Network Analysis and Political Science

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Abstract

Political science is fascinated with networks. This fascination builds on networks' descriptive appeal, and descriptions of networks play a prominent role in recent forays into network analysis. For some time, quantitative research has included node-level measures of network characteristics in standard regression models, thereby incorporating network concepts into familiar models. This approach represents an early advance for the literature but may (*a*) ignore fundamental theoretical contributions that can be found in a more structurally oriented network perspective, (*b*) focus attention on superficial aspects of networks as they feed into empirical work, and (*c*) present the network perspective as a slight tweak to standard models that assume complete independence of all relevant actors. We argue that network analysis is more than a tweak to the status quo ante; rather, it offers a means of addressing one of the holy grails of the social sciences: effectively analyzing the interdependence and flows of influence among individuals, groups, and institutions.

INTRODUCTION

Probably the most famous network graph in political science is Valdis Krebs' (2002) representation of the terrorist network that was responsible for the 9/11 attack on the World Trade Center and Pentagon. We know now that Mohammed Atta, who flew American Airlines Flight 11 into the North Tower of the World Trade Center, was a central organizing player in this terrorist operation. However, Atta's central role is not obvious unless you look at the structure of relationships among all the 19 known members of this conspiracy. Krebs' network analysis shows qualitatively and quantitatively that Atta was the ringleader of this network. Not only does Atta have many connections to the other members of this network, but in various other network statistics—such as betweenness and centrality—Atta pops up at or near the top of the calculations. Social network analysis shows—often visually, but also through quantitative measures—important aspects of social organization that are not captured by the study of individual attributes or characteristics. Over the past decade, the idea of networks has commanded the attention of many policy makers and academics, and the study of networks has made incredible advances in popularity as well as in the sophistication of the methods used for network analysis. In this article, we provide a selective review of the origins of network analysis in sociology and political science, and then describe recent methodological developments and the promise we believe they hold for research in political science.

Social network analysis refers to the study of links between nodes. To make the analysis social (rather than physical or biological), nodes typically refer to persons or organizations or states, while links represent some form of connection or flow between the nodes (e.g., friendship, trade, military engagement). The network connecting nodes via links thus represents patterns of relations among social or political actors, and can be understood as a type of structure. The motivation behind examining these characteristics is that network structure may capture important contours of opportunity and constraint that shape social, political, or economic behavior. For instance, sparse networks tend to be fragile, whereas dense networks, which have many paths between groups of nodes, are less likely to fall apart over time.

Formal network analysts typically encode empirical information about linkages between nodes into a matrix. Actors and nodes are listed on the rows and columns, and data describing connections between nodes are recorded as cell entries in the matrix, which is often called a sociomatrix. This matrix is isomorphic to a graph where links connect the nodes. The fact that networks can be represented as matrices and graphs allows us to leverage important mathematical features associated with graph structures. Two broad classes of characteristics can be elicited from network graphs: features characterizing the entire network's structure, and features describing the network position of particular nodes. At the network level, we may be interested in how sparse or dense the graph is, how tightly clustered it is, whether it shows evidence of hierarchy, or if it is fragmented and filled with holes and gaps. At the individual level, we may ask how "close" a node is to others in the network, whether the node is highly connected, is central or peripheral, or whether others are dependent on the node for access to distant others. Each of these features can be captured with a descriptive network statistic calculated on the link structure recorded in the matrix of network data. This mode of descriptive network analysis has a long tradition in sociology, where analyses have proven useful for revealing meaningful characteristics of the structure of relations that are not necessarily obvious from—nor even contained in—the type of individual-level information typically collected about node characteristics.

Methodologically, this approach grew out of Jacob Moreno's (1938, 1960) efforts to develop a science of sociometry in the early twentieth century. Moreno is perhaps best known for having invented group psychotherapy, but in the network world he is known for his invention of sociograms, which are elementary network diagrams that depict the connections among actors. As early as April 13, 1933 his work constructing a wide variety of social network maps was described in the *New York Times*. After having charted the friendship ties among 500 young women in the New York State Training School, he noted:

> If we ever get to the point of charting a whole city or whole nation, we would have an intricate maze of psychological reactions which would present a picture of a vast solar system of intangible structures, powerfully influencing conduct, as gravitation does bodies in space. Such an invisible structure underlies society and has its influence in determining the conduct of society as a whole. (*New York Times* 1933)

The idea that you could measure the actual social network, whether of a small subset of young women, an entire city, or the entire nation was a powerful idea.[1] Inspired in part by Moreno's challenge, in the 1960s, Stanley Milgram conducted the "small-world experiment," wherein he sought to estimate—through experiment—the number of steps needed to connect two randomly selected Americans.[2] Later in the century, the use of networks as a tool for identifying the structures of society gained considerable prominence in sociology largely through the work of Harrison White and his graduate students at Harvard. At about the same time, Lin Freeman and his colleagues at the University of California Irvine began to work seriously on the relationship between networks and mathematical graph theory, and as a consequence made a series of major advances in the measurement of network characteristics.

In political science, most early studies used networks as a way to visualize hierarchy, especially the hierarchy of the world system. This work includes Galtung (1971), Baumgartner & Burns (1976), and Wallerstein's (1974) widely read attempt to leverage Ferdinand Braudel's ideas and create a picture of the modern world system. In political science (unlike sociology), network analysis was largely qualitative and allegorical at this stage. One exception was among survey researchers (e.g., Robert Huckfeldt), who began to collect data about the networks surrounding individual respondents in representative samples.

Contemporary work on political networks has been stimulated by heightened interest in terrorist networks in the wake of the attack on the United States in September 2001. Coincident with this has been phenomenal growth in the availability of inadvertent and designed data on a wide range of topics that can reveal linkages among people and things. Finally, the emergence of networking technologies (*vide* Twitter as a tool of antiregime forces in Tehran) has shattered the myth upon which a lot of empirical investigations in political science were predicated; namely, that individuals don't affect other individuals who are being studied. Thus the past decade has witnessed an explosion of studies invoking the idea of "networks" across almost every topic social scientists investigate.

Because networks reflect structure, network analysis is powerful when the empirical data accurately reflect the totality of connections (or accurately reflect the absence of connections) between relevant nodes, and when these connections are durable. Even with newly available data sources, these conditions are rarely met in practice, and often what is not known (e.g., "missing data" on nodes or links) or variable is critically important for our interpretation of the network. It turns out, for instance, that measures of network centrality are highly dependent on knowledge of all the nodes and all the linkages; if data involving a highly central actor is missing, the descriptive centrality measures

[1] Moreno himself was not shy about his proclamations. In the 1930s, he estimated that there were 10–15 million isolated individuals in the United States, based solely on his study of 500 women in the New York State Training School.

[2] In fact, polymath Manfred Kochen and political scientist Ithiel de Sola Pool had speculated about this problem in an earlier manuscript that circulated in unpublished form for decades. When the journal *Social Networks* was founded in 1978, this paper was published as the lead article in the first issue (de Sola Pool & Kochen 1978/1979).

on the resulting graph will be far lower than would have been calculated if all data were available. Thus if, for example, even some of Atta's linkages were missing in the 9/11 network—because they were hidden or unobserved by analysts—then different nodes would be identified as the most central players in the network. Unfortunately, the vast majority of network analyses to date rest on the usually unreasonable assumption that all the data are static and known and observed without error. Until very recently, few studies have been able to provide probability estimates of the uncertainty that the network is correctly and completely described.

In our reading of the field, we identify three distinct approaches to studying networks in political science today: qualitative and allegorical invocation of network concepts, descriptive and statistical examination of network graphs, and latent variable approaches that explicitly model the observation of links. We summarize and evaluate each of these approaches, illustrating the kinds of questions each can address. We argue that most of political science remains focused on a descriptive, sociometric approach to network analysis, but that greater scholarly leverage will be found by exploiting newly available latent space models for graphs.

ANALOGICAL NETWORKS FOR POLITICS

Within political science, the idea of networks or actors self-consciously organized to achieve some political end has a long tradition. A nice example of this type of work is Keck & Sikkink's (1998) award-winning book, which argues that advocacy networks have long existed as a structure that facilitates collaborative and effective advocacy. They note that such networks are increasing in their importance in the realm of international affairs. For Keck & Sikkink, networks initially emerge from face-to-face encounters in which trust is established among the advocates. Keck & Sikkink focus their inquiry on the complex interactions among advocates and activists as well as their construction of broadly conformable frames of meaning and context. In this work, networks are presumed to be elusive exactly because they marry the actors and the actions to one another. Broadly speaking, a network in this sense is a social movement, and for many scholars following in this tradition, network language can easily be replaced with a social movement ontology. From this perspective, networks accomplish two things that are generally useful to advocates: They accelerate the transmission of information and they are helpful to establish and reinforce "identities" and common frames of reference.

Keck & Sikkink find that the network of activists is neither top-down and hierarchical like military organizations, nor bottom-up and market oriented like modern open economies. Rather, the network is somehow bound together by common goals, and it spans across the hierarchy and transects the utilities of a market. In Keck & Sikkink's view, the network is a unitary actor that is entirely constructed by the actions and identities of the advocates and activists (other actors). Advocacy networks act within the context of campaigns, such as the campaign to condemn Argentina's human rights policy, especially the disappearance of dissidents. These networks themselves influence the ebb and flow of politics in particular domains by rapid transmission of politically beneficial information, by the creation of symbolic frames for common interpretation of events, or by demanding that powerful agents respond to particular issues. Advocacy networks can also effectively illuminate the accountability of individuals and groups in particular domains.

The qualitative and analogical analysis of networks has proven enormously popular and has become a widespread approach in political science. Not only did Keck & Sikkink's volume win the 2000 Grawemeyer Award for World Order, but it has inspired literally thousands of other studies in the decade since its publication. The upside of this approach is that it highlights the importance of considering context and interdependencies in qualitative studies of political questions. The downside is that the exact configuration of the networks is difficult to pin down and explicitly evaluate. Many network analyses following in Keck & Sikkink's footsteps do not emphasize how variation in network structure shapes the processes under investigation.

DESCRIPTIVE AND STATISTICAL EXAMINATION OF GRAPHS

It is hard to pin down the first recognition that the entirety of social relations has strong impacts on group as well as individual behavior, though it is certainly a foundational insight for the discipline of sociology. Georg Simmel is often credited with introducing the phrase "webs of relations" into the study of society, and our notions of the importance of dyads and triads can be traced directly to his work. Moreno's creative work was also seminal, both for linking the network to individual characteristics such as mental health status, and for linking pictures of networks to mathematical representations of graphs. A group of psychologists studying small-group networks at the Massachusetts Institute of Technology, led by Alex Bavelas, pioneered the focus on network centralization as a key structural feature that relates broader network patterns to individual- and group-level outcomes.

Harrison White helped to create the modern study of social networks. White's work on social structure and social mobility was especially influential, in part because he focused not on individual attributes but rather on how relations among actors formed the architecture of social structures. Thus, to study mobility, he studied the structure of vacancies; to understand kinship, he—like anthropologists before him—studied how relations produce role structures (White 1970). But perhaps White's most significant contribution was the idea of structural equivalence. White and his associates developed an algebra for analyzing graphs and rearranging them so that similarly connected actors would be grouped into structurally equivalent (and jointly occupied) positions (Lorrain & White 1971, Boorman & White 1976, White et al. 1976). In subsequent years, White's loyal students developed his fundamental ideas, applying social network analysis in the field of sociology and a bit beyond. These students and students of students included Mark Granovetter, Kathleen Carley, Ronald Breiger, Peter Bearman, Roger Gould, Barry Wellman, Margaret Theeman, Steve Borgatti, and many others.

The preeminent example of White's impact is perhaps Granovetter's pathbreaking article on the strength of weak ties. This paper, initiated while Granovetter was a graduate student, illustrates that diffuse networks with bridging ties could be more useful in contexts such as job search and social mobilization than dense networks of many ties (Granovetter 1973). This article continues to be the most cited article in the network realm, and one of the most highly cited social science articles in any field. Granovetter attributes the origins of the paper to discussions with Harrison White and others in the Social Studies Department at Harvard in the late 1960s. Slightly outside of White's orbit, but almost as influential, is Ronald Burt, whose 1982 book expanded on Granovetter's insights and propelled the use of social network models both methodologically and practically (Burt 1982). Burt's major contribution is to introduce the idea of structural holes to network analysis, although he has also built bridges into the business world.

By the early 1980s, a "school" of empirically oriented structural network analysis had developed out of the sociological tradition. Adherents of this school studied a wide variety of topics and social processes, including cooperation (Eguíluz et al. 2005), collaboration (Uzzi & Spiro 2005), contagion (Centola & Macy 2007), diffusion (Bearman et al. 2004), deliberation and discussion (McPherson et al. 2008), violence (Kreager 2007), social connections among employees (Castilla 2005), and behavior of migrants (Korinek et al. 2005). The core idea was to treat concrete patterns of relations as fundamental structures in society; the methodological tools favored by this group were descriptive measures of complete graphs that captured key structural features of networks.[3] A summary of these core concepts is offered below:

- *Betweenness:* the extent to which a node lies between other nodes. High betweenness often implies that other nodes are dependent for access to information or valued goods (e.g., Kolaczyk et al. 2009).
- *In-degree:* the number of links sent to a node. In-degree is often used as a measure of popularity (e.g., Hämmerli et al. 2006).
- *Out-degree:* the number of links sent by a given node (e.g., Hämmerli et al. 2006).
- *Centrality:* how central or important nodes are in a network. Several measures capture aspects of this idea, including betweenness, in/out degree, and closeness (e.g., Maoz et al. 2006).
- *Prestige:* a measure of centrality that weights in-degree more highly than out-degree. High-prestige nodes are more likely to receive ties than send them.
- *Eigenvector centrality:* a measure of node centrality developed by Bonacich that assigns higher weight to links connecting a node to other central nodes. Thus, in large networks, important nodes are those that are connected to other important nodes (e.g., Fowler et al. 2007).
- *Structural equivalence:* the idea, developed by White, that similarly situated actors create a class. Structural equivalence is measured by the extent to which nodes have a common set of linkages to other nodes in the system (e.g., Cao 2009).
- *Homophily:* the tendency of similar actors to form connections to one another (McPherson et al. 2001).
- *Path length:* the number of steps it takes to connect a pair of nodes. Directly connected nodes have a path length of one; indirectly connected nodes have a path length of two. At the graph level, the average minimum path length between all pairs of nodes reflects how "small" the world is (e.g., the seminal work of de Sola Pool & Kochen 1978/1979).
- *Centralization:* a graph-level measure that tells how concentrated the links are around a small number of nodes.
- *Closeness:* a graph-level measure of how close nodes are to one another. Technically, it is the inverse of the sum of the shortest distances between each node and every other node.
- *Clustering:* a graph-level measure of the extent to which the graph contains locally dense clusters of nodes. It is measured as the probability that two associates of a node themselves are linked (e.g., Fowler et al. (2011).
- *Cliques:* dense subnetworks in which each node is connected to every other node. Members of cliques often behave similarly.
- *Bridges:* nonredundant links that connect different parts of a network. Bridges often play an important role in the diffusion of information, and because they offer brokerage opportunities, they can contribute broad social integration.
- *Density:* the ratio of ties in a network to the total possible number of ties. Dense networks, which are more tightly connected than sparse networks, are often associated with solidary and hold collective action potential.
- *Structural hole:* a gap in a network; an absent link that, if present, would create a bridge between two or more nodes (e.g., Carpenter et al. 2004).

Throughout the 1970s and 1980s, a few political scientists began to use network concepts in their research as well. Knoke (1976) began his important research into the social bases of politics. At about the same time, Franz Urban Pappi at Mannheim began to promote the use of networks in the study of policy (Laumann & Pappi 1976), work that would be elaborated and adapted during subsequent decades (Pappi

[3] An important mathematical premise of many of these measures is that the eigenstructure of the matrix/graph can be used to yield numerical information about the centrality of each node. Eigenvalues are scalars that are associated with linear systems of equations. These are sometimes referred to as characteristic or latent roots.

& Henning 1998, Roch et al. 2000). It was in the realm of American politics that the network perspective really took root. Sometime during the 1970s, Robert Huckfeldt was pointed toward the sociological network literature by his advisor, polymath John Sprague. Huckfeldt's (1977) dissertation was entitled "Political Behavior and the Social Context of Urban Neighborhoods." Huckfeldt initially seized on the idea of measuring a neighborhood social context as a network, and he recognized the significance of network ties for an individual's political behavior. His first publication used contextual language familiar to political scientists (Huckfeldt 1979), but by 1983 he had published an important piece in sociology that drew explicitly on the formal analysis of social networks (Huckfeldt 1983). Four years later, Huckfeldt & Sprague (1987) published what may have been the first article devoted to network analysis in the flagship journal of political science. Throughout the 1980s and into the current century, Huckfeldt continued to draw upon and develop the idea of social networks for studying political change, party loyalties, social class, political choice, race politics, and aspects of political communication.

By the 1990s, UCINET (**http://www.analytictech.com/ucinet/**), one of the first widely available social network analysis software packages, made it easy to calculate descriptive statistics on data arranged as networks or graphs—something that had not been feasible with the mainstream statistical computing packages such as SPSS and SAS. As a result, many political scientists followed the sociological lead and focused on the statistical description of network features, primarily concentrating on various measures of centrality, which seemed to somehow capture the concept of power.

As network analysis has penetrated the quantitative branches of political science, many scholars have incorporated node-level descriptive network statistics into standard statistical models. [Montgomery & Nyhan (2010) employ this strategy; see also Roch et al. (2000), and more recently Koger (2009).] An example from the field of international relations is the work of Maoz et al. (2006), which measures structural equivalence in terms of in-degree and out-degree and then uses these measures in a fairly catholic regression framework to test ideas about the impact of features of the network. Victor & Ringe (2009) illustrate statistical tests on some network statistics in the context of caucuses in the U.S. Congress. Fowler (2006) maps more than a quarter of a million pieces of legislation proposed between 1973 and 2004 in his study of the network structure of Congress. Fowler derives a measure of the social distance among all legislators from the network of cosponsorship; these connectedness measures are then introduced into simple regression models to predict aspects of legislative behavior, most notably showing that connected legislators tend to vote in favor of bills more often than those less connected.

Inferential Statistics

In marked contrast to analogical and/or descriptive modes of network analysis (Hafner-Burton et al. 2009), Huckfeldt's 1983 network article developed a model of the "probability that a member of group *i* in context *j* will form a friendship with another member of group *i* after *k* opportunities for friendly association" (p. 655). Although it was not fully appreciated at the time, Huckfeldt's approach brought inferential statistics into the realm of structural network analysis. Huckfeldt (1983) did not cite Frank (1971), nor the pathbreaking work of Besag (1972)—who established the then-practical approach to doing statistics on graphs known as pseudolikelihood estimation—but he did utilize (or perhaps reinvent) a strategy for estimating the probability of a graph's tie structure. By combining descriptive and inferential statistics, Huckfeldt bucked the dominant trend of network analyses, which still emphasized mathematical description. Much of the most exciting work in the study of networks now builds on efforts to use modern statistical methods to model the structure of complete networks.

Long before Huckfeldt, the earliest attempts at statistical modeling of complete social network–like data was the Bernoulli random graph distribution proposed independently by Erdos & Rényi (1959) and Rapoport (1953). Although this model is extremely important in graph theory, its underlying assumption—that network edges (links) are independent of each other—is implausible in almost all human social networks (Robins & Morris 2007). Building on Besag's (1974) seminal proof that showed how to represent a Markov random field as a probability distribution, Frank & Strauss (1986) made a crucial breakthrough. They realized that approaches from spatial statistics and statistical mechanics could be translated to social network contexts. They developed models that went beyond dyad independence, with assumptions that could be viewed as empirically and theoretically sound. Unfortunately, their paper on Markov random graphs was not given much initial attention by social network researchers. In the second half of the 1990s, Stanley Wasserman and Pip Pattison recognized the value of Frank & Strauss's work and reconnected Markov random graphs and further generalizations to the social networks field as so-called p^* models (Pattison & Wasserman 1999, Robins et al. 1999). At the same time, there was growing interest in statistical models for other types of social network data, especially models for multiple observations of networks across time (Snijders 2001).

Exponential random graph models (ERGMs) illustrate the processes that govern the formation of links in networks by including terms representing different aspects of node or network structure. In an ERGM, the predictors are functions of the ties themselves. Called "network statistics," each predictor in an ERGM represents a specific configuration of links—such as edges or triangles—that is hypothesized to occur more often or less often than expected by chance; the value of the term is a function of the number of such configurations in the network. These terms, together with their coefficients, are sufficient to represent the probability distribution over the space of networks of a given size. As these predictors are direct functions of the response variable (a tie between i and j), ERGMs can be thought of as autoregressive models, and this changes many aspects of model specification and estimation. The modeling class is general (Wasserman & Pattison 1996) and should be capable of capturing the structure of diverse empirical networks, allowing for statistical inference about that structure. The general classes of ERGMs are defined by the terms included as predictors; examples (Handcock et al. 2008) include dyadic-independent, dyadic-dependent, and curved exponential-family terms. Every predictor entered into an ERGM must have an algorithm for calculating the associated network statistic, or, more precisely, an algorithm for calculating its associated change statistic, defined as the difference in the value of the network statistic for two networks that differ from each other only in the presence or absence of a proposed edge (or edges).

More specifically, assume that Y_{ij} is a sociogram for which the entries are in the set 0,1, and are 1 for y_{ij} if and only if a "relationship" exists between i and j. A random graph model that is exponential simply expresses the probability of the graph Y as an exponential function of a set of parameters, θ, and a set of statistics, $\mathbf{s}(y)$, on the graph:

$$\mathbf{P}_\theta(Y = y) \propto \exp \theta^t \mathbf{s}(y).$$

To estimate this with standard approaches such as maximum likelihood requires evaluating the probability over all possible graphs of the same size as Y, which is not feasible. Pseudolikelihood approaches were developed, which looked at the log probability of graphs conditional on changing a single edge from 0 to 1. A more recent alternative is to use a Markov chain to sample from the distribution that produces the desired network. Fortunately, these Markov chain Monte Carlo (MCMC) estimation approaches are widely available in network software.

Underlying ERGMs is the assumption that the observed network is generated by a stochastic process in which relational ties come into being in ways that may be shaped by the presence or absence of other ties (and possibly node-level attributes). These local social processes could affect levels of reciprocity in dyadic relations, or actors with similar attributes could be more likely to form friendship ties (homophily). Or, following the logic of balance theory, slightly larger-scale influences could operate: If two unconnected actors are connected to a third actor, at some point a friendship tie is likely to form between them (transitivity). Note that in addition to the assumption of stochasticity, this description is also implicitly temporal and dynamic.

A common application of ERGMs is analyzing friendship in a school classroom. The observed network to be modeled is the network for which one will have measured friendship relations. There are many possible networks that could have been observed for that particular classroom, and the model evaluates the probability of observing that particular configuration, conditional on the hypothesized features. In other words, some structures in the network may be quite likely and some very unlikely to happen, and the set of all possible structures with some assumption about their associated probabilities is a probability distribution of graphs. The observed network is placed within this distribution rather than being compared to friendship networks in other classrooms (Robins et al. 2007).

Robins et al. (2007) present five steps for constructing an ERGM:

1. Each network tie is assumed to be a random variable, not fixed.
2. A speculation about the process that generates the network linkages is proposed. Ties can be independent of one another or contingent in some way. For example, if a node has one tie to another node with two ties, it may be more likely to have or form additional ties.
3. As a result of these speculations, the dependency structures imply a particular form to the network. Each parameter corresponds to a configuration in the network, and the model represents a distribution of random graphs that represent these configurations.
4. Complicated models are simplified by imposing constraints on some of the ties or on some of the probabilities.
5. Finally, the parameters of the model can be estimated using modern statistical and numerical techniques.

Most work on ERGMs has focused on a small set of model specifications, most commonly the Markov graphs of Frank & Strauss (1986). Recently, MCMC algorithms have been developed that produce approximate maximum-likelihood estimators. However, applying these models to observed network data often has led to problems, most notably degeneracy. Degeneracy is the phenomenon in which a seemingly reasonable model can actually be such a poor misspecification for an observed dataset as to render the observed data virtually impossible under the model. The degeneracy often prevents model estimation from converging on finite parameter estimates (Handcock 2003, Goodreau 2007).

The alternative forms proposed by Snijders et al. (2006) and Hunter & Handcock (2006), which have similar underlying interpretations but more robust properties, not only avoid degeneracy but have proven to be empirically useful. These parameterizations, combined with advances in computational algorithms, now allow one to conduct general statistical inference on networks between one and two orders of magnitude larger than those that social network analysts have long been studying. These specifications represent structural properties such as transitivity and heterogeneity of degrees by more complicated graph statistics than traditional star and triangle counts. Three kinds of statistics are proposed: geometrically weighted degree distributions, alternating k-triangles, and alternating independent two-paths (Goodreau 2007).

So far, there have been but a few applications of ERGMs in political science, but interest in these models seems to be growing. One nice example is Lazer et al. (2010), which examines whether social affiliations and political attitudes tend to coevolve. The authors find significant conformity effects that may be attributed to one's social network. This work builds methodologically on the ERGM as a way of evaluating the idea that homophily is pervasive in politics, as it is in other domains. The key result is that social and political ties are more prevalent among similar individuals. This turns out to be true in repeated examinations, and it turns out to also be true that the attitudes within a group of similar individuals tend to move closer to one another over time. This research is similar to work on the effects of networks by Christakis & Fowler (2007). More recently, Cranmer & Desmarais (2011) attempt to use this approach in longitudinal analysis.

Clearly, modern ERGMs go far beyond the first experiments with p^* models, which required a substantive interpretation of various types of links, such as 2^* (links between two nodes), 3^* (links among three), and information about the distribution of these kinds of links in particular networks. Current implementations of ERGMs are very general and allow analysts to both describe and make inferences about the network. What the ERGM approaches offer is a way to combine descriptive social network analysis with a principled approach to estimation of the probability of different complex linkage structures within the network.

Small Worlds and Power Laws

One controversial idea, promulgated from the earliest network studies, is the assertion that different kinds of networks dominate different arenas. Politics was thought to be characterized by hierarchy and trade by center–periphery structures. In the late 1990s, Watts & Strogatz (1998) reintroduced and formalized the idea of "small-world networks." These are networks in which most nodes are located in locally dense clusters but yet can "reach" all other nodes in the population via a very small number of bridging connections. Watts (2004) suggested that such small worlds characterize a wide variety of human-generated networks, in part because they offer a favorable blend of the identity advantages of dense clustering and the information advantages of bridges or short path lengths. Although more recent empirical analysis has shown mixed support for this assertion, political scientists and others have used the small-world concept to study information cascades (Fowler 2005).

Another network structure that some argue is general is a hub-and-spoke structure. For example, because of their relatively high levels of clustering, small-world networks may have hubs located between many other cliques. In hub-and-spoke networks, a small number of nodes have many more connections than average; thus, hub-and-spoke structures produce a characteristically skewed distribution in nodal degree.[4] Réka et al. (1999) showed that a process of preferential attachment, in which nodes form attachments to those nodes that already have a large number of linkages, is sufficient to generate a skewed degree distribution that follows a power law.[5] Since Barabasi's work became prominent in promoting the investigation of the degree distribution of networks via so-called fat tails, there have been many discoveries of networks that can be described as hub-dominated networks (Cederman 2003a,b), although it is increasingly recognized that generative mechanisms other than preferential attachment produce networks with fat-tailed degree distributions (Clauset et al. 2009). A recent study by Farrell & Drezner (2008) includes a careful examination of this idea. These authors note that the network of blogs may not be quite power-law distributed—even though it does seem to be highly skewed along similar lines (log normal).

In summary, social scientists are just beginning to discover the different topologies that may usefully describe a wide variety of political networks at different scales.

[4]The degree distribution of a network is simply the distribution of the number of connections held by each node.

[5]Power laws have scale invariance in which the fraction of nodes in a network having k connections is given by $P(k) \sim k^{-\gamma}$, where γ is bounded $2 < \gamma < 3$.

NETWORK DATA COLLECTION TECHNIQUES

Collecting network data is more complex than collecting other types of data commonly used in political science. The challenges are particularly acute when research questions require complete network data (as opposed to data describing the local network surrounding a randomly selected respondent), since this task requires determining both the boundary of the relevant population and the presence or absence of a tie between each pair of nodes. Sometimes, as in studies of the networks in Congress, the boundaries of a group are well defined. When the boundary of the relevant population is not known, snowball sampling (Useem 1972, Erickson 1979) and respondent-driven sampling (Salganik & Heckathorn 2004) can be useful, although each presents problems when the underlying structure of connectivity is not well understood. In general, sampling strategies appropriate for complete network analysis are very much in their infancy (e.g., Handcock & Gile 2010).

The basic tools of network data collection include questionnaires, interviews, observations, archival records, and experiments. Questionnaires and interviews typically include some means of assessing membership in a relevant group or population, either via a name generator or a roster. For example, Bearman et al. (2004) use data from the National Longitudinal Survey of Adolescent Health, a massive roster-based dataset in which a nationally representative sample of students attending 132 schools identified their friends and their sexual and romantic partners from a roster of other students attending their school. These responses enabled researchers to map the complete sexual network of an entire school.

The basic network questions ask about the presence, type, and intensity of a relationship between the respondent and other actors. Additional questions may cover the attributes of actors (age, gender, education, and occupational status in the case of individuals; or governance type, trade specialties, etc. for other types of actors). Scholars have also included questions designed to gauge perceived and objective strength of ties, including the frequency and duration of contact (Granovetter 1995), the provision of emotional support and aid within the relationship (Wellman 1982), and the social distance between nodes (Marsden & Campbell 1984).

Questionnaires are most intuitive when network nodes are individuals, but this technique can also be used when collective entities, such as nonprofit organizations, corporations, or international organizations, are nodes in the network; in such cases, an individual representing the collective reports the collective's ties (Galaskiewicz 1985, Laumann et al. 1985). When questionnaires are not feasible, interviews can be used to gather network data (Galaskiewicz 1985, Wellman & Wortley 1990).

Some scholars have collected network data by observing face-to-face interactions among small groups of actors (Bernard & Killworth 1977, Killworth & Bernard 1976), while others have turned to archival records to measure ties (Rosenthal et al. 1985, Hummon & Carley 1993, Padgett & Ansell 1993). Burt & Lin (1977) discuss how social network data can be extracted from archival data including newspapers, court records, and journal articles.

LATENT SPACE APPROACHES

Although the descriptive and inferential approaches to analyzing political networks have much to recommend them, new developments in network analysis allow us to take the inferential approach even further. Assume that there is an unobserved network that is characterized by the probability of interaction among its nodes. The goal of this approach is to use a model, plus data on observed relations, to make statements about the underlying, though unobserved, "space" in which the network actors interact. This framework may be natural in international relations, where countries are interacting with one another, but it can be more widely applied. In this conception, the data matrix represents the relations among the rows (which could be documents, people, institutions, years, or countries) and the columns (which could be any of the above). In an international relations example, the matrix might represent the trade flows among a fixed set of countries during a given year. Or the entries might represent whether the countries are at war with one another during a given period.

If the sociomatrix is composed of values in the set $\{0,1\}$, it can be thought of as a binary graph; if the values in the sociomatrix are simply in the set $\mathcal{R}$, then it can be treated as a weighted graph. In some sense this is just a matrix that contains information about the rows and the columns. In principle this could be analyzed by standard statistical frameworks, such as ANOVA. But there are many dependencies in these data that foil treating them in a standard statistical framework. In the first instance, there is an inclination for actors to behave toward others in a consistent manner, or, alternatively, for actors to be the object of consistent policies from others. For instance, the prevalence of reciprocity—a second-order dependence among observations—in directional network data challenges the basic assumption of observational independence. Various forms of third-order dependence may also be observed in networks, and treating dyads $\{i, j\}$, $\{j, k\}$, and $\{k, i\}$ as independent may ignore important patterns in network data.

Third-order dependencies includes (*a*) transitivity, (*b*) balance, and (*c*) clusterability (Wasserman & Faust 1994). Transitivity follows the familiar logic of "a friend of a friend is a friend." In particular, for directed binary data, any triad i, j, k is transitive if whenever $y_{i,j} = 1$ and $y_{j,k} = 1$, we also observe that $y_{j,k} = 1$. A triad i, j, k is said to be balanced if each pair of actors within the triad relates to the remaining third actor in an identical fashion: $y_{i,j} \times y_{j,k} \times y_{k,i} > 0$. For example, if $y_{i,j}$ is positive, then for the triad to be balanced, $y_{j,k}$ and $y_{k,i}$ must be either both positive or both negative. A triad is clusterable if it is balanced, either because all ties are positive, or because it contains one positive and two negative ties. A clusterable triad can be divided into groups where the measurements are positive within groups and negative between groups.

Because of second- and third-order dependencies, knowledge of the relations between i and j and between j and k typically reveals something about the relationship between i and k, even when we do not directly observe it. Hoff et al. (2002) note:

> In some social network data, the probability of a relational tie between two individuals may increase as the characteristics of the individuals become more similar. A subset of individuals in the population with a large number of social ties between them may be indicative of a group of individuals who have nearby positions in this space of characteristics, or "social space." If some of the characteristics are unobserved, then a probability measure over these unobserved characteristics induces a model in which the presence of two individuals is dependent on the presence of other ties.

In other words, the social space summarizing these unobserved characteristics is another image of higher-order dependence in these dyadic data. Positions in such a latent space represent these dependencies. Stated differently, once the higher-order dependencies are taken into account, the dyadic data can be analyzed by techniques such as regression that assume the data are independent of one another.

The latent space approach essentially argues that there is an unobserved multidimensional latent space in which proximity is directly related to the probability of interaction. Actors that are closer together are more likely to interact and have ties with one another, whereas actors distant in this space are less likely to interact. For signed, or valued, interactions, actors close to one another will have positive interactions; actors at opposite ends of the social space may have a high degree of interaction, but it is likely to be negative. By conceptualizing the latent space in this way, we can use it to capture the dependencies in the network such that, conditional on the latent space, the nodes in the network may be treated as independent. That is, the latent space captures the dependencies. Since these methods are just being introduced into the field of political science, we offer a brief, though somewhat technical, introduction.

Consider a model for the sociomatrix $y_{ij} = \beta^T x_{ij} + \epsilon_{ij}$. By standard assumptions, the distribution of the errors is assumed to be independently distributed (and invariant to permutations of the labels of the observations). For sociomatrices, this implies that the error distribution is exchangeable to permutations of rows and columns. Thus, for directed sociomatrices we might have a linear specification that decomposes the errors into three sorts of random effects: $\epsilon_{ij} = a_i + b_j + \gamma_{ij}$, with a, b, γ representing random variables. This implies that the covariance structure of the errors has a particular form—and by implication, so do the actual data.

This formulation is known as the round-robin tournament, and this error structure can be introduced into a linear model as:

$$\theta_{ij} = \beta^T x_{ij} + a_i + b_j + \gamma_{ij}.$$

This formulation is a generalized linear mixed-effects model in which observations are treated as conditionally independent given the random effects, but, like network data, are unconditionally dependent.[6] This approach captures first- and second-order dependencies, but third-order dependencies can be captured by a bilinear effect that is added to the linear random effects:

$$\epsilon_{ij} = a_i + b_j + \gamma_{i,j} + u_k^T v_k,$$

with $u^T v$ representing latent positions in k latent dimensions.[7]

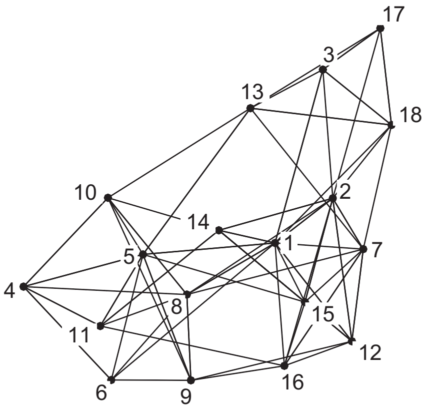
[6]The notation used here is mostly from Hoff (2005). Symmetric sociograms would have latent positions represented by $u^T u$.

[7]Various formulations exist for the metric defining this space. This product is chosen for its similarity to error metrics in the regression framework (see Hoff et al. 2002 for more details). This approach is similar to the work of Nowicki & Snijders (2001) in terms of developing stochastic blockmodels.

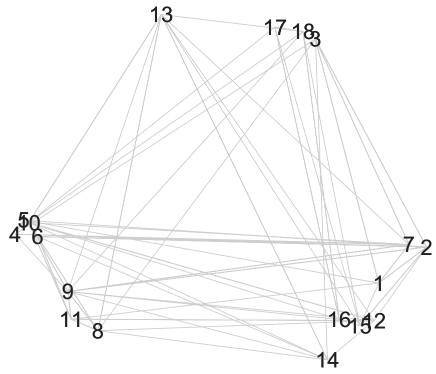
This approach can be estimated with modern statistical methods in the *R* packages `latentnet` and `eigenmodel`. The advantage of this formulation is that it permits the use of a recognizable regression framework while capturing the higher-order dependencies that typify most network data. It also accommodates attributes of nodes (separately as senders and receivers) as well as attributes of dyads themselves. In addition, it accommodates any variety of link functions, allowing binary, ordinal, and interval-level network data to be analyzed. Moreover, because it is built on a probability foundation, it can deal naturally with missing data. It has been widely used to estimate the probability of links that have not (yet) been observed, an area of inquiry known as link detection (Marchette & Priebe 2008). In terms of interpretation, the regression part is familiar, and the latent-positions part has a quasi-geographical and easy interpretation: The closer the nodes are together, the more likely they are to have linkages.

In essence, latent space models provide a principled way of locating the positions of nodes so that their distances can be meaningful in terms of the probability of interaction among them. The latent positions can be statistically estimated using Bayesian methods to estimate the probability of linkages among nodes conditional on observed data within and between the known members of the system.

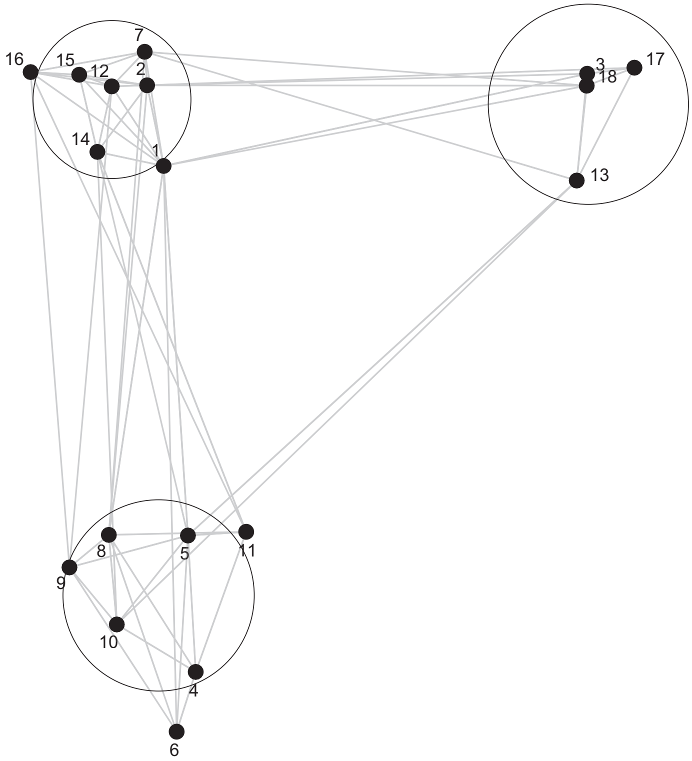
Figure 1 compares a latent space model with a more typical social network analysis of the communication and affiliation networks of 18 monks in a cloister undergoing rapid change (Sampson 1969). These data have been analyzed using many network methods, many of which reveal three groups of monks: the loyal, the outcasts, and the so-called Turks. But analyzis of the latent network clusters permits an empirical discovery or confirmation of these three groups. As shown in **Figure 1*c***, three clusters are evident in the latent analyses, and these are brought into strong visual and statistical relief by the use of latent cluster analysis, a type of latent analysis developed as an extension of latent



(a) Standard SNA Map



(b) Monks in Latent Space



(c) Monks in Latent Clusters

Figure 1

Three network representations of Sampson's (1969) monk data. (*a*) The 18 monks in the cloister are represented using a standard Fruchterman Reingold algorithm for locating nodes. Nodes 16 and 9 are close to one another because they share a linkage. (*b*) Now the same monks are located in a social space estimated by a latent space model. Three clusters are apparent. Nodes 16 and 9 are no longer close to one another because each has a greater estimated probability of being linked with separate sets of nodes. Node 16 is in a particular region of the social space, but 9 is in a different region of the latent space. (*c*) Latent cluster analysis illuminates the three distinct groups, showing the links within them as well as among them.

space analysis (Handcock et al. 2007).[8] In particular, one not only sees the three groups, but the density of links within as well as between clustered nodes.

Latent space approaches allow the empirical estimation of proximities of actors in a latent network, along with measures of uncertainty about those locations.[9] These approaches can be used to make accurate predictions about networks without requiring complete knowledge of the network as a starting point. Nodes need not be individuals; networks may include mixtures of products, experiences, groups, organizations, and individuals. Indeed, current work (McCormick & Zheng 2010a,b) has applied the latent space model developed by Hoff (2005) to study the implicit network structure gleaned from random-digit dial surveys that ask questions like "How many Kevins do you know?" Deriving representations of networks from such limited data opens up a wide range of possibilities in the realm of political science survey analysis.

AN AGENDA AND A PROGRESS REPORT

Network analysis is currently a vibrant area of political science. Lazer (2011) provides a broad overview, while Huckfeldt (2009) describes recent work in the field of American politics, Siegel (2011) reviews network analysis in comparative politics, and Hafner-Burton (2009) surveys the research in international relations. There is already an organized section of the American Political Science Association devoted to the study of networks, and with the help of the National Science Foundation and the Office of Naval Research, planning is under way for the fourth Annual Political Networks Conference (**http://sitemaker.umich.edu/fordschool-pnc/home**). Exciting new directions are emerging, including the use of agent-based simulation and analytical perspectives such as game theory that will help us better understand the relationship between networks and behavior (McCubbins et al. 2009, Hassanpour 2010). In particular, there is an emerging literature in economics dedicated to modeling the strategic formation of ties and the strategic behavior of agents linked together, but this line of inquiry is just beginning to influence political science (Bramoullé & Kranton 2007, Jackson 2008). It is clear that analysis of networks is here to stay, and that insights from network studies will be a growing part of the broader agenda in political science, in ways that are analogical, descriptive, empirical, and analytical.

In the midst of this rapid growth, an important challenge is to find the substantive concepts in political science that map most naturally to networks. Sociology marries easily to networks because sociologists are primarily interested in the relationships among individuals and groups in society. Thus, a wide variety of well-developed sociological concepts map almost directly onto the network framework and vocabulary. At the other end of the disciplinary spectrum, physicists have also easily embraced network science, not just because the cold war is over but because physical models of percolation, organization, and collapse have natural analogues in large-scale networks describing a range of activities. To date, most political scientists from a variety of subfields have found the network approach useful for identifying meso-level effects and impacts that had been ignored in their traditional arena of study, be it voting, spending, or bombing. Yet many network concepts have not yet been translated into the conceptual vocabulary of political science (and vice versa); this must happen if the full potential of a network approach to political science questions is to be realized. Fortunately, we are beyond trying to explain two-stars and three-stars in substantive terms to the political science community, and the discourse has moved toward a broader emphasis on the interdependence of actors in specific

[8] See Krivitsky & Handcock (2008) for details on software to implement such clustering.

[9] Ward & Hoff (2007) and Ward et al. (2007) provide examples in international relations; see also Greenhill (2010) and Cao (2009).

political contexts. Connecting concepts is a big challenge, but we remain optimistic; it may well be that one of the most pressing open questions in political science—how to effectively measure power and influence—can ultimately be solved in a network setting, even when the data appear to be trivial individually.[10]

Beyond forging better linkages between theoretically meaningful concepts and network characteristics, there are a few methodological problems that will need to be solved for network analysis to succeed more widely. Progress is being made on a number of fronts. First and foremost, for several decades the most powerful network analyses have required a complete map of the network. This debilitating constraint continues to plague some approaches. Fortunately, new data sources and new methodological advances (Gile & Handcock 2010) are serving to reduce this limitation. The flip side of this problem is the degeneracy problem for ERGMs. Fortunately, approaches that treat the network as a data problem, as opposed to a graph problem, offer promise in this area. Second, we have only begun to develop dynamical models of networks. This is currently one of the hottest areas in network methodology [see Krivitsky & Handcock (2008) for ERGMs, and more generally Hoff (2011), Westveld & Hoff (2011), Snijders et al. (2012)].

As noted recently in *Science* (Lazer et al. 2009), the use of network insights will be crucial in mastering the torrent of data that faces modern analysts, including political scientists. We are convinced that the growing network data cloud poses myriad new and fascinating puzzles and—in some instances—challenges our accepted answers to old questions.

[10]Interesting and promising work is being done now on the power of 140-character utterances (Baksy et al. 2011).

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