MODELING SOCIAL CHANGE WITH CELLULAR AUTOMATA

ANDRZEJ NOWAK
Institute for Social Studies
University of Warsaw
Warszawa, Poland

and

MACIEJ LEWENSTEIN
Institute for Theoretical Physics
Polish Academy of Sciences
Warszawa, Poland

In this paper we will first discuss computer simulations of social processes as models of qualitative understanding. In the second part of the paper we will present the cellular automata model of dynamic social impact (Nowak *et al.* 1990) and its applications in the areas of the formation of public opinion and social change as an example of a model of qualitative understanding.

1. Computer Simulations in the Social Sciences — Models of Qualitative Understanding

1.1. THE CONTROVERSY CONCERNING COMPUTER SIMULATIONS OF SOCIAL PROCESSES

As computer simulations are becoming increasingly popular tools in the social sciences their popularity generates a mixed reaction among social scientists. Advocates of computer simulations often write about advantages of the simulation approach. The arguments of the opponents of computer simulations are mainly formulated verbally during discussions following presentations of simulation models. Proponents of simulations view them as a powerful tool that will transform social sciences by bringing precision and rigor, into social theories (see for example Meadows *et al.* 1982; Whicker and Sigelman 1991; Séror 1994; Doran and Gilbert 1994; Hegselmann 1994, in press, and his contribution to this volume). By utilizing the speed and power of modern computers they allow to examine the consequences of complex rules and to study the dynamics of large systems. This makes them the tool of choice for dealing with complexities inherent in the domain of the social sciences. In more general terms computer simulations bring social sciences more in line with the recent developments in mathematical and natural sciences.

Opponents of computer simulations in social sciences express concern that the most valuable aspects of humanistic and social sciences cannot be captured by a formal tool. According to this view computer simulations can never fully describe the richness of psychological and social processes. Humans, especially in a social context, are too complex to be captured by a simulation program. In the social reality the outcome of most processes depends on many factors. In the social sciences the probability of making a false assumption is higher than in the natural sciences. Thus taking into account the multitude of factors that effect every social process, it is not possible that all the assumptions of a simulations are correct. Furthermore, many of factors decisive for prediction are idiosyncratic and practically impossible to be accounted for in computer simulations. The decision of an actor, for example, may depend both on his or her childhood experiences and on the emotions of the moment.

An additional criticism concerns the reproductive nature of knowledge generated by computer simulations. A computer simulations will produce the output which is totally dependent on the input to the simulation. In this respect no knowledge is generated by running computer simulations because all the knowledge had to be there initially. According to opponents of computer simulations, simulations generally trivialize our understanding of social processes by offering a mirage of precise description. In the best case this diverts attention from those theories that aim at deep understanding of the nature of social processes. In the worst case it can destroy the richness and the humanistic heritage of the social sciences.

The degree to which each of those conflicting approaches is judged to be true depends both on our understanding of the goal and nature of the social sciences and our understanding of the aims and methods of computer simulations. The goals, computer simulations are to fulfill, are usually different for computer simulations used in applications of science as contrasted to the uses of simulations in theory development.

1.2. QUANTITATIVE MODELS VS. MODELS OF QUALITATIVE UNDERSTANDING

In engineering computer simulations are widely used to solve such problems as aircraft wing designs, bridge constructions, or designing power plants.

Such applications take existing theories, describe them in some computer language, and apply them to solve practical problems. In order to get reliable quantitative answers usually a multitude of factors has to be taken into account. Usually as much detail as possible, concerning the modeled phenomena, is introduced into the simulation to make prediction more accurate. Applied simulations usually do not benefit the theory, nor they are supposed to do so. The main reasons to use this kind of simulations are: first to deal with problems of high complexity, where easy analytical solutions do not exist or would be too time consuming without the use of computer, and second, to save time and money by testing solutions with the help of a computer that would require costly testing otherwise.

A quantitative precise and reliable answer is usually expected from practically applied quantitative simulations. The cost of arriving at a wrong solution, for example by utilizing false assumption, is high. This kind of simulation needs to be based on a well tested theory, since otherwise wrong acceptance of simulation results could lead to a disaster such as an aircraft crash. In most areas of the social sciences the theories are not advanced enough to be a basis for quantitative simulation. Obtaining reliable quantitative answers from computer simulations in the social area is made even more difficult by the fact that in the social sciences the relationships between variables are usually in the form of a weak stochastic dependency.

In natural sciences enormous progress was recently achieved due to widespread use of computer simulations. Computer simulations have been one of the main tools that have allowed for the development of the theory of non-linear dynamical systems(Arnold 1978, 1983, Eckmann and Ruelle 1985; Glansdorff and Prigogine 1971; Glass and Mackey 1988; Haken 1978, 1983; Hao-Bai-Lin 1987; Moon 1987; Rasband 1990; Peitgen and Richter 1986; Ruelle 1989; Schuster 1984; Zaslavsky and Sagdeev 1988), probably the most significant event in the natural sciences in the eighties. Computer simulations also are one of the main tools of modern biology (cf. Langton *et al.* 1992; Sigmund 1993). The use of computer simulations have also underlied the creation of a new interdisciplinary area of science — complex systems. (Haken 1985; Pines 1987; Stein 1988; Weisbuch 1992; for a critical view see Horgan 1995).

The nature of those simulations is usually very different from simulations used to solve applied problems. In the development of the theory, simulations are often used to build and test models of qualitative understanding. In this approach, instead of trying to model the phenomenon in its natural complexity, one tries to isolate the most important characteristics of the modeled phenomenon, and to build the simplest possible model that can reproduce these characteristics. The phenomenon of interest, then, is explained only qualitatively through analogy to the model. The model it-self, however, is very precise and specified in terms of analytical equations or rules of computer simulation. This approach allows one to apply hard models to relatively soft data sets without worrying that one's investigation is less than scientific.

Such models are widely used in physics to model such phenomena as magnetism, hydrodynamics (Ruelle and Takens 1971), laser physics (Haken 1982), biology of ecosystems (May 1981), and modeling neural systems (Amit 1989). These models are built to gain qualitative understanding of phenomena of interest. The simplest model of ferromagnet — the Ising model is a good example. This model, built to explain magnetic phenomena, assumes that each particle of a magnetic material may have only two orientations of its magnetic moment, which are usually represented as arrows pointing up or down. This model has very little in common with physical reality, where any particle may have any orientation in a three-dimensional space but nevertheless serves as a paradigm to understand phase transitions and other collective phenomena. Relatively simple systems of differential equations such as the Lorenz model (1963) similarly serve as paradigms for our understanding of multiple phenomena in meteorology, hydrodynamics, nonlinear optics and so forth.

The application of qualitative methods in physics is well represented in statistical physics. Statistical physics deals with large systems consisting of many interacting elements, and as the name implies, uses statistical methods. Within statistical physics, one can describe collective phenomena, the emergence of patterns, self-organizations of systems, and so on. One of the main insights of statistical physics concerns the universality of qualitative mechanisms and phenomena. Although almost any system can be described by a multitude of variables, usually only a few of those variables are critical for the qualitative properties of the system. First of all, the qualitative behavior of large systems often does not depend a great deal on details involving the behavior of individual elements. This observation is of major importance for researchers. To achieve qualitative understanding, it is often possible to build simple models that capture only essential properties of the interactions in the system, which nevertheless allow for the proper description of aggregate behavior.

Second, research done in statistical physics has shown that similar rules apply to external variables influencing the system, so called control parameters. Although usually there are often many external variables influencing the behavior of any real system, some are clearly more important than others. Many variables lead only to some quantitative effect on the system's behavior. Other variables, however, may cause qualitative changes in the system's behavior. For example, a system might tend toward stability for some values of such a variable, but begin to display a breakdown in stability above a certain value of the same variable. Usually for a given system, a relatively small set of variables that influence its qualitative behavior exists. From this notion, it is clear that description of the effect of some variables is much more enlightening about the system than is description of the effect of the other variables. If we are interested only in qualitative predictions of behavior, it is usually sufficient to know the values of only a few variables describing the system. The remaining variables may be simply ignored. We may, however, want to account for the influences of those variables if we need more precise quantitative predictions.

In summary, the results of analytical reasoning and computer simulations done in natural sciences, point out that systems composed of very simple elements may behave in a very similar way to a system in which the elements are characterized in a rich way. It also shows that of the almost innumerable variables influencing a system, it may be possible to select only a few that are most important, namely, those that qualitatively change the dynamics of the system. The main challenge is how to find those critical variables. Two strategies seem possible here. The first one is simply to start from forming a more comprehensive model, such which would be acceptable from the perspective of our theoretical understanding of the phenomena. The next step is then to reduce the complexity of the model by eliminating those assumptions that are proven by subsequent research not to be critical for the behavior of the system. This strategy is likely to lead to gradual simplification of the model, but is not likely to produce a radical reduction in complexity. As an example, if the initial model is in the form of partial differential equations, this strategy may lead to reduction of the number of equations, but is unlikely to result in formulating the model in much simpler terms, such as, for example, cellular automata.

In the second strategy one tries to build the simplest possible model that would have qualitative properties of the phenomena to be modeled. The goal is to try to capture just the essence of the modeled phenomena disregarding the details. There is no simple algorithm indicating how to achieve it. Often the construction of such a model is simply an act of an insight. Sometimes just by playing with models a researcher observes that the behavior of the model resembles some real phenomenon and then the models is reconstructed to model this phenomenon explicitly. Usually the knowledge of results from previous work with similar models may be very useful. A lot of work has been done within mathematics and physics that concentrated on features of models that are critical for dynamics. Since the behavior of systems usually does not depend on the details concerning individual elements, analogies with existing models in other disciplines of sciences may prove to be very useful in constructing a model in a particular discipline. Models of cooperative behavior designed in biology (May and

Nowak 1992, 1993) provide rich insights into our understanding of features critical for the emergence of patterns of cooperation in human societies.

1.3. SIMULATIONS IN THE SOCIAL SCIENCES — MODELS OF QUALITATIVE UNDERSTANDING

One of the main reservations concerning computer simulations of social processes is related to inherent complexity of the subject matter of social sciences. According to this reservation, computer simulations of social processes simply cannot be right if one takes into account the complexity of social phenomena. Human thought and behavior, which depends both on numerous external factors and the internal workings of often elusive psychological mechanisms, is among the most complex phenomena to be explained by science. The interdependencies of different individuals increase such complexity in a multiplicative manner, making the social aspect of human behavior probably the most complex phenomena science can investigate. Even if general laws in this area can be formulated, usually they admit to important exceptions. In this view, the complexity of the causal mechanisms producing social and psychological phenomena requires models of high complexity to explain such phenomena (cf. Bandura 1982; Meehl 1978).

People and social groups, of course, are clearly different than fluids, lasers, and weather systems. The discoveries concerning the behavior of complex systems done in natural sciences are, however, of major importance for building models of social phenomena. The possibility that only a few of the variables are decisive about qualitative properties of the system's behavior provides a means by which complex social and psychological phenomena may be described in relatively simple ways. Although realistic modeling of any social group would require computer models of enormous size, an adequate model of qualitative understanding of phenomena of interest concerning this group may be constructed in a relatively simple way. Computer simulations are the tool of choice in this approach in two respects. First, they are critical for discovering which variables must be specified when building a model, second they allow to test the consequences of the model.

When a general model or a class of computer simulation models exist for a social phenomena, it is possible to vary systematically all the assumptions of the model and to observe the effects of changing both the general assumptions of the model and values of specific variables. In such a procedure one would usually observe that dropping some assumptions or substituting them with other assumptions does not have much impact on the system's behavior. Some other assumptions are, however, critical for the behavior of the system. Even slight changes of their values lead to dramatic changes in the system dynamics. The researcher may then focus, in the proper model, on the most important assumptions or factors. In other words computer simulations may greatly simplify the process of model building by eliminating the unnecessary variables and assumptions of the model.

As an example, when we were building the model of dynamic social impact of the emergence of public opinion (Nowak *et al.* 1990) we were greatly concerned with how many theoretical assumptions we had to make. It seemed that it was impossible to set the right values of all the parameters needed for the simulation and to make the right choices concerning the mechanism of change of individual characteristics. Even if the chance that each of the assumptions needed for the model was correct equaled to 90 % (an overestimate as compared to our subjective judgments), the chance that the model i.e. all of the assumptions was right, is equal to about .07 for 25 variables and assumptions. While running the simulations we discovered that variations of most of the factors did not lead to significant differences in simulation runs. A simulation program SITSIM was built to allow systematic variation of values of variables and simulation assumption (Nowak and Latané 1994). Later analytical considerations (Lewenstein *et al.* 1992) and computer simulations (Nowak and Latané 1994; Latané and Nowak in preparation) have shown that of all the factors only a few are of critical importance for the qualitative behavior of the model.

The fact the often only few variables really matter for the qualitative nature of simulation results has important implications for estimations of correctness of simulations and thus for judgments of value of simulations as tools of social sciences. Assuming that the probability of each individual assumption of a simulation model equals to .9, the probability that a model utilizing 100 assumption will be right is less than 3 in a million, model based on 25 assumptions has about .07 probability of being correct and a model based on just 5 critical assumptions is correct with a probability roughly .6 . When we take into consideration, that it is easier to make correct assumptions when one can concentrate on a smaller number of factors, the estimate is even more in favor of models of qualitative understanding.

1.3.1. *Emergence*

Serious doubts regarding computer simulations of social processes concern their usefulness. Since computer simulations require a theorist to formulate all the rules and assumptions before simulations are run, what else can we learn from actually running simulations? The same problem formulated in more positive way translates into the question: what are the main advantages computer simulations offer in the social sciences? While many specific gains may be associated with the simulation approach in the social sciences, such as imposing precision on the theory, testing theories for contradictions and so on, in our opinion the main advantages of computer simulations in the social domain are connected to insights they can offer regarding emergence and dynamics. Social scientists commonly stress that properties and behaviors of social groups and societies cannot be reduced to the averaged properties and behaviors of the individuals comprising the group or society. Rather, social groups and societies exhibit emergent properties (e.g., Durkheim 1938), that are not present at the level of individuals.

Within the framework of the dynamical systems approach in the natural sciences, it has been demonstrated that many systems studied both theoretically and experimentally in hydrodynamics (Ruelle and Takens 1971), meteorology (Lorenz 1963), laser physics (Haken 1982), and biology (Glass and Mackey 1988; Başar 1990; Amit 1989; Othmer 1986 etc.) have emergent properties. Emergence is especially characteristic of systems consisting of elements that interact in a non-linear fashion. Even if the elements of the system and their interactions are relatively simple, nonlinearities may lead to amazingly complex dynamic behavior, such as self–organization and pattern formation (see for example Haken 1978, 1982, 1983; Kelso 1984, 1988; Kelso *et al.* 1991 and refs. therein). It follows that a system composed of relatively simple interconnected elements may exhibit much greater complexity than each of the elements separately. This gain in complexity with movement from micro to macro levels of description is clearly relevant to the notion of emergence, which is often considered to be a key feature of social phenomena. The emergence of both order and chaos, for example, has been documented in systems such as neural networks (Amit 1989) and cellular automata (Wolfram 1986), where the elements are essentially binary. In such systems, emergent properties are usually exhibited at the global or macroscopic level. In other words, regularities, irregularities, and patterns can typically be detected in terms of some macroscopic rather than microscopic variables.

Emergence in systems consisting of many interacting elements is often created in process of self-organization in which order (e.g., coordination, pattern formation, growth in complexity) may arise from low level interactions without any supervision from higher order structures. The notion of self-organization can resolve the seeming paradox of complexity in the social sciences of the existence of the highest order agent responsible for imposing order on the otherwise disorganized phenomena. The success of computer simulations in the natural sciences is due in large part to their ability to provide simple explanations for complex phenomena that had previously resisted theoretical understanding. Indeed, the major accomplishment of the nonlinear dynamical systems approach, which was propelled to large degree by computer simulations, is the discovery of how complexity can arise from simplicity. Therefore often complexity may be regarded as a reverse of simplicity. By this, it provides a hope that simple easily understood, yet precise, explanations may exist for otherwise extremely complex phenomena in the domain of social sciences.

By the very definition, emergent properties cannot be trivially derived from the properties of individual elements, and are therefore difficult to predict. Computer simulations, however, allow to model individuals and their interactions and to observe to consequences of such interactions on the group level. It is important to stress the importance of visualization in this approach. Since computer simulations of this kind are of exploratory value, the researcher often does not know exactly what kind of phenomena are of interest and thus should be measured. If the results of a simulation are visualized, often naked–eye inspection may reveal the emergence of new properties on the macro level. The quality of visualization is of critical importance. The more properties of elements and the system are made visible by appropriate use of color, shape, spatial arrangement, the more apparent to the naked eye observation are the emergent properties (Brown 1995; Grave *et al.* 1994). Often just visual inspection may be sufficient to study emergent phenomena such as patterns being formed during the system's evolution. In such cases visualization serves not only the role of a heuristic for discovery, but also as a scientific proof. In other cases, however, once visual inspection discovers phenomena of interest, appropriate more precise measures may by utilized to quantitatively characterize the phenomena of interest.

1.3.2. *Dynamics*

For many years, the social sciences have been concerned with the dynamics of social processes. The importance of temporal characteristics of human thought and behavior was well recognized in social psychology where such notions as group dynamics and dynamics of attitude change are central to the theory (Shaw 1976; Brown 1988). James (1890) talked about the continuous and ever-changing stream of consciousness as the most salient characteristic of human thought. Although most researchers would agree on the importance of dynamics, there is far less consensus concerning how best to characterize dynamics theoretically and empirically (Vallacher and Nowak 1995, Nowak and Lewenstein 1994).

For the most part, dynamics have been analyzed within the framework of cause – effect assumptions. This approach is based on manipulating one or more external factors at Time 1 and observing the effects at Time 2. Despite the success of this general paradigm, however, it encounters two fundamental limitations as a general meta-theoretical model of social processes. First of all, only two points in time and their temporal order are considered (i.e. cause has to precede in time the effect). Everything that happens between those two points escapes consideration. The second is the assumptions that the dynamics simply reflects changes in some state due to some causal factor.

In natural sciences dynamics refers to either continuous change (when changes are modeled by differential equations) or to time series of discrete changes. In fact, often the temporal trajectory of changes of a system is the most revealing source of the information concerning the internal workings of a system. The same applies to the social sciences. The importance of temporal trajectory of changes is well recognized in both demography and in economical sciences. The time dimension also seems critical to understanding most of the social processes. The same social change, for example, might be considered an evolution if it occurs within the course of a century and a revolutions if it occurs within a course of a few months.

Second, traditional cause-effect approach is not well-suited to capture the insight that social processes are to a large degree internally caused, in that these processes display patterns of change even in the absence of external influences and sometimes in opposition to such influences. Such intrinsic dynamics (Vallacher and Nowak 1994) were what from beginning of social sciences was considered to be the essence of human thought and behavior. Thus, according to James (1890) thought never stood still, Cooley (1964) discussed humans' penchant for action in the absence of motives and reward contingencies, and Lewin (1936) argued that overt behavior and thinking are constant struggles to resolve conflicting motivational forces, including those operating from within the person. On the level of a social group, intrinsic dynamics is revealed for example in the phenomenon of attitudes polarization, which term refers to the fact that attitudes in an interacting group become more extreme in the course of time without any external influences (Myers and Lamm 1976; Moscovici and Zavalloni 1969).

Recent developments in the mathematical theory of dynamical systems (Arnold 1978, 1983; Eckmann and Ruelle 1985; Glansdorff and Prigogine 1971; Glass and Mackey 1988; Haken 1978, 1983; Moon 1987; Rasband 1990; Peitgen and Richter 1986; Ruelle 1989; Schuster 1984; Zaslavsky and Sagdeev 1988), however, have provided a new perspective for modeling the dynamics of social phenomena (Vallacher and Nowak 1994; Vallacher and Nowak 1995; Nowak and Lewenstein 1994). One of the factors decisive for the rapid progress in the theory of non-linear dynamical systems was the widespread use of computer simulations, which allows the precise study of the dynamical consequences of models, which cannot be solved by analytical methods. Increasing numbers of social scientists have adapted this new paradigm with a growing number of researchers reconceptualizing their theories and looking for explanations of various phenomena in terms of dynamical concepts and tools (see, for instance, Troitzsch in this volume; Hegselmann in this volume; Axelrod 1984; Nowak *et al.* 1990; Lewenstein *et al.* 1992; Newtson 1994; Başar 1990; Skarda and Freeman 1987; Vallacher and Nowak 1994, 1995, Hoyert 1992; Kohonen 1988; Baron *et al.* 1994; Eiser 1994; Hegselmann 1994; Messick and Liebrand 1995; Newtson 1994; Latané and Nowak 1994; Newtson 1994; Ostrom *et al.* 1994; Weidlich 1991; Weidlich and Haag 1983; Tesser and Achee 1994; Vallacher *et al.* 1994; Vallacher and Nowak 1995).

The dynamical systems approach is based essentially on two assumptions. First, a dynamical system exhibits intrinsic dynamics. The state of the system at a given time determines to a certain degree the state of the system at the next time, in accordance to some rule. It is important to note, however, that the rules of dynamics in general do not have to be purely deterministic and they might even involve elements of randomness. Second, a dynamical system is characterized by some extrinsic factors, which might drastically change the course of intrinsically generated dynamics. These factors are frequently called control parameters since they usually can be externally controlled. Control parameters may change in time, but this is not always the case. In contrast to variable describing the state of the system, the evolution of control parameters does not follow the rules of intrinsic dynamics. The setting of control parameters, however, determines the course of intrinsic dynamics. Even a small change of one or more control parameters can dramatically effect the system's intrinsic dynamics.

Social groups and societies may be viewed as a dynamical systems. Social groups and societies are neither static nor passive, and they display intrinsic dynamics. Even in the absence of external influences and without new information input, social processes continue to evolve and never come to rest. At the same time, it is obvious that social groups and societies react to changes in external conditions. Such reactions, of course, sometimes consist only of resistance, with little change in the state of the system. But at other times, the social system may show an exaggerated response to external factors. In other words, changes in external conditions can lead to unexpected and surprising dynamical effects.

Computer simulations are practically the most powerful tool that allows to study the dynamical consequences of social theories. In the social sciences many empirically observed relationships involve interaction effects between variables. In practice systems, that involve interactions cannot be modeled by linear equations. Since, usually only linear systems of equations are solvable by analytical means, computer simulations are often the only way to examine dynamical properties of systems. It follows that if the social sciences want to put more emphasis on dynamics of social phenomena, computer simulations are usually not only the most convenient tool but often they are the only tool that can be used to study dynamics.

In the following section of the paper we will discuss the model of dynamic social impact (Nowak *et al.* 1990) as an example of a model of qualitative understanding. Research done with this model was focused on two basic problems: how does public opinion emerge from interactions between individuals, and what is the role of individual interactions in a process of social change.

2. Dynamic Social Impact

In the social sciences, there are many theoretical approaches available for describing human interactions (Thibaut and Kelley 1959; Latané 1981; Kando 1977; Krech *et al.* 1962; Shaw and Constanzo 1982; Losada and Markovitch 1990). Individuals may affect states and behaviors of other individuals in two ways. First of all, interdependency may exist between the individuals (Thibaut and Kelley 1959; Conte *et al.* 1994). If such a relationship exists between two individuals, the choices of one individual have direct consequences for the other individual. Relationships of this kind are described by game theoretical models. The best known example concerns the prisoner's dilemma. Social dilemmas (Liebrand *et al.* 1992) provide examples of a similar type of interdependency on a larger scale: the level of society. The prototypical example of social dilemma is provided by smog in Los Angeles. Each individual's decision to use a car for a given trip makes it easier to travel for him or her but contributes to smog effecting other individuals. Computer simulations of those models have provided many important insights into consequences of various types of interdependence, most notably solving a mystery of how cooperation may emerge between egoistic individuals (Axelrod 1984). Papers by Hegselmann and Liebrand are representative of this approach in this volume, in which individual attitudes may be viewed from a functional point of view, as interwoven into the interdependencies of interests between individuals.

Individuals, however, may also exert direct influence on other people. Persuading, giving orders, providing information or just being models other imitate, all belong to this class. In the process of decision making, people interact by influencing others and being influenced, consulting others and being consulted. These interactions can be absolutely crucial to individual decisions and the emerging social processes. In fact, to a great extent interactions among the individuals comprising the social system govern the intrinsic dynamics of the system (Abelson 1964; Nowak *et al.* 1990). In the following sections of this paper we will concentrate on computer simulations of social influence processes and how they explain social change. We will use cellular automata as a vehicle to model processes of social influence and their dynamical consequences, especially social transitions.

2.1. THE MODEL OF DYNAMIC SOCIAL IMPACT

2.1.1. *Theoretical Assumptions*

An important area where the operation of processes of social influence is visible is the emergence of public opinion (Nowak *et al.* 1990). Formation and change of public opinion has been one of the main concerns of social sciences. (Moscovici 1963; Noelle-Neumann 1984; Converse 1964; Crespi 1988; Iyengar and McGuire 1992). From a theoretical point of view, the understanding of how public opinion emerges is important because it gives insight into the differences between micro (individual) and macro (social) levels of analysis (Nowak *et al.* 1990). From a practical point of view, emergence and change are relevant to important social issues, such as voting behavior, consumer preferences, and public decision making. Public opinion is also critical for the course of social transitions.

Our models are constructed as follows. In our simulations social group is assumed to consists of a set of individuals. Each individual is assumed to have an opinion on a particular issue. In the simplest case, it may be one of two possible "for" or "against" opinions, or a preference for one of two alternatives, such as choosing between two candidates in elections. In other cases, there may be more possible attitudes or opinions. People in our models differ in their respective strength, that is, in their abilities to change or support each other's opinions. Individual differences in strength are very important for the behavior of the models. It is obvious that in all real social groups individuals differ in strength. The importance of leaders for the processes taking place in groups is well recognized by the social sciences.

People interact most often and are mostly influenced by those who are close to them, such as family members, friends, and co-workers. People are also much more likely to interact with neighbors, that is, those who live close to them in physical space (Latané *et al.* 1994; Bradfort and Kent 1977; Hillier and Hanson 1990; Hillier and Penn 1991). In our simulations we assign to each individual a specific location in a social space (see Nowak et al. 1994). In most of our simulations social space was conceptualized as a two dimensional matrix of N rows and M columns of points representing locations of individuals (see also Crespi 1985). Below we will discuss the importance of the geometry of social space for the outcome of social interaction processes (see also Nowak et al. 1994). Our choice of a 2-dimensional lattice represents quite well the physical distribution of people on flat surfaces. The results of studies conducted in Boca Raton, Warsaw, and Shanghai, have shown that the probability of social interactions is decreasing as a square of physical distance (Latané *et al.* 1994; Kapuściarek and Nowak 1993).

To model social interactions, we assume that individuals communicate with others to assess the popularity of each of the possible opinions. Opinions of others located close to the subject and of those who are most influential are most highly weighted. Individual's own opinion is also taken into account in this scenario. In the course of the simulation, individuals adopt the opinions that they find prevailing in the process of interacting with others. This simple model of social interactions is not only intuitive but also agrees with a number of empirical studies. The theory of social impact (Latané 1981), built as a generalization of empirical results, states that in diverse situations where a group of people is exerting impact on an individual or on another group, the strength of this impact can be specified as a universal function of peoples' strength, immediacy, and number. Our models can incorporate these features of social interaction and lead to similar conclusions (Nowak *et al.* 1990, Nowak *et al.* 1994, Hegselmann and Nowak 1994; Szamrej *et al.* 1992, Nowak *et al.* 1993).

2.1.2. *Construction of the Models*

The computer models discussed here belong to a class of models called *cellular automata* (Wolfram 1986) that are widely used in physics (for example, to model the flow of fluids), and in various domains of biology, including neuroscience (Amit 1989; Başar 1990) and population dynamics (May 1981). Probably the best known example of cellular automata is the Game of Life (Gardner 1970). In this volume Hegselmann discusses in detail cellular automate as models of social processes. Cellular automata are dynamical systems, that is, they evolve in time. For simplicity, we may assume that time proceeds in discrete steps, t, $t+1$, $t+2$ etc. We consider individuals to be a set of formal automata located in some space. In the example discussed above example, individuals are located at the vortices of the 2–dimensional square lattice, so that their coordinates are (i,j) where i, j are integers. The state of the individual located at (i,j) at time t (that is his or her opinion) may be represented quantitatively by some set of numbers. In the case of "yes" or "no" choice, it can be conveniently represented as a number $s_{ij}(t) = \pm 1$, with 1 for "yes" and -1 for "no". The individuals influence and are influenced by other individuals. Again, in the simplest case we may assume that the individual located at (i,j) interacts most strongly with his or her nearest neighbors, that is, individuals located at $(i+1,j)$, $(i-1,j)$, $(i,j+1)$, and $(i,j-1)$.

Each individual at (i,j) adjusts his or her opinion in the following time steps according to an *updating rule*. In particular, the updating rule can have a form

$$s_{ij}(t+1) = \mathrm{sign}(\sum_{i',j'} J_{ij}^{i'j'} s_{i'j'}(t)),$$

where $J_{ij}^{i'j'}$ measures the impact of a individual located at (i',j') on the individual located at (i,j). Obviously, according to the theory of social impact (Latané 1981), $J_{ij}^{i'j'}$ decays rapidly as the distance between (i',j') and (i,j) grows. Moreover, $J_{ij}^{i'j'}$ increases with the strength of (i',j') – the individual who is the source of the impact. We shall denote the strengths parameters for individuals by f_{ij}.

In our models we have used a slightly more generalized version of the updating rule described above. Generally,

$$s_{ij}(t+1) = s_{ij}(t)\mathrm{sign}(I_s - I_p),$$

where I_s is the *supportive impact*, while I_p is the *persuasive impact*. Quite generally, one can assume that the supportive impact is a function of $\sum'_{i',j'} J_{ij}^{i'j'}$, where $\sum'$ limits the sum to supporters of $s_{ij}(t)$, i.e. to those (i',j') for which $s_{i'j'}(t) = s_{ij}(t)$. Similarly, I_p is assumed to be a function of $\sum''_{i'j'} J_{ij}^{i'j'}$, where $\sum''$ is restricted to (i',j') for which $s_{i'j'}(t) = -s_{ij}(t)$.

One of the most important aspects of the models discussed here is that individuals differ in strength and thus can be characterized by strength parameters f_{ij}. The coefficients $J_{ij}^{i'j'}$ that measure the impact of the (i',j')–th individual on the (i,j)–th individual are thus proportional to $f_{i'j'}$. In the model with nearest neighbor interactions only, we simply set $J_{ij}^{i'j'} = f_{i'j'}$ for $(i',j') \neq (i,j)$, and $J_{ij}^{ij} = \beta$. The parameter β in the latter formula determines a *self–supportiveness*, that is, the impact of (i,j)–th individual on herself or himself. The updating rule may be then termed a *weighted majority rule*. The individual located at (i,j) at the time $t+1$ would vote "yes," provided the weighted sum of opinions of his or her nearest neighbors including him or herself at time t was positive. Mathematically speaking, that means $s_{ij}(t+1) = 1$ provided

$$\beta f_{ij} s_{ij}(t) + f_{i+1j} s_{i+1j}(t) + f_{i-1j} s_{i-1j}(t) + f_{ij+1} s_{ij+1}(t) + f_{ij-1} s_{ij-1} \geq 0,$$

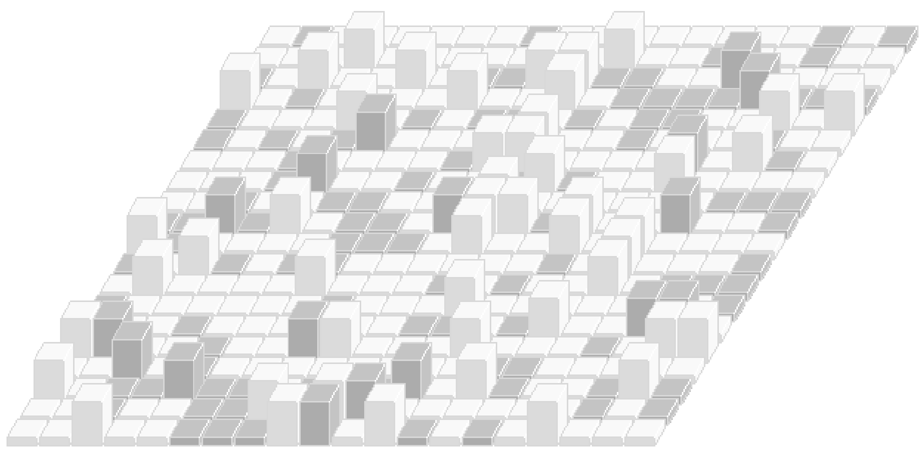
and $s_{ij}(t+1) = -1$ otherwise.

Another important aspect of our models is that typically the updating rules do not include the nearest neighbors only. Updating rules that are restricted to nearest neighbors are commonly used in physics. On the contrary, our models include the influence of every individual in the group. The influence of those individuals on a given person, however, decreases with increases in their distance from that person. We have also studied models where each individual interacts with just a few other randomly selected from those that live not further than a specified distance (Nowak *et al.* 1993; Szamrej *et al.* 1992).

2.2. INTRINSIC DYNAMICS AND EMERGENT PROPERTIES

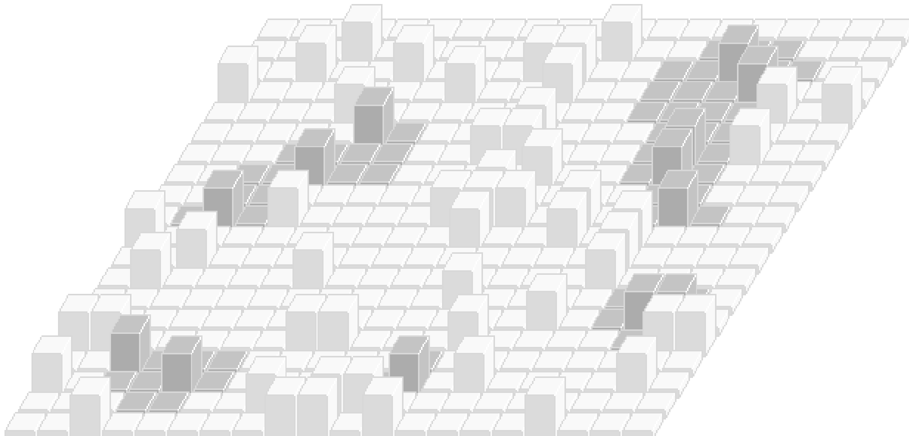
We started the simulations from a random distribution of opinions. This may be interpreted as representing the situation where initially each individual comes to his or her opinion unaware of the opinions of others. This opinion may be the result of a number of factors not accounted for in our model, such as vested interests, previous experiences, or simple reasoning about the issue. In Fig. 1, the majority of the population choose the "no" option represented by the light color. The minority of individuals, represented by the dark color, are for a "yes" choice. The height of the bars indicates the strengths of the individuals. The strength is also distributed randomly among individuals and in this model it does not change in the course of the simulation.

Figure 1. Initial random distribution of opinions in a group of 400 individuals. Color represents attitude, height represents strength.



As individuals interact in the course of the simulation, those who find the opposite opinion prevailing, change opinions. Finally, after some simulation steps an equilibrium is reached in which no one changes opinion (see Fig. 2). In comparison to the initial distribution of opinions, the final distribution is different in two respects. First of all, opinions are no longer randomly distributed. Individuals holding minority opinion are grouped in clusters or "bubbles." Clustering is reminiscent of a wide class of a real

Figure 2. Final distribution of attitudes in the group shown in Figure 1. After discussion minority opinions have polarized and clustered.



word phenomena such as the spread of accents, fashions, beliefs, and political preferences. In fact, it is difficult to find an example of opinion, fashion, or custom that is not clustered, if it was acquired through social interaction. Clustering of attitudes was empirically demonstrated in a survey study of attitudes at an MIT housing project, where people living within the same neighborhood tended to develop similar attitudes on issues concerning local policy (Festinger *et al.* 1950). The second phenomenon visible in the comparison of Fig. 1 through Fig. 5 is that the number of people holding the minority view has declined. Such a phenomenon is often referred to as *polarization* of opinions (Myers and Lamm 1976; Moscovici and Zavalloni 1969).

The formation of clusters or bubbles is a very universal phenomenon of a wide class of computer models of social change. They will form in any model that incorporates local interactions in which an individual is likely to adopt the prevailing opinion in his or her local environment. In particular, cluster formation occurs in models that incorporate elements of randomness and noise, provided the noise is not too large. It is interesting that bubbles will form even if all the individuals prefer to be in a global majority. Individuals try to establish the relative proportion of attitudes in the society by generalizing from their interaction with others. Since people are most likely to interact with those who are close to them, the result of their sampling is strongly biased in a clustered society. In fact, most individuals, even from the minority group, would come to the conclusion that their opinion is consistent with a global majority.

Figure 3. The simplest stable configuration of a minority: leader surrounded by followers.

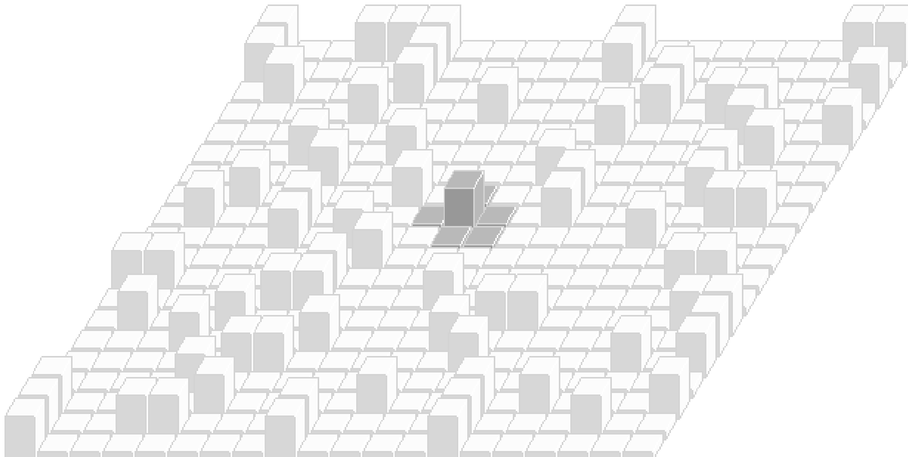
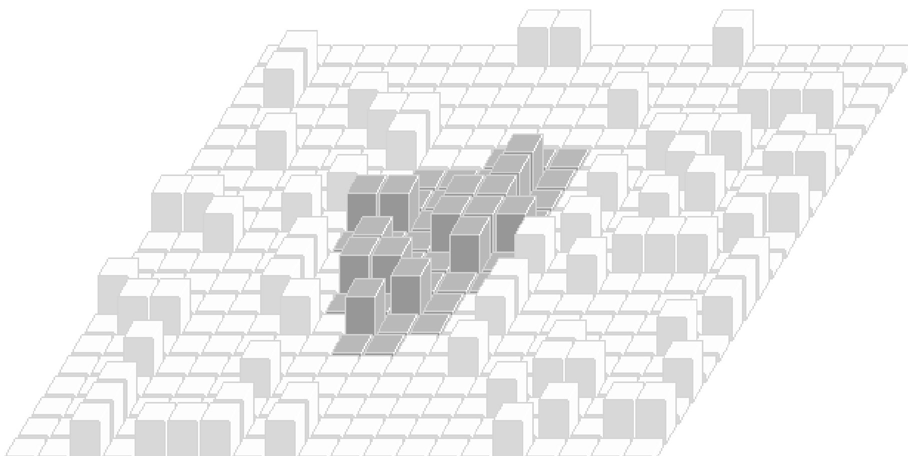


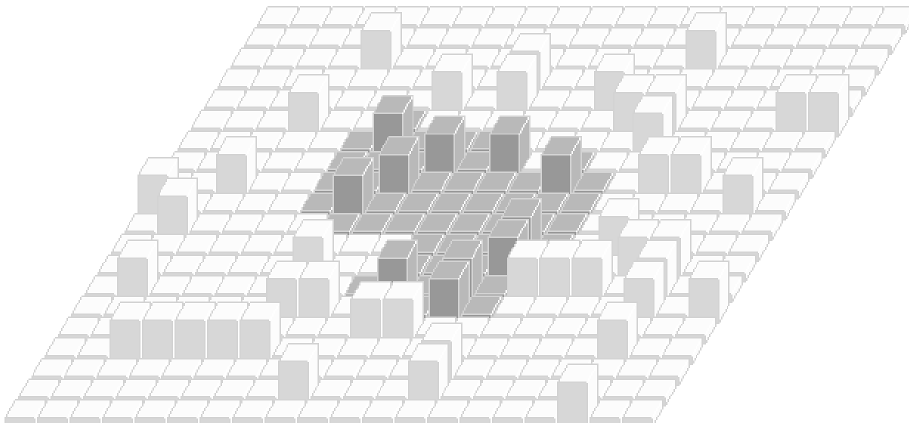
Figure 4. Several strong minority figures form a "stronghold".



2.3. FEATURES CRITICAL FOR DYNAMICS

We have analyzed a large class of models belonging to the category discussed above (Lewenstein *et al.* 1992; Latané and Nowak in preparation; Nowak *et al.* 1993, Nowak *et al.* in press). This analysis led us to the conclusion that the qualitative phenomena exhibited by the models, such as polarization and clustering, are caused by the features of the models critical for dynamics. These are:

Figure 5. A "wall" consists of several strong minority members surrounding a group of a weaker minority members.



2.3.1. *Nonlinearity of Attitude Change*

In the traditional approach of the social sciences, any attitude held by an individual was considered to be a continuous variable. Change in attitude, moreover, was assumed to be proportional to the influence (or social forces) exerted on this individual (Abelson 1964). One should stress, however, that "social forces" very often act in a nonlinear manner. That means that sometimes a small change in social forces can bring about a drastic change of attitudes. In consequence, people frequently adopt only extreme attitudes (either very positive or very negative).

This phenomenon has been illustrated empirically by Latané and Nowak (1994). In this research, the authors have measured the distribution of attitudes (measured on a Likert scale from 1 to 5) concerning diverse issues. The subjects were also asked to indicate the personal importance of these issues. It turns out that the distribution of attitudes on issues that were judged as unimportant is approximately normal. On the other hand, the distribution of attitude concerning subjectively important issues has a well developed U shape. People tend to adopt extreme attitudes on such issues. This implies that for important issues, binary representation of attitudes is adequate. Such a representation implies necessarily nonlinearity of attitude change.

2.3.2. *Individual Differences.*

Our computer simulations indicate that the time course of polarization and clustering strongly depends on the assumption that individuals differ in their respective strength parameters. The introduction of individual dif-

Figure 6. Hierarchical geometry. Top: initial configuration of attitudes, bottom: final distribution

ferences into the model is probably the most important factor that makes our model different from those studied elsewhere (Wolfram 1986; Landau and Lifshitz 1964). Mathematics and physics suggests, in fact, that the dynamics of systems consisting of "equal individuals" in the presence of infinitesimally small noise should inevitably lead to uniformity of opinions. In our case, individual differences provide a major source of minority group survival. We were not able to prove mathematically that in general such survival is eternal in the presence of some randomness. The results of our computer simulations, however, clearly indicate that the life time of minority clusters can be practically infinite.

The question "How can minority opinion survive?" may be answered by noting the formation of clusters. Those inside clusters are surrounded by others who share the same opinion. Only those located on borders are exposed to the pressure of individuals holding majority opinion. The survival of the clusters depends thus on what happens to individuals located on the borders of clusters. The borders of minority clusters are mostly convex. Members of minority located on the borders are on the average surrounded by the prevailing number of individuals holding the majority opinion. If there had not been individual differences, most individuals on the borders of minority clusters would not be able to hold their opinions. The minority clusters would gradually decrease in size and eventually vanish. The existence of individual differences in strength stops this process. An especially influential minority member located on the border may counter the prevailing number of majority members. The findings of our simulations correspond to the observations in social sciences that point to the importance of leaders in social movements.

A minority can survive in simple configurations, shown in Fig. 6. In the simplest configuration, a single strong individual is surrounded by several of weaker minority members (Fig. 3). The weaker members would not be able to maintain their opinion without the leader. It would also be difficult for the leader to survive without the followers since they also provide him or her with some support and, in addition, isolate him or her from the majority. A second configuration "stronghold" (Fig. 4) consists of a group of stronger minority members located close to each other and supporting each other. The whole group is usually surrounded by a weaker members. Note that in both of the discussed configurations, strong minority members are located inside the cluster. In the third scenario (Fig. 5), a "wall" of strong individuals is located on the borders of the cluster; it shields the weaker individuals located inside the cluster. The wall does not need to be compact, since weaker individuals who are located between stronger minority members ones are not outnumbered by majority neighbors. We should note that in our simulations we quite often observe much more complex configurations composed of combinations of simpler ones. For example, several strongholds may be located on the wall of a large minority cluster. Without other sources of influence, all the configurations described above are stable, that is, they would never change.

Usually individuals are subjected to a number of factors influencing their opinions in addition to the influence of the immediate social context. Such factors include selective exposure to media, recall of particular memories, personal experiences, and so on. The cumulative effects of such factors may be represented as a random factor or "noise" that adds up to the effect of social influence. If all the other factors have relatively small effect, as compared to the effect of social influence — or in other words, the noise is small — the picture described above will not change significantly. Even if from time to time some weak minority members change their opinion, typically their own group will be able to convert them back.

A slightly larger value of the noise, however, might cause one of the leaders in the minority group to change his or her opinion. If this leader is a part of the wall shielding weaker minority members, the cluster will start to decay rapidly. In the presence of larger noise, therefore, the clusters in principle become unstable. Typically, however, such decay will terminate in some new equilibrium as the shrinking border of the cluster encounters the resistance of the remaining strong individuals. For large clusters, such a scenario may take place many times. If we plot the size of the cluster as a function of time, the plot will consist of several periods of rapid decay separated by relatively long intervals of apparent equilibria that can be almost infinitely long. We call this type of decay staircase dynamics (Lewenstein *et al.* 1992). It should be stressed that this is a generic form of decay in systems consisting of many agents where the agents are different in strength.

2.3.3. *Geometry of Social Space.*

Figure 7. One-dimensional geometry; top: initial configuration, bottom: final distribution

Another crucial feature of our model, yet the one that is perhaps the most difficult to relate to empirical data, concerns the geometry of social space. Our computer simulations indicate very clearly that the geometry of social space determines simultaneously the character of cluster formation, the shapes of the resultant clusters, and their likelihood of survival. We illustrate this statement in the next figures , in which we compare the results of the simulation for a group of individuals experiencing (a) hierarchical (Fig. 6) and (b) one dimensional strip geometry (Fig. 7). In the case of hierarchical geometry, people are divided into groups, subgroups etc. The distance between the individuals within the same hierarchy group are relatively small, but it increases rapidly between the individuals occupying the same group at the higher hierarchy level. This feature of the geometry causes the formation of clusters mostly at the same hierarchy group. Hierarchical geometry may represent an idealization of the distances within an organization. In the case of the one dimensional geometry, the interactions of individuals are particularly weak, since they are mainly mediated through the "left" and "right" neighbors. For this reason, in one dimension two strong individuals on the borders of the cluster are sufficient for its survival. This geometry may approximate spatial arrangement of people living along a road or a river.

2.4. THE APPROACH OF STATISTICAL MECHANICS

Computer simulation models are constructed on the micro level of social reality and are based on assumptions of concerning decisions of individuals in their social context. Corresponding rules on the macro level can be formulated with the tools of statistical mechanics. Those tools allow to predict many of the results of our computer simulation (Lewenstein *et al.* 1992). The tools that we use are closely related to the synergetic approach (Weidlich 1991, Weidlich and Haag 1983, Haken 1978, 1983). These tools are particularly useful when both the number of interacting individuals and the range of interactions increase toward infinity. A strong advantage in combining computer simulations with the analytical solutions is the possibility to cross-check the results. There always is a risk that a computer simulation program may contain a bug. The risk of arriving at erroneous conclusions may be reduced if more than one computer simulation program is written and their results are cross-checked. In fact, we have by now used 7 different computer simulation programs written in FORTRAN, PASCAL, Object Oriented Pascal, C, and Warsaw Social Simulation Language to simulate emergent properties of social influence. All the computer simulations may still be based on some common assumptions of which the researchers are not aware. Computer simulations also always dealing with groups of some finite size. This limitation which may lead to treating results true only for some group sizes as general laws. Research using computer simulations has shown, that group size may be a very important factor for the results of simulations. Although this risk may be minimized by using large groups in simulation runs (some simulations of our model were done using group size roughly equal to roughly 250 thousand individuals) still the danger is there. It is also worth to note that analytical derivations of solutions for class of problems require to use complex methods of statistical physics, and there is also a chance of an error when deriving a formula or assuming a simplification. Cross checking analytically derived results with the outcomes of compute simulations allows to discover such errors.

Let us again denote individuals' opinions by $s_i = \pm 1$, for $i = 1, \ldots, N$. Each individual is characterized by a strength parameter f_i which is a random number that remains stable over time. We assume some probability distribution of the strength parameters $p(f_i)$ that is the same for all i. We also assume that "distances" of a given individual to all others are equal N, whereas the distance of an individual to him or herself is set to be β, where β is some number. The supportive impact can be then defined as

$$I_s = \frac{1}{2N} \sum_{j \neq i}^{N} f_j (1 + s_i s_j) + \beta f_i,$$

whereas the persuasive impact can be defined as

$$I_p = \frac{1}{2N} \sum_{j \neq i}^{N} f_j (1 - s_i s_j),$$

so that the dynamics becomes

$$s_i(t+1) = \mathrm{sign}(\beta f_i s_i(t) + m(t)),$$

where the *weighted majority-minority difference* $m(t)$ is defined

$$m(t) = \frac{1}{N} \sum_{j \neq i}^{N} f_j s_j.$$

Even for such simple dynamics, the dynamical order parameters are quite complex (Lewenstein *et al.* 1992). Nevertheless, in the limit of large N one is able to derive a mean field equation for the quantity $\bar{m}(t)$ which is the mean value of $m(t)$ averaged over the distributions of f_i's and over the initial distribution of attitudes. Such a mean field equation has a form of a discrete map,

$$\bar{m}(t) = f(\bar{m}(t)),$$

where the function $f(\bar{m})$ depends functionally on the distribution of f_i's and on the distribution of initial opinions. We have shown that in general, the map introduced above may have several stationary points, corresponding to increasing values of the absolute value of $\bar{m}(t)$. Each of these stationary points corresponds to subsequent "conversion" of stronger minority subgroups. In the absence of noise, each of the stationary points is stable. The introduction of small noise causes the system to jump between the stationary points. The jumps occur typically in the direction of increasing absolute value of $\bar{m}(t)$, that is, of increasing polarization. The jumps are separated by long periods of apparent quasi–stability. This is a simple example of the "staircase dynamics" discussed above. It is worth stressing that the mean field approach can be generalized to other geometries such as hierarchical geometry, random connection matrix, as well as noise. For the case of hierarchical geometry, the mean field theory predicts clustering within the hierarchy groups and staircase decay of clusters from lower to higher hierarchy levels. To trigger the decay, however, one needs much larger values of noise because the clusters in the hierarchical geometry are much more stable. Random connection networks behave similarly to fully connected networks discussed above. Interestingly, however, due to the randomness of interactions between individuals, such networks inevitably incorporate self–induced noise.

2.5. HOW CAN MINORITY OPINION GROW: MODELING SOCIAL CHANGE.

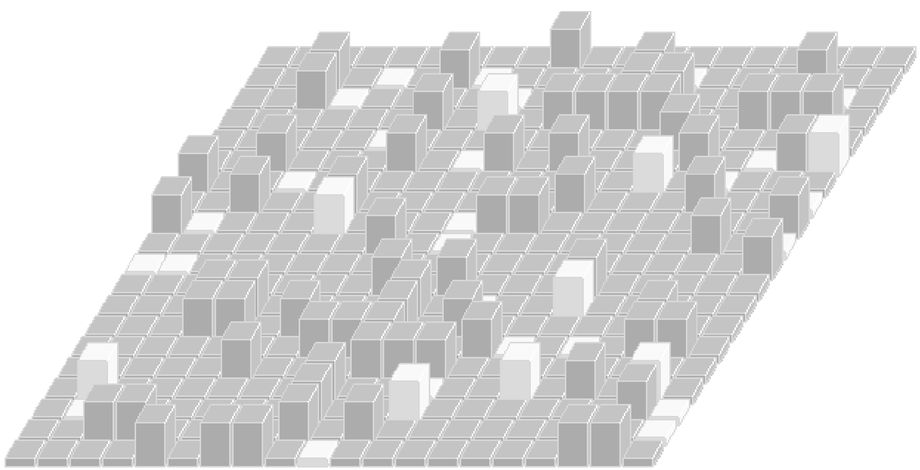
For a social change to occur usually some external conditions have to change. In the case of recent social, political and economical transitions in Eastern and Central Europe the changes of the situation in Soviet Union and the degree of control exerted by this country was clearly one of the decisive factors. In some other cases such external factors may include a change in economy, technical inventions, military interventions and so on. The change of global factors, however, almost never directly changes individual opinions and attitudes. The effects of all the factors are mediated through the process of social interactions. Before adopting an opinion individuals usually consult with others, also an opinion, that has been recently been formed usually is a subject to intense discussions. In the following section of the paper we will consider how global change is produced by joint effects of global factors and social influence, in other words how does intrinsic dynamics combine with external influence in producing a social change.

In our class of models, if social influence is the only force causing attitude change, minorities cannot grow. On the other hand, the fact, that sometimes minorities grow and become majorities is one of the main factors causing social change. The recent social transitions in Eastern and Central Europe provide examples of global change in attitudes, such that initial minorities grow and eventually become majorities. Clearly, something has to be added to our model if is to account for social change. In our previous discussion, we have assumed that all the available opinions or attitudes are equally attractive. In reality some attitude positions usually are more functional for the individual, better reflect his or her values, or are simply advocated by propaganda. Some of these preferences are specific for every individual since they reflect individual experiences, etc. Sources of other preferences are external with respect to individuals. External influences, such as provided by the media, the fiscal system, and mechanisms of political control usually change in the time of transition, so a new set of opinions becomes more attractive.

We can account for one attitude position being more attractive than the other by introducing a factor of preference, a *bias*, into the rules of opinion change. In the presence of bias, each of the individuals would more easily adopt one position than the other, taking into account not only the results of their social interactions, but also externally given preferences.

The effects of social interactions in the presence of bias are presented in Fig. 8 to 13. These figures correspond to different stages of a transition. For the beginning of simulation (Fig. 8), we have chosen a state in which 10 percent of randomly located individuals have the favorable "new" opinion represented by the light color. The dark color represents the opinion of the majority, which corresponds to old attitudes.

Figure 8. Dynamics of attitudes in the presence of "bias". (a) Initial distribution of "new" opinions.



To model the asymmetry of opinions a constant -"bias" - to the impact of the minority opinion was added. Figures 8 through 11 show the growth of the minority of the followers of the new as a result of social interactions in the presence of bias. As indicated in Figure 9, clusters are starting to form around those individuals who can be interpreted as seeds of the transition. These clusters of new continue to grow in the course of time and eventually connect to each other. The growth of the new, especially when the bias

Figure 9. Dynamics of attitudes in the presence of "bias". (b) Bias is in favor of the "new". Opinions after several rounds of discussion. Notice that the "new" enters through "bubbles" centered around the initial innovators.

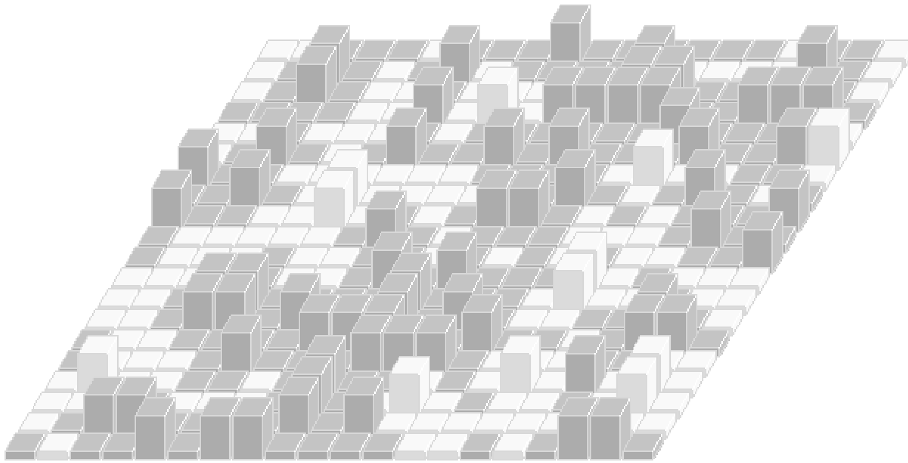
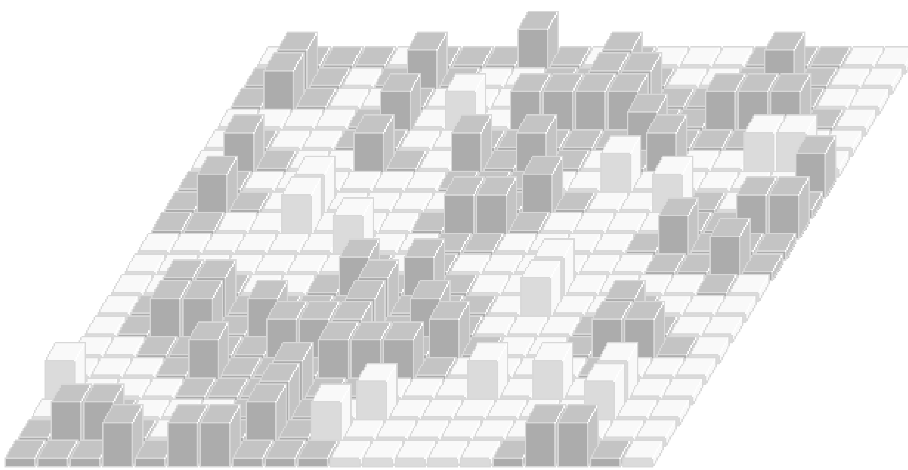


Figure 10. Dynamics of attitudes in the presence of "bias". (c) Bubbles connect as the "new" is gaining more adherents.



is not too strong follows the staircase dynamics for the reasons describe above. Eventually the new equilibrium is reached. Interestingly, despite the fact the bias is still present there are clusters of old well – entrenched in the final state of the transition.

Judging by the numbers, in the situation portrayed in the figure 11

Figure 11. Dynamics of attitudes in the presence of "bias". (d) Opinions after the "new" has prevailed. Notice that the "old" can survive in well–entrenched clusters.

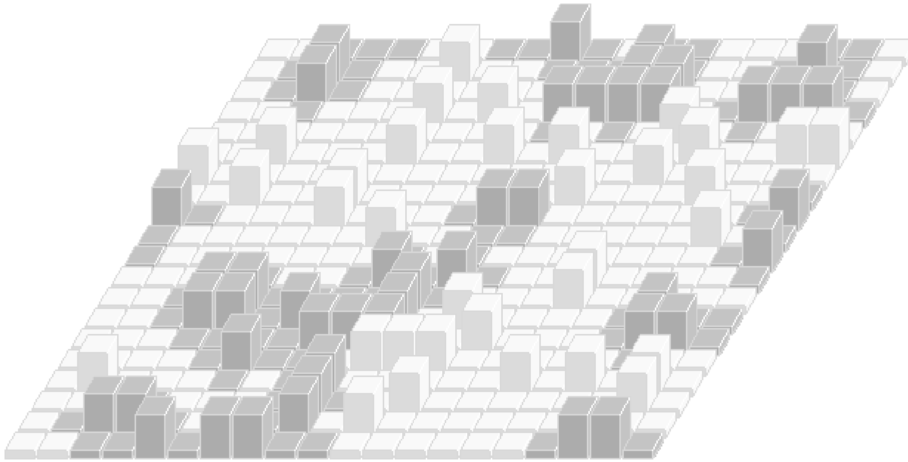
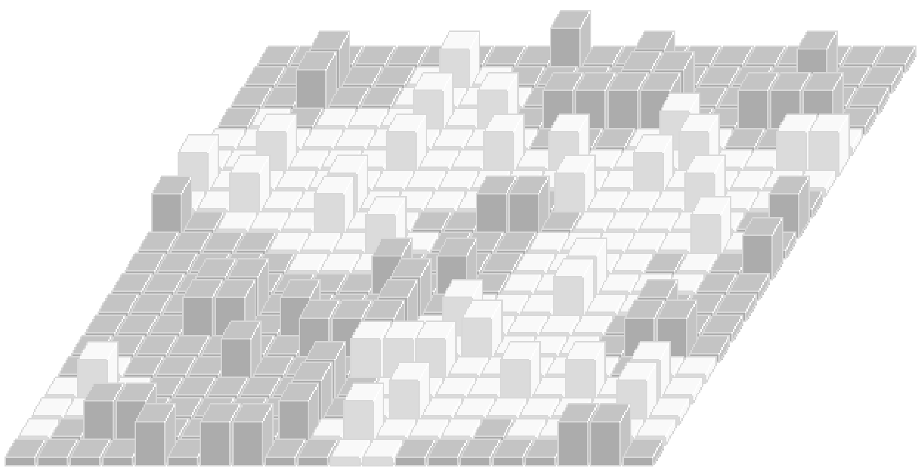
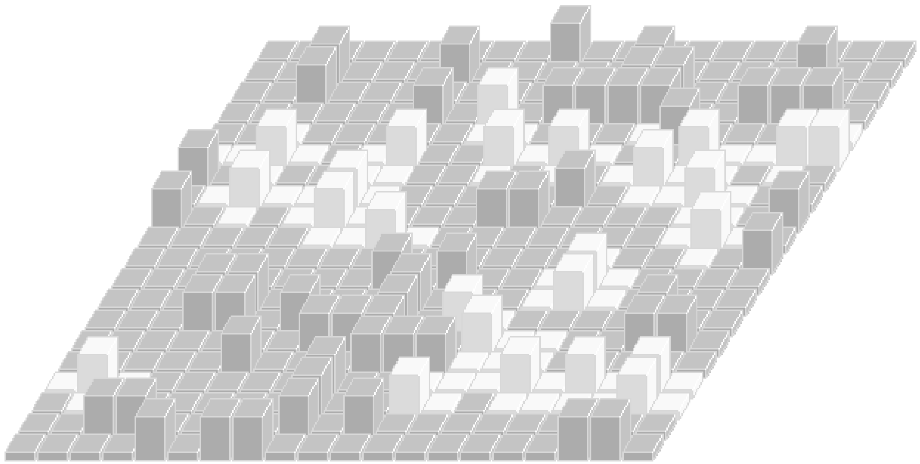


Figure 12. Dynamics of attitudes in the presence of "bias". (e) When the bias is withdrawn "old" regains popularity



the social transition has been complete. The "new" has completely prevailed and its proponents would be able to overwhelmingly win any elections or a referendum. The situation is, however, more complex. The minority owes it prevalence to the continuing presence of bias. The reason is that the strongest members of the original majority had most chance to resist change. Although they are low in numbers their average strength is high

Figure 13. Dynamics of attitudes in the presence of “bias”. (f) Bias has been reversed and now it is in favor of the “old”. It takes only a few simulations steps for the “old” to prevail. Note that in this process the “new” has formed clusters in which it can sustain the pressure of the opposing group.



and in fact they form strongholds of powerful interconnected individuals. From those strongholds they can initiate an attack on the “new”, whenever the situation is more favorable to them. The figure 12 shows the new equilibrium achieved when the bias was withdrawn corresponding to a situation when the “new’ has lost some of it’s initial appeal, and both attitudes became symmetrical. The ”old” has regained much of its ground and the proportion of people having the “new” and the “old” attitude is close to being balanced. It may well happen that the bias reverses in favor of the “old”. For example people may have found that the new is less favorable to them than they assessed, or mass media may reverse the direction of their influence. The effect of the reversal of bias is shown in the picture 13. After a short time proponents of the “old” win support of the overwhelming majority of the population. Although, the “new” is small in number , during the changes it had an opportunity to cluster. It forms strongholds in which it can resist the pressure of the “old” and wait till the bias changes in its favor. It took adherents of “new” 40 simulations steps to achieve prevalence. The victory of the “old” happens in just 5 steps. This phenomenon may be compared to the memory of a society. It looks as if the society has remembered its previous states. The tendency of a society to return to its previous states is a general one and will happen in any model in which the strongest individuals are most likely to resist the pressure to change. This mechanism may underlie a regularity observed in almost all the countries in Europe that underwent transition into a market economy. In all those countries in the first free elections the opposition had overwhelmingly won. To everybody's surprise, however, parties of communist provenience have won in the next elections.

The effect of societies having a tendency to come back to its previous states would be reversed if the strongest individuals were most likely to adopt the "new" positions. In other words, the bias would have to be positively correlated with strength. In such a situation, after the strongest individuals become advocates of the "new", other individuals in the group could follow, due to mechanisms of the intrinsic dynamics, even if the bias favoring the "new" was withdrawn. Such a scenario would be likely if adopting the "new" position was in the interest of individuals and social pressure was keeping them changing. Such a description fits the change of economic orientation during recent transformations in Eastern Europe. Starting a private business although unpopular according to old values in general may be highly profitable.

The major conclusion of the scenario presented above is that the transition occurs through the local centers of change: growing clusters of new within the sea of "old". During a transition two realities coexist: the reality of the "new" and that of the "old". Social transitions occur through the change of proportions of the two realities in favor of the "new", rather than through gradual change of all individuals from the old position to the new position. There may be, under some circumstances, a tendency for societies to return to their previous opinions.

Our analysis has some practical implications concerning facilitation of social change. Our results suggest that an effective social intervention should concentrate on changing spatially coherent areas of social network rather than dispersed individuals. Such an intervention should be aimed at well defined places, potential centers of change. Those centers will have a chance to develop into clusters and the change can diffuse from those centers to other areas. The same efforts spread spatially could run into the risk that those individuals who have changed will not find enough support for their new attitudes in their social networks, and under social pressure will revert to the old attitudes. Also important is the role of the leaders and the place in the social network the leaders are located. For example, by forming a wall a small number of leaders can protect a large number of followers.

2.6. GENERALITY OF THE MODEL.

As discussed in the beginning of the paper the behavior of the models often does not depend on the precise assumptions concerning individual elements, the same models and their qualitative results may be thus interpreted as modeling different phenomena. The model of dynamic social impact was originally constructed to model the dynamics of opinions and attitudes. Its extension allows, however to model economic transitions (Nowak *et al.* 1994, Nowak *et al.* in press). Economic and voting data in Poland suggest that in fact the "new" reality forms spatially coherent clusters. All the economic growth occurs through the expansion of existing centers of growth, regions far from the clusters of economic growth still decline despite the overall growth of the economy. The clusters of "new" go beyond economic measures and are also visible in voting for pro-reformist parties.

The connection between the changes of attitudes and economic change may seem far reaching, there is, however a clear connection between the two. Let us consider individuals, who try to start a private enterprise. First, of all, an individual must believe that starting an enterprise can be profitable. Clearly processes of social influence play an important role there. Second the individual must also know what to do to start a new enterprise. Information also to large degree disseminates through personal contacts. The spread of innovations also occurs through growing clusters and "bubbles" (Sperber 1990). To be sure, economic factors are also of major importance in this process. The survival of any enterprise to a large degree depends on local economic factors. Our models are not unique in predicting clustering effects during social transitions. Clustering effects have been demonstrated also in models stemming from the game theory (Axelrod 1984; Hegselmann this volume) in which it was demonstrated that cooperating individuals tend to cluster. Clustering effects have also been extensively discussed in economics (Myrdal 1958, Friedmann 1966, 1973). Our point is that different processes of both social and economic nature may have some common underlying mechanisms and show similar qualitative properties.

3. Conclusions and Generalizations

In first part of the paper we argued that computer simulations can be used as models of qualitative understanding of social processes. Their main functions would be to look into the emergent properties and into the dynamics of the social processes.

We have concentrated on the processes of social influence and specifically how the result in the intrinsic and extrinsic mechanism of social change. Cellular automata models are built to model social change produced by social influence. It is important to stress, that the description of individuals is greatly simplified in this approach. In fact, the description of individuals is trivial in such models and one should not claim that such description adequately represents a person in a social context. This model is not a model of an individual in a social system, but a model of aggregate behavior. The model displays intrinsic dynamics. Social change is due to intrinsic dynamics when it occurs without external influence. Clustering and polarization of opinions are the main emergent properties of intrinsic dynamics of social change. The decay in minority opinion follows a staircase dynamics. The main factors critical for the behavior of the model are: nonlinearity of attitude change, the existence of individual differences and the non-linearity of attitude change. Several factors such as the existence of randomness or the assumption about symmetry of the attitudes were important, and most of the assumptions (such as whether the simulation space has borders or is torus shaped) did not matter for the qualitative picture of simulation runs, although they could matter to some degree for quantitative results.

Social change may occur when initial minority of opinion grows and eventually prevails. Social change may be analyzed as a modification of the intrinsic dynamics by external factors. Usually in the process of social transitions same factors make the "new" more attractive than the "old". The transition occurs through the growing clusters of "new" within the sea of "old". Clustering is the necessary feature of the rapid evolution toward the "new". This is due to the fact that the fate of individuals both in the social end in the economic sense, depends to a large degree on their local environment.

We would like to stress that there are other models that attempt to describe phenomena similar to those we have considered. Some models, for example, give explicit attention to the movement of individuals in social space, and to individual interests. Thus, Schelling (1971, 1969) has shown that clustering may be achieved by the simple fact that individuals move if they are in local minority. Similar ideas have been developed by Hegselmann (this volume) and May and Nowak (1992) to describe social dynamics from the point of view of game theory. These ideas have much in common with the development of social cooperation formulated within the "prisoners dilemma paradigm" by Axelrod (1984). Although our models thus far incorporate only some of the features stressed by such theories, the mechanisms discovered in our models and the qualitative results we have obtained are observed in other models as well.

4. Acknowledgement

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