

Decision Support Systems in Policing

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Abstract

Decision Support Systems (DSS) are widely used in industry, finance and commerce to assist users with the large and rapidly growing amount of data that these institutions have to deal with. Police organisations have been slow to investigate the benefits that such systems can offer but this situation is changing. As well as seeking to improve operational performance, there are now pressing economic reasons for using I.T. systems to assist crime analysts and investigators. A short review of some of the more striking findings of psychological research in decision-making is followed by a survey of a selection of recent research into crime linkage and predictive policing using Artificial Intelligence and some of the systems currently being used in Police jurisdictions.

Keywords: decision support systems, crime analysis, predictive policing, crime linkage, artificial Intelligence

The amount of data generated by, and available to, organisations through their computer systems increases exponentially year on year and this phenomenon is accelerating. In order to deal with some of the problems that this creates for decision-takers computer programmes generically entitled “Decision Support Systems” (DSS) have been developed and are in use throughout commerce, industry and finance (Turban, et al., 2007). Police departments face the same problems in assessing and acting on information and are adopting the same strategies to assist in deploying their resources and assisting investigators. This paper is a review of systems and approaches currently being undertaken in developing and employing DSSs in Police contexts, emerging research including Artificial In-

telligence (A.I) solutions, and more widely a discussion of expert decision-making.

The major areas of application for systems are in prediction of crime “hot spots” and linkage of offences. The former is normally used in cases of “volume” crime like burglary and vehicle offences while the latter is applied to more serious offences such as rape and homicide. A 2014 survey (PERF, 2014) indicated that 38% of responding Police departments in the US were already employing “Predictive Policing” systems that are claimed to improve deployment of Police resources and reduce crime by deterring offences in areas identified as high-risk. And that 70% expected to be using this strategy within two to five years.

This field is one that lends itself to the cross-fertilisation of disciplines and the most widely discussed predictive policing system, “PredPol” (PredPol) is an innovative collaboration between Environmental Criminology, Anthropology and Mathematics that employs an algorithm first employed in Seismology to predict geological disturbances.

A criticism of Predictive Policing (Robinson & Koepke, 2016) is that by relying on historic data it predicts where crime has already occurred and that it inevitably directs the attention of Police to areas and communities that are likely to report offences. It may also be that in the case of drug abuse or other “discretionary” offences that systems become subject to a confirmation bias of continuous reinforcement of decisions as offences are uncovered in specified areas, i.e. precisely the kind of systematic distortion of the evidence that non-human decision support is supposed to be immune from.

The possibility of this process becoming a racially biased “feedback loop” where prejudiced police action is directed towards areas with high levels of minority occupation, and as a result creates increasingly distorted inputs to systems has been raised by several authors. And even that a context of incomplete and often poor recording of crime is likely to lead to invalid conclusions that: “...legitimizes the widespread criminalization of racialized districts” (Jefferson, 2018). The legal environment of predictive policing has also been questioned: Ferguson (2017) concentrates on the threat, as he sees it, to the U.S. 4th Amendment rights of suspects to be protected from “unreasonable searches and seizures” and 14th Amendment right of citizens to equal protection under the law. While accepting that predictive technology is certain to be increasingly adopted using ever more sophisticated algorithms it is argued that there must be a substantive framework of oversight to police it.

The ability to link serial crimes is of great importance to law enforcement agencies. Once a link has been established between a number of crimes then evidence collected can be combined to provide a richer profile of a criminal’s activity. The result of this combined evidence provides the opportunity for the earlier apprehension of the offender, particularly where the serial crime is of a serious nature. In this case, amongst other approaches, Artificial intelligence (AI) techniques have been employed. These have included supervised

and unsupervised neural networks, fuzzy systems, data-mining, scenario generation and Bayesian and natural language-based systems.

Decision Making

It is often assumed that human decision-making must be superior to any other form of decision-making system and that this becomes more obvious as the area in which decisions are to be made increases in complexity. Surprisingly there is a very large volume of psychological research going back many decades that strongly suggests that this assumption is not true. If this is indeed the case, then the practicability of embedding decision-making into computer-based decisions becomes not only achievable but highly desirable.

The influential work of Meehl (Meehl, 1954) into the comparative accuracy of predictions made by trained professionals and simple statistical algorithms across a wide variety of areas including academic success, criminal recidivism, and length of hospitalisation for mentally ill patients overwhelmingly demonstrated the superiority of the latter. A much later meta-analysis of 136 studies of expert as compared to statistical or algorithmic (actuarial or mechanical) predictions concluded:

“Superiority for mechanical-prediction techniques was consistent, regardless of the judgment task, type of judges, judges’ amounts of experience, or the types of data being combined” (Grove, et al., 2000, p. 19).

This position has been even more forcefully expressed in a survey of over 200 studies comparing expert and statistical predictions in “low validity” environments i.e., domains with a “significant degree of uncertainty”. In activities ranging from credit risk assessment to predictions of longevity of cancer patients algorithms were found to perform significantly better than expert opinion in 60% of cases leading to the unconditional assertion: *“In every case the accuracy of experts was matched or exceeded by a simple algorithm”* (Kahneman, 2011, p. 223).

In practice a “draw” between a highly trained decision-maker and a statistical method represents a win for the algorithm in terms of the financial investment required. There is also an advantage in the reliability of the two “systems” in that the algorithm can always be

depended upon to return the same result given the same input. This is an outcome that cannot be guaranteed in the judgement of human decision-makers even in such highly skilled occupations as radiology and clinical psychology (Goldberg, 1968). In a study of clinical diagnosis by radiologists as to whether tumours were benign (Hoffman, et al., 1968) major discrepancies were not only discovered between radiologists but individual radiologists were also found to contradict themselves in 20% of cases when presented with the same x-ray at a later date.

Some of these studies are 50 to 60 years old and their findings have been replicated many times since. They indicated that what appear to be quite complex decisions can be generated by relatively simple methods long before the astounding advances that have since been made in Computer Science and Artificial Intelligence yet the adoption of advanced decision support into areas of complexity and importance has been patchy.

The compelling implication of these findings is that such statistical techniques could be equally effective when applied to fields relating to identifying links between offences and predicting where offences are most likely to occur. There is some direct evidence that calls into question the ability of human versus “mechanical” judgement in crime analysis.

For instance, a lack of support has been reported for the supposition that analysts and investigators have a heightened ability in linking offences. An early study (Canter & Heritage, 1991) asked 28 “highly experienced” detectives to link the offences committed by 3 stranger rapists who had each committed 4 offences. The majority of subjects performed at no better than chance and when links were suggested by the subjects, the researchers commented: *“Links made by the officers were often not based on a logical combination of the material they had”* (p 4).

Comparable results have been found in a series of studies (Bennell, et al., 2010; Santtila, et al., 2004) and a similar observation made: *many trained linkage analysts rely on an experience-based, subjective, idiographic approach for selecting linking cues* (Bennell, et al., 2012, p. 630). The consequences being that the linkage of crimes was unsystemised and individual to the experimental subject.

The conjunction of the huge, disparate and ever-increasing volume of data available to police services and the evidence that human decision-making is often not only inaccurate but also unreliable is concerning. When judgements are not only wrong but inconsistently wrong this clearly supports the proposition that some form of assistance is required in order that the best and most effective decisions can be reached.

The term ‘decision support’ is often used and not always accurately, a very early definition of Decision Support Systems by the authors who coined the term is still useful and widely employed: *“Interactive computer-based systems which help decision-makers utilise data and models to solve unstructured problems.... fuzzy, complex problems for which there are no cut and dried methods”* (Gorry & Scott-Marton 1971).

Originally, these systems were intended to support and assist the decision making of the user and designers were insistent that they were not to replace them. They were not to be automated decision-makers but advances in A.I. in association with the proven effectiveness of “mechanical” methods bring this into question.

An area of crime analysis that has been the subject of a great deal of attention has been that of serious sexual offences. The two most recent reports on the investigation and prosecution of rape in the U.K. (HMIC/HMCPSI, 2012) and the Metropolitan Police Service (Angiolini, 2015) have emphasised the critical importance of identifying rape series at an early stage. Apart from the reasons already given there are pressing economic grounds for adopting computerised support in crime analysis as is clearly demonstrated when considering the case load of The Serious Crimes Analysis section (SCAS) in the United Kingdom (Angiolini, 2015). SCAS is a national unit *which works to identify the potential emergence of serial killers and serial rapists at the earliest stage of their offending* (NCA) and deals with the most serious offences including murder with a sexual motive, stranger rape and abductions. The unit employs a version of the Violent Crime Linkage Analysis System (ViCLAS) which is in practice the standard database employed for crime linkage. In 2015 4,442 crimes were referred to SCAS for analysis but the figures show a dramatic rate of ‘attrition’ at each stage of the process. Only 36% of suitable crimes are even input to the system, and of those over a quarter are discarded. As a result, only 26% of crimes agreed by SCAS to meet the criteria are analysed. In practice this means that the

large majority of offences will never be subject to linkage analysis as the cohort of unexamined rapes grows at three times the rate of those analysed. Consequently, a series of two that could be found in the eligible set of offences has a probability of 0.07 of both crimes being scrutinised and this decreases rapidly as series length increases: three crimes have a probability of less than 2% of all of them being seen. The chance of any offence proceeding to analysis is small and the probability of all offences in a series being analysed rapidly decreases as the series lengthens. It should be remembered that these offences are committed by some of the most dangerous criminals in society and the aim of SCAS is to identify them *at the earliest stage of their offending*. However, the odds against even identifying their crimes are very high with the result that the chances of finding these offenders at an early point in their criminal careers is very unlikely.

Crime Linkage

Currently there are two computer systems that dominate the area of serious crime linkage and analysis: ViCAP, the Violent Crime Apprehension Program (Howlett, et al., 1986) and ViCLAS, the Violent Crime Linkage System (Royal Canadian Mounted Police). ViCAP is the creation of the FBI at Quantico, is in use throughout the United States and has been in existence in differing forms since 1985; its use has historically been linked with theories of Douglas, Ressler and other FBI agents as outlined in the Crime Classification Manual (Douglas, et al., 1982). ViCLAS is an enhancement of ViCAP and was developed by the Royal Canadian Mounted Police (RCMP) in the early 1990s; this system is used in the UK, most of the European Union and Australasia and is licensed by the RCMP, for a fee, in these jurisdictions. Both ViCAP and ViCLAS were developed primarily by practitioners and criminologists and are essentially repositories of data which are dependent upon the training and experience of the user to maximise their potential. The influence of Computer Scientists in this arena has been slight and there has been no apparent involvement by researchers in A.I or Decision Support, functionality is restricted to the proprietary software on which the databases run and amounts to simple query and retrieval. As a result, none of the advances that have been made in these areas are incorporated in either system and they remain essentially unchanged in the last 20 – 25 years.

A research initiative between the University of Arizona and the Tucson Police Dept. produced the COPLINK system (Chen et al., 2003) multiple data sources are used, each having different user interfaces. COPLINK Connect addresses these problems by providing one easy-to-use interface that integrates different data sources such as incident records, mug shots and gang information, and allows diverse police departments to share data easily. User evaluations of the application allowed us to study the impact of COPLINK on law-enforcement personnel as well as to identify requirements for improving the system. COPLINK Connect is currently being deployed at Tucson Police Department (TPD) which offers decision support in the form of a large knowledge management system. This system uses a number of linked knowledge sources from police records, criminal histories, and reports and various textual mining and linguistic analysis methods to produce a comprehensive map of the criminal activity related to a crime under investigation and to elucidate relationships within the data. An example would be where associates, locations or vehicles were associated with a suspect. This system has now been developed into a commercial application and is available to law enforcement agencies.

A similar collaboration between the Memphis Police Department and Memphis University in the U.S.A. resulted in CRUSH - Criminal Reduction using Statistical History¹. The system utilises IBM's statistical package SPSS to analyse data from a number of crime databases to create multi-layer hot spot maps to detect patterns and trends in criminal activity. Consequently, it is claimed that police resources can be more effectively utilised and that the system has contributed to an average reduction in violent and property crime of over 15%. The Homicide Investigation Tracking System (HITS) (Washington State: Office of the Attorney General) is an application developed in Washington State in response to a number of high profile murders that is similar to ViCAP/ViCLAS in that it serves as a source of detailed information on a large number of violent and sex related crimes over a wide geographical area in the American North East.

An interesting approach (Wang, et al., 2015) employs established techniques of pattern detection in data-mining to find similarity coefficients between offences to detect series of residential burglaries in Cambridge, Massachusetts. These relate to "pattern-general

¹ <http://www-03.ibm.com/press/us/en/pressrelease/32169.wss>

similarity” that represents elements of crime that are common in most crime series such as geographical and temporal proximity and “pattern-specific similarity” that reflects within-series similarity. The use of pattern-general similarity over the set of offences generates a similarity graph where edges between crimes indicate similarity. The hypothesis being that the majority of crime series have a number of offences that exhibit the identifying features of or “core” of the series or pattern. Once cores are identified then series are found by merging overlapping cores. This hypothesis is based on the intuition of analysts and the research methodology can be summarised as: learn a similarity graph, based on previous crime series, and then mine and merge cores.

Visual Analytics for Sense-Making in Criminal Intelligence Analytics (VALCRI) is an ongoing E.U. research project that attempts to make connections in crime reports that may be missed by analysts and to present them in visual form. It employs semantic text processing and the A.I. concept of “ontologies” which are formal specifications of concepts that can be interpreted and processed by computer systems. It aims to find clusters in crime reports, which is crimes with similar features that may not be immediately apparent, using a similarity metric. Once similarity values between offences have been computed a lattice can be generated that encapsulates the relationships in the data. In one part of the system (Sacha, et al., 2017) offenders’ temporal and spatial activities can be represented and answers to questions about their activities answered by moving up or down through the lattice. This also allows for the use of “association rules” to extract information about useful relationships (Qazi, et al., 2016). Lattices can also be composed on any other aspect for which there is data such as offenders’ crime histories and associations and crime hot spots. This project is very strongly envisaged as tool to assist analysts: *VALCRI acknowledges that technology works best when it augments the cognitive abilities ... of the analyst* (Pallaris, 2017).

A collaboration between the Metropolitan Police Service (UK) and London South Bank University (Casey & Burrell, 2009; Casey & Burrell, 2010; Casey & Burrell, 2013) in which a large release of rape data was made available employs multi-dimensional scaling and fuzzy clustering to automatically generate a taxonomy of stranger rape in order to identify behavioural similarities between offences with the aim of discovering series of crimes. The strength of this approach is that

real-life descriptions such as “violent”, “middle-aged” and “controlling” that are commonly used by investigators and analysts to describe crimes can be given valid numeric values. By so doing “degrees of membership” of behavioural or descriptive dimensions such as the above can be assigned and thereby characterise the similarity between offences.

Predictive Policing

The following is widely employed classification of approaches in predictive policing (Perry, et al., 2013):

1. Methods for predicting places and times of crimes. These are essentially a police resource management tools for deploying officers to areas and at times when they are most likely to deter or encounter crime
2. Methods for predicting offenders and identifying individuals likely to commit crimes. For identifying those most probable to offend in future
3. Methods for predicting perpetrators’ identities. In order to generate offender profiles for specific offences
4. Methods for predicting victims of crimes. Used to determine those individuals or groups most at risk of becoming victims

In general, the focus of research activity and the development and implementation of systems has been heavily focussed on the first of these elements although there are instances of predicting offenders based on criminal histories and social network analysis. The most notable of these is the Strategic Subject List (SSL) more commonly known as the Chicago Heat List. In an attempt to curb the high level of gun crime in the city, all persons arrested in Chicago are given a *score* generated by an undisclosed algorithm that predicts their likelihood of perpetrating or being a victim of gun crime. It was hoped that by so doing effective interventions could be made by visiting those high on the list either to warn them of the threat or to inform them *that if they don't keep in line, there's a jail cell waiting for them* (Stroud, 2016). Currently there are over 400,000 citizens of Chicago on the SSL and its existence has unsurprisingly proved highly controversial in identifying suspects (Gosztola, 2017). There have also been objections that while an individual's presence on the list does not indicate that they are more or less likely to be a victim of a shooting they are more likely to be

arrested for a shooting (Saunders, et al., 2016). There is no data relating to convictions.

The main focus of predictive policing however is undoubtedly the prediction of locations and times where crime is most likely to occur and there are a large and increasing number of systems that promise to be able to achieve this. A selection of some of the most well-known applications are shown at table 1. The back-

ground to the recent emergence of predictive policing systems can be traced in a direct line from the work of Brantingham. P and Brantingham. P, (1981) on the geography of crime and crime pattern theory through the research of their student Rossmo (2000) on geographic profiling of crime to the work of Jeffrey Brantingham (Brantingham, et al., 2012) on the anthropology of criminal gangs and PredPol.

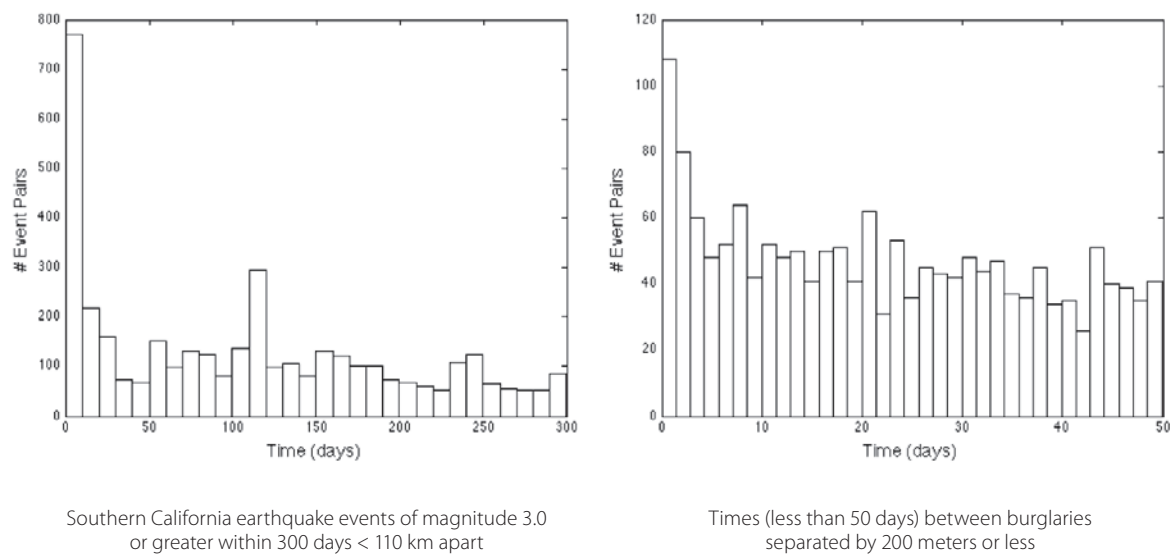
Table 1: Predictive Policing Systems

	Location	Crime types	Method	DATA
Crime Anticipation System (CAS)	Amsterdam	Property and violent	Machine learning: Neural networks	200 demographic, socio-economic & crime variables
PreCobs	Germany Switzerland	residential burglary	Undisclosed	Spatio-temporal Premises type Modus Operandi
PredPol	60+ US cities Kent, UK	Property and violent	self-exciting point process	Spatio-temporal
HunchLab	Miami	Property and violent	Machine learning: stochastic gradient boosting	"several hundred" variables: "risk terrain", crime, weather etc
CrimeScan	Chicago, Pittsburgh	Violent	Clustering: Kernel density estimation	Spatio-temporal Social indicators

based on Hardyns & Rummens (2017)

It may appear that the more data sources that a system has that the better its performance is likely to be but, as has been seen from the evidence of psychological experiment into decision-making this does not appear to be the case; simpler seems to be better. A large number of sources also requires a corresponding effort to gather and evaluate data and most importantly some method for standardising and measuring evidence so that data with different character and attributes can be effectively combined. Some of the data sources shown in table 1 are so varied that it is hard to see how this could be achieved. PredPol has the advantage of using a very small number of data variables that relate exclusively to time, date, and location of the offence and are easily evaluated and encoded. It employs a technique known as "self-exciting point process" (Mohler, et al., 2011) which is usually employed to model aftershocks from earthquakes. The issue of the use of algorithms

and transparency in modelling crime prediction as a problem for enforcement agencies and public confidence has been raised (Ferguson, 2017). Neural networks employed by CAS exemplify the "black box" in that by their nature their internal workings are not amenable to examination but as with other techniques, they depend entirely on their success for the quality of data input to them. Other systems that are commercial products do not make public the operation of the algorithms they employ for obvious reasons but equally obviously the question of transparency is apparent. The similarities between the temporal and geographic incidents of aftershocks of and the "near repeat" occurrence in burglary are shown at Figure 1. The near-repeat phenomenon found premises near to a recent burglary are at a greater risk of being subject to an offence but that risk decreases over time (Johnson & Bowers, 2004)

Figure 1 Earthquake events in S. California and near repeat burglaries - Mohler et al, (2015)

A research study that compared the effectiveness of a prediction system based on the earthquake model and crime analysts (Mohler, et al., 2015) ran a randomised control trial in three divisions of the Los Angeles Police Department and two divisions of the Kent Constabulary (U.K.). In this study, analysts were asked to predict locations of crimes on their sections and this was compared to the epidemic-type after shock sequence (ETAS) algorithm that is used by PredPol to generate its forecasts. Cells of 150 x 150 metres were specified as patrol areas and the predictions were randomly allocated to patrol staff for a 24-hour period; no patrolling officers, control or supervisory staff were aware of which prediction type they were dealing with. It was found that the ETAS model predicted areas with 1.4 – 2.2 the amount of crime that analysts did using intelligence reports and mapping software. Where officers were deployed to predict areas the ETAS forecasts were successful in reducing the crime rate in patrolled areas by 7.4% while analyst forecasts showed no significant effect on crime reduction.

Conversely a randomised field trial run by the Shreveport, Louisiana Police Department (Hunt, et al., 2014) that used logistic regression models (PILOT -Predictive Intelligence Led Operational Targeting) did not show a statistically significant reduction in crime in the identified cells. In this trial “leading indicators” were input to predict property crime within “block-sized” squares (400 x 400 feet – approximately 150 x 150 metres). The authors accept that there were problems with this research around issues of “dosage” and “fidelity” by which is meant the consistent level of police activity in identi-

fied areas and the extent to which interventions were delivered as intended. This raises the question of the difficulty of effectively implementing trials of experimental tactics in policing related issues when they are necessarily conducted in an environment in which unpredictable levels of demand are made on finite resources.

The Crime Anticipation System (CAS) in contrast to PredPol uses a large number of variables and predicts more offences including violent, theft and vehicle crime. Using neural networks, it produces a two-week prediction of crime based upon three years’ worth of data across Amsterdam and in response, police units with a city-wide remit are sent to those areas identified as most high risk. It has been reported (Hardyns & Rummen, 2017) that in a trial from October 2013 to July 2014 that the system was successful in predicting 15% of house burglaries within a 125 x 125 metre cell and 36% as “near misses”, i.e. it predicted a burglary in the neighbouring cell to where one actually occurred. The figures for street robbery or mugging are also impressive in predicting 33% of locations accurately and 57% as near misses. As always however it would be valuable to know what the baseline or “hit rate” of conventional predictive analysis running concurrently would be. It appears from the work of the Brantinghams (Brantingham & Brantingham, 1981) and others that crime, particularly violent crime, is often highly localised so predicting its future occurrence may not be as complex as might be imagined.

PreCobs (Pre – Crime Observation System) is a predictive system in use in Germany that is restricted to house

burglary and like other systems is based upon near-repeats. This system is currently in use in several German cities (Hardyns & Rummens, 2017) but there is little information available on its performance or its operation. A very recent report (Gerstner, 2017) concludes that its effect on crime reduction is unclear but is only likely to

be moderate. In considering the utility of near-repeats to other types of crimes apart from property offences the similarity of near-repeats and the temporal representation of violent gang-related events in Figure 2 is striking and suggests that the seismological model introduced to crime analysis may be generalisable.

Figure 2: Timeline of violent incidents between two Los Angeles gangs – Mohler et al. (2015)



HunchLab (Azavea) employs a very high number of variables in its operation, which presents the difficulties referred to standardising input, and also in discerning, which are the most influential elements in the data collected. Among the factors considered are crime history, socio-economic factors, near repeat data, temporal cycles and many more; it also considers Risk Terrain Modelling (RTM) which relates to the influence of geographic features on crime (Caplan & Kennedy, 2010). The system uses a form of machine learning: a stochastic gradient boosting machine (GBM) which is an enhanced application of decision trees, a widely used group of A.I. algorithms that assist in determining the best decision for a set of circumstances. There is no information currently available as to this systems performance. CrimeScan, now known as CityScan, has been in development since 2009 (Neill) and is a joint enterprise between Chicago Police Department and Carnegie Mellon University that uses a form of clustering known as kernel density estimation to predict incidents of violent crime around the city. Again, this model employs leading indicators such as emergency calls, minor crimes and anti-social behaviour as input and operates at block level in order to make its predictions.

Conclusions

In the current environment in which crime is rising again across most of Europe and enforcement budgets are being squeezed the need for assistance in deploying police resources to deter and detect crime is of great and growing importance. The volume of data coming into and being generated by policing organisations has never been greater and this may become overwhelming: for example, recently a series

of high-profile rape cases in the U.K. have collapsed because of Police failure to find vital evidence hidden in thousands of text messages, Facebook and other social media postings. This is only one instance of the difficulties faced when dealing with the unprecedented amount of information that may be relevant to an investigation and failure to uncover such data is only likely to increase in the absence of greater resources. Given that the level of personnel is unlikely to rise then the only way to expand the capacity of police departments to deal with these problems is to improve the tools that they work with. Information Retrieval is a field of Artificial Intelligence dedicated to finding information in large datasets that satisfies users' queries. Typically it would allow investigators to frame queries in natural language to a large database and have an IR system retrieve documents and answer questions on it as well as a human (Microsoft, 2018). It is also conceivable that the emerging field of "Sentiment Analysis" (Cambria, 2016) which is currently used to assess attitudes, perceptions and even emotional responses in large databases could be used to find evidence of the nature of personal relationships.

There is a large body of well-attested knowledge from research on what constitutes effective decision-making and an enormous amount of both academic and commercial research in A.I. and other disciplines into how important relationships in data can be uncovered. Crime Analysis has been slow to become involved in this effort but this is rapidly changing. As yet the answers to the problems that law enforcement faces in the present and future are not clear but there are faint and encouraging signs that they can be found given the wide variety of approaches that are being applied and tested.

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