CHAPTER 11

Social Network Analysis

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CHAPTER

Consideration of social networks has long been central to some of the most influential theories in criminology. For instance, in his theory of differential association, Sutherland (1947) posits that criminal behavior is learned through interaction in intimate social groups. This proposition helps explain one of the most robust findings in the field of criminology, namely that the bulk of delinquency is carried out in groups. Perhaps the most illustrative example of this familiar finding is Shaw and McKay's (1931) discovery that over 80% of the juveniles they observed, appearing before the Cook County Juvenile Court had accomplices. As Warr (2002, p. 3) argues, "[C]riminal conduct is predominantly social behavior. Most offenders are imbedded in a network of friends who also break the law, and the single strongest predictor of criminal behavior known to criminologists is the number of delinquent friends an individual has." This is but one example; social networks also play salient parts in theories of social control (Hirschi 1969), social disorganization and collective efficacy (Sampson and Groves 1989; Sampson et al. 1997), opportunity perspectives (Osgood et al. 1996), and even have the capacity to shape offender decision-making processes (Hochstetler 2001). Moreover, studying social networks can provide insight on crime patterns and criminal organizations (e.g., Finckenauer and Waring 1998; Natarajan 2006), and consequently inform and guide policy (e.g., Kennedy et al. 2001; McGloin 2005; Tita et al. 2005).

For researchers interested in social networks (or personal networks)[1], network analysis provides the leverage to answer questions in a more refined way than do nonrelational analyses. This analytic strategy has the primary purpose of determining, if there are regular patterns in social relationships and how these patterns may be related to attributes or behavior (Wasserman and Faust 1994). "One of the most important tasks of network analysis is to attempt to explain, at least in part, the behavior of the elements in a network by studying specific properties of the relations between these elements" (Sarnecki 2001, p. 5). Therefore, unlike other analytical procedures, network analysis turns attention away from individual attributes and toward the relationships among units. To be clear about the distinction between attributional and relational data, consider the following example: "…the value of goods that

[1] In contrast to a social network, a personal, or egocentric, network focuses on one node of interest (i.e., ego) and its alters (i.e., associates).

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a nation imports in foreign trade each year is an attribute of the nation's economy, but the volume of goods exchanged between each pair of nations measures an exchange relationship" (Knoke and Kuklinski 1982, p. 11).

Perhaps more so than other methods, network analysis is vulnerable to analysts plucking out certain measures and placing them under their current framework, paying little attention to the assumptions behind these measures (see Osgood 1998, for criminology's tendency to "steal from our friends"). As Wellman (1983, p. 156) contends, however, "the power of network analysis resides in its fundamental approach to the study of social structure and not as a bag of terms and techniques." Social network analysis is more than a set of methods – it is an orientation toward the understanding of human behavior that focuses on the importance of social relations, as well as the set of tools that enable the investigation of social relations and their consequence. While many methods in this text carry with them assumptions about the data at hand, this method also carries assumptions about the social world, namely the notions that: (1) people typically act in social systems that contain other actors who act as reference points for behavior, and (2) there is a systematic structure to these relationships (Knoke and Kuklinski 1982).

Network analysis is an approach to the study of social structure, with the premise that the best way to study a social system is to examine the ties among the members of the system. It is assumed that the pattern of these social relations, which we define as *social structure*, has implications for behavior. In contrast, social scientists have traditionally limited their focus to the role of actor attributes and norms as explanatory variables of behavior. The assumption with such an approach is that individuals with similar attributes (e.g., gender, socioeconomic status) or similar norms will behave similarly, and variation in behavior across individuals is therefore explained by differing attributes and norms (Wellman and Berkowitz 1988). Furthermore, most empirical explanations for behavior, including criminal behavior, rely upon statistical methods which assume that individuals are *independent*, autonomous units. From a theoretical standpoint, however, social network analysis focuses on the relations and *interdependence* between nodes, and how the constraints and opportunities derived from patterned relations ultimately influence behavior (Wellman 1983).

Network approaches are gaining popularity in criminology, but the formal use of network techniques and methods remains limited. Still, there are a number of theoretical traditions in criminology and criminal justice that draw upon social network conceptions to explain the causes and consequences of crime. For instance, investigations of social bonds, social disorganization, deviant peer effects, and some opportunity perspectives utilize relational conceptions. Social bond theory (Hirschi 1969) orients us to the quality of the relationships people have with other individuals and institutions (e.g., attachment and involvement). With an emphasis on the importance of relational networks to facilitate social control, much of the current theorizing in the social disorganization tradition has made use of the systemic model, which identifies the social organization of communities by focusing on local community networks (Kasarda and Janowitz 1974). Bursik and Grasmick (1993) argue that the density and extent of neighborhood networks and social bonds influence the neighborhood's capacity for social control. Next, studies of peer effects implicitly or explicitly are founded upon the assertion that social relations are necessary for the transmission of influence, skills, and norms. Learning theory (particularly differential association) orients us toward the importance of the following factors: (1) with whom a person associates; (2) the balance of individuals in the network (i.e., whether it is mostly deviant); (3) the transference of deviant norms through these links; and, (4) the quality or strength of the associations (i.e., more frequent associations can have a greater impact on behavior). Finally, recent conceptions of routine activities also root the construction of criminal opportunities in (unsupervised and unstructured) social networks (Osgood et al. 1996; see also Haynie and Osgood 2005).

Network analysis also holds utility outside theoretical inquiries. For instance, some authors have adopted network perspectives to address inter and intraorganizational relationships within the criminal justice system, focusing on such issues as intelligence sharing and whether network structure predicts policy adoption (Alter 1988; Curry and Thomas 1992; Gustafson 1997; Miller 1980; Sparrow 1991). Other work has used network analysis to address whether criminal networks actually exist (Coles 2001) and what delinquent and organized crime networks look like (Finckenauer and Waring 1998; Krohn and Thornberry 1993; McGloin 2005; Sarnecki 2001). Finally, another stream of the literature essentially advocates for its use in law enforcement investigations (Coady 1985; Davis 1981; Howlett 1980) and demonstrates how it can guide interventions (Braga et al. 2001).

Obviously, network analysis has broad utility for criminology and criminal justice. Yet, it unfortunately remains a relatively sporadic technique and approach. The purpose of this chapter is to provide the reader with a working knowledge of network analysis and to demonstrate its utility for researchers across a wide array of criminological interests. Specifically, it will offer a brief background of network analysis, basic knowledge of the requisite data, important points for consideration regarding data and sampling, and illustrate some basic analyses, supplemented by further examples of similar techniques in contemporary criminological research.

Background of Network Analysis

Social network analysis evolved from a number of diverse research traditions, including the fields of sociometry, mathematics, psychology, and anthropology. Sociometry is the study of social relations, with roots in the work of psychiatrist Jacob L. Moreno. Moreno and his colleagues sought to uncover how individuals' group relations shape their psychological development and well-being (Scott 2000). One of Moreno's (1934) most enduring contributions to social network analysis is the "sociogram," in which individuals are represented by points (i.e., nodes) and social relations are represented by lines between the points. Sociometrists argued that society is best understood not simply as an aggregate of independent individuals and their characteristics, but rather as a set of interdependent, interpersonal relations. Thus, from the perspective of sociometry, the best way to study society is to examine social relations, as well as the causes and consequences of social relations (as opposed to studying individuals as though they are totally independent).

The visual appeal of Moreno's sociogram to represent social relations became more formalized with the advent of graph theory in mathematics (Cartwright and Harary 1956; Harary et al. 1965). A graph is a set of lines connecting various points. Graph theory provides a vocabulary for describing a social network as well as a set of axioms and theorems, which can be used to understand the pattern of lines formed between points (Scott 2000). In the vocabulary of graph theory, social units are termed nodes or vertices, and the relations between units are termed arcs or edges. Diagrams, such as sociograms, are certainly appealing, but matrices are another useful tool to represent graphs and store data on social networks. The integration of algebraic models and statistical/probability theory further expanded the means to study, describe, and quantify relational data (Wasserman and Faust 1994).

In addition to the sociometric and graph theoretic foundations, the roots of modern network analysis are also found in the work of psychologists and anthropologists (see Scott 2000). First, during the 1930s, cognitive and social psychologists working under the gestalt paradigm researched group structure as well as the information flow among members. Second, scholars at Harvard University refined the premises of anthropologist A.R. Radcliffe-Brown by focusing on interpersonal relations and subgroups within social networks. Third, researchers at Manchester University focused on tribal societies, using these studies to further refine social theory and the study of community relations. Although Radcliffe-Brown was also the primary influence for the Manchester researchers, their studies tended to focus on conflict and change rather than cohesion, which served as the focus for the Harvard group (Scott 2000). Together, these streams of research, which led to theoretical, methodological, and analytical maturity and refinement, serve as the foundation for network analysis.

Network Data and Sampling Considerations

Network analysis requires different data than most criminologists typically employ. It may be clear by now that the unit of analysis in network studies is not the node or individual, but the tie between entities (i.e., links among the nodes). This tie or link can take many forms, such as kinship, friendship, co-membership, communication, trust, shared or exchanged goods, among many others.[2] Depending upon the nature of the links, as well as the research questions, these relational ties can be undirected or directed. Examples of undirected ties would include co-authorship, siblings, married partners, or an affiliation tie such as two individuals belonging to the same street gang. Directed links would include such relations as exporting products to another node, identifying someone as a friend, receiving a call in a wiretapping ring; the notion behind a directed tie is that there is a flow or direction to the relationship and it is considered important for the inquiry at hand. Directed data may be important for criminological questions of interest, perhaps in terms of directing policy (e.g., who is "organizing" the illegal market by initiating and handling contact and product exchange?) or stimulating research questions (e.g., is there a difference between someone who has reciprocal deviant friends and someone who is not viewed as a mutual friend by deviant peers). It is important to note that relational ties can also have value. For example, researchers may code relations according to some level of attachment or involvement (e.g., number of days per week two individuals communicate). These values may reflect a continuous measure or scale, they can be categorical, reflecting distinct relations (i.e., friends versus siblings), or some combination thereof. The latter example is also known as a multirelational network (i.e., two nodes may be tied together in multiple ways).

Knowing the requisite data for network analysis is one thing, but acquiring them is something else. A proper social network is fully complete and reflects the population of interest. In some cases, this is plausible. For example, perhaps the investigation is interested in the social network within a school or business – this is a population with defined boundaries around what constitutes the network. In other cases, however, sampling becomes a thorny issue, both conceptually and practically because the boundary of the population is unclear. If one is interested in deviant peer networks or street gangs, for example, and begins sampling people in a

[2] Similarly, nodes can be of many different types, including individuals, organizations, countries, and groups.

school or on the street, to complete this network, the researcher should follow-up each identified friend in what could be a never-ending snowball sample. At some point, the researcher must decide on when the boundary has been "met" and justify it accordingly. Ideally, this boundary should have conceptual merit, not simply be based on ease or previous work.

Finally, most criminological inquires wrestle with missing data and the varied techniques of how to manage it. We do not bring it up here to ruminate on this general issue, but rather to make readers aware of the domino-effect missing data can have with regard to network information. To illustrate this point, imagine a project that gathers network data on a fifth grade class, asking about friendship links among the students. The researcher is interested in drug use within the students' personal networks (i.e., "egocentric" networks). If one student was absent on the day of the survey, of course there will be no peer network data for him. Importantly, unlike with typical data, his absence can affect the degree to which other subjects have missing data. Though it arguably will not affect the structure of other students' basic networks, because they were able to identify him as a friend even though he was absent, it could impact the extent to which their peer group appears to engage in drug use. If peer drug use is based on self-reports, then if this absent student was identified as a friend in 20 networks, these 20 people now have missing data on whatever variable measures the extent of peer drug use/endorsement. Under certain circumstances therefore, the impact of missing data can quickly escalate in network studies.

A Demonstration of Network Techniques

In order to understand the utility of network analysis, even in its most basic graphical form, it is instructive to use an example dataset and carry it through the various forms of analysis and description. This chapter will use a hypothetical dataset on a supposed organized crime group, whose members are all known to police and are currently under observation through wiretapping. The nodes are therefore the individuals in this criminal group and the links are phone calls made among them.[3] In this hypothetical dataset, there are 15 individuals and the links are both directed and valued. The direction indicates who received the phone call and the value of the link indicates the number of phone calls.

After the period of observation/data collection, the data are summarized and stored in an adjacency matrix, in which the rows and columns are defined by the actors in the network and the cell values of the matrix indicate whether two actors are associated (i.e., adjacent).[4] Table 11.1 displays the hypothetical data in matrix format. For a directed network, a positive value indicates "movement" from the row to the column. A zero value in a cell indicates that the person in the relevant row did not initiate a call to the person in the relevant column. The matrix shows that person 2 called person 1, but person 1 did not ever initiate a call to person 2. In order to characterize the "value" of the link, this dataset defines the connection as a continuous variable, capturing the number of phone calls initiated by the person in the row to the person in the column. Thus, the table shows that person 9 called person 7 three times during the observation period, where as person 11 called person 3 only one time.

[3] This hypothetical example is similar to the work of Natarajan (2006), which used wiretapping information to study network attributes of a heroin distribution group in New York.

[4] In addition to adjacency matrices, there are also incident matrices, in which the rows are the nodes and the columns are incidents, events, or affiliations (i.e., the value in a cell would indicate whether a particular node was part of that specific incident, event, or affiliated with that specific group).

TABLE 11.1. Adjacency matrix for hypothetical dataset

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1		0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1.0		0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	3.0	0.0
3	0.0	2.0		0.0	0.0	0.0	10.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0		0.0	0.0	2.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
5	0.0	0.0	5.0	0.0		0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	6.0	0.0	0.0	0.0		0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0
8	0.0	0.0	0.0	2.0	0.0	0.0	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0		0.0	0.0	0.0	1.0	0.0	1.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		0.0	0.0	0.0	0.0	0.0
11	0.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0		1.0	0.0	1.0	0.0
12	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		0.0	0.0	0.0
13	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	1.0	0.0	0.0		0.0	0.0
14	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		0.0
15	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	

GRAPHICAL DISPLAYS. Maltz (1998, p. 400) argues that "when shown in graph forms data are displayed without assumption." Although social patterns may be evident in smaller adjacency matrices, as the network grows, patterns may be obscured by the sheer volume of data (i.e., there are 600 possible links within a network of only 25 people). Graphs can reveal patterns that provide a more in-depth understanding of the data at hand. Of course, nuances within sociograms of very large networks may be difficult to discern, but even these graphs may provide insight (e.g., Sarnecki 2001).

As an example, Fig. 11.1 translates the matrix in Table 11.1 into graph form. Figure 11.1a is a directed graph (i.e., the arrows point to the recipient of the phone call), but not valued (i.e., the lines do not demonstrate the frequency of such phone calls). Therefore, it treats all of the values in Table 11.1 as if they were dichotomous rather than continuous. This graph highlights some interesting findings, such as person 6 appears to be "unimportant" to the criminal enterprise, at least if phone calls are the primary means of communication. It also suggests that much of the "action" is among persons 3, 7, 9, 11, and 14. For example, both nodes 7 and 11 are communicating with many people in the network, though it seems that 7 is primarily a recipient of communication, whereas 11's role is more balanced between receiving and initiating phone calls.

The graph in Fig. 11.1b incorporates the value of the associations among the actors by affecting the thickness of the links among the nodes (i.e., thicker lines indicate more frequent contact). Though Fig. 11.1a provides a sense of the individuals most enmeshed in this network, once the values are incorporated in Fig. 11.1b, it orients investigators interested in key lines of communication to persons 3 and 7, not necessarily person 11. Moreover, whereas person 5 did not "stand out" in Fig. 11.1a, this complementary figure suggests that this actor may be more embedded in the communication network than previously thought. In this way, even simple graphs can provide insight and direction into intervention techniques and prosecutorial strategies (e.g., RICO).

A number of extant investigations in criminology and criminal justice have benefited from such graphical displays. For instance, the Boston Gun Project used network analysis in its problem analysis phase when attempting to understand the local gang landscape (Kennedy et al. 1997). As part of its endeavor to study rising gang violence and

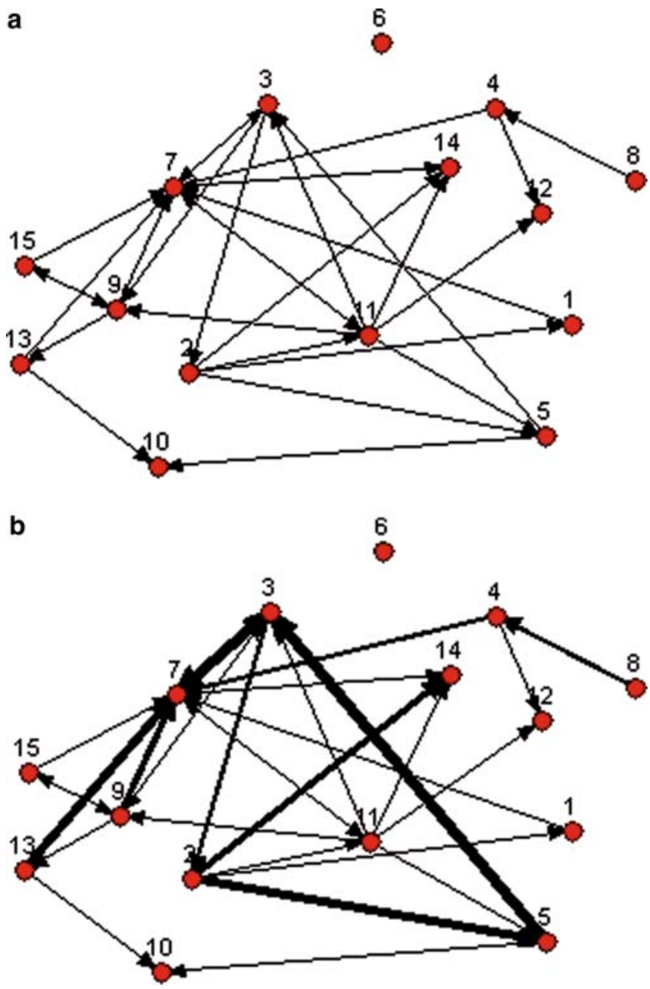

FIGURE 11.1. (**a**) Directed graph of the hypothetical dataset from Table 11.1. (**b**) Valued graph of the hypothetical dataset from Table 11.1.

youth use of firearms, the Boston Gun Project gathered data on the area gangs that were especially problematic for the local neighborhoods and the law enforcement community (Braga et al. 2001; Kennedy et al. 1996, 2001). While delineating the gangs and their respective territories, the researchers also investigated the relationships among gangs. In particular, they produced sociograms in which the gangs served as the nodes and rivalries among the gangs served as the linkages. This analysis served three important functions for the intervention. First, it allowed the stakeholders to understand why particular geographic areas were experiencing violent conflict – largely because the gangs tied to those territories were those heavily embedded in conflictual relations with other gangs. Second, it illustrated what gangs were most integral to the network – that is, the gangs that had the most connections, which nominated them for law enforcement focus and intervention. Finally, it gave insight into potential victimization on the heels of the intervention. In particular, if law enforcement directed resources at a particular gang, the rivals may take advantage of their vulnerability by engaging in aggressive dominance, leading to unintentional collateral violence. Rather than considering one gang set to the exclusion of the remainder of the landscape – a common strategy within law enforcement (Stelfox 1996) – the knowledge of the connections among the gangs provided unique leverage when undertaking the intervention strategy (see also Tita et al. 2005)

McGloin (2005) also recently used network analysis to describe the gang landscape in Newark, New Jersey. In contrast to the Boston Gun Project, the nodes in her networks were the gang members and the links were multirelational, capturing five distinct relationships that could overlap (e.g., siblings and co-defendants). The sociograms emerging from this work demonstrate that gangs in Newark are not very cohesive, but instead are characterized by a fragmented assortment of smaller subgroups. Given this network structure, the graphs drew attention to those gang members who serve as the bridge between subgroups, since they are vital to maintaining the overall connectedness of the network. From this graphical display of the data, she asserts that removing these "cut points" through police intervention may ultimately fragment the overall gang (for other examples of network graphs, see Finckenauer and Waring 1998; Sarnecki 2001; Whyte 1943).

MOVING PAST GRAPHS. Although network graphs can be very informative, investigators often have an interest in comparing networks or nodes within networks. Relying on visual assessments for such comparisons can be quite subjective. There are various network measures, however, which provide a more quantifiable metric of key concepts and therefore allow for more ready comparison. This comparison can extend from quantitative investigations focused on connections, such as those among deviant peers, to rich ethnographic work that describes social processes and interconnections. Thus, the network approach, and the measures and descriptors contained within, has the capacity to both shed insight on individual inquires, but also promote comparison and "knowledge-building" across studies (McGloin 2007).

Much of the literature investigating correlates of crime such as attachment to parents, associations with deviant peers, and the extent of neighborhood-level mutual trust and interactions typically utilize survey-based measures to describe the nature and importance of social networks. Still, there are formal measures used in network studies that move beyond these variables and provide greater analytic insight into some nuanced concepts important for theory and practice. The focus here is on these measures that derive from more precise network data, in which one has definable nodes and links (i.e., "how attached are you to your friends?" does not provide specific or precise network information). Our overview of network measures is not exhaustive; rather, we attempt to call the reader's attention to a number of measures and concepts, which are particularly useful for scholars interested in group structure and/or individual (i.e., node) positions within a network (see Wasserman and Faust 1994 for a detailed description of the many tools and techniques of network analysis).

With regard to group structure, scholars are often interested in cohesion. *Density* is a traditional measure of cohesion, which measures the proportion of ties that exist in the network to all possible ties. The density formula produces values ranging from 0, indicating no nodes in the network are linked, to 1, indicating that every possible tie in the network exists. The key pieces of information one needs to calculate density are the number of nodes ("g") and the number of linkages ("L") between nodes. One can determine density with the following formula:

$$2L/g(g-1)$$

This formula is applicable for networks with undirected linkages – for directed networks, as with our hypothetical example, the formula is slightly different. Because two ties can exist for each pair of nodes (i.e., a call from node 1 to node 2, and a call from node 2 to node 1), the formula is:

$$L/g(g-1)$$

Calculating the density for valued graphs can be slightly more complicated. According to Wasserman and Faust (1994), one way to measure the density of a valued network is to rely on the average value of the ties, but this has somewhat less intuitive appeal and is not held to the same traditional interpretation of density (i.e., a 0–1 range). For this reason, valued links are sometimes treated as if they were dichotomous when calculating density.[5]

Under the second density formula for directed networks, the density coefficient for our hypothetical dataset of wiretapped conversations is 0.138. There is no established threshold at which a network is considered "cohesive", but this network does not appear very dense. Indeed, less than 14% of all possible ties are present in the network. This would indicate that the criminal enterprise is not tightly organized, which also may be important as stakeholders attempt to understand and determine the most appropriate intervention and suppression strategies.

Though a person may not be able to speak in concrete terms about whether a network has passed the tipping point for being cohesive, one can certainly compare density values across networks and their impact on behavior. For example, Haynie (2001) incorporated the density of adolescent peer networks into an investigation of the criminogenic impact of deviant peers on delinquency. Unlike the previous example of a criminal enterprise network, the networks under focus in this investigation (via data from AddHealth) were egocentric (i.e., personal networks) rather than a global social network (e.g., an organized crime group). In a manner consistent with learning theory, she found that being part of dense school-based friendship networks amplified the deleterious effect of having deviant peers. A large body of work in network analysis has examined the repercussions of group cohesion on the behavior of group members, with the general conclusion that we should expect relatively greater homogeneity in behavior (e.g., delinquency) within cohesive groups. Groups are pressured toward uniformity as cohesiveness increases (see Friedkin 1984); it is harder for an individual in a dense group to break free from the group identity (i.e., by avoiding delinquency) than for individuals in less cohesive networks. Of course, criminologists working outside of a formal network framework have produced groundbreaking work on peer influence, but the focus is generally limited to the distribution of influence along a two-person dyad or from a generalized "group" of friends. A network approach, such as Haynie's, allows us to expand our focus and recognize that the connectivity and cohesiveness among one's peers may be extremely consequential to the behavior of the focal individual.

Density describes the cohesion of the entire network, but researchers may also be interesting in identifying cohesive subgroups within the larger network. For instance, research on street gangs has often noted that group organization tends to be loose, transient, and not very dense, but that pockets of intense cohesion do exist (e.g., Klein 1995; McGloin 2005). Theory and policy could arguably benefit from understanding whether these subgroups are responsible for a disproportionate amount of "gang crime" or whether the subgroup members can

[5] If the value of the tie does not reflect the strength of some relationship, but instead some combination of relationships (i.e., the network is multirelational), researchers also have the option of determining the density for the network across each type of relationship.

be readily distinguished from other gang members on variables of interest. A "clique" is a type of cohesive subgroup that contains at least three nodes, all of which are adjacent to (i.e., connected to) one another. Thus, cliques traditionally have a density coefficient of 1.[6]

Cliques can be difficult to identify or define in directed networks (Scott 2000). So, for illustrative purposes, the data in the hypothetical example will be recoded as dichotomous and undirected, which can be seen in Table 11.2. In this network, there are six cliques.[7] Figure 11.2 highlights one clique (in the right portion of the graph), which is comprised of nodes 3, 7, 9 and 11. This suggests that in the network, which does not have an impressively high density coefficient, there nonetheless exist collectives of interactions that are very cohesive. At first blush, therefore, though it may seem that this criminal enterprise is not well organized, it may instead be organized in a cell-like manner, in which connections are forged when and as necessary. Of course, this could prove to not be the case, but the identification of these cliques would prompt the question and facilitate a deeper understanding of the network under focus.

Researchers may also be interested in inquiries that characterize or describe the node(s). For instance, scholars can determine how embedded a person is in a social network, or how "important" s/he is to this network. There are a few ways to operationalize prominence, but one manner is to assess a node's centrality. As with density, measures of prominence can take on different calculations when the network is directed and/or valued. In an attempt to focus on basic measures and their meaning, we will focus on formulae for undirected, unvalued, graphs. Thus, the calculations here will rely on the matrix in Table 11.2. For readers interested in doing such calculations for other kinds of networks, we direct your attention to Wasserman and Faust (1994).

TABLE 11.2. Adjacency matrix with recoded data

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1		1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1.0		1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0
3	0.0	1.0		0.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0		0.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
5	0.0	1.0	1.0	0.0		0.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	1.0	0.0	1.0	1.0	0.0	0.0		0.0	1.0	0.0	1.0	0.0	1.0	1.0	1.0
8	0.0	0.0	0.0	1.0	0.0	0.0	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0		0.0	1.0	0.0	1.0	0.0	1.0
10	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0		0.0	0.0	1.0	0.0	0.0
11	0.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0		1.0	0.0	1.0	0.0
12	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0		0.0	0.0	0.0
13	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	0.0	0.0		0.0	0.0
14	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0		0.0
15	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	

[6] There are also n-cliques, which focus on geodesic distances (i.e., the shortest path between two nodes). A 1-clique would be a subgroup in which all geodesic distances among the members is 1 (i.e., a traditional clique). A 2-clique would be a subgroup in which nodes were connected to each other directly or indirectly through another node (thus, the largest geodesic distance is 2). For more information about n-cliques and other cohesive subgroups, see Scott (2000) and Wasserman and Faust (1994).

[7] The six cliques contain the following nodes: (1) 3,7,9,11; (2) 3,7,9,13; (3) 2,3,5,11; (4) 7,9,15; (5) 7,11,14; and (6) 2,11,14.

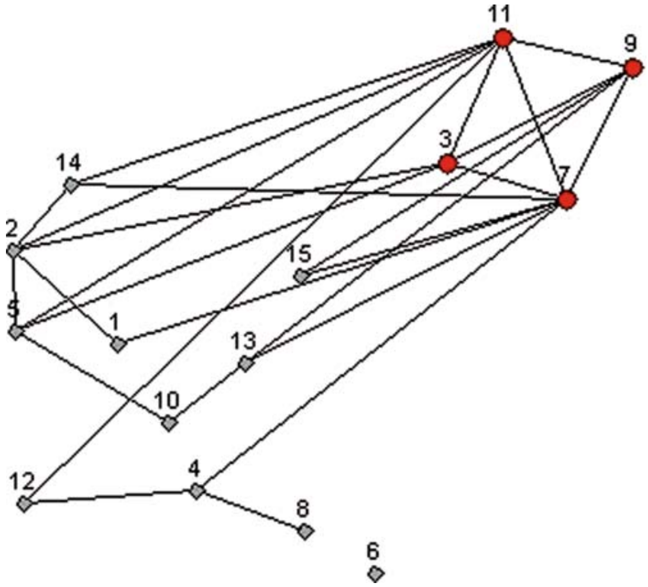

FIGURE 11.2. Cliques in the hypothetical dataset.

In its most basic form, prominence is captured as *degree centrality*. Degree refers to the number of ties connected to the node under consideration. In order to standardize this measure for comparison purposes (since degree is largely dependent on the number of nodes in the network), we divide the degree by the number of nodes in the network excluding the focal node ($g-1$) producing, a measure of degree centrality. Thus, in the hypothetical dataset, node 8 has degree of 1, and therefore a degree centrality of 0.071 (i.e., 1/14), whereas node 7 has a degree of 8 and a degree centrality of 0.571 (i.e., 8/14). Though this is a very simple measure, it nonetheless gives a sense of embeddedness, which may be quite important to certain investigations. For example, in his investigation of unemployment, Hagan (1993, p. 468) has argued that events are "not determined solely by individual propensities or states, but more significant, by socially structured connections between individuals." Being part of a deviant peer network has the capacity to affect one's own delinquency, which in turn reduces the likelihood of legitimate employment. Additionally, one can argue that this would only further embed and constrain the person within this deviant network. Thus, researchers interested in such concepts may find utility in a measure like degree centrality.

There are also other types of centrality measures that may be of greater interest for investigators. For example, betweenness centrality captures whether a node has "some control over paths in the graph" (Wasserman and Faust 1994, p. 188). A person who lies on the shortest path between other individuals arguably can control the flow of information and resources, and therefore is central and important. In specific terms, betweenness centrality assesses the extent to which one node is on other nodes' geodesics, which is defined as the shortest path between two nodes. In our hypothetical network (Fig. 11.1a), node 4 lies on the geodesic between node 8 and node 2, and therefore may control the flow of information between these latter two nodes. Each node in a network has a probability of being on the geodesic between two other nodes, and betweenness centrality is the sum of these probabilities across all pairs of nodes in the network. As with degree centrality, it must be standardized because the size of the network can influence this value, thereby making comparisons difficult. Thus, one should divide this sum by its maximum value: $[(g-1)(g-2)]/2$. Under the standardized formula, this centrality measure ranges from 0 (indicating this person has no "control" over other nodes' geodesics) to 1.

For our hypothetical dataset (see Table 11.2), this measure of centrality could shed insight on who exerts the most control over the illegal enterprise, as measured by communication among the actors. For instance, nodes 6, 8, and 15 have betweenness centrality values of 0, which might suggest that they do not occupy essential communication positions in this criminal enterprise. Nodes 4 and 11 have values of 0.148 and 0.167, respectively, indicating that some other people in the network do have to "go through" them in order to communicate with others in the network. Finally, node 7 has a betweenness centrality value of 0.361, which is the highest for the entire network. This appears to confirm the graphical displays, highlighting node 7 as a potential person of focus for additional investigations and law enforcement attention.

Finally, there are also centrality measures that address the notion that two people in a network who have equal degree centrality measures may not actually be equivalent if the individuals to whom one is connected have differing centrality. Thus, some centrality measures weigh the node's centrality by the centrality of the other nodes to which it is tied. The Bonacich centrality measure captures this concept and has been used by many researchers who have relied on the AddHealth data (e.g., Haynie 2001; McGloin and Shermer 2009; Schreck et al. 2004).

Density, centrality, and the identification of subgroups are but a few examples of the wealth of measures available to scholars interested in social networks. Though we believe network analysis remains underused in criminology, there nonetheless are a few examples that demonstrate the broad utility of such measures across a wide variety of interests. For example, the idea of weak ties and structural holes occupies a prominent place in discussions of social networks, especially in the economic sociology literature (Burt 1992; Granovetter 1973). From this work, scholars have argued that redundant networks (i.e., networks where relationships overlap with regard to the people to whom they provide contact) constrain an individual's exposure to information, skills, and opportunities. In contrast, individuals in nonredundant networks have greater returns for social investments because they have access to more diverse skills, knowledge, and opportunities (see also Davern and Hachen 2006; Lin 1982, 1990; Podolny and Baron 1997). Morselli and Tremblay (2004) recently imported this concept to criminology, finding that offenders in less redundant networks had higher criminal earnings than did their counterparts in more redundant criminal networks (see also McGloin and Piquero 2010). Next, in Haynie's (2001) previously mentioned analysis, she also investigated the conditioning effect of popularity. By turning attention to this measure (along with centrality), she found that an individual's position within his/her friendship network, not simply the cohesion of this network, also serves to moderate the impact of having deviant peers on an individual's own level of deviance. Interestingly, Schreck et al. (2004) confirmed this conditioning impact when shifting the outcome from offending to victimization. This is only a sampling of the breadth of network measures and concepts available to criminologists.

More Advanced Options. There is a wealth of social network measures that offer unique insight for researchers studying an array of theoretical and policy-relevant issues. There are also more advanced options, such as network autocorrelation models, often used to study diffusion of ideas and innovation. As we have noted, many empirical explanations for behavior, including criminal behavior, rely upon statistical methods, which assume that individuals are *independent* units. Multilevel modeling is one advance used to account for the interdependence among units, in this case among units within some cluster (e.g., neighborhoods and schools; also see descriptions of random and fixed effect models). The fact that social network analysis explicitly focuses on the *interdependence* among nodes has implications for inferential modeling. If there is interdependency among the behaviors of individuals in a social network, researchers necessarily need an inferential strategy, which captures the endogenous feedback effect of this undirected influence (Erbring and Young 1979). For some network studies, the extent of interdependence among subjects/nodes may be minimal and not require nontraditional modeling approaches. If individuals cannot be assumed to be independent, however, then analytic methods that assume independence may not be able to capture the true importance of group structure on behavior. Practically speaking, the interdependence among individuals' behavior leads to inconsistent OLS estimates of model parameters in a standard linear regression model.

A good example of the use of network autocorrelation models to directly model interdependence is Papachristos' (2009) investigation of gang conflict. From his analysis, Papachristos finds that the act of murder between members of rival gangs is best understood as a form of social contagion. Rather than random acts of violence, gang murders create an institutionalized, patterned network of conflict. Gangs continually battle over positions of dominance, and murder routinely results. Outside of criminology, Morris (1993) has also done work on diffusion, relying on more advanced modeling techniques. In particular, she adopts an epidemiological perspective and persuasively shows how social networks impact and shape the diffusion of HIV/AIDS. While it is out of the scope of this chapter to give full treatment to inferential statistics in social network analysis, we mention these points about inferential modeling to caution the reader to select the appropriate modeling strategy when conducting an analysis utilizing interdependent social units. For additional information on such modeling approaches, see Carrington et al. (2005), as well as Wasserman and Faust (1994).

SOFTWARE OPTIONS

A number of software package options exist for researchers to compute network measures, as well as visualize social networks. A fairly comprehensive list can be found at the website for the International Network for Social Network Analysis: http://www.insna.org/INSNA/soft_inf.html, and descriptions of many software packages can be found in Huisman and van Duijn (2005) and Scott (2000). Figures and calculations used in this chapter were produced in Netminer (www.netminer.com). Other popular software options include UCINET, Pajek, and STRUCTURE, among others. In most cases, the software allows the user to input or import data matrices, produce graphs, as well as explore and analyze the data.

CONCLUSION

In this chapter we have attempted to provide an overview of the development of network analysis, as well as a description of the distinctiveness of social network methodology, with the goal of providing researchers and practitioners with information on how to better understand their data, since it can impact both theoretical and policy growth and refinement. To reiterate several of the points made herein, social network analysis is more than a set of methods. It is an orientation toward the understanding of human behavior that focuses on the interdependency of individuals and how such interdependencies structure behavior. Alternatively, many of the statistical and methodological techniques described in chapters throughout the rest of this volume assume that social units are independent. Thus, social network analysis stands in marked contrast to many traditional statistical methods, and provides a set of analytic and methodological tools distinct from traditional social statistics, which are necessary to study social relations. In light of the key role many theories ascribe to social relations for the onset, persistence, frequency, and desistence of offending behavior, one could assert that criminology fundamentally must attend to the interdependencies among individuals.

The techniques covered in this chapter are in no way exhaustive, so we encourage aspiring network analysts to consult the references contained herein for further information on the vast possibilities for inquiry through social network analysis. As we have noted, social networks play a prominent role in many of the leading explanations of criminal behavior. Yet, the use of formal social network analysis is still quite limited in the fields of criminology and criminal justice. This is unfortunate since a network framework can help illuminate a number of key areas in criminology, whether by providing more refined measures of theoretical concepts, a more in-depth understanding of patterns in data, and/or guidance for policy decisions and evaluations. For instance, discussions about the shifts in peer associations and their relation to crime over the life course have occupied a prominent position in recent years. It would be greatly informative to understand how specific network connections and nodes in these networks shift and change over time, whether these patterns are systematically related to social factors, and how network stability and change is related to multiple contemporaneous and future offending dimensions, such as the frequency and seriousness of crime. One of the most innovative applications of SNA in recent years has been with understanding how to best model longitudinal network data (e.g., Snijders 2005) which coincides nicely with this proposed inquiry. To be sure, the implications of social network evolution for delinquent and criminal behavior are virtually unexplored.

In the end, there are a number of potentially fruitful research avenues, across a wide array of criminological interests, which could benefit from the unique insight offered by social network analysis. As Osgood (1998) has argued, one way for criminology and criminal justice to avoid insularity and stagnation is to keep abreast of work in other disciplines and integrate it as necessary. In light of arguments and examples presented here then, we would argue that it is certainly warranted for scholars to incorporate social network analysis into their analytic "tool box."

REFERENCES

Alter CF (1988) Function, form and change of juvenile justice systems. Child Youth Serv Rev 10:71–100

Braga AA, Kennedy DM, Waring EJ, Piehl AM (2001) Problem-oriented policing, deterrence, and youth violence: an evaluation of Boston's Operation Ceasefire. J Res Crime Delinq 38:195–225

Bursik RJ, Grasmick HG (1993) Neighborhoods and crime: the dimensions of effective community control. Lexington Books, New York

Burt RS (1992) Structural holes: the social structure of competition. Harvard University Press, Cambridge, MA

Carrington P, Scott J, Wasserman S (2005) Models and methods in social network analysis. Cambridge University Press, New York

Cartwright D, Harary F (1956) Structural balance: a generalisation of Heider's theory. Psychol Rev 63:277–292

Coady WF (1985) Automated link analysis – artificial intelligence-based tool for investigators. Police Chief 52:22–23

Coles N (2001) It's not what you know – It's who you know that counts. Analysing serious crime groups as social networks. Br J Criminol 41:580–594
Curry GD, Thomas RW (1992) Community organization and gang policy response. J Quant Criminol 8:357–374
Davern M, Hachen DS (2006) The role of information and influence in social networks: examining the association between social network structure and job mobility. Am J Econ Sociol 65:269–293
Davis RH (1981) Social network analysis – An aid in conspiracy investigations. FBI Law Enforc Bull 50:11–19
Erbring L, Young AA (1979) Individuals and social structure: contextual effects as endogenous feedback. Sociol Methods Res 17:396–430
Finckenauer JO, Waring EJ (1998) Russian mafia in America: immigration, culture, and crime. Northeastern University Press, Boston, MA
Friedkin NE (1984) Structural cohesion and equivalence explanations of social homogeneity. Sociol Methods Res 12:235–261
Granovetter M (1973) The strength of weak ties. Am J Sociol 81:1287–1303
Gustafson LFJ (1997) An historical and network analysis of the juvenile justice system in the Austin, Texas, metropolitan area. University Microfilms International, Ann Arbor, MI
Hagan J (1993) The social embeddedness of crime and unemployment. Criminology 31:465–491
Harary F, Norman R, Cartwright D (1965) Structural models: an introduction to the theory of directed graphs. Wiley, New York
Haynie DL (2001) Delinquent peers revisited: does network structure matter? Am J Sociol 106:1013–1057
Haynie DL, Osgood DW (2005) Reconsidering peers and delinquency: how do peers matter? Soc Forces 84: 1109–1130
Hirschi T (1969) Causes of delinquency. University of California Press, Berkeley, CA
Hochstetler A (2001) Opportunities and decisions: interactional dynamics in robbery and burglary groups. Criminology 39:737–764
Howlett JB (1980) Analytical investigative techniques: tools for complex criminal investigations. Police Chief 47: 42–45
Huisman M, van Duijn MAJ (2005) Software for social network analysis. In: Carrington PJ, Scott J, Wasserman S (eds) Models and methods in social network analysis. Cambridge University Press, New York
Kasarda JD, Janowitz M (1974) Community attachment in mass society. Am Sociol Rev 39:328–339
Kennedy DM, Braga AA, Piehl AM (1997) The (un)known universe: mapping gangs and gang violence in Boston. In: Weisburd D, McEwen T (eds) Crime mapping and crime prevention. Criminal Justice Press, Monsey, NY
Kennedy DM, Braga AA, Piehl AM, Waring EJ (2001) Reducing gun violence: The Boston gun project's operation ceasefire. National Institute of Justice, Washington, DC
Kennedy DM, Piehl AM, Braga AA (1996) Youth gun violence in Boston: gun markets, serious youth offenders, and a use reduction strategy. John F. Kennedy School of Government, Harvard University, Boston, MA
Klein MW (1995) The American street gang. Oxford University Press, New York
Knoke D, Kuklinski JH (1982) Network analysis. Sage, Thousand Oaks, CA
Krohn MD, Thornberry TP (1993) Network theory: a model for understanding drug abuse among African-American and Hispanic youth. In: De la Rosa M, Adrados JLR (eds) Drug abuse among minority youth: advances in research methodology, NIDA Research Monograph 130. Department of Health and Human Services, Bethesda, MD
Lin N (1982) Social resources and instrumental action. In: Marsden P, Lin N (eds) Social structure and network analysis. Sage, Beverly Hills, CA
Lin N (1990) Social resources and social mobility: a structural theory of status attainment. In: Breiger RL (ed) Social mobility and social structure. Cambridge University Press, New York
Maltz MD (1998) Visualizing homicide: a research note. J Quant Criminol 14:397–410
McGloin JM (2005) Policy and intervention considerations of a network analysis of street gangs. Criminol Public Policy 43:607–636
McGloin JM (2007) The organizational structure of street gangs in Newark, New Jersey: a network analysis methodology. J Gang Res 15:1–34
McGloin JM, Piquero AR (2010) On the relationship between co-offending network redundancy and offending versatility. J Res Crime Delinq
McGloin JM, Shermer LO (2009) Self-control and deviant peer structure. J Res Crime Delinq 46:35–72
Miller J (1980) Access to interorganizational networks as a professional resource. Am Sociol Rev 45:479–496
Moreno JL (1934) Who shall survive?. Beacon Press, New York
Morris M (1993) Epidemiology and social networks: modeling structured diffusion. Sociol Methods Res 22:99–126
Morselli C, Tremblay P (2004) Criminal achievement, offender networks and the benefits of low self-control. Criminology 42:773–804

Natarajan M (2006) Understanding the structure of a large heroin distribution network: a quantitative analysis of qualitative data. J Quant Criminol 22:171–192
Osgood DW (1998) Interdisciplinary integration: building criminology by stealing from our friends. Criminologist 23:1, 3–5, 41
Osgood DW, Wilson JK, O'Malley PM (1996) Routine activities and individual deviant behavior. Am Sociol Rev 5:635–655
Papachristos AV (2009) Murder by structure: dominance relations and the social structure of gang homicide in Chicago. Am J Sociol 115:74–128
Podolny JM, Baron J (1997) Social networks and mobility in the work place. Am Sociol Rev 62:673–694
Sampson RJ, Groves WB (1989) Community structure and crime: testing social disorganization theory. Am J Sociol 94:744–802
Sampson RJ, Raudenbush SW, Earls F (1997) Neighborhood and violent crime: a multilevel study of collective efficacy. Science 227:918–924
Sarnecki J (2001) Delinquent networks. Cambridge University Press, Cambridge, UK
Schreck CJ, Fisher BS, Miller JM (2004) The social context of violent victimization: a study of the delinquent peer effect. Justice Q 21:23–47
Scott J (2000) Social network analysis: a handbook, 2nd edn. Sage, London
Shaw C, McKay HD (1931) Report on the causes of crime, Volume II. U.S. Government Printing Office, Washington, DC
Snijders T (2005) Models for longitudinal network data. In: Carrington P, Scott J, Wasserman S (eds) Models and methods in social network analysis. Cambridge University Press, New York
Sparrow MK (1991) The application of network analysis to criminal intelligence: an assessment of the prospects. Soc Networks 13:251–274
Stelfox P (1996) Gang violence: strategic and tactical options. Crown, Manchester
Sutherland EH (1947) Principles of criminology, 4th edn. J.B. Lippincott, Philadelphia, PA
Tita G, Riley JK, Greenwood P (2005) Reducing gun violence: operation ceasefire in Los Angeles, Research in Brief. National Institute of Justice, Washington, DC
Warr M (2002) Companions in crime: the social aspects of criminal conduct. Cambridge University Press, Cambridge, UK
Wasserman S, Faust K (1994) Social network analysis: methods and applications. Cambridge University Press, Cambridge, UK
Wellman B (1983) Network analysis: some basic principles. Sociol Theory 1:155–200
Wellman B, Berkowitz SD (1988) Introduction: studying social structures. In: Wellman B, Berkowitz SD (eds) Social structures: a network approach. Cambridge University Press, Cambridge, UK
Whyte WF (1943) Street corner society. University of Chicago Press, Chicago