EVOLUTION OF SOCIAL NETWORKS

Edited by

Patrick Doreian

and

Frans N. Stokman

GORDON AND BREACH PUBLISHERS

EVOLUTION OF SOCIAL NETWORKS: PROCESSES AND PRINCIPLES

FRANS N. STOKMAN

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

PATRICK DOREIAN

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

A complicated thing is one whose existence we do not feel inclined to take for granted, because it is too "improbable". It could not have come into existence in a single act of chance. We shall explain its coming into existence as a consequence of gradual, cumulative, step-by-step transformations from simpler things, from primordial objects sufficiently simple to have come into being by chance. Just as a "big-step reductionism" cannot work as an explanation of mechanism, and must be replaced by a series of small step-by-step peelings down through hierarchy, so we can't explain a complex thing as *originating* in a single step. We must again resort to a series of small steps, this time arranged sequentially in time.

From: Richard Dawkins, *The blind watchmaker: Why the evidence of evolution reveals a universe without design*, New York: Norton, 1987, 14

1. INTRODUCTION

In the introductory chapter, we provided evidence that dynamics and evolution are not widely studied in Social Network Analysis. In most fields, collection of longitudinal social networks data requires large resources and is very time consuming. In addition, analyses of social networks require their own methods. Since mutual dependencies exist between actors and between ties in social networks, most standard statistical methods cannot be applied straightforwardly in social network studies. As a consequence, social network researchers have to rely on specific social network methods and measures. Because of the statistical complexity involved, most of them are limited for comparisons between networks of different sizes and densities and can be applied mainly applied in descriptive analyses only. Within this setting it is not surprising that most efforts are focussed on analyses of static network structures. The compendium of Wasserman and Faust (1994) and the strongly improved and extended standard computer package UCINET indicate that the social network field is now mature enough

[1]We thank Evelien Zeggelink, Bill Batchelder, and Henk Hangyi for their comments on an earlier draft.

TABLE 1
Network Evolution Processes in Chapters

Chapter	Authors	Process
6	Doreian, Kapuscinski, Krackhardt, Szczypula	Effects of *network structure* on changes in friendship choices: – reciprocity – transitivity – balance
10	Banks, Carley	Network completion models: Parameter estimation
4	Skvoretz, Faust, Fararo	Emergence of dominance structures through: 'victim' effect and *'bystander' effect*
7	Leenders	Emergence of (best) friendship ties based on: similarity of individual characteristics versus *reciprocity*
8	Leenders	Effects of simultaneous occurence of: *contagion* and *selection based on similarity*
3	Zeggelink, Stokman, Van der Bunt	Emergence of friendship networks based on: desired number of friends and *subgroup membership*
2	Flache, Macy	Emergence of ties in production groups through *exchange of:* approval against compliance versus *approval against approval*
5	Stokman, Zeggelink	Emergence of influence relations in policy network based on: power versus *policy driven* motives
9	Snijders	Parameter estimation of utility derived *network characteristics:* – reciprocity – balance

to go deep and to turn to more difficult questions of dynamics and evolution. This state of the art justifies the emphasis of the present book: to indicate some of the paths to follow rather than focusing on substantive dynamic and evolutionary results in different fields of application. While we have defined our focus in terms of techniques, tools and approaches, we believe that, for specific topics, substance is critical. Consequently, all contributions provide important substantive insights into the development of network structures in different empirical settings. To rephrase our intent, we are suggesting ideas that can be mobilized usefully within different applications.

We argued in the introductory chapter that dynamics is a broader concept than evolution. Whereas dynamics refers to change and is, in the main, purely descriptive, evolution includes explanations of dynamics. The latter refers to *underlying processes* that generate the dynamics in social networks. For this reason we first focus on the types of processes presented in the different chapters. See Table 1.

Evolution in social networks can, of course, be seen as a special case of evolutionary processes in social systems in general. Social network evolution studies might well profit from more general approaches to social evolution in computer science and artificial intelligence. From the latter, we will extract some *basic principles* of social evolution. We will consider the extent to which social network evolution studies do include such principles and, if they do not, how they can profit from the inclusion of these principles. This will lead us directly to a research agenda for future studies of network evolution.

2. SOCIAL NETWORK EVOLUTION PROCESSES

In many social network evolution studies, *the underlying process for network change is assumed to be located in the network structure.* In its most simplified form, this approach can be described as follows. Empirical social network studies show repeatedly certain network characteristics. In social network evolution studies, these characteristics are then taken as tendencies from which network change can be explained. An example of this approach can be found in the contribution of Doreian, Kapuscinski, Krackhardt and Szczypula (Chapter 6). In directed choice networks, the degree of reciprocity of choices is an important network characteristic. Empirical studies of friendship choices repeatedly report levels of reciprocity well above chance levels. If we study networks over time, can we explain network changes from a tendency towards reciprocity of friendship choices? A similar line of reasoning is followed for other important characteristics of empirical choice networks like transitivity and group balance. Doreian et al. apply these ideas to the Newcomb fraternity data (Newcomb, 1961). They show that reciprocity is well above chance level from the very beginning, but does not increase over time. In sharp contrast, transitivity of choices initially is not above chance levels but increases substantially[2] over the first eight weeks, and remains constant at a high level afterwards. Also the degree of balance tends to increase over time. One important result from this study is that different network phenomena can operate with different time scales in the same social collectivity. In addition, the study provides a new methodology for assigning values to rankings that maximize certain network characteristics (e.g. reciprocity of relations).

In contemporary sociology, much attention is given to the micro-macro link. Frequently, social phenomena are explained as the result of goal-oriented behavior of individuals. Simultaneously, the social context provides opportunities for action to some actors while impeding the actions of others. Questions on the micro-macro link become more laden with meaning if individuals act as representatives of more complex social entities such as organizations. Sometimes it is possible to treat these social entities as unitary actors with their own goals and restrictions while in more complex situations, structures with hierarchies or partially overlapping social entities (including the individuals that represent them) have to be considered. The concept "social actors" includes both individuals and higher order social entities. Social actors are the active elements in social systems with social phenomena resulting from the choices they make. Social

[2]By the third week, the amount of transitivity is significantly greater than zero.

network "structure" is one of them. If studies locate the underlying process of social network change within the network structure, it is unclear, however, whether the researchers can interpret these network characteristics as goals pursued by social actors. If this is assumed, a theorist must consider the amount of information that network members (actors) need in order to pursue such goals. Reciprocity is a characteristic of pairs, transitivity of triples, and group balance of the whole network. The higher the level of the network characteristic, the more complex the information actors need to take into account.[3] For example, group balance as a goal requires information on all network relations and the ability of network members to determine the consequences of alternative choices for group balance. An additional problem is that optimization of a certain network characteristic can be obtained by different choices. (For a more extensive discussion see Zeggelink, 1993.) For example, triples can often become (more) transitive by adding or removing choices. Moreover, the effect on the network characteristic depends on the order of the changes made. An asymmetric choice from *a* to *b* can be transformed into a symmetric relation by a choice from *b* to *a* or by *a*'s withdrawal of the choice. If they do so simultaneously, the result is again an asymmetric relation, with the ties now going from *b* to *a*. Some models try to circumvent these problems by restricting the scope of the actions to addition of new ties. The embryonic network completion models of Banks and Carley (Chapter 10) provide examples of this. However, we note, as do Banks and Carley, that the withdrawal of choices is an alternative frequently observed in reality and should not be neglected. Moreover, new problems arise as the completely connected network is the asymptotic equilibrium of most of these models. In other words, at equilibrium, all network members are equally likely to interact with all others. This is a consequence of the fact that these studies do not include restrictions on social actors and their generation of network ties. Differences in restrictions affect choices actors make and should be included as an element in any explanation of social phenomena.[4] Undoubtedly, later versions of the Banks and Carley models will incorporate these restrictions on social actors.

In the contribution by Skvoretz, Faust, and Fararo (Chapter 4) the emergence of dominance structures is explained by two mechanisms. If a network member "attacks" another network member, a dominance relation from the attacker to the victim is created with a certain likelihood. This is the "victim" effect. Other dominance relations result from the "bystander" effect. They assume a cognitive process in which bystanders tend to dominate the victim and to form a deference orientation to the attacker (and the attacker a dominance orientation to the bystander). They demonstrate that the bystander effect is a necessary condition for hierarchical structures to be formed.

Although the Skvoretz et al. model includes a more complex cognitive part than the former models, network structure is again the explanatory variable. Who is attacking whom is not related to individual characteristics and network members are not seen as purposive. The underlying process is assumed to be the adoption of expectational orientations towards one another and not a network characteristic to be optimized. The orientation is adopted on the basis of simple information, but they assume that all attacks are observed by all other network members.

[3]We do not rule out processes that are operative at the group level.

[4]Similarly, Willer and Willer (1995) show that dynamizing Network Exchange Theory results in fully connected networks of equal power for all if no restrictions on the addition of links are introduced.

In other social network evolution studies, *the underlying process for network change is assumed to be located in characteristics of the network members*. Network members are assumed to "choose" others by comparing relevant individual characteristics of the others with their own. A fundamental finding in many choice networks is that social actors with similar characteristics are more often connected with one another than with more dissimilar ones. This is known as the "similarity effect" in social networks (Schachter, 1959). Many researchers attribute this to a selection process in which social actors tend to choose similar others. The contribution of Leenders on "Dynamics of Friendship and Best Friendship Choices" (Chapter 7) is an example of this approach. His main analysis concerns the relative strength of the reciprocity effect and the similarity effect in the Hallinan class room data. Hallinan recorded "best friends" and "friends" choices of pupils in ten classes (Hallinan, 1976, 1978). In most classes these choices were recorded seven times with six weekly intervals. Most interesting are Leenders' results for the "best friends" choices. As did the original researchers, he finds a strong reciprocity effect in the data. However, the data also show a strong similarity effect based on gender. Hardly any "best friends" choices between boys and girls exist. If both effects are taken into account simultaneously, the reciprocity effect loses its statistical significance. Reciprocity is completely explained by the fact that pupils choose their best friends within their own gender group. This important substantive result stems from Leenders' new statistical tools for Markovian process models. His results show that certain network characteristics such as the degree of reciprocity are a potential result of other underlying processes rather than the driving mechanisms themselves.

If comparison of individual characteristics (e.g. similarity) drives individual choice processes in certain networks, models of network evolution have to take into account that *some of these individual characteristics evolve over time as well*. We may choose our friends because they are similar to us. This is a *selection* process. On the other hand, our interaction with our friends may well make us more similar to one another. This is a *contagion* process. If frequent discussions among friends result in similar opinions, similarity of opinion does not guide the choice process but is an effect of the network structure on individual characteristics. The network is the dependent variable in the selection process and the independent variable in the contagion process. Theoretically, the two effects can be separated. Contagion between two time periods implies a change of individual characteristics between t_1 and t_2 within a constant network, selection results in a change in the network with constant individual characteristics. In practice however, it is difficult to separate the two effects if both are operative. Nevertheless, if one of them is neglected, estimators of statistical parameters are seriously biased, as Leenders shows in his second contribution (Chapter 8). Consequently, both effects have to be taken into account in network evolution models.

So far so good, but which individual and network characteristics are important in which networks? Let us consider a few examples. In friendship networks similarity may well drive the choice process, but in functional networks complementarity of resources of other network members is likely to be more important. In friendship networks, densely connected friendship groups provide strong friendship feelings. Such groups emerge when choices are highly transitive. In information networks idiosyncratic positions filling structural holes provide strong opportunities for initiative and strategic action

(Burt, 1992). Loosely connected networks with few transitive choices contain more strategic positions to fill and are likely to be connected with more innovative systems. Whereas Burt associates social capital with structural holes, Coleman and Hoffer (1987) argue that Catholic communities have larger social capital because their communities are more densely connected than those of other groups in the United States. A densely connected community gives more control over the behavior of children because of the better information on their friends and school events. In one context (innovation), sparse networks with structural holes apparently provide social capital while in another (control) central positions in densely connected networks do this. Thus, the importance of individual and network characteristics depends on the goals of the network members and the instrumental value of network links and positions for higher ordered individual goals. Consequently, *a number of network evolution studies takes the goal structure of the network members and the instrumental character of the network as their starting point for model evolution.* Network members try to create relations and network positions that produce desired outcomes. The emergence of networks thus becomes linked with *effects on desired outcomes*. This implies the linkage of network analysis with rational choice models and social production functions within the perspective of the micro-macro link (Lindenberg, 1985; 1990a; 1995). Again, as in the approach of Leenders, the network is both a dependent and an independent variable, but now details of the micro element are unfolded.

This volume contains several examples of this approach to social network evolution. They all rely heavily on computer simulation to investigate the implications of theoretical assumptions on the evolving network structure and the effects on other outcomes. In the contribution of Zeggelink, Stokman, and Van de Bunt on the emergence of groups in the evolution of friendship networks (Chapter 3), the goal function of the network members consists of two components. The first is defined by an actor's desired number of friends. If the number of friends is smaller than the number desired, network members try to reduce the resulting tension (or utility loss) by establishing new friendship relations. The desired number of friends is the basic goal that drives the network formation in all friendship models of Zeggelink (1993). Other goals may enter into the goal function as well, such as similarity of certain individual characteristics. In that case, friendships with similar friends are considered to be more rewarding than friendships with dissimilar friends. Friendships with similar friends give, therefore, a larger tension reduction than friendships with dissimilar friends. The effects of such an additional component are investigated by comparing the resulting simulated networks with those of the basic model where the desired number of friendships is the sole postulated goal (Zeggelink, 1995). In this volume, the second component in the tension (or utility) function is not similarity of friends but membership in a friendship subgroup. Such subgroups emerge "accidentally". Once formed, friendship relations within the subgroup are more rewarding than ones with members outside the subgroup. Therefore, members of subgroups try to keep their subgroup alive and attempt to extend it without losing its defining characteristics. One of their simulation results is that more persons succeed in establishing their optimal number of friendships under the basic model than under the model that includes subgroup membership. In particular, non-subgroup members have difficulties finding enough friends. Moreover, subgroups survive better in larger populations.

Since Zeggelink et al. consider friendship as an intrinsic goal of network members, friendship relations are not instrumental for the attainment of other individual goals in their models. As a consequence, their main results concern systematic variations in network structures under different assumptions and their effects on the success of network members to obtain their desired number of friends. In sharp contrast, the contribution of Flache and Macy (Chapter 2) focuses on the instrumental value of informal networks for compliance with group obligations. They challenge the frequently found empirical relation between density of informal networks and compliance. Following Homans (1950), exchange theorists have explained this positive correlation as an exchange of peer approval for compliance. Flache and Macy rightly state that these exchange theorists overlook the possibility that network members might well exchange approval for approval. Informal network ties then obtain intrinsic value (as in the Zeggelink et al. models). They are no longer instrumental to an external goal (like compliance) and may even impede compliance to group obligations.

To investigate the validity of these assumptions, they formulate a general model in which actors make two types of choices. First, the actors decide whether to work hard or not, based on work satisfaction. Work satisfaction depends on net benefits of both work and approval from others. Subsequently they decide which other actors to approve or not. The decision to approve another actor depends on the net benefits of both his or her work efforts and of the other's approval to the decision maker. The latter is not included in Homan's original exchange model of approval against compliance. Homans' model is a special case of the more general model of Flache and Macy, the net benefits of the other's approval being zero. Since actors make these decisions simultaneously, the effects of their choices are quite uncertain. Consequently, they learn on the basis of past experiences. Although Flache and Macy's simulation results confirm that exchange of approval for approval indeed can impede compliance to group obligations, they do not refute the often reported empirical association between compliance and cohesion. They demonstrate that the effect of approval on compliance is nonmonotonic, depending on the relative values of approval and compliance. Peer pressure can well block compliance, especially when the cost of compliance is high relative to the value of approval. If not, the need of approval increases compliance considerably, but still to a level well below what would be expected if members exchanged approval solely for compliance.

In the contribution of Stokman and Zeggelink on policy networks (Chapter 5) relations are seen as instrumental for obtaining outcomes of collective decisions close to preferred outcomes. In policy networks, typically, a small number of actors are entitled to make the final decisions. Before a final decision, interested actors, in general, try to influence each other's preferences. Such an influence process requires access to other actors and effective resources. Typical resources are expertise, prestige in the field and resources indispensable for implementating decisions. Stokman and Zeggelink simulate the emerging influence relations among actors and their effect on outcomes of decisions. To this end, they assume a very simple decision and influence process. The final outcome of a decision is the mean of the preferences of the final decision makers at the moment of the vote, weighted by their voting power. Influence takes place through access relations. Access from actor i to actor j is established by an access request of actor i that is accepted by j. Access relations result in adapted preferences of actors.

The new preference of an actor i is the weighted mean of i's own preference and those of all actors with access to i at that moment. The weights of the actors depend on their resources and interest in the decision.

Access relations require time and resources. Actors therefore are assumed to be restricted in the number of access requests they can make and the number of such requests they can accept. Moreover, due to incomplete information and simultaneous actions by other actors, actors have to make simplifying assumptions and learn by experience. Stokman and Zeggelink evaluate different models corresponding to different views of politics. The model with the best predicted outcomes of decisions is policy driven. This model results also in networks with many similar structural characteristics as the empirical network. In this model, actors are confronted with two counteracting forces in their choice of which access requests to make. On the one hand, they realize that powerful actors with distant and opposite views are most attractive as targets. If successful, an access relation to such an actor will greatly affect the outcomes of decisions. On the other hand, actors realize that these actors are less likely to accept access requests than actors with more proximate preferences. Actors realize that other actors act in a similar way as they do themselves: they give high priority to access and thereby influence from like-minded other actors. Only if such actors are not present, are they willing to accept influence from more distant actors. Consequentially, actors select influence purposively to "bolster" their own position. This prevents them from changing their own preferences while trying to influence other actors to do so.

In all three individual goal oriented contributions, networks evolve because actors simultaneously optimize their network relations. Even if they have full information on the present, as both Zeggelink et al. and Flache and Macy assume, the effects of their choices may strongly deviate from their intentions. Due to the simultaneous choices of others the "present" has been changed before their own actions have come into effect. In other words, the present is the wrong situation to be optimized and others' choices should be anticipated. Such optimization problems are magnified by incomplete information. Forward-looking analytic solutions may be impossible in these situations, for actors as well as for modelers. The principles of learning from past experience (Macy, 1990; 1991) and imitating successful others (Heckathorn, 1995) become increasingly important and can very well be applied to social network evolution, as these two contributions show.

If we want to confront the results of such dynamic simulation models with empirical data, *longitudinal data sets and adequate statistical tools* are indispensable. The overview in the introductory chapter showed that the former are not widely available. Moreover, very few longitudinal data sets are reported in the literature that are available for secondary analysis and contain both changes in network ties and network effects such as changing individual characteristics.[5]

The contribution of Snijders in the present volume (Chapter 9) is a major step towards developing adequate statistical tools. The tool presented is designed to test models of simultaneously acting goal oriented actors. As in the Stokman and Zeggelink contribution, actors are assumed to be unable to optimize their utility function directly because

[5]Some data sets with these properties are being developed.

of incomplete information on the effects of alternative choices and simultaneous actions of others. Actors are therefore assumed to optimize their utility indirectly by deriving desirable network characteristics that promote their goal achievement. Examples of such network characteristics are reciprocity, transitivity, and balance. In other words, if we can deduce network characteristics from the goal functions of the actors that are causally linked with their goal attainment, we can consider these network characteristics as heuristics to be optimized. The proposed Markov chain models incorporate random change in addition to goal oriented change. They enable the estimation of parameters from observed data and can be used to measure and test the goodness of fit of the models. This proposed methodology is also of major theoretical importance. First, it integrates statistical parameter estimation and testing with goal oriented network models along the lines of "structural individualism" (see below). Second, it shows the path along which network evolution models on structural network properties can be linked with goal oriented network evolution models.

3. BASIC PRINCIPLES FOR SOCIAL NETWORK EVOLUTION MODELS

From the overview of social network evolution processes in the present volume we extract some basic principles as recommendations for future work. In these recommendations we stress the importance of taking seriously the decentralized and parallel optimization processes in social systems. In computer science and artificial intelligence we find a number of similar approaches that are aimed at modeling decentralized parallel optimization processes. These approaches stress similar principles as we have seen in this volume plus some others. We consider them as recommendations for future extensions. Of particular interest are four approaches: object-oriented models, distributed artificial intelligence, cellular automata, and neural networks.

Stokman and Van Oosten (1994) and Zeggelink (1993, 1994) stress the striking similarities in the principles of *object oriented modeling* and structural individualism. The most important characteristic of social processes is that the outcomes of "macro" processes are not simply the result of a central (planning) authority. Rather, outcomes are the intended or unintended consequences of the simultaneous choices of persons or other social units, represented by these persons (as social actors). Social actors try to realize their own goals by choosing between behavioral alternatives that are available to them under certain restrictions. This principle is the core principle in the structural individualistic approach (Wippler, 1978; Boudon and Bourricaud, 1982; Lindenberg, 1985; Coleman, 1986; 1990). Object-oriented modeling makes it possible to arrive at a direct representation of such a physical world of parallel operating actors (Goldberg and Robson, 1983). In object-oriented models, these actors are represented by objects. These objects have an internal structure which enables them to reason and to communicate with other objects. In resemblance with the physical world, the reasoning of and communications between objects in object-oriented models may take place simultaneously, may result in a diversity of actions by different objects depending on the restrictions under which they operate, and may be adapted on the basis of past experiences (Lehrmann Madsen and Moller-Pedersen, 1988). The characteristics of social systems emphasized in the structural individualistic approach (parallel, operating under different restrictions, self learning, and actors reacting to each other on the basis of which social phenomena develop) have their direct equivalents in object-oriented models.

Similar parallels exist between the structural individualistic approach and *distributed artificial intelligence* (DAI). DAI systems aim to represent systems with many agents that interact to achieve some goals regardless of whether these goals are their own or not. Cooperation is necessary to achieve these goals and cooperation requires communication and conflict resolution through negotiation (Werner and Demazeau, 1992). Doran (1989) even claims that a similar relationship between DAI and the social sciences exists as that between AI and psychology. Several applications of Carley (1986; 1992) can be seen as DAI representations of social systems.

Cellular automata (CA) were introduced by Von Neumann and Ulam in the late forties (see Von Neumann, 1966) as a representation of life and self-reproduction. CA can be seen as a simple DAI system. Automata are represented as cells in a checkerboard. Cells can be in different states, e.g. alive or dead as in Conway's "game of life". The state of a cell in the next time step depends on its own present state and the present states of all its surrounding cells (neighbors). The size of the neighborhoods vary across applications. In Conway's game neighbors are the eight adjacent cells, in other applications it may well be confined to the four cells in the horizontal and vertical directions or extended to a larger area. In this game a living cell will stay alive in the next period if and only if it has two or three living neighbors. Otherwise it will die because of overcrowding or loneliness. A dead cell will change into a living one if and only if it has exactly three living neighbors.

Conway's game of life attracted much attention in 1970 because of the rich emerging structures: some are stable while others move across the checkerboard (Hegselmann, 1996). CA are nowadays used in many disciplines to represent dynamic *local* processes. (For a classification and overview see Wolfram, 1984). In the social sciences, they are typically used to model *social dynamics* due to contagion and migration. In CA contagion models, automata (cells) cannot move. In CA migration models, automata can move to other cells if they are dissatisfied with their neighborhood. The emphasis lies on problems of self-organization. How can we explain the emergence of social order without the existence of central authorities?

In CA models, social structures typically emerge in thousands of iterations. Nowak et al. (1990), Nowak and Latané (1994), Latané et al. (1994) investigate the emergence of clusters and polarization through contagion. Starting with random distributions of attitudes among the cells on the checkerboard, they show how minorities can survive by the emergence of clusters of similarly thinking persons. Survival of minorities and polarization of attitudes and opinions can be explained by the transformation of individual attitudes and opinions into socially organized attitudes and opinions within a *social space*. Nowak et al. (1996) give very convincing empirical evidence of this mechanism in post-communist Poland. Economic development and preferences for non-communist parties go hand in hand and emerge as regional clusters.

Hegselmann (1994; 1996) developed a CA migration model to explain the emergence of solidarity among selfish persons with different needs for help. If persons are dissatisfied with the help they can expect from their neighbors, they can move to a new neighborhood with better possibilities. These improved possibilities depend on the ability and willingness of neighbors to help. Starting from random distributions of persons in different help categories, he shows the emergence of spatial clusters of persons in the same or adjacent help categories. The most and least healthy persons experience most difficulties in finding help. The first because the are not willing to help others, the latter because they are unable to help others.

Hegselmann (1996) based the adequacy of CA to model social systems on many points of similarity between CA and social dynamics. Cells, as basic units, correspond to the individuals as the basic units in a society. Cells can be in different states and individuals can choose between alternatives or adopt certain attitudes. The state of a cell affects the state of its neighbors as individuals affect each other mutually. Both in CA and social systems, this interdependence is local and based on local information only. Neighborhoods are overlapping as social interactions have an overlapping structure. CA applications in mathematics and natural sciences aim at modeling the emergence of order and dynamic processes that explain macro effects from micro rules. Social scientists have similar aims regarding social order and dynamics.

Our main concern with CA is the simple structure assumed by these models. In most applications, neighborhoods have equal sizes for each cell. If we would apply the same CA contagion principles to social networks, neighborhoods and their overlap can vary systematically across actors. Similarly, the strength of contagion can be varied by assigning weights to (not necessarily symmetric) relations between actors. If social network contagion models would incorporate the other principles of CA models, they would take the distributed and local character of information and contagion more seriously. On the other hand, such social network contagion models could incorporate contagion processes both through communication and social comparison. CA models do not differentiate these two processes and that both operate is well known from the social network literature.[6] In addition, CA migration models can be replaced by social network selection models. This all would pave the way towards systematic research into self-organization processes in social networks.

Although CA aim to model distributed processes, they usually do not represent parallelism. Either all cells are activated sequentially or through random selection. Parallelism is one of the main features of *artificial neural network models* (Rumelhart and McClelland, 1986; Gallant, 1994).[7] An artificial neural network consists of a number of neurons each with a very simple internal state where a single value of a variable represents its activity level. Neurons are connected to each other and the environment by means of directed or undirected connections. Through these connections, neurons receive influence from the environment and influence each other's activity level and the environment.

Another main feature of a neural network model is its learning capacity. The most widely applied neural network models are based on supervised learning models in which a central target is specified. The learning process consists of the adaptation of both the

[6]Leenders (1995) shows that it is very difficult to distinguish the two in empirical research. He convincingly shows that it would be false to equate contagion through communication with cohesion and contagion through social comparison with (structural) equivalence as some researchers do.

[7]Neural network applications on single processor computers also use, sometimes, random selection procedures instead of parallel ones. We argue, below, that social processes are often parallel and it is vital to represent them as such.

weights of the connections and the activity levels of the neurons until the output of the neural network matches the target. Neurons only learn by using information received through their connections with other neurons or the environment. This information is used to determine whether their activity level and strengths of incoming connections are appropriate. If not, both are adapted in two different subprocesses. In the first, the activity level is adapted through incoming signals from other neurons and the environment. Thus, the structure of connections determines the activity level of the neurons. In the second subprocess, neurons evaluate the incoming signals in order to distinguish profitable from unprofitable connections. This results in the strengthening of profitable connections and the weakening of unprofitable ones. Optimization takes place therefore at the level of the neurons in view of targets at the network level.[8] This makes neural network models with supervised learning particularly interesting for social systems where such central targets can be assumed, as in organizations.

More interesting for social network modeling are the more experimental unsupervised learning models. In these models no feedback on performance is available as there are no criteria to distinguish correct from wrong answers. The most that can be expected from these models is the construction of groups of similar input patterns, known as *clustering* and used for pattern recognition. For example, Balakrishnan et al. (1994) compare neural network solutions with a traditional clustering method (K-means) on simulated data with known cluster solutions. For social science applications the most interesting result is the emerging structure among the neurons as a representation of a self-organizing social network. Ossipow and Ritschard (1993) apply Kohonen's unsupervised learning model for the study of parliamentary debate. The neuron that is most sensitive to a given input becomes an attractor. This means that the cells in the neighborhood of this neuron tend to modify their own sensitivities by imitating those of the attractor. A more extensive introduction to attractor neural network models and their value as models of social dynamics is given in Nowak (1996).

The major difference between neurons and social actors is the more complex structure of the latter. Stokman et al. (1994) see four main differences in the behavior of neurons and social actors: (1) social actors have more alternative actions to choose from; (2) social actors have more learning strategies, in particular they do not solely learn from past experience but also from imitating successful others; (3) social actors have limited resources and can consequently interact only with a limited number of others and (4) interactions between social actors are, in general, only effective when both sides agree on the interaction. Nevertheless, models of social network evolution could profit from the inclusion of the main principles of neural networks. First, it will result in the representation of the parallel nature of social processes with its far reaching consequences for the optimization of social actors. Second, social network evolution models will incorporate learning models based on local and incomplete information only. Third, they will include the basic idea that evolution involves both changes in characteristics of social actors and in tie strengths.

We now summarize the main guiding principles we recommend for future social network evolution studies. See Table 2.

[8]Neurons can learn in both unsupervised and supervised models.

TABLE 2
Principles of Social Network Evolution Models

Basic Principles	Derived Guidelines
Instrumental value of network ties for social actors	Analysis of goal structure of social actors
Partial and local information only	– Adaptive learning by experience and imitation
Parallel optimizing social actors	– Emergence of ties requires decisions by two actors (e.g. request and acceptance)
Simple models	– priority for analytic solutions above simulation – adding complexity stepwise
Sufficient empirical references	estimating parameters and testing goodness-of-fit by combining: – controlled experiments – longitudinal data collection – statistical models

The first guiding principle is that **the instrumental character of the network** should be taken as the starting point for modeling network evolution. Network ties, like friendship ties, can have intrinsic value. Their value can also be related to external goals of individual actors like access to important resources of other actors (for example information in job searches). Also, their value can be related to their effect on collective outcomes like group performance in the Flache/Macy chapter and collective decisions in the Stokman/Zeggelink contribution. The principle requires, therefore, the elaboration of the **goal structure of the network members**. Lindenberg's elaboration of the homo socio-oeconomicus and social production functions might be helpful in this respect (Lindenberg, 1990b; 1985; 1990a). At the highest level of abstraction, actors are assumed to have monotonically increasing utility functions related to universal goals, like physical well-being and social approval. Actors have, however, different instrumental preferences for the means that lead to the ultimate goals (Lindenberg, 1990b: 741). Examples of instrumental goals in different settings are compliance and approval in the Flache/Macy and collective decision outcomes in the Stokman/Zeggelink contributions. The first can still be modeled by monotonically increasing utility functions, but the latter cannot. Whereas one decision outcome can produce social well-being or social approval for one set of people, another outcome can be better for others. In other words, each actor orders outcomes in terms of the contribution the outcome makes to the actor's universal goals.[9] If more goals are simultaneously involved, such as approval and compliance or several decisions, the relative importance of the goals may well vary systematically from actor to actor. Salience is introduced for that purpose

[9]These outcomes are not necessarily dichotomous, like pro or con, but may well consist of a certain amount of an outcome, for example, the size of a budget or the height of a new building.

[10]We acknowledge that some actors may have global knowledge and there may be processes operative at the network level. Even so, it seems that for understanding actors' action and the structural consequences of those actions, it is more appropriate to assume actors act with local information.

in the Stokman/Zeggelink model where the different goals are subsequently combined into one utility function.

The second basic principle we recommend deals with the information social actors possess. We advocate models in which actors optimize based on **local information** only.[10] None of the contributions in this volume incorporates that idea systematically. It would open, however, important new perspectives and raise new questions such as: Can higher levels of reciprocity in larger groups simply be explained by local visibility (see Doreian et al. in Chapter 6 and Leenders in Chapter 7)? What are the bystander effects for the emergence of dominance structures in larger groups when attacks are solely observed by actors in the direct neighborhood (see Skvoretz et al. in Chapter 4)? What are the effects of approval on compliance if we can observe compliance solely in our neighborhood (see Flache/Macy in Chapter 2)? What effects would this have on the structure of the approval network? Would we observe similar forms of self-organization as CA models show, for example in the form of complying islands? If we would know the policy positions and saliences only in our (policy) neighborhood and have to guess those of our adversaries, which effects would that have on the emergence of access relations and outcomes of decisions? These questions may even be extended to the important question of the delivery of sincere and strategic information if we have to rely on information of others (Stokman and Stokman, 1995).

As we stated before, even with full information the rationality of social actors is seriously hampered by the fact that actors optimize simultaneously. This implies that their rationally chosen alternatives may appear to be suboptimal because they did not anticipate the actions of other actors at all or in a proper way. For this reason we recommend the inclusion of **parallelism** in social network evolution models as the third basic principle. Parallelism and limited local information (certainly in combination with each other) have a number of consequences for social network evolution models. First, they make inevitable the definition of instrumental goals for actors that are only roughly related to the ultimate instrumental goals in the system (*heuristics*). Second, actors should have the capability to evaluate the *ex ante* assumptions as they may turn out to be unrealistic *ex post* (*e.g.* that other actors behave in a certain way). Consequently, actors should be able to evaluate the ultimate success of these heuristics and the assumptions upon which they are based and actors should be able to adapt them in case of frequent failure. In other words, actors should have the ability for *adaptive learning*. Examples of learning from experience were given in the Flache/Macy contribution (see also Macy, 1990; 1991; 1993) and in the one by Stokman and Zeggelink (Chapter 5). We think it is worthwhile to consider also imitation learning models in social network evolution models, as proposed, among others, by Axelrod (1984) and Heckathorn (1995).[11] If we would combine Heckathorn's imitation model of successful strategies with ideas of parallel, local processes in social networks, we would likely get fundamentally different results. Along the lines of research into self-organization we expect the survival of a larger variety of strategies by the emergence of local clusters. The third consequence of parallelism is that changes take place both simultaneously and

[11]Genetic algorithms is a third learning model that could be applied (see also Bainbridge et al., 1994, in their overview of artificial social intelligence). Although they are very efficient for solving a wide variety of problems, we think that they are remote from actual learning processes in social systems.

sequentially. This can be modeled in parallel computer processes, but it can also be modeled by splitting network changes into two steps. In the first step, all actors make proposals to establish relations with others (*access requests*). In the second step, all actors *accept* the most profitable ones.[12] A network relation is then the result of a request that is accepted. Established relations subsequently induce changes in individual characteristics and affect the relative strength of relations. At the collective level, the resulting network induces a structure and, in instrumental networks, other collective outcomes.

If the choice process of requests is more important than that of acceptance, we may of course make the simplifying assumption that all requests are accepted. The distinction between the request and acceptance step can also be very useful for modeling the formation of cognitive network representations and misperceptions, for example if not all requests are perceived. It is the actor's cognitive representation of networks and not the actual network that constraints his or her behavior. Moreover, systematic biases in social perception have been demonstrated to exist (Freeman et al., 1987; Krackhardt, 1987; Kumbasar et al., 1994). It seems promising to extend these static analyses to the emergence of cognitive structures and the learning processes involved, making use of the principles listed here.

The next basic principles are more related to research strategy than to desirable properties of the models. We realize that the above recommendations quickly result in complex models. Nevertheless, we strongly recommend starting with **simple models** (the fourth basic principle). Scientific models do not aim to mimic reality. Scientific models should be as simple as possible and as complex as necessary. If the aim is prediction or explanation, the argument that processes in reality are more complex or different does not invalidate a model. If the aim is to represent a process itself, it is important to start solely with its most characterizing kernel. The literature shows that simple models can have quite far reaching and unintended effects (Schelling, 1978; Coleman, 1990). Moreover, simple models might have *analytic solutions*. Such solutions do not solely provide stronger evidence as more complex models can often incorporate them by using computer simulations for more complex parts. Abell (1989), Raub and Weesie (1990), Snijders et al. (1994) are examples of innovative game theoretical solutions within the context of networks. As another example, Hegselmann (1994, 1996) combines analytic game theoretical solutions with a CA simulation model. *Stepwise addition of complexity* makes it possible to investigate effects of each complicating step systematically and to evaluate the resulting improvement of the model. This method of model construction is known as the method of decreasing abstraction (Lindenberg, 1992).

The fifth basic principle is that the models should have **sufficient empirical references**. Models should have at least testable consequences and the potential to be falsified. Models without such references may well generate interesting ideas and insights, but they do not contribute to well founded empirical theories of social networks and their evolution. The latter is the aim of an empirical social science. Statistical

[12]The two steps from which social relations emerge points to a graph theoretical representation of social networks by demiarcs instead of arcs (Harary, 1971).

models are strongly prefered, as they enable **the estimation of essential parameters and to test the goodness-of-fit of the models**. This principle requires at least specification of *controlled experiments* and types of real-life data necessary for testing. We hope it will lead to a much larger number of *longitudinal network datasets* than those presently available. Such datasets should not be confined to network changes but should include changing individual characteristics and macro-effects when appropriate. Such an integration of theoretical models and empirical testing will provoke more applications of already existing tools and the development of new *statistical models*. Particularly, Markov models and the dynamic versions of network autocorrelation models seem very useful. In these models, both the actor attributes and the structures within which they are embedded can change (Holland and Leinhardt, 1977; Doreian, 1989; 1990; Wasserman, 1979; 1980; Leenders, 1995). Preferably, such statistical models should be based directly on the theoretical models and take into account the complexity and mutual dependencies of social network data. Snijders et al. (1994) and the contribution of Snijders in this volume are such examples. Presently the latter model is limited to applications where structural network restrictions (such as reciprocity and balance) can be deduced from the goal structure of actors. We believe that such statistical models can be extended to goodness of fit tests that are also based on comparisons of predicted and empirical effects, both at the individual and at the macro level. Banks and Carley (Chapter 10) also point towards statistical procedures for estimating social network process models.

The implementation of the above principles requires a close collaboration of quite different expertises. In particular, it requires complicated mathematical, statistical, computational, sociological and empirical contributions. A really interdisciplinary approach and collaboration is required. So, let us do it!

REFERENCES

Abell, P. (1989) "Games in Networks. A Sociological Theory of Voluntary Associations." *Rationality and Society* **1:** 259–282.

Axelrod, R. (1984) *The Evolution of Cooperation*. New York: Basic Books.

Balakrishnan, P. V. (Sundar), Cooper, M. C., Varghese, S. J., and Philip, A. L. (1994) "A Study of the Classification Capabilities of Neural Networks Using Unsupervised Learning: A Comparison With K-Means Clustering." *Psychometrika* **59:** 509–525.

Bainbridge, W. S., Edward, E. B., Kathleen, M. C., David, R. Heise, Macy, M. W., Markovsky, B., and Skvoretz, J. (1994) "Artificial Social Intelligence." *Annual Review of Sociology* **20:** 407–436.

Boudon, R. and Bourricaud, F. (1982) *Dictionnaire Critique de la Sociologie*, Paris: Presses Universitaires de France.

Burt, R. S. (1992) *Structural Holes. The Social Structure of Competition*. Cambridge, Mass.: Harvard Univ. Press.

Carley, K. M. (1986) "An Approach for Relating Social Structure to Cognitive Structure." *Journal of Mathematical Sociology* **12:** 137–189.

Carley, K. M. (1992) "Organizational Learning and Personnel Turnover." *Organization Science* **3:** 2–46.

Coleman, J. S. (1986) "Micro foundations and macrosocial theory." In S. Lindenberg, J. S. Coleman and S. Nowak (Eds.), *Approaches to social theory*, New York: Russell Sage Foundation, 345–363.

Coleman, J. (1990) *Foundations of Social Theory*. Cambridge: The Belknap Press.

Coleman, J. S., and Hoffer, T. (1987) *Public and Private High Schools — The Impact of Communities*. New York: Basic Books.

Doran, J. (1989) "Distributed artificial intelligence and modelling in socio-cultural systems." In L. A. Murray and J. T. E. Richardson (Eds.), *Intelligent Systems in a Human Context. Development, Implications, and Applications*, Oxford: Oxford University Press, 71–91.

Doreian, P. (1989) "Two Regimes of Network Autocorrelation." In M. Kochen (Ed.), *The Small World*, Ablex, 280–295.

Doreian, P. (1990) "Network Autocorrelation Models: Problems and Prospects." In D. A. Griffith (Ed.), *Spatial Statistics: Past, Present and Future. Monograph 12.*, Ann Arbor: Institute of Mathematical Geography, 369–389.

Freeman, L. C., Romney, A. Kimball, and Freeman, S. C. (1987) "Cognitive structure and Informant Accuracy." *American Anthropologist* **89**: 311–325.

Gallant, S. I. (1994) *Neural Network Learning and Expert Systems*. Cambridge, Mass.: MIT Press.

Goldberg, A. and Robson, D. (1983) *Smalltalk–80. The language and its implementation*, Reading, Mass.: Addison-Wesley.

Hallinan, M. T. (1976) "Friendship patterns in open and traditional classrooms." *Sociology of Education* **49**; 254–265.

Hallinan, M. T. (1978) "The Process of Friendship Formation." *Social Networks* **1**: 193–210.

Harary, F. (1971) "Demiarcs: An Atomistic Approach to Relational Systems and Group Dynamics." *Journal of Mathematical Sociology* **1**: 195–205.

Heckathorn, D. D. (1995) "The Dynamics and Dilemmas of Collective Actions." *American Sociological Review* **60**.

Hegselmann, R. (1994) "Zur Selbstorganisation von Solidarnetzwerken unter Ungleichen. Ein Simulationsmodell." In V. Arnold et al. (Eds.), *Wirtschaftsethische Perspektiven I: Theorie, Ordnungsfrage, Internationale Institutionen*, Berlin: Duncker & Humblot, 105–129.

Hegselmann, R. (1996) "Modeling Social Dynamics by Cellular Automata." In W. B. G. Liebrand, A. Nowak, R. Hegselmann (Eds.), *Computer modeling of network dynamics.*

Holland, P. W., and Leinhardt, S. (1977) "A Dynamic Model for Social Networks." *Journal of Mathematical Sociology* **5**: 5–20.

Homans, G. C. (1950) *The Human Group*. New York: Harcourt Brace.

Kohonen, T. (1989) *Self-Organization and Associative Memory*. Berlin: Springer Verlag, 3rd ed.

Krackhardt, D. (1987) "Cognitive Social Structures." *Social Networks* **9**: 109–134.

Kumbasar, E., Romney, A. Kimball, and Batchelder, W. H. (1994) "Systematic Biases in Social Perception." *American Journal of Sociology* **100**: 477–505.

Latané, B., Nowak, A., and Liu, J. H. (1994) "Dynamism, Polarization, and Clustering as Order Parameters of Social Systems." *Behavioural Science* **39**: 1–24.

Leenders, R. Th. A. J. (1995) *Structure and Influence. Statistical Models for the Dynamics of Actor Attributes, Network Structure and Their Interdependence*. Amsterdam: Thesis Publishers.

Lehermann, M., Moller-Pedersen, O., and Moller-Pedersen, B. (1988) "What Object-Oriented Programming May Be — and What It Does Not Have to Be." In S. Gjessing and K. Nygaard (Eds.), *ECOOP 88. European Conference on Object-Oriented Programming*, Berlin: Verlag.

Lindenberg, S. M. (1985) "An Assessment of the New Political Economy." *Sociological Theory* **3**: 99–111.

Lindenberg, S. M. (1990a) "Towards the construction of interdisciplinary theoretical models to explain demographic behaviour: a comment." In C. A. Hazeu and G. A. B. Frinking (Eds.), *Emerging Issues in Demographic Research*, Amsterdam: Elsevier Science Publishers, 199–217.

Lindenberg, S. M. (1990b) "Homo Socio-oeconomicus: The Emergence of a General Model of Man in the Social Sciences." *Journal of Institutional and Theoretical Economics* **146**: 727–748.

Lindenberg, S. M. (1992) "The Method of Decreasing Abstraction." In J.S. Coleman and T.J. Fararo (Eds.), *Rational Choice Theory: Advocacy and Critique*, Newbury Park: Sage, 3–20.

Lindenberg, S. M. (1995) "Complex Contraint Modeling (CCM): A Bridge Between Rational Choice and Structuralism. Comment." *Journal of Institutional and Theoretical Economics* **151**: 80–88.

Macy, M. W. (1990) "Learning Theory and The logic of critical Mass." *American Sociological Review* **55**: 809–826.

Macy, M. W. (1991) "Learning to Cooperate: Stochastic and Tacit Collusion in Social Exchange." *American Journal of Sociology* **97**: 808–843.

Macy, M. W. (1993) "Backward-Looking Social Control." *American Sociological Review* **58**: 819–837.

Newcomb, T. N. (1961) *The Acquaintance Process*. New York: Holt, Rine hart and Winston.

Nowak, A., Szamrej, J., and Latané, B. (1990) "From Private Attitude to Public Opinion: A Dynamic Theory of Social Impact." *Psychological Review* **97**: 362–376.

Nowak, A., and Latané, B. (1994) "Simulating the Emergence of Social order from Individual Behavior." In N. Gilbert and J. Doran (Eds.), *Simulating Societies: The Computer Simulation of Social Phenomena*, London: University College London Press, 63–84.

Nowak, A., Lewenstein, M., and Szamrej, J. (1996) "Bubbles — A Model of Social Transition." *Scientific American*.

Nowak, A. (1996) "Attractor Neural Networks as Models of Social Dynamics." In W. B. G. Liebrand, A. Nowak, R. Hegselmann (Eds.), *Computer modeling of network dynamics.*

Ossipow, W., and Ritschard, G. (1993) "Formation du savoir démocratique. Essay d'analyse neuromimétique." In O. Boussaid, M. Brissaud, G. Ritschard, J. P. Royet (Eds.), *Pluridisciplinarité dans les sciences cognitives*, Paris: Hermès, 128–141.

Raub, W., and Weesie, J. (1990) "Reputation and Efficiency in Social Interactions: An Example of Network Effects." *American Journal of Sociology* **96**: 626–654.

Rumelhart, D. E., and McClelland, J. L. (1986) *Parallel Distributed Processing. Explorations in the Microstructure of Cognition. Volume 1: Foundations.* Cambridge, Mass.: MIT Press.

Schachter, S. (1959) *The Psychology of Affiliation.* Stanford: Stanford University Press.

Schelling, T. (1978) *Micromotives and Macrobehavior.* New York: Norton.

Snijders, T., Marcel van, D., and Weesie, J. (1994) "Who Contributes to Public Goods? With an Application to Local Economic Policies in the Netherlands." *Journal of Mathematical Sociology* **19**: 149–164.

Stokman, F. N., and Oosten, R. V. (1994) "The Exchange of Voting Positions: An Object-Oriented Model of Policy Networks." In B. Bueno de Mesquita and F. N. Stokman (Eds.), *European Community Decision Making. Models, Applications, and Comparisons*, New Haven: Yale University Press, 105–127.

Stokman, F. N., Hangyi, H. T. and Zeggelink, E. P. H. (1994) *Social networks and Principles of Self-Organization.* Paper presented at the Social Science Information Technology 94 Conference, Amsterdam: December 7–9.

Stokman, F. N., and Stokman, J. V. (1995) "Strategic Control and Interests. Its Effects on Decision Outcomes." *Journal of Mathematical Sociology* **20**: 289–317.

Von Neumann, J. (1966) *Theory of Self-Reproducting Automata.* Urbana: University of Illinois Press.

Wasserman, S. (1979) "A Stochastic Model for Directed graphs with Transition Rates Determined by reciprocity." In K. F. Schuessler (Ed.), *Sociological Methodology — 1980*, San Francisco: Jossey-Bass.

Wasserman, S. (1980) "Analyzing Social Networks as Stochastic Processes." *Journal of the American Statistical Association* **75**: 280–294.

Wasserman, S., and Faust, K. (1994) *Social Network Analysis: Methods and Applications.* Cambridge: Cambridge Univ. Press.

Werner, E., and Demazeau, Y. (1992) "The Design of Multi-Agent Systems." In E. Werner and Y. Demazeau (Eds.), *Decentralized A.I. 3. Proceedings of the Third European Workshop on Modelling Autonomous Agents in a Multi-Agent World*, Amsterdam: North-Holland, 3–28.

Willer, D., and Willer, R. (1995) *Exchange Network Dynamics and Structural Agency.* Paper presented at the ASA Annual Conference, Washington, August.

Wippler, R. (1978) "The structural-individualistic approach in Dutch sociology: toward an explanatory social science." *The Netherlands Journal of Sociology* **14**: 135–155.

Wolfram, S. (1984) *Universality and Complexity in Cellular Automata*, Physica.

Zeggelink, E. P. H. (1993) *Strangers into Friends. The Evolution of Friendship Networks Using An Individual Oriented Modeling Approach.* Amsterdam: Thesis Publishers.

Zeggelink, E. (1994) "Dynamics of Structure: An Individual Oriented Approach." *Social Networks* **16**: 295–333.

Zeggelink, E. (1995) "Evolving Friendship Networks: An Individual Oriented Approach Implementing Similarity." *Social Networks* **17**: 83–110.