EVOLUTION OF SOCIAL NETWORKS

Patrick Doreian

and

Frans N. Stokman

RDON AND BREACH PUBLISHERS

THE DYNAMICS AND EVOLUTION OF SOCIAL NETWORKS

PATRICK DOREIAN

Department of Sociology, University of Pittsburgh, U.S.A.

FRANS N. STOKMAN

Interuniversity Center for Social Science Theory and Methodology, University of Groningen, The Netherlands

This volume is predicated on two very simple assumptions: there is a need for explicit dynamic social network models and the social networks community is ready for them. Indeed, there are some dynamic models available already. The contributions contained in this volume build on the earlier research and are intended to contribute to, and extend, those lines of work. Our introduction starts with the twin ideas of structure and process and moves to a characterization of network dynamics and the evolution of social networks.

1. SOCIAL STRUCTURE AND SOCIAL PROCESSES

While it seems straightforward to define, and describe, social network structures, the task of describing social network processes is much harder. Moreover, attempts to model these processes create many difficult technical problems. We discuss some of these and emphasize that we have constrained our discussion in consequential ways. First, we focus on empirical issues. Obviously, this includes the idea of data analysis for observed network phenomena, but we extend the term to include the generation of simulated data based on theoretical models. Second, we are concerned with explicit formal models. These can take the form of mathematical representations and/or algorithmic statements of process rules. While purely verbal formulations provide valuable insights into network processes and are a rich source for ideas, they remain outside the scope of this discussion.

1.1. Structures

The simplest, and most fundamental, definition of structure is a set of social actors with a social relation defined over them. A small group of "people" and the relation "friendship" and social service organizations with the relation "referring clients" provide two examples. This definition of structure has been extended in several directions. One is to consider multiple relations for a set of social actors. Continuing the inter-organizational example, the additional relations could be "provides services", "coordinates", "sends money" or "provides political support". The Bank Wiring Room data (Roethlisberger and Dickson, 1939; Homans, 1950) is a widely used and cited network with multiple relations that include friendship, antagonism, playing games and helping. As far as representational tools are concerned, graphs can be used for a single relation and multigraphs or hypergraphs can be used for multiple relations.

A second fundamental type of relation is "membership" where social actors belong to two distinct types that are mapped to each other under an inclusion rule. Two example are individuals belonging to friendship groups and individuals on organizational boards. For the latter, individuals as directors belong to organizational boards. Breiger (1974) provides an elegant discussion of the "duality" between people and groups. The analyses of these (two mode) data structures involve the membership tie plus two ties that can be generated from it: (1) a collectivity-to-collectivity relation and (2) an individual-to-individual relation. Using the director-board example, there is a relation over the directors (joint membership) and one over the companies (shared directors).

A related, but distinct, idea is one where there are multiple levels for a network. If we think of people and friendship groups, the set of network ties among the individuals belonging to these groups can be aggregated to form relations between the groups. Or, as another example, people working for social service agencies have many social ties among themselves (as representatives of their agencies) that, when aggregated, generate relational ties between their organizations. This can be expanded into a systematic effort to understand the "micro-macro relationship" where there are distinct relations among the actors at each level. The processes at the two levels are assumed to be coupled. Representing and understanding the dynamics of this coupling of relations is a non-trivial task.[1]

Another extension comes if we think of networks as networks of networks (Wellman, 1988). If societal sectors are institutionalized (Scott and Meyer, 1991), then an inter-organizational network could be represented as a network of organizations within sectors that are then linked in some fashion. Or, if the focus is on the provision of services, different client pools define networks of organizations serving people in those pools. Then, for multiple problem clients, these specific networks are linked into a broader network. Put differently, networks can be nested within broader networks. This becomes complicated if the nesting and aggregation aspects are intertwined with the aggregated ties differing from, and not mapping cleanly to, the nested ties. But even with this difficulty, the task of describing structure is simply one of defining social actors, defining the relevant social relations and describing them with some appropriate tools.

1.2. Processes

Social network processes seem more elusive for formal model building. In part, this stems from the simple idea that structures seem easier to observe: we can take snapshots at specific moments in time. To get at the idea of social network processes, we look closely at each term. We start with the idea of process. It is instructive to consult a

[1] We consider some possible avenues of research for modeling network dynamics in the final chapter.

dictionary.[2] Consider the following three definitions of a process: (1) "a series of actions or operations used in making or manufacturing or achieving something"; (2) "a series of changes" and (3) "a course of events or time". Next, Lenski et al. (1991: 438–9), in their text on human societies, define the term "social" as "having to do with relationships among the members of societies". This points towards a network representation and we have already defined the term network. Lenski et al. view process as "a series of events with a definable outcome". By linking these ideas, we view a social network process as a series of events involving relationships that generate (specific) network structures. More glibly, *network processes are series of events that create, sustain and dissolve social structures.*

Clearly, any network structure can be defined formally — we can use any of the tools used to "describe" structure — and so have a "definable outcome". Assembling a series of descriptions of structure through time will satisfy the second meaning of "process". This seems an important step as we are compelled to look at networks with a through time perspective. In one sense, the last two dictionary meanings of process are the same. However, we will draw the following distinction and view a "*course* of events" as having some coherence. Events at one point in time are conditioned, in part, by the events that went before them: networks evolve. Specifying how this occurs — and the mechanisms involved — remains a difficult set of tasks.

It seems reasonable that many social network processes are volitional in the sense that actors have purposes, consistent with the first dictionary definition of process. Actors make choices over their use of time and, together with other actors, act in order to do something. Organizations forming "action sets" do so to act in concert. This leads to the formation of a network of organizations for some purpose. Continuing the inter-organizational example, organizational fields form. But this is seldom all of the story. The networks that form do so only partially by design. They are also shaped in unintended ways. An extant network facilitates some actions (and actors) and inhibits other actions (and actors). Put differently, the form of the network is relevant for its own evolution. In a specific empirical context there will be a sequence of network events which can be viewed as stemming from a network process.

At a minimum, studying network processes requires the use of time in addition to descriptions of network structures. Any cross-sectional description of a network at a single point of time does *not* describe a process. This would be statics rather than dynamics. It is possible that network data are collected overtime and then collapsed to form a single description. Kapferer (1969) does this, as did Roethlisberger and Dickson (1939). While it is possible to interpret these structural descriptions as an equilibrium state (for some — probably unknown — process), we do not include them within the domain of network processes. There has to be change (or not) *through time* which requires temporally ordered information rather than information summarized over a period of time.

To help set the stage for our discussion, we examined the first sixteen volumes of *Social Networks* to see how often process in the "series of events" sense was featured in its pages. Of the 285 articles published between 1978 and 1994 we found 47 contained

[2] The one that was handy when writing this was the *Oxford American Dictionary*, New York: Oxford University Press, 1980.

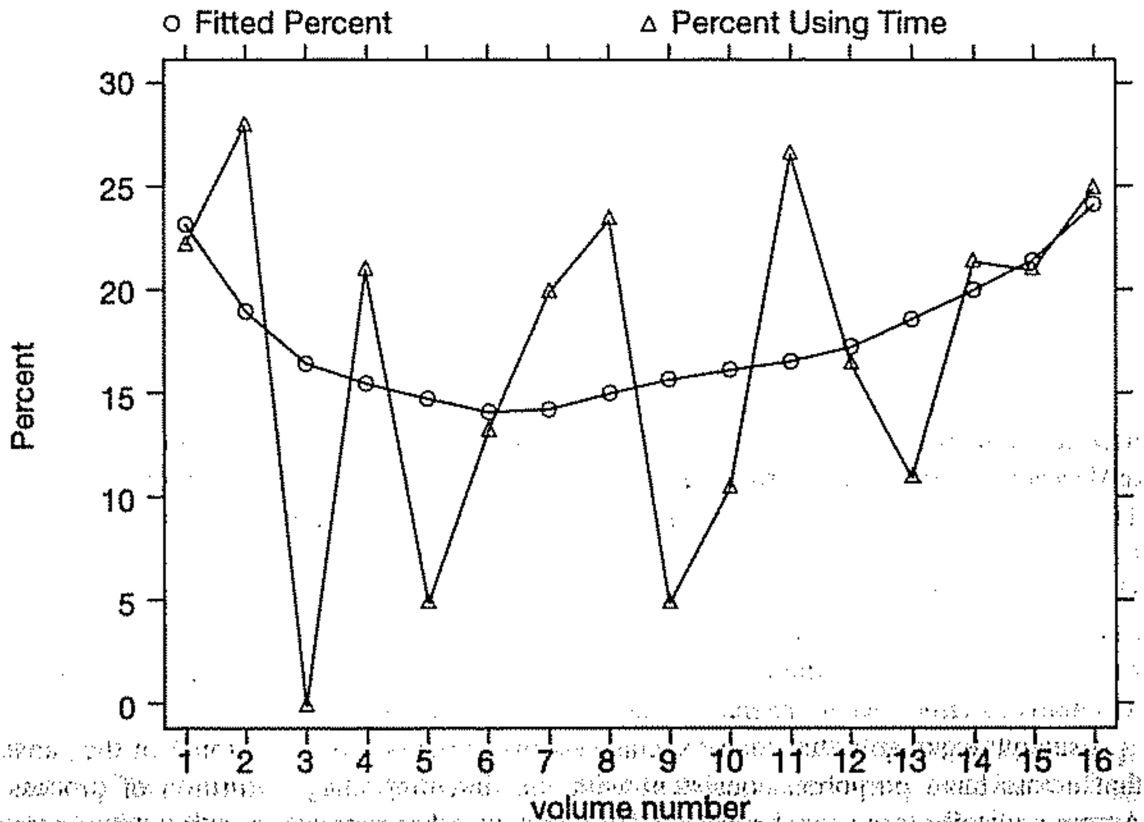

FIGURE 1.1. Percent of articles using time.

the use of time.[3] Is this 16% incidence rate small? Before answering this largely rhetorical but difficult question, we need to say more about the coding of articles in terms of processual ideas. Any article with data at one point in time was coded as a non-process article. Some articles with processual words — like "dynamics", "formation" and "disintegration" — in their titles were coded as non-processual if their data were cross-sectional. Consistent with the above argument, articles describing network structures at equilibrium were excluded also. Papers on biased network theory (even though the terminal state or distribution could only come as the result of a process operating with biases captured in parameters) were coded non-processual.[4] Also, articles that used through time data but discarded the temporal information — for example Bonacich's (1991) use of the Davis et al.(1941) *Deep South* data[5] — were not included among the processual articles.

Rather than respond to the overall 16% in the rhetorical question, we look at the distibution through time of the use of time in articles found in *Social Networks*. This is shown in Figure 1. The high water marks, as it were, were in Volume 2 and Volume 11 when 28% and 27% respectively of the articles were processual. The graph also

[3]Note that we did not write "only 47".

[4]If these articles were recoded as processual, the incidence of processual articles would rise to around 20%.

[5]He appears to use these network data — or one that is isomorphic.

shows the lowess[6] smoothed trajectory (Cleveland, 1979) which suggests the incidence of processual work is increasing currently — as do the raw data on the right. As we believe we are in an era when it will be fruitful to focus more on social network processes, this is a trend we like. Looking at the 16 volumes of *Social Networks* makes it clear that many of the cross-sectional articles are devoted to the development and discussion of procedures for describing structure. This is *not* a lament over the dearth of process and time in social networks research.[7] If network processes are characterized as series of structures through time, there is a clear need to have sound structural tools. Indeed, using poor structural tools will threaten any effort to track structure through time, let alone provide the basis for attempts to "explain" structural phenomena. So while the Bonacich (1991) article is non-processual, it does lay out tools that will be very useful in studying networks through time.

It is tempting to treat "evolution of networks" and "network dynamics" as interchangeable terms. For us they have different meanings. We take network dynamics as the more general term and a generic statement of changes through time. The term evolution of networks has a stricter meaning that captures the idea of understanding change via some *understood* process. If we can lay out the "rules" governing the sequence of changes through time we have some understanding of a process that goes beyond simply observing change. Of course, a network system can be in equilibrium — consistent with the idea that some processes maintain structures. Paradoxically, the idea of a process may not be less relevant when there is no change through time. Without an understanding of a network process all we have is a single description. If we can locate that description in a through time framework, we can say something about the process(es) sustaining the (described) network.

2. PROCESS AS CHANGE IN SOCIAL STRUCTURES

There is a class of models, and corresponding network issues, that belongs here only partially. Articles that use processual ideas simply as illustrations and those advocating the use of processual mathematical ideas without specifying how this could be done are both put to one side. Undoubtably they will inspire future work but, for now, we will pay them no heed beyond the idea that change is important and that certain tools (say, difference equations or differential equations) may have great utility in modeling change.

We defined structure in terms of social actors and social relations and process as (generated) sequences of network events. To complete the picture of work in *Social Networks*, roughly 55% of the 47 processual articles are straightforward descriptions of networks through time.[8] As such, they provide a point of departure for a systematic look at ways in which network processes are studied. We note, at the outset, that it will be difficult to categorize all published (or potential) models in an unequivocal fashion. Moreover, new work will break new ground and make this categorization outdated.

[6]This stands for LOcally WEighted Sums of Squares.

[7]Strictly, of course, we should limit this statement to social network research as reflected in the articles included in *Social Networks*.

[8]Note, again, we did not put the word 'only' into this sentence.

2.1. Predicting Future Attributes from Structural Information

Following Leenders (1995), we label models predicting some attribute(s) of actors (or the extent to which actors are similar with respect to one or more attributes) from information concerning their structural locations in networks as "contagion models". See also Burt (1982). For the purposes of this discussion, we do not include conventional network autocorrelation models within this category when they are formulated in cross-sectional terms. A model of the form $y = \rho Wy + X\beta + \epsilon$, with ϵ a white noise term, is not processual. If, however, it takes a form like $y_{t+1} = \rho W(t)y_t + X_t\beta + \epsilon(t+1)$ we would regard it as a processual model.

Johnson (1986) uses the extent to which actors are structurally equivalent in a network of commercial fishermen as a predictor of the *temporal order* in which the fishermen adopted innovations in fishing technology. As he points out, it is necessary to control for other predictors (which may overwhelm the network component empirically). Even so, it is using network information to predict nodal attributes at later (and distributed) points in time. Krackhardt (1988) uses the Sampson (1968) data on relational ties among a group of trainee monks to predict similarity in the order in which the monks departed the monastery, either by expulsion or voluntarily. This example fits less well within this category as the constructed dependent variable, in matrix form, seems to discard the temporal information for the modeling component.

Experiments are another source for studies where structure predicts future outcomes. Clearly, the early Leavitt (1951) and Bavalas (1950) experiments with task oriented groups have this feature. The variable maniplated experimentally was the communication structure of the group and the primary response variable was the time taken by the group to complete a collective task. We emphasize that this is a group level outcome. As such, it expands the domain of models with network structure predicting collective attributes. Experiments founded in exchange theory fit here as well. Again, the manipulated variable is the stucture of the experimental group and the outcomes include a set of exchange rates. See, for example, Willer (1992) and the articles contained in the special issue of *Social Networks* edited by him. We also include the Iacobucci and Hopkins (1994) study in this broad category of models.

2.2. Describing Network Structure through Time

Attempts that describe structural information through time clearly satisfy the "series of events" definition of process. However, this can be done in a variety of ways and it is worthwhile to examine how this can be done.

2.2.1. Describing All of the Network Data

The simplest form is to present the complete information for one or more social relations. Freeman (1984) does these for several relations among members of an Electronic Information Exchange System (EIES)[9] and members of INSNA in the late 1970s. He examined relations like awareness and acquaintanceship among these

[9]Different groups participated in the EIES experiment (see Hiltz and Turoff (1978)). The Freeman study used only the data for the social networks group on EIES.

networkers at three points in time. In doing so, he faced the problem that through time studies, in one way or another, usually have serious rates of attrition.[10] Dealing with attrition is a serious conceptual and technical problem in general, and may be particularly acute for network studies.

Kapferer (1972) reports two sociograms, at two points in time, for a group of people working at a tailor's shop in Africa. Each network is an aggregation, through time, of interactions recorded by a fieldworker.[11] Network analysts can use any set of network tools to characterize the two structures and compare them. There is one troublesome complication. Some of the people present at the first time point were no longer present at the second time point and some of those present at the second time point were not part of the earlier network. Most re-analyses of these data focus on the 39 individuals present at both times. While this seems reasonable for these data, a full capacity for modeling networks through time should include both departures and arrivals of actors to the network, especially the former.

The two-mode *Deep South* data (Davis et al. 1941) showing the attendance of 18 women at 14 events distributed through time can also be viewed as the display of all of the data. In terms of our discussion here, any description or reanalysis of these data not including the temporal information does not belong here nor in the next category we discuss. For example, the Phillips and Conviser (1972) re-analysis of these data discards time and is excluded. However, the Doreian (1980) re-analysis was focused on the emergence of subgroup structure through time and belongs here.

2.2.2. Describing Structural Characteristics

Most reports of networks are couched in terms of selected structural features relevant for particular analyses. In the context of structural balance theory, and its generalization by Davis (1967), Doreian and Mrvar (1996) present a partitioning approach that simultaneously establishes partitions as close to balance as possible and provides measures of the extent to which the signed network is imbalanced. Both their imbalance measures and the partitions through time of the Sampson (1968) data exemplify descriptions of structural characteristics. Stokman et al. (1988), as part of a larger study of corporate interlocks in the Netherlands, show data on the continuity, severance and restoration of interlocks through five consecutive 5-year intervals from 1960 through 1980. Ornstein (1982) presents a very similar description for Canada using 5-year intervals from 1946 through 1975.[12] Both examples are fully consistent with the idea that processes create, sustain and dissolve structures. Fennema and Schijf (1978/79) present information through time on corporate interlocks (with a focus on banks) in Germany (for 1902, 1910, 1912 and 1927), Spain (for 1957 and 1967) and the USA (for 1935 and 1965). These examples, in addition to being interesting in their own right,

[10] He reports that 97 people provided responses for the INSNA survey and 29 people responded to the two EIES questionnaires. However, only 16 people provided responses to all three instruments.

[11] The classic Bank Wiring Room data reported by Roethlisberger and Dickson (1939), although reported for one point in time, has the same general form of an aggregation of through time distributed actions. For both examples, the temporal information is no longer available and we have to assume that the data represent an equilibrium state. This may, or may not, be veridical.

[12] He also presents data for 1976–77.

suggest that obtaining through time information on network ties is far more straightforward when archival records are available.

Cohen (1978/79) employs archival data of a different sort. The Hollingshead (1949) and Coleman (1961) studies both took place in Elmtown. The data were collected in 1942 and 1958 respectively and contained enough information on youth friendship choices to permit comparisons in terms of friendship clique structures and dating. (Socio-economic status homophily for friendship and dating was important in 1942 but unimportant in 1958.) This was an imaginative way of getting temporal network structural information although the time interval between the two "waves" of data was completely arbitrary. Barnett and Rice (1985) used the EIES data for the different groups that participated in the experiment to track connectedness and centrality each month for a 25 month period of time.

As a final example, Nakao and Romney (1993) used the classic Newcomb (1961) data for a longitudinal description of subgroup formation. There were 17 men living in a pseudo fraternity for a 15 week period. Every week (with one exception) each man ranked all other 16 men in terms of how much they liked them and these responses through time form the data base used by Nakao and Romney. Using a variety of tools, including a measure of association for ordinal variables and multidimensional scaling, they examined the through time variations in intra-pair attractiveness, each man's popularity and individual agreement with group consensus.

In principle, any structural characteristic can be described through time. For some studies there were just two time periods, our minimal criterion for inclusion within processual studies. Other studies have three times points. For such limited numbers of time points, with the selection of network characteristics, simple comparisons can be made. Such descriptions have the form of comparative statics. For a larger number of time periods, properties can be tracked through time and have the potential for richer statements concerning network processes.

2.2.3. Impacts of Events on Structure

Social networks are located within, and are founded on, some physical infrastructure. Communication via telephone requires cables and optical fibers. Moving people and objects on the ground frequently requires the use of bicycles, automobiles or trucks. These all require systems of roads and bridges. Lee (1980) describes a kind of naturalistic "experiment" following the collapse of a major bridge in an urban area. He examined the long-term disruption of social networks following this event. More generally, when disasters in the form of hurricanes, tornadoes, earthquakes and floods occur they do great physical damage and wreak social havoc. All social networks, including those that are institutionalized, are disrupted or shattered. In areas at risk, there are emergency service networks with local and state police departments, ambulances and hospitals. Even though the members of these networks have response procedures in place and have plans for coordination, it seems that actual disasters create totally new circumstances. Depending on the specifics of a disaster, relations change and other organizations and individuals arrive to offer help. The actions of military units, specialty outfits like underwater rescue teams, fire brigades, emergency services departments, state agencies and national governmental agencies all have to be coordinated. In a very short period inter-organizational networks form and change during the course of a collective response. Drabek et al.(1981) provide analyses of the network structure of search and rescue operations.[13]

2.3. Network Structures Unfolding through Time

It is clear that, in general, social networks are generated through a series of events occurring through time but not on a schedule. Yet many of the examples we have discussed thus far impose some structure on time or the way in which time is used in an analysis. The Newcomb (1961) data were collected weekly which probably had little to do with the timing of the phenomena studied. The various cited examples of corporate interlocks all use seemingly arbitrary delineations of time, with time intervals defined in terms of 5 or 10. Or, the dates are determined by data availability. Certainly, this was the case for the Cohen (1979) study. For the experiments, the time ordering of stimulus and response is enough (although some studies do have a time limit on how long the subjects are given for a response).[14] Each of the Drabek et al. (1981) search and rescue inter-organizational networks had four time periods around disasters that were simply ordered.

In the area of citation analyses there are some studies of the unfolding of processes. One was conducted by Hummon and Doreian (1989) using data on the development of the DNA literature. The network nodes were scientific publications and the links were citations backwards through time (which can also be viewed as travel forwards of useful information). The nodes are distributed through time at irregular intervals. Even here, however, the actual length of time intervals between the publication of results on the DNA area were not used, just their order in time. Similar analyses were done for the scientific pulications of centrality-productivity literature[15] (Hummon et al., 1990) and network analysis (Hummon and Carley, 1993).

Michaelson (1993) studied the development of a scientific specialty through time. Central to her analysis was the diffusion of the ideas of positions and relational structures among a set of network analysts interested in role analysis. These scholars were linked by a variety of social relations that were relevant to the adoption (or not) of the new ideas created by Lorrain and White (1971). The relevant events among these scholars were also distributed unevenly through time as suggested by Michaelson's ethnographic report. Yet even here, much of the temporal information is reported in calendar years. This seems appropriate for the reports of publication activity as the institution of scholarly journals is defined in terms of volumes, issues and years. For friendship ties and collegial relations, years may not be the best reporting units for event sequences. Again, this not meant as a lament. Rather, it is a pointer to a serious issue.

If social networks unfold through time and if the timing of events is relevant then we need to preserve the temporal information. In turn, this implies that we need to know, or learn, the appropriate time scale of the network phenomena we study. This is another non-trivial task.

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[13]The data published are for one stage of the rescue effort, making them cross-sectional, but Drabek and his colleagues did collect network data for the time prior to each disaster and at later stages of the emergence response efforts.

[14]It seems that such limits are imposed for the convenience of the experimenter or to manage the use of the laboratory within which the experiment is conducted. In the main, they do nor seem intrinsically a part of the substantive content of the experimental study.

[15]Many of the articles in this literature would fit within the experimental studies considered in Section 2.1.

2.4. Change as Transitions through Time

Thus far, our discussion has focused on describing change with time as some medium within which change occurs. Another research tradition models change in terms of transitions. Hammer (1980) presented some data addressing the idea that data on network structure at one time point can be used to study network properties at a second time point. She showed that the probability of having direct connections between actors at one point in time is a function of both the intensity of the connection between the actors and the number of connections they share with other actors at a prior time point. Freeman's (1984) study of some of the EIES data also used time periods and transitions between states. Dyadic ties could be in any of 4 states (null, asymmetric, pseudo-symmetric[16] and symmetric). With three time points he constructs the transition matrices between these states for transitions from t_1 to t_2 and from t_2 to t_3 as descriptions.

Hallinan (1978) studied the process of friendship formation among school children. She used five grades of children and obtained friendship choices from them six times during the school year. In addition to creating useful data for her own research, Hallinan's data have been used by other researchers using dynamic modeling techniques. By using a continuous time Markov process where the transition probabilities are governed by a set of differential equations, she analysed the stability of ties and the direction of change for the asymmetric ties.

Runger and Wasserman (1979/80) used Hallinan's data as part of their longitudinal analysis of friendship networks. Their focus was more on reciprocity and probabilities of dyadic change. The methods they presented were extensions and applications of procedures developed by Wasserman (1980). Other relevant work in this area includes Tuma and Hallinan (1979) and Iacobucci (1989). The use of both continuous time and discrete time Markov processes seems a promising way of modeling network change. For an extensive discussion of these methods, including the earlier p_1-model of Holland and Leinhardt (1981) and extensions into log-linear models for network analysis, see Wasserman and Faust (1994) and Leenders (1995).

3. DEVELOPING APPROACHES FOR STUDYING NETWORK CHANGE

While many network analytic techniques can be used for making descriptions of networks through time, some tools are developed explicitly for process representation and for building dynamic models of social networks. We discuss briefly statistical methods, network methods and simulation methods.

3.1. Statistical Methods for Dynamic Models of Networks

The work we described in Section 2.4 all contain methods invented or adapted for modeling change in social networks. Thus Hallinan (1978), Runger and Wasserman (1979/80), Wasserman (1980), Iacobucci (1989) and Iacobucci and Hopkins (1994) have all contributed to this literature. Some of the models and methods described in Tuma and Hannan (1984) will be of value.

[16]This is a pair of reciprocal directed relational ties.

It is tempting to view network "models" based on transitions or changes of state as somehow more advanced than the simple descriptions of networks through time. Certainly, they are technically more demanding but this feature, by itself, is not enough to judge them as superior. While the word "model" sounds more grand, using it in place of the term "only a description" is not enough either. Even so, grounding methods in probabalistic assumptions (and distributions) and seeking *tests* of the estimated parameters is a major additional step — or leap.

All of the descriptive tools discussed in Section 2 and the descriptions they generate are useful. They provide empirical information that is relevent for a modeling effort. If we have a series of measures of, say, connectivity, cliquishness, density, extent of structural equivalence etc., we need to know if there has been any real change in these measures (and the network properties operationalized in them). Empirically, if there are real changes we need to be in a position to model the network processes creating those changes. If there is no real change, efforts to model or interpret the apparent changes would be pointless. This sounds like a simple task but it, too, is technically difficult.

Quadratic assignment procedures (QAP) (Hubert and Schultz, 1976) have been used by Baker and Hubert (1981) as a way of measuring the conformity of two sociomatrices. If the two networks are defined for the same group of actors at two points in time, then QAP provides a way of measuring change in the group structure as represented in those matrices. Another approach has been developed by Snijders (1990). The actual test is conditional on the entire graph at the first time point, the number of new arcs to and from each actor as well as the number of ties between each pair of actors that disappear by the second time point. Wasserman (1987) has also developed ways of measuring the conformity of two sociomatrices. Snijders compares the relative merits of the two approaches. For our purposes here, it is enough to note that methods are being developed that allow us to decide if there has been real change in structural characteristics through time.

More recently, Sanil et al. (1995) present explicit probability models for networks that change though time and maximum likelihood methods for estimating the parameters of those models. The promise of their methods is that if theories of change can be put in a parametric form, they can be formally tested. Thus far, the models they discuss are restricted to networks where the number of nodes are fixed. This is a limitation but we can look forward to a time when the number of nodes in the network is not fixed.

3.2. Network Methods for Network Change

An example of developing new network methods is found in Hummon and Doreian (1989 a,b) for citation networks among scientific productions. These methods were mentioned in Section 2.2.3. Price (1965) and Garfield (1979) pioneered work on such scientific networks and there has been much work on citation analysis and co-citation analysis. The novel feature of the methods proposed by Hummon and Doreian was to develop ways of counting paths in citation networks in order to establish the "main path" through the literature of a scientific specialty. A single main path was found in the DNA example. For the literature on centrality and small group productivity (Hummon et al., 1990), a single main path was found but it then split into two distinct paths. One focused on the mathematics of centrality while the other contained experimental work. These methods were generalized by Hummon and Carley (1993) to allow the detection of many main paths through the literature of social network analysis as a scientific specialty.

3.3. Network Simulations for Network Evolution

Thus far, our discussion has not strayed far from the empirical realm. In the main, the contributions to the literature that grapple with social network change do one of two things. The first is the presentation and discussion of mathematical ideas with potential relevance for studying social networks through time, for example difference equations, differential equations or Markovian processes. We have paid little attention to this part of this literature. The second activity uses specific models of network change and ways of mobilizing these models empirically. As we have indicated, there are many fruitful empirical studies of social networks through time. Yet it is clear that something is missing in this empirical literature. While some network change models do incorporate theoretical ideas, seldom is the time scale of the network phenomena included. This may or may not be a problem.

We consider the problematic aspect first. Events can be ordered in time with the timing absent. In the DNA citation example (Hummon and Doreian, 1989a), the publications have dates but the time intervals between publication dates were not considered. All that was included was the time ordering — a later paper cited an earlier paper. In another kind of design, researchers, for example Cohen (1979), can use two time points without paying much attention to the interval separating them.[17] The argument remains the same for studies using more than two time points. If we do not know the time scales of the phenomena studied, it seems hard to construct adequate theories and generate appropriate data collection strategies. As stated, this is a conceptual point but it has an empirical component also. For example, in the context of using differential equation models, the aliasing problem can arise when two sets of temporal observations cannot be distinguished even when they have very different time scales. (Of course, in this example, an observer would be unlucky by observing the processes at exactly the time points when they cannot be distinguished.) Put more forcefully, one implication of these arguments is that we frequently do not know what to look for, empirically, in terms of time.

This last point may have little consequence if, under general conditions, the "time scale problem" is not important. There are social network processes where events occur irregularly. It seems reasonable to specify models or processes that include this, making a rigid insistance of knowing the time scale secondary. We observe behaviorial acts through time that, in some fashion, generate actor attributes, network ties and hence networks. Specifying how these processes operate with regard to time is difficult. One approach to this class of problems is via simulation, although this is not the only use for this procedure.

[17] There is a literature on the use of differential equations and the role (and problems) of using integral equations for estimation purposes where the period of time between time points has some relevance. See, for example, Tuma and Hannan (1984). Even here, however, the time scale of the phenomena studied may have no correspondence with the time intervals used between observational periods.

Simulation is a very useful tool that has opened a third broad approach to studying network change. If we can write down a set of process equations or a precise set of algorithmic statements that govern change, we can implement them via simulations which present the implications of the theory, or theories, represented in the equations or algorithmic rules. These simulations have their prime focus on theory and the generation of information based on theory. They may have an additional payoff if they allow us to see how observable phenomena, consistent with the theory implemented in the simulations, would be distributed in time. At a minimum, this would provide clues for what should be looked for (and when to look) while seeking empirical data. We note that the "models" in the simulation can be deterministic or stochastic. The former seem consistent with the idea of having a time scale while the latter seem consistent with events distributed irregularly.

Simulations can be mobilized for a single network with one set of actors and relations defined over them. It is worth noting that they are (perhaps more) relevant also when there are different types of social actors. If we consider people belonging to collectivities (for example, groups or organizations) there are network processes that operate at both levels. The behavior of the people and their networks are micro-phenomena while the actions of the collectivities and their networks are macro-phenomena. The two processes are likely to be coupled. Modeling this coupling — the macro-micro linkage — will be a formidable task. In this context, both Zeggelink (1993, 1994) and Fararo and Hummon (1994) use discrete event simulation as a tool for theory development.

Zeggelink (1994) uses object-oriented simulation to study friendship formation. Part of the output shows the evolution of group and subgroup structures through time. Network parameters can be constructed to characterize structural properties like reciprocity, transitivity and segmentation. When these parameters are varied across simulations, the simulations generate observable sequences of network outcomes and establish theories of network evolution.

Hummon and Fararo (1995a) combine object-oriented methods with discrete event simulation techniques to implement models of network change. The network is an object and the simulation includes *the addition and deletion of nodes and ties*. Hummon and Fararo are explicit also about using simulation to generate theory. Their primary application is the generation of hierarchy in dominance structures. Subsequent work includes structural balance theory where actors' images of the network are also treated as objects (Hummon and Fararo, 1995b).

We have one final remark, before turning to the contributions in this volume: there is immense potential for linking theories, simulations and data analysis for a sustained study of network dynamics and network evolution. We believe that this effort will shift the research emphasis, and subsequent understanding, from the dynamics of social networks to the evolution of social networks.

4. CONTRIBUTIONS TO NETWORK DYNAMICS AND EVOLUTION MODELS

This section provides a brief overview of the following chapters, all of which are intended as further contributions to the study of social networks through time. Some are descriptive, some focus on processes unfolding through time, some use simulation and some focus on statistical methods. In short, they represent the approaches we have outlined for the study of network evolution.

4.1. Simulations of Network Evolution and Outcomes

Flache and Macy (Chapter 2) consider small groups and focus on compliance and approval. Their theoretical framework is found within exchange theory and rational actor models. The simulation they use involves a stochastic learning model and they examine closely the argument that compliance is exchanged for approval in small groups. That approval is exchanged for compliance in small groups (Homans, 1950) is part of the received wisdom. Using parameterized equations that describe actor level processes they are able to generate conditions under which approval is exchanged for approval *without* compliance. This is an interesting and provocative result that shows some of the power of simulation tools for exploring theoretical ideas.

Zeggelink, Stokman and van de Bunt (Chapter 3) examine the emergence of subgoups and contribute to the theory of group formation. This is an extension of the work found in Zeggelink (1994). They formulate a generative mechanism for rational actors operating under structural constraints. Their formal models are graph theoretic and they use a tension function for the generative mechanism under the assumption that actors act in order to minimize tension. Their simulations are constructed within an object-oriented programming environment. Apart from their intrinsic interest, these simulations also form the basis for specifying the kinds of data that would be needed to test this type of model empirically.

Skvoretz, Faust and Fararo (Chapter 4) also focus on the generation of social structures. They formulate social psychological processes that operate at the dyadic level and, via simulation, show how these processes aggregate to generate stable ranked systems. Their work is part of a broader research effort to integrate structural theories within the rubric of E-state structuralism. For the broader effort, see Fararo and Skvoretz (1986) and Fararo et al. (1994).

Skokman and Zeggelink (Chapter 5) present an analysis of policy networks. More specifically, they specify different models (and mechanisms) for the evolution of policy networks. One model is driven by power mechanisms while the other focuses on policy issues. These theoretical models are implemented via object-oriented simulation techniques. The simulations generate policy outcomes consistent with the substantive ideas represented within them. In a novel way, these outcomes are evaluated in the light of real political policy decisions. The policy driven models fare much better than the power driven models.

4.2. Empirical Studies of Network Evolution and Outcomes

Doreian et al. (Chapter 6) look closely at some through time mechanisms for change in small group structure through time. They focus on establishing the amount of reciprocity and transitivity in sociometric choices and the amount of (generalized) structural imbalance in the group structure as a whole. These processes are studied separately and optimization methods are used for modeling and measuring these structural properties. They use the classic Newcomb (1961) data and show that, as processes, reciprocity and transitivity have different time scales and through time there is movement towards generalized balance.

Leenders (Chapter 7) substantive focus is on friendship choices in small groups. He uses theories of structural balance and social exchange to formulate a continuous time Markov model expressed in terms of differential equations. By using the solution equations and estimation methods developed from the work of Wasserman (1980) he presents models that incorporate some actor attribute variables while focusing on reciprocity and similarity effects. Using Hallinan's (1978) data on friendship choices of school children he formulates new hypotheses that can be tested within this modeling framework.

4.3. Statistical Models for Network Evolution

Leenders (Chapter 8) tackles an important substantive and technical problem. There are contagion models where network structure is used to predict attributes of the actors linked by social networks. This is part of the classical homophily argument that members of a network become like one another as part of a network process. See, for example, Burt (1982). In these models the network is assumed to be fixed. There are also selection models where actors form relations with each other, in part, on the basis of their attributes. Attribute similarity, attributes that are complementary or both can form bases for establishing network ties. In these models, the usual assumption is that the attributes are fixed. Leenders points out that both the network ties and the actor atributes can be changing and we need a modeling capability that can accomodate this. He proposes combining autocorrelation models for contagion models with continuous time Markov models for the selection models. Leenders also describes ways in which these models can be estimated and explores some of the consequences stemming from misspecifications of the sort when only one of the two types of models is considered.

Snijders (Chapter 9) proposes models for network change for small groups that are grounded in structural balance theory and rational actor models. These models take the form of Markov chains in continuous time and Snijders presents a dramatic new estimation method. The proposed statistical procedures are based on the method of moments, as a general strategy, and use (statistical) simulation methods to estimate the theoretical moments. He also uses the classic Newcomb (1961) data to illustrate the use of these new methods. Banks and Carley (Chapter 10) describe a set of mathematical models for the evolution of social networks in the form of directed graphs where the nodes of the network are fixed. This work represents an extension of the methods proposed by Sanil et al. (1994) and a presents a broad description of a general framework for estimating specific theoretically based models.

4.4. Future Directions

The final chapter (11) uses chapters 1–10 as a foundation for identifying future directions for the study of network changes and, more importantly, network evolution. It is very clear that network analysts and scholars in related fields are developing sets of formal tools with great promise for modeling and understanding network evolution and network dynamics.

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