

**ÇUKUROVA UNIVERSITY  
INSTITUTE OF NATURAL AND APPLIED SCIENCES**

**PhD THESIS**

**Mehmet Sait VURAL**

**DEVELOPING A CRIME ANALYSIS SIMULATOR USING  
MACHINE LEARNING METHODS.**

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**MAKİNE ÖĞRENME YÖNTEMLERİNİ KULLANARAK BİR SUÇ  
ANALİZİ SİMÜLATÖRÜNÜN GELİŞTİRİLMESİ**

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## ABSTRACT

## PhD THESIS

# DEVELOPING A CRIME ANALYSIS SIMULATOR USING MACHINE LEARNING METHODS

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Crime analysis plays important role in prevention of crimes, investigate the relations among crimes, detection of criminals, helping police investigations and revealing the events quickly. In addition, it is also important to perform crime analysis for efficient use of human and technical resources. In the thesis, crime analysis is performed by using a forecasting model based on Bayesian network. As a result, decision-making system based on GIS (Geographical Information System) is proposed. Thus, the synthetic crime dataset is used to find potential criminals from crime events or crime clues. Generally five contributions are provided in this thesis: First, a parametric model is proposed to generate the incident-level crime datasets involving crimes, criminals and criminals' suspicious acquaintances where the parameters are used for fine tuned adaptation of the model. The model is based on GIS by approximating the characteristics of the population in real-life. The model can also produce random geographical maps and distribute population, crimes and criminals to the geography based on real-life approximations. Second, it is used to determine the relationship between crimes and criminal. It will be detected tendencies of criminals in relation to other crimes. At the same time, trends in the types of crime can be determined as temporal, spatial and regional. Third, a clustering based method is proposed to infer the closely related incidents using hybrid similarity metrics and it is demonstrated a decision-making process using hierarchical clustering algorithms in finding important patterns between criminals' social network and crimes in trend. Fourth, this thesis demonstrate the results of some queries related to crime analysis over the GIS dataset. Aim of this analysis, it is the detection of possible criminals by using the available data and clues about crime analysis on given synthetic dataset. Finally, relations among crime/criminal groups will be revealed in social network. In the determination of any criminal, the criminal may be found to be closer to which criminal organizations. As a result, it is possible to reach the leaders of the crime organization through the acquaintances of criminals and criminals on the suspect list.

**Key Words:** Crime/Criminal Analysis, Bayesian Network, Artificial DataSET, Hybrid Metrics, Criminal's Acquaintances in Social Network Analysis.

## ÖZ

### DOKTORA TEZİ

#### MAKİNE ÖĞRENME YÖNTEMLERİNİ KULLANARAK BİR SUÇ ANALİZİ SİMÜLATÖRÜNÜN GELİŞTİRİLMESİ

Mehmet Sait VURAL

#### ÇUKUROVA ÜNİVERSİTESİ FEN BİLİMLERİ ENSTİTÜSÜ ELEKTRİK ELEKTRONİK MÜHENDİSLİĞİ ANABİLİM DALI

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Suç analizi, suçların önlenmesinde, suçlar arasındaki ilişkilerin araştırılması, suçluların tespiti, polis soruşturmasına yardımcı olma ve olayları hızlı bir şekilde ortaya koymada önemli rol oynamaktadır. Ayrıca, insan ve teknik kaynakların etkin kullanımı için suç analizinin yapılması da önemlidir. Tezde suç analizi için, Bayes ağına dayalı bir tahmin modeli kullanılmıştır. Sonuç olarak, CBS (Coğrafi Bilgi Sistemleri)'ye dayanan bir karar alma sistemi böylelikle önerilmektedir. Böylece, suç/suçlu veri seti ve suç olayları arasındaki suç eğilimlerini ve potansiyel suçluyu bulma gibi problemlere çözüm olmaktadır.

Özetle, bu tezde genel olarak beş katkı sağlanmakta ve tüm bu yapılar tek bir çatı altında toplanarak bir suç analiz simülatörü oluşturulmaktadır. Bu konulardan ilki, suç ve suçluların şüpheli tanıdıklarını içeren olay-düzeyindeki suç veri kümelerini oluşturmak için parametrik bir model önerilmiştir. Bu model ile, veri kümeleri, nüfusun gerçek hayatta modellenmesiyle gerçek bir senaryo kavramı içinde oluşturulmuştur. Model aynı zamanda rastgele coğrafi haritalar üretebilir ve gerçek yaşam yaklaşımlarına dayanarak coğrafyaya nüfus, suç ve suçluları dağıtabilir. İkinci olarak, suç olayları ile suç arasındaki ilişkinin belirlenmesinde kullanılabilir. Burada suçluların diğer suçlarla ilgili eğilimlerinin de tespiti yapılmaktadır. Üçüncüsü, karma benzerlik ölçütlerini kullanarak yakın ilişkili suç olaylarını ortaya çıkarmak için kümeleme temelli bir yöntemde önerilmiştir. Böylelikle suçluların sosyal ağı ve suçlar arasındaki eğilimleri bulmada hiyerarşik kümeleme algoritmalarını kullanarak bir karar alma sürecinde gösterilmektedir. Dördüncüsü ise, CBS veri seti üzerinde suç analizi ile ilgili elde edilen verileri ve ipuçlarını kullanarak olası suçlunun tespit edilmesidir. Son olarak, suç grupları arasındaki ilişkiyi tespit etmede, sosyal ağ içindeki suçlunun bulunmasında ve suç örgütleri ile suçluların tanıdıkları aracılığıyla suç örgütlerinin liderlerine ulaşmada yeni bir algoritma ve model önerilmiştir.

**Anahtar Kelimeler:** Suç/Suçlu Analizi, Bayes Ağı, Yapay VeriSeti, Hibrit Metrikler, Sosyal Ağ Analizinde Suçlunun Tanındıkları

## **EXTENDED ABSTRACT**

Crime analysis plays important role in prevention of crimes, investigate the relations among crimes, detection of criminals, helping police investigations and revealing the events quickly. In addition, it is also important to perform crime analysis for efficient use of human and technical resources.

Crime analysis is described as the process that investigates the distribution of crime types, the relation among the crimes and the detection of the criminal over geographical regions and their possible future trends. Thus, the relations among the other crimes that are affected by a particular crime could also be revealed and analysed. Within the framework of the analysis process, statistical information related to crimes, such as distributions of crimes, their increase or decrease, and their locations, are also evaluated.

The subject of this thesis is based on crime analysis and the prediction of crime. Five important contributions are provided. These five issues; Synthetic crime data set by using artificial intelligence methods, identifying the link between the types of crime and the determination of the relationship between the types of crime, using a hybrid method to determine the similarities between the crime events, using the crime parameters to predict the crime and using the list of suspected acquaintances on crime social network structures is estimated.

The major subject of this thesis is in criminal prediction area. Apart from this concept as basically, two major contributions are provided. First, a parametric model is proposed to generate the incident-level crime datasets involving crimes, criminals and criminals' suspicious acquaintances where the parameters are used for fine tuned adaptation of the model. The model is based on GIS (Geographical Information System) by approximating the characteristics of the population in real-life. The model generates a dataset based on the user input. After generation of dataset, the first phase is analysis of criminal relations using statistical techniques, such as, Gaussian Mixture Models and K-Means clustering.

At this point, the main motivation is to develop the decision making method and provide a test environment. Due to security and privacy concerns, it is currently the best solution to create a synthetic data set, as actual data sets of criminal and crime cannot be widely accessed by independent researchers. It can be assumed that crime analysis methods can be tested using synthetic data. The crime data is composed of the characteristics of the crime. These include: types of crime, crime scene, incident time, criminal identity and criminals' acquaintances.

Often law enforcement agencies use many channels to obtain data about the(potential) incidents without publicly sharing the collected data due to official regulations. Also, the detailed information about the criminals cannot be publicly available due to safety of the personal rights. Thus, in practice, the crime related data such as the crime types, criminals' identifications, the time and place of incidents, criminals' suspicious acquaintance and so on, is very expensive to obtain. Moreover, even such a crime data is obtained in some way, the number of observations and the data distribution characteristics would not be sufficient to develop a crime analysis method. Hence various datasets containing different data patterns and different geographical information are needed, e.g. to test the performance of the crime analysis methods. Especially, government agencies cannot share information about incident level crime events such as the identity of the criminals, the time and place of the events, and the acquaintances of criminals, for official reasons. Therefore, in practice, it is difficult to get crime data for this reason. The synthetical production of the crime data set is therefore of great importance.

For synthetically crime dataset, the model consists of a three-stage phase in which the first universe includes the creation of a geographical map; the second stage includes the distribution of crime events on the map, and the third stage involves the distribution of criminals and their criminal acquaintances. The geographic map is based on the polygonal representation of the regions where the points of the polygons and the centers of the region are assumed to be given here.

The synthetic formation of the crime data set is the first step for analysis. After this stage, other topics will be discussed. The first of these issues is the determination of crime trends. Here, two concepts are discussed. The first is the relationship between crimes. It is the determination of the places where the crimes are concentrated according to the regions and the locations of the crime areas and the locations of the next region.

The second is the identification of the possibility of criminal to handle other types of crime, except for their current crimes. The link between the criminal and other crimes will be determined in this way. The software used will be analyzed with these two conditions for trend concepts.

It is an important factor for the analysis of criminal tendencies in the determination of crime trends. Because it is necessary to define the tendency of a criminal to calculate the relationship between crimes. Thus, the main objective is to determine the similarities and closeness among all crimes in a crime database by this method. The main motivation point is the trends between the criminals who commit to similar crimes and the possibilities of handling these criminals in the next step and the crime types between crimes.

It is determined by crime trends that crime events are identified as probability points between regions or among themselves. Therefore, it can be predicted that there are similarities and affinities between the crime events. It is important to analyze clustering and expose these affinities using hybrid methods.

Another issue examined in the concept of crime analysis is the close relationship between the records of criminal events. Here, the methodology used in the trend analysis for the similarity of crime events is followed for the same purpose. The main purpose of using hybrid metrics is that the feature vectors are not in the same format in both length and data format. Hence, the similarity between any pair of vectors requires complex distance measurements or transformations. One of the solutions presented here is to reflect the feature vector space on the similarity area called the similarity between each event point pair. The

idea is based on the similarities between a pair of events, as well as the similarities between features. The aim of each pair of events, which have five parameters of each crime, is to compare all the features of crime. However, in this comparison, the similarity of each feature will be determined. The similarity of crime events: the type of crimes will be determined through criminals, and the similarity of criminals will be determined by the primary (direct) acquaintances of the criminal. However, the other two parameters of a crime event, time and place information, will be calculated by using the euclid method for both crime events, and finally, by the acquaintances mentioned in each crime incident, a criterion for these two criminal events will be determined through secondary (indirect) acquaintances.

Secondary acquaintances are a list of acquaintances of criminal or acquaintances of acquaintances of the criminals. All crime events will be calculated in this way and the proximity between the crime events will be determined. As a result, the motivation of this approach is that crime analysis methods generally do not require complete realistic data to develop and test decision-making algorithms. Thus, crime level data at the event level is to use both quantitative and categorical information with the length of unstable feature vectors.

With the analysis, an application has been developed that produces crime data at the event level and supports the query-based crime analysis in the GIS (Geographical Information Systems) map. The proposed system has been developed to reveal links to events that are difficult to obtain in practice. In addition, clustering-based decision-making algorithms have been provided for crime analysis. With the model, it is possible to measure clustering performance by using clustering of events from one or more relevant perspectives and using the proposed performance measure.

The most important analysis of the thesis is the creation of a prediction model based on Bayesian network. In the prediction model, the purpose of this analysis is to find out the most likely crime among the crime data set by using the parametric clues of the crime events. In addition, performance tests are carried out

as an effective analysis, which is the accuracy, sensitivity, effectiveness and prediction of crime in criminal cases. A practical model based on the Naive Bayes classifier is proposed with new methodologies for the crime prediction problem.

The proposed model is practical because of the simplicity that comes from the assumption of Naive Bayes' independence. Moreover, the model easily fits the assumption of independence as it succeeds in reducing the suspect list of 80%. Experimental results show that the proposed model can be used in criminology with the success rate of 80% for the security forces to find criminals. As a result, a potential potential criminal is identified by a GIS-based decision-making system.

Analysis of the concepts related to each other complement each other. Analyzes the crime events in a clustered manner. The similarities of the crime clusters are remarkable in these analyzes. In this detail, it is necessary to examine the crimes as a group. Therefore, the concept of crime/criminal social networking is needed. Within this social network concept, it is possible to analyze the movements and structures of criminal groups and terrorist groups. It is possible to determine the relationship between the criminal organizations and the persons or individuals identified as suspected persons and to determine which group is more likely to be involved in this group. Within the framework of the analysis, it is possible not only to identify a criminal but also to find similarities between criminal organizations. The most important concept in this analysis is the part of acquaintances used to find criminals. In particular, it is possible to control the familiar parameters used in the detection of the criminal not only in relation to the criminal, but also in the relations between the acquaintances and institutions. In the two ways, the concept of primary and secondary acquaintances is used from the criminal determination through suspicious acquaintances used in the analysis. These are the identification of the criminal's list of suspects identified by the user interface through the acquaintance of the criminal through the influence of the acquaintances of the criminal in the solution of the crime.

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## LIST OF ABBREVIATIONS

|                      |   |                                                            |
|----------------------|---|------------------------------------------------------------|
| <i>ACQ</i>           | : | Criminal's Acquaintances                                   |
| <i>AI</i>            | : | Artificial Intelligence                                    |
| <i>BN</i>            | : | Bayesian Network                                           |
| <i>CDCRP</i>         | : | Crime Driven Causal Relation perspective                   |
| <i>CRM</i>           | : | Criminal                                                   |
| <i>CRIMINAL ID</i>   | : | Criminal Identification                                    |
| <i>D_TREE</i>        | : | Decision Tree                                              |
| <i>GMM</i>           | : | Gaussian Mixture Model                                     |
| <i>GIS</i>           | : | Geographical Information System                            |
| <i>ID3</i>           | : | Iterative Dichotomiser 3 Algorithms                        |
| <i>K-NN</i>          | : | K Nearest Neighbour                                        |
| <i>L<sub>I</sub></i> | : | Location of incident I                                     |
| <i>LOC</i>           | : | Location                                                   |
| <i>NB</i>            | : | Naïve Bayes                                                |
| <i>NI</i>            | : | Number of Incidents                                        |
| <i>NR</i>            | : | Number of Region                                           |
| <i>PDFS</i>          | : | Probability Density Functions                              |
| <i>POR</i>           | : | Population in region                                       |
| <i>PPTC</i>          | : | Probability Propagation in the trees of the sets algorithm |
| <i>PRIM_PROB</i>     | : | Primary probability                                        |
| <i>R<sub>I</sub></i> | : | Region of I                                                |
| <i>SEC_PROB</i>      | : | Secondday probability                                      |
| <i>SETOFACQ</i>      | : | Set of Acquaintances of Criminal                           |
| <i>SNA</i>           | : | Social Network Analysis                                    |
| <i>SLIST</i>         | : | Suspected List                                             |



**1. INTRODUCTION**

One of the most important problems of today and tomorrow is crime incidents that is increasing day by day. Relationships between crime and criminals in crime cases are sometimes complex. Such situations are causing major problems for the security forces. Therefore, a scientific approach is needed to solve such problems. Techniques used in crime science due to these needs are established for crime analysis.

There are many definitions for crime analysis. In this definitions, the necessity of planning various structures to prevent crime is discussed. In particular, the most obvious of these definitions provides solutions to assist operational and security forces to prevent crime. These solutions are defined as a systematic and analytical process that provides more accurate information in the determination of various models and crime tendencies, which categorize crime events. Thus, it supports a series of actions to prevent crime, such as crime analysis, personnel distribution, operational investigation, operational investigation and analysis, and necessary planning and research to prevent future events (Anonymous, 2016).

Another definition of crime analysis is expressed as a system of categorical classification of temporal and spatial problems of security forces in regions with a certain population. Thus, this approach will help to reduce crime and disorder. The most important benefit of such systems is that it helps the analysts to solve crime cases (Brown, 1998). By this way, simulations and analyzes and crime events will be shown statistically. It is a phenomenon that has been added to this topic as user-based in the creation of all statistical events in a visual map. (Harries, 1999) and (Paulsen et al., 2004).

The purpose of the crime analysis is to prevent the crime and to quickly solve the crime events. In a crime analysis it is possible to use not only statistical studies, analyzes and graphics but also different purposes. First, the forecast is determined by a system of crime events. Within this predicted structure, crime

profiles, social incidents of crime events and temporal and spatial analysis are possible. In this way, analyzes are made with the necessary forecasting models to prevent a crime event before it occurs. The aim here is not to prevent 100% of the future crime, but to allow a precaution against a potential threat and problem.

Generally, crime analysis decision making processes consist of supervised observations or unsupervised observations. It uses supervised and verbal supervised learning, which is the province of these two learning methods. Whereas unsupervised will use direct data. For example, artificial neural networks in crime analysis for supervised.

The clustering algorithms that are k-means and dbsc, which are one of the unsupervised learning techniques, are used here (Divya et al., 2014). In order to reach a conclusion from similar events, the above method uses the unsupervised learning approach since it needs to be clustered. In this study, cluster-based crime analysis can be used to find criminals, past and future trends (Keogh and Lin, 2005), (Enzman and Podana, 2010) and (Rani and Rajasree, 2014).

For example, finding the crime/criminal of an incident requires an analysis of the qualifications of the event. Decision-making processes are used in these analyzes. Sometimes similar events may need to be analyzed together. In some cases, it may be necessary to collect events belonging to certain characteristics in a cluster. Therefore, in general, cluster-based crime analysis can be used to find relationships between events. As a result, in a cluster-based analysis, decision making techniques can be solved together with past and future crime trends.

Geographical locations are great importance for crime analysis and forecasting systems. The statistical data to be constructed constitute a great infrastructure for forecasting systems within geographic information systems. Geographic information such as the scene of the event, as well as the features of the places, can be used to arrive at important results in the decision-making process (Akpınar, 2005). Some statistical studies (Canter, 2009), (Laverly and Moore, 2005) and (Rossma, 2000) have shown that crimes have significant correlations

with time and geographical location. Some areas of criminology, such as crime mapping, dasymmetric mapping, geographic profiling, and crime prediction, use relationships between geography and criminal data (Poulsen and Kennedy, 2004), (Kianmehr and Reda, 2008), (Pitale and Ambhaikar, 2012), (Rani and Rajasree, 2014), (Rossmo, 2000), (Rossmo et al., 2005) and (Liu and Brown, 2003).

Geographical information systems are not only crime incidents but also a structure that facilitates the mapping and visualization of geographic spatial concepts. The spatial location of crime is one of the important factors in resolving the crime (Paulsen and Kennedy, 2004). Today, when electronic data is used, crime incidents are visualized on maps. In this way, crime incidents can occur in geographical relations with each other. For example, crime can provide for the crimes recorded in the database and the allocation of security units in a possible crime center.

In this context, the crime analysis includes statistical demonstration of crimes, detection of criminals, pre-detection of suspicions (Vural and Gök, 2017). In this way, crime incidents will be prevented and solutions will be provided more rapidly. Therefore, a variety of software has been implemented so that the above mentioned topics can help the security forces.

Such software requires access to incident-level data for crime parameters. However, accessing this data is not always easy. This is because of personal rights and official restrictions. As seen in the studies, there are more studies in which aggregate data are processed rather than event level data.

### **1.1. Incident-level and Aggregate -Level and Data Acquisition Problem**

Government agencies cannot share information about incident level crime events such as the identity of the criminals, the time and place of the events, and the acquaintances of criminals, for official reasons. Therefore, in practice, data on crime are aggregated by storing data at the incident level.

In literature the study of incident-level crime data is very limited and instead the aggregate-level data that is obtained by applying certain grouping functions to incident-level data are more common. However, aggregate-level dataset can't be used for criminal prediction problem since such dataset only gives summary information and hides criminal related information. Thus, recent works considered the generation of the incident-level crime data synthetically by modeling the population characteristics in real life. The work assumes that developing a solution method to the criminal prediction problem doesn't necessarily require a real dataset instead a semi-realistic dataset can be sufficient for some subset of solution methods (Vural and Gök, 2017) and (Toole et al., 2010).

Moreover, even when incident-level data is made available for researchers, the number of observations (incidents) and the data distribution characteristics would not be sufficient to develop a crime analysis method. Hence, various datasets containing different data patterns and different geographical information are needed, e.g., to develop and test the crime analysis methods (Brown, 1998), (Gnana and Punithavalliv, 2012) and (Calhoun, 2008).

In addition, event(incident)-level data is a part of numerical expressions. This can include numerical data such as time information of a crime event, as well as different data such as types of crimes. However, it is not possible to give a certain measure within the list of acquaintances. This list with a variable structure cannot be fixed in length. includes heterogeneous data types such as numerical and categorical. Importantly, the dating list is not fixed in length. Therefore, when analyzing the crime events, the feature vectors also cause unstable. This implies, indirectly, the need to know and monitor the characteristics of many data in developing and testing a variety of methods for analyzing a crime data set in a certain region.

An important problem of the scientists working on developing efficient crime analysis methods and algorithms is the data acquisition process which has many limitations due to practical reasons.

Often law enforcement agencies use many channels to obtain data about the (potential) incidents without publicly sharing the collected data due to official regulations. Also, the detailed information about the criminals cannot be publicly available due to safety of the personal rights. Thus, in practice, the crime related data such as the crime types, criminals' identifications, the time and place of incidents, criminals' suspicious acquaintance and so on, is very expensive to obtain. Moreover, even such a crime data is obtained in some way, the number of observations and the data distribution characteristics would not be sufficient to develop a crime analysis method. Hence various datasets containing different data patterns and different geographical information are needed, e.g, to test the performance of the crime analysis methods (Calhoun, 2008) and (Usha and Rameshkumar, 2014).

Assuming more features such as incident time and location, which are continuous types, one can anticipate narrowing the list of suspects. Each feature of the dataset, is more like a hint towards finding the criminals. The dataset features above are studied in for visualization of cluster analysis (Xiang et al.,2005). However, these works only attempt to discover the closely related incidents and doesn't provide a method for finding the criminals of a particular incident.

## **1.2. Thesis contribution**

The crime incidents are continuing to grow in rate and complexity. Over the past decade law enforcement agencies have gathered a large amount of crime data. This brings both opportunities and challenges for researchers and analyzers. For example, while monitoring the relationship between crime incidents, it is necessary to examine the source of the crime. This can help the security forces. Therefore, a systematic approach to crime analysis is needed. With this approach, concepts such as analysis, definition, patterns and tendency of crime incidents can be easily calculated. The science of criminology supports the security forces to analyze and

prevent crime. Thus, analyzes are carried out by using interdisciplinary studies such as statistics and artificial intelligence.

In this thesis, five contributions are provided:

First, a parametric model is proposed to generate the incident-level crime datasets involving crimes, GIS, criminals and criminals' suspicious acquaintances where the parameters are used for fine tuned adaptation of the model. The datasets are generated by modeling the population in real-life. The model can also produce random geographical maps and distribute population, crimes and criminals to the geography based on real-life approximations (Vural et al., 2013).

Second, the relationship between the crime events and the relationship between the crime is determined in the determination of the relationship. Here, it was determined that the criminals were related to other crimes and the inclinations of the types of crimes were found.

Third, a clustering based method is proposed to infer the closely related incidents using hybrid similarity metrics and it is demonstrated a decision-making process using hierarchical clustering algorithms in finding important patterns between criminals' social network and crimes in trend (Xiang, 2005), (Andresen, 2011), (Corduas and Piccolo, 2008), (Vural et al., 2014) and (Everitt, 1993).

Fourth, this thesis demonstrate the results of some queries related to crime analysis over the GIS dataset and discover committing criminal on given synthetic dataset(Vural et al, 2013), (Vural and Gök, 2017),(Toole, 2010) and (Saravanan et al., 2013). Thus, according to the parameters of the crime events, the possible criminal was identified.

Finally, it is used to detect the relationship between crime groups and reach the leaders of the crime organizations with through criminals and criminal's acquaintances. As well as for this concept, it is to help finding the criminal that is nearest to which crime groups in social network. Apart from this concept it can be helped to find the closeness of crime organisations.

### 1.3. Proposed Solution

In this section, a GIS model to generate the incident-level crime datasets is presented. The model can use the geographical maps and distribute population, crimes and criminals to the geography based on real-life approximations. It can generate random GIS maps or can use the existing maps that are based polygon representation. The datasets are generated by modeling the population in real-life. Then, an unsupervised decision-making process using hierarchical clustering algorithms in finding closely related incidents is demonstrated.

The clustering process is based on using hybrid similarity metrics to account for unstable and heterogeneous nature of the feature vectors. Finally, the results of some queries related to crime analysis over the GIS dataset are demonstrated. The other contribution is to predict both of the crime trend concepts. One of these is found crime trend in future based on certain geographic locations. The other one is detected to criminal trends among crime events. Essential point of this motivation take the determine closeness crimes. It is important role of criminal trends for finding closeness crime types. The proximity of a criminal group and other criminal groups can be measured by the decision-making structure that will be established when criminals can commit a certain crime and to commit other crimes. Thus, similarities will be found from the inclinations of those who have committed these two types of crimes. This concept, which carries the originality as a concept, is a subject not frequently researched in the literature. More trend studies consist of studies such as trend in a certain region and determination of possible locations in the future.

Among the various techniques developed for criminal prediction, Bayesian Network Model generation method is preferred in this thesis. A GIS based decision-making system using Bayesian network model is proposed to find criminals over an incident-level crime data. In the literature, there is no study with Bayesian network that aims to find criminals over an incident-level data with the criminals' acquaintances included. The acquaintances are considered to be either

the suspects whose names are involved in incidents or the acquaintances of the criminal when the criminal is known. Incident-level data is generated synthetically using Gaussian Mixture model and k-means clustering algorithms. In the development of Bayesian network model, Bayes chain rules are used. The proposed system is tested for the criminal prediction problem using the cross-validation and the experimental results show that the proposed system provides high scores in finding of suspected criminals.

Besides the Bayesian analysis, the simulation with other techniques which are decision tree, Naïve Bayesian etc. are compared. The most appropriate technique on this problem for comparison is the Naïve Bayesian theory. This is done by simulation that uses Naive Bayesian classification techniques for criminal prediction. In addition, this framework defines a new approach to identify criminals with certain crime parameters. The focal point of this framework is to build a crime scene architecture that combines relevant crime parameters. Naive Bayes algorithm is used in the system to create knowledge base and perform real time analysis.

It is believed that with such detailed information about each crime the crime patterns, which aren't discernible before can be found. With the improvements in computing, newer and more robust algorithms are being developed every day to extract data and forecast the unseen. In this study, the proposed system will help the law enforcement agencies to identify patterns easily by presenting the patterns extracted from the data set in an intuitive manner to help them fight crime more efficiently.

In summary, crime data used in literature often does not reflect the incident-level information such as the criminals' identifications and their suspicious acquaintances. The work using these datasets are strictly adhered to the practical limitations. However, handling the crime incidents requires analyzing not only the crime and geographical information but also the criminal information such as the criminals' identifications and their suspicious acquaintances. For example,

analyzing the social network of criminals in connection with an incident may enable to discover various patterns such as networks of crimes in trend and the interrelations among the incidents. Furthermore, developing decision-making methods that analyze the incident-level data, e.g. to inspect the criminals of the incident or interrelations among the incidents, does not necessarily require actual restricted law enforcement data. Synthetic datasets containing different data patterns can provide sufficient information, to develop and test the crime analysis methods.

#### **1.4. Thesis Organisation**

This thesis consists of five parts. The introductory part explains the general purpose of the thesis. In addition, this work is highlighted in the background. Thus, the work done throughout the thesis is presented under this concept.

Chapter 2 introduces the relevant literature showing the work done previously in the area of crime analysis and its related issues, the uses and the applications of crime analysis and crime/criminal models with supported relevant references.

Chapter 3 shows how to generate crime data set, the system model and formulization of the problem. After the crime dataset, analysis of crime incidents is done. In these analyzes, the relationship between crime trends, detection of criminals from crime parameters, analysis of closely related hybrid structures between crime incidents, and the impact of criminals' acquaintances are shown using a bayesian network model.

Chapter 4 demonstrates the experimental results of the proposed methods.

Chapter 5 summarizes the work, and discusses the future trends and directions of improving this work.



## 2. PREVIOUS RESEARCH

In the last 20 years, many scholars have dealt with the concept of crime analysis in different ways and have done various studies in this direction. These studies will be briefly mentioned in the study, which will be used in the thesis. Although the work done differs in certain issues, they share several common components. These shared common concepts always agree that crime analysis supports the security forces and uses systematic methods and information. In this chapter will review some of the important studies in crime analysis tools in Table 2.1.

Table 2.1. Important previous work referenced

| Previous Work             | Year | Problem                        | Data Set         |
|---------------------------|------|--------------------------------|------------------|
| Enzmann and Podanna       | 2010 | Crime Data Set                 | Survey           |
| Vural et al.              | 2013 | Crime Data Set                 | Synthetic        |
| Pflueger et al.           | 2015 | Predictive criminal recidivism | Real             |
| Ayat et al.               | 2013 | Crime prediction               | Real             |
| Horwath and Kolomaznikova | 2003 | Crime analysis                 | Survey/Synthetic |
| Vural et al.              | 2014 | Clustering                     | Synthetic        |
| Khan and Bhagat           | 2013 | Clustering                     | Real/Synthetic   |
| Andresen                  | 2011 | Social Network Analysis        | Real             |
| Liu and Brown             | 2003 | Criminal prediction            | Real             |
| Vural and Gök             | 2016 | Criminal prediction            | Syntetic         |
| Rossmo                    | 2000 | Geograhhic profiling           | Real/Survey      |
| Harries                   | 1999 | Mapping Crime                  | Real             |
| Andrade and Ferreira      | 2012 | Crime Scene investigation      | Synthetic        |
| Akpınar                   | 2005 | Crime Analysis and GIS         | Real             |

### 2.1. Crime Dataset

Crime analysis work has increased in recent years. Many different approaches have enabled the creation of analyzes over different topics. Many of these studies have used statistical analysis where the crime data have been obtained either from official authorities (Anonymous, 2012a), (Anonymous, 2012b) and (Anonymous, 2015c) or acquired through surveys (Anonymous, 2013a) and (Anonymous, 2015b). The resulting data is then filtered and shared with the public through the websites. For example, some institutions such as U.S. North Carolina Department of Justice, Interpol, UNODC, the European Sourcebook, Oakland Police Department publish crime data in a certain period using their web sites (Anonymous, 2013a), (Anonymous, 2013c), (Anonymous, 2012b), (Anonymous, 2012a) and (Anonymous, 2013b). In the literature, the work related to the crime analysis uses well known crime datasets, which are publicly available through web sites, where the criminal related information is hidden for criminals' safety.

Most of the data sets used are stored as different databases. These different database formats may not be suitable for every analysis. For reasons other than geographic location, institutions have opened up these databases to the use of users in a limited way. For example, some institutions such as the US Department of Justice of North Carolina, Interpol, UNODC provide periodic reports of crime events against the city of Boston in these formats (Anonymous, 2015c).

The formats in the data set presented for use by many analysts may vary depending on the structure of the analysis. The biggest reason for these differences is that the crime parameters are different. Besides, it is an important factor in the way the crime events are presented. In this way, the difference of the format is in two ways. The first is that the data set keeps all events separately, while the crime events are event-based. In the other, institutions categorize crime events according to certain criteria and present them in a categorized form. For this reason, datasets are considered as event-based and total-level.

### 2.2. Aggregate/Incident Level Data

The type of information given in the datasets also varies. Some datasets provide only the crime-types and their frequencies in a particular region. Some of them provide additional data such as locality (town/city/county), latitude, and additional information as given in (Al-janabi, 2011). Crime datasets in literature can be broadly classified according to whether they provide incident-level data or aggregate-level data (Anonymous, 2012b). In incident-level datasets (Vural et al., 2013), data is given separately for each crime incident whereas in aggregate-level datasets, incidents are grouped and summary data is given for a particular criterion such as geographical region or time period.

Criminologists often have limited access to related the incident level crime data. Differences in data collection methods and data storage formats between law enforcement agencies create difficulties in obtaining the incident level crime data, especially for cross national studies. There are cross national crime datas committed by international organizations such as the International Police Force (Anonymous, 2012b), the United Nations Crime Investigations (Anonymous, 2013c) and the European SourceBook (Anonymous, 2012a). However, these data sets are also at the collective level. In a special emphasis on data accessibility, the review of resources on cross national crime has been given (Anonymous, 2013c). The reliability and validity of the datasets are important issues and have been discussed elsewhere in the literature. Since 2000 Interpol has no longer provided the crime data to public, but to authorized police users, due to the potential misuse of these data (Anonymous, 2012b).

### 2.3. Crime Prediction

Since the crime prediction problem requires the crime related details, aggregate-level data cannot be used for this purpose. However, incident-level data is hardly available with limited criminal information since these types of information are confidential. Even the criminal information is coded in some way;

it is still open to exposure when the time and location info is available. All of these factors have limited the works related to criminal prediction in literature (Vural and Gök, 2017), and lead the current efforts to generate synthetic crime data (Vural et al., 2013). The basic philosophy of these efforts lies on the fact that artificially generated synthetic dataset can be used for some subset of solutions to the criminal prediction problem.

#### **2.4. Crime Trends**

The relationship among the crimes were found to have similarities within a certain geographical location (Akpınar, 2005), (Canter, 2009) and (Vural et al., 2014). Occurring crimes as coordinates in a certain spatial and time can be seen in different geographical areas. Thus, according to regions the change of crimes can be seen. Besides, trended crime types of the people living in an area can be determined. Some of these studies show us the importance of crime trends (Enzman and Podana, 2010), (Holst and Bjurling, 2013), (Mohammad et al., 2014) and (Rani and Rajasree, 2014).

The analysis of these trends, patterns and hot spots give clues as to the cause of the crime that arises in your community. Apart from the fact that the crime has only begun to take place, information such as where the crime is committed, how many times it has occurred, and by whom it is committed is obtained. This information has been developed for effective methods and strategies. By preventing personal grievances, criminal incidents will be reduced. For this reason, one of the solution points in preventing crime events is to direct the necessary personnel to intervene in the event as soon as possible. For this reason, it is more common for crime/criminal tendencies to be seen in places where the population is concentrated.

How the population density is a factor in the prevention of crime is related to other factors such as cultural, economic and so on. For this reason, law enforcement agencies are part of this concept. (Ayat et al., 2013).

### 2.5. Artificial Intelligence Techniques

In cases where statistical analysis is insufficient for the crime analysis, it is necessary to analyze the crime events with the methods of decision making with certain methods. Therefore, artificial intelligence methods are essential aspects of crime analysis concept. In general, the work related to crime analysis visualization methods (Brunsdon et al, 2007), (Akpınar, 2005) and (Xiang et al., 2005), statistical analysis (Holst and Bjurling, 2013) and, supervised learning (Jain et al., 2014) and unsupervised learning techniques (Corsini, 2006) and (Mackenzie, 1995).

Visualization involves visual representation of the relationship between geography and other crime data such as the GIS based crime mapping (Harries, 1999) and (Akpınar, 2005) dasymetric mapping (Poulsen and Kennedy, 2004), geographic profiling (Canter, 2009), (Rossmo, 2000) and (Laverty and Moore, 2005), crime prediction (Pitale and Ambhaikar, 2012), (Rajasree, 2014) and (Saravanan et al., 2013) etc. On the other hand, to discover the relations between crime data, statistical methods and unsupervised learning techniques, such as clustering methods, are more commonly used.

Clustering techniques are used in such studies as criminal association analysis (Upadhyaya and Jain, 2013), (Vural et al., 2014) and (Andresen, 2011), criminal behavior analysis (Baumgartner, 2005), (Ewart and Oatley, 2003) and (Toole et al., 2010) crime pattern recognition (Akpınar, 2005) and (Brunsdon, 2007), incident pattern recognition (Coffman and Marcus, 2004) to discover the patterns or groups that have similar features in crime data.

Data mining techniques are also used to make criminal analysis (Khan and Bhagat, 2013) and (Lie and Brown, 2003). Among the cited research, (Patil and Sherekar, 2013) is important from the perspective of this thesis since it uses Naïve Bayes method. In a study in which performance measurements were evaluated, which method gave better results was examined. Naïve Bayes and J48 classification algorithms were compared. The Naive Bayes algorithm here is

basically an algorithm based on Bayesian method. The other algorithm, J48, is a structure used as a decision tree algorithm. Only the higher classification accuracy was not obtained with the study. Instead, a comparative assessment of these two classifiers is made in the context of the financial data set. The Weka tool was used for this evaluation. According to the results of the data in this study, these two structures showed more efficient and more accurate results.

## **2.6. Cluster Analysis**

Clustering techniques are also effective in criminal organization, and predicting the relationship between the crime place and the crime cluster will certainly lead to an increase in crime prevention strategies (Andresen, 2011) and (Khan and Bhagat, 2013). These techniques aims to divide the data into classes. It uses class similarity to maximize or minimize the most similar features according to the available data. For example, these techniques are used to separate groups of different gangs as they are used to identify suspected perpetrators in a similar way. (Horvath and Kolomaznikova, 2003). These techniques do not have a set of predefined classes for assigning items.

Clustering techniques were used in a variety of artificial intelligence techniques or decision making approaches in prediction crime or criminals, crime trends and the effective use of crime analysis. Decision-making perspective of the crime analysis either uses supervised such as analysis using neural networks (Ayat et al., 2013) and (Jain et al., 2014) or unsupervised approach such as analysis using clustering techniques (Vural et al., 2014) and (Wang et al., 2006). Just as mentioned, artificial intelligence and data mining techniques make the work of the security forces easier. In an effort to address this issue, with the structure developed, analyzes developed to prevent crime will eventually provide a more effective structure to the security forces and minimize crime incidents. The classification of the research has been emphasized again. It is an effort by the police to keep crime incidents together and to use this data, which is kept in a

similar way. Classifications are also used to distinguish between group clusters. Thus, each item is clustered for a certain group. This group can already be in a certain character group (Wang, 2006).

Clustering algorithms are used to group crime events that have a certain geographical location. This information groups statistically significant data showing similar characteristics (Vural et al, 2014) and (Harada and Shimada, 2006). This information groups statistically significant data showing similar characteristics. Through the program, crime incidents that can occur in a geographical area are probabilistically detected. Potential locations are then forwarded to crime analysts (Akpınar, 2005) and (Vural et al., 2013). It is often used to help determine the manner in which crime is committed and to accelerate the process of deterrence (Wanawe et al., 2014).

Clustering techniques group similar data items according to the given similarity metric, where the feature extraction and the selection of the similarity metrics highly affect the final results (Corduas and Piccolo, 2008) and (Al-janabi, 2011). These techniques are effective in criminal organizations and crime relations. Through this analysis, it will be discovered the relationship between crime and geography where committed to crime. For example, some fields of criminology including crime mapping (Harries, 1999), dasymmetric mapping (Poulsen and Kennedy, 2004), geographic profiling (Baumgartner et al., 2008) and crime forecasting (Gorr and Harries, 2003), (Zenn et al, 2007) and (Pflueger, 2015) arose about the relations between geography and other crime data. Cluster analysis is also used in mining associations (Brown, 1998), (Kahn and Bhagat, 2013), (Nath, 2006), (Sujatha and Ezhilmaran, 2013) and (Wang et al., 2006) where association of the clusters with the important crime attributes is considered. In a similar way, a particular area is given when grouping statistically significant crimes and identifying problematic areas by clustering methods (Upadhyaya and Jain, 2013).

Various clustering methods are used in crime analysis. In some of these methods, many clustering algorithms are compared. Some of these methods are k-means, DBScan, hierarchical clustering and kernel density.

In a study using GIS in Turkey, a method was developed to determine the distribution of crime on land use variables. With this method developed, spatial data analysis is carried out with real mapping methods of geographic information systems. In the study, the core estimation method was used as a method and the event trends of land use were analyzed. The closest neighborhood clustering method was used in the analysis of tendency (Akpınar, 2005) and (Andresen, 2011).

Clustering algorithms are used to help identify crime models. K-means improvement method is used. In this study, semi-supervised learning techniques are not only used to obtain information from criminal records, but are also weighted by the attributes of box clustering tools and techniques to help improve predictable accuracy (Janabi, 2011) and (Zhen et al, 2007). A comparison of various clustering methods in crime analysis including k-means, dbscan, and hierarchical clustering is given in (Wanawe et al., 2014) and (Divya et al., 2014). Cluster analysis is also used in mining associations where association of the clusters with the important crime attributes is considered.

In one study, compared two sets of cluster analyzes for the detection of crime models (Khan and Bhagat, 2013). With a clustering-based mapping approach, it has been designed as a layer of geographic information within a geographic area. In GIS, all data is stored in this way. It is clustered with the data set algorithms in the geographic area. These clusters are spatially grouped. This grouping is expressed as regions. The spatial clusters of point data in each layer are expressed in terms of regions (Andresen, 2011), (Moon and Carley, 2007) and (Poulsen and Kennedy, 2004). Together with normal crime, clustering techniques have been used to identify illegal events on the Internet. In a work done, the spread of these malicious software or messages is under a special structure. In this way, it

is possible to identify the people who make these publications within the area defined as cyber crime.

### 2.7. Criminal Analysis

When examining previous studies on crime prediction, it appears that there are problems accessing event level data. Various crime parameters are needed to find criminals. Some of these crime parameters should be analyzed in the theory of geographical information with the various profiles of criminals, crimes committed by criminals, characteristics and criminals together. For this reason, it has been shown how important other parameters are for estimating the crime. These properties vary according to the definition of the data set. Thus, some approaches have been identified and the criminality estimated. For example, in some studies (Andresen, 2011) and (Akpınar, 2005), such as time and space, they should be analyzed at first sight and on the other hand, based on crime/criminal information. According to criminal behavior and crime structures, crime analysis and identification of criminal identities have been carried out (Holst and Bjurling, 2013), (Pflueger, 2015), (Porter and Brown, 2007), (Sharma, 2014) and (Liu and Brown, 2003).

One of the research proposed a rapid structure that responds to the determination of the most likely suspects spatially or even coordinately within the GIS structure (Toole et al., 2010), (Saravanan, 2013) and (Vural et al., 2013). The proposed structure consists of mobile mapping of geographic information systems (Akpınar, 2005).

Basic crime characteristics in a particular area by crime union analysis and the relationship of these properties are described in (Usha and Rameshkumar, 2014) and (Zhen et al., 2007). Analyzes of crime incidents and analytical findings in spatial and temporal deductions have been less studied than analyzes of crime characteristics. Even in these constructions, other crime parameters are fewer than those analyzed. As the quality of the parameters increases, more accurate results

can be achieved in the analyzes. By co-analysis of these parameters in these geographical areas and structures, the processes will further assist the security forces. In the related works (Baumgartner, 2005), (Calvo-Armengol and Zenou, 2006) and (Ewart and Oatley, 2003), efforts have been made to the criminal behavior analysis by analyzing the crimes committed by the criminals over time (Holst and Bjurling, 2013), (Eagle and Plotkin, 2010), (Brunsdon and Corcoran, 2007), (Keogh and Lin, 2005), (Law and Matthew, 2014) and (Corduas and Piccolo, 2008).

Authorized units only provide limited access to incident-level data, such as the time and location of incidents and criminal info, due to the probability of misuse of the information published and violation of the personal rights. For example, Oakland Police Department hides the criminal related information that is to be remained confidential for the safety issues (Anonymous, 2013b). Furthermore, the shared information in the crime dataset varies. As some datasets (Janabi, 2011) only cover the number of crimes and the crime types in a particular area, some others (Harada and Shimada, 2006) include additional information like latitude, and location (town/city/country). As some Wang et al., (2006) provides criminals' characteristics without giving the criminal identity, some others (Baumgartner, 2005) prefer coding the criminal identification.

In the literature, another branch of study about criminal analysis is the criminal profiling (Baumgartner, 2005). In a criminal predicting case, there is a study based on the interpretation of the criminal's profile and other information obtained at the place where the crime occurred. For example, the purpose of this study is to know some of the characteristics and behaviors of the offender in order to create a solution-oriented structure where there is more than one person with a high probability of committing a crime. These studies may be particularly influential on the criminal profile of crimes committed by the same criminal (Canter, 2009). According to the surveys conducted, most of the crimes are committed by those who are in the minority. It is difficult to determine whether

more than one crime is committed by the same offender (Lavery and Moore, 2005). Behaviors exhibited by criminals involved in crime are often used to establish criminal connections (Sherman et al., 1989). In Law et al. (2014), a statistical model was used to examine the differences and changes in crime incidents. This statistical model determines the change of statistical data (Enzman and Podana, 2010). Thus, according to the statistical data, it shows that an event has changed in that region. With such an indicator, it means that the criminal case in that area should be examined based on the present evidence.

Criminal behavior analysis is a structure that over time will examine the behavior of criminals. With this behavior, many crime prediction problems have contributed to preventing and resolving crime incidents (Ewart and Oatley, 2003). Criminal behavior can greatly reflect the characteristics of criminals. The prediction of the types of crime is the result of the classification of the characteristics of many criminals according to certain criteria (Kianmehr and Reda, 2008). In such analyzes, the results of different algorithms need to be examined together to form a more accurate structure for crime behavior. Sometimes, if there are missing data before starting an analysis, these should be determined first. In a study on this problem, three algorithms were searched for this problem. Specifically, the C4.5 algorithm for the Decision tree, the Naive Bayesian algorithm based on Bayes theorem, and the nearest neighboring KNN algorithms have been tested comparatively. Thus, in these comparisons against this problem, it will be more clear which of these algorithms will be more effective with different algorithms in the solution point of the missing data and the events will be interpreted for the problem.

## **2.8. Bayesian Network for Crime Analysis**

This structure, known as Bayesian networks, shows causally interconnected networks. It provides a method of representing relationships between Bayesian networks and uncertain relationships and unpredictable links. This method focuses

on relational structures rather than the structure and definition of a scientific problem. It gives information about the effects of this event on another event when there is any event for a node between the nodes. Therefore, in such networks, both uncertain and unpredictable situations are detected and they are used to analyze these situations in a networked framework.

Classification calculations and estimation of uncertainty events were performed with the Bayesian approach. Experts tend to help discover trends (Mohammad, 2014), make predictions (Vural and Gök, 2017), obtain necessary information on samples of crime incidents, the acquired information finds samples and possible explanations of networks based on crime incidents, show crime networks on a map (Vural et al., 2013), (Akpınar, 2005) and (Calvo-armengol and Zenou, 2006) and by making inferences from the data, helps to identify who is the likely criminal in the list of doubts (Vural and Gök, 2017).

It is grouped by bringing together the features that characterize crime incidents in certain characteristics. These constructions are structures that can be defined as parametric variables for a crime scene. These structures are parametric crime elements such as the type of crime, the place of the crime, the temporal information that is committed the crime, and other characteristics. These features of clustering are based on the concept of determining the relationship among crime incidents, which have similar characteristics within structures that are not closely related in the beginning (Vural et al., 2014).

Both classifications and clustering results are used in predicting the criminal and criminal tendencies and behavior of given objects. The data set, which will be necessary for both criminal and crime incidents, can be collected from free sites on the internet prepared by the security forces because of structures based on the protection of personal rights. As mentioned earlier, some of these data have some real problems a method has been adopted in this way. With the help of some of the techniques used, the given data are prepared for further processing according to their important characteristics, before being subjected to certain operations. This

will lead to clearer information. With this clear information, more accurate results will be obtained against the events. The data in these correct approaches are useful in the discovery of different crime and criminal trends. Such data are grouped among themselves and processed by taking into account important characteristic features such as criminal behavior (Holst and Bjurling, 2013) and (Toole et al., 2010).

Today, the places where crime occurs are in fact the same or similar places. It is so obvious that crime events are happening around here. In fact, a statistical study can determine where crimes have taken place. It is also known that in such places more crimes have been committed. It is possible to predict the crimes and times that will occur in certain regions over time. Through intelligent systems, safety forces can be located in a more intense and accessible position over time in those areas. A possible problem with this aim is to prevent the crime that will occur with a quicker response. A similar study shows that there is an interest in predicting where crimes will take place, for example, to help police and other preventive measures be effectively deployed. A model has been developed in this study to make similar estimates.

The statistical distribution of violent crimes has been examined through the model developed. In this study, a modeling of temporal and spatial dependencies has been realized. In a crime, where the crime occurred at a certain time that the crime committed is fixed. Therefore, it is necessary to think of these two concepts together in such analyzes. It is a fact that temporal and spatial concepts are related to each other. In fact, temporal change of crime follows time series analysis as structure, while spatial sampling is irregular. These samples do not show a lot of variation throughout a location. Instead, spatial discrete regions appear to exhibit related crime models.

Some studies explore the non-parametric Bayesian approach and the clustering of time-specific time series. Then, how the common variables are added to the account in this framework (Wang et al., 2006), (Keogh and Lin, 2005) and

(Holst and Bjurling, 2013) the above-mentioned approaches have been shown through analysis of violent crimes reported weekly in Washington, between 2001 and 2008 (Cooper and Erica, 2012). The generated estimates perform better than the standard methods. Besides, the prediction modeling system also provides useful tools such as prediction intervals on temporal positions of crime events.

The other study provides a methodology for obtaining the Bayesian network's criminal behavior model from a database of cleaned murders (Boondao, 2004). This can actually be defined as a smart detective tool. Just as it is in a film scenario, it is a structure such as a criminal case or an accusation from the existing evidence. With the bayesian network to be used, it can extract the character of an unknown criminal from crime scene. A Bayesian network was used to find inferences from an unknown activity, as seen in previous literature searches. Here, for the same purpose, the profile of the criminal and its features are discussed. When the spatial structures are examined, the identity structure of the criminal can be analyzed from the crime events probable in these places. With this analysis, spatial information analysis will be able to eliminate a large part of the suspects that are available as a list of criminals. It will give us a great convenience in solving the problem. If there are many criminals involved in a crime before the analysis is done, this rate will vary greatly and will decrease. Thus, the security forces will play a faster role in resolving a crime. Not only does it reveal a crime and a similar crime parameter, it can be found in typical characteristics of the criminal. This study shows that 80% of the criminal traits are accurately predicted in new single-victim killings, and this accuracy is 95.6% when confidence levels are taken into consideration (Baumgartner, 2008).

Law et al. (2014), A new set of crime prediction models is introduced using Bayesian learning theory. This event is mostly about the places and trends that criminals will choose. For example, it is possible that a thief identified in a particular geographical area and who is constantly reporting petrol stations is likely to commit a similar crime within that region. Because criminals who commit

similar crimes have a tendency in this direction. Therefore, it is more likely to rob a petrol station. The roads to be traced here are built from here. In addition to this, the determination of places to commit such crimes is expressed as a trip journey. There are many potential theses factors that affect the subsequent site selection for a series of offenders, most of which are related to geographic information. For each factor, the likelihood of being the next crime zone in a particular geographical area is derived from the Trip Journey (Canter, 2009) to the classical crime prediction theory. By this method, a geographical profile with a different distribution is formed. The final prediction is made by combining all the geographical profiles with the available functions, with the effect functions adjusted adaptively to the Bayesian learning theory.

In Gansu, China, a series of crimes committed in the criminal data set are tested to find out the intentions of any criminal and find the next crime scene. Based on statistical data on crime trends, a further study was carried out that included analysis of the next crime incident from previous data. In this study, the presence of hot spots where crime incidents took place was determined. In these regions, when not only spatial but also temporal data are examined, a model is proposed about the next crime incident by making meaningful conclusions with the clustering of past crime incidents. Using spatial selection models, analysis does not consider criminal decision-making processes as human-initiated events (Horvath and Kolomaznikova, 2003).

It is available in studies that investigate behavioral disorders and characters of criminals. In the whole literature, investigations related to crime aim to prevent crime. In studies involving interpretations of psychological events and character traits, both the prevention of crime and the structure of the criminal are taken into consideration. Therefore, the character structure, profile and trends of the criminal are very important. That is why crime incidents are not only statistical analysis but also character structure and psychological tendency. Therefore, a bayesian network structure is formed from the behavioral samples of the offender. It is seen that this

network of behavior is related to the psychological behavior movements of the criminal when the murders are examined from the crime events. Internal relations can be determined with the model created by these relations. The crime data obtained are the links involved in a criminal database containing crimes and criminals that commit murder. The British police organization used such approaches to solve these problems from the 1970s. In this research, greedy search k2 learning algorithm has been modified for these approaches. Thus, a method was developed to reduce the search area in the bayes network to determine the independent relationships. With this method, the independence relations between the nodes will be determined. This will allow analysis and forecasting when there is missing information or parametric information (Baumgartner, 2005).

In an investigation related to the prediction models based on the Bayesian theory from the profiles and behaviors, It is seen that the accuracy rate of the estimates obtained from the deductions of the criminal profiles out of the behavior patterns observed in the model crime locations generated by the modified k2 algorithm is higher than the rates before the modified version. The modified algorithm has a value of 79%, measured in the same mode as the original K2 algorithm. This rate was 15% better. The k2 algorithm was used again in the previously used methods. Again, in a similar study by the same authors, the level of reliability was emphasized at this time in determining the offense based on estimates. It has been shown that the level of uncertainty here becomes more apparent with this method. As the uncertainty is removed, reliability has increased in proportion to the rate. Each parameter of crime incidents is handled separately and a reliability measure of these variables is determined. In summary, all these unified structures have become more evident by eliminating uncertainties, A model has been developed to make the variables more reliable. Thus, the number of suspects in a murder case was reduced to a minimum level (Baumgartner, 2008).

In this thesis, a Bayesian network is proposed, which is a prediction model for the problem of guilty estimation. The proposed model is provided in a GIS

system that visualizes various aspects of crime data models on a user-defined map. Although there are some studies using Bayesian networks related to the subject, there is no such study as criminal prediction. Some of the work done is limited to studies involving foresight and prediction, such as crime prediction analysis (Gorr and Harries, 2003) or criminal profile creation (Canter, 2009). Furthermore, the works only provide classification of criminal characteristics or behaviors over a limited data excluding the criminal acquaintance information.

In summary, in the literature there is no work analyzing the criminal social network based on the other incident-level crime data for criminal prediction problem. There exists a work over the terrorist network to discover the connections between the terrorists and other suspects (Dombroski and Carley, 2002). This concept requires that crime events be examined in a SNA. The concept of SNA is used as a preferred method to conduct analysis after the study of terrorist groups together. Since the relationship of criminals is assessed in this concept, these studies can only be used in place of SNA analysis, time, type of crime, and so on. It analyzes the data related to other crimes without analyzing it (Koelle et al., 2006).

The proposed model generates incident-level data and hence enables crime analysis with the primary focuses on incident-level functionalities such as finding interrelations among the incidents by considering any crime attributes, e.g. criminal and the social network of criminals. It is important to investigate criminal in social network where they are related among criminals. Therefore, Bayesian network is used to solve this problem in social network.

The proposed model is provided inside a GIS system that visualizes the various characteristics of the data patterns over a user defined map. Although there exists some studies using Bayesian networks, these works provide either crime trends analysis (Ayat et al., 2013) or intrusion detection system, spam filtering (Sagale and Kale, 2014) without studying the criminal prediction problem. These works provide either criminal behavior analysis or criminal profiling without studying the criminal prediction problem. These works only provide classification

of criminal characteristics/behaviors over a limited data excluding the criminal acquaintance information.

There is a study in which spatial relations in an area are expressed in certain indicators by neighborhood analysis. The consequences are of great importance in the sense of local crime models (Taheri et al., 2014). Although spatial autocorrelation is known to have existed for a long time with crime, this analysis is shown to be a different conjecture that is spatially probable (Andresen, 2011), (Moon and Carley, 2007) and (Law and Chan, 2012).

Contrary to other crime incidents, criminals have almost no work studying in a social network. Although social network analysis (Xiao and Fan, 2014) and (Carrington, 2011) is a widely used tool in criminal investigations, the automatic criminal analysis over such a network is very limited again due to data accessing difficulties.

In summary, datasets used in literature commonly don't provide incident-level data such as the criminals' identifications and their suspicious acquaintances (Vural and Gök, 2017). The works using these datasets are strictly adhered to the practical limitations. However, highlighting the crime incidents requires analyzing not only the crime and geographical information but also the criminal information such as the criminals' identifications and their acquaintances who are also criminals.

Analyzing the social network of criminals in connection with an incident enables to discover not only the criminals of the incident but also various patterns such as networks of crimes in trend and the probabilistic relations among the incident related data (Yang and NG, 2007). Furthermore, developing decision-making methods that analyze the incident-level data, e.g to inspect the criminals of the incident, does not necessarily require fully realistic datasets (Vural and Gök, 2017). Hence various datasets containing different data patterns are needed, e.g, to develop, train and test the crime analysis methods.

The deficiencies seen especially in the literature review have been added to the thesis. These are original structures. Artificial crime data set created by addition of crime, determination of crime/criminal trends from crime events, determination of similarities of crime with hybrid measurements, estimation of crime from crime event parameters, location of criminal in social network, relations with organizational structure of criminals and relations between groups. The structure is combined under one roof and a different simulation has been created.





**3. PROPOSED SOLUTION**

In daily life, most of the problems encountered or solved by the police are not related to crime. Most of the problems experienced today are caused by stress. These are the factors that affect life negatively. The concept that creates such factors can be a structure that is not related to the criminal. To give an example, the problems of murder, other than drug crimes. These uncomfortable situations, the operation of false burglar alarms, noise complaints from the city and problems such as traffic control problems can be counted. However, the rest are related to the real crime. There are several goals for crime analysis that can be considered. Law enforcement agencies, which need to be considered in their crime analysis analysis, generally have four main objectives. These problems are common problems with the analysis of the crime that is encountered. Of course there are other problems than these problems. The topics covered in the thesis include some of these main problems, but there are also different concepts of crime, especially in the issues that the law enforcement officers are confronted with outside the thesis.

The first aim of the crime analysis is to help the arrest of the law enforcement officers. For example, a detective might be investigating a case of robbery by a perpetrator using a particular criminal method. But the detective can not always find the right solution. There is a need for other materials that can help detective. It will be necessary to utilize the benefits of technology in clearing up a crime. In fact, a criminal analyst can help identify and investigate a database of previous robberies from similar incidents.

This is very necessary for forecasting systems. It is aimed to be able to be determined beforehand in different approaches here. It is aimed to prevent crime by developing some methods besides catching crime. Another goal is to remove the crime disorder and determine the crime analysis to respond to such problems. For example, a criminal analyst can help with the analysis of housing theft to examine how, when, and where it is stolen with stolen property. The analyst may also use

this information to develop crime prevention proposals for specific areas. The main purpose here will be to help identify what to pursue in the next similar crime and to ensure that the problem is solved more quickly.

The third objective of the crime analysis is to reduce crime incidents and irregularities of the security forces. That is why the role of crime analysts is to assist law enforcement agencies in this endeavor by investigating and analyzing suspicious situations and other problems. This research is to be able to provide a structure that they can use to study and address these problems before the larger crime problems.

The goal of crime analysis is to create a structure that will facilitate the evaluation of criminal incidents by helping the security forces with computer aided software. All of the methods used are to ensure that these programs are prevented by playing a more effective role in response to events. In order to prevent increasing crime incidents, methods are emerging. In addition, criminal analysts assist police departments in assessing internal procedures, such as structuring a geographic area according to crime prediction procedures, predicting and allocating staff needs, and improving performance measures.

The basic reasons explained above have been updated with certain criticisms and used in crime simulations in the thesis. These topics are Synthetic crime dataset generation, Crime trends among criminals, Crime data using clustering with hybrid metrics, Criminal analysis and Criminals detected through acquaintances. These are examined in crime analysis simulation. The way in which they perceived the criminal as well as the influence within the social network structure has been examined. These concepts are discussed separately below. It has been shown that different results can be obtained with the structures studied in this way.

### **3.1. Data Set Generation and System Model**

The most necessary structure in the framework of a crime analysis is to have a database primarily. Analyzes are made with the help of these crime data sets.

Analysis of crime data sets are available in two ways. While most of them are in real data sets, very few of them are artificially created data sets. The artificial data to be generated can be generated in sets close to the reality of crime incidents. It is composed of various criteria such as closely related to the truth, what criteria the distribution will take place, and determining the crime incidents according to the regions. Because of this, it is necessary to analyze geographical information systems.

In this chapter, the proposed GIS model that generates the incident-level data is formulated.

The generated crime data involves following crime attributes: crime types, incident place, incident time, criminal identification, and criminals' acquaintances that are criminal too. Figure 3.1 shows the relation among the crime attributes. The model consists of three sequential phases where the first phase involves creation of the geographical map, second phase involves the distribution of the crime incidents over the map, and the third phase involves the distribution of the criminals and their acquaintances over the crimes. The geographical map is based on the polygon representation of regions where the points of the polygons and the coordinates of the centers of the region are assumed to be given here. If the centers are not given, simply the geometric means of the regions could be used.

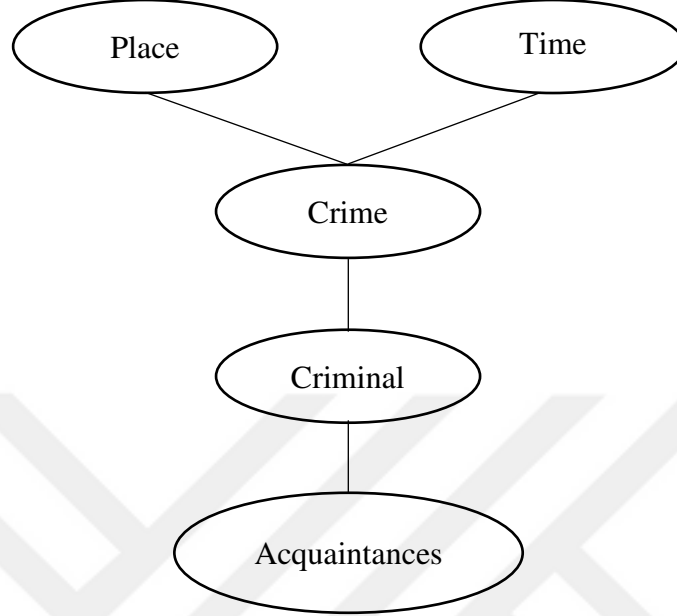


Figure 3.1. Relation among crime attributes

The model also supports generation of random maps where the map parameters, such as the number of regions and map size, are given via the user interface of the model. The detailed information about the generation of the random map is given in the problem formalization section.

In the second phase, all of the incidents are distributed over the map according to a Gaussian mixture and instantiated with the incident time, place and crime types. Each region center is used as the mean of its Gaussian component and variances are randomly formed using the given parameters via the user interface as well as the shape dynamics of the region. The main philosophy behind the use of the mixture of Gaussians method is that occurrences of crimes have usually higher density around the population centers in real life. Moreover, a Gaussian mixture can model any population structure if suitable Gaussian parameters are given.

In the last phase, all the criminals with the associated acquaintances are distributed over the crimes. The distribution of acquaintances arises around many

localities. Majority of the acquaintances are selected randomly around the home locality (e.g. municipal/town/city) and some are around the incident localities. Minority of the acquaintances are selected across the map locality. The home and incident localities are modeled by a mixture of Gaussians whereas the map locality is modeled by uniform distribution. The reason of this approach is that people usually have higher number of acquaintances in local regions, e.g. in their living places as well as the incident places. The detailed information about the phases of the system is given in the problem formulation.

### 3.1.1. Problem Formulation for Synthetic Data Set

The most necessary structure in the framework of a crime analysis is to have a database primarily. Analyses are made with the help of these crime data sets. There are two sets of crime data sets for analysis. While most of them are in real data sets, very few of them are artificially created data sets. The dataset to be used in the thesis is the dataset to be artificially produced. The artificial data set to be created has to produce a realistic scenario of crime incidents. It is closely related to the truth, the criteria on how the distribution will take place, and the criteria for determining crime incidents according to regions. Because of this, it will be necessary to analyze the events according to the geographic information systems as the analysis needs to be done on the geographical areas.

Many crime scenes within a certain geographical area will be distributed on the map. For the crime data set below, a certain number of areas and crime were taken into account. The goal is to produce a prototype. In this prototype, the crime data set can be formed with all the information such as the total number of crimes to be distributed.

In this section, formulation of each phase is given. Figure 3.2 shows an example map involving the first two phases, which generate a random map with six regions and four crime types denoted by different geometric symbols. The following notation is used in the rest of the thesis:  $R_i$  denotes the region  $i$ , and is

the NR number of regions, Incident<sub>i</sub> denotes the i<sup>th</sup>. Incident, and NI is the number of incidents, Place<sub>i</sub> denotes the place of Incident<sub>i</sub> POR<sub>i</sub> denotes the population in R<sub>i</sub>, Time<sub>i</sub> denotes the time of the Incident<sub>i</sub>, Crime<sub>i</sub> is the crime type of Incident<sub>i</sub>, and Criminal<sub>i</sub> is the criminal identity of Incident<sub>i</sub>;

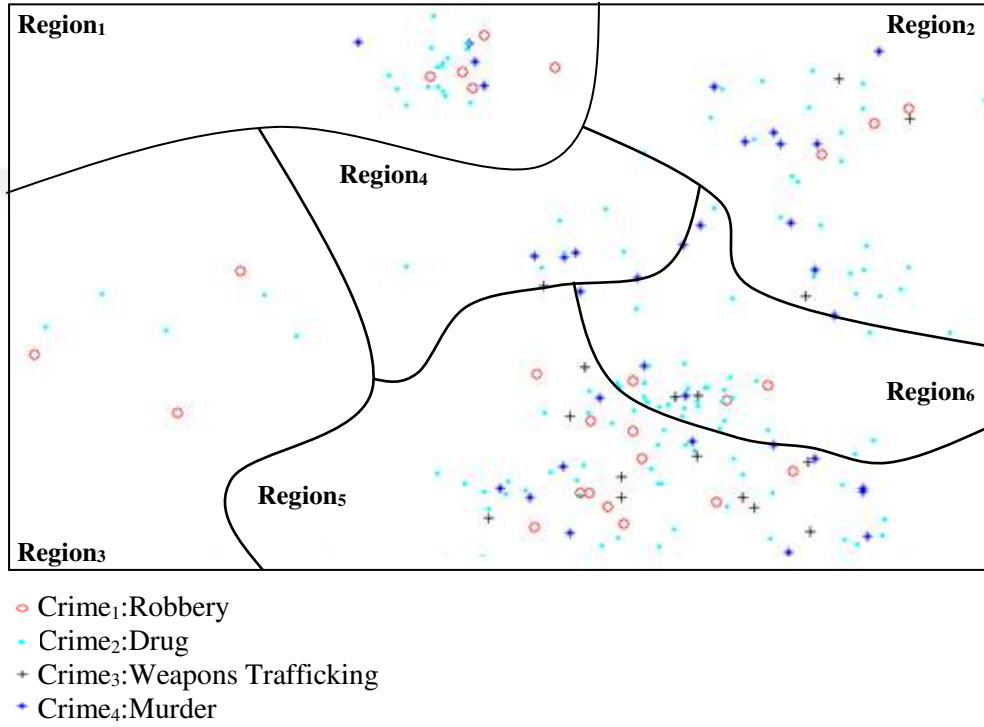


Figure 3.2. Distribution crimes over the map

The random map is generated by two steps. In the first step, an initial distribution is generated using a mixture of Gaussians, with the number of Gaussian is the number of crime types. User sets the parameters for the distribution. In second step, the initial distribution is divided into clusters using the k-means clustering with  $k=NR$ , where the clusters are the regions and cluster centroids are the centers of the regions. The second phase involves the generation of the incident distribution over the map. Let  $Location(x)$  denotes the probability

distribution of the incidents' places in the map and acquired with the following Gaussian mixture distribution(Eq. 3.1).

$$Location(x) = p(x|R_1) * P(R_1) + p(x|R_2) * P(R_2) + \dots + p(x|R_{NR}) * P(R_{NR}) \quad (3.1)$$

where  $P_{Ri} = \frac{POR_i}{\sum POR}$  and each conditional  $p(x|R_i)$  corresponds to i. Gaussian component, which is formulated by the probability density function of the normal distribution(Eq. 3.2),

$$p(x|R_i) = \frac{1}{\sigma_i \sqrt{2\pi}} e^{-(x-\mu_i)^2 / (2\sigma_i^2)} \quad (3.2)$$

where  $\mu_i$  and  $\sigma_i^2$  are center and variance of the population of  $R_i$  respectively. The second phase also generates the other attributes of the crime incidents, such as time, crime types and criminal information given at Eq. 3.3-3.5. The parameters of the simulation system, and others are calculated based on the equiprobable assumption, the conditional  $p(x|L_{NL})$  is the uniform distribution across the map, conditionals  $p(x|L_i)$  with  $i=1..3$  are Gaussian distributions around the home locality, and others are Gaussian distributions around incident locality.

$$Time_i = SD + (ED - SD) * Rand_i \quad (3.3)$$

Here,  $Rand_i$  is a uniform distribution in [0-1] range. SD and ED denote the start and end dates of the time interval to be observed, which are given as parameters of the system. At this stage, the incident time, crime type and criminal information are generated through (Eq. 3.4, 3.5).

$$Crime_i = 1 + (Max\_Crime - 1) * Rand_i \quad (3.4)$$

Here, Max\_Crime represents the maximum number of crime types, given as parameter of the system.

$$Criminal_i = 1 + (Max\_Criminal - 1) * Rand_i \quad (3.5)$$

Here Max\_Criminal is the maximum number of criminals, given as parameter of the system.

The final stage includes the distribution of all criminals and their acquaintances over crimes. The distribution of the acquaintances are modeled by considering three types of localities, namely home locality, incident locality and map locality, formulated in Eq. 3.6.

- The home locality is modeled by a mixture of three Gaussians where each Gaussian corresponds to different degree of locality around the home place, e.g. municipal/town/city.
- Incident locality is modeled by unimodal Gaussian around the incident locations.
- Map locality is modeled by the uniform distribution across the map.

The home locality covers the most of the acquaintances of a particular criminal. Hence, it should have the highest weight in computations whereas the map locality should have the lowest weight for the model to be more practical. In Figure 3.3, the acquaintance distribution of a particular criminal are visualized around different local centers for demonstration purpose.

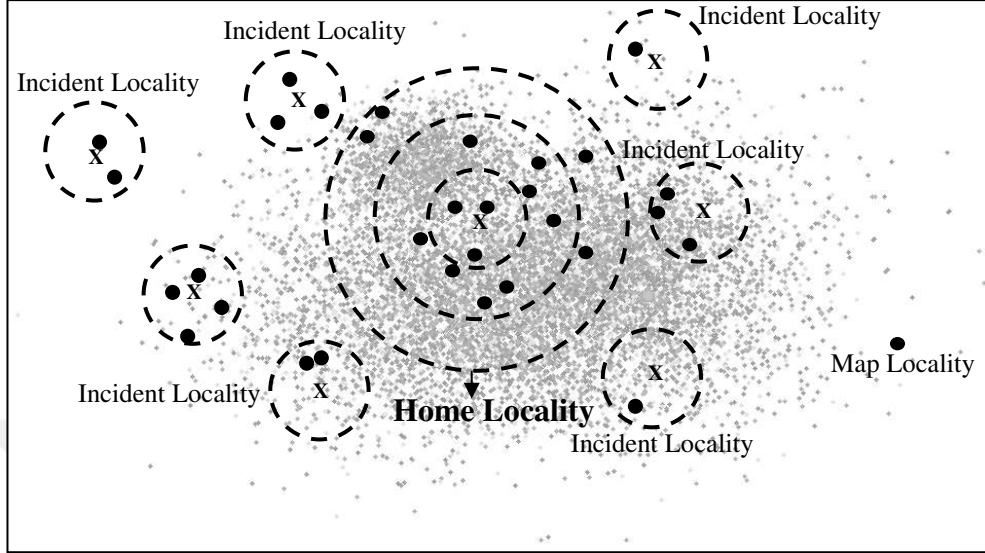


Figure 3.3. Distribution acquaintances with Gaussian Model

Let  $L_i$  be  $i$ . locality of the criminal among  $NL$  number of total local centers, which includes the home, incident and map localities. Then,  $AcqLocation_i(x)$  represents the probability distribution of acquaintances belonging to  $Criminal_i$  and can be modeled with the Gaussian Mixture at Eq. 3.6.

$$AcqLocation_i(x) = p(x|L_1) * P(L_1) + p(x|L_2) * P(L_2) + p(x|L_3) * P(L_3) + \dots + p(x|L_{NL}) * P(L_{NL}) \quad (3.6)$$

The feature vectors resulting from the dataset generation phase are shown in Eq.3.7.

$$CrimeIncident_i = (Crime_i, Criminal_i, Time_i, Location_i, AcqList_i) \quad (3.7)$$

where  $AcqList_i$  is the list of acquaintance determined by  $AcqLocation_i(x)$  for  $i = 1..NL$ .

With all these data, a crime data set based on a geographic information system and in a near realistic scenario was created. Crime, criminal, time parameters as well as place and acquaintance parameters have been taken into account by considering certain criteria. So each crime event consists of these five parameters.

### **3.2. Relation Between Crime Incidents**

#### **3.2.1. Crime Trend**

Tendency is a graphical representation of all kinds of curvilinear movements rising and falling over time under the influence of mathematics and statistics. In another expression, tendency is used to express trend, direction, tendency. In its most common form in our daily lives, this concept is used to describe a behavior in fashion, technology and/or business areas, a practical movement, a situation made by the vast majority of the population over the last two to five and ten years. Trends are self-generated in their own space, in their own local/global conditions of their own time. No trend will suddenly emerge. It is wrong to examine trends under a single structure. Interdisciplinary studies are of great importance. Because it is a fact that an area examined in trends is interacting with different areas. For this reason, it is seen that for a tendency many factors such as sociological structure, economic conditions, social and cultural activities emerge with their own conditions. The time-space-conditions that prepare to emerge gradually develop and disperse in the triangle. The main topics in trend research are future predictions, testing of these predictions and/or estimates with interdisciplinary studies, and development of ideas that can be considered past and future.

Crime trends is important role in this century. Increasing crimes are created getting more problems for human beings. It is needed to bring new proposal in struggle with crime and criminal problems. First, it is needed to determine the problem about crime and criminal. For example, when did occur crime? Which crime committed? Where was the most committed crime? What was the most

committed crimes on a particular geographical area? Which or how many times committed crimes by criminal? Was there any relation among crimes?

Such questions can be replicated and such types questions will impel us to investigate relationship among crimes. So, the crime incidents with the obtained information can be prevented before the creation of the crimes.

Tendencies are occasionally repeated concepts in certain areas. Trends are used in criminal and criminal areas as well as in different areas. Similar events from a specific area will show here that the likelihood of a similar event is strong again. For example, if there are traffic accidents on the same road on the highway then it is needed to be examined. In such a case, when traffic accidents recorded in the accident database are manually interpreted, information is given to the police units so that no traffic accidents occur again. It is necessary to take precautions immediately in order not to accident in the same places as location. That is why there is a need for intelligent systems that interpret traffic accidents recorded in the accident data set and notify where it is needed, just like crime prevention. The detection of trends has become a concept that will be beneficial to mankind in many ways.

Trends should not be used manually but should be examined under an intelligent structure. These intelligent structures are used in the detection of crime and criminal tendencies. When the crime incidents are examined, it is seen that they are related to each other on the basis of both crime and criminality. A criminal can commit a different offense. There are various reasons for this. These reasons can be considered as social structure, spatial structure and characteristic structure of person. Particularly, it is seen that those who commit certain types of crime tend to have similar crimes in this group. The tendency not only resembles the criminals but also resembles spatial tendencies. For example, entertainment centers tend to be more commit to crime. Such structures also indicate a strong link between crime and spatial. Therefore, the use of crime and spatial in geographic information systems is of great importance in terms of solution of the crime.

A criminal tendency is defined as the monitoring of changes in the structure of a particular geographical region and at a certain time on selected crime types. Crime trends are a concept that holds many different problems together. These types of problems are not only confined to crime and criminals but also to other crime parameters. But crime trends seem to focus mostly on crime and criminals within the framework of analysis of the crime. The main aim of this scope is found the way to prevent crimes. To find criminal trends, it is necessary to determine the places or regions where crime incidents occur. After that, it will need to determine the characteristics of the crime.

A few advantages related to the solution of the criminal trends with an intelligent system are listed below.

1. Determination of intensity situations occurring in crime areas
2. Detection of an event that may occur from crime
3. The situation of other crimes emerging from a crime
4. By examining the intensity distributions of crime events, determination detection of the next region.
5. Describe the sections where trends are detected in crime incidents

In this part of the thesis firstly information about crime/criminal trends from crime incidents will be given. Then, researches and studies related to this subject will be mentioned, and in the last section, the solutions suggested according to problem are presented. In summary, detect to the crime trend in this thesis will be determined the possibilities of other crime committing by those who commit a crime and it will be determined relation among trend of crimes.

**3.2.2. Relations Crime Incidents and Criminal Trend in Social Structures**

Relationships between crime incidents can be included problems such as criminal tendencies, links between crimes, and the identification of criminals. When crime incidents and their relation to each other are examined, some logical relations between crime relations should be mentioned. The most important of these logical connections is the concept of criminal tendency. Therefore, criminal tendencies are important subject at this point. The criminal tendency is influenced by the social structure. Both crime and criminal trend studies, in population distributions and social structure play an important role.

This structure is examined the impact of population change, and social change as well as other parameters among other crime groups. So, the tendencies of crime events through parameters can be analyzed more easily. As a result, it shows how the trends emerge and how they can be resolved. Because a crime incidents may start to show differences when examined according to the regions. These differences can bring material to the forefront, such as the spread of crimes. Trends can be determined according to the increase and decrease in the areas where the diffusion population is concentrated.

As well as these factors, generally it shows that criminal tendencies in population distribution are effective in social structure. In social structure is important to find any crime, which related to time and spatial and so on. For example, it is seen that those who live in poor and poor areas are inclined to crimes. On the contrary, the places where the crime rate is high are the rich ones. Thus, according to the type of crime and its structure, the tendency can vary under this social structure. Therefore this feature can not be neglected in the distribution of crime incidents.

**3.2.3. Crime Trend in Literature**

Generally, Crime trends at the literature research are mentioned about criminal, behavioral of criminals, distribution of crimes, conception of spatial and temporal investigation and the structures in social network.

Recently, time series plays an important role in finding clustering research, especially suicidal similar tendencies. There has been an increased interest in crime analysis with clustering operations. Multivariate time series data at different time points are analyzed. With the analysis done, it helps to identify the criminal tendencies that the law enforcement officers are interested in. Police management and trend analysis at the state and county levels are used to resolve new criminal cases. Therefore, a prediction model has been introduced to prevent similar types of crime in the future (Ewart and Oatley, 2003) and (Keogh and Lin, 2005)

In studies related to crime trends is more often encountered analysis of crime incidents. There are many studies about the concept of timing within these analyzes. The time parameter in crime incidents is the study of crime types and crime incidents that occur in a certain time period. One of the important factors in the occurrence of a crime event at a certain time interval is the place relation. There is a difference in the number of crime incidents among various places in a region. Crime incidents that occur in places of entertainment such as bar are higher than in other areas. These results make us important in the framework of analysis in places of crime.

In the last 40 years, the places where the crime has been committed vary according to the regions. A study has been carried out to show that the places in this geographical area are more intense than those in larger areas and criminal cases in smaller areas (Akpınar, 2005).

Also time is an important parameter. In detecting when criminal incidents happen is useful in terms of crime prevention procedures. For this, the concepts of spatial and temporal parameters are related to each other in the study of crime incidents. These parameters are important arguments at the point of resolving a

crime incidents. Criminal tendencies have brought with them the convictions that some events may happen again as time and place. When the impact of crime incidents according to place is examined, population densities and social structures are influential in criminal tendencies. Social constructs reveal situations that can lead people to commit crimes. Therefore, the economic structure and character structure of the criminals are influenced by these factors.

It is thought that places are important especially when examining crime trends in geographical situation. One study in this area can be called hot spot police. These terms are used to refer to specific streets in relatively small areas (Sherman et al., 1989).

The most important parameters in crime analysis are crime type, time and space concepts. For example, there is a study about the hot-spot places that is thought to be insecure for a group of people who were determined from the expressions of victims and geo-coordinates of the incident (Sherman et al., 1989), (Moon and Carley, 2007) and (Harada and Shimada, 2006). In case of scrutinizing all the crime dataset manually, even with a whole team it is not possible to realize such information. It will also determine the exact location of the clusters to determine clusters of related activities.

Moreover, there is also study to understand crime tendencies and risks in small areas in detail. In this study, a prediction model has been developed because of the criminal trend in each area and on a general average tendency. Different probabilities of zone-specific criminal tendencies are analyzed from the average tendency. In this analysis, a new approach to identifying hot/cold spots has been developed by mapping events. Although the hot spot is more crime points, the cold spots show places where there is no crime. Elsewhere, cold spots are defined as places of low crime. These concepts emphasize specific places where the crime situation worsens or develops (Sherman et al., 1989), (Aldor-Noiman et al., 2016) and (Law et al., 2014)

In Akpınar (2005), to infer implicit patterns by parsing the textual content, apart from explicit information for each incident such as type of the crime, time and location are tried. For instance, from the descriptions of victims and the geo coordinates of the incidents, it is possible to identify hot-spots which are considered unsafe for a particular category of people. Such information cannot be realized even when dedicating an entire team to manually sift through the whole crime data set. Furthermore, because it has accuated data about the time and the locations of such incidents, we can spatially model the findings to identify clusters of related activities and also use this knowledge to predict future incidents.

Despite the structural data, all patterns have nested positions. In order to view these patterns, the data requires a lot more processing. Unlike other areas of transaction, association analysis is a common approach in such mining projects. For this reason, there is no rule prepared beforehand for the crime incidents. To determine the event clusters that happen together, it will be useful to exceed the spatial and temporal distribution of events. It is possible to find the spatial-temporal clusters of all crime events and to control the models in the subtypes for a high-level design.

In studies on the persons who committed the crime are important place for this concept. Here, especially the people who lived in prison, both in prison life and the criminal process after leaving the prison has been revealed through various investigations. Therefore, there are many studies conducted among prisoners. In one of these studies has been conducted on crime and criminal. In this study, criminal tendencies were investigated by determining the crime rates again after the prisoners were released from prison.

A similar study of the above-mentioned studies is a study of the sociological and psychological effects of prisoners. In one study, a survey was conducted on the conduct and behavior of prisoners, apart from finding criminals and analyzing crime. A survey has been conducted on the psychological structures of both criminals who are not in prison and prisoners in prison. In this study, the reasons

leading to suicide were determined. The most important part of this finding has been shown to be related to sociodemographic factors. With these methods, prisoners were informed about some problems such as tendencies towards crime, structural differences, behavior patterns. It has been stated in the research that collecting these individuals can be effective treatment of these factors for their recruitment and treatment.

Law and Chan (2012) and Andresen (2011) spatial distribution in sociodemographic distribution is very important. It is aimed to evaluate recent trends in spatial distribution. These data are made meaningful by way of sampling from the spatial presence of alcohol. The importance of using low-level descriptive data to understand these trends is emphasized. This study is concerned with the relationship between alcohol models and trend types and these areas. Obtained findings provide detailed, longitudinal information about the location and structure of alcohol sales locations (Robert, 2010) and (Berchiolla et al., 2013).

Social structure is a phenomenon that has significant effects on crime incidents. That is why there are studies about the physical environment and the connection with crime. In similar areas, it is seen that crimes of the same kind are constantly repeated. At the same time, parameters such as the location and timing of crime incidents have been examined in such studies. Apart from this, criminal tendencies can be detected with links between places where the crime is committed. When correlations are examined, they are involved in studies of the criminal character. It is focused on the social structure of society and individuals. Taylor and Gottfredson (1986), emphasize that spatial structures are an important point in criminal activity. It has been shown that a crime is absolutely social, and that the concept of crime is related to this structure. It is seen that the physical environment is influenced by the gathering of incidents that are related to crime under a certain structure.

Social network analysis is a known fact when environmental phenomena are influenced by each other. As it is known, this information is processed by the city

planners through a geographical information system and the selection of the most accurate and possible location of some physical structures is a great advantage in preventing crime. The construction of a school-like structure in an environment with bars and entertainment places can lead to negative trends that may occur in the future. Such problems can be prevented through such systems. Because in such places crime incidents occur more than other places. Child-aged individuals can be pushed into these problems. Therefore, there is great benefit in creating such systems integrated with city planners with intelligent inferences (Jacobs, 1961). Some studies have shown that crime incidents are linked to the physical environment. Especially in criminal activities such as theft and auto theft, changes have been observed in certain places. There is evidence of these changes in a logical systematic sequence (Akpınar, 2005), (Brunsdon et al., 2007) and (Taylor and Gottfredson, 1986).

All these studies show that where environmental factors are taken into account, there are places where crime can be committed in rich neighborhoods. Thus crime such as theft will be geographically determined locally in the social structure. This study will be able to find the places where the theft is done and the tendencies.

The increase in pre-school crime rates necessitated the necessary steps and investigations to prevent this. A number of studies have been conducted to test the relationship between international trends and arrest and criminal tendencies. In particular, there are studies in which specific arrest rates for a certain age group are determined and predicted. This has led to different pre-school crime trends among crime categories and countries (Nevin, 2007).

Crime trends vary by age. In an age-based study, it has been shown that the trend of suicide among young people is higher than that of adults.

There are some studies that take into account the families of 4th and 12th Grade Students' Associated Attitudes. In these studies, the children's family prints and the bullying that they encounter have been addressed. Bullying and pressure

are a major problem. In the last decade, various media and government institutions have pointed to this problem. This study investigated whether these associations between 2005 and 2014 showed a difference as a function of differences and school-level variables (Whitted and Dupper, 2005) and (Juvonen and Graham, 2014).

Criminal tendencies have brought with them the convictions that some events may happen again as time and place. These basic concepts and these concepts can be done in different evaluations. In a study on crime and criminal trends, trends were reported according to reports held in Japan. This shows that the trends of fraud and identity theft are the changes between the specified dates (Potchak, 2002). When the impact of crime incidents according to place is examined, population densities and social structures are influential in criminal tendencies. For this reason, if a real approach to crime analysis is to be done, it is absolutely necessary to examine crime incidents within the concept of social networking. When the economic structure and character structure of criminals are examined, it is seen that these structures are effective in a trending social network.

Some work has been done on preventing the crime rates in the social media. One of these, crimes between 2004 and 2013 in Malaysia have been examined to distinguish the underlying events of violence. Effective methods and strategies for reducing violent crimes have been established in a research. For this reason, it will be necessary to look at trends in violent offenses over time and trends to identify these important variations. These trends are very important for such crime incidents. Thanks to these trends, a design has been created that will benefit the security forces to a great extent. Trends do not always detect the next point from previous data. This is a very important criterion, but there are different approaches. So it is not just the way to describe the trend. It is in the form of change and differentiation of the crime types according to the regions (Muhammad et al., 2014).

In a study on crime tendencies, there are studies on urban sprawl, population density and contemporary migration tendencies in rural areas. A study was conducted on the urban distribution of rural municipalities and the crime and criminal tendencies of population density. The crime survey, which may potentially affect the population density, the social institutions of the neighborhoods, is examined. A sample model of the data obtained from the difference reports between 2000 and 2010 for 142 municipalities measuring the strength of the city's qualifications and population and the interaction of material crimes was established (Bouchard and Nguyen, 2010).

There is a publication on social network analysis that examines the relationship between crime and criminals. In this study, it is informed about the definition of crime incidents in social network framework. The links between crime types and criminals within the social network structure are mentioned. Besides this, the concept of organized crime and the importance of social network in the concept of this crime are mentioned.

As a result, the application area of social network analysis is threefold. These will be taken into account by the fact that organizations tend to be inclined to the effect of personal networks on crime. By this means, it will be possible to determine what kind of crimes are committed by an organization and some links can be determined by these means. Another point is the interaction of neighboring networks. More than one group is investigating crime and relation to each other. This area has common actions, and it can be reached as if these groups are in contact with each other. In fact, intergroup relations are determined without precisely specifying the groups as criminal groups. The last part actually shows something similar to the first two parts. But there is a more special case. In this structure, the activities and organizations of the structures which are now characterized and defined as crime groups are being investigated (Carrington, 2011).

Social network analysis has developed important simulations to prevent crime. (SNA) are first combined under a special tool to calculate the properties of nodes in a network. In this way, a social networking that can not be secured can be provided a structure that increases the integrity and reliability ratings (Coffman and Marcus, 2004) and (Koelle et al., 2006).

In a simulated study, a group is a terrorist group. For this, metric values are needed in social network analysis. These values were obtained by using statistical classifiers. In this simulation it is a study of the methodology and results of an evidence work that characterizes the persons in the data set as being terrorist or non-terrorist. Simulated data sets are modeled within cell organizations and social interactions emerging from more typical social structures. Bayesian classification is used in the modeling. With the simulation, three types of classification were done first. These are the classification of cell leaders, cell members and non-terrorists. In the next simulation, terrorism and terrorism classified were carried out (Coffman and Marcus, 2004).

However, secret organizations such as terrorist organizations have normally different structures. The general shape and function of these structures is not the same as the others. Because of this, terror groups have different network structures than typical hierarchical organizations. In particular such types of cells tend to be cellular and diffuse. For this reason, most people do not know how this works. Instead, they try to think of them hierarchically. The reliability of information in a secondary question. Although there is a lot of information about the size, shape, and structure of these networks, the information obtained may be incomplete and incorrect. By assessing these difficulties, analysts' alternative tactics need to be evaluated against and assessed against the problems. Some strategies have not been set for the solution of the problems and some tools and approaches should be applied (Carley et al., 2002).

In addition to terrorist anomalies, there are studies in which these terrorist organizations are made in a certain geographical trend. The future performance of

terrorist groups within a particular social network is also assessed. In Moon and Carley (2007), terrorist interactions have allowed us to have some knowledge of the geographical location and development of social areas. This view should be examined when social and spatial relations develop over time. These structures are being investigated through predictions of management, command and control structures and intelligence analysis. It may be possible in this way to recognize future social and spatial distributions, hot spots and organizational weak spots. Historically, such estimates are largely dependent on qualitative data analysis by subject matter experts. Many researchers have tried to solve using multiple agent models and simulations. Simulations deal with short-term organizational changes. In general, two perspectives have been examined. These are the effects of changes in the social network and the effects of geographic change. Both perspectives show the dimensions of the performance of the future tendency in the emerging work.

Today, weblogs created for internet users play an important role in the framework of social network analysis. Web logs are a website created by an author. Now, terrorist groups are communicating via social networks for any crime. The law enforcement agencies can be monitored their social networks to prevent crime. With social network analysis, it is possible to reach terrorist activities in these diaries. These may contain information on measures to be taken against terrorist acts. Police forces are following such social networks to prevent crime. Social logs have been reviewed for logs stored under Web logs. Thus, the study of this type of social network analysis and visualization of the results are kept under a single structure (Yang and NG, 2007).

#### **3.2.4. System Simulation**

There is a need for a system model, as seen in the literature on crime above. Interpretation of data either manually or statistically is now a necessity. Due to the repetition of criminal incidents in a region, various intelligent systems are needed to prevent them.

Nowadays, it is a fact that crime analysis programs enable a great profit to the security forces. It is possible to detect criminal tendencies by analyzing the connections among the types of crimes. Therefore, the crime analysis necessitates a dataset generated by the realistic method. It is implemented all operation on this crime dataset.

Aim of this scope is divided two part. One of these, the relationship among crimes in a certain geographical area is detected. The other one is determined criminal trend.

### **3.2.5. Definition of System Model**

Today, it is a fact that crime analysis programs provide a great benefit to the safety forces. With the analysis of the relationships between the types of crime, it is possible to determine trends. For this reason, a data set which is produced by a realistic method is needed for crime analysis. In the previous work, mostly benchmark are used. In this work, the most important task is to generate our data set with working parameters which comes from a simulator and is more useful for user.

Even though all the patterns are coalesced into one location with the structured data, they are discernible to the naked eye. In order to view these patterns the data requires a lot more processing. Unlike other domains like transactions, association analysis is a very common approach in such data mining projects. Therefore, there aren't predefined rules that can be applied to the crime dataset. So as to infer clusters of incidents that occur together, it is aimed to take advantage of the spatial and temporal distribution of incidents. On a high level design, It could be found spatio-temporal clusters of all crime events and check for patterns in sub-types.

As mentioned earlier, the same criminal data set will be used in the calculation of criminal trends. For this data set, crime and criminals will be related through N sampling. First, all crimes distributed on the geographical map and the crimes committed by those crimes will be identified for similar crimes. Coordinate

information will not be used for the time and location of the crime here. For this reason, the tendency of criminal will be investigated by connections between types of crime. During this detection, time of crime incident, the place information which is x and y coordinates and acquaintances of the criminal from the crime scene parameters will not be used. Only criminals are looked at in relation to crime. So, the simulator will use an appropriate mathematical model to investigate query crimes and analysed crime in relation to the existence of relationships between crimes.

### **3.2.6. Problem Formulation of Crime Trend**

There are many studies of criminal trends above. Most of these studies have been conducted in the context of certain geographical psychological trends of crime, tendencies of children in school age, criminal tendencies of criminals coming from prison and social network. Nevertheless, there is no study of the likelihood of criminal and tendencies of a criminal to commit another offense.

There are few studies on the probability of criminal to commit other crimes. In the following sections, information on the crime/crime tendency will be given about this study.

Two concepts are primarily addressed here. It is calculated in both structures with the same logic. The first of these is the relationship between crimes. It will be determined where crimes concentrate on the territories and where crime zones jumped into the next zone.

The second is the point at which investigated criminals are able to detect other committing crime possibilities. It will be used together in these two cases. Because, in order to identity the trend of a criminal is needed to calculate the relation among the crimes. Those who commit a crime in the criminal data set tendency towards other crimes is an important influence estimating criminal who commits the crime of the target.

The basic purpose is the identification of common points among all crimes in a crime database. If criminals who commit similar crimes and possible crimes that could be committed in the next step of these crimes can be detected. So the trend is the key motivation point here.

As a technique, only two crimes are compared between crimes. If there is more than two crimes, then it will be a combination of two crimes. For example, for three crimes, crime is expressed as a combination of two crimes.  $S_i$ ,  $S_j$  and  $S_k$  crimes will be held in the  $(S_i, S_j)$ ,  $(S_i, S_k)$  and  $(S_j, S_k)$  structures. These combinations are shown in the graphic below (Figure 3.4).

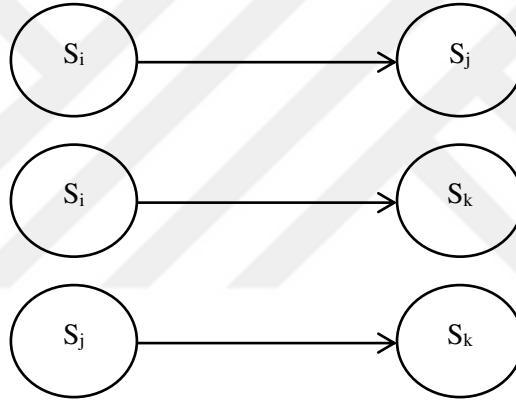


Figure 3.4. Interrelation between crimes

It is necessary to focus on two concepts because of the relation of the offenses. One of these concepts is the crime being examined and the other is the crime concept being questioned. The concept of crime analyzed is the meaning of the crime investigated according to the available evidence. However, the crime investigated is the questioned crime process. The relationship between the two crimes is shown below. In these crimes,  $S_i$  is the crime that is examined and  $S_j$  is the crime that is being investigated. The desired process,  $S_i$  is the probability of those who commit the analysed crime to commit the query crime  $S_j$ . According to the bayesian network, this process is called  $P(S_j | S_i)$  in Figure 3.5.

Here it is tried to find out the probabilities of committing  $S_i$  crime of the criminals who commit  $S_j$  crime. For doing this, it is utilized a foresight and prediction model called Bayesian Network Model that is an artificial technique used in probability.

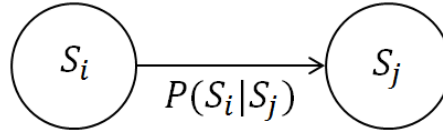


Figure 3.5.  $S_i$  is the probability of those who commit the analysed crime to commit the query crime  $S_j$

Thus, the crimes are extracted according to the Bayesian formulas. According to the obtained results, crime types that occur in a region can be determined. Not only crime types but also crime similarities in among regions can be detected. The trends can be displayed in this way as a possible Figure 3.6.

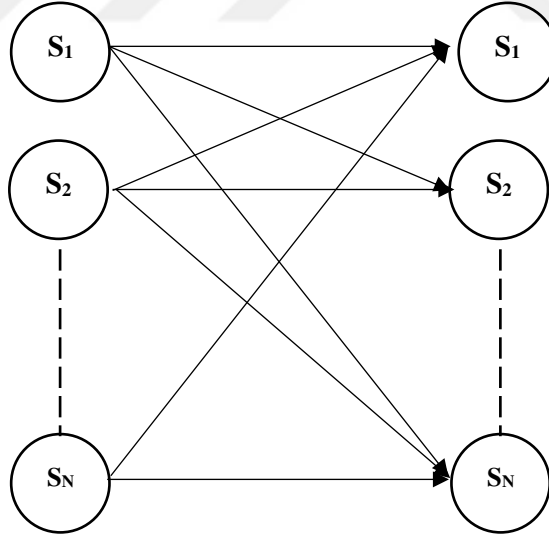


Figure 3.6. Relation among crimes.

Spatial structures are important in the analysis of crime incidents that occur in a region. These structures can also help the functioning of the institutions of the government. Predictive systems can be provided for people to live more comfortably when trends are taken into consideration. For example, when it is desired to set up an entertainment center, the system checks the previous data and determines the types of crime that occur in such places. The required government agency will receive information about the forecasting system of a recreation site for which a geographical area is desired. If there is a place near the entertainment center, such as a school or library, the system will report that it is objectionable. As a result, it is aimed to protect children from crime as much as they can. Because alcohol, drugs and quarrels are especially popular in places of entertainment. A crime will ensure that such offenses are taken away from children as much as possible. For this reason, the tendency among crimes is important to prevent before a crime occurs.

The tendency of crimes can be determined by controlling the relation of all crimes. it can be found in statistical analysis which crime types have been further processed in a region. It is then possible to find out which crime is tendency to all crimes. According to the results, the higher the trend of the crime in a certain region, the higher the likelihood of the crime being processed.

Crime trends may show tendency for years, regions and types of crime. According to years, it can be seen which tendency of crime is processed more at certain time intervals. Today, the effects of these trends on sociological, psychological and other fields are an important issue in crime tendency. According to the regions, there is a similarity in crimes in close regions if trendy attention is paid. Apart from that, in the regions where similar crimes are committed, it is the top level in the interactions between crimes. When these regions are examined based on crime, it can be determined in which direction the criminal tendencies progress. Such inferences will inform us about the distribution and leap of crime

types, as well as information on which crime route may be likely to occur in a similar area (Figure 3.7 and Table 3.1).

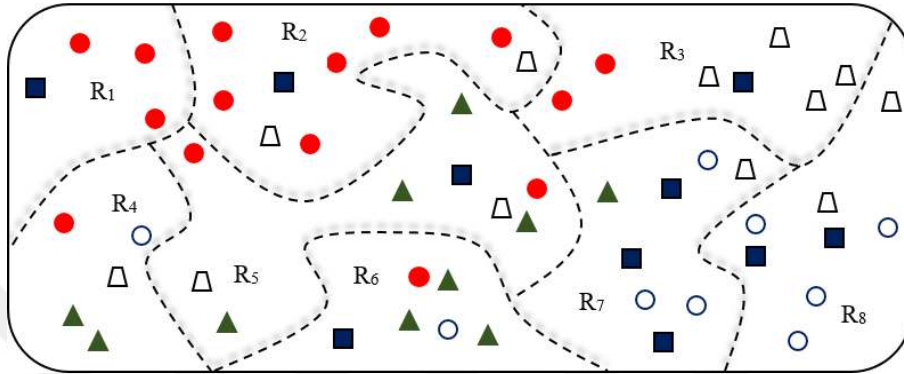


Figure 3.7. Different type of crimes in map

Table 3.1. Crime rates according to region

| Region         | S <sub>1</sub> ● | S <sub>2</sub> ■ | S <sub>3</sub> ▲ | S <sub>4</sub> △ | S <sub>5</sub> ○ |
|----------------|------------------|------------------|------------------|------------------|------------------|
| R <sub>1</sub> | 3                | 1                | 0                | 0                | 0                |
| R <sub>2</sub> | 6                | 1                | 0                | 1                | 0                |
| R <sub>3</sub> | 2                | 1                | 0                | 4                | 0                |
| R <sub>4</sub> | 1                | 0                | 2                | 1                | 1                |
| R <sub>5</sub> | 2                | 1                | 4                | 2                | 0                |
| R <sub>6</sub> | 1                | 1                | 3                | 0                | 1                |
| R <sub>7</sub> | 0                | 3                | 1                | 1                | 3                |
| R <sub>8</sub> | 0                | 2                | 0                | 2                | 4                |

When the distributions of the crimes committed in the 8 regions above are analyzed statistically, similar crimes are seen to occur in the nearby areas. For example, it is observed that the S<sub>1</sub> crime has jumped into the from region 1(R<sub>1</sub>) to region2(R<sub>2</sub>). A total of 5 crimes were searched in the R<sub>2</sub> region of those who committed S<sub>1</sub> crime in region 1(R<sub>1</sub>). The most committed crime in area region 2(R<sub>2</sub>) is crime1(S<sub>1</sub>). Other crimes are S<sub>2</sub> and S<sub>4</sub> crimes. It is seemed that there is no

tendency for those who committed crime  $S_1$  in region 1 to commit crimes  $S_3$  and  $S_5$  in region 2. All these correlations are shown in Eq. 3.8.

$$P(R_2, S_i | R_1, S_1) = \frac{P(R_2, S_i, R_1, S_1)}{P(R_1, S_1)} \quad (3.8)$$

The maximum value will be determined using equality 3.8 in all crimes that occur in a region. The value found is the closeness of the crimes between the two regions (Eq. 3.9). This shows us the direction of the tendency between crimes. In the same way, by using the bayesian formula, according to the years, the trend of the crimes can be followed and the daily trend can be found from the past years.

$$S_{\text{Crime\_id}} = \max[P(R_2, S_1 | R_1, S_1), P(R_2, S_2 | R_1, S_1), \dots, P(R_2, S_5 | R_1, S_1)] \quad (3.9)$$

### 3.2.7. System Model and Problem Formulation for Criminal Trend

The second point for the criminal trend is similar to the previous formulation. The only difference is the identification of criminals. In comparing two crimes is calculated probability of committing other crime of criminals. The system model and the problem formulation for detecting criminals are below. In system model, For a criminal to tend to other offenses, five patterns in this model need to be known (Figure 3.5). The first of these is the probability of a criminal offense. In this probability, the frequency of crime committed by the criminal must be found. Then, the crime trend will be determined as calculated in the above form. The probability of the other criminal in the criminal data set will be calculated. Finally the formula is concluded taking into consideration the probability of other crime committed by the criminals.

Showing regard to system model model, the probabilities and committing situation of analyzed and query crimes in the database need to be calculated first. It

is called prior probability that is directly proportional probability with number of crimes and analysis of dataset only, regardless of a condition.

Each crime is represented by mathematical model which is also available in the crimes related with each other (Figure 3.4). Also, with this model analysis process is implemented and the information given in a particular geographic area will be scattered (Figure 3.5). In order to distribute data with artificial intelligence methods, The Gaussian Mixture and K means Clustering Algorithms will be used.

The general mathematical model which will be used in determining the relationship among crimes is below (Figure 3.8).

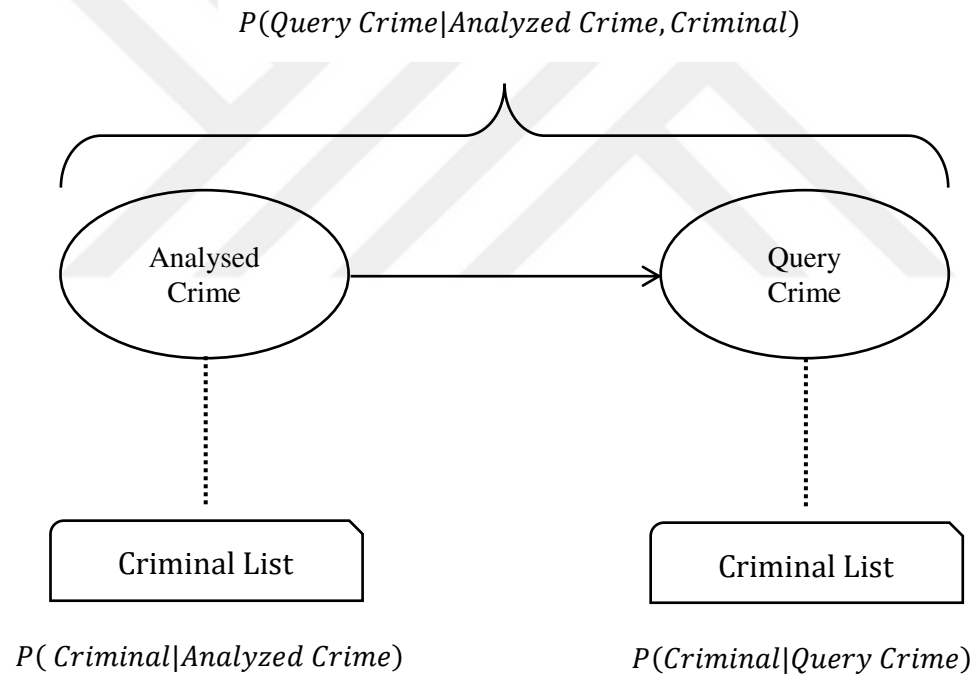


Figure 3.8. The mathematical model for criminal detection according to crimes

The trends formula for the influence of the criminals in between crimes are shown above. Eq. 3.10 is the formula for finding the criminal tendency according to the system model in Figure 3.8 above. According to the system model, the

purpose is to find the criminal that needs to be questioned. The formulation of the model of which general form is given above according to Bayesian network is below (Eq. 3.10). In addition, some of the terms to be used in determining the trends between crimes are given in Table 3.2.

Table 3.2. Definition variables in formula

| Trend Formula                                                  | Explanation                                                                         |
|----------------------------------------------------------------|-------------------------------------------------------------------------------------|
| $P(\text{Query Crime} \text{Analyzed Crime}, \text{Criminal})$ | The probability of committed query crime for criminal who committed analysed crime  |
| $P(\text{Query Crime})$                                        | Probability of Query Crime in DataSet                                               |
| $P(\text{Analyzed Crime})$                                     | Probability of analyzed Crime in DataSet                                            |
| $P(\text{Criminal} \text{Analyzed Crime})$                     | Probability of criminal who commits the analyzed Crime in DataSet                   |
| $P(\text{Criminal} \text{Query Crime})$                        | Probability of criminalr who commits the Query Crime in DataSet                     |
| $P(\text{Query Crime}   \text{Analyzed Crime})$                | Probabilities of committing query crime of the criminals who commit analyzed crime. |

$$P(\text{Query Crime}|\text{Analyzed Crime}, \text{Criminal}) = P(\text{Analyzed Crime}) \times P(\text{Criminal}|\text{Analyzed Crime}) \times P(\text{Query Crime} | \text{Analyzed Crime}) \times P(\text{Query Crime}) + P(\text{Criminal}|\text{Query Crime}) \quad (3.10)$$

$P(\text{Query Crime}|\text{Analyzed Crime}, \text{Criminal})$  is probability committed query crime of criminal who committed analysed crime. it is found to other crime

tendency for criminal in any crime. Therefore, it is necessary to consider the records in the crime data set.

Two crimes will be identified first in these records. it will be checked whether a criminal who committed the first crime committed the other crime. The criminal trend formula consists of five main sub formulas. if it is desired to examine them separately, then the purpose of each formula is specified. First, the crime to be investigated is the crime analyzed. It will be detected of analyzed crime type that how many times repeated in crime data set ( $P(\text{Analyzed Crime})$ ). This calculation for  $P(\text{Analyzed Crime})$  is the same in the query crime for  $P(\text{Query Crime})$ .  $S_i$  is the analyzed crime and  $S_j$  is the query crime (Eq. 3.11). All these calculations are called as primary probabilities for crimes in this model.

$$P(S_i \text{ or } S_j) = \frac{\text{The number of the crime } S_i \text{ or } S_j}{\text{The number of crimes}} \quad (3.11)$$

To find out the probability of criminals in a crime dataset, It is necessary to determine how many times the relevant crime has been committed in the crime dataset. The formula Eq. 3.12. will be used for each offender in the calculation process.

$$P(\text{Criminal} | \text{Crime}) = \frac{\text{Number of Criminal in Crime}}{\text{The number of crime}} \quad (3.12)$$

In the analyzed formula, it has been playing a significant role in the connection of both crime communication with each other except only the different probabilities of crimes. Because by the time an offender who commit a crime commits another one, these people will need to be feature in a foresight analysis. Therefore, it is needed to check the relationship of offenders committing both crimes.  $S_i S_j$  part in the formula is utilized to control if offenders who committed analyzed crime committed query crime or not. The probability in this control is

$PS_iS_j$ . Although it is shown differently in demonstration,  $PS_iS_j$  or  $P(S_j|S_i)$  means finding the probability of committing  $S_i$  crime of the people who commit  $S_j$  crime. The probabilities for persons having committed the crime  $S_j$  to commit the crime  $S_i$  (Eq. 3.13-3.15).

$$P(S_j | S_i) = \frac{P(S_i, S_j)}{P(S_i)} = \frac{P(S_i \cap S_j)}{P(S_i)} \quad (3.13)$$

$$P(S_i \cap S_j) = P(S_i | S_j) \times P(S_j) \quad (3.14)$$

$$P(S_j | S_i) = \frac{P(S_i | S_j) \times P(S_j)}{P(S_i)} \quad (3.15)$$

The probability for criminal having committed the crime  $S_i$  to commit the crime  $S_j$  are shown by re-formulation of different variables below (Eq. 3.16).

$$P(S_j | S_i, Criminal) = P(S_i) \times P(Criminal | S_i) \times P(S_j | S_i) \times P(S_j) + P(Criminal | S_j) \quad (3.16)$$

Our first priority is the determining the relation of the crime  $S_i$  with crime  $S_j$ . With this method, the relation of crime  $S_i$  from the crime  $S_j$  may also be identified. Here when it is a matter of the relations between two crimes, the situation of every crime committed in database and the probability of committing other crimes of offenders who committed these crime will be determined. The priority that will be identified in each process is the matter of finding the probabilities of committing other crime of the group which committed a crime. Only crime and criminals are utilized as parameter. If an inspected offender commits the questioned crime, the trend automatically indicates that this offender can commit that crime more than

the others. Therefore, it is aimed to increase the committing probability effect of criminal in  $P(Criminal|S_j)$ .

In summary, crime trends are used to detect criminal trends to other crimes. Trends can be detected with many different features. However, in this thesis, the situation of the criminals is more emphasized in the Crime analysis framework. The main act is to find criminal offenses that are likely to commit this crime according to what is available when a crime is committed. Unlike the crime trend, it is the estimate of who operates this crime when a crime is committed with different parameters.

Firstly, trends from inter-crime relations were identified. With this determination, the offender began to be examined in the concept. Afterwards, the detections and trends of the criminals were found. The last point in this ongoing logical connection will be the detection of the criminal with different rapametres. Here, only crime and criminal parameters are used in the previous operations. With the simulation to be created, the criminal detection from some parameters will be done according to bayesian theory. The parameters to be used here are not only crime and criminal but also time, place and familiar parameters. Since the main part of the thesis is guilty determination, the necessary system model and problem formulation are explained in the following sections.

### 3.3. The Formulation of Hybrid Metrics in Crime Data Analysis

Another point that is examined within the concept of crime analysis is the close relation between records of crime incidents. For the trend described above, the same goal is pursued here as to how the similarity of crime incidents is mentioned. The biggest challenge in databases is that feature vectors are not the same in both length and data format. Hence, similarity between any pair of vectors requires complex distance measurements or transformations. One of the solutions provided here is to reflect the feature vector space on the similarity area, which is called the similarity between each pair of event points. The idea is based on

similarities between a pair of events, similarities between features at the same time. The purpose of each pair event that have five parameter of each crime incident is to compare all the features of the crime events. However, in this comparison, the similarity of each property will be determined.

As a result, the motivation of this approach is, in general, that crime analysis methods do not need a full set of realistic data to develop and test decision-making algorithms. The motivation behind the use of hybrid metrics is to use both quantitative and categorical information with the lengths of the unstable feature vectors of event-level crime data. Thus, an application that generates crime data at the incident level and supports query-based crime analysis on the GIS map has been developed.

The proposed system was developed to provide incident-level data that is difficult to obtain in practice. Although the data generated by our agent is not exactly realistic, it is sufficient to develop a decision-making algorithm for crime analysis. With the resulting model, various GIS related queries can be shown on the GIS map to provide visual analysis. In addition, clustering based decision making algorithms for crime analysis were provided. With the model, it is possible to measure clustering performance using clustering of events from one or more relevant perspectives and using the proposed performance metric. Details are given below. In this detail, how similarities are categorized and all the structures used in the formula are explained separately.

Now let us briefly explain the whole formulation in the context of the causality of these details. One challenge of the dataset is that the feature vectors are not uniform in both length and data format. So the similarity between any pair of vectors requires sophisticated distance metrics or transformations. One solution, provided here, is to project (transform) the feature vector space onto the so called similarity space where each point is the similarity between an incident pair. The idea is the similarity between a pair of incidents is based on the inter-similarities

between features of same time. So the similarity space consists of quadruples:  $(SimCrime, SimCriminal, SimPlaceTime, SimAcq)$ .

where each dimension describes a similarity with respect to the given perspective. Let  $Incident_i$  and  $Incident_j$  be two vectors. The similarity between them is denoted by  $Sim(i,j)$  and formulized at Eq. 3.17-3.22;

$$\begin{aligned} Sim(i,j) &= \sqrt{SimCrime(i,j)^2 + SimCriminal(i,j)^2 + SimPlaceTime(i,j)^2 + SimAcq(i,j)^2} \end{aligned} \quad (3.17)$$

$$SimCrime_{i,j} = \frac{|(\cup_{Crime=Crime_i} Criminal) \cap (\cup_{Crime=Crime_j} Criminal)|}{Max(|\cup_{Crime=Crime_i} Criminal|, |\cup_{Crime=Crime_j} Criminal|)} \quad (3.18)$$

$$\begin{aligned} SimCriminal_{i,j} &= \frac{|(\cup_{Criminal_i \in Acquaintances} Criminal) \cap (\cup_{Criminal_j \in Acquaintances} Criminal)|}{Max(|\cup_{Criminal_i \in Acquaintances} Criminal|, |\cup_{Criminal_j \in Acquaintances} Criminal|)} \end{aligned} \quad (3.19)$$

$$DistSimPlace_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2 + (t_j - t_i)^2} \quad (3.20)$$

$$SimPlaceTime_{ij} = \frac{DistSimPlace_{ij}}{Max(DistSimPlace)} \quad (3.21)$$

$$\begin{aligned}
& SimAcq_{i,j} \\
&= \frac{|Acquaintances_i \cap Acquaintances_j|}{Max(|Acquaintances_i|, |Acquaintances_j|)} + \frac{1}{2} \\
&* \frac{|Acquaintances(Acquaintances_i) \cap Acquaintances(Acquaintances_j)|}{Max(|Acquaintances(Acquaintances_i)|, |Acquaintances(Acquaintances_j)|)} \\
& \quad (3.22)
\end{aligned}$$

where  $U_{X \text{ op } Y} Z$  is the set of values of the attribute  $Z$  that belongs to the incidents selected by the operation “ $X \text{ op } Y$ ”. That is, “ $X \text{ op } Y$ ” selects the incidents in the dataset;  $Z$  selects the attribute in the incident.

The similarity with respect to the time and place of the incidents becomes meaningful in finding relation between incidents if both are close to each other. So  $SimPlaceTime$  is grouped as one perspective in Eq. 3.20-3.21. Since they are numeric, Euclid similarity is used to define the similarity with the time and place perspective.  $SimCrime$  and  $SimCriminal$  are both categorical types so their similarity measures are based on the operations on the set. Their formulas at Eq. 3.18-3.19 are empirically found to be better than the Jackkard similarity. Similarity between the two acquaintance sets is defined in Eq. 3.22. Acquaintances of acquaintance is actually a recursive process that requires some stopping criteria, here dept. Thus, the set of all acquaintances that can be reachable from the criminal could be considered as the social network of the criminal with some depth constraint, here 2.

### 3.3.1. Performance Metrics: Crime-Driven Causal Relation

Since the original cluster labels are assumed to be unavailable, measuring the clustering performance of the proposed method becomes a challenge. In this thesis, first we empirically show the performance of the proposed method. Then, it is provided a quantitative measurement, called as Crime-Driven Causal Relation Performance. The causal relation actually defines a performance from one

important perspective, but not the all perspectives. If it is known that one perspective creates a true relation between incidents, any successful algorithm is expected not to violate the truths of this perspective relation. That is, a successful algorithm should not conflict with the true relation from a particular perspective. It is defined a perspective from the causal relation between incidents. Let

$$\text{Incident}_i = \{\text{Criminal}_i, \text{Crime}_i, \text{Place}_i, \text{Time}_i, \text{Acq\_list}_i\}$$

where  $\text{Criminal}_i$  is the criminal ID of the  $i$ . incident,  $\text{Crime}_i$  is the the crime type of the  $i$ . incident, and so on.  $\text{Incident}_j$  is causally related to the  $\text{Incident}_i$  denoted as simply  $i \rightarrow j$ , if following conditions are hold:

- 1-  $\text{Time}_i < \text{Time}_j$
- 2-  $\text{Acq\_list}_i \cap \text{Criminal}_j \neq \emptyset$

$\text{Incident}_j$  is crime-driven causally related to the  $\text{Incident}_i$  if the following additional condition is hold:

- 3-  $\{\text{Crime} | \text{Crime is committed by criminal}_i \text{ before time}_j\} \cap \text{Crime}_j \neq \emptyset$

Crime-Driven Causal Relation partitions the overall set into overlapping clusters where each cluster contain pairs of causally related incidents. The overlapping sets are converted to disjoint sets by making simple conflict resolution assumptions such as “closer time is better to define a true perspective”. For example, if there exist  $i \rightarrow k$  and  $j \rightarrow k$  then  $i \rightarrow k$  if  $\text{time}_i - \text{time}_j < \text{time}_i - \text{time}_k$   $j \rightarrow k$  otherwise.

If the cluster labels generated by the Crime-Driven Causal Relation is used as an original cluster labels, then the labels that proposed algorithm produced could

be compared based on the False-Alarm Rate. False Alarms indicate the number of incident pairs that are clustered as related by the proposed algorithm, although they are actually not according to the original cluster label. A successful algorithm should make the False-Alarm rate as small as possible, which in turns shows the degree that the algorithm validates the truth of the Crime-Driven Causal Relation perspective.

### **3.4. Artificial Intelligence Techniques**

Various algorithms have been used for intelligent systems used for the analysis of crime incidents. Some of these algorithms are described above. The gaussian mixture model used in the crime data set, the bayesian network used for crime trends, and the k means algorithm used in various clustering processes are some of them. Other algorithms that will be used for criminal detection, which is also the most important part of crime simulation, will be explained after this section. So, briefly, the information about these algorithms is explained in this section and the following section. Expert systems and artificial intelligence tools play an important role in the clarify and improvement of such topics. The changes and monitoring areas of these structures have been successfully demonstrated. For example, crime, crime tendencies, creating criminal profiling and serial criminals. Then they will be used these techniques for our simulator. The used techniques will be shown in the following section.

#### **3.4.1. Gaussian Mixture Model**

There are usually many methods for data clustering. One of these is the gauss model. With this model, a gaussian mixture model is preferred in the approach where there is a single structure distribution and more than one distribution. In a similar way, clustering algorithms are used with grouping of data. With these algorithms, the conditional probability is determined by the component with the highest value. K-clustering and GMM use a recursive algorithmic

structure for clustering of data between groups with the most accurate and precise data. The GMM from these two constructs is preferable instead of the k-cluster algorithm in determining the mutual relations when the clusters are at different sizes. Each piece of data in the structure realized for clustering is represented in a cluster. The probability of each data belonging to this cluster indicates the likelihood of belonging to the cluster.

The Gaussian distribution is a single-mode normal distribution. This means that if it is wanted to model a reference point with more than one vertex, it is needed to use different approaches. In such an approach, only one normal Gaussian is not enough. Therefore, more than one gaussian distribution will be used which is specified as the same type. In fact, more than one of these distributions will have to be mixed. Mixing will collect the results of every Gaussian in the mixture. That is, all data points in this frame will be transferred to all distributions in the mixture one by one, and the results will be summed to a single weight. This model used for the crime data set carries out three types of distributions on the same map, namely home locality, incident locality and map locality, especially in the distribution of acquaintances. These three distributions take place on this map with GMM. Here three centers for distribution will be selected according to certain criteria. In Gaussian, the distribution shape and density will be determined in a parametric manner. so that multiple distributions will be made according to this propagation.

#### **3.4.2. Bayesian Network Model**

Bayesian Networks are directed graphs that represent dependencies between variables in a probabilistic model. Bayes theorem is often used in probabilistic and forecasting problems. In general terms, this theorem shows the relationships that exist in the structure of simple and conditional probabilities. The events shown are possible with the structures expressed as nodes. In these structures, for example, take two nodes. Bayes can be used to measure the interrelationships of these two structures. Let's get two nodes called A and B. The probability of the A event for

these two nodes is conditionally dependent on another event B. Thus, the probability of an event A will generally be different from the probability of a conditional A (Eq. 3.23). However, there is a definite relationship between the two and Bayes' theorem will show this relation. Already Bayes is a mechanism that determines the closeness or distance between two nodes by this method. The Bayesian approach to the problem of merging data sets is evaluated within a probability framework. There are two concepts of approach. These are prior and posterior concepts. These relations are established through these concepts (Wright and Yann, 2004) and (Andrade and Ferreira, 2012).

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad (3.23)$$

A prior probability can be expressed as the probability that an event is independent of other events without being controlled. Prior probability is the probability of being interpreted as an explanation of what is known about a variable in the absence of evidence, independent of the other factor. More generally, a desired event in a data set is the possible value in the data set regardless of other events. Posterior probability is a probability concept calculated in relation to other nodes and events. Thus, the probability that the variable taking posterior evidence into account is conditional.

It starts the decision-making process for all statistically available information with Bayes. It is aimed to reduce the amount of uncertainty present in the problem in this decision making process. When new information is obtained, it must be handled with any previous information to form statistical methods. This information is combined with previous information. This is why Bayesian approach is used to combine new information with previous information. Selective networks are a common tool used to expose the uncertainty problem in intelligent

systems and to code it (Boondao, 2004). These Nets are based on inference algorithms to compute beliefs in the context of observed evidence.

The following sections briefly discuss the problems in these areas, the formulas and solutions to these problems.

A new model needs to be created from the data. Just as in crime analysis, it will be used the parameters of this as a node and create a structure to calculate the possible values of the data taken from the dataset and to remove the associations. Random analysis will provide an official basis for this structure. According to Bayes' rule, the calculation of  $P(\text{crime}|\text{location})$  of the posterior model probability will require the formulation of three constructs. It is calculated from the knowledge of a spatial position that knowledge of which crimes will be committed in that region. These are the probable cases of crime investigated in that region. This value is denoted by  $P(\text{Crime})$ . In the same way,  $P(\text{Location})$  is calculated for the situation in the place. This information is called prior probability because it is information that can be obtained from the crime database without any connection. However, the conditional computation of these two constructs and the computation of  $P(\text{crime}|\text{place})$  information will need to be computed in the conditional probability  $P(\text{location}|\text{crime})$ . In the next sections, how to use Bayesian for crime analysis and the selection of Model priorities is discussed in the next section (Canter, 2009).

Another use of Bayes theorem is the chain rule. This structure is called full joint distribution. In this rule, it is determined that the conditional variable that should be calculated for each node is associated with all variables in this model. It therefore benefits from conditional and marginal independence between the components in the distribution. In these conditional distributions, variables in the model and parents should be used together. The parent variable to which each node is connected is first calculated in terms of the previous probability value. This value is then used together with conditional probability values that are likely to be parent-tested child nodes. In this model, this structure will be used under a single formula for all variables.

More concretely, in the case of interrogation of more than one structure in the chain rule, the common structure of the  $P(X_1, X_2, \dots, X_n)$  field of  $n$  variables can be calculated as Eq. 3.24 when there are fields of  $n$  parameters. BN and local PDFs are considered.

$$P(X_1, X_1, X_1, \dots, X_1) = \prod_{i=1..n} P(X_i | Pa(X_i)) \quad (3.24)$$

where  $Pa(X_i)$  is the root of the  $X_i$  variable in the Bayes network. That is the main node. The conditional probabilities of  $P(X_i | Pa(X_i))$  are the probability  $X_i$ , given node of the parents of the  $X_i$  as  $Pa(X_i)$  in the equation. Thus, a local structure specified for each variable will be defined.

In summary, the reasons for choosing Bayesian networks as a tool for our ideas are:

1. They are graphical models that can show clear and intuitive relationships.
2. Constitutions that can reasonably represent causal relations.
3. They can turn uncertainties into a more specific structure.
4. Despite the name uncertainty theory, they deal with uncertainties.
5. They can be used to show indirect links in addition to direct causality.

Despite the use of a bayes network to detect crime trends, the naive bayes, a derivative of the bayes structure, will be used to detect the criminal. Therefore, it is necessary to give brief information about the naive bayes approach.

#### 3.4.2.1. Naïve Bayes Network

A Naive Bayesian classifier is based on the Bayesian formula. With this method, strong assumptions of pure independence are used. The structure, which is generally defined as a simple probability classifier, is based on a certain

formulation and application. If it is used as another name, it can be called an independent feature model (Lepora, 2010) and (Vural and Gök, 2017).

In simple terms, it assumes that a particular property of a constructed class is in no way related to another construct of existence.

Depending on the probability model, the naive Bayesian classifier is a supervised learning model. This model can be trained very efficiently compared to other models. In many practical applications this method is used for parametric variable estimation. This structure is calculated in all the structures using the maximum likelihood method with Naive bayes. In other words, Bayes works with the pure Bayesian model without using a belief structure, Bayesian theory.

It seems to be a significant advantage that the Naive Bayes classifier trains the data with less data than the other models in predicting the required parameters.

#### **3.4.3. K-Means Algorithms**

In the machine learning framework, clustering algorithms are used to group data with their common properties. Interesting constructs can be found with these algorithms. Considering a dataset, it is determined by these clustering algorithms which datasets belong to the specified classes. One of the most popular algorithms for clustering objects is the k-means algorithm. Thus, it was aimed to separate clusters according to the characteristics of the data.

K-means is an unsupervised learning algorithm. Working logic is quite simple. First, the clustering of the number of classes of data will be determined for the geographical location or graph. Within this will be selected centers to be the top point (Al-janabi, 2011) and (Corsini et al., 2006). The main idea is to define the k-center, which is one for each cluster. These centers will be selected in the most appropriate form in the selection. If the selection centers are not correctly selected then they can lead to different results. To make a good selection that is optimized, it needed to place these choices as far away as possible. The next step is to connect this data to the nearest center for the location of the data in a given data set.

If some more k-means event is embodied, a random cluster center should be chosen as the number of selected clusters as mentioned above. The data distributed through this selection will be grouped. Therefore, it will be necessary to find the closest points to these selected cluster centers and to assign them to the related cluster. Various measurement algorithms can be used here. the cluster was determined by this distribution at the beginning. But k-means does not end here. Because, after the data are clustered, many centers are selected and new centers will be assigned for the clustered structures in those centers. As a result of this assignment, the points closest to the new cluster center will be identified and given to these clusters. As can be seen, the data in the other cluster is in the other cluster in the next step. This new cluster centering and clustering event continues until there is no movement change of the data. The loop will continue until it is decided exactly which cluster the data is in. If cluster centers do not change, the algorithm will stop. This will find the final state with this clustering algorithm.

Simply k-means clustering is an algorithm used to classify the clustering group  $K$  according to the attributes and properties of objects. Distance measurements should be minimized in measurement calculations. In these measurements, the sum of the squares of the distances between the cluster center corresponding to the data is used here. Thus the data will be classified in the direction of the K-means cluster (Divya et al., 2014) and (Al-janabi, 2011).

### 3.5. System Model for Criminal Prediction

In this section, the proposed Bayesian Network model is formulized for the criminal prediction problem. The main reason to use the Bayesian network model is that it is effective in expressing the causal relationships among incident variables, and hence, in finding the suspect probabilities with the given clues. In a Bayesian network, first the relationship among variables needs to be modeled. The relationship is created using one way links without loops.

Abbreviations, definitions and system model used in this thesis are given in the Figure 3.9 and Table 3.3 below.

Table 3.3. Definitions and abbreviations of the Criminal prediction parameters

| Variable             | Definition                                   | Abbreviation |
|----------------------|----------------------------------------------|--------------|
| <b>Crime</b>         | It shows the type of crime.                  | -            |
| <b>Criminal</b>      | It shows the person who committed the crime. | -            |
| <b>Location</b>      | It shows where the offense occurred          | Loc.         |
| <b>Date</b>          | It shows the date when the crime occurred    | -            |
| <b>Acquaintances</b> | It shows acquaintance of the criminal        | Acq.         |
| <b>#</b>             | It shows the number of element               | -            |

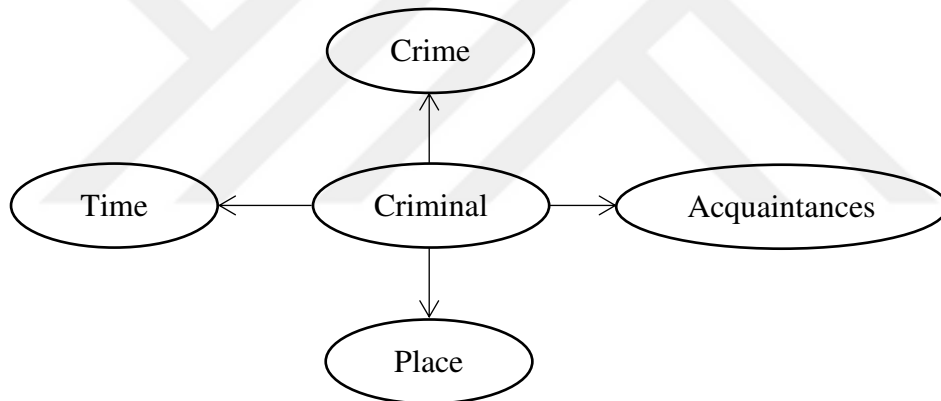


Figure 3.9. System model for criminal prediction

### 3.5.1. Problem Formulation

In this section, the proposed Naive Bayesian Network model is formulized for the criminal prediction problem. The Naïve Bayesian classifier is a classifier based on Bayes's theorem. It is quite a simple probability classifier that it uses the naive assumptions about its fundamental purpose property independence. Despite of its independence assumption, Naïve Bayesian classifier is proved to be quite useful in modelling the conditions of complex real world problem. Throughout this

section, the incident variables are indicated in bold and lowercased fonts whereas their values are in italic fonts with uppercased capital. The proposed model, shown in Figure 3.6, is constructed to express the probability of each **criminal** when the incident **date** and **location**, **crime** and **criminal** names, and criminals' **acquaintances** are given as clues. When used as a learner, the best model is the one that maximizes the learning performance, rather than best expressing the true relations among variables. In this context, **crime**, **location** and **date** variables are considered to act on the **criminals** variable. The network formed by the **criminal's acquaintances** has also influences on criminals. But here, those except the **acquaintances** and acquaintances of the **acquaintances** (secondary acquaintances) are not considered due to its negligible effect on the result and reducing the computational complexity. In practice, acquaintance list also includes those suspected criminals involved in the incident. With the proposed Naive Bayesian network, the criminal probability given the crime variables in Figure 3.2 is modeled at Eq. 3.25.

$$\begin{aligned}
 &P(\textit{criminal} \mid \textit{location}, \textit{time}, \textit{crime}, \textit{acquaintances}) \\
 &= \frac{P(\textit{criminal}, \textit{location}, \textit{time}, \textit{crime}, \textit{acquaintances})}{P(\textit{location}, \textit{time}, \textit{crime}, \textit{acquaintances})}
 \end{aligned} \tag{3.25}$$

where  $P(\textit{criminal} \mid \textit{location}, \textit{time}, \textit{crime}, \textit{acquaintances})$  joint distribution must be formulized according to the Naive Bayesian network model given in Figure 3.2. Probabilistic model of Naïve Bayesian Classifier is as follows (Eq. 3.2). Let  $X$  be a node (variable), and  $Pa(X)$  be the parent node of  $X$  in the network, then the joint probability distribution can be formalized using the parent-child relation as follows (Eq. 3.24). If the Eq. 3.24 is applied to the model in Figure 3.2, then the following equation can be obtained (Eq. 3.26).

$$\begin{aligned}
& P(\text{criminal}|\text{location}, \text{time}, \text{crime}, \text{acquaintances}) \\
&= P(\text{location}) \times P(\text{criminal} | \text{location}) \times P(\text{time}) \\
&\times P(\text{criminal}|\text{time}) \times P(\text{crime}) \\
&\times P(\text{criminal}|\text{crime}) \times P(\text{acquaintances}) \\
&\times P(\text{criminal}|\text{acquaintances})
\end{aligned} \tag{3.26}$$

Eq. 3.26 consists of the products of priori probabilities and conditional probabilities. Hence each term must be formulized separately. However, according to the model, it is necessary to consider the impact of the **acquaintances** in Eq. 3.26 on the acquaintances of the **acquaintances** (secondary - acquaintances). The **secondary-acquaintances** are recognized directly by the **acquaintances** of the criminal, which is denoted as SetofAcq (**acquaintances**) for a given acquaintance. In this context, the formula of Eq. 3.26 for a particular acquaintance is given at Eq. 3.27 and for all acquaintance it is given at Eq. 3.28.

$$\begin{aligned}
& P(\text{criminal}|\text{location}, \text{time}, \text{crime}, \text{acquaintances}) \\
&= P(\text{location}) \times P(\text{criminal} | \text{location}) \times P(\text{time}) \\
&\times P(\text{criminal}|\text{time}) \times P(\text{crime}) \\
&\times P(\text{criminal}|\text{crime}) \\
&\times \sum_{T \in \text{SetofAcq}(\text{acquaintances})} (P(\text{acquaintances})) \\
&\times P(\text{criminal}|\text{acquaintances}) \\
&\times P(T|\text{acquaintances}) \times P(\text{Criminal}|T)
\end{aligned} \tag{3.27}$$

$$\begin{aligned}
& P(\mathbf{criminal}|\mathbf{location}, \mathbf{time}, \mathbf{crime}, \mathbf{acquaintances}) \\
&= \sum_{T \in \text{Set of Acq}(\mathbf{acquaintances})} P(\mathbf{criminal}, \mathbf{location}, \mathbf{time}, \mathbf{crime}, T)
\end{aligned} \tag{3.28}$$

Prior probabilities at Eq. 3.27 are formulized through. Eq. (3.29-3.33), and conditional probabilities are formulized through Eqs. (3.34-3.36). The notation,  $N_{\text{logical\_op}}$ , used in the formulas represents the number of incidents that matches the given logical expression in the notation by scanning the N number of crime incidents. Here the ‘logical\_expression’ is a logical sentence consisting of x op y type of expressions where x is variable, y is value, and op is the logical operator.

$$P(\mathbf{location} = \mathbf{location}) = \frac{N_{\mathbf{location} \in \text{neighborhood}(\mathbf{location}, h)}}{N} \tag{3.29}$$

$$P(\mathbf{time} = \mathbf{Time}) = \frac{N_{\mathbf{time} \in \text{neighborhood}(\mathbf{Time}, t)}}{N} \tag{3.30}$$

$$P(\mathbf{criminal} = \mathbf{Criminal}) = \frac{N_{\mathbf{criminal} = \mathbf{Criminal}}}{N} \tag{3.31}$$

$$P(\mathbf{crime} = \mathbf{Crime}) = \frac{N_{\mathbf{crime} = \mathbf{Crime}}}{N} \tag{3.32}$$

The prior probability  $P(\mathbf{acquaintances})$ , used at Eq.3.27, is formalized at Eq. 3.33 by using **acquaintances** variables.

$$\begin{aligned}
& P(\mathbf{acquaintance} = \mathbf{Criminal}) = P(\mathbf{acquaintances} \supseteq \mathbf{Criminal}) = \\
& \frac{N_{\mathbf{acquaintances} \supseteq \mathbf{Criminal}}}{N}
\end{aligned} \tag{3.33}$$

$$\begin{aligned}
& P(\mathbf{criminal} = \mathbf{Criminal} \mid \mathbf{location} = \mathbf{location}) \\
&= \frac{N_{(\mathbf{criminal}=\mathbf{Criminal} \wedge \mathbf{location}=\mathbf{location})}/N}{N_{\mathbf{location} \in \text{neighborhood}(\mathbf{location},h)}/N} \\
&= \frac{P(\mathbf{criminal} = \mathbf{Criminal}, \mathbf{location} = \mathbf{location})}{P(\mathbf{location} = \mathbf{location})} \\
&= \frac{N_{(\mathbf{criminal}=\mathbf{Criminal} \wedge \mathbf{location}=\mathbf{location})}}{N_{\mathbf{location} \in \text{neighborhood}(\mathbf{location},h)}}
\end{aligned} \tag{3.34}$$

$$\begin{aligned}
& P(\mathbf{criminal} = \mathbf{Criminal} \mid \mathbf{time} = \mathbf{Time}) \\
&= \frac{P(\mathbf{criminal} = \mathbf{Criminal}, \mathbf{time} = \mathbf{Time})}{P(\mathbf{time} = \mathbf{Time})} \\
&= \frac{N_{(\mathbf{criminal}=\mathbf{Criminal} \wedge \mathbf{time}=\mathbf{Time})}/N}{N_{\mathbf{time} \in \text{neighborhood}(\mathbf{Time},t)}/N} \\
&= \frac{N_{(\mathbf{criminal}=\mathbf{Criminal} \wedge \mathbf{time}=\mathbf{Time})}}{N_{\mathbf{time} \in \text{neighborhood}(\mathbf{Time},t)}}
\end{aligned} \tag{3.35}$$

$$\begin{aligned}
& P(\mathbf{criminal} = \mathbf{Criminal} \mid \mathbf{crime} = \mathbf{Crime}) \\
&= \frac{P(\mathbf{criminal} = \mathbf{Criminal}, \mathbf{crime} = \mathbf{Crime})}{P(\mathbf{crime} = \mathbf{Crime})} \\
&= \frac{N_{(\mathbf{criminal}=\mathbf{Criminal} \wedge \mathbf{crime}=\mathbf{Crime})}/N}{N_{\mathbf{crime}=\mathbf{Crime}}/N} \\
&= \frac{N_{(\mathbf{criminal}=\mathbf{Criminal} \wedge \mathbf{crime}=\mathbf{Crime})}}{N_{\mathbf{crime}=\mathbf{Crime}}}
\end{aligned} \tag{3.36}$$

$$\begin{aligned}
& P(\mathbf{criminal} = Criminal \mid \mathbf{acquaintances} \supseteq Criminal) \\
&= \frac{P(\mathbf{criminal} = Criminal, \mathbf{acquaintances} \supseteq Criminal)}{P(\mathbf{criminal} = Criminal)} \\
&= \frac{N_{(\mathbf{criminal}=Criminal \wedge \mathbf{acquaintances} \supseteq Criminal)} / N}{N_{\mathbf{acquaintances} \supseteq Criminal} / N} \\
&= \frac{N_{(\mathbf{criminal}=Criminal \wedge \mathbf{acquaintances} \supseteq Criminal)}}{N_{\mathbf{acquaintances} \supseteq Criminal}}
\end{aligned} \tag{3.37}$$

The conditional probability  $P(\mathbf{criminal} \mid \mathbf{acquaintances})$  used at Eq. 3.27, is formalized at Eq. 3.38 by using **acquaintances** variables.

$$\begin{aligned}
& P(\text{SetofAcq}(\mathbf{acquaintances}) \supseteq Criminal \mid \mathbf{acquaintances} \supseteq Criminal) \\
&= \frac{P(\text{SetofAcq}(\mathbf{acquaintances}) \supseteq Criminal, \mathbf{acquaintances} \supseteq Criminal)}{P(\mathbf{acquaintances} \supseteq Criminal)} \\
&= \frac{N_{(\text{SetofAcq}(\mathbf{acquaintances}) \supseteq Criminal \wedge \mathbf{acquaintances} \supseteq Criminal)} / N}{N_{\mathbf{acquaintances} \supseteq Criminal} / N} \\
&= \frac{N_{(\text{SetofAcq}(\mathbf{acquaintances}) \supseteq Criminal \wedge \mathbf{acquaintances} \supseteq Criminal)}}{N_{\mathbf{acquaintances} \supseteq Criminal}}
\end{aligned} \tag{3.38}$$

The conditional probability  $P(T \mid \mathbf{acquaintances})$  used at Eq. 3.27, is formalized at Eq. 3.38 by using **acquaintances** variables. The conditional probability  $P(\mathbf{criminal} \mid T)$  used at Eq. 3.27, is formalized at Eq. 3.39 by using **acquaintances** variables.

$$\begin{aligned}
& P(\mathbf{criminal} = \mathbf{Criminal} | \text{SetofAcq}(\mathbf{acquaintances}) \supseteq \mathbf{Criminal}) \\
&= \frac{P(\mathbf{criminal} = \mathbf{Criminal}, \text{SetofAcq}(\mathbf{acquaintances}) \supseteq \mathbf{Criminal})}{P(\text{SetofAcq}(\mathbf{acquaintances}) \supseteq \mathbf{Criminal})} \\
&= \frac{N_{(\mathbf{criminal}=\mathbf{Criminal} \wedge \text{SetofAcq}(\mathbf{acquaintances}) \supseteq \mathbf{Criminal})} / N}{N_{\text{SetofAcq}(\mathbf{acquaintances}) \supseteq \mathbf{Criminal}} / N} \\
&= \frac{N_{(\mathbf{criminal}=\mathbf{Criminal} \wedge \text{SetofAcq}(\mathbf{acquaintances}) \supseteq \mathbf{Criminal})}}{N_{\text{SetofAcq}(\mathbf{acquaintances}) \supseteq \mathbf{Criminal}}}
\end{aligned} \tag{3.39}$$

Detection of the criminal, who have the highest probability, is formulized using joint probability distribution,  $P(\mathbf{criminal}, \mathbf{location}, \mathbf{time}, \mathbf{crime}, \mathbf{acquaintances})$ , as follows (Eq. 3.40).

$$\begin{aligned}
& \mathbf{Criminal}_{id} \\
&= \underset{i=1..N}{\operatorname{argmax}} P(\mathbf{Criminal}_i | \mathbf{location}, \mathbf{time}, \mathbf{crime}, \mathbf{acquaintances})
\end{aligned} \tag{3.40}$$

### 3.5.2. Performance Scores/Accuracy Rate

The data set has been created primarily to make the most common methods of crime analysis that will be used Bayesian Network Model. Bayesian probability theory means using once system as probabilistic is to design a model.

In order to measure the accuracy of the proposed method, the dataset is divided into training and test set by using cross-validation method. 1000 samples are used in the tests where randomly selected 90% is used for training and the remaining 10% is for testing.

If it is assumed  $k_{\mathbf{Criminal}}$  to denote the top index of the **criminal** in the criminal list sorted according to the  $P(\mathbf{criminal} | \mathbf{location}, \mathbf{date}, \mathbf{crime}, \mathbf{acquaintances})$  formula, accuracy rate can be given over K number of criminals as follows (Eq. 3.41).

$$\%Accuracy\ Rate(Criminal): 100 - (k_{Criminal}/K \times 100) \quad (3.41)$$

### 3.6. Comparison Between Naïve Bayes And Decision Tree

#### 3.6.1. Decision Tree

Decision tree is a classification method that forms a tree structure of decision nodes according to parent and child structures. In the tree learning process, the learned information is modeled on a tree as root and leaf. All internal nodes of this tree show the inputs. The decision tree algorithm was developed by dividing the data set into smaller pieces. A decision node can be represented as the master node. Here, one or more sub-branches can be divided into this structure. The first node is called the root node. The other nodes are leaf nodes that are separated depending on each main node. The decision in the tree can be categorical and numerical. So, for a decision tree, it needs to be drawn and structured first. Then the probability of occurrence of events and the benefit of the expected return will have to be calculated. The target will be reached with the highest expected return. These concepts are briefly mentioned in the following sections.

The main motivation of the algorithm is to separate the input data back into the same class label as a clustering algorithm.

#### 3.6.2. Decision tree in Literature

Researchers develop different decision trees algorithms for a long time, developing performance and capabilities to achieve different types of data. It consists of a decision tree, a root node as a structure, branches and leaf nodes. The inner node comes as a feature through a test. Each one determines the outcome of the test and has a class label on the leaf node. Each branch node comes in a variety of options to choose from. Each leaf node represents a decision in the decision tree.

Nevertheless, many of the previous studies merely incorporate considerations about the correctness of the learning algorithms. In the machine learning community, an accepted conclusion is the decision tree learning algorithm

for prediction accuracy, C4.5 (Gao et al., 2011), and Naïve Bayes' similarity (Sagale and Kale, 2014), (Vural and Gök, 2017) and (Taheri, 2014). These studies are of great value in predicting the types of problems for which decision tree methods are appropriate. There are terrific programs that grow trees and set rules against simple Bayesian classifiers in several medical areas.

### 3.6.3. Entropy

Entropy, known as the uncertainty measure of a random variable that is the result of an experiment or observation, is the expected value of the information contained in all samples for a process. Information is an information criterion for the occurrence of a random event. Equal probability situations represent high uncertainty. According to Shannon, when a situation in a system changes, the change in entropy defines the information gained. Accordingly, the change in maximum uncertainty will probably provide maximum information. An example of an entropy representation is  $E(S)$ . Entropy  $E(S)$  is a measure of the amount of uncertainty in the dataset  $S$ .

For this reason, the choices in the root nodes are formed by dividing the sub-cluster corresponding to all the different values of the region attribute. This node can have a gradually repeating structure through sub-clusters thanks to the evaluation technique. It is created through leaf nodes and until all sub-clusters are pure with zero entropy. If the samples are all regular and homogeneous, the entropy becomes zero. If the ratios are equal, then entropy is 1. Entropy formulation is below (Eq 3.43).

$$E(S) = \sum_{i=1}^C -p_i \times \log_2 p_i \quad (3.43)$$

$S$  indicates the feature. All values that the variable  $S$  can take are calculated separately in the data set.  $C$  is the maximum value of the variable  $S$ . So, Entropy is not only calculated on aim. Also entropy can be calculated on attribute. But while

calculating this, aim is taken into account. The calculation of each value in the data set within this concept is shown below. (Eq. 3.44):

$$E(T, X) = \sum_{c \in X} P(c)E(c) \quad (3.44)$$

For instance, T represents a variable in the data set, and X is possible values for this variable. Here's exactly how ID3 and other variables work. The ID3 algorithm is described later. A criterion for attribute selection is found the best attribute. When selected the attribute that produces the purest nodes, it will result in the smallest tree. Entropy is used in measuring the information gain and indicates the uncertainty and the probability of occurrence of unexpected situation. It is defined as information gain.

#### 3.6.4. Information Gain

The knowledge gain is the measure of the contrast in the entropy after the set has been separated in any attribute. If each tree is found for information acquisition of the system tree, the entity with the maximum information gain for the partition called argmax value must be chosen. Until the leaf node with Entropy = 0 is reached, this root reaches the applied id3 algorithm for each child node. In ID3, C4.5 decision tree methods, to identify the most distinguishing quality information gain is measured for each quality (Eq. 3.45).

$$\begin{aligned} \text{Information gain} \\ &= (\text{Information before split}) - (\text{Information after split}) \end{aligned} \quad (3.45)$$

#### 3.6.5. Decision tree Algorithm

Decision tree is a very common method for informative learning. The most commonly used algorithms are ID3 and C4.5. The general steps of algorithm:

Steps of the algorithm:

1. Create the T learning set
2. Identify the best separating samples in a T set
3. Create a node of the tree with the selected attribute and create child nodes or leaves of the tree from that node. Identify examples of child data sets of child nodes
4. For each child dataset created in step 3
  - ✓ If all the samples are in the same class,
  - ✓ If there is no quality left to split the samples,
  - ✓ If there is no example with the value of the remaining attributes, terminate the process. Otherwise, continue from step 2 to separate the subset of data.

The basic idea is to reconstruct the input data with the aid of the allocation and grouping algorithm. Grouping continues until all group items have the same class label.

### 3.6.6. ID3 Algorithm

The ID3 algorithm is an algorithm based on entropy. The meaning of ID3 is the Iterative Dichotomizer 3 algorithm, which only works with categorical data. Entropy is used to determine complexities. A dataset with similar data for entropy will be close to 0. If not, it will be 1. This will show that similar data are not available.

Qualities are independent of each other. In this algorithm, the objective is to make the trees in the learning set as similar as possible when the tree is being created, and the tree will be determined in this way. Decision means that if the depth of the tree is small, it will be profitable at the maximum level. For all parameters in a dataset, this algorithm is used to determine the shape of the tree and

the leaf nodes of the root. For the data here, entropy and gain values of these parameters will have to be calculated. In this calculation, the property with the highest value as gain will be set as root. If there is a structure with ambiguity in the property value searched for leaf nodes, then the rest of the properties other than root will be accounted for as gain and the decision tree will be created in this way. According to the decision tree, the mechanism will work and the result data will be obtained. If there is a probable calculation of a probability in another event from an activity in the bayes network structure, the solutions and results obtained by reading the tree for the same purpose will be seen here. Therefore, the learned classification model is a decision tree that is used effectively and is shown in ID3 tree.

To summarize; Decision trees divide multidimensional data into other pieces according to a specified quality, and at each step it decides what kind of process to perform according to which property of the data. It is very important to decide which node to partition in decision trees. If it is not started from the appropriate node, the number of nodes and leaves in the tree will be too large. Instead of solving complexity, it reveals bigger problems. Selection of attributes for branching First, the entropy of the class property is computed. Finally, the entropy of all feature vectors from the entropy of the class property is subtracted and the gain criterion for each feature is calculated. The feature vector with the largest gain is chosen as the branch node for that iteration (Gao, 2011) and (Kaise and Xiang-Tao, 2009).

### 3.6.7. The Example for Classification of Criminals

The ID3 algorithm is used to identify the criminal and determine the appropriate decision tree. In this algorithm, other features besides guilty are the variables of crime, time and place. It will be necessary to first decide which of the other three features to choose in the detection of N criminals. The gain value of each feature will be calculated to determine this decision. The maximum value will

be found with the concept of Argmax. Then the feature with the maximum value will be set as the new root. The random data used here will be chosen because the property named time has a higher value. If this structure is repeatedly ambiguous, these calculations will be done again and new root and branches will be detected. Thus a decision tree will be formed. (Eq. 3.46).

$$Root = \begin{cases} Information\ Gain(Crime, Criminal) \\ Information\ Gain(Place, Criminal) \\ Information\ Gain(Time, Criminal) \end{cases} \quad (3.46)$$

First, it is needed to set a category for our data worms, which are criminals, crime, time and place. The most appropriate category of this problem is criminality. transactions must be adjusted according to the offender. This adjustment decision is very important for the start of the tree. The first determining structure for decision trees is to determine the root. In case of interpretation of the lower branch data set from root structure, it is determined which criminal is to be found from this structure. First of all, entropy will be used when root is determined from 3 areas. For entropy, the maximum rate of knowledge gained by these three specializations, by category, will make this expertise a new root. Thus the first rate to be calculated is to calculate the entropy rate of the accused data.

For this reason, **time** is the highest gain and is used as the decision quality in the root node. The root will examine all possible values of the property **time** and create it as leaf node for root named **time**. This process will continue until all data are categorized perfectly. The route determines the decision tree obtained on the independent variables ratios in the new examples by applying the partition rules.

#### 3.6.7.1. Entropy(Criminal)

While calculating criminal category entropy, all existing criminals' existence situations in the dataset will be taken into account. It is given as the addition of

logarithmic response at base 2 with each criminal repetition number in N item data. After this calculation, each attribute rate will be calculated separately.

- Entropy(Crime, Criminal)
- Entropy(Time, Criminal)
- Entropy(Place, Criminal)

They will be calculated. After this calculation, information gain rate for each speciality will be found. From the found information gain rates, the maximum one will be the root and transaction will go on till the last speciality rate found.

As example, the crime entropy will be calculated first for the crime. Then, Information gain will be found the crime feature based on crime (Eq. 3.47).

$$\begin{aligned}
 \text{Information gain}(\text{Crime, Criminal}) \\
 &= \text{Entropy}(\text{Criminal}) - \text{Entropy}(\text{Crime, Criminal})
 \end{aligned}
 \tag{3.47}$$

The techniques used to solve decision-making problems are closely related to the decision-making problem. According to this, decision problems, depending on the information level about the variables that decision maker cannot control, can be classified as decision making in certainty, uncertainty and risk situations. The main system model obtained after the calculations is as shown in Figure 3.10.

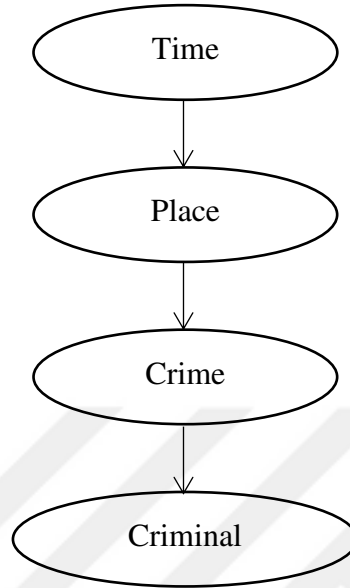


Figure 3.10. System model for ID3

Each property value will be calculated and added to the node point. Based on all the information, it will be decided which of the parameters is the priority. This property is **time** variable ( $T_1, T_2, \dots, T_n$ ). The new node found will be the **time**. After this stage, the algorithm will continue until the latest structure that is the **criminal** (Figure 3.11).

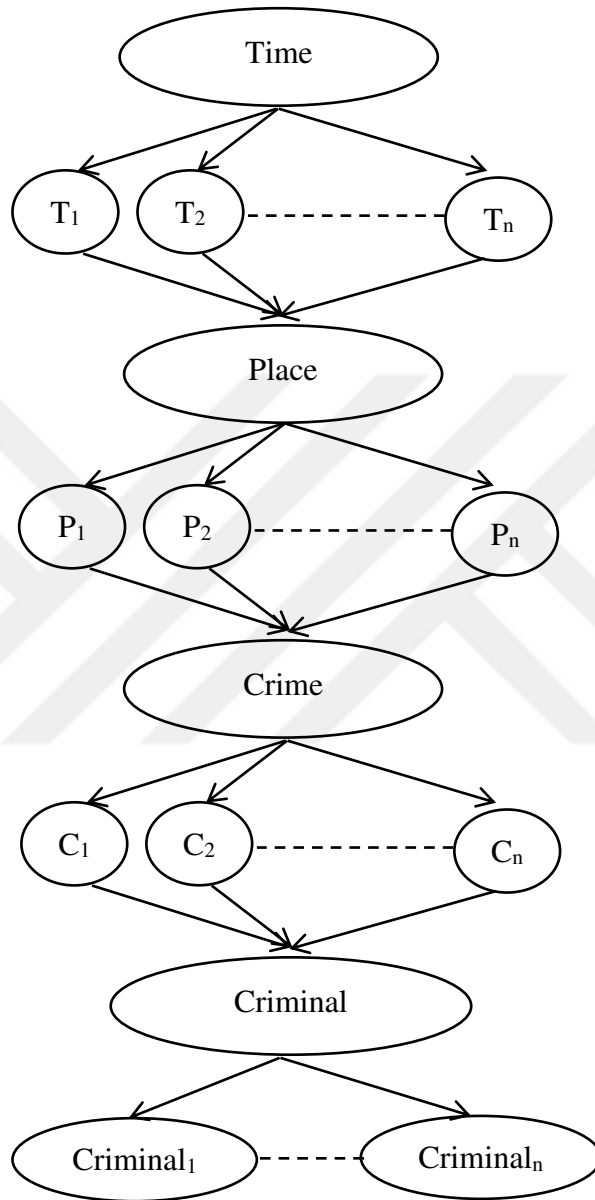


Figure 3.11. Criminal detection according to ID3 algorithm

All the calculations used when reaching the criminal are for the formation of the above system structure. After this step, it is the finding of the criminal investigated according to the information given.

As a result, the solution to this problem shows that ID3 is easy to use. In the first use, there is a manual change of the expert to build in the classification tree. It can be applied decision tree algorithms such as ID3 in large quantities, and at the same time, it can be obtained valuable predictions. These estimates, evaluates the behavior future the problem. The decision is that the choice of the tree is more important than the others. ID3 uses a fixed set of samples to construct the decision tree. The resulting tree is used to classify future examples.

### **3.7. Impact of Acquaintance**

#### **3.7.1. Importance of Acquaintance and Distributions**

The impact of acquaintances for suspects and criminals is an important detail in detecting criminals. The acquaintances used in the above-mentioned system model are shown in different variations by considering them in detail here. Because in this simulation, one of the three main purposes is the effect of acquaintances.

In the determination of the types of investigation, for the process of detecting criminals, such as crime-criminal relationship and criminal-acquaintance, will be benefited through this system. The data to be used from a geographical area examined is stored in the dataset in a registered format. The related records are examined in a related social network concept. Also organized crimes can be solved with these effect in social network framework. it is because of the interrelationship among the people in the criminal organizations. These relations are resolved using the social network structure in this problem. This will allow the establishment of a specific forecast if there is only a crime network map in the system. The existence of links to one of the crime nets is showing of the crime networks. The members of these crime networks have bilateral relations with each other. So in a criminal network, criminals are connected to each other. Therefore, the concept of

acquaintances are important in the point of social networking, and the relationship of acquaintances with criminals is examined.

Certain criteria must also be taken into consideration when distributing acquaintances over a map or region. These criteria ensure that the process to be performed is more realistic. In the calculation of the crime above, both the influence of the acquaintances and the role of other parameters are mentioned. Below, the link between the criminal and the acquaintances is shown with the necessary formulas. But it seems to have been distributed by taking into account geographical locations with a reasonable distribution at the random choice of acquaintances.

The distribution is applied by certain methods in centers where the distribution is concentrated, where the probability of crime is likely to occur and where the offenders live. For this reason, it is known that a region is composed of cities, towns and villages. Therefore, according to these criteria in the distribution of acquaintances, it is arranged according to places where the probability of crime is high. The Gaussian distribution will be applied to cities, towns and villages respectively. First, the distribution will be randomly selected. It will be set at random near the location of the closest coordinate points to be determined in the entire data set. This is where the guilty acquaintance list for each criminal is determined. If they produce what they know in a more realistic way, they should be systematically organized. So the first step is to scan all the data in the dataset. It is the distance between two points in the geographical map. Then, the distances closest to the coordinates of the offense, which is a list of acquaintances, are determined.

In the distribution of acquaintances, it is necessary to say a certain social network analysis. As a result, the concept of social networking should be mentioned in a platform where organize crimes that have more than one criminal are found. The social network formed by the criminal's acquaintances has also influences on criminals. But here, those except the acquaintances and

acquaintances of the acquaintances (secondary acquaintances) are not considered due to its negligible effect on the result and reducing the computational complexity. In practice, acquaintance list also includes those suspected criminals involved in the incident.

Both the records of the security units and the investigations show that the criminal is a criminal environment like himself. This criminal environment is sometimes made up of people who have committed common crimes and sometimes who have committed different kinds of crimes. So, there is a similarity in geographical position. It is observed that a criminal investigated, especially for a some crimes such as a thief, has a relation with criminals in close location. It is also known that, in general terms, the acquaintances of the criminals lie close to each other in geographical coordinates. In other words, it is not only that the crime place is common but that it is related to where the criminals live in.

There is an opposing relationship between the geographical location and the places where the theft is made. While the geographical locations where the thieves are located are the poor regions, the places where the thieves are made are rich regions. This is the opposite situation. But there is a similarity in the geographical position of the thief's friends. Therefore, this information is not to be ignored. While the crime data set was being prepared, the places where the crimes were committed were tried to be formed by considering these criteria in this system.

For simulations, the list of acquaintances of each criminal is formed in this way. The suspect list from the simulation is a user-defined parameter. This parameter will be used to detect the offender. This will determine the closeness between the criminal to be investigated and the suspects. Besides, the related lists of suspects and criminals coming from the system will be handled with familiar lists of each criminal. At this point the influence of the acquaintances will be arised. As a result, it will be checked whether there is a direct or indirect link between the offender and the suspect list. It is need not to forget that all the

suspects on the list are criminals. These offenders are registered with their acquaintances in the crime dataset.

### **3.7.2. Relationship Among Organized Crimes in Social Network**

The important thing here is the necessity of knowing some concepts when an analysis is done first. The people who are included in the concept of acquaintances consist of people who commit crime. A criminal organization can be established by means of which criminals found in the structure are guilty of acquaintance with each other. Thus the prominence of social network analysis is emerged. Here, people on the list of acquaintances know each other. However, this information is not always true. For example, for an organize crime organization, the link between the bottom member and the top member may not be mutual.

The leader of the organization may not always recognize the member, but he knows and knows the leader of the member organization. Thus, the organization leader may be the leader of the organization on the list of acquaintances of the organization member while the organization member is absent from the list of activities. The following result of this is obtained. On the list of acquaintances, it is understood that information about a criminal may be a common criminal offense, a friend's circle of the offender or a criminal. So it may not be just people who have committed a common crime. The units of enforcement take into account those acquaintances who have arisen from the different parameters mentioned above in relation to the familiar environment of the offenders in such events. This is often a clue to reaching criminals and a useful construct to solve the problem. The direct link between a suspect and a criminal must then be considered in connection with what the offender knows. Primary acquaintances is the structure that will control this connection.

As a result, mafia and similar organize criminal organizations can be revealed through simulation. The people in the criminal organizations can be found close to the members of the organization. In addition, different criminal

organizations can examine each other members of the organization. As a result of this examination, relations between these structures can be revealed. all these questions are resolved using social network analysis.

### **3.7.3. The Role of Acquaintances for Suspected List**

The suspicious list selected by the user is used in the detection of the criminal by way of acquaintances. The criminals found in this list will be checked for their relationship with the investigated criminals and acquaintances. The aim is that at least one of the criminals on the suspect list is the same as the investigated criminal. If this is not the case, then a similarity will be checked with acquaintances of the investigated criminal. Therefore, finding such a evidence with acquaintances parameter will be an important clue to the criminal determination. As mentioned before, there may not always be a direct connection between the suspects list and the criminal. This case does not mean that there is no connection. It will only show that it does not have a strong bond. Therefore, strong links are checked first. if there is no strong bond then weak connections are checked. So the list of suspects and their acquaintances will be examined first with the criminal and then with the criminal's acquaintances. The figure for such links is given below.

For the role of acquaintances at the point of resolution of the problem, if there is no data available in the detection of any criminal, then it must be checked in different structures. That is why suspects may be contributing to a problem, even if it is weak. Therefore, the impact of acquaintances is an important detail.

### **3.7.4. System Model and Parameters for Acquaintances**

The mathematical model formed for the criminal prediction of primary and secondary acquaintances is below Figure 3.12.

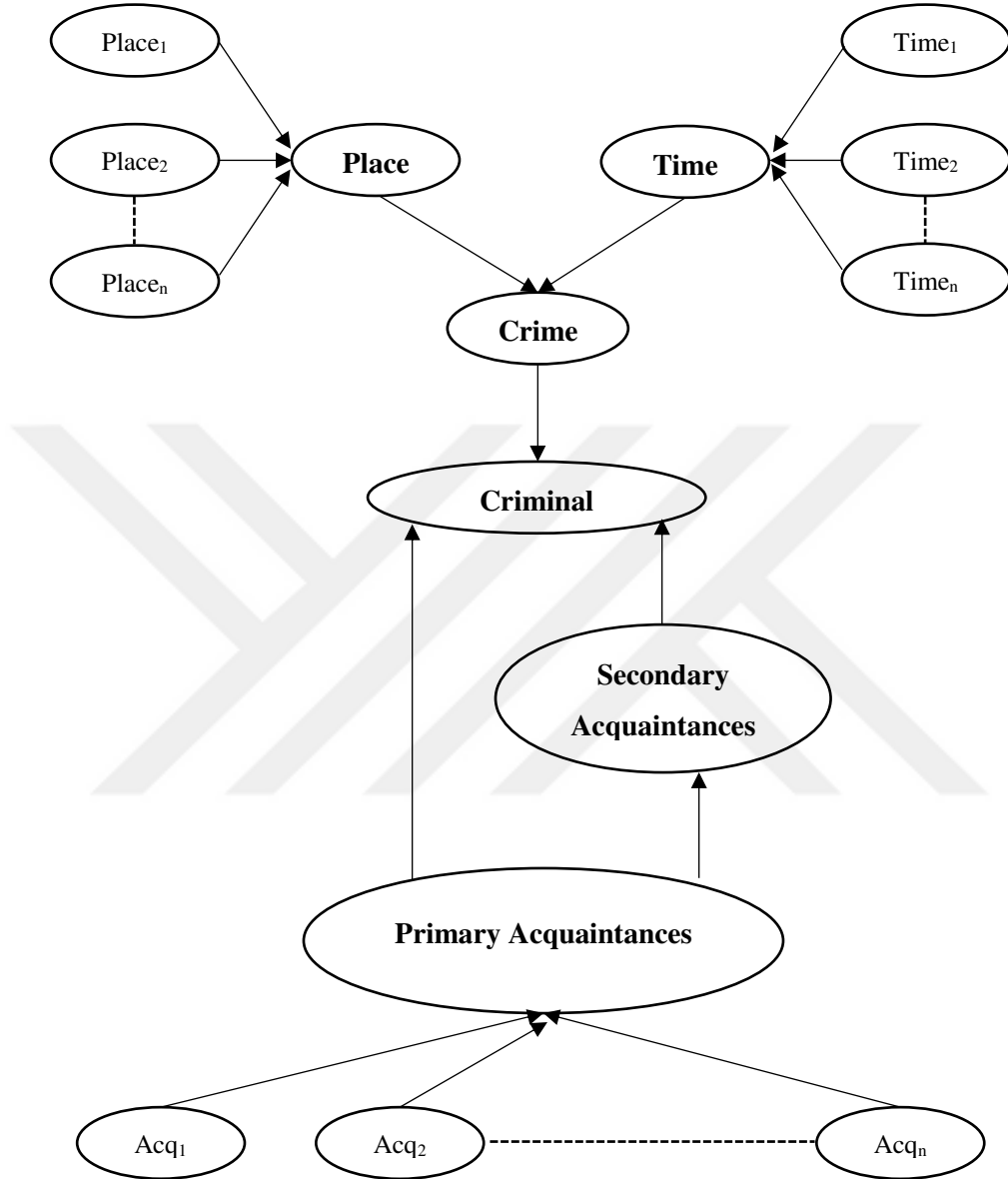


Figure 3.12. Crime attributes considered in the dataset

**3.7.5. Problem Formulation**

There will be necessary calculations to determine the relationship of the acquaintances with the offenders. In this calculation, for every acquaintance, the relationship with the committing crime and the relationship with the criminal must be formulated. Therefore, criminal probability values will be found for each recording region according to Bayes' theorem. There are two types of connections between an investigated criminal and a suspect. These are direct and indirect connections.

The problem formulation of the penalty effect of acquaintances requires parameters to be sent by the system. From the parameters sent by the system, the list of suspects will be searched for the effects of the acquaintances. The current parameters will be used to determine which offense is more appropriate than these data.

Some parameters are needed to detect a criminal. In the presence of guilty, the importance of these parameters is great. The parameters used in the above given formulas are the minimum parameters. For a more realistic approach in the prototype created, the target can be approached more by increasing the number of parameters. Therefore, the familiar parameters to be used are one of the parameters required for this prototype.

The system will be determined the number of acquaintances with maximum and minimum intervals for each familiarity. Common criminals will be detected. So, the connection of these common criminals are revealed. Other parameters in this connection will be considered. Such as, crime,time and place. The concept of crime, time and place can be decisive for such events. but these parameters may not always be sufficient. Sometimes, when these clues are insufficient, the offender may not be detected. In such a case, the relationship of the criminals to each other may be important.

It is used acquaintances parameter in insufficient clues. The system will be determined the acquaintances between maximum and minimum intervals for each criminals. These values are selected randomly.

#### **3.7.6. Primary and Secondary Acquaintances Concepts**

When this model is used in the detection of offenders, the effect of acquaintances affects both the primary and secondary acquaintances. The primary acquaintances directly compares the suspect list with the offender. However, the secondary acquaintances is calculated when there is no primary acquaintances. The link with the indirect criminal will be detected in the secondary acquaintances. The relationship between the criminal and the suspect list will then be checked. So, Not only is the criminal determined, but also the influence of the acquaintances among organized criminal organizations is being investigated. The relationship with the concept of proximity can be found in this way in the detection of any criminal in these examinations.

The use of acquaintances in-model for criminal estimation is shown above in Figure 3.12. It is necessary to deal with the information detected at the interface in this usage separately. Therefore, the influence of two kinds of acquaintances will have to be mentioned. These effects are the primary acquaintances and secondary acquaintances. The primary acquaintances is direct links and the secondary acquaintances is indirect links. The following table is given some abbreviations and explanations of some of the terms used in the problem formulation in Table 3.4.

Table 3.4. Abbreviation of Primary and Secondary Acq. parameters

| Attributes                             | Name               |
|----------------------------------------|--------------------|
| Queried Criminal                       | Crm                |
| Suspected List                         | Slist              |
| Acquaintances of queried Criminal      | Crm <sup>acq</sup> |
| The acquaintances of Slist in n degree | Slist <sup>n</sup> |
| Impact factor of acquaintances         | K                  |
| Primary Probability                    | Prim_prob          |
| Secondary Probability                  | Sec_prob           |
| Depth of impact factor                 | N                  |

It is necessary to explain some concepts in the above table according to the system model. Two of the most important of these concepts are Prim\_prob and Sec\_prob.

Crm shows the crime to be investigated in Table 3.4. Another important parameter is the Slist variable. Slist is the suspect list. The people in this list are criminals. The criminals on the list are the selected offenders from the simulation. Crm<sup>acq</sup> is a list of acquaintances linked to the criminal investigated. This list like Slist may have many people or the list may be empty. The information on the criminals held at this list will be checked with the criminal as Crm. The suspect list consists of user-selected criminals. It is bounded by system for each criminal in this list. It has a list of acquaintances randomly generated by the simulation considering these limits. Acquaintances parameter in range for user interface is determined between minimum and maximum value.

The Prim\_prob will check whether there is a direct link between investigated criminal and the suspect list coming from the simulation. When the Prim\_prob is calculated, the relationship between the criminals on the suspect list and the investigated criminal is checked.

The secondary acquaintances should be checked when there is no primary acquaintances. The secondary acquaintances are called the Sec\_prob. If there is no such direct connection then other connections are checked. So, indirect links should be considered when there is no direct link. Another structure under the influence of acquaintances for indirect link is the list of secondary acquaintances which is called Sec\_prob. It is important point that Sec\_prob is not easy to solve relation problem between Crm and Slist everytime. Problems may arise at the point of resolution of a connection with secondary acquaintances, which are called indirectly. There may not always obtain a result in the first step in the secondary connection. These problems are solved by the depth of the secondary acquaintances.

This is due to the fact that the situation is not as close as direct connection. the link between the offender and the acquaintances of slist is considered different in the secondary connection. However, the familiar list of the offender should be considered different from the Slist. Such a computational approach would be a more realistic approach. The secondary probability has a more complex structure than the primary probability. Here, each of the suspicious elements must be examined separately.

### 3.7.7. Impact Factor “k” and “n”

According to the given system model, there is a variable called impact factor in the calculation of Prim\_prob and Sec\_prob expressions. This variable is denoted by "k". The impact factor show us how strong or weak the bond between the offender and suspect list is. When there is a link between the Slist and the criminal, the depth is used when it finds that this bond is in the order of the level. It is shown as “n”. However, every k value will be determined at the "n" level, which is the depth value between the acquaintances and the offender. The Table 3.5 below shows the status of the suspect list according to the depth of the list.

Table 3.5. The suspect list with acquaintances in nth degree

| n(Depth Grade) | Slist                                          | Slist <sup>n</sup> |
|----------------|------------------------------------------------|--------------------|
| 1              | The suspect list                               | Slist <sup>1</sup> |
| 2              | Acquaintances of suspect list                  | Slist <sup>2</sup> |
| 3              | Acquaintances of acquaintances of suspect list | Slist <sup>3</sup> |

Slist variant is list of suspects. When it is level 1 there is the Slist<sup>1</sup> itself. This applies to Sec\_prob as depth grade. If  $n = 2$  then it means that they acquaintances of the first degree of Slist<sup>1</sup>. It means Acq(Slist). The final depth for Sec\_prob is grade 3. This means that it is acquaintances of Slist<sup>2</sup> and shown as Slist<sup>3</sup>. The following table shows the relationship between Slist and effect factor for Sec\_prob. For  $n=1$ , this table also takes the value  $k = 1/2$  when it is in relation to the offender. As mentioned above, when  $n = 1$ , both Prim\_prob and Sec\_prob are calculated, and after  $n=1$ , only sec\_prob will be calculated. After this point, the impact factor will be  $(1/2)^n$  when there is a link between the Slist and the offender. If there is a link between the Slist and the offender's acquaintances, the k-value will be  $(1/2)^{n-1}$ . Therefore, the impact factor for Slist<sup>1</sup> is  $1/2$ . For Slist<sup>2</sup>, two values are mentioned. The value in connection with the offender is calculated as  $1/2$ . However, if there is a correlation with acquaintances of criminal, then  $k = 1/4$ . The same applies to Slist<sup>3</sup>, which will be used in the third degree. In relation to Crm,  $k=1/4$ . In case of connection with Crm<sup>acq</sup> it will be  $1/8$ .

As a result, this impact factor is particularly used in indirectly connected structures. Because there may not always be an indirect connection when there is no direct connection. Therefore, it is necessary to find out at which step of the secondary connection there is a relation. it will be necessary to find a connection at the level of the indirect link. The level and the way of connection are different from each other. Therefore, the first thing to check is: Is there a connection with the offender? If there is no connection with the criminal, then it will be checked

whether the criminal is connected to what he knows. According to rating, if the influence factor in the secondary relationship is related to the crimina then impact factor as  $k$  is selected  $(1/2)^n$ . If the Slist is related to the acquaintances of investigated criminas as Crm then " $k$ " is selected value is determined by  $(1/2)^{n-1}$  in Table 3.6. Below are the required calculations with this formulation. Detecting impact factor as " $k$ " is determined between Slist and investigated criminal as Crm according to  $n$ th layer. Considering the dataset, it can be revealed very deep relations but in every deep relation relation among criminals will decrease in this rate. Especially, in the control of relations like terrorist groups, mafia etc., these constructions has been playing an important role.

Table 3.6. The impact factor in  $n^{\text{th}}$  degree for sec\_prob

| n(Depth Grade) | Criminal           | Slist <sup>n</sup> | k(impact factor) |
|----------------|--------------------|--------------------|------------------|
| 1              | Crm <sup>acq</sup> | Slist <sup>1</sup> | $(1/2)^n$        |
| 2              | Crm                | Slist <sup>2</sup> | $(1/2)^{n-1}$    |
| 2              | Crm <sup>acq</sup> | Slist <sup>2</sup> | $(1/2)^n$        |
| 3              | Crm                | Slist <sup>3</sup> | $(1/2)^{n-1}$    |
| 3              | Crm <sup>acq</sup> | Slist <sup>3</sup> | $(1/2)^n$        |

the algorithm to be used for the influence of acquaintances in the detection of criminal in the light of these calculations is given below in Figure 3.13.

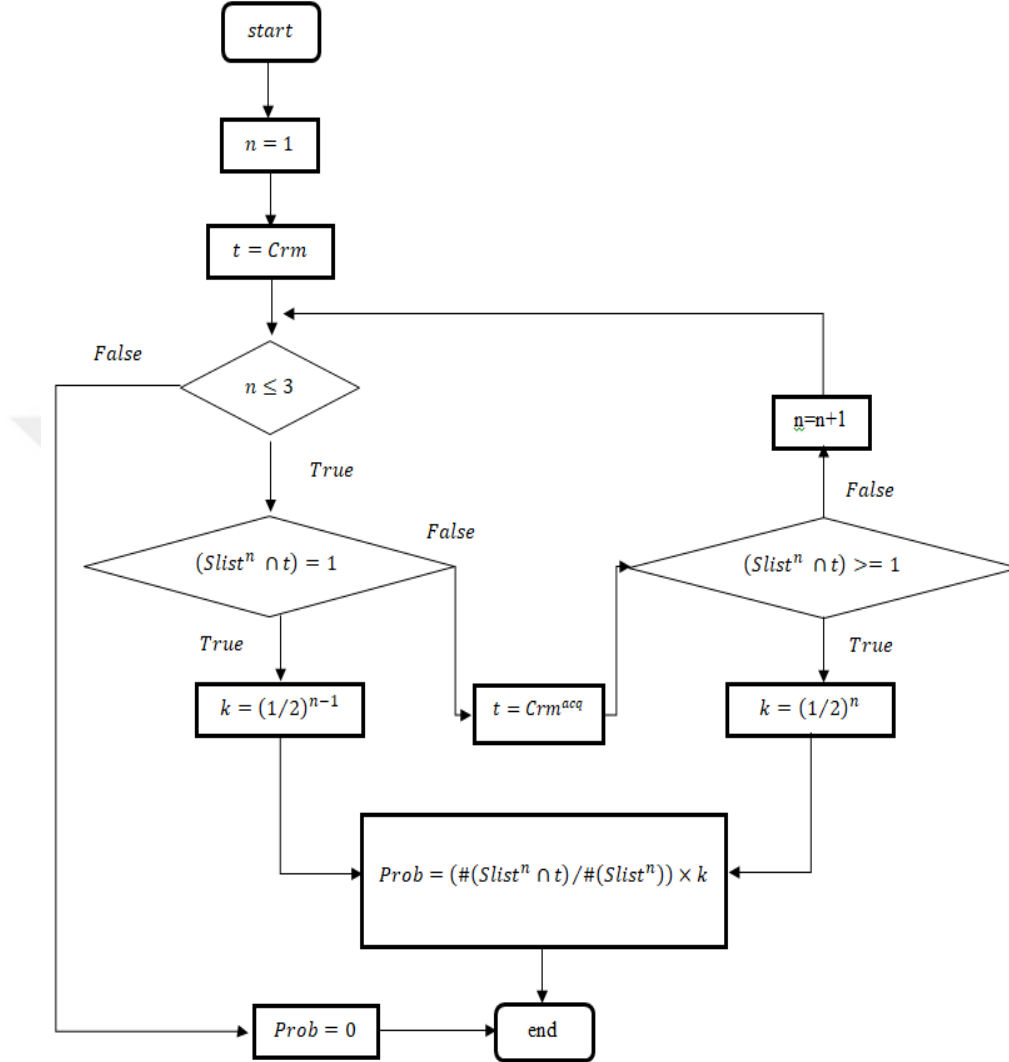


Figure 3.13. Flowchart of influence acquaintances for predicting criminals

The different representations between Prim\_prob and Sec\_prob are not specifically mentioned in the algorithm. These variables are described as technical terms. Because the probability of acquaintance effect of criminal in the calculation is examined. The importance detail in this point is to control whether is direct bond or not. Impact factor is used to establish a bond. This variable is also used to

rate the proximity calculation. Prim\_prob will be computed when  $n = 1$  according to the above algorithm. So impact factor "k" for Prim\_prob is  $1/2$ . Because of Prim\_prob for Slist is connected to investigated criminal as knowing Crm. Everytime, comparison with Crm depth grade for k is  $(n-1)$ . otherwise it will be used as "n".

If there is a relation in the indirect way, impact factor for depth grade has to be calculated surely. For sec\_prob, the states of Slist must be taken into account with respectively. The variants of Slist itself, its acquaintances and acquaintances of its acquaintances will be included in this questionnaire. But if there is not relation for Slist in first step then it must be controlled bond for acquaintances of Slist as Slist<sup>2</sup>. This impact factor with depth grade will be used to calculate connections for Sec\_prob. Operations with Slist between Crm and Crm<sup>acq</sup> will continue until  $n = 3^{\text{th}}$  degree. If there is no such situation in Slist<sup>3</sup>, the algorithm will terminate. If the criminal sought in a dataset can not be found on several occasions, the transactions are not continued until they are found. Because this is not a realistic approach. If it is continue in this way using depth grade connection, since almost everyone will be connected to each other. The problem is, how far will this process go? After each transaction, it is tried to obtain a more realistic approach by decreasing the effect of the impact factor according to the transaction rate. This rate is determined by the impact factor which is used as k in algortihm. This is why the "k" impact factor is maintained to a depth grade of  $n = 3$

If Prim\_prob is being calculated and it is directly controlled by the offender, it will be linked directly to the suspicious list itself when it becomes Slist<sup>1</sup>. Only the connection of Slist<sup>1</sup> with Crm<sup>acq</sup> will be checked for  $n=1$  with Sec\_prob. Otherwise, for  $n \geq 2$  the Slist will be checked with both Crm and Crm<sup>acq</sup>. That's why Slist<sup>2</sup> shows the acquaintances of the suspect list. As the value increases for each n, it is expressed that the suspect list acquires a degree deeper. In these connections, there is a closer connection with each Crm, so the impact factor is  $n-1$ .

Whereas if it is in contact with  $Crm^{acq}$  then depth grade for impact factor will be "n".

The formulation of acquaintances is calculated with formulas with three different and three layer depths. The primary acquaintances list is calculated with the first formula at  $n=1$  level. It must be controlled whether there is a link between the suspect list and the criminal investigated at this level. this will only be calculated for the Prim\_prob and the impact factor is calculated to be only  $(1/2)^{n-1}$  for  $n = 1$ . If there is a bond, it is due to the presence of a common element. The purpose of common element is presence similarity where element of suspect list with Crm. The number of members in the suspect list is indicated by #Slist for each level. For Sec\_prob, If there is a correlation with Crm then it is indicated by impact factor  $(1/2)^{n-1}$ . In the opposite case, Therefore, the impact factor value  $(1/2)^n$  is calculated when there is correlation with  $Crm^{acq}$ . Whether it is Prim\_prob or Sec\_prob, the impact factor effect is shown for all of them in Figure 3.14.

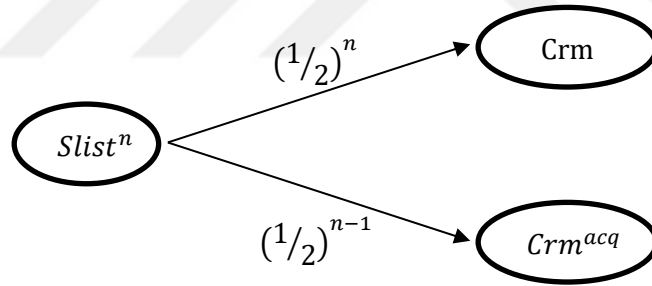


Figure 3.14. Relation between Slist and Crm

Prim\_prob is the computational intersection process required for the link structure between the list of acquaintances and the offender. Thus, the primary probability is to be found by calculating the common elements of the offender's acquaintances (Eq. 3.48). If any offender cluster and a query offender intersect, it means that they are in relation directly. However, this is not valid all the time. Because connections in the system sometimes may not be clear. For this reason, it is possible to determine the connections gradually by revealing them in different

ways. If the query offender is not on the list given, then a new subquery will be needed to actualize. In the new query, the similarity of query offender's acquaintances and the offender cluster should be controlled. Thus, possible similarities and connections among the data will be found.

$$Prim\_prob = \frac{\#(Slist^n \cap Crm)}{\#(Slist^n)} \times \left(\frac{1}{2}\right)^{n-1}, n = 1 \quad (3.48)$$

In the absence of the Prim\_prob connection, the presence of the Sec\_prob connection should be checked. This connection is calculated by the value  $(1/2)^{n-1}$  in relation to Crm as mentioned above. In the other case,  $(1/2)^n$  value will be calculated as impact factor. The Slist at each level will be compared to both of them, which are criminals and criminals acquaintances. Sec\_prob connection ( $n=1$ ). the layer is only correlated to  $Crm^{acq}$ . However, for Sec\_prob ( $n > 1$ ), it is applied in both formulations (Eq. 3.49, 3.50).

$$Sec\_prob = \frac{\#(Slist^n \cap Crm)}{\#(Slist^n)} \times \left(\frac{1}{2}\right)^{n-1} \quad (3.49)$$

$$Sec\_prob = \frac{\#(Slist^n \cap Crm^{acq})}{\#(Slist^n)} \times \left(\frac{1}{2}\right)^n \quad (3.50)$$

The acquaintancer parameters used to detect the offender are described in the relevant section. However, this parameter can be used for different purposes. Thus, the terms used in the familiar parameters are explained below in both the criminal determination and the formulation required for other situations.

This model not only takes into account the existing legal standards, but also the discretionary powers and human factors involved in the prosecution of criminal cases. The aim of this approach is to provide solutions to existing models and criminal systems when they are inadequate.

As well as detection of criminals using acquaintances influences within the resulting structure:

- 1) The crimes committed by the organization can be detected
- 2) Relationships between criminal organizations can be identified
- 3) These institutions may be close to each other
- 4) It is possible to predict which one of the criminal or suspect is closer to the criminal network
- 5) It can be used to reach organization leaders

#### 4. EXPERIMENTS AND RESULTS

First, it has been considered the creation of synthetic artificial crime data set for N samples in this simulator. After that, in this work subjects related with crimes, crime trends and predicting criminals are discussed. Besides this subject, it is used various artificial techniques to test our a simulator and compare its performance with the other algorithms. In addition, a criminal social network structure in the determination of the criminal in the experimental results is another point to be examined. The acquaintances parameters used in the detection of criminal are separately addressed. So, these are used to measure similarities to the suspect list.

##### 4.1. Synthetic Crime Dataset

Three experiments using the parameters in Table 4.1 are performed.

Table 4.1. Parameter values used in the experiments

| #Incidents | #Crime<br>Types | #Criminal | #Region | #Acquaintances | #Elapsed<br>Time(Sec.) |
|------------|-----------------|-----------|---------|----------------|------------------------|
| 1000       | 9               | 100       | 5       | 10             | 23.0                   |
| 5000       | 9               | 100       | 5       | 10             | 180.2                  |
| 10000      | 9               | 100       | 5       | 10             | 494.1                  |

The user interface of the simulation system is shown in Figure 4.1 The user interface is simply divided into four panels, which are the panels for crime-events, crime-types, map/incident locations and criminals. Crime-events panel simulates the number of incidents and the time of interval that the incidents occurred.

**Crime Simulation**

|                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |                                                                                                                                                  |                                                                                                                                                                                                                    |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Crime Events</b><br>Number of Events: <input type="text" value="10000"/><br>Date:<br>Start Date: <input type="text" value="1971"/> End Date: <input type="text" value="2013"/>                                                                                                                                                                                                                                                                                                                                                                                 | <b>Crime Types</b><br>Number of Crime Types: <input type="text" value="9"/><br>Distribution of Crime Types: <input type="text" value="Uniform"/> | <b>Criminals</b><br>Max. Number of Criminals: <input type="text" value="500"/><br>Distribution of Criminals: <input type="text" value="Uniform"/><br>Max. Number of Acquaintances: <input type="text" value="30"/> |
| <b>Map/Incident Locations</b><br>Number of Regions: <input type="text" value="18"/> Map Size: X: <input type="text" value="200"/> Y: <input type="text" value="200"/><br>Centers Distribution of the Region: <input type="text" value="Uniform"/><br>Minimum Distance Between Centers: <input type="text" value="50"/><br>Distribution of Incident Locations: <input type="text" value="Gaussian"/> <input type="text" value="1"/> - <input type="text" value="10"/><br><div style="text-align: center; font-size: small;">Min. Variance      Max. Variance</div> |                                                                                                                                                  |                                                                                                                                                                                                                    |
| <input type="button" value="Create DataSet"/>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     |                                                                                                                                                  |                                                                                                                                                                                                                    |

Figure 4.1. User-interface of the simulation system

Map/Incident location panel includes the user parameters that describe the generation of random maps and the incident distribution across the map. The map is created with the given map size with a constraint that the minimum distance between region centers conforms to the user defined parameter. The incident locations are generated randomly using the given distribution type. In the experiments, the incident locations are distributed around the centers using the mixture of Gaussians. Criminal's panels involve the user defined parameters for criminal related information such as the number of criminals, their acquaintances, and the distribution of acquaintances around the localities. For demonstration purpose, it is selected 1000 incidents, which are distributed across the 5 regions given in Figure 4.2, and showed three query based analysis. The results are given in Figure 4.2-4.4.

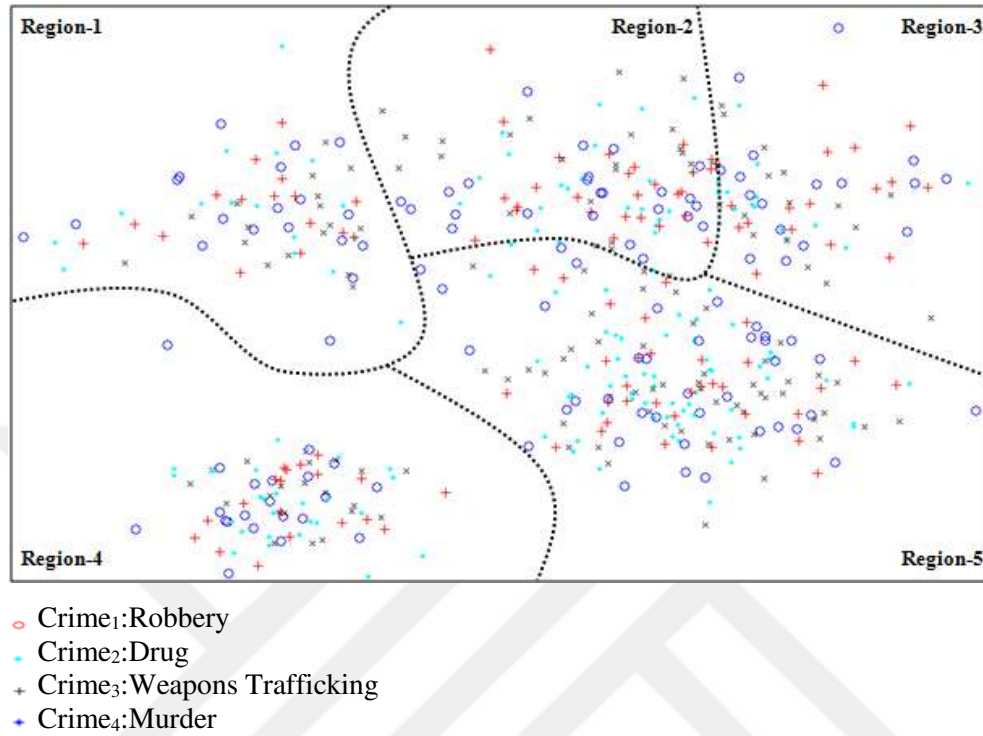


Figure 4.2. The results of the first query on GIS map.

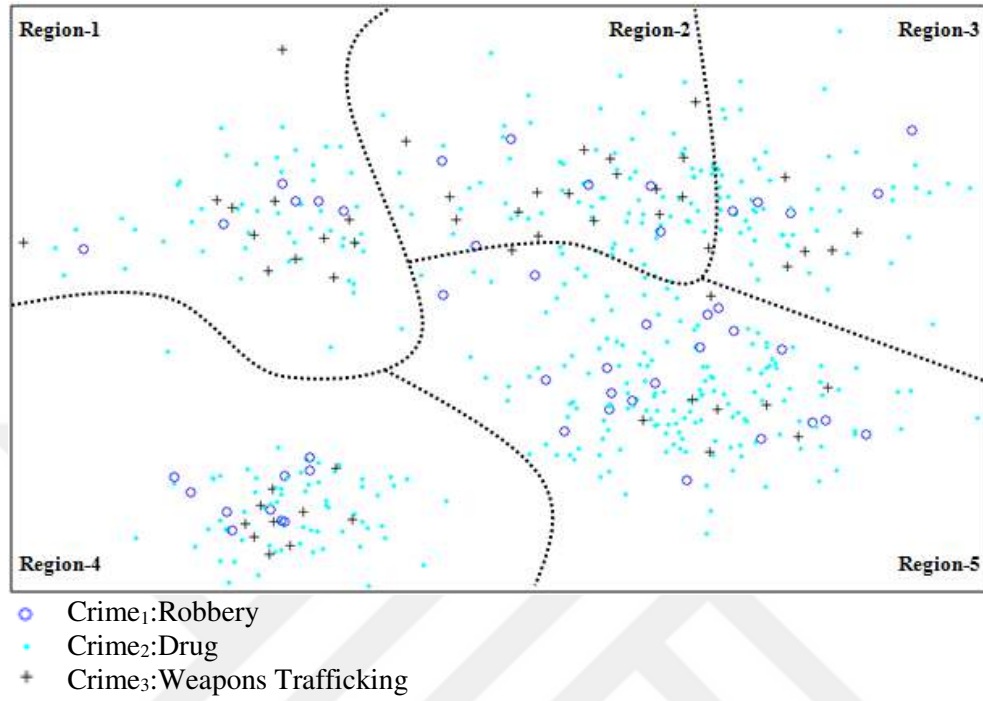


Figure 4.3. The results of the second query on GIS map.

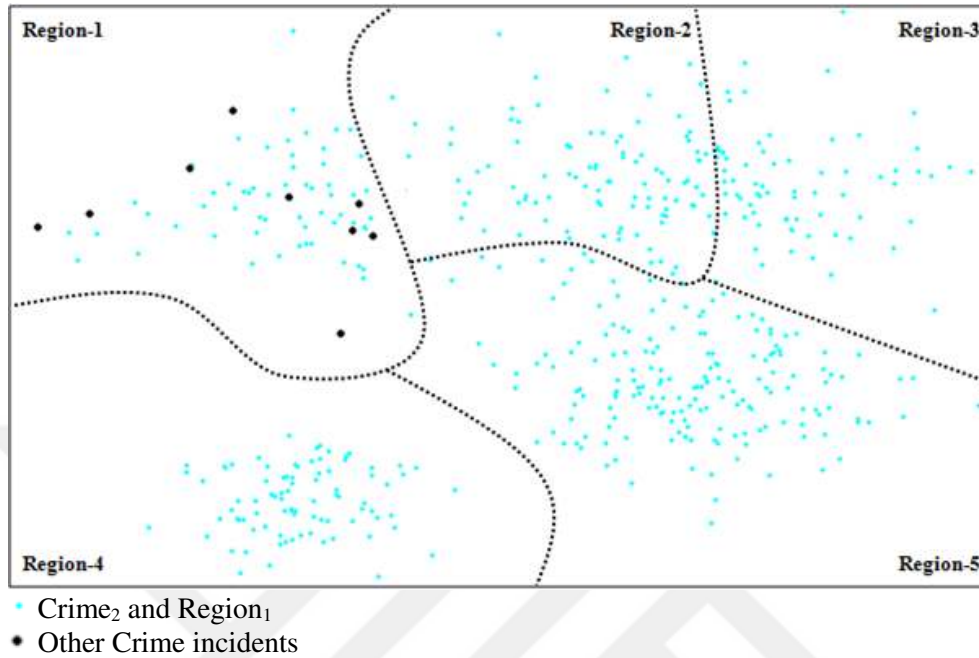


Figure 4.4. The results of the third query on GIS map.

The first query is to ask for incidents of three crime types, namely crime<sub>1</sub>, crime<sub>2</sub> and crime<sub>3</sub>. The query is as follows; “show all where crime\_type =crime<sub>1</sub> OR crime\_type=crime<sub>2</sub> OR crime\_type=crime<sub>3</sub>”. The result of the query is shown in Figure 4.3 with the incidents of interest denoted by different geometric signs, others are by dot.

The second query is to ask for the incidents committed by any criminal that can be reachable from the two criminals, named criminal<sub>1</sub> and criminal<sub>2</sub>, through their acquaintances or acquaintances of acquaintance. Acquaintances of acquaintance is actually a recursive process that requires some stopping criteria here, that is depth. Thus, the set of all acquaintances that can be reachable from the criminal could be considered as the social network of the criminal with some depth constraint. SocialNetwork(criminal<sub>1</sub>, depth) is a function that retrieves the set of all criminals that can be reached through acquaintance of any intermediate criminal that is already in the network. The query is structured as follows; “show all where

criminal in SocialNetwork(criminal<sub>1</sub>,2) OR criminal in SocialNetwork(criminal<sub>2</sub>, 2)”. The result of the query is shown in Figure 4.4.

The third query is to ask for incidents of a given crime type, Crime<sub>2</sub>, in Region<sub>1</sub>. The query structure is as follows; “show all where crime\_type =crime<sub>2</sub> AND region=Region<sub>1</sub>”. The result of the query is shown in Figure 4.4. For demonstration purpose, the incident-level data that returns as a result of the third query is shown in Table 4.2. Time is the offset in number of seconds from the Jan 1, 1970 UTC.

Table 4.2. Incident –level data that returns as a result of the third query

| Crime   | Criminal Id. | Time     | Place      | Region | Acquaintances Id   |
|---------|--------------|----------|------------|--------|--------------------|
| Crime-2 | 56           | 21083654 | 4.8 123.1  | 1      | 2,33,42,74         |
| Crime-2 | 32           | 88428    | 15.2 128.8 | 1      | 16,39,66           |
| Crime-2 | 1            | 18405236 | 36.9 144.5 | 1      | 3, 61,64,89        |
| Crime-2 | 83           | 5099614  | 45.8 162.1 | 1      | 4, 98              |
| Crime-2 | 86           | 10456408 | 56.2 133.8 | 1      | 3,17,34,67,91      |
| Crime-2 | 41           | 13134861 | 80.1 130.1 | 1      | 27,42,47,83,95,100 |
| Crime-2 | 27           | 20997266 | 79.3 131.3 | 1      | 16,29,31,58,94     |
| Crime-2 | 61           | 2680392  | 77.4 87.0  | 1      | 30                 |
| Crime-2 | 5            | 5186027  | 83.3 130.0 | 1      | 8, 72,77,83        |

Criminal Id. : 56 is Criminal-56.

#### 4.2. Crime Trends

Crime analysis function consists of six parameters. First of all it will be observed all criminals inside a crime. After that it will be selected target crime which is called Query Crime and then it will be able to find out to make inference interrelation crimes between analysed crime and query crime.

In the simplest case, function will work by the help of system. The most important parameters are the number of sampling, where each crime sample is located, criminal, time, coordinates values and acquaintances list.

All of the parameters for creating crime dataset were generated randomly. For example, criminal distribution was determined according to the maximum number of criminals chosen from the simulation and. A random number between the rate identified by the user and 1 will be determined. The determined criminal number and N samplings will form the crime dataset. In the same way, the acquaintances list will be determined with the random number in the simulation and for every criminal, acquaintances as the appointed rate between the rate entered from the simulation and 1 will have been found. The crime dataset will be formed with the time showing criminals' committing crime time and the coordinate information of the place where the crime was committed.

Especially, it needs analysis to find relation between crimes. For this analysis, the relation between crimes requires a mathematical model. Based on this model, the six parameters which are distributed as random are considered. It consists of crime, criminal, the total number of records,...etc. Our main motivation, for here, is detected probability of committing crime for each criminal who committed any other crime. So, firstly any crime, which is called the studied crime in crime dataset will be studied. Criminal who is committing crime as studied crime will be chosen in the database and it will be calculated in relation to a crime that will be questioned. In the calculation, the probability committing of query crime for each of criminal will be found. After that committing probability of two crimes will be detected. It determines prior probability of two crimes in crime dataset. At last, each of criminals will be searched at query crime.

In the randomly generated criminal data set, five crimes and eight regions were processed. Below is the analysis of the criminal trends over the eight regions over the years. According to the findings, it can be seen that the trends in crimes  $s_1$  and  $s_5$  are noticeable in region  $R_1$ . Almost similar tendencies are observed in other

crimes, whereas in the analysis according to years it seems that  $S_1$  crime has decreased, whereas  $S_5$  crime has increased tendency. the average trend in offenses committed in regions is in regions  $R_1$  and  $R_3$ . However, in some regions it is observed that crime rates have increased while some regions have also decreased. The crime tendency after the 1991-2000 years in the  $R_2$  region has been increasing for ten years. It is a region that is most likely to increase in the next 10 years after 2017. When  $R_2$  region is examined, it is crimes  $S_2$ ,  $S_4$  and  $S_5$  that crime tendencies increase. In the next 10 years, the types of crime that should be caught are possible crimes.

Between 1950 and 2017, graphs of crime trends by region were shown. When these graphs are examined, factors such as increase and decrease factors will be examined. It can also be seen in interaction with one of the crimes and leaping into the regions. In this respect, only graphical analysis can be used to establish relations between regions and crimes. On the basis of regions, it can be determined by which crime rates the crime rate has increased over which region. The opposite is true of course. However, the part concerned is being discussed on the increase in crime because of reasons and measures of increase in crime. This increase is due to population density, economic structure and other factors are emerging in a structure that is effective. In the  $R_1$ ,  $R_2$ ,  $R_3$  and  $R_5$  fields, different values are observed at various time intervals. In fact, as a result, there is a stable situation between 1950 and 2017. Even if the population density increases, there is not an excessive increase. whereas in the  $R_4$  and  $R_8$  region it is observed to be a big shot in the crime. At this point, the types of crimes committed in these regions according to years are a point to be dismissed. Because in areas near this region, it can be determined which crimes are affected by  $R_4$ . In other words, if a crime in the  $R_4$  region has decreased in a certain period of time, then a decrease in the neighboring regions can be seen as a trend factor between these regions. In the  $R_6$  and  $R_7$  regions, there has also been a decline in crime.

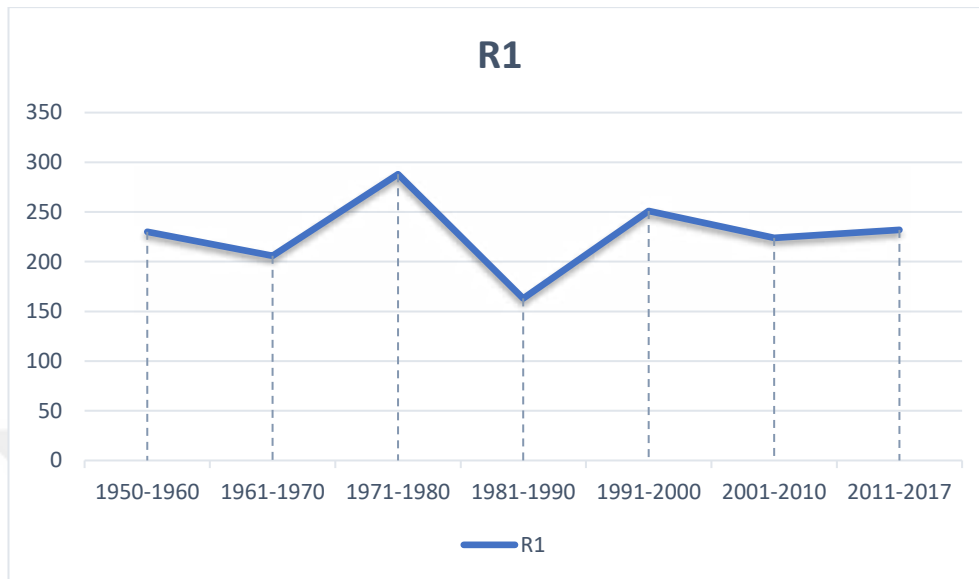


Figure 4.5. Crime Rates in region 1(R1)

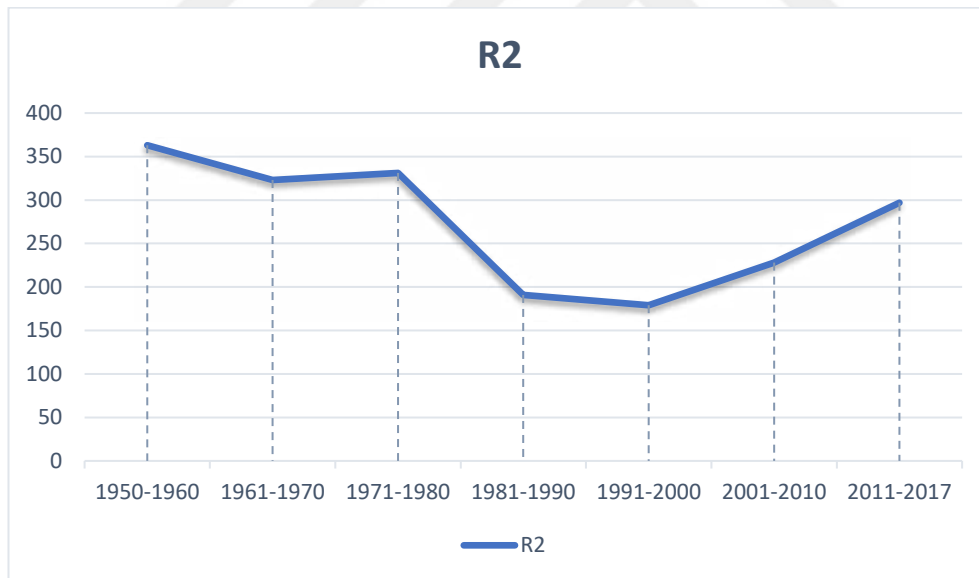


Figure 4.6. Crime Rates in region 2

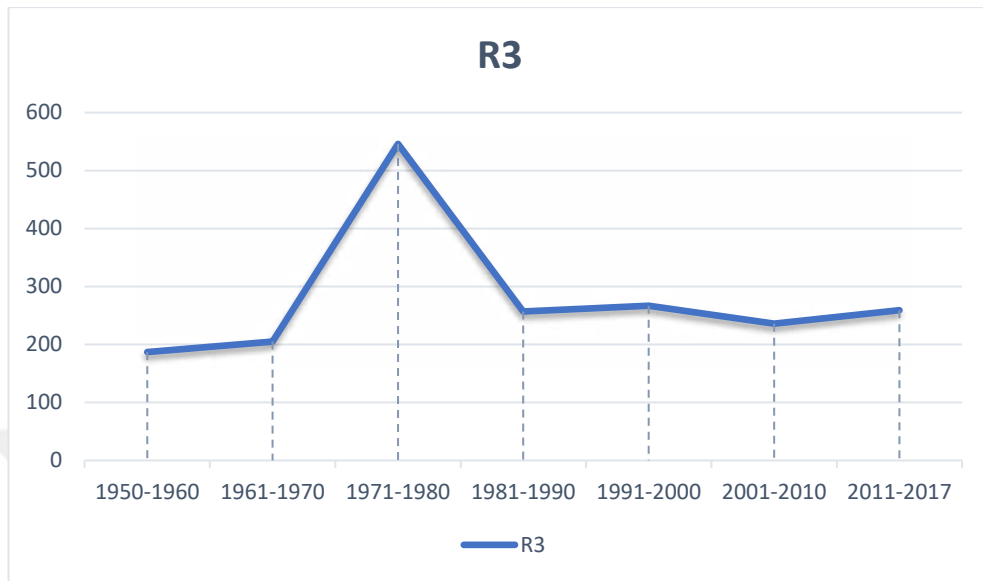


Figure 4.7. Crime Rates in region 3

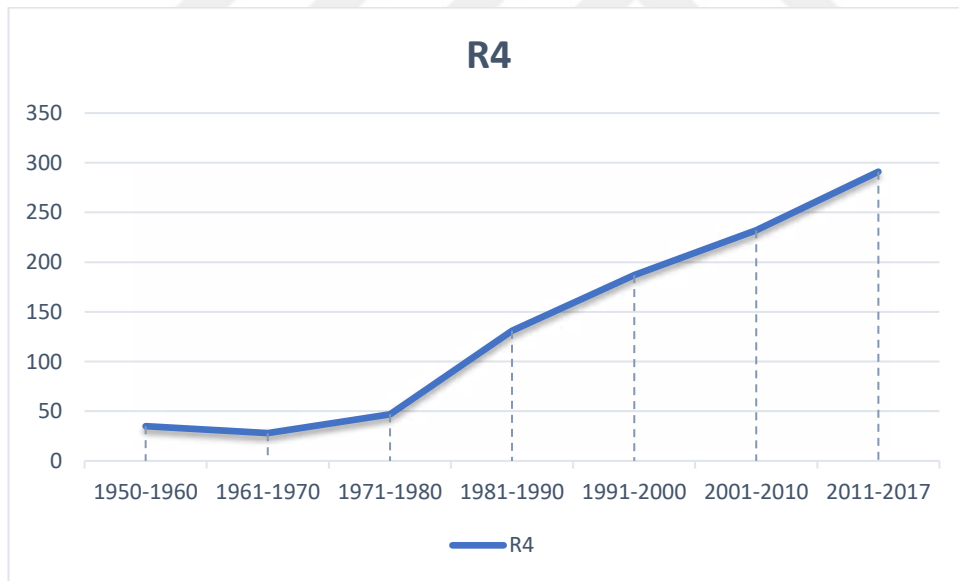


Figure 4.8. Crime Rates in region 4

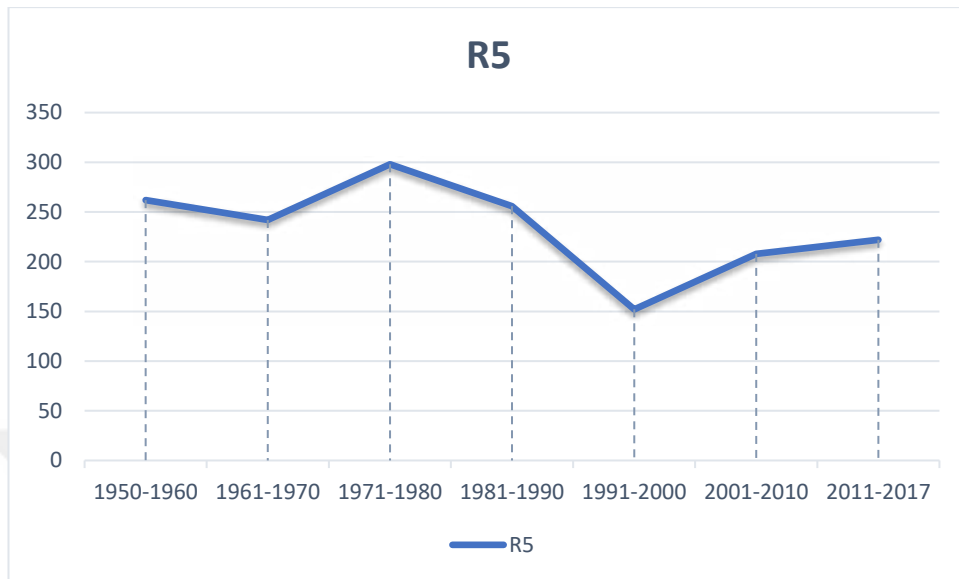


Figure 4.9. Crime Rates in region 5

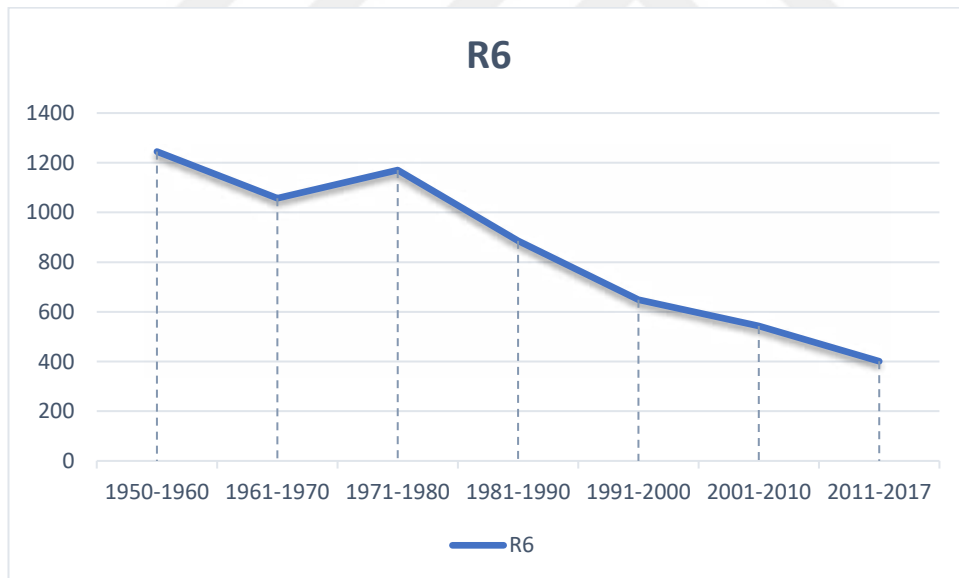


Figure 4.10. Crime Rates in region 6

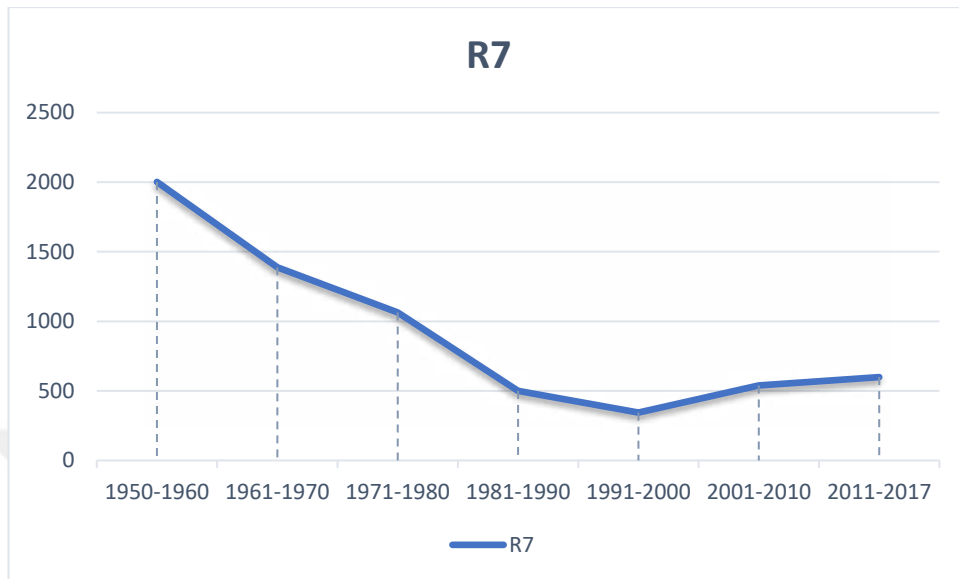


Figure 4.11. Crime Rates in region 7

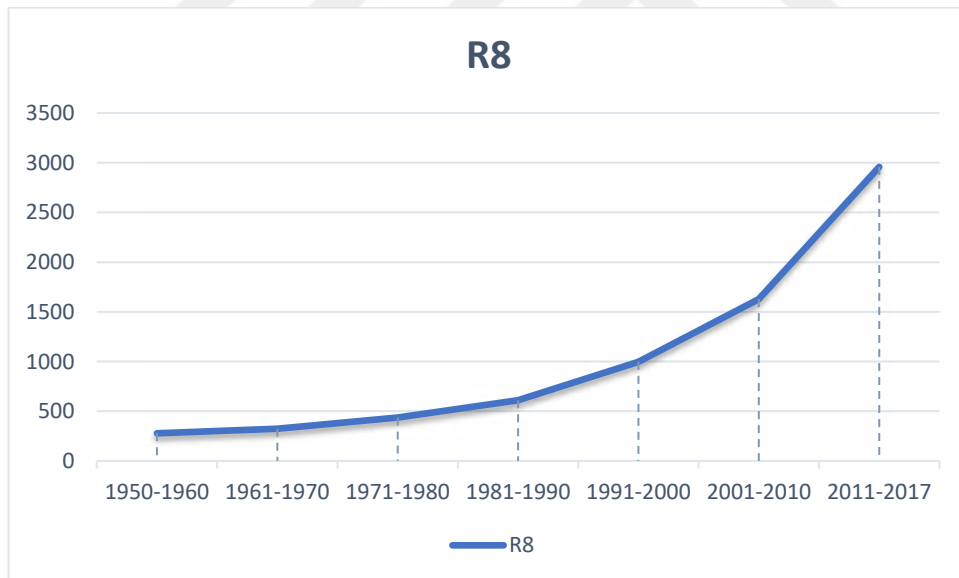


Figure 4.12. Crime Rates in region 8

Above, only the strain rates in the regions have been examined. However, the trend phenomenon depends on a wide variety of parameters. Therefore, if the population increases, the increase in crime rate is a very natural situation. In addition, a jump to 170 crime rates from 150 crimes may not show a great tendency graphically while 15 criminal cases are observed as a huge increase in 10 criminal cases. So it is a point to be examined with all parameters. Otherwise, graphics can be misleading. In addition, the fact that 4 of the five crime types in a region are not processed and that only one crime is processed more than the previous periods does not show that the crime types and proportions in the region have decreased by the same amount. For example, the patterns of crime in a region are shown in the following graphs.  $S_5$  is the tendency to increase whatever the period is. Here is the most noticeable increase and the most important type of crime is  $S_5$ .

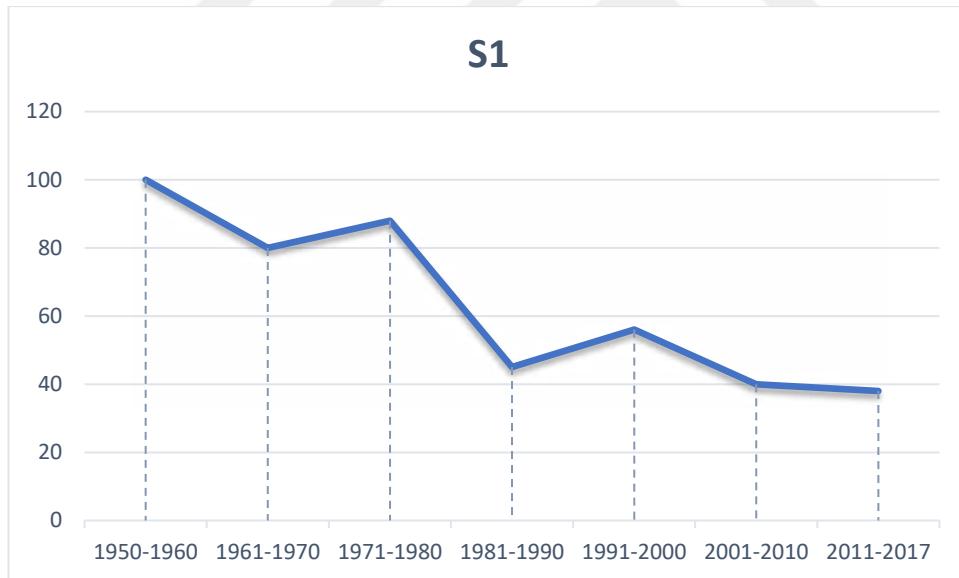
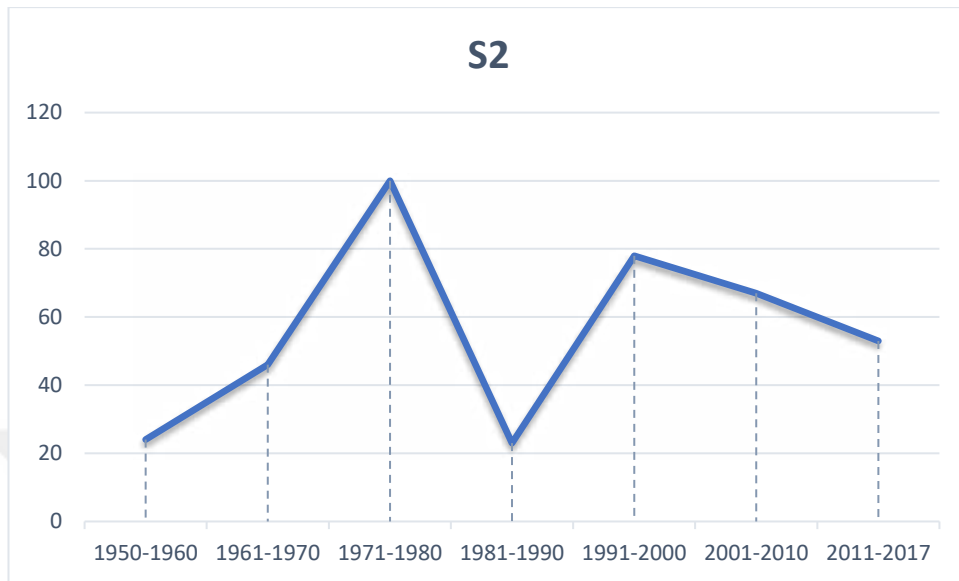
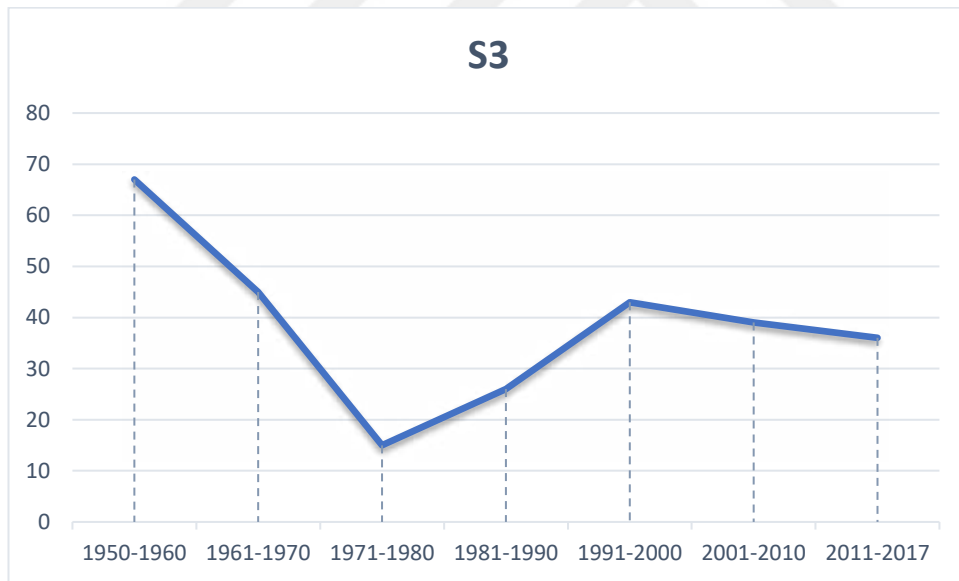
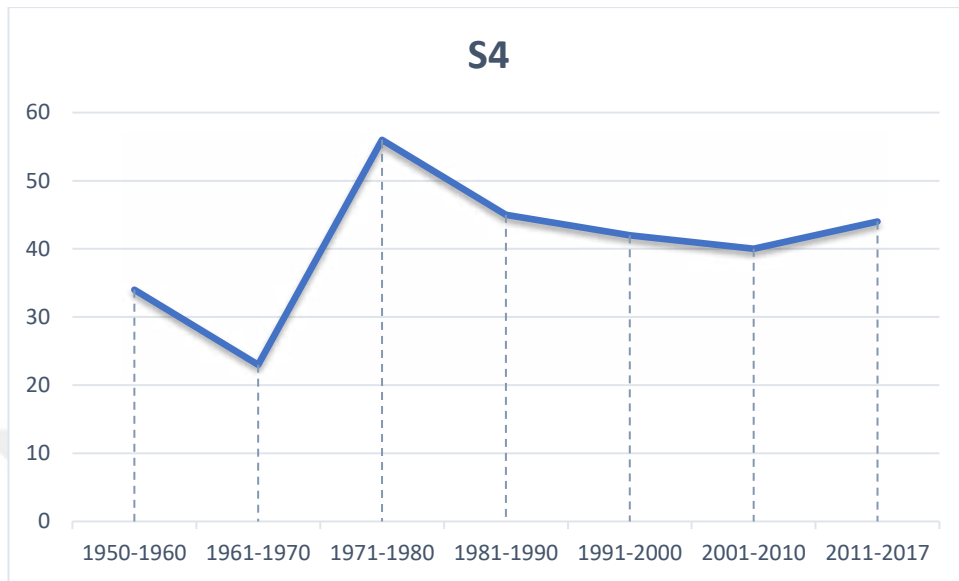
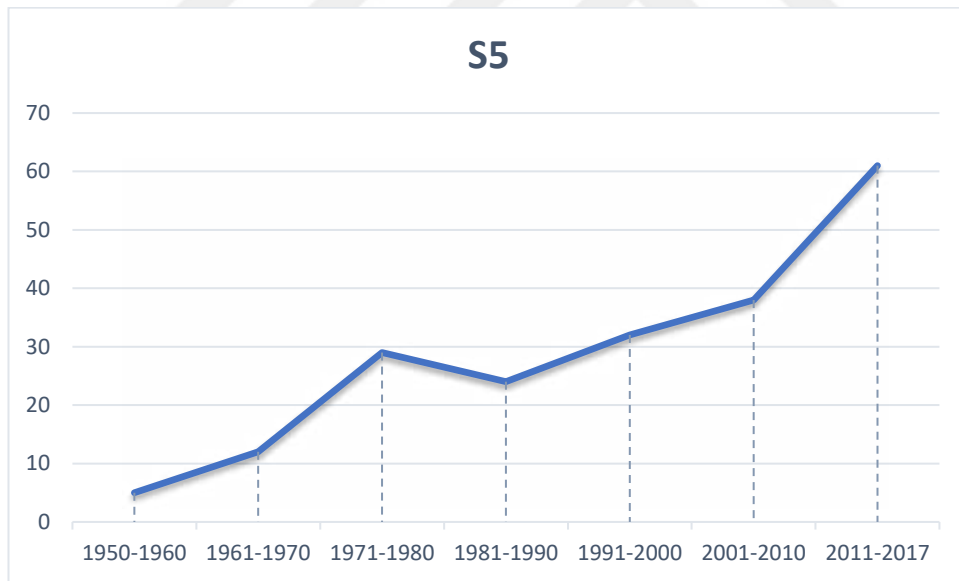


Figure 4.13. Crime rate for  $S_1$  by the years

Figure 4.14. Crime rate for  $S_2$  by the yearsFigure 4.15. Crime rate for  $S_3$  by the years

Figure 4.16. Crime rate for  $S_4$  by the yearsFigure 4.17. Crime rate for  $S_5$  by the years

#### 4.2.1. Tests for Crime Prediction Among Criminal

As shown on Table 4.3 name of the criminal and criminal id are given, the number of committing criminal repetition as Criminal Rep. and  $S_1$  crime on the database and prior probability rates are indicated.

Lastly, Query prob and its probability of committing  $S_2$  crime and its percentage (%) will be found. In consideration of the information on the table and carried out analysis, it is seen that ‘criminal 18’ has the most probability of committing  $S_2$  crime. Law enforcement agencies will be informed that criminal 18 may be the person who has the most probability of committing the query crime in the carried out analysis.

Records chosen randomly with the Gaussian model as 20 offenders and maximum 5 acquaintances of each offenders had been examined on the work done over 1000 examples. In the sampling on the test/the tests performed on 3 crimes in total : the probabilities of  $S_2$  crime committing of the people who commit  $S_1$  crime were indicated in detail on the table below (Table 4.3).

Table 4.3. Test Results for 1000 sample data

| Criminal          | Criminal Rep. | Prior Probability | Query Probability |
|-------------------|---------------|-------------------|-------------------|
| Criminal1         | 22            | 0.0512            | 0.0644            |
| Criminal10        | 19            | 0.0552            | 0.0430            |
| Criminal11        | 27            | 0.0628            | 0.0445            |
| Criminal12        | 23            | 0.0568            | 0.0537            |
| ⋮                 | ⋮             | ⋮                 | ⋮                 |
| Criminal17        | 17            | 0.0395            | 0.0536            |
| <b>Criminal18</b> | 28            | 0.0651            | <b>0.0852</b>     |
| Criminal19        | 24            | 0.0558            | 0.0430            |
| Criminal2         | 16            | 0.0372            | 0.0536            |
| ⋮                 | ⋮             | ⋮                 | ⋮                 |

The table indication obtained above, having the probabilities of committing  $S_2$  crime of all the criminals who committed  $S_1$  crime and ‘criminal 18’ who has the maximum rates involves the highest rate is indicated graphically in Figure 4.18.

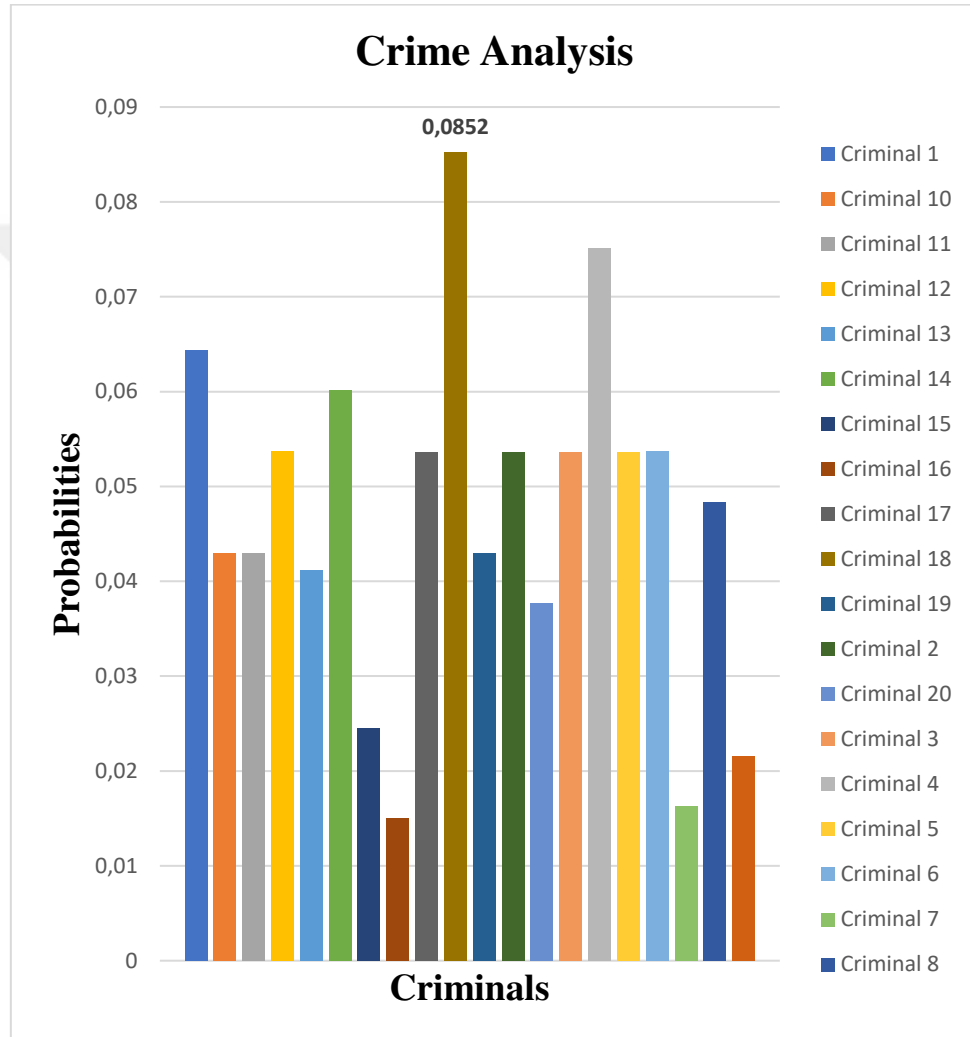


Figure 4.18. Graph related about possibilities of criminals

According to the results of other tests done as a result of statistical forecasting system, based on the data according to different parameters as a result of queries form took place in consequence of five tests and results (Table 4.4-4.5). At the formulation of the crime dataset in the simulation that present facilities to the last user, maximum offender and maximum acquaintances will be chosen randomly for the N sample data identified by the user (Maximum offender  $\geq$  Maximum acquaintances).

Five samplings chosen by the user are indicated in the table below. In this table, the data of five tests that has different parameter rates and in consideration of these data, results obtained and the probabilities of the offenders who has the highest results are indicated in the construction based on the mathematical model as related among crimes.

Table 4.4. Five test results for Crime Analysis Simulator

|                                     | Test1          | Test2          | Test3          | Test4          | Test5          |
|-------------------------------------|----------------|----------------|----------------|----------------|----------------|
| <i>Analysed Crime</i>               | S <sub>1</sub> | S <sub>2</sub> | S <sub>3</sub> | S <sub>1</sub> | S <sub>2</sub> |
| <i>Query Crime</i>                  | S <sub>2</sub> | S <sub>3</sub> | S <sub>2</sub> | S <sub>2</sub> | S <sub>3</sub> |
| <i>Number of Sample</i>             | 100            | 100            | 100            | 500            | 1000           |
| <i>Max. Number of Acquaintances</i> | 10             | 10             | 10             | 17             | 25             |
| <i>Number of Crime Types</i>        | 3              | 3              | 3              | 3              | 3              |

Crime dataset are formed according to the five samplings and parameters identified by the user as indicated in the Table 4.4 above. Based on the Bayes model, the information in Table 4.5 is reached. This information shows the offender who has the highest rate and the probability of this offender by applying the Bayesian formula according to the parameters given for each test.

Table 4.5. According to test results, offender and probability of offender

| Tests        | The highest rate of criminal | Probability of committing crime |
|--------------|------------------------------|---------------------------------|
| <i>Test1</i> | Criminal 5                   | 0.2208                          |
| <i>Test2</i> | Criminal 9                   | 0.1940                          |
| <i>Test3</i> | Criminal 6                   | 0.2302                          |
| <i>Test4</i> | Criminal 12                  | 0.3406                          |
| <i>Test5</i> | Criminal 19                  | 0.0591                          |

Criminal 5: The name or identification of the criminal

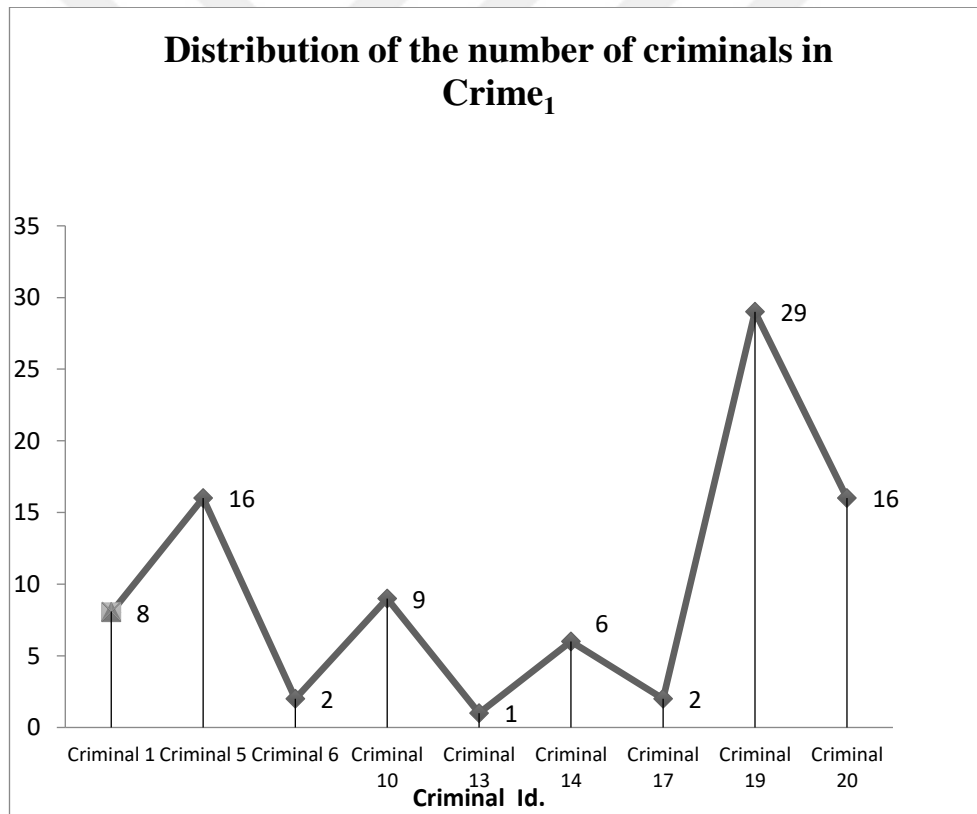
The one of the experimental test is below. The examination for any crime was made by considering the criminal distribution (e.g. Crime<sub>1</sub>). Thus, to see the Criminal distribution, it is necessary to look at the point at which the prior probability value of the criminal on the graph is located.

For any tests above, offenders, the repetition numbers of offenders in crime<sub>1</sub> and the probability of committing query crime are indicated in Table 4.6. The probability of committing the most questioned crime in crime<sub>1</sub> is seen that it is criminal 19 and 0.325843. Besides this, three distribution of the probabilities of these offenders in crime<sub>1</sub> is indicated in Table 4.7.

As it is either in Figure 4.19, 4.20 and in Table 4.6, possible 5 offenders will be chosen from the table or figure when data like the most looked for 5 offenders wanted.

Table 4.6. Criminals and the Possibilities in Crime<sub>1</sub>

| Criminal Id. | # of Criminal | Possibility of Criminal |
|--------------|---------------|-------------------------|
| Criminal-1   | 8             | 0.089888                |
| Criminal-5   | 16            | 0.179775                |
| Criminal-6   | 2             | 0.022472                |
| Criminal-10  | 9             | 0.101124                |
| Criminal-13  | 1             | 0.011236                |
| Criminal-14  | 6             | 0.067416                |
| Criminal-17  | 2             | 0.022472                |
| Criminal-19  | 29            | 0.325843                |
| Criminal-20  | 16            | 0.179775                |

Figure 4.19. Distribution of the number of criminals in Crime<sub>1</sub>.

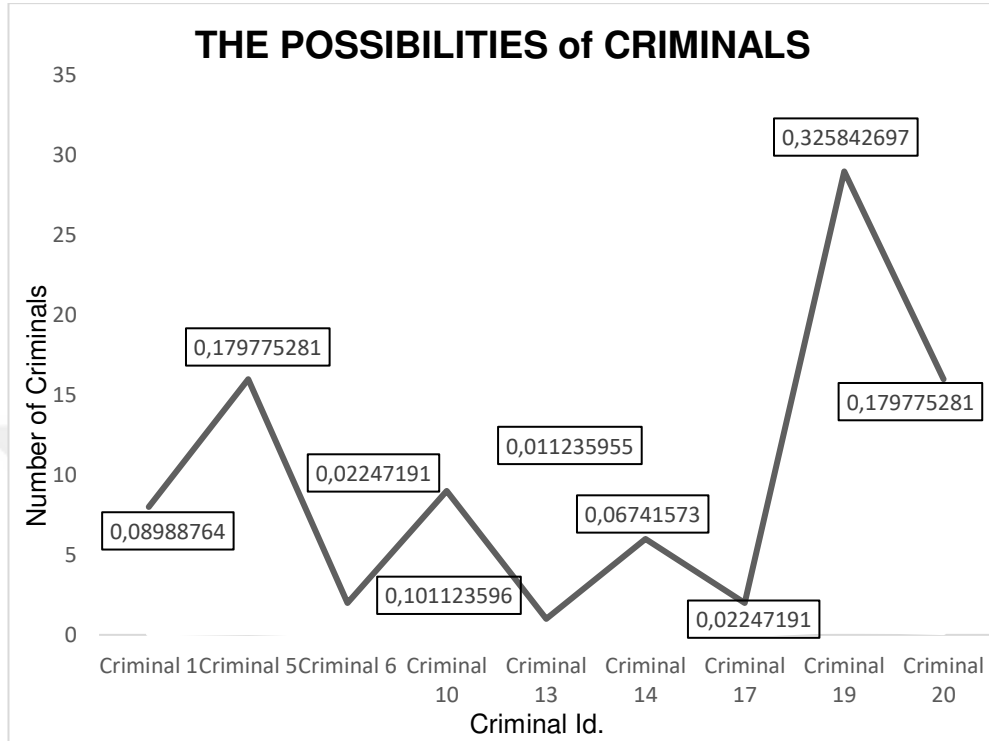


Figure 4.20. Criminals and the possibilities in Crime<sub>1</sub>.

The following Table 4.7, shows test results according to crime analysis simulation. There are five tests on simulation, found out criminal and the highest probability value in analysed crime.

Table 4.7. Simulation Tests for Crime Trends among Criminals

| Parameters            | Test1   | Test2   | Test3   | Test4   | Test5   |
|-----------------------|---------|---------|---------|---------|---------|
| <i>Analysed Crime</i> | Crime-1 | Crime-2 | Crime-3 | Crime-1 | Crime-2 |
| <i>Query Crime</i>    | Crime-2 | Crime-3 | Crime-2 | Crime-2 | Crime-3 |
| <i>N</i>              | 1000    | 1000    | 1000    | 5000    | 10000   |
| <i># Acq.</i>         | 10      | 10      | 10      | 8       | 50      |
| <i>#Criminal</i>      | 100     | 100     | 100     | 170     | 250     |
| <i>#Crime</i>         | 3       | 3       | 3       | 3       | 3       |
| <i>Criminal Id.</i>   | 51      | 9       | 60      | 129     | 215     |
| <i>Probabilites</i>   | 0.2208  | 0.1940  | 0.2302  | 0.3406  | 0.0591  |

# Acq. : Number of Acquaintances List

For Test4, it is applicated for 5000 sample. The number of criminal is between 1 and 170. The system will select randomly, and all of the criminals are investigated. As a result of these queries, the person with criminal id 129 has the highest score.

The value found was 0.3406 as the posterior probability value calculated according to the Bayesian formula. A functional parameter to be sent to the matlab program will be interrogated. In the determination of crime trends, the probability value for the criminal trend will be determined in the following equation. (Eq. 4.1).

$$\text{Crime\_Analyse}(\text{Crime}_1, \text{Crime}_2, 5000, 3, 170, 8) = \{\text{Criminal 129}, 0.3406\} \quad (4.1)$$

Various experiments are done based on simulation that consists of system parameters. Table 4.8 used different values for some of the system parameters. Thus, it is checked whether the simulation is working or not.

Table 4.8. Used parameters in the experiments

| # of Incidents | # of Regions | # of Crimes | # of Criminal | # of Acq. |
|----------------|--------------|-------------|---------------|-----------|
| 1000           | 8            | 5           | 50            | 10        |
| 1000           | 5            | 3           | 50            | 10        |
| 1000           | 5            | 3           | 10            | 10        |
| 3000           | 10           | 30          | 500           | 10        |
| 3000           | 10           | 30          | 400           | 30        |
| 3000           | 10           | 30          | 500           | 30        |
| 3000           | 20           | 30          | 500           | 30        |
| 3000           | 20           | 50          | 500           | 30        |
| 3000           | 20           | 50          | 1000          | 30        |
| 1000           | 20           | 50          | 1000          | 50        |
| 10000          | 20           | 50          | 1000          | 100       |

Simulation of the system, as a working principle, is divided into four panels which are Crime events panel, Crime Types, Crime Locations Panel and Offenders Panel. Each panel of this application will be used to compute the forecasting system. First panel is ,Crime Events, locates the number of events which means total data for this simulation. The choice of date consists of two parts. The first one is the start date of committing crime and the other is the end date of committing crime. In Crime types panel,it gives a number of crime types whose range is between 1 and maximum crime types from simulation for all events. After picking of the crime types, it needs to determine how many regions there are. That is the number of events which was distributed around centers of this map. Therefore, distance between centers must be specific. This rate is taken by maximum distance between centers in crime location panel. So, distribution of these data will be collected by this simulation. This distribution has two choices. Each of two choices is interested with form of distribution. When a uniform distribution is chosen, the

variance parameter is not required. Variance parameter, the range between minimum variance and maximum variance, is needed only to pick of Gaussian. Distribution data is distributed as crime after it is assigned to crime types to each data as the number of crime types. Crime incidents are distributed as randomly. It will do date parameter at the same time. The last step is picking with offenders. The first thing you need to know is, how many criminals should be determined. This knowledge will come from Max. Number of criminals choice in criminal's panel (Figure 4.21).

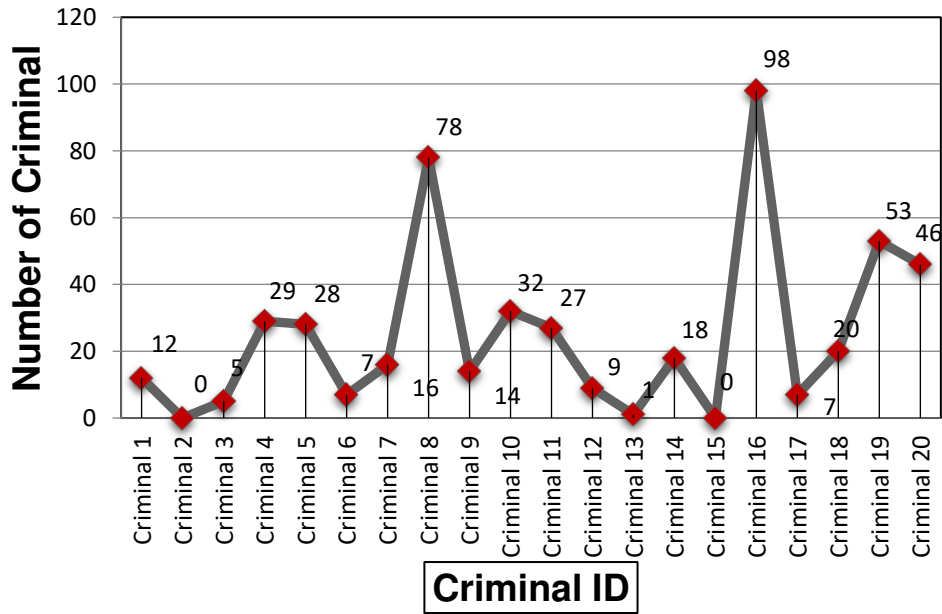


Figure 4.21. Distribution number of criminal in DataSet

Apart from this information, it will be determined acquaintances each of offenders. The list of acquaintances is computed with the given criteria. For example, Maximum number of acquaintances, distribution of acquaintance with variance and percentage rate. Each of offender acquaintances list assigned randomly. Sometimes, it may be as a number of max. Number in criminal's panel

or between 1 and maximum number of acquaintances or may be none. While it is created acquaintances first any point in map is selected. This point is denoted any criminal. Firstly, it is selected the nearest circle that is shown in the distribution of acquaintances-1. It is Gaussian distribution giving variance and percentage which is priority and probability.

In addition to these, N sample of data will be used for the simulation. The first work to be done, is to distribute crimes on the map of N data. After the distribution of crime, we need to know when crime is committed So, it will be entered the date range which is divided into two main groups. The first one is date and the other one is time. Therefore, Time factor is in conjunction of two groups. Until now, distribution of crimes is realized to a specific time range. Each data in Data Set will be kept within a certain time as coordinate values which are X and Y coordinates on map.

The distribution of crime on the map is done according to some methods. For example Gaussian distribution method. Distribution of crimes should be separated in different districts on the map. These districts show the center of crimes because crime rate is higher in the city center than others. Every coordinate data shows that a crime is committed at a certain period of time and deterministic district on map. So, the parts of data are coordinates which means that place, time and district. In parallel, it is needed to assign criminals who commit the crime. These criminals are assigned randomly, and the range of the criminal comes from simulation between 1 and maximum number of criminal value. To find relation of criminals, the acquaintance list is needed. Also, the list is required to be familiar with the criminal that is assigned to each data. It is necessary to require for the connection of an acquaintance criminal. To create a list of acquaintance as approximate realistic, first of all it needs to detect analyzed criminals showing where they lived on map. The next step should be assigning number of acquaintances which are displayed in different values for each criminal. The length of list belonging each criminal will be different. Therefore, the creation of this list

according to parameters will vary than other components. Acquaintances list consists of three main parts. First, analyzed criminal locations on the map shall be determined. This determining operation is detected to have same identity. The next step is chosen one that will be selected randomly on map. Chosen criminal is center of all criminal whose id's are same value. It is called home locality. The home locality means center of the criminals that have same criminal id. The concept of Home locality shows the population density which is more than other place where crime is committed and in other words, this is home of criminal. Actually, it is divided into three sub categories. These categories will help to find the list of acquaintances. For this reason, the densest of population is center of home locality like town, city and country. For example, if criminal lives in Mersin, then Crime rate is higher than Erdemli. So, if any criminal is analysed, then generally, his acquaintances are nearest points to him. Created acquaintances list will select many criminals in this region. On the other hand, the offender's crime was committed somewhere outside the home locality on the map. These places are called incident locality whose distribution is Gaussian. Last step is last place for acquaintances. The last place is apart from these places on the map. Remaining part of criminal will be selected in the last grouping that is called Map Locality. In below tables, there is a list of acquaintances. Here is a scenario closer to reality with uniform distribution created. All components were used as parametric which was traded according to the values from the simulation. The system works as parametric. These values are composed of data from simulations. Thus, criminals and their acquaintances are created around certain centers. Criminals and acquaintances are determined by the values entered from simulation. In the below figure, created values entered by the user on the map with coordinate data are shown in the data set. This data set consists of N records. Each of these records shall be expressed with the list of criminal and that the criminal's acquaintances list, the coordinate data, the time, the crime and the offender.

So far, the part of stage is creation of the data set. After that, the crime analysis and forecasting system will be discussed. With this prediction, system will be found committing query crime probability of criminals who commit analysed crime. For this reason, first analyzed crime is selected. Then query crime will be selected. After that, the system will work with query button. Analysis of all offenders in the criminal will operate in accordance with the basic mathematical model in Figure 3.10 and will find prior probability values for crimes and criminals in crimes. After calculating prior probabilities, posterior probability values will be found.

Between the years 1971 and 2013, a crime dataset with 10.000 records which will consist of 9 crimes would be formed. In that crime dataset that will be formed, a form with maximum 500 criminals and maximum 30 suspicious acquaintances of each criminal will be distributed randomly. The distribution of the acquaintances is explained in Figure 4.22 subject above. Here, acquaintances will be identified in the simulation parameters in Gaussian distribution. In the system which also has the demonstration on the map, the crime events' places will be determined between the given coordinate rates  $x$  and  $y$ . The crime dataset that will be formed in this map will consist of 18 regions in 10000 records. Since every region will have the centers, it will be provided that the centers will be in definite borders. Therefore, minimum distances were encoded as 20 units. Since this distribution will be Gaussian, our crime dataset will be formed according to the stated criteria and models in such a way that the variance rates of distribution will be between 1 -10.

**Crime Simulation**

|                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         |                                                                                                                                                  |                                                                                                                                                                                                                    |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Crime Events</b><br>Number of Events: <input type="text" value="10000"/><br>Date:<br>Start Date: <input type="text" value="1971"/> End Date: <input type="text" value="2013"/>                                                                                                                                                                                                                                                                                                                                       | <b>Crime Types</b><br>Number of Crime Types: <input type="text" value="9"/><br>Distribution of Crime Types: <input type="text" value="Uniform"/> | <b>Criminals</b><br>Max. Number of Criminals: <input type="text" value="500"/><br>Distribution of Criminals: <input type="text" value="Uniform"/><br>Max. Number of Acquaintances: <input type="text" value="30"/> |
| <b>Map/Incident Locations</b><br>Number of Regions: <input type="text" value="18"/> Map Size: X: <input type="text" value="200"/> Y: <input type="text" value="200"/><br>Centers Distribution of the Region: <input type="text" value="Uniform"/><br>Minimum Distance Between Centers: <input type="text" value="50"/><br>Distribution of Incident Locations: <input type="text" value="Gaussian"/> <input type="text" value="1"/> - <input type="text" value="10"/><br><small>Min. Variance      Max. Variance</small> |                                                                                                                                                  |                                                                                                                                                                                                                    |
| <input type="button" value="Create DataSet"/>                                                                                                                                                                                                                                                                                                                                                                                                                                                                           |                                                                                                                                                  |                                                                                                                                                                                                                    |

Figure 4.22. Crime Analysis simulation

The distribution of 10000 data is shown in Figure 4.23.

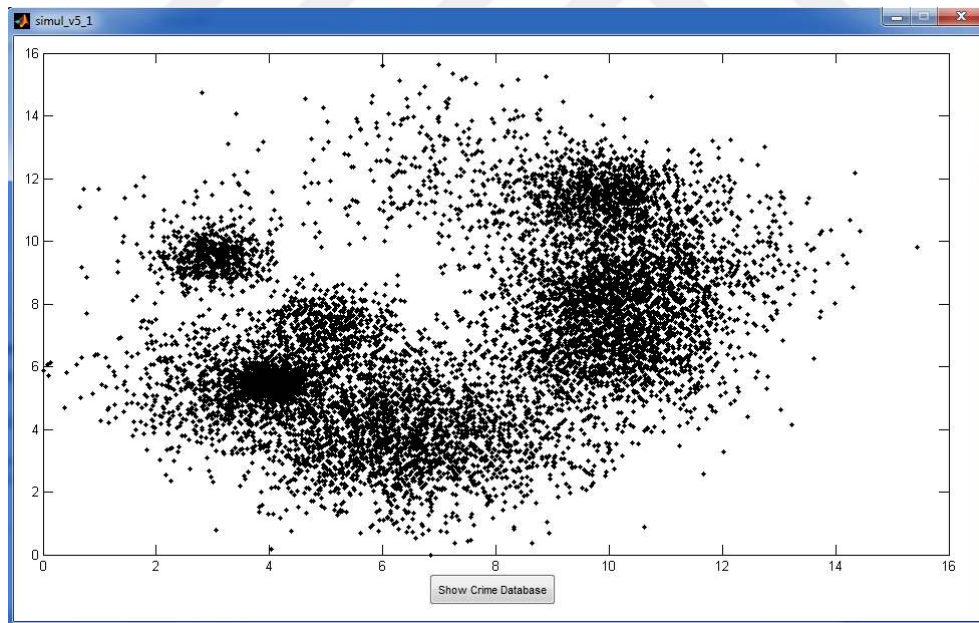
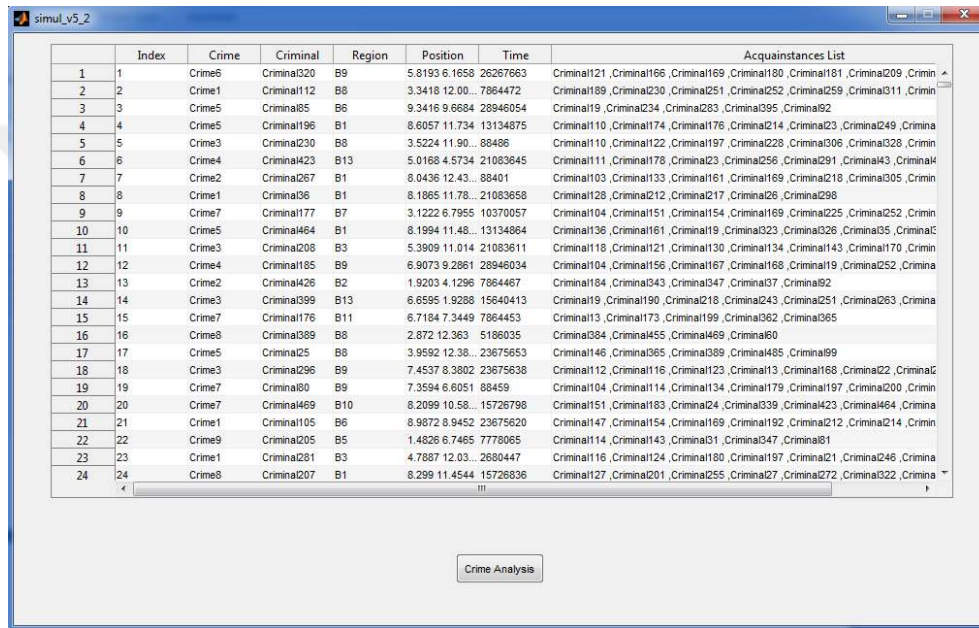


Figure 4.23. Distribution number of crime incidents in DataSet

According to the defined criteria above, in the formed crime dataset every point shows a criminal. For this reason, this criminal has an id value, the crime that was committed, the location of the committing crime, the coordinates of this region, time of the crime and suspicious acquaintances criminals. In the Figure 4.24 below for each of these 10000 records available information is presented.



|   | Index | Crime  | Criminal    | Region | Position      | Time     | Acquaintances List                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              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| 1 | 1     | Crime6 | Criminal320 | B9     | 5.8193 6.1658 | 26267663 | Criminal121, Criminal166, Criminal169, Criminal180, Criminal181, Criminal209, Criminal210, Criminal211, Criminal212, Criminal213, Criminal214, Criminal215, Criminal216, Criminal217, Criminal218, Criminal219, Criminal220, Criminal221, Criminal222, Criminal223, Criminal224, Criminal225, Criminal226, Criminal227, Criminal228, Criminal229, Criminal230, Criminal231, Criminal232, Criminal233, Criminal234, Criminal235, Criminal236, Criminal237, Criminal238, Criminal239, Criminal240, Criminal241, Criminal242, Criminal243, Criminal244, Criminal245, Criminal246, Criminal247, Criminal248, Criminal249, Criminal250, Criminal251, Criminal252, Criminal253, Criminal254, Criminal255, Criminal256, Criminal257, Criminal258, Criminal259, Criminal260, Criminal261, Criminal262, Criminal263, Criminal264, Criminal265, Criminal266, Criminal267, Criminal268, Criminal269, Criminal270, Criminal271, Criminal272, Criminal273, Criminal274, 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Criminal968, Criminal969, Criminal970, Criminal971, Criminal972, Criminal973, Criminal974, Criminal975, Criminal976, Criminal977, Criminal978, Criminal979, Criminal980, Criminal981, Criminal982, Criminal983, Criminal984, Criminal985, Criminal986, Criminal987, Criminal988, Criminal989, Criminal990, Criminal991, Criminal992, Criminal993, Criminal994, Criminal995, Criminal996, Criminal997, Criminal998, Criminal999, Criminal1000 |

Figure 4.24. Generated Crime DataSet on Simulation

Artificial data set is shown in the section after creation (Fig. 4.24). However, the number of time data is converted to number format with datenum. In fact, the data table listed on the screen is as shown in the Figure 4.25. The crime data set will have the same parameters but the time format will be different. For example, it is displayed in the user interface in hours, minutes and seconds when it is desired to display a different screen image in a section.

|   |    |   |             |                      |                        |
|---|----|---|-------------|----------------------|------------------------|
| 2 | 17 | 1 | 27-Aug-1974 | 109.276 - 52.3881    | 26 ,30 ,84 ,97         |
| 1 | 94 | 1 | 20-Oct-2011 | 117.1226 - 66.5399   | 26 ,66 ,84 ,97         |
| 3 | 19 | 3 | 14-Oct-1983 | 302.6757 - 186.36... | 26 ,30 ,84 ,97         |
| 2 | 63 | 5 | 21-Feb-1999 | 68.0056 - 263.1998   | 26 ,66 ,84 ,97         |
| 2 | 3  | 5 | 03-Jan-1969 | 25.8253 - 258.6525   | 26 ,30 ,84 ,97         |
| 2 | 22 | 3 | 09-Nov-1962 | 285.7564 - 80.5072   | 26 ,30 ,84 ,97         |
| 1 | 3  | 5 | 02-Aug-1986 | 43.6457 - 300.8718   | 26 ,30 ,84 ,97         |
| 3 | 15 | 5 | 04-Nov-2017 | 31.622 - 303.408     | 26 ,66 ,84 ,97         |
| 3 | 19 | 5 | 06-Dec-1997 | 102.5041 - 261.55... | 26 ,30 ,84 ,97         |
| 1 | 54 | 1 | 05-Jun-1996 | 104.0675 - 46.2025   | 26 ,30 ,66 ,84 ,97     |
| 2 | 59 | 1 | 14-Nov-1974 | 112.7416 - 100.13... | 22 ,26 ,30 ,31 ,84 ,97 |
| 2 | 82 | 2 | 28-Jun-2009 | 345.8135 - 156.40... | 26 ,66 ,84 ,87 ,97     |
| 3 | 91 | 5 | 05-Apr-2018 | 87.5663 - 269.638    | 26 ,30 ,66 ,84 ,97     |
| 3 | 26 | 3 | 09-Sep-1987 | 211.1137 - 51.6974   | 66 ,84 ,97             |
| 1 | 9  | 5 | 22-Jul-1999 | 21.7716 - 270.4198   | 26 ,66 ,84 ,97         |
| 1 | 13 | 5 | 22-Jul-2008 | 23.5557 - 290.8993   | 26 ,30 ,84 ,97         |
| 3 | 56 | 4 | 11-May-1998 | 238.8996 - 141.93... | 26 ,66 ,84 ,97         |
| 3 | 56 | 4 | 28-Nov-1974 | 162.288 - 122.1348   | 26 ,66 ,84 ,97         |
| 2 | 96 | 3 | 24-Dec-1971 | 273.9448 - 160.23... | 26 ,66 ,84 ,97         |
| 1 | 3  | 3 | 14-Dec-1970 | 275.2694 - 140.15... | 26 ,30 ,84 ,97         |
| 2 | 24 | 3 | 27-Dec-2004 | 279.3735 - 115.80... | 26 ,30 ,66 ,84 ,97     |
| 2 | 38 | 4 | 09-Mar-1977 | 215.2917 - 162.68... | 26 ,66 ,84 ,97         |

Figure 4.25. The section of crime data set with real date.

Crime dataset was determined with the simulation. The next step is the practical fixation point between the relation of two crimes. As indicated with the necessary formulas according to Bayesian network above, it is the fixation of the probability of committing query crime of all the criminals who committed an analyzed crime. As seen in Figure 4.26, in the crime dataset with 10000, criminal who committed crime 1 will be scanned from the criminals who committed crime 4. With given criteria and artificial intelligence techniques, criminal 423 is determined to have the highest rates of the probability of committing crime. At the same time, with all the other data of this criminal, the information about when and in which region the criminal again committed the crime, is given in the table. Anyway, when looked at the table, it is seen that the data of the found criminal coincide with the criminal in the region-1 where is called B1.

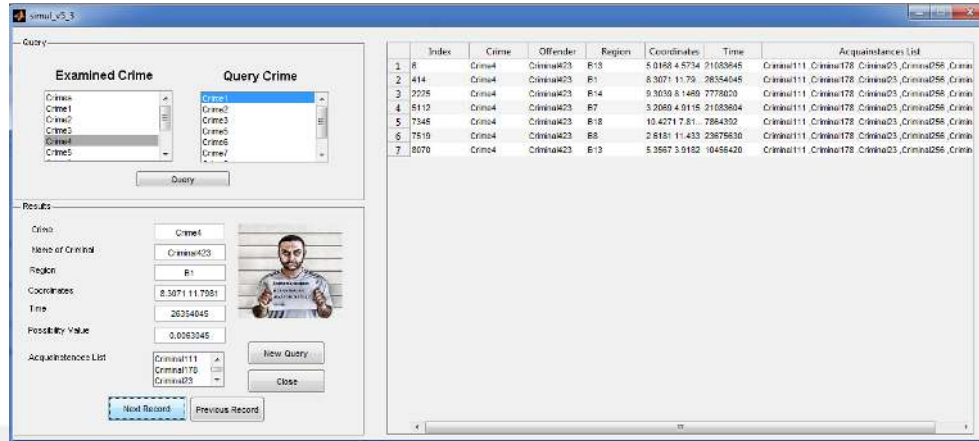


Figure 4.26. The Detection of Criminal based on Forecasting System

### 4.3. Hybrid Metrics

Three clustering experiments using the parameters are performed. The user interface of the simulation system is shown in Figure 4.27. The user interface is simply divided into four panels, which are the panels for crime-events, crime-types, map/incident locations and criminals. Crime-events panel simulates the number of incidents and the time interval that the incidents occurred.

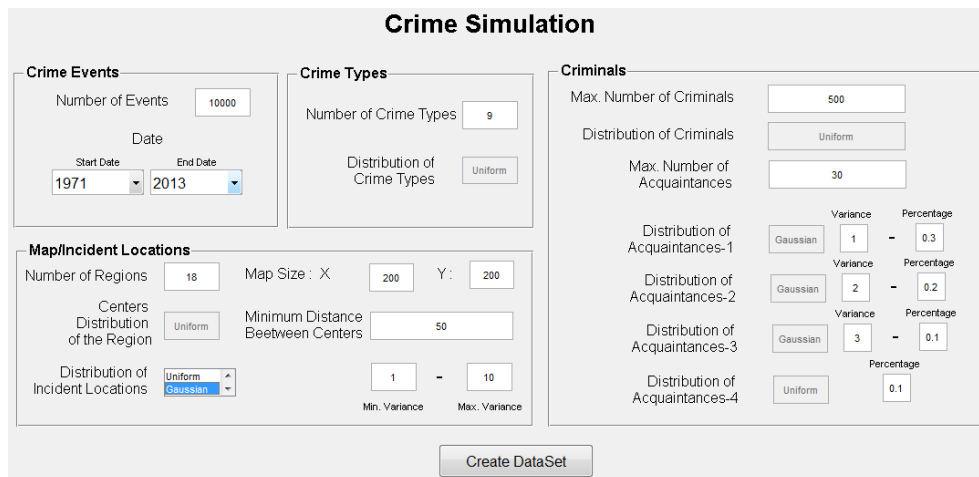


Figure 4.27. User-interface of the simulation system

Map/Incident location panel includes the user parameters that describe the generation of random maps and the incident distribution across the map. The map is created with the given map size with a constraint that the minimum distance between region centers conforms to the user defined parameter. The incident locations are generated randomly using the given distribution type. In the experiments, the incident locations are distributed around the centers using the mixture of Gaussians. Criminal's panels involve the user defined parameters for criminal related information such as the number of criminals, their acquaintances, and the distribution of acquaintances around the localities.

For the purpose of demonstration, it is selected 300 incidents, which are distributed across the 5 regions given in Figure 4.28-4.31. Figure 4.29 shows the distribution of the crime types over the geographical map. Figure 4.30 and Table 4.9 show the result of the clustering process where only three clusters (cluster#1, cluster#12, and cluster#20) are shown for demonstration purpose. The clustering process is acquired using hierarchical clustering method over the proposed similarity metric for crime incidents. Hierarchical clustering is an agglomerative clustering method. This method of thinking is to create a hierarchy of clusters that takes the two closest subsets of each iteration step and combines them. This process is usually continued until there is one large cluster containing all the vectors. It is empirically showed the performance of the hierarchical clustering as demonstrated in Table 4.10 where the related features are underlined for visualization. In Table 4.10, the incidents are only considered in Cluster#20 (Figure 4.31). The results show that the proposed method well groups the incidents that are related. The results also conform to the Crime-Driven Causal Relation with 96% performance at worst as shown in Table 4.11.

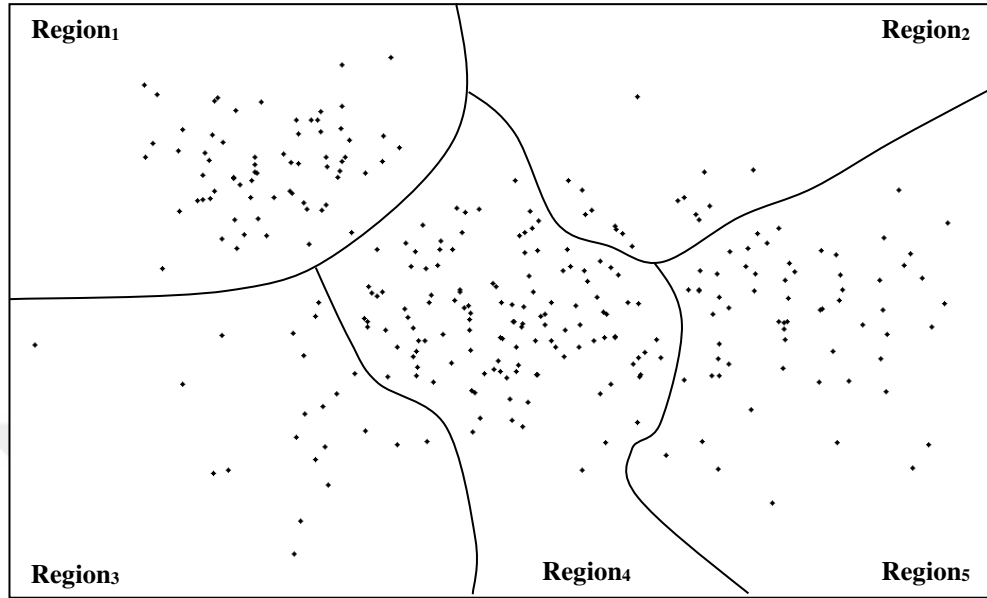
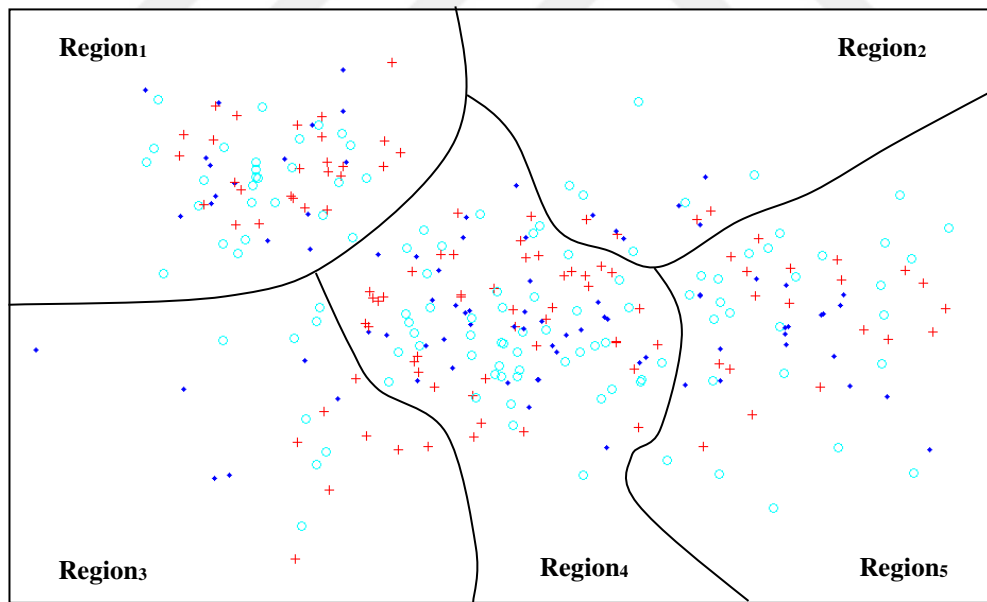


Figure 4.28. Distribution of crime incidents over the geographical map.



- + Crime<sub>1</sub>:Robbery
- Crime<sub>2</sub>:Drug
- Crime<sub>3</sub>:Weapons Trafficking

Figure 4.29. Distribution of the crime types over the geographical map.

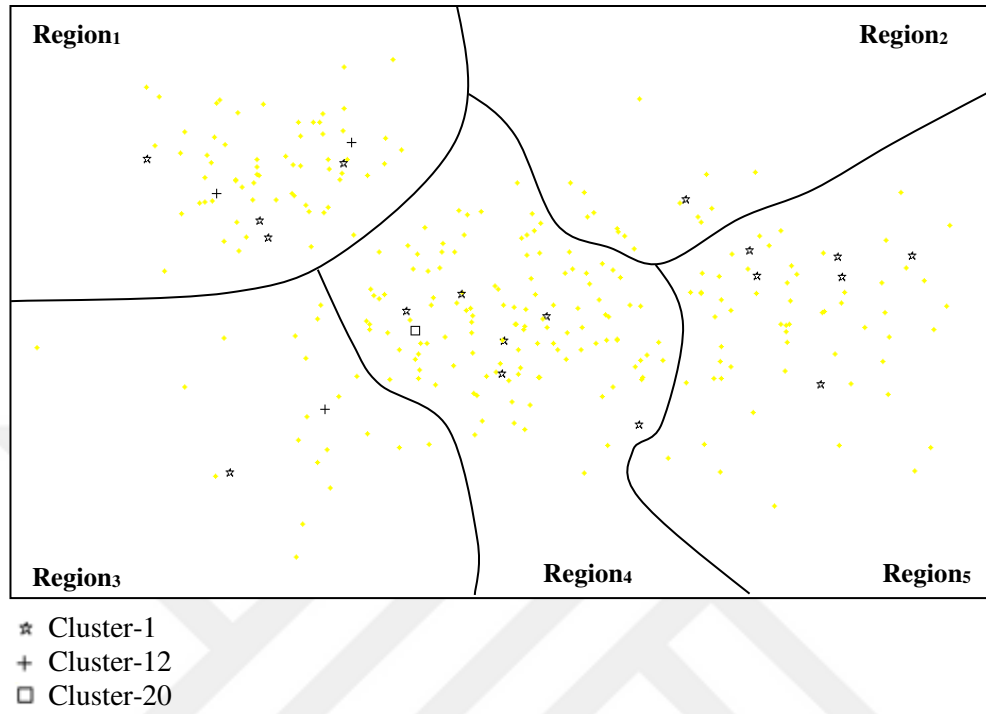


Figure 4.30. The results of clustering with 3 clusters demonstrated

Table 4.9. Demonstration of incident-level data and their clusters

| Crime Id. | Criminal Id. | Time     | Region | Place    | Acq. Id.       | Cluster |
|-----------|--------------|----------|--------|----------|----------------|---------|
| 1         | 24           | 23675645 | 1      | 1.7-6.6  | 2,5,20,22,26   | 20      |
| 1         | 11           | 23675595 | 1      | 3.0-8.1  | 5,12,25,30     | 20      |
| 1         | 26           | 13134854 | 3      | 2.7-1.7  | 10,12,16,18    | 1       |
| 1         | 26           | 23675609 | 5      | 10.3-2.3 | 10,12,16,18    | 20      |
| 1         | 7            | 23675597 | 4      | 7.5-1.3  | 2,10,12,19,24  | 20      |
| 1         | 3            | 23675658 | 4      | 4.8-4.7  | 12,15,16,28,30 | 20      |
| 1         | 12           | 23675586 | 4      | 6.1-4.1  | 9,10,23,24     | 20      |
| 1         | 9            | 23675605 | 5      | 10.6-5.1 | 3,6,20,24,29   | 20      |
| 1         | 18           | 23675635 | 5      | 10.6-5.7 | 12,17,25       | 20      |
| 3         | 26           | 23675615 | 3      | 1.2-0.1  | 10,12,16,18    | 20      |
| 3         | 26           | 13134854 | 1      | 1.0-7.4  | 10,12,16,18    | 1       |
| 3         | 11           | 23675625 | 1      | 1.8-6.2  | 5,12,25,30     | 20      |
| 3         | 7            | 23675617 | 5      | 9.3-5.2  | 2,10,12,19,24  | 20      |
| 2         | 18           | 23675595 | 2      | 8.2-7.2  | 12,17,25       | 20      |
| 2         | 20           | 13134848 | 1      | 3.1-8.7  | 1,6,8,9,30     | 1       |
| 2         | 15           | 23675629 | 5      | 11.7-5.7 | 4,11,14,19,20  | 20      |
| 2         | 30           | 23675642 | 4      | 5.5-3.5  | 3,7,10,20      | 20      |
| 2         | 29           | 23675624 | 4      | 3.9-4.3  | 12,14,16,22,30 | 20      |
| 2         | 4            | 23675593 | 1      | 0.0-8.3  | 10,22,24,27,29 | 20      |
| 2         | 24           | 23675651 | 5      | 9.2-5.8  | 2,5,20,22,26   | 20      |
| 2         | 19           | 23675623 | 4      | 5.4-2.6  | 7,21,23,24,27  | 20      |
| 2         | 17           | 20997200 | 4      | 4.1-3.7  | 3,5,10,25,28   | 12      |

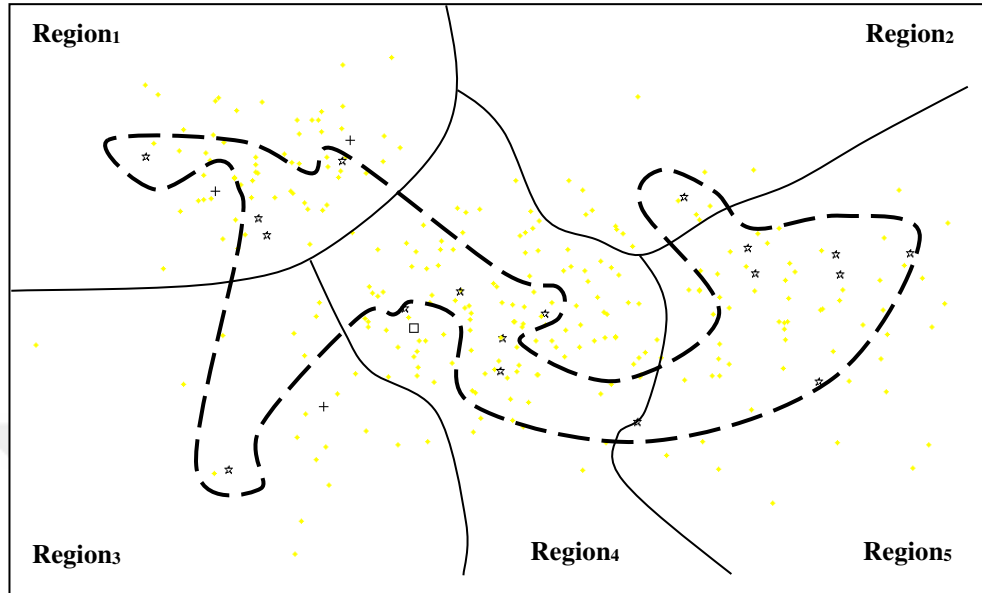


Figure 4.31. The results of clustering over GIS map with one cluster demonstrated.

Table 4.10. Demonstration of empirical analysis for clustering performance

| Crime Id. | Criminal Id. | Time            | Region   | Place           | Acq. Id.       | Cluster |
|-----------|--------------|-----------------|----------|-----------------|----------------|---------|
| <u>1</u>  | 24           | <u>23675645</u> | <u>1</u> | <u>1.7-6.6</u>  | 2,5,20,22,26   | 20      |
| <u>1</u>  | 11           | <u>23675595</u> | <u>1</u> | <u>3.0-8.1</u>  | 5,12,25,30     | 20      |
| <u>1</u>  | 7            | <u>23675597</u> | <u>4</u> | 7.5-1.3         | 2,10,12,19,24  | 20      |
| <u>1</u>  | 12           | <u>23675586</u> | <u>4</u> | 6.1-4.1         | 9,10,23,24     | 20      |
| <u>1</u>  | 3            | 23675658        | <u>4</u> | 4.8-4.7         | 12,15,16,28,30 | 20      |
| <u>1</u>  | 9            | <u>23675605</u> | <u>5</u> | <u>10.6-5.1</u> | 3,6,20,24,29   | 20      |
| <u>1</u>  | 18           | 23675635        | <u>5</u> | <u>10.6-5.7</u> | 12,17,25       | 20      |
| <u>1</u>  | 26           | <u>23675609</u> | <u>5</u> | 10.3-2.3        | 10,12,16,18    | 20      |
| <u>3</u>  | 26           | <u>23675615</u> | 3        | <u>1.2-0.1</u>  | 10,12,16,18    | 20      |
| <u>3</u>  | 7            | <u>23675617</u> | 5        | 9.3-5.2         | 2,10,12,19,24  | 20      |
| <u>3</u>  | 11           | 23675625        | 1        | <u>1.8-6.2</u>  | 5,12,25,30     | 20      |
| <u>2</u>  | 24           | <u>23675651</u> | <u>5</u> | <u>9.2-5.8</u>  | 2,5,20,22,26   | 20      |
| <u>2</u>  | 15           | <u>23675629</u> | <u>5</u> | 11.7-5.7        | 4,11,14,19,20  | 20      |
| <u>2</u>  | 18           | 23675595        | 2        | <u>8.2-7.2</u>  | 12,17,25       | 20      |
| 2         | 4            | 23675593        | 1        | 0.0-8.3         | 10,22,24,27,29 | 20      |
| 2         | 30           | 23675642        | <u>4</u> | <u>5.5-3.5</u>  | 3,7,10,20      | 20      |
| 2         | 19           | <u>23675623</u> | <u>4</u> | <u>5.4-2.6</u>  | 7,21,23,24,27  | 20      |
| 2         | 29           | <u>23675624</u> | <u>4</u> | 3.9-4.3         | 12,14,16,22,30 | 20      |

Table 4.11. Causal Relation Performance of the Experiments

| Experiment Id. | # of Incidents | Causal Relation Performance(%) |
|----------------|----------------|--------------------------------|
| Experiment #1  | 1000           | 100                            |
| Experiment #2  | 5000           | 98.2                           |
| Experiment #3  | 10000          | 96.95                          |

#### 4.4. Bayesian Network Analysis for Criminal Prediction

The important parameters used in the experiments are given in Table 4.12. Experimental results involves two parts, which are generation of the synthetic dataset and tests for criminal prediction. A particular section of the generated synthetic datasets is shown for visualization purpose in Table 4.13 for  $N = 1000$  incidents. The test results for criminal prediction are also demonstrated as particular sections in Table 4.14-4.16 where the criminal predictions are performed over  $N = 1000$  crime incidents.

Table 4.12. The parameters used in the experiments

| # Incidents(N) | # Crime | # Criminal | # Acq. | Loc. (km) | Time (day) |
|----------------|---------|------------|--------|-----------|------------|
| {100-5000}     | 3-7     | 10-200     | 2-20   | 1%-10%    | 1%-10%     |

In generation of the synthetic dataset, the spatial neighborhood  $h$  parameter is described as the local neighborhood around the incident location. In experiments, the  $h$  parameter was used with changing values in between 1%-10% of the geographical map of the area. Similarly the temporal neighborhood  $t$  parameter is described as the local neighborhood around the incident time. The  $t$  parameter was used with changing values in between 1%-10% of the maximum time interval of the incident times.

Table 4.13. A section of synthetic dataset for N=1000 incidents

|     | <b>Crime Type</b> | <b>Criminal ID</b> | <b>Time</b> | <b>Location</b> | <b>Acquaintances</b>     |
|-----|-------------------|--------------------|-------------|-----------------|--------------------------|
| 110 | 2                 | 10                 | 19-Jan-1998 | 117.5-105.8     | 4,37,47,48,56,67,78,99   |
| 111 | 3                 | 24                 | 22-Jul-1985 | 58.5-403.1      | 9,13,16,67,69            |
| 112 | 1                 | 81                 | 12-Apr-1989 | 161.2-92.0      | 2,16,22,23,66,73,76,99   |
| 113 | 2                 | 8                  | 11-Jun-2008 | 173.6-165.1     | 6,18                     |
| 114 | 3                 | 14                 | 25-Apr-2013 | 173.8-115.6     | 44,45,64,76,97           |
| 115 | 1                 | 76                 | 11-May-2006 | 51.2-359.8      | 69,78,84,99              |
| 116 | 3                 | 14                 | 20-Nov-1996 | 26.7-350.8      | 44,45,64,76,97           |
| 117 | 3                 | 6                  | 26-Aug-2001 | 178.1-149.1     | 1,13,43,54,66,80,84,86   |
| 118 | 1                 | 24                 | 14-Dec-1984 | 103.8-170.4     | 9,13,16,67,69            |
| 119 | 2                 | 28                 | 05-Feb-2015 | 149.2-160.8     | 46,58,60,77,88           |
| 120 | 1                 | 7                  | 22-Apr-2006 | 178.2-122.0     | 4,20,24,26,97            |
| 121 | 3                 | 76                 | 29-Dec-1999 | 28.1-376.7      | 69,78,84,99              |
| 122 | 1                 | 27                 | 16-Mar-2004 | 160.0-148.4     | 22,59,66,73,80           |
| 123 | 1                 | 97                 | 06-Aug-2008 | 32.8-500.0      | 1,2,15,38,53,76,77,79,88 |
| 124 | 1                 | 48                 | 11-Dec-2006 | 44.3-356.9      | 13,27,28,65,71           |

The experiments here assume the following parameters to be given, incident time and location, crime and criminal's acquaintances, which are considered as clues to predict the criminal. Given the parameters, the aim is to find the most likely criminal and the predicted criminals are given Table 4.14 – 4.16 with their accuracy rates. The accuracy rate is computed using the actual test set according to the equation at Eq. 3.42 and given only for the predicted criminal. The predicted criminals are identified by the Predicted Criminal ID, who has the highest suspect probability according to the model. The results also provide a list of most likely criminals with decreasing suspect probability, who are called as Suspected Criminals in the tables. Thus, the Predicted Criminal ID is the first criminal of the Suspected Criminal list. Seven experiments are performed for the corresponding seven datasets of different sizes (N=100-5000), and the results are summarized in Table 4.16. Each experiment in Table 5 involves 100 tests. Each test in the experiments describes a particular incident whose criminal is assumed to be unknown and, thus need to be predicted based on the given clues.

In Table 4.16, the details of a particular experiment with 1000 incidents are shown as demonstration purpose in Table 4 where the details of a particular test, Test #1, are given in Table 4.14. That is, the Suspected Criminal list of Test#1 in Table 4.15 is given in Table 4.14 for visualization purpose, where only the most suspected 20 persons are listed for the dataset of 1000 incidents. The results show that the proposed model can significantly reduce the suspect list. Generally, the predicted criminals can achieve to fall into the most likely suspects in top 20%, which means 80% accuracy rate on the average.

Table 4.14. Suspected Criminals in top 20 for the dataset having N=1000 incidents.

|    | <b>Crime Type</b> | <b>Location</b> | <b>Time</b> | <b>Criminal Prob.</b> | <b>Suspected Criminal ID</b> |
|----|-------------------|-----------------|-------------|-----------------------|------------------------------|
| 1  | 1                 | 288.5 - 848.3   | 25-Feb-1986 | 5.903e-008            | 13                           |
| 2  | 3                 | 241.9 - 806.9   | 20-Oct-2004 | 4.0143e-008           | 34                           |
| 3  | 3                 | 245.4 - 799.5   | 29-Aug-1908 | 2.56e-008             | 14                           |
| 4  | 3                 | 0.0 - 208.5     | 25-Nov-1975 | 2.5147e-008           | 19                           |
| 5  | 1                 | 251.1 - 766.8   | 26-Jun-1955 | 2.4683e-008           | 20                           |
| 6  | 1                 | 334.2 - 926.1   | 23-Jun-1989 | 1.9804e-008           | 42                           |
| 7  | 2                 | 270.2 - 910.2   | 25-Nov-1984 | 1.9742e-008           | 4                            |
| 8  | 1                 | 321.1 - 884.5   | 18-May-1935 | 1.6174e-008           | 41                           |
| 9  | 3                 | 267.4 - 496.6   | 01-Mar-2005 | 1.4383e-008           | 25                           |
| 10 | 2                 | 377.0 - 857.8   | 23-Mar-1978 | 1.4017e-008           | 23                           |
| 11 | 2                 | 302.4 - 845.2   | 01-Oct-1988 | 8.7668e-009           | 36                           |
| 12 | 3                 | 186.5 - 792.3   | 16-Dec-2009 | 8.4953e-009           | 18                           |
| 13 | 2                 | 233.4 - 728.1   | 04-Nov-1979 | 6.9624e-009           | 43                           |
| 14 | 1                 | 354.7 - 176.0   | 29-May-1935 | 5.1488e-009           | 7                            |
| 15 | 2                 | 38.1 - 145.1    | 03-Sep-1988 | 5.0841e-009           | 5                            |
| 16 | 1                 | 301.2 - 926.7   | 16-Dec-1963 | 4.5484e-009           | 6                            |
| 17 | 2                 | 317.3 - 901.5   | 08-Nov-1941 | 4.2678e-009           | 49                           |
| 18 | 1                 | 116.7 - 195.2   | 19-Apr-1962 | 4.1065e-009           | 21                           |
| 19 | 2                 | 136.3 - 685.4   | 15-May-1999 | 2.9161e-009           | 29                           |
| 20 | 2                 | 120.7 - 124.8   | 03-Dec-1993 | 2.8683e-009           | 45                           |

In Table 4.14, the predicted criminal (given in bold) is the first suspected criminal in the list, whose criminal ID is 13 in this case. However, the actual criminal should be criminal 45 (given in bold) who is at the 20th rank of the list. According to this test, the accuracy rate is 80%. Thus, the model can shrink the size of the suspect list in 80% rate.

Table 4.15. Test Results and accuracy rates for the dataset of N=1000 incidents

| <b>Given Parameters</b>      | <b>Test1</b>  | <b>Test2</b>  | <b>Test3</b>   | <b>..</b> | <b>Test100</b> |
|------------------------------|---------------|---------------|----------------|-----------|----------------|
| <i>Crime</i>                 | 1             | 3             | 1              | .         | 2              |
| <i>Incident time</i>         | 03/12/1993    | 1/3/1987      | 2/2/2012       | .         | 07/08/1990     |
| <i>Incident location</i>     | (120.7,124.8) | (56.1, 112.7) | (199.8, 126.1) | .         | (55.2, 100.0)  |
| <i>List of Acq. Ids</i>      | 2,3,41,67     | 3,45,89       | 1,4,67,89,93   | .         | 23,45,69       |
| <i>Criminal ID</i>           | 45            | 74            | 11             | .         | 72             |
| <i>Predicted Criminal ID</i> | 13            | 100           | 56             | .         | 88             |
| <i>Accuracy Rate (%)</i>     | 80            | 71            | 65             | .         | 79             |

Table 4.16. Experiment results and accuracy rates for various datasets

| <b># of Incidents</b> | <b>Accuracy Rate</b> |
|-----------------------|----------------------|
| 100                   | 80.00%               |
| 300                   | 79.36%               |
| 500                   | 67.43%               |
| 1000                  | 80.00%               |
| 2000                  | 79.30%               |
| 3000                  | 78.62%               |
| 5000                  | 81.66%               |

#### 4.4.1. Comparision between decision tree and Bayesian network

The experimental results obtained for criminals analysis will be compared with decision tree. The goal is to find which classifier gives the best result. The application of decision trees in classification was popularized in machine learning. It can also provide clues and evidences for police to resolve cases and to prevent crimes. After that the performance accuracy results will be analysed between two classifiers. In order to validate the performance, the proposed method is compared with decision tree. Comparison results are shown in the following Figure 4.32.

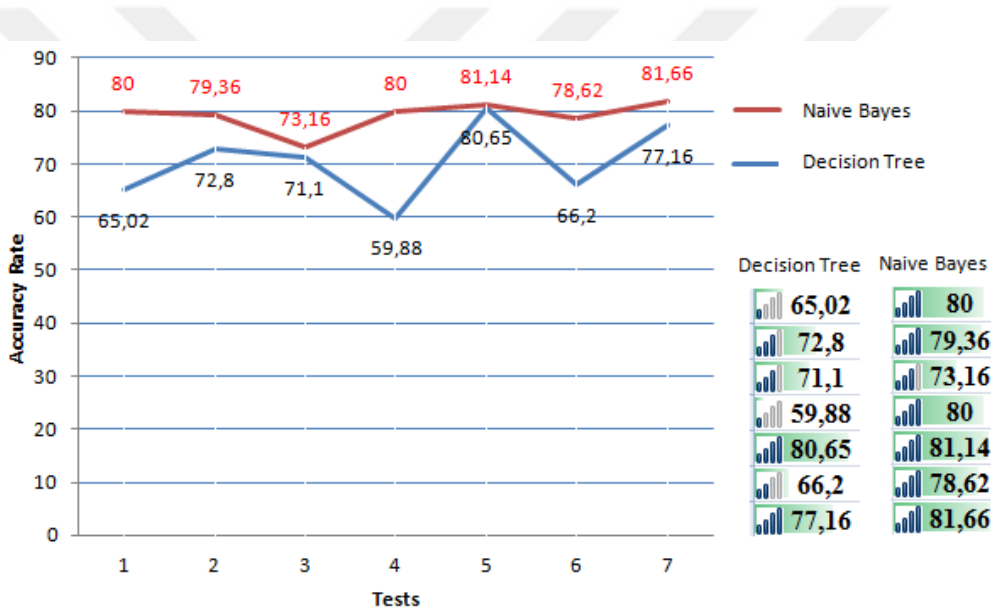


Figure 4.32. Experiment results and accuracy rates between Decision Tree and Naïve Bayes.

The two techniques have been implemented to predict the criminal of the crime incidents. As shown above, if the rate of population increases then the accuracy rate increases. According to the results shown in figure, Naive Bayes algorithm outperforms the Decision Tree technique especially with large numbers of incidents due to the increased computational complexity of the Decision Tree technique. As a result, the comparison showed that Naive Bayes has higher

sensitivity than the decision tree algorithm. Seven(7) different tests are applied to report the standard deviation including test set rotates for various data sets. The results are shown in Figure 4.33. So, differences among all tests are shown as deviation report.

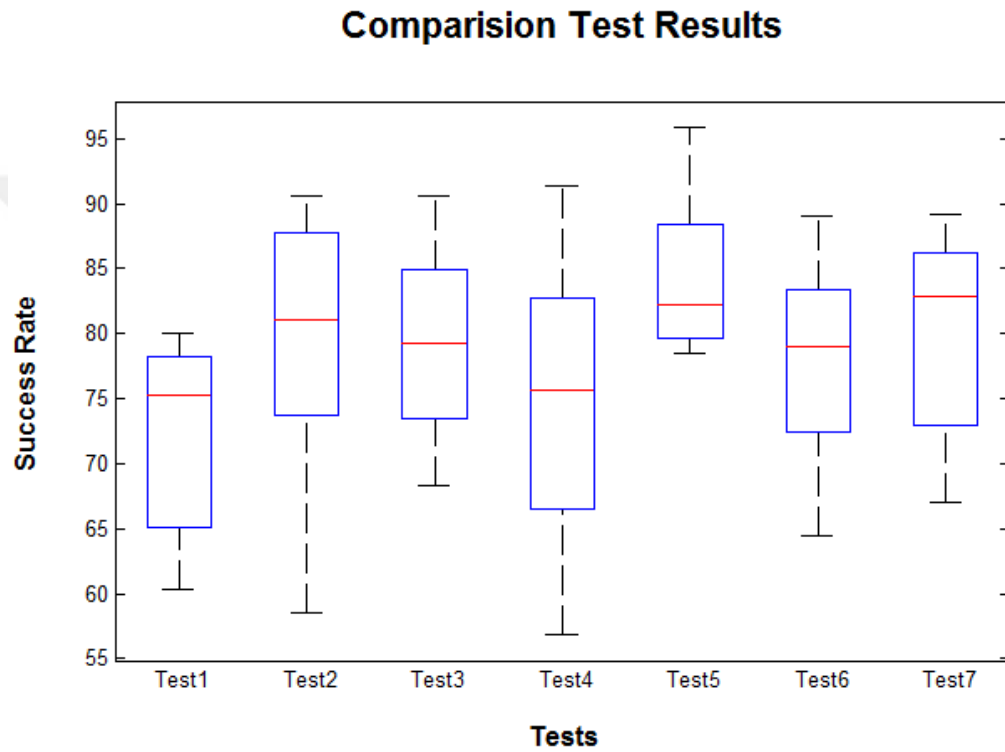


Figure 4.33. Test sets for standard deviation

#### 4.5. Tests for Impact Factor of Acquaintances

Acquaintances list is not only related criminal acquaintances but also acquaintances of criminal acquaintances list. Because crime analysis is effected by the new approach. Acquaintances of acquaintance is actually a recursive process that requires some stopping criteria, here dept. Thus, the set of all acquaintances that can be reachable from the criminal could be considered as the social network of the criminal with some depth constraint, here 2. So it will found acquaintances

which are primary acquaintances and secondary acquaintances. Primary acq. who are performed two phases, one of them is first part of primary Acquaintances that come from simulator interface. The other one is acquaintances of suspect criminal who is called secondary acquaintances.

In the light of the information above, when the acquaintance factor of the criminal in the system whose id is 1 steps in, it can be determined which suspicious will come into prominence and which suspicious knows criminal better in revealing the criminal. For example, while controlling the indirect relation of the criminals (11,12,16) in the suspicious list of the criminal 1 id, the relation of criminal who has 1 id with every suspicious acquaintances (4,13,16,27) will be controlled. First the acquaintances of every criminal in the suspicious list will be determined and the probability rate between this list and the criminal who has 1 id number will be found. As seen in the table below, when it is not possible to have direct relation between suspicious people who have (11,12,16) id given us as the suspicious list and criminal, then it will be controlled by the secondary acquaintances way. In this control step, it is observed that the criminal having the number 16 has the higher rate of secondary probability compared with the others. As a result of this, it will be possible to reveal the criminal by deriving the number 16 suspicious from the suspicious list (Figure 4.34).

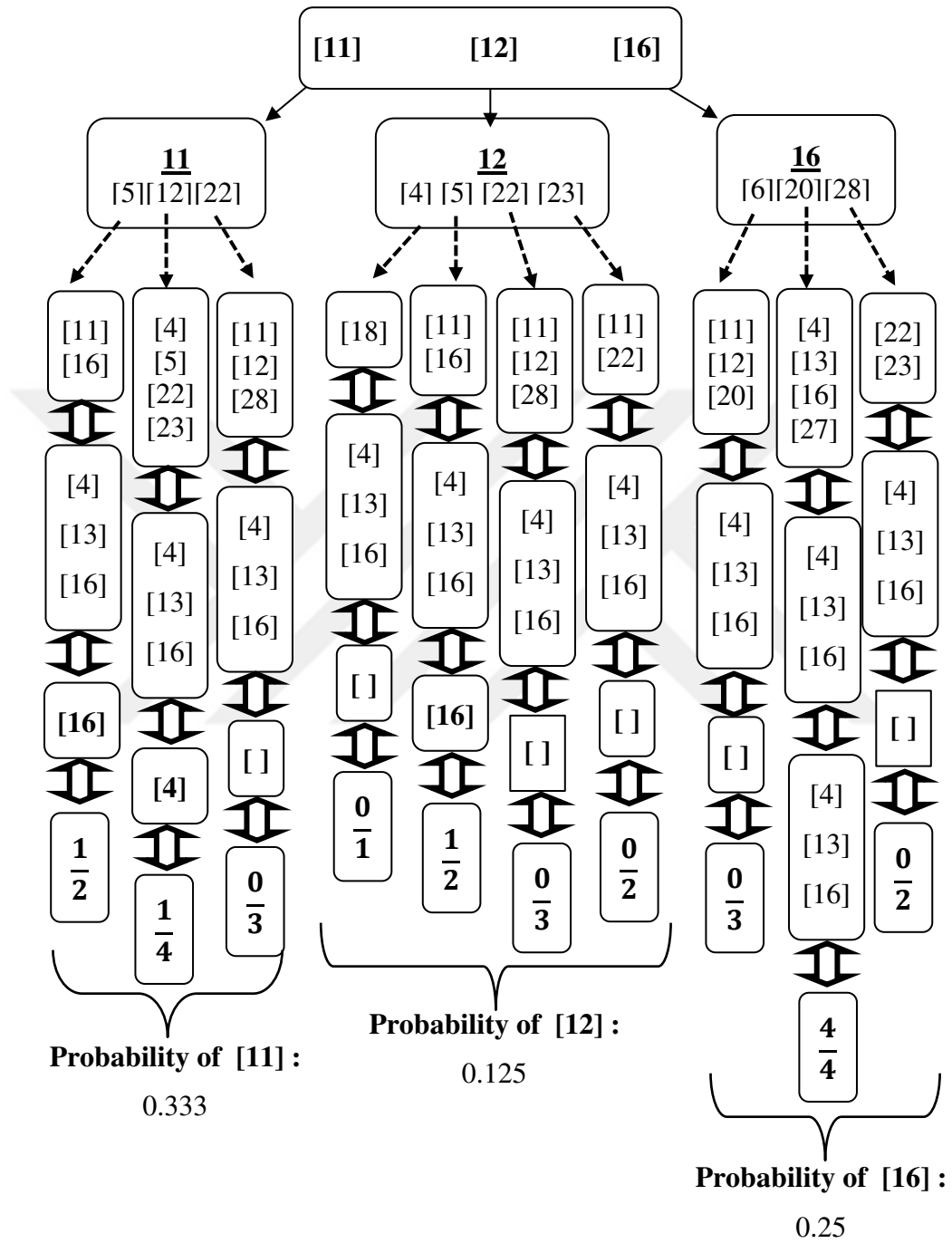


Figure 4.34. The sample of Secondary Acquaintances

It is used here in a similar way to the structure used in hybrid metrics in general. In fact, the structure used to find similarities between the acquaintances is evaluated by considering the algorithm given above. Both methods will be considered primary and secondary acquaintances. For the  $N = 100$  sampling, the suspected list of 20 criminals will be examined. After the calculation is made, the criminal is identified which is most similar to the suspect list. All these data and calculations according to the algorithm are shown in the following table (Table 4.17).

Table 4.17. Finding criminal from given suspected list

| Criminal_id | Acquaintances of Criminal_id | Performance Score |
|-------------|------------------------------|-------------------|
| 1           | 2,4,9,11,15,16               | 0.3333            |
| 2           | 1,6                          | 0.1667            |
| 3           | $\emptyset$                  | 0                 |
| 4           | $\emptyset$                  | 0                 |
| 5           | 1,4,15,19                    | 0.3333            |
| 6           | 3,8,12,13,18,20              | 0.3333            |
| 7           | 1,5,17,18,20                 | 0.3333            |
| 8           | 1,2,4,11,15,19               | 0.3333            |
| 9           | $\emptyset$                  | 0                 |
| 10          | 1,4,12,13,16                 | 0.3333            |
| 11          | 8,14                         | 0.0313            |
| 12          | 3,16,20                      | 0.3333            |
| 13          | 18                           | 0.0313            |
| 14          | 10,19,20                     | 0.3333            |
| 15          | 6,7,13,16,17                 | 0.0833            |
| 16          | 1,4,5,8,17                   | 0.3333            |
| 17          | 2,6,12,13,14,15,20           | 0.3333            |
| 18          | 10,13,19,20                  | 0.3333            |
| <b>19</b>   | <b>4,9,10,11,12,14,16,20</b> | <b>0.5</b>        |
| 20          | 1,9,16                       | 0.3333            |

Suspected List={4,9,20}

Twenty criminals have been investigated. It appears that the person closest to the list of suspects among the criminals is the criminal number 19. It is possible

to reach another criminal through criminals by going out of this knowledgeable path. Also in social network analysis, criminal organizations can be controlled in relation to each other.



## 5. CONCLUSION

Today, regional and national crime solving problems, and ensuring the security of the city in taking effective measures against crime information and analysis tools are needed. Crime analyses Simulator is to investigate the relations among crimes, suspected criminals and the involving geographical places. Thus, the relations among the other crimes that are affected by a particular crime could also be revealed and analyzed in this system. Within the framework of the analysis process, statistical information related to crimes, such as distributions of crimes, their increase or decrease, and their locations, is also evaluated.

In the literature, the more aggregate-level crime data were studied. There is not works according to detection of criminal . These works are related to operating decision-making process incident-level on crime data. Furthermore, in related studies was observed to be insufficient probabilistic relationships among incident-level crime events. In this study, crime analysis based on GIS was performed in a simulation environment. Since there is not already an existing dataset for crime analysis, which is difficult to achieve in practice from incident-level data closer reality synthetic dataset is created. The synthetic dataset, although not realistic to do analysis and testing operations will be sufficient. Analysis required to process queries based on geographic information systems will be shown as visually on maps. Thus through an analysis of the dataset, it is proposed a decision-making system based on Gaussian Mixture Model, K-Means, Bayesian Network.

In this study, a sample data set is available for a geographic area close to the truth there is no one set of data for the analysis of crime by ensuring the formation of providing statistical information to the end user, perform queries with parameters, which determine the intensity of crime trends, crime and a criminal offense apart from finding the probabilities of occurrence, resulting crimes who may be likely to work with a structure that can respond to questions with the work of artificial intelligence created a simulator of crime analysis.

As a result of the summation of the five main headings, the first one is the formation of artificial crime data, the second is to determine the tendency of relations between the crimes, the third is to measure the similarities between the crime events, the fourth is the crime prediction by using artificial intelligence techniques and the final part is the detection of the criminal through the criminal's acquaintances from suspects in the social network.

**Crime dataset:** It is proposed a parametric model to generate the incident-level crime datasets which is hard to obtain in practice, involving crimes, GIS, criminals' identifications and their suspicious acquaintances where the parameters are used for fine tuned adaptation of the model. Though the data generated by our tool is not exactly realistic, the data generated by it is sufficient to test any decision-making algorithm for crime analysis. With the resulting model, various GIS related queries can be demonstrated on the GIS map to enable the visual analysis of the incidents.

**Crime/Criminal Trends:** The crime simulation system that generates incident-level crime data and support query based crime analysis on GIS map was developed. Following the development of the main system, because other queries can be added easily. For example, some of the suspects, other than the high slope of crime detection, prediction can be considered as a potential criminal. Similarly, the shape of the spread of a crime, where it can reach its forecast of the future, be able to provide the opportunity to increase crime prevention measures. Thus, detection of offenders, crime prevention or reduction efforts are much easier. Importantly, the development of decision-making algorithms for crime analysis, which require incident-level data for developing and testing, can be enabled. With its parameters, the model can be adopted to different geography and population characteristics. Therefore, it is detected potential criminal among crime events that are social-networks. As a result of these pocesses, within our framework Bayesian network has been found out more appropriate than other techniques. So Bayesian network based inference system that explores the interrelations between the crimes

and criminals was developed. It was also added a user-interface support to our system where the queries can be formed and the results of the queries can be shown.

**Relationship Among Crime Events with Hybrid Metrics:** The relationship of crime incidents to each other has been examined. In these relations, the incidence of the offenders to other crimes has been determined. Hybrid metrics have been used to find similarities between similar criminal elements outside the trend section. In addition, cluster based decision making algorithms for crime analysis were provided. The model measures cluster performance using clustering of events in one or more relevant perspectives and using the proposed performance metric.

**Criminal Prediction:** A practical model based on the Naive Bayes classifier is proposed with novel methodologies applied for the criminal prediction problem. The incident-level crime data are generated synthetically by the model itself, otherwise which is hard to obtain in practice. The proposed model is practical due to the simplicity caused by the independence assumption of the Naive Bayes. Moreover, the model is moderately fit with the independence assumption in that the model achieves reducing the suspect list with 80% rate. The experimental results showed that the proposed model can be used in criminology with its averagely 78.05% success rate in order to help security forces to find the criminal of the incidents. One more significant of the proposed model is its ability to take the acquaintances into decision-making process. However, new approaches are needed to solve the criminal prediction problem with better accuracy rates. The work encourages further studies on the criminal prediction problem with its new methodologies for both crime dataset generation and decision-making process.

Based on the objectives, as well as the literature reviewed, as well as the discussions made from the analysis, it is desirable to draw the following conclusions:

Consequently,

- Generates incident-level synthetic crime data
- Comparisons of the simulation tests based on bayesian network on simulators.
- Solve criminal prediction problem.
- The most likely criminal over 78.05% success rate on the average.

**Impact of Acquaintances:** The impact of acquaintances is examined in social network analysis. Especially the degree of proximity of the criminal investigated by the primary and secondary links is determined. This concept, which can be of great use to law enforcement officers, will be freed from manual constructions and interpretations. Great convenience is provided by such an intelligent system. For example, in order to reach the leader of the organization in the organization members who are caught by a mafia connection, the persons who are members of these crime structures should be identified and the relations in this hierarchy must be considered. With this prototype created, it is possible to solve such problems. With this structure, the following results have been achieved. These are;

- Reach the criminal from the acquaintance
- Determination of relations between criminals
- Discovery of connections between criminal organizations

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