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An Introduction to Social Network Analysis for Personality and Social Psychologists

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Abstract

Social network analysis (SNA) is a methodology for studying the connections and behavior of individuals within social groups. Despite its relevance to social and personality psychology, SNA has been underutilized in these fields. We first examine the paucity of SNA research in social and personality journals. Next we describe methodological decisions that must be made before collecting social network data, with benefits and drawbacks for each. We discuss common SNAs and give an overview of software available for SNA. We provide examples from the literature of SNA for both one-mode and two-mode network data. Finally, we make recommendations to researchers considering incorporating SNA into their research.

Keywords

social networks, social network analysis, groups, methods, interpersonal relations

Although most research in social and personality psychology focuses on individuals, those individuals are embedded in larger social networks. Social network analysis (SNA) is ideally suited for social–personality psychology because it integrates individuals and the relationships among them. SNA makes social structure visible by quantifying the relationships among people as emergent properties of the network. SNA may therefore hold untapped potential for understanding individual differences and behaviors within a social context.

The historical roots of SNA began with Jacob Moreno's creation of the field of *sociometry*, which focused on mapping social communities using a visualization called a *sociogram* (Moreno, 1934). As sociometry matured, it moved from a purely descriptive paradigm to incorporate quantitative analyses from graph theory, algebra, and statistics (for a description of these historical foundations, see Wasserman & Faust, 1994).

Some of the terminology used in SNA is specific to the field. We therefore define some terms before proceeding with examples of their use. Individuals in SNA are often called *actors*, emphasizing their interactive role in the social network. More often, graph theory terminology is used, referring to individuals simply as *nodes* or *vertices*. The connections between these nodes are likewise described using graph theoretical terms as *ties* or *edges*. These ties can represent any sort of relationship between two people, such as level of acquaintance, liking, trust, or even negative relationships such as disliking. It is often useful to distinguish between a focal individual of interest and others to whom that person is connected. The focal individual is referred to as *ego*, whereas others are referred to as *alters*. Any individual can be thought of as both an ego and an alter to other individuals, in the same way that individuals can be both an actor and a partner in dyadic models (Kenny, Kashy, & Cook, 2006).

Social Networks in Personality and Social Psychology

Because social networks represent relationships (ties) among people (nodes) in groups, they should interest both social and personality psychologists. In fact, social psychology luminaries such as Lewin (1948), Milgram (1967), and Festinger, Schachter, and Back (1950) helped pioneer research on social networks. However, sociologists and anthropologists have developed many of the analytic approaches used in SNA over the past five decades (e.g., Borgatti, Everett, & Johnson, 2013; Knoke & Yang, 2008). More broadly, developments such as small-world (Watts & Strogatz, 1998) and scale-free (Barabási & Bonabeau, 2003) networks have helped to model contagion, computer networks, and even neuronal organization. Network models of personality (Cramer et al., 2012) and pathology (Borsboom, 2017) as interconnected components of individual differences also provide intriguing new applications of networks.

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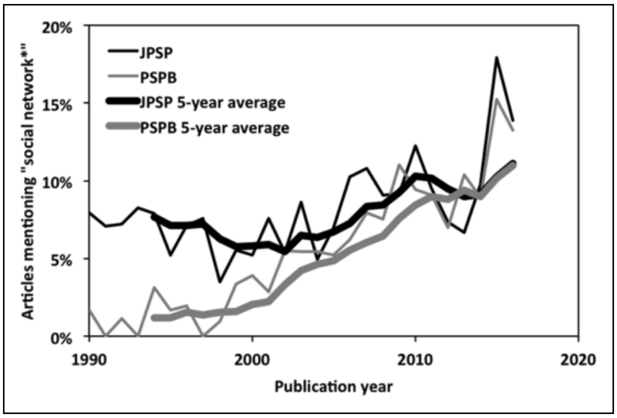

Figure 1. Percentages of *JPSP* (black) or *PSPB* (gray) articles mentioning "social network" or "social networks" over time. Thin lines show raw data; thick lines show 5-year moving averages (e.g., 1994 reflects the average of 1990–1994). *JPSP* = *Journal of Personality and Social Psychology*; *PSPB* = *Personality and Social Psychology Bulletin.*

Although interest in social networks has likely increased over time among social–personality psychologists, many remain unaware of the rich analytic approaches available via SNA. To test this assumption, we performed article searches within *Journal of Personality and Social Psychology* (*JPSP*) and *Personality and Social Psychology Bulletin* (*PSPB*) using Google Scholar for each year from 1990 to (mid-August) 2016 using the terms "social network" or "social networks." We divided article counts by the number of articles published each year in each journal and converted proportions to percentages. We took 5-year moving averages of the percentages to graph change over time (Figure 1, thick lines). Both journals showed substantial growth in the number of articles mentioning social network(s) over time. Although *PSPB* showed a steeper increase over time than *JPSP*, 11% of the articles in both journals currently mention social networks. Thus, mentions of social networks—which likely reflect *interest*—appear to be increasing in social–personality psychology, although some of this increase relates to the rise of online social networks (Crosier, Webster, & Dillon, 2012). But what about SNA?

To address this question, we again performed similar searches, but using the term "social network analysis," yielding only 17 articles in *JPSP* and *PSPB* combined since 1990. Of these 17 articles, only 12 collected social network data and only 9 used SNA. For comparison, we searched for "social network analysis" in a top sociology journal (*American Journal of Sociology*), which yielded 85 articles since 1990. Thus, although personality and social psychologists appear interested in social networks, they lag far behind their social science peers in utilizing SNA. In the sections below, we provide social–personality psychologists with a brief introduction to SNA.

Egocentric Versus Sociocentric Networks

An important distinction in SNA is between *egocentric* (or *personal*) networks and *sociocentric* (or *whole*) networks. The choice of whether to collect sociocentric or egocentric data is a fundamental decision in a network study, affecting the methodology, analysis, and interpretation of data at every stage.

Sociocentric Networks

Sociocentric networks assess the pattern of relationships within an entire *bounded network*; that is, all of the individuals within some structural or conceptual boundary. A sociocentric network might comprise the members of a family or fraternity, workers in an office, or attendees of an academic preconference. Determining the boundaries of a network is difficult, as they can be arbitrary. That is, although preconference attendance may be well defined, the boundaries of an extended family or a community may be less clear-cut, making it difficult to establish inclusion criteria (Butts, 2008).

Once the boundaries of the network are determined, the connection between every pair of individuals within the network is assessed. Most often, this is done through a *roster*, a survey in which each individual receives a list of all members of the network, and indicates his or her relationship with each person on the roster. This allows for recognition of names, which may prompt the identification of less-salient relationships.

A second approach is through a *network generator*. In this method, each participant is prompted to nominate individuals in the network with whom he or she has a connection of the desired sort (e.g., friendship, collaboration). These nominations may be used simply as evidence of ties, or more detailed follow-up questions or ratings may be requested for each name generated. Network generators are often used with large networks, saving participants from rating hundreds or thousands of names, most of whom may not be relevant to a given participant. However, this method relies on free recall, making it likely that some connections, particularly weaker ones, will be missed (Ferligoj & Hlebec, 1999; Neyer, 1997).

Lastly, ties can be identified based on extrinsic data. We might quantify the strength of a connection between two people based on the number of e-mails sent or papers coauthored or record interactions through observations. Given the fallibility of human memory, this method is more reliable than self-report (Bernard, Killworth, Kronenfeld, & Sailer, 1984) for assessing specific details of interactions (e.g., "How many times did you e-mail each person?") or interactions at a single time point (e.g., "Whom did you talk to at the board meeting last week?"). However, when assessing attitudes (e.g., "How much do you like each person?") or long-standing relationship patterns (e.g., "Whom do you usually talk to at board meetings?"), self-report appears to be an equally reliable indicator (Freeman & Romney, 1987).

By quantifying the connections within an entire network, sociocentric data provide a rich and complex depiction of social relationships. We see who is connected to whom and who *isn't*. We can also examine indirect connections two or more steps removed (e.g., "Are smokers more likely to be friends with people who are themselves friends with many smokers?"). There are, however, limitations to a sociocentric approach. Sociocentric studies only provide information about the social context in question. A participant may have few connections at work, but a rich social life outside work. A sociocentric study of the work network would therefore not fully reflect the individual's social connections, leading to erroneous conclusions. Moreover, because SNA examines the interrelatedness of nodes, missing nodes can change the network's structure. Nonresponders are therefore of more concern than in traditional psychology studies, in which participation is inevitably less than 100%. Analyses using both real (Costenbader & Valente, 2003; Kossinets, 2006; Smith & Moody, 2013) and simulated networks (Borgatti, Carley, & Krackhardt, 2006; Huisman, 2006) have demonstrated that the quality of data decreases proportionally to the amount of missing data.

One way of dealing with missing network data is to remove all data related to the missing individual, including ties directed toward that node. This approach, however, eliminates valuable data and can itself change network structure (Robins, 2015). An alternate approach is the reconstruction method (Stork & Richards, 1992), by assuming reciprocity for missing data. That is, if Jerry says he is friends with George, but George did not participate in our study, we can assume that George would consider Jerry a friend as well. Simulation studies (Huisman, 2006) suggest that this approach is effective in imputing data when up to 40% of the network is absent, although it fails when both members of a dyad are missing, or if we would not expect two members of a dyad to respond the same way about each other (Borgatti et al., 2013).

Egocentric Networks

Due to the methodological hurdles of sociocentric networks, psychological researchers often use a second type of SNA, the *egocentric* (or personal) network. Rather than assessing all connections in a bounded group, egocentric networks assess the connections of specific respondents. Using a network generator, each participant provides a list of his or her relationships of a requested type (e.g., "friends," "important people in your life"). This list may be constrained to a particular social domain (e.g., workplace, family) or be unrestricted. Second, the attributes of each alter are elicited from the participant. These may be demographic (e.g., "How old is X?"), relational (e.g., "How well do you know X?," "How often do you ask X for advice?"), or any other attribute of the alter (e.g., "How extraverted is X?"). Finally, to generate the network structure, the participant identifies the relationship between each pair of alters, using any relationship metric specified by the researchers (e.g., "Are X and Y friends?," "How often do X and Y spend time together?"). Rating the alter relationships is the most burdensome aspect of the assessment, as the number of pairings increases exponentially with each additional alter. Although requiring more alters provides more data, ego-network structural metrics have shown that there is little benefit in increasing the number of alters from 35 to 45, and that as few as 25 alters is adequate for most analyses (Golinelli et al., 2010; McCarty, Killworth, & Rennell, 2007).

Egocentric networks are easier to collect and less reliant on obtaining complete data because they assess each individual's personal network. They are also able to assess an individual's relationships across different contexts, rather than being restricted to relationships within a bounded network. Their primary drawback, however, is that egocentric networks are entirely subjective. All of the information about alters and their network connections is based on the participant's perceptions, rather than those of the alters themselves. Thus, the information obtained may be biased by the participant's personality, lack of knowledge, or other factors (Casciaro, 1998; Clifton, Turkheimer, & Oltmanns, 2007).

The Ties That Bind

Directed Versus Undirected Networks

The ties that link network nodes can be directed (Lucy likes Schroeder, but Schroeder doesn't like Lucy) or undirected (two authors publish a paper together). *Directed* ties allow for asymmetrical or unreciprocated relationships. In contrast, *undirected* ties often signify affiliation of some sort that is fairly objective (e.g., two senators are members of the same committee) and are inherently mutual and reciprocal. An example of this distinction in groups is that liking and friendship data (How much do you like X?) often yield directed ties, whereas acquaintance data (Have you met X?) often yield undirected ties. In the sections below, we give examples of both directed ties (liking among *Game of Thrones* characters) and undirected ties (Florentine family intermarriages, sexual networks).

Valued Versus Binary Ties

In social networks, ties can be binary (e.g., present or absent) or valued (e.g., a Likert-type scale of friendship strength: 0 = *unacquainted*, 1 = *acquaintance*, 2 = *friend*). Valued data often paint a richer picture of relationships, but calculation and estimation procedures can be more complex. Consequently, although variants allowing valued data have been developed for most procedures, many software packages still require binary data for some of these, meaning researchers may need to dichotomize valued data into binary data. Dichotomizing data is generally a poor analytic choice because it discards meaningful variance and reduces power (Irwin & McClelland, 2003; Thomas & Blitzstein, 2011). If the researcher must dichotomize, this is usually done using cut points. Based on the scale above, a researcher could dichotomize ties at either the acquaintance (≥ 1) or friend (≥ 2) level, resulting in different binary networks. To avoid bias (Simons, Nelson, & Simonsohn, 2011), researchers should ideally decide cut points of ties a priori.

Table 1 shows two hypothetical matrices of liking among six fictional characters on the HBO television show *Game of Thrones*. The top matrix shows valued ties, whereas the bottom matrix shows binary ties produced by dichotomizing the valued ties at ≥ 1 (i.e., valued ties of one or greater become one in the binary matrix, whereas zeros remain the same; Figure 1). Using

Table 1. Valued and Binary Liking Data Among Six Fictional Characters and Their Centrality Metrics.

							Centrality[a]		
	Person						Degree		
Person	Cat	Dany	Ned	Jorah	Petyr	Sansa	In	Out	Betweenness
Valued									
Cat	0	0	2	0	1	2	7	5	15
Dany	0	0	0	0	0	0	5	0	0
Ned	2	2	0	0	0	2	4	6	15
Jorah	0	3	0	0	0	0	0	3	0
Petyr	3	0	0	0	0	3	1	6	0
Sansa	2	0	2	0	0	0	7	4	5
Binary									
Cat	0	0	1	0	1	1	3	3	3
Dany	0	0	0	0	0	0	2	0	0
Ned	1	1	0	0	0	1	2	3	3
Jorah	0	1	0	0	0	0	0	1	0
Petyr	1	0	0	0	0	1	1	2	0
Sansa	1	0	1	0	0	0	3	2	1

Note. Values: 0 = *don't know or don't like*, 1 = *mixed feelings*, 2 = *familial bond*, 3 = *obsession*.
[a]Because of unreciprocated directional ties, this network is not completely connected; technically, closeness centrality cannot be computed because some distances are infinite.

valued versus binary data produce different—but often correlated—analytic results.

Statistical Analyses

Social networks consist of individuals nested within dyadic relationships nested within networks, and analyses can be conducted at any of these levels, depending on the information desired.

Individual-Level Analyses

It is often useful to characterize individuals based on position within the network. *Centrality* is an umbrella term that reflects how well connected a person is to the rest of the network. Table 1 contains two types of centrality measures for both valued (top) and binary (bottom) ties. In addition, because the data are directed (Jorah is obsessed with Dany, but Dany doesn't like Jorah), we can distinguish between ingoing and outgoing ties for *degree centrality* and *closeness centrality*.

Degree centrality. Degree centrality is the simplest centrality measure because one simply sums row or column ties to obtain outgoing and incoming ties, respectively. The same principles apply to valued and binary data. For the valued data, Ned and Petyr have the highest outdegree (outgoing) centrality scores (6); however, without looking closely at the data, we cannot infer whether they feel somewhat close to several people (Ned), feel extremely close to only a couple of people (Petyr), or some combination. When we examine outdegree centrality in the binary data, we see that Cat and Ned have the highest scores (3), which now simply reflect any liking, irrespective of strength (Figure 2).

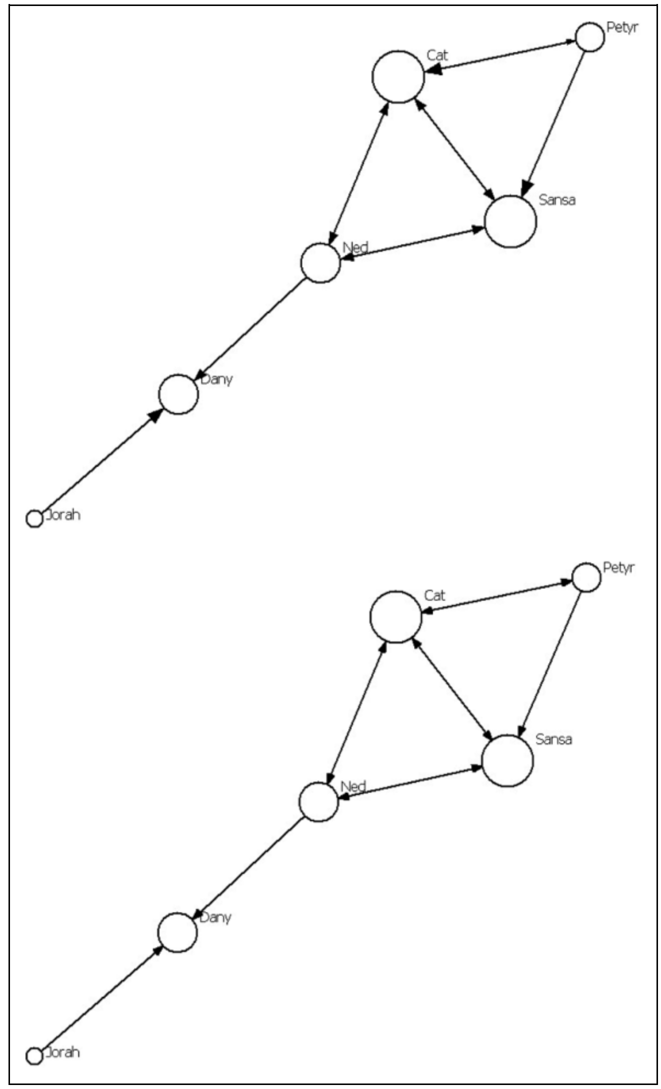

Figure 2. Valued (top) and binary (bottom) sociograms for Table 1 data. In top panel, larger arrowheads connote stronger ties. In both panels, larger nodes reflect greater indegree centrality.

Whereas outdegree centrality often reflects gregariousness (liking others), indegree centrality reflects popularity (being liked by others). In the valued data, Cat and Sansa—who are generally liked by others—have the highest scores (7), whereas Jorah—who is liked by no one—has the lowest (0). In this case, the indegree for valued and binary data correlate nearly perfectly, though this need not be the case, as shown above for outdegree. In social–personality psychology, avoidant attachment related negatively to indegree centrality in classroom friendship networks (Webster, Gesselman, & Crosier, 2016).

Betweenness centrality. Betweenness centrality measures how often a node bridges the shortest path between two other nodes. To find the betweenness for a given node, one (a) determines the shortest path(s) between each pair of nodes in the network,

Table 2. Arranged Intermarriages Among 16 Florentine Families (1394–1434), Degree and Closeness Centrality, and Wealth (1427).

		Family																		Closeness Centrality[a]		Wealth[b]	
	Family	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Degree Centrality	Farness	Raw	Standardized	Lira	Log
1	Acciaiuol	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	54	.019	.278	10	4.00
2	Albizzi	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	3	45	.022	.333	36	4.56
3	Barbadori	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	2	48	.021	.312	55	4.74
4	Bischeri	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	3	51	.020	.294	44	4.64
5	Castellan	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	3	52	.019	.288	20	4.30
6	Ginori	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	58	.017	.259	32	4.51
7	Guadagni	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	4	46	.022	.326	8	3.90
8	Lambertes	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	59	.017	.254	42	4.62
9	Medici	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	1	6	41	.024	.366	103	5.01
10	Pazzi	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	65	.015	.231	48	4.68
11	Peruzzi	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	3	54	.019	.278	49	4.69
12	Pucci	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	240[c]	.004	.062	3	3.48
13	Ridolfi	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	3	44	.023	.341	27	4.43
14	Salviati	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	2	52	.019	.288	10	4.00
15	Strozzi	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	4	48	.021	.312	146	5.16
16	Tornabuon	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	3	45	.022	.333	48	4.68

Source. Breiger and Pattison (1986), Kent (1978), and Padgett and Ansell (1993).
[a]Raw closeness centrality is the reciprocal of distance; it is standardized by dividing by $N - 1$ nodes. [b]Family net wealth in 1427 in thousands of Lira ("Lira") or $\log_{10}$(Lira) ("Log"). [c]Pucci is an isolate; its farness can be defined as infinite or as $N \times (N - 1)$ nodes.

(b) computes the proportion of these shortest paths that pass through a given node, and (c) sums these proportions across all possible node pairs in the network. The resulting sums reflect each node's betweenness in the network. Betweenness often reflects a node's influence or importance in its social network. In our fictitious example, which distinguishes between ingoing and outgoing ties, Cat and Ned share the highest betweenness centrality, followed by Sansa, then the remaining three. This remains true regardless of whether valued or binary data are used.

For example, using the binary directional data, the betweenness centrality score for Sansa is 1.0. There are five nodes other than Sansa, and with directed ties, there are $N \times (N - 1) = 5 \times (5 - 1) = 20$ unique ties to consider. Of these 20 directional ties, Sansa lies between only (a) Petyr to Ned and (b) Petyr to Dany; for the other 18 directional paths, Sansa gets a score of 0. Because there are two shortest Petyr-to-Ned paths (Petyr → Sansa → Ned, Petyr → Cat → Ned), and Sana occupies only one of those two paths, she gets a score of ½ for the Petyr-to-Ned connection. Similarly, because there are two Petyr-to-Dany paths (Petyr → Sansa → Ned → Dany, Petyr → Cat → Ned → Dany), and Sana again occupies only one of those paths, she also gets a score of ½ for the Petyr-to-Dany connection. We sum these scores (½ + ½ = 1) to get Sansa's betweenness total for the binary directional data.

In contrast to Sansa, Cat has a betweenness centrality score of 3.0 (again using the binary-directed data). Among the 20 directional ties to consider for Cat, the Petyr-to-Ned and Petyr-to-Dany paths yield the same scores they did for Sansa (½ and ½, respectively). In contrast, because the Petyr–Cat tie is bidirectional whereas the Petyr–Sansa is unidirectional (Petyr → Sansa is unreciprocated), there are two additional betweeness scores for Cat (Sansa → Cat → Petyr, Ned → Cat → Petyr). And because Cat is the *only* node connecting each of these pairs (i.e., Sansa-to-Petyr and Ned-to-Petyr), she gets score of $1 \div 1 = 1$ for each. Thus, Cat's total betweenness centrality score is ½ + ½ + 1 + 1 = 3. Note that not all betweenness procedures distinguish between ingoing and outgoing ties; had this not been the case, then Cat and Sansa would have had equal betweenness scores.

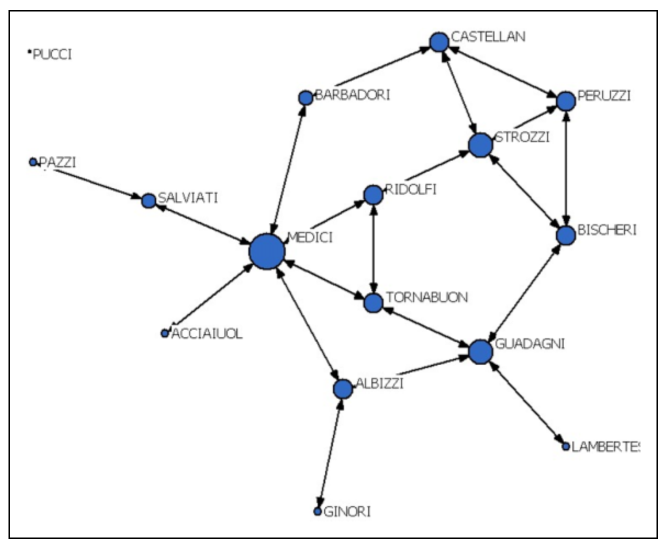

Figure 3. Sociogram of intermarriages among 16 Florentine families sized by degree centrality, 1394–1434 (Table 2). *Source*. Breiger and Pattison (1986), Kent (1978), and Padgett and Ansell (1993).

Data analysis. Once centrality or other individual-level characteristics are computed, these can be used as individual difference variables. For example, once centrality scores are

Table 3. Two-Mode Sexual Network: Sexual Relations Among 39 People (18 Men, 21 Women), Their Degree Centrality, and Bar Patronage.

	Men																		
Women	m012	m013	m016	*m017*	m019	m025	m026	m201	m202	m203	m204	m206	m207	m208	m209	m210	m526	m551	**Degree**
f009	1	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	**4**
f010	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	**1**
f011	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	**5**
f012	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	**1**
f014	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f015	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	**2**
f017	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**1**
f019	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	**3**
f020	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	**3**
f022	0	0	1	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1	**7**
f033	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f034	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f035	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f038	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f201	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
f202	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f307	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**1**
f336	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f514	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**1**
f533	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f900	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**1**
Degree	**3**	**1**	**5**	**7**	**1**	**1**	**2**	**2**	**2**	**2**	**1**	**2**	**2**	**1**	**1**	**1**	**4**	**2**	—

Source. De, Singh, Wong, Yacoub, and Jolly (2004, p. 283, figure 1).
Note. The boldface values indicate degree centrality scores for men (bottom) and women (right). The italicized values represent person who regularly attended a local bar.

computed, we could examine the association between each individual's outdegree and extroversion or agreeableness scores via general linear models. However, social network data sometimes show nonindependence in the same way that group (Kenny, 1981) or spatial (Webster, 2017) data can. Although some SNA procedures provide ways to correct for network dependence (see below), researchers wishing to focus on individual-level analyses can assess and correct for nonindependence in SNA data using the same spatial regression procedures used for geographic data (Ward & Gleditsch, 2008; Webster, 2017).

Relational-Level Analyses

At the relational level, we can examine patterns and test hypotheses regarding the ties between individuals. Because individuals in the network are in relationship with one another, data gathered from them are likely to be correlated, violating the assumption of independence in traditional statistical analyses (Kenny et al., 2006). Relational data must therefore be analyzed using techniques that do not assume independence, often through computer simulation of thousands of comparable networks, to determine the probability of generating observed networks purely by chance (Borgatti et al., 2013).

A common relational-level question is whether individuals tend to have ties with others that they are similar to (in terms of traits, interests, or other characteristics), known as

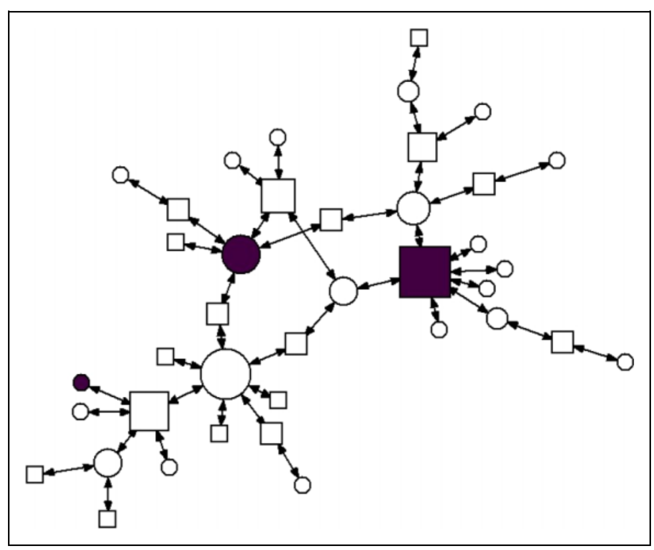

Figure 4. Sexual network sociogram of heterosexual pairings among 18 men (squares) and 21 women (circles) in Alberta, Canada (Table 3). Node size shows degree centrality. Black nodes show people who attended the same bar. *Source.* De, Singh, Wong, Yacoub, and Jolly (2004).

homophily (McPherson, Smith-Lovin, & Cook, 2001). For cross-sectional data, such analyses can be conducted by constructing a new matrix identifying whether the members of each dyad are identical (for categorical attributes) or calculating a difference score (for continuous attributes; Borgatti

Table 4. Two-Mode Sexual Network Collapsed Into a One-Mode Network Among 18 Men Linked by 21 Women With Whom They Have Had Sex.

	m012	m013	m016	*m017*	m019	m025	m026	m201	m202	m203	m204	m206	m207	m208	m209	m210	m526	m551
m012	**3**	1	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0
m013	1	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
m016	0	0	**5**	0	1	1	0	0	0	0	0	1	1	1	1	1	0	1
m017	1	0	0	**7**	0	0	1	1	1	0	0	1	0	0	0	0	1	0
m019	0	0	1	0	**1**	0	0	0	0	0	0	0	0	0	0	1	0	0
m025	0	0	1	0	0	**1**	0	0	0	0	0	1	1	1	1	0	0	1
m026	0	0	0	1	0	0	**2**	0	0	0	0	0	0	0	0	0	0	0
m201	1	0	0	1	0	0	0	**2**	1	0	0	0	0	0	0	0	0	0
m202	1	0	0	1	0	0	0	1	**2**	1	1	0	0	0	0	0	1	1
m203	0	0	0	0	0	0	0	0	1	**2**	1	0	0	0	0	0	1	1
m204	0	0	0	0	0	0	0	0	1	1	**1**	0	0	0	0	0	1	1
m206	0	0	1	1	0	1	0	0	0	0	0	**2**	1	1	1	0	1	1
m207	0	0	1	0	0	1	0	0	0	0	0	1	**2**	1	1	0	0	1
m208	0	0	1	0	0	1	0	0	0	0	0	1	1	**1**	1	0	0	1
m209	0	0	1	0	0	1	0	0	0	0	0	1	1	1	**1**	0	0	1
m210	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	**1**	0	0
m526	0	0	0	1	0	0	0	0	1	1	1	1	0	0	0	0	**4**	1
m551	0	0	1	0	0	1	0	0	1	1	1	1	1	1	1	0	1	**2**

Source. De, Singh, Wong, Yacoub, and Jolly (2004, p. 283, figure 1).
Note. The boldface values indicate degree centrality scores for men (diagonal). The italicized values indicate man who regularly attended a local bar.

et al., 2013). This matrix of attribute similarity is then used to predict the matrix of dyadic ties, using Quadratic Assignment Procedures, a family of correlation and regression analogues for matrices (Dekker, Krackhardt, & Snijders, 2007; Krackhardt, 1988).

Cross-sectional data do not allow for differentiation between homophily due to selection (similar actors preferentially forming ties) and influence (actors with ties to one another becoming more similar; Steglich, Snijders, & Pearson, 2010). A relatively new approach to relational-level analyses is exponential random graph modeling (ERGM). ERGM simulates all possible random networks based on specified parameters of the target network (e.g., number of nodes, number of ties; Robins & Lusher, 2013). ERGM then compares these random networks to the target network, using Markov chain Monte Carlo estimation to determine the probability of each tie in the network being present (Robins, Pattison, Kalish, & Lusher, 2007). In addition, node attributes can be included as covariates, allowing estimation of how these attributes relate to the likelihood of ties between individuals. ERGM can also be used with longitudinal networks, estimating the probability of new ties forming based on node attributes such as personality or behaviors and differentiating between selection and influence. For example, Selfhout and colleagues (2010) found selection homophily in the formation of college friendship networks, such that people with similar levels of extroversion were more likely to form friendships with one another.

Network-Level Analyses

Finally, characteristics of entire networks may be assessed and compared with other networks. For example, the *density* of a network is computed as the proportion of ties that exist, relative to the number that could possibly exist (Wasserman & Faust, 1994). Other common network-level characteristics include *reciprocity*, the proportion of ties in a directed network that are reciprocated, and *transitivity*, the probability of balanced triads in a network, such that if A and B are connected, and B and C are connected, then A and C are also connected (Wasserman & Faust, 1994). These network-level statistics are not absolute metrics, and depending on the type of network (e.g., large corporation, small sorority) and operationalization of ties (e.g., “acquainted with,” “romantically involved with”), one expects differing levels of density, reciprocity, and transitivity (Borgatti et al., 2013). These are therefore best understood in a relative way, to compare, for example, the egocentric friendship networks of individuals with differing levels of extroversion (Kalish & Robins, 2006).

Software

Numerous software tools have been developed to analyze network data. *UCINET* (Borgatti, Everett, & Freeman, 2002) is a user-friendly, general-purpose program that can conduct a wide range of SNA procedures using a menu-driven graphic user interface. There are also many resources available for UCINET, including an online tutorial (Hanneman & Riddle, 2005) and an introductory textbook (Borgatti et al., 2013).

Some programs specialize in producing detailed network graphs in addition to conducting analyses. These visualization programs include *Gephi* (Bastian, Heymann, & Jacomy, 2009), *Netdraw* (Borgatti, 2002), and *SocNetV* (Kalamaras, 2015). Other standalone programs combine both analytic and visualization aspects including *NetMiner 4* (a multipurpose program), *ORA-LITE* (emphasizing dynamic longitudinal networks and identifying vulnerabilities in networks; Carley, 2014), and *Pajek* (Mrvar & Batagelj, 1996). Although *Pajek* (the Slovenian word for "spider") can be daunting for new users, it specializes in analyzing extremely large networks, up to one billion nodes with unlimited ties (Mrvar & Batagelj, 2016).

Finally, in recent years, several packages have been developed as add-ons to the statistical software *R* (R Core Team, 2014). *sna* (Butts, 2014) and *igraph* (Csardi & Nepusz, 2006) are multifunction *R* packages for network data sets. Specialized *R* packages are also the primary means of conducting ERGM analyses; the *RSiena* package (Ripley, Boitmanis, Snijders, & Schoenenberger, 2016) and *statnet* suite of packages (Handcock et al., 2015) both allow ERGM analyses of cross-sectional and longitudinal data, albeit with slightly different approaches (for a review of those differences, see Leifeld & Cranmer, 2016).

Examples From the Literature

Medici Money and Florentine Families

Data description. These social network data consist of intermarriages (ties) among 16 Florentine families (nodes) from 1394 to 1434 (see Breiger & Pattison, 1986; Kent, 1978; Padgett & Ansell, 1993). The data form a 16 $\times$ 16 symmetric matrix of binary undirected marriage ties (1 = *presence*, 0 = *absence*; Table 2 and Figure 3). From these data, we can calculate degree centrality by summing across the rows (or the columns when using symmetric matrices).

Closeness centrality. Like degree and betweenness, closeness centrality is another measure of node importance. Calculating closeness in undirected networks such as this is more straightforward than directed ones. To calculate closeness centrality for each node (Family), we first define *farness* as the sum of the shortest geodesic distances from a focal node (e.g., Medici) to all other nodes in the network. Because the Pucci family is an isolate (unconnected to the other 15 families), its farness is technically infinite; however, assuming infinity can cause estimation difficulties. For isolates, we can substitute the maximum possible distance, which is the total number of nodes (16). Thus, for the Medici, there are six, five, three, and one families with geodesic distance 1, 2, 3, and 16, respectively (Figure 3). The Medici's farness score is thus $(6 \times 1) + (5 \times 2) + (3 \times 3) + (1 \times 16) = 6 + 10 + 9 + 16 = 41$. We perform the same procedure to calculate farness for the remaining 15 families. The raw closeness centrality scores are the reciprocals of the farness scores (e.g., Medici = 1/41 = 0.024). Standardized closeness centrality scores are the raw score divided by the total number of nodes, less 1 (e.g., Medici = $0.024 \div (16 - 1) = 0.366$).

Results. Family degree ($M = 2.50$, standard deviation [SD] = 1.51) and standardized closeness ($M = .28$, $SD = .07$) centrality were positively correlated ($r(14) = .76$, 95% CI [.42, .91], $p < .001$). Because family net wealth was positively skewed, we normalized wealth with a log transformation ($M = 4.46$, $SD = .43$). Log family wealth correlated with both intermarriage degree centrality ($r(14) = .51$ [.02, .80], $p = .044$) and closeness centrality ($r(14) = .59$ [.13, .84], $p = .017$). We also assessed spatial or network dependence in these data using Moran's (1950a, 1950b) I statistic, which can range from -1 to 1. Because these data showed no evidence of dependence ($I = .043$, $z = .77$, $p = .44$), there was no need to correct for it in our analysis (Webster, 2017). Although correlated, the causal direction linking wealth and degree centrality is empirically ambiguous, but likely bidirectional: Wealth influences arranged marriages with the prospect of producing even greater wealth. In any case, these social network data appear to reflect the rise of the Medici family's political and economic influence in 15th-century Florence.

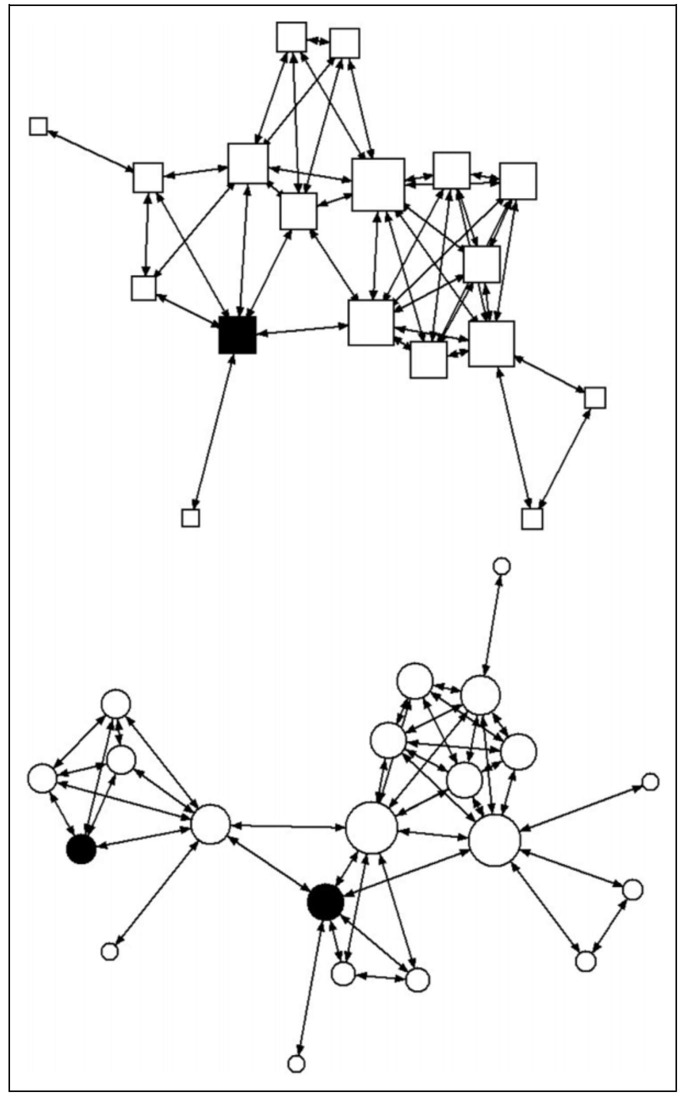

Figure 5. Sexual network sociograms among 18 men linked by women (top) and 21 women linked by men (bottom; see Tables 4 and 5). Node sizes show degree centrality. Black nodes show people who attended the same Alberta bar. *Source*. De, Singh, Wong, Yacoub, and Jolly (2004).

Table 5. Two-Mode Sexual Network Collapsed Into a One-Mode Network Among 21 Women Linked by 18 Men With Whom They Have Had Sex.

	f009	f010	*f011*	f012	*f014*	f015	f017	f019	f020	f022	f033	f034	f035	f038	f201	f202	f307	f336	f514	f533	f900
f009	**4**	0	1	0	0	1	0	1	0	0	1	1	1	0	1	1	1	1	0	0	0
f010	0	**1**	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
f011	1	0	**5**	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	1	0	1
f012	0	0	0	**1**	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
f014	0	0	0	0	**1**	0	0	0	1	1	0	0	0	1	0	0	0	0	0	1	0
f015	1	1	0	0	0	**2**	0	1	0	0	1	1	1	0	0	0	0	1	0	0	0
f017	0	0	1	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
f019	1	0	1	0	0	1	0	**3**	0	1	1	1	1	0	0	0	0	1	1	0	1
f020	0	0	0	0	1	0	0	0	**3**	1	0	0	0	1	0	0	0	0	0	1	0
f022	0	0	1	1	1	0	0	1	1	**7**	0	0	0	1	0	0	0	0	0	1	0
f033	1	0	0	0	0	1	0	1	0	0	**1**	1	1	0	0	0	0	1	0	0	0
f034	1	0	0	0	0	1	0	1	0	0	1	**1**	1	0	0	0	0	1	0	0	0
f035	1	0	0	0	0	1	0	1	0	0	1	1	**1**	0	0	0	0	1	0	0	0
f038	0	0	0	0	1	0	0	0	1	1	0	0	0	**1**	0	0	0	0	0	1	0
f201	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**	1	0	0	0	0	0
f202	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**	0	0	0	0	0
f307	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0
f336	1	0	0	0	0	1	0	1	0	0	1	1	1	0	0	0	0	**1**	0	0	0
f514	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**1**	0	1
f533	0	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	**1**	0
f900	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	**1**

Source. De, Singh, Wong, Yacoub, and Jolly (2004, p. 283, figure 1).
Note. The boldface values indicate degree centrality scores for women (diagonal). The italicized values indicate woman who regularly attended a local bar.

A Sexual Network

Data description. Up to this point, we have discussed *one-mode networks*, where the rows and columns are the same actors arranged in a square matrix. SNA can also evaluate *two-mode networks*, where the rows and columns differ, often forming a rectangular matrix. The two-mode social network data used here (Table 3 and Figure 4) reflect a subset of heterosexual sexual relationships among 18 men and 21 women (De, Singh, Wong, Yacoub, & Jolly, 2004). The nodes reflect the 39-person sample and the ties indicate people who have shared sexual relations (1 = *had sex*, 0 = *did not have sex*). These data form an 18 row × 21 column rectangular matrix with asymmetric ties. From these data, we can calculate degree centrality by summing across the rows (for men) or the columns (for women). The original investigators (De et al., 2004) also recorded whether people patronized a particular bar that was attended by multiple participants in the sample.

Results. We examined the effects of gender and bar patronage on degree centrality. The 18 men ($M = 2.22$, $SD = 1.63$) and 21 women ($M = 1.90$, $SD = 1.64$) showed no difference in their network degree centrality, $t(37) = .60$, $p = .55$, $d = .20$, $r = .10$ [−.22, .40]. The three people who regularly patronized a bar of interest in this study ($M = 4.33$, $SD = 3.06$) had reliably higher degree centrality than those who did not ($M = 1.86$, $SD = 1.36$), $t(37) = 2.75$, $p = .009$, $d = .90$, $r = .41$ [.11, .64]. Because degree centrality is often positively skewed and leptokurtic (Judd, McClelland, & Ryan, 2009; McClelland, 2014), as was the case here, data transformations are often necessary. We reran this analysis using both square root ($\text{Degree}^{1/2}$; $p = .020$, $d = .80$) and log (ln(Degree); $p = .046$, $d = .68$) transformations, which yielded weaker—but likely more robust—effect sizes.

Collapsing two-mode data into one-mode networks. Two-mode data (e.g., most heterosexual sexual networks) can be collapsed and reexpressed as 2 one-mode networks—one for each dimension (e.g., one for men and one for women). For example, from these two-mode data, we can extract a one-mode matrix reflecting either the 18 men as nodes and the women they have shared as ties (Table 4; Figure 5, top) or the 21 women as nodes and the men they have shared as ties (Table 5; Figure 5, bottom). Note that the degree centrality scores from the original two-mode matrix now appear along the diagonals for men and women in their respective one-mode matrices. Reevaluating two-mode as one-mode networks allows researchers to gain new insights into network structure that might otherwise be obscured by complexity. For example, men's and women's networks had slightly different densities of .29 and .22, respectively.

Summary and Recommendations

Interest in social networks is increasing, and social–personality psychologists—who are inherently interested in people (nodes) and the relations among them (ties)—should consider collecting and analyzing social network data to address person-, dyad-, and group-level questions. When collecting social network data, we first urge researchers to carefully consider their choices (e.g., egocentric vs. sociocentric network, one- or two-mode network, directed vs. undirected ties, binary vs. valued ties). Second, we recommend that researchers choose SNA metrics that best test their hypotheses (e.g., density, reciprocity, different types of centrality). Third, we stress that researchers can easily incorporate traditional methods along with social networks (e.g., random assignment of conditions to persons, dyads, or whole networks; addition of individual difference measures; incorporation of daily diary or longitudinal designs). Because SNA allows researchers to examine personal, dyadic, and group processes in the same study, we believe it has the potential to integrate and advance both the methods and theories used in social and personality psychology.

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