8

Cohesion and Groups

When does a collection of individuals become a group or a community? What holds groups, communities, and societies together, even as individuals come and go? These questions concern social cohesion, the bonds through which otherwise disconnected individuals become part of something larger and more lasting than themselves. Social cohesion is perhaps the most central issue in the founding of sociology as a discipline, and its relevance persists today. Social network analysis has much to offer in making the study of social cohesion more formal and precise. Whereas in the previous chapter we examined structures from the standpoint of their constituent elements of dyads and triads, here we step back to try to see more of the bigger structural picture through the overall pattern of ties in a network.

8.1 STICKING TOGETHER

During periods of social unrest, people frequently begin asking big questions: How fragmented are we? Do our differences outweigh our commonalities? What are the possibilities for cooperation among groups who have very different ideas or interests? Since its inception as a discipline, sociology has puzzled over these questions of *social integration* in an attempt to identify the "glue" that holds a society together. Questions of social integration are inherently structural – that is, they concern the arrangements of ties in a group or population, as well as what flows through these ties. Durkheim (1893) worried that society could fall apart in the absence of social bonds. In his view, as societies grow in size and complexity, they develop a more specialized division of labor, which threatens the traditional social bonds based on localized communities held together by commonly shared beliefs and understandings. Durkheim saw a new form of solidarity arising from the interdependence among functionally differentiated roles – or, rather, that was what he thought possible.

Network approaches have taken on such issues of social integration. Connectionist and positional network approaches speak to fundamentally different (albeit possibly complementary) ways that groups and larger social collectivities become integrated. For connectionists, integration is found in the transfer of important resources, including emotions and support, through a population. In this connectionist view, to study what holds a social collectivity together is to study the pathways through which resources flow. Of particular interest to connectionists are the smaller groups in larger networks that are more like tight-knit communities. In contrast, for positional approaches, integration occurs at a higher level of abstraction. For positional researchers, integration is found in how nodes occupy positions that fit together in more or less integrated and stable formations. In contrast to the connectionist view, positional approaches might even consider *nodes with no direct ties* as occupying the same type of position with respect to the larger social structure – that is, such nodes share similar roles and have similar patterns of ties to others.

Studies of social integration rest on notions of *cohesion*, examining the social forces that create and sustain bonds among individuals. Cohesion can be conceptualized and measured at various levels of analysis. At the individual level, people experience cohesion as a feeling of connection – a "we feeling" – with others. At the group level, such individual feelings are thought to arise from interactions and exchanges that produce an awareness of and reliance on others. Thus, cohesiveness as a personal feeling is afforded by social structures and the roles they assign to people; when people coordinate well with others to perform these roles, they experience feelings of belonging. Although both connectionist and positional approaches inform our knowledge of cohesion, connectionist approaches have been overwhelmingly dominant in this regard. For this reason, we cover connectionist approaches in greater detail in this chapter and reserve our discussion of positional approaches for Chapter 10.

8.2 COHESION AND CONNECTION

How are groups more or less cohesive? Here, we outline structural ways of conceptualizing and measuring what holds groups together. We start with Figure 8.1, which describes two dimensions that jointly determine how well notions of cohesion generally affect our understanding of the group and community structure in a network.

We term the row dimension *social connectivity* because it captures the extent to which ties in a network connect actors to each other. The relation between cohesion and social connectivity is intuitive. When all nodes are directly connected to one another (a complete clique), the network is clearly quite cohesive; but when all nodes are disconnected, it is clearly fragmented and not much of a "network" at all. As it turns out, most networks are somewhere in the middle in

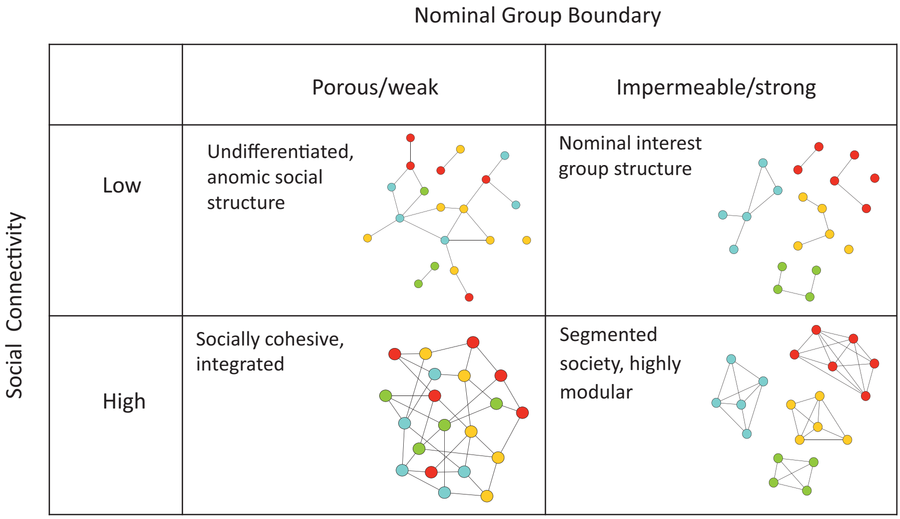

FIGURE 8.1 Conceptualizing the social cohesiveness of networks

terms of connectivity, and, as we will discuss later, the connectivity of most networks is deeply dependent on the exact *pattern* of connectivity. Intuitively, the social connectivity dimension captures how well network ties hold the collective together. At a minimum, networks and subnetworks should be largely connected to be considered cohesive. But are connections all that matter?

The column dimension recognizes the likelihood of a *nominal group boundary* – that is, collectivities often distinguish in-group from out-group via some categorical membership criteria. This is depicted as different color nodes in the figure. In White's (1965) famous discussion of categories and networks, what he termed *CATNET systems* are those where some nominal category is salient and shapes the likelihood that interaction occurs. In fact, White argued that a category is meaningful only to the extent that it shapes social relations. Base categories – race, class, and gender – matter precisely because they shape how people treat one another differentially within and between such categories. In that sense, categories and networks are duals of each other – that is, one implies the other, albeit seen through a slightly different lens. Salient categories define groups by distinction and govern the likelihood of seeing a tie from one category to another.

By combining these two dimensions, we are able to conceptualize different types of network systems. When both dimensions are low, the social system is probably a network in name only and can reasonably be thought of as independent interactions, such as in a classical market or random contacts in places like train stations. Situations such as these are useful for us mainly as null models against which we compare real-world networks. When both dimensions are high, we have a classically segmented social system – that is, strongly homophilous groups with minimal links between them. Pure cases of segmented social systems are rare: traditional caste systems, cults, or perhaps strong political alliances. And yet, informal social systems almost always have some level of segmentation built around consolidated social categories, particularly as social systems increase in scales. Very large networks, with millions if not billions of nodes, are often weakly connected collections of distinct subgroups. The recognition that such groups rest on both strong connectivity and a clear distinction between "us" and "them" has driven most of the work discussed here on the "community detection" problem.

We can also consider cases approximating the off-diagonal cells in Figure 8.1. Situations where boundary salience is high but connectivity is low (upper-right) likely describes low-investment interactions in settings with some entrance selection criteria. Clear examples would be voluntary interactions on topic-based social media or online discussion forums (like Reddit or YouTube) in which people select their audience based on some joint interest and where interactions happen within those specific settings about those specific topics. Because such interactions tend to be localized on particular issues for each audience, people tend not to have strongly redundantly linked relations and often make posts that, while possibly seen by others in the forum, usually do not cascade into deep interactions. When boundary salience is low but connectivity is high, we have integrated social systems where the category is simply irrelevant. This is a situation where the category is not organizing relations, but the network as a whole is socially integrated. In such situations, the entire setting is cohesive, and the setting admits to few divisions. These sorts of settings tend to have high diffusion potential and are robust to disruption. Sociologically, they mirror ideal-typical social integration, where individuals might differ on a category but that category does not segregate the network. Often, some higher-order identity has taken precedence over the nonsalient ones, as in military recruit networks where the experience of going through boot camp lessens the salience of ascribed attributes within the unit.

Of course, real-world settings are usually mixes of these ideal types. To the extent that they approach the ideal type in the lower right cell, networks often suggest the kind of fragmentation feared by Durkheim and others; to the extent that they approach the lower left cell, networks indicate a kind of pluralistic integration. Metrics aimed at capturing social cohesion often depend on one dimension more than the other; thus, we will refer back to Figure 8.1 as an organizing rubric for thinking through network cohesion measurement.

8.2.1 Measuring Connectivity

A number of empirical correlates are involved in determining whether a network can be thought of as cohesive, including (1) the strength of the relation in question, (2) the number of ties in the network (i.e., density), and (3) the

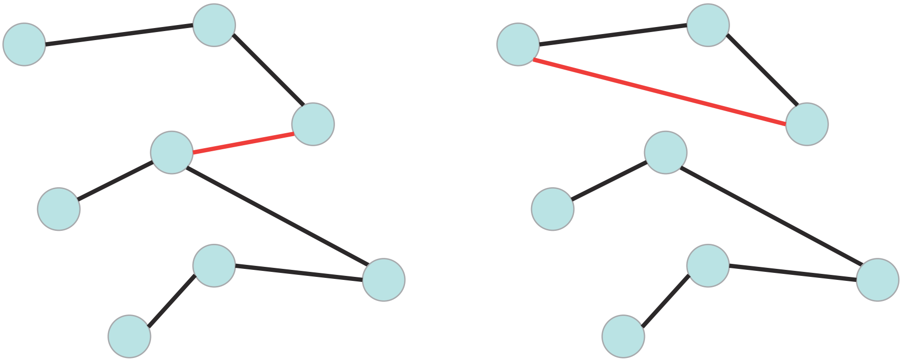

FIGURE 8.2 Network density versus connectivity

arrangement of those ties in a pattern. Considering (1) and (2), for example, a dense network of strong friendship ties has considerable face validity as a measure of cohesion at the dyad level. However, as demonstrated in Figure 8.2, the arrangement of ties is key to understanding the cohesion of the network. Both networks in the figure have the same number of nodes and ties. Although the arrangement in the second network differs merely with respect to a single tie (shown in red), this small change alters the overall pattern such that the second structure becomes disconnected.

Many real-world networks have many ties, but these ties are not arranged in ways that are strongly connected at the level of the entire network. They are more like many high peaks with low valleys in a ridge structure. For example, based strictly on the number of friendships, most high schools would appear highly connected; however, most of the ties are highly concentrated within groups. And consider again the high school romantic partner network, with its long chains. This structure has a much narrower set of connections than is typical of friendship networks and thus has very different implications for the possible flow of STDs than what friendship clusters might predict.

Friedkin (1998) introduced the metaphor of *ridge structures* when thinking about such differing patterns of connectivity in larger network structures. Ridge structures are characterized by overlapping regions of greater and lesser connectivity, in the same way that a topographical map of mountain ranges provides a view from above that reveals higher and lower levels of connectivity. Like a topographical map, network ridge structures are composed of peaks of high connectivity and ridges at lower levels. The ridge structure concept provides a flexible way to think about even extremely large networks as connected ramifying structures through which important resources are likely to flow.

Consider the image shown in Figure 8.3. Here, one can imagine that Node 7 is the peak of a mountain range, with two ridge lines having different levels of connectivity. As we touched on in Chapter 5, larger networks with hundreds or even thousands of nodes can be visualized using topological techniques that

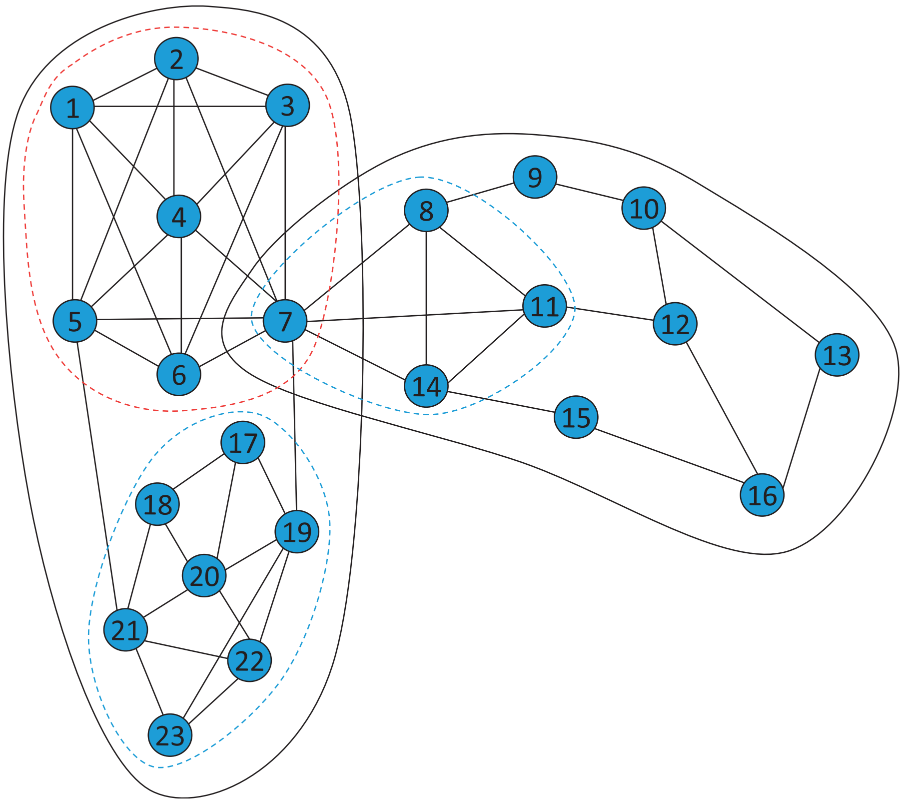

FIGURE 8.3 A simple ridge structure

show varying levels of density and resemble actual mountain chains. Ridge structures are therefore networks or parts of a larger network that have a relatively high level of connectivity between their most densely interconnected regions. The point here is that a structure that is more connected as a ridge structure – that is, one with a higher ridge line of high density that acts as a connective spine for the structure – has a greater capacity for social integration through more rapid and complete flows of important resources.

No single measure sufficiently captures every aspect of connectivity. Instead, measurement often requires a sustained effort, using various indicators and likely various network images that present a valid understanding of the network's connectivity and implications for such sociological principles as cohesion and solidarity. Measures summarizing properties at the level of the entire network are called *graph-level indicators*. The most common indicator of connectivity is network *density*, which again is simply the total number of ties in a network divided by the total number of possible ties. For a network with undirected ties, density can be written as $m/(\frac{1}{2}(N \times N) - N)$, where m is the total number of ties and N is the number of nodes in the network.

The two network images in Figure 8.3 have the same density value of 0.25, indicating that 25 percent of all possible ties exist in each network (seven of twenty-eight). Density clearly shows one facet of connectivity, but it is not a very detailed one and on its own can be deceiving, as demonstrated in the figure; again, the pattern of ties is just as important as their overall number. In addition, density is almost always lower in large networks than in small ones because the denominator grows with the square of the number of nodes, but the sum of ties usually grows linearly. Moreover, density on its own fails to account for the strength of the ties. In many instances, stronger ties (e.g., best friends) may be more important for some types of cohesion but are less dense than weaker ties (e.g., acquaintances). Thus, simply examining the density without taking into account the value of the tie could lead to false impressions of connectivity. Density is still an essential network property, but it generally provides only a first glimpse into connectivity.

What are some other possible measures? One possibility is to gauge the overall pattern of ties as a more or less jagged ridge structure, using the *clustering coefficient*. This measure brings us back to the importance of triads, discussed in the last chapter, and the notion of *transitivity*: the extent to which triads are "closed," or as balance theory more colloquially states, the extent to which "friends of friends are friends." In undirected networks, the clustering coefficient becomes a simple ratio of the count of the number of closed triads to the total number of triads (both open and closed). Networks composed of a higher proportion of closed triads are generally clumpier because for a given number of ties, having many triads turns the network in on itself, effectively creating a boundary-salient cluster. Generalizations of the clustering coefficient for directed networks and weighted networks also exist (e.g., Fagiolo 2007). Combined with the overall density measure, clustering can provide insights into whether the structure is globally dense but locally sparse, or perhaps globally sparse but locally dense.

Another possibility is to look at nodes that are fully connected through at least one path (where i can reach j by following the adjacent edges in the network), which is called a network *component*. Counting the number of components in a network therefore gives a better sense of the overall pattern of connectivity. For example, although the density of the two networks in Figure 8.2 is the same, the first network has one component, and the second network has two components (so that a node in the top half of the network cannot reach a node in the bottom half). The number and size of components is therefore another good indicator of connectivity because it shows the extent to which each node is *reachable* – that is, directly or indirectly tied to the other nodes. Components are easy to identify in undirected networks, as reachability from i to j always implies reachability from j to i. Reachability becomes more complicated to determine when ties are directed and the direction involves a flow that is of interest to the researcher. In such cases, determining the reachability of two nodes must account for directed paths.

In directed networks, we distinguish between *strong* and *weak components*. A strong component takes the direction of ties into account, so that only mutually reachable nodes are included in the component. To be included in the strong component, a node must be able to directly or indirectly send to *and* receive from all other nodes in that component. A weak component ignores the direction of the tie and includes all connected nodes, as in the simpler case of undirected networks. A simple summary measure of the component distribution is the pairwise reachability score, which is the sum of the number of pairs who share a component divided by the number of pairs in the network. For Figure 8.2, reachability is 1.0 for the network on the left but 0.46 for the one on the right.

Although they provide a sense of the reachability of nodes, components do not provide a sense of *how far apart* nodes are from one another with respect to the structure and consequently how long something would have to travel to connect two nodes. For example, a communication network may be fully connected within a single component but may vary considerably in how long a message from one node to another would have to travel through many intervening nodes to reach its target. Structures with longer paths are likely to suffer more frequent distortions as the message becomes slightly altered at each step of transfer (as in the telephone game). In this case, a more cohesive structure would be one in which the targets of a message have shorter paths. This idea of path lengths has already been discussed, but here one can think of how path lengths indicate something of an entire network's cohesiveness.

Geodesics, which you will recall are the shortest paths between two nodes, can be used to generate two graph-level indicators. First, the *diameter* of an entire network can be assessed by examining all the geodesics between each pair of nodes in a network and then taking the longest geodesic. This "longest shortest" path reveals something about the overall connectivity of the network structure by indicating the maximum number of intermediary nodes that would need to be involved in any flow across the entire network. A second geodesic graph-level indicator is the *average path length* of the geodesics between all pairs of nodes in a network. The average geodesic length is perhaps a more reliable graph-level indicator than diameter because it aggregates more information into a single measure. Complications arise in using geodesics in networks with two or more components, as there are no shortest paths between entirely disconnected nodes (the distance is technically infinite). This is why centrality scores (see Chapter 9) often use the inverse of distance.

Other connectivity measures may be useful in many cases. Often a more realistic comparison is via a random walk process, which builds from the number of hops a node would have to make to connect two nodes if, at each step of the hop, the node picked the next direction at random. The "hitting

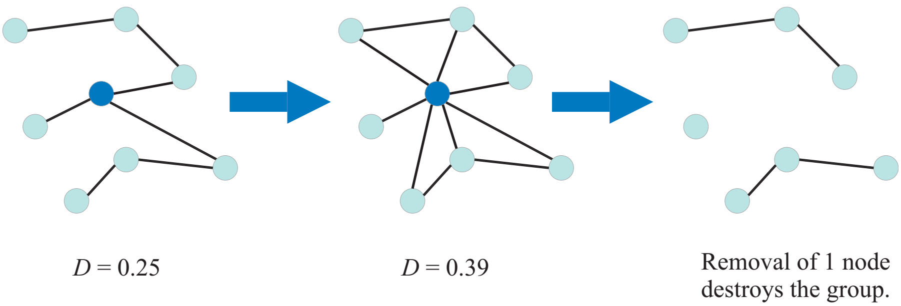

FIGURE 8.4 Connectivity as robustness to node removal

time" is the expected number of hops needed for i to reach j. Because the number of random hops from i to j need not equal the number from j to i (intuitively, if i is less central than j, then it is easier for i to reach j than vice versa), one usually calculates "commute distance" rather than hitting time – that is, the expected number of hops needed to walk from i to j and back to i, which is symmetric. The researcher may also look to the distribution of pairwise distances in a network to get a sense of how spread out it is. One may then split the distances into, say, quintiles and examine the nodes within these levels of cohesion or use distribution comparison methods to nicely summarize the total structural difference between two networks (Handcock & Morris 2006).

Another way to approach cohesion from a connectivity perspective is to consider how difficult it is to break a group apart. Groups that are harder to break apart are more cohesive. This idea was at the core of Simmel's (1950) perspective of the triad as sociologically more meaningful than the dyad because the triad is more robust to the removal of one of its members: with the removal of one member, a triad will become a dyad, but a dyad will become a lone individual. Extending this logic beyond the triad to larger structures, one can think of robustness to removal – or connectivity – as the extent to which a network will remain connected even as nodes are removed. Recall that a key aspect of connectivity is that one is concerned with the arrangement of edges, not necessarily the number. For example, consider the network shown in Figure 8.4.

Even though the network density increases from 0.25 to 0.39, which might normally suggest a more cohesive structure, this increased connectivity is entirely reliant on a single node establishing more ties. The removal of this node would break the structure into three separate parts. From the viewpoint of the group's vulnerability to dissolution, then, the first two structures are equivalent. This illustrates the important issue that networks will vary considerably in how much they are connected by one or a few nodes that link otherwise disconnected parts of the structure. Such individual nodes holding a structure together are called *cutpoints*. Networks with fewer cutpoints are more connected. Further, as in the example shown in the figure, meaningful cutpoints tend to be more central to the overall structure.

8.2.2 Small-World Connectivity

So far, we have focused on the structure of ties as the basis of connectivity without considering differences that may exist in the ties themselves. Granovetter (1973) radically reshaped our understanding of connectivity by drawing attention to the different dynamics among strong and weak ties. Building on Heider's first rule of balance theory, Granovetter showed that transitivity applies only to strong ties, whereas weak ties are often intransitive (i.e., the acquaintance of an acquaintance is not generally an acquaintance). From this basic principle, Granovetter inferred a social-structural pattern in which friendships tend to cluster in smaller groups of strong ties linked with one another by weak ties. In Friedkin's formulation of ridge structures, this is a special case involving many high peaks connected by low ranges.

Such a structure has come to be known as a *small world* for its ability to quickly connect actors who in many ways are socially or geographically distant. This structure helps explain the so-called small-world phenomenon, as when strangers meeting will sometimes exclaim, "What a small world!" when they learn of a mutual contact. In a field experiment illustrating this concept, Milgram (1967) attempted to have a stockbroker in Boston receive packets given to randomly selected people at varying levels of geographic and social distance. The results demonstrated the now famous notion of six degrees of separation, with six being the average number of paths or hops necessary for linking random individuals to the stockbroker (whether or not such paths were geodesics is unknown; for a telling reanalysis, see White 1970b). The relatively short path lengths connecting random nodes in a rather huge network tended to pass through individuals who had high social visibility and held prominent positions in their local communities. In more structural terms, these were individuals with greater centrality. It is worth remembering, however, that the packet failed to reach the target altogether in a high proportion of cases; thus, six degrees separated those individuals who were willing to participate and were reachable in the first place!

Watts and Strogatz (1998) formalized the small-world approach and ways for detecting such structures. In their view, a small-world network structure is large, sparsely connected at the global level, relatively decentralized, and yet also highly clustered. Consequently, the small-world phenomenon operates largely through people who are weakly connected, but these weak ties have important consequences for diffusion processes. For example, diseases will move slowly when networks are highly clustered and approach local maxima but may then spike suddenly and grow as bridging ties lead to a new dense area of the global social structure. This is a very different view of connectivity than the one suggested by structures held together by a few highly central actors (i.e., "stars"). Small worlds form a robust structure for conveying flows, although subsequent work has shown that diffusion is slowed considerably when the item being passed is risky or when a behavior being influenced is perhaps more

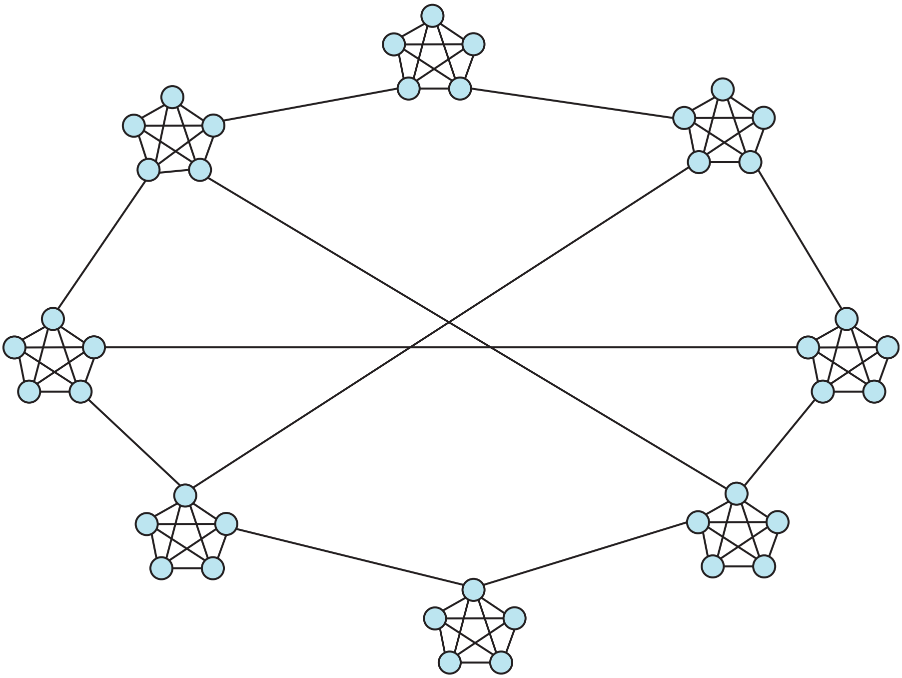

FIGURE 8.5 Ideal-typical small-world network structure

deeply ingrained, in which cases the spread may require multiple partners to adopt or change before an individual will also adopt or change (Centola 2010)

How can one measure the smallness of a world? Watts and Strogatz showed that a small-world structure can be characterized using the ratio of the clustering coefficient to the average path length in the network. That is, small worlds are both clustered *and* have short average path distances. This seems like a paradox until one examines how random ties entering into an otherwise clustered world can create global shortcuts. Consider the structure shown in Figure 8.5.

Here, one sees that a relatively small number of random intransitive (and presumably weak) ties between clusters is sufficient to dramatically lower the overall average path length among *all* the nodes. Thus, the image of a small world adds another layer of complexity to our original view of cohesion depicted in Figure 8.1 by suggesting that the lower-right network may prevail among strong ties and the lower-left network may prevail among weak ties. Thus, being connected in a small world entails both dense local clusters and sparse bridges across homogeneous subgroups.

Gauging the smallness of one's world of nodes and ties requires some additional leverage, either statistical or computational, because the small-world measure is sensitive to size, degree, and type of network in question. For directed one-mode networks, the expected value of the clustering coefficient in a random network with arbitrary degree distribution is given by:

$$C_r = \frac{1}{n}\frac{\left[\langle k^2\rangle - \langle k\rangle\right]^2}{\langle k\rangle^3}, \tag{8.1}$$

where n is the number of nodes in the network and $\langle k\rangle$ and $\langle k^2\rangle$ are the mean degree and mean-square degree, respectively (see Newman 2018; Newman, Strogatz, & Watts 1999). The expected value of the average path length is given by:

$$L_r = \frac{\log(n/z_1)}{\log(z_2/z_1)} + 1, \tag{8.2}$$

where n is the number of nodes, z_1 is the mean degree, and z_2 is the mean number of people two steps away. Intuitively, this equation tells us that the average distance between people decreases as the number of people two steps away are increasingly unique – that is, when z_2 is much larger than z_1. In such cases, the denominator becomes larger, and the overall quantity becomes smaller. This general insight is the root of much work on "biased network" models (Skvoretz, Fararo, & Agneessens 2004), which characterize the probability of reaching new nodes in a random graph as a function of the greater-than-chance likelihood of closing a local triad (the meaning of "bias" in this literature).

A small-world network is one where the clustering is much higher than one would expect by chance and the distance is closer than expected by chance. The original work thus defined the small-world quotient as:

$$\sigma = \frac{C/C_r}{L/L_r}. \tag{8.3}$$

However, this measure tends to be quite sensitive to the size of the network. More recent measures "double normalize" to account for these sorts of size differences. For example, Neal (2017) proposed the small-world index (SWI) as:

$$\mathrm{SWI} = \frac{L - L_l}{L_r - L_l} \times \frac{C - C_r}{C_l - C_r}, \tag{8.4a}$$

where L_l and C_l are, respectively, the path length and clustering expected in a lattice network of the same size and average degree k, given by:

$$C_l = \frac{3(k-2)}{4(k-1)} \tag{8.4b}$$

$$L_l = \frac{n}{2k}. \tag{8.4c}$$

These models assume a large sparse network; thus, they do not work particularly well on small graphs or networks produced by co-occurrences (which we cover more in Chapter 11). For example, collaboration networks (authors linked to each other) are actually the one-mode projection of a two-mode authorship graph (authors linked to papers). Because each paper of size q has to create a fully connected clique of size q, such networks are much more clustered than one would expect by chance and, as such, appear to be more "small world-ish" than they actually are. Formulas like those above for gauging small worlds exist for bipartite projections (Newman, Strogatz, & Watts 1999), but they have not been used often.

In practice, there are often many features driving the shape of a network beyond simple degree distribution. In most cases, a better approach is to simulate networks of the same size, density, and relevant constraints (such as authorship distribution on papers) but to randomly rewire the ties (assign the ties to randomly selected dyads). The small-world coefficient in one's observed network can then be compared to a distribution of small-world coefficients from a large number of bootstrapped random networks. Because most real-world networks will be smaller worlds than random networks, this procedure may require further comparison of networks – for example, researchers might compare multiple high schools or might compare the same high schools over time – to have some analytic purchase on just how small a world it is, after all.

8.3 DETECTING AND EXTRACTING SUBGROUPS

So far, we have examined cohesion from the standpoint of an entire structure. We have proposed ways of conceptualizing and measuring networks as having continuously varying amounts of cohesion – that is, all the aforementioned measures provide graph-level indicators of connectivity as a single measure. While useful at comparing the cohesiveness of networks, these measures do not provide a view into what parts of a structure are *more or less* cohesive and where these parts do or do not overlap. To accomplish these goals, network researchers have developed additional tools to better see *subgroups*, collections of more or less cohesive nodes in a network. These subgroups may be inductively generated from the structure of ties within a network or deductively imposed on the nodes based on a theoretical or substantive interest.

One deductive way to think about cohesion is in terms of nominal boundary conditions and network ties (see Figure 8.1). From this perspective, the researcher asks how the structure of ties separates individuals into subgroups based on node-level qualities. Similar to studying residential racial segregation as the likelihood of contact, network research looks to the structures of interpersonal ties to examine specific intra- and intergroup relations. This approach often involves the use of social categories (e.g., race, class, gender) to define a division of network nodes and then an examination of either how salient the boundary is between groups or the connectivity within groups. For example, research on racial segregation in friendships might begin by using racial categories to classify nodes and then examining the likelihood of ties within and between these subgroups in a high school friendship network. If the racial categories are not

TABLE 8.1 *Odds ratios as a measure of group segregation*

	Member of	
	Same Group	**Different Group**
Friends	A	B
Not Friends	C	D

important in shaping social relations, one would expect friendship ties to be distributed randomly with respect to racial attributes. Freeman (1978a) introduced the *segregation index* to capture this idea as the difference between the number of cross-subgroup ties expected by chance and the number of ties observed, written as $E(X)$ and X, respectively, in the following:

$$Seg = \frac{E(X) - X}{E(X)}. \tag{8.5}$$

By comparing the racial segregation score of several high school friendship networks, the researcher may gain insights into the contexts that facilitate racial integration.

While it is intuitive and provides a simple link to residential segregation, Freeman's index has two important limitations. First, it is not margin free: changing the distribution of the category of interest (say, race) by a constant but not changing the core association between race and friendship choice yields a different segregation score. One antidote to this problem is to use odds ratios. In this case, an odds ratio calculates the relative likelihood that two people in the same category will choose each other as friends. The odds ratio is calculated based on the number of ties among a group and the group's relative size; as illustrated in Table 8.1, then, the odds ratio is calculated as $\frac{AD}{BC}$. Unlike the segregation index, the odds ratio provides a summary measure of the likelihood of intergroup ties that is consistent across networks with different numbers of nodes and subgroups.

Second, the segregation index has no clear maximum. The value of the index can be higher if all nodes are assigned to a single group than if each node is assigned to the most empirically valid group. Because the measure tends to have a monotonically changing score, it is difficult to use the measure as an objective function when searching for informal groups.

A satisfying and contemporary alternative to the segregation index that solves both of these problems is the *modularity score*, which reorganizes the comparison to random in a way that can be maximized meaningfully.

$$\sum_{ij} \frac{1}{2m} \left(A_{ij} - \gamma \frac{K_i K_j}{2m} \right) \delta(C_i C_j). \tag{8.6}$$

Here, m is the number of edges; K is the degree; A_{ij} is the edge weight between ij; $\delta(C_i C_j)$ indicates same group or not; and γ is the resolution parameter.

Substantively, the formula has four parts. The first term $(1/2m)$ is a normalization for size of the network. Within the parentheses, the first part (A_{ij}) captures the observed connectivity, $\gamma(K_iK_j/2m)$ captures the expected value under a particular random mixing model (here, degree mixing), and $\delta(C_iC_j)$ indicates the sorting of nodes into communities. The sum thus increases because there are more ties within group (A_{ij} and $C_i = C_j$) than would be expected by chance $(K_iK_j/2m)$.

The score ranges from −1 to +1, with zero indicating random mixing and 1 indicating complete fragmentation (all ties within the community). Maximizing the score provides a sensible approach to inducing subsets of nodes that have very high within-group density and very low between-group density – a process called *community detection*.

The two features of modularity that carry theoretical weight are the random model and the resolution parameter. Different random mixing models (e.g., simple density, degree matching, two-mode) have been developed for different types of network structures. The resolution parameter captures how different from random mixing a weight needs to be before it contributes to the overall modularity score. When γ is set to be small, the weight need not be too big, and thus the researcher tends to find the maximum modularity in partitions with a small number of big groups. On the other hand, setting γ to be large reveals many smaller groups. The resolution parameter is thus a knob of sorts that tunes modularity to find groups of different scales.

8.4 SUBGROUPS AS COMMUNITIES

From the connectionist standpoint, subgroups of interest are often considered *communities*: these have both dense social bonds through which important resources flow and clear boundaries segregating them from each other. As in the ideal-typical lower-right network in Figure 8.1 at the outset of this chapter, communities tend to be primary groups in which there are strong positive bonds associated with shared identities, cultures, and emotional attachments that give rise to strong ties. At a basic level, a primary group in a larger network structure should have a tie density *within* the group that is higher than the tie density *outside* the group. Such regions of varying density are, by definition, more likely in larger networks in which the number of realized ties quickly begins to outnumber the possible ties. Social forces exist that generate clusters of ties, and theories of tie formation posit a number of plausible mechanisms, which are covered in Chapter 13.

How does one identify and extract such subgroups? The key methodological issue becomes the threshold for determining the density for qualifying a group of nodes as a community. Researchers follow several approaches for detecting the number of communities within networks. Several now-classic measures use graph theory to operationalize group connectivity, boundary salience, or both. We discuss these next. However, in practice, as we will go on to note, many of

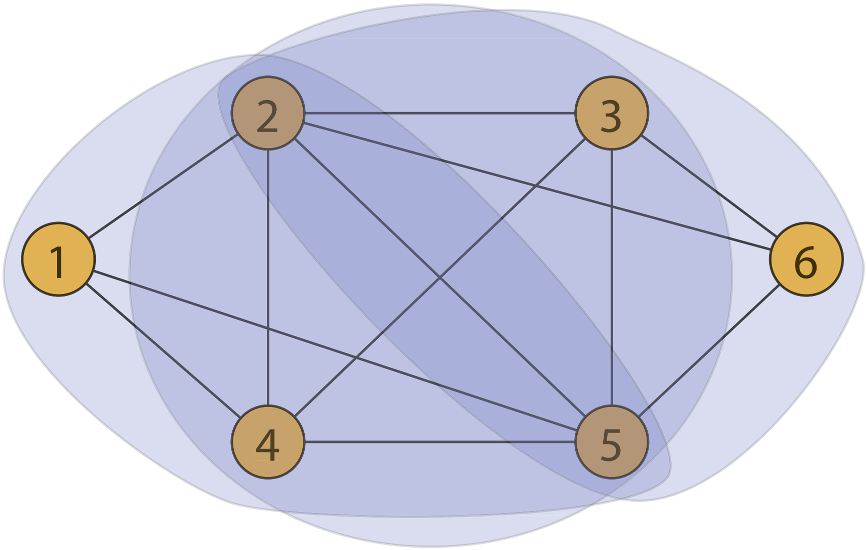

FIGURE 8.6 Small network with many overlapping cliques

these measures are now used more to describe communities found in other ways than to operationalize subgroups.

8.4.1 Graph-Theoretic Approaches

A *clique* is a maximally connected subgroup (i.e., all nodes have ties with one another) and therefore maximizes the connectivity dimension of groups. Many of the features we intuitively think of as characteristic of social subgroups are maximal in a clique. Within a clique, every triad is transitive (i.e., every friend of a friend is also a friend). Consequently, cliques have a density of 1.0, and all nodes are maximally proximate (all dyadic distances = 1). One has to remove $n - 1$ other nodes in a clique to disconnect it, so cliques are also maximally robust to disruption.

However, in most social networks, as a measure of subgroup membership, cliques have two related problems. First, most networks have many small cliques that heavily overlap with one another. Cliques can overlap by as many as $n - 1$ nodes, which means that dense clusters often have many overlapping cliques. Consider the small example in Figure 8.6, which has only six nodes but three deeply overlapping cliques.

Second, because determining cliques does not take into account ties to nodes *outside* of the clique, cliques can be embedded within much wider and denser networks. We could, for example, add any number of ties to each of the nodes

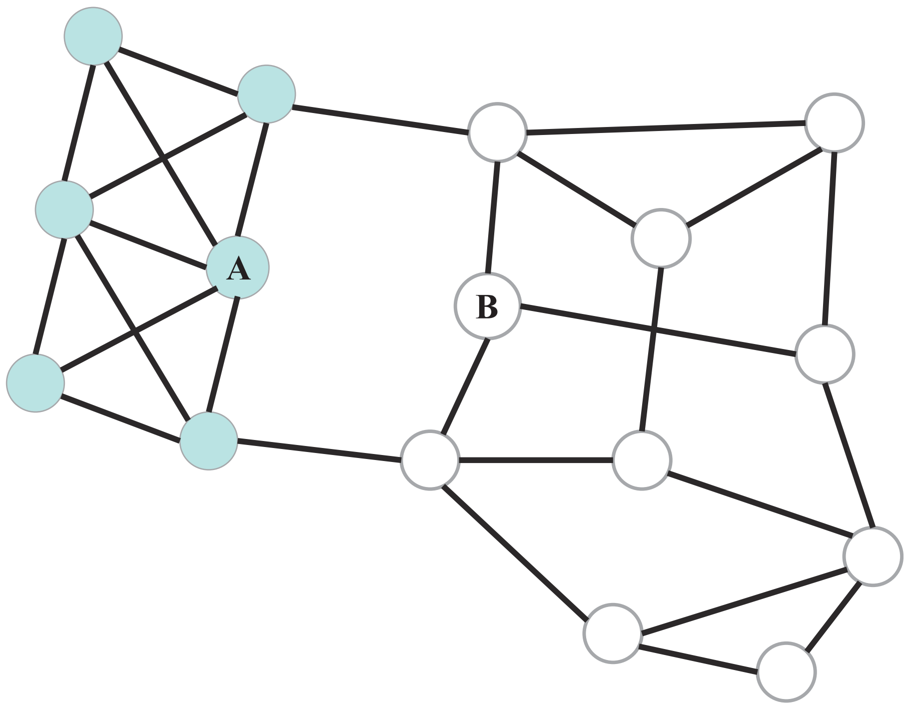

FIGURE 8.7 Network with two 3-cores

in Figure 8.6, reaching out to new nodes, and the clique memberships would not change. Clique membership is thus a good indicator of close connectivity, and the proportion of nodes within a subgroup that share a clique might be a good descriptive measure of connectivity. However, clique memberships and overlaps are rarely sufficient in defining subgroups.

These core limitations have led to generalizations of cliques that are, in themselves, often good measures of the connectivity dimension of group cohesion. For example, the *k-core* is a subgroup in which each node has ties to at least *k* other nodes in the core group. The limitation to ties within the group starts to capture the boundary feature, albeit only indirectly. A *3-core* would therefore be a subgroup in which each node has at least three ties within that core group. An example is illustrated in Figure 8.7, which contains two 3-cores, one shown in blue and the other in white. Again, as a measure of the connectivity dimension, this is useful to indicate how much relational overlap there is in the setting. One could, for example, use the average pairwise *k*-core value to indicate social cohesion; (sub)graphs with higher *k*-cohesion have more shared relations. Like all graph-theoretic models, the measures can be quite sensitive to small changes in the graph. For example, if A and B were to become friends, then the entire structure would become a single 3-core.[1] For this reason, the researcher should employ additional techniques to validate results.

Other graph-theoretic approaches perform similar tasks. They begin by identifying subgroups that are more cohesive and then modifying the criteria for connectivity to see the various regions of cohesion within the structure. A *k-plex*, for example, is like a *k*-core but is indexed to the size of the group: in a *k*-plex, every node is connected to at least *n–k* other nodes. An *n-clique* is a subgroup in which every node is connected by a path of distance *n* or less. A clique in the strictest definition is therefore a 1-clique, and relaxing this to a 2-clique would mean that all nodes are connected with one another directly or through paths of no more than length 2. One may add more stipulations to such definitions. For example, an *n-clan* is an *n*-clique with the added stipulation that all the paths of length *n* must be within the same group of nodes – that is, all nodes are within a subgroup with no more than *n* diameter.

8.4.2 Heuristic Approaches

Most contemporary approaches to community detection have moved away from formal structural definitions. Instead, the trend has been to rely more on computational power to extract communities by optimizing the internal cohesion and boundary salience simultaneously. These sorts of attempts have a long history, dating back at least to the NEGOPY routine from the 1970s (see Richards & Rice 1981), but the field has exploded in recent years (e.g., Moody & Mucha 2013; Mucha et al. 2010). The general challenge with all these approaches is limited computational speed: in larger networks, it is impossible to try all possible assignments of nodes to all possible numbers and sizes of groups.[2] Thus, a bit like visualization layout strategies, each algorithm tries to find the best solution by maximizing a feature that is highly correlated with the general notion of groups.

Although many algorithms are available, they generally fit into one of four broad types of approaches, each turning on a somewhat different algorithmic strategy: (1) spectral methods, (2) divisive methods, (3) diffusion-simulation methods, and (4) direct modularity-maximization methods.

8.4.2.1 Spectral Methods

The earliest attempts at stepping past simple graph-theoretic methods adopted tools from psychometrics and measurement theory used to create low-dimensional representations of high-dimensional data objects. *Factor analysis*,

[1] One key advantage of *k*-cores is that they are fast to compute. So, in very large networks, it is often useful to identify what proportion of nodes are in the largest 3-core, the largest 4-core, and so on, up to some high level of *k*-core connectivity. This *core collapse sequence* identifies roughly when groups rapidly break apart.

[2] iGraph does offer "cluster_optimal" as an option, which does this all-possibilities search. Even on the fastest machines, graphs of more than dozens of nodes are prohibitively time consuming.

for example, is a well-known tool in survey research for combining information on multiple questions into a single summary scale, which works by identifying sets of questions that are highly correlated with one another. Early network methodologists recognized that the inverse of the distance matrix can be treated much like a correlation matrix and that the same factor-analytic tools can be applied to the network. Sets of nodes that are very close to one another in the network are akin to highly correlated questions in a survey and form a single group. This approach, famously used by Cairns and Cairns (1991) to examine peer groups of young adolescents, is among the most common approaches used in developmental psychology. One key advantage of this approach is that authors borrow decision rules from psychometrics, generally considering a factor to be a group if it has an eigenvalue greater than 1. A second advantage is that, as with factor analysis, cross-factor loadings can be used to identify the groups to which a person is connected.

These approaches have been extended as a broad class of *spectral methods* that use the underlying mathematical machinery of factor analysis (a singular value decomposition of an adjacency matrix) to identify groups in networks. Because the models tend to be fast and work well on large networks with clear divisions, they can often be used to preprocess very large networks. However, in our experience, they tend to underperform relative to methods designed specifically in small to medium-sized networks.

8.4.2.2 Divisive Methods

An alternative approach rests on *divisive methods* to find the best spot to break a network apart by deleting nodes or edges. The instinct here is that when a network is split along natural fault lines, the remaining unsplit parts are cohesive groups. The best known of these methods is Newman and Girvan's (2004) *edge betweenness* algorithm. Edge betweenness can be thought of as an extension of *node betweenness*, which is defined as the number of shortest paths a node is part of. Similarly, one can identify the number of shortest paths an edge is on to define edge betweenness. If the researcher iteratively calculates edge betweenness and then removes the edge with the highest score, eventually the network will break into disconnected components; this would be the first split. The process is repeated on the new components until all edges are removed, retaining the set of splits that also maximizes the modularity score (see Equation 8.2). The slowest step in this algorithm is recomputing edge betweenness after each edge removal, but it is an essential step; one cannot simply sort edges in betweenness order based on the full global structure. This algorithm generally performs quite well, returning groups that have the highest modularity scores among the available alternatives, although it is somewhat slower to run.

8.4.2.3 Diffusion-Simulation Methods

The third general approach stems from the idea of social diffusion. In this clearly connectionist view, cohesive groups communicate a lot with each other and share information accordingly. As such, they tend to develop their own unique sets of ideas and shared worldviews that distinguish them from other groups. By simulating a randomly seeded diffusion process many times over a network, the researcher can directly look for sets of nodes that have much in common (see Moody 2001). Recent developments in this area mimic a packet transfer (*label propagation*) or agglomerating sequence of strings built on random walks (known as a *walktrap*). One clear advantage of these methods is that they tend to be quite fast and substantively often match some underlying social diffusion process we are interested in capturing on the network (as we will cover in Chapter 14).

8.4.2.4 Direct Modularity-Maximization Methods

The final approach attempts to maximize an objective function directly related to the groupness of the network. The most common choices are cases that maximize modularity (e.g., Louvain) or odds of an in-group tie (e.g., stochastic blockmodels, KliqueFinder [Frank 1995]). Although these choices represent subtle differences in the approach taken to implement the search over the implicit *state space* (i.e., the set of configurations or states that are possible solutions), the basic idea is the same: slowly grow the partition based on pairs of nodes that are most likely to be in the same cluster, add nodes to clusters they are most strongly connected to, and then swap nodes in or out to adjust and search for an alternative and possibly better fit. The Louvain implementation (Blondel et al. 2008) is a well-known version of this approach that works quickly and has proven largely robust to starting values and data error, particularly implementations that include steps for checking and revising early steps in the algorithmic process (Batagelj & Mrvar 1999; the "Leiden" method [Traag, Waltman, & van Eck 2019]). Modularity-maximization methods will also behave accurately when using valued as well as binary data.

8.5 COMPARISONS AND SENSITIVITY ANALYSES

At this point, you might be wondering which method is best. You might be wanting a fairly straightforward way to compare the many techniques we have introduced and objectively decide on one. We have bad news. The reason we present you with so many options is that really there is no one best way to find communities. In general, we would say that seeing cohesion at the network level is a simpler goal than extracting cohesive subgroups. In fact, you may be able to use the techniques aimed at seeing cohesion as a way to sidestep community detection and extraction. For example, you might simply measure pairwise connectivity instead of trying to see who is in "the same" group. Measuring pairwise connectivity may be particularly useful when dealing with large networks where convergence time can be costly.

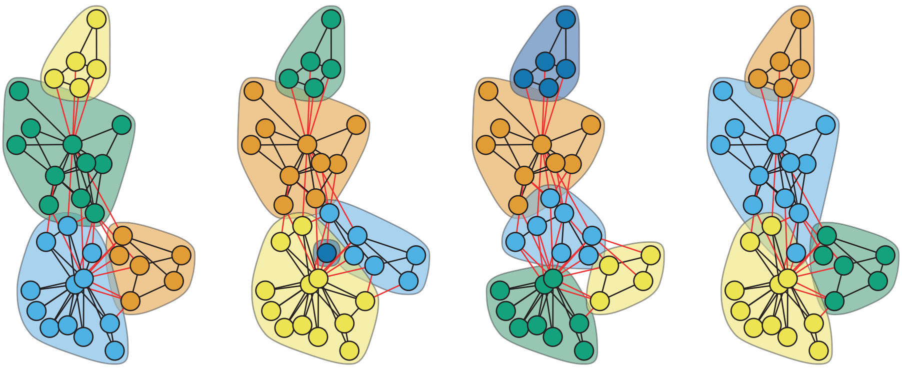

FIGURE 8.8 Comparing four approaches to deriving cohesive subgroups

Recall that one of our primary goals in this book is to point out that many method problems are really theory problems in disguise. Instead of wracking your head about the multitude of ways you could possibly partition your network into subgroups, step back and ask whether your theory requires it. If you are simply interested in seeing how cohesive your network is, you may be able to do just fine without agonizing over subgroup extraction and instead look to measures of similarity, cohesion, and distance among your nodes. When you really do need to partition your network, you will want to combine your substantive knowledge of your data with results from a few different approaches and those that align best with your theoretical approach (e.g., Smith et al. 2020).

Figure 8.8 provides a comparison of these four types of clustering applied to the same network (the karate club data introduced in Chapter 5). Clearly, these methods produce very similar results. However, differences do exist, and it is not clear *a priori* which method is the most suitable for a given network. This leads, once again, to the need to examine consistencies across models and report any glaring problems.

There are two additional frustrations with modularity-maximization methods. The first is determining the number of communities that naturally occur in the network. Some algorithms automatically identify the number of clusters based on the objective of modularity maximization (e.g., walktrap, Louvain). But even with these approaches, users often have to choose a parameter, which indirectly affects the number of clusters returned (the length of the random walks for walktrap, or the resolution value for Louvain). Others ask the user to prespecify the number of clusters directly. Unfortunately, there is rarely a principled way to sidestep this problem that does not involve reversion to some other (almost) arbitrary decision rule. As such, the best option for most applications is to explore multiple solutions and look for consistency across solutions.

For modularity-maximization routines, one usually does a sweep across a wide range of the resolution parameters to see how resolution changes. Weir et al. (2018) showed that there is a fairly limited set of solutions that maximize modularity for a given resolution parameter and provided a rubric for performing this sort of sweep with their CHAMP (Convex Hull of Admissible Modularity Partitions) method. The main result of their work is that the modularity-maximizing set of partitions fall along a convex hull in the space defined by the resolution parameter and the modularity score. As such, any solution that does not fall on that hull has not succeeded at maximizing the modularity at that resolution and need not be examined. Moreover, there is an identity defined by a simple line on this hull, such that each partition on the same line is exactly equivalent – even if found under different resolution searches. Thus, when searching for the best-fitting solutions, the researcher can actually minimize the sets being compared because many will be equivalent. Consider Figure 8.9, which layers over the number of groups identified and placement on the optimal hull.

This plot summarizes the best-fitting partitions from a search set over 175 runs of the Louvain model at a resolution ranging from 0.3 to 2.0. The green O signs indicate the number of communities identified at that resolution parameter value; for example, at the default 1.0, we have 8 communities. We

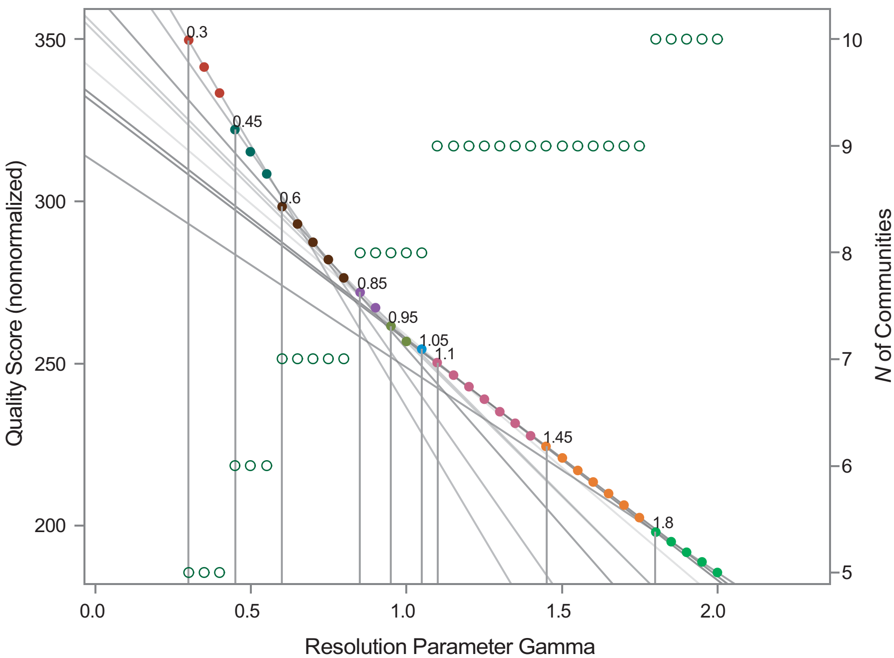

FIGURE 8.9 Resolution parameter sweep

see that the number of communities levels off at 9 across a wide range of resolution values – from approximately 1.1 to 1.8. A stable number of communities is usually a good sign that these are "real" communities. The colored points along the hull indicate sets of points with the same slope in the resolution-by-fit space. It turns out that all solutions with the same slope will be equivalent. Interestingly, in this case, there are distinct solutions within the same size sets. Looking at the line along the hull, we see that for the eight-community solution we have three distinct solutions: one starting at resolution 0.85, one at 0.95, and one at 1.05. For the nine-community solution, we have one solution that runs from 1.1 to 1.43 and another from 1.1 to 1.45. Each color is a unique solution, so despite having produced 175 runs, we have only nine unique maximizing solutions to examine by hand, making it tractable to examine substantively how they differ.

The second common frustration with these approaches is replicability. Even if the same number of communities is specified, different algorithms (and sometimes different runs of the same algorithm) will produce different solutions (as demonstrated in Figure 8.8). For very large networks for which users are trying to simply reduce a too-cumbersome network into a manageable size, these sorts of differences probably do not matter much: the difference between 1,000 communities and 1,100 communities in a network of millions of nodes is probably trivial. But in moderate and small networks, these differences can often matter. For example, in Figure 8.8, the spectral clustering solution differs from all the others in how the top five nodes are treated. Substantive familiarity with a case is usually the best solution to this problem. In the spirit of turning a bug into a feature, one approach that is starting to gain traction is to combine the information from multiple methods into a reweighted network (called *consensus clustering*).

As with all data analysis, the researcher engaged in partitioning networks into communities will need to be guided by theory, substance, and methodological practicality. Comparing results and checking their sensitivity to alternate specifications is a best practice in network analysis.

8.6 STRUCTURES OF COMMUNITIES

While community detection techniques allow the researcher to identify the number of more or less cohesive subgroups, additional methods help examine how subgroups interrelate within a larger structure. Subgroups may be loosely tied to one another, as we saw with the example of small-world structures, which are characterized by tightly knit subgroups connected through relatively weak links. In contrast to small-world structures, subgroups may be tightly coupled with one another through thick interfaces. Again, one can consider these different types of ridge structures with varying peaks and more or less connective ridgelines.

To gauge such structures of communities, Moody and White (2003) developed a technique called *cohesive blocking* in homage to role analysis (discussed in the next chapter). Cohesive blocking examines a network in its entirety and then divides it by removing the smallest subsets of nodes that will disconnect the network (called *cut sets*). The minimum size of the cut set needed to disconnect the graph defines its connectivity. The nodes in the cut set are then added to each "side" of the cut, and the process repeats. Thus, at each stage of the process, the graph is cut at its weakest points. Importantly, though, the researcher also keeps track of how each new graph is related to the prior set, yielding a tree that provides a history of differential embeddedness for all the groups. Theoretically, there is a nice dualism to the identification of cut sets: each (sub)network that can be disconnected by removing k-nodes must also have k nonoverlapping paths linking every pair of nodes in that (sub)network. This allows us to think about how easily various things can diffuse through a network, given that we would expect easier flow in places with many nonoverlapping paths (think of traffic forced to ride across a single bridge compared with places where there are alternative routes).

The cohesive blocking approach builds a nested view of connectivity as *structural cohesion* – a view based on where networks may be more readily split into subgroups. Recall that a component is a network or subnetwork in which all members are reachable through at least a single path. A *k-component* is a maximal subgraph where all members are connected by k node-independent paths which, equivalently, means that at least k nodes would have to be deleted to disconnect them.[3] For example, a 3-component is a subnetwork in which all its nodes have at least three node-independent paths linking each pair of nodes. We discuss procedures for extracting and examining various *k-connected* components in the R tutorial for this chapter. For now, we can use this idea to characterize an entire network structure as having greater connectivity to the extent that it is k-connected at a higher level of k. A network in which three nodes would need to be removed for the structure to be no longer connected (k = 3), also called a *tricomponent*, has a higher level of connectivity than networks where k equals 2 (a *bicomponent*) or 1 (a *component*).

The technique outlined by Moody and White (2003) operationalizes this approach and gives views of various levels of connectivity in a network and the nesting of subgroups. Beginning with a network component as a single connected entity, the technique then iteratively searches for k-connected subgroups at higher levels of k, producing a nested view of the subgroups as connectivity sets. Figure 8.10 shows the connectivity sets for the network

[3] Note that k-components are similar to k-cores but not the same: all k-components are k-cores, but not all k-cores are k-components. There is no node-removal constraint on k-cores because they are defined only by the number of ties shared.

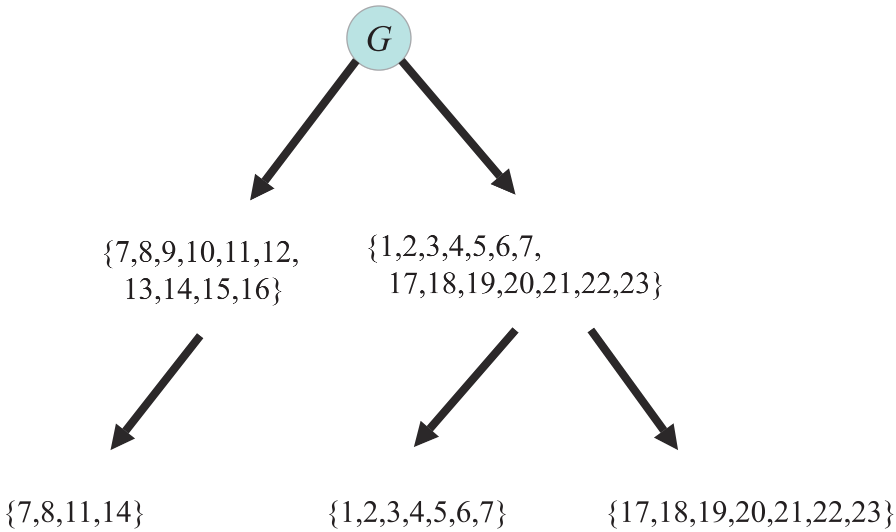

FIGURE 8.10 Connectivity sets for Figure 8.3

graph *G* (taken from the graph in Figure 8.3). Thus, we return to the notion that networks have overlapping regions of connectivity – that is, a ridge structure.

The relatedness of the network can also be seen by building a *blocking matrix*. A blocking matrix rearranges nodes into connectivity sets by permuting the rows and columns of a matrix. For illustration, we sorted the matrix in Table 8.2 to correspond with Figure 8.10. Here, one sees Nodes 1–7 all belong to the same 5-component; Node 7 also belongs to Nodes 8, 11, and 14; that 3-component is embedded within a larger 2-component; and so on. The entire network is connected and therefore is a 1-component. This blocking matrix nicely illustrates the pairwise node connectivity and the global "blocks" of the network. For total network models, summary statistics on the blocking matrix (e.g., mean or median) can be used to summarize the network cohesion overall and to rank networks by their path-based diffusion risk. Moody and Benton (2016), for example, showed that networks with high pairwise average connectivity are at greater risk of disease spread, regardless of relational timing.

Structural cohesion takes us full circle to the roots of connectivity methods. Networks with higher levels of *k*-connectivity have greater numbers of alternate routes linking each node to every other node. The greater the number of alternative paths, the more readily things flow through the network, improving diffusion. For cultural items, such as beliefs or norms, those who are most strongly and redundantly linked to each other would be expected to share the most common information and thus hold the most similar views. For example,

TABLE 8.2 *Blocking matrix*

	1	2	3	4	5	6	7	8	11	14	9	10	12	13	15	16	17	18	19	20	21	22	23
1	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
2	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
3	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
4	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
5	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
6	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
7	5	5	5	5	5	5	5	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2
8	1	1	1	1	1	1	3	3	3	3	2	2	2	2	2	2	1	1	1	1	1	1	1
11	1	1	1	1	1	1	3	3	3	3	2	2	2	2	2	2	1	1	1	1	1	1	1
14	1	1	1	1	1	1	3	3	3	3	2	2	2	2	2	2	1	1	1	1	1	1	1
9	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
10	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
12	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
13	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
15	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
16	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
17	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3
18	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3
19	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3
20	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3
21	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3
22	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3
23	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3

Moody and White (2003), reanalyzing data from Mizruchi (1982), showed that firms that are more structurally cohesive tend to behave similarly with respect to political activity.

8.7 SUMMARY

In this chapter, we discussed the core issue of cohesion and connectivity: what holds a group, community, or society together. Although this is a much larger philosophical and substantive problem than social networks can fully capture, social network analysis provides a set of formal techniques for identifying groups and subgroups and examining how they interrelate with one another. These methods fit naturally with the vision set out by sociologists from the inception of the discipline. However, cohesion and connectivity are variable aspects of any system. The same methods we outlined here are currently being applied in a wide number of settings to explore topics ranging from the interconnectedness of transportation systems to the consequences of removing species in a networked ecology. Connectedness is, in many ways, the *leitmotif* of our current era of rapid flows of communication, trade, and migration; but paradoxically, so too is the constant sense of disconnection and fragmentation. Network methods have much to offer in better understanding this tension between growing connection and disconnection and seeing this tension's structural origins.

SUGGESTED FURTHER READING

Abbe, Emmanuel. 2018. "Community Detection and Stochastic Block Models: Recent Developments." *Journal of Machine Learning and Research* 18: 1–86. (A nice review of the stochastic blockmodel approach to community detection.)

Christakis, Nicholas. 2019. *Blueprint: The Evolutionary Origins of a Good Society*. New York: Little, Brown Spark. (A sweeping evolutionary perspective that synthesizes a great deal of research on networks and cohesion.)

Coleman, James. 1961. *The Adolescent Society*. Glencoe, IL: The Free Press. (An early study of fully connected cliques within ten high schools, relating them to notions of the leading crowd and other groups.)

Everton, Sean F. 2018. *Networks and Religion: Ties That Bind, Loose, Build-Up, and Tear Down*. New York: Cambridge University Press. (Works through a series of models in fruitfully combining the social scientific study of religion with network modeling.)

Fortunato, Santo. 2010. "Community Detection in Graphs." *Physics Reports* 486: 75–174. (A comprehensive 100-page review on the problem of community detection in physics.)

Freeman, Linton C. 1972. "Segregation in Social Networks." *Sociological Methods and Research* 6: 411–30.

1992. "The Sociological Concept of 'Group': An Empirical Test of Two Models." *American Journal of Sociology* 98(1):152–66. (Freeman devoted much energy to

the theoretical problem of cohesive groups, and these papers exemplify his approach, which should help guide sociological approaches to identification of communities.)

Granovetter, Mark. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology* 91: 481–510. (Embeddedness is the individual dual to collective cohesion. Here Granovetter powerfully demonstrates how action models must include localized resources and constraints captured by networks to avoid being either atomistic or overdetermined. The paper has become the classic statement of networks and economic action. See also Uzzi 1997.)

Knoke, David. 1990. *Political Networks: The Structural Perspective*. New York: Cambridge University Press. (Knoke has set the agenda for network analysis of politics. This work provides a summary of network models for political action across a broad set of empirical cases.)

Lee, Cheol-Sung. 2018. *When Solidarity Works: Labor Civic Networks and the Welfare States in the Market Reform Era*. New York: Cambridge University Press. (Provides a detailed analysis of worker solidarity and cohesion across four countries; an excellent application of structural thinking and network analysis to substantive questions of cohesion.)

Lin, Nan. 2002. *Social Capital: A Theory of Social Structure and Action*. New York: Cambridge University Press. (See previous note in Chapter 1.)

Markovsky, Barry, and Edward J. Lawler. 1994. "A New Theory of Social Solidarity." Pp. 113–37 in *Advances in Group Processes*, vol. 11, edited by B. Markovsky, J. O'Brien, and K. Heimer. Greenwich, CT: JAI Press. (Provides a clear social psychological foundation for social cohesion, which can then inform network methods.)

Mucha, Peter J., Thomas Richardson, Kevin Macon, Mason A. Porter, and Jukka-Pekka Onnela. 2010. "Community Structure in Time-Dependent, Multiscale, and Multiplex Networks." *Science* 328: 876–78. (Shows how one can leverage multilayer networks to find communities that bridge waves in dynamic data.)

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White, Douglas R., and Ulla Johansen. 2006. *Network Analysis and Ethnographic Problems: Process Models of a Turkish Nomad Clan*. Lanham, MD: Lexington Books. (Applies insights from structural cohesion and kinship structures to identify how changes in network cohesion reflect broader social change.)