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Published in:
Computational and Mathematical Organization Theory

DOI:
10.1007/BF00240423

Computational & Mathematical Organization Theory 2:2 (1996): 115–138

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Abstract

The aim of this paper is to explain principles of object oriented modeling in the scope of modeling dynamic social networks. As such, the approach of object oriented modeling is advocated within the field of organizational research that focuses on networks.

We provide a brief introduction into the field of social networks and present an overview of existing network models and methods. Subsequently we introduce an elementary problem field in the social sciences in general, and in studies of organizational change and design in particular: the micro-macro link. We argue that the most appropriate way to handle this problem is the principle of methodological individualism. For social network analysis, to contribute to this theoretical perspective, it should include an individual choice mechanism and become more dynamically oriented. Subsequently, object oriented modeling is advocated as a tool to meet these requirements for social network analysis. We show that characteristics of social systems that are emphasized in the methodological individualistic approach have their direct equivalences in object oriented models. The link between the micro level where actors act, and the macro level where phenomena occur as a consequence and cause of these actions, can be modelled in a straightforward way.

Keywords: social networks, objected oriented modeling, dynamics

1 Introduction

Social networks play an important role in explaining social phenomena. A social network consists of a set of *units* and the *relationships* among them. The units are usually called the actors and can be persons, groups of persons, organizations, nations, and so forth. The relationships among the units vary from friendship to advice-seeking, from kinship to influence, and from communication to membership, to mention only a few. As such, the network structures may summarize political, economic, behavioral, and social systems of any kind and thereby represent for example personal networks, informal and formal networks within organizations, or interorganizational networks. They are studied in a broad variety of applications, some of them to be found in Holland and Leinhardt (1979), Knoke and Kuklinski (1982), Wellman and Berkowitz (1988), and Weesie and Flap (1990). Wasserman and Galaskiewicz (1994) and Nohria and Eccles (1992) provide an overview of applications of network analysis in organization studies.

All elements of a social network (units, relationships, and the network itself) have specific properties and yet are highly interdependent. In the research field of social networks, on the whole, the *'pattern'* or *'structure'* of relationships among the units is analyzed. Subsequently, it is used to solely *describe* features of the total network or to *explain* behavior of the units in the network and as a consequence explain social phenomena. Today, social network analysis is a well established approach with a variety of applications that makes use of a broad range of theoretical foundations and methodological techniques that stimulate developments in each other's direction. Theoretical basics can be found in Berkowitz (1982), Burt (1982), and Scott (1991). Methodological principles are given in Freeman et al. (1989), Harary et al. (1965), and Wasserman and Faust (1994).

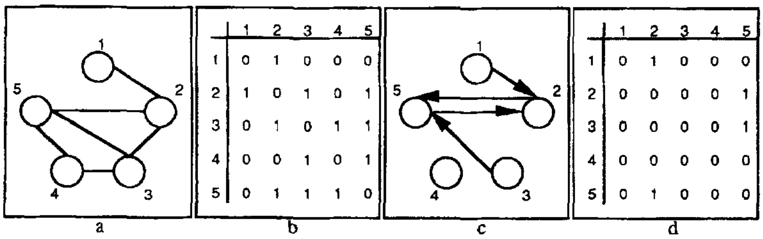
Within the scope of this paper we focus only on so-called total or whole networks.[1] Concepts, tools, and measures have been developed to define and calculate a variety of interesting aspects of social networks. In general these characterizations concern structure or composition. *Structure* refers to the agglomeration of relationships in the network and thereby mainly describes what happens between pairs of individuals. The *composition* of a network describes the overall picture of (constant or time-varying) actor characteristics, such as age and gender for individuals, and size and type of business for organizations as actors. When the pattern of relationships, structure, is studied, a number of different structural parameters is available. Frequently, the parameters are used to describe the network structure per se (Sprenger and Stokman 1989). More complex studies employ the structural properties as relevant factors in explaining behavior of the units that belong to the network. Then, differences and similarities in the positions (or roles) of individuals in the network are used to explain differences and correspondences of the behavior, well-being or functional ability of these individuals. So-called structurally equivalent individuals for example, are individuals that have the same relations with the same others. They are generally assumed to behave or to be influenced in the same way. Positions in a network may also indicate special capacities for coordination in the social system (managers within an organization usually have typical relations with specific others, and thereby a managerial function). Other structural features, for instance relational properties like subgroup membership, are also used in the explanation of individual behavior or attribute values. Subgroups with many internal relations are frequently used to indicate homogeneous attitude groups with strong internal influence mechanisms. Other types of research focus on the effects of network structure on outcomes at a more global level, such as the diffusion of information or diseases, and the outcomes of decision making processes.

As shown above, in most studies the network is assumed to be given, not varying, and the effect of structure on the individual is the focal point of investigation. Research has seldom been conducted on processes in the opposite direction, i.e. the evolution of network structure as a result of individual behavior. The main aim of the present paper is to show how *object-oriented modeling* of social networks can give a new impetus to social network analysis by focusing on these kinds of *dynamic processes.*

An overview of the present main analytic perspectives in social network analysis will first be given in Section 2. In Section 3 we argue that social networks play a double role in micro-macro transformations. The network as the macro level constrains the behavior of the units at the micro level, but is also the result of these individual actions. In order to model this phenomenon of mutual dependence properly, the models of Section 2 do not fulfil, and a dynamic, actor oriented approach to social network analysis is required, which is advocated in Section 4. Throughout the paper we use a simple example for illustration, but also briefly present a number of other studies, in which the approach presented here, has been or is applied. In Section 5 we summarize the message of this paper.

2 Main Analytic Perspectives In Social Network Analysis

Social network analysis draws on a variety of both sociological and non-sociological theories. The main mathematical foundations underlying social network analysis are: graph theory, matrix theory, probability theory, statistical and algebraic theories. Three types of network representations dominate: the visual representation (*sociogram*), the sociometric representation (*adjacency matrix*), and the algebraic representation (Harary 1969, Harary et al. 1965). The former two are most common and presented in Figure 1: (a) and (c) show sociograms, (b) and (d) show the corresponding adjacency matrices that are usually used to calculate properties of the network. As mentioned in Section 1, different types of actors (units) may exist among which various types of relationships can be present. In graph theory these units are called vertices, points or *nodes*. The networks in Figure 1 consist of 5 nodes. Every row and column in the matrices of Figure 1b and Figure 1d correspond to a node. Nodal properties of attributes can be denoted either next to the node or as possible various different colors of the nodes. This is not depicted in Figure 1, but will be illustrated in Section 3 when we introduce a simple example.



	1	2	3	4	5
1	0	1	0	0	0
2	1	0	1	0	1
3	0	1	0	1	1
4	0	0	1	0	1
5	0	1	1	1	0

b

	1	2	3	4	5
1	0	1	0	0	0
2	0	0	0	0	1
3	0	0	0	0	1
4	0	0	0	0	0
5	0	1	0	0	0

d

Figure 1. Representations of graphs and digraphs

Relationships can be *undirected* or *directed*. Undirected relationships are unordered pairs of nodes, and are called edges, lines, ties or simply relations. They are represented by regular lines, such as the one between nodes 1 and 2 in Figure 1a. This is also represented by a 1 in the cells (1,2) and (2,1) of the adjacency matrix in Figure 1b. When no relationship exists between two nodes, this is represented by a 0 in the matrix. Relationships with oneself are usually not allowed (zero diagonal). In case of undirected relations, the adjacency matrix is always symmetric, and the representation of the set of nodes together with the set of relations that exist between them is called the graph. Not only the absence or presence of a relationships can be examined, but also whether the relationship is positive, neutral, or negative (*signed*), or strong or weak (*valued*). Accordingly different ways of graphical- and matrix representations exist.

Directed relations or choices are ordered pairs of nodes and are called arcs, directed lines, ties, choices, or arrows. They are represented by arrows such as the one from node 3 to node 5 in Figure 1c. The corresponding adjacency matrix is not necessarily symmetric, and the network is called a *digraph.*

Many analyses in social network applications are based on the so-called *dyad* and the *triad.* A dyad is a subset of two actors and the (possible) ties between them. Dyads are more relevant for digraphs than for graphs. In a digraph of N nodes, exactly $\binom{N}{2}$ dyads exist. Since an arrow between two nodes can be present or absent in either of the two directions, a dyad can be in the four different states presented in Figure 2.

Figure 2. Different states of a dyad in a digraph

The dyad is, or the choices are, called mutual if the arrow is in both directions. Mutual choices are also called reciprocated choices. The dyad is asymmetric if an arrow exists in only one direction; such a choice is often referred to as an unreciprocated choice. If no arrow exists in either direction, the dyad is called a null dyad. If the ordering of the nodes in the dyad is ignored, three different states remain because the two asymmetric states can no longer be distinguished.

Triads are relevant both for graphs and for digraphs. A triad is an unordered subset of three nodes and the configuration of the set of all edges present between them. In a graph of N nodes, $\binom{N}{3}$ triads exist. Since an edge between two nodes in a graph can be either absent or present 2^3 different triad types exist. If the identity of the nodes is irrelevant, the remaining 4 possible triad types in an undirected graph are presented in Figure 3. The meaning of transitivity will be explained shortly.

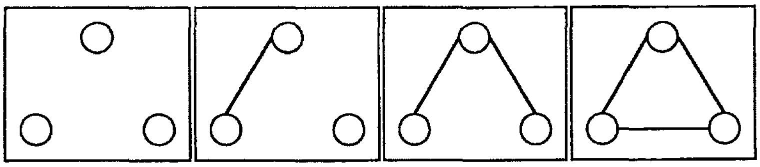


Figure 3. Different states of a triad in a graph

Both for dyads and triads, overall summaries exist that count the number of different dyad or triad types. These summaries are called dyad census and triad census respectively (see for example Holland and Leinhardt 1976, Wasserman and Faust 1994).

Present models to analyze, describe, and explain or predict social networks can be classified into two main categories: *static* models (Section 2.1) and *dynamic* models (Section 2.2).[2] In recent social network literature, increasing emphasis has been given to dynamic network problems. Everybody recognizes that dynamics cannot be denied when studying networks, but they are often ignored. An explanation is of course that complexity of the models increases when time dependence of the process under consideration is recognized. Static models, that do not consider change and assume that networks do not evolve over time, are therefore often applied. Nevertheless, in many cases, these static models meet the requirements of the user who wants descriptions of the network at a specific time point.

2.1 Static models

We distinguish the static models in *descriptive* and *predictive* or explanatory models. As mentioned above, most static models are used to analyze or describe the structure of a network at a certain time. A number of different computer programs is available for these purposes, of which the majority can handle the models to be described below.[3] The descriptive models can be distinguished in:

Centrality models : One of the very frequently used methods in social network analysis is the identification of the most important or prominent actors in the network. It concerns location in the network and has been referred to with a variety of definitions. In undirected graphs, such important actors are called the central actors. In principle, centrality can be considered to measure something like 'relative' participation or involvement in ties. Three different definitions exist that are summarized by Freeman (1979): *degree centrality* measures the relative number of other nodes a node is connected to; *closeness centrality* measures overall distances to other nodes (Bavelas 1950, Leavit 1951, Beauchamp 1965); *betweenness centrality* measures strategic location between other nodes (Anthonisse 1971, Popping 1989). Recently developed approaches concern the definition of centrality for valued graphs (Freeman et al. 1991) and the definition of Hage and Harary (1995).

Centrality in directed graphs has been referred to as prestige, status, rank, and popularity. In directed graphs, actors are prestigious if they receive many choices or arcs, or have a strategic location with respect to all possible connections in the network (Bonacich 1987, French 1956, Hoede 1978, Hubbell 1965, Katz 1953, Taylor 1969, White and Borgatti 1994). In organizational studies, correspondences and differences between such centrality measures based on either formal or informal relations are interesting. Applications of centrality measures, e.g. in the determination of power of actors within an organization, are to be found in Nohria and Eccles (1992).

In contrast to actor level measures, network measures of centrality represent the variability or heterogeneity of actor centralities within the network. Such graph centrality models enable the researcher to compare different networks in terms of their integration, segregation, and centralization (Freeman 1979, Hoivik and Gleditsch 1975, Snijders 1981, Baerveldt and Snijders 1994). Within a hierarchical network structure of an organization for instance, actor centralities based on formal relations may be very heterogeneous.

Cohesion models: One of the other major activities of social network analysts is the identification of cohesive subgroups within networks by the use of cohesion models. It has been difficult to give precise definitions of such *subgroups*. The intuitive notion is generally very clear and captures that subgroups are sets of actors with relatively many, strong, positive, and frequent relations to each other in combination with relatively few relations to actors outside the subgroup. Such groups may emerge informally within specific departments of an organization for example. The mathematical synonym of a subgroup is much more difficult to define. As a result, many different definitions exist that focus on different aspects of the cohesiveness of the group. These aspects are: mutuality of relations and relations to all other group members (e.g. clique (Luce and Perry 1949, Alba 1973)); closeness or reachability of group members (e.g. n-clique, n-clan and n-club (Mokken 1979) and component); frequency of relations (e.g. k-plex and k-core (Seidman and Foster 1978, Seidman 1983)); relative frequency of relations between group members compared to non-group members (e.g. LS set, lambda-set (Seidman 1983, Borgatti et al 1990)). Overviews of the use of such cohesion models in sociological network applications and the different definitions are given by Frank (1995), Freeman (1992), and Zeggelink (1993).

Equivalence and similarity models: These models detect actors and subsets of actors with comparable *positions* in the same network. Comparability can be defined as correspondence in pattern of relations. The earliest definition of equivalence is *structural equivalence* and stems from Lorrain and White (1971) and White et al. (1976). Structural equivalence criteria detect nodes in a network or in networks who have exactly the same relations with exactly the same others. Later extensions emphasize the similarity of positions based on the same relations not with the same others, but comparable others (e.g. similarity of positions across organizations at the same hierarchical level). Summaries of these mainly algebraic methods can be found in Faust (1988), Faust and Wasserman (1992), and Pattison (1988). More sophisticated applications of algebra in social network analysis are to be found in Boyd (1991) and Pattison (1993).[4]

Models of structural holes: Models of structural holes detect positions in networks that provide *strategic advantages* for its occupants for positive network changes (Burt 1992). Structural holes are associated with unique information from linking different subgroups in organizations, providing extra opportunity for new solutions and promotion.

Balance models: The best known *predictive* static models exist in the framework of classical structural balance theory (Heider 1958). Balance theory focuses mainly on relationships in a triad, and extends conclusions to the level of the whole network. Signed graphs are considered, where the sign of a relationship either denotes whether it is positive or negative, or denotes presence or absence of the tie. A triad is called *balanced,* if all three relations are positive or if two are negative and one positive, i.e. if the product of signs of the three relations is positive. Balanced triads are assumed to produce cognitive balance for triad members, unbalanced triads give cognitive dissonance (e.g. because the two friends of one of the triad's members do not like each other). The earlier generalizations to more than three entities are introduced by Cartwright & Harary (1956). Davis (1963) uses balance theory to explain the tendency for social groups to become balanced: friends of friends will become friends, enemies of enemies will become friends, enemies of friends and friends of enemies will become enemies. The network will polarize into two different subgroups within which the relations are solely positive and between which the relations are negative.[5] Davis (1967) subsequently introduces *clustering,* a general type of balancing, allowing for multiple, rather than two, clusters. Translated into sociological terms it means that all people who like each other are in the same subgroup, and all who dislike each other are in different subgroups. In adapted versions of the theory, digraphs become relevant. Mutual, asymmetric, and null dyads come into play, and triads in particular play a very important role. In the *ranked-cluster* model, all asymmetric choices are between clusters, and all mutual choices are within clusters. The asymmetric choices establish a hierarchy (Davis & Leinhardt 1972). The final most general model captures strict balance, clustering, as well as ranking of the previous model versions (Holland & Leinhardt 1971, 1972), and is extended by Hallinan (1974). These latter models are also called *transitivity* models. A triad consisting of i, j, and k is transitive if the existence of a relation between i and j, and between j and k, implies a relation between i and k. This is illustrated in Figure 3. Triads (a) and (b) are neutral triads because the conditions are not valid. Triad (c) is intransitive because the relationships between two pairs of the triad do not imply the third relationship. Triad (d) is transitive. Transitivity is such a prominent structural property in social network data that many methods actually focus on finding remaining structure in the data after having removed transitivity tendencies. Johnsen's models (1986, 1989) more or less capture all these models, but also predict other structures that cannot be predicted in the balance framework.

As presented above, balance theory can best be applied in small networks, and as such has been important in sociological, social psychological, and anthropological applications, mainly because it is so appropriate for sentiment relations. It is less appropriate to be used in economic or political contexts.

Statistical models: Statistical models provide useful statistics to summarize important aspects of network structure and are used to test theoretical propositions about social network structures. They can be distinguished in individual, relational and structural analyses and usually cannot handle these different levels simultaneously because independence between the individual units is assumed.[6] Overviews are given in Frank (1991) and Wasserman and Faust (1994). The models are generally based on probability distributions of subgraphs, in general the dyad and the triad census. The dyad census can be used to test the presence of reciprocity effects in the network (Holland and Leinhardt 1976, Snijders 1991), whereas the triad census can be used to statistically test balance (transitivity) models (Holland and Leinhardt 1970, 1975, Snijders and Stokman 1987). Other statistical models (so-called p_1-models) estimate individual activity and attraction effects, and reciprocity effects from the overall picture of dyad states (Figure 2) (among others: Fienberg and Wasserman 1981, Holland and Leinhardt 1981, Wasserman and Weaver 1985, Wong 1987, Strauss and Ikeda 1990). The p_2-model (Van Duijn 1995) reformulates the p_1-model by explicitly taking into account the dependencies between ties in a dyad. The model furthermore allows for random effects and the use of actor covariates. The model has recently been applied to examine the influence of formal structure of an organization (like stratification and seniority aspects and office membership) on interactions, such as advice seeking, among its members (Lazega and Van Duijn 1996).

2.2 *Dynamic models*

In the Seventies, much attention was paid to the development of models that could study networks over time. The majority of these models, both *deterministic* and *stochastic*, has a methodological and no theoretical foundation. For that reason we present only a short summary and indicate the types of questions they can answer in organization research.

The *deterministic* models predict the effect of any change in the system with certainty. Most of them are based on differential equations which are either too much focused on aggregate variables that are difficult to capture or measure (Abelson and Bernstein 1963, Festinger 1950, French 1956, Simon 1957). They are only applicable to a narrow field of problems, assuming that reinforcement on attitudes leads to strengthening of relations (Hunter 1978, 1979, Killworth and Bernard 1976). No empirical tests of the models prevail. Other approaches based on differential equations can be found in Doreian (1979). Fiksel (1980) uses the state space nature of nodes in a network and shows how the model can be applied to the evolution of network structure. A globally defined goal for network structure in terms of balance is specified and the individual states are adapted appropriately (in terms of positive and negative relations toward others).

Few other deterministic dynamic models exist in the framework of balance theory which attempt to specify how an unbalanced structure changes into a balanced structure (Hummel and Sodeur 1990, Krempel 1987, 1988). Such dynamic versions of balance theory that attempt to specify how unbalanced network structures change into balanced structures are complicated and indeterminate because crude assumptions, like independence of triads, have to be made. These theories postulate that those relations that lead to imbalanced structures will be removed, and new relations will be formed that lead to an increase of the amount of balance in the network.

Only recently, new developments have taken place within this or related paradigms where the underlying processes for network change and evolution are assumed to be located within the network structure itself (Doreian et al. 1996, Banks and Carley 1996, Skvoretz et al. 1996).

Stochastic dynamic models are more prevalent and usually study dynamics of networks as stochastic processes, or more particularly, Markov processes. The basic idea of Markov models is to conceive the social network structure as changing from one state into another over time where impetus for change comes only from the present network structure (Holland and Leinhardt 1977a, 1977b). In most models, dyads or triads are the units of analysis and probabilities of change from state to state, as depicted in Figure 2 or Figure 3, are examined (Katz and Proctor 1959, Rainio 1966, Sörensen and Hallinan 1976). The dyads or triads are assumed to be conditionally independent and to have stationary transition probabilities, and homogeneity among actors is assumed (Hallinan 1979, Runger and Wasserman 1979, Wasserman 1978, 1980a, 1980b).[7] Leenders (1995), however, recently developed Markov models that do not assume stationarity and can incorporate actor-level effects. As such he could distinguish the differential effects of similarity and reciprocity in network evolution (Leenders 1996).[8]

Let us summarize the kind of static and dynamic models that exist for the application of social network analysis. Most *static* models are *descriptive* and detect, for example, correspondences and differences between positions of actors in the network, or outstanding cohesive patterns of relations in the network. *Predictive* static models exist in the framework of balance theory or among the statistical models. The latter mainly focus on dyad and triad distributions and lack a theoretical foundation. *Dynamic* models are either *deterministic* or *stochastic*. The deterministic models have a strong theoretical foundation but are difficult to formalize exactly and test empirically. Most stochastic models are based on well developed methodological principles but lack a theoretical basis. Moreover, typical of most of these dynamic models is that future structure is only predicted from existing (and past) structure. Only effects from dyadic and triadic levels in the structure are considered as causes for change. Dyads and triads are not the best units of analysis because decisions on establishing or dissolving relationships are not made at these levels. It is the actor (the node) who takes the decisions and thereby influences dyad, triad and network structure. The actor, however, seldom comes into play in current models thereby hampering the development of a theoretical foundation (for exceptions see later sections, and Snijders 1996). The models are too much focused on dyads and triads, such that the link from the micro to the macro level cannot be made. Why this link is important will be explained in Section 3.

3 Social Networks In The Perspective Of The Micro-Macro Link

From the very beginning, social network analysis has been linked to outcomes and performances (e.g. in small task oriented groups). In doing so, the emphasis has been put on the static representation and analysis of network structures and positions of actors in them. Notwithstanding the interesting results of these applications, their static character and emphasis on structure (with no or a low attention to the content) precludes them from playing an important role in explaining outcomes of *dynamic* processes within social systems. One of the most interesting problems in social systems is the emergence of macro phenomena from micro phenomena: How do attributes and behavior at the *micro level* influence characteristics and behavior at the *macro level?* If we can answer such a question social network analysis becomes relevant for organizational *change* and *design.* If the structure of an organization or social system (network) is considered as macro level and the micro level comprises the individual actors (nodes), this situation can be grasped in terms of social networks. Arrow 1 in Figure 4 represents the macro-micro link mainly studied by researchers who are interested in descriptive network analyses, or who want to explain how network structure affects individual behavior and characteristics.

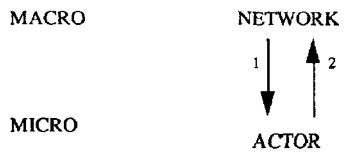


Figure 4. Mutual interaction between network (macro level) and actor (micro level)

The causes of sociometric structure are as interesting as the consequences of that structure. Arrow 2, in the direction from the actor to the network, is particularly important when relationships emerge from individual choice and thus are not predetermined. In this case, actors initiate, build, maintain, and break up relationships and thereby determine the overall structure of relationships. The examination of these phenomena is not simple because causes and consequences of network structure are not completely separable issues. Actors actively (either consciously or unconsciously) construct a network and simultaneously react to it. The network, indirectly or directly, constrains as well as provides opportunities for choices of the actors. The structure might even exert so much influence on choice alternatives that it counteracts individual preferences because behavior of the actor heavily depends on behavior of present others (Allan 1990, Blum 1985, Wrightsman and Deaux 1981). The transformation from micro to macro is therefore not a simple sum of individual actions. Consequently, to study network evolution, both directions, from the actor to the network as well as from the network to the actor need to be taken into account. Moreover, dynamics should be taken into account (Stokman and Doreian 1996).

A very appropriate way to approach this problem, especially in the field of social networks with conveniently defined levels of analysis, is the principle of *methodological* or *structural individualism* (Boudon and Bourricaud 1982, Coleman 1986, 1990, Lindenberg 1985, Wippler 1978). In this approach, choices of actors are *goal-directed* and based on their evaluation of available *alternatives*. The alternatives and their evaluations depend on objective *restrictions* (such as their positions in networks) as well as on subjectively perceived restrictions (framing effects). Moreover, the choice of the actor is embedded in the context of the *simultaneous* acts of other actors and consequently, rationally chosen alternatives might appear to be suboptimal because the actor did not anticipate the actions of other actors at all or in a proper way. The simultaneous acts of all actors affect the macro level. As such a mutual dependency exists constantly between arrows 1 and 2 in Figure 4.

The limitations mentioned above are reinforced by the fact that actors, in contrast to central (planning) authorities, have limited information on the system and on the state and intended actions of other actors. This makes it inevitable for actors in certain situations, first, to define instrumental goals that are only roughly related to the ultimate instrumental goals in the system and, secondly, to make unrealistic assumptions (e.g. about the behavior of other actors). Actors however evaluate the ultimate success of their strategies and assumptions in the light of their own goals. This may result in adapted behavior based on changes in the environment (partly the result of their own actions) and on behavior observed from others.

Some excellent examples of linking micro level mechanisms to macro level phenomena as described above, but not necessarily network oriented, can be found in the work of Carley and co-authors. Carley and Prietula (1994) develop a general theory (ACTS theory) of organizational behavior based on an extended model of bounded rationality. Organizational behavior is considered as an emergent property from groups of deliberating actors acting within a certain set of constraints and opportunities. The emphasis is on individual cognition as in the theory of constructuralism (Carley 1991a, 1991b) which focuses on acquisition and exchange of information and knowledge. This theory assumes that individuals interact, exchange information, and on the basis of their information, reconceptualize their relationships to all other individuals.

To contribute to the above mentioned theoretical perspectives, social network analysis should not only become more dynamically oriented, but should also incorporate an individual choice mechanism and get linked to other methodologies in which choices of actors play a central role, in particular applied game and decision theory.[9] In complex situations and large networks it is necessary to rely on computer simulations, because the models will soon become too complex to handle analytically (see also Carley (1989, 1991a, 1991b)).

Application of principles and techniques of object oriented modeling makes it possible to integrate the above methodologies into one system for the analysis, simulation, and optimization of dynamic processes, representing these processes as dynamic networks of self-learning, concurrently operating and interacting actors. This will be shown in more detail in Section 4.

We first introduce a simple example that will be used throughout the rest of this paper to illustrate the principles of both social network analysis and object oriented modeling. Consider the set of 10 actors (individuals) in Figure 5.

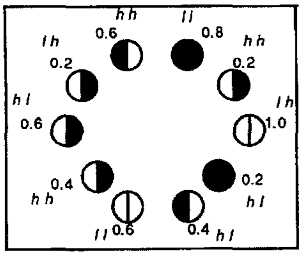


Figure 5. Illustrative example: initial distribution of individual actor attributes in population of 10 actors

The actors in this population are initially unrelated (no edges between them), but we assume that all actors want to become connected to certain others dependent on these others' characteristics. The characteristics of the actors are shown in this graphical representation. Two dichotomous individual characteristics are represented by the black and/or white halves of every single node. A third individual attribute is interval-scaled and represented as one of the values (0.2, 0.4, 0.6, 0.8, 1.0) next to the node. We assume that the actors want to become related to those who are as similar as possible to them on the dichotomous characteristics (e.g. opinions), and to those who have a higher value on the interval-scaled attribute. This attribute can be considered to represent a status dimension. The letters h and l represent whether the corresponding actor attaches high or low importance respectively to the two dichotomous characteristics. We assume that the salience of the status dimension is intermediate and equal for all actors. The dynamic process in this population is in the first place the formation, maintenance, and dissolution of relationships as a result of preferences for certain individual characteristics. These dynamics are modelled as choices (directed arrows) from actors to each other. Once choices are mutual (see Figure 2), we assume that a relationship exists. In making such choices, the actors take into account that the probability of actually establishing a relationship with another actor depends on status differences between them. Simultaneous with the relationship formation process, a social influence process takes place because established relationships have their effects on the individual attributes. We assume that the dichotomous characteristics are subject to change: their values change dependent on the corresponding attribute values of related actors, weighted by their saliences and by status differences between the individuals. The connection to the micro-macro problem is evident. On the one hand, interaction partners are chosen on the basis of their characteristics; on the other hand, these characteristics change as a result of the established relationships.

4 Object Oriented Modeling As A Tool

The computer methodology of object oriented modeling makes it possible to arrive at a direct representation of a physical world of concurrently operating actors as described in Section 3 (Goldberg and Robson 1983). The usefulness of object oriented modeling or programming for these kinds of extensions of social network analysis will be demonstrated after we have presented a brief technical introduction on object oriented modeling (among others: Mullin 1989, Pinson and Wiener 1988). This summary may be skipped by those readers familiar with the technical principles of object oriented modeling, or those who are not interested in such technical details. The remainder of this paper can be read without any difficulty.

Several object oriented languages exist: Smalltalk, C++, Objective-C, Object Pascal, and many others. The emphasis in this section is on Smalltalk properties (Goldberg and Robson 1983, Objectworks Smalltalk-80 1989, Objectworks Smalltalk-4 1990, Visual Works 1995), but general characteristics of object oriented programming will also be discussed.

Object oriented languages are not based on the conventional principle to distinguish data and programs, but based on objects and messages sent to these objects. In a conventional procedural programming language, like Pascal, a procedure typically performs multiple operations and handles several items of data.[10] An application consists of a collection of procedures that act on a set of data. In an object oriented language, on the other hand, an application is a collection of data objects that interact with one another via built-in methods. Object oriented modeling is based on the principle that objects act and react in a shared environment by communicating through the ability to send and receive messages.

An object consists of a one or more private variables (data) and a set of methods for accessing and manipulating the data. Consequently, objects behave in a uniform fashion, without regard to the data they contain, because they are not defined on the data on which they operate. The two parts of the object, data and methods, are called state and behavior respectively. The name of the method, called a message, is used by other objects to invoke the operation with the specific object. These characteristics of the objects enable them to reason and communicate with other objects.

Thus, every object has a set of properties, features and messages to which it responds. Objects that have similar properties are grouped in classes. Objects of the same class are treated identically to each other and respond to the same set of messages.[11] Differences between objects are however also very important and therefore instance variables are specific to every existing object. Instance methods provide access to private data (instance variables) of an object and many other operations that are object-specific. The distinction between class-specific and object-specific properties reduces the redundancy that would occur if every object would have been defined separately. Classes that on their turn share similarities in the sense of belonging to the same application, are assigned to one category.

Classes are ordered in a hierarchy. The principle of inheritance accounts for the organization and maintenance of the collection of classes by specifying that properties are inherited from superclasses. Instances of a subclass have at least the same properties as objects in the parent or superclass, but new, more specialized properties can be added or modified. Consequently, the lower the level in the hierarchy, the higher the specialization of the class whereas a higher level in the hierarchy represents more generalization. Inheritance applies to methods as well as to variables. It provides an enormous simplification because it reduces the number of elements that must be specified and remembered.

The last characteristic of object oriented languages to mention here is polymorphism. It specifies that the same message can be sent to different objects and that each object responds appropriately in its own way, which may depend on certain values of object attributes. This does of course only occur in subclasses or across classes, not in the same class. According to this principle, methods can be redefined in subclasses; this is called method overriding.

Thus, in summary, the most important characteristics of the object oriented approach are that processing is instigated by sending messages to objects, object behavior is described in classes, data are stored as objects with automatic deallocation, and principles of inheritance and polymorphism apply.[12]

The most important advantage of object oriented programming compared to procedural programming is that the gap between the real world domain and the computer domain is much smaller. Every object has its own characteristic state (represented by its data) and characteristic behavior (represented by its 'methods') and as such behaves uniformly. This is useful in particular in the scope of social network analysis where individual attributes and behavior and the differences among them, are as important as the relationships between the actors. As Hummon and Fararo (1994) noted, the verbal mode of theory development is closer to the principles of object oriented programming than conventional structured programming. Furthermore, since both social network analysis and object oriented languages are based on relationships between units (structures of objects are generally represented in a digraph), getting the two to know each other will definitely yield benefits for the field of social networks.[13] For us, the object oriented approach seems *the* way to model the interactions between actors (at the micro level) as well as between actors and network at a certain time (interaction between the micro and macro levels). Actors, but also choices, relations, and the network are defined as objects. Since the two components of an object can be regarded as its state and behavior, the similarity with the real world view is very obvious: like actors in the physical world, objects have an internal structure that enable them to reason and to communicate with other objects. The reasoning of and communications between objects may take place simultaneously, and constraints and opportunities arising from the presence of other actors in the network are implicitly taken into account. The main advantages of object oriented models in comparison to existing network models are the easy incorporation of *heterogeneity, dyad and triad dependence,* and *learning* principles. Since the behavior of every actor can be defined separately in methods characteristic for that object, *heterogeneity,* which we have shown to be extremely difficult to implement in conventional models of social network analysis, can easily be applied.

> Consider our example introduced in Figure 5 again. Not only does every actor in the population have actor-specific attributes, every actor also has its own behavioral rules, partly determined by the differences in salience values h and l attached to the corresponding attributes. Another difference in behavioral rules emerges from that fact that status differences determine probabilities of actually succeeding in establishing a relationship. The larger the difference in status values, the smaller the probability that a relationship between the actors will actually be established. The actors take these probabilities into account when determining to which actors they should make offers.

Based on the same arguments, precisely an object oriented approach, in contrast to current network models, can handle dyad and even triad interdependence.

> Dyad, triad, and even higher dependencies exist in our illustrative example in a number of different ways. As a result of the fact that every actor has only limited time and energy to maintain relationships, the presence of a relationship between i and j, may limit the possible existence of a relationship between i and k. Other dependencies arise through the process of social influence. Suppose i is related to j, and j is related to k. If i influences j, k is indirectly influenced through the relationship with j.

Finally, with an object oriented approach, actions may be adapted on the basis of past experiences (Lehrmann, Madsen and Moller-Pedersen 1988). The representation of actors as adaptive learning objects gives these objects similar characteristics as 'self-organizing systems', known from neural networks (see e.g. Rumelhart and McClelland 1987).

> Since probabilities of success depend on status differences and availability of preferred partners, actors in our example may adapt their estimations of these probabilities on their experiences in the population. The fewer another actor undertakes action to establish a relationship with him or her, the smaller he or she estimates the probability of establishing a relationship with that specific other.

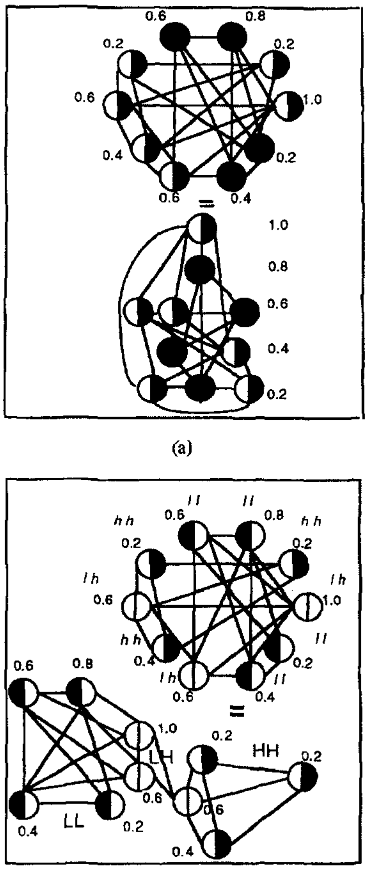
Having showed the usefulness of object oriented principles for our specific illustrative example, we want to end this section by describing some other studies that show the utilities of object oriented modeling for analyzing social processes. Stokman and co-authors developed dynamic policy network models to represent informal and formal policy processes into one integrated model resulting in fair predictions of outcomes of complicated policy processes (among others, Stokman and Van den Bos 1992, Stokman and Van Oosten 1994, Stokman and Zeggelink, 1996a). Zeggelink (1993, 1994, 1995) used object oriented modeling to study the evolution of friendship networks. De Vos and Zeggelink (1994) modelled the emergence of reciprocal altruism and group living with object oriented simulation models of human social evolution. Van Roozendaal and Zeggelink (1996) study formation of coalitions in multi-party democracies on the basis of simulation results of object oriented models. Snijders (1996) developed stochastic actor oriented models for network change. Verkama et al. (1994) use object oriented simulation programs to study the effects of different individual behavioral patterns with regard to cognitive limitations and principles of bounded rationality. Levitt et al. (1994) simulate a virtual design team based on the work of Masuch and LaPotin (1989) and Carley et al. (1990). These studies model how intelligent actors communicate and cooperate to perform a distributed decision making task.

Concluding, the principles of the methodological individualistic approach, in particular within social networks, and those of object oriented modeling are so strikingly similar that object oriented programming is seen as the appropriate instrument for an adequate representation of social networks and their dynamic processes.

Let us finally return to our illustrative example. Based on one such single distribution of individual attributes the set of by 10 actors, simulations can be run on the basis of the behavioral rules introduced earlier. The results of these simulations tell us something about the interaction between the selection process and the social influence processes that take place simultaneously (see also Leenders 1995). They also show us what the effects of different distributions of dichotomous and interval-scaled variables are, and what the differences are between status dimensions and 'comparison' dimensions. Stokman and Zeggelink (1996b) show that some distributions of characteristics always result in one and only one network structure, whereas others may result in many structures. The latter show the effects of cumulative selection: the final state of the system heavily depends on the early choices made and the effects they have on later ones. The importance of cumulative effects is well known in theories of biological evolution (Dawkins 1987).

Figure 6 illustrates this. It shows two of many possible equilibrium networks that result from the initial distribution in Figure 5 when all actors want to establish by 5 relationships (not everybody has to succeed) and when both values and saliences of issues are subject to social influence. Network (a) is the least segmented, and relatively hierarchical, network that emerges. All actors become unanimous on the second issue, but remain divided on the first. Network (b) is the most segmented network that can emerge. The 'completely white' actors link the two subgroups within which complete homogeneity exists but that are mirrored to one another. The linking actors are thus similar with the one subgroup on one issue and with the other subgroup on the other issue. It is interesting to note that it is more difficult to establish relations in the more segmented network. The mean number of relations per actor in Figure 6b (4.2) is smaller than in Figure 6a (4.6).

We refer to Stokman and Zeggelink (1996b) for a detailed introduction, explanation, and description of simulation results for different types of processes with this and other initial situations.



(a)

(b)

Figure 6. Two possible equilibrium networks resulting from initial situation in Figure 5

5 Summary

After a brief introduction into the field of social networks in general and an overview of existing network models and methods in particular, a very elementary problem field in social sciences was introduced: the micro-macro link. This field is also prominent in organization studies when studying organization change and design. It was argued that the most appropriate way to handle this problem is the principle of methodological individualism. For social network analysis, to contribute to this theoretical perspective, it should include an individual choice mechanism and become more dynamically oriented. Subsequently, object oriented modeling was advocated as a tool to meet these requirements for social network analysis. It was shown that characteristics of social systems that are emphasized in the methodological individualistic approach have their direct equivalences in object oriented models. The link between the micro level where actors act, and the macro level where phenomena occur as a consequence and cause of these actions, can be modelled in a straightforward way. As such the field of organizational research, when studying, among other things, organizational change and design, can benefit from object oriented models of dynamic social networks.

Acknowledgements

Part of this paper has been presented at the "Expert Meeting on Demographic Software and Micro-computing: Strategies for the Future," The Hague, Netherlands, 29 June–3 July 1992.

Part of the research of the first author has been made possible by a fellowship of the Royal Netherlands Academy of Arts and Sciences.

We are indebted to the anonymous reviewers for their critical comments on an earlier version of this paper.

Notes

1 So-called *ego-centered* or *personal networks* are of a completely different type. The individual of interest is taken as the focal point (Barnes 1979; Mitchell 1969; Fischer 1982a) and the corresponding research generates a collection of ego-centered networks, one for every individual in the study.

2 We do not review *large scale* network models in which a detailed description of the network is usually of minor interest, as in *random* and *biased* net models. Basic introductions to the use of large scale models in the studies of diffusion and contagion can be found in Kemeny and Snell (1962), Coleman (1964), and Bartholomew (1967). More specific large scale social network models can be found in, among others, Fararo and Skvoretz (1984), and Skvoretz (1991).

3 Apart from stand-alone programs for specific network procedures, at least six software packages exist in which a broad range of procedures is implemented. An overview of these programs is given in Wasserman and Faust (1994).

4 Statistical models for algebraic network methods have only recently been developed (e.g. Anderson et al. 1992, Pattison and Wasserman 1995, Snijders and Nowicki 1994).

5 It can be proven that a graph is balanced if all the cycles of length 3 in it have positive signs (product). Moreover, every balanced graph can be partitioned into two disjoint clusters.

6 Wellman et al. (1991) present a new methodological approach to integrate individual, relational and structural analysis by introducing so-called relational and structural parameters that complement conventional models.

7 When dependence is included by conditioning on certain structural characteristics (Snijders 1990), the model becomes mathematically unattractive and parameters are difficult to estimate.

8 Other stochastic approaches study associations among the time measurements to examine which aspects of previous structure best predict the present network structure. Such models are extensions based on the p^1 −models described above (Wasserman 1987, Wasserman and Iacobucci 1988) or build on complicated conditionally uniform distributions of networks without any real underlying sociological theory of change (Holland and Leinhardt 1976, Snijders 1991).

9 In contrast to network theory, in game and decision theory, outcomes at the macro level are already considered as the consequences of simultaneously acting actors. Notwithstanding its power in many applications, game and decision theory have analytical solutions only for small numbers of actors in relatively simple situations.

[10] Data base structure and procedure code are separate system elements which can lead to an enormous number of modifications when some small element in the program or type of data structure changes. Data and procedure have to be updated separately, several procedures often require the same change and unrelated code in each procedure has to be checked and recompiled. These changes can be made much more easily and intelligently in an object oriented language because data are made 'smart'.

[11] All common properties of objects in a class are defined as class variables and methods and every object is then an instance of the class. Class variables are shared by all objects in a class and are usually used as control variables. Class methods are used for three main purposes: the initialization of the class, the creation of instances (objects) and answering general inquiries.

[12] The language only defines syntax for the declaration of object names and values, the sending of messages and the definition of new classes and methods. More is not necessary because literally everything is an object and the whole system is organized by one and only one principle: control structures are achieved by sending messages. Most other (non-object-oriented) languages have to provide complex syntax for declaring data types and control structures. Furthermore, in an object-oriented environment, different applications and projects can easily use each other's program code as long as it is written as general as possible. The objective of object-oriented programming is to distribute computation evenly across the system, instead of building one large computing engine in conventional programming that knows how to do everything. Objects refer to each other and other objects will not unnecessarily do things that other objects were created for (Mullin, 1989).

[13] This is not to say that object oriented modeling would not be possible with a conventional language, a procedural conversion language. Object oriented languages just allow for more simplicity and versatility.

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