Chapter 2
Social Network Analysis in Predictive Policing

Police departments have long used crime data analysis to assess the past, but the recent advances in the field of data science have introduced a new paradigm, called *predictive policing* which aims to predict the future. Predictive policing as a multidisciplinary approach brings together data mining and criminological theories which leads to crime reduction and prevention. Predictive policing is based on the idea that while some crime is random, the majority of it is not. In predictive policing crime patterns are learnt from historical data to predict future crimes.

Social connections and processes have a central role in criminology. But in the recent decades criminologists turned their attention to criminal networks to study the onset, maintenance, and desistance of criminal behavior [14]. More than two decades ago, Reiss [17] argued that "understanding co-offending is central to understanding the etiology of crime and the effects of intervention strategies." Meanwhile, influenced by increasing academic and societal awareness of the importance of social networks, law enforcement and intelligence agencies have come to realize the value of detailed knowledge of co-offending networks [4, 10, 14, 15, 17, 18].

In this chapter, we first discuss conventional crime analysis and predictive policing as a new perspective in crime-fighting strategies. Then, we introduce social network analysis and review general related work in co-offending network analysis. Finally, we briefly introduce different tasks of social network analysis in predictive policing studied in the next chapters of this book.

2.1 Conventional Crime Analysis

Analysis of crime has a long history, but *crime analysis* as a discipline is established when the first modern police started to work in London in the early nineteenth century [1]. After the constitution of the London police force in the 1820s, this force

M.A. Tayebi, U. Glässer, *Social Network Analysis in Predictive Policing*,
Lecture Notes in Social Networks, DOI 10.1007/978-3-319-41492-8_2

initiated a detective department with the responsibility of detecting crime patterns to solving crimes. The earliest source known for the term crime analysis is the book *police administration* published in 1963 [29]:

> The crime-analysis section studies daily reports of serious crimes in order to determine the location, time, special characteristics, similarities to other criminal attacks, and various significant facts that may help to identify either a criminal or the existence of a pattern of criminal activity. Such information is helpful in planning the operations of a division or district.

In the 1970s, the government of the USA tried to increase the ability of police departments in using crime analysis by inviting academics and practitioners. Later a group of academics started to emphasize the importance of characteristics of criminal events such as the location of crime which initiated the geographic analysis of crime. In the 1990s, with the increase of computer power, analyzing large crime dataset becomes computationally feasible, and police agencies tend to use crime analysis tools to generate analytical reports [19].

The main purpose of the crime analysis is crime reduction. In the policing approaches few mainstreams can be observed which get advantage of crime analysis [19]:

- **Standard model of policing.** The standard model of policing uses law enforcement in a reactive manner. Crime analysis helps in efficient allocation of police resources geographically and temporally.
- **Community policing.** Community policing strategies benefit from partnership and collaboration of the community to understand and solve the problems. The main role of crime analysis in these strategies is providing information to citizens.
- **Disorder policing.** Disorder policing or broken window policing is applying strict law enforcement procedures to minor offences to prevent happening of more serious crimes. Crime analysis is helpful in evaluating the disorder policing approaches.
- **Problem-oriented policing.** In problem-oriented policing the goal is diagnosing problems within the community and developing appropriate responses which solve the cause of the problems. Crime analysis is used in all phases of a problem-oriented policing strategy including scan, analysis, response, and assess.
- **Hotspots policing.** Hotspots policing is a location-based policing in which the police resources are allocated to different areas proportional to crime rate of each area. Crime analysis is used in identifying the hotspots.

Crime analysis contributed to the operational, tactical, and strategic police decision making for decades, but in the recent decade the emergence of data science field has arisen a new paradigm in this discipline called predictive policing introduced in the next section.

2.2 Predictive Policing

"Predictive policing refers to any policing strategy or tactic that develops and uses information and advanced analysis to inform forward-thinking crime prevention" [26], which involves multiple disciplines to form the rules and develop the models. Given that research strongly supports that crime is not random but rather occurs in patterns, the goal of predictive policing methods is to extract crime patterns from historical data at both macro and micro scales as a basis for prediction and prevention of future crimes [3, 8, 22–25]. This approach uses data-driven tools that benefit from data mining and machine learning techniques for predicting crime locations and temporal characteristics of criminal behavior.

Predictive analysis for policing can be divided into four classes:

- **Predicting offenders.** The goal is predicting future offenders using the history of individuals such as features of their living environment and behavioral patterns.
- **Predicting victims.** This is about identifying individuals who more likely than others may become victims and predicting risky situations for potential victims.
- **Predicting criminal collaborations.** Predicting likely future collaboration between offenders and the type of associated crime.
- **Predicting crime locations.** This task aims at predicting the location of future crimes at individual and aggregate level.

In this research our focus is on different problems related to the last two tasks: predicting criminal collaborations and crime locations. For solving this problems we use social network analysis methods. In the next sections we discuss social network analysis and its applications for predictive policing.

2.3 Social Network Analysis

Social networks represent relationships among social entities. Normally, such relationships can be represented as a network. Examples include interactions between members of a group (like family, friends, or neighbors) or economic relationships between businesses. Social networks are important in many respects. Social influence may motivate someone to buy a product, to commit a crime, and any other decision can be interpreted and modeled under a social network structure. Spread of diseases such as AIDS infection and the diffusion of information and word of mouth also strongly depend on the topology of social networks.

Social network analysis (SNA) focuses on structural aspects of networks to detect and interpret the patterns of social entities [28]. SNA essentially takes a network with nodes and edges and finds distinguished properties of the network through formal analysis. Data mining is the process of finding patterns and knowledge hidden in large databases [9]. Data mining methods are increasingly being applied to social networks, and there is substantial overlap and synergy with SNA.

New techniques for the analysis and mining of social networks are developed for a broad range of domains, including health [27] and criminology [31]. These methods can be categorized depending on the level of granularity at which the network is analyzed [2]: (1) methods that determine properties of the social network as a whole; (2) methods that discover important subnetworks; (3) methods that analyze individual network nodes; and (4) methods that characterize network evolution. In the following, we list the primary tasks of SNA:

- *Centrality analysis* [28] aims at determining more important actors of a social network so as to understand their prestige, importance, or influence in a network.
- *Community detection* [6] methods identify groups of actors that are more densely connected among each other than with the rest of the network.
- *Information diffusion* [12] studies the flow of information through networks and proposes abstract models of that diffusion such as the Independent Cascade model.
- *Link prediction* [13] aims at predicting for a given social network how its structure evolves over time, that is, what new links will likely form.
- *Generative models* [5] are probabilistic models which simulate the topology, temporal dynamics, and patterns of large real-world networks.

SNA also greatly benefits from visual analysis techniques. Visualizing structural information in social networks enables SNA experts to intuitively make conclusions about social networks that might remain hidden even after getting SNA results. Different methods of visualizing the information in a social network providing examples of the ways in which spatial position, color, size, and shape can be used to represent information are mentioned in [7].

In the next section we introduce co-offending networks as a special type of social networks.

2.4 Co-offending Networks

Criminal organizational systems differ in terms of their scope, form, and content. They can be a simple co-offending looking for opportunistic crimes, or a complex organized crime group involved in serious crimes. They can be formed based on one-time partisanship for committing a crime, or their existence can have continuity over time and across different crime types [4]. In a criminal organization system interaction among actors can be initiated from family, friendship, or ethnic ties. Here, our focus is on co-offending networks.

A *co-offending network* is a network of offenders who have committed crimes together [17]. With increasing attention to SNA, law enforcement and intelligence agencies have come to realize the importance of detailed knowledge about co-offending networks. Groups and organizations that engage in conspiracies, terroristic activities and crimes like drug trafficking typically do this in a concealed fashion, trying to hide their illegal activities. In analyzing such activities, investigations do not only focus on individual suspects but also examine criminal groups and illegal organization and their behavior.

Thus, it is important to identify co-offending networks in data resources readily available to investigators, such as police arrest data and court data, and study them using social network analysis methods. In turn, social network analysis can provide useful information about individuals as well. For example, investigators could determine who are key players, and subject them to closer inspection. In general, knowledge about co-offending network structures provides a basis for law enforcement agencies to make strategic or tactical decisions.

Several empirical studies that use social network analysis methods to analyze co-offending networks have focused on the stability of associations in such networks. Reiss [17] concludes that the majority of co-offending groups are unstable, and their relationships are short-lived. This is corroborated by McGloin et al. [15], who showed that there is some stability in co-offending relationships over time for frequent offenders, but in general, delinquents do not tend to reuse co-offenders. Reiss et al. [18] also found that co-offenders have many different partners, and are unlikely to commit crimes with the same individuals over time. However, Reiss [17] also states that high frequency offenders are "active recruiters to delinquent groups and can be important targets for law enforcement." It should be noted that the findings of these works were obtained on very small datasets: 205 individuals in [18], and 5600 individuals in [15], and may therefore not be representative.

These studies only analyzed co-offending networks. Smith [21] widened the scope of co-offending network analysis, enhancing the network by including extra information, particularly for the purpose of criminal intelligence analysis. For example, nodes of the network could be offenders, but also police officers, reports, or anything that can be represented as an entity. Links are associated with labels which denote the type of the relationship between the two entities, such as "mentions" or "reported by." A similar approach was taken by Kaza et al. [11], who explored the use of criminal activity networks to analyze information from law enforcement and other sources for transportation and border security. The authors defined the criminal activity network as a network of interconnected criminals, vehicles, and locations based on law enforcement records, and concluded that including especially vehicular data in criminal activity network is important, because vehicles provide new investigative points.

A slightly different take on widening the scope of co-offending network analysis was taken by Xu et al. [30], who employed the idea of a "concept space" in order to establish the strength of links between offenders. Not only the frequency of co-offending, but also event and narrative data were used to construct an undirected but weighted co-offending network. The goal was to identify central members and communities within the network, as well as interactions between communities. By applying cluster analysis in order to detect subgroups within the network they were able to detect overall network structures which could then be used by criminal investigators to further their investigations.

COPLINK [10] was one of the first large-scale research projects in crime data mining, and an excellent work in criminal network analysis. It is remarkable in its practicality, being integrated with and used in the workflow of the Tucson Police Department. Xu et al. [31] built on this when they created CrimeNet Explorer, a framework for criminal network knowledge discovery incorporating hierarchical clustering, SNA methods, and multidimensional scaling. The authors further expanded the research in [30] and designed a full-fledged system capable of incorporating external data, such as phone records and report narratives, in order to establish stronger ties between individual offenders. Their results were compared to the domain knowledge offered by the Tucson Police Department, whose jurisdiction the data came from.

2.5 Co-offending Network Analysis in Practice

Co-offending network analysis contributes to predictive policing by detecting hidden links and predicting potential links among offenders. In this section, we introduce important applications of co-offending network analysis in predictive policing which are covered in this research.

- **Co-offending network disruption.** Actors of a social network can be categorized based on their relations in the network. Actors in the same category may take similar roles within an organization, community, or whole network. These roles are usually depend on the network structure and the actors' position in the network. For instance, actors who are located in the central positions of a social network may be detected as key players in that network. Actors who are connected to many other actors may be viewed as socially active players, and actors who are frequently observed by other actors may be identified as popular players.

  In the co-offending networks disruption problem the goal is finding a set of players whose removal creates a network with the least possible cohesion. In other words, their removal maximally destabilizes the network. This task is critical in the co-offending network analysis where removing the key players may sabotage the network and decrease the aggregate crime rate. We study this problem in Chap. 3.
- **Organized crime group detection.** Organized crime is a major international concern. Organized crime groups produce disproportionate harm to societies, and an increasing volume of violence is related to their activities. Since the aim of organized crime groups is gaining material benefit they try to access to resources that can be profitably exploited. In terms of economic-related crimes (e.g., credit and debit card fraud) organized crime costs Canadians five billion dollar a year [20].

  Understanding the structure of organized crime groups and the factors that impact on it is crucial to combat organized crime. There are several possible perspectives how to define the structure of organized crime groups, but recent criminological studies are increasingly focusing on using social network analysis for this purpose. The idea of using social network analysis is that links between offenders and subgroups of an organized crime group are critical determinant of the performance and sustainability of organized crime groups [16]. In Chap. 4, we study the organized crime group detection problem.

- **Suspect investigation.** Security services can more precisely focus their efforts based on probable relationships in criminal networks that have previously not observed. Traditional suspect investigation methods use partial knowledge discovered from crime scene to identify potential suspects. Co-offending network analysis as a complement of criminal profiling methods can contribute to the suspect investigation task in cases with multiple offenders committing a crime, but a subset of offenders are charged. This issue is addressed in Chap. 5.
- **Co-offence prediction.** Link prediction is an important task in social network analysis that can help to study and understand the network structure. Link prediction methods can be used to extract missing information, identify hidden links, evaluate network evolution mechanisms, and so on. Co-offence prediction can be defined as link prediction problem for co-offending networks. Chapter 6 is about the co-offence prediction problem.
- **Personalized crime location prediction.** An important aspect of crime is the geographic location that crime happens. Every neighborhood provides some condition in which criminal behavior takes place, but crime distribution in city neighborhoods is not even. Understanding the spatial patterns of crime is essential for law enforcement agencies to design efficient crime reduction and prevention policies. Although mining spatial patterns of crime data in the aggregate level took special attention in the criminology literature, there is not that much work about crime spatial patterns for individual offenders. This problem is addressed in Chap. 7.

References

1. R. Boba, *Crime Analysis and Crime Mapping* (Sage, Thousand Oaks, 2013)
2. U. Brandes, T. Erlebach, *Network Analysis: Methodological Foundations*. Lecture Notes in Computer Science/Theoretical Computer Science and General Issues (Springer, Heidelberg, 2005)
3. P.L. Brantingham, M. Ester, R. Frank, U. Glässer, M.A. Tayebi, Co-offending network mining, in *Counterterrorism and Open Source Intelligence*, ed. by U.K. Wiil (Springer, Vienna, 2011), pp. 73–102
4. M. Carlo, *Inside Criminal Networks* (Springer, New York, 2009)
5. D. Chakrabarti, C. Faloutsos, Graph mining: laws, generators, and algorithms. ACM Comput. Surv. **38**(1), Article 2 (2006)
6. J. Chen, O.R. Zaïane, R. Goebel, Detecting communities in social networks using max-min modularity, in *Proceedings of SIAM International Conference on Data Mining (SDM'09)* (2009), pp. 978–989
7. L.C. Freeman. Visualizing social networks. J. Soc. Struct. **1**(1), 4 (2000)
8. U. Glässer, M.A. Taybei, P.L. Brantingham, P.J. Brantingham, Estimating possible criminal organizations from co-offending data. *Public Safety Canada* (2012)
9. J. Han, M. Kamber, *Data Mining: Concepts and Techniques* (Morgan Kaufmann, San Francisco, 2006)

10. R.V. Hauck, H. Atabakhsh, P. Ongvasith, H. Gupta, H. Chen, Using Coplink to analyze criminal-justice data. Computer **35**(3), 30–37 (2002)
11. S. Kaza, H. Chen, Effect of inventor status on intra-organizational innovation evolution, in *Proceedings of the 42nd Hawaii International Conference on System Sciences (HICSS'09)* (2009), pp. 1–10
12. D. Kempe, J. Kleinberg, É. Tardos, Influential nodes in a diffusion model for social networks. Autom. Lang. Program. **3580**, 1127–1138 (2005)
13. D. Liben-Nowell, J. Kleinberg, The link prediction problem for social networks, in *Proceedings of the 12st ACM international conference on Information and knowledge management (CIKM'03)* (2003), pp. 556–559
14. J.M. McGloin, A.R. Piquero, On the relationship between co-offending network redundancy and offending versatility. J. Res. Crime Delinq. **47**(1), 63–90 (2009)
15. J.M. McGloin, C.J. Sullivan, A.R. Piquero, S. Bacon, Investigating the stability of co-offending and co-offenders among a sample of youthful offenders. Criminology **46**(1), 155–188 (2008)
16. C. Moselli, T. Gabor, J. Kiedrowski, The factors that shape organized crime. *Public Safety Canada* (2010)
17. A.J. Reiss Jr., Co-offending and criminal careers. Crime Justice **10**, 117–170 (1988)
18. A.J. Reiss Jr., D.P. Farrington, Advancing knowledge about co-offending: results from a prospective longitudinal survey of london males. J. Crim. Law Criminol. **82**, 360–395 (1991)
19. R.B. Santos, *Crime Cnalysis with Crime Mapping* (Sage, Thousand Oaks, 2012)
20. Serious and organized crime (2015). Retrieved from http://www.rcmp-grc.gc.ca/soc-cgco/index-eng.htm
21. M.N. Smith, P.J.H. King, Incrementally visualising criminal networks, in *Proceedings of the Sixth International Conference on Information Visualisation (IV'02)* (2002), pp. 76–81
22. M.A. Tayebi, U. Glässer, Investigating organized crime groups: a social network analysis perspective, in *Proceedings of the 2012 International Conference on Advances in Social Networks Analysis and Mining (ASONAM'12)* (2012), pp. 565–572
23. M.A. Tayebi, L. Bakker, U. Glässer, V. Dabbaghian, Locating central actors in co-offending networks, in *Proceedings of the 2011 International Conference on Advances in Social Networks Analysis and Mining (ASONAM'11)* (2011), pp. 171–179
24. M.A. Tayebi, R. Frank, U. Glässer, Understanding the link between social and spatial distance in the crime world, in *Proceedings of the 20nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL GIS'12)* (2012), pp. 550–553
25. M.A. Tayebi, M. Ester, U. Glässer, P.L. Brantingham, Spatially embedded co-offence prediction using supervised learning, in *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'14)* (2014), pp. 1789–1798
26. C. Uchida, *A National Discussion on Predictive Policing: Defining Our Terms and Mapping Successful Implementation Strategies* (National Institute of Justice, Washington, 2012)
27. T.W. Valente, *Social Networks and Health: Models, Methods, and Applications* (Oxford University Press, Oxford, 2010)
28. S. Wasserman, K. Faust, *Social Network Analysis: Methods and Applications* (Cambridge University Press, New York, 1994)
29. O.W. Wilson, *Police Administration* (McGraw-Hill, New York, 1963)
30. J.J. Xu, H. Chen, Untangling criminal networks: a case study. Intell. Secur. Inform. **2665**, 958–958 (2003)
31. J.J. Xu, H. Chen, CrimeNet explorer: a framework for criminal network knowledge discovery. ACM Trans. Inf. Syst. **23**(2), 201–226 (2005)