Relational Concepts, Measurement, and Data Collection

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Abstract and Keywords

Political phenomena are inherently relational, so it is natural that network analysis should come to play an important role in the study of politics. And yet relational data present special practical and methodological problems. The network data scholars would like to collect are often incomplete or altogether inaccessible. It is tempting to take whatever data are available and treat these as a proxy for the desired variables. This chapter reviews the most prominent relational concepts in political science and the operationalization strategies and data collection techniques typically employed. It then examines common practices for handling missing data and identifies recent innovations in this area. Finally, the chapter recommends that political scientists give more consideration to the concept development and measurement phases of research design and proposes possible directions for the development of network measurement models.

Keywords: relational concepts, network measurement, validity and reliability, research design, missing data, network boundaries, latent relations

Introduction

POLITICAL life, like social life in general, is fundamentally relational.[1] Politics is the product of relations between humans within institutions and in society, and political outcomes are thus rooted in human relations. As such, scholars study many political phenomena that are relational in nature. Seminal works in political science identify relational concepts such as persuasion, power, interaction, homophily,[2] and trust as critical factors in shaping political phenomena. And yet political science as a field has only recently begun to embrace the theoretical perspectives and empirical techniques known collectively as social network analysis (SNA[3]), approaches specifically tailored to the evaluation of relationships and designed for grappling with the complexity of relational phenomena.

As political scientists become more comfortable with the network analytic perspective broadly defined, we become increasingly conscious of the particular subtleties involved in *political* network analysis; better able to generate and refine network theories of political institutions, behavior, interstate relations, and so forth; and consequently more aware of the shortcomings in our earlier attempts to operationalize and measure political relationships of interest.

Despite the surge of interest in political network analysis over the past decade, several areas of study (e.g., analyses of bureaucracies, inter-organizational power, and relative success of social movements) underutilize network analysis, given the relational concepts central to their most prominent theories. In the areas that have already benefited from a network perspective, increased attention to the discrepancies between latent and observed networks (i.e., the gap between the theoretical network we wish to study (p. 176) and its representation in collected data), greater care in handling the problem of missing data, and more precise specification of units and levels of analysis constitute worthy goals. We begin here by reviewing the use of network analysis in political science since 2000, with an eye toward the relational concepts of existing studies, their research designs, and yet understudied areas.[4] We rely additionally on this recent literature to review common data collection, measurement, and design choices. Most of the chapter deals with common questions scholars must confront when designing political network analyses.

Prominent Relational Concepts in Political Science Studied with Network Techniques

In surveying the literature, we find that SNA of political phenomena has been concentrated in a few main areas of substantive inquiry, including political behavior/political psychology, legislative behavior, interest groups and political parties, and international organizations/trade. Many of the network studies in the realm of behavior/psychology consider the effect of an individual's egocentric or personal network (ego network)—the local subnetwork as provided through the respondent's point of view—on particular political behaviors (Eveland and Hively, 2009; Klofstad, 2007, 2009; Lazer et al., 2010; McClurg, 2006; Bello and Rolfe, 2014). Legislative scholars have taken observable shared behaviors (such as cosponsorship, covoting, and shared membership on committees and in legislative member organizations) to construct and analyze whole networks of federal or state legislators (Porter et al., 2005; Fowler, 2006; Victor and Ringe, 2009; Tam Cho and Fowler, 2010; Bratton and Rouse, 2011; Kirkland, 2011, 2012; Alvarez and Sinclair, 2012; Ringe and Victor, 2013; Kirkland and Gross, 2014; Parigi and Sartori, 2014). Others have relied on shared communication, contributions, and endorsement data to construct and analyze interest group networks and their intersection with party organizations (Carpenter, Esterling, and Lazer, 2004; Grossmann and Dominguez, 2009; Heaney and Lorenz, 2013; Heaney et al., 2012; Koger, Masket, and Noel, 2009, 2010). Box-Steffensmeier and Christenson (2014) use the filing of amicus briefs from 1930 to 2009 as a measure of dynamic relationships between interest groups before the US Supreme Court. In international relations, shared membership in intergovernmental organizations (IGOs), alliances, and the flow of migrants and goods make up the ties that bind states and predict conflict and policy change (Hafner-Burton and Montgomery, 2006; Breunig et al., 2012; Dorussen and Ward, 2008; Manger, Pickup, and Snijders, 2012; Rhue and Sundararajan, 2014). Certain types of relations may be considered "negative," as in the case of economic sanctions linking pairs of countries via negative directional ties (Cranmer et al., 2014).[5] Finally, political scientists in the areas of public administration/public policy have used network analysis to examine the directional flows of innovations and communication between organizations (Desmarais, Harden, and Boehmke, 2015; Provan, Huang, and Milward, 2009; Garrett and Jansa, 2015; Scholz, Berardo, and Kile, 2008). While scholars in this area have played key roles (p. 177) in the development of SNA for organizational behavior (e.g., Krackhardt and Stern, 1988; Krackhardt, 1992), political scientists studying policy processes have been slower to adopt such approaches.

Furthermore, a number of areas in political science are just beginning to incorporate social network perspectives in a systematic manner, opening pathways to new insights. While sociologists have been using network theory and analysis to study the structure and efficacy of movements for decades (e.g., Tilly, 1978; Rosenthal et al., 1985; Tarrow, 1994), political scientists have built a wealth of knowledge about elite responsiveness and the policymaking process; integration of these separate traditions can bring new focus to the processes through which social movements exact political and policy change. We are already seeing some examples of such creative fusion. Heaney and Rojas (2015) examine the effects of the anti-Iraq war movement on the Democratic Party by looking at the mobilization of an antiwar activist network. Similarly, Hadden (2015) studies the internal organization and tactics of the climate change movement and its effects on global policy from a networks perspective. Recent work by Carpenter and Moore (2014) articulates a rich relational theory of social movement institutionalization and political influence in which women's suffrage groups benefited from the social structures female activists built during the antislavery movement.

Common Practices in Designing Political Networks Research

Political network analysts have employed a wide variety of research designs according to their own particular research questions and the obstacles they face. While SNA design options abound, the political scientist intending to incorporate network analysis into a research agenda should be aware of common practices.

A large number of network studies use surveys for data collection. Survey-based data have been used most extensively in political behavior studies, especially investigations of the influence of social ties on knowledge and activity (e.g., Eveland and Kleinman, 2013; McClurg, 2006). A survey instrument may ostensibly allow direct measurement of the relation of interest. For example, one may measure political communication by simply querying individuals about their communication partners. Of course, such surveys do not permit direct measurement per se; unless we legitimately wish to study the network of *recollected* encounters, we will in fact be gathering values on a proxy variable subject to potentially large measurement errors. Moreover, in the mass political behavior setting, the construction of a whole social network is practically impossible; we inevitably sample respondents from the universe of communicators, and surely some communication partners will go unmentioned by any respondents. Thus, survey-based analyses of this sort almost always focus on the effects of one's ego network (ego-net) on personal attributes (see Huckfeldt et al., 2000; Lazer et al., 2010; McClurg, 2006; Klofstad, 2009; Jang, 2009). The advantage of ego-net analyses remains the typical independence of the (p. 178) ego-nets relative to one another, allowing the application of conventional sampling and inferential statistics.[6]

Researchers wishing to examine behavior in elite networks are less likely to find themselves restricted to ego-net analyses. In such cases, the network boundaries are more clearly defined. Within a clearly delineated network, such as relationships among legislators in a single session (e.g., Sarbaugh-Thompson et al., 2006; Ringe, Victor, and Gross, 2013; Leifeld and Schneider, 2012), nonresponse may still plague survey administration, but at least a complete list of nodes is easily obtained and objectively verifiable. A number of articles in the public policy and public administration literature also used survey-based data to analyze information exchange among networks of subgovernments (Huang and Provan, 2007; Provan, Huang, and Milward, 2009) and between public officials and policy advocates (Schloz, Berardo, and Kile, 2008). Although survey based, these studies are able to construct a whole network—or very close to it—because of their focus on a clearly defined elite population.

Observational data more frequently constitute the basis for political network analyses. Unfortunately, the lack of frequency with which we encounter observational data capturing the relational constructs we wish to study means even greater potential slippage between the latent relational concept and operationalization. Consider, for example, the reliance on cosponsorship as proxy for more general social ties between legislators (see Kirkland [2011] and Tam Cho and Fowler [2010] for discussion), covoting as proxy for shared policy agreement (Alvarez and Sinclair, 2012), co-contributing financial support to candidates or ballot initiatives as operationalization of coalition building (Bowler and Hanneman, 2006; Grossmann and Dominguez, 2009), comembership in alliances or IGOs as measure of shared affinity (Maoz et al., 2006), and co-caucus membership as operationalization of capacity for information sharing (Victor and Ringe, 2009). As researchers build on the excellent scholarship of these and other authors, we might wish to reflect on whether we should argue more forcefully for the value of studying these observed behaviors for their own sake (e.g., cosponsorship) or should identify other observable indicators of the latent construct we wish to study (see Kessler and Krehbiel, 1996; Koger, 2003). If one wants to examine the behavior of cosponsorship itself, one can safely assume that data on cosponsorship are indeed capturing the relationship of interest. But if cosponsorship data are used as a proxy for some other relation of interest, a strong argument is needed to justify why this is appropriate, or we need other indicators that—together with cosponsorship—can be used to tap the latent concept.[7]

Although *social* network analysis typically implies the study of connections among individual sentient beings, in network analysis more generally, a node need not always correspond to a person or animal. Indeed, while the phrase *political network analysis* most often refers to a special case of SNA, network analysis applied to political research extends beyond simple interpersonal relations. An increasing number of studies involve the measurement of relations among concepts and other entities. Examples include mapping the path of innovation diffusion (Desmarais, Harden, and Boehmke, 2015; Garrett (p. 179) and Jansa, 2015), proximity of human rights violations (Fariss and Schnakenberg, 2014), and similarity between party platforms (Maoz and Somer-Topcu, 2010). In these studies the nodes are more abstract objects—states, rights, platforms, respectively—and the ties represent particular relations measured on pairs.

Key Researcher Considerations

As the research process involved in studying networks has its own idiosyncrasies that set it apart from individual attribute-oriented studies, the investigator faces a number of choices that should be considered at the outset. Not all of these are straightforward, and no two researchers investigating the very same phenomenon are apt to make identical choices. We next provide a set of key questions that researchers should ask themselves early on in the research process, as the answers—and indeed the questioning process itself—will shape the research design.[8]

Is a Network Representation Appropriate?

In some cases, it is quite obvious that one is dealing explicitly with a network, such as when relationships are explicit and connections are essential to the research question. In fact, whenever one is interested in relational data observed on a set of individuals, it is generally advisable to conceptualize this as a network, even if the research questions aren't formally network questions and one's theory is not particularly motivated by structural considerations. This is due to the fundamental autocorrelation problem in relational data: unless the researcher is sampling independent dyads (no nodes in common among the sampled dyads and little chance of direct interaction), it is crucial that the dependence structure among dyads be addressed in some way (e.g., Boehmke, 2009; Cranmer and Desmarais, 2011; Bowers et al., 2013). Network representations have become the standard way of modeling the inherent complexity arising from relational data in social science.[9] To see why conventional statistical models are insufficient, one need only consider as an example the relational variable *military belligerence*. For example, it should be obvious that whether Germany has been at war with the United Kingdom during some timeframe is not independent of whether Germany has been at war with the United States during that period. When interdependence is particularly high—that is, it is not likely that the units being studied are behaving independently—there is the potential for bias in model estimates (e.g., Boehmke, 2009). Even if one is not theorizing about such things as network effects or networked concepts such as centrality or connectedness, it is natural to think in network terms in order to take advantage of the inferential machinery that generations of network scholars have assembled. The bottom line is that one must grapple with dyadic interdependence.

(p. 180) Unit of Analysis and Levels of Analysis

An initial, basic question faced in conventional empirical research is that of the appropriate unit of analysis. What sorts of entities have the attributes being measured by the variables of interest? Senators, nations, bills, bureaus, corporations, families? How exactly are data aggregated, or—equivalently—what sorts of objects inhabit each row of the associated rectangular data set? The collection and management of relational data may be more complicated than for individual (nodal) data, but awareness of one's unit of analysis remains crucial to clear thinking about all aspects of the design and measurement process. In general, researchers will be dealing with *dyads*—pairs of nodes—as the basic unit of analysis, although individual nodal attributes will often play a role in analysis as well. At first this may sound like a minor difference from units of analysis typical in non-network studies; after all, we're just shifting from single nodes to pairs of nodes, and it is not unusual to encounter aggregated units of analysis such as households or census tracts in the nonrelational context. The essential difference is that aggregated units of analysis are nonoverlapping in the non-network setting. The complexity inherent in network data arises from the basic fact that dyads overlap and, in fact, can overlap in ways that are not always straightforward (e.g., in two-mode—or bipartite—networks, where the set of nodes is partitioned and each dyad consists of one node drawn from each subset).

An additional related consideration specific to the study of network data is that the researcher may pursue multiple *levels of analysis* [10] potentially within a single study. Just as a biological scientist may study the human body at the systemic level as interactions among systems (nervous, circulation, digestive, etc.), or instead investigate individual organs within these systems, or even drill all the way down to the molecular level, so too may the political scientist study the networked body politic at multiple levels, including—most commonly—nodes, dyads, communities, or the network as a whole.

The research question drives one's choice of level of analysis and determines whether it will be sufficient to confine oneself to a single level. For example, if one seeks to explain dyadic variation (e.g., whether two voters discuss politics, conflict between two nations, or presence of links in a global supply chain), then one will conduct dyad-level analysis. If one is interested in understanding variation at the network level—for example, whether public opinion about Congress predicts the degree to which clusters of legislators cooperate or, alternatively, isolate themselves—then one will need to collect several instances of whole-network data. Often, explanatory and response variables involve measurements taken at different levels of analysis. The researcher should consider whether, for instance, the hypothesis at hand holds that individual-level attributes should predict triad-level outcomes (e.g., if triadic closure is more likely to occur when all three individuals share a particular attribute), that network-level properties predict individual-level outcomes (e.g., density of political conversation network increases probability that each member will turn out to vote), or that dyadic relations predict other dyadic (p. 181) relations (e.g., high level of trade between two nations corresponding to tendency to sign extradition treaties).

Ego-nets constitute yet another possible level of analysis and to some extent represent a distinct analytical approach. Although many have come to associate SNA with whole-network studies, ego-net analysis offers some notable advantages as a form of relational inference. If interest lies in predicting relations from nodal attributes or vice versa, it makes sense to sample individuals and collect data on them and their immediate contacts. This is the one type of network analysis in which the traditional sampling apparatus may be applicable and nonresponse plausibly construed as missing at random (MAR).[11] As long as a researcher is willing to make the assumptions that the individual ego-nets are independent and that the nonresponse mechanism is related only to variables collected, that researcher is on fairly solid methodological ground. For the independence assumption to be reasonable, at the very least it must be true that no alters should appear as egos in the study (Robins, 2015, 52). Borgatti et al. (2013, 270–276) note that the most prominent questions addressed with an ego-net design focus on processes related to social capital or social homogeneity; in either case, the researcher wishes to understand how individuals' interpersonal contexts affect their own attributes and behaviors. Thus, key explanatory values are relational or aggregates of relational variables (e.g., density of one's personal network, tendency toward reciprocity), and the response variable measures some individual attribute. In political research, we might wish to better understand political capital, self-efficacy, political socialization, knowledge, voting behavior, or ideology. In such research, one's direct connections (and the interconnections among those to whom they are connected) are most germane.[12]

Level of Measurement

In nodal (as opposed to relational) variable analysis, we commonly consider what level of measurement is most appropriate—or simply practical for data collection—before we decide which sorts of graphical representations and summary statistics will be well suited to the data. For example, one simple distinction is between categorical (nominal, ordinal) and numerical (ratio-interval), with numerical measurements made on either discrete (countable) or continuous (uncountable) sets. By far the most common choice for relational measurement level is binary nominal, indicating simply whether some relationship is present or absent. Sometimes this choice is justified by theoretical considerations (e.g., a bureaucrat either answers to another person as his or her superior or does not, a potential donor either does or does not donate to a campaign, two members of a legislature serve on a common committee or do not, one nation either does or does not have an extradition treaty with another). Although it may be possible to measure such relations more precisely, presence or absence is often the most important concern; indeed, it may be quite difficult if not impossible to obtain more granular measurements. Furthermore, many of the technical underpinnings of network analysis rest (p. 182) on dichotomous ties. In particular, to take advantage of most common features of mathematical graph theory presumes simple presence or absence of ties in a network. Various configurations—hubs and spokes, closed triads, and so forth—tied to social network theory are inherently discrete.

And yet it is not always clear that this is suitable for political applications. Take, for instance, policy diffusion among states or nations. One might represent the United States as a network in which two states sharing a border are considered linked. Were it the case that policies only diffused geographically, this would be suitable. But states may copy policy innovations from any other state and are not limited to their immediately surrounding neighbors (Karch, 2007). One way to handle this is to assume that links must either be absent or present between each pair of states, but we are unable to directly observe these links. Bill similarity data (Garrett and Jansa, 2015), or repeated measurement of the order of adoption among states (Desmarais, Harden, and Boehmke, 2015), are then taken to be indicators of the hidden network. This is a modeling simplification that may be necessary in order to utilize the usual network toolkit—based in large part on the discrete mathematics and representation derived from graph theory (Barnes and Harary, 1983)—but a more accurate representation might allow for a complete network (ties between every pair of states), where the weight on edge *i,j* represents the propensity of state *j* to borrow legislative language from state *i* and each state has a nonzero probability of adopting legislation from every other state.

An additional question the researcher faces is whether these measurements will be *undirected* or *directed*. Some political relations (e.g., power, donation) are inherently directed, while others are clearly undirected (e.g., shared affiliation, personal contact). Relationships that are inherently directional may be represented as undirected, but not vice versa. Why should one represent an asymmetric relationship as if undirected? Wouldn't that be throwing away information? It depends on the theory driving the research. Although trust is directed, it may be that some outcome is predicted whenever a trust relation in either direction exists, or only when a reciprocated trust relationship exists. Moreover, a number of whole-network analysis procedures are defined only on sets of undirected ties or are more reliable for these types of edges. Whenever calculating, reporting, and attempting to interpret a network statistic, one should always clarify whether it is appropriate for undirected ties, directed ties (*arcs*), or both.

It is especially important to investigate accepted practice, since it is not uncommon for network software packages to carry out calculations even if the results may be nonsensical. Different packages may have different default rules for handling data in such cases (e.g., whether—and how—to transform directed ties into undirected ties or to simply generate an error message), so it is preferable to be proactive and handle any necessary transformations oneself. For example, any statistic—such as betweenness centrality—that relies on *geodesics* (shortest distances) between pairs of nodes does not take direction into account. Suppose the relation of interest is *information sharing*. Whether two individuals should be considered linked if either shares information with the other or only if information flows in both directions is a substantive issue, to be resolved by the **(p. 183)** researcher based on theoretical considerations. In some cases, it may even be necessary to establish more complicated rules for determining the distance between two nodes (e.g., the shortest path allowing flow of information in either direction via a sequence of arcs arranged tip to tail). The bottom line is that it is essential to think carefully about the research claim being investigated rather than just leaving measurement decisions up to arbitrary software defaults.

Often the focus of a network study is not on properties of relations themselves, predictors of relational outcomes, or consequences of relationships for individual attributes, but instead on some aggregation at the subgroup or whole-network level, or measures associated with each node's position in the whole network. The researcher should clarify at the outset whether the research aim will depend on such aggregation. Whether such aggregate measures as centrality, connectedness, and clique membership are meaningful depends strongly on the nature of the relational variables and measurement error. One should not assume that such aggregate statistics automatically make sense simply because they can be calculated. The better one understands the operationalization of the relation of interest, the better one will be able to assess whether the proposed aggregation of measurements will be edifying or misleading.

Do the Relations Link the Same Types of Nodes?

An observed relational phenomenon of interest may directly connect a pair of actors (or other nodes), but often the connection is indirect, existing by virtue of shared interaction with another sort of node. In some cases, the distinction is left implicit in analyzing a resulting network; in fact, the difference between what SNA scholars term *one-mode* and *two-mode* networks may at times be subtle. Examples of clear one-mode (or unipartite[13]) networks include those based on surveys in which actors identify alters with whom they share some relation (friendship, trust, animosity), while the quintessential two-mode (bipartite) network is one based on shared affiliations (e.g., memberships, attendance at social functions). In the murky middle lie networks easily represented as unipartite, but at least implicitly based on connections via other objects. For example, imagine that we wish to construct a network of politicians based on shared interests. If "shared interest" is kept vague—perhaps by asking members of a parliament to indicate who, among their colleagues, shares interests with them—a unipartite network results. If, on the other hand, we are to use archival data to identify *specific* shared interests, then we are starting from a bipartite network (Ringe and Victor, 2013), with each tie connecting one person and one interest. The researcher must then either choose a strategy for collapsing this into a unipartite network or deal explicitly with the various types of interests each pair shares.

The vast majority of analyses conducted on bipartite networks begin by collapsing their given networks into a single mode (node-type) of interest. To date, the tools available for unipartite network analysis are far more extensive and amenable to (p. 184) interpretation, so this tendency is unsurprising. The rules employed in transforming a bipartite into a unipartite graph, however, should be defended by the researcher, and if they seem too arbitrary, different choices should be attempted to see how measurements are affected. For example, a legislative cosponsorship network looks quite dense if a single act of cosponsorship counts as a tie between two legislators; if we instead only count acts of cosponsorship on bills with fewer than *n* cosponsors or require repeated instances of collaboration before registering a link, we will wind up with a sparser network indicating stronger ties. In fact, examining different versions of a network representation in this manner can be illuminating.

However one goes about collapsing a multimode network, one should remember that potentially important information will be lost. In the cosponsorship example, we wind up ignoring attributes of the bills and count them as interchangeable. Few studies in political science analyze uncollapsed bipartite network data. Skinner, Masket, and Dulio (2012) are an exception; they explore the influence of tax-exempt political organizations known as 527s within the extended Republican and Democratic Party networks. The authors constructed a two-mode network in which 527s are connected with other party organizations if their staff members used to work for the other organizations. By multiple nodal and network level measures, the authors find that 527s are essential players in party politics, providing coordination within parties and hierarchical structure to the extended party networks. Collapsing the data would not have allowed the authors to analyze the unique contribution of 527s in facilitating the formation of party networks.[14]

Just as network structure and analysis involves various complications absent from conventional unit-by-variable “rectangular” data sets, threats to validity and reliability plague relational analyses. Next we discuss some of these threats, options for dealing with them, and ways in which we have yet to satisfactorily address network measurement problems.

Measurement Error: Validity, Reliability, Missing Data

If threats to validity and reliability abound in social science, the difficulties associated with these and other forms of measurement error in network analyses are greater still. Ronald Burt’s claim that missing data are “doubly a curse” for social network analysts—due to the special challenges that arise through the greater complexity and sensitivity of such data (1987)—extends to other network measurement issues. Though missing data may be the most vexing problem for analysts, multiple sources of measurement error limit our ability to formulate widely applicable solutions. In this section we consider key threats to accurate measurement; review a few key sensitivity analyses; and discuss different frameworks for addressing these threats through design, modeling, and simulation-based sensitivity analysis conducted on a case-by-case basis.

(p. 185) Within the SNA literature, scholars discussing missing data and other sources of measurement error have approached the topic by demonstrating the particular vulnerabilities of network data to validity and reliability threats. Two authors influential in designing early statistical network models, Holland and Leinhardt (1973), pointed out that the usual notion of observed structure being composed of “true structure plus noise” may not be terribly well suited to networks. They claimed that, in fact, most representations of social networks contain distortions that are far from simple to correct, even with sophisticated modeling. And yet network researchers, at the time the article was written, typically presumed the face validity of their data, treating the error mechanisms as essentially ignorable. Holland and Leinhardt faulted researchers' "inability to distinguish structural complexity from measurement error" and invited them to instead think in terms of the "compatibility" of observed and true networks, a more flexible way of viewing such discrepancies. It is interesting to note that Holland and Leinhardt described the situation as one of a *latent* network, not directly observed, and an *observed* network that consists of imperfect relational indicators. At the time, practical applications of what we now call latent variable modeling—including factor analysis, latent trait analysis, and latent class analysis—were still quite limited by computational constraints, and classical measurement theory continued to dominate, so it should come as no surprise that network researchers did not propose a latent network model formally connected to these other areas of latent structure analysis.

Left unquestioned in this earlier work is whether the relational constructs themselves are well defined. Commonly studied concepts such as friendship, trust, and sexual contact have relatively straightforward meanings, with researcher definitions unlikely to cause much controversy.[15] This is less often the case with concepts such as political influence, political support, adoption of policy innovation, and other phenomena attracting the greatest attention among *political* network analysts. As a consequence, the single most important step we can take to improve the validity of our research is to thoughtfully define and operationalize our relational concepts. The most compelling criticisms of political network analyses often amount to the simple assessment: "I'm not sure you're measuring what you think you're measuring." If we have not clearly defined the relations of interest and made a convincing case that we have chosen a reasonable measurement strategy, no amount of post hoc tinkering or statistical adjustment will help.[16]

Types of Network Measurement Errors

Assuming concepts have been clearly defined and mapped to observable variables, a number of other key hurdles remain. Wang et al. (2012) identify six types of network measurement errors:

- false negative/positive nodes
- false negative/positive edges
- falsely aggregated/disaggregated nodes

(p. 186)

These error types include missing data as a special case (yielding false negative nodes or false negative edges), most typically resulting from an incomplete node census, nonresponse, or censored observations. These authors further refine the thinking about network measurement error by identifying *three* levels of interpretation: the *ideal network* (similar to what we call "latent" and Holland and Leinhardt call "true"); the *clean* *network*, the encoded network data in the absence of measurement error; and the *observed network*, which the researcher actually gets to see. Scholars generally emphasize discrepancies between the clean and observed networks; when they refer to a "true network," they are in fact conflating the ideal and clean networks and ignoring the aforementioned difficulties associated with operationalization.

The likelihood of encountering each of the six errors mentioned above (and listed in table 7.1) depends on the research design employed. In survey-based network research, nonresponse may lead to both *false negative nodes* and *false negative edges*, but not necessarily. In some areas of political science, the *boundary specification* problem—the question of which nodes should be included in the network of interest—is trivial. For example, names of legislators, nations, and lobbyists may be publicly available and accessible with minimal effort, circumventing the risk of incorrectly omitting nodes. In whole-network surveys of elite actors, nonresponse may result in false negative edges, as the nonresponders will not have reported the presence or absence of ties to others, but this does not rule out the use of other sources of information on such ties.[17] In personal (p. 187) network (ego-net) studies, where egos' local networks are assumed to be independent of one another, nonresponse does not pose the same risks as for whole networks. Threats to validity and reliability in these studies bear more resemblance to corresponding ones in non-network designs.

Table 7.1 Types of Network Measurement Errors

Types	**Example**	**Example of Resulting Problems**
False Positive Node	Including a Democrat in a Republican fundraising network	Density underestimated; study validity threatened
False Negative Node	Excluding a legislator from the cosponsorship network	Depends on node's importance (e.g., may drastically alter connectivity, centrality scores)
False Positive Edge	Inferring a policy diffusion path that did not really occur	Overestimated density
False Negative Edge	Legislative offices failing to report joint policy meeting	Underestimated density
Falsely Aggregated Node	Counting Bill Nelson (D-FL) and Ben Nelson (D-NE) as the same node	Overestimated degree distribution
Falsely Disaggregated Node	Counting Al Franken and Alfred Stuart Franken as two different nodes	Underestimated degree distribution

The problem of incorrectly including individual nodes (*false positive nodes*) is analogous to coverage problems in standard surveys (e.g., including a sixteen-year-old on a list of potential voters). This is one of the easier measurement problems to address. In the case of a survey, one may ask qualifying questions at the start and eliminate such nodes from consideration. In many cases, these "errors" involve a judgment call. In such cases, it is incumbent upon the researcher to carefully stipulate the nodes to be included, offer justification, and indicate the measures taken to ensure that those meeting proposed criteria will be included, and no others.

More generally, *boundary specification* issues (Laumann et al., 1983; Kossinets, 2006) are analogous to defining the target population, with the caveat that sloppiness can more easily result in large errors in inference. Even when defining the boundary seems trivial, we often find ourselves with choices to make and defend; if examining the network of cosponsorship support during a given term, shall we include only those who serve a full term? More than half? What if a senator is absent for much of the session while campaigning for president and manages to avoid voting on any controversial bills?

On the other hand, in some newer types of research—on social media, for instance—false positive nodes and edges can more easily slip through unnoticed. For example, if we were to study linking behavior among political blogs, a lack of direct human oversight is likely to promote the inclusion of nonblogs and links to advertisers. A choice must be made between pruning the network back by hand, building automated tools to discern true positives from junk, or acknowledging the likely noise in the observed network.

Reliability troubles abound in self-reported relationships, as the presence or absence of a relationship is rather subjective. Suppose, for example, we are interested in contact between legislative staffers (as in Ringe et al., 2013). We may ask staffers to indicate those with whom they have had a conversation over the past week. Some will misremember and claim interactions that actually took place more than a week ago, while others will forget a conversation that occurred during the past week. These would appear to be cases of false positive and false negative edges, respectively. But are we truly intending to study the network of contact in an arbitrary week? More likely, such a question is intended as a proxy for something not directly observable, such as *frequent contact*. Frequent contact is correlated with *contact in the past week*, but also correlated with *recalled contact in the past week*, even if that recollection is incorrect. Indeed, rather than a network of recent contact, measured with error, we might instead say that we have measured a network of *perceived* recent contact, measured perfectly! Something subtle is at work here, suggesting that what are characterized as "errors" of measurement may in certain cases be better addressed in the operationalization process. The **(p. 188)** chance of capturing a latent construct such as regular interpersonal contact through a number of different manifest variables suggests the enticing idea of creating network factor or latent trait models, a possibility that has yet to be pursued. Rather than simply choosing a single proxy variable for frequent contact, information sharing, willingness to collaborate, or any other relational concept, we might instead use several correlated measures that all imperfectly capture it.

When Wang et al. (2012) refer to *falsely aggregated* or *disaggregated nodes*, they are referring to disambiguation, a data entry and management issue. For example, we would be falsely aggregating nodes if we conflated Bill Nelson (D-FL) and Ben Nelson (D-NE) in an analysis of the 2003–2004 US Senate. On the other hand, if we somehow managed to count Al Franken and Alfred Stuart Franken as two separate people in the 2013–2014 Senate, we would be falsely disaggregating nodes. Checks on clerical mistakes such as these are easier when dealing with a set of legislators than, say, the linking behavior among thousands of websites. In the latter case, renaming of websites and slight changes in domain names can make such errors more common.

It is impossible to offer an authoritative list of problems resulting from these six errors. Much depends on the underlying generating process of the "true network" being studied. Because network data are interdependent, a single incorrectly measured node or edge may have little importance for characterizing the entire network or inferring parameters of a network model, or it may prove catastrophic. Thus, the principal issue is our inability to confidently quantify uncertainty. We list a few likely estimation problems in table 7.1, but these should be taken with a grain of salt. Some estimation may be more or less robust to errors depending on features of the network. See Wang et al. (2012) for comparisons of difficulties likely to arise from each error type, based on simulations employing a few simple assumptions. In general, they find that networks with low average clustering and node degree distributions not too positively skewed tend to be the most robust to various types of measurement error.

Additional Issues with Aggregation: Persistent vs. Fleeting Ties

Other common problems might also be understood as aggregation or disaggregation issues. Consider, for example, how relational phenomena are aggregated over time; while social network ties are nearly always portrayed as persisting through time,[18] some may more accurately be thought of as fleeting or even instantaneously experienced. Here, the line between conceptual definition and measurement error becomes blurred: two entities may be considered to be at war (persistent), or they may have simply experienced an act of belligerence (fleeting). A senator may be supportive of another's legislative agenda (persistent) or may simply have cosponsored this colleague's bill (fleeting). A presidential candidate may have an acrimonious relationship with an opponent on social media (persistent), or may simply issue an isolated snipe (fleeting) (Gross and Johnson, 2016). (p. 189) When working with relational event data, one option is to explicitly study these dynamics through longitudinal analysis. Promising new approaches include relational event modeling (Butts, 2008)—a flexible extension to event history (survival) analysis—and other forms of social sequence analysis (Cornwell, 2015). James Kitts (2014) argues that we need to move "beyond networks" in conceptualizing and theorizing about relational interactions, freeing us to look in more detail at the complex dynamics involved. Alternatively, one might consider the relational variable of interest to be a latent propensity toward interaction and treat the fleeting instances as indicators of that underlying tendency.

We face similar choices in individual-oriented research, as we decide among various research designs, based on data availability, theoretical considerations, and our research questions. In network analysis, however, the implications of such choices are—unsurprisingly—more complicated. When we posit network ties based on fleeting events and then analyze the resulting "networks," we take a conceptual leap that, at the very least, should be explicitly mentioned and defended. We may, for example, say that we are analyzing a network of "political information flow" that is operationalized as linking people who have shared an email containing politically relevant content at some point in the past six months. If we wish to make a claim about the shortest path information may take to pass from one node to another and base inferences about who the important conduits for information are, we may have difficulty convincing a critical audience that our operationalization supports such claims. The gap between what has been measured and more general assumptions about information flow becomes more problematic at the whole-network level.

Borgatti et al. (2013, 31) present a typology of common dyadic phenomena in four types to help researchers identify the relationships they are dealing: *co-occurrences* (comembership, coparticipation, physical distance, attribute similarity), *social relations* (kinship, affect, familiarity), *interactions* (transactions and other activity), and *flows* (ideas, information, products, infectious disease). Some types of co-occurrence persist through time (e.g., similarities, shared memberships), while others may be fleeting events (e.g., joint attendance at a convention). Social relations tend to be persistent, in some cases essentially permanent (e.g., familial ties) and in others subject to change (e.g., affection). Interactions and flows may involve isolated incidents connecting nodes (e.g., makes campaign donation, speaks at campaign event), but patterns of such phenomena (e.g., repeated donations, touring with campaign) may constitute persistent ties. Borgatti et al. (2013) point out that certain relational behaviors are "institutionalized," taking on a reality that transcends individual perception. A number of such relations are of interest to political scientists, increasingly accessible through archival data. For instance, if a lobbyist has previously worked for three elected officials, this may be a matter of public record; their relationship may be independently corroborated, sparing us dependence on less reliable self-reporting.

(p. 190) Missing Data

The most serious threat to the measurement integrity of a network study is also the most common: missing data. Modern approaches to handling missing observations in statistical inference rely heavily on the assumption that individual observations are independent. The now standard typology—missing completely at random (MCAR), at random (MAR), and not at random (MNAR)—classifies scenarios according to the broad class of mechanism responsible for the encountered missingness. Accepted methods for grappling with all three situations—even the most problematic one, in which the mechanism responsible for missing data is dependent on unobserved variables (MNAR)—assume that each data point's propensity to be missing is unrelated to that of each other data point. Such an assumption does not hold in full network studies. Worse still, network statistics have the potential to be quite sensitive to even a single missing dyadic observation, so missing data at the levels typically encountered certainly have the potential to wreak havoc.

In most whole-network studies in the social sciences, the goal is to collect a census, rather than a sample of the population. Random sampling of nodes or dyads is not a sensible strategy, since there is no general statistical theory linking a subnetwork's statistics to corresponding parameters for the full network from which it is sampled. In fact, one point of view holds that in a whole network study, there is but a single observation (n = 1), so sampling obliterates our only observation. If we wish to describe low-level structures in a network (e.g., particular triads, in-stars, and clusters), we are out of luck, as the sampling process complicates descriptions of particular patterns of interaction beyond what is practical. Thus, the most frequently offered suggestions involve strategies for mitigating nonresponse and advice for proceeding with extreme caution in interpreting results if missing data cannot be avoided. The bottom line is that in contrast to node attribute estimation on independent observations, *no broadly applicable sampling theory for networks exists*. Any such theory requires strong assumptions about the nature of the underlying "true" graph structure from which nodes and edges are being sampled. That said, certain aspects of network topology—density or average degree, for example—may be easier to estimate through sampling than others. Kolaczyk (2009) describes the challenge of network sampling in technical detail, connecting it to the literature on traditional sampling theory. Our own pessimism about the outlook for a general theory for network sampling should not be interpreted as a call to ignore sampling issues or to only analyze completely observed graphs. Rather, applied network analysts will likely always need to argue on a case-by-case basis, demonstrating sensitivity to sampling error via simulations under various plausible assumptions.

Methodological work on the problem of missing data in networks has been rather scarce, not only because of the serious difficulties involved, but also because solutions tend to be narrowly applicable. Authors focusing on this issue in depth have offered three types of contributions: (1) studies aimed at understanding the systematic patterns of missingness and sensitivity analyses to establish the robustness of particular (p. 191) network statistics in the presence of missing data, (2) network imputation strategies, (3) and direct modeling of missingness within broader statistical models. In an early example of the first type, Burt (1987, 67) concentrated on ego networks—generally the least susceptible to the ravages of missingness—and using the 1985 General Social Survey, found that nonreporting of links among alters was correlated with the strength of ties, implying nonignorability. In the context of an example from political communication, this means that if we were to ask a survey respondent to name people with whom he or she has discussed an upcoming election, we would expect the respondent to be less likely to mention actual conversation partners to whom he or she is weakly tied; if asked to indicate pairs of discussion partners who have talked to one another about the election, we would be especially unlikely to name dyads composed of those to whom we are weakly tied.

Three common reasons for units to be missing are unit nonresponse; misspecification of the network boundary; and "vertex degree censoring" due to *fixed-choice designs*, wherein respondents are asked to nominate up to some small number of partners (Kossinets, 2006, 248). Kossinets finds several network level statistics—including assortativity, coefficient mean degree (average ties per node), clustering coefficient, size of the largest component, and mean path in the largest component—to be quite sensitive to vertex degree censoring and/or network boundary misspecification, while these tended to be more robust to unit nonresponse. The article includes exploratory analysis indicating sensitivity as a function of missingness. This article is especially important for the example it provides to researchers of how to go about doing sensitivity analyses for themselves on their own projects.

Whereas imputation strategies have become a matter of best practice in many areas of data analysis, their suitability for networks is less clear. While others (e.g., Robins et al., 2004) have been dismissive of such approaches, Huisman (2009) maintains cautious optimism for network imputation, especially if the missingness remains below 20 or 30 percent. In weighing imputation against simple node deletion (i.e., analyzing the network of respondents and ignoring the nonrespondents), the take-away message is that there is no general preferred solution. As long as the proportion missing was low, bias was found to be limited, and thus imputation was not especially helpful. Different imputation strategies offered a comparative advantage as the proportion missing increased. These included *reconstruction*, random imputation, and *hot deck imputation*, depending on the specific nature of missingness encountered.[19]

Missingness may also be directly modeled. Robins et al. (2004) have adapted the basic ERGM (p*) model to handle nonrespondents as particular types of nodes, so that links from respondent to nonrespondent are distinct from those connecting two respondents.[20] Handcock and Gile (2007, 2010) have also offered a likelihood approach that takes advantage of all information, including partial observations. An examination of goodness of fit, based on likelihood ratio statistics, indicates a much better fit for the all-observation approach (AO) than the respondent-only (RO) approach, though they also discuss the circumstances under which RO may be preferable, such as when arcs are reasonably assumed independent and nonresponse is explained by observed variables only. (p. 192) The AO approach makes use of information on the size of the full network, as well as the respondent to nonrespondent arcs, and the additional data seem to contain valuable information. Still, Handcock and Gile find that certain parameter estimates are comparable across the two approaches.

Huisman and Steglich (2008) review other methods of dealing with missingness, including modeling nonrespondents separately (Robins et al., 2004) or using Markov-chain Monte Carlo simulation to repeatedly sample the conditional distribution and impute the data (Handcock and Gile, 2006). But these methods (1) assume that you know which nodes are missing and (2) provide no solution for longitudinal network data. To address the first point, in snowball samples the researcher should have some knowledge of which respondents are missing from “nomination” or “outdegree” information. However, missingness can also come from boundary specification or thresholds placed on ties. To address the second point, longitudinal networks can suffer from the usual item or unit nonresponse, but also panel nonresponse. To solve this, Huisman and Steglich (2008) suggest modeling the joining and leaving times as exogenous attributes.

The Future of Political Relational Measurement

Many of the complications researchers face in the analysis of political networks stem from the fact that in political science we rarely have the luxury of working with an easily measured relation. Political concepts such as influence and cooperation can be defined and then operationalized as network ties in a variety of ways, and choosing appropriately among these for a given research application is a task not to be treated lightly. Too often, however, we simply make do with a single, readily accessible, relational variable and treat it as synonymous with our concept of interest. During operationalization, there is necessarily slippage between the latent relation and the manifest (observed) relation, just as there is slippage between individual latent attributes and corresponding manifest variables. In conventional nonrelational statistics, best practices leverage the associations among multiple imperfect measurements to tap into the underlying variable of interest, but we have yet to develop comparable techniques suited to network analysis. While SNA has benefited from numerous advances in statistical inference, modeling, and network-level descriptive measures, we have paid relatively little attention to the more basic question of careful relational conceptualization, operationalization, and dyadic measurement. The less confidence we have in dyad-level measurements, the weaker is the foundation on which all other network analysis is based. To paraphrase Gary Robins (2015, 118), network measurement has simply not kept pace with or taken advantage of the breathtaking advances in psychometrics over the past several decades. We agree with Robins that "too many (p. 193) network analysts are too addicted to their analysis and not enough focused on their measurement." And thus we have yet to develop "methods akin to network factor analysis" or even broadly applicable "serious indices of validity and reliability." We believe that these are natural areas of priority for methodological research going forward.

The Latent Relation Measured through Multiplex Networks

Latent variable measurement models were developed primarily within the social and behavioral sciences as a principled means of constructing measures of complex concepts. Bartholomew et al. (2011) offer a unified treatment of such measurement models, which include factor analysis, latent class analysis, and latent trait models (known in educational testing as item response theory). The logic of latent variable modeling and its application to the problem of slippage between operationalized variables and the theoretical concepts they are intended to capture might be further generalized to measurement of relations in political networks. Ideally, one selects potential indicators composed of two sources of variability: the latent concept and the variability unique to the indicator. Some models allow for additional sources of variability, such as multidimensional latent concepts and clusters of indicators with shared idiosyncratic variability. All share a single basic strategy: individually, the measures are imperfect reflections of the latent concept, but together, any common variation shared by them all will serve as more accurate proxy for the latent concept. Technically, this leads to the primary assumption at the heart of all such models, that of *local (conditional) independence*: conditional on a unit's value on the latent variable, the unit's values (or responses) on all indicators will be independent of one another. In other words, the only thing driving correlation among responses should be the concept we intend to measure. If the latent variable is an individual respondent's *political self-efficacy*, for example, we might assume that answers to (1) a question asking whether one feels one's opinion on policy is important and (2) a question on the importance of voting are connected only to the extent that they are partially driven by one's feeling of political self-efficacy. Knowing an individual's answer to one question would help us guess his or her likely answer to the other, but if we could somehow observe the person's level of self-efficacy directly, knowing the answer to one question would offer no additional help in guessing the answer to the other.

What would this look like for a relational concept? One can imagine asking a number of relational questions of respondents, although the respondent burden may be too heavy for full network surveys with many nodes. It is difficult enough to persuade legislative staffers, for instance, to list other staffers with whom they've had a meeting in the past month; how much more difficult it would be to get them to list those with whom they interact socially, those they have emailed, those with whom they have collaborated on getting a bill passed, and so forth. We are starting to see some research (p. 194) that makes use of multiple relational variables, leading to the analysis of *multiplex networks*. Multiplex networks, or multiplex data, are "data that describe multiple relations among the same set of actors" (Hanneman and Riddle, 2005). Applications of multiplex networks in political science are not exactly ubiquitous, but seem to be gaining traction. Heaney (2014) uses three relations to build and analyze an influence-reputation network among interest groups; Shrestha and Feiock (2009) examine contractual agreements between local governments on many different services (and thus many different relations); and Cranmer, Menninga, and Mucha (2015) use multiple relations among countries to detect distinct communities in the international system. Thus far, political network studies have been limited to examining how the different relations in the multiplex relate to one another (Heaney, 2014; Shrestha and Feiock, 2009) and using multiplex networks to answer questions at the subnetwork level (Cranmer, Menninga, and Mucha, 2015). Alternatively, we envision multiplex networks as analogous to multiple indicators used in latent variable models, so that each layer serves as a manifest network for an unobserved latent network. For example, to study the latent network of international belligerence, we might construct a multiplex network with layers devoted to different indicators of tension and use the relationships among the layers to get at the abstract construct of interest.[21]

Why not simply use existing latent variable models for relational variables? The key problem is, of course, the complex interdependence common to all network modeling. Certainly as a first step we might choose to naively assume conditional independence among all indicator relations connecting two nodes, given the latent relationship between them. Latent variable techniques even include goodness-of-fit-indexes to check how well the assumption holds. However, if threats to local independence in individual-level measurement models abound, they surely would pose a far greater threat in a hypothetical latent network model. Interdependence within and across layers of the multiplex would likely wreak havoc on the naïve extension of factor analysis, latent trait analysis, and others. To make progress on such models, we would want to develop some theoretical constraints on the sorts of multiplex interdependence to expect, and then collect evidence of such constraints in the real world and/or indications of robustness to departures from these constraints.

Concluding Comments

In this chapter we have reviewed existing studies that use SNA to study political phenomena and identified the kinds of relations commonly studied. Several relations, such as interest group partnerships, congressional cosponsorship, and international trade and conflict, have enjoyed a flourishing of network analyses focused on the complete network, while studies of various relations within one's ego-net also have long been prominent in political behavior. We have also outlined several points scholars need to consider when designing a network analysis of a political phenomenon. The extant literature has a mixed record of clarity in assumptions about the network design, and (p. 195) potential solutions to some of the challenges (such as missing data) are still evolving. Approaches to research design once seemingly off limits for political network analysis—most notably, experiments (e.g., Bond et al., 2012)—are now possible, if challenging and ethically delicate. Measurement in the context of causal inference brings its own set of considerations (Fowler et al., 2011). Being clear in one's decisions regarding the level of analysis, missing data, aggregation, and even whether a network depiction is appropriate will only strengthen one's work and the field as a whole. A number of relations of interest to political and policy researchers remain understudied, in part because of the uneven diffusion of SNA techniques and lack of confidence in or familiarity with existing methods of network analysis. By developing potential techniques for better measuring the latent relations we care about, network methodologists would go a long way toward bringing relational measurement best practices into line with best practices in individual-level designs. Our goal is for this chapter to provide intrepid political scholars with a blueprint to what has been studied, how it has been studied, what challenges exist for all network designs, and how we might confront these challenges.

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Notes:

(1.) The term *relational* is widely used whenever units of analysis are connected. Its application is indeed broad enough to include abstract relationships—as in the case of *relational databases*, in which data fields are connected in sometimes complex patterns—but in social science, we typically talk of *relational* data whenever individual observations/cases/objects of study are connected to one another, particularly when the connections themselves are of interest. McClurg and Young (2011) argue that *power*, a unifying concept among political scientists, "is, at its very core, *relational*" and consequently call for a "relational political science" as a counterpoint to the prominent individualistic theoretical traditions so prominent in our field (e.g., rational choice, behavioralism, new institutionalism).

(2.) According to the definition provided by Prell (2012, 129), *homophily* is the tendency for individuals to "prefer to have social relationships with others who are similar to themselves." Homophily is both the product of human interactions and a cause of those interactions: individuals are both drawn to interact with those similar to themselves and tend to become more like those they regularly interact with.

(3.) We think of political network analysis as most often a special case of social network analysis and so use the common acronym SNA throughout the chapter.

(4.) We focus on studies that use observational data as opposed to experimental studies. Network experiments have been conducted mostly in the lab (e.g., McCubbins et al., 2009). Bond et al. (2012) conduct a rare network-based field study via Facebook, but this is an exception, as one can almost never ethically manipulate ties in a field study, just signals about node attributes.

(5.) In international relations, there is also a small but growing body of work using SNA to study terrorist networks (e.g., Krebs, 2002; Pedahzur and Perliger, 2006).

(6.) More detailed discussion of this point follows the subsections "Is a Network Representation Appropriate?" and "Missing Data" in this chapter.

(7.) Possible strategies for using multiple measures to represent a latent relation of interest are discussed more thoroughly in the subsection "The Latent Relation Measured through Multiplex Networks" in this chapter.

(8.) Extended treatments of the research design process for social network analysis may be found in several recent books (e.g., Prell, 2012, ch. 3; Borgatti et al., 2013, chs. 3–5; Robins, 2015, ch. 3). Together with classic treatments such as Wasserman and Faust (1994), these have influenced our thinking on the essential components of political network research design.

(9.) See Handcock and Gile (2010, 5) for more on the network as convenient device. Other related frameworks have emerged as well, such as the social relations model in psychology (Kenny et al., 2006) and probabilistic/statistical relational models in machine learning (Getoor, 2007; Neville and Jensen, 2007).

(10.) Note the distinctions among three separate but similarly named terms employed here: unit of analysis, level of analysis, and level of measurement. Further confusing matters, we typically encounter a fourth, related term from grade school: *unit of measurement* refers to the reference unit to be used in interval-level measurements (e.g., kilometers, lbs, hours, thousands of $ GDP per capita, number of emails *i* sends to *j* per week).

(11.) We mean missing at random in the same sense as Little and Rubin (1987).

(12.) This is true unless one wishes to know how this translates to system-wide dynamics; see Bond et al. (2012) for an example from voter turnout at the whole network level.

(13.) The terms *unipartite, bipartite*, and *multipartite* apply, strictly speaking, to the graphs used to represent networks rather than the networks themselves. In a bipartite graph, ties occur only between objects of distinct types. For instance, if L is a set of legislators and C is the set of committees on which legislators serve (as in Porter et al., 2005), then a legislative committee network would be a type of affiliation network we might represent with a bipartite graph, edges exclusively connecting pairs of nodes drawn one from each set. We prefer these terms to one-mode, two-mode, etc., to avoid confusion with the unrelated statistical term "mode."

(14.) More work has been done outside of political science in the modeling of bipartite political networks. For example, in computer science, Akoglu (2014) developed an algorithm for analyzing signed bipartite networks.

(15.) This is not to say that these terms have universal definitions—they certainly do not—but only that an author's operationalization of such concepts is unlikely to attract theoretically relevant criticism.

(16.) This is parallel to measurement error in all of statistics. If one is simply measuring a concept completely wrong, say by counting heartbeats to measure lung capacity, estimates will be wrong, and incorrect inferences will be made. We reiterate that no amount of postestimate adjustment will correct for the mismeasurement of the concepts of interest.

(17.) The ethics of incorporating data on nonrespondents are debatable, though researchers are likely on more solid ground when studying public officials. See Borgatti and Molina (2005) for more on ethical considerations.

(18.) Persistent ties are elsewhere called "continuous" ties. We eschew this usage to avoid confusion with the sense of continuity in the domain of certain numeric data (continuous vs. discrete).

(19.) Huisman (2009) finds that imputation by reconstruction works well for undirected networks with low to medium missingness. Imputation by reconstruction does not work as well in directed networks, but still generally outperforms other imputation techniques (ignoring the missingness, preferential attachment, hot decking, imputing zeros).

(20.) Links between two nonrespondents are necessarily unobserved.

(21.) See Hanneman and Riddle (2005) for the basics of working with multiplex network data. See also Snijders, Lomi, and Torlo (2013) for modeling unipartite and bipartite multiplex networks.

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