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Dynamical Minimalism: Why Less is More in Psychology

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The principle of parsimony, embraced in all areas of science, states that simple explanations are preferable to complex explanations in theory construction. Parsimony, however, can necessitate a trade-off with depth and richness in understanding. The approach of dynamical minimalism avoids this trade-off. The goal of this approach is to identify the simplest mechanisms and fewest variables capable of producing the phenomenon in question. A dynamical model in which change is produced by simple rules repetitively interacting with each other can exhibit unexpected and complex properties. It is thus possible to explain complex psychological and social phenomena with very simple models if these models are dynamic. In dynamical minimalist theories, then, the principle of parsimony can be followed without sacrificing depth in understanding. Computer simulations have proven especially useful for investigating the emergent properties of simple models.

Each person represents the intersection of numerous influences from other people. For me this is more than recognition of a truism. It is a way that allows me to trace the roots of my approach to theory building in social psychology. It also provides the essence of my theoretical thinking about social psychological phenomena. My approach to building theory in social sciences has evolved as a result of my interactions with a number of individuals, each of whom has shaped my thinking about a theory in a different way. And the theories that have resulted from these influences have at their core the assumption that human behavior is a highly dynamic affair, evolving in accordance with the interaction of multiple influences—including the influences of other people. But although an appreciation for complexity is at the heart of my approach, the orientation that has evolved over the years can be defined as minimalist, in that I look for the simplest set of assumptions and the fewest variables to account for human behavior. Complexity and minimalism may seem contradictory, but I have learned that these ideas are in fact quite complementary and define what can be termed the approach of dynamical minimalism.

The Evolution of a Scientific Attitude

My first exposure to social science theorizing occurred in my interactions with my father, Stefan Nowak, a sociologist and philosopher of science (e.g., S. Nowak, 1976, 1978). For him the issue of how social theories should be build was a passion, and he perceived himself more as a methodologist and philosopher of science than a sociologist. He would try to explain to me the positivist approach and the ideas of reductionism. The questions as to what needs to be assumed in the theory and what can be proven empirically fueled our interactions even before I had finished high school, and they significantly contributed to my decision to study psychology.

The insights he imparted to me regarding neopositivism prepared me for a subsequent stage in the evolution of my theoretical approach, which was inspired by my collaboration with Maciej Lewenstein, a theoretical physicist. This collaboration instilled in me an appreciation for concreteness and precision in theory construction. But, perhaps more important, I developed a recognition that diverse phenomena can be framed in terms of common rules and properties. The trick was to develop formal models that captured what is invariant across topics and levels of analysis, yet maintain appreciation of what is unique to each area of scientific inquiry. Together, Lewenstein and I (e.g., Lewenstein & Nowak, 1989a, 1989b; Lewenstein, Nowak, & Latané, 1993) developed models in which elements at the individual level—whether neurons or people—influenced one another to produce complexity at the aggregrate level—whether in brains or in social groups. Complexity, in other words, was an emergent property rather than a feature that was inherent in the individual elements themselves. We employed computer simulations to demonstrate how simple rules of interaction among simple elements can promote the

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emergence of highly complex phenomena. The collaborations with Lewenstein thus provided a very clear lesson that complexity and minimalism are not contradictory but rather provide a coherent picture of human dynamics.

The next step in the evolution of my understanding of social psychological theory came from my collaboration with Bibb Latané. In developing and testing the model of dynamic social impact (Nowak, Szamrej, & Latané, 1990), I could confront my dynamical understanding of theory in social psychology with requirements of rigorous methodology of empirically oriented social psychology. This collaboration has taught me that empirical research is a crucial element in the development of a theory in social psychology. In building the theoretical accounts of a phenomenon, it is critical not only to account for existing empirical results but also to be able to predict new phenomena not predicted by other theories and to actually demonstrate them in empirical research. In discussions with Bibb Latané, I developed my understanding that in dynamical research, theory, simulation, and empirical research form a whole whereby each element plays an important role for the two other elements. The development of a theory happens through repeated iteration of computer simulations that investigate the properties of the theoretical model and empirical investigations that test the model's assumptions and predictions. Without the empirical component, the value of the theory is greatly diminished. Without empirical tests, a theory built only on a simulation model presents more a formal model of abstract phenomena than a theory of a true social phenomenon. It was this mix of simulations and experimentation that distinguished the dynamical theory of social impact from most other computational micro–macro models of social processes.

I have also realized the importance of understanding the essential aspects of the phenomenon that is the focus of a theory. It is critical, of course, to anchor the phenomenon in existing theories. Interestingly enough, Bibb Latané explicitly formulated advice in theory construction, which to a certain degree I had already followed. He learned this rule, which he described as the main secret in theory building, from his advisor Stanley Schachter, who in turn had learned the rule from his advisor Kurt Lewin. Simply put, if you want to built a theory of social phenomena, try to build it before you study other theories of the phenomenon. It is difficult to create a novel theory by following the footsteps of others. You certainly need to study other relevant theories, of course, but only after you have developed the main thrust of your own theory.

Perhaps the greatest influence for my current understanding of theories came from my long-standing collaboration with Robin Vallacher. In our research (Nowak & Vallacher, 1998; Vallacher & Nowak, 1994, 1997), we have tried to build dynamical theories of phenomena from different levels of social reality, as well as explicitly address the issue of how dynamical theories should be constructed. Although often our theoretical interest was focused on finding dynamical principles that are invariant across level of psychological reality, Vallacher paid special attention to the subtle nature of specific psychological phenomena. My lesson was that in building dynamical models of social phenomena, one of the most difficult tasks is to preserve the depth of the understanding of theories formulated in social psychology.

Perhaps the most important message of my collaboration with both Latané and Vallacher is that if one believes that the theory is right and fascinating, one should follow this avenue, even if it is novel and risky to pursue. Both these established researchers have pursued ideas that at the time were hardly mainstream and thus might be viewed as somewhat risky, even if such pursuit entailed a departure from their ongoing lines of theory and research.

The Essence of Dynamical Minimalism

My approach to theory construction has been inspired by many people with different orientations, personalities, and scientific agendas. Yet these influences have converged in important respects and have instilled in me a set of assumptions about human behavior and the means by which human behavior should be investigated. Perhaps the basic lesson is this: To appreciate what is unique about human behavior, we first need to identify what is common across all domains of scientific inquiry. Ironically, what is unique to humans can be understood in terms of general principles that apply in highly disparate levels of scientific inquiry and that cut across levels of scientific explanation. I call this approach dynamical minimalism. It is minimalist in that it attempts to identify the simplest mechanisms that can produce the phenomenon that we are trying to explain.. It is dynamical in that it assumes that the behavior of systems evolves in time through repeated interaction of these fundamental features.

This approach resolves the apparent trade-offs in the construction of social theories. Two canonical assumptions in theory construction are parsimony and reduction. The law of parsimony states that simple explanations should always be preferred. The trade-off is that simple theories may strip the phenomenon of its complexity. The other notion, reduction, postulates that a true explanation must be grounded in only the most rudimentary features of the phenomena. In its extreme one would be left with trying to explain jury decisions with opening ion channels in neurons or, going even further, with quantum wave equations. The trade-off here is that for the sake of reduction, one necessarily strips all the other levels of their significance.

In dynamical minimalism, in contrast, these trade-offs in theory construction are not necessary. Indeed, it is precisely a concern with simple assumptions involving rudimentary elements that allows us to construct theories that incorporate the rich complexity of human behavior and explain the significance of different levels of psychological and social reality.

To apply the principles of dynamical minimalism to the field of social psychology, it is first necessary to discuss the basic assumptions and features of complex systems generally. This insight into the nature of complexity would not have been possible without the advent of high-speed computers and the use of computer simulations. Building on this depiction, I discuss how this approach and its means of implementation have begun to generate insight into different facets of human complexity as well as outline a new theoretical synthesis of an otherwise fragmented field.

From Simple Rules to Complex Properties

The discovery that complex properties may emerge from simple rules is one of the most important discoveries of modern science (e.g., Holland, 1995; Johnson, 2001; Kaufman, 1995; Waldrop, 1992; Wolfram, 2002). Many discoveries across diverse disciplines of science show that extremely simple rules can produce complex phenomena. This is especially characteristic of systems consisting of elements that interact in a nonlinear fashion. Even if the system's elements are relatively simple, nonlinearity in their interactions may lead to highly complex dynamic behavior, such as self-organization and pattern formation (cf. Camazine, 2002; Haken, 1978; Johnson, 2001; Kelso, 1995; Prigogene & Stengers, 1984; Wolfram, 2002). The emergence of both order and chaos, for example, has been documented in neural networks (Amit, 1989) and cellular automata (Wolfram, 1986, 2002), in which the basic elements are essentially binary.

In the dynamical systems approach, it has been shown that even systems composed of a few variables may display very complex patterns of temporal changes (Shuster, 1984). The temporal trajectory of such a system may be chaotic and unpredictable over longer time periods. Such a dynamic is characteristic of weather patterns modeled in meteorology (Lorenz, 1963) or in hydrodynamics (Ruelle & Takens, 1971). Complexity may also be produced in a spatial pattern Very simple rules of interaction of nearby cells, for example, can reproduce the patterns of pigmentations observed in living organisms or shapes of plants and shells (e.g., Meinhart, 1995; Wolfram, 2002) or in the arrangement of columns in visual cortex (Miller, Keller, & Stryler, 1989). Within psychology, the appearance of complexity from simple rules has been demonstrated in both cognitive (Port & van Gelder, 1995) and social psychology (Nowak & Vallacher, 1998; Read & Miller, 1998; Vallacher, Read, & Nowak, 2002).

The realization that complexity may be the flip side of simplicity, rather than its opposition, has profound consequences for theory construction in the social sciences. If simple rules can produce complex phenomena, then complex processes and structures can be explained by simple models. This provides a way to follow the principle of parsimony without sacrificing the depths of our understanding or trivializing what we are trying to explain. It follows that a simple model can be built that will exhibit the complex properties of a psychological or social phenomenon. Complexity may appear in systems governed by simple rules only if these rules interact with each other or with the environment (Goldstein, 1999; Weisbuch, 1992). The minimalist model thus needs to be dynamic.

Building a Theory Based on Emergence

Social psychology has always been concerned with the means by which the individual elements of a phenomenon (e.g., thoughts, behaviors, individual actors) are combined into orderly and complex structures that can perform complex functions such as decision making, goal attainment, or maintaining group coherence. Social psychological theory often assumed that some higher level agent is necessary to impose structure and order on lower level elements. With respect to the human mind, for example, such concerns often led to the notion of the homunculus—the mind-within-the-mind that itself could not be explained without invoking an infinite regress.

The principle of self-organization, a fundamental feature of nonlinear dynamical systems, provides a very different picture of the relation between lower level elements and higher order structure. The basic idea is that the local interactions among low-level elements, in which each element adjusts to other elements without reference to a global pattern, may lead to the emergence of highly coherent structures and behavior on the level of the whole. Such structures then may provide in turn coordination for the lower level elements (Haken, 1978; Kelso, 1995). No higher order agent is necessary for the emergence of such coordinative structures (Camazine, 2003; Gell-Man, 1994; Haken, 1982). Rather than being imposed on the system from above or from outside the system altogether, the higher order structures emerge from the internal workings of the system itself or from interaction of the system with its environment. In this process, the system loses degrees of freedom and the state of the system may be described by a small number of variables. Ironically, then, complex systems can sometimes be described by fewer variables than can relatively simple systems.

The proper theory of the coordination of individual activities in ant colonies does not require an assumption of the ant queen who knows what the pattern should be. Instead, the assumption that each ant reacts to the pattern of activities of other nearby ants is sufficient to explain the differentiation and complexity of life in a swarm (Bonabeau & Théraulaz, 2000). In a process in which individual cells can assemble into an organism in a slime mold, there is no center of coordination; no cell knows the shape of the resultant organism. Instead each cell follows simple rules of interaction with the neighboring cells (Resnik, 1999). This idea can be readily applied to psychological phenomena. The process in which every individual adopts the prevailing attitude of the individual's interaction partners leads to the emergence of coherent spatial patterns of individual opinions on the level of the social group (Nowak et al., 1990). The emergence of self-structure can be modeled in a similar fashion. (Nowak, Vallacher, Tesser, & Borkowski, 2000). In both models, the individual elements (people, thoughts) have no notion of the overall pattern on the macro level. The pattern simply emerges from rules governing individual behavior.

Mechanisms of Emergence

Cellular automata (Von Neumann, 1966; Wolfram, 1986, 2002) are the models of choice for simulating the emergence of patterns from local interactions among elements. A cellular automaton is a computer simulation model composed of elements adopting discrete states; these elements are arranged in a discrete spatial arrangement such as a 2D lattice, and the time proceeds in discrete states. Each cell is characterized by its location and its state. In cellular automaton, the interaction rules are local, in that the state of each cell depends on the state of neighboring states in a way specified by a specific rule. Even very simple rules can produce amazingly complex dynamics, and no direct relation exists between the complexity of the rules and the complexity of the resultant dynamics (Wolfram, 2002).

Cellular automata are especially well suited for simulating social processes (Hegselman, 1996; Nowak & Vallacher, 2002). Each cell corresponds to an individual. Neighborhood structures created by spatial proximity can capture the locality of human interactions. Each individual can thus react to the social context created by other nearby individuals. The updating rules can specify principles governing changes of states of individuals (such as attitude change) or their location in space.

Systems may also self-organize in the process of interaction with their environment. This may happen either in the process of learning or evolution. In this case, the minimalist approach to theory construction is to establish the minimal assumptions that will allow the system to self-organize in the process of interaction with the environment. In a minimalist approach to the question of how can children learn grammar (Culicover & Nowak, 2003), computer simulations were used to establish the minimal mechanisms necessary for the system to be able to develop mechanisms for parsing of sentences. Transcripts of the language spoken to a child were fed into a computer. The number of mechanisms contained in the program was systematically varied. The question was what features of the grammar can the program learn under which types of assumptions. The results indicated that the ability to statistically analyze the regularities in the language is not sufficient for learning the grammar. Such learning is possible, however, when the meaning of the sentences is present when the system is learning them and if in the systems there are mechanisms that can find correspondences between meaning and form. In this approach the minimal assumptions do not correspond to a structure of the system, but rather they concern mechanisms by which the structure may be acquired in interaction with the environment.

Two types of models are most common in which self-organization appears though interaction with the environment. Connectionist models (cf. Hopfield, 1982; McClelland & Rumelhart, 1986; O'Reilly & Munakata, 2000), also referred to as artificial neural networks, are composed of simple elements interpreted as neurons and connections between them, which correspond to synapses. Despite the simplicity of rules governing their behavior, connectionist models can show a host of emergent functions such as a capacity for pattern recognition that surpasses that of humans, generalization, learning statistical regularities of language (Elman, 1995), functioning as content addressable memories, and so on. Recently a host of models of social psychological processes have been built within the framework of connectionist models (cf. Read & Miller 1998; Smith, 1996).

Genetic algorithms (Holland, 1975) are computer simulations that model evolutionary processes. A number of individual elements are simulated on a computer, each equipped with specific characteristics encoded by a set of genes. These elements interact with each other or with their environment in a way specified by their characteristics. A fitness function specifies criteria for determining how well each individual satisfies the requirements of the environment. The individuals with a low value of fitness are eliminated in a process resembling natural selection. Individuals with a high value of fitness replicate producing an offspring. Mutation may alter randomly the genes in the process of reproduction, which introduces variation into population. Because the least fit are eliminated and the best fit reproduce, the level of fitness in the population increases in the course of computer simulation.

Genetic algorithms are capable of producing highly complex structures and solving very difficult problems. Despite the simplicity of the mechanisms, these procedures can lead to the emergence of structures capable of performing surprisingly complex functions. Genetic algorithms can, for example, evolve solutions to mathematical problems that humans can't solve and computer programs capable of performing functions that are difficult for human programmers to program. Within the social sciences, for example, a genetic algorithm was applied to the task of explaining how cooperation can emerge from the concern with maximizing one's own outcomes (Axelrod, 1984).

Levels of Description

The approach of reductionism argues that, in principle, properties of a whole must be reducible to properties its component parts. Along these lines one might try to explain the link between poverty and crime as a group analog of the frustration–aggression principle. In the view of simple reductionism, the complexity of the whole would be dependent on the complexity of its components.

The notion of emergence (Durkheim, 1938; Stephan, 2003) directly counters the claims of reductionism. Radically new properties emerge at each higher level of description. The properties of a group are markedly different from the properties of group members, and thus the laws formulated on the individual level cannot explain laws governing social groups. In a similar vein, in the domain of human cognition, the information processing approach is explicitly based on antireductionist assumptions (Pylyshyn, 1981). In this view, the human mind is just an information-processing device, and the essence of its function are operations on symbols. The underlying biological machinery of the brain is irrelevant to the cognitive functions it performs, and these functions might be carried out in any physical system capable of adequate manipulation of symbols, for example, a computer. The laws that govern the symbolic operations of the mind can be explained in terms of information processing and are shared with logic, computer science, and in particular with artificial intelligence, whereas the laws that govern the brain are biological in nature and shared with other biological systems.

Dynamical minimalism removes the contradiction between reductionism and emergence. It shows how the principle of parsimony may be applied without detracting from depth of understanding. The aim of the theory according to this approach is not to describe the higher level phenomena in terms of the lower level phenomena; rather, it is to propose rules at the lower level from which the higher level phenomenon emerges in its natural form and complexity.

Models of Qualitative Understanding

Models of qualitative understanding allow us to combine the rigor associated with precise models and the heuristics of verbally stated theories. Although precise, often mathematically expressed rules are used to build models that are investigated by computer simulations, the generic properties of these models can be expressed in verbal theories. In this approach, one does not strive to find an exact match between the model and empirical data, but rather attempts to achieve qualitative understanding of the phenomenon. As Fiske (this issue) observes, in psychology, even if theories are built in the form of mathematical theories, usually they are absorbed by the field of psychology as their verbal descriptions. Dynamical minimalist models that are most likely to have an impact on psychological theories are models of qualitative understanding.

It can be noted in this regard that physics and other natural sciences also use the qualitative approach. In complex nonlinear systems, prediction may be difficult and limited, or simply impossible (e.g., Schuster, 1984; Wolfram, 2002). We may concentrate, however, on finding patterns in the data instead of testing predictions (Nowak, Lewenstein, & Vallacher, 1994). In this approach, one tries to isolate and explain the most important features, which often are the qualitative aspects of the phenomenon.

Usually in science, we look for patterns that correspond to a causal relation in which one event reliably follows another. Other patterns may express a linear relation, in which the values of one variable are correlated with values of another variable. Many other kinds of relations are also possible, however, that cannot be subsumed by causality or linearity. Examples include the wavelike pattern of an individual's behavior (Newtson, 1994), the complex forms of behavior coordination between individuals in relationships (Baron, Amazeen, & Beek, 1994; Nowak, Vallacher, & Zachowski, 2001), the spatial distribution of attitudes in a society (Nowak et al., 1990), the distributions of attitude values on a dimension (Latané & Nowak, 1994), the oscillations over time in social judgment (Vallacher, Nowak, & Kaufman, 1994), the regularity of changes of oscillations in self-evaluative thought (Vallacher, Nowak, Froehlich, & Rockloff, 2002), and patterns of movement coordination (Kelso, 1995).

From the dynamical point of view, perhaps the pattern most frequently assumed by psychological theories is that of the system converging on a point attractor. In the absence of outside forces, the system will converge on a specific value. The system is trying to stabilize on this value and resist perturbations. If perturbations occur, the system will engage mechanisms designed to reinstate this value (Nowak & Lewenstein, 1994). Homeostasis (Cannon, 1932; Hull, 1943) is an example of fixed-point attractor dynamics, as are the notions of optimality (Berlyne, 1960) and standards of self-regulation (Carver & Scheier, 1998; Powers, 1973).

More than one attractor can exist in a system. A qualitative change in dynamics would correspond to the change in the system's number or type of attractors. This type of change, called *bifurcation*, is a fundamental feature of dynamical system theory (Ruelle, 1989). How a change in a system's attractors can occur is also the subject of catastrophe theory (Thom, 1972). A model of qualitative understanding would attempt to explain the change in the structure of a system's attractors. Such models in psychology have been implemented with respect to attraction and love (Nowak & Vallacher, 1998; Tesser & Achee, 1994) and the distribution of attitudes in a social system (Latané & Nowak, 1994). In such models, insights from formal models are usually presented as verbal theories rather than as mathematical formulas.

Qualitative models offer fundamental understanding of social phenomena from a new perspective. Even if the model makes predictions that are trivial from the point of view of social science, what may be not trivial is the simplicity of rules that allow us to make such predictions. Although it may be unrealistic to seek a direct match between the phenomenon and the model, the model indicates the most important factors affecting the phenomenon and in what manner the phenomenon will change following changes of these factors.

Models of qualitative understanding may even be used to plan practical interventions. The knowledge of qualitative factors influencing social change that emerged as a result of computer simulations of social influence models, for example, has made it possible to plan a successful large-scale program aimed at reducing unemployment (Nowak, Kus, Urbaniak, & Zarycki, 2001; Nowak & Vallacher, 2001).

Computer Simulations

In recent years, computer simulations have proven to be the tool of choice in developing models of social dynamics (Gilbert & Troizsch, 1999; Liebrandt, Nowak, & Hegselman, 1996; Nowak & Vallacher, 2002). Computers enable one to investigate a large number of interacting elements and to track the behavior generated by these interactions over many trials. There are many approaches to computer simulation in both the natural and social sciences (Hegselman, Troitzch, & Muller, 1996). In social psychology, the most popular approach models the emergence of global properties from the interactions of individual elements. In models of social cognition, elements correspond to components of the cognitive system, and the global level refers to macroscopic properties of the system such as decisions and judgments (cf. Smith, 1996). At a higher level of social reality, elements correspond to individuals and the system-level properties refer to such group-level phenomena as the emergence of public opinion (Nowak et al., 1990) and cooperation in social dilemma situations (e.g., Messick & Liebrand, 1995).

Among the many advantages of computer simulation (cf. Gilbert & Troizsch, 1999; Liebrand, Nowak, & Hegselman, 1996; Nowak & Vallacher, 2002, Nowak, Vallacher, & Burnstein, 1998), two are particularly noteworthy with respect to social psychology. Computer simulations, first of all, allow one to investigate the relation between micro and macro levels of social reality. In a prototypical example, we can equip individual elements with established rules of behavior. Because there are many such elements in a computer simulation, we can observe how these rules give rise to global properties for the set of elements as a whole. In a reversal of this procedure, we can start with known global phenomena and trace backwards to discover what rules on the level of individual elements are necessary to produce the system-level phenomena.

The second noteworthy advantage of computer simulations is their capacity to reveal temporal patterns. In social psychology, temporal aspects of interpersonal phenomena are largely unexplored. Yet, in many instances it is unreasonable to expect the effects of a given cause to be revealed immediately. An insult may produce hate, but the development of such a feeling may take a relatively long time to develop. Although love at first sight is a frequent subject of novels and movies, in reality many interactions and prolonged contact may be necessary for a romantic attraction to develop. The very nature of computer simulations makes it very easy to study the effects of multiple iterations of a given process. Decades of real time, and thousands of real interactions, may be compressed into seconds of computer time, revealing delayed consequences that simply cannot be observed in real time. In sum, computer simulations are ideal tools to investigate the dynamic consequences of a theory.

Computers are also the most potent tool for visualization of both experimental and simulation data. Computer visualization makes it possible to discover patterns existing in reality and predicted by theory. With visualization, one can literally see the emergence of temporal and spatial patterns in a social psychological process, whether the spread of public opinion through social influence (Nowak et al., 1990) or the progressive differentiation of self-concept through socially provided feedback on one's qualities (Nowak et al., 2000). The comparison of patterns inherent in experimental data and produced by computer simulation of a model provides a new means of verifying a theory.

Bridging Levels of Description

Computer simulations are most useful for investigating phenomena across levels of description. In such simulations rules and interactions at the lower level produce emergent properties at the higher level. Interesting properties are not input into the model at the micro level. Models are usually trivial at the level at which they are constructed. Properties become interesting at a macro level. Consider, for example, the relation between specific thoughts and higher order mental structures, such as attitudes and self-concept. In a recent model of self-concept (Nowak et al., 2000), the micro level corresponds to individual elements of self-relevant information. The properties of these elements are extremely simple: An element has a value of centrality (importance) and position in a grid such that neighboring elements are relevant to each other in content. These properties do not change in the course of the simulations. Each element has also valence (positive or negative). The rule of self-organization is amazingly simple: Each element adopts the valence that is prevailing among the neighboring elements. As computer simulation reveals, interaction of such simple elements produces effects observed in many psychological experiments concerning self-structure such as evaluative integration and differentiation, positivity bias, and resistance to incoming disconfirming information. What is interesting in this simulation does not concern the low-level description, but the fact that such a simple description can produce a host of phenomena empirically observed in the research on self.

Computer Simulation and Theory Construction

The essence of the minimalist theory is to find the minimal conditions under which interesting patterns will emerge. To construct a minimalist model, we need to include in the model only the essential features and rules. Systematic use of computer simulations can tell us which properties of the model are critical for emergence. The first step is to establish the conditions defining the class of models in which the phenomenon of interest occurs. In the search for the critical properties, one progressively strips the model of its features until the emergent phenomenon vanishes. Alternatively, features can be varied and substituted by other features to establish which combinations of features are necessary for emergence to occur. Those features that are absolutely necessary for the phenomenon to emerge constitute the minimalist model. The rest of the features may be ignored in the explanation of the essence of the emergence, even if we know that they appear in reality.

Computer simulations may be used to check which variables correspond to control and order parameters of the model (e.g., Latané & Nowak, 1997). To identify the control parameters, one has to run the computer simulation model and systematically vary all the variables in the model. By observing the model's behavior, one can identify the qualitative states or patterns exhibited by the model. For a variable to qualify as an order parameter, different values should distinguish between these qualitatively different states (e.g., Latané, Nowak, & Liu, 1994). Control parameters, meanwhile, are those variables that decide which pattern of dynamics the system adopts. As opposed to other factors influencing the system, in other words, variation in the magnitude of control parameters result in qualitative changes (i.e., phase transitions) in the behavior of the system. Other variables, although they may have quantitative influence, are of secondary importance.

For a model to be complete so that it can serve as a basis for computer simulations, it must contain more assumptions then the minimalist set of essential features. By using computer simulations, and systematically varying all the assumptions, we can isolate the most important assumptions and then concentrate our efforts on empirical verification of only these assumptions. 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 90% (an overestimate as compared to our subjective judgments), the chance that the model (i.e., all of the assumptions) was right equaled 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 & Latané, 1994). Later analytical considerations (Lewenstein et al., 1993) and computer simulations (Nowak & Latané, 1994) have shown that of all the factors, three are of critical importance for the qualitative behavior of the model: the geometry of social space in which interactions take place, the existence of individual differences between individuals, and the nonlinearity of the change of attitudes. 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.

Because the essence of the model is the transition between micro and macro levels, the model should also be tested on both the micro and level. On the micro level, it is important to verify empirically the viability of the model's assumptions. On the macro level, predictions concerning the properties and behavior of the model need to be subject to empirical tests. By itself, the ability of the model to match quantitatively the pattern of experimental data is not a sufficient criterion for accepting the model.

Minimalist Psychology

Construction of theory in psychology faces difficult choices. Because the subject matter of psychology is highly complex, describing it in simple terms is likely to trivialize the phenomena and lose the depth of our understanding. Occam's razor, on the other hand, requires that the simplest theory of the phenomenon be accepted. Integration of our knowledge indicates the need for reductive explanation, whereas the emergent nature of psychological and social phenomena indicates that no reduction is possible.

Dynamical minimalism invalidates the long-cherished assumption regarding the apparent contradiction between parsimony and complexity as well as between reduction and emergence. In dynamical models, simple rules on the lower level can lead to the emergence of very complex structures and processes an the higher level. Thus without forfeiting our depth of understanding regarding the phenomena, we can propose simple rules that will generate the phenomenon in its complexity.

Beyond that, dynamical minimalism offers the promise of providing coherence to a highly fragmented field. This is possible because this approach identifies formal principles that cut across common boundaries. Although two structures or processes may have very different surface properties, the underlying rules leading to the emergence of their properties may be the same. Public opinion and self-understanding are very different phenomena, for example, but very similar rules may underlie the emergence of coherence in both phenomena (e.g., Nowak et al., 1990, 2000). Because dynamical minimalism explicitly provides a means of integrating different levels or reality, it offers a unique link between our understanding of micro and macro levels of social reality.

Theory constructed in the tradition of dynamical minimalism has a specific form. It concentrates on providing very simple explanations of complex phenomena. It is simple to the point of sounding trivial in its description of the micro level. The essence of the theory is in finding the correspondence between simple rules at the micro level and properties to be explained on the macro level. The rules specify systems dynamics, and only this dynamics leads to the emergence of the phenomenon we are trying to explain.

Computer simulations are the tools of choice in finding the macro consequences of different rules acting on the micro level. The principle of computational equivalence states that "all the processes both natural and produced by humans may be viewed as computations" (Wolfram, 2002, p. 715). Computer simulations give us the chance to observe emergent properties in seconds or minutes, rather than having to wait for years or decades for the process to conclude in reality.

As with all theories, dynamical minimalist theories need to be verified empirically. In fact, the success of a theory that follows the principles of dynamical minimalism is to maintain a balance among the development of a theory, computer simulations, and empirical verification.

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