CHAPTER 2

BACKGROUND OF THE STUDY

2.1 INTRODUCTION

In this chapter, the study of clustering based on crime similarity relates to previous works on subspace clustering, existing classification algorithms for finding the crime classification based on the crime attribute. It also deals with how to forecast the crime based on the simulation, functions and parameters used in the existing simulation to forecast. In section 2.2, it is shown that the existing subspace clustering techniques most relate to this study. In section 2.3, it compares various grids based subspace clustering algorithms and the benchmarks. In Section 2.4, it is shown that the existing data mining classification algorithms relate to a Tree induction method for crime classification. In section 2.5, it is shown how to identify the positive and negative characters of the particular class of the crime. In section 2.6, it compares the existing classification algorithms which relate to this study. Section 2.7, shows the previous works done in simulations for forecasting crime.

2.2 RELATED SUBSPACE CLUSTERING ALGORITHMS

There are several recent studies focusing on mining subspace clusters embedded in high-dimensional regions. Still, sturdy relationships might exist among a group of objects even though they are so much apart from each other as measured by distance functions (such as Euclidean) used
frequently in traditional clustering algorithms. It is essential to identify clusters of objects that manifest coherent patterns. A variety of applications, as well as microarray analysis, Electronic commerce collaborative filtering and crime density clusters identifications will benefit quick algorithms which will capture such patterns.

**CLIQUE (CLustering In QUEst) Algorithm for Clustering**

It creates the use of ideas of density and grid based techniques. In the initial step, CLIQUE partitions the n dimensional data space S into non-overlapping rectangular components. The components are obtained by partitioning each dimension into a number of intervals of equal length. Number of intervals are an input parameter; selectivity of a component is outlined because the total data points are contained in it. A component u is dense if selectivity is bigger than the threshold, where the density threshold is another input parameter. A unit within the subspace is the intersection of an interval of each of the K attributes. A cluster could be a maximal set of connected dense components. 2 K-dimensional components u1, u2 are connected if they need a regular feature. The dense components are then connected to create clusters. It uses an apriori algorithm (bottom up algorithm) to search out dense units. The dense units are identified by employing a fact that if a K dimension component (a1, b1)* (a2, b2) … (ak, bk) is dense, then any k-1 dimension unit (a1,b1) * (a2,b2)… (aik-1,bik-1) is additionally dense where (ai, bi) is that the interval of the component within the ith dimension.
STING Algorithm for Clustering

STING (A Statistical INformation Grid Approach to spatial Data Mining) could be a grid based multi resolution clustering technique within which the spatial area is split into rectangular cells and employs a hierarchical structure. There are typically many stages of such rectangular cells equivalent to completely different stages of declarations. Each cell at a high stage is partitioned to generate child cells at a subordinate level. A cell in level $i$ corresponds to the union of its children at a level $i + 1$. Every cell has 4 children and every child corresponds to at least one quadrant of the parent cell.

Statistical data regarding the attributes in every grid cell compute and store, mean, Standard Deviation maximum and minimum values and stored. Arithmetic parameters of higher stages cells can simply be computed from the parameters of minor level cells. For each cell, there are attribute self-determining parameters and attribute child parameters.
i. Attribute self-determining parameter: count

ii. Attribute child parameters

When the data are loaded into the database, the parameter count, mean, standard Deviation, min, max of the bottom stage cells are calculated directly from the data. First, a layer is resolve from which the query processing process is to start. This layer may consist of a small number of cells. Each cell in this layer test checks the relevancy of the cell by computing assurance internal. Unrelated cells are removed and this process is repeated until the bottom layer is reached.

**Merging of Adaptive Intervals Approach (MAFIA) for Clustering**

MAFIA advances CLIQUE by launching the impression of adaptive grids. The Adaptive grids moderate one among the core problems of grid-based approach: the exchange between computationally exhaustive well grids and inaccurate common grids. A primarily well grained histogram is employed to mix bins in areas that have a density less than average. The outcomes are a variable dimension grid structure with better resolution in areas with high density, i.e. areas that are more striking. The bottom-up approach utilized by CLIQUE for candidate creation is replaced with the exclusion that any $K_i^2$ corresponding dimensions can surface for two $K_i^1$ dimensional candidates to be connected into a k dimensional candidate, not basically the primary $K_i^2$ dimensions. CLIQUE and MAFIA computer overlapping clusters whereas the outstanding ways are targeted at computing a partition of the data set.

**Projection-Based Clustering Algorithm (PROCLUS) for Clustering**

PROCLUS is a projection-based clustering algorithm. PROCLUS generates subspace clusters by allowing for every cluster C a subspace which
gives up the best cluster for the connected axes-parallel projection of the cluster. The cluster calculation itself is based on a hill-climbing method comparable to the CLARANS limited search approach. An early set of possible cluster midpoints $M$ is selected based on an adapted greedy approach, for each iteration the algorithm then finds out the best dimensions of subspaces connected with each midpoint in the set of current midpoint $M \frac{1}{2} M$. Specified a maximal round neighborhood $L_i$ of a midpoint $m_i$ that does not have any other $m_j \in M$, the middling distance $X_{i:j}$ of a neighborhood point $L_i$ to $m_i$ beside dimension $j$ is resolute. The best dimensions are selected as the smallest $X_{i:j}$, returning to the suggestion that along an appropriate dimension of a midpoint $m_i$ points should be close to that midpoint.

**Ranks Interesting Subspaces of a Data Set (RIS) for Clustering**

The method is based on the ideas of density and center objects first defined in the background of the DBSCAN algorithm. In fundamental nature, those subspaces are considered most interesting that contains the maximum number of points in $\varepsilon$ neighborhoods approximately core objects in the subspace. At the last, the algorithm first calculates for every core object $o$ those subspaces in which $o$ can still be considered a core object in a bottom-up approach. The set of subspaces is consequently pruned where advanced dimensional subspaces are of higher quality than their lower dimensional projections. Additionally, a heuristic approach is offered to prune those $k$ dimensional subspaces that can be considered a mixture of a high-quality $K_i$ dimensional subspace and a low-quality $1$ dimensional space. The surveillance behind this latter reduction is that a $k$ dimensional subspace ensuing from such a mixture is not the best possible $k$ dimensional subspace for the subsequent clustering.
2.3 COMPARISON OF GRID BASED SUBSPACE CLUSTERING ALGORITHMS

Table 2.1 Comparison of Clustering Algorithms

<table>
<thead>
<tr>
<th>Algorithm Name</th>
<th>Data type</th>
<th>Important Parameters</th>
<th>Method</th>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLIQUE</td>
<td>Numerical data</td>
<td>1. Number of Intervals 2. Density Threshold</td>
<td>Bottom up Approach</td>
<td>Connected Dimensions grid only forms clusters</td>
<td>Not Connected Means it is Ideal</td>
</tr>
<tr>
<td>STING</td>
<td>Spatial Data</td>
<td>Number of Objects in Cell</td>
<td>Query Processing</td>
<td>Test all the Internal cell</td>
<td>Unrelated Data is removed at last.</td>
</tr>
<tr>
<td>MAFIA</td>
<td>Numerical Data</td>
<td>1. self-determining parameter 2. child parameters</td>
<td>Bottom up Approach</td>
<td>Overlapping Clusters are Computed</td>
<td>Produce higher resolution high density regions only</td>
</tr>
<tr>
<td>RIS</td>
<td>Subspace Dataset</td>
<td>Core Object of Subspace</td>
<td>1. Heuristic 2. Pruning</td>
<td>Mixture of High quality Dimensions Cell</td>
<td>Core Objects O are Tested in Bottom up Approach and pruned.</td>
</tr>
<tr>
<td>PROCLUS</td>
<td>Axes-Parallel Points</td>
<td>Midpoints</td>
<td>Hill-climbing</td>
<td>Find the Cluster density based on Neighborhood Point</td>
<td>It is adapted Greedy Approach</td>
</tr>
</tbody>
</table>

2.4 RELATED CLASSIFICATIONS ALGORITHMS

Classification techniques have been established to be very successful for crime analysis and crime forecasting. It might be applied to categorize crime data. The distributed data mining algorithm uses a practical value algorithm to calculate C4.5 algorithm, CART algorithm and naïve Bayesian classification algorithms. The technique was applied to crime attribute classifications. The neural mining approach uses rule-based association rules to mine representative data. The approach discusses the importance of use of existing non-numeric data in crime analysis and crime forecasting.
Naive Bayesian Algorithm for Crime Classification

Naive Bayesian classification considers that the crime attributes of an instance are self-determining, given the target crime attribute. The target is to allocate a new instance of the class that has the highest successive likelihood. The algorithm is very successful and can give improved predictive accuracy when compared to C4.5 decision trees and back propagation which was used in crime classification.

Decision Trees and Tree Induction Methods

Decision trees are machine learning techniques that communicate self-determining attributes and a needy attribute in a tree-shaped structure. Classification regulations take out from decision trees, are IF-THEN expressions in which the necessities are logically ANDed and all the experiments have to succeed if each rule is to be produced. The associated applications include the analysis of instances from serious crimes such as drug related homicides crimes, serial sex crimes and homeland security.

C4.5 algorithm is used to divide data based on sections based and to generate expressive classification rules that can be used to classify a new occurrence. C4.5 algorithm can assist to make predictions and to extract crime patterns. It creates regulations from trees and handles numeric crime attributes, absent values, pruning and estimating error rates. The classification and learning steps are usually fast. But, performance decrease can occur when C4.5 algorithm is applied to large datasets. C5.0 algorithm illustrates marginal improvements to decision tree induction. There are 4 main classification techniques used in classification applications.

1. Classifiers
2. Integrate multiple classifiers
3. ANN approach to clustering

4. Visualization techniques to describe the patterns.

**Decision Tree Based Algorithm**

Explaining the classification problem is a two-step procedure:

i) Decision tree induction- constructs a Decision Tree (DT).

ii) Apply the DT to determine its class. Rules can be generated that are easy to interpret.

There are three basic steps used in this classification algorithm. They are as follows:

1. Assume there are two outputs, crime space and crime time. The decision tree starts as a single node N representing the dataset. If the occurrences of the tree are of the same type crime space, next node becomes a leaf and is labeled as crime space.

2. Or else, the algorithm uses an Entropy method, Gini Index method and Classification Error to measure the degree of contamination for selecting the attribute that will best separate the data into individual classes.

3. Entropy is calculated as the sum of the conditional probabilities of an event \((p_i)\) times its information required for the event in subsets \((b_i)\). Note that \(b_i = - \log_2 p_i\) in the case of a simple binary split into two classes.
C4.5 Algorithm for Crime Classification

In this method, expected information required to classify a given occurrence is: If entropy is the amount of information provided by the outcome of a random variable, conditional entropy can be defined as the amount of information about the outcome of one random variable provided by the outcome of a second random variable. The C4.5 algorithm calculates the information gain of each attribute. The attribute with the highest information gain is the one selected for test attribute.

\[
\text{Gain (attr)} = \text{Entropy of parent table} - E(A)
\]

After finding the gain information, a branch is shaped for each known value of the test attribute. The C4.5 algorithm uses the same process iteratively to form a decision tree at each separately. Once an attribute has occurred at a node, it need not be considered in any of the node’s descendents.

The iterative separation stops when one of the conditions is satisfied: a) The examples of the given node belong to the same class or there is no node for further partitioned and b) there is no samples for branch test attribute.

2.5 EVALUATION OF TRUE POSITIVE AND FALSE NEGATIVE IN CLASSIFICATION

There are two ways to examine the performance of classifiers: confusion matrix and to use an ROC graph. Specified a class, Cj and a tuple, ti, that tuple might or might not be allocated to that class while its actual membership might or might not be in that class.

There are four possible outcomes with the classification as: true positives, false positives, true negatives and false negatives.
Observed

<table>
<thead>
<tr>
<th></th>
<th>Crime</th>
<th>Crime Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime</td>
<td>TP</td>
<td>FP</td>
</tr>
<tr>
<td>Crime Class</td>
<td>FN</td>
<td>TN</td>
</tr>
</tbody>
</table>

**Figure 2.2 Confusion Matrix**

Figure 2.2 shows a confusion matrix used for finding the true positive and false negative analysis in classification algorithms.

### 2.6 COMPARISON OF CLASSIFICATION ALGORITHMS

**Table 2.2 Comparison of Classification Algorithms**

<table>
<thead>
<tr>
<th>Algorithm Name</th>
<th>Important Parameters</th>
<th>Method</th>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve Bayesian classification</td>
<td>Database with classifiers</td>
<td>Decision Trees and Back Propagation</td>
<td>An instance of Class created for Targeted crime</td>
<td>Accuracy Compared by other Algorithms</td>
</tr>
<tr>
<td>C4.5, C5.0 Algorithm</td>
<td>Classification Rule Based data</td>
<td>Decision Tree Induction</td>
<td>Clustering and Visualization Are Possible for Classifiers</td>
<td>Splitting of Tree is not easy</td>
</tr>
<tr>
<td>CART</td>
<td>Categorize Crime data</td>
<td>Rule-Based Classification</td>
<td>A rule can generate Easy to Interpret</td>
<td>Class Determination in DT is difficult</td>
</tr>
</tbody>
</table>

### 2.7 EXISTING FORECASTING SIMULATIONS

In the increasing literature of criminology, there are many widely stated crime theories that created important contributions to the understanding of how crime incidents occurred and distributed across space. During the recent advances in environmental criminology and computational criminology in conflict, those future crime events can be estimated or simulated. Used for
simulation approaches, as a discussion of the cellular automata and multi-agent based simulation are included in this review to provide the background platform for developing simulation for crime forecasting.

**Crime Simulations**

After tracking how crime distributed and how the crime occurred, crime often face a difficult task of having to predict or estimate future trends in a What If analysis setting. Brantingham and Brantingham (2004) suggest that simulations would be an effective solution for approximating future developments with current settings under a defined set of assumptions.

How a spatial crime pattern can develop is usually an extended temporal method. Just like the method of urbanization, such future phenomena may be best studied by suggesting that of simulations as a result of which they have a tendency to be irreversible processes. Once a collection of assumptions is outlined to replicate how the underlying factors can bring modification over the studied time amount, simulations will be applied to get different situations based on different settings of the underlying facts or different assumptions (Liu and Eck 2008).

Computer simulations are disputed by (Brantingham and Brantingham 2004) to be another two existing analytic methods for crime studies. The strength and effectiveness of computer simulations do not seem to be, however, totally determined. However, in many ways, these are tough to evaluate as they need a methodological shift from standard statistical summaries to addressing the validity of linking individual interacting behavioral mechanism to combine behavioral patterns.
Cellular Automata Simulation for Crime

Benenson and Torrens (2005) cellular automata was first launched by Neumann in the early 1950’s. With this being established, Wolfram extended the utilization of cellular automata to alternative fields and applications. In view of the fact that the 1990’s, cellular automata has been established and joined with GIS for numerous spatial applications. For instance, (Takeyama and Couclelis 1997) incorporated cellular automata with GIS to perform map algebra. (Wu 1999) uses CA to examine space-time processes in a GIS environment. In line with (Goodchild 2003) CA has been identified collectively of the outstanding advances in GIS modeling.

Batty et al (2005) In geographical framework, a significant amount of work on cellular automata have been focused on modeling urban dynamic, (Barredo et al 2003) urban growth, (Torrens 2006) and urban sprawl, with very restricted pointing out of crime. Fundamentally, cellular automata could be a discrete model consisting of an infinite number of regular grid cells, every in one among a number of circumstances. When applied to real world issues, the model usually consists of a finite number of cells. The condition of a cell at time t is a function of the circumstances of a finite number of cells at time t-1. These neighbors are a variety of cells relative to the specified cell. (Benenson and Torrens 2005) Two regular neighborhood types; there are the single point adjacency and non-single point adjacency for neighborhood type.

For the duration of a simulation run, each cell has the similar rule for revising, based on the values in its neighborhood. In common, the state of automation will be outlined as a function of the circumstances of the automation of the central cell and its neighbors, the position of transition rules needed to adapt the automation over time. Whereas simulating how cells alter their circumstances, their locations in their particular neighborhoods remain constant over time. This is called the stationary of the automata. Between
neighboring cells, information will be exchanged over time that allows for spatial information propagation.

**Multi-Agent Based Simulation for Crime**

A newer technique for simulation is an agent-based simulation model that is commonly known from two key fundamentals: independent decision-making entities known as agents and a few kinds of network or environment they populate. Agents have specified the flexibility to think about individual-oriented performances, permitting human-like decision. This is often a key distinction; the MABS has from cellular automata. During a simulation runtime, agents execute a spread of performances in unity with multiple sets of rules that govern how they understand, explain and act in a given situation. These rules outline how they interact with each other, how they read the environment and how they change the environment. The combined behavior of agents is used to inspect the appearance of macro level patterns by simulating micro level interactions over frequent iterations of the model.

Franklin and Graesser (1996), An agent is outlined as: “An autonomous agent and an MABS could be a system of multiple agents situated within and part of surroundings”. Agents sense and act on their surroundings over time. During these surroundings, agents pursue their own program that is fined as and is ruled by the rules defined by simulation style.

Agents are mixed (Terna 1998), not averaged illustration as in other modeling approaches. Additionally, agents in an MABS can be practical about reaching their set of goals. When simulated in an MABS, criminals were observed as a group of self-organizing behaviors. As an example, Singh (2005) was implemented MABS with Abstract State Machine (ASM) that simulates crime as discrete event for analytical and descriptive modeling of
crime patterns. In terms of MABS software, there is various commercial and open source agent development environments offered. These embrace, however not restricted to, SWARM, Repast, NetLogo, Mason, Agent Analyst and other test beds developed by several other research groups.

**Simulation Features**

The Existing analytical techniques like GIS, time series analysis, regression, and multi-level modeling present significant tools for those involved in the spatial and temporal distribution of crime events. In recent research, however, a brand new paradigm of applying simulation as a method of research has materialized as an alternate to existing techniques. This can be partly as a result of increasing computing power that permits finishing an outsized volume of computation during a short time that attainable within the past. Additionally, the data, usually freely accessible over the net with solely nominal prices, have enabled exploratory studies that are beyond imagination within the past.

As a result, current analysis has explained and justified the suitability of simulation techniques with environmental criminology. Brantingham and Brantinham (2004) appropriate efforts have provided a conceptual framework for such models of criminal activities. Birks et al (2008) Moreover, a variety of researchers have reported that simulation models will produce reasonable outputs when compared with real world crime clarifications.

Brantingham and Brantingham (2004) require the employment of simulation in criminology research. This decision has resulted during a range of studies as reviewed in (Brantingham et al 2005). In what seems to be the foremost comprehensive approach, (Groff 2006) dole out the variety of experimental studies using an approach of coupling Repast and ArcGIS, with
Seattle street theft and GIS crime data. It incorporates each routine activity theory and rational choice theory for theory testing, but not predictive of crime. Graf (2006) a collection of simulation environments has also been employed, but the approach of combination with GIS seems to be winning the upper hand. In terms of simulating individual behaviors of the agents, the Monte Carlo simulation comes close to estimated decision-making processes and the Object-Oriented style may be used to model advanced sets of characteristics of the agents and also the rules governing them.

Recent criminological analysis using such techniques remains in its experimental stages. Graf (2006) the most important work up to now during this area has targeted on routine activity theories of crime, albeit some use has been about ideas of enclosed rationality or utility for agent decision-making. Townsley and Johnson (2008) summarize how simulation methods might be used to make valid causal inferences within the social sciences, exclusively the study of crime. They dispute that significant threats to validity exist for simulations which if researchers do not actively take measures to reduce these crimes.

**Experiments of Crime Simulation**

Brantingham et al (2008) Mastermind is an interdisciplinary research project in computational criminology jointly managed with the Software Technology Lab at Simon Fraser University. Its foremost focus is on developing a complete computational structure for conceptual semantic modeling, discrete crime event simulation. Additionally, it had been designed for machine-assisted evaluation and validation of discrete event models used in crime analysis and anticipation. The particular focus here is on spatiotemporal characteristics of crime in urban environments, probably involving multiple offenders and multiple targets. (Borger and Stark 2003) Mastermind project is devised based on the abstract state machine formalism
and abstraction principles, a general computational paradigm for mathematical modeling of discrete dynamic system. Mastermind project system is targeted at criminologists for justification of crime patterns, for validating hypothetical theories, at police agencies for prediction of criminal behaviors, exploration support to identify and prioritize potential suspects, at town planner for effective urban planning by taking the geography of crime into consideration. When Mastermind is employed as a tool for experimental analysis, uses probabilistic methods and supporting tools to evaluate an airport security system (Glasser et al 2006).

Brantingham et al (2008) suggests four benefits of conducting crime simulations:

1. Theorizing the crime
2. Estimating the crime
3. Testing the crime,
4. Planning the crime

Liu (2007) Suggested to use six characteristics that are proposed as a structure for categorizing various approaches to simulating crime. These six characteristics of simulations are:

(1) Continuity: continuous or discrete simulation systems
(2) Environment: artificial or real environment in simulations
(3) Foundation: data-driven or theory-based simulation systems
(4) Movement: simulation with mobile or stationary agents and other components
(5) Probabilistic: deterministic or stochastic simulation systems
(6) Scale: micro or macro simulation systems.
By means of these six characteristics, Brantingham et al (2008) sets off on to classifying simulations by functions for crime theory elaboration, assessment of hidden phenomena, policy designing, and program testing. Finally, Brantingham et al (2008) jointly categorizes simulations as per ways used in the simulations as standard theorizing, simulation for elaboration and qualitative, non experimental, quasi-experimental, randomized tests as either theorizing investigations or studies that check theories.

2.8 AGGREGATIVE VS. NON AGGREGATIVE ANALYSIS

Despite reasonable illustration of statistical examples, the crime-reporting is sometimes based mostly on some geopolitical entities or some random units that are noticeably heterogeneous. Almost like most of different social sciences, crime analyses additionally take this approach to examining how patterns of crime events were formed and altered.

Preferably, analytical areas ought to be of more or less equal population size to make sure comparability of the studied phenomena between area units. As found out by (Cliff et al 1975), learning spatial distributions of geographical phenomena usually needs regionalization that in flip usually is achieved by regionalization of individual sample or observations. This method is usually referred to as aggregation. Alternatively, disaggregate data or information or samples have been collected for individual objects. For instance, Liu et al (2005) obtained and applied micro level data in simulating crime patterns.
There are several examples during which crime studies use area units because of the analytic structure. For instance, study journey to residential burglary using data that are aggregated at the block cluster level (Hayslett-McCall et al 2008). Similarly, (Quijada et al 2005) census data were used with System Dynamics to simulate criminality rates in an exceedingly vector environment. It must not be troublesome to assemble even additional examples of crime studies with census unit-based analytical structure.

It ought to be noted that when crime analysis is meted out with large area components, however, that there is the aforesaid possibility of ecological misleading notion. This can be mixture of knowledge that often uses one measure of the studied phenomena to represent what occur within the entire area unit.

Brantingham et al (2008) high levels of autocorrelation need of independence of examinations, and analyses that make it not easy to track individuals in a changing environment produce limits of statistics as the model building technique. Tobler (1970) consistent with Tobler’s First Law of Geography, models collected for relating distributions of geographic phenomena tend not to have the independence among them to accommodate the independence assumption that almost all statistical ways need. For this motivation, analyzing crime patterns need special attention to modifying or extending the applied methods to account for the spatial dependency among samples.

Besides the problems of spatial dependency and ecological erroneous belief, geographic units used for simulation and analysis must not be too small as a result of the distribution of crime which is usually not homogeneous across the study area. For instance, (Osgood 2000) notes that
aggregate crime rate from small populations cause two issues for ordinary least square regress: one violates the idea of homogeneity of error variance as a result of the precision of the estimated crime rate depends on population size and the other violates the idea of traditional error distribution because the distribution becomes increasingly tilted as crime rates approach the lower certain of zero.

Swartz (2000) using aggregate data for crime analysis has the benefits of the wider data availability and needs less training on the utilization of analytical methods. On the other hand, lack of precision and details when using aggregate data for analysis, the flexibility of describing spatial patterns usually failed furthermore as not having the ability to explain the processes with that pattern that are formed.

Smith et al (2000) for simulation of crime events and patterns, in several cases, disaggregated analysis permits higher integration between RA and SD theories. This is often as a result of individual characteristics of crime events, criminals, or targets will be simulated by multiple agents, similar to the complex reality nearer than a straightforward CA. It ought to be noted, though, that disaggregated data are harder to gather, to update and to keep up than aggregated data. Additionally, disaggregate data are expensive and time-consuming whereas processing and analyzing them.

2.9 CONCLUSION

The existing connected crime forecasting clustering simulation literature presents made discussion on building crime theories that facilitate to explain how crimes are dedicated, how environmental issues have an effect on the crime actions and with recent researches, how the geography of crime is
created and varying. Since environmental criminology and computational criminology, simulation has been suggested as a possible approach to testing varied crime theories and to providing in-depth understanding of crime patterns.

The next chapter demonstrates the methodology of crime classification, clustering and optimizing the crime hotspots primarily based on the density of the crime and also the functions of forecasting simulation functions to analyze the environmental profile with police management areas within Chennai city and its association with serious crime classes.