Draft 3 CMOT-1a.doc
(first complete draft)

Embeddedness in Multiple Networks, Organization Theory and Structural Cohesion Theory

Douglas R. White
Walter W. Powell
Jason Owen-Smith

May 2003

Special Issue on Mathematical representations for the analysis of social networks within and between organizations

Guest Editors: Alessandro Lomi and Phillipa Pattison

Computational and Mathematical Organization Theory

- a journal devoted to (mathematical, statistical, computer) models of social organizations

Editors:

Kathleen M. Carley
William A. Wallace

Introduction

We review here a number of linked developments in network theory and methodology as they impact on organization theory: new developments in the theory of network embeddedness, the navigability of strong ties hypothesis, predictive structural cohesion theory (self-embedding cohesive groups, ridge structures, etc.), plus methods and problems related to modeling network dynamics. After reviewing some of the evidence supporting new theories and models, we focus on the several example of informal and formal organizations. The implications explored here for the mathematical modeling of networks and for network advances that affect organization theory offer some new perspectives on how to measure several new variables and concepts such as structural cohesion and navigability not previously not taken into account in organization theory, and how to understand and model the dynamics whereby organizational fields are constructed. Some defects in exponential random graph (erg) and scale-free network models are noted, as are some of the advantages of McFadden discrete choice modeling for understanding network dynamics.

The approaches to the social structure and dynamics of organizational fields presented here provide some rather major surprises. For one, the navigability of strong ties hypothesis suggests what some of our very general models of the terrain of social structure are far too narrow to encompass much stronger models that have very wide applications. The Granovetter model of small world networks forming organizational fields with clusters of strong ties and weak ties that provide bridges between them fits a kind of standard American middle-class model of social structure: friends, neighbors and workmates as important kinds of links, with cross-cutting organizational networks stemming from corporations, church and voluntary groups. The hypothesis of strong-tie navigable small works offers a very different picture of organizational fields that may have far wider application and surprising insights about self-organization emergent out of network dynamics. Concepts of ridge structures developed by Friedkin as a contribution to the theory of cohesion offer some useful leads. We develop several formal definitions that extend the ridge structure model in useful directions that relate to small world navigability and problems in organizational theory.

Predictive structural cohesion theory also provides some surprises. Hierarchically stacked and potentially overlapping multiconnected blocks seem to have large downstream consequences, and seem to be one of the possible large basins of attraction in organizational fields of certain types (possibly associated with strong-tie navigable small worlds), as is evidenced by the biotech study. They cannot, however, be modeled by current methodology of exponential random graph models since they are not strictly local structures or clusters like cliques but contain and abundance of structural holes. They allow us to think, however, about the effects of more distributed and delocalized types of groups that may have strong effects in network dynamics and the topologies emergent form network dynamics that shape organizational fields and typical behaviors in those fields.

The final surprise is the deconstruction of Barabási's scale-free model of self-organization and emergence in 'real networks,' and the replacement of some fallacious assumptions that accompany that model with a more realistic appraisal of the micro-macro linkages that operate through network dynamics, as are particularly evident from the biotech study.

Multiple Networks, Strength of Ties, Small Worlds

The "strength of weak ties" (SWT: Granovetter 1973) is one of the most cited hypothesis in the networks literature: in a sufficiently large organization, network of organization, or small world network in which there are many nodes and relationships are clustered, the hypothesis is that most of the bridges between clusters are formed by weak ties. Strong ties are those that tend to have some or all the following characteristics: they are direct, multiplex, intense, and often involve or involved at some point frequent interaction. The hypothesis posits that strong ties are more likely to be clustered than weak ties (e.g., uniplex, less intense, infrequent and often indirect, as in acquaintanceship of a friend of a friend), and more likely to be reciprocal and transitive.

The "navigability of strong ties" (NST: White and Houseman 2002) is an hypothesis that posits the existence of a very different and much stronger model of social structure in a small world (SW: again, a SW is a network with many nodes, clustered relations, and low average distances relative to the number of nodes). Where the NST model applies, low average distances are found in paths of strong ties, although weak ties may also be present. The NST model implies the SWT model but not vice versa.[1] Where only the SWT model applies, low average distances are found in paths that involve weak ties, but not in those that involve paths composed only of strong ties.

Hypotheses such as these assume a rich network of multiple types of ties, the type of network typically encountered by an ethnographer, an organizational researcher, or by survey research. Such studies are attentive to the rich variety of ties that exist in social worlds. Rich networks of multiple relations and multiple types of actors, social worlds, also tend to elicit hypotheses that are formulated in intuitive or heuristic terms, like 'weak' or 'strong,' mixed with formal concepts such as bridge, clustering or transitivity. The more intuitive terms need to be clarified or specified (possibly 'discovered' in a particular network context) before such hypotheses are fully operationalized and susceptible to testing.

One of the differences between an NST small world and one that is exclusively SWT, speaking intuitively, is that in the NST world people have to be absorbed into a strong tie to do business. The knowledge industry of biotechnology, which is heavily dependent on collaboration and outsourcing, is a good example of this process. A biotech firm must master a whole series of complex processes that are part of the research development and eventual manufacture. It is only when a process is mastered that the firm can afford to outsource this task in a division of labor that leaves members of the firm free to work on other aspects and processes of their business. Hence the collaborative ties between firms will involve reciprocity and equality in terms of master and trust with regard to the processes involved in their collaboration, and the tie will be of high intensity and frequency since it involves outsourcing a process that is integral to the firm.

Japanese *kirietsu* (companies linked together by formal or informal bonds to accomplish the same objectives) also has the quality that firms have to be absorbed into a strong tie to do business. The *kirietsu* network of (mostly) Japanese firms is lean, flat, flexible, and involves high-commitment ties. Chinese (largely) family business networks that extend worldwide from provincial entrepreneurs, while they may differ from *kirietsu* operationally, have similar morphologies based on strong-tie networks.

Informal economic activity, which constitutes over 60% of the world economy, is also constituted within NST small worlds due to the need for trust and reciprocity between the partners linked in these economies. Thomas (1992, 1995, 2000, 2001) divides the IEA into four sectors: household; informal labor sector; underground economy; and criminal economy (Table 1). For example: the value of housework alone in the United States is estimated at 30-40 percent of the national income; the informal sector often constitutes more than 50% of the urban labor force in much of the third world; the underground sector was measured in the 1970s in the U.S. in the range of 10 percent of measured gross national product; while extent of criminal activity simply reported by investigations U.S. corporations in the last year has been in the hundreds of billions.

(Insert Table 1 about here)

Mutability

Strong ties are not necessarily durable ties, and strong-tie subnetworks are often ones of high mutability of ties. To say that in the NST world people have to be absorbed into a strong tie to do business seems to require some entry or transformation process whereby strong ties are flexibly created and may later be terminated. The Chinese institution of *guanxi* (Bell 2000), for example, is a transformative process whereby two migrants create an immediate strong tie, with potential benefits of reciprocity, upon recognizing each other as coming from the same home province.

Transitivity of is a common procedure for the mutability of strong ties: A-B might be a strong tie of trust, as is B-C, with C previously unknown to A, so upon introduction by B, A and C have a heightened possibility of forming a strong tie. Part of the SWT hypothesis is that strong ties have a heightened probability of transitivity, which is taken as evidence of clustering of ties, but in a mutable strong-tie network, there must also be (a) many intransitive strong-tie chains and (b) many transitive strong-tie triples that do not form complete strong-tie subgraphs.

Chaining is another means of strong-tie mutability, as in the case of Mexican *compadrazgo* relationships of ritual co0sponsorshop (White et al 2002): here, one may ask a *compadre* with a relationship of *confianza* (trust and reciprocity) to help do a favor by asking one of their *compadres*, and so on down the chain (rather like the original Travers and Milgram (1969) small-world experiment) until the right person to do the favor is located and the favor is done.

In the knowledge industry of biotechnology (Powell, White, Koput and Owen-Smith 2002), contracts between firms, or between firms and other partners (pharmaceuticals, universities, laboratories and medical complexes, venture capital, and government agencies) are normally of a three-year duration, and turn over relatively frequently.

Embeddedness

Within the context of richly differentiated networks, another powerful intuitive idea is that some of the phenomena of interest are 'embedded.' Embeddedness, as formulated by Granovetter (1985), indicates that actors who are integrated in dense clusters or multiplex relations of social networks face different sets of resources and constraints than those who are not embedded in such networks. Granovetter (1992: 33) delineates the key division between "local" and "structural" embeddedness:

> "Embeddedness" refers to the fact that economic action and outcomes, like all social action and outcomes, are affected by actors' dyadic (pairwise) relations *and* by the structure of the overall network of relations. As a shorthand, I will refer to these as the relational and the structural aspects of embeddedness. The structural aspect is especially crucial to keep in mind because it is easy to slip into "dyadic atomization," a type of reductionism. (italics in original)

He further specifies (p. 35) his understanding of structural embeddedness as the degree to which actors are involved in cohesive groups:

> [T]o the extent that a dyad's mutual contacts are connected to one another, there is more efficient information spread about what members of the pair are doing, and thus better ability to shape behavior. Such cohesive groups are better not only at spreading information, but also at generating normative, symbolic, and cultural structures that affect our behavior."

Navigability

The key problem in strong-tie small worlds is navigability, roughly stated as the ability to use network ties or hubs to search at relatively short distances through strong ties in the network for targets that can both transformed into new (strong) ties and that may be useful for purposes of reciprocity, incorporation, or exchange. A simple example of a perfect hub is the phone book: from a searcher to the hub to the target constitutes a distance-two search, and constitutes the population as a small world that is partially clustered in terms of the nodes listed in the yellow pages. This small world population, however, is not a NST but a navigable SWT small world. NST small worlds are more typically informal networks that are much more decentralized than phone-book networks.

The criterion of whether a network is navigable is whether there a low-complexity search algorithm, such as choosing someone in one's network neighborhood who seems to be closer to the target on some criteria, that is capable of finding targets in relatively few moves. When ties are distributed completely at random (i.e., the Erdös graph in which edges are formed with equal probability across all pairs of nodes), navigability is precluded by the fact that moving to a node that is apparently 'closer' to the target does not improve the probability that this next node has the target node within its neighborhood. As Kleinberg (2000) was the first to show, only a limited range of network topologies will satisfy navigability. His model, in fact, required a perfect fit between the distance decay parameter k for probability of ties in a space of dimension k', where navigability is possible only where k=k'. Watts, Dodds and Newman (2002) showed a more robust range of network topologies. They "sought to identify a family of realistic social network models for complex small worlds with strong upper limits on how many links an individual may possess. They imbue the actors in their network models with social identities. Social distance between pairs of individuals is then defined by differences in the taxonomically organized categories of identity. Like Kleinberg, they find that the ability to search and find specific targets depends on the network having not only short network distances, but also links constructed with probabilities that decay exponentially with social distance. By tuning the exponential parameter for social-distance decay of link probability, their family of models generate networks that have searchability as well as short average network distances, and they match up to describe the results of Milgram's original SW experiment" (White and Houseman 2002:73-74):

> The SSW networks of Watts, Dodds and Newman demonstrate some further properties. Searchability increases when the hierarchies of identity are multiple rather than singular, and when these multiple identities cross-cut one another, in the sense of statistical independence. This allows one step in a search to be taken on the basis of one aspect of the target's identity, while a next step might be taken on the basis of another aspect. Such cross-cuts move much more quickly towards the target since they move the search out of a cluster of ties in the network that reflects similarities on only one attribute (for which there may be many independent clusters) towards clusters that have many of the target's attributes, and in which local ties in the cluster are more likely to lead directly to or close to the target. The introduction of multiple social dimensions leads to a much more robust result—i.e., networks are searchable for a broad range of parameters— which is very different from Kleinberg's singular condition. For navigability they require, however, not just social identities, but a network that is constructed with distance decay across the proximities defined by similarities in identities.

Multiple levels of actors: Networks of networks

While we have distinguished the formal economy of markets from informal economic activities, we have not made a conceptual distinction here between formal networks and informal networks, or, grievously, between networks and organizations. Although many authors use various metaphors from transitions *from* networks *to* organizations, such distinctions miss the point: organizations are composed of networks, and these networks operate at multiple levels: networks of ideas and classifications (such as a formal charter for an organization), networks of overlapping groups or positions, networks of individuals, contractual networks between corporations, and so forth. The idea that organizations emerge within social fields constituted by networks, however, is conveyed by metaphors such as "networks into organizations" or "Markets from Networks" (H. White 2002a,b). Networks, viewed horizontally, at one level, may obviously congeal into emergent phenomena (such as markets) that are organizationally more tightly wired or institutionalized.

Viewed vertically, however, when you open up a node in a real-world network, other networks are found within. The metaphor here is often that of networks of networks. Operationally, however, a more precise image is provided by the formalism of networks within the nodes of higher-order networks. This is how Harary and Batell (1981) define a system. The nodes of multilevel networks, then, are not only individuals, but groups, organizations, corporations, and other embedded networks.

More generally, the notion of embedded fields encompasses emergent phenomena at one level, such as bondings in a field of atoms or atomisms, that lead to a higher-order field at the next level, such as the formation of molecules. The interactions between molecules are governed by additional chemical processes that overlay the atomistic statistical interactions that occur prior to molecular bonding. Note that the increased generality of the concept of fields, which may be organized hierarchically in certain ways, but in which lower-order phenomena (such as the atoms in molecules) may affect interaction at the higher level. This is precisely how physics and chemistry are linked, in that it is the open rings of atoms shared at the molecular level that create the probabilities of chemical bondings among molecules.

Powell et al. (2003) are among those who argue, along similar lines, that "the study of the macro dynamics of networks [within fields, say, of bondings between corporations] should be central to the understanding of how fields evolve."[2] In the social sciences, however, they argue that the lack of connection between analyses of fields and networks is rooted in several features of contemporary research:

> "There is an abundance of research in network analysis on why ties form between two actors and what the consequences are of having a particular position in a network. Salancik (1995) observed, however, that most network research has taken an individual-level perspective, and missed out on the opportunity to illuminate the structure of collective action. McPherson et al (2001) note in a recent review essay that there are few studies that employ longitudinal data to analyze networks. Burt (2000) has voiced a similar concern that most studies of network structure are cross-sectional. In the most comprehensive text on network methods,

> there is only a paragraph on network dynamics in a section of future directions (Wasserman and Faust, 1994). Thus while some progress has been made analyzing the dynamics of dyads (Lincoln et al, 1996; Gulati and Gargiulo, 1998; Stuart, 1998), little attention has been given to the evolution of entire networks."

> "There are a number of excellent studies of the structuring of organizational fields (DiMaggio, 1991; Thornton, 1995; Dezalay and Garth, 1996; Ferguson, 1998; Scott et al, 2000; Hoffman, 2001; Morrill and Owen-Smith, 2002). An organizational field is a community of organizations that engage in common activities and are subject to similar reputational and regulatory pressures (DiMaggio and Powell, 1983). Such fields have been defined as "a network, or a configuration, of relations between positions" (Bourdieu, 1992), and as "centers of debates in which competing interests negotiate over the interpretation of key issues" (Hoffman, 1999:351). Fields emerge when social, technological, or economic changes exert pressure on existing relations, and reconfigure both models of action and the structure of interaction. But despite the relational focus on how different actors and organizations constitute a recognized arena of social and economic activity, studies of fields have not analyzed the interactions of multiple, overlapping networks or the regulated reproduction of network ties through time. This linkage between network dynamics and the evolving structure of fields needs to be made in order to make progress in explaining how the behavior of actors or organizations of one kind or another influence the actions of organizations of another kind."

Cohesion

Among the processes of network emergence, a central element missing in most of the social and natural science network studies has been a theoretical and methodological adequate concept and measurement of structural cohesion.

One of the most difficult processes to understand has been how groups emerge from networks. Sociologically, a <u>group</u> is a set of people claiming membership in a common organization, or attributed to belong to a common organization. How then can emergent network processes lead to the formation of groups, when networks are composed of relationships between people? Is there not a disjunction here of levels of analysis? The same problem attaches to groups as sets of organizations. What is missing here, epistemologically, are the concepts of embedded networks and the concept of feedback between the different components of networked systems.

One of the contributions of mathematics, in the theory of graphs, is the discovery of some basic structures and processes of networks that are literally <u>self-embedding</u>, where sets of nodes ("groups" as sets of people, for example) emerge explicitly from patterns of relationship. This is the intuitive idea when network researchers speak of "dense subnetworks" within larger network. Here, however, with the idea of relative density, what is envisioned is feedback between the clusters that may emerge in networks, and the process of individuals attributing to themselves or to sets of others the property of membership in the emergent set of nodes in such clusters. Clustering, however, is a rather weak concept for finding boundaries of emergent subsets in networks (Kleinberg 2002).

The crucial mathematical concept for emergent cohesive subsets in networks, however, was discovered by Karl Menger (1927). Graph theorists regard his discovery as one of their half-dozen most fundamental theorems since it identifies a formal identity between a key structural characteristic of graphs and a basic property of traversal or transportability in networks. The structural characteristic, named ***k-connectivity***, is the minimum number of nodes that must be removed to disconnect a graph or maximal subgraph (***k-component***). A graph is said to be n-connected if its k-connectivity is at least n. The transportability feature is the maximum number of node-independent paths between every pair of nodes in a group or maximal subgraph (which turns out to be equivalent to the k-component with the same value k as in k-connectivity).

A second theorem analogous to Menger's, the famous Ford-Fulkerson (1956) theorem, has been widely used in transportation theory to determine maximum transport capacities. It states the equivalence of the minimum number of edges (or sum of weighted edges) that must be removed to disconnect a graph or maximal subgraph (k-edge-component) and the maximum number (or sum of flow capacities) of edge-independent paths between every pair of nodes in a group or maximal subgraph (equivalent to the k-edge-component with the same value k as in k-edge-connectivity).

Only this second theorem has been used to study cohesion and fragmentation in social networks (Zachary 1975, 1977). Harary et al. (1965) proposed, however, as White and Harary (2001) were able to show more conclusively, that it is the first form of the Menger theorem that is the proper measure of how much cohesion accrues to groups as subsets of nodes in a network as a function of the relation of nodes in a subgraph, which is what Moody and White (2003) have come to call "structural cohesion." Consider for example two cliques, each consisting of three persons, that share one node in common. As shown in Figure 1, the edge connectivity of this graph is two (each pair of nodes, such as person 1 and 2, has two edge-independent paths between them; and the graph is separable only by removal of at least two edges), while the node connectivity is only one (each pair of nodes has only one or more node-independent paths between them, as we can see from the fact that all paths from node 1 to node 2 must pass through the central node; and the graph is separable removal of a single edge). Cohesion via a node-connectivity of k has two different facets: one is invulnerability to disconnection by removal of fewer than k of its members. Hence, as defined by Moody and White (2003): "The *structural cohesion* of a group is … the minimum number *k* of its actors whose removal would not allow the group to remain connected or would reduce the group to but a single member." The other and equivalent facet is that a group with structural cohesion k has at least k node-independent paths (like independent chains whose strength in connecting the nodes is additive) between every pairs of members.

(Insert Figure 1 about here)

Formalizing Friedkin's Theory of Ridge Structures

Friedkin (1998:125-135, 145-147) develops a theoretical model of ridge structures in formal or voluntary organizations that that serve to reliably coordinate differentiated social positions. A *ridge structure* is

> "a more or less ramifying social manifold in which all actors are joined via sequentially overlapping and densely populated regions of social space."
>
> "[C]orporate institutions might be usefully reconceptualized … within a larger theory about the origins and shape of social space. Such a theory would be concerned with the effects of social conditions and events on the definition of social space, the distribution of actors in this space, the configuration of social ties, and the influence network that joints social positions." (p. 210-11).

Friedkin takes as an axiom of structural analysis that "the probability of a social tie is negatively associated with the distance between the positions of actors in social space (Laumann and Knoke 1986; Blau 1994)." He argues (pp. 125-126) that this axiom insures that "ridge structures produce sequentially intersecting cohesive subsets of actors," which is the core of his theory of what serves to reliably coordinate differentiated social positions.

Friedkin provides no precise and single method for delimiting ridge structures, other than stringing together a series of supporting models—blockmodeling, link-pin organizations, social circles, short-circuits, transitivity, balance theory, triads analysis, clustering, and the like. Because of this it is more useful to drop his axiom, from which he tries to derive the connections among these diverse models, and to begin with a formal definition of ridge structure as a structure of sequentially intersecting cohesive subsets of actors. Indeed, the necessity for taking a simpler approach to formalizing Friedkin's theory of ridge structures is found in Bourgeois and Friedkin (2001), where they find counterexamples to the purported axiom of structural analysis that "the probability of a social tie is negatively associated with the distance between the positions of actors in social space."

A formal definition of ridge structures can be derived from that of *k-components* as maximal, k-connected, cohesive subgraphs of any given network (White and Harary 2001). A *k-ridge-supporting structure*, or *k-ridge structure* for short, is a set of n (k+1)-components that are connected, with intersections containing at least k nodes, where each k-component has node connectivity (c_i for i=1, n) greater than

k. A k-ridge structure has connectivity k but supports a series of connected (k+1)-components, i.e., of connectivity k+1.

Figure 2 provides an illustration for a k-ridge structure. Each of the darker circles represents a k-component of a graph where $k \geq 4$. The labeling convention is that a number contained in the intersection of two ovals represents the number of nodes in the intersection of two k-components whose connectivity is indicated by numbers enclosed in a single oval. In this example, k = 3. There may be other intersections with fewer than k nodes, but they are not part of the structure, which in this case is a 3-ridge structure. Most of the k-components in this example have connectivity 4, and most of the intersections have 3 nodes, so that the ensemble of intersecting 4-components in the 3-ridge structure will have connectivity 3, and will be embedded in a 3-component of the graph. There may also be some k-components in a k-ridge structure, however, that have connectivity greater that k+1, as for example the 6-component embedded in the 5-component embedded in the 4-component in Figure 2.

(Insert Figures 2A and 2B about here)

The two types of numbers in the diagram of a k-ridge structure are thus of two different sorts: one a property of a maximal subgraph and the other the number of nodes in the intersection of two or more maximal subgraph. It is useful to know from graph theory that these two numbers are in a necessary relation of inequality: two k-components can have no more than k-1 nodes in common. Further, for k > 0, all k-components are necessary embedded in (k-1) components (Harary 1969; White and Harary 2001). The 0-component of a graph is by definition the entire graph, even if it is disconnected, a 1-component (simple component) is a connected subgraph, and so forth.

Defined in this way ridge structures offer a rigorous graph theoretic definition and have most of the properties associated with Friedkin's idea about social spaces or manifolds that form the communicative spines of organizations. Intuitively, what defines a ridge structure at level k is that is the smallest isocline (minimal subgraph of connectivity k) within which the higher ridges occur. The higher ridges are all the k+1 components within the k-component in which the k-ridge structure is embedded.

Note that some of the ovals in Figure 2 merely touch and do not overlap, a situation that indicates that they share a single node in common. These are what Friedkin, following Likert (1961), calls the link-pins of organizations: individuals who belong to two distinct cohesive groups in which they are a supervisor in one and are supervised in the other. Likert's model of short-circuits in an organization as a cohesive groups that span three levels of supervisory authority (and overlap with other cohesive groups) can be modeled by a combination of cohesive groups and supervisory relations.

Tie Strength and Cohesion in Ridge Structures

Friedkin's theory about the origins and shape of social spaces posits that ridge structures are useful for studying how organizations consisting of differentiated social positions are reliably coordinated. His theory integrates many of the major hypotheses developed in the study of social networks, such as the different implications of ties within networks or organizations that are *strong* in the sense of high investment of time and affect, or *weak*. As Granovetter (1973) argued, strong ties are more likely to be found within cliques or clusters, hence more transitive, while bridges between cliques or clusters are more likely to be weak.

Generalizing to cohesion, strong ties are more likely to be found in more cohesive k-components (i.e., higher k), while k-components that are lower in cohesion (lower k) are more likely to be weak. One of the implications of weak-tie structure is that if an organization consists of differentiated social or structural positions, then weak ties are likely to distribute themselves widely between as well as within structural positions.

A *k-ridge ordering* is a series of embedded k-ridge structures, from k=1 to K. The *k-ridge orderings* of a network or organization consist of all the distinct k-ridge orderings. In this case, we can add to the general model of social spaces the following hypothesis:

> The k-ridge orderings of weak ties (or weak plus strong ties) in an organization will tend consist of a single embedded structure, whereas the k-ridge orderings of strong ties along will tend to consist of multiple and overlapping embedded structures (as in Figure 2A).

In a k-ridge structure, every pair of nodes is connected by at least k node-independent paths, and the structure cannot be disconnected by removal of fewer than k nodes. The cohesiveness of the structure is at level k, which is what gives it the ability to reliably coordinate differentiated social positions. Note that this achievement is all the more remarkable in the k-ridge orderings of figure 2A, which is what Friedkin addresses in his book.

Every node i a k-ridge structure, however, is a member of a subgraph with connectivity k+1 in which every pair of nodes is connected by at least k+1 node-independent paths, and the structure cannot be disconnected by removal of fewer than k+1 nodes. In the k-ridge orderings of figure 2A, the higher-order k-components have a greater potential for transmission within their own unit, i.e., they act as amplifiers. The communications still have to pass thru, however, the intersection zones of lower k-connectivity, which is what concepts such as Likert's (1961) link-pins and shortcuts in organizations are all about: what are the effective interfaces and how do they operate with respect to supervisory authority?

Ridge structures, then, give a very different account of the communicative spines of organizations as opposed to the navigability of free-form networks as small worlds. They give an account of how units of organizations with higher levels of cohesion act as transmission amplifiers through the redundancies of multiple channels, and thus overcoming the distance decay that typically operates with single-path network transition. Secondly, they focus on the interfaces between high cohesion subgroups, especially with regard to supervisory relations that are conference with quality and implementation. Third, they explain how reliable transmission at a distance can occur between distant social positions in an organization or network, by interfacing and high cohesion groups that are interfaced. Fourth, they explain how weak ties can be occur between nodes or individuals that are very distant, but where there is high solidarity in terms of perceived agreement and acknowledged influence. Friedkin's theory of ridge structures, then, when amplified by cohesion theory, provides a powerful model of organizations.

Testing Predictive Structural Cohesion Theory

The measurement of structural cohesion in a network consisting of a single type of relation is a strictly deterministic algorithm with a unique result that assigns each node to one for more k-components (k-cohesive blocks). Subsets of blocks may be hierarchically organized in the sense that a block that is k-cohesive for k>1 is necessarily also cohesive at level k-1. Thus a 3-component (tricomponent) is necessarily nested within a bicomponent that is within a simple connected component. Unlike blockmodeling (White, Boorman and Breiger 1976), the k-components of a network may overlap, and are totally different in their construction, one suitable for detection of emergent groups, and the other for detection of emergent roles.

Since there is no ambiguity about how structural cohesion assigns memberships in stacked and scalable cohesive subgroups, this structural aspect of network measurement is well suited for testing the theory that the emergent property of cohesive groups as defined by k-component patterns of ties in networks has the testable antecedents and consequences that would be expected from a theory of relational cohesion. Spelling out the implications and predictions of this type of theory was a task undertaken under the rubric of testing "Predictive Structural Cohesion (PSC) Theory."[3]

The two types of measures of structural cohesion that have been investigated to date will be reviewed here by way of an introduction to their application to organization theory, using as an example the Powell et al. (2003) study of the biotech industry. The first measure predicting the behavior of nodes in longitudinal study of networks simply from k-component membership. The second makes use of the idea that k-components are social groups (set of individuals, and thus super-nodes) that are self-embedded within a network in the sense that they are directly emergent from properties of the relations in the network itself. For this measure, Moody and White (2003) use the deepest level k at which a given node is a member of a self-embedded k-component.

Figure 3 replicates an example of the argument for PSC Theory made by White and Harary (2001). It consists of a series of snapshots in panels a, b, and c for the network of friendships at successive times in Zachary's (1975, 1977) longitudinal study of the effect of conflict on social dynamics among members of a Karate club. The disputants are labeled T for the karate teacher and A for the club administrator. Levels of cohesion (k-components) are coded by color. When members with ties to both leaders T and A are forced to choose between them, removing the red lines, two cohesive hierarchies form that bifurcate the club. White and Harary show that the structural separability of the graph following choices of which leader to follow for those connected to both predicts the actual lines of the split into two clubs. Further they argue that node-connectivity provides a more parsimonious and theoretically satisfying way to predict emergent factions in the club than Zachary's use of the Ford-Fulkerson theorem to determine the minimum edge-cut as a faction predictor.

(Insert Figure 3 about here)

Figure 4 shows the result of using the Moody-White algorithm for finding nested cohesive subgroups to color code social embeddedness of students in high school friendship networks. The example is for one of the twelve schools that Moody and White (2003) picked randomly from the AddHealth network database (Fischhoff, Nightingale, and Iannotta 2002) in order to test PSC Theory. The dependent variable was a multivariate scaling measure of high tested reliability for questions on school attachment as reported by each student. The structural cohesion measure outperformed other network and attribute variables in predicting the outcome variables using multiple regression. The regression coefficients for school attachment replicate for friendship networks and school attachments in all 12 randomly selected American high schools from the AddHealth Study. For the example in Figure 4, the approximate boundaries of different grade levels are superimposed to show patterns that vary from school to school in the distribution of cohesive subgroups across grade levels. In this school, for example, the cohesion of 7th-graders is organized in a core/periphery; those of 8th graders into two cliques, one hyper-solidary, the other marginalized; the cohesion of 9th graders is more uniform transitional and more central into the networks of upper-grade students; 10th graders tend to hang out on margins of the cohesive group of seniors; and the 11th-12th- are integrated into the main cohesive k-components, but also show more individual and subgroup freedom to break away from the cohesive subgroups of the others, i.e., to marginalize with respect to the school (perhaps integrating with others outside the school).

(Insert Figure 4 about here)

Moody and White (2003) also tested the predictiveness of the embeddedness measure of cohesion are against the outcome variables of similarity in corporate donations to political parties in the Mizruchi's corporate interlock study. The cohesion variables again outperformed other network and attribute variables in predicting the outcome variables using multiple regression.

Figures 4 and 5 show parts of the genealogical dataset used to compute structural cohesion in a Turkish pastoral nomad clan having Arabic-type patrilineage structure and Arabic-type marriage patterns favoring marriages with close relatives (White and Johansen, in press; White and Houseman 2002). In this type of society groups of sublineage members emerge out of networks in the sense that they choose to affiliate with the group of descendants of a common patrilineal ancestor two to four generations back. Sublineages are subtrees of the patrilineal tree structure, and two of them will overlap if one is higher on the tree than the other. Marriage within the lineage, between patrilineal first, second or third cousins, reinforce the bicomponent structural cohesion of competing sublineages. Figure 7 shows how marriage frequencies decline with an inverse 1.6 power law decay with kinship distance, a statistical relationship that holds both within sublineages and between distinct patrilineages. Since intermarriage is the most frequent pattern, members of distinct patrilineages in Middle Eastern societies with this type of lineage and marriage patterns often interpret frequent intermarriage between their groups as an indication that they must have been patrilineally related further back in time than anyone living can actually reckon.

(Insert Figures 5 to 7 about here)

Table 2 supports PSC Theory for this kinship system: it shows a strong correlation ($r = .95$ without the two middle rows) between membership in the cohesive bicomponent of the kinship and marriage network and clan members who stay with their nomadic kin rather than outmigrate. Further, the structure of his nomad kinship and marriage network follows the logic of NST small worlds (White and Houseman 2002) once we understand that the strong ties are those between lineage segments that exchange brides reciprocally, thereby engendering trust and frequent visiting. Using the method of triad census (Batagelj and Mrvar 2001) on the network of marriages between sublineages, Table 3 shows that marriage reciprocal marriage links tend to be much higher that expected in a random distribution of ties, and that this is true both for transitive triples and for chains of reciprocal marriages, fitting a strong-tie small world model.

(Insert Tables 2 and 3 about here)

A navigable strong-tie small world or NST network is consistent with the power-law coefficient of 1.6 shown in Figure 7. Although this coefficient is somewhat less than the inverse distance-squared decay expected for network navigability in a two-dimensional spatial grid typical of geographic configurations, the nomads do not inhabit a planar 2-dimensional geography, but something closer to a one-dimensional strip (a plane with length many times longer than its width) corresponding to the pastures that surround their annual north-south migration route. The coefficient of 1.6 might then be considered a close fit to the predictions for navigability that derive from Kleinberg's (2000) navigable small world model. Figure 8 shows that the spring-embedded scaling of the marriage frequencies between lineages also fits a dimensionality that is more linear than planar, approaching the value of the power-law coefficient. The search dynamics for partners in economic exchanges can follow the chains of strong (reciprocated) ties that link the lineage segments into a small world, while the search dynamics for spouses, given the modesty and protection of single women in a rural Islamic society, is that of intermediate sublineages within chains of sublineages linked by reciprocal marriages serve as meeting points to introduce a boy and girl from two the neighbors of the mediators.

(Insert Figure 8 about here)

PSC Theory applies equally well to European and other kinship and marriage systems in which marriage between blood marriage is avoided. Brudner and White (1997), for example, find that bicomponent structural cohesion (or structural endogamy) in the kinship and marriage network of an Austrian farming valley creates a division between bicomponent members and nonmembers that correlates very highly (as with the Turkish nomads) with those who inherit family farmsteads and undivided lands and those who do not, and are thereby partitioned into emigration or non-farming professions. Social class formation is receiving attention from the perspective of the structural endogamy version of PSC Theory. A preliminary analysis by White and Houseman (2002) shows that there are power-law distributions on the frequencies of different marital relinking among families that fits the structural endogamy version of PSC for many societies that forbid close marriages among consanguineals, where as there are power-law distributions on the frequencies of different types of blood marriage in more lineage-oriented systems. The direction of this research is to provide and explore a new theory of complexity and self-organization from the study of the dynamics of informal organizations such as kinship and marriage networks.

Applications to Formal Organizations

Not all the ideas in this paper have been fully explored, but selected applications to formal organizations may provide useful examples. We begin with some of the early work on PSC Theory by Friedkin, then move to a test of PSC hypotheses by Moody and White (2003), and end by considering some of the unpublished findings of Powell et al (2002) on the biotech industry.

Organizational Influence

Friedkin's (1998:157-162) analysis of the Columbia faculty is an excellent example of PSC theory applied to ridge structures. Figure 9 shows in the top panel the structural positions of Social Science faculty using blockmodeling analysis. Because he assumes that occupations of the same position are likely to be internally cohesion, he takes this to be a ridge structure. It is not necessarily a k-ridge structure as we have defined it, but that does not belie the usefulness of the example nor his ridge-model, which he uses here and for other Columbia faculties (Physical and Biological Sciences) to predict acknowledged interpersonal influences, as shown in the lower panel of the figure. Table 4 shows the cross-tabulation of ridge cohesion in the top panel of Figure 9 with acknowledged influence in the lower panel. The high reciprocal attachments all translate into influence. Directional attachments both translate into reciprocal influence. Edge bridge relationships generate no influence, which argues for the importance of cohesion and mutual memberships rather than single-link attachment as a source of influence. Only in two cases are there influences without attachments, for Psychology with Sociology and Economics. Here, however, Friedkin could argue for a strong ridge structure connecting Psychology to Sociology via the interdisciplinary cluster, and a weaker ridge connecting to Economics via the same intermediary, without using edge bridges.

(Insert Table 4 about here)

Bourgeois and Friedkin (2001) do not revisit the issue of multiconnectivity in their study of social ties in six school board policy groups but the effect of distance between the structural positions of actors and the correlation between solidarity (perceived agreement and acknowledged influence) and the existence of a direct interpersonal tie. Their finding of either a negative correlation or one where the effects of a tie *increase* solidarity with greater distance runs counter to the assumption of most sociological theories—which Friedkin (1998) had taken as axiomatic— that solidarity attenuates with the distance between social positions.[4] This could indicate that multiconnectivity and other sources of cohesion have effects that do not decay so easily with distances as is assumed by most organizational theories. Friedkin's (1993) earlier organizational case study of a issue resolution of teachers in a public school supports this idea. Here, the finding is that social cohesion (measured by an access measure that incorporates number of communication paths, length of paths, and strengths of constituent ties along paths) is the primary determinant of issue-related communication, which are in turn the primary predictors of issue-related influence, controlling for rewards, coercion, authority and expertise that have influence through the elementary structure of differential power.

Similarity of Political Contributions

Moody and White (2003:116-119) used PSC theory to analyze the similarity of political contributions of American businesses, using Mizruchi's (1992) data on the 57 largest manufacturing firms in the twenty major U.S. standard industrial (SIC) categories. They found an embedded cohesion structure in which 51 of the 57 industrial firms were in the largest bicomponent. The level of embedding in this cohesive structure, however, net of Mizruchi's other industry variables (in which interlock with common financial instructions and firms having defense contracts were important predictors), was found to have a significant effect on similarity of political contributions. When degree and betweenness centrality were entered into the regression, they were found to have no effect independent of cohesive embedding and Mizruchi's industry variables.

Collaboration in Biotechnology as a Field of Embedded Networks

The goal of Powell et al.'s (2002) study of interorganizational collaborative ties was to account for

> "the development and elaboration of the commercial field of biotechnology, showing how the formation, dissolution, and rewiring of network ties over a twelve-year period, from 1988 to 1999, has shaped the opportunity structure of the field.[5] By mapping changing network configurations, we discern how logics of attachment shift over time, and chart multiple influences on the varied participants in the field. Our effort is part of a more general move in the social sciences to analyze momentum, sequences, turning points, and path dependencies (see Abbott, 2001, for a fine general overview). By linking network topology and field dynamics, we consider social change not as an invariant process affecting all participants equally, but as reverberations felt in different ways depending on an organization's institutional status and location in the overall network as that structure evolves over time."

Like Barabási (2002, 2003) we observed a scale-free distribution of degree of linkage of firms in the biotechnical industry, which is typical of networks with preferential attachments and a tendency towards the formation of central hubs. Knowledge of the industry however, led us to question whether this power law tendency was due not to a preference for attachment to more central nodes but towards attachments that allowed diversification of ties and greater cohesive integration within the biotechnical knowledge industry. We developed a series pf arguments

> "concerning how the topology of a network and the rules of attachment among its constituents guide the choice of partners and shape the trajectory of the field. As organizations enter this arena and relationships deepen and expand, significant structural changes occur. To analyze and understand these emergent network structures, we use a triangulation of methods. We first analyze the expansion of the network to see if the process is random or uniform. We expect to find that as new organizations join the network, there is an attachment bias of a higher probability of being linked to an organization that already has ties (de Solla Price, 1965, 1980; Barabási, 2002). We turn next to closer examination of the processes that underlie attachment bias. We map the development of the field by drawing network configurations to create a framework with which to view network dynamics. Pajek (de Nooy, Mrvar, and Batagelj, 2003) is our software package of choice for the representation of network dynamics. Pajek allows us to analyze nearly 3,000 nodes at a time, and to identify cohesive subsets such as multi-connected components (White and Harary 2001: 12-14).

In our study we presented a selection of network visualizations to highlight both the evolving topology of the field and the processes by which new ties and organizations are added. We then turned to a statistical examination of network formation and dissolution, and assess the effects of alternative mechanisms of attachment.

McFadden's Discrete Choice Model of Network Dynamics

"To find out how a system behaves in particular circumstances ... simulate each step in its evolution explicitly" (Wolfram 1988:187) is an apt summary of Powell, White, Koput and Owen-Smith's (2003) use of McFadden's discrete choice variant of conditional logit regression to "test to see if the basis of attraction is accumulative advantage, similarity, follow-the-trend, or diversity. We consider whether the process of attachment is altered as an organization ages (e.g., early starter advantage) and its portfolio of connections changes, and how micro-level choices and macro-network trends co-evolve."

Their hypothesis was that cohesive blocks play a major role in the networks dynamics of link formation and repeat links in the evolution of the biotech industry, in keeping with hypotheses from PSC Theory. It was tempting to follow the simplest route for assessing network dynamics that Barabási (2002) had laid out by looking at the overall and changing degree distributions of the nodes in the network. The model that he formulated to explain the recurrence of scale-free power laws for the degree distributions of 'real networks,' however, what he and others now call the *scale-free model*, contains an elementary mistake: he mistakes consequent (scale-free power law degree distributions) for the antecedent in his model, preferential attachment. Preferential attachment, the tendency for new nodes in a network to attach to existing nodes with a probability biased towards those with higher degree, does generate power law degree distributions. But power law degree distributions may also be generated by other processes of attachment. The problem was to determine empirically what those processes were in the evolution of the biotech industry, step by step, and edge by edge.

Here, we take a very limited piece of the biotech analysis: net of other factors, what are the significant predictors from cohesion measures and their interactions to and new and to repeat ties. Table 5 summarizes the findings on preferences for diversity and cohesion in new and repeat attachments in the industry. Only the significance levels of the predicted attachments are shown. Here we are interested simply in the patterns of how cohesion and diversity affect new attachments and repeat attachments

(Insert Table 5 about here)

Five patterns are evident in Table 5 (net of other factors presented in the original study), for 1-mode attachments among biotech firms and 2-mode attachments with non-biotech partners.

1. The robust predictors of **new and repeat ties** are:

- *Partner Cohesion* and *Prospective Diversity*, but not Firm Diversity
- For 1-mode attachments, *these predictors are heightened* in *period 3* (1997-1999)
- For 2-mode attachments, *they interact with* Firm Cohesion and Firm Diversity.
- Except for 1-mode repeat ties: <u>Shared Cohesion</u> and <u>Partner Diversity</u>
- Except for 1-mode new ties: <u>Distance-2 Diversity</u>

2. The robust predictors of **new ties** only are:

- *Partner Cohesion and Prospective Diversity* interact with Firm Cohesion
- For 2-mode attachments, <u>Shared Cohesion and Partner Diversity</u> interact with Firm Cohesion and Firm Diversity; Firm Cohesion and Diversity interact with <u>Distance-2 Diversity</u>, etc.
- For 2-mode attachments, <u>these predictors</u> are heightened in *period 3* (1997-1999)
- For 2-mode attachments, Timeline interacts with *Partner Cohesion* alone and with Firm Cohesion

3. The predictors of **repeat ties** only are:
- For 2-mode attachments, Timeline interacts with Shared Cohesion, Partner Diversity and Distance-2 Diversity

Temporal changes are one of the patterns in these findings. The period3 interactions with *Partner Cohesion* and *Prospective Diversity* for **new and repeat** 1-mode attachment and with Shared Cohesion and Partner Diversity for **new** tie 2-mode attachments suggest that the industry is growing more oriented with time to a **preference for multiconnectivy**. This is reinforced by the Timeline interaction for **repeat tie** 2-mode attachment with Shared Cohesion, Partner Diversity and Distance-2 Diversity.

Figure 10 shows the degree distributions for the 1-mode data for each of the twelve years from 1988 to 1999. The distribution is log-log on the degree and frequency axes, and the relatively straight line for the 1988 distribution shows a relatively close fit to a power law. By 1999, however, the distribution shifts to exponential. This is what we would expect as the industry shifts from one based on NIH and government agency and a few biotech hubs as central to the industry to an industry with strong preferential attachments for multiconnectivity in the form of diversification of partners and cohesive integration.

(Insert Figure 10 about here)

The k-ridge structure of biotechnology, we have argued, is not dependent on strong-tie and relatively exclusive clusters, such as in the type of differentiated social positions in organizational fields envisioned by Friedkin and diagrammed by was of illustration in Figure 2A. Rather, if we are correct about preferential k-connectivity and diversification, the k-ridge structure should be one where flexible and shifting ties span the field and create the type of single hierarchical cohesive embedded we see in Figure 2B. And that is exactly what we find in our visualizations of the network structure of the industry.

Figure 11 shows the slope of the k-ridge structure on a log-log graph where the x axis is the connectivity k of the nested k-ridges and the y axis is the number of firms with that connectivity. The connectivity slope is power-law, which is an indicator that perhaps it is not degree centrality that is the preferential attachment, as in Barabási's one-scale-free model-fits-all model of networks, but rather connectivity the is the organizing preferential attachment.

(Insert Figure 11 about here)

Self-Embedded Cohesive Blocks and the Markov Assumption

The current generation of statistical packages for fitting statistical models to the structural biases that shape social networks, such as p* (Wasserman and Pattison 1996; Pattison, and Wasserman 1999) or exponential random graph (erg) models (Skvoretz 2002; Lomi and Pattison 2003), depend on a logic of local effects that seem to preclude the effects of cohesive blocks. Since these methods depend on the effect of subtracting particular edges or adding edges randomly to a network, they need to recompute the proximal effects of such changes, and to the extent that cohesive blocks are affected, they are not easily modeled by proximal effects, if at all. The restriction of these models to purely local interactions, they rely on a ‘Markovian assumption‘ in which potential ties between nodes are assumed to be conditionally dependent if and only if they are in the neighborhood of a common node. This allows ties to be considered both as dependent on their neighbors and participating in the neighborhoods of other ties. The cost is the rather unfortunate exclusion of non-local phenomena such as cohesive blocks.

Conclusion

The format of this article, as a review of recent work on structural cohesion and organizational theory, provided a certain amount of license to consider how different aspects of network theory connect. A reading of Friedkin’s (1998) work on social influence, the culmination of twenty years of work touching off and on again on the concept of cohesion provided an unexpected confluence of two lines of theory into one. Friedkin uses the concept of cohesion, but the highest graph theoretic measure of cohesion that he uses is based on the cohesion category proposed by Harary, Norman, and Cartwright (1965).[6] The formal definition of a k-ridge structure proposed here unifies the work on cohesion reviewed here, including Friedkin’s theoretical model of ridge structures in formal or voluntary organizations that that serve to reliably coordinate differentiated social positions. The kind of unification that this provides for cohesion theory connects back to the ideas about navigability and navigability of strong ties that we reviewed early in this paper. Those ideas relate to networks as small worlds, e.g., operating as an economy, or a generalized medium of navigation. Navigability operates in a much stronger form within organizations, where the cohesion of multiconnectivity and ridge structures may act to overcome the effects of distance decay effects in communication and transmission. In that context, the structure of interfaces between higher order ridge components is also important (see Figures 2A and 9) . Organizational fields, however, such as we have explored for biotechnology, may operate in a competitive mode, such as Barabási’s model of scale-free networks (with hubs competing for and attracting preferential attachments), or in a cooperative mode with a single hierarchical embedding of cohesion (as in Figure 2B), such as we see in the knowledge industry of biotechnology. In that structure, unlike the presumably preferential power-law attachments that we see in Barabási’s model, we see in Figure 11 that the preferential power-law attachments are not for degree centrality, but for cohesion, and the preferences for cohesion and diversity are amply demonstrated in the McFadden discrete choice analysis of the evolution of the network. As that analysis and Figure 10 have shown, however, what appears to have happened in that organizational field, between 1988 and 1999, is a transition from Barabási-type competitive preferential attachment to degree (power law) to a collaborative preferential attachment to diversity and cohesion in which the degree distribution shifts to exponential. There is ample room here, in the development of cohesion theory, for the development and testing of a host of new hypotheses. What is exciting about this field of research is that there is now a methodology in place for Predictive Social Cohesion as a theory to be developed and tested.

References

Barabási, A.-L.. (2002),.Linked: The New Science of Networks. Perseus Publishing, Cambridge, MA.

Batagelj, V., and A. Mrvar. (1998), Pajek—A Program for Large Net-works Analysis. Connections 21 (2), 47-57. University of Ljubljana. http://vlado.fmf.unilj.si/pub/networks/pajek. For a description of the program see http://vlado.fmf.uni-lj.si/pub/networks/pajek/pajek.pdf or http://vlado.fmf.uni-lj.si/pub/networks/pajek/sunbelt.97/pajek.htm. An introduction to drawing genealogies with Pajek is found at http://vlado.fmf.uni-lj.si/pub/networks/doc/sitges.pdf.

Batagelj, V., and A. Mrvar (2001), A subquadratic triad census algorithm for large sparse networks with small maximum degree. Social Networks 23: 237-243

Batagelj, V., and A. Mrvar (2002), Pajek—Analysis and Visualization of Large Networks. LNCS 2265. Berlin: Springer, 477-478. Bell, D. (2000), "Guanxi: A nesting of groups, Current Anthropology, 41 (1): 132-138. URL http://orion.oac.uci.edu/~dbell/guanxi.pdf

Brudner, L. A., and D. R. White (1997), "Class, Property and Structural Endogamy: Visualizing Networked Histories," Theory and Society 25:161-208.

Bourgeois, M. and Noah E. Friedkin. 2001. The Distant Core: Social Solidarity, Social Distance, and Interpersonal Ties. *Social Networks* 23: 245-260.

Friedkin, Noah E. 1983. Horizons of Observability and Limits of Informal Control in Organizations. *Social Forces* 62:54-77.

——— 1984. Structural Cohesion and Equivalence Explanations of Social Homogeneity. *Sociological Methods & Research* 12: 235-261.

——— 1993. Structural Bases of Interpersonal Influence in Groups: A Longitudinal Case Study American Sociological Review 58: 861-872.

——— 1998. *A Structural Theory of Social Influence*. New York: Cambridge University Press.

Ford, L. R., and D. R. Fulkerson (1956), Maximal flow through a network. Canadian Journal of Mathematics 8:399-404.

Fischhoff, B., E. O. Nightingale, and J. G. Iannotta, Eds. (2002), Adolescent Risk and Vulnerability: Concepts and Measurement (AddHealth Study), The National Academy Press, Washington, DC. URL: http://www.cpc.unc.edu/addhealth

Granovetter, M. (1973), "The Strength of Weak Ties." American Journal of Sociology, 78(6): 1360-1380.

Granovetter, M. (1985), "Economic Action and Social Structure: The Problem of Embeddedness." American Journal of Sociology, 91(3): 481-510.

Granovetter, M. (1992), "Problems of Explanation in Economic Sociology," in N. Nohria and R. Eccles (Eds.) Networks and Organizations, Boston, MA: Harvard Business School Press. Pp. 25-56.

Granovetter, M. (1995), "Coase Revisited: Business Groups in the Modern Economy". Industrial and Corporate Change 4(1): 93-130.

Granovetter, M. (1995), Getting a Job: A Study of Contacts and Careers, 2nd Edition (with a new Preface and a new chapter updating research and theory since the 1974 edition). University of Chicago Press, Chicago, IL.

Granovetter, M. (2000), "Social Networks in Silicon Valley". With Emilio Castilla, Hokyu Hwang and Ellen Granovetter. Pp. 218-247 in Chong-Moon Lee, William F. Miller, Marguerite Gong Hancock, and Henry S. Rowen, editors, The Silicon Valley Edge. Stanford: Stanford University Press.

Granovetter, M. (2001), The Sociology of Economic Life, 2nd edition, edited with Richard Swedberg. Boulder, CO: Westview Press.

Granovetter, M. (2002), "A Theoretical Agenda for Economic Sociology". Forthcoming in Mauro Guillen, Randall Collins, Paula England and Marshall Meyer, editors. The New Economic Sociology: Developments in an Emerging Field. New York: Russell Sage Foundation.

Harary, F., and M. Batell (1981), What is a system? Social Networks 3:29-40.

Harary, F., R. Norman, and D. Cartwright (1965), Structural Models: An Introduction to the Theory of Directed Graphs, Wiley, New York:NY.

Kleinberg, J. (2000), “Navigation in a Small World,” Nature, 406:845.

Kleinberg, J. (2002), “An Impossibility Theorem for Clustering,” Artificial and Machine Learning Seminar, URL: http://l2r.cs.uiuc.edu/~cogcomp/AIML/papers.html, University of Illinois at Urbana-Champaign.

Likert, R. 1961. *New Patterns of Management*. New York: McGraw Hill.

Lomi, A., and P. Pattison (2003 ms.),The Ties That Make The Market: An Empirical Study Of The Organization Of Production Relations Across Multiple Networks.

Menger, K. (1927), "Zur allgemeinen Kurventheorie," Fundamenta Mathematicae 10:96-115.

Moody, J., and D. R. White (2003), Social Cohesion and Embeddedness: A Hierarchical Conception of Social Groups. American Sociological Review 8(1):1-25. URL preprint: http://www.santafe.edu/sfi/publications/Abstracts/00-08-049abs.html.

Pattison, P.E., and S. Wasserman (1999), “Logit models and logistic regressions for social networks, II. Multivariate relationships. British Journal of Mathematical and Statistical Psychology, 52: 169-193.

Powell, W. W., D. R. White, K. W. Koput and J. Owen-Smith. (2003), “Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences. Submitted to: American Journal of Sociology.

Skvoretz, J. (2002), Complexity Theory and Models for Social Networks. Complexity 8(1):47-55.

Thomas, J.J. (1992), Informal Economic Activity. Harvester Wheatsheaf, Hemel Hempstead.

Thomas, J.J. (1995), Surviving in the City: The Urban Informal Sector in Latin America Pluto Press, London.

Thomas, J.J. (2000), "The Black Economy," World Economy 1 (1): 167-175.

Thomas, J.J. (2001) What Is the Informal Economy, Anyway?” SAIS Review 21(1):1-11 http://muse.jhu.edu/journals/sais_review/v021/21.1thomas.html

Travers, J., and S. Milgram (1969), “An Experimental Study of the Small World Problem." Sociometry, 32(4):425-443.

Wasserman, S., and P.E. Pattison (1996), “Logit Models and Logistic Regression for Social Networks, I. An Introduction to Markov Random Graphs and p*.” Psychometrika 60: 401-425.

Watts, Duncan J., Peter S. Dodds and Mark E. J. Newman. Identity and Search in Social Networks. Science 2002, 296:1302-1305.
White, D. R., and M. Houseman (2002), "The Navigability of Strong Ties: Small Worlds, Tie Strength and Network Topology." Complexity 8(1):72-81.
White, D. R., and U. Johansen (In Press), Network Analysis and Ethnographic Problems: Process Models of a Turkish Nomad Clan, Lexington Press, Boston, MA. Distribution by AltaMira Press.
White, D. R., M. Schnegg, L. A. Brudner and H. G. Nutini (2002), "Conectividad Múltiple, Fronteras e Integración: Compadrazgo y Parentesco en Tlaxcala Rural," in J. Gil-Mendieta and S. Schmidt (Eds.), Análisis de Redes: Aplicaciones en Ciencias Sociales, Mexico, D.F.: IIMAS- UNAM. (Instituto de Investigaciones en Mathemáticas Aplicadas y en Systemas- Universidad Nacional Autónoma de México) pp. 41-94.
White, H. C. (2002a), Markets from Networks: Socioeconomic Models of Production. Princeton University Press, Princeton, PA.
White, H. C. (2002b), How Businesses Mobilize Production Through Markets: Parametric Modeling of Path-dependent Outcomes in Network Flows," Complexity 8(1):87-95.
White, H. C., S. A. Boorman, and R. L. Breiger (1976), "Social Structure From Multiple Networks I." American Journal of Sociology 81:730-780.
Wolfram, S. (1988), Emerging Syntheses in Science: Proceedings of the Founding Workshops of the Santa Fe Institute, (Addison-Wesley, 1988) 183-189. Url: Complex Systems Theory. http://www.stephenwolfram.com/publications/articles/general/88-complex/2/text.html
Zachary, W. W. 1975. The Cybernetics of Conflict in a Small Group: An Information Flow Model. Unpublished M.A. Thesis, Department of Anthropology, Temple University.
Zachary, W. W. 1977. “An Information Flow Model for Conflict and Fission in Small Groups.” Journal of Anthropological Research 33:452-73.

Table 1: The Structure of Informal Economic Activity			
Sector	**Market Transactions**	**Output**	**Production/ Distribution**
Household	No	Legal	Legal
Informal	Yes	Legal	Quasi-Legal
Underground	Yes	Legal	Illegal
Criminal	Yes	Illegal	Illegal

Source: Based on Thomas (1992) p. 6, Table 1.1

Table 2: Test of Hypothesis 4.4—Relinking and Cohesion

Pearson's coefficient r = .95 without the two middle rows

	Relinked Marriages	Non-Relinking Marriages	Totals
villagers who became clan members	**2****	1**	3
clan member and			
clan wife	**148**	0	148
Hayta*, Honamlĭ*, Sarĭkeçili wife	**12**	14	26
left for village life	13	**23**	36
village wife (34) or husband (1)	11	**24**	35
Cĭrĭklĭ*,Tĭrtar wife	2	**3**	5
Horzum*,Karakolunlu*,Tekeli* wife	0	**9**	9
left for another tribe	0	**8**	8
villagers not joined to clan	1	**3****	4
Totals	189	85	274

* tribes **non-clan by origin

Table 3: Results of the Triad Census among Sublineages

Type	Number of triads (ni)	Expected (ei)	Chi Ratio (ni-ei)/ei	Probability	Model
3 - 102	**146**	55.06	1.65	p<.001	**Balance**
16 - 300	**128**	29.01	3.41	p<.001	**Balance**
1 - 003	**73**	14.60	4.00	p<.001	**Clusterability**
2 - 012	**140**	98.22	0.43	p<.001	**Transitivity**
15 - 210	175	155.22	0.13	p=.11 (n.s.)	Hierarchical Clusters
11 - 201	**135**	69.22	0.95	p<.001	**Forbidden (Reciprocity Chains)**

Table 4: Prediction from Ridge Attachment to Influence

N=15	**INFLUENCE** Reciprocal	Directional or Reciprocal	None
ATTACHMENT			
High	2	1	
Directional		2	
Edge Bridge only			4
None		2	4

Gamma = .714, tau-b = .55, Somer's D=.5, p < .02.

Table 5: McFadden Discrete Choice Model Predictions for Biotech Attachments

Biotechnical Corporations 1988-1999, N=472, and 3000 Partners	1-Mode: Biotech to Biotech		2-Mode: Biotech to Partners	
Definitions				
Partner Cohesion	k-component		k-component	
Shared Cohesion	k-components		k-components (highest)	
Partner Collaborative Diversity	Activity-by-form		Activity	
Firm Diversity	Activity-by-form			
Prospective Diversity	Ditto: change in		Ditto: change in	
Distance-2 Collaborative Diversity	For DBFs of partner		For DBFs of partner	
	New Ties	**Repeat Ties**	**New Ties**	**Repeat Ties**
Multiconnectivity (Cohesion and Diversity)				
Partner Cohesion	** — —	** **	** ** **	— * *
Shared Cohesion	* ** *	— —	** ** **	** ** **
Partner Collaborative Diversity	** ** *	— —	** — **	** ** ~
Firm Diversity	— — —	— —	— — —	— — —
Prospective Diversity	— ** **	** **	** ** —	** ~ **
Distance-2 Collaborative Diversity	— ~ —	** **	** ** **	** — ~
Contingencies				
Firm Age x Shared Cohesion	* *			
Firm Cohesion x Prior Experience				** **
Firm Cohesion x Partner Cohesion	** **		** **	* *
Firm Cohesion x Shared Cohesion			** *	
Firm Cohesion x Partner Collaborative Diversity			— **	
Firm Cohesion x Prospective Diversity	** **		** **	
Firm Cohesion x Distance-2 Collab. Diversity			** **	
Firm Collab. Diversity x Partner Collab. Diversity			** —	
Firm Collab. Diversity x Prospective Diversity			** **	** **
Firm Collab. Diversity x Dist.-2 Collab. Diversity			** **	** **
Period3 (1997-1999) Interactions				
Period3 x Partner Cohesion	*			
Period3 x Partner *Collaborative* Diversity	*			
Period3 x Prospective Diversity	**		**	
Period3 x Firm Cohesion x Prospective Diversity	**		**	
Period3 x Firm Cohesion x Partner Diversity			**	
Period3 x Firm Diversity x Prospective Diversity			*	
Timeline (linear time from 1987) Interactions				
Timeline x Partner Cohesion			*	~
Timeline x Firm Cohesion x Partner Cohesion			*	~
Timeline x Shared Cohesion				*
Timeline x Partner Collaborative Diversity				**
Timeline x Distance-2 Collaborative Diversity				**

** = p < .01; * = p <.05; ~ = p < .10

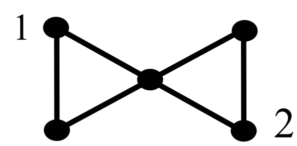


FIGURE 1. The bow tie graph. The lowest order of graph (*n* = 5) at which edge and node connectivities differ (node connectivity = 1, while edge connectivity = 2).

Figure 2A: A 3-ridge structure supporting overlapping 4-components

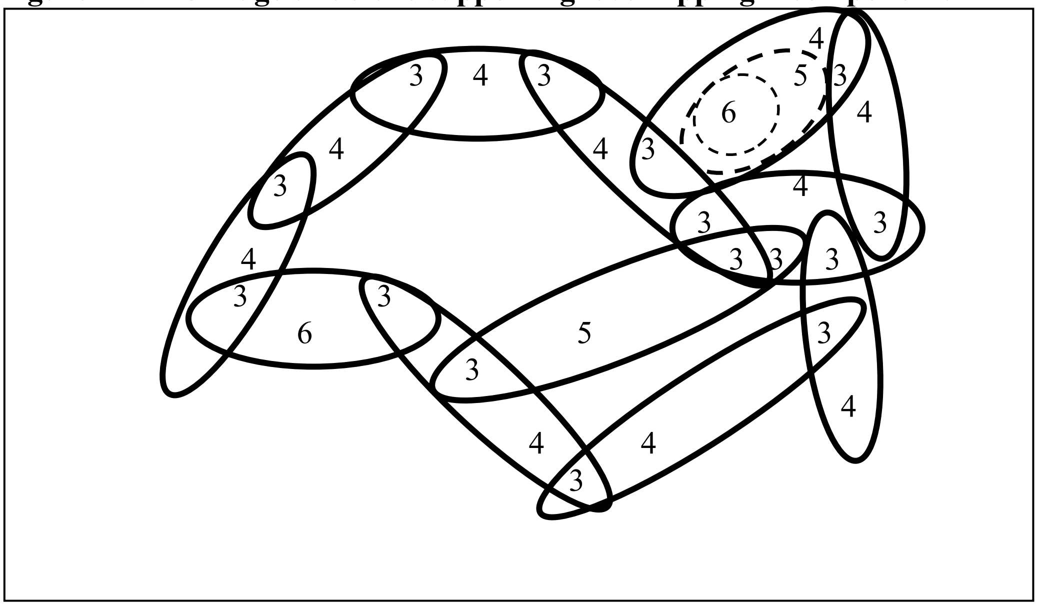


Figure 2B: A ridge structure supporting a single embedding of k-components

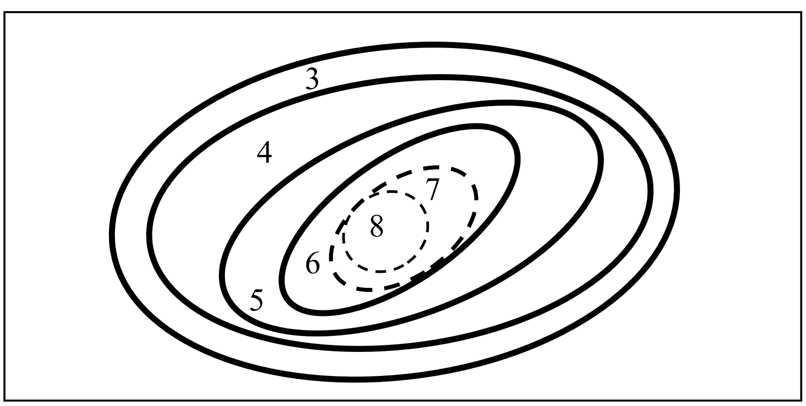
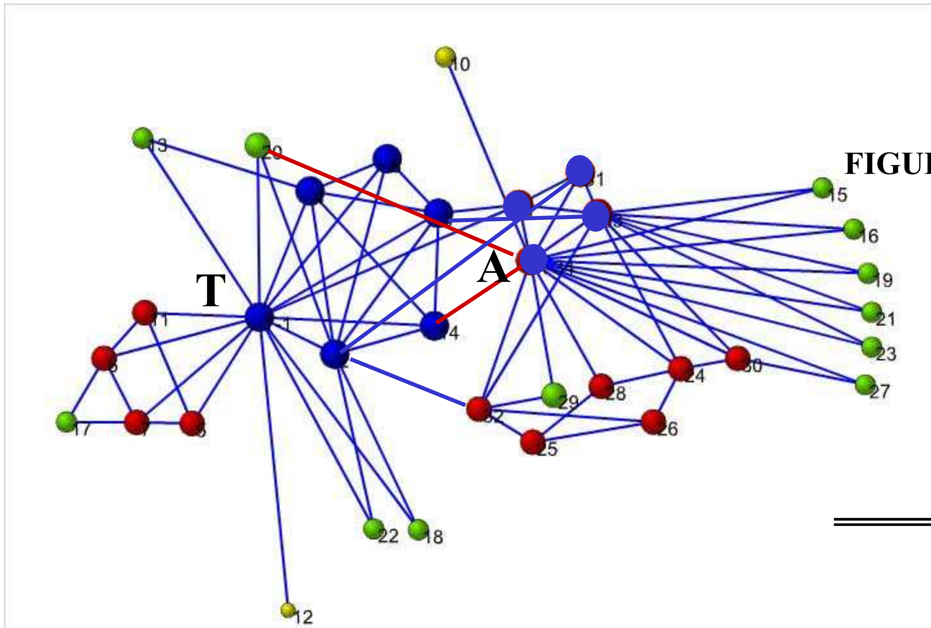
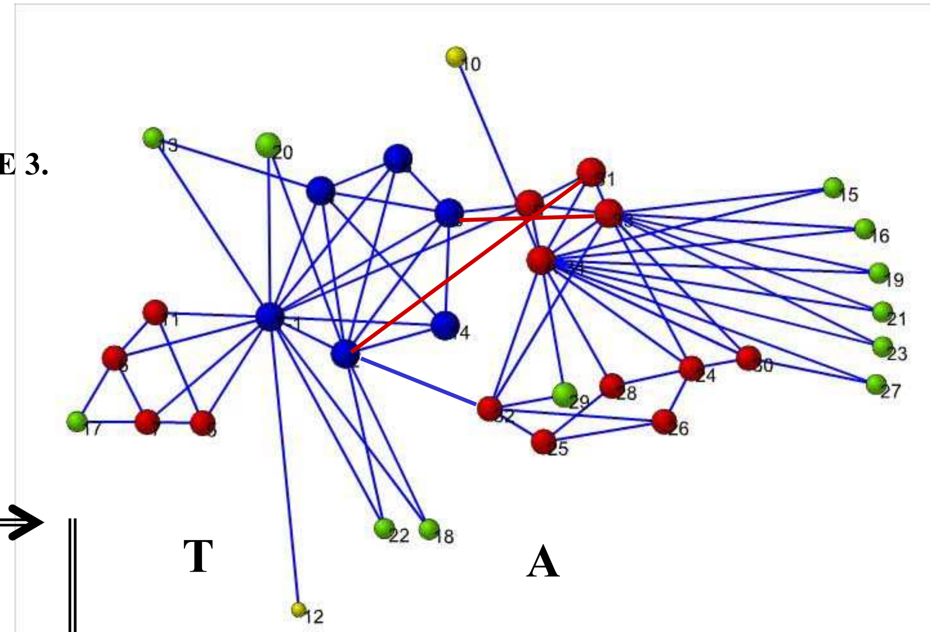


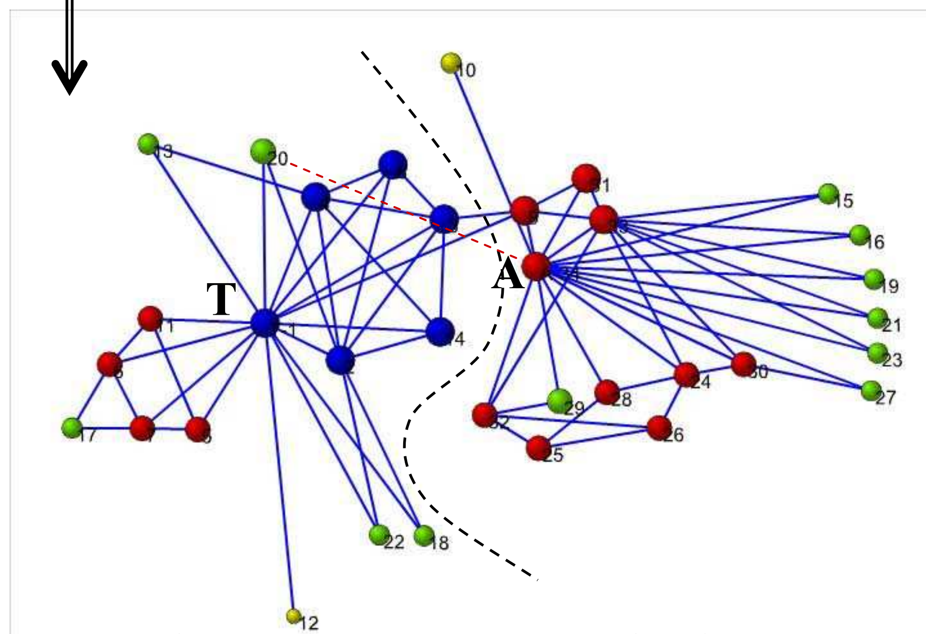
FIGURE 3.



T and A start to fight: some must choose sides



Opposing cohesive sides emerge



The sides separate along cohesive fracture

members of a group with cohesion level k automatically have at least k different ways of being connected through (k) node-independent paths

T = karate teacher

A = club administrator

Block Connectivity:

Blue k=4 (quadricomponent)

Red k=3 (tricomponent)

Green k=2 (bicomponent)

Yellow k=1 (component)

Figure 2a,b,c Data source: Wayne Zachary, 1977. An Information Flow Model for Conflict and Fission in Small Groups. **Journal of Anthropological Research** 33:452-73.

Figure 4. Friendship Cohesion in an American high school

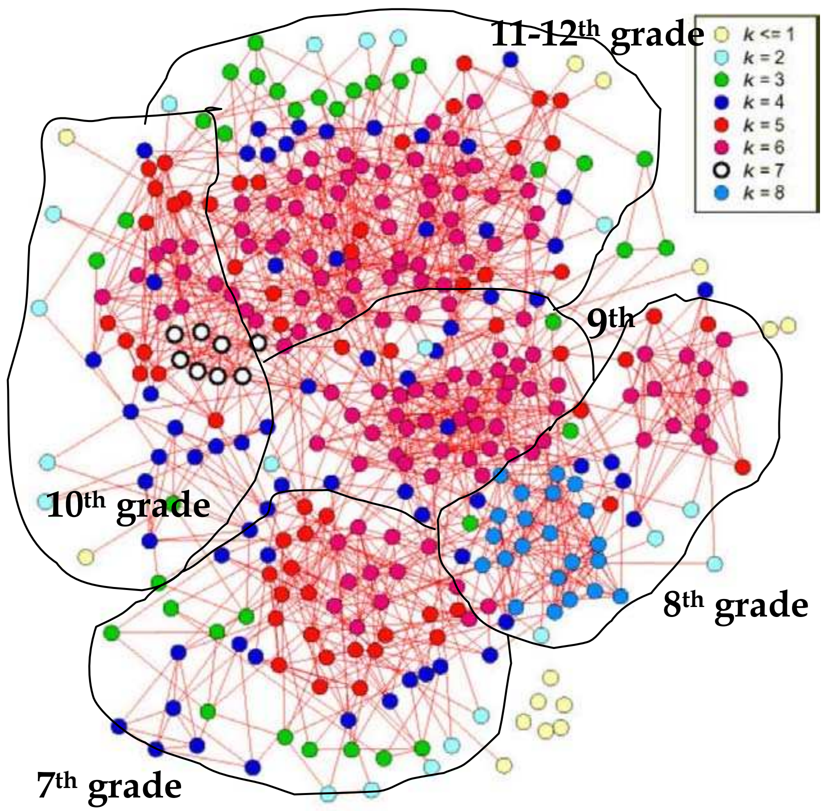


Figure 5.
Segment of a Turkish Nomad Clan Genealogy

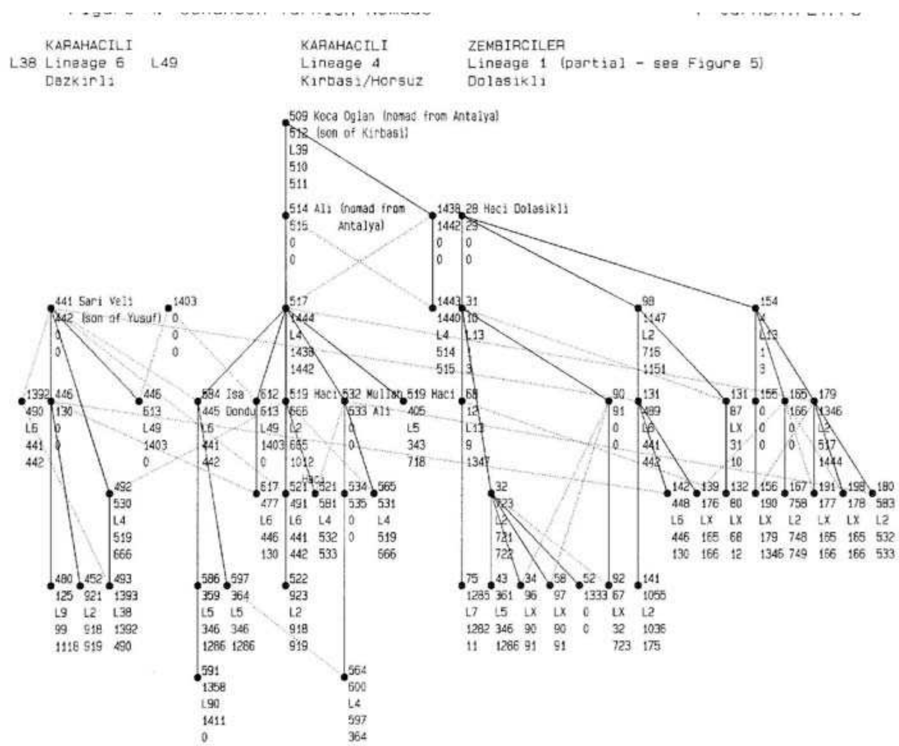


Figure 6. Kinship Network of a Turkish Nomad Clan

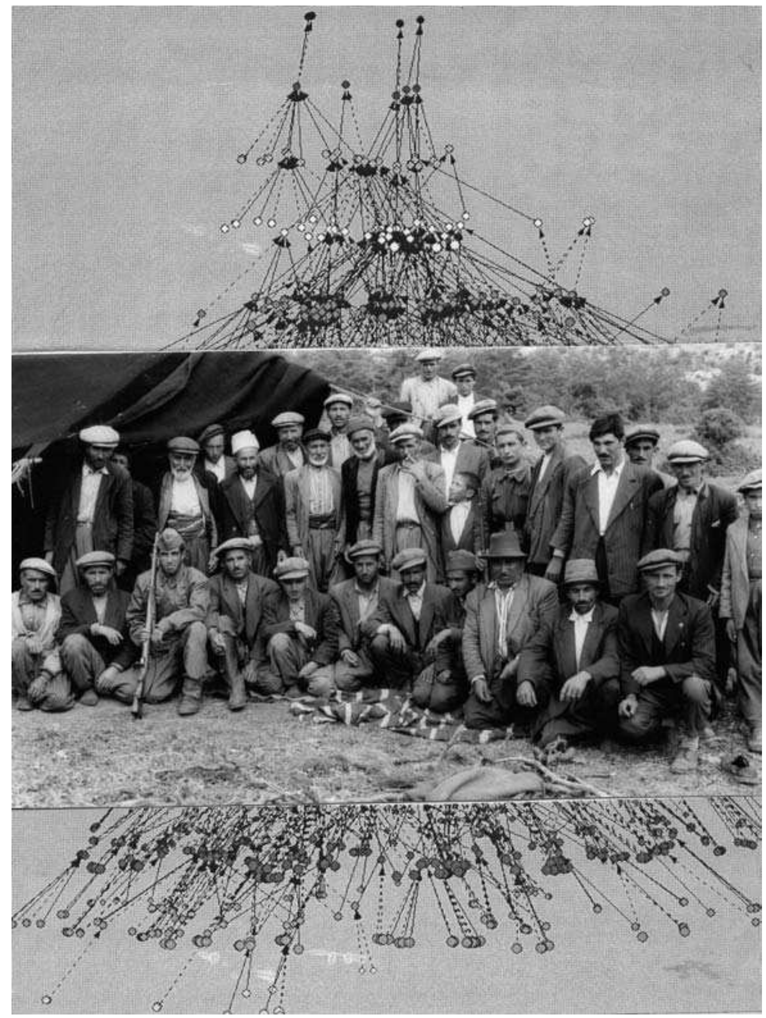


Figure 7. Decay of marriage frequencies with kinship distance

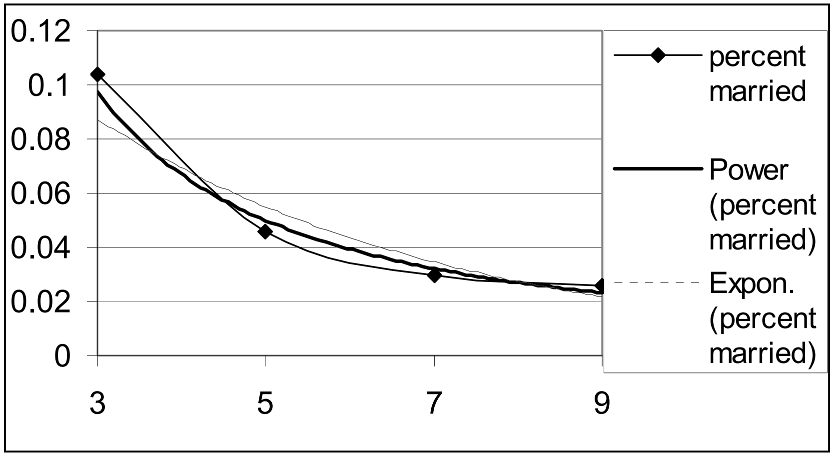


Figure 8. Densities of marriage patterns among lineages

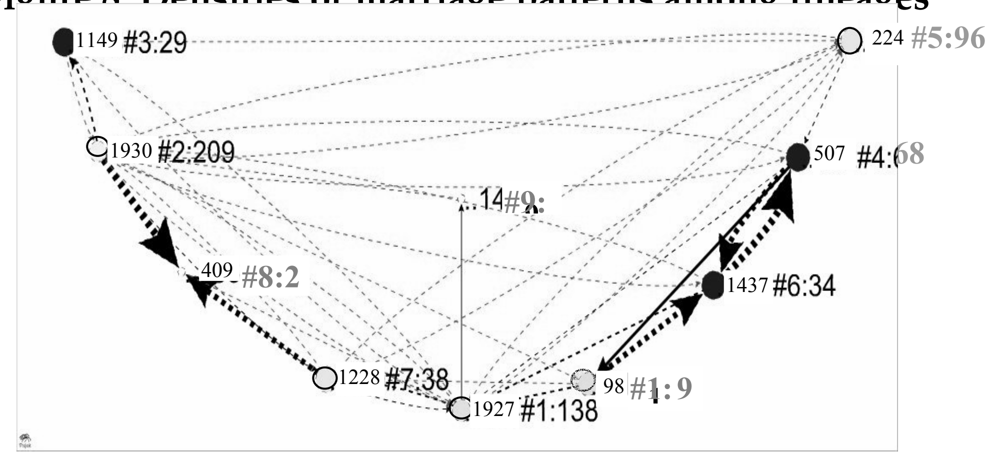
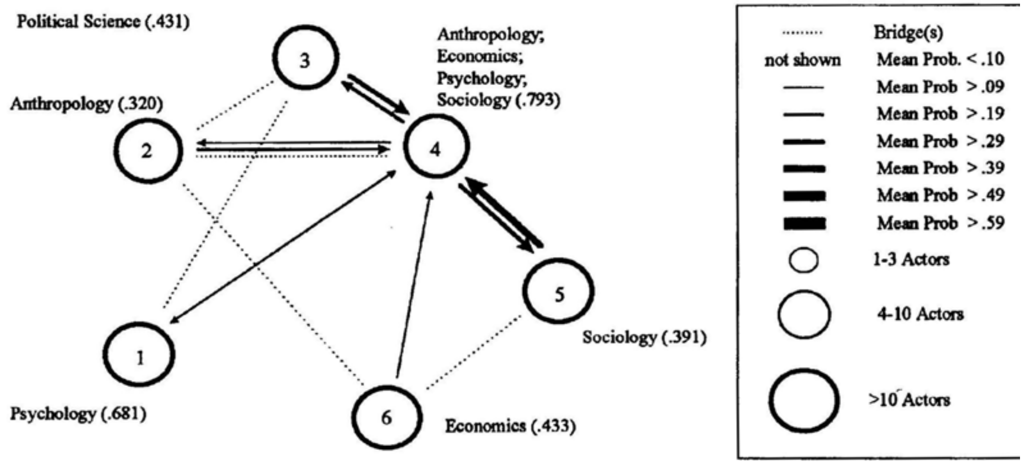
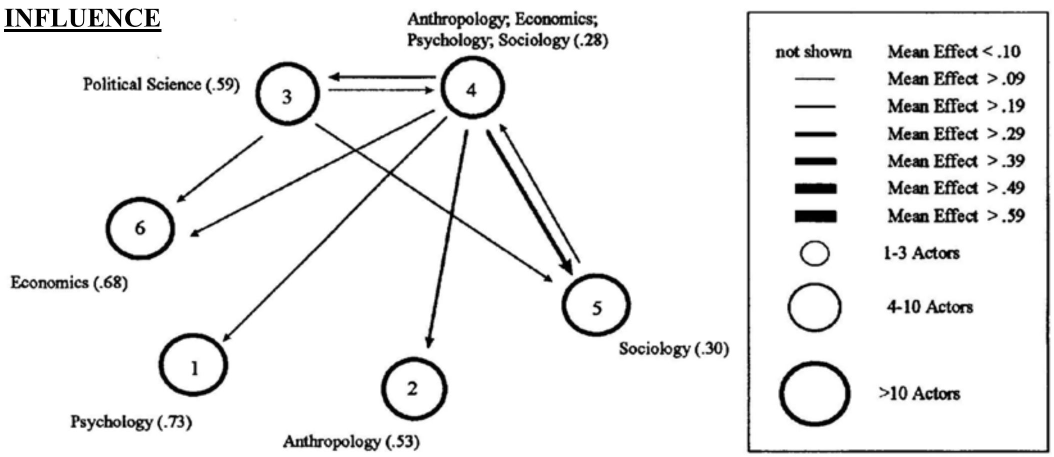


Figure 9: Ridge-model of Attachments between blockmodel positions for Social Science faculty predicting Acknowledged Influence

ATTACHMENT



INFLUENCE



Source: Friedkin (1998: 156 and 175).

Figure 10: Temporal Shift in 1-mode biotech Degree Distributions, 1988-1999, from Power Law to Exponential, Contra the Barabási scale-free network model

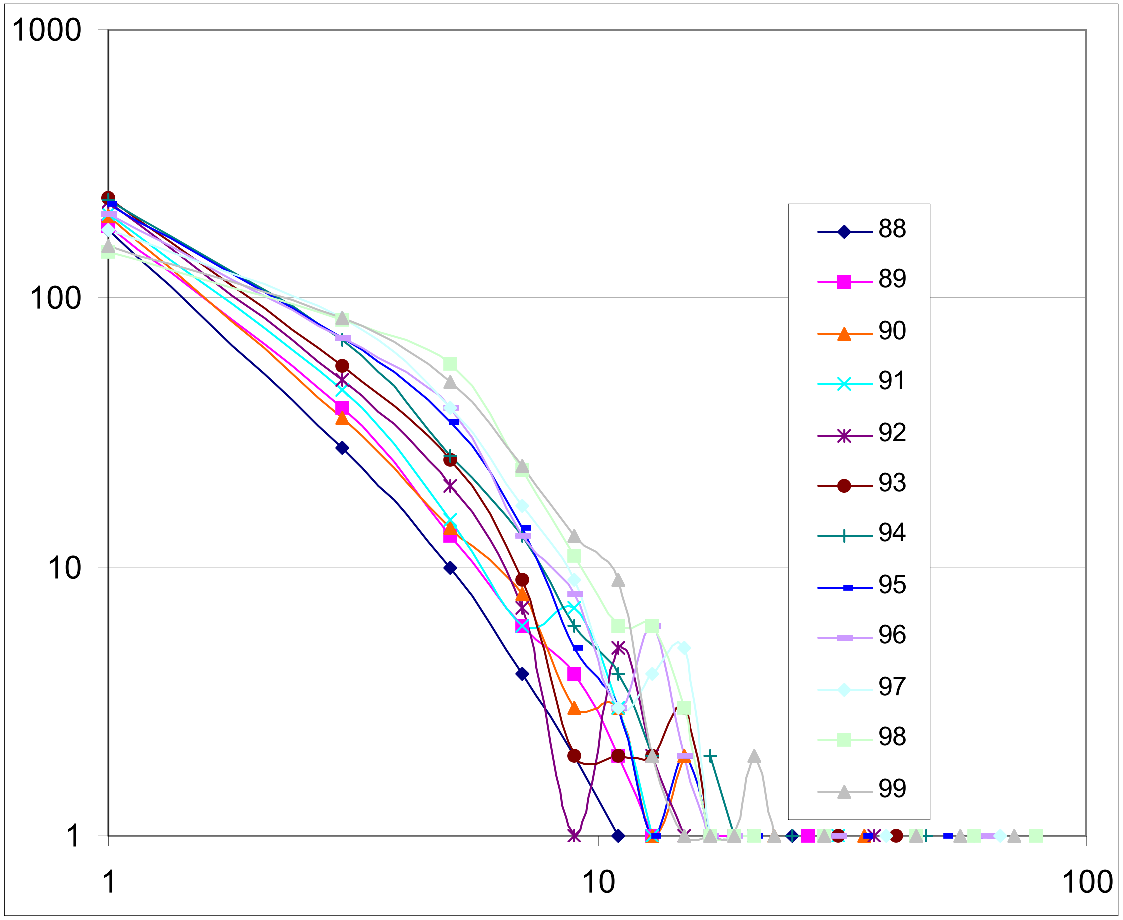
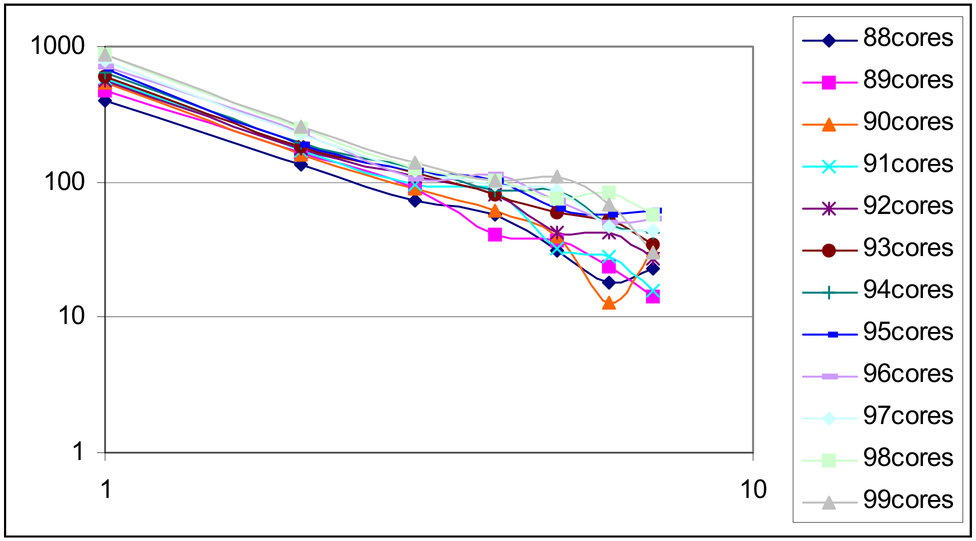


Figure 11: The power-law slope of the k-ridge structure for the 1-mode biotech network



FOOTNOTES TO TEXT

[1] Since most networks contain low- as well as high-frequency ties, low- as well as high-intensity ties, uniplex as well as multiplex relations, weak ties usually outnumber strong ties. Intuitively, then, the paths composed exclusively of strong ties between pairs or nodes will be considerable outnumbered by paths that involve one or more weak ties. Hence where the NST model applies the SWT will apply as well, but not vice versa.

[2] "Research by physicists interested in networks has ranged widely from the cellular level, a network of chemicals connected by pathways of chemical reactions, to scientific collaboration networks, linked by coauthorships and co-citations, to the world-wide web, an immense virtual network of websites connected by hyperlinks (Albert, Jeong, and Barabási, 1999; Jeong et al, 2000; Newman, 2001; Watts and Strogatz, 1998). Albert and Barabási (2002) and Barabási (2002) provide excellent technical and general overviews of this burgeoning literature on the network topology of different fields, highlighting key organizing principles that guide interactions among the component parts of fields."

[3] Longitudinal Network Studies and Predictive Social Cohesion Theory was the subject of investigation of NSF grant BCS-9978282 awarded to D. R. White, and which supported the collaborative work of White and Harary (2001) and Moody and White (2003), among other studies.

[4] They show that while interpersonal ties foster social solidarity, and the expected negative effects of social distance may be salient in certain core-periphery structures, these negative effects are not ubiquitous implications of social differentiation but properties of particular forms of social organization.

[5] They "use the term field rather than industry or population intentionally. Biotechnology is not a separate industrial sector with well-defined boundaries. Universities, government labs, and nonprofit hospitals and research institutes are a critical part of the field; while on the commercial side, both established pharmaceutical firms and dedicated biotechnology companies are involved in bringing new medicines to market. Thus, field captures the diversity of organizations more aptly than any other term."

[6] Categorical connectivity or the category of connectivity (Friedkin 1968:164) refers to four categories of reachability in a directed graph defined by Harary, Norman and Cartwright (1965): unilateral (one or the other of each pair can reach the other on a directed path), weak (every node can reach any other through a semipath, and strong (every node can reach any other through a directed path), and disconnected (tyhere is some node that cannot reach another through a semipath). In contrast, connectivity level as used in this paper corresponds to the type of connectivity in Menger's Theorem (Harary 1969), e.g., the number of nodes whose removal is needed to disconnect a graph, and the minimum number of node-independent paths between pairs of nodes in the graph (White and Harary 2001).