Measures for Egocentric Network Analysis

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Objectives

In this chapter, you will learn an array of ways in which properties of ego networks are conceptualized and measured. You will learn about how ego network data differ from complete network data, particularly in terms of data collection, management, and analysis. In addition, you will learn about the types of questions that egocentric analyses can address. A majority of this chapter is dedicated to the different indices that are used to characterize ego networks, with special attention given to the types and sources of data that are needed to calculate these indices. The conceptual and measurement tools in this chapter are essential for performing the more advanced egocentric analyses that are introduced in subsequent chapters.

Egos and Alters

It is generally agreed that being connected to others matters. Students who can get support from other high-achieving students do better. Teachers who share best practices with others expand their own teaching repertoires. School leaders who can turn to the “right” others for advice are in a better position to make good decisions. Implicit in all three situations is that an individual's (ego) connections with others (alters) provides access to some instrumental (e.g., advice) or expressive (e.g., support) resource that may, in turn, be beneficial. The structure and content of these relations between an ego and a set of alters is the focus of egocentric network analysis. Egocentric analysis shifts the analytical lens onto a sole ego actor and concentrates on the local pattern of relations in which that ego is embedded as well as the types of resources to which those relations provide access.

Purpose

Whereas the previous chapter focused on concepts and measures most appropriate for complete network analysis, this chapter shifts the perspective to the analytical level of a sole focal actor—ego. Here, the emphasis is on an individual (ego) and her or his connections with others (alters). Therefore, egocentric analysis is primarily concerned with describing how individuals are embedded in local social structures and, ultimately, how these individual indices of social structure relate to varied outcomes. For example, ego-level analysis can be used to ask questions such as whether a “well-connected” teacher is more or less likely to be measured as an effective teacher or whether students whose connections are to similar others are at a disadvantage when it comes to learning something new. Unlike the previous chapter, the focus is on an individual actor and that actor's relations—local structures that are referred to as ego-neighborhoods. This chapter introduces the concepts and measures that are used to describe properties related to these neighborhoods. The following chapters go on to demonstrate how these different indices are then used in statistical models that associate these properties with outcomes that are of interest to educational researchers.

Why Study Ego Networks?

The study of ego networks represents the intersection of the social network perspective and its emphasis on the importance of relations and the types of data that have long been preferred by mainstream social science. That is, ego-level analyses can and often do incorporate information about actors' attributes as well as their relations with others. An ego's network is considered a source of an array of important resources, including support, information, normative pressures, influence, and so on. All these different resources shape an individual ego's attitudes and behaviors. For example, as hypothesized by Coleman (1990), if a student's parent is embedded in a dense, redundant ego network with other students' parents (an ego network in which all parents know each other), then these networks with high social closure provide an important source of monitoring that exerts normative pressure on that student's behavior. Or consider Maroulis and Gomez's (2008) study of students within one small high school. Using ego network data, they concluded that egos with highly dense networks that consist of low-performing peers yield the largest negative effect on student achievement, and highly dense ego networks of high-performing peers yield the largest positive effect on achievement. Both examples are grounded in the broad literature on social capital (Chapter 10 is dedicated to this topic) and demonstrate how theory and sociometric data are used to examine the importance of an ego's immediate alters on ego's behaviors and attitudes. Generally, there are two instances in which egocentric analyses are warranted. The first instance if is one's research question is about individual entities across different settings (networks). For example, does the size of a student's within-school friendship network influence his or her attachment to school? To address this question, you would need information about the size of each ego's friendship network (the number of alters that the person has nominated as friends) and some composite measure of school attachment likely derived from a set of survey items. Alternately, you would also use an egocentric approach if your research question is about different patterns of interaction within defined groups. An example of this would be a question such as whether a teacher's centrality is related to his or her attitude toward a school reform effort. Theories that frame these types of questions focus on (1) the topography of an ego's network and (2) the composition of that network, including the attributes of the alters to whom ego is connected.

Sources of Egocentric Data

The concepts and measures to be discussed in this chapter can be used on complete networks or egocentric data. The difference is that the focal analytical point is the ego and how that ego actor is embedded in some larger social structure. Ego actors can be individual persons, groups, or even some larger entity. Education-related ego network analysis typically focuses on individual actors such as students (Farmer et al. 2011), teachers (Penuel, Riel, Krause, & Frank, 2009), or administrators (Moolenaar, Daly, & Sleegers, 2011).

There are two ways in which ego network data emerge (Hanneman & Riddle, 2011b). First, ego network data can be generated from a sociometric survey administered to some sample of respondents, such as 1,500 children drawn from the population of 3.4 million pre–K through Grade 8 students. Using this example, you could survey all children in the sample and ask them to identify all the others with whom they have some type of relation and then report on the connections among these others. In addition, the survey could capture attributes about these named others, including, for example, gender. Alternatively, you could also employ a snowball approach in which each ego identifies others with whom they have some relation, then these others are asked about their relations with additional others. As the process moves forward, the size of the network increases until all egos of the component originally sampled are included. This latter approach, as noted in Chapter 3, is useful in finding members of hard-to-reach populations. As such, its use in educational research is not widespread. Most egocentric studies in educational research draw a sample from a target population and employ a sociometric instrument to collect relational and attribute data.

Egocentric network data generated in this manner, however, cannot be used to describe the overall embeddedness of the networks in some larger population. On the other hand, they can be used to indicate the prevalence of different kinds of ego networks in even very large samples. Analyses done along these lines result in a data structure that consists of a collection of networks. Because the actors in each network (ego and alters) are likely to be different, each pair of actors (ego and alter) needs to be treated as a separate row in a standard actor-by-attribute data file. This process is described in Chapter 4 under the section “Managing Relational Data.”

A second way in which ego network data can be generated is by extracting them from complete network studies. This is the approach that will be used to generate the example data referenced in this chapter. Using this approach, you might, for example, extract all the ego networks from a complete network so that the ego networks of tenured teachers could be compared to the ego networks of untenured teachers; therefore, you can ask a question such as whether tenured teachers have denser ego networks than untenured teachers. However, when generating a sample of ego networks from a complete network, a thorny analytical issue arises: each ego network is not independent of the other; therefore, normal statistical assumptions do not apply. Part III wades into these issues by reviewing the different ways in which properties of complete or ego networks can be statistically analyzed.

It should be noted that, unless sampled from a dense complete network (i.e., one in which ego and alters are well connected), it is unlikely that one's ego network will overlap with another's (Knoke & Yang, 2008). Therefore, the measures discussed in this chapter are based on the attributes of alters associated with unconnected respondents (egos). Of course, this approach contrasts with the concepts and measures discussed in the preceding chapter in which the focus was on all the ties among actors in a network whose boundary was clearly specified (complete network-level analyses).

In addition, most analyses of ego networks use binary data: Two actors are either connected or they are not. This makes the analytical task of defining an ego's “neighborhood” much easier. However, if the relational data between ego and alter is valued—that is, the strength of the tie has been measured—you have to decide the point at which a tie exists. For example, if you have information on the frequency with which ego collaborates with a given alter measured on a four-point frequency scale ranging from 1 (the least frequent) to 4 (1–2 times a week), then a choice has to be made as to whether an alter is considered part of that ego's neighborhood. This is typically done by exploring several different cut-off values and working with the one that makes the most sense given your conceptualization of the relation.

Finally, while most analyses of ego networks use simple graphs—binary data that simply indicate whether an undirected tie is present between two actors—it is possible to incorporate directed relations into ego network analysis. This enables you to define two different types of ego neighborhoods (Hanneman & Riddle, 2011b). The first is an “out neighborhood,” which includes all the actors to whom ego sends a tie. Conversely, a directed ego network can be defined as an “in neighborhood,” which simply includes all those actors who send ties to ego. Using these two types of neighborhoods, you could also define a neighborhood as consisting only of reciprocated ties. The choice of defining ego neighborhoods is driven by the questions motivating the research.

Example Data

To describe and define these ego-level concepts and measures, this chapter will rely on the School Leaders data set. More specifically, these ego network data have been transformed so that they are nondirected and binary; a tie is either present or absent and is nonvalued. This is the simplest type of ego network data, which makes defining the ego neighborhood a straightforward task. In addition, these ego-level data have been extracted from the complete network; therefore, they have been generated by the second of two means just discussed. Given that the original data set captures 11 relations among 43 actors over 3 years, this chapter will focus on and present a narrower sliver of these rich data.

Recall from Chapter 4 that these multiplex data include ties that have been measured on a four-point frequency scale, with a high score of 4 indicating that ego engaged in that relation 1 to 2 times a week. Therefore, in addition to selecting only one relation on which to focus, the data have been transformed so that a tie between two actors is either present or not (a process referred to as dichotomization). More specifically, the egocentric concepts and measures to be demonstrated through these data will focus on the “information about work-related topics” relation. To generate these relational data, ego was asked, “How often do you turn to each Administrative Team member for information on work-related topics?” The data have been dichotomized so that only those ties that were originally coded a 3 or 4 are now 1s, indicating that there is a relation between ego and alter. Any tie that was originally absent or coded 1 or 2 is now a 0, indicating that a tie does not exist. Furthermore, the relations were symmetrized using a weak criterion: If one actor reported a tie (1), then the relation is considered present. As noted earlier, it is possible to examine directed relations in egocentric network studies, or what are referred to as out- and in-neighborhoods: ties sent or ties received. Finally, since the data were collected once every 3 years, this chapter will focus solely on this one nondirected relation in the third year. These decisions were primarily driven by this chapter's intent of keeping the presentation of egocentric analyses as succinct as possible. Along these lines, seven of the most commonly used concepts and their related measures are presented using these data and analyzed at the ego level.

There are two different ways in which egocentric data extracted from the School Leaders data set can be stored and managed prior to analysis. The first manner is most appropriate when ego network data from some larger population of individuals has been sampled. When collected in this manner, you need to keep track of lots of different information: characteristics of ego, characteristics of ties that ego has with alters, characteristics of alters, and aggregated characteristics of each ego network. Managing all this different information requires that the data be reshaped so that each ego–alter pair, in essence, becomes its own data file. A survey, for example, that captures five different types of relations and up to five alters generates 25 data files. All these dyadic data files can then be read into a few different programs (e.g., R, GAUSS, STATA/MATA) that will then append them into one data file with ego's unique ID, alters' IDs, and any other data needed for the alters. These applications, which employ matrix-level programming language, can then be used to calculate an array of aggregated measures related to ego's networks (discussed in this chapter). This is the format in which ego network data are stored, managed, and processed when collected from a sample of egos drawn from a target population. Managing ego network data in this manner requires you to be fluent and comfortable moving data from one format to another, often across different computer applications. Fortunately, there are several how-to guides that users can consult when doing this type of work using applications such as SAS (Haythornthwaite & Wellman, 1996) and SPSS (Müller, Wellman, & Marin, 1999). There are also some tools available that calculate ego network measures (the same measures to be discussed in this chapter) and export them into these common statistical packages (e.g., Egonet and E-Net, discussed in the book's final chapter).

Egocentric network data can also be stored in a nodelist format, which is an efficient way to store binary ego data that have been extracted from a complete network and is the preferred method for widely used applications designed exclusively for social network analysis. Attribute data can also be stored in this format, which enables these types of variables to be merged with the relational data (this utility is also available in these applications). Because the example egos used in this chapter data have been extracted from a complete network study, this latter nodelist format is preferred. Table 7.1 shows the egocentric network data for three school leaders (Leaders 1, 25, and 35) as well as a separate data file that includes data on two attribute variables (self-efficacy score and gender) in nodelist format for all 17 actors that are included in these ego networks. For example, Leader 1's ego neighborhood consists of Leaders 3, 4, 18, 27, 28, 36, and 38; that is, Leader 1 exchanges information about work-related topics with these seven different alters. The bottom panel in Table 7.1 includes information on two attribute variables for all 17 actors (columns 2 and 3). For example, Leader 1 has a value of 1 under the column labeled gender (1 = Female; 2 = Male) and an efficacy score of 6.05. Once the data are in either format (dyadic or nodelist), it becomes possible to examine an array of characteristics that illustrate an ego's neighborhood.

Table 7.1 Egocentric Network Data for Three School Leaders in Nodelist Format. For example, Leader 1's ego neighborhood consists of Leaders 3, 4, 18, 27, 28, 36, and 38; that is, Leader 1 exchanges information about work-related topics with these seven different alters. The bottom panel in Table 7.1 includes information on two attribute variables for all 17 actors (columns 2 and 3). For example, Leader 1 has a value of 1 under the column labeled gender (1 = Female; 2 = Male) and an efficacy score of 6.05. Once the data are in either format (dyadic or nodelist), it becomes possible to examine an array of characteristics that illustrate an ego's neighborhood.

```
DL
N = 17
FORMAT = NODELIST1 DIAGONAL PRESENT

 1   3   4  18  27  28  36  38
25   3   4  18  27   8  21  24  32  34  42
35  21  13

DL
NR = 17, NC = 2
Gender Efficacy

     1      1      6.05
    13      1      8.27
    18      2      5.00
    21      2      7.44
    24      1      5.22
    25      1      6.94
    27      1      5.06
    28      2      7.61
     3      1      7.39
    32      1      5.88
    34      2      5.11
    35      2      7.44
    36      1      7.72
    38      2      7.56
     4      1      4.89
    42      2      8.06
     8      2      7.50
```

Egocentric Measures

Regardless of how they are stored and managed, there are two types of measures that can emerge from egocentric data (Valente, 2010). First, compositional measures are those created by counting or taking the average of egocentric network variables. An example of this type of measure in the School Leaders data set would be the number or proportion of principals in one's ego network. A similar example that focuses on attitudes in one's ego network would be the number or proportion of those alters with high or favorable perceptions of innovation (another attribute that was measured on the survey instrument across all 3 years of data collection). Variance measures, the second type of measure to emerge from egocentric data, are simply those that are derived by calculating the variance or standard deviation of the egocentric network variables. For example, the standard deviation of the "raw" efficacy scores is a variance measure, which would serve as an indication of the amount of variability in efficacy available in one's egocentric network. Another example from an egocentric study of students would be the standard deviation of the grade point average of an ego's alters.

Table 7.2 Types of Questions Used to Elicit Egocentric Network Data. Data generated from these types of questions can be used to create compositional and variance measures on each ego's network.

Characteristic	*Example*
Strength of relationship	Closeness, acquaintance, stranger, how long known
Frequency of interaction	How often talked to, how often sought advice from
Type of relation	Family, friend, colleague
Socio-economic characteristics	Educational attainment, income, occupational title
Demographic characteristics	Race, age, sex
Substantive characteristics	Attend class regularly, perceptions on innovation, support current administration
Content of interaction	Discuss work-related issues, seek advice from, or input on a work decision

Source: Valente, T. W. (2010). *Social networks and health: Models, methods, and applications*. New York: Oxford University Press.

Taken together, egocentric network data are used to describe an individual actor's personal network. Building on the information introduced in Chapter 4, there are seven types of network questions that can be asked to induce information about one's ego networks. Table 7.2 reviews these seven types. Both compositional and variance measures can be derived from these questions. These measures can then be related to an individual ego's attitudes and behaviors. There are several standard measures that can be calculated from egocentric network data, including size, strength, diversity, centrality, constraint, and brokerage. In some cases, these measures require relational data and attribute data from both ego and alter. In other cases, the measures simply require relational data.

Size

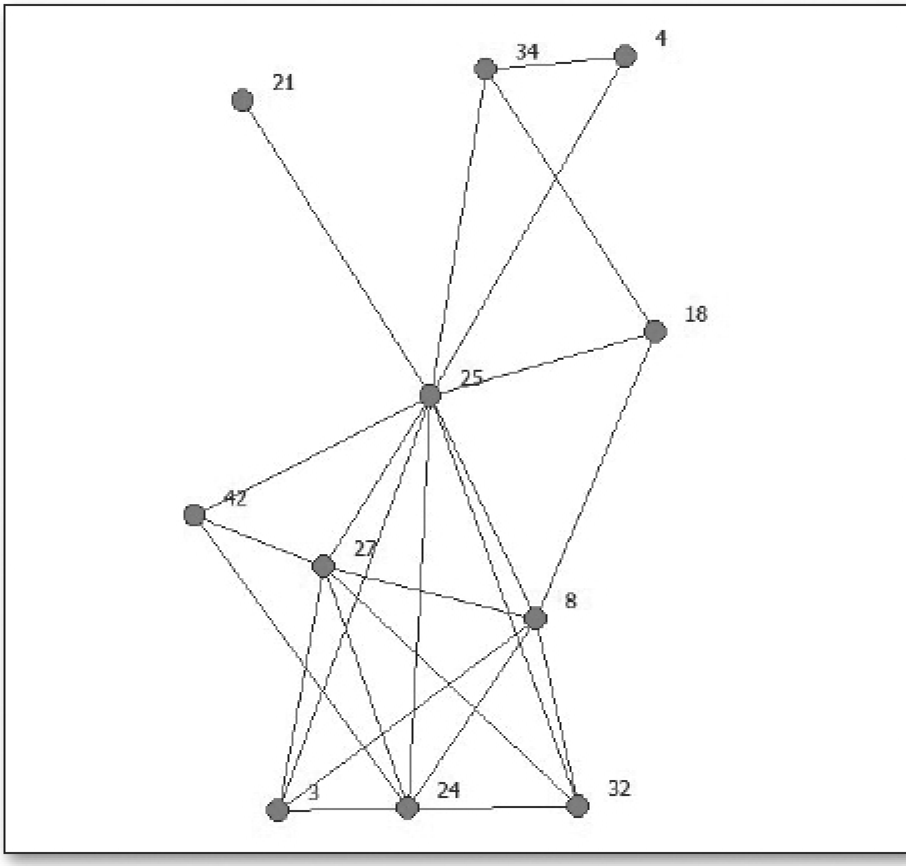
This first characteristic of an ego's neighborhood, size, is very much related to the same idea for a whole network (the same goes for the next two characteristics: density and distance). This is one of the most straightforward characteristics of an ego network: the number of alters that are directly connected to ego, a calculation that only requires relational data. Here, you simply need relational data about the number of alters with whom ego is connected. Size, therefore, is a count of the number of alters provided in responses to a name generator. The size of ego networks typically ranges from 0 to 6, since a name generator typically limits the number of alters that ego can list. In the School Leaders data set, egos were given a list of potential alters, therefore providing a high upper limit on the number of alters in one's network. As discussed in Chapter 4, you must be mindful of the cognitive burden that any name generator places on the respondent.

Consider Leader 25, row 2 in Table 7.1. This table indicates that the size of that ego's network is 10; ego has 10 others with whom he or she exchanges information on work-related topics. Size matters, as it indicates the amount of potential resources available in one's network. For example, a school leader with a small ego network may be at a disadvantage when it comes finding out information about topics relevant to one's job performance. While this makes sense on some level, this is the type of issue that can be investigated and formally tested using egocentric data. Figure 7.1 provides a graph that illustrates the size of Leader 25's egocentric network. From this figure, it is plainly evident that ego exchanges information about work-related topics with a fairly large number of other school leaders.

Density

A second standard characteristic of an ego's neighborhood is density: the extent to which an ego actor's alters are connected to one another. Similar to density measured at the complete network level, this measure is a percentage calculated from the number of ties present divided by the total number of potential ties. More formally, assuming that relations are nondirected binary (present/absent) ties, the density, *D*, measure is the ratio of the number of reported dyadic ties, *L*, among alters divided by the maximum possible dyadic ties (Knoke & Yang, 2008):

Figure 7.1 Graph of One School Leader's Egocentric Network (Leader 25). School Leader 25 has 10 alters—that is, 10 others with whom he or she exchanges information on work-related topics.



$$D = \frac{L}{C_N^2} \qquad \text{[Equation 7.1]}$$

where $C_2^N = \frac{N!}{2! \times (N-2)!}$. For example, suppose ego has five alters and reports only three relations among them. Because $C_5^3 = \frac{5!}{3! \times (5-3)} = \frac{(1 \times 2 \times 3 \times 4 \times 5)}{(1 \times 2 \times 3) \times (1 \times 2)} = \frac{120}{12} = 10$, the density is $D = \frac{L}{C_N^2} = \frac{3}{10} = 0.30$ or 30%. The closer this value is to 1.0, the denser one's ego network. This formula can also be adapted to handle binary directed relations, valued nondirected relations, and valued directed egocentric data. But, given the transformation of the School Leaders data set, Equation 7.1 is appropriate, as the data are binary and nondirected; that is, either a mutual relation is present between actors or it is absent. Applying this equation to School Leader 25, the density of her egocentric network is 0.31, suggesting that slightly less than one-third of potential ties are present in this ego's network.

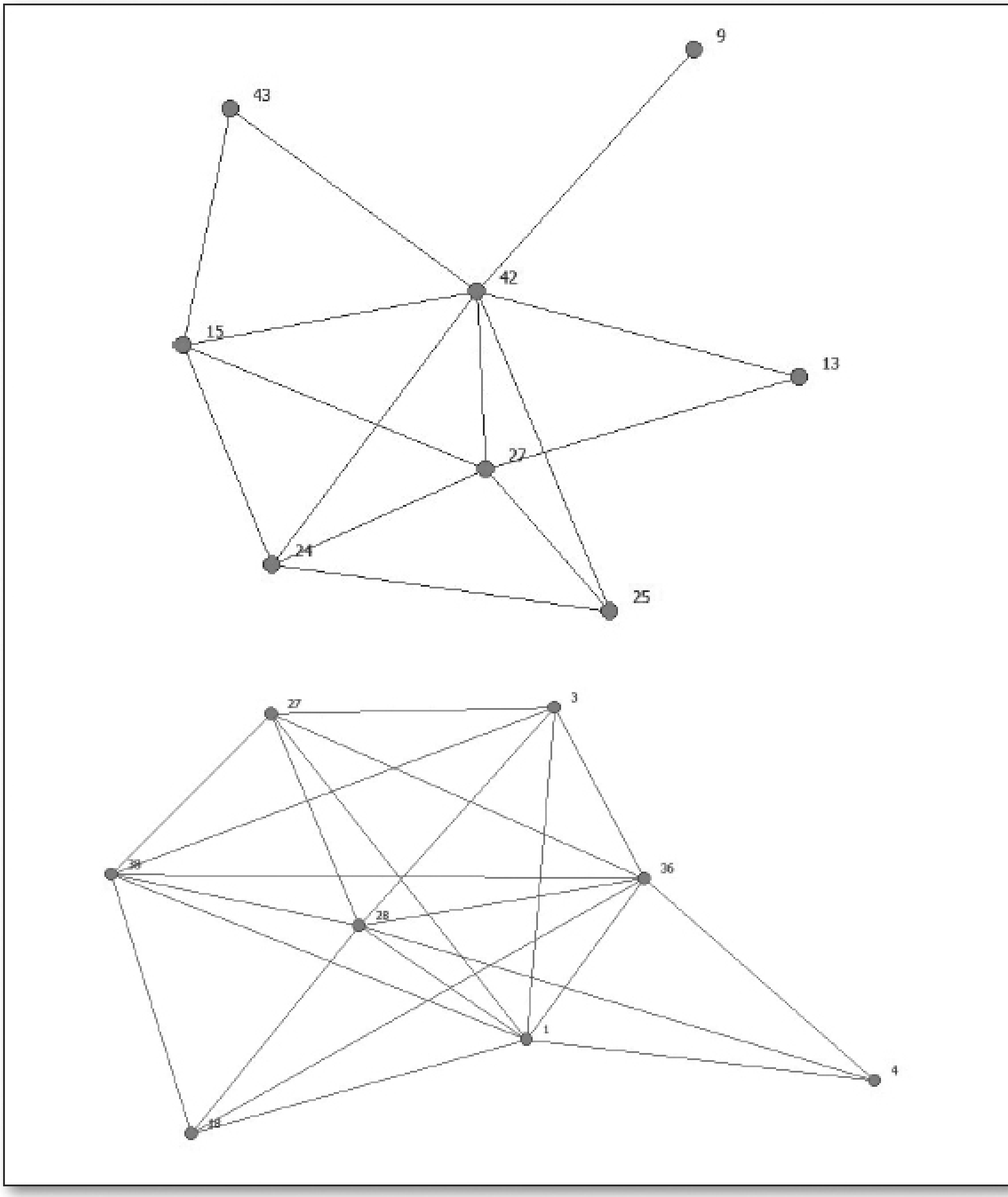
Regardless of which density formula you need in order to compute this characteristic, the important piece to keep in mind is that the instrument used to collect egocentric data must elicit alter-to-alter data. Put another way, in addition to collecting relational data about ego and his or her alters, relational information on each pair of alters must also be collected. This is automatically done when egocentric studies are derived from complete networks (as in the School Leaders data). However, when egocentric data are sampled from some target population, the name interpreter must induce this type of relational data. This is typically done by asking ego to evaluate the relationship between each pair of alters, a process that puts a burden on the ego respondent.

Similar to measuring density on a complete network, the measurement of egocentric density is important for several reasons. Dense local structures exhibit high social closure, indicating that one's behaviors or attitudes are unlikely to escape the observation or critique of others. Viewed from this perspective, dense networks reinforce prevailing norms and behaviors and insulate one from outside influences (these can be, however, either good or bad). Those ego neighborhoods that display little social closure—that is, they are less dense—may have greater freedom to act or think but have limited access to the instrumental or expressive resources available in their local neighborhoods. These less dense networks, often referred to as radial networks, can also be favorable or unfavorable, depending on the behavior or attitude that you are interesting in studying. In fact, density is a foundational concept and measure in the literature on social capital. Figure 7.2 shows two ego networks from the School Leaders data set that are of the same size—meaning that they have the same number of alters (seven)—yet they vary in terms of their density. For example, the density for School Leader 1 is 71% versus 33% for School Leader 42. When comparing these two figures, it is evident there is more connectivity among alters in School Leader 1's egocentric network than there is 42's.

Distance and Diameter

The next two characteristics of egocentric neighborhoods are closely related. The measures for these characteristics parallel those for complete networks, the difference of course being that they are calculated on each ego network separately. The first of these, average geodesic distance, simply refers to the mean of the shortest path lengths among all connected pairs of alters in ego's network. If every actor is connected to every

Figure 7.2 Graphs of Two Egocentric Networks with the Same Number of Alters, but Different Densities. The density for School Leader 1 is 71% (bottom) versus 33% for School Leader 42 (top).



other actor (therefore, density = 100%), the average geodesic distance is one. Second, the diameter of an ego network equals the length of the longest path between connected actors. This translates into the number of “steps” that separate the two most distant actors in an ego's network.

Applying these measures to School Leaders 1, 25, and 35 highlights the differences among these three ego networks. For example, the average geodesic distance for School Leader 1 is 1.29, meaning that, on average, it takes a little more than one “step” for any actor to reach another. This value, however, cannot even be calculated for the other two ego networks because if one or more pairs of alters cannot reach the other except through ego, this measure is undefined and left blank. The diameter of School Leader 1's network, which equals 2.00, is also different from the other two egos. Again, the diameter for these two egos cannot be calculated, as one or more pairs of alters in these ego networks cannot reach the other except through ego, so this measure is also undefined and will be blank.

Figure 7.3 Egocentric Network of School Leader 35 Showing Distance and Diameter. School Leader 35's ego network is small (size), with its two alters unable to exchange information work-related topics without going “through” ego.

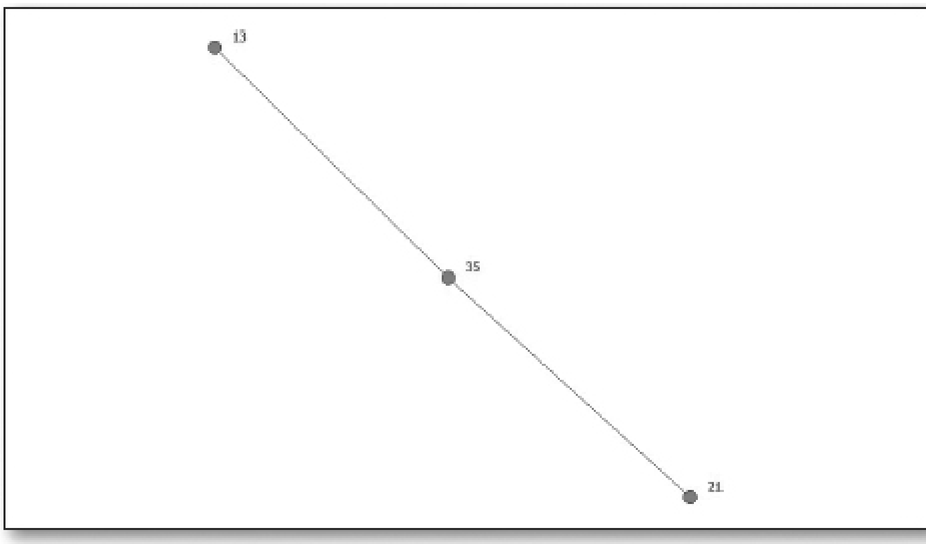


Figure 7.3 illustrates this point by showing a graph of School Leader 35's ego network. It is obvious that this ego's network size equals 2, and that those two alters are only connected to ego. The average geodesic distance and diameter cannot be calculated, as School Leaders 21 and 13 cannot reach each other except through ego (School Leader 35). Recall that the relation constituting these ego networks is “exchange information on work-related topics.” Therefore, School Leader 35's ego network is small (size), with its two alters unable to exchange information on work-related topics without going “through” ego. Given these characteristics, you can question whether such an ego network is disadvantageous for School Leader 35, particularly if these characteristics were related to an outcome such as the successful implementation of a schoolwide reform effort. An ego network that is both small and so poorly connected is unlikely to be associated with this particular desired outcome, a hypothesis that can be formally tested, which is discussed in the following chapter.

Tie Strength

Another characteristic of ego networks that may be of interest to educational researchers is tie strength. This characteristic shifts the focus onto the strength of the relationship between ego and each named alter

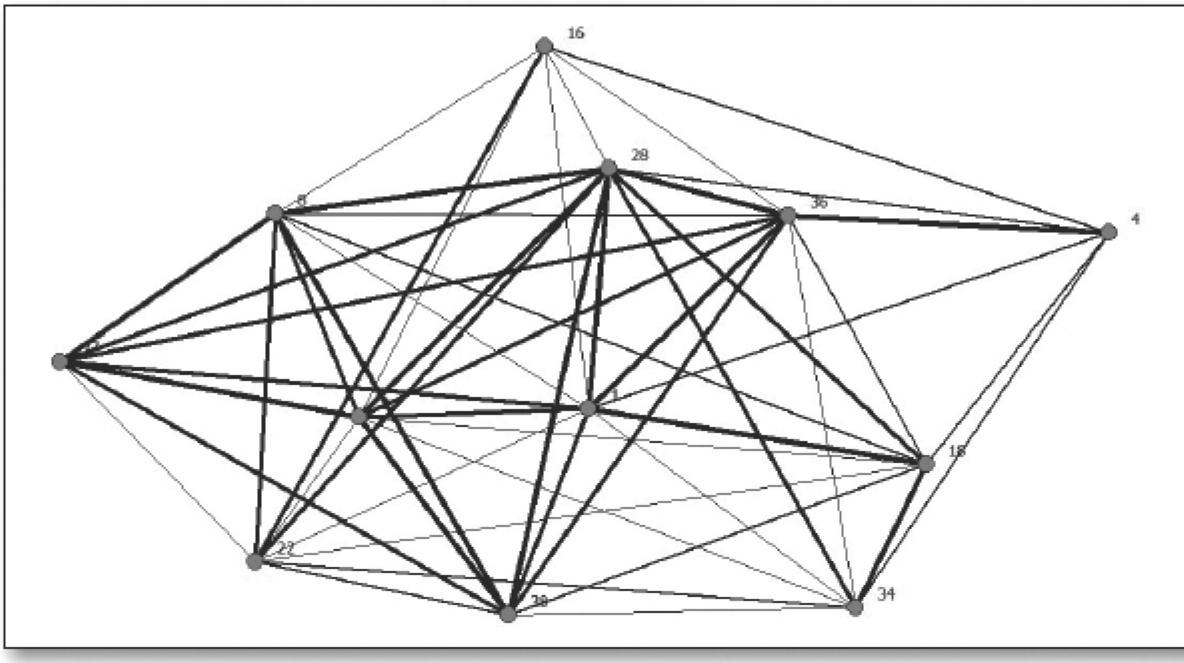
(Valente, 2010). Therefore, unlike the example School Leaders data used through this chapter, the relational data must be “valued,” indicating that there are variations in either the strength or frequency of relations between ego and each alter. The example data used in this chapter were transformed so that a relation is either absent or present (dichotomized) and nondirectional (symmetrized). However, the original data were, in fact, valued and directional, allowing tie strength to be incorporated into the analysis.

Tie strength has been a core idea throughout the network field, with weak ties serving as important bridges between different groups and strong ties being influential in behavioral adoption. Generally, weak ties are important for the spread of instrumental resources (e.g., work-related advice), while strong ties are important for expressive resources (e.g., guidance on personal matters) (Lin, 2001a). Stated another way, weak ties are important for transmitting information but less so for transmitting behavioral influence (Valente, 2010). Granovetter's (1973) classic work has laid much of the foundation for much of the work that has focused on the tie strength.

Figure 7.4 shows how tie strength can be incorporated into an egocentric analysis. This graph shows an ego (School Leader 1) and its relations with 11 alters, as well as the valued, nondirectional relations among those 11 alters. Thicker lines indicate that ego and alter exchange information about work-related topics more frequently (3–4 times per week) than thinner lines (not frequently); therefore, thicker lines are “stronger” ties and thinner lines are “weaker” ties.

To calculate a compositional measure of this ego's tie strength, you would simply need to calculate the mean and standard deviation of tie strength between this ego and its 11 alters (this calculation would, therefore, exclude alter-to-alter tie strength). Specifically, the values for these 11 ties are: 3, 2, 1, 1, 4, 1, 3, 4, 1, 4, and 3. The mean for these values equals 2.45 and the standard deviation is 1.29. These compositional measures can be used to explain an individual's behavior or attitudes. For example, it might be hypothesized that school leaders with more high-average tie strength but varied personal networks (on “exchange information about work-related advice”) are more likely to be innovative. These school leaders are probably exposed to more varied perspectives and can therefore draw on these differences to generate fresh ideas. This very idea is at the core of Granovetter's strength-of-weak-ties argument.

Figure 7.4 Graph of School Leader 1's Two-Step Ego Network. This graph shows how tie strength can be incorporated into an egocentric analysis. This graph shows an ego (School Leader 1) and its relations with 11 alters, as well as the valued, nondirectional relations among those 11 alters. Thicker lines indicate that ego and alter exchange information about work-related topics more frequently (3–4 times per week) than thinner lines (not frequently); therefore, thicker lines are "stronger" ties and thinner lines are "weaker" ties.



Diversity

Another way in which an ego network can be characterized draws on the attributes of those alters to which ego is connected. This is very similar to the previous measure of tie strength, the difference being that diversity can also capture the extent of heterogeneity of social characteristics of the alters in an ego's network (Knoke & Yang, 2008). For example, depending on the level of measurement of alters' characteristics, egocentric diversity can be measured by the standard deviation for continuous variables or by an index of qualitative variation for categorical variables.

Two examples highlight the way in which egocentric diversity can be measured. For instance, you might expect that an ego teacher whose alters have, on average, higher scores on a measure of teacher effectiveness and less variation (therefore a lower standard deviation) would be more likely to be rated as highly effective. When a characteristic such as this (teacher effectiveness) is measured on a continuous level, the standard deviation indicates the variable's diversity within a given ego's network. The formula of this is:

$$ {}^{S}X_i = \sqrt{\frac{\sum_{j=1}^{N}(X_{ij}-\overline{X})^2}{N-1}} \qquad \text{[Equation 7.2]} $$

where for the *i*th ego with *N* alters, the *j*th alter's characteristic X*ij* is a continuous variable. The mean of the standard deviations for all egos reflects the attribute's diversity in a sample of egos. Therefore, to get a sense of the diversity of teacher effectiveness in a sample of egos, you would simply have to average across the standard deviations for each ego.

A second example highlights how egocentric diversity can be captured for a categorical variable. To do so, you would calculate an index of qualitative variation (IQV; Knoke & Yang, 2008). For the *i*th ego with *N* alters, where the alters are classified into *K* (discrete or ordered) categories, the IQV is

$$ IQV_i = \frac{1-\sum_{j=1}^{K} p_j^2}{(K-1)/K} \qquad \text{[Equation 7.3]} $$

where $p^2 j$ is the percentage of alters in the *j*th category. The IQV is a standardized measure ranging from 0 to 1, where 0 indicates that all *N* cases are in one category and 1 indicates that that alters are equally dispersed across the *K* categories. For example, if a school leader (ego) names four white and one nonwhite alters, the race composition IQV is $\frac{1-[(0.8)^2+(0.2)^2]}{(2-1)/2} = 0.64$, whereas if a school leader were to name three whites and two nonwhites, there is a race composition IQV of 0.96. Therefore, this latter egocentric network has greater racial diversity.

Centrality

Centrality has been an important concept and measure in social network analysis for some time. Graph theory has been put to use in social network analysis to identify those prominent or important actors at the group (complete network analysis) or individual levels (egocentric analysis). The focus here is on the latter, in which centrality concepts and measures have been used to quantify an ego's prominence or importance in his or her ego neighborhood. Because most centrality indicators require only binary tie measurement (a tie is either present or absent), the concepts and measures rely on the transformed School Leaders data described earlier in this chapter. In addition, the focus will be on nondirected relations, but these measures can handle directed relational data.

Conceptually, centrality captures the extent to which a focal actor occupies an important position of prestige and visibility. Typically, being at the center of things is viewed as a good thing. Consequently, centrality has been an important focus of social network analysts. However, there are numerous ways to measure centrality (Borgatti & Everett, 2006), each emphasizing a slightly different way in which centrality is conceptualized. These varied measures were summarized and further developed by Freeman (1979), in which he introduced three core properties of centrality measures (Valente, 2010):

They can be calculated on individuals, referred to as point or node centrality.
The point centrality measure should be normalized by the size of the network so that calculations from different networks can be compared.
A complete network centralization score can be computed, indicating the degree of centralization derived from a specific measure.

Degree

This is most frequently used centrality measure, and it is directly related to egocentric network size described earlier. *Degree* is the number of ties to and from an ego. Obviously, in a directed egocentric network, *in-degree* is the number of ties received, whereas *out-degree* is the number of ties sent. However, to make this metric more useful, it can be normalized so that ego networks of different sizes can be compared. This requires that the number of ties be divided by the number of maximum number possible, which is $N - 1$. Therefore, normalized degree centrality can vary from 0 to 1, with scores closer to 1 indicating higher centrality. Formally, an ego's degree centralization, C_D, is represented as (Freeman, 1979)

$$C_D = \sum \frac{d_i}{N-1} \qquad \text{[Equation 7.4]}$$

where d_i is the number of ego's ties. This formula can be applied to both in-degrees and out-degrees, assuming one's relational data are directional. However, it cannot be applied to valued data. In addition, this calculation is only appropriate when egocentric data have been derived from a complete network.

For example, to calculate the degree of centrality of School Leader 25 (Figure 7.1), you would first need to identify the number of degrees in this ego's network (degrees = 10) and the total size of the network since, theoretically, an actor in the School Leaders data set can be nominated by everyone else in the network ($N - 1 = 42$). Therefore, the normalized degree centrality for School Leader 25 is 10/42 = 0.24 or, 24% after multiplying by 100. Normalized degree centrality can serve as a useful indicator for personal attributes and can be correlated with a number of other individual-level education outcomes. Spillane, Healey, and Kim (2010), for example, use an individual's in-degree centrality to define whether a school staff member was an advice giver (those with in-degrees greater than two were considered as such).

Closeness

Degree centrality is a local measure because it can be calculated without needing information about the overall pattern of relations among ego and alters. Therefore, a shortcoming of this measure is that it does not take into account indirect ties among all the alters in an ego's network. The second centrality measure, *closeness*, does this by requiring information on the pattern of ties in an ego's network; that is, it requires data about the relation between each pair of ego's named alters (two-step ego neighborhoods—“friends of friends”). Therefore, this and the next centrality measure (betweenness centrality) are most easily calculated when you are examining ego networks derived from a complete network, as is the case with egocentric analyses derived from the School Leaders data set. This centrality measure is intuitively appealing in that being "close" to others may provide an advantage by, for example, giving you early access to new information. Closeness can also be used to indicate how quickly an actor can exchange something with others, for example, by communicating directly or through very few intermediaries (Knoke & Yang, 2008).

Closeness centrality captures the average distance an actor is from all other actors in the network and is a function of an actor's geodesic distance to others, which equals the length of shortest path connecting a pair of actors. Actor closeness centrality is calculated as the inverse of the sum of the geodesic distances between actor *i* and the *g* – 1 actors in the network. The formula for this measure is:

$$C_c(N_i) = \frac{1}{\left[\sum_{j=1}^{g} d(N_i, N_j)\right]} (i \neq j) \qquad \text{[Equation 7.4]}$$

This measure, of course, requires an actor to have at least one tie to another actor. Therefore, it cannot be calculated for isolated actors, those without any connections to others. When an actor is close to others, *CC* = 1/(*g*-1). This, however, varies with the network's overall size. Therefore, to control for the size of the network, this formula can be standardized, which then allows for meaningful comparisons across networks. Closeness centrality is standardized by simply multiplying it by (*g* – 1), where *g* equals the number of actors in one's egocentric network.

For example, the normalized closeness centrality for School Leader 1 is 0.50. This was calculated by summing the geodesic distances between School Leader 1 and the other 42 actors in the network, dividing this by 1, and then multiplying it by 42, (*g* – 1). The higher an actor's centrality score (1.0 is the maximum value), the closer it is to others in the sense that the actor can reach other actors through shorter distances (Knoke & Yang, 2008).

Moolenaar, Daly, and Sleegers (2010) employ a measure of closeness centrality in their investigation of the relationship between transformational leadership and schools' innovative climates, hypothesizing that a principal's closeness centrality mediates this relationship. According to their conceptualization, closeness centrality indicates how "close" a principal is to the team members, or how quickly a principal can reach all team members through the social network. Closeness centrality is thus interpreted as a measure of "reachability" by the principal. The higher a principal's closeness centrality, the quicker information dispensed by the principal will reach all team members. In contrast to degree centrality, closeness centrality includes principals' indirect relationships to all team members. Uzzi (1996) suggests that not only direct but also indirect connections are important, as these relationships may dampen or enhance leaders' effectiveness.

Moolenaar, Daly, and Sleegers (2010) go on to argue that, by occupying a more central position, a leader is more often sought for resources (friendship, expertise, etc.) and has easier access to resources, information, or support from the social network (Adler & Kwon, 2002). Moreover, having more relationships increases a leader's opportunities to access novel information (Balkundi & Kilduff, 2006; Krackhardt, 1996). This access to diverse resources provides a central leader with the possibility to guide the flow of information and resources within the team (Burt, 2004). A leader may use the power and status attained through occupying a central position to direct certain knowledge and information to the right people who might need it most. Therefore, they hypothesize (and ultimately confirm) that principals who hold more central positions, as assessed by higher degree centrality and closeness centrality, are associated with schools that are characterized by more innovative climates.

Betweenness

This third centrality measure captures how actors control or mediate the relations between pairs of actors that are not directly connected. Suppose, for example, that a principal wants to exchange resources with another principal in the same school district, but in order to get these resources, he has to go through one or more intermediaries. This gives those intermediaries who are positioned "between" the principals more power and influence. To the extent that the principal can pursue multiple pathways to reach these others, the dependency on any single intermediary is reduced (Hanneman & Riddle, 2011b). Therefore, betweenness centrality measures the degree to which other actors lie on the shortest geodesic path between pairs of actors in the network. Therefore, this measure is an important indicator of control over information exchange or resource flows within a network (Knoke & Yang, 2008). The more any given actor is located on the path between numerous dyads, the higher that actor's potential to control network interactions. If principals in the school district contact one other principal to facilitate the exchange of resources among all principals, this second principal serves as an important conduit through which transactions occur. This concept and its associated measure is very appealing, as it captures the degree to which an actor occupies a strategically important position.

Like closeness centrality, you can calculate a point measure for betweenness as well as a normalized version. Point betweenness is calculated by counting the number of times an actor lies on the shortest paths connecting all other actors in the network. The normalized version, which again enables a comparison across networks, is calculated as (Freeman, 1979):

$$C_b = \frac{\frac{g_{ij} p_k}{g_{ij}}}{n^2 - 3n + 2} \qquad \text{[Equation 7.5]}$$

where $gijpk$ counts the number of times point k lies on the geodesic (shortest path) connecting all other actors (i and j) and gij is the total number of geodesics in the network. Betweenness is, therefore, the frequency with which an actor lies on the shortest path connecting other actors in the network. The maximum value that the numerator can have is $n^2 - 3n + 2$, which is the normalization factor. When an actor's normalized betweenness is 1, that actor falls on the geodesic (shortest) path of every pair of actors among the remaining $g - 1$ actors. Therefore, the closer an actor's standardized betweenness centrality is to 1, the more that actor controls the flow of resources across the network.

Betweenness centrality has been employed in a number of education-related studies. For example, in Spillane, Healey, and Kim's (2010) study on the relations between schools' formal and informal organization and how this relates to managing and leading instruction in schools, they examine both an individual's in-degree centrality and the normalized betweenness scores. This allows them to capture how “central” a school's staff member is in the flow of information from two slightly different conceptualizations. Combining these individual measures with subgroup and school levels of analyses, they conclude that those formally designated as school leaders were more likely than their colleagues without this designation to connect staff members who weren't otherwise connected. They conclude that this finding suggests that these formal leaders serve as key intermediaries among school staff.

Intuitively, these three different centrality measures (degree, closeness, and betweenness) are similar, leading you to conclude that they are correlated. However, this correlation is far from 1 (Valente, 2010), as they each capture a different view or purpose of centrality. Degree, for example, is a more localized measure, capturing the degree to which an actor is connected to other actors regardless of how those other actors are related to each other. Closeness centrality, on the other hand, captures a communication role such that actors with high closeness scores can exchange something with many others relatively quickly. Finally, betweenness centrality measures a gatekeeping function—if a school leader, for example, with a high betweenness score dislikes an idea, its spread to other actors in the network might be hindered. Conversely, if the leader likes the idea, the idea may move more freely to other parts of the network.

Because of these slight but important differences, these three measures often identify different actors as being central. For example, consider Figure 7.5, which shows the complete network of School Leaders on the “information about work-related topics” relation. Three different centrality scores (degree, closeness, and betweenness) were calculated for each of the 43 actors in this network. Table 7.3 reports these scores. For example, School Leaders 28 and 38 have the highest degree centrality scores, as well as the highest closeness centrality scores. Finally, these same two leaders also have the highest betweenness centrality scores. This is confirmed by the graph in Figure 7.5, in which it is evident that these leaders are central to the network. This finding, however, is the exception; often these three measures will yield different results (Costenbader & Valente, 2003). Costenbader and Valente (2003) report that the overall average correlation

Figure 7.5 Graph of School Leaders "Information About Work-Related Topics" Complete Network (*N* = 43). Using relational information from this complete network, it is possible to calculate different centrality scores for each ego, specifically, degree, closeness, and betweenness centrality.

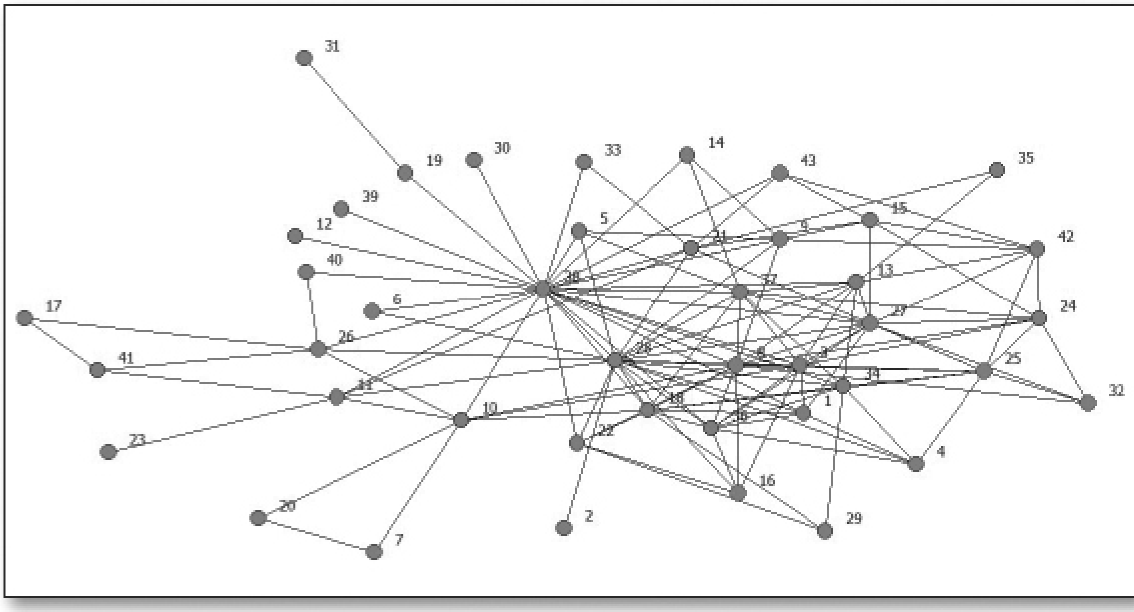


Table 7.3 Three Different Normalized Centrality Scores for School Leaders' "Information About Work-Related Topics" Network.

	Degree	*Closeness*	*Betweenness*
1	0.17	0.50	0.00
2	0.02	0.38	0.00
3	0.29	0.54	0.03
4	0.12	0.42	0.00
5	0.10	0.46	0.00
6	0.05	0.44	0.00
7	0.05	0.34	0.00
8	0.36	0.57	0.06
9	0.14	0.48	0.01
10	0.19	0.51	0.10
11	0.14	0.50	0.08
12	0.02	0.42	0.00
13	0.21	0.51	0.03
14	0.07	0.44	0.00
15	0.14	0.47	0.01
16	0.12	0.43	0.00
17	0.05	0.33	0.00
18	0.26	0.53	0.03
19	0.05	0.43	0.05
20	0.05	0.34	0.00
21	0.19	0.51	0.04
22	0.14	0.48	0.01
23	0.02	0.33	0.00
24	0.19	0.42	0.01

	Degree	*Closeness*	*Betweenness*
25	0.24	0.45	0.02
26	0.14	0.48	0.07
27	0.31	0.53	0.04
28	0.50	0.62	0.16
29	0.07	0.37	0.00
30	0.02	0.42	0.00
31	0.02	0.30	0.00
32	0.10	0.40	0.00
33	0.05	0.44	0.00
34	0.21	0.51	0.02
35	0.05	0.37	0.00
36	0.24	0.51	0.01
37	0.26	0.53	0.02
38	0.64	0.73	0.47
39	0.02	0.42	0.00
40	0.07	0.44	0.00
41	0.10	0.35	0.00
42	0.19	0.40	0.01
43	0.10	0.46	0.00

among these and other centrality measures is slightly more than 0.50, a moderately strong relationship. They conclude that these centrality measures represent a consistent concept, but there is some distinctiveness to each individual measure.

All three centrality measures can also be adapted and applied to complete network-level data analysis, measuring the degree to which a given centrality measure varies across the network's actors. Employing these and other centrality measures at this level would require you to shift analytical focus from the egocentric to the complete network level. For a review of how these measures can be adapted and applied to the analysis of complete networks, see Wasserman and Faust (1994) or Freeman (1979).

In addition to these three common centrality measures, at least seven others have been developed, most of which require that egos be examined as part of a larger complete network. These alternative centrality measures include eigenvector centrality (Bonacich, 1972), entropy (Tutzauer, 2007), power (Bonacich, 1987), Katz centrality (1953), and random-walk centrality introduced by Noh and Rieger (2004). These different centrality measures can be calculated in most common social network-analysis software applications. But, before deciding which measure or combinations of measures to employ, you must have an understanding of the strengths and purposes of each measure. For example, link centrality, which enables you to determine which relations are most central to a network, is very useful if you want to identify which relationships are most central. Removing a “central” tie would therefore interrupt the flow of resources more than would the removal of any other tie. On the other hand, a centrality measure such as power centrality is useful because you are able to vary the degree to which the centrality of ego's neighbors is included in the calculation (Valente, 2010). One way, of course, to identify the most appropriate centrality measures given your research interest is to use the precedent established by those working in similar topical areas.

Constraint

Another measure of egocentric networks, constraint, extends the egocentric network density measure to include more information about the structural pattern of relations among ego's alters. Therefore, similar to density, this measure requires that you have not only relational data on ego and his or her alters but also relational data on each pair of named alters. This is fairly straightforward if you extract egocentric data from a complete network study, but it poses of larger burden on the respondent if these type of data are collected from a sample of egos drawn from some larger population.

Constraint can be demonstrated through the following example from Hanneman and Riddle (2011b). Consider a network of three students: A, B, and C. Each student is connected to the two others. Suppose Student A wanted to influence or exchange resources with another student. Assume that both Students B and C may also have some interest in engaging in some interaction or exchange. Student A is not in a strong position because both of A's potential exchange partners (Students B and C) have alternatives to interacting with A. For example, they could choose to isolate A and then only interact or exchange with each other.

The example they offer then asks that you now imagine a “structural hole” (Burt, 1992) between Students B and C. That is, a relation is absent, preventing B and C from interacting or exchanging. This could happen because B and C do not know each other, dislike each other, or there are high transaction “costs” involved in forming a relation. In this situation, Student A is at an advantage because she or he has two possible interaction partners, whereas B and C have only one choice (Student A). Student A can be considered to be in a more powerful position since she or he is not constrained by the possibility of being excluded from the possible interaction.

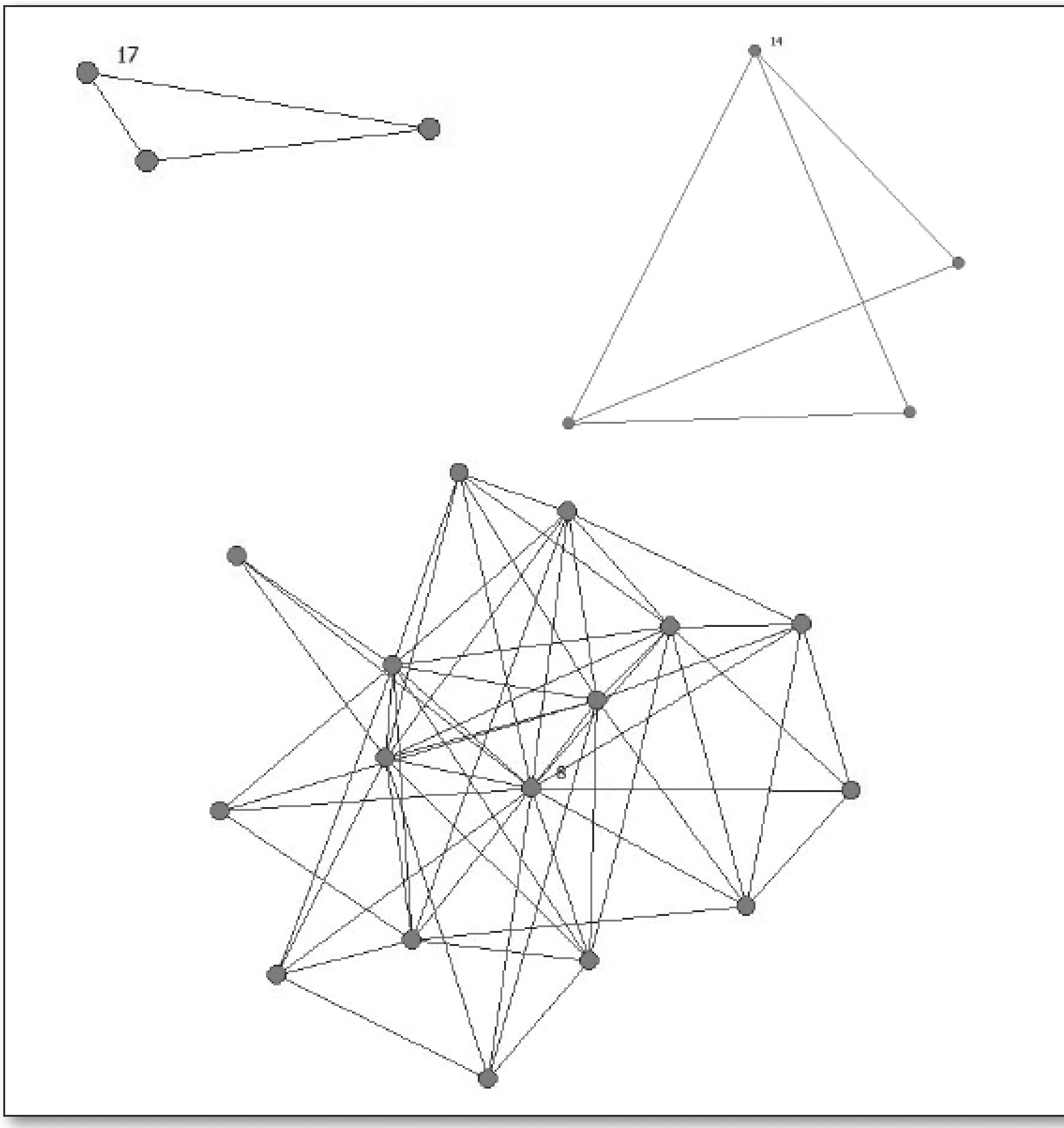
Burt (1992) developed a number of measures related to this concept of structural holes, most of which are computed on binary relational data that can be either directed or nondirected (valued data can also be used, but the interpretation becomes much more difficult). The most common measure of structural holes is constraint. Others include efficiency, hierarchy, and effective size. Constraint can be considered the degree to which an ego's alters are connected to each other; therefore, ego's behaviors and attitudes are more likely “controlled” by his or her personal network. In an ego network with low constraint, one's alters are not connected to one another, which may prevent alters from colluding to keep information from ego. This measure is calculated as follows (Burt, 1992, p. 55, Equation 2):

$$C_i = (p_{ij} + \sum_q p_{iq} p_{qj})^2,\ q \neq i, j$$

Admittedly, while the logic of the measure is pretty simple, its calculation is not. In short, what the calculation does is add the degree to which each of the alters is connected to the others in the focal ego's network. This may seem similar to density, but the difference is that constraint uses more information from the ego network (Valente, 2010). Low constraint scores (closer to 0) indicate that the ego occupies a position of structural holes in which they can access different parts of the network more effectively. In addition, if an ego has low constraint and high betweenness centrality scores, this ego is likely to serve as “bridge” to other parts of the network, a key position in a network's social structure. Drawing from a population of business managers, Burt (2004) has amassed an impressive body of evidence showing that low constraint is associated with an array of favorable outcomes, including early promotion, greater compensation, and higher levels of innovation. Egos with high constraint, on the other hand, may lose freedom of action and may be not have access to diverse streams of information.

Figure 7.6 shows the ego networks of three different ego actors extracted from the School Leaders data set on the “exchange information about work-related topics” relation, which is a binary, undirected relation. These graphs illustrate the different levels of constraint across three ego networks. For example, School Leader 8, with a network size of 15, has a constraint score of 0.24, indicating that this leader occupies a position in which he or she has a large number of alternative exchange partners. Contrast this with the ego network of School Leader 17, whose network is small (2), dense (1.0), and highly constrained (1.13). It is very likely that this leader may be at a serious disadvantage when it comes to acquiring new or diverse streams of information about work-related topics. School Leader 14 has a constraint score of 0.84, a moderate level of constraint. Given these scores, you can hypothesize and test whether leaders who occupy structural holes are more likely to innovate. This type of inferential analysis is introduced in the following chapter.

Figure 7.6 Graphs of Three Ego Networks (School Leaders 8, 14, and 17) With Different Levels of Constraint. These graphs illustrate the different levels of constraint across three ego networks. For example, School Leader 8 (bottom), with a network size of 15, has a constraint score of 0.24, indicating that this leader occupies a position in which he or she has a large number of alternative exchange partners. Contrast this with the ego network of School Leader 17 (top), whose network is small (2), dense (1.0), and highly constrained (1.13).



Brokerage

A final concept and measure that describes an ego's local social structure is brokerage. Here, the egocentric network must be part of a larger, complete network. Brokerage can be thought of as an extension of betweenness centrality and structural holes analyses in that it, too, focuses on the extent to which a focal ego is located “between” two alters. Gould and Fernandez (1989) extend this idea in an attractive way that accounts for the possibility that egos and their alters might also be affiliated with social groups (Hanneman & Riddle, 2011b). Fernandez and Gould also examined the ways in which actors’ embedding might constrain their behavior. However, they took a quite different approach; they focused on the roles that ego plays in connecting groups. That is, this notion of “brokerage” examines ego's relations with its neighborhood from the perspective of ego acting as an “agent” in relations across groups (though, as a practical matter, the groups in brokerage analysis can be individuals).

To examine an actor's brokerage, you find every instance in which that actor lies on the directed path between two others. Each actor, therefore, has numerous opportunities to act as a broker. Each time an ego acts as a broker, the types of actors that ego is between are examined. To do so, the group memberships of all three actors must also be incorporated into the analysis, requiring that attribute data be collected along with the relational data. There are five possible combinations of brokerage roles, which are displayed at the top of the output in Figure 7.7.

Consider the following example, which illustrates these roles using a focal actor, ego (Hanneman & Riddle, 2011b). If ego falls on a directed path between two members of the same category as itself (e.g., an English teacher falling between two other English teachers in a path), ego is referred to as a *coordinator*. If ego falls on the path between two members of a group of which it is not a part, the ego is called a *consultant* (e.g., an English teacher falling on the path from one math teacher to another). If ego falls on the path from a member of another group to a member of its own group, the ego is called a *gatekeeper*. Such a situation may arise when, for example, an English teacher falls on the path from a math teacher to another English teacher. If ego falls on the path from a member of its own group to a member of another group, ego is considered a *representative* (e.g., the English teacher falls on the path from English teacher to math teacher). Finally, if ego falls on a path from a member of one group to another but is not a member of either group, ego is a *liaison* (e.g., the English teacher falls on the path from science teacher to math teacher).

The first two brokerage roles involve mediation between members of one group. In the first role, coordinator, the mediator is also part of the group. In the second role (consultant), two members of a group use a mediator from the outside. The other three brokerage roles describe mediation between members of different groups. The gatekeeper regulates the flow of resources *to* his or her groups, while the representative regulates the flow *from* his or her group. The liaison mediates between members of different groups but does not belong to either group. These five roles were initially conceived for directed networks, namely transaction networks (de Nooy, Mrvar, & Batagelj, 2005). However, the directionality is only needed to differentiate between the representative and gatekeeper roles. The other three roles are also apparent in undirected relations, so they can be applied to undirected networks if you do not distinguish between representatives and gatekeepers (in an undirected network, there is no difference between roles).

Figure 7.7 Partial UCINET Output of a Basic Analysis of Brokerage Roles for School Leaders 1, 2, 3, 21, 5, and 7. From this output, it is evident that School Leaders 3 and 21 are key levers of connectivity between females and males.

```
GOULD & FERNANDEZ BROKERAGE MEASURES

Unnormalized Brokerage Scores

                 1         2         3         4         5         6
         Coordinat Gatekeepe Represent Consultan   Liaison     Total
        ------------------------------------------------------------
     1 |         2         6         2         1         0        11 |
     2 |         0         0         0         0         0         0 |
     3 |        20         8        14         2         0        44 |
       -------------------------------------------------------------
    21 |         9         8         5         3         0        25 |
     5 |         0         0         1         0         0         1 |
     7 |         0         0         0         0         0         0 |
        ------------------------------------------------------------



Legend: (given flow 1-->2-->3, where 2 is the broker)
      Coordinator:  A-->A-->A  (all nodes belong to same group)
       Gatekeeper:  B-->A-->A  (source belongs to different group)
   Representative:  A-->A-->B  (recipient belongs to different group)
       Consultant:  B-->A-->B  (broker belongs to different group)
          Liaison:  B-->A-->C  (all nodes belong to different groups)
```

To further illustrate these different roles, consider the ego networks for School Leaders 1, 2, 3, 21, and 5. These networks consist of directional (nonvalued) data on the “turn to for information on work-related topics” relation and attribute data on school leaders’ gender (group 1 = female). As an aside, the attribute data can also be a vector of categorical demographic data (e.g., gender) or a vector that identifies the group affiliation of an actor that has been assigned through one of the means (e.g., cliques) introduced in the previous chapter. Figure 7.7, for the sake of presentation, shows the partial UCINET output of a basic analysis of brokerage roles for these leaders. The actors have been grouped together by a vector (partition) for gender: Leaders 1, 2, and 3, for example, are female and the other three are male. Each row in this condensed output counts the “raw” (unnormalized) number of times each of the six school leaders plays each of the five brokerage roles in the whole (N = 43) graph. This calculation, rather than using the complete network, can also be restricted to each ego's one-step neighborhood. From this output, it is evident that School Leaders 3 and 21 are key levers of connectivity between females and males. School Leaders 2 and 3, one female and one male, have zero incidents of overall brokerage. None of the six leaders acts as liaison, which is not surprising given that there are only two groups (males and females) and acting in this role requires that egos be affiliated with one of at least three groups. Finally, there are few incidents of leaders serving as consultants, which is also to be expected given that it would be odd for two leaders to bring in a mediator of the opposite gender in order to broker an exchange of work-related topics. It would not, however, be so odd if the partition vector were an attribute such as whether one was a senior or junior school leader (in terms of seniority). In this instance, it would make more sense if a junior leader were to turn to a senior leader (ego) in order to facilitate an exchange with a junior colleague. Therefore, the choice of partition vector (i.e., the group to which one belongs) should make sense given one's topical focus.

Summary

This chapter introduced several of the most common concepts and measures related to analysis of egocentric networks. What distinguishes analyses that operate at this level, as opposed to complete-level network analyses, is that the focus is a sole ego actor's pattern of relations with those alters that constitute his or her own ego neighborhood. Egocentric data can be collected by asking individuals to name those with whom they share a relation (name generator) and then asking that they evaluate the relations among those that have been named (name interpreter). When sampled and collected in this manner, egocentric data can be used to characterize the personal networks of populations. Egocentric data can also be extracted from a complete network study. The School Leaders data cited throughout this chapter relied on egocentric data collected through this manner.

Once the egocentric data have been collected and organized, a number of different measures can be calculated to reveal different properties. These properties are related to connectivity (size and density), centrality (degree and betweenness centrality), structural holes (constraint), and brokerage (coordinator, gatekeeper). These different measures describe the content and contours of an ego's neighborhood. Researchers have used these and other measures to test whether they are associated with an array of outcomes relevant to educational researchers. The following chapter gently introduces the ways in which these indices, as well as those measured at the complete level, can be used to more formally make predictions, test hypotheses, and even generalize to larger populations.

Chapter Follow-Up

Locate an egocentric network study that addresses something related to educational research. What makes this an egocentric network study? How were the egocentric network data collected? What measures of egos’ networks were included in the analysis?

Assume you wanted to examine whether a student's popularity was associated with her or his attachment to school. How could you use a measure introduced in this chapter to capture “popularity”? Why did you select this measure over any others? Would you simply need ego-to-alter data or also alter-to-alter data?

If you wanted to examine the process through which a school reform initiative spreads throughout a school district, which egocentric concepts and measures would you employ?

Critical Questions to Ask about Studies that Employ Egocentric Network Analysis

How were the ego network data collected? Were they randomly sampled from a population, or were they collected as part of a complete network study?

What questions were asked in order to identify ego's alters? Or was the respondent provided a list of potential alters?

What other information about the alters was collected?

What egocentric measures were calculated? Did these measures make use of any information about tie strength or any other alter attributes?

If a measure of centrality was calculated, why was one measure chosen over the other possible options?

Essential Reading

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