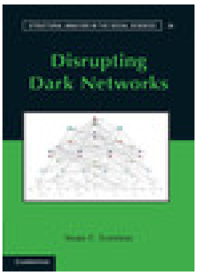

Disrupting Dark Networks

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Chapter

7 - Centrality, Power, and Prestige pp. 206-252

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7

Centrality, Power, and Prestige

7.1 Introduction

Of all the social network analysis metrics, centrality is perhaps the most intuitive, which probably explains why it is one of the oldest concepts in social network analysis. Notions that certain actors are more central than others can be traced at least as far back as Jacob Moreno's (1953) conception of sociometric stars and isolates (Wasserman and Faust 1994:169), and its formal properties were among the first to be tested experimentally (Bavelas 1948, 1950; Leavitt 1951). Exchange theorists (Cook and Emerson 1978; Cook et al. 1983; Cook et al. 1986; Cook and Whitmeyer 1992; Emerson 1962, 1972a, b, 1976) built upon these early experiments to further our understanding of the relation between centrality and power,[1] and scholars such as Linton Freeman (1977, 1979), Phillip Bonacich (1972a, 1987), Noah Friedkin (1991), and Steve Borgatti and Martin Everett (e.g., Borgatti 2005; Borgatti and Everett 2006; Everett and Borgatti 2005) have refined and expanded the measures of centrality available to analysts who have used them to explore a number of different social phenomena.

Researchers conceptualize centrality in a variety of ways (Bonacich 1987; Borgatti 2005; Borgatti and Everett 2006; Freeman 1979;

[1] Interestingly, while power is a central concern of social network analysts, many ignore the contributions of exchange theory, probably because of its close association with rational choice theory, which not only assumes that actors are driven by instrumental concerns but also takes issue with certain structuralist positions in sociology that hold that all important social phenomena can be explained, if not completely, at least substantially by social structure (see discussion of structure and agency in Chapter 1). However, like social network analysis, exchange theory conceptualizes social structure in terms of actors and ties. Moreover, its fundamental unit of analysis is not the individual actor but rather the relationship between actors. It does, nevertheless, depart from those forms of network analysis that only focus on social structure and do not take the interests of individual actors into consideration (Cook and Whitmeyer 1992).

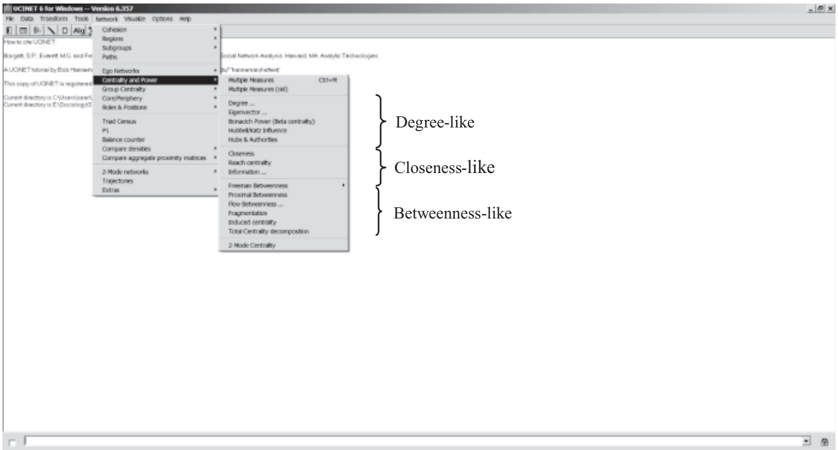


Figure 7.1. UCINET's Centrality and Power Menut

Wasserman and Faust 1994). A central actor can be seen as someone who has numerous ties to other actors (e.g., degree centrality), as someone who has numerous ties to highly central actors (e.g., eigenvector centrality, hubs, and authorities), as someone who is close (in terms of path distance) to other actors in the network (e.g., closeness centrality), or as someone who lies on the shortest path between numerous pairs of actors in a network (e.g., betweenness centrality). These, of course, are not the only centrality measures available to researchers. In fact, if one takes into account the different available options, UCINET currently implements over twenty centrality measures. Most of these are variations of the aforementioned. Freeman (1979), in fact, argues that centrality measures can be sorted into three broad families or classifications: degree-like centrality, closeness-like centrality, and betweenness-like centrality (Borgatti and Everett 2006). Indeed, close inspection of UCINET's centrality measure options (*Network>Centrality and Power*) reveals that this is how they are organized (Figure 7.1). While some may disagree with Freeman's classification, it does provide a useful starting point for our discussion of centrality. The rest of this section provides a brief overview of available centrality metrics and is organized in terms of degree-like, closeness-like, and betweenness-like centrality. The following two sections then look at how analysts can use centrality metrics to capture notions of power (Section 7.2) and prestige (Section 7.3), respectively. As with previous chapters, these two sections provide working examples using UCINET/NetDraw, Pajek, and ORA while analyzing Noordin's network. The final section (7.4) summarizes what has been covered, what we have learned about Noordin's network, and how this might inform attempts to disrupt dark networks.

[UCINET] Network >Centrality and Power

Figure 7.1 highlights several of the degree-, closeness-, and betweenness-like centrality measures available in UCINET, many of which are also available in Pajek and ORA. In what follows, we begin by considering the degree-like measures, which all assume that the number of an actor's ties is important in determining an actor's centrality. We then explore a variety of closeness-like measures where the path distance between actors is of overriding concern. Finally, we briefly examine betweenness-like measures, which assume that lying between other actors in a network should be considered important when measuring centrality.

Degree-Like Measures

The simplest and most common degree-like measure is, of course, degree centrality (Freeman 1979), which, when working with binary (i.e., dichotomized) network data, is simply a count of an actor's ties. If you are examining valued network data, then it equals the sum of the value of an actor's ties. Although researchers often prefer estimating degree centrality with binary data (i.e., they want the count of each actor's ties), it can be useful for examining valued data if, for example, the value of each tie is a measure of tie strength. In other words, if two actors, A and B, both have five ties, but most or all of A's are strong ties, whereas most or all of B's are weak ties, A will have a higher degree-centrality score than B.

Eigenvector centrality (Bonacich 1972a) is considered a degree-like measure (Borgatti and Everett 2006) because like degree centrality, it counts the number of ties of each actor. It differs in that it weights the score by the centrality of the actors to whom he or she is connected. Kleinberg's (1999) "hubs and authorities" measure, which was developed to rank pages on the World Wide Web, is based on the same assumption as eigenvector centrality and, in fact, produces identical scores. One advantage that it has over eigenvector centrality is that it can be applied to directed networks, which are often useful for measuring an actor's prestige within a network. Google's Page Rank algorithm is also a variant on eigenvector centrality (Austin 2011). The Hubbel and Katz (and Taylor) influence measures (Hubbell 1965; Katz 1953; Taylor 1969) are in many ways precursors to Bonacich's eigenvector centrality; quite early on, in fact, Bonacich noted the similarity of Hubbell's equation and the definition of an eigenvector (Bonacich 1972a; Borgatti and Everett 2006). Bonacich's power (or beta) centrality is similar to his eigenvector centrality, except that it introduces a parameter that allows researchers "to vary the degree and direction (positive or negative) of the dependence on each unit's score on the score of other units" (Bonacich 1987:1173). In other words, when the parameter is a negative value, an actor's score is higher when it is connected to actors with low power, and when the parameter is a positive value an actor's score is higher when it is connected to actors with high power.

Degree-like measures differ in many respects, but they each begin with a count of the number of an actor's ties, assuming that "count" is an important characteristic in measuring an actor's centrality. By contrast, closeness-like measures begin with the lengths of the paths in which actor is involved, assuming that how far (or close) an actor is to other actors is an important factor in determining an actor's centrality and power. We now turn to an overview of closeness-like measures.

Closeness-Like Measures

The best-known closeness centrality measure is Freeman's (1979), which calculates the average geodesic distance that each actor is from every other actor in the network. Freeman's measure is technically a distance or farness measure rather than a closeness measure, so it is generally "normalized" so that a score of 1.00 indicates that an actor is one step away from every other actor in the network, while scores nearing 0.00 are approaching the maximum distance possible from every other actor in the network.

As we have mentioned before and will explore in more detail, Freeman's measure is unusable with a disconnected network, which either requires researchers to modify the network in some way (e.g., removing isolates, extracting the largest weak component) or use an alternative measure. One such alternative measure that we will consider (and that we briefly encountered in our discussion of fragmentation) is average reciprocal distance (ARD) closeness centrality. Reach (or k-path) centrality (Sade 1989) is another closeness-like measure that counts the number of nodes each node can reach in k steps or less. When $k = 1$, the resulting score is the same as degree centrality; when it equals $n - 1$ (i.e., the size of the network less 1, which is its maximum value), the resulting score (when it is normalized) equals ARD closeness centrality plus one. One other closeness measure is Stephenson and Zelen's (1989) information centrality that attempts to estimate the information contained on all paths originating with each actor. It takes into account all paths between two actors (including but not limited to the geodesics) and assigns them weights based on their lengths. "A weighted function of this combined path is then calculated, using as weights the inverses of the lengths of the paths being combined" (Wasserman and Faust 1994:193).

Like with degree-like measures, closeness-like measures differ in their particulars but share a common characteristic: Namely, they take into account the length of the paths with which each actor is involved in calculating their centrality. Degree- and closeness-like measures also share a common characteristic: They focus on paths that begin or end with particular actors. By contrast, betweenness-like measures, which we consider next, focus on the paths that pass through actors on their way to somewhere else (Borgatti and Everett 2006), assuming that lying on the path between two actors is a structural feature that should be considered when evaluating the centrality and power of actors.

Betweenness-Like Measures

The most widely used betweenness-like measure is Freeman's (1979) node betweenness centrality, which measures the extent to which each actor in a network lies on the shortest paths (i.e., geodesics) connecting all pairs of actors in the network. We encountered a variation on this algorithm in the previous chapter, edge betweenness, which measures the degree to which each edge in a network lies on the geodesics linking all pairs of actors in the network.

A weakness of betweenness centrality is that there is no guarantee that two actors will always follow the shortest path between them. They may choose another path, even if it is longer and less efficient. Flow betweenness centrality (Freeman, Borgatti, and White 1991) takes into account this possibility. It assumes that actors will use all pathways between them in proportion to the length of the pathways. It measures the proportion of the entire flow between two actors that occurs on paths of which a particular actor is a part. In other words, each actor's flow betweenness score captures the extent to which each actor is involved in all of the flows between all other pairs of actors in the network (Hanneman and Riddle 2005, 2011:366–367).

Proximal betweenness estimates the proportion of all geodesics linking two actors (e.g., A and C) that pass through a particular actor (e.g., B) who is the second to last actor (i.e., the penultimate actor) on the geodesic. In other words, on the geodesic that runs from actor A to C and passes through B, B would be considered the penultimate actor if the tie between B and C is the last edge of the geodesic. Proximal betweenness can therefore be thought of as a measure of the number of times an actor occurs in a penultimate position on a geodesic.

One last betweenness-like centrality measure worth noting is fragmentation centrality, which we discussed somewhat at length in Chapter 5. As we noted there, this algorithm calculates a series of scores for each actor in the network that indicates (1) what the network fragmentation will be; (2) what the distance-weighted network fragmentation will be; (3) what the change in network fragmentation will be; (4) what the change in distance-weighted network fragmentation will be; (5) what the percent change in fragmentation will be; and (6) what the percent change in distance-weighted fragmentation will be if they are removed from the network.

Summary

In what follows we will not consider all these measures; instead, we will focus on those that analysts tend to use the most: in particular, degree, closeness, betweenness, and eigenvector (hubs and authorities) centrality. And unlike previous chapters, the formulas for many (not all) of these measures are included in order to illustrate the similarity between some measures (e.g., alternative closeness scores) and how we can normalize them so that they are comparable across networks. The remainder of the chapter is divided into two main sections: The first focuses on those centrality measures that researchers use to estimate power within a network; the second focuses on those that researchers use to estimate prestige. In each section we begin with how to estimate the metrics in UCINET and NetDraw before moving on to Pajek and ORA.

7.2 Centrality and Power

Centrality in UCINET

Degree Centrality in UCINET. As noted previously the most common (and oldest) measure of centrality is degree centrality, which in an undirected, binary network[2] is simply a count of the number of ties each actor has (i.e., the number of the neighbors). Because degree centrality depends on network size n (degree centrality's maximum value is $n - 1$, that is, where an actor has a tie to every other actor in the network), it is generally advisable to normalize it, which allows you to compare the measure across different-sized networks. Raw (i.e., nonnormalized) degree centrality is calculated as follows:

$$C_i^{DEG} = \sum_{j=1}^{n} x_{ij} \tag{7.1}$$

Normalized degree centrality is calculated as follows:

$$C_i^{NDEG} = \frac{\sum_{j=1}^{n} x_{ij}}{n-1} \tag{7.2}$$

where the numerator is an actor's raw degree score (equation 7.1) and the denominator is network size minus the actor. Comparing the two formulas, one can see that normalized degree is simply the ratio of the sum of each actor's ties over total possible ties.

[2] An undirected, dichotomous network is one that contains only edges (not arcs) and the presence or absence of a tie is indicated by either a "1" or a "0."

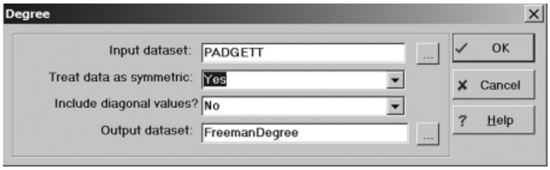


Figure 7.2. UCINET's Degree Centrality Dialog Box

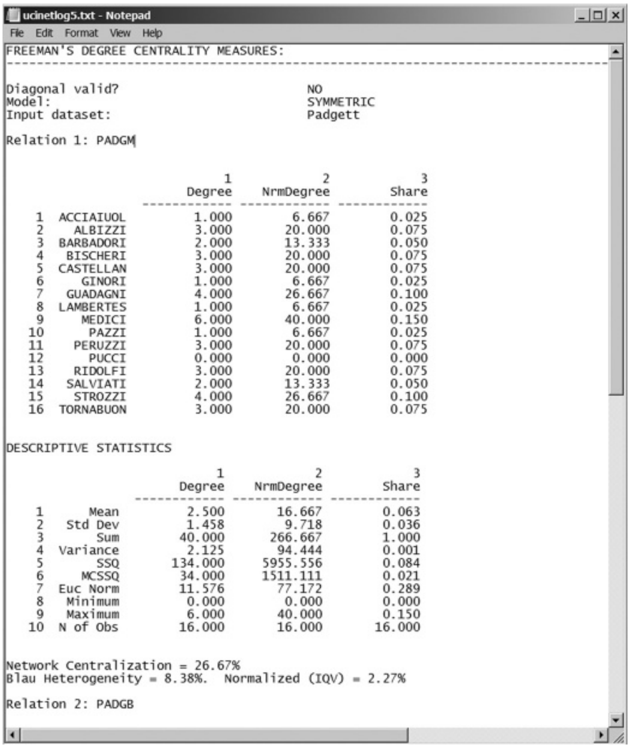
[UCINET] Network >Centrality and Power

Network >Centrality >Degree

In UCINET, all of the algorithms for estimating actor centrality are found in the *Network>Centrality and Power* submenu. Let us begin with a simple example: the business and marital ties between Renaissance Florentine families collected and recorded by John Padgett and Christopher Ansell (1993). Select the *Degree* centrality command found in the *Network>Centrality* submenu, which brings up a dialog box similar to Figure 7.2. Select the `Padgett.##h` file, accept UCINET's defaults[3] (unless you want to change the name of the output file) and click "OK."

This will call up a UCINET output log that should look similar to Figure 7.3. The first item listed is a table that itemizes the (1) degree centrality; (2) normalized degree centrality (expressed as a percentage for each actor); and (3) share of each actor in the network, which is each actor's centrality measure divided by the sum of all of the actor centralities in the network (thus, they sum to one). The output log also includes a handful of descriptive statistics (some of which we examined in Chapter 5), such as the mean/average degree centrality, standard deviation, variance, minimum value, and maximum value. Following the descriptive statistics is the degree network centralization index expressed as a percentage (which we also examined in Chapter 5) as well as two additional measures that we do not consider in this book. Because this is a stacked matrix, if you scroll down the output log, you will discover that not only does the output include centrality measures for the marriage data but also for the business data. As you can see, the Medici family is the most central in terms of both marriage and business ties. Earlier, we noted that sometimes we will be working with valued data where the value in each matrix cell may represent tie strength between actors, the sum of ties between actors, etc. In such cases degree centrality will equal the sum of the tie values. It also means that the calculations of network centralization and normalized degree centrality will sometimes yield scores greater than one, which is why with valued data, we should focus only on nonnormalized values and ignore degree centralization scores. If we are working with valued data but do not want to take into account cell values (or we want to estimate the degree centralization of a valued network),

[3] Although UCINET's default setting for treating the data as symmetric is "Yes," sometimes it defaults to "No." For now, be sure that it is set to "Yes" as in Figure 7.2.



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```
FREEMAN'S DEGREE CENTRALITY MEASURES:
------------------------------------------------------------------------------

Diagonal valid?                          NO
Model:                                   SYMMETRIC
Input dataset:                           Padgett

Relation 1: PADGM


                            1           2           3
                       Degree   NrmDegree       Share
                 ------------ ------------ ------------
  1  ACCIAIUOL          1.000       6.667       0.025
  2    ALBIZZI          3.000      20.000       0.075
  3  BARBADORI          2.000      13.333       0.050
  4   BISCHERI          3.000      20.000       0.075
  5  CASTELLAN          3.000      20.000       0.075
  6     GINORI          1.000       6.667       0.025
  7   GUADAGNI          4.000      26.667       0.100
  8  LAMBERTES          1.000       6.667       0.025
  9     MEDICI          6.000      40.000       0.150
 10      PAZZI          1.000       6.667       0.025
 11    PERUZZI          3.000      20.000       0.075
 12      PUCCI          0.000       0.000       0.000
 13    RIDOLFI          3.000      20.000       0.075
 14   SALVIATI          2.000      13.333       0.050
 15    STROZZI          4.000      26.667       0.100
 16  TORNABUON          3.000      20.000       0.075


DESCRIPTIVE STATISTICS

                           1            2            3
                      Degree    NrmDegree        Share
                ------------ ------------ ------------
  1       Mean         2.500       16.667        0.063
  2    Std Dev         1.458        9.718        0.036
  3        Sum        40.000      266.667        1.000
  4   Variance         2.125       94.444        0.001
  5        SSQ       134.000     5955.556        0.084
  6      MCSSQ        34.000     1511.111        0.021
  7   Euc Norm        11.576       77.172        0.289
  8    Minimum         0.000        0.000        0.000
  9    Maximum         6.000       40.000        0.150
 10   N of Obs        16.000       16.000       16.000


Network Centralization = 26.67%
Blau Heterogeneity = 8.38%.  Normalized (IQV) = 2.27%

Relation 2: PADGB
```

Figure 7.3. UCINET's Degree Centrality Output Log (Padgett Data)

we need to first dichotomize (i.e., binarize) the network with UCINET's *Transform>Dichotomize* command.

Turning to Noordin's network, select the *Degree* centrality command in the *Network>Centrality and Power* submenu and choose the `Alive Combined Network.##h` network file. Accept UCINET's defaults (change the name of the output file) and click "OK." The output log (Figure 7.4) lists the degree centrality scores of each actor; because the network is dichotomized, the scores indicate the number of each actor's "neighbors." Note that in contrast to the output log displayed in Figure 7.3, here UCINET lists the degree centrality scores of each actor in descending order. This is because in this case we are analyzing a single relation rather than a stacked (i.e., multirelational) network. When working with the latter, UCINET cannot place the actors in rank order because their ranking typically differs from network to network.

Network >Centrality and Power >Degree

Looking at Noordin's combined alive network, it is not surprising that Noordin is the most central actor. It is his network, after all. Note that although there is considerable variation in centrality scores among the first seven or eight actors, the variation among the remainder is minimal.

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FREEMAN'S DEGREE CENTRALITY MEASURES:

Diagonal valid? NO
Model: SYMMETRIC
Input dataset: Alive Complete Network

		1 Degree	2 NrmDegree	3 Share
50	Noordin Mohammed Top	46.000	67.647	0.052
60	Suramto	28.000	41.176	0.032
63	Ubeid	27.000	39.706	0.031
38	Iwan Dharmawan	25.000	36.765	0.028
4	Abdullah Sunata	25.000	36.765	0.028
58	Son Hadi	24.000	35.294	0.027
23	Dulmatin	21.000	30.882	0.024
29	Harun	20.000	29.412	0.023
44	Mohamed Saifuddin (alias Faiz)	20.000	29.412	0.023
7	Abu Fida	20.000	29.412	0.023
28	Hari Kuncoro	19.000	27.941	0.022
36	Irun Hidayat	19.000	27.941	0.022
9	Achmad Hasan	19.000	27.941	0.022
31	Heri Sigu Samboja	18.000	26.471	0.020
43	Mohamed Rais	17.000	25.000	0.019
35	Iqbal Huseini	17.000	25.000	0.019
65	Umar Patek	17.000	25.000	0.019
67	Urwah	17.000	25.000	0.019
42	Mohamed Ihsan	17.000	25.000	0.019
12	Ahmad Rofiq Ridho	17.000	25.000	0.019
69	Zulkarnaen	17.000	25.000	0.019
27	Hambali	16.000	23.529	0.018
5	Abu Bakar Ba'asyir	16.000	23.529	0.018
17	Apuy	16.000	23.529	0.018
64	Umar	16.000	23.529	0.018
11	Agus Ahmad	16.000	23.529	0.018
68	Usman bin Sef	16.000	23.529	0.018
33	Imam Samudra	16.000	23.529	0.018
19	Asep Jaja	15.000	22.059	0.017
24	Enceng Kurnia	15.000	22.059	0.017
62	Toni Togar	15.000	22.059	0.017
61	Tohir	15.000	22.059	0.017
15	Ali Ghufron	14.000	20.588	0.016
2	Abdul Rauf	14.000	20.588	0.016
57	Sardona Siliwangi	14.000	20.588	0.016
20	Chandra	14.000	20.588	0.016
51	Purnama Putra	14.000	20.588	0.016
37	Ismail	13.000	19.118	0.015
55	Salman	13.000	19.118	0.015
22	Dani Chandra	12.000	17.647	0.014
18	Aris Munandar	11.000	16.176	0.013
66	Umar Wayan	10.000	14.706	0.011
10	Adung	10.000	14.706	0.011
6	Abu Dujanah	10.000	14.706	0.011

Figure 7.4. UCINET's Degree Centrality Output (Noordin Alive Combined Network)

Indeed, there is very little difference between the scores of the remaining actors. This illustrates why arbitrary cutoffs (e.g., top-ten lists) that purport to distinguish between high- and low-value targets can be misleading.

This relative lack of variation in degree centrality scores is captured by the network map presented in Figure 7.5, where node size varies in terms of actor's degree centrality. Aside from Noordin (circled), one can see that a number of actors score similar in terms of degree centrality. To be sure, actors on the periphery of the network score considerably lower than do those in the middle, but once one moves just one or two steps inward from the periphery, the variation between actors is minimal. Results such as these should give pause to analysts using social network analysis to craft disruption strategies. As noted previously, an arbitrary cutoff that attempts to distinguish between high- and low-value targets could lead one to draw unwarranted conclusions. Moreover, it suggests that the removal of key individuals, except for perhaps Noordin, may have little

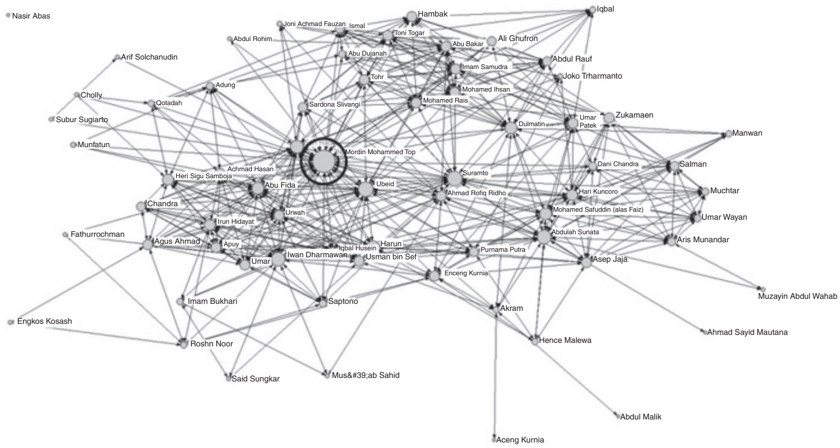


Figure 7.5. Noordin Alive Combined Network (Node Size = Degree) (Pajek)

or no disruptive effect on the network. In other words, what this example illustrates (or at least attempts to illustrate) is the importance of combining the analysis of metrics with the visual inspection of network maps. Metrics by themselves may not adequately capture the nature of network and may lead analysts to make ill-advised strategic decisions.

While we only illustrated calculating the degree centrality scores for combined alive network, Table 7.1 summarizes the normalized degree centrality scores for the top-ten actors (including ties) in all five of the alive networks. A cutoff of ten has been used here, not because it is ideal (indeed, in light of the previous paragraph's discussion and the display in Figure 7.5, it probably is not) but because it is impractical to present larger tables given the space constraints we are faced with here. Nevertheless, these results do suggest some things about the network. For example, there are several individuals (e.g., Noordin, Suramto, Son Hadi) who are central in a number of different networks (those who score in the top ten in three or more networks are in bold in the table), while others are central in only one or two (e.g., Mohamed Rais, Abu Bakar Ba'asyir, Dulmatin), suggesting that when identifying key individuals, we will want to pay close attention to which network they are affiliated with. The rankings also indicate that the business and finance network is very different from the others. Our previous topographical analysis (see Chapter 5) found that this network is much sparser than the others. Here, we can see that individuals who do not appear to play central roles in other networks do so in the business and finance network. Again, while we do not want to deduce too much from this table, the results are suggestive and probably warrant further analysis.

Table 7.1. *Normalized degree centrality of Noordin alive networks*

Trust network	Operational network	Communication network	Business & finance network	Combined network
Noordin Top (23.53)	**Noordin Top** (50.00)	**Noordin Top** (51.47)	**Son Hadi** (7.35)	**Noordin Top** (67.65)
Mohamed Rais (22.06)	**Iwan Dharmawan** (33.82)	Ahmad Rofiq Ridho (20.59)	Achmad Hasan (5.88)	**Suramto** (41.18)
Abu Bakar Ba'asyir (20.59)	**Ubeid** (30.88)	**Abdullah Sunata** (17.65)	**Suramto** (5.88)	**Ubeid** (39.71)
Tohir (20.59)	**Abdullah Sunata** (29.41)	Purnama Putra (16.18)	Usman bin Sef (5.88)	**Abdullah Sunata** (36.76)
Ubeid (19.12)	Harun (29.41)	**Abu Fida** (14.71)	Ismail (4.41)	**Iwan Dharmawan** (36.76)
Iwan Dharmawan (17.65)	Faiz (29.41)	**Iwan Dharmawan** (14.71)	Mohamed Rais (4.41)	**Son Hadi** (36.76)
Dulmatin (16.18)	**Abu Fida** (26.47)	Adung (13.24)	**Noordin Top** (4.41)	Dulmatin (30.88)
Suramto (16.18)	**Suramto** (26.47)	Usman bin Sef (13.24)	Agus Ahmad (2.94)	**Abu Fida** (29.41)
Ahmad Rofiq Ridho (14.71)	Hari Kuncoro (25.00)	Akram (11.76)	Asep Jaja (2.94)	Harun (29.41)
Sardona Siliwangi (14.71)	Irun Hidayat (25.00)	**Ubeid** (11.76)	Chandra (2.94)	Faiz (29.41)
Son Hadi (14.71)			Purnama Putra (2.94)	
			Rosihin Noor (2.94)	

Closeness Centrality in UCINET. As noted previously the most widely used closeness measure is Freeman's (1979), in which an actor's closeness score is based on the total distance between one actor and all other actors, where larger distances yield lower closeness centrality scores and vice versa. This measure is implemented in UCINET, NetDraw, Pajek, and ORA. UCINET actually generates two closeness scores: (1) "Farness," which is the average sum of all geodesic distances between each actor and all other actors in the network:

$$C_i^{FAR} = \sum_{j=1}^{n} d_{ij} \tag{7.3}$$

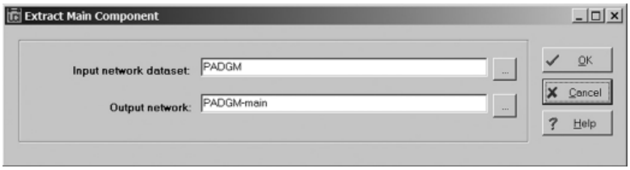


Figure 7.6. UCINET's Extract Main Component Dialog Box

where $\sum_{j=1}^{n} d_{ij}$ represents the sum of all the geodesic distances between pairs of actors i and j; (2) and "Normalized Closeness," which is the ratio of the number of other actors in a network (i.e., $n-1$) over the sum of all geodesic distances between the actor and all other actors in the network (i.e., each actor's farness score):

$$C_i^{CLO} = \frac{1}{\sum_{j=1}^{n} d_{ij}} \tag{7.4}$$

$$C_i^{NCLO} = \frac{n-1}{\sum_{j=1}^{n} d_{ij}} \tag{7.5}$$

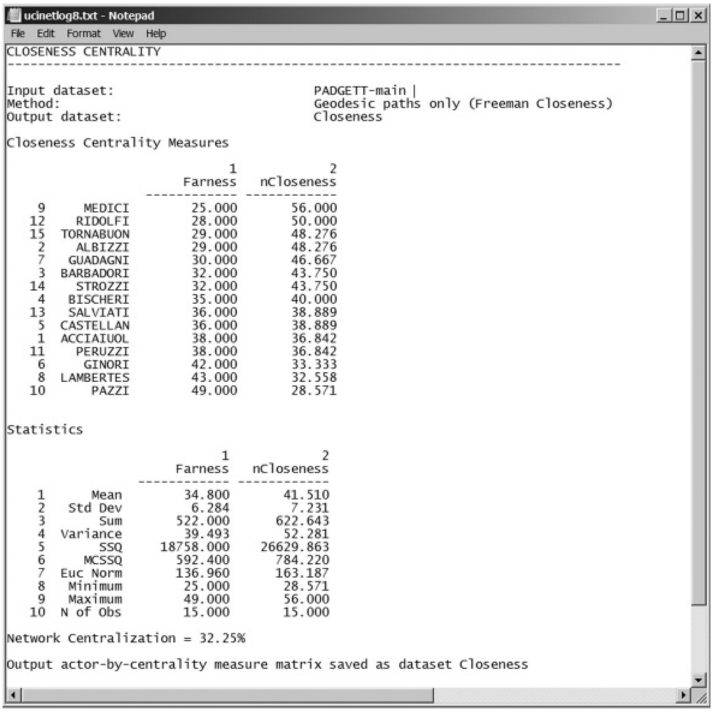
As you can see, the normalized closeness is derived from a nonnormalized score (equation 7.4), which is simply the inverse of the farness score. Placing the number of actors in the network in the numerator (equation 7.5) successfully normalizes the score because $n-1$ equals the minimum farness score actors can obtain if they are one step away (i.e., they are adjacent) from every other actor in the network. Thus, an actor's closeness score will equal 1.00 if they are one step away from all other actors in the network; it will equal 0.50 if they are, on average, two steps away, and so on.

As noted, Freeman's measure of closeness cannot be calculated when a network is disconnected because the distance between two disconnected actors is infinite. Thus, to use Freeman's measure with a disconnected network, we need to first extract the network's largest weak component (also known as its "main" component). As it turns out, the Padgett marriage and business networks are disconnected. Both contain an isolated family – the Pucci family. Thankfully, UCINET has made extracting main components a relatively easy task with its *Data>Extract>Main Component* command,[4] which calls up a dialog box (Figure 7.6) where you can select the network from which you want to extract the main component. Here,

Data>Extract >Main Component

4 When a disconnected network only contains isolates (rather than separate clusters of actors), an alternative method of extracting the main component is to use UCINET's *Data>Remove>Remove Isolates* command.

Data>Remove >Remove Isolates



```
ucinetlog8.txt - Notepad
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CLOSENESS CENTRALITY
--------------------------------------------------------------------------------

Input dataset:                          PADGETT-main |
Method:                                 Geodesic paths only (Freeman Closeness)
Output dataset:                         Closeness

Closeness Centrality Measures

                              1            2
                        Farness   nCloseness
                   ------------ ------------
  9      MEDICI          25.000       56.000
 12     RIDOLFI          28.000       50.000
 15   TORNABUON          29.000       48.276
  2     ALBIZZI          29.000       48.276
  7    GUADAGNI          30.000       46.667
  3   BARBADORI          32.000       43.750
 14     STROZZI          32.000       43.750
  4    BISCHERI          35.000       40.000
 13    SALVIATI          36.000       38.889
  5   CASTELLAN          36.000       38.889
  1   ACCIAIUOL          38.000       36.842
 11     PERUZZI          38.000       36.842
  6      GINORI          42.000       33.333
  8   LAMBERTES          43.000       32.558
 10       PAZZI          49.000       28.571


Statistics

                              1            2
                        Farness   nCloseness
                   ------------ ------------
  1        Mean          34.800       41.510
  2     Std Dev           6.284        7.231
  3         Sum         522.000      622.643
  4    Variance          39.493       52.281
  5         SSQ       18758.000    26629.863
  6       MCSSQ         592.400      784.220
  7    Euc Norm         136.960      163.187
  8     Minimum          25.000       28.571
  9     Maximum          49.000       56.000
 10    N of Obs          15.000       15.000

Network Centralization = 32.25%

Output actor-by-centrality measure matrix saved as dataset Closeness
```

Figure 7.7. UCINET's Freeman Closeness Centrality Output

we have selected the Padgett marriage data (PADGM). It is important to note that this function does not work with stacked networks. If you do select a stacked network, it will only extract the main component of the first network.

Network >Centrality Power >Closeness

To calculate closeness centrality in UCINET we use the *Network>Centrality and Power>Closeness* command and the newly generated (isolate-free) network. UCINET's closeness centrality output (Figure 7.7) is somewhat similar to its degree centrality output.[5] Note that the output lists and ranks the actors in terms of closeness/farness: The actor that is closer, on average, to all other actors in the network is listed first, whereas the actor that is farthest, on average, from all other actors is listed last. An actor's farness score is the sum of the lengths of the geodesics to every other actor, whereas an actor's closeness score ("nCloseness") is the total number of other actors (i.e., $n - 1$, which in this case equals 14) divided by the actor's farness score. As you can see the Medici family is closer (on average) to every other actor in the

[5] It is important to note, however, that unlike its degree centrality algorithm, UCINET closeness algorithm *only calculates closeness centrality for the first network in a stacked network*.

network. Because its score is larger than 50 (56.00), we know that the average path length between the Medicis and all other families is less than 2.00. Similarly, the Ginori family's closeness score (33.33) tells us that they are, on average, three steps away from every other family in the network. Like the output log for degree centrality, this one also includes descriptive statistics, such as the mean closeness centrality, standard deviation, variance, minimum value, and maximum value. Following this, the closeness network centralization index is listed.

As we noted in Chapter 5 when discussing closeness centralization, Freeman's closeness measure is not the only one available in UCINET. One alternative (that is currently can only available in UCINET) is to sum (and average) the reciprocal distance between all actors. Average reciprocal distance (ARD) is attractive because it can be used with disconnected networks (Borgatti 2006):

$$C_i^{RD} = \sum_{j=1}^{n} \frac{1}{d_{ij}} \tag{7.6}$$

Note the similarity between this measure and Freeman's nonnormalized closeness score (equation 7.4). In both cases the geodesic distance between actors is included in the denominator. However, with Freeman's measure, the distances are summed first before being placed in the denominator, but because infinite distances cannot be summed (at least in ways that provide meaningful results), the calculation becomes impossible, which is why we cannot use it with disconnected networks. With ARD, however, the reciprocal of the distances is calculated first and then summed, and since the reciprocal of infinity is conventionally set to zero, it is includable in the summation, and the measure can be used with disconnected networks. ARD is probably also a better approach than Freeman's measure when calculating the closeness centrality for actors included in the main component (and setting the scores of all others in the network to zero), because with ARD, all network actors and those that are located in clusters (but not the largest cluster/component) receive a score of greater than zero. ARD is normalized by placing the number of other actors (i.e., $n - 1$) in the denominator (rather than in the numerator as with Freeman's measure):

$$C_i^{ARD} = \frac{\sum_{j=1}^{n} \frac{1}{d_{ij}}}{n-1} \tag{7.7}$$

This is because ARD reaches its maximum value when an actor is adjacent to all other actors in the network (i.e., when it equals $n - 1$), which means that its normalized score will equal 1.00 when it is one step away from every other actor in the network. Currently, UCINET is the only one

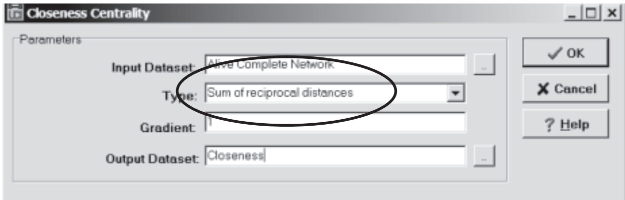
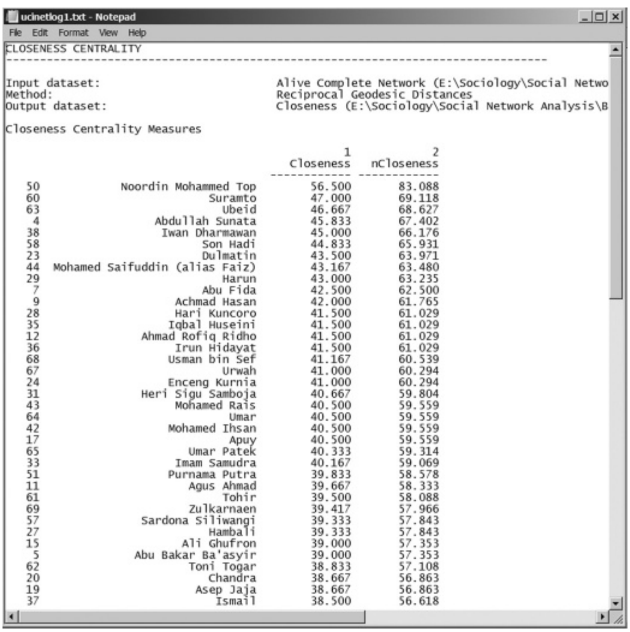


Figure 7.8. UCINET's Closeness Centrality Dialog Box

of the four SNA packages considered in this monograph that estimates ARD, but one gets the sense that it may eventually become the standard. As we will see, UCINET now includes ARD rather than the Freeman measure of closeness in its multiple centrality measure command.

Network >Centrality Power >Closeness

ARD closeness centrality is accessed with the same closeness command used to get Freeman's measure (*Network>Centrality and Power>Closeness*), except rather than accepting UCINET's default, select the "Sum of reciprocal distances" option in the dialog box (Figure 7.8) and then click "OK." This will generate output (Figure 7.9) similar to the output obtained from Freeman's measure. However, rather than farness and closeness scores, with ARD you get raw and normalized closeness scores.



ucinetlog1.txt - Notepad

```
CLOSENESS CENTRALITY
------------------------------------------------------------------------------

Input dataset:                          Alive Complete Network (E:\Sociology\Social Netwo
Method:                                 Reciprocal Geodesic Distances
Output dataset:                         Closeness (E:\Sociology\Social Network Analysis\B

Closeness Centrality Measures

                                                   1            2
                                           Closeness   nCloseness
                                        ------------ ------------
  50          Noordin Mohammed Top            56.500       83.088
  60                       Suramto            47.000       69.118
  63                         Ubeid            46.667       68.627
   4                Abdullah Sunata           45.833       67.402
  38               Iwan Dharmawan             45.000       66.176
  58                     Son Hadi             44.833       65.931
  23                     Dulmatin             43.500       63.971
  44  Mohamed Saifuddin (alias Faiz)          43.167       63.480
  29                        Harun             43.000       63.235
   7                     Abu Fida             42.500       62.500
   9                 Achmad Hasan             42.000       61.765
  28                Hari Kuncoro              41.500       61.029
  35                Iqbal Huseini             41.500       61.029
  12             Ahmad Rofiq Ridho            41.500       61.029
  36                 Irun Hidayat             41.500       61.029
  68                Usman bin Sef             41.167       60.539
  67                        Urwah             41.000       60.294
  24               Enceng Kurnia              41.000       60.294
  31            Heri Sigu Samboja             40.667       59.804
  43                 Mohamed Rais             40.500       59.559
  64                         Umar             40.500       59.559
  42               Mohamed Ihsan              40.500       59.559
  17                         Apuy             40.500       59.559
  65                   Umar Patek             40.333       59.314
  33                 Imam Samudra             40.167       59.069
  51                Purnama Putra             39.833       58.578
  11                  Agus Ahmad              39.667       58.333
  61                        Tohir             39.500       58.088
  69                   Zulkarnaen             39.417       57.966
  57            Sardona Siliwangi             39.333       57.843
  27                      Hambali             39.333       57.843
  15                  Ali Ghufron             39.000       57.353
   5             Abu Bakar Ba'asyir           39.000       57.353
  62                   Toni Togar             38.833       57.108
  20                      Chandra             38.667       56.863
  19                    Asep Jaja             38.667       56.863
  37                       Ismail             38.500       56.618
```

Figure 7.9. UCINET's Closeness (ARD) Centrality Output

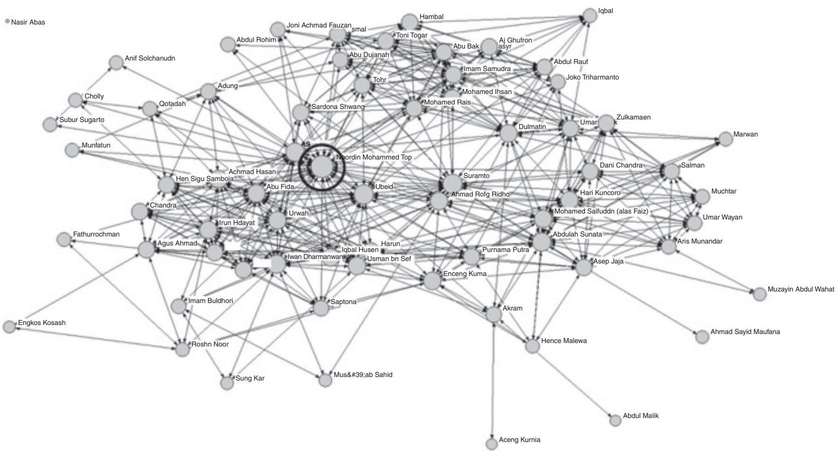


Figure 7.10. Noordin Alive Combined Network (Node Size = ARD) (Pajek)

Once again, Noordin is the most central actor. He is closer, on average, to other actors in the network than are any of the other actors in the network. Moreover, he is followed in rank by many of the same individuals who ranked closely behind him in terms of degree centrality (Figure 7.4).[6] This is not unusual, as actors who score high on one measure of centrality often score high on others (but not always), and we saw that degree and closeness centrality share certain similarities to one another.

It is notable that there is even less variation here than there was with degree centrality, which raises many of the same concerns we discussed with regard to degree centrality and again highlights the importance of the visual inspection of network maps (see Figure 7.10) before drawing conclusions about the network.

Table 7.2 summarizes the normalized ARD closeness centrality scores for the top-ten actors (including ties) in all five of the alive networks. Individuals who rank in the top ten of three or more networks are highlighted in bold type. Here again, the results are suggestive. A number of those who were central in terms of degree centrality are central in terms of closeness, and there are several individuals who are central across several networks, while there are others who are only central in one or two. The rankings also indicate that the business and finance network is very different from the others. Actors who are central here are not elsewhere. Of course, like before, we do not want to deduce too much from this table, but the results do provide food for thought.

[6] In terms of rank order, these scores are comparable (but not identical) to the closeness centrality scores estimated using Freeman's closeness algorithm (not shown) with the complete alive network with isolates removed.

Table 7.2. *Normalized closeness (ARD) centrality of Noordin alive networks*

Trust network	Operational network	Communication network	Business & finance network	Combined network
Noordin Top (52.33)	**Noordin Top** (68.87)	**Noordin Top** (70.10)	Son Hadi (5.88)	**Noordin Top** (83.09)
Mohamed Rais (49.44)	**Iwan Dharmawan** (58.46)	Ahmad Rofiq Ridho (53.16)	Achmad Hasan (5.15)	**Suramto** (69.12)
Ubeid (48.77)	Faiz (58.09)	**Abdullah Sunata** (50.22)	**Suramto** (5.15)	**Ubeid** (68.63)
Abu Bakar Ba'asyir (48.77)	Ubeid (57.72)	Purnama Putra (49.24)	Usman bin Sef (5.15)	**Abdullah Sunata** (67.40)
Tohir (47.84)	Harun (57.11)	**Iwan Dharmawan** (48.01)	Chandra (3.68)	**Iwan Dharmawan** (66.18)
Iwan Dharmawan (47.06)	**Abdullah Sunata** (55.88)	Abu Fida (47.77)	Ismail (2.94)	Son Hadi (65.93)
Ahmad Rofiq Ridho (46.32)	Suramto (55.64)	Usman bin Sef (47.03)	Mohamed Rais (2.94)	Dulmatin (63.97)
Dulmatin (45.15)	Abu Fida (54.53)	Akram (47.03)	**Noordin Top** (2.94)	Faiz (63.48)
Suramto (44.66)	Hari Kuncoro (53.43)	**Ubeid** (46.79)	Agus Ahmad (1.47)	Harun (63.24)
Abu Dujanah (43.43)	Apuy (53.06)	Adung (46.30)	Asep Jaja (1.47)	Abu Fida (62.50)
	Umar (53.06)		Purnama Putra (1.47)	
	Urwah (53.06)		Rosihin Noor (1.47)	

Betweenness Centrality in UCINET. Betweenness centrality differs from degree and closeness centrality in that it assumes that an actor is in a position of potential power over any two other actors when it lies on the shortest path (geodesic) between them in a given network of relations. "Loosely described, the betweenness centrality of a node is the number of times that any actor needs a given actor to reach any other actor" (Borgatti and Everett 2006:474). Formally, if we let g_{ij} indicate the number of geodesics from actor i to actor j and g_{ikj} indicate the number of geodesic paths from actor i to actor j that pass through actor k, then the betweenness centrality equals

$$C_i^{BET} = \sum_i \sum_j \frac{g_{ikj}}{g_{ij}} \tag{7.8}$$

```
ucinetlog4.txt - Notepad
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FREEMAN BETWEENNESS CENTRALITY
--------------------------------------------------------------------------------

Input dataset:                          Alive Complete Network

Important note: this routine binarizes but does NOT symmetrize.

Un-normalized centralization: 44012.220

                                                  1            2
                                        Betweenness nBetweenness
                                        ----------- ------------
 50           Noordin Mohammed Top          672.061       29.502
  4                Abdullah Sunata          206.149        9.050
 60                        Suramto          163.158        7.162
 14                          Akram          131.844        5.788
 38                 Iwan Dharmawan          103.996        4.565
 23                        Dulmatin          82.413        3.618
 12               Ahmad Rofiq Ridho          78.319        3.438
 63                          Ubeid           77.376        3.397
 68                  Usman bin Sef           63.515        2.788
 58                       Son Hadi           60.783        2.668
 44  Mohamed Saifuddin (alias Faiz)          60.452        2.654
 11                     Agus Ahmad           58.893        2.585
 24                  Enceng Kurnia           58.816        2.582
 65                     Umar Patek           47.143        2.070
 29                          Harun           44.700        1.962
 28                    Hari Kuncoro          42.868        1.882
 69                     Zulkarnaen           39.830        1.748
  5               Abu Bakar Ba'asyir         28.382        1.246
 36                    Irun Hidayat          27.715        1.217
 33                    Imam Samudra          19.602        0.860
  7                       Abu Fida           19.395        0.851
  9                    Achmad Hasan          18.194        0.799
 35                  Iqbal Huseini           17.443        0.766
 31               Heri Sigu Samboja          17.354        0.762
 51                  Purnama Putra           16.536        0.726
 19                      Asep Jaja           16.010        0.703
 27                        Hambali           15.093        0.663
 53                    Rosihin Noor          14.679        0.644
 42                  Mohamed Ihsan           14.627        0.642
 57               Sardona Siliwangi          13.490        0.592
 22                    Dani Chandra          12.132        0.533
 32                    Imam Bukhori          10.749        0.472
 43                    Mohamed Rais           9.521        0.418
 62                      Toni Togar           9.520        0.418
 10                          Adung            9.180        0.403
 37                         Ismail            8.495        0.373
 15                     Ali Ghufron           8.356        0.367
 18                   Aris Munandar           8.323        0.365
```

Figure 7.11. UCINET's Betweenness Centrality Output Log

In short, betweenness centrality measures actor k's share of all shortest paths from actor i to actor j, summed across all choices of actors i and j:

$$C_i^{NBET} = \frac{\sum_i \sum_j \frac{g_{ikj}}{g_{ij}}}{(n-1)(n-2)/2} \tag{7.9}$$

Because an actor's betweenness centrality is a function of the number of pairs of actors in a network, we can normalize it by dividing through by the number of pairs of actors that do not include actor k, which equals $(n-1)\,(n-2)/2$ (equation 7.9).

To calculate betweenness centrality in UCINET, select the *Freeman Betweenness>Node Betweenness* command from the *Network>Centrality and Power* submenu (dialog box not shown). As with closeness centrality, the output generated by UCINET (Figure 7.11) differs somewhat from that the degree centrality output. For instance, like closeness centrality UCINET only calculates betweenness centrality for the first matrix in the dataset, which means that if we want betweenness scores for all of the networks in a stacked dataset, we would first have to extract

Freeman Betweenness> Node Betweenness

Network >Centrality and Power

Table 7.3. *Normalized betweenness centrality of Noordin alive networks*

Trust network	Operational network	Communication network	Business & finance network	Combined network
Noordin Top (21.93)	**Noordin Top** (30.40)	**Noordin Top** (55.74)	Son Hadi (0.13)	**Noordin Top** (29.50)
Iwan Dharmawan (17.10)	Faiz (10.69)	Abu Dujanah (10.50)		**Abdullah Sunata** (9.04)
Ahmad Rofiq Ridho (15.09)	Suramto (5.67)	**Abdullah Sunata** (10.49)		Suramto (7.16)
Abdullah Sunata (12.18)	**Ahmad Rofiq Ridho** (4.91)	**Ahmad Rofiq Ridho** (8.11)		**Akram** (5.79)
Usman bin Sef (8.76)	**Iwan Dharmawan (4.70)**	Zulkarnaen (7.77)		**Iwan Dharmawan** (4.57)
Abu Bakar Ba'asyir (7.93)	**Abdullah Sunata** (4.19)	**Iwan Dharmawan** (6.95)		Dulmatin (3.62)
Ubeid (7.78)	Harun (3.31)	**Akram** (6.19)		**Ahmad Rofiq Ridho** (3.44)
Faiz (6.07)	Hambali (3.08)	Aris Munandar (5.31)		Ubeid (3.40)
Akram (5.95)	Mohamed Ihsan (3.08)	Purnama Putra (4.89)		Usman bin Sef (2.79)
Adung (5.19)	Toni Togar (3.08)	Agus Ahmad (3.15)		Son Hadi (2.67)

each network and estimate betweenness centrality for each of them separately. However, like degree centrality UCINET provides both raw and normalized betweenness scores as well as a number of descriptive statistics, including mean, variation, standard deviation, and network. Note also that UCINET automatically binarizes the network before making its calculation, which means that you will receive the same scores whether you are analyzing a valued or dichotomized network. Put differently, if you are examining a valued network, you do not have to dichotomize it prior to estimating betweenness centrality. UCINET does it for you.

Looking at the betweenness centrality scores for the combined alive Noordin network, we can see that, once again, Noordin is the most central and a number of the individuals we saw when calculating degree and closeness centrality appear in this output as well. What is striking, however, is that there is far more variability between the actors scores.

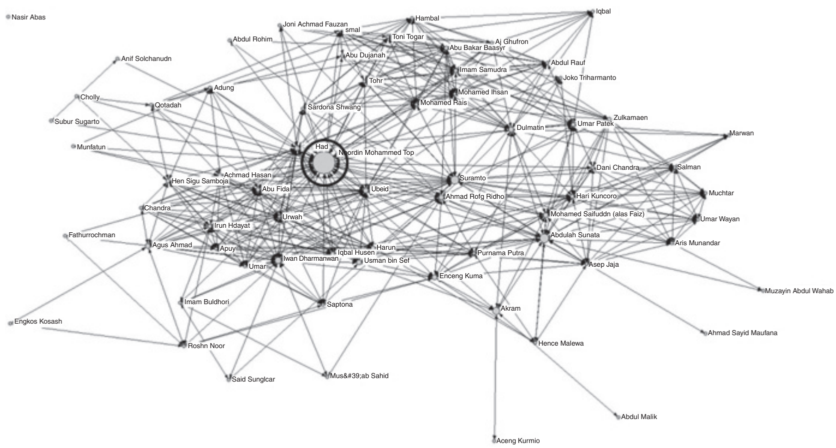


Figure 7.12. Noordin Alive Combined Network (Node Size = Betweenness) (Pajek)

Although this can be detected with a close inspection of UCINET's output (see Table 7.3), it is even more obvious in the network map where node size is allowed to vary by betweenness centrality (Figure 7.12).

Table 7.3 summarizes the normalized betweenness centrality scores for the top-ten actors for all five alive networks. Although many of the individuals listed here were listed in Tables 7.1 and 7.2, there are a number of "new" ones. What might we be able to do with this information? The variability between scores suggests that in this case at least, this measure might be delineating between high- and low-value individuals. We should be cautious because as with all social network analysis metrics, betweenness centrality only measures an actor's potential power, not necessarily their actual power. They could be complete idiots and only find themselves in the position they are in out of "luck." There is no guarantee that they recognize their structural power or have the ability to capitalize on it. That said, analysts have successfully used high betweenness centrality measures to target individuals within dark networks for the planting of misinformation in order to sow seeds of distrust and cause the network to implode (Anonymous 2009).

Eigenvector Centrality in UCINET. Eigenvector centrality assumes that ties to highly central actors are more important than are ties to peripheral actors and as such weights an actor's centrality by the centrality scores of its neighbors (i.e., the actors to which it has ties). Formally, if A is an adjacency matrix (i.e., a one-mode network), then we can allow for this

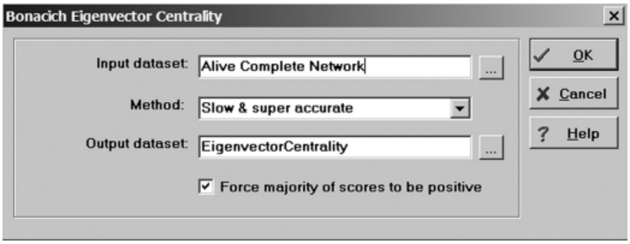


Figure 7.13. UCINET Eigenvector Centrality Dialog Box

effect by making actor *i*'s centrality proportional to the average of the centralities of *i*'s neighbors:

$$C_i^{EIG} = \frac{1}{\lambda} \sum_{j=1}^{n} A_{ij} x_j \tag{7.10}$$

where λ is a constant and *i*'s associated eigenvalue; the largest eigenvalue is generally preferred (Bonacich 1987). The normalized eigenvector centrality is the scaled eigenvector centrality divided by the maximum difference possible, expressed as a percentage (Borgatti, Everett, and Freeman 2011):

$$C_i^{NEIG} = \frac{\frac{1}{\lambda} \sum_{j=1}^{n} A_{ij} x_j}{C_{Max}^{EIG}} \tag{7.11}$$

Network >Centrality Eigenvector

To compute eigenvector centrality in UCINET, select the *Eigenvector* command under the *Network>Centrality and Power* submenu, which calls up a dialog box similar to Figure 7.13. A few items are worth noting here. First, as long as you are not analyzing a very large network, you will generally want to select the "Slow & super accurate" option. With a large network, you will probably be better off choosing the "Fast – for large matrices" option. Second, you will also want to check the box at the bottom of the dialog box that forces most scores to be positive. Finally, when calculating eigenvector centrality for several networks, you will want to provide your own name for the output dataset rather than accepting UCINET's default file name.

UCINET's output (Figure 7.14) first lists a series of eigenvalues before each actor's eigenvector centrality scores. Like the output for degree and closeness centrality, it provides a number of descriptive statistics, including network centralization based on closeness. However, analysts need to be careful because UCINET's output lists the actor's scores in the order they appear in the network, not in their rank order, which means that at a glance, you cannot determine which actors are more central than others.

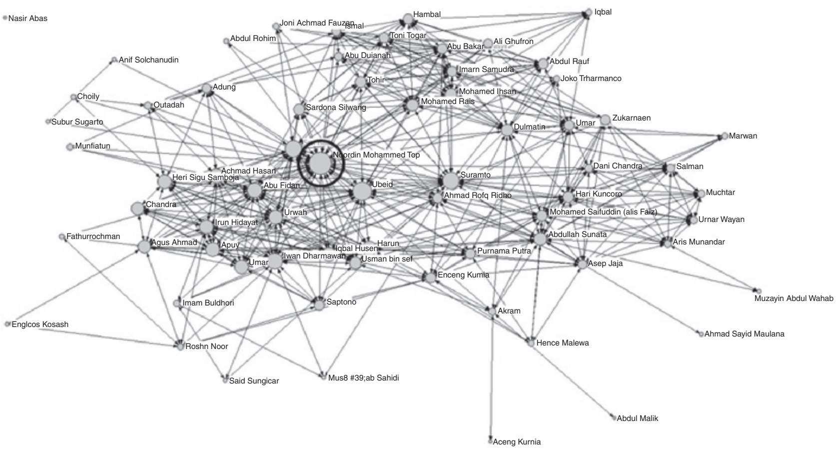


Figure 7.14. Noordin Alive Combined Network (Node Size = Eigenvector) (Pajek)

Table 7.4 summarizes the eigenvector centrality scores for all five alive networks. As before, Noordin is the most central actor in the combined network, but as with the degree and closeness centrality, there is minimal variation in the scores (see Figure 7.15). This, of course, raises the same issues that we have discussed, suggesting that at least in the case of the combined network, eigenvector centrality may not be an ideal metric for identifying central players. Interestingly, Noordin does not rank first in the trust network, as he has previously in terms of eigenvector centrality. In fact, he is not even in the top five. Instead, the top-ranked individual is Mohammed Rais, who previously ranked high (but not first) in terms of degree and closeness centrality, followed by Tohir, Abu Bakar Ba'asyir, Ubeid, and Suramto. What this may suggest is that if Noordin were to be removed from the network, these individuals, with their connections to other central members of the network, may be the most likely candidates to succeed Noordin.[7]

Multiple Centrality Measures in UCINET. UCINET includes a *Multiple Measures* command under the *Network>Centrality and Power* submenu, which calculates a number of centrality measures, including degree, closeness (ARD), betweenness, and eigenvector centrality along with Bonacich's power centrality (a degree-like measure that is a variation on eigenvector centrality), and *k*-step reach centrality (a closeness-like measure). You do not have to estimate all six metrics; the multiple measures dialog box (Figure 7.16) allows you to select which measures you

Network >Centrality and Power Multiple Measures

[7] Noordin was killed in a fire fight with Indonesian authorities in September 2009. Some members did attempt to join with other Indonesian terrorists, but many were caught in a raid in Aceh, Indonesia, in early 2010 (International Crisis Group 2010).

Table 7.4. *Normalized eigenvector centrality of Noordin alive networks*

Trust Network	Operational Network	Communication Network	Business & Finance Network	Combined Network
Mohamed Rais (48.65)	**Noordin Top** (40.01)	**Noordin Top** (72.67)	**Son Hadi** (74.05)	**Noordin Top** (43.53)
Tohir (45.69)	**Ubeid** (37.02)	Ahmad Rofiq Ridho (38.46)	Achmad Hasan (68.18)	**Ubeid** (34.44)
Abu Bakar Ba'asyir (37.56)	Iwan Dharmawan (35.98)	Purnama Putra (32.87)	**Suramto** (68.18)	**Son Hadi** (30.76)
Ubeid (36.52)	Harun (34.70)	**Abu Fida** (31.02)	Usman bin Sef (68.18)	**Suramto** (30.65)
Suramto (36.13)	**Abu Fida** (33.32)	Abdullah Sunata (28.97)	Chandra (24.00)	Iwan Dharmawan (28.99)
Noordin Top (34.38)	Apuy (32.08)	Usman bin Sef (28.27)	Ismail (1.27)	**Abu Fida** (27.13)
Sardona Siliwangi (33.69)	Umar (32.08)	Adung (27.25)		Harun (26.51)
Mohamed Ihsan (31.88)	Urwah (32.08)	Ubeid (26.97)		Achmad Hasan (25.77)
Dulmatin (28.95)	Irun Hidayat (31.78)	**Son Hadi** (23.97)		Urwah (25.03)
Ali Ghufron (28.24)	Heri Sigu Samboja (30.88)	Enceng Kurnia (23.59)		Irun Hidayat (24.79)

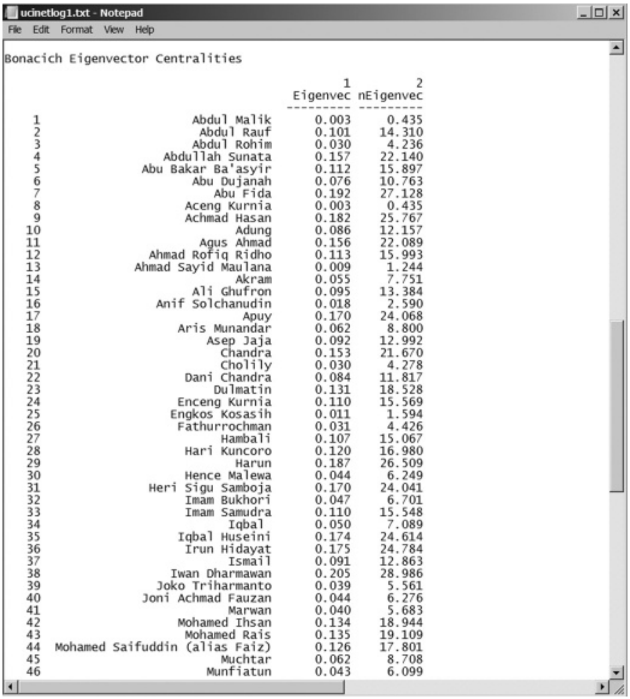
want. This is a handy feature when analyzing larger networks because the larger the network, the longer it takes for UCINET to calculate the scores. Note also that you can indicate whether the data are directed or undirected, or you can let UCINET detect it on its own, and you can ask for raw or normalized scores. Note also that the function is designed for binary data, so if you use it with valued data, UCINET will dichotomize the network before calculating any metrics.

Excursus: Correlating Centrality Metrics with Attributes

Finally, you may be interested in seeing how much various centrality measures correlate with ordered or continuous attributes, such as age or education. It makes no sense, of course, to estimate the correlation between centrality and a nominal attribute such as nationality, role, or gender.

Tools>Testing Hypotheses >Node-Level >Regression

To do this in UCINET, we use UCINET's *Tools>Testing Hypotheses>Node-Level>Regression* command, which calls up a dialog box



ucinetlog1.txt - Notepad

File Edit Format View Help

Bonacich Eigenvector Centralities

		1 Eigenvec	2 nEigenvec
1	Abdul Malik	0.003	0.435
2	Abdul Rauf	0.101	14.310
3	Abdul Rohim	0.030	4.236
4	Abdullah Sunata	0.157	22.140
5	Abu Bakar Ba'asyir	0.112	15.897
6	Abu Dujanah	0.076	10.763
7	Abu Fida	0.192	27.128
8	Aceng Kurnia	0.003	0.435
9	Achmad Hasan	0.182	25.767
10	Adung	0.086	12.157
11	Agus Ahmad	0.156	22.089
12	Ahmad Rofiq Ridho	0.113	15.993
13	Ahmad Sayid Maulana	0.009	1.244
14	Akram	0.055	7.751
15	Ali Ghufron	0.095	13.384
16	Anif Solchanudin	0.018	2.590
17	Apuy	0.170	24.068
18	Aris Munandar	0.062	8.800
19	Asep Jaja	0.092	12.992
20	Chandra	0.153	21.670
21	Cholily	0.030	4.278
22	Dani Chandra	0.084	11.817
23	Dulmatin	0.131	18.528
24	Enceng Kurnia	0.110	15.569
25	Engkos Kosasih	0.011	1.594
26	Fathurrochman	0.031	4.426
27	Hambali	0.107	15.067
28	Hari Kuncoro	0.120	16.980
29	Harun	0.187	26.509
30	Hence Malewa	0.044	6.249
31	Heri Sigu Samboja	0.170	24.041
32	Imam Bukhori	0.047	6.701
33	Imam Samudra	0.110	15.548
34	Iqbal	0.050	7.089
35	Iqbal Huseini	0.174	24.614
36	Irun Hidayat	0.175	24.784
37	Ismail	0.091	12.863
38	Iwan Dharmawan	0.205	28.986
39	Joko Triharmanto	0.039	5.561
40	Joni Achmad Fauzan	0.044	6.276
41	Marwan	0.040	5.683
42	Mohamed Ihsan	0.134	18.944
43	Mohamed Rais	0.135	19.109
44	Mohamed Saifuddin (alias Faiz)	0.126	17.801
45	Muchtar	0.062	8.708
46	Munfiatun	0.043	6.099

Figure 7.15. UCINET Eigenvector Centrality Output

(Figure 7.17) in which you indicate the "dependent" variable (i.e., education level) is the first column of the Attribute dataset. You will also need to indicate your independent variables, which in this case are all the columns from the Alive Combined Network-cent dataset, which was created with UCINET's multiple measures command. Clicking "OK" generates an output similar to Figure 7.18. For now we will only pay

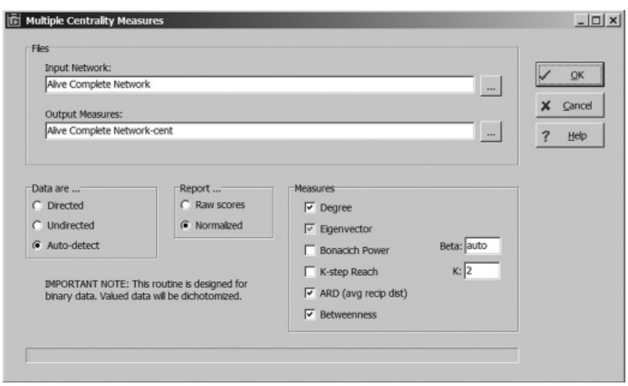


Figure 7.16. UCINET Multiple Centrality Measures Dialog Box

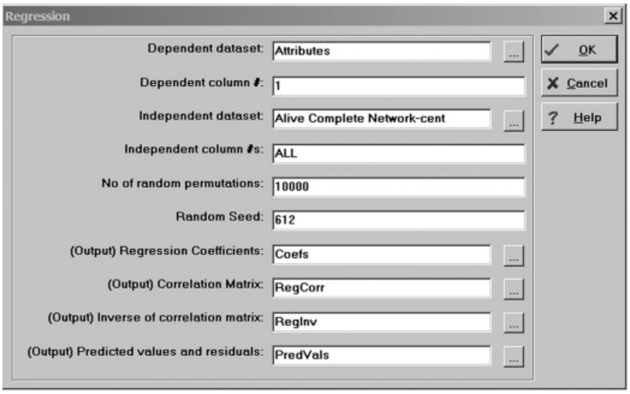
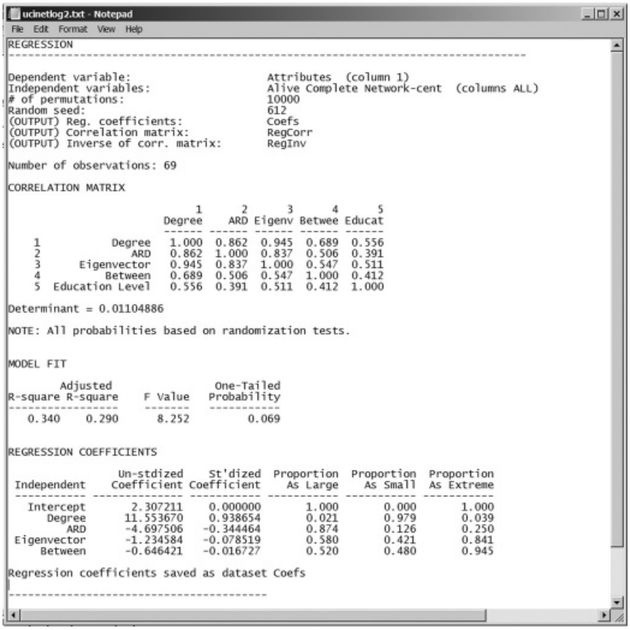


Figure 7.17. UCINET Regression Dialog Box

attention to the correlation matrix at the top of the screen because we are not estimating a formal regression model (see, however, Chapter 11). Looking at the matrix you can see that education (column 5) is positively correlated with degree, closeness (ARD), betweenness, and eigenvector centrality, all of which suggests (but does not prove) that individuals



```
REGRESSION
--------------------------------------------------------------------------------

Dependent variable:                        Attributes  (column 1)
Independent variables:                     Alive Complete Network-cent  (columns ALL)
# of permutations:                         10000
Random seed:                               612
(OUTPUT) Reg. coefficients:                Coefs
(OUTPUT) Correlation matrix:               RegCorr
(OUTPUT) Inverse of corr. matrix:          RegInv

Number of observations: 69

CORRELATION MATRIX

                             1      2      3      4      5
                        Degree    ARD Eigenv Betwee Educat
                        ------ ------ ------ ------ ------
    1            Degree  1.000  0.862  0.945  0.689  0.556
    2               ARD  0.862  1.000  0.837  0.506  0.391
    3       Eigenvector  0.945  0.837  1.000  0.547  0.511
    4           Between  0.689  0.506  0.547  1.000  0.412
    5   Education Level  0.556  0.391  0.511  0.412  1.000

Determinant = 0.01104886

NOTE: All probabilities based on randomization tests.


MODEL FIT

         Adjusted              One-Tailed
R-square R-square     F Value  Probability
-----------------     -------  -----------
   0.340    0.290       8.252        0.069


REGRESSION COEFFICIENTS

                   Un-stdized    St'dized  Proportion  Proportion  Proportion
 Independent      Coefficient Coefficient    As Large    As Small  As Extreme
 ----------- -------------- ----------- ----------- ----------- -----------
   Intercept        2.307211    0.000000       1.000       0.000       1.000
      Degree       11.553670    0.938654       0.021       0.979       0.039
         ARD       -4.697506   -0.344464       0.874       0.126       0.250
 Eigenvector       -1.234584   -0.078519       0.580       0.421       0.841
     Between       -0.646421   -0.016727       0.520       0.480       0.945

Regression coefficients saved as dataset Coefs

----------------------------------------
```

Figure 7.18. UCINET Regression Output Log

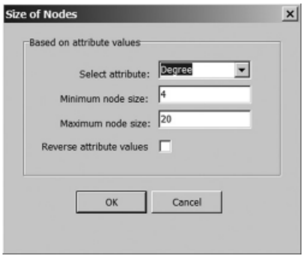


Figure 7.19. NetDraw Size of Nodes Dialog Box

with higher levels of education are more likely to be in positions of power than are those with lower levels of education.[8]

Centrality in NetDraw

Centrality scores are essentially attributes of actors, which means that we can use them to vary the size of nodes in network maps. In this section we will first examine how to use centrality scores calculated in UCINET to modify our visualization of networks in NetDraw. Then, we will see that NetDraw also includes a feature for calculating centrality scores that can then be utilized in our visualizations.

Visualizing UCINET Centrality Scores in NetDraw. In NetDraw, open the `Alive Combined Network.##h` data file, and energize it by choosing one of its layout algorithms. Next, open the multiple measures centrality attribute file associated with this data (i.e., `Alive Combined Network-cent.##h`). Then, using the *Properties>Nodes>Symbol>Size>Attribute-based* command select one or more of the centrality measures (in the Size of Nodes dialog box – see Figure 7.19) to vary the size of the nodes. If you choose degree centrality (as in Figure 7.19), then you will end up with a network map similar (but not identical) to Figure 7.5. If you choose ARD (closeness), then your network map will look similar to Figure 7.10; if you choose betweenness, then it will look like Figure 7.12; if you choose eigenvector, then it will look like Figure 7.15. You can also save your network maps as metafiles, bitmaps, and jpegs with NetDraw's *File>Save Diagram As* command.

[NetDraw]

Properties >Nodes >Symbol>Size >Attribute-based

File>Save Diagram As

Estimating Centrality Scores in NetDraw. NetDraw also calculates centrality measures with its *Analysis>Centrality measures* command. This calls up a dialog box (Figure 7.20) where you can choose which

Analysis >Centrality measures

[8] See Chapter 11 for a discussion of how to determine whether a particular correlation or regression coefficient is statistically significant.

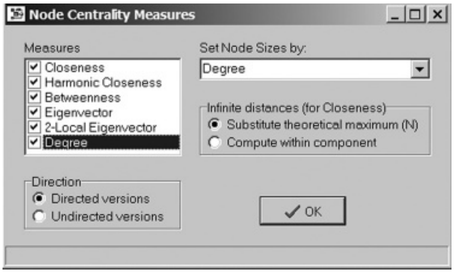


Figure 7.20. NetDraw Centrality Measures Dialog Box

centrality measures you want NetDraw to calculate. Note also that NetDraw has yet to implement ARD, but it does allow you to substitute a theoretical maximum based on network size for disconnected actors; it also allows you to compute only the closeness centrality within each component (not just the main component). You can also indicate what measure you want NetDraw to use to set the node size. Regardless of what you choose here, you can always change it later with *Properties>Nodes>Symbol>Size>Attribute-based* command. Another thing to keep in mind when estimating centrality in NetDraw is that if you load a stacked matrix into NetDraw (i.e., where multiple types of ties are listed in the relations box found on the right side of NetDraw), it will only calculate centrality on the relations that are checked. For example, if you read in the stacked Noordin trust network but only select the friendship network, NetDraw will only calculate centrality for the friendship network. If you select the kinship and friendship network, it will calculate centrality on the combined kinship and friendship network, and so on.

Properties >Nodes >Symbol>Size >Attribute-based

Centrality in Pajek

Estimating centrality in Pajek is relatively straightforward, although to date it has only implemented four centrality algorithms: degree, closeness, betweenness, and eigenvector (hubs and authorities). It is possible to visualize other measures of centrality in Pajek, but you need to estimate the scores in another program such as UCINET and then import the scores into Pajek as either a partition or vector.

[Pajek] File>Pajek Project File>Read

Net >Partitions >Degree>Input, Output, All

Degree Centrality in Pajek. Begin by reading the `Noordin Alive Network.paj` project file into Pajek. Pajek treats degree centrality as a discrete, rather than as a continuous, attribute of an actor (i.e., it is always an integer), so Pajek stores it as a partition. To calculate degree centrality in Pajek, choose either the *Input*, *Output*, or *All* option found under the *Net>Partitions>Degree* submenu. *Input* counts all incoming

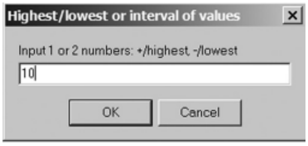


Figure 7.21. Pajek Info Partition/Vector Dialog Box

lines (indegree), *Output* counts all outgoing lines (outdegree), and *All* counts both. Note that an edge, which has no direction, is considered to be incoming as well as outgoing, so each edge is counted only once by all three commands. In other words, in an undirected network it makes no difference whether you select *Input*, *Output*, or *All*. As we will see when we are looking at measures of prestige, however, your selection does matter with directed networks. You should also be aware that when an undirected network is exported from UCINET and read into Pajek, edges become arcs, and you will need to symmetrize your data (i.e., make it symmetric) before calculating degree centrality, using the *Net>Transform>Arcs➔Edges>All* command. Pajek will ask whether you want to create a new network (select Yes) and whether you want to remove multiple lines and loops (select option 5, single line).

Net >Transform >Arcs➔Edges >All

When you estimate degree centrality Pajek, it generates both a partition, which stores the raw degree centrality scores, and a vector, which stores the normalized degree centrality scores. One way to examine the raw scores is to select the *File>Partition>Edit* command (or select the "Edit" radio button). This calls up an editing box that allows you to not only scroll through each actor's scores but also edit them if you so choose. Another way is to use Pajek's *Info>Partition* command. If you accept Pajek's defaults in the resulting dialog boxes, you will be provided basic information about the degree centrality scores. If you want more information, in the first dialog box (Figure 7.21) you can indicate that you want to get the scores of actors in rank order. If you type "10," Pajek will list the top-ten ranked actors; if you type "20," Pajek will list the top twenty, and so on (if you type "–10," Pajek will list the bottom ten). You can obtain similar information on the normalized score using Pajek's *File>Vector>Edit* and *Info>Vector* commands.

File >Partition >Edit

Info >Partition

File>Vector >Edit

Info>Vector

In Pajek, partitions can be used to alter the color of nodes, whereas vectors can be used to alter the size of nodes. To illustrate this, with the alive trust network (the network which the following example used to estimate degree centrality) showing in the first Network drop-down menu, the "All Degree partition of N (69)" showing in the first Partition drop-down menu, and the "Normalized All Degree partition of N1 (69)" showing in the first Vector drop-down menu, view the network with node size adjusted for degree centrality by selecting the *Draw>Draw-Partition-Vector* command and then using one of the two-dimensional

Draw >Draw-Partition-Vector

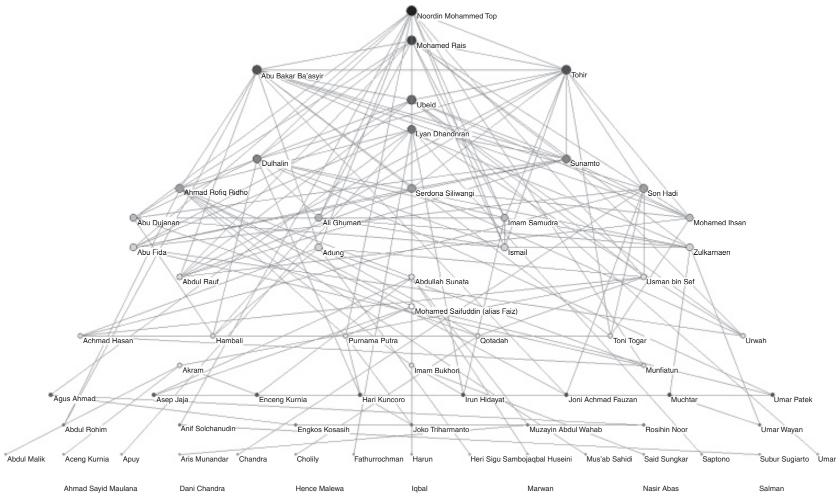


Figure 7.22. Pajek Drawing of Alive Trust Network, Layered by Degree Centrality

layout algorithms (be sure that the *Options>Value of Lines>Similarities* command is checked). If the node sizes do not seem to vary, you may need to adjust them using the *Size>of Vertices* option under the *Options* menu. Select "0" to tell Pajek to automatically adjust the size of the nodes.

[Draw] Options >Size>of Vertices

In Pajek it is fairly easy to layer networks based on an attribute, such as degree centrality. To do this with the current network, indicate that it is a two-dimensional layout with the *Layers>Type of Layout>2D* command found in the draw screen, and then tell Pajek to layer the drawing in the "y-direction" with the *Layers>In y direction* command. This will place Noordin at the bottom of the drawing (i.e., the person with the highest degree centrality) and those with the lowest degree centrality at the top. If you hold down the "X" key, you can rotate the drawing so that Noordin is at the top. Now your drawing is layered in terms of degree centrality with everyone having the same degree centrality located at the same horizontal level (Figure 7.22).

Layers >Type of Layout>2D

Layers>In y direction

[Main Screen]

Closeness Centrality in Pajek. In Pajek, the computation of closeness and betweenness centrality is similar to that of degree, except that Pajek treats both as vectors rather than partitions because they are continuous rather than discrete measures. Consequently, the centrality command for both are located in *Net>Vector>Centrality* submenu. The command to compute closeness centrality for all vertices in the network includes *Input*, *Output*, and *All* options, which with an undirected network yield the same results. If the network is disconnected (i.e., where there are isolates),

Net >Vector >Centrality >Closeness >Input, Output, All

Pajek assigns isolated actors a closeness score of "0." Of course, because all the alive networks are disconnected, we should probably first identify each network's weak components with Pajek's *Net>Components>Weak* command, and then extract the largest component from each with Pajek's *Operations>Extract from Network>Partition* command before estimating closeness centrality.

You can examine the scores of individual actors by selecting the *File>Vector>Edit* command (or select the "Edit" radio button). This calls up an editing box that allows you to not only scroll through each actor's scores but also edit them if you so choose. Or, you can use Pajek's *Info>Vector* command, which functions much like its *Info>Partition* command. That is, if you accept Pajek's defaults in the resulting dialog boxes, you will be provided basic information about the closeness centrality scores. If you want more information, in the first dialog box (Figure 7.22) you can indicate that you want to get the scores of actors in rank order. In other words, if you type "10," Pajek will list the top-ten ranked actors; if you type "20," Pajek will list the top twenty, and so on.

File>Vector >Edit

Info>Vector

Betweenness Centrality in Pajek. Betweenness centrality is calculated and visualized in Pajek in essentially the same way that we estimated closeness centrality, using the *Net>Vector>Centrality>Betweenness* command. However, because betweenness centrality does not take the direction of ties into consideration, only the path length between actors, Pajek does not include *In*, *Out*, and *All* options for betweenness. When you issue this command, Pajek creates a vector that you can examine using Pajek's *File>Vector>Edit* and *Info>Vector* commands or view with the Noordin network using the *Draw>Draw-Vector* command.

Net>Vector >Centrality >Betweenness

File>Vector >Edit

Info>Vector

Draw>Draw-Vector

Eigenvector (Hubs and Authorities) Centrality in Pajek. Technically, Pajek does not estimate eigenvector centrality, but it does include an equivalent set of metrics known as "hubs and authorities" The hubs and authorities algorithm was initially designed for identifying Web pages that functioned as hubs and ones that functioned as authorities. A good *hub* is defined as one that points to many good *authorities*, and a good *authority* is one that is pointed to by many good *hubs* (Kleinberg 1999). Consequently, the algorithm is designed to work with directed networks, but when used with undirected networks, it generates identical hubs and authorities scores.

To obtain hubs and authorities scores in Pajek we use the *Net>Vector>Important Vertices>1-Mode: Hubs and Authorities* command, which calls up two dialog boxes that at first blush can be confusing. The first asks how many hubs you want; the second asks how many authorities. What Pajek is asking is how many hubs and authorities you want Pajek to identify for the hubs and authority partition it will create. The

Net>Vector >Important Vertices >1-Mode: Hubs and Authorities

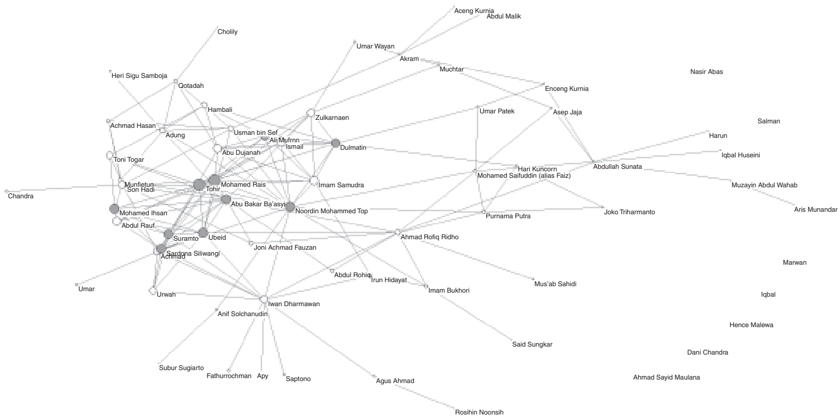


Figure 7.23. Alive Trust Network, Top-Ten Hubs/Authorities Highlighted (Pajek)

default is ten, but you can indicate however many you want. After you work your way through the dialog boxes, Pajek generates a partition and a vector that you can view in the draw screen using the same command that you used previously (Figure 7.23). In Figure 7.23 the size of the nodes varies based on eigenvector (hubs and authorities) centrality, and the actors ranked in the top ten are colored gray.

Excursus: Correlation in Pajek

To calculate the correlation between education and degree centrality in Pajek, highlight both vectors in the Vector drop-down menus (see Figure 7.24). If only one Vector drop-down menu is showing, click on the "Vector" speed button. To calculate the correlation between the two vectors, issue Pajek's *Vectors>Info* command, which will generate a report (not shown) that details the correlation between the two vectors.

Vectors>Info

Figure 7.24. Pajek Main Screen

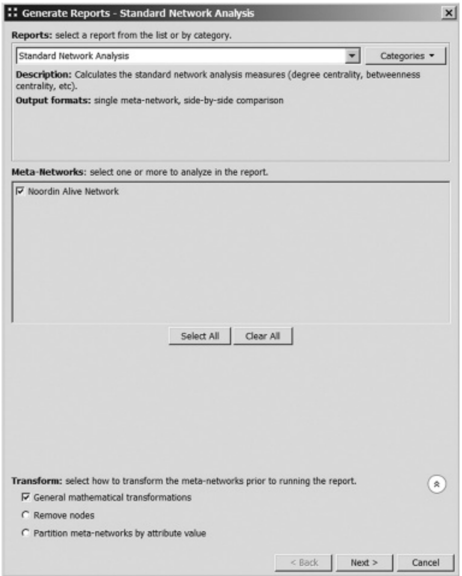


Figure 7.25. ORA's Generate Reports Dialog Box

Centrality in ORA

Begin by opening the alive Noordin meta-network (`Alive Noordin Network.xml`) using ORA's *File>Open Meta-Network* command. Once again the report that interests us here is the Standard Network Analysis report, which can be accessed using ORA's *Analysis>Generate Reports>Locate Key Entities>Standard Network Analysis* command.

[ORA] File>Open Meta-Network

Analysis >Generate Reports >Locate Key Entities >Standard Network Analysis

This brings up a dialog box similar to Figure 7.25. Because these networks are already dichotomized, there is no need to binarize them. However, if we were working with a valued network but wanted to analyze it dichotomously, then we would want to select the "General mathematical transformations" option (see Figure 7.25), and then at the next dialog box (not shown) we could indicate that we wanted to binarize the network before estimating any metrics. In the next dialog box (Figure 7.26) make sure that all five networks are selected so that ORA will calculate metrics for all five networks.

At the top of the next dialog box (not shown) check to see that the number of ranked nodes to be displayed is at least ten. Click the "Next" button, and in what is the final dialog box, select both the "Text" and "HTML" options, choose where you want ORA's output to go, provide a name for the output file(s), and click "Finish." Once ORA finishes running, you will note that it produces a tremendous amount of output. The first HTML file (which will appear in your Internet browser) serves as a directory, of sorts, with links to pages that describe the data analyzed

Figure 7.26. ORA's Generate Reports Dialog Box

as well as reports for each of the networks.[9] Scroll down through the HTML output and note that it generates graphics that you may want to use for presentations. You need to be careful here, though, because some of the graphs (e.g., the graph of "key nodes") are summaries of all of the measures computed in the report, even if some are effectively counted more than once (e.g., eigenvector centrality, hubs, authorities), or if some are inapplicable because of the type of data being analyzed (e.g., undirected instead of directed, closeness centrality with disconnected graphs, etc.). Each of the reports contains a tremendous amount of metrics (e.g., degree, closeness, eigenvector, hub, authority, information, betweenness, etc.) – both raw (unscaled) and normalized (value) – some of which apply to this network and some that do not. For example, because the traditional closeness centrality measure was used and this is a disconnected network, the results are incorrect. One "centrality" measure that ORA includes is a count of the number of cliques to which actors belong. As noted in the previous chapter, clique analysis is one of the oldest but most restrictive methods for identifying clusters within a network, but because individual actors can be members of more than one clique, many analysts find it unhelpful for identifying distinct clusters within a network. However, the count of the number of cliques to which actors belong tends to correlate highly with other centrality measures, so it is sometimes used as

[9] In order to see all of the HTML output, you may need to turn off your pop-up blocker.

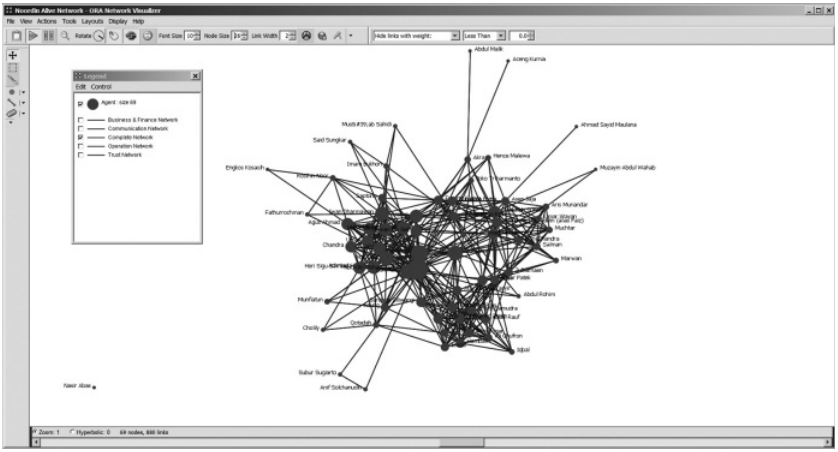


Figure 7.27. ORA Network Map with Node Size Varying by Eigenvector Centrality

a proxy for centrality. A very helpful part of the output is the "Key Nodes Table," which appears at the very end of the report. It lists the top-ten actors (because we told ORA to list the top ten) in terms of the four centrality measures that we have focused on in this chapter (although it does not display the scores).

Return to ORA's main screen and visualize the network. Next, select the *Display Node Appearance>Size Nodes by Attribute or Measure* command. This brings up the "Node Size Selector" dialog box (not shown), which allows you to vary the size of the nodes by various measures. One of the most helpful features of this dialog box is that when you place your mouse next to a measure, a pop-up box appears that explains what the measure is and what it represents. Finally, choose a measure and click on "Close." The actors in your network map should now vary in size by the measure you have selected. In the network map of the alive combined network (Figure 7.27), the nodes vary in terms of eigenvector centrality.

Display Node Appearance >Size Nodes by Attribute or Measure

Summary

Until now, we have considered measures for undirected networks. We now turn to metrics designed for analyzing directed networks and capturing the notion of prestige. The most common measure of prestige builds upon degree centrality, but there are other approaches. Because the Noordin data are undirected, we will use Krackhardt's advice and friendship networks, which are discussed in more detail in the following section.

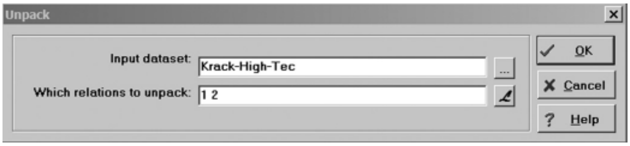


Figure 7.28. UCINET's Unpack Dialog Box

7.3 Centrality and Prestige

Social network researchers sometimes define a "prestigious actor as one who is the object of extensive ties" (Wasserman and Faust 1994:174), which is why they often use indegree centrality as a measure of prestige, which is the count of incoming ties. For example, a member of a dark network to whom people go to for advice (e.g., a mentor) could be seen as enjoying higher levels of prestige than those who only seek advice from others. Of course, if we were looking at the flow of money and other financial resources through a dark network, then outdegree might be a better measure of prestige. As we will see, there are measures of prestige, but indegree (and outdegree) centrality is typically the place where analysts start.

Because calculating indegree and outdegree centrality scores requires directional (i.e., asymmetric) network data, we will use data collected by David Krackhardt from the managers of a company that manufactured high-tech equipment on the West Coast (`Krack-High-Tec.##h`). According to the description of the dataset in UCINET (Borgatti, Everett, and Freeman 2011), at the time of Krackhardt's study, the firm had been in existence for ten years, produced high-tech machinery for other companies and employed approximately one hundred people, twenty-one of whom were managers (see also Krackhardt 1987a, 1992); these managers serve as the actors in the dataset. Krackhardt gave each manager a roster of the names of the other managers and asked to check the other managers to whom they would go for advice at work ("Advice") and with whom they were friends ("Friends"). He also collected data on "who reports to whom" for all twenty-one managers ("Reports to").

Estimating Prestige in UCINET

Indegree (and Outdegree) Centrality. Because the Krackhardt data are stored in three stacked 21 by 21 matrices, the first thing we need to do is unpack the advice and friendship matrices with UCINET's *Data>Unpack* command, which brings up UCINET's Unpack dialog box (Figure 7.28). Next, click on the "*L*" button to the right of the *Which relations to unpack* drop-down menu. This brings up the "Select labels" dialog box. Highlight the advice and friendship networks and click "OK." The "Unpack" dialog box should look similar to Figure 7.28. Click "OK."

[UCINET] Data >Unpack

```
ucinetlog2.txt - Notepad
File  Edit  Format  View  Help
FREEMAN'S DEGREE CENTRALITY MEASURES
--------------------------------------------------------------------------------

Diagonal valid?                         NO
Model:                                  ASYMMETRIC
Input dataset:                          ADVICE

                          1            2            3            4
                  OutDegree     InDegree    NrmOutDeg     NrmInDeg
               ------------ ------------ ------------ ------------
   15  15            20.000        4.000      100.000       20.000
   18  18            17.000       15.000       85.000       75.000
    3   3            15.000        5.000       75.000       25.000
    5   5            15.000        5.000       75.000       25.000
   10  10            14.000        9.000       70.000       45.000
    9   9            13.000        4.000       65.000       20.000
    4   4            12.000        8.000       60.000       40.000
   20  20            12.000        8.000       60.000       40.000
   21  21            11.000       15.000       55.000       75.000
   19  19            11.000        4.000       55.000       20.000
    8   8             8.000       10.000       40.000       50.000
    7   7             8.000       13.000       40.000       65.000
    1   1             6.000       13.000       30.000       65.000
   13  13             6.000        4.000       30.000       20.000
   17  17             5.000        9.000       25.000       45.000
   16  16             4.000        8.000       20.000       40.000
   14  14             4.000       10.000       20.000       50.000
    2   2             3.000       18.000       15.000       90.000
   11  11             3.000       11.000       15.000       55.000
   12  12             2.000        7.000       10.000       35.000
    6   6             1.000       10.000        5.000       50.000


DESCRIPTIVE STATISTICS

                                1            2            3            4
                        OutDegree     InDegree    NrmOutDeg     NrmInDeg
                     ------------ ------------ ------------ ------------
    1       Mean            9.048        9.048       45.238       45.238
    2    Std Dev            5.323        3.970       26.613       19.849
    3        Sum          190.000      190.000      950.000      950.000
    4   Variance           28.331       15.760      708.277      393.991
    5        SSQ         2314.000     2050.000    57850.000    51250.000
    6      MCSSQ          594.952      330.952    14873.810     8273.810
    7   Euc Norm           48.104       45.277      240.520      226.385
    8    Minimum            1.000        4.000        5.000       20.000
    9    Maximum           20.000       18.000      100.000       90.000
   10   N of Obs           21.000       21.000       21.000       21.000

Network Centralization (Outdegree) = 57.500%
Network Centralization (Indegree) = 47.000%
```

Figure 7.29. UCINET's Indegree (and Outdegree) Centrality Output

Data >Data Editors >Matrix Editor

[UCINET Spreadsheet] File>Open file>Save as multiple files

An alternative method for unpacking stacked networks (and a relatively new addition to UCINET) is to read the Krackhardt data into the UCINET internal spreadsheet program (accessed by the *Data>Data Editors>Matrix Editor* command), and resave the dataset using the *File>Save as multiple files* command. Unlike the "Unpack" command, you cannot choose the networks you want to extract. Instead, it will extract all the files in the data file. Nevertheless, it is a relatively convenient and alternative way to unpack stacked network data.

Network >Centrality and Power>Degree

To calculate indegree centrality in UCINET, first select the *Degree* option found under the *Network>Centrality and Power* submenu. This will bring up UCINET's "Degree Centrality" dialog box (not shown). Make sure that the advice network is highlighted in the "Input dataset" option box. Next, select the "No" option in the "Treat data as symmetric" option box; this tells UCINET to calculate both the indegree and outdegree centrality scores of each actor in a network. (When you select "Yes," it calculates and then selects the higher of the indegree or outdegree centrality of each actor.) Click "OK," and UCINET will generate output similar to that in Figure 7.29.

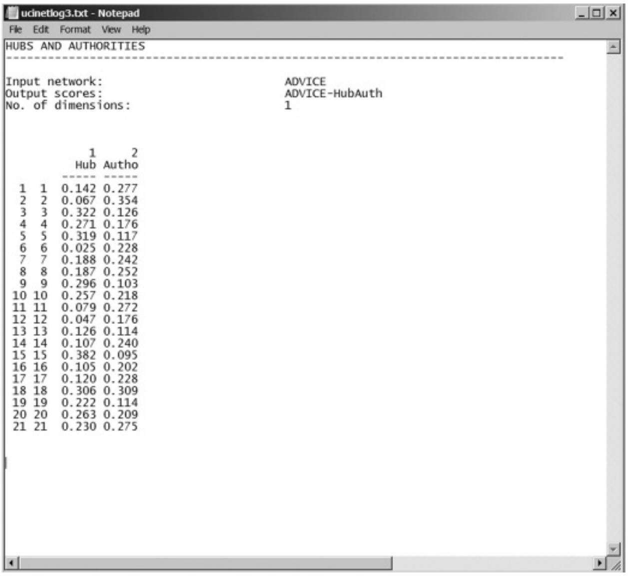
The output is similar to the standard degree centrality report, except that now it distinguishes between indegree and outdegree and does not report a share score. Note that outdegree is listed first, then indegree, so if we want to use indegree as a measure of prestige, we need to look to the second (and fourth) columns. Also, UCINET lists the actors in terms of declining outdegree scores, not their indegree scores, so we simply cannot look at the top of the list to find our most prestigious actor. According to the indegree scores, the advice of manager #2 is sought out more than any other manager's advice (indegree centrality = 18), so we could conclude that in terms of the advice network, manager #2 is the most prestigious and is followed closely by managers #18 and #21, whose indegree centrality scores equal 15. If we were to make the assumption that outdegree is a measure of insecurity, then manager #15 is clearly the least secure with an outdegree score of 20, meaning he or she seeks the advice of every other manager in the company. Of course, this may not be a good assumption because manager #18 scores second highest in terms of outdegree, and as we just saw, he or she ranks second in terms of indegree. As always, we need to be careful when interpreting our results. Repeat this step using the friendship network. In terms of the friendship network, which actor enjoys the highest level of prestige?

Network >Centrality and Power >Hubs & Authorities

Hubs and Authorities. Hubs and authorities scores offer another approach to estimating prestige in a network, and although we did not mention it in our previous discussion of eigenvector centrality, these scores can be estimated in UCINET with the *Network>Centrality and Power>Hubs & Authorities* command. If you recall, the hubs and authorities algorithm was initially designed for ranking web pages. A good *hub* is defined as one that points to many good *authorities*, and a good *authority* is one that is pointed to by many good *hubs* (Kleinberg 1999). Thus, in terms of prestige, it allows analysts to not only take into account the number of ties an actor receives (i.e., an authority) but also to weight those ties by whether the actor that is sending the tie (i.e., a hub) also sends ties to other prestigious actors in the network. This command generates an output similar to Figure 7.30.

As you can see, the hubs scores, which are similar to outdegree scores, are listed first, and the authority scores, which are similar to indegree scores, are listed second. Manager #2 is still ranked the highest in terms of prestige (i.e., authority) and #18 ranks second, but #21 is no longer tied with #18. In fact, manager #21 actually ranks behind manager #1. Why? Because the managers who seek the advice of manager #18 tend to seek the advice of other managers who score high in terms of authority, more often than do the managers who seek advice from manager #21.

Reach Centrality. As de Nooy et al. (2005) have noted, indegree centrality is a somewhat limited prestige measure because it only considers direct


ucinetlog3.txt - Notepad

File Edit Format View Help

HUBS AND AUTHORITIES

Input network:	ADVICE
Output scores:	ADVICE-HubAuth
No. of dimensions:	1

		1 Hub	2 Autho
1	1	0.142	0.277
2	2	0.067	0.354
3	3	0.322	0.126
4	4	0.271	0.176
5	5	0.319	0.117
6	6	0.025	0.228
7	7	0.188	0.242
8	8	0.187	0.252
9	9	0.296	0.103
10	10	0.257	0.218
11	11	0.079	0.272
12	12	0.047	0.176
13	13	0.126	0.114
14	14	0.107	0.240
15	15	0.382	0.095
16	16	0.105	0.202
17	17	0.120	0.228
18	18	0.306	0.309
19	19	0.222	0.114
20	20	0.263	0.209
21	21	0.230	0.275

Figure 7.30. UCINET's Hubs and Authorities Output

choices (see also Wasserman and Faust 1994:203–205). Consequently, social network analysts have developed alternative measures that take into account direct and indirect choices. Reach centrality is one such measure. As discussed previously, it counts the number of nodes that each node can reach (or be reached) in k steps or less. When $k = 1$, the resulting score is the same as degree centrality, which means that if we are analyzing a directed network, the resulting scores will equal indegree and outdegree centrality. When $k = n - 1$ (i.e., the size of the network less 1, which is its maximum value), its raw score equals the total number of actors that can be reached in $n - 1$ (i.e., k) steps. Therefore, the resulting raw scores equal the total direct and indirect choices each actor receives (or sends, if we are focusing on outdegree). As we will see further on in this chapter, this is similar to what Pajek refers to as an actor's input (or output) domain.

Calculating reach centrality in UCINET is as straightforward as any of the other centrality measures. The command is located in the *Centrality and Power* submenu. The command first calculates the weighted distance reach centrality of each node, which is the sum of the number of actors that can be reached in k steps divided by k, which is the same as ARD centrality plus one. Figure 7.31 presents a portion of UCINET's reach centrality output with regard to Krackhardt's advice network. Here again, manager #2 ranks first in terms of this measure of prestige with #18 and #21 tied for second.

Network >Centrality and Power>Reach Centrality

```
ucinetlog8.txt - Notepad
File  Edit  Format  View  Help
REACH CENTRALITY
------------------------------------------------------------------------------

Input dataset:                         ADVICE
Output dataset:                        ActorByDistanceReach

Note: Data not symmetric, therefore separate in-closeness &
out-closeness computed.


Reach Centrality

                  1         2         3         4
          OutdwReac IndwReach nOutdwRea nIndwReac
          --------- --------- --------- ---------
   15        21.000    12.167     1.000     0.579
   18        19.500    18.500     0.929     0.881
    3        18.500    13.333     0.881     0.635
    5        18.500    12.667     0.881     0.603
   10        18.000    14.833     0.857     0.706
    9        17.500    12.167     0.833     0.579
    4        17.000    15.000     0.810     0.714
   20        17.000    14.833     0.810     0.706
   21        16.500    18.500     0.786     0.881
   19        16.500    12.167     0.786     0.579
    8        15.000    16.000     0.714     0.762
    7        15.000    17.500     0.714     0.833
    1        14.000    17.000     0.667     0.810
   13        14.000    12.167     0.667     0.579
   14        13.000    16.000     0.619     0.762
   16        12.833    14.500     0.611     0.690
   17        12.667    15.500     0.603     0.738
    2        11.167    20.000     0.532     0.952
   11        11.167    16.333     0.532     0.778
   12        10.667    14.333     0.508     0.683
    6        10.000    16.000     0.476     0.762
```

Figure 7.31. UCINET's Reach Centrality Output

Estimating Prestige in Pajek

File>Project
File>Read
Net>Partitions>Degree>Input
Info>Partition

Indegree and Outdegree Centrality. Read the Krackhardt project file (`Krack-High-Tec.paj`) into Pajek. Make sure that the advice network is listed in the first Network drop-down menu. Select the *Net>Partitions>Degree>Input* command, which creates a new partition (and a vector) based on indegree. You can use the *Info>Partition* command to obtain a ranking of the indegree scores. Be sure that the new partition is showing in the first Partition drop-down menu. In the first dialog box, type "21," which indicates that you want to see the top twenty-one scores (in this case, the scores for all the managers in the network); in the second box accept Pajek's default. This should create a report that looks something like Figure 7.32.

The upper part of the report ("The highest clusters values") ranks the actors in terms of indegree centrality (*Cluster* is the indegree centrality score), while the lower portion ("Frequency distribution of cluster values") indicates the number of actors in each cluster/class. Thus, manager #2 has an indegree centrality of 18 and there are four actors (19.05 percent of the network) with an indegree centrality of 4, which is the lowest score in the network, whereas only one actor has an indegree centrality of 18, which as we have already seen, is the highest score in the network. If you close the report menu and select the *File>Partition>Edit* command, a window will be called up that displays the indegree centrality measures of each actor in the network.

File>Partition>Edit

Report

File

2. Input Degree partition of N1 (21)

Dimension: 21
The lowest value: 4
The highest value: 18

The highest clusters values:

Rank	Vertex	Cluster	Id
1	2	18	2
2	21	15	21
3	18	15	18
4	7	13	7
5	1	13	1
6	11	11	11
7	14	10	14
8	6	10	6
9	8	10	8
10	10	9	10
11	17	9	17
12	20	8	20
13	4	8	4
14	16	8	16
15	12	7	12
16	3	5	3
17	5	5	5
18	15	4	15
19	9	4	9
20	19	4	19
21	13	4	13

Frequency distribution of cluster values:

Cluster	Freq	Freq%	CumFreq	CumFreq%	Representative
4	4	19.0476	4	19.0476	9
5	2	9.5238	6	28.5714	3
7	1	4.7619	7	33.3333	12
8	3	14.2857	10	47.6190	4
9	2	9.5238	12	57.1429	10
10	3	14.2857	15	71.4286	6
11	1	4.7619	16	76.1905	11
13	2	9.5238	18	85.7143	1
15	2	9.5238	20	95.2381	18
18	1	4.7619	21	100.0000	2
Sum	21	100.0000			

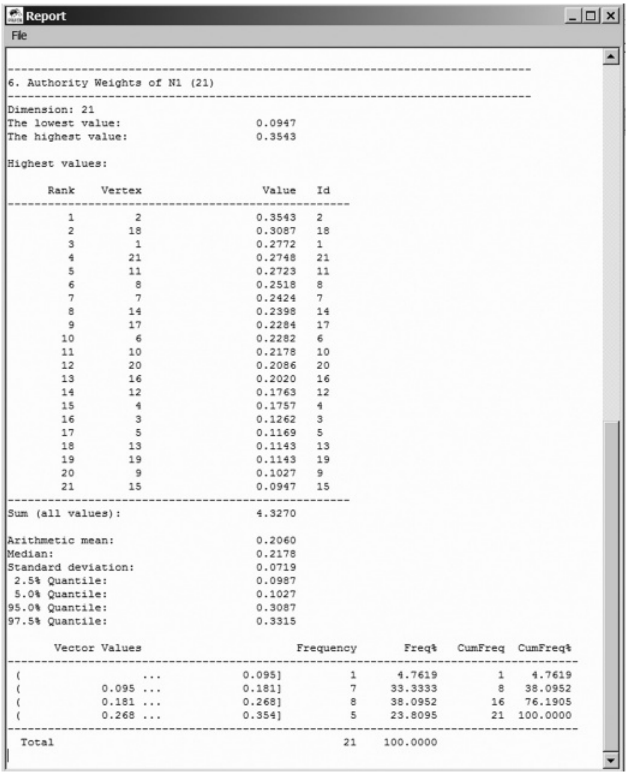
Figure 7.32. Pajek's Partition Information Report (Indegree Centrality Scores)

Hubs and Authorities. In the previous section we learned how Pajek estimates hubs and authorities centrality scores with its *Net>Vector> Important Vertices>1-Mode:Hubs-Authorities* command. Pajek's *Info> Vector* feature produces a report (Figure 7.33) that lists the authority scores for the advice network (remember to indicate in the first dialog box that you want to see the scores for all twenty-one managers). As you can see, Pajek's results are the same as UCINET's, which is what we would expect.

Net >Vector >Important Vertices >1-Mode:Hubs-Authorities

Info>Vector

Input Domain and Proximity Prestige. Indegree centrality is a somewhat restricted measure of prestige because it only considers direct choices. As a result, Pajek's developers have included routines for two additional measures that can be used to estimate actor prestige: input domain and proximity prestige (Lin 1976; Wasserman and Faust 1994:203–205). Input domain is a measure of prestige that counts all people by whom someone is chosen whether directly or indirectly. The larger a person's input


Report

File

6. Authority Weights of N1 (21)

Dimension: 21
The lowest value: 0.0947
The highest value: 0.3543

Highest values:

Rank	Vertex	Value	Id
1	2	0.3543	2
2	18	0.3087	18
3	1	0.2772	1
4	21	0.2748	21
5	11	0.2723	11
6	8	0.2518	8
7	7	0.2424	7
8	14	0.2398	14
9	17	0.2284	17
10	6	0.2282	6
11	10	0.2178	10
12	20	0.2086	20
13	16	0.2020	16
14	12	0.1763	12
15	4	0.1757	4
16	3	0.1262	3
17	5	0.1169	5
18	13	0.1143	13
19	19	0.1143	19
20	9	0.1027	9
21	15	0.0947	15

Sum (all values): 4.3270

Arithmetic mean:	0.2060
Median:	0.2178
Standard deviation:	0.0719
2.5% Quantile:	0.0987
5.0% Quantile:	0.1027
95.0% Quantile:	0.3087
97.5% Quantile:	0.3315

Vector Values	Frequency	Freq%	CumFreq	CumFreq%
(... 0.095]	1	4.7619	1	4.7619
(0.095 ... 0.181]	7	33.3333	8	38.0952
(0.181 ... 0.268]	8	38.0952	16	76.1905
(0.268 ... 0.354]	5	23.8095	21	100.0000
Total	21	100.0000		

Figure 7.33. Pajek's Partition Information Report (Authority Scores)

domain, the higher his or her prestige. To calculate input domain, use Pajek's *Net>Partitions>Domain>Input* command. A dialog box allows you to specify a maximum distance for the input domain. To begin with, accept Pajek's default ("0," no limit). This produces one partition and two vectors. The partition specifies the number of actors in each actor's input domain. The vector labeled "Normalized Size of input domain" lists the size of each actor's input domain as a proportion of all actors (minus the actor itself), and the second vector gives the average distance to an actor from all other actors in its input domain. We will use these two vectors when calculating proximity prestige. After ensuring that the new partition is listed in the first Partition drop-down menu, use the *Info>Partition* command to obtain a ranking of the actors in terms of input domain (Figure 7.34).

Net >Partitions >Domain >Input

Info>Partition

As Figure 7.34 illustrates, an actor's unrestricted input domain is an imperfect measure of prestige. In a well-connected network such as this one, it often contains all or almost all other actors, so it does a poor job of distinguishing between actors. Indeed, Krackhardt's advice network

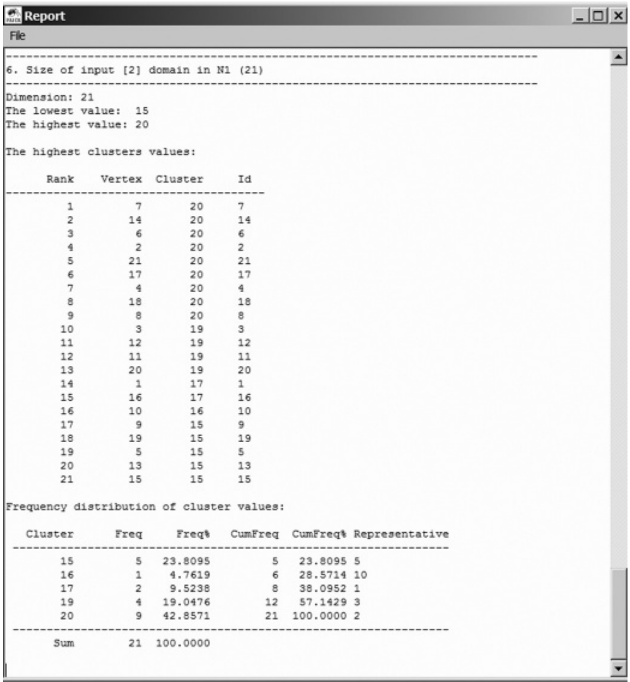
```
Report
File
--------------------------------------------------------------------------------
4. Size of input domain in N1 (21)
--------------------------------------------------------------------------------
Dimension: 21
The lowest value:  20
The highest value: 20

The highest clusters values:

      Rank    Vertex  Cluster     Id
---------------------------------------
         1         1       20     1
         2        21       20     21
         3        20       20     20
         4        19       20     19
         5        18       20     18
         6        17       20     17
         7        16       20     16
         8        15       20     15
         9        14       20     14
        10        13       20     13
        11        12       20     12
        12        11       20     11
        13        10       20     10
        14         9       20     9
        15         8       20     8
        16         7       20     7
        17         6       20     6
        18         5       20     5
        19         4       20     4
        20         3       20     3
        21         2       20     2

Frequency distribution of cluster values:

   Cluster       Freq     Freq%   CumFreq  CumFreq% Representative
 -----------------------------------------------------------------
        20         21  100.0000        21  100.0000 1
 -----------------------------------------------------------------
       Sum         21  100.0000
```

Figure 7.34. Pajek's Partition Information Report (Input Domain)

does not distinguish the actors at all. Each actor's unrestricted input domain equals twenty. One solution to this is to assume that choices by closer actors (in terms of path length) are more important than they are from distant actors and then restrict the input domain to neighbors at a prespecified maximum distance chosen by the analyst. For example, Christakis and Fowler (2009) have argued that a person's influence ceases to have a noticeable effect on others beyond three degrees of separation,[10] so they might argue that the influence that each manager has in terms of advice giving does not extend beyond a path length of three (i.e., an advisee of an advisee of an advisee); thus, we should restrict the input domain to three. In the case of the advice network, however, because each manager is within three steps of every other actor in the network, we get the same scores as before (i.e., each actor's input domain equals twenty). With a restricted input domain of two, though, we do get some differentiation in the scores (Figure 7.35), but not too much.

The choice of a maximum distance from neighbors within a restricted input domain can be somewhat arbitrary. The concept of proximity prestige overcomes this by taking into account all actors within an actor's input domain while weighting choices by closer neighbors higher than

[10] Christakis and Fowler's method for estimating this effect has been persuasively challenged on mathematical and statistical grounds (Cohen-Cole and Fletcher 2008; Lyons 2011).


Report

File

```
------------------------------------------------------------------------------
6. Size of input [2] domain in N1 (21)
------------------------------------------------------------------------------
Dimension: 21
The lowest value:  15
The highest value: 20

The highest clusters values:

      Rank    Vertex  Cluster     Id
---------------------------------------
         1         7       20     7
         2        14       20     14
         3         6       20     6
         4         2       20     2
         5        21       20     21
         6        17       20     17
         7         4       20     4
         8        18       20     18
         9         8       20     8
        10         3       19     3
        11        12       19     12
        12        11       19     11
        13        20       19     20
        14         1       17     1
        15        16       17     16
        16        10       16     10
        17         9       15     9
        18        19       15     19
        19         5       15     5
        20        13       15     13
        21        15       15     15

Frequency distribution of cluster values:

   Cluster      Freq      Freq%   CumFreq  CumFreq% Representative
 ------------------------------------------------------------------
        15         5    23.8095         5    23.8095 5
        16         1     4.7619         6    28.5714 10
        17         2     9.5238         8    38.0952 1
        19         4    19.0476        12    57.1429 3
        20         9    42.8571        21   100.0000 2
------------------------------------------------------------------
       Sum        21   100.0000
```

Figure 7.35. Pajek's Partition Information Report (Restricted Input Domain)

those of distant neighbors. In other words, a choice by a close neighbor contributes more to an actor's proximity prestige than does a choice by a distant neighbor. This helps analysts avoid the problem we ran into previously with unrestricted input domain (i.e., in a well-connected network unrestricted input domain does a poor job of distinguishing between actors). At the same time, however, because proximity prestige does take into account the choices from distant actors, they are not entirely discounted as they might be with restricted input domain. Consequently, many distant choices may contribute as much as a single close choice (de Nooy et al. 2005:197).

To calculate proximity prestige, we divide the unrestricted (and normalized) input domain size by the average distance. To do this, first be sure that the vector with the normalized size of the input domain ("Normalized Size of input domain in N1 (21)") is highlighted in the first Vector drop-down menu and the vector with average distances ("Average distance from input domain in N1 (21)") is highlighted in the second Vector drop-down menu (Figure 7.36).

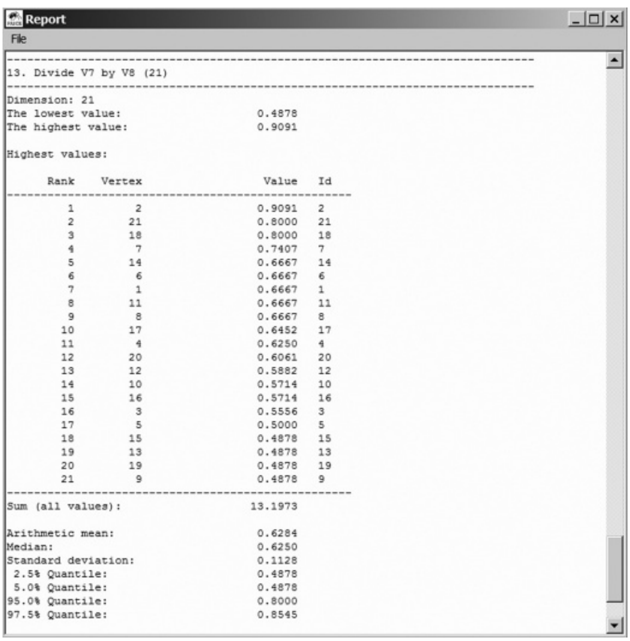
Vectors >Divide First by Second

Then, choose the command *Divide First by Second* in the *Vectors* menu. This will create a new vector containing the proximity prestige

Figure 7.36. Pajek's Main Screen

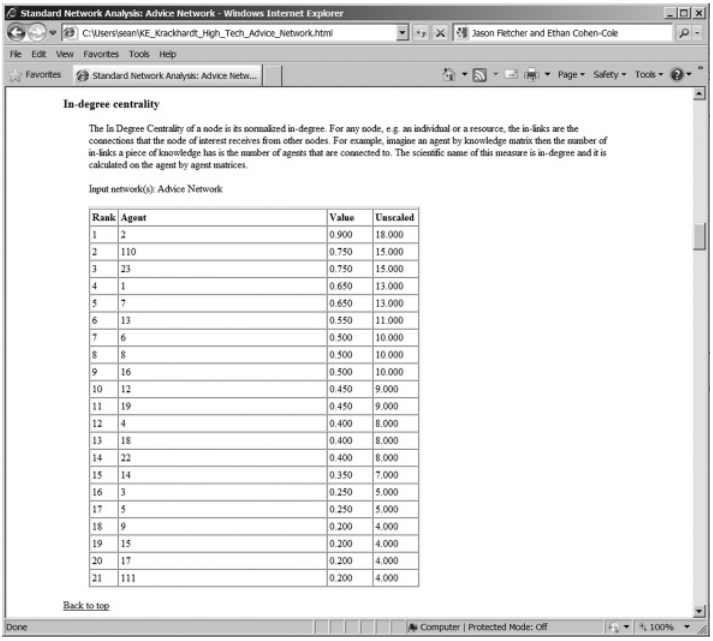
scores of all vertices. If we examine them with the *Info>Vector* command (Figure 7.37), we can see that manager #2 is ranked highest with managers #21 and #18, who are tied with one another and not too far behind. They are followed by manager #7, after whom are managers #14, #6, #1, and #11, with all the same score. *Info>Vector*

Although this set of rankings is similar to those found using the indegree and authority algorithms, it is not identical. Which one should you use? There is no hard-and-fast rule. In general, you will want to compare the rankings. Here, manager #2 has consistently been ranked first with #21 and #18 always near the top. After that the rankings become a little muddier, but managers #1, #7, #11, and #14 are always in the running.


Report
File

```
13. Divide V7 by V8 (21)
Dimension: 21
The lowest value:               0.4878
The highest value:              0.9091

Highest values:

      Rank    Vertex            Value   Id
         1         2            0.9091  2
         2        21            0.8000  21
         3        18            0.8000  18
         4         7            0.7407  7
         5        14            0.6667  14
         6         6            0.6667  6
         7         1            0.6667  1
         8        11            0.6667  11
         9         8            0.6667  8
        10        17            0.6452  17
        11         4            0.6250  4
        12        20            0.6061  20
        13        12            0.5882  12
        14        10            0.5714  10
        15        16            0.5714  16
        16         3            0.5556  3
        17         5            0.5000  5
        18        15            0.4878  15
        19        13            0.4878  13
        20        19            0.4878  19
        21         9            0.4878  9

Sum (all values):              13.1973

Arithmetic mean:                0.6284
Median:                         0.6250
Standard deviation:             0.1128
 2.5% Quantile:                 0.4878
 5.0% Quantile:                 0.4878
95.0% Quantile:                 0.8000
97.5% Quantile:                 0.8545
```

Figure 7.37. Pajek's Vector Information Report (Proximity Prestige)


Standard Network Analysis: Advice Network - Windows Internet Explorer

In-degree centrality

The In Degree Centrality of a node is its normalized in-degree. For any node, e.g. an individual or a resource, the in-links are the connections that the node of interest receives from other nodes. For example, imagine an agent by knowledge matrix then the number of in-links a piece of knowledge has is the number of agents that are connected to. The scientific name of this measure is in-degree and it is calculated on the agent by agent matrices.

Input network(s): Advice Network

Rank	Agent	Value	Unscaled
1	2	0.900	18.000
2	110	0.750	15.000
3	23	0.750	15.000
4	1	0.650	13.000
5	7	0.650	13.000
6	13	0.550	11.000
7	6	0.500	10.000
8	8	0.500	10.000
9	16	0.500	10.000
10	12	0.450	9.000
11	19	0.450	9.000
12	4	0.400	8.000
13	18	0.400	8.000
14	22	0.400	8.000
15	14	0.350	7.000
16	3	0.250	5.000
17	5	0.250	5.000
18	9	0.200	4.000
19	15	0.200	4.000
20	17	0.200	4.000
21	111	0.200	4.000

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Figure 7.38. ORA's Standard Network Analysis Report (Indegree Centrality)

Estimating Prestige in ORA

[ORA] File>Open Meta-Network

Analysis >Generate Reports >Locate Key Entities >Standard Network Analysis

Indegree and outdegree scores are included in ORA's standard network analysis report. Thus, after reading the Krackhardt meta-network file (`Krackhardt High Tech.xml`) into ORA with its *File>Open Meta-Network* command, issue its *Analysis>Generate Reports>Locate Key Entities>Standard Network Analysis* command. In the second dialog box ensure that the advice network is selected and change the number of ranked nodes to be displayed to twenty-one. Click "Next" and in the dialog box select both the "Text" and "HTML" options; choose where you want ORA's output to go, provide a name for the output file(s), and click "Finish." As before, ORA will produce a lot of output, and to see all the HTML output, you may need to turn off your pop-up blocker. Because we indicated that we wanted ORA to list the top twenty-one actors (rather than the default of ten), all the tables in the report include scores for each manager in the network. Figure 7.38 displays only the indegree centrality results, but it should be noted that ORA's standard network analysis report includes hubs and authorities scores too.

[ORA-Visualizer] Display Node Appearance >Size Nodes by Attribute or Measure

Return to ORA's main screen and visualize the advice network. Next, select the *Display Node Appearance>Size Nodes by Attribute or Measure* command. This brings up the "Node Size Selector Dialog Box" (not

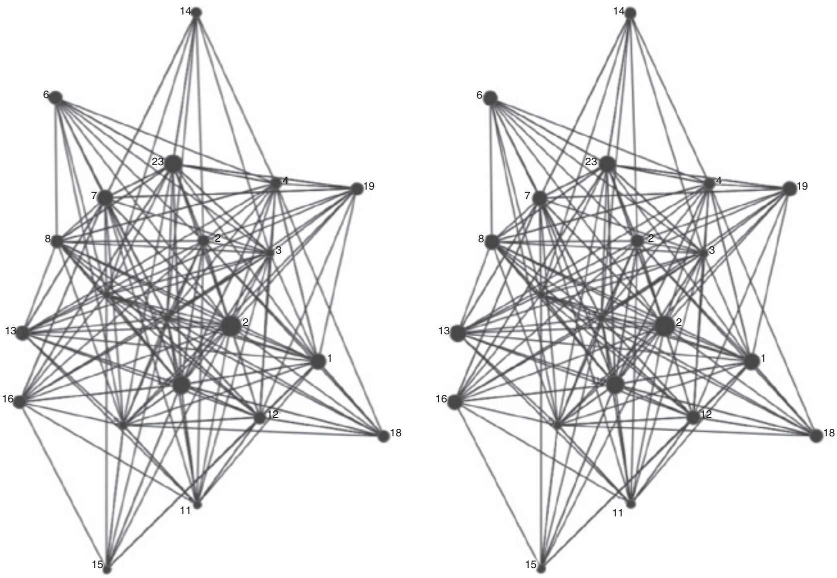

Figure 7.39. Advice Network with Node Size by Indegree and Authority Centrality (ORA)

shown), which if you recall allows you to vary the size of the node by various measures. If you choose indegree centrality and click "Close," the actors in your network map will vary in size in terms of indegree centrality. If you choose authority centrality, the actors in your network map will vary in size in terms of authority centrality. Figure 7.39 presents the advice network with the nodes varying in terms of indegree centrality (left) and authority centrality (right). Although the network maps are not identical, their difference is minimal, suggesting that both measures are tapping into the same dynamic.

7.4 Summary and Conclusion

In this chapter we have explored one of the oldest, and perhaps the most intuitive, social network analysis metrics. It has been used by social psychologists (Bavelas 1950; Moreno 1953) and exchange theorists (Cook and Emerson 1978; Cook et al. 1983; Cook et al. 1986; Cook and Whitmeyer 1992; Emerson 1962, 1972a, b, 1976), and has been formalized by others (Bonacich 1972a, b, 1987; Borgatti 2005; Borgatti and Everett 2006; Everett and Borgatti 2005; Freeman 1977, 1979; Friedkin 1991). We have seen that a central actor can be seen as someone who has numerous ties to other actors (e.g., degree centrality), as someone who has numerous ties to highly central actors (e.g., eigenvector centrality, hubs and authorities), as someone who is close (in terms of path distance) to other actors in the network (e.g., closeness centrality), or as someone who lies on the shortest path between numerous pairs of actors in a network (e.g., betweenness centrality). In addition to considering measures of centrality, we briefly explored how with directed (i.e., asymmetric) networks, "indegree and outdegree" and "hubs and authorities," centrality can potentially be used as measures of prestige. We also explored two variations on the former measures that take into account direct and indirect choices.

What did we learn about Noordin Top's network? We discovered that in addition to Noordin Top, there were a handful of individuals who repeatedly scored high in terms of various measures of centrality across the trust, operational, communication, and combined networks. The one exception was the business and finance network, which as we have seen in previous chapters differs substantially from the other networks. What should we do with this knowledge? As we noted in Chapter 2, it is tempting to use it for the kinetic targeting of high-value actors, but this is not always the best use of resources and often ignores possible second- and third-order effects. For example, anecdotal evidence suggests that direct attacks on insurgents may sometimes worsen the threat (Schmitt and Perlez 2009) by multiplying enemies instead of subtracting them (Flynn, Pottinger, and Batchelor 2010:8). One option has already been mentioned (see Chapter 6): Namely, we might want to monitor individuals who score high in terms of centrality with the hope of improving our knowledge of the network and the selection of strategies adopted (Arquilla 2009:34). Another approach might be to use what we learned about the communication network to craft information operation (IO) disruption strategies that seek to compromise the cell phone and online connections of highly central actors. Finally, we may want to consider using low centrality scores to identify peripheral actors in the network who may be open to reintegration and rehabilitation programs.