Chapter 1

Networks, Ethnography, and Emergence

The question posed in this introductory chapter is a general one: How do new ways of thinking about networks increase our understanding of theoretical and ethnographic problems in the social sciences? Network research links to the ethnographer's concern at a practical level. What are the new theoretical insights and discoveries that devolve from network analysis? What justifies the additional steps needed to construct network databases out of ethnographic materials? These concerns link back to questions of theoretical import: What does combining networks and complexity contribute to anthropological and social science theory? The three sections of the introduction take up these questions.

First, under *Networks and Ethnography*, we recount the limitations of anthropological network approaches developed in the 1960s. We explain how subsequent long-term fieldwork projects began to make apparent the inadequacies of ethnographic description to deal with change and of classical anthropological theory to deal with dynamics. Long-term fieldwork not only provoked recognition of the difficulties of explaining dynamic processes and opened new challenges for anthropology but also offered up the kinds of data needed to address change.

We take up our second issue in a very general format that addresses the practical concerns and research issues of ethnographers under *Ethnography and Complex Interactive Processes*. Some have perceived inadequacies in standard anthropological techniques: Why is the basic practice of ethnography, which can potentially produce data for network analysis, not sufficient in itself? Without such analysis, what is lacking in an ethnographer's perception of complex interactive processes and how they operate? How is ethnography enhanced when combined with the further steps and insights of network analysis?

We advance four general propositions and several additional hypotheses that link network analysis and theory to the problem of explaining emergence and dynamics in complex interactions such as we observe in ethnographic field situations and that are observed in other disciplines. Clarification of what the concept of emergence means is one of the sidebars of the chapter and will be illustrated in this section. We illustrate how understanding micro-macro linkages can be instrumental in framing explanatory principles. We also go beyond this approach to cases where dynamic processes occur in networks in ways not explained by micro-macro linkages when we must turn to other principles. The examples that we use to illustrate the connections between complexity theory, network theory, and problems of explanation in ethnography link to the types of questions we address in our case study and the findings of our analyses.

The final section of this chapter, *Emergence and Network Analysis in Ethnography* returns to the problem of the field ethnographer and her attempt to capture the complexities of human behavior. It deals with how anthropological theory falls short and how much further it can go in dealing with these complexities. We offer five propositions as to what kinds of problems require network analysis to reach to the level of understanding explanatory principles. In developing appropriate theory, we reopen the distinction between social structure and social organization to argue for an additional level of analytic constructions to fill the theoretical and analytical gap that remains between structure and behavior. Some of these levels involve the recognition of social groups, rules, and roles that emerge out of interaction and that are rendered by network analysis.

Networks and Ethnography

Anthropology is in a particularly enviable position: When anthropologists put together a network database for a population that has been studied ethnographically, they already know a great deal about the society from the work of the ethnographer. They have field notes and writings on patterns of interaction, significant groups and organizations, occupations, and activities, sayings, beliefs, and norms. Collecting such data is one of the great challenges of and contributions made by ethnography. The ethnographer has, for example, to note stated rules and derive unstated rules that appear to govern behavior. When these rules are broken, observations are made of a series of consequences and the sanctions that may come into play. She will ask about, research, and write down the history of groups, organizations, individuals, and historical movements and events that have affected the population. She will work through her data on social organization, institutions, change, and the effect of interactions with the larger world, and much more. A good deal of baseline data will result from ethnography, especially where genealogies have been recorded and where information on memberships in groups and life history events such as migration histories are available. Altogether, ethnography offers rich data and grounding for network analysis.

What need or use is there, however, of putting together many of the same observations that the ethnographer uses in the construction of ethnographic writings into a coded format that allows further analysis of social networks? Won't putting together such data and analyzing more precisely how people are related simply contribute to more statistics about what we already know through good ethnography? The answers depend on the assumptions and approaches we bring to network analysis.

The Path of Network Analysis in the 1960s

The Manchester school, focused initially around Max Gluckman, was known in anthropology for rich scholarly work in the study of social change and dynamics. It was one of the earliest groups to utilize a network approach to ethnography. Turner (1957), for example, used a dynamical network approach through the informal use of community-level genealogical diagrams in his influential social drama paradigm. At Cambridge, Barnes (1954) had argued for viewing the whole of social life in terms of networks but he restricted his analysis to informal interpersonal ties, as these connect tangentially to any outside the institutional structures of the larger society.[1] While the network metaphor of Radcliffe-Brown had made a simplistic equation between one society and one network, network studies in the urban context, edited by Mitchell (1969), offered the possibility of looking more microscopically at how people interacted in these complex and fluid situations. For many of the network researchers of the 1960s the processes of mixing and change they noted in the urban environment proved exciting. Network analysis allowed them to visualize structure and changes in structure in the microcosms of personal networks, networks within organizations, and complex networks of interaction within heterogeneous groupings of people. Mitchell and his colleagues made contributions that opened up a new set of problems concerning the formation of group norms, interethnic identity, social control, conflict, crisis, as well as kinship, friendship, and organizational networks. Still, except for Mitchell himself, most of the anthropologists collecting network data in the 1960s and early 1970s dropped network analysis to take up new methods along with new problems they encountered in transactional analysis, the social drama paradigm, conflict, ritual, or cultural symbols.

The Manchester school approach led by Mitchell (1969) did not envision the more general possibility of embedding anthropological problems in a network approach in which the network data is suited to the problem. Their views of the contribution of network data and network analyses were highly restrictive, rarely if ever rising to the level of interactions between multiple networks in different domains or at different scales. Even for community studies, the methods of choice were institutional analyses that were wedded to structure-functionalism or functionalist varieties of conflict theory. Mitchell and others in his group failed to see network studies as providing contributions in this context that institutional analyses could not provide. The presumption stemming from structure-functionalism was that shared culture and a stable social structure were intrinsic to social life in traditional rural communities, barring periods of change and adjustments like those studied by Turner (1957). It was only with migration, mixing of populations, multiethnic groups, industrialization, and globalization that they recognized pressures toward change and rapid adjustment as features of social life that they thought required network analysis if only because of the fluidity of these processes. Members of the Manchester school tended to treat networks as special types of structures that required a distinct toolkit rather than as a more general and flexible ontology for situating social theory. The network approaches of the 1960s and early 1970s were abandoned by practicing ethnologists well before many of the newer network modeling approaches had developed. For most anthropologists, the uses of network concepts reverted to those of the earlier structure-functional period in anthropology, as metaphors for social relationships.

A Network Paradigm Developed in Long-Term Field Studies

The development of social network approaches after the 1960s took place largely in disciplines other than anthropology. Some of the early successes of the network approach in sociology consisted of applications of network analysis to community studies using a survey approach (Laumann 1973, Laumann and Pappi 1976). In contrast to the participant observation methods of anthropologists, surveys of this scale seem formidably expensive. This is one of the differences between the two disciplines that lent themselves to very different trajectories of the network approach in sociology and anthropology. It may come as no surprise that long-term studies, in which anthropologists have invested considerable time in the systematic analysis of their data, constitute the major area where network approaches have been intensively explored. In the past decade, the effort that anthropologists have put into long-term field sites began to pay off. Brudner and White (1997), Schweizer (1997), the survey volumes by Schweizer and White (1998) and Kemper and Royce (2002; see Johansen and White 2002), and, more recently, the longitudinal network study of Schnegg (2003) provide longitudinal studies of the dynamics of social networks. Payoffs of longitudinal analyses have also been evident in historical network studies with an ethnographic orientation (Stovel, Savage, and Bearman 1996, Padgett 2002, 2003).

The rich ethnographic context that long-term field site and historical data bring to network analysis has begun to contribute in major ways to foundational theory in the social sciences. The outcomes of experiments in network analysis have provided frameworks for seeing how various types of phenomena are linked to one another through their embeddings in a plurality of overlapping and interpenetrating configurations (Padgett and Ansell 1993, Padgett 2002, 2003). Breakthroughs have resulted in the study of feedback processes among multiple embedded network processes (Padgett 2001; White and Houseman 2002) and new understandings of social dynamics as a synthesis of network theories. Studies in this context have begun to integrate, in an emergent network theory, "models of how complex, information processing, self-reflective, self-restructuring systems operate, develop and change" (Read 1990: 55).

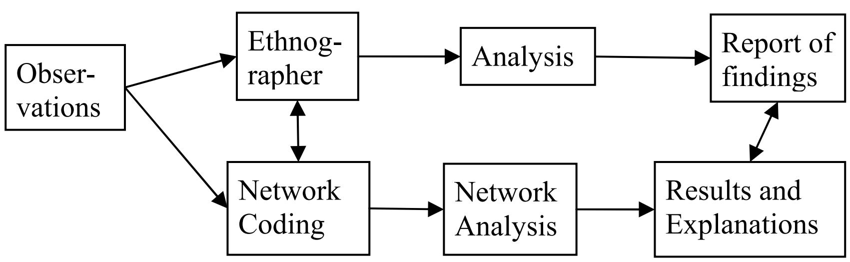
What Is Different Now?

Decades have passed since the 1960s when anthropologists first considered network approaches to ethnographic investigations. Network analysis is now in easy reach of the average investigator—whether the methods used include participant observation, survey, use of historical archives, censuses, or a combination of different sources and methods. In a field study of one or two years, most anthropologists already contextualize their data in ways that are suitable for a network format for further analysis. Genealogies are one example of potentially rich network data but most areas of study lend themselves to asking how elements are connected, how observed connections change over time, and how they link to other domains of inquiry. A full range of questions can be explored using software to easily code data, show linkages, provide for graphic representation, and analyze large networks with thousands, or potentially hundreds of thousands, of elements.

Since the 1960s, in other areas of the social and biophysical sciences many important network properties have been discovered, and the types of concepts, variables, theories, and methods contributed by network approaches have drastically altered and expanded. Earlier studies of egocentric and small group networks, manageable using the methods of analysis of the 1960s, have advanced and evolved into analysis of networks on large scales and suited to different kinds of problems. New variables and new types of findings that deal with structural cohesion, for example, are central to a new paradigm of scientific thinking in which causes and consequences are not conceived of as mechanical or produced by repetition or conformity to fixed rules or norms but rather as emergent processes in complex fields of interaction. The findings within this paradigm, moreover, are often predictive, explanatory, and robust. Coupled with broad-scale network approaches, concepts of complexity and emergence offer new sources of theoretical understanding.

While a "network study" seemed at one time to present a formidable problem involving much expense in data collection, it is now apparent that even the simple conversion of data normally collected in the course of ethnographic study, especially if conducted over time, offers unique benefits. We can think of these benefits in terms of a controlled simulation, as diagrammed in Figure 1.1. The benefits here derive from taking the same data as are used by the ethnographer in analyzing observations to produce an ethnographic report but, through the avenue of network coding and analysis, to reach a set of results and explanations that may add entirely new dimensions and explanations to the ethnography. Without network analysis, ethnographers often use network metaphors to describe and theorize about what they observe. What we hope to show in this chapter and book are the kinds of new results and explanations that can be reached by taking a network path to coding and analysis.

Figure 1.1: Network Analysis as Controlled Simulation



Ethnography and Complex Interactive Processes

Why do we need network analysis in the content of ethnography today? What does a network approach may contribute that goes beyond and supplements the normal practice of ethnography generally? This involves understanding phenomena that result from complex interactive processes in which theory and explanation do not derive from reductive principles and definitions or assumptions that narrow the scope of inquiry. This provides not just a new perspective on problems such as network embeddedness (Granovetter 1985) or, for example, globalization but also awareness of potentially new explanatory principles for the relationships between micro- and more macro-processes and levels of analysis. Ethnography as a scientific discipline has tended to be reductive and somewhat resistant, with some exceptions (e.g., Johnson 1982, Lansing 1991), to considering complex interactive processes. The classical insistence among ethnographers, for example, is that the chunks of social structure that they discover through fieldwork must come labeled and verbalized by their informants, as if social structure does not exist unless it passes first through the filter of cognition, language, and shared culture at the symbolic level. Behavior itself, however, is an instantiation of a symbolic system: like any other sign or symbol, behavior can be read or interpreted. Behavior has implications for structure and process, and where behavior has clear-cut structural implications it is often taken for granted, unnamed or unlabeled, and underverbalized. Good ethnographers put back the contexts and relationships that make such logics intelligible. For such ethnographers, network representations and analyses may yield significant new understandings.

Network Theory and Emergence: Four Propositions

The importance of network theory in the social sciences today might be seen to rest in part on a relational ontology that allows us to move between different scales of resolution:

> A relational ontology in the tradition of classical economists, many nineteenth century social analysis, American pragmatists, or the richer recent versions of network and institutional analysis . . . provides a simple way of concatenating from the small scale to the large or vice versa; of identifying analogous causal processes at different scales; and of integrating such troublesome phenomena as constructed social identities into sound historical analysis. (Tilly 1997:1)

While part of the relational ontology that Tilly refers to has deep intellectual roots, the richer recent versions of network and institutional analysis also connect to new concepts about how complex outcomes emerge out of interactions, which may result from very simple principles. Ethnographers have tended not to use such concepts because there has been no clear road map as to how to use them more precisely in ways that contribute to anthropological theory and to ethnographic practice.

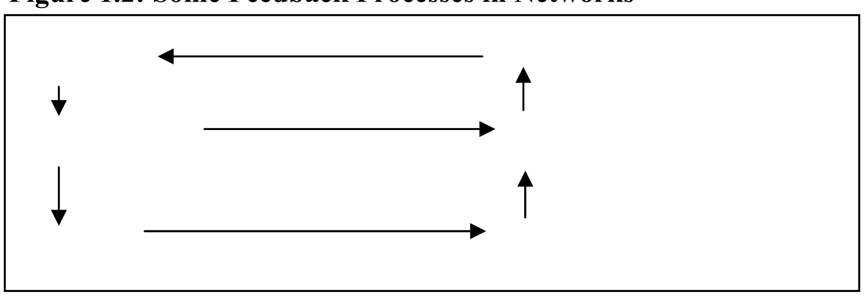
The four propositions that follow add to the relational ontology of network analysis in a way that shows how social theory can derive in part directly from understanding how locally observable interaction within networks leads to global properties of networks that alter the context of interactions and provide an understanding of feedbacks between dynamics (in behavior) and structure. These are what we call *micro-macro* linkages. A simple way of putting this is that there are some fundamental theoretical explanations for what we observe that can be learned from network analysis beyond the normal practice of ethnography. Some of this knowledge can be gained or duplicated by knowing the micro-macro linkages, making only the *local* observations needed through ethnography, and deducing the macro or global linkages and their consequences. In a broader network ontology, however, local observations will not suffice for understanding many phenomena. Here, analyses of local and global network measures are needed rather than reliance on network metaphors. Metaphors for network interaction are simply not up to the intellectual task of understanding the complexities that arise from interaction. The propositions that follow attempt to put in place this broader ontology. Instead of the usual distinction between social organization and social structure, for example, we add another ontological level: network dynamics, as studied through the assembly of network representations of empirical observations and the analysis of network data so constituted.

Our propositions are not merely interesting features or corollaries of network analysis but deal with how to constitute explanatory theories and what it takes to observe some of the critical phenomena resultant from social interaction. In some places, for example, for some of the micro-macro linkages, we make use of theorems and mathematical proofs but the propositions themselves are sensitizing epistemic statements of what we can and need to look for to derive the benefits from network analysis that are critical to any theoretical enterprise in the social sciences, including the interpretation of ethnographic case material. They also show the links between social science research and concepts in complexity theory, such as emergence and micro-macro explanatory principles.

Proposition 1. Networks have structural properties (local and global) that have important feedback on behavior and cognition.

When people interact, their behavior and their comprehension of that behavior shape some of the local or ego-based properties of their networks (Figure 1.2). Some people have more links than others (indegree and outdegree), for example. People may choose friends so as to avoid inconsistencies, like friends of friends who are enemies; and they are also more likely to choose friends who are already friends of friends. Preferences for buying a new computer may reflect the number of people with whom you can exchange files. The number of friends a person has may affect the probability that others will choose them for a new friendship. Each different kind of behavior sets up certain shapes and variabilities as to how networks look from the individual's perspective. These are micro properties of a network. Micro properties may have consequences, as shown by the two downward arrows in Figure 1.2. Among the consequences are emergent properties that we may identify as those that bring about "entitivity" because they emerge along with discrete network units of organization that are consequential in having effects on other behaviors. These we call *configurational effects*. The entitivity of emergent network-units of organization increases when these structures themselves are robust, resistant to disruption, and operate to catalyze or organize action within the network. Further, these may include effects on the macro properties of a network. Macro properties of networks may or may not be directly linked to micro properties but in either case macro properties alter the context of everyone in a network, and may affect how people interact. This is the feedback loop shown by the outer circuit of arrows in Figure 1.2. In this diagram as elsewhere we use micro as roughly synonymous in a network context with local, meaning something—like a pattern of behavior or neighborhood configuration—that can be located within the neighborhood of a specific individual, node, or typical node in the network.

Figure 1.2: Some Feedback Processes in Networks



Cognition and culture, while not treated in this book, also fit into the network framework for studying micro-macro linkages. Because networks include nodes, links, and the attributes of both, data on the cognition of individuals falls under the heading of micro properties, while shared cultural items have a distribution in a network that constitutes a macro property. To build a proper bridge between social networks on the one hand and cognition and culture on the other, we have to use multi-level network representations. These representations would set about to link the elements of cognition, for example, as existing both inside and outside the individual as an entity, and to set about identifying the linkage processes in cognition, the micro-macro links within cognition, and its emergent properties, cohesive units, and so forth. Multilevel analyses that extend to the variable cognitive units and linkages of individuals situated in an environment, however, are beyond the scope of this book. We will focus on social networks and behavior.

We use macro and global synonymously in a network context to refer to something that is a property of the whole network. While l*ocal density* refers to the average proportion of nodes connected to a given node that are connected, for example, *global density* is the proportion of all pairs of nodes that are connected. In certain kinds of networks, such as a square grid with nodes at the intersections, local density can be low (with a cluster coefficient of zero within local neighborhoods) while global density can be made extremely high by adding links between pairs of nodes at a distance greater than two. There is no micro-macro linkage that predicts local from global density or vice versa. For other local and global properties of networks, however, there are such linkages.

Micro-macro linkages are crucial to equipping network analysis with a theoretical understanding of social dynamics. To make sense of findings and their significance it is important to understand how micro-macro linkages work. Take, for example, the local property of *degree*, that is, the number of links of each node. If e is the number of symmetric links or *edges* in a network of n nodes, the average e/n of local degree is a property with a micro-macro linkage.[2] The relation between average degree e/n and the global density of edges $e/n(n\text{-}1)$ is a linear function of n-1, density = average degree/(n-1). Both properties are important for network dynamics. If e edges connect pairs of nodes randomly, when e surpasses $n/2$ a phase transition begins from a network having tiny "islands" of successively connected pairs in a disconnected "sea" to one having larger connected "islands." When e reaches the size of n there emerge many large "islands" containing cycles, "bridges" between the "islands," and "peninsulas" of connected nodes that radiate off the cycles. After this transition, the global network is almost certain to have a connected component that is giant relative to the others, containing most of the nodes. Becoming connected alters the dynamic of the network. Thus, given a model of simple random formation of edges, there are more complex micro-macro predictions from local structure to the emergence of global network properties that have a new potential for interactivity across the network. Predictions will vary, however, according to the processes by which links are formed, which may be treated probabilistically.

The *degree sequence* of a network is the distribution of numbers of nodes n_k that have degree k. This distribution is usually not a normal distribution with variation around an average described by standard deviations. Instead, the processes of attachment to other nodes are often found to be biased by preferences, attractiveness, or the payoffs of different sorts of attachments to the parties involved. These processes, which may be probabilistic, have distinctive consequences for micro-macro linkages. Comparing the properties of degree sequences offers the ethnographer an indirect means of studying the effects of preferences, attractiveness, or payoffs of different types of interaction. For example, when people make new or replace old with new connections (Eppstein and Wang 2002) to others (e.g., phone calls, friends) with a probability proportional to their degree (k for a given node u) we have at the micro-level a *preferential attachment* to degree. The attachment might be to indegree, that is, copying the behavior of others, or to outdegree, that is, sampling randomly one's own internal address book according to how often that address has been used in the past.

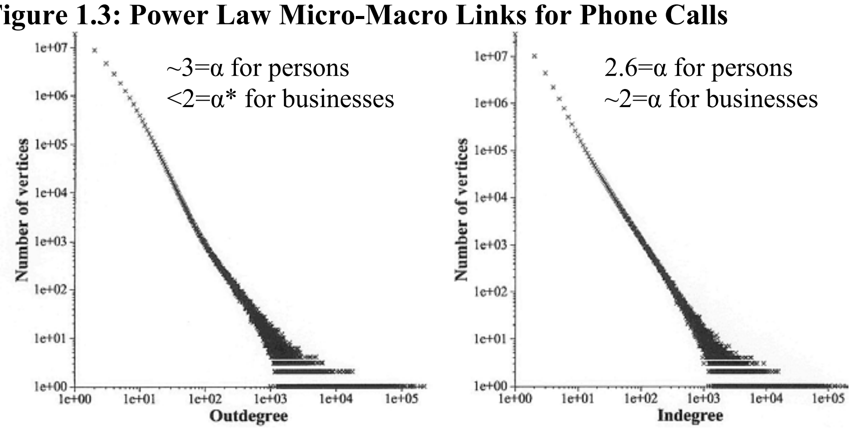
For anthropology, preferential distributions of links to nodes or types of nodes in a network provide a new approach to the study of preferences in kinship behavior. The probabilistic approach leads to understanding micro-macro linkages that can equip network topologies and social organization with self-organizing dynamics in relation to people's behavioral preferences.[3]

The probabilistic theory of network topology and dynamics

Degree sequences are distributions that affect how ties are formed (if how many ties a node has alters its popularity), and how ties are formed affects the degree distribution. Understanding this feedback is a crucial component of the theory of network topology and dynamics in the feedback between structure and behavior. If new connections or replacements of old ones in a network are governed by a probabilistic process of selecting other nodes proportional to their degree, a macro property follows for the network that has very different consequences than simple random edges. Preferential attachment to indegree is such a process: each node has the same probability of creating a new outgoing edge but the probability that any given node u will be selected for this edge is proportional to u's indegree k_u, $P(k_u) \sim k_u$. The indegree k can be thought of as the "popularity" of u. The probability $P(k)$ that a node in the network interacts with k other nodes proves to decay as an inverse *power law*, $P(k)=A \cdot k^{-\alpha}$. The constant A is determined by the number of nodes in the network and as that number gets larger, α will approach from below the value of 3; also a proven mathematical result. This is a strong micro-macro linkage because the size of the network is the only free parameter.[4] Further, a power law is scale-free in the sense that α is not affected by changes in the scale of k, such as multiplying or dividing by 10 or 100 or 1000. Understanding of power laws is needed for understanding self-organization that operates similarly independent of scale. In this they differ from other distributions such as the normal curve or an exponential distribution where $f(k)=B + C^{-k\beta}$ is strongly affected by changes in the scale of k, which is itself part of the exponent.[5]

There are many networks, however, that fit the $f(k)=A \cdot k^{-\alpha}$ equation for power-law attachments but where α diverges from the expected value of 3, and not simply because of the smallness in the size of the network. For these networks, researchers have been trying to understand the ways in which micro-macro linkages come about between local attachment behavior and the global value of α (Bornholdt and Schuster 2003, Dorogovtsev and Mendes 2002, 2003).[6] Data from Bell Labs for 53 million phone calls in the USA in a single day, for example, exhibit aggregate power-law attachments, as shown in Figure 1.3 for outgoing calls (left) and a very similar power-law degree distribution for incoming calls (Figure 1.3: right). A straight-line fit for distributions like these, with logged variables on the axes, is indicative of power-law relationships.[7] Here $\alpha_{out}=\alpha_{in}=2.1$ overall.[8]

Figure 1.3: Power Law Micro-Macro Links for Phone Calls



The number of vertices for each possible outdegree for the call graph of a typical day.

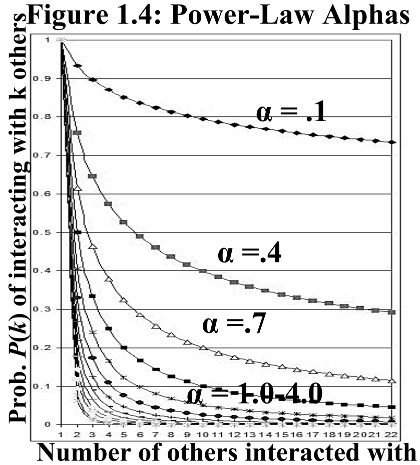
The number of vertices for each possible indegree for the call graph of a typical day

Log-log graphs courtesy of Fan Chung, UCSD, for the Bell Labs calling graphs results. While the very slight bow in the leftmost graph faintly resembles the right half of a normal curve, any such resemblance disappears when raw degree and raw frequency are plotted, and the indegreee distribution is hardly discernable from perfect power law.[9]

The phone call example is important for the general argument in this book about self-organizing properties in social organization because it is a case where the number of nodes is sufficiently large that the mathematical model of "pure" preferential attachment predicts from micro-macro linkage that the power-law (alpha) slopes for degree distributions will equal 3, but in fact the alphas are much smaller. This is because preferential attachment by degree is not the only process of tie-formation that is operative. Thus, the slopes and shapes of such curves are indicative of behavioral processes that contain a preferential attachment component but where other factors are at work as well.[10] This will also be seen when we examine a range of other kinds of networks.

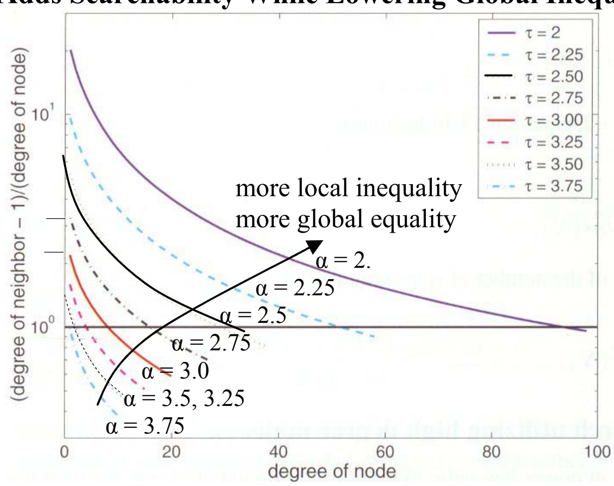
Figure 1.4 shows, for power-law distributions with alphas that range from α=.1 (top of figure) to α=4.0 (bottom of figure) in increments of .3, the probabilities $P(k)$ that a node in the network interacts with k other nodes, $P(k)=A\cdot k^{-\alpha}$. The relative proportions of nodes can be gauged from these graphs. As can be seen, α=4.0 is almost a square distribution in that almost all the nodes are of degree 1, very few are of degree 2, and the numbers from 3 onward are almost negligible while inequalities are extreme in the upper tail of the distribution. As alpha increases, global inequality increases because the tail of the distribution (fewer hubs with higher degree) becomes more stretched out, and inequalities are less likely to be found for a randomly chosen node within its local neighborhood. Above α = 3 local inequality is no longer noticeable and extrapolated variance becomes infinite as the relative proportion of nodes shrinks as it extends the tail of the distribution.[11] For 1 < α < 1.8, neighborhood inequalities of degree become so heterogeneous that the connections of local hubs lead in different directions and search becomes difficult because there are too many choices that don't lead to a given target. Between α ~ 2.4 and α ~ 1.8 local neighborhoods tend to be searchable. In our Chapter 5 we will employ these models of searchability to analyze the potential for navigability and self-organizing properties of kinship networks.

Figure 1.4: Power-Law Alphas



Searchability and navigability in networks with power-law attachments are feasible, and thus a general property of the network, only when most of its nodes can expect to have a neighbor that is more central as the next step in a search. Crucial facts about network search processes from Adamic, Lukose, and Huberman (2003:302) allow us to derive some general properties that carry over to important dimensions of social organization in interpersonal networks that have a power-law attachment component. Their results, in Figure 1.5, allow us to interpret the salience of inequalities in local neighborhoods. The figure shows the average richest-neighbor ratio of degrees for nodes whose degree is n (highest neighbor-degree divided by n). Local inequalities increase with lower values of α, even as global inequalities decrease. At α = 3, hubs with 10 or more edges cannot expect to have a neighbor with more edges, so their search capacity is hampered. In contrast, nodes with 10 to 50 edges in a network with α = 2 can expect to have a neighbor with somewhere between 8 times to twice as many edges, hence the network is likely to have navigability as a macro property.

Figure 1.5: Lower α in Power-Law Distributions Increases Local Inequality, Adds Searchability While Lowering Global Inequality



Adapted from Adamic, Lukose and Huberman (2003)

In a network with extreme inequalities occurring far from the average neighborhood such as those with α > 3 in the lower left corner of Figure 1.5, the average local neighborhood is too egalitarian to allow searchability; One's neighbors are almost all of the time too much like oneself. More local inequality allows for more hubs within one's neighborhood, or neighbors' neighborhoods. The availability and use of local hubs facilitates quicker searches, as does the presence of hubs in the locality of the destination of the search (the latter are often called authorities). Local inequality facilitates search, especially in the range in Figure 1.5 between the two solid lines above the axis of 2 < α < 2.5.

The power law slope α of a degree distribution serves as a double-edged measure with opposite implications for local and global inequality. Various kinds of feedback can occur between global structure and local behavior, as diagrammed in Figure 1.2. One type of feedback occurs through variations in searchability; the ability of an average local node to find some target in the network by sending messages only through the local neighborhoods of nodes that successively link an initial node to a target. When nodes alter their behavior to use local hubs for searchability, the local/global balance of connections and the degree distribution is changed. When the degree distribution changes, it alters the usefulness of local hubs for searchability. A balance may be struck between these two processes.

Thus, alongside our first micro-macro linkage between preferential attachment, network size, and $\alpha \sim 3$, further feedback between local behavior and power coefficients comes about when global $\alpha \leq 3$, which entails locally perceptible inequalities: With local processes toward and away from local inequality, including copying, competing with, exchanging, or cooperating with neighbors, α may settle into equilibrium. Networks dominated by preferential attachments, then, may be self-organizing at the local level when competing processes are operative.

Another type of feedback between the behavior of nodes in a network and its macro properties may involve differences in the local versus global perceptions of different types of players. In the phone call example, for example, private citizens typically organize their behavior according to local information. Outgoing calls in the lower (private) range of Figure 1.3 approach $\alpha_{out} \sim 3$ as predicted by the "pure" preferential attachment model for very large networks. Businesses, in contrast, will typically collect more global information to serve as a base for targeting calls. In Figure 3 again, α_{out} is < 2 (more locally unequal) in the upper range of the distribution that includes more businesses and automated phone calls.[12] Other factors that come into play that might push away from preferential attachments and inequalities would be evident if we looked more closely at examples of networks other than phone calls, as we shall do for kinship behaviors. In the study of kinship, it will also prove important to distinguish properties of networks among corporate kin groups, as we do in Chapter 7, from those of individuals.

The alpha parameter of networks with a preferential attachment component has strong implications for overall topological properties of a network, as seen in the case of navigability. There is important micro-macro feedback between behaviors of nodes and whether their network will be navigable, with α in the range that encompasses 2 to 2.3. We might expect that technological networks such as power grids, for example, lack the potential for self-organization that is provided by appropriate parameters of preferential attachment. Moreover, when $\alpha > 3$, feedbacks between local behavior and power coefficients are unlikely because the dampening of local perceptions of inequality reduces the possibility for feedback. $\alpha \sim 3$ is the threshold for resilient feedback and diffusion (including epidemics) in many scale-free network processes. Self-organizing properties in this case may be lacking at the level of micro-macro linkages, where agency is involved, although long-run evolutionary selection may be operative.[13] Variations in local network behaviors such as mean sexual contacts, however, may significantly affect global properties that feed back on the recurrence or control of epidemic disease.[14]

Thus, networks, through elementary processes of interaction in these examples and others suggested by the list in Table 1.1, mediate many highly complex and nonobvious outcomes. Some networks, of course, like those for friendship ties, do not show power-law distributions because, along with other constraints such as time and energy, preferential attachments are operating both to degree and to other factors.

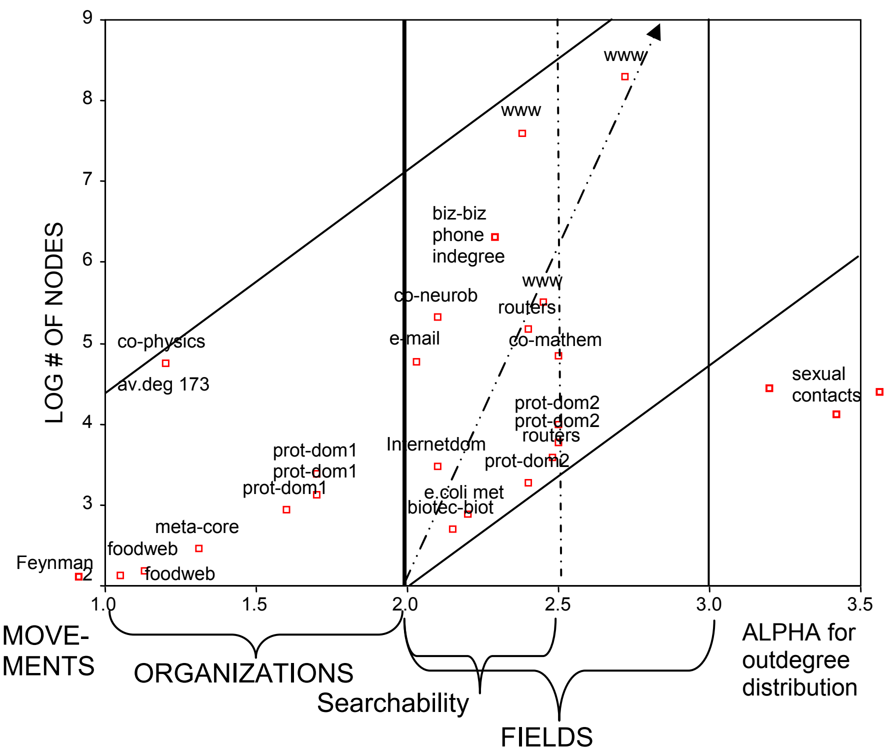
Examples of networks classified by type of scaling, and power-law scaling characteristics, for size, degree, degree correlation, and clustering are given in Table 1.1, which is compiled from diverse sources such as Barabási (2003:72), Newman (2003:37), Wuchty (2001), and personal communications with Wuchty and Chris Volinsky of AT&T. The same data but only for the power-law networks, are shown in Figure 1.6, which gives a scatterplot of the power coefficient and the sizes of the networks in more detail. Because the figure allows an overview of network topologies associated with power-law degree distributions, which have micro-macro linkages, it is presented and discussed first. Table 1.1 has the details on the networks that are labeled in the figure.

These examples will prove especially helpful when it comes to interpreting our data on the Turkish nomads, where we find power-law distributions that apply to rank preferences on different kinds of marriages. We view these in the same manner as power-law degree distributions, not in the manner of physicists trying to find universality classes to explain broad classes of phenomena but to understand preference gradients probabilistically. Here, the theory of scale-free and broad-scale phenomena in networks proves to be extremely useful.

We also want to explain here our perspective as anthropologists on issues of scale-free networks:

First comes the matter of size, where Figure 1.6 is especially relevant. For most physicists, scale-free phenomena apply to large or even infinite networks. The mathematics of network topologies (Dorogovtsev and Mendes 2003), however, shows that in the pure type of preferential attachment in networks, the power coefficient α approaches the value of 3 asymptotically, from below, as the size of the network increases. This relationship is shown also for empirical networks, as is indicated in Figure 1.6 by the large broken diagonal arrow. In the existing datasets, the WWW is our largest available network for study, and its α is closest to 3 in the approach from below. In general, except for sexual contacts as an STD-transmission network, all the α values are less than 3, and there is a strong overall correlation between increase in the size of the network and increase in α toward 3. As we have seen, for epidemiological reasons, having α > 3 is advantageous for sexual contacts in large populations because it makes possible the existence of a threshold for average number of contacts below which epidemic transmissions subside.

Figure 1.6: Covariation between Power-Law Coefficients and Size for Scale-Free Networks, Showing the Ranges on Network Topologies



Second, at a given size, there is a latitude in Figure 1.6 of one unit in the α value within the upper and lower diagonal lines of constraint for the correlation between α and network size.[15] While roughly constrained by size, variations in α also reflect other preferential gradients and constraints, often in combination, and in levels and differences in social organization that are not determined by size alone.

When thinking about size in the context of scale-free networks and ethnographic networks, we need to make the link between the smaller context of an ethnographic study—a context of smaller network size—and the larger social networks in which the network under study is embedded. Imagine expanding the territorial unit of the study tenfold, or a hundredfold, or a thousandfold. If the smaller network has scale-free properties, and is representative of larger social and territorial units in which it is embedded, we can entertain the possibility of extrapolating its scale-free properties to these larger units. What we observe may be representative of much larger-scale phenomena, but Figure 1.6 would also suggest that as we move up in scale, the alpha coefficient is likely to decrease. Navigability at one level might be diminished at a level an order of magnitude larger, and lost when a level 100 times the size is reached.

Third, as shown in the brackets at the bottom of Figure 1.6, the network topologies for different values of α have sociological significance. Very large networks, with values of α above 2.4, have heavy tails in the distribution of hubs that are sufficiently extreme to make hubs of little use within the average neighborhood in navigating the network. Only the WWW with its specialized search engines and web crawlers exist at this level. Our view is that in the range $2 < \alpha < 3$ the scale-free networks that we observe are *social fields* where there are few organizational constraints on interaction, whereas in the range $1 < \alpha < 2$ what we see are networks that are dominated by organizational constraints that involve local hubs and hierarchies with overlap between the more specialized cohesive components of organizations (White, Owen-Smith, Moody and Powell 2004).

Fourth, within these ranges of α for fields and organizations, the value of α for empirical networks reflects not only preferential attachment by degree but a likelihood, in our ontology, that the magnitude of α is downgraded in part by the addition of local constraints. This is our explanation for why, at levels of α close to one, we find airline routes in the USA and charismatic movements with $\alpha < 1$; and for small networks with a small $\alpha > 1$. These latter include ecological food webs (which also tend to be exponential or single-scale), the protein interactions of multi-celled organisms, the less frequent and specialized co-occurrence frequencies of words in English, physics coauthorships, the organization of WWW sites, and the high frequency range of the outgoing biz-biz phone calls (business-to-business, and thus highly organizationally constrained; these results were estimated from new data provided by Volinsky and AT&T in which biz-biz networks were broken out separately).

In Table 1.1, a full range of empirical networks that have been studied by scores of researchers are classified as whether they are: (a) broad-scale or scale-free in having power-law degree distributions for which α is not affected by changes in the scale of k (e.g., multiplying or dividing by 10, 100, or 1000) or a single broad but limited scale over which power-law distributions hold; (b) broken-scale, where power-law degree distributions show a threshold where the power coefficient changes, or (c) single-scale, that is, not power law (log-log linear) but exponential (linear on linear-log scales) or Gaussian (normal-curve variation) in the degree distribution.

Table 1.1: Small-World Networks, Ordered by Scaling Characteristics for Power Law, Size, Degree, Degree Correlation, and Clustering

Small-World Networks	Networks	Sizes	*Average degree*	*Degree correlation*	*Clustering*	*References*
a. Broad-Scale α < 1	US airports 97	3.3×10^2	6.4		High	White
	Feynman graph diffusion	1.2×10^2	5.2			Bettencourt
$1 < \alpha < 2$	Food webs (expon.)	10^2	4-10	Negative	High	Various*
	Higher Protein Dom.	10^3	1-9	Negative	High	Wuchty
	Lower word co-occur.	4.6×10^5	n.a.(70)	Pos	High	Solé et al.
	SPIRES coauthors	5.6×10^4	173	Pos	High	Newman
	WWW sites	2.6×10^5	?	Pos	High	Huberman
	Upper Biz-Biz out	1.1×10^5	n.a.	Pos	High	Volinsky
$2 < \alpha < 2.4$	E. Coli metabolic	7.7×10^2	7.4	Negative	?	Jeong et al.
	Internet domains, aut.	10^3	~3.5	Negative	High	Various**
	Biz-Biz phone calls in	1.6×10^6	1.9/day	Pos	?	Volinsky
	Email	2.6×10^5	2.9	Pos	?	Ebel et al
	n-Biology coauthors	2.1×10^5	11.5	Pos	?	Barabási
$2.4 < \alpha < 3.0$	Metabolic	3.1×10^2	28.3	Negative	High	Wagner/Fell
	Higher Protein Dom.	10^3	~ 2	Negative	High	Wuchty
	Internet routers	10^3-10^5	~ 2.5	Negative	?	Various**
	Math coauthors	7.1×10^4	3.9	Pos	?	Barabási
	WWW	10^5-10^8	4-7	Pos	?	Various
	Upper word co-occur.	4.6×10^5	n.a.(70)	Pos	?	Solé et al.
	Lower Biz-Biz out	2.1×10^5	n.a.	Pos	?	Volinsky
$\alpha \sim 3.0$						
$3 < \alpha < 4$	Sexual contacts	Multiple		Pos	Low	Various***
b. Broken-Scale	Phone calls					
	Word co-occurrence					
	neurons, c. elegans					
c. Single Scale	Words, synonyms					
	acquaintanceships					
	friendships					
	company directors					
	Comic book networks					
	Power grid					

* Montoya and Solé, others. **Faloutsos; Pastor-Satorras. *** See text.

The scale-free and broad-scale networks in Table 1.1 are roughly ordered into sets according to the theoretically important distinctions as to the value of their α coefficients (Dorogovtsev and Mendes 2002,2003). Thus we list sets of examples by their designation (such as the SPIRES physics coauthorship network) under a general range of coefficients, and in the next column give the sizes of the networks measured in powers of 10. The importance of average degree for each of these networks, in the next column of the table, has already been discussed in terms of micro-macro linkages and in terms of epidemic or diffusion thresholds.

Principles of the classification and some of the judgments about broad-, broken- or single-scale networks are from Amaral et al. (2000a). Single-scale networks lack power-law degree distributions, while broken-scale networks have two or more distinct power-law regimes, and broad-scale ones have them for an extensive range but not the entire range of the distribution. We classified broad-scale with scale-free in most cases, especially because we do not believe that any of these networks are truly scale-free and we see them as composed of diverse kinds of attachment preferences (or constraints) rather then a single type (for partial confirmation, see Powell, White, Koput, and Owen-Smith 2004).

Two new items appear in the columns on the right of Table 1.1: characteristic negative or positive degree correlations and magnitudes of the clustering coefficient. We discuss them in reverse order. The last column of the table gives the name of a principal author or authors who have studied a given dataset. In the case of various studies by separate sets of authors, Barabási (2003) may be consulted for references.

The coefficient of clustering is a measure of local organization within the immediate neighborhood of the average node. It is measured by the number of triples (times 3 for normalization) in a network over the number of pairs of adjacent edges. To estimate whether this coefficient is high relative to its expected value we used the method of Bollobás and Riordan (2003) to compute the expected value in the scale-free model, and graded the coefficients as high when they are 100 times in excess of the expected value.[16] All the measured values, especially at the lower end where they have been more frequently computed, are high, which is what makes these networks small-world in addition to scale-free.

Characteristic negative or positive degree correlations are the most significant markers of the distinctiveness of social versus nonsocial networks (Newman and Park 2003). They correspond to assortative mixing in the positive case and disassortative mixing in the negative case. They are also an indicator, in both cases, that scale-free networks evolve and adapt in relation to functional requisites and preference gradients, gradients that are not uniformly dominated only by preferential attachment to degree. According to Maslov et al. (2002) and Amaral et al. (2000b), all the nonsocial networks, including biological and technological networks, have greater than expected disassortative mixing between nodes of high and low degree. In a technological and evolutionary sense, hubs are often selected to link as many outliers as possible. This does not require a selective preference, however, because Maslov et al. show that the suppression of multiple edges that are combined into one edge in a network pushes the degree correlation in the negative direction at the level of statistical significance that is observed for most networks. Newman and Park argue that special preference gradients are needed to produce assortative mixing in networks, as they observe in such examples as citation networks, boards of directors, and others. In this case there is greater than expected assortative mixing between nodes of higher degree but the preference may be an attraction to higher orders of cohesive connectivity, as observed by Powell, White, Koput, and Owen-Smith (2004), or to segregate into groups or communities. Tendencies for cohesive groups to form in biological networks may occur alongside those of negative degree correlation, however, fostered by natural selection rather than the preference gradients of social networks.

Generalizing the theory of network topology and dynamics

We need to understand the theory of scale-free phenomena in order to interpret results when we find power-law distributions in our own network data. Probabilistic models of scale-free networks are difficult to use to derive micro-macro linkages, however, because they can be derived from many different types of models. Hence, we want to extract the main classes of observations about micro-macro linkages. Our scaling of types of people chosen in marriage from the Turkish nomad data from Chapter 7 fits into the classification of scale-free networks at the level of searchable fields that contain local organizations. Although kinship networks do not have power-law degree distributions per se because kinship links are single-scale rather than scale-free, which renders comparison of our findings on preference gradients more difficult, we hypothesize that the same types of principles apply:

> **Hypothesis 1.1:** Scale-free phenomena in social networks that veer toward an alpha power of 3 or greater have fewer organizational constraints on the individual actor or node while those that are closer to an $\alpha \sim 1$ have more imposed organizational constraints.[17]

This hypothesis is supported for the contrasts between food webs (1.05-1.13) versus Internet webs (WWW: 2.1-2.2) and routers (2.4-2.5), physicists (1.2) versus mathematicians (2.5), biotech with partners (1.5-1.8) versus biotech with biotechs 2-2.3), protein interactions (Wuchty 2001) of advanced eukaryotes (1.6-1.7) versus prokaryotes and single-cell eukaryotes (2.4-2.5), and organizational (1.8-2.0) versus private calling (2.6-3.0).[18] In the broken-scale category of networks, the word co-occurrence network (Ferrer i Cancho and Solé 2001) divides into a language-core (slope 2.7) regime at high frequency and less well shared language-periphery of specialized terms (slope 1.5). We can also posit an evolutionary pathway whereby:

> **Hypothesis 1.2:** Starting from a model of pure preferential attachment where $\alpha \sim 3$ (micro-macro linkage 1), there is local navigability in scale-free networks with clustering and use of local hubs for searches for $\alpha \leq 3$ that would allow an evolutionary pathway driven by local search behavior (micro-macro linkage 2) for increased use of local hubs and reduction in the alpha parameter as local inequality increases. It may be out of this emergent process that organizational structures and constraints emerge.
>
> **Hypothesis 1.3:** Further, with greater global equality paradoxically concomitant with the rise in local inequality as alpha moves from 3 toward 1, there may be (1) macro benefits in the distribution of resources with global equality, and (2) the evolution from diffusive rates of distribution to directed velocities of resource flows that are concomitant with the evolution of organizations.
>
> **Hypothesis 1.4:** The transition from $\alpha \sim 3$ to $\alpha \rightarrow 1$ is also density driven.

The example of power laws governing usage of the phone network highlights six important points. First, power laws illustrate various types of phenomena that are common in social processes. We find similar phenomena in our study of Turkish nomads, and the processes we identify in our case study generalize to self-organizing processes in other societies.[19] Some of these phenomena are explored in Chapter 7 where we translate the dynamics of scale-free models into a domain where it applies to kinship behavior, namely, in the type of person who is chosen in marriage. Here the power-law distribution on marriage-type frequencies, translated into a probabilistic model of preferential attachment for closer ties balanced by competing processes that distribute ties.

Second, there are ranges within scale-free phenomena where self-organizing properties can operate at the local level. In our Turkish study, marriage choices can be explained as a self-organizing equilibrium that has a host of additional consequences for social organization, structure, and dynamics. This illustrates the network phenomenon of micro-macro linkages where there is feedback between local behavior and structural properties that have further effects that affect in turn local behavior.

Third, there are important lessons that bear on social organization from the Bell Labs example about average behaviors and group-level behaviors. We cannot take literally that people call phone numbers randomly with a uniform bias toward popular phone numbers.[20] Peoples' calls, like friendships, also cluster into communities, as measured by the coefficient of clustering in Table 1.1. The graph from Aiello, Chung, and Lu (2000:10) that follows their graph that is reproduced in our Figure 1.3 shows the distribution by size of connected components of the phone-to-phone network on the day studied, according to the frequency of these sizes. This too follows a power law. It appears that communities of different sizes replicate the power-law relationships of the earlier pair of graphs in Figure 1.3, each at a different scale. This exemplifies a scale-free relationship characteristic of many self-organizing systems. The biotech industry examples raise similar caveats, as does our study of Turkish nomads. Our glossary gives details for power-law phenomena and their connections with complexity theory, including self-organizing feedback between micro and macro levels of interaction networks.

Fourth, it is important to recognize multiple levels in social networks, such as the distinction between people at one level and businesses made up of people at another. Even if there are some scale-free invariants across levels, it is equally important to attend to the differences between them. The distinction applies in the examples we have discussed to phone callers, collaborative contracts made by biotech firms (Powell, White, Koput and Owen-Smith 2004), where the type of partner makes a difference, and to the case of our Turkish nomads, where individual and lineage level behaviors and networks are distinguished.

Fifth, scale-free power laws and micro-macro linkages, wherever they occur, capture very interesting properties of real social networks. Other properties, such as small-world characteristics of networks, and searchability, have already come into play in our scale-free examples, as they will our study of the Turkish Aydınlı.

Sixth, we can begin to see that from a careful examination of the structural properties of networks, we can formulate some general dynamical and evolutionary principles.

Probabilistic principles are perhaps the most difficult to master in the theory of network topology and dynamics that informs a new understanding of the feedback between structure and behavior. They are crucial, however, for a new type of anthropological research that is capable of understanding and dealing with preferential and behavioral gradients rather than stylized rules purported to characterize cultural and social systems. Some of the principles that follow are more immediately relevant to anthropological theory because they are easier to grasp and the micro-macro linkages appear in a more familiar and deterministic form that is no less powerful but far easier to apply and verify in ethnographic research.

> ***Proposition 2. Micro-macro (and macro-macro) linkages offer explanatory principles, some of which are highly deterministic.***

Micro-macro linkages predict global from local structure in networks. They give explanatory purchase on how local properties of nodes or their neighborhoods connect to global properties of the network.[21] Understanding such links can lead to a reevaluation of fundamental theory. Many such linkages are much simpler than the probabilistic scale-free networks, which are models of biased random graphs. In one set of examples of micro-macro linkage, what Arthur (1990) called a *network externality* or what we call a configurational effect—adding value through network sharing—has altered one of the basic assumptions of economics, namely that of uniformly decreasing returns. The case of two incompatible computer systems, one of which has n users, the other m users, is illustrative. The value of each system increases with the number of pairs in each group of users, $n \cdot n$ and $m \cdot m$, respectively. Every time the first group gains a member, the number of pairs of users who can share that technology rises by $(n+1)^2/n^2 \sim n+1$, that is, with increasing returns. A local process of adding a single node to a network operates through a micro-macro network multiplier to produce a nonlinear global property of groups for whom manufacturers compete to add value through compatibilities and sharing.[22]

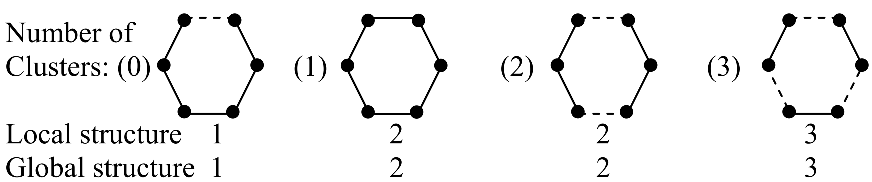
Structural *equivalence* (see Glossary) illustrates a micro-macro link between the neighborhoods of nodes as a local structure and the global structure of a network. Methods for using this mapping to create an image of the relations among positions that are emergent from structural equivalence are called *blockmodeling*. By measuring similarity of positions of nodes in a network by the extent to which they are connected to identical alters, blockmodeling leads to insights about the structure of social roles and how they concatenate the local and the global (Brym 1988, Stovel, Savage, and Bearman 1996, Kim and Bearman 1997).

Graph theory provides important contributions to identifying structural properties with micro-macro linkages. Clustering and balance, for example, are structural properties of *signed graphs* that have positive (+)

and negative (-) ties between nodes. Here we can speak of local rules whose repeated application automatically generates larger network structures. Theorems about signed graphs specify the micro-macro linkages between more extended local configurations of nodes and global properties of the larger graph. For ease of understanding balance and clustering, we can exemplify our positive ties by (+) =reciprocal friendships and our negative ties by (-) =reciprocal enmities.

A signed graph is *clustered* when its nodes can be divided into nonoverlapping clusters so that all the positive ties are within clusters and all the negative ties are between clusters. Figure 1.7, in which negative ties are indicated by dotted lines, shows four signed graphs with no, one, two, and three clusters, moving from left to right; the left most cannot be a single cluster because it contains a negative tie and so is unclusterable. The *clustering theorem* states as an equivalence that a graph is clustered when it has no cycle with a single negative (e.g., enmity) link. This is a micro-macro linkage where calculations of localized traversal structures (cycles starting from and returning to an ego) predict the degree of global clustering.[23] The clustering coefficient C that measures the extent to which those linked to a focal node are themselves linked (C_u for each node, and C as an aggregate across nodes) is also a local property that has a direct macro link. As C increases to 1, the entire graph becomes clustered. The coefficient T of transitivity of a graph has the same type of micro-macro linkage: when T is 1 for an entire graph, the graph is clustered.[24]

Figure 1.7: Signed Graphs with (0), (1), (2), and (3) Clusters



A signed graph is *balanced* when its nodes can be partitioned into two so that all negative ties are between and all positive ties are within clusters.[25] The balance theorem states as an equivalence that a graph is balanced when it has no cycle with an odd number of negative links. Only the two centermost graphs in Figure 1.7 are balanced: the two others have a cycle with an odd number of negative ties.[26] Calculations of localized traversal structures again predict degree of global balance.[27]

Some properties of networks have micro-macro linkages while others do not. Local and global degree have no micro-macro linkage, as noted earlier. Reciprocity as a local property has no macro implications for a network other than short-circuiting the possibilities for directed cycles (or indirect exchange). Measures of the centrality of a node or edge that depend on its position in the global pattern of a network already conflate the micro- and macro-levels. This eliminates the possibility of micro-macro linkages, which require that properties at different levels be defined independently in order to serve as explanatory principles.[28]

Structural cohesion is an example of a structural property that has many predictable effects and two equivalent macro properties. One of the macro-property definitions is that a *k-connected* subnetwork cannot be disconnected by removing fewer than k of its members. The other is that a subnetwork with cohesion level k is one that every pair of nodes has at least k paths and between them no two of which have an intermediate node in common. One of the deeper theorems in graph theory is the equivalence of these two properties, subsumed under the concept of connectivity level k.

The macro-macro linkage in this case helps to explain the predictive power of structural cohesion (connectivity k) at different hierarchical levels, which are ensembles of cohesive embeddings whose depths are measured by k (see Moody and White 2003). These multilevel embeddings correspond to stacks of embedded subnetworks having successively higher cohesion (and fewer members) the higher in the stack. The *k-components* of a network are maximal k-connected subgraphs. If they are of different levels of cohesion they may nest into hierarchies but any two k-connected subnetworks may have at most k-1 nodes in common. It is not so easy, however, to find a micro-property that serves to characterize cohesive neighborhoods in a network in a way that corresponds to the macro properties of k-components, and so to discover a new micro-macro linkage.

Proposition 3. Many structural properties have configurational effects, whether or not they have micro-macro linkages.

Many structural properties of a network may have predictable configurational effects on its future development, whether or not they have micro-macro linkages. They are established by empirical research by testing for predictive consequences that are replicable across different studies.[29] These effects make networks worthy of study in relation to many other phenomena.

In our study of the Turkish Aydınlı, reciprocity and structural cohesion are found to have major effects on a series of other outcomes, including properties of self-organization that govern kinship and corporate group organization, in ways that are similar to the dynamic of our example of a power-law model for formation of ties where we used preferential attachment to friends proportional to their popularity.

Proposition 4. Emergents may be local or nonlocal, depending on whether they have micro-macro linkages

An *emergent*, in the simplest sense, is a structural property that has configurational effects.[30] One way this is sometimes expressed is that when observing a network of interactions that is changing, something occurs that has not happened before, that breaks the rules for previous interactions, where further investigation shows that this something new does not occur until the changes in the network reach a particular configuration. Emergence is often defined as a surprising outcome of complex interactions to encompass this type of discovery. That definition, however, has the defect of subjectivity and dependence on our current state of knowledge, as, for example, about micro-macro linkages.[31] If we go back to the simpler criterion, however, we may find that the "something new" simply follows as a direct corollary of the network configuration of its micro-macro linkages and is not really an emergent. It may prove more useful to retain the term emergent to cover a broader set of possibilities concerning the appearance of new phenomena but to distinguish between emergents with a known micro-macro linkage and those with no known micro-macro linkage. We will call the cases of the former *locally based emergents* if the micro property is readily apparent to a local observer and *nonlocal emergents* otherwise—including the case where there is no micro-macro linkage. In either case the emergent, by independent empirical criteria, is taken to be one with configurational effects. Discoveries of new micro-macro linkages that explain emergents may be as important as investigating emergent properties for which no such linkages are known.[32]

We can now return to our examples of micro-macro linkages under Proposition 2 to sort out once again what is local and what is global, and how these may or may not be linked. Our first example, the model of preferential attachment, contains a micro property that is observable from local-level data, and so is a locally based emergent with a micro-macro linkage. The second, network externalities, is also a locally based emergent. In our third example, structural equivalence and blockmodeling, the criteria for micro or local structure were also locally observable but were expanded to include neighborhoods of nodes for which similarities link to global equivalence sets. In defining clustering and balance, however, the micro structure reached a level of abstraction that included cycles in which you can trace a path out from a starting node and back on a route that never repeats the same node twice. More abstract levels such as these at which micro and macro structures are connected require proof by theorems (e.g., Harary 1969) that are often beyond simple intuition but the global clusterings are so evident in these cases that they may provide a basis for local observability, assuming that you know what to look for.

Measures of centrality, however, are nonlocal properties if they depend on analysis of the positions of nodes or edges in the global network structure. We would not call having higher centrality an emergent property because, unlike cohesion, no emergence of a distinctive entity is usually implied. Reciprocity, on the other hand, considered as a micro property of dyadic relations, has no macro linkages but considered as a macro property in relation to a pair of endnodes is a nonlocal emergent. Reciprocity, that is, often involves a transformation of two independent nodes into an interdependent entity, the dyad. No micro-macro linkage seems to exist here because it is not possible in general to derive the distribution of reciprocity from knowledge of the attributes of pairs.

Structural cohesion has macro-macro linkages and may have micro-macro linkages if it is true that k-components are equivalent to (k-1)-cycle-components. In any case, the precise identification of k-components is beyond the capabilities of an observer who is not equipped with an algorithm of sufficient complexity. Structural cohesion is a hierarchically organized series of nonlocal emergents. Like balance and clustering, however, human beings in stable networks are in all likelihood very good at intuitive detection and making judgments about structurally cohesive groups.

Blockmodeling may also be based on global criteria for evaluating patterned equivalence. An alternative to blockmodeling based on structural equivalence, for example, compares pairs of nodes to identify regularly equivalent sets for nodes that by recursion have equivalent relations with equivalent sets of others. While structural equivalence entails a local neighborhood criterion, regular equivalence is identified by whether pairs of nodes are embedded in the same patterns of cycles. When applied to similarities in patterns of connected networks there will be local-global connections.[33] When applied to disconnected networks, as when finding a conceptual analogy between one narrative and another, we are studying nonlocal emergent patterns.

Nonlocal emergence can appear in unexpected places. Even for something as simple as whether pairs of nodes have reciprocal ties to have micro-macro linkage would require predicting reciprocity from properties of the individual nodes, which is not obvious from first principles. Tipping points often involve critical network densities at which new phenomena emerge. As an aggregate of nodal degree, tipping points have micro-macro linkages. If tipping points are dependent on structural cohesion, they involve nonlocal emergents.

Ethnography and Emergence

Ethnographers are in general very good at observing behavior and formulating rules based on observations. They can compare people's stated rules with patterns derived from observation, and they can predict or account for people's behavior accordingly. They can also formulate rules for exceptions to the rules, and get a good idea of how stated norms and actual behaviors differ, especially when they assimilate their normative thinking to that of the people studied but remain alert to discrepant behavior, i.e., they obtain the view of these people.

The relevance of emergents for ethnography is that there are some areas in which there are nonlocal emergents (centrality, reciprocity, structural cohesion, regular equivalence, more is different in terms of tipping points) that may, first, reflect and reveal powerful constraints and second, have powerful effects on their own. These may include effects on or constraints of social behavior, cognition, economics, politics, linguistic practices, and other domains that ethnographers study for which understanding will remain incomplete without network studies. Further, our theoretical understanding of emergent behavior will be sorely inadequate without an appreciation of how micro-macro linkages operate—as explanatory principles—within a network framework.

It would be immensely valuable for ethnographers to be able to show from empirical data over time how emergent processes happen in actuality. This is a major lacuna in field studies and in theoretical arguments. The inability to do so reflects an inadequacy rooted in widespread anthropological assumptions that the rules of behavior derived from observation should be fixed or static. Ethnographers need to be able to account for how rule-sets evolve, and how rules and social groups emerge out of interaction. Work with simulation models demonstrates how this might occur in ethnographic cases (e.g., Lansing 1991). Time lag in the dynamics of how patterns build up, reach thresholds, change form, and cycle downward is often involved. Dynamical models need to be sensitive to critical densities in networks and to demographics with time lags that produce nonlinear effects (Turchin 2003). Ethnographers possess the kind of data, that is, demographic and network data, to examine such processes directly and empirically, in observations over time or in time-coded network data.

Table 1.2 summarizes our discussion of structural properties. They can be classified into (1) Rule-specified properties, such as a customary rule of residence or one that governs membership in named groups, and (2) Rule-unspecified structural properties that are emergent in complex interactive processes (i.e., in networks) and that have demonstrable effects on interactions. Once a given property has emerged, passed some threshold, or in proportion to the extent to which the property is present, for example, the effects of an emergent property may be demonstrated.

Table 1.2: Classification of Some Structural Principles

Type of Property	**Micro-Macro Linkages** No	Yes
Rule-specified	***Mechanical model***, e.g., Named groups, Reciprocity, Cliques	***Mechanical model***, e.g., Matrimonial moieties
	Statistical model e.g., Residential clusters	***Statistical model***, e.g., MBD marriage preference
Rule-unspecified Emergents: Structural properties with configurational effects	***Nonlocal emergents***, e.g., Centrality, Structural cohesion, Regular equivalence, More is Different	***Local emergents***, e.g., Preferential attachment and power-law for popularity, Structural equivalence, Clustering, Balance

The rows in Table 1.2 distinguish rule-specified structural properties from rule-unspecified emergents and the columns subdivide these according to whether there are relevant micro-macro linkages within the model itself that would also explain the link between behavior observed at the local level and resultant structural properties at the global level. The micro-macro link might be seen as (1) a rule-specified property where the rule can also be seen as a relationship that has global implications for a network or (2) an emergent local property in a network specified as a pattern or probabilistic model that has global implications.

Anthropologists have tended to keep to narrow classes of static models for describing observed behavior in their ethnographies and in explaining the behavior observed. These correspond to properties of the first type and first row of the table: models of rule-specified behavior, either in the form of mechanical models or statistical models.

Examples of rule-specified principles of structuration that lack micro-macro linkages are reciprocity, mechanical models that assume a mutually exclusive sorting of individuals in named groups, and statistical models of residential patterns and clusters, given the fact that there are usual options or alternative patterns to residential choice. Cliques are another example: the local rule is easily specified but because cliques can overlap, their existence has no clear micro-macro linkage to global structure.

The anthropological model of matrimonial moieties is an example of a rule-specified property with a micro-macro linkage. In a moiety, the rule of marriage is that men of one group marry, reciprocally, the women of the other moiety, with locally identified membership being named and inherited in one of the two gender lines of descent. Moiety structure as a mechanical model sets up a micro-macro linkage between category membership and relational networks; the moiety rules operate locally in a way that is easily observable, and the global model of moiety organization is easily tested. If adhered to, the local rules and the global structure can hardly fail to be isomorphic as a single integrated structure.

Other types of marriage rules described by anthropologists, such as preferential marriage between MBD/FZS, also have micro-macro linkages but of a statistical sort, such as the tendency for MBD marriages to form a series of distributed links between local groups, whereas FZD marriages tend to form repeated reciprocal linkages over time (see Chapter 4). It is also possible to imagine an unrealistic extension of the statistical model to a mechanical one in which every marriage is with a MBD. In this case, the micro-macro clustering theorem illustrated in Figure 1.7 will predict from local behavior governed by the prescriptive cousin marriage rule that there must exist descent groups for which all marriages are between exogamous groups. If there are two groups, all the members of one group marry members of another (a matrimonial moiety, following the rule for balance). The same may be true for more than two groups but the more relaxed model of clustering allows members of one group to marry into any of the others. The question of what locally observed patterns of behavior imply for global social structure was a principal issue of the anthropological debate, for example, as in the case of the Purum (Schneider 1965).[34]

The focus of the second row of Table 1.2 is on emergent properties that provide some of the commonly used principles in the social sciences for describing structuration.[35] The distinctions in this row of the table have been discussed under emergents and micro-macro linkages. Structural cohesion, for example, is a nonlocal emergent except for the special case of cliques, which can be specified by an explicit rule. Its structural configurations are not so easily observable by ethnographers. Because they are not so easily observed without the use of network or dynamical analysis, the consequences of their configurations or time lags may come as surprising theoretical insights. Explorations of these structural properties with network analysis have the potential to make important contributions to ethnography in ways that are not easily achievable by other means.[36]

A key point of our discussion is that we are not just modeling nodes and links but are looking for some sort of interaction or action. In some sense, our mechanical model is nodes and links but the "statistical model" is actions that are linked by network and graph theoretic properties. As we move from description to theory a question arises that processes of interaction and emergence may help answer: How are concrete actions of self-reflective agents, who have rich decision processes and information processing and who are deeply embedded in social worlds, interrelated with the processes of emergence and change in the self-structuring systems they operate? Can we account for how organization, groups, institutions, and norms emerge and change and thus go beyond static representations? [37] Can we understand and model social processes and resultant cultural configurations more productively?

In the long run, questions like these constitute crucial concerns for the development of an anthropological network approach. Network theory in anthropology is not a closed book but, rather, one that is still being written. With further applications of a network-epistemic framework to case studies, it ought to be possible to provide answers to questions such as these and to give them prominence as organizing themes of an anthropological network theory through a build-out of the "relational ontology" that set the theme for this chapter. The steps toward a complete construction of this ontology could then be laid out in an argument. The crux of that argument would be the analytic connection between types of behaviors or links and the production of the model of the network as a system of such behavior or links. The reordering of our discussion and the comparison of case studies is not our object in this book but an argument of this sort might proceed in this order:

1) types of behavior and links
2) the relevant properties for constructing networks
3) the networks and their micro-macro links
4) feedback from global networks properties back to behavior
5) network analysis as theoretical simulation.

Unexpected Change: Emergence and Ethnography

Investigations into surprising outcomes that emerge from interaction have shown that change may occur without any new external event to precipitate the change or that serves to explain the change as a reaction to some new external context. When network configurations are at certain thresholds, dramatic and sudden change may also occur through cascades of interactive events, like the fall of the Iron Curtain. This is the field of study of complex behavior. Emergence of complex and unexpected outcomes from simple rules of interaction is the focus of study in this field.[38] Knowing the micro-macro linkages that might produce some phenomena does not make them predictable as to when they will happen, however, because structural properties tend to be distributed phenomena.[39] Structural properties with configurational effects can also be surprising in that they may lead to very rapid and unexpected change even if they have micro-macro linkages.

Those who research issues of complexity arising out of interactive systems and those who research networks have come to a common conclusion: when some new, unexpected, and unpredictable pattern emerges out of interaction, it is something within the structure or the dynamics or evolution of the network that has changed, such as reaching a critical density. Critical mass or tipping points are one model for such phenomena.[40]

Unexpected changes are regularly observed by those ethnographers who have returned to their field sites at various intervals, and by those who had done social histories of the communities they study. Historical and long-term studies have dissolved the myth of stability of the rural community.

When does Network Analysis Matter?

Having introduced some of the concepts of network and complexity theory concerning structural effects, interaction, and micro-macro linkages, we can offer ethnographers some general propositions about where and how the study of networks will matter:

> **Proposition A.** To the extent that global or structural properties of networks have effects that change over time and derive from micro-macro or mechanical linkages that are easily observed and stated, the ethnographer can grasp and analyze their implications directly, and network analysis may be unnecessary.

Ethnographers easily recognize and describe moiety systems, for example, which have an easily stated mechanical model for rules of inherited membership in opposing moieties and obligatory marriage between members of different moieties, consistent with Proposition A. Australian section systems, however, which often have named moieties inherited by a rule of descent with alternating generations of named section memberships in the same descent line, have generated much confusion over the validity of "unnamed groups." The logic of section systems creates an "unnamed moiety" in the opposite descent line whose existence as a social or implicit category is purely hypothetical. This residual and redundant category is unnecessary for the calculation of section membership and for identifying appropriate mates. The skepticism that abounds about "unnamed moieties" is well deserved. Our framework would lead us to side with the skeptics because the construct has no distinctive consequences independent of the named sections and named moiety. We would not call them a network emergent. In contrast, our approach to sidedness, as defined earlier, offers an example of how we validate a pattern that is unnamed but emergent from practice and that has definitive global consequences for network structure and subsequent behavior.

> **Proposition B.** When network properties and effects that change over time do not derive from micro-macro or mechanical linkages that are easily observed and stated, good ethnography that derives useful theoretical understandings of structure and change in social and cultural phenomena requires network analysis as a matter of course.

In Australian section systems, for example, the analytic problem of unnamed groups that requires network analysis is not that of "unnamed moieties" but of classificatory descent groups (see Denham and White 2004). These can be derived from micro-macro linkages only on the basis of imposing strict demographic constraints on the relative ages of spouses (Tjon Sie Fat 1983, Denham, McDaniel and Atkins 1979).

> **Proposition C.** Similarly, when micro-macro links are probabilistic, network analysis will be crucial to the kinds of estimation of probabilities that can lead to theoretical understanding.

This kind of estimation from analysis of genealogical networks for the Alyawarra is precisely what Denham and White (2004) set out to do in order to resolve many of the epistemic disputes over Australian sections systems and for the Alyawarra and closely related Aranda cases in particular.

Analytic problems that derive from the preferential attachment models underlying the phone-call example and the types of networks whose characteristics are summarized Table 1.1 also fall under the heading of probabilistic micro-macro linkages.[41] These are often the most difficult to analyze (see Powell, White, Koput and Owen-Smith 2004). The use of degree distribution micro properties, however, is a means of opening up the classical anthropological problems of identifying preferences.

> **Proposition D.** When micro-macro links are sufficiently abstract as to require proof by theorems, network analysis will be crucial to theoretical understanding.

> **Proposition E.** Similarly, when micro properties of behavior in a network are sufficiently vague or ambiguous when formulated as rules or patterns by the ethnographer, network analysis may be crucial to theoretical understanding.

Edmund Leach's study *Pul Eliya* (1961) provides an excellent example because he published complete records of genealogies, land transactions, and political officeholdings along with narratives in which individuals were identified by codes that identified them in the genealogical, residential, and landholding networks. He only hints at certain of the network patterns that were discovered in a network analysis of his data by Houseman and White (1998a), which showed a complex form of sideness in which women could switch the matrimonial side they would normally inherit if they lacked brothers and stood to inherit agnatic property and if they took a husband from such a distant village that his sidedness did not become an issue. These findings explained many of the otherwise anomalous patterns of behavior recounted in Leach's ethnography.

What these propositions and examples show is that if anthropologists begin to think of their ethnographies and ethnographic problems in terms of the basic intuitions of network analysis they may discover common principles that are amenable to testing as hypotheses that may solve a wide range of open problems and controversies in social and ethnological theory and ethnohistory. One example is the applicability of network analysis to understand dynamical and structural principles that apply in circumstances in which the relationships in the network have a weak or negative self organizing effect (like a negative rule of prohibiting marriage with anyone you are connected to).[42]

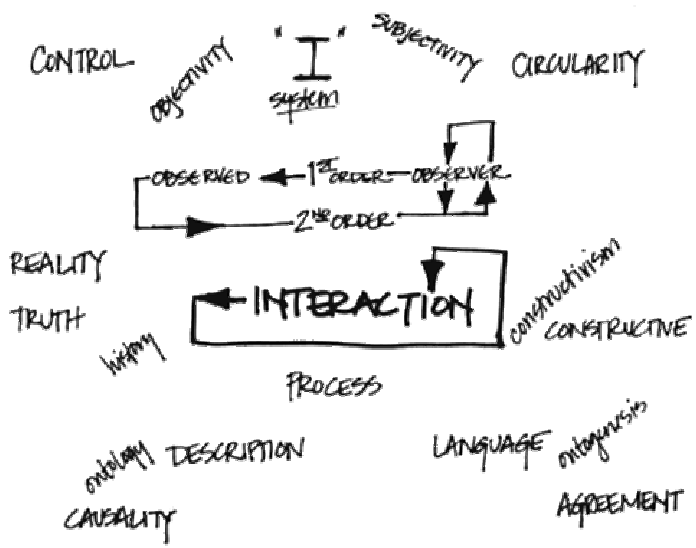
Sidedness: An Example Where Propositions B through E Apply[43]

Balance or *sidedness* in a marriage network is a good example of a phenomenon that is difficult to observe ethnographically, consistent with Propositions B through E, because, unlike moieties, it does not come neatly packaged in named divisions and a recognized rule of descent through which they are inherited.

Sidedness exists in a marriage network wherever positive and negative relations can be assigned analytically to male and female links (in either order), and there are no cycles of marriage in which the product of the signs of gender links are negative. It took nearly 100 years, from Morgan (1871) to Lounsbury (1964), for this type of balance to be recognized in sided kinship terminology where ego has one set of terms for those in "my group" and an opposing set that distinguished the descent lines of "those we marry." It took another thirty years for this possibility to be precisely described for kinship networks independently of named moieties (White and Jorion 1992, 1996) and to discover sidedness empirically in societies throughout lowland South America and in South Asia (Houseman and White 1998a, b). Ethnographers in these and similar types of societies are negligent if they fail to consider sidedness as a societal possibility. White (1999) set about to validate these findings by showing through a statistical network analysis that the behaviors that generated sidedness were local behaviors that individuals could recognize and act upon, such as marriages with certain relatively close and identifiable or traceable types of kin. That approach, which depended on a comparison of actual behavior to simulated random behavior under identical demographic constraints, established a principle for network analysis of the utmost importance: unnamed types of global behavior can be validated by finding the local recognizable behaviors that generate them. The micro-macro link is established here not only by the balance theorem but by detailed analysis of the ethnographic network data to understand how it is that localized structures of sidedness are intentionally created, recognized, and utilized by people in their everyday lives.

These are the kinds of discoveries for which there are whole subfields of anthropology waiting to be understood and existing data to be reexamined. Sidedness may be taken as an emergent perhaps not for the people studied but for the ethnographer who has no theory to explain why global structures of sidedness are found throughout much of lowland South America and South Asia with consequential correlates in inheritance practices, kinship terminologies, political succession, concepts of identity and exchange, and a host of other domains. For the skeptical ethnographer who wishes to report only groups that are explicitly named or rules explicitly stated, sidedness as an emergent must be either rejected (even though people usually will have ways of explicating their practices) or remain a mystery. At two steps into network or graph theory, however, the mystery is solved by the balance theorem, of which practitioners are intuitively aware in their very practice: if local behavior is perfectly balanced in a connected network, global behavior must necessarily be perfectly balanced as well. Ethnographers now must confront new uncharted phenomena: the existence of actual and validated sidedness structures and hundreds of societies where relevant data on social organization ought to be reexamined if ethnographers were blinded by their biases against unnamed structures.

Emergence and Network Analysis in Ethnography



Paul Pangaro 1990, Course Description (Cybernetics)

Social Organization and Structure

The distinction between structure and organization provides an ethnographic starting point for the study of emergence: social organization defined as the fluctuating patterns of social behavior—"people getting things done by planned action . . . , action in sequences in conformity with selected social ends"—and social structure as the stable configurations that are replicated over time—"those social relations[44] which seem to be of critical importance for the behaviour of members of the society, so that if such were not in operation, the society could not be said to exist in that form" (Firth 1951:31, 36). In this conception stasis, change and the relation between them require explanation. In Firth's conception it is not rules but social relations that emerge, remain, overlay, merge, fade, dissolve, and reemerge, and that may call up new conceptualizations.

Each pattern of relations at a point of time has structure, and some retain robust configurations or resilient refittings that adjust to changing circumstances. Extending Firth's insights, because networks lend themselves to identifying structural patterns of social relations at different points in time, we can look at how these patterns change with time.

Organizations and Groups

Given the limits of knowledge in an ethnographer's practice, Leaf's (2004a) review of network and ceremonial analysis contains an argument that resonates with our view of the contributions of network analysis:

> Organizations are arrangements of positions or relations with some common . . . purpose, such that those who occupy the positions or relations have mutual rights and obligations. Organizations are not groups. Groups are recognized sets of actual individuals. While organizations are usually formed by groups, groups rarely form just one organization. Virtually all important groups in a community are multiply organized.
>
> If culture were unitary─if in every community there were just one system of ideas and values attached to one social organization─the relationship between organizational ideas or rules and actual group characteristics would be straightforward and we could apply the simplistic norm-versus-compliance or structure-versus-behavior way of speaking that dominates Positivistic sociological theory. But because culture is not unitary the relationship between "social structure" and "social organization" is complex and for a long line of Positivistic ethnological theorists from Radcliffe-Brown to Bourdieu, the inability to describe it has consistently led to confused and arbitrary prescriptions for social theory as such. (Leaf 2004a:303)

We are attempting to break out and provide an alternative to the norm-versus-compliance and structure-versus-behavior ways of speaking that dominate social theory in our ontology of network analysis. For us, as with Leaf, the behavior of people who interact in the context of multiple groups and organizations is crucial to ethnography but this multiplicity also makes it impossible for people to conform to a uniform set of rules:

> We can think of groups and organizations as existing in the ethnographic now. When we conduct a field study they are what we observe most directly. We readily find sets of people who identify themselves as associated with one another and usually with some material apparatus, and there are organizational charters that the members of such groups can describe and hold each other to. Over time, however, the group characteristics and the organizational forms interact and the results of this interaction are not

> predictable from the group characteristics and organizational ideas alone. The relationships people form on the basis of any one organization necessarily reflect their commitments in terms of their other organizations they use, and also in terms of what is being done in related organizations in other groups. . . . [T]he group's organizations . . . cannot be expected to conform to the "rules" of just one organization. (Leaf 2004a:303-304)

The problem of representing institutions as seeming to be "organizational totalities that encompass many separate and smaller aspects of specific types of organizations," for Leaf, "is that it is quite literally an illusion, socially constructed by very definite and describable indigenous processes," and in this we are in complete accord.[45]

Emergent Rules and Emergent Groups

The common anthropological idea of representing culture by a shared set of rules, in Leaf's view and ours, is largely a façade. Behind the appearance of shared cultural or institutional forms for any given community or society there lies far more heterogeneity and structural variability than the anthropological construct of "shared rules" is wont to admit. Of course, it is well accepted and widely understood in anthropology that stated rules (normative statements) often fail to fit actual behavior. For many anthropologists, the problem of heterogeneity and appearance is a slippery slope that requires resistance in the form of insisting that patterns of behavior described by anthropologists should be limited to those commonly recognized and named by indigenous informants. Having labels for things seems to be, for many anthropologists, a criterion for something in the domain of culture. The validity of unnamed groups and social rules that are unrecognized has been long-debated in anthropology (see our discussion of section systems under proposition A).

One way to address the unlikely possibility that social rules will conform to a single organization and constitute a unitary description of behavior "is to focus one or more type of relations, trace out the way individuals are connected through them for an entire community, and compare this pattern with what we would expect from the corresponding organizational rules." For Leaf (2004a), this is the contribution of network analysis.[46] The social interactions of people form social networks. A network thus formed represents the choices, collaborations, and contestations of a multitude of actors. The central focus of network analysis is on patterns of interaction: they tell us a great deal about human agents and agency in the contexts of continuity and change.

Just as we may distinguish between stated and emergent rules, however, there is at least the possibility of distinguishing between named and unnamed *groups*. Leaf, however, does not discuss this latter distinction. We are confident he would agree that unnamed groups not only exist but that, through network analysis, they can be identified and their *cohesion* (resistance to disruption; consequentiality) validated.[47]

One of the three studies Leaf cites does exactly this.[48] Moody and White (2003) define structural cohesion in terms of patterns of relationships that in turn define clearly delineated emergent groups. In one of the examples that they use to validate predictiveness, it is the structurally cohesive groups of students that are emergent and that have as a predictive consequence significantly higher self-reports of attachment to school, co-varying with higher levels of cohesion. Similarly, Brudner and White (1997) show emergence of a class division out of structural cohesion of a delineated group emergent through marriages. These are clearly groups and not roles. You belong to a friendship group; you belong to a class. A casual observer might not know from simple observation and the naming of groups what group a particular student or farmer belongs to because these groups are much looser in density than cliques and, hence, less visible to the outsider. A trained ethnographer is in the same predicament. Insiders, however, often have more extended knowledge of the boundaries of their cohesiveness and solidarity. Not to know about cohesive groups in the emergent sense of structural cohesion is a liability that can often lead to serious consequences and is one of the things that people in close communities usually pay close attention to in their social life.

Emergent groups have important implications for anthropological discovery and theory. If we can learn to recognize emergent groups by their structural cohesion, for example, we may also come to recognize other differentials, as, for example, that a difference in the structural cohesion of groups also operates as a power differential that is asymmetrically distributed across members of a community. This is as evident in the world economic network as in the nomad clan discussed in this book. Recognition of asymmetry and inequality seems to be something that many ethnographers resist in their descriptions.[49]

New questions and problems can come out of the maturation of a network ontology for social theory and observation. To what extent over time, for example, are named groups a product of organizations even though in the short term such groups (and emergent groups) construct organizations? How can we characterize these sorts of feedback?

Cohesion and Emergent Groups

Cohesion is a structural property: resistance and reaction as an organized entity vis-à-vis outside perturbations or events. It entails bonding, sticking together, coherent resistance, and reactivity to outside perturbation, or disruption (see Roehner and Syme 2002). Cohesive groups have something of a mixture of the properties of an organization—"people getting things done by [planned] action . . . in sequences [in conformity with selected social ends]"—and of social structure as stable configurations. Just as Firth (1951) showed the need for a concept of social organization as a bridging analytic concept between structure and behavior, emergent cohesive groups provide a further dynamic bridge between structure and organization. To specify our contribution more precisely, an organization, as an indigenously constructed set of mutual expectations, is generally unspecified in time. Our networks, based on observed relationships recorded in a systematic dataset, are specified in time. As the network property of cohesion emerges in a network, the individuals in the cohesive set are taking on, through concrete social relationships, the form of an organization. Network analysis, then, provides a means for studying how organizations come about, how they are maintained and transformed, and how they are dissolved.

A cohesive group does not need a plan and a selection of social ends to resist its disruption and destruction. Cohesion has "etic" and "emic" aspects that do not always match. A cohesive group as defined etically from network analysis may have the properties of resistance and reactivity independently of "emic" definitions. If it has these properties it is, in our terms, an emergent group defined by a structural property (here, a particular kind of structured subgroup) of networks. It may also be a nonlocal emergent out of interaction in a network. This relates back to the third of our propositions regarding network theory, namely, that emergents in networks are structural properties (and emergent entities) that have predictable and replicable consequences for changes in the phenomena we are studying. While one kind of group is those sets of people associated with or defined by name, another kind, the locally or nonlocally emergent group, includes structural entities that are changing, often becoming entities or organizations, and these changes may give rise to new configurational effects. From the viewpoint of network structure, the multiconnected group with level k of structural cohesion provides a cohesive unit with the internal dynamical quality of being able to coordinate, synchronize, store, delay, and respond—all of which require robust internal communication among its parts (Moody and White 2003).

So? If you cannot see these emergent groups as a fieldworker, do they have any reality? If they are not easily observable, why bother with them? We ought to care about cohesively emergent structures, however, if they have configurational effects. Does an emphasis on emergence unlock significant ways to understand micro- and macro-historical change and group process? In this book we look at emergent groups in a way that could not possibly be divined by ethnographers, as they are not predictable in any obvious way from local rules of interaction;[50] yet, they have truly surprising properties and configurational effects.

It can be objected that cliques rather than structurally cohesive groups are the more natural candidates for emergent cohesive groups: they are sets of people all of whom have ties to one another, such as a set of friends. Cliques are defined relationally and so don't have to be named by their members in order to exist, so we might call them unnamed groups. But an ethnographer would not need network analysis to identify cliques even though they are defined by networks because they are in principle easy to deduce from local knowledge alone: To find a clique of friends you may start with one person, and if they will tell you who are their friends, you create a distinct clique for each complete subgraph of ego's friends, that is, where all are friends of one another, assuming you can find that out reliably.[51] Cliques are locally emergent groups because an ethnographer can identify them by observation and questioning, and people usually have indexical ways of referring to the cliques of which they are members. We might deduce from our Proposition A that ethnographers would do clique analysis rather informally because if one can know people's relationships in the first place they are easy to identify.

Factions as secret groups among friends or allies are another good example of Proposition A, this time requiring effort at reconstruction that might well rely on inferences from network analysis because faction membership is not a public matter and broad consensus identification of members is lacking. With greater attention to the details of the shifting relationships that constitute factions comes a deeper understanding that factions are themselves forever shifting (Leaf 2001).

It also happens that cliques are a terrible concept for either an ethnographer or network analyst to work with because of the strict definition of a clique as a maximal set of persons all of whom are related by some tie such as friendship. There will often be hundreds of cliques in a moderate-sized network. The problem is that cliques in which all pairs are connected will overlap in a myriad of ways that may not lead to any coherence except that there might be a few distinct larger clusters, and these clusters will have ill-defined boundaries. Such clusters that do exist will usually be evident to various insiders. If we take a certain cocktail party at a university gathering, for example, one might recognize that the physical scientists form one cluster, the humanists another, and so forth, with plenty of overlap. If so, these clusters can be named, their characteristics are part of local knowledge, at least on the part of some, and so forth.

Because many individuals will typically be members of multiple overlapping cliques simultaneously, cliques do not correspond to a single organizational type and because of the problem of overlap they cannot constitute groupings in which a set of rules or conventions is shared. They may shift dynamically in that individuals who belong to more than one clique typically change from one to another depending on context.[52] Cohesive groups, however, may be sufficiently coherent that they operate as organizations with a singleness of purpose. Degree of consensus in a structurally cohesive hierarchy might be expected to mirror the levels in the hierarchy. Even informal consensus, which this kind of in-built hierarchy facilitates, may be sufficient to construct informally shared purposefulness without the need for a formal plan or charter. Cliques, because they represent in the strict sense complete connectedness, such as face-to-face interactions in small groups, are best considered as maximally dense communicative or interactive contexts that are embedded within larger cohesive groups that have more definable boundaries. Further, cliques are not the units of maximally cohesive groups. These are defined as sets of people who (a) cannot be separated by removal by fewer than k members, (b) all have k or more paths that connect them to others but not through the same linking nodes, and (c) have a measurable level—namely the maximal value of k—of structural cohesion.

What Figure 1.8 shows is a network with cohesion of level 4 that contains a clique with four persons {9,10,11,12}. The clique itself has a cohesion level of 3. The structurally cohesive groups consisting of persons 1-8, or 1-12 thus have a level of cohesion of four, which exceeds that of the clique of four.[53] There are other cliques in this network that are of size three—{1,2,8}, {4,5,6}, {4,6,7}, {1,7,8}, {1,2,5}, {2,3,8}, {3,4,6}—but it is not the size of cliques that defines cohesion.

Figure 1.8: A Cohesive Group that excludes a clique

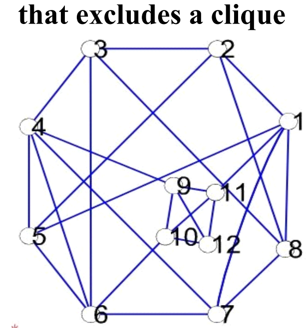
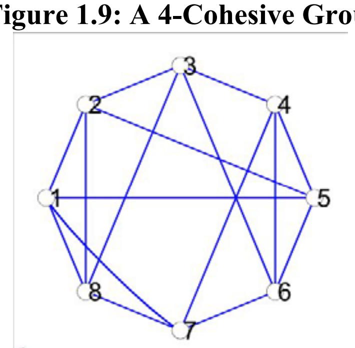


Figure 1.9 shows a cohesive subgroup of the network in 1.7 that cannot be disconnected by removal

Figure 1.9: A 4-Cohesive Group



of fewer than four nodes. Node 3 becomes disconnected from 4, 5, and 7 only if 2, 4, 6, and 8 are removed. Similarly for other nodes. The 4-clique in Figure 1.8 does not have this property: 12 can be separated from other nodes by removal of three nodes out of the 4-clique.

This kind of distributed pattern of cohesion ought to be surprising to an ethnographer: the identification of the boundaries of cohesive groups is not intuitively obvious. It will be useful and necessary to detect such emergent groups by means of network analysis if such groups have important consequences independent of other network properties or attributions of individuals.

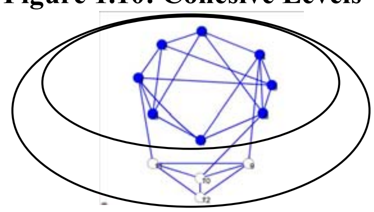
Given a well-grounded concept of emergence out of network interaction, we begin to have a framework for understanding the approaches and goals of many of our network analyses, why they are crucial for the practice of ethnography, how they connect with the theory of emergent phenomena and complexity, and how they change our ability to understand social cognition and discourse. As an example of the latter, one of the great lacunae of ethnography is the understanding of "emic" concepts that have shifting referents because the referents themselves are emergents, as is the case with structural cohesion. Only once we are attuned to network concepts such as structural cohesion might we be able to understand indigenous references to emergent groups that have shifting boundaries, for example. Still, the identification of cohesive subgroups in a social network does not require that the relationships in question (e.g., those of kinship) have logical consistency. A tendency toward logical consistency within a cohesively interacting group is not a presupposition needed to study interaction and may be an outcome of interaction that depends on the extent to which the emergent cohesive group operates as a purposive organization that evolves its own codes, procedures, and sequences of actions to meet social ends.

Structural Cohesion as a Nonlocal Emergent

Structural cohesion is a structural property that provides a way of mapping out an important internally variable property of cohesive embeddedness in networks. This property is one we use extensively in our network analyses; here, we show how it relates to emergent groups. It is not directly observable by ethnographers but has a wide range of important predictable consequences (Moody and White 2003, Brudner and White 1997, White and Harary 2001). It is a nonlocal emergent based on formal definitions that gives rise to a descriptive measure or structural variable as to how emergent blocks within a network are hierarchically stacked by level of multiconnectivity. The *multiconnectivity* of a pair of nodes in a graph is the maximum number of paths between them that have no linking nodes in common. It bears repeating that a largest set of nodes (individuals, families, etc.) with multiconnectivity k within the graph is a *k-component.* Here k is also equivalent to the minimum number of nodes that, if removed, would separate the subgraph (also called the size of the cut set of the subgraph).

Figure 1.10 revisits our example, this time showing how our level-4 cohesive group of 8 persons (the dark nodes) is embedded within a larger level-3 cohesive group of 12 that includes those in the 4-clique (the lower, white nodes).

Figure 1.10: Cohesive Levels



Higher levels of k-connectivity are always embedded in lower ones, forming a hierarchy of levels of cohesion. It bears repeating that multiconnectivity hierarchies may overlap but the overlaps are limited to a smaller number of nodes than the cut-set sizes for the overlapping k-components. So formulated, structural cohesion at different levels in multiconnectivity hierarchies have configurational effects on organizational communication and efficiency, economic exchange, the dynamics of power and prestige, formation of social class, and a host of other phenomena.

The predictive power of multiconnectivity hierarchies as empirical measures of structural cohesion derives from how they are analytically constructed from some of the fundamental theorems about graphs: theorems of multiconnectivity that establish formal equivalence between a structural property of the cut-set size of a graph and a traversal property of a graph, its minimum multiconnectivity number. These two facets of structurally cohesive blocks give them a resistance to disconnection and a capacity for redundant transmission at different levels, both of which are measured by the same parameter k that defines k-components. The utility, computability, rationale, and predictiveness of measures of structure cohesion are amply presented by Moody and White (2003). Because we use this concept in our analyses, we expand below on some of its properties.

Bounded and Overlapping Multiconnectivity Hierarchies

Multiconnectivity groups in a network are emergent structures with boundaries that are precise, unambiguous, and easily identifiable by the appropriate cohesion-finding algorithm (Moody and White 2003). Multi-connectivity theorems are directly applicable to the sociological concept of cohesion and thus describe and measure the distribution of different levels of structural cohesion in social groups. Where multiconnectivity groups occur outside the context of named social groups, they may define structurally cohesive groups that may be treated as emergents, hence, locally noticeable in "emic" terms as well, provided that it can be shown that these emergents have configurational effects.

The idea of boundaries within a network based on levels of network cohesion deserves some preliminary amplification for several reasons. First, group boundaries are of fundamental importance and interest to anthropology. Second, the boundary problem is a central area of recent advance in network methodology (White and Harary 2001). Boundaries can be clearly delineated for those subgroups of a network that have different degrees of cohesion. This defines a measure of variability in cohesive memberships that applies to individuals. Third, these boundaries may change over time, and such changes, because they are precisely specified, are valuable in studying network dynamics. Fourth, the structural cohesion variables constitute in their own right a set of measures of cohesion that have demonstrable and replicable effects across many different types of network studies. In the same year that Hage and Harary (1997) used the concept of k-components as a measure of the "toughness" or robustness of networks, Brudner and White (1997) used it to show how network processes of family inheritance and the decision making of individuals in marriage choices mutually affect one another in the process of class formation. Powell, White, Koput, and Owen-Smith (2004) used k-components in their findings that as the world biotechnology industry evolved a network of collaborative contracts in the period of study from 1988-1999, the predominant predictor of how firms chose partners, alone or in concert with other variables, was the multiconnectivity of partners. Our analyses make considerable use of variables that deal with structural cohesion.

Our approach takes the bounded units defined by subgroup cohesion to provide an independent variable in networks of relationships recorded in long-term studies by ethnographers for purposes of testing new hypotheses about the effects of structural cohesion. We expected this approach to work because Moody and White (2003) found multiconnectivity and *social embeddedness*—the deepest k-components to which actors belong (for higher values of k-connectivity) in larger cohesive groups—to outperform many other potential predictors of downstream consequences of cohesion, both network variables and individual level attributes.[54] Many of our hypotheses concern the feedback relationships between individual decision making and their social embeddedness. We also look at group-level processes, such as how people "vote," via their network behavior, for the emergence of leaders, how such group-level processes interact with individual level characteristics, such as those of emergent leaders, and the way that emergent leaders were embedded in the network. Further, we find that the structural cohesion that surrounds intergenerational transmission and reproduction is organized in emergent multiconnectivity groups that operate as the social embeddings of the primary action groups in the society we study.

Edges and Boundaries

This book is not a network ethnography in the narrow sense of a descriptive study of networks of relationships in an ethnographic setting. Rather, it focuses on the use of ethnographically collected data to direct our attention to concepts that posit and derive theoretical propositions from a series of "edges of community" for which some relationships point outside and others inside. Because many graph theorists conceive of relationships as boundary crossings spanning different nodes or spaces, they use the term edges as we do here for concrete relations as well as analytical boundaries. A comparison of inwardness versus outwardness is undertaken to ask what different types of edges entail for boundaries and boundary crossings for communities, ethnicities, societies, and cultures.

This view of a network study and its place in the study of culture and social interaction also expands the standard sociological concept of a network study (e.g., Laumann, Marsden, and Prensky 1989) as one that must specify an organic boundary to the network to be studied, which is a nod, again, to self-closure. This requires using either a nominalist approach in which network members are defined by their attributes, their statements, lists of members of groups, and so on, or a realist approach that starts from a given group and extends the boundaries of the study to all those connected to it. Our approach is not simply one that takes a realist approach and looks at how network members are socially embedded. This much is already prefigured in Radcliffe-Brown's conception of networks, which came to be implemented for a time in sociology under the assumption that patterns found in the blockmodeling of social roles, for example, were intrinsically stable and demarcated mutually exclusive sets of people. Rather, it enlarges the way the realist approach itself is currently constructed. Boundaries of networks should not be established simply or artificially by the reach of the sample of network observations but by how various overlapping and cross-cutting embeddings are defined by boundary conditions of multiple overlapping subgroups in a network. Rather than try to segregate mutually exclusive sets of individuals who occupy certain roles, as in the blockmodeling approach that partitions the nodes in a network according to patterns of ties, the theory of cohesive blocking constructs a different framework what captures the fact of overlapping, embedded, and cross-cutting subsets as part of the very phenomena of cohesion itself.

This approach to network studies often makes use of situations in which a complete network survey is done for a group such as a community (Brudner and White 1997) or an industry (Powell, White, Koput, and Owen-Smith 2004) but links between members of this group to the outside are also elicited without extending a complete mapping of the network to the internal relations among "outside" nodes.

Our study of the Aydınlı, as with previous studies ranging from a Mexican village to the industry of biotechnology,[55] includes links among members of the nomad clan in residence but also links to those who have left the clan and migrated to settle in villages, towns, or other nomad groups, and utilizes comparisons between stayers and leavers to test some of our hypotheses about the effects of social cohesion. This is not a totalizing approach but one that pays attention to similarities in patterns of connection to these outside nodes and to consequences of these external interactions.

Further Reading

Classics in the anthropological study of networks from the 1950s through the 1970s include Barnes (1954), Bott (1957), Turner (1957), Mitchell (1969), Kapferer (1972), and Boissevain (1974). For readings and introductions to networks as an intellectual paradigm in the social sciences in ways not envisioned by anthropologists of the 1960s see Wellman and Berkowitz (1988, 1997) and Berkowitz (1982) Recent introductions to social network analysis include Degenne and Forsé (1997) and Scott (2000). Detailed methods and guides to analysis are featured in Wasserman and Faust (1994) and de Nooy, Mrvar and Batagelj (2003). Batagelj and Mrvar (1998) and Borgatti, Everett and Freeman 1995a, b) provide computer programs and manuals for network analysis.

Notes

(see http://eclectic.ss.uci.edu/~drwhite/turks/NomadBiblio.pdf for the web version of the bibliography)

1. John Barnes' (1954:43) network study of a fishing village in southwest Norway was seminal in its claim, following the metaphor of Radcliffe-Brown, that the whole of social life could be seen as "a set of points some of which are joined by lines" to form a "total network" of relations, but this was not the approach that he cultivated. He focused on the informal sphere of interpersonal relations, a "partial network" of kinship, friendship, and neighboring within this total network. While he showed how these primordial relations linked community members into the national society, he did not go further to show how networks constituted and linked into a variety of economic, political and other institutions. Rather, he saw the primordial relations of kinship, friendship and neighboring as constituting a relatively distinct and integrated sphere of informal interpersonal relations. In using this approach for community study, however, he in many ways surpassed Mitchell's conception of the use of network analysis strictly as a set of tools rather than as an approach to social theory.

2. The average of a local property is still considered to be a local property.

3. An extended version of micro-macro probabilistic models as applied to organizational behavior is given in White, Owen-Smith, Moody and Powell (2004).

4. The number of nodes *m* is the only parameter in the pure scale-free model. Barabási, Dezsö, Ravasz, Yook and Oltavai (2002) show that degree distributions generated by this model are rescaled in f(k)/2m2, α=3.

5. By taking logs of both sides of an equation we see that the exponential log f(k) = constant + k log C is a linear relation between k and the log of its frequency f(k), while for the power law log f(k) = A - α·log(x), which is a linear relationship in a log-log plot.

6. This linkage is probabilistic and therefore difficult to match directly against empirical data, but Bollobás and Riordan (2003) provide the best probabilistic treatment of micro-macro linkage. The result that α=3 is derived from numerical simulation but is also proven as a mathematical theorem for a continuous-time dynamical rate equation for changes in *ku* and by a master equation approach (Albert and Barabási 2001:28). While Albert and Barabási (2001) regard preferential attachment and incremental growth as both necessary for power-law distributions of degree, Eppstein and Wang (2002) show that power-law distributions can result equally well from random replacement of connections by preferential attachment, without incremental growth.

7. Again, if f(x) = A·*x*-α, then log(f(x)) = A – α·log(x), which is a linear relationship in a log-log plot.

8. Power-law distributions for preferential attachment in networks entail an extended range of network hubs, which are linked to unusually high numbers of others.

9. Source: http://www.math.ucsd.edu/~fan/random.pdf (Aiello, Chung and Lu 2000).

10 We may also ask questions that are more detailed about observed degree distributions such as those in Figure 1.3. Why do these two distributions differ, for example, even if modestly, such as the slight bow in the outgoing calls

graph? Could these deviations from the power-law model be due to differences at different levels of scale in the calling behavior of individuals compared to that of businesses, which use calling campaigns, automatic dialing, and computerized directories? The shift in the outgoing calls plot is where individuals tend to leave off calling (~60 calls a day) and mass dialing takes over. For calls in the lower (private) range, does $\alpha out \sim 3$, approach the theoretical model? For the upper range of the distribution, where automated phone calls occur, $\alpha out < 2$. This shift in slopes diminishes for αin to a difference of 2.6 (lower range) to ~2 (upper range).

11. When $1 > a \rightarrow 0$ the probability of calling any given number, or being called, becomes more uniform, and the distribution shifts to exponential decay and eventually becomes Gaussian at $\alpha=0$. For any uniform random graph with y vertices of degree x such that $\log(y) = A - \alpha \cdot \log(x)$, if $\alpha < 1$ the graph is almost surely connected, $1 < \alpha < 2$ entails that nearly all nodes are connected while smaller components tend to be isolates; large hubs are relatively more frequent. For $2 < \alpha < 3.4785$ there is a giant component and smaller components are of size order log(n), and for $\alpha > 3.4785$ there is almost surely no giant component (Aiello, Chung, and Lu 2000:3).

12. Further, because private citizens are not overburdened with calls, businesses often make extra efforts to seek targeted call campaigns (and exchanges of specialized target lists) that increase local inequality for their outgoing call. Private citizens seem to have greater local inequality for incoming than for outgoing calls, which might result from this targeting by businesses. Businesses may have more global inequality (higher α) in their incoming than their outgoing calls, which might reflect private callers' stronger tendency to strict preferential attachment to degree that would necessarily approach the theoretical model of $\alpha \sim 3$ in such a large network. Note also that the shift of the alpha parameter for outdegree diminishes in the indegree graph for α_{in}, but not entirely, to a difference of 2.6 to ~2.

[13] The balance of processes and local-global feedback in a network can also be seen in terms of the transition from a controlled disease to an epidemic. This occurs where the number of nodes that become ill and contagious per unit time exceeds the number that recovers. In a network this threshold to epidemic spread of disease normally occurs where the mean degree of nodes exceeds the variance in degree, so standard policy for AIDS and STDs is to try to reduce the mean number of sexual contacts. This is effective when the tail of the degree distribution is not 'too fat', where $2 < \alpha < 3$, where the variance is infinite. When $\alpha > 3$, however, the tail is so extreme it is no longer 'fat' enough to create infinite variance. Infinite variance is a sufficient condition for diffusion epidemics to occur in network transmission. Thus, in a world population that is practically infinite, however, if $2 < \alpha < 3$ for the network of sexual contacts, the variance $\langle k^2 \rangle$ of degree is nearly infinite and epidemics cannot be controlled because an epidemic threshold is absent (Dorogovtsev and Mendes 2003:188-189). When $\alpha > 3$, however, epidemics are not inevitable (Liljeros et al. 2001, 2003, Jones and Handcock 2003) and the epidemic threshold will depend on the contact mean

and other factors.

Understandably, then, for a world population, $\alpha = 3$ should be the dividing line between networks that transmit disease through sexual contacts, with the healthy state being $\alpha > 3$, and other networks that transmit information and resources and have local organization and neighborhood heterogeneity, with the normal state for networks being $\alpha < 3$.

14. Probability models are themselves complex, however, and the debate over the relationship between network topology and social policy concerning AIDS and STDs illustrates the importance of understanding how micro-macro linkages. Some researchers advocate reduction of sexual contacts that act as hubs in a transmission network (Ball 2001, Barabási 2002, Dezső and Barabási 2001, Pastor-Satorras and Vespignani, 2001a, b). Others have shown, however, that sexual contact networks have multiple independent paths of cohesive connection even for sets of nodes of low degree, so that reduction of activity by sexual hubs will not eliminate STD transmission (Moody 2002a, b).

15. We have not invented these constraint lines ourselves: they are also found as derivations from the mathematical models of Dorogovtsev and Mendes (2002:29).

16. Barabási (2003:72) does not give the clustering coefficient nor the coefficient under the null hypothesis, as does Newman (2003:37). Bollobás and Riordan (2003:21) derive the expected clustering coefficient $\hat{C}$ in a scale-free model as a function of n=number of nodes and m=av.degree m as $\hat{C}$ = (log n)2 (m-1)/8n. Because we have n and the average degree for each network in Table 1.1, expected coefficients were calculated from these values.

17. This hypothesis cannot be tested with the clustering coefficient, which is too crude a measure, nor by cohesive subunits (Moody and White 2003) because the index of organizational constraints is not simply larger cohesive structures. The problem is addressed by White, Powell, Owen-Smith, and Moody (2004). Briefly, with fewer organizational constraints (approaching $\alpha \sim 3$) there will be large cohesive subsets that nest hierarchically but do not form intricate patterns of overlaps (k-ridges), while more organizational constraints in the case where 3 >> α -> 1 will have intricate overlaps or k-ridges among cohesive subsets. Barabási, Dezsö, Ravasz, Yook,. and Oltavai (2004) show the presence of clustered hierarchical organization for autonomous domains on the Internet, S. Cerevisiae protein interactions, movie actors, and word co-occurrence but not in the technology graphs for Internet router networks and power grids.

18. Possibly also for E. coli metabolic pathways for core substrates (1.6) vs. all reactants (2.3). This contrast will be seen to work also for Turkish nomad sublineages (~1, but single-scale) vs. individuals (2-2.3) in scaling marriage behaviors. The explanation for differences between incoming (1.5) vs. outgoing (2.0) email might be different, and the problem of asymmetry between incoming and outgoing power coefficients needs to be considered separately.

19. See White and Houseman (2002) and other articles in the same journal issue.

20. That is, if we compared random pairs of callers we suspect there would be

little correlation among those who were called.

21. Such rules are called local when they are observable locally, from egocentric or node-centered perspectives, and when they replicate within each of the local segments the network to which they apply.

22. Arthur (1990) called attention to network externalities and micro-macro linkages to alter the economic axiom that there exist no positive feedback returns to scale in the economy. Similarly, the adoption of innovation involves network processes in which diffusion multipliers, resistances, and critical *tipping* points are reflected in the typical S-shaped curve of adoption through time.

23. The local rule to discover whether or the extent to which a graph is clustered is one of traversing all cycles that start and end with the same node (out from and back to ego) to find those with a single negative edge. One of the implications of the clustering theorem is that the degree of global clustering in a graph can be measured by the extent to which local clustering is present. For example, if we count the number C of confirmations and D of disconfirmations between negative ties and the absence of predicted positive ties from clustering, the coefficient (C-D)/(C+D) is an interpretable coefficient varying between perfect conformity (+1) and perfect disconformity (-1). Graph (0) in Figure 1.2, for example has a coefficient of -1.

24. The clustering and transitivity coefficients are applicable to graphs with a single kind of ties and allow a micro-macro linkage to be specified according to local properties in ego's immediate neighborhood. Signed graphs, however, increase the complexity of specifying local neighborhoods (in this case, dependent on cycles) in order to demonstrate micro-macro linkages.

25. Clustering and balance properties are also satisfied in the trivial cases of no clusters (no relations of either the positive or negative type) or a single cluster (no negative relations).

26. Here the local traversal rule by which we can discover whether or the extent to which a graph is balanced is to check all cycles that start and end with a given node (ego) to find those with an odd number of negative edges. For balance and clustering the local rule needs testing only for a single node in each connected subgraph.

27. To summarize the micro-macro linkages in Figure 1.2:

rule (1)=global structure 1 (unclustered) applies to all graphs that have a cycle containing one negative link;

rule (2)=global structure 2 (balanced) to those in which no cycle has an odd number of negative links, and

rule (3)=global structure 3 (clustered) applies to those in which no cycle has a single negative link.

There is a perfect correlation between the local rules and the global structures. Under Figure 1.2 are two lines for local and global properties of the four graphs that show the correlation for these examples, but it holds for all signed graphs and for digraphs in which the reciprocal and directed ties are regarded as positive and negative edges, respectively.

28. The curvature coefficient K (see Glossary), however, which measures weak transitivity in the presence of local reciprocity, does have a micro-macro linkage, in that as $K \rightarrow 1$, the digraph in which all edges are symmetrized becomes clustered.

29. In researching the effects of structural properties, of course, interactions between them have also to be considered.

30. Glossary items dealing with emergents treat their relations to one another and with concepts linked to complexity and complexity theory. It will be useful for the reader to review how these definitions are interrelated.

31. Definitions of emergent phenomena that rely on the notion of surprise, which is historically relative to a state of knowledge, seem to obscure the issue of complexity arising out of interaction.

32. In this way of defining emergents, given a state of current knowledge about micro-macro linkages, non-local emergents may become locally-based emergents by discovery of a new micro-macro linkage. Surprise has shifted from the emergent, to a well-grounded concept that is open to the possibility of new scientific knowledge. The contribution to complexity theory in this simplification of the concept of emergents is that one can look to configurational effects of network or other structural properties to try to explain emergent phenomena, and to not have to rely exclusively on simulations.

33. Regular equivalence, for example, captures the global core-periphery structure of the world economy (Smith and White 1992) rather than the regional substructures that are identified by structural equivalence blockmodels. The global structure maps back to connected substructures. The global structure represents the fact that participants in similar parts of a world economy global structure may behave in similar ways. This may also be due to the convergence of role relations in structurally similar positions in the network and the working of empirical recursion through the logic of concerted action as disseminated through the vehicle of the network. Convergence of this sort is often a recursive process that may fit quite well the recursive nature of regular equivalence. The dependence on near and distant relationships is a common property of many centrality measures. Degree centrality, however, is a simple local measure of the number of connections for each node.

34. Schneider was apparently unaware that between 1953 and 1959 graph theorist Frank Harary had provided the theorems for micro-macro linkage between local and global balance properties of networks, a finding that was published in the Norman, Cartwright, and Harary textbook of 1965. Only in 1967 did James Davis generalize the micro-macro theorem for clustering.

35. Similarly for the principle of duality (the use of polar opposites) in human thought: While the principle of contrast is a necessary feature of organized thought, closure into polar opposites may be a construct of the investigator rather than a universally valid assumption about consequential structures involved in cognition.

36. A third type of structural property is not included in Table 1.1 but may be

distinguished by default. These are properties of interaction that result from counting or aggregation, such as noting that a certain percentage of people in a given population share a certain trait or assortment of traits, possibly correlated, such as wearing neckties and flying in airplanes, which in and of themselves may be inconsequential in explaining other behaviors. In contrast to emergents, simple aggregates have no configurational effects. This applies to examples in which adding instances of something has few or no consequences—More is Same—or in which items are correlated (neckties and use of airplanes) but in ways that are not consequential. Similarly, referring to "culture" as the observation that people in a local area share certain characteristics is a construct with little consequence in and of itself, and does not constitute an explanation for what is shared or why. Use of shared culture as an explanation for observed behavior is often reified, raising something that results from a process to the status of something explained by its own intrinsic attributes.

37. The self-reflective agents referred to in this reprasing of Read (1990) are people, while the self-structuring systems they operate do not act like persons and do not have agency: their self-organization must be accounted for by other principles.

38. The element of surprise in this definition is both disconcerting and logically incomplete as such surprise may give way to understanding. As this field advances, of course, more and more of the micro-macro linkages will also be found, so that surprising phenomena once discussed as emergents will no longer be surprising to scientists once their locally-based micro-macro linkages are understood. What is disconcerting here is the implied hierarchy of understanding, with scientists at the top. The practice of ethnography and ethnographic writing should encompass the understandings of people studied, and those of the reader, those of the ethnographer in the role of assimilating the views of the people studied and in the role of scientist and comparativist. There are many cases in which the people studied are telling things the ethnographer is resistant to because of his or her background assumptions, and if possible, these should be considered as potential sources of hypotheses and theory that are at present outside the ken of the ethnographer.

39. An example from another field is the knowledge that earthquakes are caused by critical thresholds for the release of pressures along networks of fissures. They obey regular laws but that does not make them predictable as to timing.

40. These entail the idea of a new property that is emergent out of interaction, often because of a gradual building of critical mass in the form of network density or cohesion that shifts the dominant social pressures for or against some outcome. Gladwell (2000), for example, explored the metaphor of "word-of-mouth epidemics" in a series of pop-sociology articles for the *New Yorker*, illustrating for events such as the cleanup of crime in the Giuliani administration or the success of Paul Revere's ride the role of three pivotal types of nodes in micro-macro linkages. These are, in his metaphorical analysis: the Connectors, sociable personalities who bring people together (hubs; nodes with high inde-

gree and attractiveness); the Salesmen, adept at persuading the unenlightened (another type of hub, with high outdegree and influence rather than attractiveness); and the Mavens, who like to pass along knowledge (which emphasizes network betweenness). The success of Paul Revere, in his analysis, depended on his micro behavior as a Maven and a Connector to a substantial fraction of the population who raised the revolutionary militia.

41. To resolve the open questions surrounding the Bell Telephone data shown in Figure 1.3, Doug White and Chris Volinsky of Bell Labs are undertaking a restudy of phone call outdegree and indegree distributions broken out by type of customer.

42. The middle portion of endnote 45, which begins "For theory and application . . . ," is relevant here.

43. Reciprocity, structural cohesion, and small worlds are also good examples where Proposition B will apply.

44. Leaf commented on this quote in saying; "Notice, however, this is not rules. This was an important confusion for Firth." Given our discussion of rules and the anthropologist's tendency to fall back on rules as a means of organizing ethnography, we consider Firth's insistence on formulating social organization and structure in terms of social relations as a major step forward.

45. Leaf's paragraphs on institutions are worth quoting in their entirety:

> Institutions are yet another type of organizational phenomenon—different from both organizations and groups as well as from networks or emergent patterns. In conventional social theory, institutions have often been described as organizations on a very large scale: "the" family, "the" legal system, "the" economy, "the" class system and so on. They seem to be organizational totalities that encompass many separate and smaller aspects of specific types of organizations. "The American family" seems to encompass American household groups, extended kindreds, lineages, generations, marriage rules, inheritance rules and so on. "British law" seems to encompass law offices, courts, the police, the training systems and aspects of Parliament.
>
> The problem with this representation is that it is quite literally an illusion, socially constructed by very definite and describable indigenous processes. When we try to elicit the properties of institutions in the way we elicit the properties of actual organizations, we cannot obtain them. Instead, we are met with confusion upon confusion. Defined roles and relations simply do not connect up; purposes disappear in muddles.
>
> There are two main reasons for this. First, institutions do not have specifiable memberships as do organizations. Second, they do not imply a set of mutually consistent performance expectations. The ideas of the different information systems that these omnibus projections lump together are not the same. Usually, they are not even mutually compatible. The relation between two people as husband-wife to each other is not necessarily logically consistent with the relationship between father and mother from the point of view of a child; the idea of a relation between two men in a South Asian

household in a managerial sense is not the same as the relation between brothers in a kinship sense. A lawyer's obligation to the court in his capacity as an officer of the court is not the same as, and may not be consistent with, his relation to his client as the client's "zealous friend." In an actual group such conflicts are avoided by mutual agreements about context separation—who does what in which context. For an "institution" in the abstract, there are no such understandings because there is no one to arrive at them. Organizations link actual expectations among actual people. Institutions are organizing presumptions that appear to lie behind them in the way a row of lights suggests a row behind or beneath the lights, but actually "appear" is all there is to it. (Leaf 2004:305-306)

46. "This is what White's network analysis does, in what amounts to a three-pronged attack. First, it provides a precise way to describe the linkages formed based on the organizational charters, leading to what White calls the "emergent rules" as contrasted with the stated rules. White has applied this approach in describing marriage relations in certain kinds of kinship systems (cf. White 1999), trade relationships in the world economy (Smith and White 1992), the emergence of school attachment out of cohesive subgroups in high school friendship networks (Moody and White 2003), and other types of relations. Second, he has also formulated ways to express the expectations for such patterns implicit in the stated organizational rules and compare them with the emergent rules (see also White 1999). Third, this automatically generates the possibility of finding relationships between the emergent rules and the stated rules over time. And finally, multiple network analyses in a single community can be treated as overlays─relating, for example, marriage networks to economic networks─which can let us see how the organizational consequences of such organizational rules interact." (Leaf 2004a:304)

47. For theory and application of cohesion as an explanatory variable for emergent groups in historical dynamics, see Turchin (2003). Confusion for many anthropologists about the ontology of groups might arise from the fact that groups usually take their names from organizations. While one might argue that consequences of group membership can be assimilated to emergent rules as if they applied to an organization (e.g., the community, the world economy), this is akin to the illusion that integrative and homogeneous institutions enact and give charter to a set of uniform rules. Group membership rules are typically characterized not only by a positive rule, such as "marry in, stay in" but also a negative and exclusionary rule, such as "marry out, and move out." Such rules are of a different order, as they are situated on the inclusion/exclusion boundary of groups, and the group concept is more appropriate to them, while the concept of a rule falsely homogenizes how it applies to a population. Groups are heterogeneous, while rules are constructed to be homogeneous even while they admit exceptions.

48. It would seem logically consistent to do so, but, when queried on this point, Leaf responded in personal communication that "emergent groups" is not

a concept he could accept: A group for Leaf could not be emergent; in his vocabulary, it is by definition named.

49. White, Murdock, and Scaglion (1972) give an example of the resistance to principles of asymmetry in the anthropological descriptions of the Natchez nobility, for whom several generations of American anthropologists imposed symmetric rules of descent and group recruitment contrary to clearly stated historical accounts by French contemporaries of the Natchez that record those rules as asymmetric. While this study lead to the withdrawal from standard textbooks of the Natchez case as an example of the paradoxical nature of descent rules, White, Murdock, and Scaglion's (1972) discovery of the "symmetry paradox" in the culture of ethnographers has been virtually uncited.

50. In actuality, the cohesive groups that we will define can be constructed by traversal properties, but in a way that is sufficiently complicated that we will call them non-local emergent groups. This is also suggestive of the fact that they are not complete graphs nor necessarily of very high density.

51. Human beings are very good at identifying cliques, even to the point where if they see a set of people in a local context who are interacting in a way that connects a certain subset and if the interactions are positive, such as friendships, they tend to assume that all the people in that subset are in a clique (Freeman 1996).

52. A clique is so lacking in robustness that removal of a single tie within it breaks it into two overlapping cliques. In contrast, a member of a level k cohesive group is also embedded in lower-level cohesive groups and random removal of ties will often not affect the boundaries of cohesion at all, or may cause a single node to drop to the lower-level cohesion group without otherwise affecting the group structure.

53. In the definition of structural cohesion, cliques with n nodes have a cohesion level of n-1.

54. The measure here is how many levels are required in the decomposition of a network by a method of successive cuts to reach the k-component of a particular individual.

55. In a study of social networks in a village of Tlaxcala in Mexico (White et al., 2002), we elicited complete inventories of many types of relationships among the villagers which allowed a analysis of networks for which the data were relatively complete, which is called 1-mode network analysis. In addition, villagers listed complete inventories for the same types of relationships with others outside the village. This provided a 2-mode network of ties between one set of people and a completely different set of alters without attempting to inventory the relationships among the alters outside the village in a kind of endless struggle to make a complete network out of a snowball sample. Comparisons between 1-mode and 2-mode sets of network data led in this case (as in the Powell et al. study of the biotech industry) to useful and illuminating findings as to the saliencies and differential effects of internal and external ties for the group or groups studied.