Review of Current Crime Prediction Techniques

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Abstract

Police analysts are required to unravel the complexities in data to assist operational personnel in arresting offenders and directing crime prevention strategies. However, the volume of crime that is being committed and the awareness of modern criminals make this a daunting task. The ability to analyse this amount of data with its inherent complexities without using computational support puts a strain on human resources. This paper examines the current techniques that are used to predict crime and criminality. Over time, these techniques have been refined and have achieved limited success. They are concentrated into three categories: statistical methods, these mainly relate to the journey to crime, age of offending and offending behaviour; techniques using geographical information systems that identify crime hot spots, repeat victimisation, crime attractors and crime generators; a miscellaneous group which includes machine learning techniques to identify patterns in criminal behaviour and studies involving re-offending. The majority of current techniques involve the prediction of either a single offender's criminality or a single crime type's next offence. These results are of only limited use in practical policing. It is our contention that Knowledge Discovery in Databases should be used on all crime types together with offender data, as a whole, to predict crime and criminality within a small geographical area of a police force.

1. Introduction

The role of computers has been increased in all walks of life from the finance sector to supermarkets. In recent years police forces have been enhancing their traditional method of crime reporting with new technological advancements to increase their output by efficiently recording crimes to aid their investigation (Adderley and Musgrove 1999). Data is not just a record of crimes, it also contains valuable information that could be used to link crime scenes based on the modus operandi (MO) of the offender(s), suggest which offenders may be responsible for the crime and also identify those offenders who work in teams (offender networks) etc. In today's world, computers are playing a major role in the investigation of all types of crime from those that are considered as volume crime (burglary, vehicle crime etc.) to major crime such as fraud, drug trafficking, murder etc.

It is not an easy task for a Police analyst to manually unravel the inherent complexities within police data and this problem is compounded when the analysis is undertaken by a team. The distribution of the data to the team may cause significant information, which could be useful to solve the crimes, to be missed as each member is not in possession of all relevant facts. For a long time, criminologists and statisticians have been applying their skills and knowledge trying to predict when and where the next set of crimes will occur, with varying degrees of success. The volume of crime and the greater awareness of modern criminals put a strain on the existing methods. Human reasoning fails when presented with millions of records. Therefore, there is clearly a requirement for a tool kit to assist in analyzing the data which will make the best use of limited resources. Knowledge Discovery in Databases (KDD) techniques can be used to reveal knowledge which is beyond intuition.

The aim of this study is to examine the current techniques used in crime prediction.

1.1 Knowledge Discovery in Databases

KDD is a process that allows users to search for valuable information in large databases (Weiss and Indurkhya 1998). It combines statistical modelling, machine learning, database storage and AI technologies. In policing, the vital aim of KDD is the prediction of human behaviour, which is by far its most common business application (Mena 2003); this can be tailored to cater for the needs of security forces to detect and deter the criminals. Since 9/11, the use of KDD has increased in the areas of criminal detection, security and behavioural profiling. Behavioural profiling is the ability to find the patterns of unlawful activity, to predict the likely location and time of crimes, and to identify their perpetrators (Mena 2003). The Home Office (Home Office 2000) has recognized the significance of spatial data analysis at local level to understand crimes. Generally, the information stored in police systems has been used to investigate mainly major serious crimes as described above; the primarily used techniques being specialised database management systems and data visualization systems (Adderley and Musgrove 2001). Surveys reveal that the use of mapping tools have increased in the security forces of USA and UK (Mamalian and LaVigne 1999; Corcoran and Ware 2001).

KDD is the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data (Fayyad et al. 1996a). KDD refers to the overall process of discovering useful knowledge from data, and data mining refers to a particular step in this process (Fayyad et al. 1996b). Brachman and Anand (1995) has presented a methodology for KDD which has been enhances towards business by Chapman et al (1998) and further enhanced into clearly defined stages (Debuse et al. 1999):-
- Problem Specification
- Resourcing
- Data Cleansing
- Pre-Processing
- Data Mining
- Evaluation of results

- Interpretation of results
- Exploitation of results
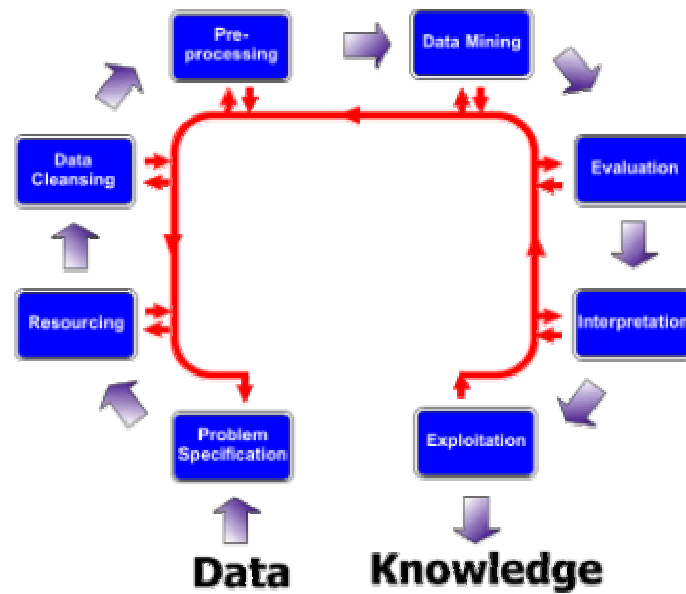
Figure 1 below illustrates the stages.

Figure 1: KDD Roadmap

2. Crime Facts

Crime is "An act committed or omitted in violation of a law forbidding or commanding it and for which punishment is imposed upon conviction" (http://dictionary.reference.com/search?q=crime). Recorded crime statistics have been collated since 1857. Police recorded crime statistics provide a good measure of trends in well-reported crime which could be used at local level to analyse the pattern of crime. However, they do not include crimes that have not been reported to police or that the police decided not to record. In contrast, the British Crime Survey (BCS) provides better trends on crime and includes crimes that are not reported to police. It is also unaffected by the changes in the levels of reporting to the police (Nicholas et al. 2005)

We have categorised crimes into two types:
- Major crimes: Murders, rapes etc.
- Volume crimes: Burglary, vehicle crime, robbery, theft, damage etc.

Property crimes such as burglary, theft and criminal damage account for the majority of both BCS (78 percent) and recorded crimes (75 percent) (Nicholas et al. 2005).

Residential burglary is considered as one of the most distressing crimes, damaging physical and emotional peace of mind of the victims, which in 92% of incidents outweighs the value of the property stolen. Fear of repeat burglary often affects women in particular and such feelings of insecurity last up to 18 months after initial burglary, some of the victims even considered moving home to less affected crime areas (Coupe and Griffiths 1996). Coupe and Griffiths (1996) found that only 6% of burglary cases were solved and a third would be cleared up in the long run. However, most of the cases would not be solved and offenders will never be caught. The West Midlands Police area, whose data is used for this study, had a significantly higher percentage of people who were worried about burglary, vehicle and violent crime compared with average. Figures are shown in below Figure 2 (O'Shea et al. 2005).
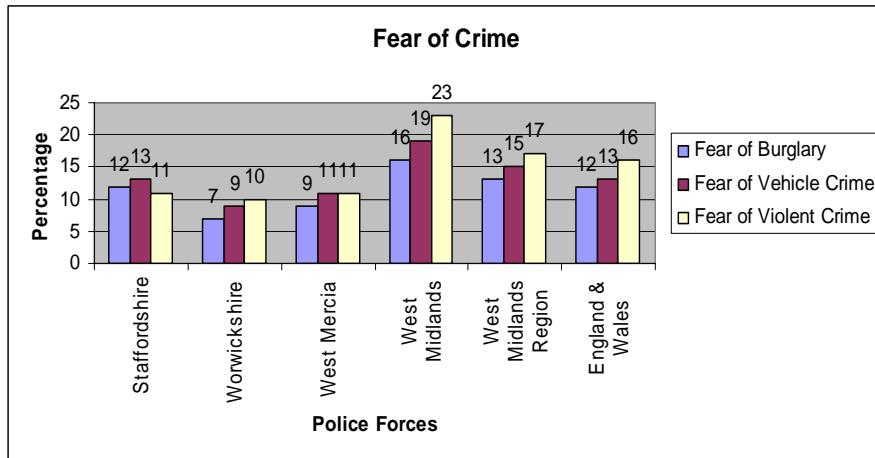

Figure 2: Fear of burglary, vehicle, and violent crime by police force area, 2004/05 BCS

The cost of volume crimes, both in financial and emotional terms, makes their effective targeting essential.

2.1 Crime Recording Process

Whenever a crime is committed, a police officer visits the crime scene or the report is taken by telephone, which is known as the crime report. All UK police forces record their crime reports in a similar way but in different computer systems. The variables stored may be known in a variety of ways but comprise the following: -

- Time, day and date of the crime
- Offence type (there are in excess of 800 different Home Office crime codes), contains unique crime classifications which would be difficult to analyse. For example burglary could be classified as one of the following:-

    1. Burglary Dwelling

        2.   Burglary Other Building
        3.   Distraction Burglary
        4.   Aggravated Burglary Dwelling
        5.   Aggravated Burglary Other Building
- Location of crime to include post code and Ordnance Survey grid references
- Victim information
- Modus operandi (MO) identifies how the crime has been committed.

Depending upon the crime recording system used by each individual force the data fields will be a mixture of structured data fields that may be validated (or not) and free text fields. The free text may not even contain key words or phrases and will contain non standard abbreviations, mis-spellings and, on occasion, contradictory information. For example the structured fields may identify that for a domestic burglary offence the intruder gained entry via the front door but the free text may state that entry was gained via the front window.

The aim of collecting the data is both to solve the crime and to provide required performance information rather than to create a research database. Thus, the quantity and quality of information recorded varies considerably from case to case. It is often imprecise, and is almost certainly at times inaccurate. Crime data is very noisy (random error or variance in a measured variable) and contains lots of missing values. Unstructured and inconsistent data formats make it very complicated to automate the analytical processes.

Table 1 below is an example of the crime data set illustrating the quality issues described above.

Field	% Complete	Valid Records	Null Value	Empty String	White Space	Blank Value
CRIME_REF	100	1580916	0	0	0	0
CRIME_NUM...	100	1580916	0	0	0	0
DATE_FIRST...	100	1580916	0	0	0	0
TIME_FIRST_...	100	1580916	0	0	0	0
DAY_FIRST_...	100	1580916	0	0	0	0
DATE_LAST_...	86.44	1366588	214328	0	0	0
TIME_LAST_...	86.44	1366588	214328	0	0	0
DAY_LAST_C...	86.44	1366588	214328	0	0	0
LOCN_STRE...	99.82	1578029	2887	0	0	0
LOCN_DISTR...	89.45	1414208	166708	0	0	0
LOCN_TOWN	97.23	1537090	43826	0	0	0
LOCN_POST...	72.73	1149784	429743	1389	1389	0
GRID_REF_N...	99.52	1573356	7560	0	0	0
GRID_REF_E...	99.52	1573344	7572	0	0	0
BEAT_NUMB...	100	1580916	0	0	0	0
BEAT_AREA	100	1580916	0	0	0	0
BEAT_NUMB...	100	1580916	0	0	0	0
SECTOR	89.89	1421131	159785	0	0	0
OFFENCE	100	1580916	0	0	0	0
ED_CODE	100	1580916	0	0	0	0
DETECTED	100	1580916	0	0	0	0
CUC_CODE	25.66	405664	1175252	0	0	0
NCR_CODE	4.4	69543	1511373	0	0	0
HOMC_CODE	100	1580916	0	0	0	0
HOOC_CODE	100	1580916	0	0	0	0

Table1: Statistical report of Anonymous crime dataset

2.2 Environmental Criminology

Understanding the behaviour of offenders plays a significant role in understanding and predicting crime and criminality (Adderley and Musgrove 2003). It would, therefore, be helpful to be familiar with the theories of environmental criminology.

2.2.1 Routine Activity Theory

According to Cohen and Felson (1979), the union of three elements in time and space are required for a crime to occur: a likely offender, a suitable target and the absence of a capable guardian against crime. This theory is summarised in Figure 3 below. Policing traditionally focuses upon the offender part of the triangle but crimes could be prevented or reduced by interacting with any aspect of the triangle.

Figure 3 : Diagrammatic representaion of routine activity theory
(http://www.crimereduction.gov.uk/skills08.htm)

2.2.2 Crime Pattern Theory

This theory is helpful in establishing how people interact with their spatial environment and has three main notions: nodes, paths and edges (Policing and Reducing Crime Unit 1998, Brantingham and Brantingham 1991). 'Nodes' is a term from transportation which relates to where people travel to and from. A node is a base for oneself such as home, school, shopping centre etc. Such places can not only generate crime within but also nearby, for example, tight security at some place (Football ground, bar etc.) may generate more crimes and disorder outside of the enclosure/building.

Paths are the travel routes which people take to go to their work, entertainment, and other daily activities; in a nutshell it joins nodes. Most people are creatures of habit; and follow the same route to go to the same place or nodes. These paths are closely related to where they fall victim to crime. The third concept of crime pattern theory, edges refers to the boundaries of areas where people live, work, and shop or seek entertainment. These edges are prone to some crimes such as racial, robberies, shoplifting because people seldom know each other at edges so after committing crime they go back to their haven. Insiders usually commit crimes around their base (home, office etc) whereas outsiders commit crimes at edges.

2.2.3 Rational Choice Perspective Theory

This theory focuses upon the offender's decision making processes. Its main hypothesis is that offending is purposive behaviour which helps the offender in some way. It believes that an offender has an objective to commit a crime even if these goals are immediate and consider only a few benefits and risk at a time (Clarke and Felson, 1993). For example, if mobile telephone or wallet is visible in a car and no one is around it might tempt an offender to grasp the opportunity.

2.2.4 Awareness Theory

(Brantingham & Brantingham 1991) has suggested that crime has four dimensions: victim, offender, geo-temporal and legal. Concentrating on the spatial element of crime is significant to understand the behaviour of offenders. A crime's space can be chosen either on purpose or accidentally by either the victim or the offender according to their life styles. Several things have an effect on the crime rate of an area. For example, what type of people live in particular space and what type of security is available.

3. Current Crime and Offending Prediction Techniques

The 'holy grail' in policing is to be able to predict when and where the next crime or set of crimes will occur. This, of course, in a holistic sense is not currently possible. Many attempts have been made in the crime prediction arena, each of which has had limited success. Most of these attempts have been either concerned with the crime and criminality relating to either a single offender or a single crime type. The sections below discuss the current crime prediction techniques.

3.1 Statistical Methods

Most burglary (69%) and violence (55%) offenders live within one mile of the scene of the crime. Only 8% of burglars and 15% of violence offenders live more than 5 miles away from the crime scene (Farrington and Lambert 2000). Canter (1994) also found that scene of a crime is a key feature to the address or home base of an offender. Crimes occur in close proximity to the offender's residence (Rossmo 2000) and there is a distance decay pattern for crime trips (Brantingham and Brantingham 1984).
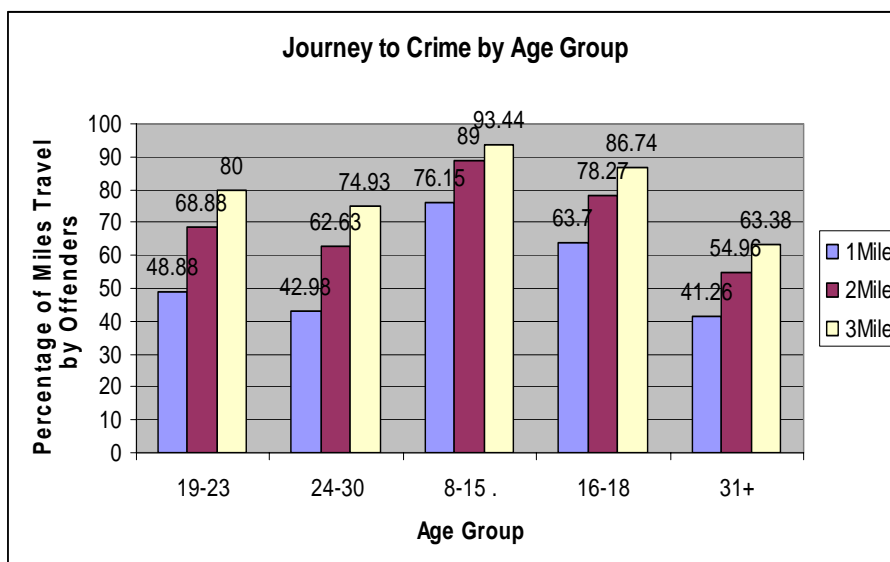
Figure 4: Distance travelled by age

Using West Midlands Police crime data, Figure 4, we have confirmed the statement mentioned in academic papers listed above. The left hand column of each age band clearly demonstrates that a large proportion of offenders commit their crime (burglary dwelling house, burglary other building, dwelling damage, robbery and vehicle crime) within one mile of their home address. The figures in the chart are accumulative.

If there is a lack of physical evidence, the behaviour of an offender has been used to suggest that the offender may be responsible for other undetected crime. In these instances the main emphasis is on the MO i.e. offender's 'way of working' (Davies, 1992). The search for a common behavioural thread linking the offence of a single individual may be like searching for a needle in a haystack that is not there. "Behavioural consistency by offenders is something that still needs to be proved" (Grubin et al. 2001). Here data mining could help to find the links.

3.2 Miscellaneous Methods

Crime prediction, prevention and detection with data mining is an exciting new area, which brings together the disciplines of statistics, machine learning, artificial intelligence, criminology, psychology and database technology. Adderley and Musgrove (2001) have documented the development of investigation tools that make the most of computing power as a mechanism to help the solution of both major and volume crime each of which require a different strategy for investigation. Several academic ventures have made an abortive attempt to use artificial intelligence (AI) to identify volume crimes such as burglary (Lucas 1986 and Charles 1998). In contrary to their prototype success, they could not transform

into practical working systems because they were standalone systems requiring the duplication of data inputting, as they could not be easily integrated into existing police systems. They also lacked robustness and could not adjust to shifting environmental changes. This has engendered suspicion within policing regarding the usefulness of AI techniques (Adderley and Musgrove 2001). There are only few examples of using data mining on crime data (see Adderley 2004; Brown 1998).

There are several other techniques that have been used by several researchers. Chau et al (2002) has used entity extraction to discover the patterns that identify person names, their addresses, vehicles and other characteristics. Some of the approaches, such as string comparator, social network analysis and deviation detection are described in Chen et al (2004) to use on crime data in understanding criminal behaviour. Hauk et al (2002) have used the concept space algorithm on crime data to detect abnormal activities. Once these activities are identified it may be possible to predict the next occurrence of such activity. Several algorithms have been used by Oatley et al (2004) to match and link burglary crimes together into a crime series. Having ascertained that a series is occurring it is possible to suggest, from that data, where the next crime in that series will occur.

Criminal histories have been used traditionally in criminology to predict re-conviction and re-offending. This convention began by 'Ernest W. Burgess' in the 1920s by trying to identify those who would be most appropriate to parole (Mannheim 1965). If forensic and physical evidence is available then it is easy to link the crimes or classify the crimes and attribute them to a single offender. "When such evidence is unavailable, analysis of offence behaviour may be used to identify a linked series of crimes" (Grubin 2001). Repeat victimisation has also be used to assist the prediction (Ewart and Oatley 2003).

There is a strong association between past and present criminal behaviour (Nagin and Paternoster, 2000). Future events are based on the past events, which has helped in the prediction of crime (Johnson and Bowers 2004).

3.3 Geographical Information System Methods

(Brantingham & Brantingham 1995) propose that crime hot spots are developed in areas of the community that can be labelled as crime generators, such as entertainment areas and shopping malls. However, unsteady hot-spots are probably to be the outcome of prolific offenders targeting one area at irregular intervals (Townsley 2000). The techniques used by police forces to identify hot-spots are not always consistent. Crime problems in areas designated as hot-spots may be momentary, and may disappear before resources are officially allocated to those areas. Other than being a crime generator, there are a variety of reasons why a particular geographical area is regarded as a hot-spot. For example, the crime rate could be caused by a prolific offender being released from prison or due to a particular community event occurring. These hot-spots can be used as good predictors of crime and criminality.

As stated above, several researchers have found that prior victimisation is a good predictor of future risk (Polvi et al, 1991; Farrell and Pease 1993; Anderson et al.

1995); repeat victimisation (RV), when it occurs, tends to occur swiftly (e.g. Polvi et al. 1991; Anderson et al., 1995; Johnson et al., 1997). Deprived regions are more affected by repeat victimization (Johnson et al. 1997), in regions with high crime event rates (Trickett et al. 1995), and in regions designated as hot-spots (Johnson et al. 1997, Townsley et al. 2000). Several researchers have interviewed offenders and established that they target the same property repeatedly because they know their way around and know the remaining property or what property is likely to have been replaced that they can steal again (Winkel 1991; Gill and Matthews, 1994; Ericsson, 1995). Johnson and Bowers, (2004) suggests that burglary offences cluster in space and time. They have made an analogy with optimal foraging theory (Krebs and Davies 1987; 64 – 6) which minimises the rate of being caught and amount of time while maximising the reward. This reasoning would imply short-run outbreaks or spates of burglary in a neighbourhood are possibly the result of a single criminal or a team of criminals' activity. On the basis of optimal foraging theory, domestic burglaries shift over time, such that the location of clusters is not predictable over periods of three or more months. However, although clusters do not remain in the same location over time, they tend to move in a 'slippery' manner, moving to nearby areas at successive points in time (Johnson and Bowers, 2004). Different types of geographical area suffer from different levels of victimisation and re-victimisation (Johnson et al. 1997). The central conclusion is that, in affluent areas, "a burglary event is a predictor of significantly elevated rates of burglary offences within 1-2 months and within a range of up to 300-400 metres of a burgled home" (Johnson and Bowers 2004).

Targets or potential victims are very unevenly distributed across space and time. For instance, street robbery requires the presence of victims on the street. Certain parts of cities (at certain times of day) have many pedestrians. In other parts of cities and at other times of day, the streets may be deserted. Auto theft obviously requires that the offender locate an automobile in time and space. Clearly automobiles are unevenly distributed in space and the distribution of them changes radically between working and nonworking hours. All this information would be useful in the prediction process.

4. Discussion

Current prediction techniques have had limited success in operational policing. Many researches have spent time analysing large amounts of police related data with a view to predicting either where the next crime or set of crimes will occur. There are two main areas where these prediction techniques have been concentrated: -

1. An individual crime type
2. An offender's movements

There are two subsidiary areas where these techniques have been concentrated:-

1. Repeat victimisation
2. Hot-spot analysis

In our view by limiting the research to a single crime type or offender or geographical area the ability to predict has limited value to operational policing. In order to effectively prevent crime and arrest offenders, it is necessary to effectively target the geographical area where crimes are occurring or will occur. This is ALL crime and not just an individual crime type. Therefore, we suggest that KDD could be and should be used on all crime types together with offender data, as a whole, to predict crime and criminality.

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