at Level 1, classrooms at Level 2, and schools at Level 3. Each higher-level (say, Level 2) model takes into account the nested nature of data collected at a lower level (say, Level 1). Thus, the hierarchical nature of the data is completely and efficiently captured in HLM (Raudenbush & Bryk, 1988).

—Chao-Ying Joanne Peng

See also CROSS-SECTIONAL DESIGN

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NETWORK ANALYSIS

Network analysis is the interdisciplinary study of social relations and has roots in anthropology, sociology, psychology, and applied mathematics. It conceives of social structure in relational terms, and its most fundamental construct is that of a *social network,* comprising at the most basic level a set of *social actors* and a set of *relational ties* connecting pairs of these actors. A primary assumption is that social actors are interdependent and that the relational ties among them have important consequences for each social actor as well as for the larger social groupings that they comprise.

The *nodes* or *members* of the network can be groups or organizations as well as people. Network analysis involves a combination of theorizing, model building, and empirical research, including (possibly) sophisticated data analysis. The goal is to study network structure, often analyzed using such concepts as density, centrality, prestige, mutuality, and role. Social network data sets are occasionally multidimensional and/or longitudinal, and they often include information about *actor attribute*s, such as actor age, gender, ethnicity, attitudes, and beliefs.

A basic premise of the social network paradigm is that knowledge about the structure of social relationships enriches explanations based on knowledge about the attributes of the actors alone. Whenever the social context of individual actors under study is relevant, relational information can be gathered and studied. Network analysis goes beyond measurements taken on individuals to analyze data on patterns of relational ties and to examine how the existence and functioning of such ties are constrained by the social networks in which individual actors are embedded. For example, one might measure the relations "communicate with," "live near," "feel hostility toward," and "go to for social support" on a group of workers. Some network analyses are longitudinal, viewing changing social structure as an outcome of underlying processes. Others link individuals to events (affiliation networks), such as a set of individuals participating in a set of community activities.

Network structure can be studied at many different levels: the dyad, triad, subgroup, or even the entire network. Furthermore, network theories can be postulated at a variety of different levels. Although this multilevel aspect of network analysis allows different structural questions to be posed and studied simultaneously, it usually requires the use of methods that go beyond the standard approach of treating each individual as an independent unit of analysis. This is especially true for studying a *complete* or whole network: a census of a well-defined population of social actors in which all ties, of various types, among all the actors are measured. Such analyses might study structural balance in small groups, transitive flows of information through indirect ties, structural equivalence in organizations, or patterns of relations in a set of organizations.

For example, network analysis allows a researcher to model the interdependencies of organization members. The paradigm provides concepts, theories, and methods to investigate how informal organizational structures intersect with formal bureaucratic structures in the unfolding flow of work-related actions of organizational members and in their evolving sets

of knowledge and beliefs. Hence, it has informed many of the topics of organizational behavior, such as leadership, attitudes, work roles, turnover, and computer-supported cooperative work.

HISTORICAL BACKGROUND

Network analysis has developed out of several research traditions, including (a) the birth of sociometry in the 1930s spawned by the work of the psychiatrist Jacob L. Moreno; (b) ethnographic efforts in the 1950s and 1960s to understand migrations from tribal villages to polyglot cities, especially the research of A. R. Radcliffe-Brown; (c) survey research since the 1950s to describe the nature of personal communities, social support, and social mobilization; and (d) archival analysis to understand the structure of interorganizational and international ties. Also noteworthy is the work of Claude Lévi-Strauss, who was the first to introduce formal notions of kinship, thereby leading to a mathematical algebraic theory of relations, and the work of Anatol Rapoport, perhaps the first to propose an elaborate statistical model of relational ties and flow through various nodes.

Highlights of the field include the adoption of sophisticated mathematical models, especially discrete mathematics and graph theory, in the 1940s and 1950s. Concepts such as transitivity, structural equivalence, the strength of weak ties, and centrality arose from network research by James A. Davis, Samuel Leinhardt, Paul Holland, Harrison White, Mark Granovetter, and Linton Freeman in the 1960s and 1970s. Despite the separateness of these many research beginnings, the field grew and was drawn together in the 1970s by formulations in graph theory and advances in computing. Network analysis, as a distinct research endeavor, was born in the early 1970s. Noteworthy in its birth are the pioneering text by Harary, Norman, and Cartwright (1965); the appearance in the late 1970s of network analysis software, much of it arising at the University of California, Irvine; and annual conferences of network analysts, now sponsored by the International Network for Social Network Analysis. These well-known "Sunbelt" Social Network Conferences now draw as many as 400 international participants. A number of fields, such as organizational science, have experienced rapid growth through the adoption of a network perspective.

Over the years, the social network analytic perspective has been used to gain increased understanding of many diverse phenomena in the social and behavioral sciences, including (taken from Wasserman & Faust, 1994)

- Occupational mobility
- Urbanization
- World political and economic systems
- Community elite decision making
- Social support
- Community psychology
- Group problem solving
- Diffusion and adoption of information
- Corporate interlocking
- Belief systems
- Social cognition
- Markets
- Sociology of science
- Exchange and power
- Consensus and social influence
- Coalition formation

In addition, it offers the potential to understand many contemporary issues, including

- The Internet
- Knowledge and distributed intelligence
- Computer-mediated communication
- Terrorism
- Metabolic systems
- Health, illness, and epidemiology, especially of HIV

Before a discussion of the details of various network research methods, we mention in passing a number of important measurement approaches.

MEASUREMENT

Complete Networks

In complete network studies, a census of network ties is taken for all members of a prespecified population of network members. A variety of methods may be used to observe the network ties (e.g., survey, archival, participant observation), and observations may be made on a number of different types of network tie. Studies of complete networks are often appropriate when it is desirable to understand the action of network members in terms of their location in a broader social

system (e.g., their centrality in the network, or more generally in terms of their patterns of connections to other network members). Likewise, it may be necessary to observe a complete network when properties of the network as a whole are of interest (e.g., its degree of centralization, fragmentation, or connectedness).

Ego-Centered Networks

The size and scope of complete networks generally preclude the study of all the ties and possibly all the nodes in a large, possibly unbounded population. To study such phenomena, researchers often use survey research to study a sample of personal networks (often called *ego-centered* or *local* networks). These smaller networks consist of the set of specified ties that links *focal persons* (or *egos*) at the centers of these networks to a set of close "associates" or *alters.* Such studies focus on an ego's ties and on ties among ego's alters. Ego-centered networks can include relations such as kinship, weak ties, frequent contact, and provision of emotional or instrumental aid. These relations can be characterized by their variety, content, strength, and structure. Thus, analysts might study network member *composition* (such as the percentage of women providing social or emotional support, for example, or basic actor attributes more generally); network characteristics (e.g., percentage of dyads that are mutual); measures of *relational association* (do strong ties with immediate kin also imply supportive relationships?); and network structure (how densely knit are various relations? do actors cluster in any meaningful way?).

SNOWBALL SAMPLING AND LINK TRACING STUDIES

Another possibility, to study large networks, is simply to sample nodes or ties. Sampling theory for networks contains a small number of important results (e.g., estimation of subgraphs or subcomponents; many originated with Ove Frank) as well as a number of unique techniques or strategies such as snowball sampling, in which a number of nodes are sampled, then those linked to this original sample are sampled, and so forth, in a multistage process. In a link-tracing sampling design, emphasis is on the links rather than the actors—a set of social links is followed from one respondent to another. For hard-to-access or hidden populations, such designs are considered the most practical way to obtain a sample of nodes.

COGNITIVE SOCIAL STRUCTURES

Social network studies of *social cognition* investigate how individual network actors perceive the ties of others and the social structures in which they are contained. Such studies often involve the measurement of multiple perspectives on a network, for instance, by observing each network member's view of who is tied to whom in the network. David Krackhardt referred to the resulting data arrays as *cognitive social structures.* Research has focused on clarifying the various ways in which social cognition may be related to network locations: (a) People's positions in social structures may determine the specific information to which they are exposed, and hence, their perception; (b) structural position may be related to characteristic patterns of social interactions; (c) structural position may frame social cognitions by affecting people's perceptions of their social locales.

METHODS

Social network analysts have developed methods and tools for the study of relational data. The techniques include graph theoretic methods developed by mathematicians (many of which involve counting various types of subgraphs); algebraic models popularized by mathematical sociologists and psychologists; and statistical models, which include the social relations model from social psychology and the recent family of random graphs first introduced into the network literature by Ove Frank and David Strauss. Software packages to fit these models are widely available.

Exciting recent developments in network methods have occurred in the statistical arena and reflect the increasing theoretical focus in the social and behavioral sciences on the interdependence of social actors in dynamic, network-based social settings. Therefore, a growing importance has been accorded the problem of constructing theoretically and empirically plausible parametric models for structural network phenomena and their changes over time. Substantial advances in statistical computing are now allowing researchers to more easily fit these more complex models to data.

SOME NOTATION

In the simplest case, network studies involve a single type of directed or nondirected tie measured for all pairs of a node set $N = \{1, 2, \ldots, n\}$ of individual actors. The observed tie linking node i to node j ($i, j \in N$) can be denoted by x_{ij} and is often defined to take the value 1 if the tie is observed to be present and 0 otherwise. The network may be either *directed* (in which case x_{ij} and x_{ji} are distinguished and may take different values) or *nondirected* (in which case x_{ij} and x_{ji} are not distinguished and are necessarily equal in value). Other cases of interest include the following:

1. *Valued* networks, where x_{ij} takes values in the set $\{0, 1, \ldots, C - 1\}$.
2. *Time-dependent* networks, where x_{ijt} represents the tie from node i to node j at time t.
3. *Multiple relational* or *multivariate* networks, where x_{ijk} represents the tie of type k from node i to node j (with $k \in R = \{1, 2, \ldots, r\}$, a fixed set of *types* of tie).

In most of the statistical literature on network methods, the set N is regarded as fixed and the network ties are assumed to be random. In this case, the tie linking node i to node j may be denoted by the random variable X_{ij} and the $n \times n$ array $X = [X_{ij}]$ of random variables can be regarded as the adjacency matrix of a *random (directed) graph* on N. The state space of all possible realizations of these arrays is Ω_n. The array $x = [x_{ij}]$ denotes a realization of X.

GRAPH THEORETIC TECHNIQUES

Graph theory has played a critical role in the development of network analysis. Graph theoretical techniques underlie approaches to understanding cohesiveness, connectedness, and fragmentation in networks. Fundamental measures of a network include its *density* (the proportion of possible ties in the network that are actually observed) and the degree sequence of its nodes. In a nondirected network, the *degree* d_i of node i is the number of distinct nodes to which node i is connected ($d_i = \Sigma_{j \in N} x_{ij}$). In a directed network, sequences of *indegrees* ($\Sigma_{j \in N} x_{ji}$) and *outdegrees* ($\Sigma_{j \in N} x_{ij}$) are of interest. Methods for characterizing and identifying cohesive subsets in a network have depended on the notion of a *clique* (a subgraph of network nodes, every pair of which is connected) as well as on a variety of generalizations (including k-clique, k-plex, k-core, LS-set, and k-connected subgraph).

Our understanding of connectedness, connectivity, and centralization is also informed by the distribution of path lengths in a network. A *path* of length k from one node i to another node j is defined by a sequence $i = i_1, i_2, \ldots, i_{k+1} = j$ of distinct nodes such that i_h and i_{h+1} are connected by a network tie. If there is no path from i to j of length $n - 1$ or less, then j is not reachable from i and the distance from i to j is said to be infinite; otherwise, the distance from i to j is the length of the shortest path from i to j. A directed network is *strongly connected* if each node is reachable from each other node; it is *weakly connected* if, for every pair of nodes, at least one of the pair is reachable from the other. For nondirected networks, a network is connected if each node is reachable from each other node, and the *connectivity, κ,* is the least number of nodes whose removal results in a disconnected (or trivial) subgraph.

Graphs that contain many cohesive subsets as well as short paths, on average, are often termed *small world* networks, following early work by Stanley Milgram, and more recent work by Duncan Watts. Characterizations of the centrality of each actor in the network are typically based on the actor's degree (*degree* centrality), on the lengths of paths from the actor to all other actors (*closeness* centrality), or on the extent to which the shortest paths between other actors pass through the given actor (*betweenness* centrality). Measures of network *centralization* signify the extent of heterogeneity among actors in these different forms of centrality.

ALGEBRAIC TECHNIQUES

Closely related to graph theoretic approaches is a collection of algebraic techniques that has been developed to understand social roles and structural regularities in networks. Characterizations of role have developed in terms of mappings on networks, and descriptions of structural regularities have been facilitated by the construction of algebras among labeled network walks. An important proposition about what it means for two actors to have the same social role is embedded in the notion of *structural equivalence:* Two actors are said to be *structurally equivalent* if they relate to and are related by every other network actor in exactly the same way (thus, nodes i and j are

structurally equivalent if, for all $k \in N$, $x_{ik} = x_{jk}$ and $x_{ki} = x_{kj}$). Generalizations to automorphic and regular equivalence are based on more general mappings on N and capture the notion that similarly positioned network nodes are related to *similar* others in the same way.

Approaches to describing structural regularities in multiple networks have grown out of earlier characterizations of structure in kinship systems, and can be defined in terms of labeled walks in multiple networks. Two nodes i and j are connected by a labeled *walk* of type $k_1 k_2 \cdots k_h$ if there is a sequence of nodes $i = i_1, i_2, \ldots, i_{h+1} = j$ such that i_q is connected to i_{q+1} by a tie of type k_q (note that the nodes in the sequence need not all be distinct, so that a walk is a more general construction than a path). Each sequence $k_1 k_2 \cdots k_h$ of tie labels defines a derived network whose ties signify the presence of labeled walks of that specified type among pairs of network nodes. Equality and ordering relations among these derived networks lead to various algebraic structures (including *semigroups* and partially ordered semigroups) and describe observed regularities in the structure of walks and paths in the multiple network. For example, *transitivity* in a directed network with ties of type k is a form of structural regularity associated with the observation that walks of type kk link two nodes only if the nodes are also linked by a walk of type k.

STATISTICAL TECHNIQUES

A simple statistical model for a (directed) graph assumes a BERNOULLI distribution, in which each edge, or tie, is statistically independent of all others and governed by a theoretical probability P_{ij}. In addition to edge independence, simplified versions also assume equal probabilities across ties; other versions allow the probabilities to depend on structural parameters. These distributions often have been used as models for at least 40 years, but are of questionable utility because of the independence assumption.

Dyadic Structure in Networks

Statistical models for social network phenomena have been developed from their edge-independent beginnings in a number of major ways. The p_1 model recognized the theoretical and empirical importance

of dyadic structure in social networks, that is, of the interdependence of the variables x_{ij} and x_{ji}. This class of Bernoulli dyad distributions and their generalization to valued, multivariate, and time-dependent forms gave parametric expression to ideas of reciprocity and exchange in dyads and their development over time. The model assumes that each dyad (x_{ij}, x_{ji}) is independent of every other and, in a commonly constrained form, specifies

$$P(X = x)$$
$$= \pi_{i<j} \exp\left[\lambda_{ij} + \theta\left(\sum_{i<j} x_{ij}\right) + \rho\left(\sum_{i<j} x_{ij} x_{ji}\right) \right.$$
$$\left. + \alpha_i\left(\sum_j x_{ij}\right) + \beta_j\left(\sum_i x_{ij} x_{ji}\right) \right],$$

$$(1)$$

where θ is a density parameter, ρ is a reciprocity parameter, the parameters α_i and β_j reflect individual differences in expansiveness and popularity, and λ_{ij} ensures that probabilities for each dyad sum to 1. This is a LOG-LINEAR MODEL and easily fit. Generalizations of this model are numerous, and include *stochastic block models,* representing hypotheses about the interdependence of social positions and the patterning of network ties; mixed models, such as p_2; and *latent space models* for networks.

Null Models for Networks

The assumption of dyadic independence is questionable. Thus, another series of developments has been motivated by the problem of assessing the degree and nature of departures from simple structural assumptions like dyadic independence. A number of *conditional uniform* random graph distributions were introduced as null models for exploring the structural features of social networks. These distributions, denoted by $U|Q$, are defined over subsets Q of the state space Ω_n of directed graphs and assign equal probability to each member of Q. The subset Q is usually chosen to have some specified set of properties (e.g., a fixed number of mutual, asymmetric, and null dyads). When Q is equal to Ω_n, the distribution is referred to as the *uniform* (di)graph distribution, and is equivalent to a Bernoulli distribution with homogeneous tie probabilities. Enumeration of the

members of Q and simulation of $U|Q$ are often straightforward, although certain cases, such as the distribution that is conditional on the indegree and outdegree of each node i in the network, require more complicated approaches.

A typical application of these distributions is to assess whether the occurrence of certain higher-order (e.g., triadic) features in an observed network is unusual, given the assumption that the data arose from a uniform distribution that is conditional on plausible lower-order (e.g., dyadic) features. This general approach has also been developed for the analysis of multiple networks. The best known example is probably Frank Baker and Larry Hubert's Quadratic Assignment Procedure (QAP) for networks. In this case, the association between two graphs defined on the same set of nodes is assessed using a uniform multigraph distribution that is conditional on the unlabeled graph structure of each constituent graph.

Extradyadic Local Structure in Networks

A significant step in the development of parametric statistical models for social networks was taken by Frank and Strauss (1986) with the introduction of the class of *Markov random graphs.* This class of models permitted the parameterization of extradyadic local structural forms and so allowed a more explicit link between some important theoretical propositions and statistical network models. These models are based on the fact that the Hammersley-Clifford theorem provides a general probability distribution for X from a specification of which pairs (X_{ij}, X_{k1}) of tie random variables are conditionally dependent, given the values of all other random variables.

Specifically, define a *dependence graph* $\mathbf{D}$ with node set $N(\mathbf{D}) = \{(X_{ij}: i, j \in N, i \neq j)\}$ and edge set $E(\mathbf{D}) = \{(X_{ij}, X_{k1}): X_{ij}$ and X_{k1} are assumed to be conditionally dependent, given the rest of $X\}$. Frank and Strauss used $\mathbf{D}$ to obtain a model for $\Pr(X = x)$, denoted p^* by later researchers, in terms of parameters and substructures corresponding to cliques of $\mathbf{D}$. The model has the form

$$\Pr(X = x) = p^*(x)$$

$$= (1/c) \exp \left[\sum_{P \supseteq N(D)} \alpha_P z_P(x) \right], \quad (2)$$

where

1. The summation is over all cliques P of $\mathbf{D}$ [with a *clique* of $\mathbf{D}$ defined as a nonempty subset P of $N(\mathbf{D})$ such that $|P| = 1$ or $(X_{ij}, X_{k1}) \in E(\mathbf{D})$ for all $X_{ij}, X_{k1} \in P$].
2. $z_P(x) = \Pi_{X_{ij} \in P} x_{ij}$ is the (observed) *network statistic* corresponding to the clique P of $\mathbf{D}$
3. $c = \sum_{\mathbf{x}} \exp \left\{ \sum_P \alpha_P z_P(x) \right\}$ is a *normalizing* quantity.

One possible dependence assumption is Markov, in which $(X_{ij}, X_{k1}) \in E(\mathbf{D})$ whenever $\{i, j\} \cap \{k, l\} \neq \varnothing$. This assumption implies that the occurrence of a network tie from one node to another is conditionally dependent on the presence or absence of other ties in a *local neighborhood* of the tie. A Markovian local neighborhood for X_{ij} comprises all possible ties involving i and/or j. Many other dependence assumptions are also possible, and the task of identifying appropriate dependence assumptions in any modeling venture poses a significant theoretical challenge.

These random graph models permit the parameterization of many important ideas about local structure in univariate social networks, including transitivity, local clustering, degree variability, and centralization. Valued, multiple, and temporal generalizations also lead to parameterizations of substantively interesting multirelational concepts, such as those associated with balance and clusterability, generalized transitivity and exchange, and the strength of weak ties. Pseudo-maximum likelihood estimation is easy; maximum likelihood estimation is difficult, but not impossible.

Dynamic Models

A significant challenge is to develop models for the emergence of network phenomena, including the evolution of networks and the unfolding of individual actions (e.g., voting, attitude change, decision making) and interpersonal transactions (e.g., patterns of communication or interpersonal exchange) in the context of long-standing relational ties. Early attempts to model the evolution of networks in either discrete or continuous time assumed dyad independence and Markov processes in time. A step toward continuous time MARKOV CHAIN models for network evolution that relaxes the assumption of dyad independence has been taken by Tom Snijders and colleagues. This approach also illustrates the potentially

valuable role of simulation techniques for models that make empirically plausible assumptions; clearly, such methods provide a promising focus for future development. Computational models based on simulations are becoming increasingly popular in network analysis; however, the development of associated model evaluation approaches poses a significant challenge.

Current research (as of 2003), including future challenges, such as statistical estimation of complex model parameters, model evaluation, and dynamic statistical models for longitudinal data, can be found in Carrington, Scott, and Wasserman (2003). Applications of the techniques and definitions mentioned here can be found in Scott (1992) and Wasserman and Faust (1994).

—Stanley Wasserman and Philippa Pattison

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NEURAL NETWORK

Neural networks are adaptive statistical models based on an analogy with the structure of the brain. They are *adaptive* because they can learn to estimate the PARAMETERS of some population using a small number of exemplars (one or a few) at a time. They do not differ *essentially* from standard statistical MODELS. For example, one can find neural network architectures akin to DISCRIMINANT ANALYSIS, PRINCIPAL COMPONENTS ANALYSIS, LOGISTIC REGRESSION, and other techniques. In fact, the same mathematical tools can be used to analyze standard statistical models and neural networks. Neural networks are used as *statistical tools* in a variety of fields, including psychology, statistics, engineering, econometrics, and even physics. They are used also as *models* of cognitive processes by neuro- and cognitive scientists.

Basically, neural networks are built from simple units, sometimes called *neurons* or cells by analogy with the real thing. These units are linked by a set of weighted connections. Learning is usually accomplished by modification of the connection weights. Each unit CODES or corresponds to a feature or a characteristic of a pattern that we want to analyze or that we want to use as a PREDICTOR VARIABLE.

These networks usually organize their units into several layers. The first layer is called the *input* layer, and the last one is the *output* layer. The intermediate layers (if any) are called the *hidden* layers. The information to be analyzed is fed to the neurons of the first layer and then propagated to the neurons of the second layer for further processing. The result of this processing is then propagated to the next layer and so on until the last layer. Each unit receives some information from other units (or from the external world through some devices) and processes this information, which will be converted into the output of the unit.

The goal of the network is to learn or to discover some association between input and output patterns, or to analyze, or to find the structure of the input patterns. The learning process is achieved through the modification of the connection weights between units. In statistical terms, this is equivalent to interpreting the value of the connections between units as parameters (e.g., like the values of a and b in the REGRESSION equation $y = a + bx$) to be estimated. The learning