# The SAGE Handbook of Social Network Analysis

## The Development of Social Network Analysis – with an Emphasis on Recent Events

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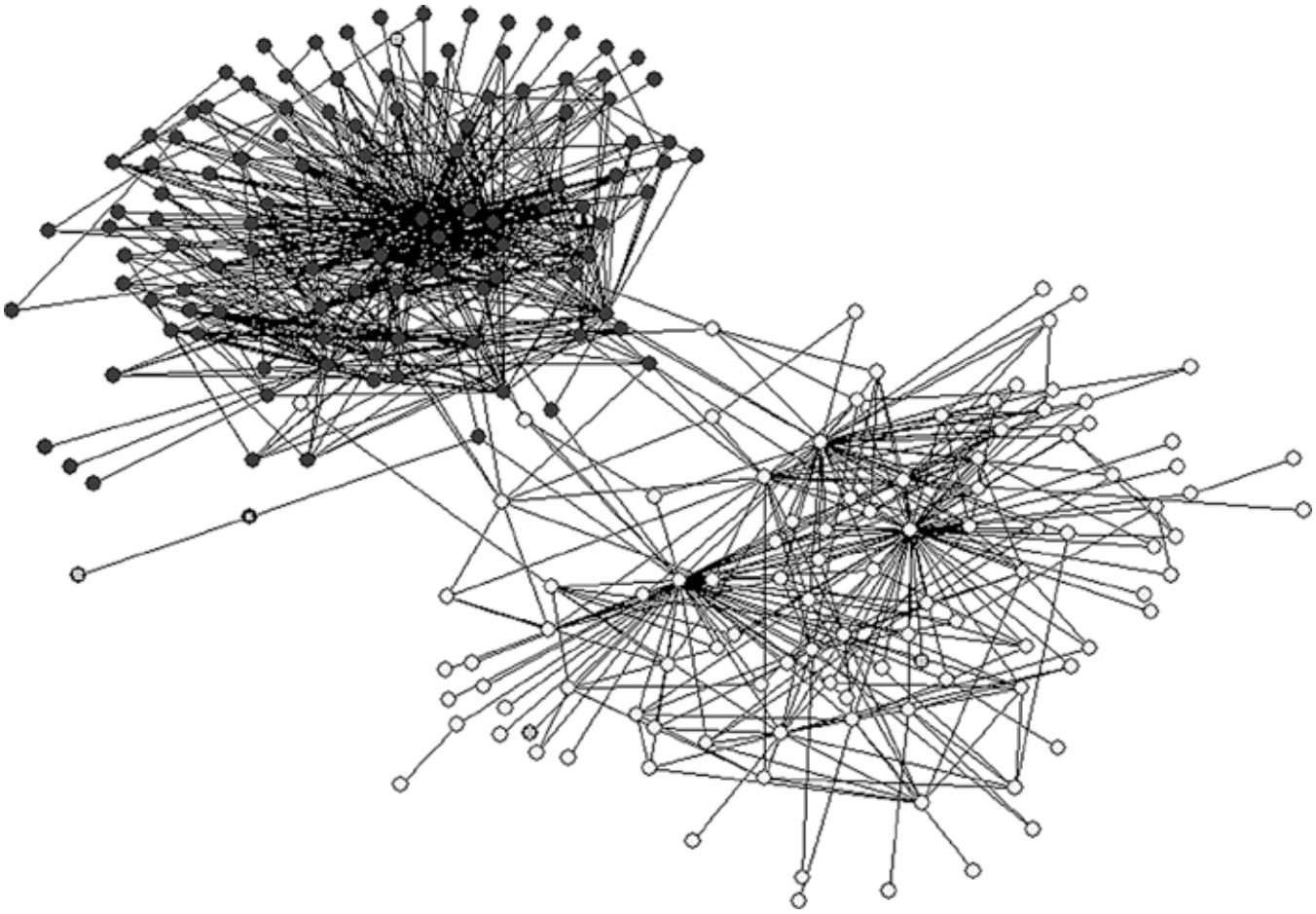

Moreover, Figure 3.3 also shows that, at that point, 98 percent of the citations were made within either the physics community or the social network community. For the most part, physicists ignored the earlier work by social network analysts. And social network analysts responded in kind.

Physicists were also quick to follow up on Barabási and Albert's work on degree distributions. According to Google Scholar, their first paper had received over 4,000 citations as of mid-November 2008. But practically none of those citations were produced by social network analysts.

It soon became evident that the physicists' interest in social networks was not going to be confined to small-world phenomena and degree distributions. Members of the physics community quickly began to explore other problems that had traditionally belonged to social network analysts. Nor was that interest restricted to physicists. At the same time, physicists succeeded in getting biologists and computer scientists involved in their efforts. Two main foci of this new thrust involved the study of cohesive groups, or what physicists call *communities,* and the study of the positions that nodes occupy in a network—particularly their centrality. I will review these foci in the next two sections.

## Cohesive Groups or Communities

The notion of cohesive groups is foundational in sociology. Early sociologists (Tönnies, 1855/1936; Maine, 1861/1931; Durkheim, 1893/1964; Spencer, 1897; Cooley, 1909/1962) talked about little else. Their work provided an intuitive "feel" for groups, but it did not define groups in any systematic way.

When the social network perspective emerged, however, network analysts set out to specify groups in struc-

tural terms. Freeman and Webster (1994) described the observation behind this structural perspective on groups:

> Whenever human association is examined, we see what can be described as thick spots—relatively unchanging clusters or collections of individuals who are linked by frequent interaction and often by sentimental ties. These are surrounded by thin areas where interaction does occur, but tends to be less frequent and to involve very little if any sentiment.

Thus, the social ties within a cohesive group will tend to be dense; most individuals in the group will be linked to a great many other group members. Moreover, those in-group ties will tend to display clustering—where, as described above, friends of friends are friends. In contrast, relatively few social ties will link members of different groups, and clustering will be relatively rare.

An early social network analyst, George Homans (1950: 84), spelled out the intuitive basis for the social network conception of cohesive groups:

> A group is defined by the interactions of its members. If we say that individuals A, B, C, D, E, … form a group, this will mean that at least the following circumstances hold. Within a given period of time, A interacts more often with B, C, D, E, … than he does with M, N, L, O, P, … whom we choose to consider outsiders or members of other groups. B also interacts more often with A, C, D, E, … than he does with outsiders, and so on for the other members of the group. It is possible just by counting interactions to map out a group quantitatively distinct from others.

Over the years, network analysts have proposed dozens of models of cohesive groups. These models serve to define groups in structural terms and provide procedures to find groups in network data. They all try to capture something close to Homans's intuition in one way or another. Some of them represent groups in terms of on/off or binary links among actors (e.g., Luce and Perry, 1949; Mokken, 1979). Others represent them in terms of quantitative links that index the strength of ties linking pairs of actors (e.g., Sailer and Gaulin, 1984; Freeman, 1992).

Currently, then, we have a huge number of models of cohesive groups. Most of them were reviewed by Wasserman and Faust (1994). Some were algebraic (e.g., Breiger, 1974; Freeman and White, 1993), some were graph theoretic (e.g., Alba, 1973; Moody and White, 2003), some were built on probability theory (e.g., Frank, 1995; Skvoritz and Faust, 1999), and some were based on matrix permutation (e.g., Beum and Brundage, 1950; Seary and Richards, 2003). All, however, were designed to specify the properties of groups in exact terms, to uncover group structure in network data, or both.

Over the years social network analysts have also drawn on various computational algorithms in an attempt to uncover groups. These include multidimensional scaling (Freeman et al., 1987; Arabie and Carroll, 1989); various versions of singular value decomposition, including principal components analysis and correspondence analysis (Levine, 1972; Roberts, 2000); hierarchical clustering (Breiger et al., 1975; Wasserman and Faust, 1994: 382–83); the max-cut min-flow algorithm (Zachary, 1977, Blythe, 2006); simulated annealing (Boyd, 1991: 223; Dekker, 2001); and the genetic algorithm (Freeman, 1993; Borgatti and Everett, 1997).

In social network research, the general tendency over the years has been to move from binary representations to representations in which the links between nodes take numeric values that represent the strengths of connections. At the same time social network analysts have gradually shifted from building algebraic and graph theoretic models to developing models grounded in probability theory. And, as time has passed, they have relied more often on the use of computational procedures to uncover groups.

A notable exception to this trend can be found in an article by Moody and White (2003). They used graph theory to define *structural cohesion*. They defined structural cohesion "… as the minimum number of actors who, if removed from a group, would disconnect the group." Then they went on to define *embeddedness* in terms

of a hierarchical nesting of cohesive structures. This approach represents a new and sophisticated version of the traditional social network model building.

Since the early 1970s, mathematicians and computer scientists had also been interested in groups or communities. They defined that interest in terms of *graph partitioning* (Fiedler, 1973, 1975; Parlett, 1980; Fiduccia and Mattheyses, 1982; Glover, 1989, 1990; Pothen et al., 1990). Social network analysts recognized this tradition when the work by Glover was cited and integrated into the program UCINet (Borgatti et al., 1992). And in 1993 the link in the other direction was made when a team composed of an electrical engineer and a computer engineer, Wu and Leahy (1993), cited the work of a statistician and social network analyst, Hubert (1974). And in 2000 three computer scientists, Flake, Lawrence, and Giles (2000), cited the social network text by Scott (1992).

Until quite recently, however, these efforts did not stir up much interest in the physics community. Instead, the physicists turned to the procedures developed in social network analysis. Girvan and Newman (2002) adapted the social network model of betweenness centrality (Freeman, 1977) to the task of uncovering groups. Their adaptation was based on the betweenness of graph edges, rather than nodes, and the result was a new algorithm for partitioning graphs.

Edge betweenness refers to the degree to which an edge in the graph falls along a shortest path linking every pair of nodes. A path in a graph is a sequence of nodes and edges beginning and ending with nodes. Girvan and Newman reasoned that since there should be relatively few edges linking individuals in different groups, those linking edges should display a high degree of betweenness. So they began by removing the edge with the highest betweenness, and they continued that process until the graph was partitioned.

Two years later Newman and Girvan (2004) published a follow-up article. Their second paper again focused on edge removal, but this time they introduced an alternative model that had two intuitive foundations. In one, they showed that random walks between all pairs of nodes would determine the betweenness of edges—not just along shortest paths, but along all the paths linking pairs of nodes. The other intuition was motivated by a physical model where edges were defined as resistors that impeded the flow of current between nodes. The edge with the lowest current flow was removed. If that did not yield a partition the process was continued until partitioning did take place. These two models produced the same partitions.

Newman and Girvan went on to show that all of their algorithms always partitioned the data even though some of the partitions might not reflect the presence of actual communities. So they introduced a measure called *modularity*. Modularity is based on the ratio of within-partition ties to those that cross partition boundaries and compares that ratio to its expected value when ties are produced at random. Thus, it provides an index of the degree to which each partition embodies a group- or community-like form.

The result of the two papers by Girvan and Newman was dramatic. Both physicists and computer scientists quickly developed an interest in groups or communities. Radicchi and colleagues (2004) specified two kinds of communities. One was characterized as “strong;” it defined a partition as a community if it met the condition that every node had more within-group ties than cross-cutting ones.[4] The other they characterized as “weak.” It proposed that a partition was a community if the total number of ties within each partition was greater than the total number of ties linking nodes in the partition to nodes outside the partition.

Radicci et al. also pointed out that the Girvan and Newman betweenness-based algorithm was computationally slow. So they introduced a new, more efficient measure. They reasoned that edges that bridge between communities are likely to be involved in very few 3-cycles (where friends of friends are friends). So they based their measure on the number of 3-cycles in which each edge is involved, and they showed that their measure had moderate negative correlation with the Girvan-Newman measure. The number of 3-cycles in which an edge is involved, then, turns out to be inversely related to the betweenness of that edge.

Newman (2004) quickly jumped back in. He, too, was troubled by the slowness of the Girvan-Newman algorithm for finding communities. So he proposed a fast “greedy” algorithm. A greedy algorithm makes the optimal choice at each step in a process, without regard to the long-term consequences of that choice.[5] In this case, Newman proposed starting a process by having each cluster contain a single node. Then, at each stage in the process, the pair of clusters that yields the highest modularity is merged.

The concern with computing speed seems to have started a race to see who could develop the fastest algorithm to cluster nodes in terms of their modularity. A computer scientist, Clauset, working with two physicists, Clauset et al. (2004), was able to speed up Newman's “greedy” algorithm. Two more computer scientists, Duch and Arenas (2005), devised an algorithm to speed it up even more. And in 2006 Newman showed how to gain still more speed by applying singular value decomposition to the modularity matrix. Then, in 2007, a computer scientist, Djidjev, developed a still faster algorithm for constructing partitions based on modularities.

Continuing the search for speed, two other computer scientists, Pons and Latapy (2006), took an entirely different approach. They reasoned that since communities are clusters of densely linked nodes that are only sparsely linked together, a short (two- or three-step) random walk should typically stay within the community in which it is started. They proposed an algorithm that begins with a series of randomly selected starter nodes. Each starter is used to generate a random walk. Then the starters, along with the nodes that are reached, are tallied as linked. The likelihood is that once these results are cumulated, they will display the clustered communities. Finally, two industrial engineers and a physicist, Raghavan, Albert, and Kumara (2007), produced a very fast algorithm based on graph coloring. Nodes begin with unique colors, then, iteratively, each acquires the color of the majority of their immediate neighbors.

Other quite different procedures were also introduced. A physicist and a computer scientist, Wu and Huberman (2004), developed a model based on assuming that edges are resistors, as was the case in the earlier model introduced by Newman and Girvan. But Wu and Huberman's model turns out to be much more complicated and ad hoc. Four physicists, Capocci, Servedio, Caldarelli, and Colaiori (2004), suggested using singular value decomposition to uncover communities. And three others, Fortunato, Latora, and Marchiori (2004), proposed a variation of edge centrality called “information centrality.” Their centrality is based on the inverse of the shortest path length connecting each pair of nodes. The physicists Palla et al. (2005) defined communities as cliques and focused on patterning of clique overlap. Reichardt and Bornholdt (2006) used simulated annealing to search for partitions that yield communities that have a large number of ties within groups and a small number of ties that cut across groups.

Some of these ideas, like overlapping cliques and simulated annealing, will be familiar to seasoned social network analysts. Many others, however, are new and several are quite creative. In particular, edge betweenness, modularity, the use of 3-cycles, short random walks, and graph coloring appear to have promise.

Almost all of these contributions focused on building new tools to uncover groups or communities. They all reported applications to data, but for the most part their applications were merely illustrative. The main thrust of this research has been to build better and faster group-finding algorithms. That preoccupation with developing ever-faster algorithms may not seem too important to most social network analysts, but many applications — particularly those in biology — involve data sets that involve connections linking hundreds of thousands or millions of nodes. For those applications, speed is essential.

## Positions

Concern with the positions occupied by individual actors has been the second main theme in social network analysis. Four kinds of positions have been defined. First, positions in groups — *core* and *periphery* — have been specified. Second, a good deal of attention has been focused on *social roles*. Third, some attention has

(Freeman, 2008). In addition, a few physicists have attended the annual Sun Belt social network meetings,[6] and a few social network analysts have been invited to the meetings of the physicists.[7] Representatives of each discipline are beginning to publish in journals usually associated with the other.[8] There are even some joint publications (e.g., Reichardt and White, 2007; Salganik et al., 2006).

My earlier hope for rapprochement between physics and social network analysis, it seems, is beginning to take place. All that is required now is that the social network analysts relax their claim to ownership of the field. The physicists are making important contributions to what could easily end up as a collective effort.[9]

# Notes

1 Important publications from each of these centers are listed in Freeman (2004).

2 Scott, in the current volume, also describes the entry of physicists into social network analysis. His description centers on their theoretical perspective.

3 The Barabási and Albert model, however, turns out to be essentially the same as that proposed by a social network analyst, Derek de Solla Price, in 1976.

4 They did not cite the similar social network models introduced by Sailer and Gaulin (1984).

5 Hierarchical clustering is an example of a greedy algorithm.

6 Freeman (2004: 166) mentions the attendance of the physicists Watts, Newman, and Hoser at social network meetings.

7 The social network analysts Vladimir Batagelj and Linton Freeman were invited to the Summer Workshop in Complex Systems and Networks, put on by physicists in Transylvania in 2007.

8 See, for example, the physicists Watts (1999), Holme, Edling, Liljeros (2004), and Newman (2005) publishing in Social Networks or network analysts Borgatti et al. (2009) appearing in Science.

9 A hopeful sign is that Jeroen Bruggeman (2008) cites 77 reports by physicists in a book about social network analysis.

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- physicists
- nodes
- social networks
- social network analysis
- network analysis
- algorithms
- modularity

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