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Introduction of STEM: Space-Time-Event Model for Crime Pattern Analysis

[1]Kelvin Leong, [2]Stephen Chan, [2]Vincent Ng and [2]Simon Shiu
[1]School of Accounting and Finance, [2]Department of Computing,
The Hong Kong Polytechnic University, Hong Kong

Abstract: Successful law enforcement depends upon information availability. In criminal knowledge discovery, many techniques have been developed for analysis, mapping, modeling and prediction. However, most approaches treat the spatial and temporal aspects of crime as distinct entities, thus, ignoring the necessary interaction of space and time to produce criminal opportunities. In this study, a new crime pattern analysis model, STEM (Space-Time-Event Model) is presented. The new model allows users to investigate the spatio-temporal patterns of events. We also discuss relevant crime theories and related data mining methods. Two experiments were conduced to test the model. Using STEM, we found strong correlations between holidays and crime clusters. On the other hand, we could not find obvious seasonal dependency, at least in our test data set. These findings are corroborated by related empirical crime studies.

Key words: Spatial-temporal data mining, crime analysis, data mining, knowledge discovery, association rule, clustering

INTRODUCTION

Criminologists are interested in analyzing crime patterns because understanding offender behavior can help crime reduction and prevention. Underlying theories that help explain crime behavior include environmental criminology of Brantingham and Brantingham (1991), routine activity theory suggested by Cohen and Felson (1979) and rational choice theory proposed by Derek and Clarke (1986). Environmental criminology focuses on criminal patterns within particular environments and analyzes the impacts of these external variables on people's cognitive behavior. Routine activities theory suggests that a crime requires a motivated offender, a suitable target and the absence of a capable guardian. Rational choice theory believes that reasoning actor, who weighs means and ends, costs and benefits and makes a rational choice.

Crimes are also known to vary with time and location (Skogan, 1990; Loukaitou, 1999). Xue and Brown (2003) analyzed criminal behavior in space and time as spatial choice models and showed that they provide efficient and accurate predictions of future crime patterns. On the other hand, Clarke (1995) showed that situational crime prevention can reduce crime by altering the environment. It aims to stop crime before they occur. Situational crime prevention can also mean improving street lighting, adding video surveillance cameras or just getting more pedestrians on the streets.

In crime analysis, the challenge of knowledge discovery is the interplay between space, time and the event. As per Ratcliffe (2002), crime follows opportunity, it does not necessarily follow that opportunities remain constant over time. Brantingham and Brantingham (1984) explains that opportunities are unevenly distributed across time and space and the availability of motivated offenders and suitable targets changes for many locations throughout the day.

In recent years, data mining techniques has begun to be explored and integrated into crime analysis. Data mining, sometimes called knowledge discovery, is the process of analyzing data from different perspectives and summarizing it into useful information. Technically, data mining is the process of finding correlations or patterns in large relational databases. However, most data mining techniques deal with one or the other of spatial or temporal semantics, with very few handling both at the same time. In this study, we present STEM (Space-Time-Event Model) to fill this gap. Our interest arises from a desire to discover patterns relating spatial, temporal and crime type data to discover crime pattern. Currently, we are not aware of such integrated model available for crime pattern discovery purpose. This model enables the decision maker to acquire comprehensive knowledge from the dynamic spatio-temporal relationship of event and to achieve crime prevention purpose.

Corresponding Author: Kelvin Leong, School of Accounting and Finance, The Hong Kong Polytechnic University, Hong Kong

MATERIALS AND METHODS

Spatial crime analysis and hotspot techniques: Spatial analysis approaches play a key role in crime prevention planning. The hotspot technique is widely used for crime analysis. A hotspot is a geographical area with higher-than-average incidences of certain disordered events, or an area where people have a higher than average risk of victimization. This is interesting because everything is related to everything else but nearby things are more related than distant things (Tobler, 1970). Several clustering techniques include point locations, hierarchical, partitioning, density and clumping techniques etc are used to find hotspot. According to Gonzales *et al.* (2005), the general techniques for discovering crime hotspots were mean center, standard deviation distance, standard deviation ellipse and data clustering.

Temporal crime analysis: Time is often a critical factor in crime analysis. Gail *et al.* (2006), lists possible questions/functions on time data:

- Given a moving feature, where has it been and where is it likely to go next?
- Given a series of events, is there a temporal pattern?
- Given a type of geospatial change, is there a pattern in how, when or where the change occurs?

Traditionally regression is widely adopted to support crime pattern discoveries. Typical examples such as in (Brown and Oxford, 2001), criminologists employed routine activity theory and broken windows theory to evaluate several regression models for breaking and entering crime prediction.

However, the basis of regression technique is to observe a long period of time, usually >10 years. For examples (Cohen and Felson, 1979), the study analysis the crime rate in United States from 1947-1974 and concluded the positive and significant relationship between household activity variable and crime rate trend. Greenberg (2001) collected 31 years data, from 1946-1997, to study the crime-unemployment relationship, Cohen and Felson (1980) study the reason of continued increases of crime in the 1960's and early 1970's despite the decrease in a variety of factors that many believed led to crime, It finds that in order for a crime to occur, a motivated offender, a suitable target and the lack of a capable guardian must converge in both space and time.

Spatio-temporal mining and association rule: One of the purposes of spatio-temporal data mining is to reveal the spatial and temporal relationships among spatial entities at various levels of detail (granularity) (Yao, 2003). Association rule mining (Agrawal *et al.*, 1993) finds interesting associations and/or correlation relationships among large set of data items. This is a popular and well researched technique in data mining. Many methods of association rule mining have been developed for spatial and temporal knowledge discovery.

Spatial association rules is an approach to discover association rules among spatial itemsets and possibly some non-spatial itemsets, while temporal association rules (Ale and Rossi, 2000) is the approach to discover the interesting association rules, which only appear in particular time period.

Based on temporal association rule, calendar-based temporal association rules (Li *et al.*, 2003) discovers association rules during the time intervals specified by user-given calendar schemas. In this approach, the calendar schemas are used to make the discovered temporal association rules easier to understand. The calendar schema is in the form <year, month, day>, where year, month and day may be a wildcard symbol*. For example, <2007,*, 6> corresponds to the time intervals, each consisting of the 6th day of a month in year 2007. Two types of associations rules, precise-match and fuzzy-match, can be discovered for association rules hold during every interval and most of these intervals, respectively.

Temporal Association Rules (TAR) on evolving numerical attributes (Wang *et al.*, 2001) intends to discover temporal association rules that capture the correlation among numerical attribute evolutions. TAR has been implemented to support the discoveries of crime patterns in a district of Hong Kong (Ng *et al.*, 2007).

A recent study of Grubesic and Mack (2008), explores the utility of statistical measures for identifying and comparing the spatio-temporal footprints of different crime types. The study shows that different crime types have dramatically different spatio-temporal signatures.

Brown *et al.* (2001) assumed criminal incidents were random events in space and time and a model based on transition density was suggested. It reported on the use of locations and location features of prior crimes to predict the probable areas of future crimes. A spatio-temporal framework suggested for crime reduction by Ratcliffe (2004) presented spatial and temporal hotspots in a matrix format. Corresponding crime prevention resources such as plain clothes patrols, improved lighting, CCTV etc are rearranged to combat crime. Leong *et al.* (2008) proposed a framework to measure the crime pattern displacement or diffusion. Crime displacement implies removing opportunity for crime does not actually prevent crime but merely moves it around.

Crime analysis in practice: Crime analysis is increasingly automated. Regional Crime Analysis Program (ReCAP) (Brown *et al*., 2000) is a framework for mining crime data, applying data fusion to integrate data from multiple sources and data mining to discover patterns and relationships. The Criminal Relationship Visualizer in CopLink (Chen *et al*., 2003) helps law enforcement officials to process large amount of criminal related data and leads by associating different entities. It presents relationships between different crime related entities, such as people involved in crime, time, location, organization. Beside, CopLink connect is a subsystem for data sharing between diverse police departments. CopLink detect is another subsystem, which makes use of the concept space technique to identify and visualize associations among data objects. The underlying information space contains detailed criminal case reports, in the form of both structured and unstructured data. However, CopLink detect does not currently produce maps, nor does it support temporal analysis or visualizations.

Henry and Bryan (2000) intends to demonstrate the usage of GIS in crime analysis instead of hidden crime pattern discovery. It facilitates GIS to provide insights into the spatio-temporal distribution of motor vehicle theft.

STAC Block (1995) is developed by the Illinois Criminal Justice Information Authority and supported by the US. Department of Justice, Bureau of Justice Statistics. This is a tool to find and examine Hot Spot areas on the map. It consists of 2 PC software programs the time analyzer and the space analyzer. The STAC Space Analyzer is not a mapping package, but is a tool to find and examine Hot Spot Areas on the map, while the time program helps determine the most likely time of day and day of week that a particular type of crime will occur. However, these 2 programs are not combined.

A number of visual tools are reported by Adrienko and Adrienko (2004) to explore spatial-temporal variations in crime data, including animated thematic maps, map series, value flow maps, time graphs, etc., enhanced by attribute transformations, while these tools are focused more on visualization.

Proposed model for crime analysis

Introduction of STEM: Let Y be a relational database consisting of raw data of daily transactions. Let R be a relation specified for STEM purpose. Y generates different Rs. Each R represents a specific temporal view, such as week, month, holiday, quarter etc. In STEM, data are ETL (extracted, transformed and loaded) into relation R from Y. The relation R could be created on the fly or be updated as realized table from the relational database Y. Each R consists of 3 attributes: spatial attribute, temporal attribute and event type attribute. The event type attribute could be all kinds but spatial or temporal data. For example, we can use disease type for disease pattern analysis or use crime type for crime pattern discovery. Mining patterns in STEM is to identify significant spatio-temporal event rules.

STEM consists of 2 major phases, data transformation and knowledge discovery. Figure 1 illustrates of the overall concept of STEM. In phase 1 spatial data are transformed by clustering; this process can help user to reduce the size of the data set. As a result, decision maker can focus on predefined number of clusters; it makes resource planning more efficient. On the other hand, temporal data are mapped into meaningful format, it allows user to represent the original date attribute into a more appropriate representations, such as month, holiday etc. For the event type information, the selected features will be extracted directly from the original database. Phase 2 is knowledge discovery. Association rule mining is applied in STEM.

As an example, suppose we have a relational database as Table 1, based on different temporal views, we can create different Rs. For example, an R with quarter view is represented as Table 2. The number of transactions in R and Y should be equal. Table 3 shows the concepts of mapping.

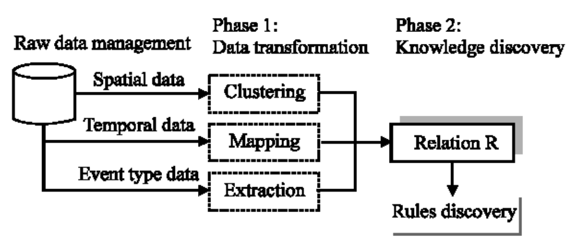

Fig. 1: Concept diagram of STEM

Table 1: Relational database

Trans ID	Location	Date	Event type	Others
T001	A street	01-May-08	Theft	-
T002	B street	01-May-08	Robbery	-
T003	C street	11-July-08	Theft	-

Table 2: R with quarter view

Trans ID	Space	Time	Event
T001	Cluster 1	Quarter 2	Theft
T002	Cluster 1	Quarter 2	Robbery
T003	Cluster 3	Quarter 3	Theft

Table 3: Mapping concept

Trans ID	Space	Time	Event
Transactions from Y			
T001	Building A	07-June-08	Rain
T002	Building B	07-June-08	Sunny
T003	Building A	09-June-08	Sunny
T004	Building C	10-June-08	Rain
Transactions from R			
T001	Cluster 1	Saturday	Rain
T002	Cluster 2	Saturday	Sunny
T003	Cluster 1	Monday	Sunny
T004	Cluster 2	Tuesday	Rain

Phase one: data transformation

Clustering: A cluster is a collection of objects, which are similar to each other and are dissimilar to the objects belonging to other clusters. In our approach, the similarity criterion is Euclidean distance. The 1st phase of STEM is to identify hotspots by clustering techniques. The aim is to derive a set of hotspots with the numbers of hotspot defined by the user. We allow the users to specify, the number of hotspots as a practical consideration. In crime prevention planning, police officers would divide a region into several smaller patrol areas (beats). Very often, the desired number of clusters depends on available resources. Hence, we allow the user to choose the number of hotspot but retain an unsupervised approach to locate those hotspots. In STEM, a hierarchical method is used for clustering purpose. Cluster is the standard format to represent spatial information. Each cluster stands for a spatial control unit. User can decide the number of units (clusters) as per available resources.

Hierarchical methods: In hierarchical clustering, the data are not partitioned into a particular cluster in a single step. Instead, a series of partitions take place, which may run from a single cluster containing all objects to n clusters, each containing a single object. The clusters are constructed in 3 steps. The 1st step pair-wise distance computes the Euclidean distance between pairs of all objects. The 2nd step creates a hierarchical cluster tree using the weighted average distance. The final step constructs clusters from the hierarchical cluster tree. The number of clusters created is per user defined. Figure 2 shows the clustering algorithm in STEM.

Temporal data mapping: Many researches have established the temporal dependency of criminal activities. For example, Jacob and Lefgren (2003) discovered that the level of property crime committed by juveniles decrease by 14% on days when school is in session. This is possibly because teenager has more spare time in long school holidays to commit crime. Beside, some other studies have discovered seasonal crime patterns (Siegel, 2006; Sorensen, 2004).

Algorithm: Clustering
Inputs: The number of clusters n and a database containing x, y coordinates data
Output: A set of n clusters
Method: Pair-wise distance calculation for all events of x, y coordinate location
Form n clusters per user defined

Fig. 2: Clustering

The crime patterns of winter peaks are observed in many European countries. One reason may be that the days are shorter in the winter, affording offender greater concealment in the dark. These 2 examples explain that the user can analyze crime pattern by means of different temporal representations.

Calendar attribute can be represented in many ways depending on the context. Moreover, calendar attribute in different forms will provide not only different meaning but also different hints for crime analysis. For example, 25th December 2008 can be represented as holiday or winter. These 2 temporal meanings (holiday and seasonal) can give users different views to analyze crime. In order to allow user to manage temporal data meanings for crime analysis, we propose temporal data mapping based on the concept of Domain Generalization Graph (DGG) (Hamilton *et al*., 1996; Hamilton and Hilderman, 2001).The purpose is to helps user to conceptualize temporal data into different meaning formats, such as holiday, day of week, month etc. For example, based on DGG, user can represent 1st January 2008 to holiday or weekday. This mapping allows user to analyze crime pattern based on different temporal views. Figure 3 shows an example of DGG.

Phase 2

Knowledge discovery: Association rule mining (Agrawal *et al*., 1993) is a popular and well researched technique for discovering interesting relations among large set of data items. For example, police officer may be interested to know if certain groups of crimes consistently occur together. The basic principles and concepts of association rule are as the following. Let D be a database of transactions and $I = \{i_1, i_2, \ldots, i_n\}$ be a set of literals. Each transaction T consists of a set of items where $T \subseteq I$. An association rule is an expression of the form: $X \Rightarrow Y$ where X and Y are set of some items (itemset) in I and Y does not present in X. An association rule has 2 set of thresholds to express the degree of relationship about the rule. Firstly, the support supp (X) of an itemset X is defined as the proportion of transactions in the data set, which contain the itemset.

Secondly, the confidence of a rule is defined as conf ($X \Rightarrow Y$). It can be interpreted as the probability that occurrence of X causes occurrence of Y.

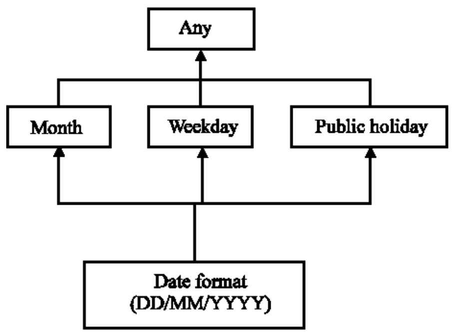

Fig. 3: An example of DGG diagram

For a rule to be interesting, the rule must satisfy a user-specified minimum support and a user-specified minimum confidence at the same time. To achieve this, association rule generation is a 2-step process. First, minimum support is applied to find all frequent itemsets in a database. In a 2nd step, these frequent itemsets and the minimum confidence constraint are used to form rules.

RESULTS AND DISCUSSION

We have adopted the new model, STEM, to support crime analysis for a district in Hong Kong. The idea is to develop a system, which can help crime analyst to trace common criminal patterns within the district by providing intelligent spatial and temporal analysis tools, together with a visualization of geographical information. The data used here is a crime database for a 2 year period in the early 2000's. There are a total of 6,076 instances in the crime history of the district in that period.

Implementation: The entire model is implemented into 4 parts, association rule mining, clustering, data management and visualization. All data are stored and managed in MS Access 2003 database. Spatial clusters visualization is performed in Map WindowsGIS. Totally 10 clusters have been generated for experiment purpose. Our experiments are based on these clusters for knowledge discovery.

Experiment 1

Clusters, holiday and crime types relationship: Some researches has proved the existing of relationship in between holiday and crime, such as Jacob and Lefgren (2003) suggested that the level of property crime committed by juveniles decrease by 14% on days when school is in session, but the level of violent crime increases by 28% on such days.

In 1st experiment, we attempt to investigate the format of relationship in the district. In phase 1, we had converted the calendar date attribute into holiday indicator and then we executed phase 2. Set minimum support 10% (equivalent to 608 instances) and minimum confidence 60%, the 5 best rules (i.e., highest confidence rate) are listed in Fig. 4. Rule 1 shows strong relationship between cluster α and holiday, 97% of crime cases in cluster α occurred during non-holiday. The assoication can be explained by the environment of this cluster. The area occupied by cluster α is a commercial zone, where only few workers stay during the holidays. As a result, opportunities (potential victims) for crime are reduced. This explanation can be applied to rule 4 as well.

We find that most of obtaining property by deception (rule 2), shop theft (rule 3) and miscellaneous theft (rule 3) occurred during non-holidays. Rule 2 is easy to understand because obtaining property by deception is a kind of white collar crime, which usually happens on working days. Rule 2 may comes as a bit of surprise that shop theft is not frequent on holidays. However, it is possible that many family type retail shops located in the district are closed on the holidays. Thus, the crime rate drops as well. Such rules provide hints to crime analysis for further investigation. For example, we can include the percentage of shops that are open on a particular day as an attribute for rule mining or refinement. Figure 5 shows the cluster α and cluster δ.

Experiment 2

Clusters, quarter and crime types relationship: In this experiment, we combine clusters, quarter and crime types for analysis. Given minimum support 3% (equivalent 182 instances) and minimum confidence 25%, the best 5 rules (i.e. highest confidence rate) are listed in Fig. 6.

Rule 1 shows miscellaneous theft mainly occurred in quarter 4. Similarly, most miscellaneous theft occurred in the 2nd half of the year (quarter 3 and 4) as per rule 2 and rule 5. On the other hand, the peak crime quarters for cluster β were Q2 and Q4. We believe that the main reason is because 2 long holidays, National day and Christmas, are in 2nd half of year. However, these findings can only reflect non-obvious relationships but can not reveal the strong association between clusters, quarter and crime types.

To prove further, we may then include holiday and non-holiday as an attribute or refine the granularity of the temporal attribute. Figure 7 shows the cluster β.

On the other hand, the low confidence rate may indicate that the seasonal dependency of criminal activities is not strong. This crime pattern has been discussed in previous research. Yan (2004) discovered this Hong Kong experience by examination of the rates of property crime in Hong Kong for the period 1991-2000. To determine the seasonal dependency, regression analysis

1. Clusters = α 658≥holiday = Non-holiday 640, conf: (0.97)
2. Offence = OBTAINING-PROPERTY-BY-DECEPTION 683 ≥ holiday = Non-holiday 662, conf: (0.97)
3. Offence = THEFT-(SHOPTHEFT) 669≥holiday = Non-holiday 647, conf: (0.97)
4. Cluster = δ545≥holiday = Non-holiday 525, conf: (0.96)
5. Offence = THEFT-(MISC) 1719 holiday = Non-holiday 1643, conf: (0.96)

Fig. 4: The 5 best rules of experiment 1

Fig. 5: Cluster α (left) and cluster δ (right)

1. Offence = THEFT-(MISC) 1719≥quarter = Q4 607, conf: (0.35)
2. Quarter = Q4 1886≥Offence = THEFT-(MISC) 607, conf: (0.32)
3. Clusters = β1371≥quarter = Q4 413, conf: (0.3)
4. Clusters = β1371≥quarter = Q2 397, conf: (0.29)
5. Quarter = Q3 1602≥Offence = THEFT-(MISC) 428, conf: (0.27)

Fig. 6: The 5 best rules of experiment 2

Fig. 7: Cluster β

(using dummy variables) and Analysis of Variance (ANOVA) were employed; the result shows no seasonal dependency.

The finding concludes that economic needs are a prominent factor, instead of the effect of the season; it also can be used to support our results in experiment 2. The low confidence rate result implies that seasonal relationship in our data is not apparent. The higher crime rate in 2nd half of year is mainly caused by holiday's factor (economic needs).

CONCLUSION

Previous research demonstrated that crime can be reduced by altering the environment. It is possible to stopping crime events before they occur. To achieve this, understanding criminal behavior and pattern is necessary. Space, time and event are critical knowledge ingredients of the crime analysis. Despite many data mining techniques have been applied for crime analysis, most of them treat the spatial and temporal aspects of crime as distinct entities, only very few handling both together. A new model, Space-Time-Event Model (STEM), has been introduced. The model incorporates space, time and event into consideration for crime pattern discovery purpose. The research reported in this study, could be viewed as a step towards enhancing the completeness of crime pattern analysis.

Major crime theories and related data mining studies have been discussed in the study. We also tested the results of STEM by applying it to crime data in a district of Hong Kong. For this data set, the rules generated from our model corroborated by previous empirical crime studies.

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