societies and complex modern ones. In simple societies such as small, largely independent communities, each community contains people who vary fully in age, status, and other important social attributes. But each of these different people knows most or all of the others, so each has more or less the same network and is exposed to the same influences. Given a small population, each person must interact with each of the others a good deal in varied ways, so the shared influences are strong. Thus people can develop little individuality or differentiation in their social experiences or their tastes. In more complex modern societies, people can selectively affiliate with others who share their particular tastes and interests, as in joining a voluntary association dedicated to one's profession or one's hobby. Within a special interest group, relationships are narrow, focused on the special interest itself, so they strongly reinforce that interest without affecting other tastes or interests much. Each member can and often does have other interests which can be quite different from the outside interests of fellow members. Indeed, Simmel portrays the modern person as one who lives at the unique intersection of his or her own particular collection of formal or informal groupings devoted to a range of particular tastes. This uniqueness of social and cultural influence is the critical foundation of modern individualism. Though Simmel does not emphasize this, it is clear that this modern condition does not hold to the same degree for everyone in a modern society: the multiplicity of affiliations grows with social status. For example, research in dozens of countries shows that those with higher education or occupation prestige belong to a greater number of voluntary associations. Thus class predicts variety of affiliations and hence variety in networks, variety in tastes, and individuation, a pattern echoing the discussion of the North American pattern above.

Changes over smaller ranges of time are also of interest. Most strikingly, we know very little about changes over time in people's lives, since there are no substantial studies of networks, culture, and class over time. This leaves us unsure of the causal connections among these; we suspect that each of the three affects the others, but have no evidence that this is the case, nor do we know the details of the mutual influences. For example, are some effects faster than others? Does a change in job alter networks immediately as former work colleagues are lost and replaced while a change in networks takes some time to lead to a new job? Is the pace of change faster at some times in life, especially perhaps in the turbulent and changeful transition from youth to adulthood? We also know little of the processes by which networks affect cultures, or culture affects networks, or each shapes and is shaped by class; most of our research shows strong and interesting correlations but only offers speculation about how these correlations develop over time. These are exciting directions for future work.

See also: Cultural Expression and Action; Cultural Variations in Interpersonal Relationships; Culture, Sociology of; Network Analysis; Networks: Social; Simmel, Georg (1858–1918); Social Networks and Gender

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Networks: Social

Social network analysis in general studies the behavior of the individual at the micro level, the pattern of relationships (network structure) at the macro level, and the interactions between the two. The analysis of the interaction structures that is involved in social network analysis is an important element in the analysis of the micro–macro link, the way in which individual behavior and social phenomena are connected with one another. In this perspective, social networks are both the cause of and the result of individual behavior. Social networks provide and limit opportunities of individual choices, whereas at the same time individuals initiate, construct, maintain, and break up relationships and by doing so determine the global structure of the network. However, network structure as it exists is seldom constructed consciously by its individuals. It is often the unintended effect of individual actions and can as such be called a spontaneous order.

1. *Theoretical Perspectives*

Which network structures and positions create strong opportunities or, on the contrary, strong constraints depends on the instrumental value of the relationships under study. *Social capital* is the opportunity structure created by social relationships (Lin 1982, Coleman 1990, Burt 1992). Social capital gives individuals access to resources of others that can be exploited for the realization of their goals. The amount of social capital depends on the amount of these resources, their value for the goal realization of the individual, and the willingness of others to mobilize them (Flap 1999). The value of the resources for the individual strongly depends on functional interdependence, the willingness of others to mobilize resources for the individual on their perception of the interdependence (i.e., the cognitive dependence). Differences in functional and cognitive interdependence explain why certain researchers emphasize other network structures and positions as contributing to an individual's social capital. For example, Coleman (1990) stresses the importance of large and dense networks for control in his study of school communities. Large and dense networks create shared information, high visibility, and common norms in a community. Burt (1992), on the other hand, stresses the importance of unique and nonoverlapping relationships for acquiring unique information in organizations, giving individuals a better chance to find creative solutions for problems and thus providing them better opportunities for career.

Functional and cognitive interdependencies differ particularly between strong and weak ties (Granovetter 1973). Strong ties are valued in themselves. The ties are not primarily instrumental for the attainment of other goals. Their value is based on the other individual as a person and the quality of the relationship with that individual. Family and friendship ties are typical examples of such relationships. Strong ties tend to be reciprocal, transitive, and clustered. Strong ties give a sense of belonging to a group and the group often has priority above the individual and individual relationships. Sharing is often based on need and norms tend to promote equality (Lindenberg 1998). Creating negative attitudes towards other groups often helps to strengthen the predominance of the group, which may give strong negative externalities for society as a whole (think of gangs and other criminal organizations). Weak ties are valuable long-term relationships but their value is primarily instrumental, related to higher ordered goals, goals not primarily located in the relationship or individuals themselves. Weak ties tend to be less clustered; the group is less dominant and often only vaguely delineated. Reciprocity based on equity norms prevails.

The fact that social networks create conditions for cooperation through information and sanctioning is due to exchange processes that create win–win situations (Homans 1950, Blau 1964). A fruitful and very promising approach is the study of the effects of social networks in noncooperative game theory (Raub and Weesie 1990, Flache and Macy 1996, Bienenstock and Bonacich 1992). Network exchange theory specifically investigates the effects of network structures on the choice between alternative exchanges and on exchange rates (Willer 1999). Major effects are particularly due to possibilities for social actors to exclude others. Exchange network theory illustrates again that effects of network structures are context-sensitive and cannot be generalized without taking the context and substance into account. From this perspective it is to be regretted that the splitting of private resources is the dominant situation considered in exchange network theory. The integration of exchange theory and social networks has also been proven to be very successful in the field of policy networks. Most of these models build on Coleman's social exchange model and confine exchanges to influence network relationships (Laumann et al. 1987). These models make the step from micro behavior to macro effects explicit and are able to predict outcomes of decisions, to derive the power of social actors and the value of decisions. Later models try to solve a number of remaining theoretical issues (Stokman and Van den Bos 1992, Pappi and Henning 1998).

2. *Network Analysis: Concepts and Techniques*

In the social network literature the emphasis lies on the description of static network structure. The best illustration of this can be found in the handbook by Wasserman and Faust (1994) and the computer package *Ucinet* (developed by Borgatti, Everett, and Freeman) that contain most current static network methods. A large number of other network studies examine the effects of the network structure on the behavior and attributes of the network members, the effects of the macro structure on micro behavior. In these studies, the network is considered given and constant, and the ways in which this network influences processes or individuals in the network is examined. In many of these studies, only relationships of the individuals under investigation are collected (at most combined with their perception of the relationships among their network members). These *ego-centered network studies* examine the effects of differences in size and composition of the personal networks and the multiplexity of an individual's personal relations (Wellman and Berkowitz 1997). Examples of effects studied are an individual's social well-being, social support, health, labor market position, career. Only recently has more attention been given to the evolution of social networks and the interplay and feedback mechanisms between macro structure and microbehavior.

In social network analysis a large number of measures have been developed to characterize and compare network structures and positions in networks. Depending on what determines differences in opportunity structures, the analysis can be focused on differences in centrality, on the investigation of strongly connected clusters, of positions that are structurally equivalent in networks, or of unique positions. Other measures enable the comparison of network structures as a whole, e.g., the investigation of their effectiveness for goal achievement. In addition, statistical network models can be used for testing structure against null models, for parameter estimation, and, more recently, for testing network effects of different incentive structures.

2.1 Representation of Social Networks

Most social network measures start from a representation of points and lines. The points usually represent individuals or other social actors like organizations or positions in organizations. Lines represent relationships between social actors. Any type of dyadic relationship can be represented, but most common are communication, friendship choices, advice, trust, influence, and exchange relationships. Most of these relationships are not necessarily reciprocal. In that case, directed lines can be used. Vertices are sometimes used for points, arcs for directed lines, and edges for undirected ones. This representation makes it possible to apply graph theory, a branch of discrete mathematics. Many concepts and theorems of graph theory can meaningfully be applied in social network analysis (see particularly Harary et al. 1965). Connecting positive or negative signs to directed lines enables the representation of positive and negative ties. Heider's representation of the cognitive balance theory as a signed graph with three points is well known. An individual under study can have a positive or negative relationship to another person. Both persons can have a positive or negative attitude toward another object (e.g., a third person or a certain activity). The cognitive system of the individual under study is in balance if and only if all three relationships are positive or two of them are negative. Harary et al. (1965) generalized the idea of balance to a whole social system. In a valued graph, values are attached to the (directed) lines, and in a multi graph different types of relationships are distinguished.

Major computational possibilities became possible by the representation of a social network in a matrix. Moreno (1934) introduced such a representation for friendship choices in a school class. The rows and columns represent the points, and the cells the relationships from the row to the column point. In an adjacency matrix only ones (for a directed line from the row point to the column point) or zeros (no such line) are used. In a signed graph positive ties are represented by $+1$ and negative ones by -1. In a valued graph the values of the ties can be given. Stacked matrices are used to represent multi graphs. Modern relational databases make a more efficient representation of social networks possible in one or more tables for points (with the possibility of adding many variables for the points) and a table for each type of relationship (possibly with many relationship variables). The most important measures and approaches in the different classes are summarized below.

2.2 Actor Centrality

Depending on the instrumental value of the social network under investigation, central social actors may have better opportunities to realize their goals than less central ones. But also the type of centrality that is relevant for differences in opportunity structures may vary. Assuming a social network that represents communication, Freeman (1978) classifies the many centrality measures into three classes. A fourth class measures prestige or status. Measures based on the degree, the number of points with which a point is directly connected, indicate the communication activity of a point. In directed networks, centrality in terms of outdegree and indegree should be distinguished. In friendship choice networks the number of choices received (indegree) generally indicates centrality (popularity); in influence networks centrality is based on the number of outgoing relationships (outdegree). Degree-based measures indicate local centrality, as the global structure of the network is not taken into account (think of the éminence grise's important tie to the throne). Distance-based measures indicate the relative proximity of points with other points in the network and the extent to which a point can communicate with other points independently of others. In this context, the distance from a point to another point is the minimum number of ties that must be used to transmit a message to that point, the length of a shortest path. Betweenness or rush is the third type of centrality and measures how important a point is for the transmission of information between other points. Betweenness measures assume that information is mainly transmitted through shortest paths, connections based on the lowest number of consecutive ties. Status-based measures take all direct and indirect connections into account. They were originally developed to indicate centrality in influence networks.

2.3 Network Centrality

Again depending on the instrumental value of the social network under investigation, certain network structures are more effective than others. Three dimensions of social network structure dominate in the literature. The first is network *density*, the number of existing relationships relative to the possible number. Dense networks are more important for control and sanctioning than for information. Dense networks tend to generate a lot of redundant information. They generate many constraints and are inefficient for creative new solutions (Burt 1992). Comparing densities of networks of quite different sizes is difficult, as large networks tend to be sparse. A comparison in terms of mean degrees is a better alternative in such cases. The second is network *centralization*. In connected networks, high centralization corresponds with a high variance of the degrees of the points. Snijders (1981) derived the maximal possible values of the variance, given the number of points or given the number of points and lines. He also derived the expected variance for different null models under the same two conditions. This makes a good comparison of centralization possible in networks of different sizes and densities. The third is *clustering* and *segmentation*. A simple measure of segmentation is S_3, the number of pairs of points at distance two or higher divided by the number of pairs of points at distance three or higher (Baerveldt and Snijders 1994). Closely connected to the question of clustering and segmentation is the detection of dense clusters in a network.

2.4 Detection of Equivalent Sets

Whereas in the detection of dense clusters the emphasis lies on the relationships, analysis of equivalence is focused on the detection of similar positions of points in the network. The basic idea behind equivalence is that two or more points with a similar position in the network have the same opportunity structure. Two points are structurally equivalent if and only if they have identical sets of points to which they have outgoing relationships and from which they have incoming relationships. If more types of ties are considered, this should be the case for each type. Two points are regularly equivalent if the points with which they are directly connected are themselves equivalent rather than identical. For example, in a hierarchical organization, chiefs of different production units supervise different individuals, but their place in the organization is identical. They probably have the same incentive structure. In these cases regular equivalence represents the theoretical notion better than structural equivalence. Depending on the definition of the desired equivalence, many types of regular equivalence have been distinguished. Everett and Borgatti (1994) give a general definition of equivalence and show that all types, including structural equivalence, are specifications of a common class. As strict structural or regular equivalence is unlikely to occur in reality, methods have been developed to detect equivalent sets based on similarity measures between positions. Methods differ in terms of the type of similarity measure used and in terms of the grouping method to arrive at a partition of the points in more or less equivalent sets.

2.5 Statistical Models for Static Network Analysis

Statistical models for social networks are more difficult to derive because the relationships between the points cannot be treated as independent observations. Unbiased estimation of parameters is only possible by taking these dependencies into account. Consequently, maximum likelihood estimation is often not possible and estimation methods have to be used that are based on computer-simulated approximations. Dependencies between relationships also complicate the choice of null models. An illustration of the latter is the statistical analysis of local structure in networks, known as the triad count. The triad count aims to investigate which types of triads are overrepresented and which ones are underrepresented in a network. For example, if friendship choices tend to be transitive, then triads with intransitive choices tend to be underrepresented while triads with transitive choices tend to be overrepresented. From empirical studies, it is well known that individuals tend to differ systematically in terms of the number of friendship choices they make (activity) and receive (popularity). Moreover, friendship choices tend to be reciprocal, i.e., mutual choices tend to be overrepresented. Ideally, testing transitivity in friendship networks should be tested against a null model that conditions for the outdegrees, indegrees, and the number of reciprocal choices in a network. Recent statistical models, based on simulated approximations, do so, but in the earlier models either null models were used that only take the number of mutual choices into account (e.g., the MAN null model) or the outdegrees and/or indegrees of the points. Any linear combination of triad types can be tested against these null models, thus enabling the testing of different characteristics of local structure (Holland and Leinhardt 1975).

Most recent statistical models start from the assumption that the relationship between any two points *A* and *B* can be described by four states: a reciprocal choice, an asymmetric choice from *A* to *B*, an asymmetric choice from *B* to *A*, and no choice. The four states can be seen as a realization of a stochastic process. They estimate for each point a sender (activity) and a receiver (popularity) parameter and for the network as a whole a density and a reciprocity parameter. Later models also include the estimation of higher order parameters, like triadic dependencies as e.g., transitivity (Wasserman and Pattison 1996). Subsequently, a type of logistic regression makes it possible to explain variation of these parameters over individuals and subgroups (Lazega and Van Duijn 1997). For example, assume girls (sex equals 1) tend to make more friendship choices than boys (sex equals 0). A positive sender effect of sex implies a larger probability of a relationship from a high scoring point on that variable (a girl) than from a low scoring point (boy) to some other point. Density and reciprocity effects are often defined by the (absolute) differences of the scores of the points on the variable. If boys and girls tend to make more friendship choices within their own groups, we find a negative effect of the absolute difference of the sex scores on the density parameter.

2.6 Evolution and Network Dynamics

In network evolution, two processes take place simultaneously. On the one hand, social actors shape the network by initiating, constructing, maintaining, and breaking up relationships. On the other hand, attributes (behavior, opinions, attitudes) of social actors are partly shaped by their relationships. Increasingly, Markov models are used for the analysis of network change, and spatial autocorrelation models for influence processes. Integration of the two processes requires further integration of theory and statistical testing. The first steps in this direction have been taken.

Holland and Leinhardt (1977) introduced Markov processes as the general framework for stochastic models of network evolution. The basic idea of Markov models is to conceive the social network structure as changing from one state into another over time. The unit of analysis is usually the dyad with its four possible states (see above). The parameters that govern the process concern the likelihood of transition from one of these four states into another. The original Markov models assume that the parameters are stationary over the whole process and that the population is homogeneous. Recent models have considerably increased the analytic possibilities of Markov models by eliminating these strongly limiting assumptions. Now, change parameters may well be dependent on the stage of network development and different for pairs within and between subgroups (Leenders 1996). An important next step is Snijders' integration of Markov models with random utility models, thus realizing a much stronger link between theory and statistical testing (Snijders 1996). In these models, random utility modeling is used to derive which network characteristics or interactions between individual and network characteristics are likely to produce high utility and thus are likely to govern network change. For each of these utility components, parameters are estimated indicating their strength.

Spatial autocorrelation models, such as those proposed by Doreian et al. (1984), Friedkin and Johnsen (1997) and Leenders (1997), are often used to model the influence process. In the most commonly used spatial autocorrelation models, it is assumed that influence on an individual characteristic (like behavior, opinion, or attitude) is only partly determined by the relationships in a network (estimated by the parameter α). The other part depends on other individual characteristics, like one's own background characteristics. The network part of social influence is assumed to be determined by a matrix of weighted influence relations where the total incoming influences on an actor sum to 1.

3. Conclusion

Since the early 1970s there has been impressive cumulative progress in social network analysis and research. From a rather isolated field, strongly oriented to descriptive structural and static analysis, social network analysis has grown into a well-embedded field, widely accepted as highly important for solving central theoretical problems of cooperation and coordination. With the growing importance of social networks in the information society with virtual communities developing in many segments of society, its importance and contributions to theoretical solutions can only grow. Issues of scope are challenging. Objects of study will vary from small group networks to social networks of billions of points. New techniques to visualize networks are also challenging. These allow certain structural characteristics to become visible and the effects of changes on these characteristics to become transparent. These developments can be followed by linking with the international virtual community of INSNA (the International Network for Social Network Analysis) and the links to be found there (http://www.heinz.cmu.edu/project/INSNA).

See also: Coleman, James Samuel (1926–95); Cooperation: Sociological Aspects; Exchange: Social; Game Theory; Influence: Social; Integration: Social; Interorganizational Relationships and Networks; Macrosociology–Microsociology; Network Analysis; Networks and Linkages: Cultural Aspects; Rational Choice Theory in Sociology; Social Capital; Social Networks and Gender; Solidarity, Sociology of; Structure: Social; Trust, Sociology of

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F. N. Stokman

Neumann, John von (1903–57)

John von Neumann was born Janos Neumann on December 28, 1903. He was the eldest son of Miksa (Max) Neumann and Margit (Margaret) Kann. The family prospered in the last decades before World War I. Max Neumann was a lawyer who was well known in banking circles, and he was later a banker. He was subsequently ennobled, hence the 'von' in John's name.

Max Neumann instilled his ardent love of high culture into his children. In the atmosphere in which John spent his childhood, his phenomenal precociousness in mathematics was soon discovered. His gymnasium teacher pointed out to John's father that there was no point in John's studying mathematics in school. Mature mathematicians were engaged as private tutors. His first paper, written jointly with one of them, appeared in 1922. John was recognized as a professional mathematician before he was 18.

After receiving his *matura*, von Neumann enrolled as a mathematics student in the University of Budapest. However, he did not attend classes and he only appeared at the end of each semester to take examinations. He was simultaneously enrolled first at the University of Berlin, Germany then in the *Eidgenossische Technische Hochschule* in Zurich, Switzerland. He received his doctorate in mathematics from the University of Budapest and the degree of *Diplomingenieur* in chemistry from the *Eidgenossische Technische Hochschule* almost simultaneously. The study of chemistry was probably motivated by the increasing importance of its applications in military technology. Toward the end of his life, von Neumann's most

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