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Basics of Social Network Analysis

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Learning Objectives

- Describe basic concepts in social network analysis (SNA) such as nodes, actors, and ties or relations
- Identify different types of social networks, such as directed or undirected, binary or valued, and bipartite or one-mode
- Assess research designs in social network research, and distinguish **sampling units**, relational forms and contents, and levels of analysis
- Identify network actors at different levels of analysis (e.g., individuals or aggregate units) when reading social network literature
- Describe bipartite networks, know when to use them, and what their advantages are
- Explain the three theoretical assumptions that undergird social network studies
- Discuss problems of causality in social network analysis, and suggest methods to establish causality in network studies

1.1 Introduction

The term “social network” entered everyday language with the advent of the Internet. As a result, most people will connect the term with the Internet and social media platforms, but it has in fact a much broader application, as we will see shortly. Still, pictures like Figure 1.1 are what most people will think of when they hear the word “social network”: thousands of points connected to each other. In this particular case, the points represent political blogs in the United States (grey ones are Republican, and dark grey ones are Democrat), the ties indicating hyperlinks between them. The polarization between the two parties in real life is clearly reflected online as well.

SOCIAL NETWORK IN ACTION: THOSE REAL-LIFE SOCIAL NETWORKS

At the individual level, people form friendships, become enemies, and help each other by passing useful information, giving rides, fixing cars and houses, and providing emotional support; pupils play together or fight with each other; co-workers collaborate, collude, or backstab; and college students form study groups or social clubs. At the group or team level, teams compete and collaborate as well as imitate

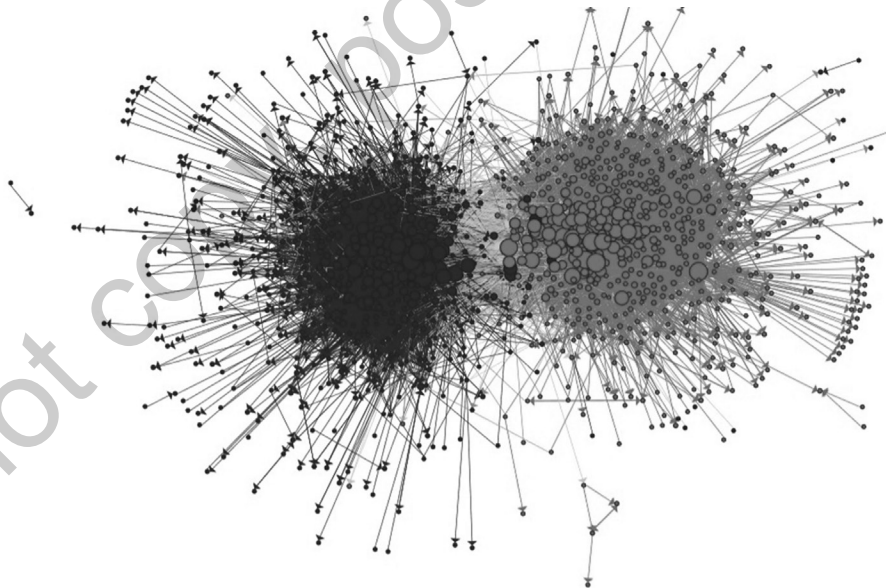
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and emulate each other. Organizations may collude or compete for scarce resources, be it tangible goods, such as bank loans, markets, or valuable material input, or intangible ones, such as reputation and legitimacy. Nation states wage war against each other, form alliances, and interact in different international organizations. All these actions involve at least two people, and we can thus envision the combined actions as a network between the actors involved.

In other cases, the points may be users of social media platforms such as Facebook (Menlo Park, CA), where the links indicate friends or “likes,” or Twitter (San Francisco, CA), where the links may be “retweets” or “followers.” In this chapter, we will start by describing some real-life social networks such as pre-World War I (WWI) international networks and the *Star Wars* (see Kurtz, 1977) character network. Then, we

FIGURE 1.1 ● Political Blogosphere in the United States in 2004



Notes: Political blogs in the United States in 2004: Democrats in dark grey, Republican in grey. Light grey links indicate hyperlinks across the aisle. Adapted from Adamic, L. A., & Glance, N. (2005). The political blogosphere and the 2004 US election: Divided they blog. In *Proceedings of the 3rd International Workshop on Link Discovery* (pp. 36–43). New York, NY: ACM.

will discuss the basic components of a network, types of social network, and levels of analysis in social network studies. We also will illustrate the theoretical aspects of social network analysis, covering such topics as the social network as institutions, the theoretical assumptions, and **causality** issues with social network analysis. We will conclude this chapter with a brief history of social network analysis, underscoring its multidisciplinary roots and strengths.

To start, social networks have been a defining feature of society since the early dawn of humanity—people have always interacted with each other or have made friends or enemies. These social interactions can be depicted as networks between individuals but also between smaller and larger groups of people. Figure 1.2 displays a network of the latter: the alliance networks between European countries before (top) and after (bottom) the Archduke of Austria-Hungary was assassinated by a Serbian nationalist, an event that precipitated the cataclysm of WWI.

The assassination and the subsequent war between Austria and Serbia pulled their respective allies into the fray. The bottom of Figure 1.2 shows how their declarations of war on each other resulted in some members searching and finding new allies, which then got attacked by members of the opposite side, until the war engulfed half the world. In the world of social networks, actors never act in isolation. Instead they influence and are influenced by others. Therefore, the consequences of their actions may reach well beyond their immediate environment. The goal of this book is to provide the reader with the tools to understand these interactions and interdependencies that affect both the small world of our immediate friends, online or offline, and the larger world of national blogospheres, global alliances, or trade networks.

But the analysis of social networks has even more applications, some of which may be surprising or whimsical. Take Figure 1.3 as an example, which displays a network of characters from the *Star Wars* franchise, connected by whether they share scenes in two different *Star Wars* movies.

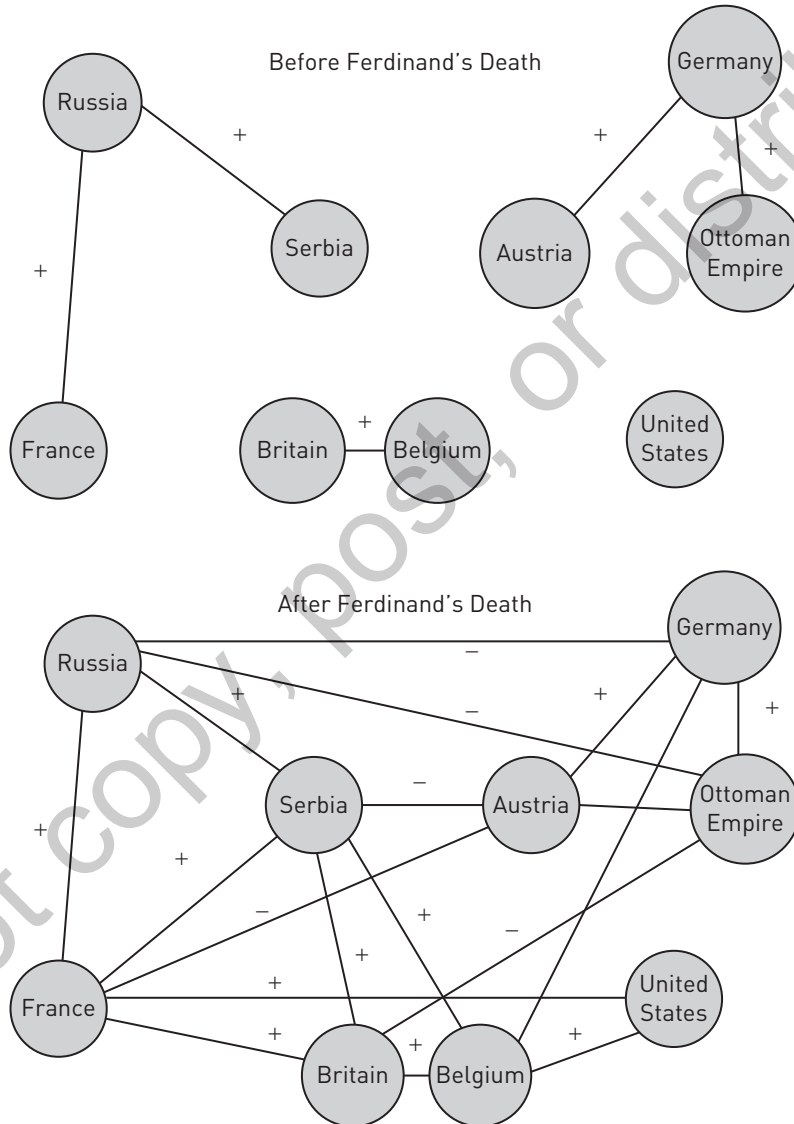
What may at first appear only of interest to fans of the series could, in fact, convey a deeper insight into good storytelling. Or so the author of the relevant blog post, Evelina Gabasova (2016), claims. She has found that the protagonist of the more popular second three episodes, Luke Skywalker, indirectly connects many other characters through shared scenes (he is *betweenness central*—see Chapter 3), whereas the main character of the first three episodes, Anakin Skywalker, occupies a less central network position.

In short: Social network analysis has a wide variety of applications. But the term “network” has become vague exactly because of its increasingly widespread use. It is thus important that we start by defining what social network analysts mean when they talk about networks.

1.2 The Social Network and How to Represent It

A social network consists of a set of **nodes** (sometimes referred to as *actors* or *vertices* in graph theory) connected via some type of **relations**, which are also called *ties*, *links*, *arcs*, or *edges*. The nodes usually represent actors, be that individuals, groups, teams,

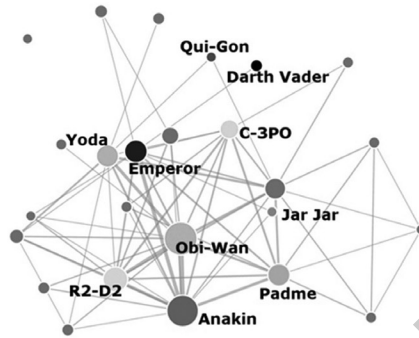
FIGURE 1.2 ● Alliance and Enemy Networks Before and After the Death of Archduke Ferdinand



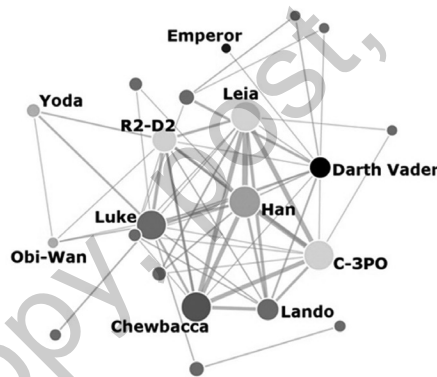
Notes: Some alliances and war declarations were left out for clarity. Adapted from Assassination of Archduke Franz Ferdinand [Course blog]. Retrieved June 7, 2016, from <https://blogs.cornell.edu/info2040/2015/09/14/assassination-of-archduke-franz-ferdinand/>

FIGURE 1.3 • *Star Wars* Character Network

Episode III: Revenge of the Sith



Episode V: The Empire Strikes Back



Notes: Co-appearances of *Star Wars* characters in the same scene in two *Star Wars* movies. The main character in the relatively unpopular Episode III (Anakin) is more peripheral to the network than the main character in Episode V (Luke), who directly and indirectly connects other characters. Adapted from Gabasova, E. (2016, January 25). *Star Wars* social networks: The Force Awakens [Blog]. Retrieved June 7, 2016, from <http://evelinag.com/blog/2015/12-15-star-wars-social-network/index.html>

communities, organizations, political parties, or even nation states. *Social* networks thus either have nodes that are social beings or organizations (lobbyists, voters, parties, etc.) or ties that represent some form of social interaction (voting for a candidate, re-tweeting a message, etc.). The relations between the nodes can be multidimensional and can include a whole array of different relationship types.

Unlike data used in other fields of statistical analysis, network data always consists of at least two datasets: a regular dataset—sometimes called the *nodelist*—where the nodes are the units of observation (i.e., the rows) and a dataset that defines the relationships

among those units of observation. The latter may have different shapes—the two most common ones are called **adjacency matrix** and **edgelist**. In an adjacency matrix (or simply *network matrix*), the nodes constitute both the rows and the columns, and the cells specify if and what kind of relationship exists between the nodes in the row and in the column. An edgelist is a dataset in which each existing tie, with both actors involved and the nature of their relationship, is listed as one observation. Adjacency matrices can be transformed into edgelists, and vice versa.

Figure 1.4 illustrates this with an example network of 10 individuals: At the bottom right, we see the graph or network illustration; the actors or nodes are usually represented as circles, but different shapes or colors can be used to indicate different groups or types of actors. In this example, the two colors indicate the actor's genders. The relations are represented by lines between the two actors.

Although such a visual display of a network can be insightful, it is not useful for statistical analysis, for which we need the nodelist (top left) and the adjacency matrix (top right) or edgelist (bottom left). The nodelist can have all sorts of additional information about the actors. Only one thing is absolutely necessary: an unambiguous identifier for each actor. This identifier can be a name, as long as no two actors share the same name, or a number. In our case, it is the first character of the actor's name.

An unambiguous identifier is important because it links entries in the relationship database (the adjacency matrix or edgelist) with the corresponding node. In the case of the adjacency matrix, the identifier appears again as the names of the rows and columns. We therefore know that column and row A indicate A's (Andrei's) ties. In the simplest case, the **binary** network, we simply distinguish whether a tie does or does not exist between a pair of actors. A cell with a one indicates that the actor in the row and in the column share a tie, a zero that they do not. Another way to represent the same information is the edgelist. This dataset has as many rows as there are ties and two or more columns. In each row, the two identifiers of the nodes connected by the tie are listed.

Figure 1.4 has presented perhaps the most common example of a social network: a group of humans connected by, for instance, friendship ties. But as we've seen at the beginning, nodes need not be individuals. Many disciplines within the social sciences use social network analysis, and the node's level of aggregation may reflect the disciplinary difference. Sociologists often take the individual as the node, focusing on the formation of friendship, liking, trust, and support between different individuals. They may also study networks between aggregate units, such as communities, teams, organizations, and states. Political scientists analyze networks between political actors on both levels, such as politicians, voters, parties, or nation states. Economists and management scholars are interested in for-profit firms as actors, the process of maintaining and managing of network alliances, the evolution of network alliances, and the consequences of networks on the firms.

The ties examined also vary. In fact, there can always be multiple networks for a given set of actors as different types of relations define different types of network. In Figure 1.4, we could, for instance, imagine a second adjacency matrix or edgelist that

FIGURE 1.4 • Example (Undirected, Binary) Network Graph With Its Nodelist, Adjacency Matrix, and Edgelist

Nodelist

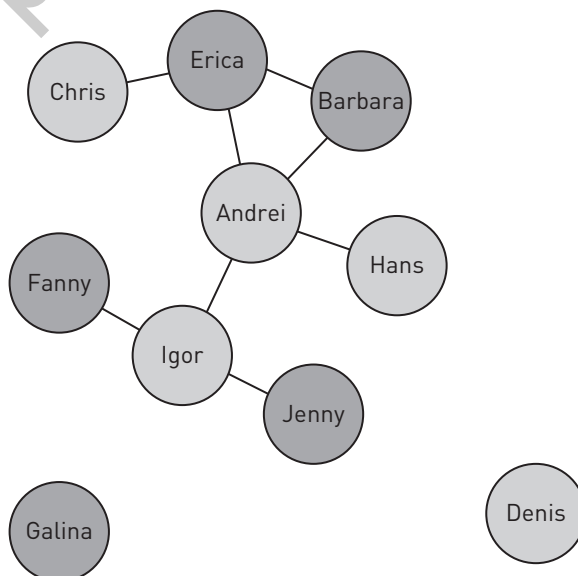
A	Andrei	male	Russian
B	Barbara	female	US
C	Chris	male	US
D	Denis	male	Russian
E	Erica	female	German
F	Fanny	female	British
G	Galina	female	Russian
H	Hans	male	German
I	Igor	male	Russian
J	Jenny	female	British

Adjacency matrix

	A	B	C	D	E	F	G	H	I	J
A	0	1	0	0	1	0	0	1	1	0
B	1	0	0	0	1	0	0	0	0	0
C	0	0	0	0	1	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	0
E	1	1	1	0	0	0	0	0	0	0
F	0	0	0	0	0	0	0	0	1	0
G	0	0	0	0	0	0	0	0	0	0
H	1	0	0	0	0	0	0	0	0	0
I	1	0	0	0	0	1	0	0	0	1
J	0	0	0	0	0	0	0	0	1	0

Edgelist (undirected)

A	B
A	E
A	H
A	I
E	B
E	C
I	F
I	J



records the enmities among the 10 people, which would likely look very different. In a company, a formal hierarchical network among employees, defined by who is allowed to give orders to whom, will not always be the same as an informal network defined by who is seeking advice from whom. The official leader in the formal hierarchy may not necessarily be the most important person in the informal advice-seeking network.

1.3 Types of Networks

Depending on the nature of the relationship, **networks** or **graphs** can be **directed** or **undirected**. Directed graphs consist of relations between pairs of actors, or **dyads**, which are not necessarily mutual. Figure 1.5 shows a directed version of the network discussed earlier: Now, friendships are not necessarily reciprocated. Although Erica considers Chris to be her friend, Chris does not share that feeling. Many other relations are directed, for instance, seeking advice from someone or passing a message to him or her. The members of a dyad connected by a directed tie cannot switch places without change of meaning: A seeking advice from B is not the same as B seeking advice from A. In the latter case, B would thus often be called the **sender** or **source**, whereas A is called the **receiver** or **target** (Knoke & Burt, 1983). Note how the edgelist in Figure 1.5 now distinguishes between a source and a target column. And although the adjacency matrix in Figure 1.4 was symmetrical (if one was in row A, column B, one was in row B, column A), this is not true for the matrix here.

A directed tie implies an asymmetric relationship. But it may still be reciprocated in some form, and this can make the label “sender” or “receiver” somewhat arbitrary: Employer–employee relations are clearly directed, but the employer could be the receiver (of the work carried out by the employee) or the sender (of the salary). It is thus particularly important to specify clearly what a tie signifies in a particular network.¹ Undirected graphs, in contrast, contain relations that do not distinguish between senders and receivers. Alliance partners, classmate or co-worker relationships, information exchanges, or marriages all fall into this category.

It is possible to combine both directed and undirected ties into one network: If John considers Aisha his friend, and Aisha shares this feeling, then John may have a directed tie to Amy (who does not consider him to be her friend) and an undirected tie to Aisha. Nevertheless, it is more common and usually less confusing to stick with one type of network and instead to create a graph in which a tie leads from John to Aisha and another one from Aisha to John. Such a configuration is called a **reciprocated tie**. In many social networks, reciprocated relations occur much more frequently than would be expected if such relations were formed at random. In Figure 1.5, there is a reciprocated tie between Andrei and Hans, who both nominate each other as friends.

¹ This is of course true for all social science concepts and pertains therefore to the other terms defined in this book. Nevertheless, confusion about the definition and measurement of connections seems particularly common when discussing networks.

FIGURE 1.5 • Example (Directed, Binary) Network Graph With Its Nodelist, Adjacency Matrix, and Edgelist

Nodelist

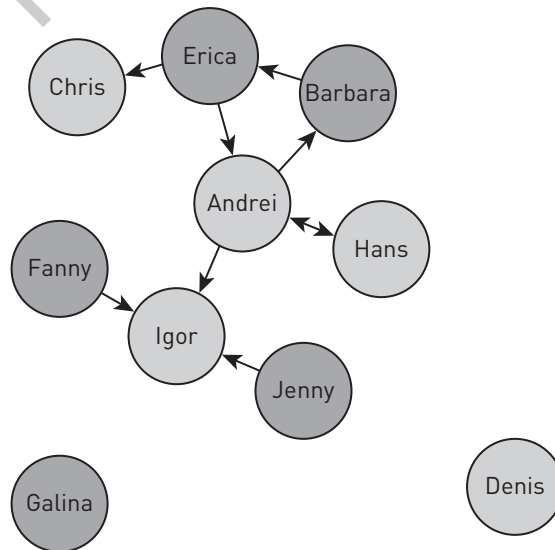
A	Andrei	male	Russian
B	Barbara	female	US
C	Chris	male	US
D	Denis	male	Russian
E	Erica	female	German
F	Fanny	female	British
G	Galina	female	Russian
H	Hans	male	German
I	Igor	male	Russian
J	Jenny	female	British

Adjacency matrix

	A	B	C	D	E	F	G	H	I	J
A	0	1	0	0	0	0	0	1	1	0
B	0	0	0	0	1	0	0	0	0	0
C	0	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	0
E	1	0	1	0	0	0	0	0	0	0
F	0	0	0	0	0	0	0	0	1	0
G	0	0	0	0	0	0	0	0	0	0
H	1	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	1	0

Edgelist (directed)

Source	Target
A	B
A	H
A	I
B	E
E	A
E	C
F	I
H	A
J	I

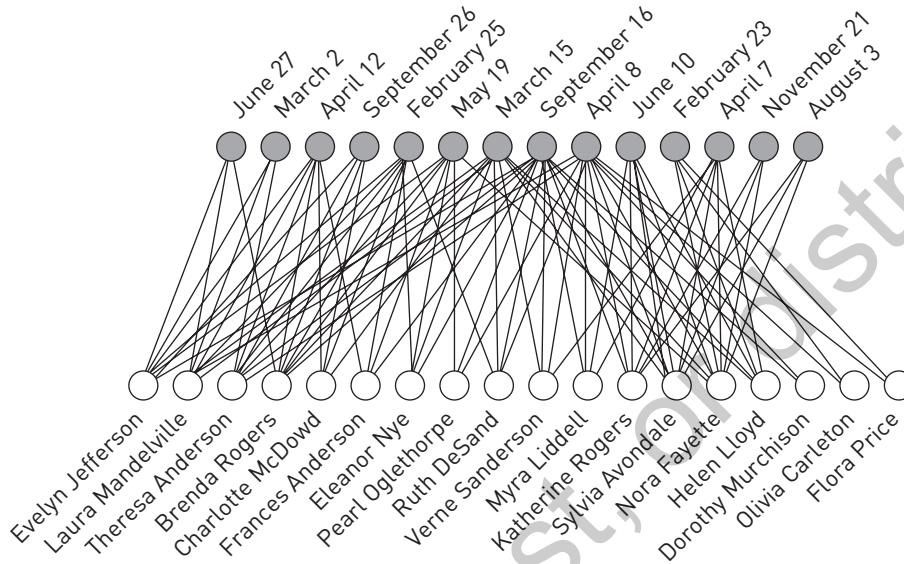


Social network data can also be distinguished by the values that are attached to the ties that link network actors. If the network data only capture presence or absence of certain relations, then the social network is called a *binary network*, in which values of 0 and 1 indicate the presence or absence, respectively, of the specified ties. In contrast, other network data reflects relational intensity between network actors on an ordinal or continuous scale, which results in a **valued network**. The choice between collecting binary or valued network data rests with the researcher. Compared with valued data, binary data are easier to collect and do not create as much of a burden to the informants. But valued data are usually more informative than are binary data. For example, a communication network among co-workers measured on a binary scale (0/1) may not be as revealing as on a valued scale (0, 1, 2, 3 . . .). Almost all co-workers communicate with each other at some point, but some of them exchange a great deal of information, whereas others have short and superficial interactions. Unlike binary data, valued network data capture those fine-grained differences.

NETWORK IN ACTION: A TYPOLOGY OF NETWORK TIES

- Transaction relations: actors exchange control over physical or symbolic objects; most economic exchanges fall in this category.
- Communication relations: almost all kinds of social networks can be used to pass messages between the actors.
- Instrumental relations: actors contact one another to obtain tangible goods, assistance, or information. Examples of instrumental relations include employers using existing employees for recruitment of talents, employees using personal networks to obtain jobs, people using friends or neighbors to attend to their houses while they are away, friends giving rides, fixing cars, repairing houses, and providing day care.
- Sentiment relations: relations that are used to express emotions, such as affection, frustration, admiration, deference, and hostility.
- Authority/power relations: most of those network relations occur in formal hierarchical organizations where social actors assume formal roles and positions; accepting responsibilities, obligations, and privileges; receiving and sending commands; and reporting or being reported to.
- Kinship and descent relations: relations between family members linked via biological ties.

Finally, relationships can be of different kinds. An almost unlimited number of relationship types exists. The box provides one possible typology suggested by David Knoke and Song Yang (2008, p. 12). There are at least two ways to deal with data on several kinds of relationships: One option is to combine them all into one **matrix** or edgelist. In this case, the matrix cell will be filled with a description of the relationship or a number corresponding to the relationship type. This approach becomes difficult if several different types of relationships exist between the same pair of nodes. In edgelist

FIGURE 1.6 • Affiliation Network of the “Southern Women Study”

Note: Adapted from Newman, M. E. (2010). *Networks: An introduction* (p. 39). New York, NY: Oxford University Press.

form, the edgelist will contain an additional column, in which the relationship is described. An alternative approach is creating multiple matrices and edgelists among the same set of nodes: one for each type of relationship.

So far we have discussed only networks in which the nodes are on the same aggregate level: They are either all individuals or all organizations or countries, for instance. We have a special name for those types of networks: **one-mode networks**. Bipartite networks (also called **bipartite graphs**), on the other hand, have two sets of nodes on different levels of aggregation, and the ties indicate membership or participation by the members of one set in the other. For example, individuals (one set of nodes) have a tie with each organization (the other set of nodes) to which they belong. Such networks are often used when social scientists cannot ask actors to report their relations with other actors or directly observe their interaction. They then resort to indirect methods of inferring ties through reports or archival data of the social events in which actors participate, or the organizations to which they belong.

For example, Allison Davis, Burleigh Gardner, and Mary Gardner (1941) made use of newspaper reports to study the social network of 18 women in the American South. This famous study, often called the “Southern Women Study,” contains a sample of 14 social events and a set of 18 women attending each of the 14 events. The network is depicted in Figure 1.6, where the top nodes indicate events, which were attended

by the bottom nodes connected to them. So, for instance, Evelyn Jefferson, Laura Mandeville, and Brenda Rodgers took part in the event on June 27.

In Chapter 3, we will discuss how such a network can be analyzed and even turned into the more familiar one-mode or *unipartite network* presented earlier. In the case of the southern women, it turns out that such an analysis shows how they were likely split in two groups that had little contact with each other.

1.4 Network Parts and Levels of Analysis

One of the biggest advantages of social network analysis is that it helps address the multilevel phenomenon by combining individual-level (micro-level) behavior with macro-level environments. In a non-network setting, we are often forced to focus unduly either just on the individual and his or her behavior (why does a pupil skip class?) or only on the level of society (how does the high school or the government address truancy?). The network perspective makes it easier to build the connection between the individual behavior and the systemic changes or vice versa. For instance, a pupil may be the first to form a friendship with someone from another classroom. This individual act builds a connection between two gossip networks that were not previously connected. The fact that rumors now can spread between both classrooms may create changes that affect everyone involved, not just the two new friends.

Depending on one's viewpoint (the **level of analysis**), a social network is a collection of individual actors, of dyadic pairs, of small groups (triad structures, cliques, or clusters, as we will discuss shortly), or of a wider environment or society (the entire network). We can thus easily switch from an analysis of the individual to that of the group, examining the influence and position of an actor within the group (or cluster), and the effect of the group on the actor and vice versa.

Individual actors are the lowest level of analysis, often representing the individual human being, or else collective entities such as organizations or communities. Nevertheless, unlike in the **atomistic model** (see Sections 1.5 and 1.6), where individual actors do not influence each other, actors in a network design are at least aware of each other's existence, and their interaction is likely what interests us most.

Dyadic pairs, pairs of two actors in a network, are the most important units of analysis in many network studies. In undirected full networks with N actors, where the direction of relation between a pair is irrelevant (because if John marries Amy, Amy also marries John), the total number of dyadic pairs is

$$\frac{N!}{2(N-2)!}$$

or simply $(N(N-1)) / 2$. For example, a network with 20 actors would have 190 dyadic pairs

$$\left(\frac{20!}{2(20-2)!} = \frac{19 \times 20}{2} = 190 \right)$$

In a directed network with N actors, the total number of dyadic pairs is

$$\frac{N!}{(N-2)!}$$

Thus, a network with 20 actors would have 380 dyadic pairs. Note that this computation ignores the possibility of loops (ties that connect an actor to him- or herself), the occurrence of which presents great challenges to the computation of dyadic pairs (Newman, 2010, pp. 137–139).

Dyadic level network analysis is common in social network studies. In management science, strategic alliances between pairs of firms form the fundamental unit of analysis for interfirm network studies (Carpenter, Li, & Jiang, 2012; Gulati, 1995). In public health, Suzanne Wenzel et al. (2012) studied pairs of homeless youth and showed how risky sexual behavior leads to **HIV/AIDS** infection. Dyadic studies also often explore the commonality between two connected actors. In social networks, **homophily** is common—a term indicating that individuals who are similar to each other are more likely to form a tie between themselves. Do birds of a feather flock together, or do opposites attract? Those questions are often asked and addressed by network studies focusing on dyadic levels.

Triadic structures, consisting of three social actors, are a level of analysis that has particularly fascinated sociologists. They were the first to notice the phenomenon of **triadic closure** (Davis & Leinhardt, 1972) or *transitivity*. Triadic closure is the tendency of “friends of friends to be friends”: If John is friends with Amy and with Yuki, then Yuki and Amy are also likely to be friends (in Figure 1.4, Erica, Barbara, and Andrei form such a triad). Such a process is common in social networks. Sometimes, the triadic process is more complex, however. The enemy of my enemy may not be an enemy but an ally, for instance. Triadic structures can be overwhelming in number—the total enumeration of triadic structure for a network with 20 actors is 1,140 or

$$\frac{20!}{17! \times 3!}$$

triads for undirected graphs and 6,840 or

$$\frac{20!}{17!}$$

for directed ones. Fortunately, high-speed computers and recent developments in social network modeling make systemic analysis with triads possible. In particular, exponential random graph/ p^* models, which we will discuss in Chapter 4, can help analyze such endogenous structural features.

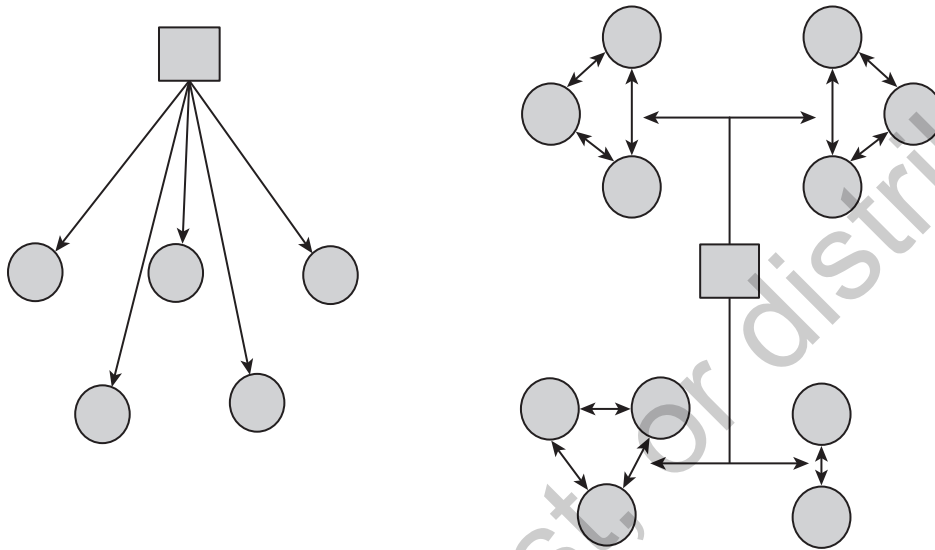
A substructure, subgroup, or subgraph, such as a **clique**, is an important unit of analysis in social networks studies. In its most general definition, the clique is a substructure in which actors are connected with each other in a particular way. Often they are more densely connected to each other than to other members of the network.

We will discuss the many different possible substructures, including cliques, clusters, (weakly and strongly) connected components, circles, k-cores, n-cores, k-plex, and n-plex in Chapter 4.

The **full or complete network**, or graph, is the most important macro-level unit of analysis in social network studies. Networks have many different characteristics that can explain outcomes on the individual and the network level, such as **density** (the proportion of ties present; see Chapter 3) or **centralization** (the degree to which nodes have, for instance, the same number of ties; see Chapter 3). Empirically, researchers that use this level of analysis sometimes compare several networks with each other: Michael Fritsch and Martina Kauffeld-Monz (2010), for instance, have studied 16 German innovation networks, finding that strong ties and dense networks disseminate information and knowledge more successfully than sparse networks with weak ties. Other researchers are interested in knowing what formative processes have led to the shape of a particular network, or how unusual specific features (e.g., the number of *closed triangles*) in a network are. In Chapter 4, we will discuss **ERGM (exponential random graph models)/P***, a method that helps answer such questions (Lusher, Koskinen, & Robins, 2013).

The previously mentioned studies are representative of two different approaches in social network analysis: The latter treats the network as a dependent variable, trying to explain its formation. In the former, the social network is an independent variable, which affects the outcome on the aggregate level. Such a separation of the analytical focus suits the scientific study of social network well, but in reality, the two processes (the formation of the social network and its impact) are usually interdependent, creating a fascinating challenge to social scientists. One application of full network analysis is to map the instructorship in different classrooms. Figure 1.7 displays the two hypothetical types of instructorship. On the left is the traditional teaching method, in which the instructor only gives lectures to students. On the right is the innovative teaching method, in which the instructor also organizes small discussion groups. Such different network configurations can serve as dependent variables in empirical studies that endeavor to identify the causes of such disparity in instructorship. The network configurations can also be the key independent variables that produce different results to students, measured with student evaluations of the class, or the average grade. By following such an approach, one can examine an important empirical question “is student-participatory teaching more effective than the traditional method?”

Another well-known characteristic of a network is its average path length, popularized in the term “six degrees of separation.” We can calculate the average path length by measuring the shortest path that connects each pair of individuals along network ties and by taking the average of all those paths. Researchers have found evidence (see box) that all individuals on this planet can reach another through on average only five intermediaries (i.e., through six intermediate ties or steps). This is also known as the **small-world phenomenon**.

FIGURE 1.7 • Typology of Different Teaching Methods

Note: Square: teacher; circle: students.

SOCIAL NETWORK IN ACTION: THE SMALL-WORLD EXPERIMENT

The “small-world” experiment was conducted by social psychologist Stanley Milgram (1967). In the experiment, he asked volunteers in two different U.S. states to relay a briefcase to a stockbroker in Boston, MA. The subjects were given a description of the target but not his address, and they were only allowed to pass the briefcase on to someone they knew on a personal basis (and who they thought would be closer to the target). Many briefcases never arrived, but those that did passed on average through the hands of five intermediaries. Hence, Milgram concluded that every U.S. citizen is connected to everybody else within the United States through no more than five intermediary steps. This finding has been the subject of both anecdotal and scientific fascination. For example, the “Bacon number” calculates the path length that connects any actor to Kevin Bacon in a network of co-appearances in the same movie. With the appearance of the Internet and social media, the world seems to have become even smaller—a recent study showed that the average path length connecting any two Facebook users in the world is only 4.74 (Ugander, Karrer, Backstrom, & Marlow, 2011).

1.5 Networks as Social Structure and Institution

Social sciences often divide their research subject into two spheres: that of the individual and that of a more abstract, aggregate social context that constrains the individual's actions and which he or she is able to influence only marginally. In the case of political science, the latter is the state and its institutions, whereas economists focus on the market, and sociologists study society. In such a framework, networks hold, as hinted at in the previous section, an oddly intermediate position. Network relations, directed or undirected, are not individual attributes. Rather, they are dyadic properties connected to both actors involved. Like the social context, the network is thus in many ways external to an individual actor, who might only have limited ability to change its structure. The actor's position in that network can enable or restrict: Having a tie to an owner of a company may grant access to a job, whereas holding a peripheral position in the network makes it less likely that one hears certain news. And the network structure does not just influence the outcomes of individual nodes but also of the whole group connected through it: Diseases may travel slowly or fail to spread among a group of individuals with few connections, for instance.

But neither is the network just an externally given group-level characteristic: The network structure is the result of the combined actions of its nodes, who form friendships, send e-mails, or dissolve contracts. These combined actions are not a simple aggregation of individual attributes either: A marriage between two "nice" persons does not guarantee a lifelong relationship, and simple summation of the actor attributes of a social network does not always predict the performance or outcome of the network system—a network with the most talented physicians isolated from each other is not conducive to information sharing and mutual learning. Conversely, social network performance cannot be reduced to individual attributes. A highly successful team with many innovations and patents can be the result of great collaborations between its members who complement each other's expertise through networking but who might not be (individual) geniuses. Sociologists like Mustafa Emirbayer (1997) have thus argued that networks are a conceptual bridge between the individual and the societal level, explaining how both levels influence and mutually change each other.

1.6 Theoretical Assumptions

Social network analysis is thus not simply a set of methodological tools to detect and analyze human relationships and interaction. This point is best illustrated by Mark Granovetter's (1985) classic piece on social embeddedness and economic action and by Emirbayer's (1997) manifesto on relational sociology. Granovetter (1985) emphasized the importance of embeddedness, social relations, and social networks to overcome both the economist's undersocialized view of human behavior and the oversocialized view by sociologists. He proposed decentralized networks as a third way to govern interfirm relations, challenging transaction-cost economy's standard view that the

only two options are either hierarchical integration into one entity or lateral contract between two different entities.

The network perspective stresses structural relations as its key orienting principle where social structure consists of regularities in the patterns of relations among concrete entities. The central objectives in social network analysis are to measure and represent these structural relations accurately, as well as to explain both why they occur and what their consequences are. Knoke and Yang (2008, pp. 4–6) suggested that social network analysis relies on the following three assumptions.

First, structural relations are often more important for understanding observed behaviors than attributes such as age, gender, values, race, education, and income. For example, people make decisions about their political views and actions, such as whether to vote, whom to vote for, or to support or oppose certain political bills based on their network and interpersonal ties with other people. Several studies by a group of political scientists (Fowler, Heaney, Nickerson, Padgett, & Sinclair, 2011) have shown that social networks often exert independent influences on political actions. Social network analysis rightly treats attributes and identities of social actors as more fluid than in the traditional atomistic studies, which examine individuals without taking into account their relationships with others. But in the social network approach, almost all individual-level attributes are highly contingent on specific time and place. Student–teacher relations, for instance, dissolve with the end of the class and have a different meaning inside and outside the classroom. A woman who holds a menial job requiring little initiative could become an outspoken and assertive leader in local city governance. Such drastic changes sit perfectly well with the network view that is premised on a **structural-relational model**. One's behaviors, such as with whom one talks, how he or she talks, and what he or she talks about, are highly contextual, depending on the social context that is constructed by many other relations and ties between many other actors.

Second, social networks affect perceptions, beliefs, and actions through a variety of structural mechanisms that are socially constructed by relations among entities. In his famous study on the “strength of weak ties,” Granovetter (1973) demonstrated that job seekers often obtain less useful information from their close contacts than from acquaintances because the former mainly provide redundant information already known to the job seekers. This finding may admittedly apply to the U.S. context only. Yanjie Bian (1997) found that in China, strong ties are more useful for finding a job because close contacts are more willing to influence the hiring process. Another example for how findings may depend on the context is provided in a public health study documenting two sexual contact networks in Colorado and Georgia. The former experienced decreasing network cohesion, resulting in low HIV transmission, whereas the Georgia one went through increasing cohesion, producing fast syphilis transmission (Potterat, Rothenberg, & Muth, 1999). Thus, the network cohesion, which results mostly from dyadic interactions between pairs of participants, has an impact on the transmission of sexual diseases among those network actors.

The third underlying assumption is that structural relations should be viewed as dynamic processes. Network structures are continually changing through interactions among their constituent individuals, teams, organizations, or nations. Scholars in management have long observed the evolutionary nature of interfirm relations (Gulati, 1995, 1998; Kenis & Knoke, 2002). In organization field networks, antecedent communication affects subsequent strategic alliance choices, which alter the later flow of information, providing constraints and opportunities to each firm in the network (Kenis & Knoke, 2002). Between a pair of firms, strategic alliances start with the most contractual governance forms; but over time, they are relaxed to adopt less rigorous contractual forms to reflect more mutual understanding and trust developed between the pair (Gulati, 1995).

1.7 Causality in Social Network Studies

Nevertheless, the fluidity and flexibility of networks described earlier also pose big problems to social scientists, who are often interested in uncovering the causes of social phenomena. In Chapter 5 of this book, for instance, researchers try to understand why some job seekers find a position, whereas others do not. What causes some pupils to turn to petty crime (Chapter 6)? Why do people vote (Chapter 8)? In all these cases, we find that social connections and networks influence people's behavior. But **causality ambiguity** often makes establishing *causal effects* in social settings difficult because either cause and effect cannot be clearly distinguished or we might not observe the true cause of the phenomenon. We know that individuals with a high income also have a high level of education. But did their education help them find a well-paid job? Or did their high income allow them to attend higher education? Or is the cause their parents, who financed their education and helped them find a high-income position?

One key area in social network research is the examination of social influence, also called peer pressure, relational effects, or contagion. This area denotes the phenomenon in which the behavior or attitude of actor A influences the behavior or attitude of other actors to which actor A is directly or indirectly connected through social ties (VanderWeele & An, 2013). Common examples can be found in the field of health (Chapter 7), such as smoking, drinking, obesity, or depression.

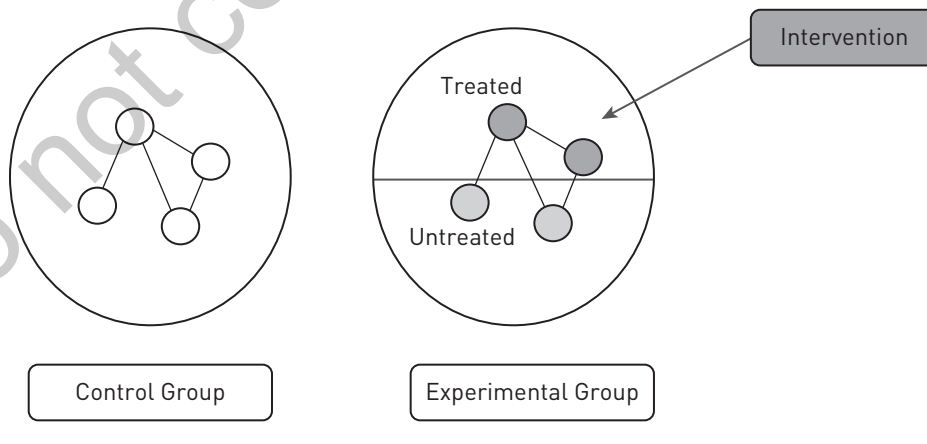
But if researchers find that smokers tend to be friends with other smokers, does this mean that smoking is “contagious?” Does it prove that Aisha's smoking habit “caused” Ben to pick up the habit as well? Not necessarily. It is also plausible that people with the same status—smoker or nonsmoker—come to form social relations with each other in a process introduced earlier called *homophily*. In other words, rather than smoking habits spreading from one person to the other through social ties, smoker/nonsmoker status may bundle people with the same habits together. These are two different causal mechanisms: In the case of peer pressure or social influence, the connection to a smoker causes smoking. In the homophily mechanism, the shared smoking habit is the cause of the tie or friendship formation.

In addition to social influence and homophily, there is a third possible mechanism: environmental confounding. Unobserved environmental factors can also play a role in determining the outcomes of interests between network peers. For example, growing up in a social environment where smoking is either stigmatized or encouraged can explain why nonsmokers or smokers tend to cluster together. Fortunately, recent social network research has developed methods to distinguish among influence, homophily, and environmental confounding, identifying a clearer pattern of causality between network variables.

One of those methods takes advantage of the conventional experimental method, changing a few features to make the method feasible for social network studies. This **partial treatment group design** (see Figure 1.8) assigns units with natural social boundaries, such as classrooms, clubs, or military units, to the control and experimental group. In the experimental group, researchers randomly select individuals to be subjected to the treatment or external intervention (the dark grey actors in Figure 1.8). Those who are not selected in the experimental group, along with all individuals in the control group, are left untreated. Researchers then measure the outcomes of all individuals in the control and experimental groups. The key in this process is the comparison between individuals in the experimental group who did not receive intervention (the light grey individuals in Figure 1.8) and those in the control group (white). The difference between the two group averages can be attributed to the spillover effect or peer influence from those in the experimental group who received the intervention to those who did not.

A specific example can illustrate how the partial treatment group design can establish causal effects in networks. Assume that we want to understand how a smoking prevention program helps reduce smoking. We randomly select two military units for control and experimental groups. In the experimental group, we randomly select a few

FIGURE 1.8 • Illustration of the Partial Treatment Group Design



soldiers to watch a documentary on the hazards of smoking, but we leave the rest of the unit unaware of the prevention program. Afterward, we measure the prevalence of smoking in both control and experimental groups. If the prevention program works, we would expect the soldiers of the control unit to smoke more than those of the experimental unit. The difference between smoking behavior in the control unit and that of those soldiers of the experimental unit who watched the documentary tells us the direct causal effect of the prevention program. The difference between control unit and soldiers in the experimental unit who did not watch the documentary gives us the size of the spillover effect—the indirect effect of the prevention program.

Experimental designs are usually the best way to establish causal mechanisms, but it is not always possible or ethical to assign random actors to receive interventions: Clearly, we cannot force subjects to start taking intravenous drugs or to contract HIV just to measure spillover effects. In these cases, **longitudinal data** from social networks can help identify causality between social network actors. In longitudinal social network studies, researchers collect individuals' behaviors and traits, as well as their connections, across multiple time periods. Researchers can therefore observe the order in which ties are formed and behaviors or attitudes change. By assuming that causes happen earlier than effects, a researcher can distinguish between homophily and social influence. This distinction is imperfect, however, as humans sometimes act in anticipation of other's behavior. For instance, an individual may start smoking because he wants to be friends with a smoker. He will thus first become a smoker and only afterward form a tie to the smoker, making it look like an example of the homophily mechanism, even though he was in fact influenced by his future friend's smoking behavior. The longitudinal social network design may also not be able to exclude the possibility of environmental confounding.

1.8 A Brief History of Social Network Analysis

Nowadays, social network analysis is often associated with social media, such as Facebook and Twitter. The analysis of social media data is indeed a promising avenue to study human interaction that researchers have only started to explore (Ellison, Vitak, Gray, & Lampe, 2014; Lewis, Kaufman, Gonzalez, Wimmer, & Christakis, 2008). In looking back, however, academic fascination with social networks has a long history, beginning as early as the late 19th century, when sociologists such as Georg Simmel, Émile Durkheim, and Max Weber propagated the structural perspective in the study of human behaviors. The scholar who is credited for laying the foundation for modern social network analysis is the psychiatrist Jacob Moreno (Freeman, 2004). Moreno was interested in how an individual's psychological well-being was linked to his or her relations with other individuals. Together with Helen Jennings, Moreno developed a technique called "sociometry" to visualize individuals and their interpersonal relations with their contacts. Sociometry drew huge attention from academics and elsewhere as it can reveal the hidden structure of complex interpersonal networks through simple and straightforward visualization. Moreno and Jennings later founded

a journal called *Sociometry*, devoted to publishing articles examining structural relations, networks, and their effects on human behaviors and psychological states.

But according to Linton Freeman (2004), social network analysis experienced a “dark age” shortly after Moreno’s groundbreaking work, during which it ceased to be the focus of social sciences—it was not identifiable as a theoretical perspective or as an approach to data collection and analysis. Still, social network analysts continued their research at several important universities. One of those strongholds was the University of Michigan in the 1960s when Edward Laumann, a Harvard graduate under Talcott Parsons, George Homans, and Harrison White, conducted social network analysis of politics, sexual behaviors, and stratifications. Laumann has trained many doctoral students, many of whom are leaders in social network analysis today: Ronald Burt, Peter Marsden, Joseph Galaskiewicz, and David Knoke, to name a few.

The “dark ages” ended in the 1970s when Harrison White at Harvard revived the social network analysis with his path-breaking work on structural equivalence and “blockmodeling” (Freeman, 2004). In addition to this foundational research, White produced a group of doctoral students who are now distinguished scholars in social network analysis, such as Peter Bearman, Philip Bonacich, Ronald Breiger, Kathleen Carley, Bonnie Erickson, Claude Fischer, Mark Granovetter, and Barry Wellman.

Another important school that contributes to current social network analysis is the University of California at Irvine (UCI). UCI capitalizes greatly from its flexible structure that facilitates significant multidisciplinary efforts in its building of social network concentration. Thanks to the leadership of James March, then the dean of the School of Social Sciences, and his successor Linton Freeman, the school was able to develop a Ph.D. concentration in social network analysis, which drew expertise not only from social sciences but also heavily from mathematics. The school at UCI soon became a hub attracting renowned U.S. scholars, such as Ronald Burt, Patrick Doreian, and Harrison White, as well as international scholars such as Wenhong Zhang from Shanghai University, China. UCI also hosted conferences that featured many mathematicians of social network analysis, such as Martin Everett, Tom A.B. Snijders, Stanley Wasserman, Stephen Borgatti, and Philippa Pattison.

Social network analysis started off as a multidisciplinary effort, and it has benefitted greatly from its multidisciplinary traditions (Knoke & Yang, 2008; Newman, 2010). Its scope includes psychology, sociology, economics, and recently political science. It is also a branch within network analysis, which covers science majors such as computer science, mathematics, statistics, physics, biology, and food science (Yang, 2013). One of the most exciting and recent developments in network analysis is exponential random graph modeling (ERGM), which will be discussed in Chapter 4 of this book. ERGM allows for examining the wide range of mechanisms that could have given rise to the social network of interest and explores how the actors within the network decide to form ties. Two other monographs provide much fuller treatment to the methodology. One is an edited volume by Dean Lusher et al. (2013), and another is Jenine Harris’s (2014) introduction monograph to ERGM, which provides a hands-on tutorial to the ERGM using *R*.

End-of-Chapter Questions

1. Imagine a network that describes which countries trade with each other. Who are the actors in this network? What are the ties?
2. Is a “marriage network” in which multiple families are tied with each other through marriages a directed or an undirected network? How about a network of friendship ties between classmates?
3. What are the differences between binary and valued social networks? Imagine a network of militarized conflict between nations. What do the ties represent in a binary network? In a valued network?
4. What is a bipartite network? Produce an example of a bipartite network. What are the main differences between a bipartite network and other types of (one-mode) networks?
5. Design a network study that can capture the informal advising network among employees in a workplace, and compare the network with the formal hierarchical structure depicting the hierarchical relations between those employees.
6. Discuss the three theoretical assumptions that undergird the social network analyses.
7. In a directed network of 50 actors/nodes, how many dyadic pairs and triadic pairs does it have?
8. Explain how you would use the partial treatment group design to determine whether a drug prevention program can curb the drug use among a group of students living in the same university dorm.