); (2) other time-dependent variables (weather, seasons, events, holidays, week/weekend, etc.); (3) opportunity variables (population density, escape routes such as distance to highway or the intersection of important routes, presence of public places, bars, (night) shops, etc.); and (4) precursor crimes (preceding crime events, e.g., escalation of violence). These data are typically collected from official sources: police statistics for crime variables and national or regional census bureaus for demographic, socio-economic, and opportunity variables.

Types of Statistical Models

One of the main characteristics of predictive policing is the use of advanced statistical models, specifically machine learning models. Machine learning models are characterized by a higher predictive power and offer an improved prediction performance when handling complex data (Haykin 2009). Neural networks are the best-known type of model in this category. Neural networks learn to recognize patterns in the data and self-correct in iterative cycles based on the known (historical) values of the response variable. However, the structure of this type of model can be considered a black box: there is no insight into the actual relation between the predictor variables and the response variable. This means in practice that this type of model, in contrast to the more traditional statistical models such as logistic regression, have no explaining value.

Next to machine learning models, there are also statistical models adapted specifically for predictive policing that have been proposed in the literature (among others Mohler et al. 2011; Wang and Brown 2012; Wang et al. 2012; Wang et al. 2013). These models can be divided into two main groups: near-repeat models and time-space models. The first group focusses on a specific phenomenon recognized mainly in home burglaries: when a burglary takes place, other homes within a certain distance have within a certain time frame a higher risk of also being burglarised. This is comparable with repeat victimization, but instead of the same victim undergoing a crime repeatedly, it is the near environment falling victim (hence near-repeat). Based on this phenomenon several models have been developed, also taking inspiration from similar natural phenomena. For example, Townsley et al. (2003) developed a model based on epidemiological models used to simulate the spread of a contagious disease. Mohler et al. (2011; Short et al. 2008; Short et al. 2009) developed a model based on the modeling of earthquake aftershocks. The main advantage of these types of models is that they do not need much information: time, place, and type of crime suffice. Their effectiveness derives from the above mentioned near-repeat phenomenon and the fact that the near-repeats act as proxies for the underlying factors making a certain area attractive for crime. However, this is also their main disadvantage: they only focus on this phenomenon and are usually not that flexible to incorporate other information as well.

Time-space models on the other hand have as their main advantage that they do allow the incorporation of many variables from various sources. Generally, these models are adaptions of statistical methods extensively used in other domains practicing predictive analysis. Wang and Brown (2012) developed a model adapted from a generalized additive model (GAM*)*. This is a type of generalized linear model (GLM), a group of models suited for data not meeting the normality assumption of linear regression, which is for example the case if the outcome variable is not continuous but discrete, as is the case for predictive analysis, where the outcome variable is generally binary (event or no event). A GAM allows even more flexibility when dealing with complex data, but at the expense of interpretability. The main disadvantage of the time-space models is that a determination and selection of the most relevant indicators is needed. Often this is circumvented by using a large number of indicators, whereby some of those indicators are not certain to be an effective indicator of crime, and applying a form of variable selection before or during the modeling (e.g., automatic variable selection based on the improvement of predictive power of the model) to retain or weigh only the most important indicators. There is however the danger of fitting an overly complex model. Ideally, the selection of indicator variables is (also) based on previous knowledge from criminological theory or previous empirical research.

Current Existing Applications

Currently there are four main applications of predictive policing being used in European and American police departments, which we discuss in detail hereafter: CAS (Crime Anticipation System) in the Netherlands, PreCobs in Germany and Switzerland, PredPol in the UK and US and Hunchlab in the US. Other countries, such as Austria, are currently studying the possible implementation of predictive policing (Glasner 2015). Moreover, several software companies such as IBM (IBM n.d.), Hitachi (Hitachi 2015), and Microsoft (Rivero 2015) are also developing and distributing their own predictive analysis software solutions for police services.

Crime Anticipation System (CAS)

The Crime Anticipation System (CAS) was originally developed by the Amsterdam police department to focus on the so-called high impact crimes, crime types which do not only occur often, but also strongly impact the victims: home burglaries, robberies, and mugging. Meanwhile CAS has been extended with pickpocketing, car burglaries, violent crimes, office burglaries, and bicycle theft (Willems 2015). Predictions are made for each two-week period, based on historical data for 200 demographic, socio-economic and crime opportunity variables, collected by the *Centraal Bureau voor de Statistiek* (Central Bureau of Statistics, the main governmental agency in the Netherlands responsible for collecting census data). Although this ensures that a wide range of information is available to base the crime predictions on, the high number of variables also complicates the modeling process. It is also likely that not every variable is as informative for predicting crime or does not add any new information relative to other variables. However, the high number of variables makes it difficult to assess the relative contribution of each variable.

Every two weeks the statistical model is retrained based on data from the previous three years. This three-year period of historical data was estimated to be the most efficient as the predictions no longer increase significantly even using more data. Only the top 3% highest risk locations (grid cells) are mapped. This is a practical choice, which takes into account the available police capacity. The risk locations are also color coded: red for the highest percentage, orange for the following percentage, and yellow for the final percentage. The 2-week predictions are further refined by using a second model which makes predictions for each 8-h period, which is the duration of one shift at the police department of Amsterdam, for the locations which were already selected by the first model. The Amsterdam police department uses so-called 'flex teams' to make use of the predictions in practice. These are teams which are not bound to a specific district, but can be deployed all over Amsterdam. For each flex team two analysts give advice based on the CAS risk predictions. CAS outputs its predictions on a grid map of Amsterdam with each cell 125 by 125 m large (see Fig. 2).

For the period from October 2013 until July 2014, CAS could predict 15% of home burglaries in Amsterdam correctly and 36% almost correctly (i.e., a crime event was predicted in a neighboring gridcell of an actual crime event) (De Graauw 2014, 33). For mugging 33% of incidents were correctly predicted and 57% almost (De Graauw 2014, 38). Additionally, it appears that teams working mainly with CAS (the flex teams) have become more efficient and have gained in visibility toward the general public. Whether CAS is also able to achieve an effective decrease in crime rates, is unclear. In Amsterdam, the use of CAS has been successfully evaluated internally and an extension is planned to other Dutch cities such as

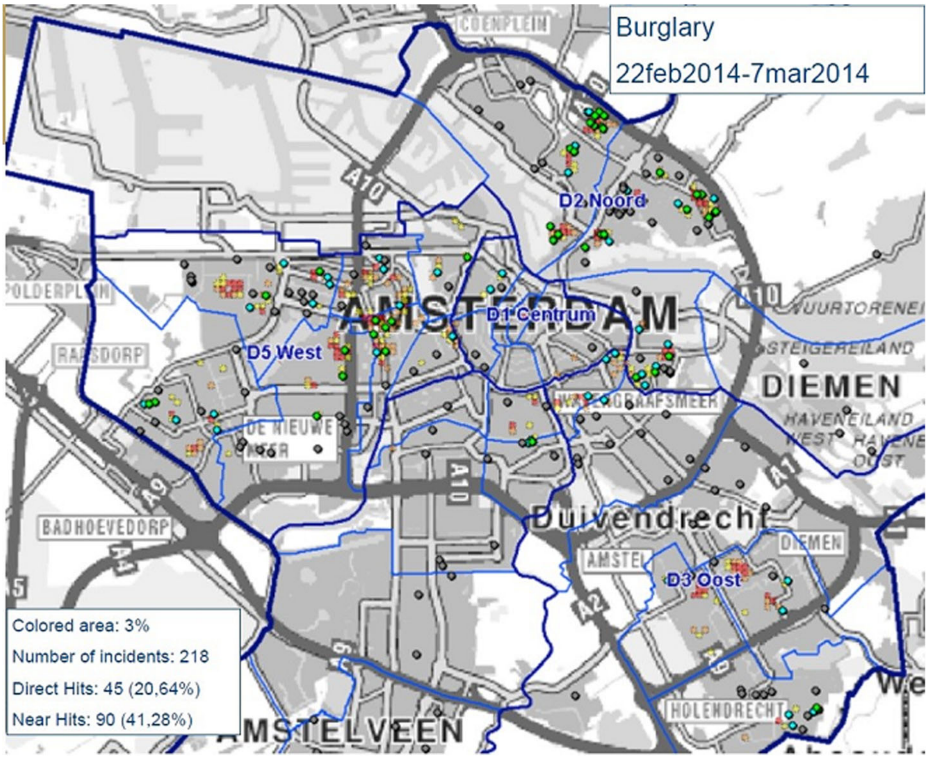

Fig. 2 Example output of CAS (Willems 2015)

Maastricht, Groningen, Eindhoven, Breda, and Tilburg. The intention is also to integrate CAS with national databases and mobile devices used by police officers in the field.

PreCobs

PreCobs has been developed by the Institut für musterbasierte Prognosetechnik (ifmPt) in Oberhausen (Germany). It is a commercial software package, but offers an all-in solution, allowing police departments to easily use the software without too many additional investments in technology or trained staff. Unlike most of the other discussed applications, it is only applicable to one crime type: home burglaries (Tageswohnungseinbrüche). The pilot project for this software was conducted in winter 2010–2011 in Duisburg (Germany). Since then PreCobs has been introduced in several other cities in Germany (München, Nürnberg, Ansbach, Stuttgart, and Karlsruhe) and Switzerland (Zürich, Basel, and Aargau) (IfmPt n.d.). PreCobs analyzes crime data based on the near-repeat principle and outputs a grid map with color coded cells based on the risk of new crime events. Each grid cell is 250 by 250 m large (see Fig. 3). To estimate the risk, PreCobs uses time, place, and characteristics such as modus operandi and house type of past burglaries in the area (Rest 2014). No information on the performance of PreCobs is available at this time.

PredPol

PredPol was originally developed for the Los Angeles Police Department (LAPD) in cooperation with the University of California in Los Angeles (UCLA, US). Meanwhile PredPol has been introduced in several US cities such as Los Angeles, Atlanta, Richmond, and Modesto. Recently PredPol has also set foot in Europe, specifically in the UK, where it has notably been introduced in London, Kent, and Yorkshire. One of the biggest advantages of PredPol is that it, like PreCobs, offers a user-friendly, all-in solution. It does not require additional software or statistical knowledge other than the basic training which is given to police officers using

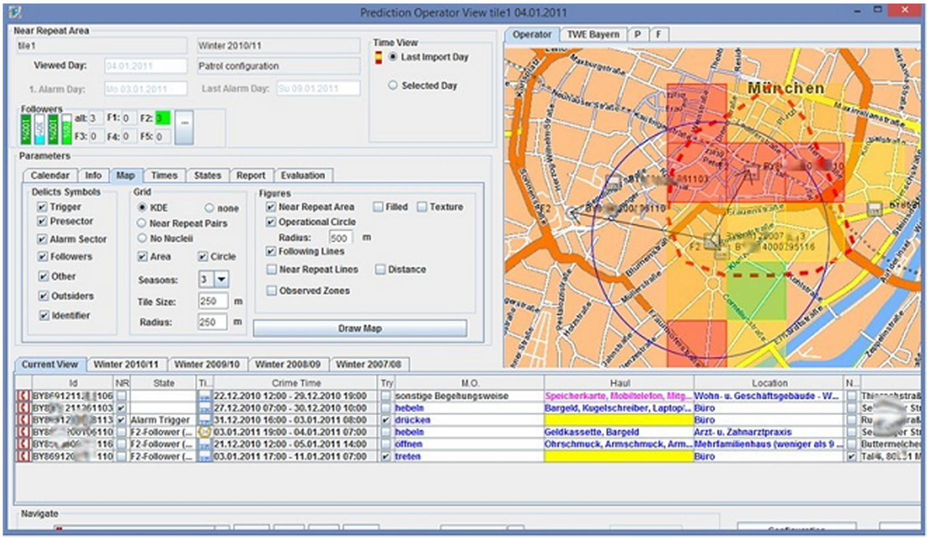

Fig. 3 Example output of PreCobs (IfmPt n.d.)

PredPol to allow them to correctly read and interpret the outputted data and maps. However, this also makes PredPol somewhat inflexible, as including new crime types or data might depend on what PredPol offers. As the predictions are essentially outsourced to PredPol, this might be problematic as it entails allowing PredPol, a private commercial company, access to crime data which is generally considered to be sensitive. For these reasons some police departments in Europe, prefer a system under their control such as CAS in Amsterdam.

PredPol's underlying model is based on a mathematical model which originally served to predict aftershocks of earthquakes (Mohler et al. 2011) and which uses only three variables: time, place, and type of crime. PredPol motivates this by claiming that this avoids any form of profiling or subjectivity. Crime risk predictions generated by PredPol are mapped on a grid with a single cell size of 500 ft.by 500 ft. (ca. 150 m × 150 m) (see Fig. 4).

Different crime types are displayed on the same map, but a specific crime type can be filtered out. Likewise, time and spatial range can be chosen by the user. Generally, a new map is generated for each shift. The generated maps can also be sent to mobile devices which can be used in the field by police officers. Additionally, police officers' locations and time spent in a specific grid cell can be registered, allowing police activity to be taken into account in an evaluation of the application.

A randomized field experiment in Los Angeles (US), testing the effectiveness of the methodology used by PredPol against the existing best practice of hotspot maps produced by dedicated crime analysts, showed that, on average, 1.4 to 2.2 times more crime was predicted by the predictive policing approach compared to existing best practices. Additionally, directing police patrols based on the predictions provided by the predictive policing approach led to an average crime volume reduction of 7.4% (Mohler et al. 2016).

Hunchlab

Hunchlab was developed over the course of several years, based on previous experiences with hotspot models and in cooperation with university partners, in this case Temple University and

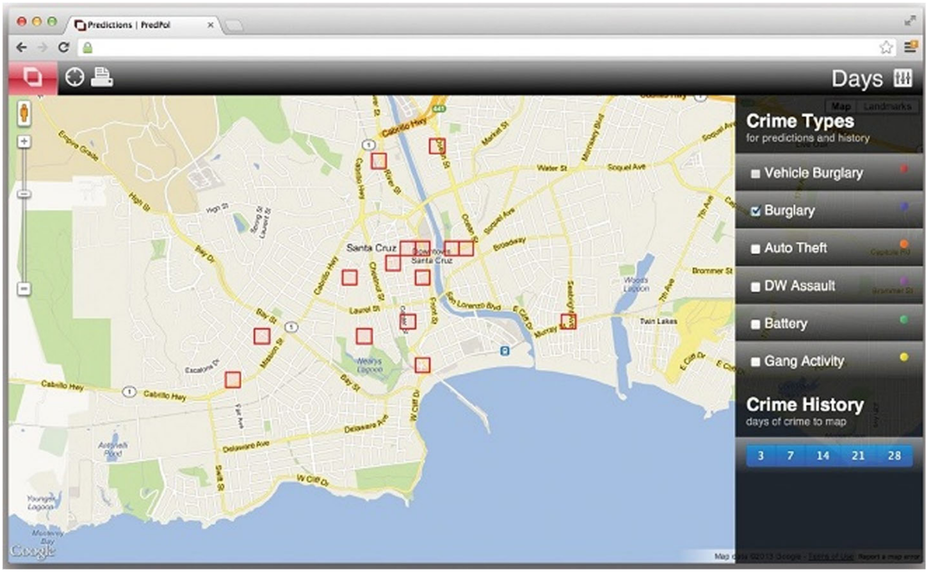

Fig. 4 Example output of PredPol (Bachner 2013)

Rutgers University (Azavea 2015). Contrary to PredPol, Hunchlab does not make use of only place, time, and type of crime, but uses several hundred variables at the same time. This choice is motivated by the need to avoid the results being skewed by, for example, increased police activity when using only police registered crime data. To counter this, a diverse and wide range of variables are used (Azavea 2015). In this respect Hunchlab mostly resembles CAS in the Netherlands. As is the case with CAS, two groups of variables used to predict the risk of new crime events can be distinguished: crime history and opportunity characteristics. Hunchlab also makes use of machine learning models (Azavea 2015).

Contrary to the other discussed predictive policing application, Hunchlab does not use a fixed size for the grid cells. Depending on the needs and wishes of the police department a grid cell size can be chosen between 100 by 100 to 250 by 250 m (Azavea 2015). For each cell a single risk percentage for a group of crime types is calculated based on a weighted sum of the risk for each crime type separately. Which crime types are included and how they are weighted can be determined depending on the priorities chosen by the police department (Azavea 2015). The distinction between different crime types does not disappear entirely however as a color code indicates for which crime type the risk of a new crime event is the greatest (see Fig. 5).

Currently, no concrete data are available on the effectiveness of Hunchlab. However, a field experiment using Hunchlab, the Philadelphia predictive policing experiment (Temple Univesity n.d.), is ongoing.

Comparison of Current Existing Applications

The different applications differ in types of crime, variables used, and grid cell size (see Table 1 for an overview). Even though they have the same objective, namely the prediction of

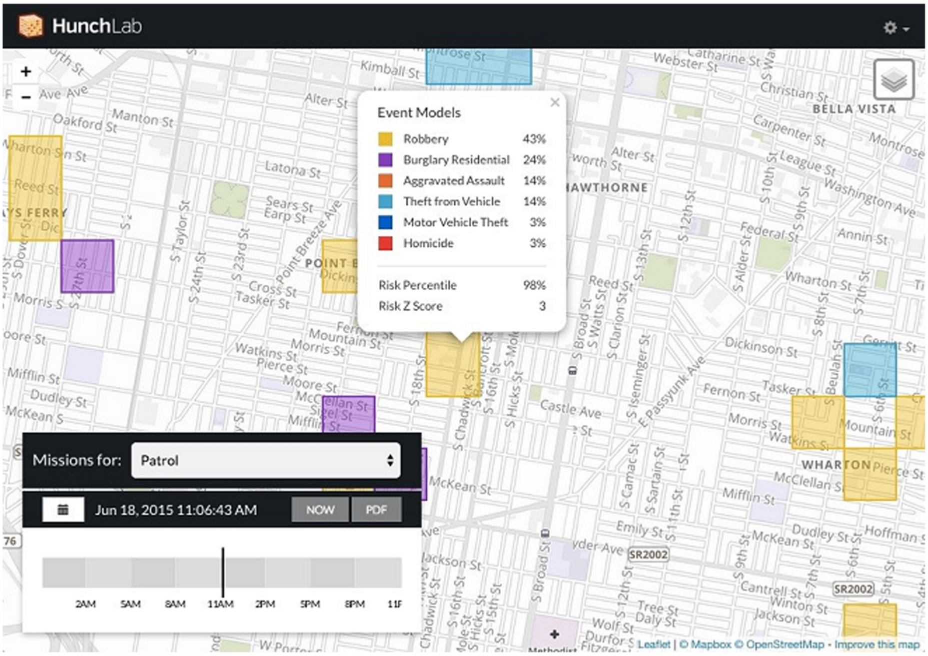

Fig. 5 Example output of HunchLab (Azavea 2015)

Table 1 Overview of the characteristics of the current applications of predictive policing

	Crime anticipation system	PreCobs	PredPol	Hunchlab
Crime types	Property & violent crimes	Only home burglary	Property & violent crimes	Property & violent crimes
Method	Machine learning: neural network model	Undisclosed	Self-exciting point process models	Machine learning: stochastic gradient boosting machine
Variables	N = ca.200: crime history, socio-economic and crime opportunity variables	N = ca.10: crime variables	N = 3: time, place and type of crime	N = ca.100–200: crime history, socio-economic and crime-opportunity variables
Grid resolution	125x125m	250x250m	150x150m	100×100 to 250x250m
Temporal resolution	Two-week periods with categorisation in 8-h shifts	daily	8 h shifts	Per one hour to shifts of several hours

new crime events, this differential methodology shows that predictive policing can be implemented in various ways, likely depending on the needs or wishes of the police departments using predictive policing, for example, in determining priority crime types or the size of the predicted risk areas, which need to be to be practical for police officers in the field.

Factors to Consider in Determining the Effectiveness of Predictive Policing

To determine whether or not predictive policing can be considered an effective method, several factors need to be considered. The aim of this paragraph is to discuss the factors that need to be taken into account when evaluating the effectiveness of predictive policing: what can we currently say about the effectiveness of predictive policing, how should predictive policing be evaluated, and what are the ethical, juridical, and ideological considerations that need to be made?

What can we Currently say About the Effectiveness of Predictive Policing?

Predictive analysis has proven its worth in other areas, but because it is a relatively new development within criminology, there is limited objective information available regarding its effectiveness for policing. Although internal evaluations and the evaluation study of the PredPol methodology in Kent and Los Angeles (Mohler et al. 2016, see supra) are positive, not all applications of predictive policing have been successful, as the results of the Shreveport Police predictive policing experiment, one of the first field experiments of predictive policing, show. Shreveport Police (Louisiana, US) set up a randomized field experiment in 2012 with the help of research from RAND (*Research ANd Development*; a US non-profit research institute), evaluating the implementation of predictive policing against the current standard analysis based on intelligence-led policing (Hunt et al. 2014). The results were unsatisfactory: although the costs of predictive policing were 6 to 10% lower than the standard analysis, no significant decrease in crime rate was established. The researches could not explain this failing of predictive policing unambiguously. Although the results indicated that the use of predictive policing was no better than the current standard practice except from a cost-effectiveness point of view, they also reported some problems influencing the results: (1) the low statistical power of the test (statistical power was only 20% while 80% is the general standard), meaning the test was unable to detect a difference in crime rates or it was caused by inadequate operational implementation by the police department; and (2) the actual amount of resources used turned out to decrease near the end of the test and varied significantly depending on the neighborhood (Hunt et al. 2014, 49–50). These problems make it impossible to conclusively state in this case whether or not predictive policing works.

The problems of the Shreveport Police experiment do show that there are some practical hurdles that need to be overcome for predictive policing to be implemented effectively. If police departments cannot effectively use predictive policing in practice, it ultimately does not matter how well its crime predictions are. A key point in this is to clearly communicate to and involve police officers in the data collection process and evaluation of predictive policing and to allow them to implement their intuition and knowledge in making use of the resulting crime predictions. Otherwise, police might refuse the use of predictive policing as they consider its predictions to be not grounded in reality or superfluous (e.g., Tchekmedyian 2016).

How Should Predictive Policing be Evaluated?

The effectiveness of predictive policing is generally evaluated using three criteria: (1) effectiveness of the predictive analysis (how many correct predictions were made or how many crimes were missed by the predictions?); (2) crime rates before predictive policing was introduced versus after it was introduced (an indirect and likely delayed effect because of more efficient policing); and (3) costs relative to current methods being replaced by predictive policing. Additionally, police units using predictive policing in practice are also often questioned regarding their experiences.

Because of the problems mentioned above and in expectation of more research concerning the effectiveness of predictive policing in the long term, most (internal) evaluations focus on the effectiveness of the predictive analysis itself, namely how correct its predictions are, as this is easily and quickly measured (see Rummens et al. 2017). The underlying assumption is that if the provided information is better, eventually police response will also become more efficient. The general measures used are the *direct hit percentage* (the number of correctly predicted incidents relative to the total number of crimes) and *near hit percentage* (the number of incidents which where almost predicted correctly, in the sense that the actual crime events took place in the immediate neighborhood of the predicted risk location). However, to determine the long-term effectiveness of predictive policing, these measures are not enough.

There is an important distinction between the effectiveness of the predictions made by applying predictive policing and the effectiveness of predictive policing itself. To achieve the latter, an adequate response strategy by police units is equally important to achieve a clear effect. The relation between the use of predictive policing (and crime analysis in general) is after all realized by an efficient police operational strategy making the most use out of the results of the predictive analysis (Santos 2014; Ratcliffe 2016). One important aspect in this respect, is the direction of the police officer in the field, which can differ from country to country. It is for example possible to assign a police unit exclusively to the predicted risk zones, or to include these risk zones in the usual patrol routes. Moreover, proactive and specific police strategies focussing on a small spatial level (e.g., a city block) have been shown to be among the most effective strategies (Telep 2009; Lum et al. 2011). To evaluate this effect and the long-term effectiveness of predictive policing, more field experiments are needed. This is certainly the case for the effects of predictive policing in the long term, specifically whether or not its use can realize a decrease in crime rates. Evaluating the effect of using predictive policing on crime rates is especially challenging as a correlation of the use of predictive policing with decreasing crime rates does not necessarily imply causation. Its effect needs to be isolated from other causes influencing crime rates.

What are the Ethical, Juridical, and Ideological Considerations That Need to be Made?

The application of predictive policing has also been met with ethical, juridical, and ideological questions and criticisms (see Moses & Chan for an overview of key issues and underlying assumptions of predictive policing). The collection of large amounts of data (big data) by the government, but also commercial companies, raises privacy concerns as there is often not enough transparency about what and how much data are collected. Relevant questions in this respect are which data may be collected, under which conditions and for what purpose, relative to the applicable privacy laws. The use of predictive analysis itself is also associated with certain pitfalls. For example, the question arises whether a prediction is sufficient for police to take action, what this means for police accountability (Moses and Chan 2016), and whether this might lead to a higher risk of ethnic profiling and the neglect of basic principles such as the presumption of innocence (Ferguson 2012). Additionally, there is the danger of relying too much on technical tools (Van Brakel and De Hert 2011), without taking into account the limits and constraints inherent to the method, leading to fewer resources where they are also or even more needed and less room for close contact with the general public, for example in the form of community policing.

Applications of predictive analysis generally require advanced software and advanced knowledge of statistics. Several companies have developed software packages, some of which offer all-in solutions, from collecting and cleaning the data to analyzing and outputting concrete results. This is sometimes seen as a transfer of police responsibilities and tasks to a private company. This privatizing of police tasks is controversial because a commercial company's first aim is to be profitable and because of the possible consequences for crucial domains such as privacy and procedural justice (Byrne and Marx 2011). A counterargument is that this should not be seen exclusively as a threat, but also an opportunity for the police to focus on its core tasks and responsibilities. Additionally, software companies providing predictive analysis software and media coverage of predictive policing often exaggerate its possibilities: predictive analysis is presented as a technique which can literally predict crime while in reality, it only predicts the statistical probability (or likelihood) of a new crime event (see below). This can be countered by clearly communicating the possibilities of predictive analysis, its role as a complementary tool, and, more importantly, its limits.

Conclusions and Recommendations

The main aim of this article was to give insight into what predictive policing is and how it can be used to anticipate crime. At its core, predictive policing can be considered a tool that uses advanced statistical analysis to predict time and place with a high risk of new crime events. The advantage predictive policing offers compared to more traditional methods is that it takes into account both the time and spatial dimensions and that it is a predictive method rather than an explorative pattern recognition method. It is characterized by the use of advanced statistical methods and the use of a micro geographic level of analysis.

The current existing applications of predictive policing report, mainly based on internal evaluations, good results and associate these tentatively with a decrease in crime rates. Because the use of predictive policing is only a recent evolution in criminology, the long-term effectiveness of this method cannot be confirmed as of yet. A potential effect on crime rates is also difficult to establish as a decrease in crime rates is only an indirect effect of the use of predictive policing. It is especially dependent on the way the information it offers is handled. The use of predictive policing has received some criticism because it raises some ethical and juridical questions in connection with privacy and in what measure the police should rely on its results. To successfully apply predictive policing, these challenges need to be addressed.

Further scientific methodological research is needed to determine whether predictive policing can substantially predict crime events and to determine whether or not the predictive power is large enough to give predictive policing a clear advantage over current methods used. Additionally, it needs to be determined if and how predictive policing can be successfully used within different police departments and areas. Specifically, more field experiments focussing on the implementation of predictive policing comparing predictive policing with current methods and involving police services are needed to gain more insight into these aspects and how they can influence the performance of predictive policing.

The following three main policy recommendations for the implementation of predictive policing can be formulated: (1) reliable data collection, (2) clear communication between different police units and hierarchy levels, and (3) police response strategy. Firstly, it is important to provide a reliable data collection. The data quality will after all impact the eventual quality of the risk predictions significantly. An evaluation of data quality and the data collection process within a police department is therefore necessary to ensure the successful use of predictive policing. Similarly, it might be prudent to evaluate how data quality issues can influence prediction performance.

Secondly, the communication between different police units and hierarchical levels needs to be clear. Predictive policing has interdisciplinary characteristics: it requires cooperation between different units, backgrounds, and specializations. The data miner or statistician building and training the statistical model has for example not the practical experience of police officers in the field and can thus benefit from their feedback. Also of importance is the way the predictions are communicated to the police officers: an analyst might for example act as a go-between or the prediction maps might be made available to each officer. Failing to take this into account, might result in police officers being unwilling or unable to use predictive policing correctly.

Thirdly, the police response strategy for the provided risk predictions is also of importance. The long-term aim of predictive policing is to establish a decrease in crime rate by promoting a more efficient use of police resources. To realize this, it is important to contemplate the way the risk predictions are handled. At this time, police response strategy and its effect on the (long-term) efficacy of predictive policing is one of the most understudied aspects of the application of predictive policing.

From this contribution, it is clear that several important conditions need to be taken into account and there is a need for thorough empirical tests and evaluations for predictive policing to be considered an effective tool. Nevertheless, if the above considerations are addressed, it seems that predictive policing has the potential to become a paramount crime fighting tool in the medium to long term.

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