ON COMMUNICATION. AN INTERDISCIPLINARY AND MATHEMATICAL APPROACH

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ON COMMUNICATION.
AN INTERDISCIPLINARY AND MATHEMATICAL APPROACH

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PREFACE

This book originated in the last four years when we were lecturing both in communication and computer science at the University of Duisburg-Essen, Germany. Therefore, it was rather obvious for us to integrate these two scientific disciplines and to analyze the problem of the general logic of communicative processes by the use of suited computer models and mathematical concepts. The result of these efforts is this book and it is up to the readers if our attempts are successful.

We could never have finished this study without the enthusiastic interest of many students in both sciences. Several of them are named in the book who implemented specific computer programs as part of their respective MA-thesis. We have also to thank several colleagues in communication and computer science, who supported our work in many ways. We frequently experienced that the old and venerable paradigm of especially the German University "the unity of research and teaching" (Humboldt) is far from dead and can be updated any time, provided a suited research project.

Our special thanks go to Jörn Schmidt from the former Center for Interdisciplinary Research in Higher Education at our University, whose constant help was invaluable to us.

Each new scientific approach is only possible because it stands, to quote Newton, “on the shoulders of giants”. Therefore, we dedicate this book *in memoriam* to two great pioneers in communication science, namely Claude E. Shannon and Gerold Ungeheuer.

Essen, Summer 2006

Jürgen Klüver   Christina Klüver

CHAPTER 1

INTRODUCTION: COMMUNICATION – PROBLEMS OF A CONCEPT AND A NEW METHODICAL APPROACH

If any researcher wants to write about the social and/or cognitive conditions of human life then it is nearly impossible not to mention communication in one or another sense. Therefore, one can take any social and cognitive discipline like sociology, economics, psychology or anthropology and one will find communication at its core or at least at its periphery. The number of books that have been written on communication from one point of view or the other has for a long time transcended the receptive capabilities of single researchers. Thus being the case it seems quite hopeless to write about this subject without repeating considerations and insights that others have found out long ago.

To make matters even worse, communication is also a concept that is frequently used in the natural and computer sciences. Biological cells are "communicating" in order to generate and to preserve the organism; computer programs are "communicating" and sharing "information" and of course humans and computers are also "communicating". Apparently the whole universe can be looked at as one gigantic communicative system; therefore, writing on communication is to write about everything.

Yet despite the fact that communication is probably one of the most used concepts in scientific – and non-scientific – discourses there is no general theory of communication scientific users of this concept will agree upon. On the contrary, it may be that the nearly universal use of the term of communication is only possible *because* there is no general theory of communication, and not even a general definition that is obligatory for scientific users. Communication seems to be fruitful for rather different applications because no particular discipline may claim it as its rightful domain and define it in a way all scientific users have to acknowledge.

To be sure, there are numerous definitions of communication and many theoretical attempts to analyze it. But none of these, as important as they are for specific disciplines, are obligatory for other scientists and in particular for scientists from other disciplines. The sociologically grounded definitions by Luhmann (1984) for example are not relevant for cognitive scientists; the considerations of Bateson (1970 and 1972) are not interesting for most of social scientists, and reflections on communication by psychologists will be ignored by computer scientists, natural scientists, and social scientists likewise.

In our opinion it is not by chance that communication is one of the most used concepts in scientific and everyday discourses. In a rather abstract sense communication is indeed the key concept for many different phenomena and, therefore, scientists from different disciplines are bound to use it in their own fashion, although the term is often not precisely defined. The general definition of communication that we shall introduce and use for the purpose of this book is in contrast to the different definitions used in specific disciplines applicable to rather diverse realms of research, i.e., physical, biological, and social-cognitive fields as well as to computer science. Of course, definitions on such general levels often tend to be empty, that is they are not fruitful for particular empirical investigations. Yet we hope that the definition we give and that is formulated in terms of complex systems theory will be not only general but also useful to specific empirical research.

As there is no general definition of communication there is also no general precise theory of it that earns the name. There is of course the "mathematical theory of communication" by Shannon and Weaver (1949) that is frequently used in the natural and computer sciences. But this theory deals "only" with the concept of information, as Shannon and Weaver explicitly pointed out, and it does not analyze the concept of meaning. In particular, nothing is said by this theory about the aspects of human communication. Therefore, the theoretical schema of Shannon and Weaver may be still useful for technical purposes and in the natural sciences, but a lot of social and cognitive scientists has often and rightly stressed the point that human communication cannot be reduced to the information processing models in the tradition of Shannon and Weaver (e.g. Krallmann and Ziemann, 2001). Although we believe that the Shannon-Weaver approach is still useful and hence use the basic idea of their definition of information for our theoretical goals, we also believe that this approach must be enlarged in several ways. In chapter 3 we shall reformulate their famous definition of the degree of information and show that it is possible to give a similar definition that is compatible with an according definition of meaning.

Although the approach of Shannon and Weaver is much too restricted for the use of social and cognitive investigations it is one of the few attempts to deal with the problem of communication in a precise, i.e. mathematical manner. Therefore, it is, e.g., no accident that often the term "theory of communication" is identified with their theoretical frame, i.e., as "the study of the principles and the methods by which information is conveyed" (Oxford Dictionary 9th edition). In this sense their approach still must be looked at as paradigmatic and other approaches like, e.g., the "situational theory" of Barwise and Perry (1987) did not reach the level of that classical theory (cf. also Devlin, 1991). On the other hand, the numerous attempts of philosophers, cognitive and social scientists to catch the complexity of communication and to take into account the fact that communication has something to do with the transfer of "meaning", never succeeded to give precise, i.e., formal foundations for a theory of communication in a strict scientific sense. On the contrary, many researchers on communication from the social and cognitive sciences and the humanities seem to believe that a formally precise theory of communication is not possible at all. As a result, nearly each theorist gives his own definitions and uses the concepts accordingly.

It is not the purpose of this book to enumerate and discuss all the important approaches with respect to the theoretical foundations of communication (cf. e.g. Anderson, 1996; Favre-Bulle, 2001). We rather try to develop some new ways to deal with this problem and to show the possibility of a precise theory of communication. Because the methodical way we use in this study is still comparatively new for most researchers in the social and even cognitive sciences we first have to explain our own theoretical framework and give some introduction into the key concepts and formal methods that we shall use. To put it into a nutshell, we shall define communicative processes as complex dynamical systems that depend on their social context on the one hand and the particular cognitive dynamics on the other hand that is generated by the communicative processes. Therefore, communication has to be understood as the interdependency of two kinds of dynamics, i.e., a social interactional one and a cognitive one. Because we are able to demonstrate that both social and cognitive dynamics can be defined in a precise mathematical way, it seems possible to reach the goal of a mathematical theory of communication that is not restricted in the way the classical approach of Shannon and Weaver and their followers was and still is.

By aspiring such an ambitious goal we have to prove, of course, that our theoretical frame is capable to define not only the concept of information but at least also that of meaning. Although the terms of information and meaning are often used as equivalent in everyday language – and not only there – it is quite clear that these concepts are by no means synonymous. On hindsight it seems a bit unfortunate that Shannon and Weaver on the one hand explicitly stated that they did not deal with "meaning" but that on the other hand they named their theory as a mathematical theory of *communication*. In this way they suggested that communicative processes are just the transfer of information and because they defined "information" in the famous way burrowed from thermodynamics they seemed to imply that communicative processes are something akin to thermo dynamical ones. In other words, they seemed to postulate a particular form of epistemological reductionism, i.e., the reduction of communication to physical processes. We do not know if this was indeed their intention, but it is a fact that their theory was not seldom understood that way. It is no wonder that social and cognitive scientists often believed that such a theory is rather useless for their own problems.

The basic assumption of our approach is at the core a truism: communication is understood as a basically social process that is regulated by certain social rules of interaction on the one hand and determined by cognitive processes of the communicators on the other hand. Therefore, communication is indeed at the core of society and cognition likewise: social actors communicatively interact via the regulation of social rules and thus generate social reality, but social actions are also determined by the cognitive world views of the actors in a specific situation (Berger and Luckmann, 1966). In this sense all social interactions are communicative processes because they depend on the respective social rules *and* the beliefs, knowledge etc. of the communicators, i.e., their cognitive processes. Being a social actor is being a communicator – even Robinson had to construct his own communicative community first with himself and later with Friday in order to remain a social being.

To be sure, human actions are not to be reduced to communication alone. The well-known distinction of Habermas (e.g. Habermas, 1968) between labor as action in regard to material reality on the one hand and social interaction on the other demonstrates that societies are not only communicative systems as, e.g., Luhmann and his followers believe. The "material basis" (Marx) of society is not to be neglected if one thinks about society as a whole. Societies are not isolated monads but are systems within a material environment and the according development of the *Produktivkräfte* (forces of production) determine the evolution of societies as much as the development of social structures. Therefore, it is necessary to place communication in the context of Max Weber's famous definition of *social* action distinguished from the non social form of labor. By taking this *caveat* into account one can say that society is generated and reproduced by social actions and the *social* organization of labor; in this sense communication is indeed at the core of society and hence it is no accident that all social sciences have to deal with this concept.

The social process of communication is also crucial for cognitive processes, in particular cognitive development, as has often been pointed out. It is also no accident that even neurobiologists recently admit that the human brain can only completely be understood as the result of communicative processes, i.e., social interactions (cf. Singer, 2000). Of course, cognition cannot be reduced to communication either. There are a lot of cognitive processes that can only be understood as "autopoietic" (Maturana, 1982) self-organizing processes of the brain (or the mind, respectively). But cognitive development as well as every advanced cognitive achievement depends on social environments and that is on communication. Therefore communication is a key concept not only in the social sciences but in the cognitive sciences too. We shall more thoroughly deal with these problem in the following chapters.

In contrast to the definition of the Oxford Dictionary we understand communication not only as the transfer or exchange of information but also and probably even more important as an exchange of *meaning*. We are quite aware of the fact that "meaning" is even more ambiguous than "communication"; that is why we have to give a precise definition of meaning in the terms of our theoretical frame. But no theory of communication can claim conceptual completeness that does not capture the concept of meaning; in particular it must be shown that "information" and "meaning" are on the one hand different concepts but that on the other hand they must be understood as two aspects of the same process.

The methodical approach we develop in this book consists of a) the theoretical frame of complex dynamical systems theory and b) the use of computer simulations, i.e., the construction of formal models and their experimental investigations by the runs of the according computer programs. In addition we shall show that and how particular computer based models of communicative processes can be empirically validated. Because we use specific models and computer programs of a kind that is called "Soft Computing" – a term created by Zadeh, the inventor of fuzzy set theory – we shall introduce not only the theoretical frame but the formal models of Soft Computing too. To put it into a nutshell, we "translate" the concept of communicative processes into the particular theoretical and mathematical concepts of complex systems theory, develop according computer programs based on the techniques of Soft Computing, perform computer experiments in order to gain some general insights into the regularities of communicative processes, and last but not least undertake to validate some of the programs by comparisons with empirical social experiments. In order to do this we have, of course, to define – and discriminate – the different aspects or "dimensions" respectively of the complex process of communication. In particular, we shall demonstrate how the modeling of the social and cognitive dimensions of communication can be done.

To be sure, we do not claim to give a *complete* theory of communication in this book, which is for several reasons at present not possible. But we hope to demonstrate that a "mathematical theory of communication", to quote Shannon and Weaver again, can now be considered as a concrete goal, namely a theory that is not reductionist in the sense that it reduces the general phenomenon of communication to the too narrow frames of physical concepts.

According to these theoretical and methodical considerations we can now present a general definition of communicative processes; if it is not explicitly said otherwise communication is understood here as communication between human communicators: Communication is a (dynamical) process that consists of at least two *communicators* A and B who perform *communicative* acts. Each communicator must be considered as a *complex cognitive system*; the communicative acts generate a *cognitive dynamics* in each of the respective communicators. The communicative acts are to be understood as the transfer and exchange of *meaning and information*; the acts are regulated by *social rules and rules of the production of signs*; the signs are often coded as symbols. Therefore a communicative situation – or a communicative system respectively – consists of different communicators, certain social rules that regulate the *interactional dynamics* between the communicators, *semiotic production rules* that regulate the combination of the signs or symbols respectively, which are used in the communicative situation, and *cognitive rules* that regulate the cognitive dynamics of the communicators. The communicative process understood this way is started with the introduction of a communicative theme that generates certain initial cognitive states of the communicators.

The communicative process then must be considered as a two-dimensional dynamical process: on the one hand the social rules and social "topology" (see below next chapter) generate a particular interactional dynamics between the communicators; on the other hand cognitive rules and cognitive topologies generate a certain cognitive dynamics, i.e., the cognitive processing of the messages; finally the whole communicative process and its particular dynamics is regulated by a mutual interdependency of the interactional and the cognitive dynamics. We may therefore characterize the dynamics of communication as the result of two interplaying kinds of dynamics, which is determined by three types of rules. Yet in many cases it is sufficient to consider only the social and cognitive levels of communication.

Readers who are acquainted with the general semiotic theory of signs will immediately perceive the proximity of this general definition to the three-dimensional model of signs by Morris (1970). "Meaning" and "information", of course, refer to the semantic dimension of signs; social rules and topologies refer to the pragmatic dimension and the concept of semiotic production rules refers to the syntactical dimension. In a rather abstract sense our general definition may be understood as the transformation of the classical model of Morris into the framework of complex dynamical systems. By the way, this definition of communicative processes demonstrates the advantages of our particular approach. It allows to model communication, cognition and social interaction quite naturally within one and the same theoretical framework.

To be sure, such a general and abstract definition tells us nothing about the particular kinds of dynamics and the kind of interdependency between them. In particular nothing is said about the definitions of meaning and information in terms of complex systems theory. Because these two concepts are the decisive concepts for each communicative theory we have to clarify them. But as the according definitions are based on the conceptual framework of complex systems theory we have to start with an excursion into this field. Readers who are already acquainted with the general concepts of complex systems theory may, of course, pass over this chapter and go directly on to the definition of meaning and information.

CHAPTER 2

EXCURSION INTO COMPLEX SYSTEMS THEORY

2.1. GENERAL CONCEPTS

Although or perhaps because the concept of "complex systems" is nowadays used in rather different contexts the meaning of this concept is by no means always clear; in particular the combination of "complex systems" with the methodical and theoretical terms of "systems dynamics" is still not very frequent in the cognitive and social sciences. Therefore we give a brief introduction into the main concepts of these fields; for more details we refer to the respective literature (cf. Kauffman, 1995; Mainzer, 1997; Gell-Mann, 1994; Holland, 1998; Klüver, 2000). Nevertheless we shall see that it is necessary for our purposes to enlarge the well-known definitions.

According to the classical definition of von Bertalanffy (1956) a system is defined as a set of elements, which interact via local rules of interaction. The elements of the system are characterized by a particular state at a certain time t; the interactions of the elements determine the changing of the element's states. The whole system is at time t in a systems state S_t ; this state is usually defined by a mathematical aggregation of the element's states at the same time. Because the local rules of interaction determine the changing of the element's states, the rules also determine the changing of the system's state. Therefore, we may consider the ensemble of the local rules of interaction as a system function f that recursively generates new systems states from the preceding ones. In a more formal sense we obtain

$$(1) \qquad f(S_t) = S_{t+1},$$

if we designate S_{t+1} as the system's state at time $t+1$. In general, if we call S_0 the initial state of the system, e.g., at time $t=0$ when our observations of the system start, we obtain

$$(2) \qquad f^{n+1}(S_0) = S_n,$$

if we designate by f^n the nth iteration of f and by S_n the nth state that is generated by the recursive applications of the ensemble f of the rules of interaction. In a mathematical sense we may consider f as a mapping from state S_k to the state S_{k+1}.

This general definition, of course, says nothing about the particular rules and the order of recursively generated states. The system function f may be a deterministic one, if all the local rules are deterministic, and it may be a stochastic function. In the later chapters of this book we shall introduce rather different kinds of rules and according systems functions.

The dynamics of a system is now defined as the particular succession of states that is generated by the local rules, i.e., the system function. It is important to note that the dynamics of systems defined in this way is always an emergent phenomenon produced by the local interactions. Often the dynamics of a system is considered as a path in the state space of the system: each specific state is defined as a point in a multi-dimensional space that consists of all possible states the system can *principally* realize. The particular path a system generates by applying the system function is called the trajectory of the system. Note that a specific trajectory is dependent not only on the rules, i.e. the systems function f, but also on the particular initial state(s) S_0.

Often the trajectories of systems are visualized in a two-dimensional state space or in a plane that is defined by two dimensions of the states of the elements and hence of the system. As an example we give two visualizations of the model of a predator-prey system that was constructed by us and Jörn Schmidt on the basis of a cellular automaton (see below). The figure 1 shows the trajectory of the system, the figure 2 shows the variation of the number of preys and predators respectively with a time curve for each population.

Often the dynamics of a complex system is characterized by particular states S_A that have the property

(3) $$f^n(S_A) = S_A,$$

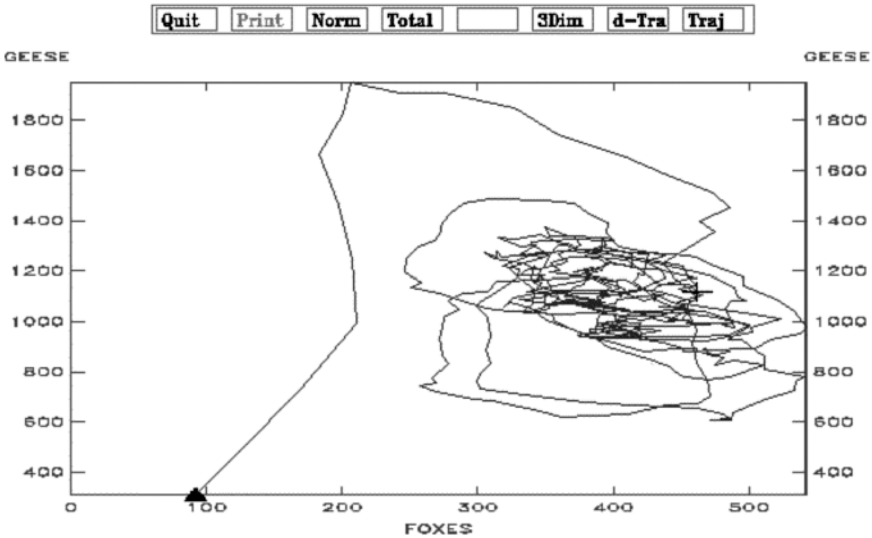

Figure 1. The trajectory of a predator-prey system in a two dimensional state space; the dimensions are defined by the numbers of prey and predator respectively

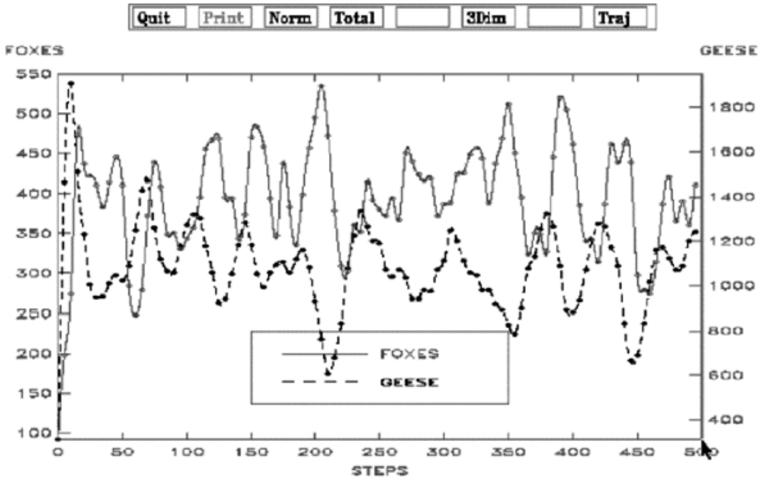

Figure 2. The interdependent variations of the numbers of prey and predator; the connected curve illustrates the variation of the number of prey, the other that of the predator

for all n. In this case S_A is called a point attractor of the trajectory of the system or briefly a point attractor of the system. If we get

$$(4) \qquad f^k(S_A) \text{ and}$$
$$f^i(S_A) = S_A \text{ for } i = n * k$$

we speak of a (simple) attractor of period k; in this case the attractor contains all the states the system generates between the first and the second time of the generation of S_A. In other words, an attractor "attracts" the trajectory of the system and keeps it at this state (point attractor) or in the successive k states that define an attractor of period k. Mathematically speaking, an attractor is characterized as a point or a segment in the state space that draws the trajectory to the point or segment respectively. Readers who are acquainted with the mathematics of function theory will perceive that the attractor concept is basically nothing else than the well known "eigenvalues" of a function introduced by Hilbert. The definition given above is a generalization of it in the sense that it is also applicable to discrete system functions. In chaos theory often so called "strange attractors" are investigated too. Strange attractors are also defined by a segment of the state space that the trajectory does not leave any more; in that segment the trajectory may reach any point of the segment and is only difficult to predict. Such systems are called chaotic or quasi chaotic.

Because the specific trajectories of a system are, as we said, dependent on the system functions and the respective initial states, a system may generate rather different attractors according to the respective initial states. In particular a system may generate several different states after the initial state before it reaches an attractor. The succession of these states is called the preperiod of the respective attractor.

The trajectories of a system which start at different initial states may finally reach the same attractor. The set of all initial states that are characterized by the same attractor S_A as the final point or segment in the state space of their trajectories is called the basin of attraction of the attractor S_A. With a picture from Kauffman (1995) one canvisualize the basin of attraction as a set of different creeks all flowing from different mountains into the same lake. The set of all basins of attractions of a system is the basin of attraction field, i.e., the set of all equivalence classes of initial states defined by their generation of the respective same attractors. In other words, an element of the basin of attraction field is a class of trajectories that all end in the same attractor.

Wolfram (2002) has classified the dynamics of complex systems by introducing four different complexity classes, the so called Wolfram classes. Class 1 is the simplest and is characterized by the fact that all different initial states lead to one and the same attractor, usually a point attractor. Class 2 generates different attractors but only point attractors or those with rather short periods. Class 3 is the class of chaotic or quasi chaotic systems: their trajectories are characterized by attractors with very long periods and even strange attractors. Class 4 is a mixture between class 2 and class 3: it generates all types of attractors with the exception of strange attractors; the different attractors do not influence the whole system but can remain locally fixed. In contrast to class 4, systems of class 3 literally never get any rest, i.e., never reach point attractors because all parts of the system influence the other ones. Systems belonging to class 3 and 4 are very sensitive in regard to initial states: they generate nearly always different attractors when starting with different initial states. Systems of class 1 and 2 on the other hand always or often are not susceptible to the changing of initial states; that fact explains in a very general mathematical way why many complex systems, e.g., physical ones, come back to rest after having been disturbed by external causes.

Kauffman (1993, 1995), Langton (1992) and others have shown that it is possible to predict the *principal* kind of dynamics a system may obtain by so called ordering

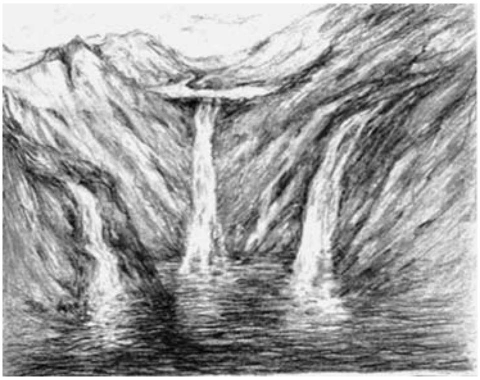

Figure 3. Visualization of a basin of attraction (drawn by Magdalena Stoica)

parameters (Klüver, 2000, 2002). Ordering parameters are a property of the specific rule ensembles of a system: for example, if the number of possible states that the elements of a system may obtain is two, e.g., 1 and 0, and if the rules are such that the state 1 is reached in proportion 3/4 to state 0, then the so called P-parameter of the system's rules is $P = 0.75$; if both states can equally frequent be obtained, then $P = 0.5$ and if only one state can be reached for all elements then $P = 1$. The interesting point is now that only rules with $0.5 \leq P \leq ca.0.65$ can generate trajectories that belong to Wolfram class 3 or 4. Rule ensembles with all other P-values generate only trajectories belonging to class 1 or 2. The other known ordering parameters have similar characteristics, namely that only small ranges of their values generate trajectories with complex dynamics, i.e., dynamics belonging to Wolfram classes 3 or 4. It seems a safe conclusion that the "origins of order" (Kauffman, 1993), i.e., complex systems whose trajectories reach simple attractors with only very small periods is just a question of mathematical probability: order must necessarily evolve because it is much more probable than systems with no simple attractors or those with long periods.[1]

When speaking of the rule ensembles of complex systems another important distinction must be made: complex systems are not only defined by their local rules of interaction that determine the changing of the element's states but also by "topological" rules that determine which elements can interact with which others (Klüver, 2000; Klüver and Schmidt, 1999a). Rules of interaction are executed if the respective local conditions are fulfilled, but the rules do not tell us which elements of the system will interact at all. This is determined by the topology of the system, i.e., rules that define the possibility of local interaction. The frequently only metaphorically used concept of the "structure" of a system means in a precise sense just that. In many cases the topology of a system can be characterized by a binary adjacency matrix that tells if certain elements interact or if they interact only via other elements (cf. Freeman, 1989 for the case of social networks).

It is interesting to note that the topology of a system also determines its dynamics: Klüver and Schmidt (1999b) discovered another ordering parameter v that exhibits a characteristic of the adjacency matrix of Boolean networks (see below). Roughly speaking this ordering parameter defines the mean value of the influences certain elements have on other ones. If all elements have equal influence on the other ones, the parameter value is $v = 0$; if the influences are such that they are extremely unequally distributed, then $v = 1$. As an ordering parameter v has the effect that a topology with $0 \leq v \leq 0.25$ generates complex dynamics, i.e., trajectories belonging to Wolfram classes 3 and 4; $0.25 < v \leq 1$ generates only simple trajectories. In other words, the more equal the elements are in regard to the possibilities of influencing other elements, the more complex the system's behavior will be and vice versa.

[1] It must be noted that these results with respect to ordering parameters are "only" statistical ones: there are always exceptions, i.e. systems whose parameter values do not follow these regularities. Therefore, the probability of the emergence of order is still valid but only as a statistical regularity. But these are questions for specialists (cf. Klüver et al. forthcoming).

Because the other ordering parameters also measure certain degrees of inequality, although in other dimensions, it seems plausible to postulate a conjecture of equality:

The more equal a system is in different dimensions, the more complex its behavior – its dynamics – will be and vice versa. Because only rather high degrees of equality will generate complex dynamics the origins of order is a consequence from the fact that most systems will necessarily exhibit more degrees of inequality than of equality (Klüver, 2002).

These considerations demonstrate that a lot can be learned about the regularities that determine the behavior of dynamical systems by applying the concepts of complex systems theory. Yet these concepts do not take into account the important cases when systems evolve, i.e., when they do not keep their rules of interaction and/or their respective topology constant. After all, a lot of very important processes of complex systems can only be understood by taking into consideration that rules of interaction and topologies can and will be changed. Among those processes are biological evolution, individual learning and sociocultural evolution (Klüver, 2002). Therefore the definitions given so far must be extended.

We call a system *adaptive* if it is capable to change its rules of interaction and/or its topology according to certain demands of its environment. In particular an adaptive system must be able to evaluate its own states with respect to the environmental criteria and change its rules and topology accordingly. In order to do this an adaptive system must have some *meta rules* that regulate the changing of the local rules and topology; the evaluation of its own states must be done by the equivalent of some *evaluation or fitness function* respectively. Therefore, an adaptive system is characterized a) by its rules of interaction and its topology, b) by the meta rules that determine the variation of the interaction rules and the topology and c) by an evaluation function that determines if and when the rules of interaction have to be changed. For example, the concept of "environment" may include emotional states of communicative actors. The according evaluation function refers in this case to the emotion of well being of the actors. Another example is the respective scientific community of a certain research group. The according evaluation function measures the research success of the group with respect to the state of the art of the respective scientific discipline.

Well known examples of adaptive systems in this precise sense are biological species (not individual organisms) that change the genomes of the individuals by the well known "genetic operators" of mutation and recombination with respect to certain physical environments (biological fitness). It is important to note that these adaptive systems have no goal, i.e., they do not orientate themselves explicitly to the environment. They rather try different possibilities, that is different individuals, and keep the most suited ones. The meta rules in this case are the genetic operators and their operations on the individual genotypes; the evaluation function is the natural selection that determines the individual fitness of the members of the species. Although the meta rules operate on the individual genotypes only the species as a whole is adaptive in a strict sense.

Another example that will be studied in the next chapters is the learning process of single systems. We shall see that in a strict sense individual learning consists mainly of the variation of local cognitive topologies; the meta rules in this case are different learning rules that operate on the topology. The evaluation function is mainly an immediate feed back from the environment of the learning system that consists in the measuring of the respective learning errors the system has made during its learning process.

A final example of adaptive systems are sociocultural systems that evolve by the variation of their social structure, i.e., their rules of interaction and their social topology, and by the enlargement and variation of their culture, i.e., their knowledge about the world (Klüver, 2002). The meta rules in this case can be very different, for instance the "rules" of social revolutions, democratic reforms, cultural exchange and so forth. The same holds for evaluation functions that have to take into account the material wealth of the citizens, cultural traditions, national identities etc.

In the case of adaptive systems the concept of attractor has to be extended too. Whether a trajectory reaches an attractor depends, as we saw, on the rules of interaction, the topology and the initial states. Adaptive dynamics on the other hand are characterized by the variation of rules and topology likewise and therefore adaptive systems can become independent from the constraints of their initial states. In particular, because the adaptive processes are characterized by certain criteria – learning goals, biological fitness, the welfare of a country –, they may be mathematically considered as special kinds of optimization processes: they are judged according to the criterion if they have reached certain optima in their whole space of possible goals; evolutionary biologists speak in this respect of a fitness landscape. The respective goal or optimum is the point in the state space where the adaptive process will stop, i.e., the meta rules will not change any more the rules of interaction including the topology. This aspect must be a bit more thoroughly analyzed.

The variation of the rules and topology by meta rules is itself a process that must be understood as the iterative application of certain rules – in this case meta rules. In the case of non adaptive systems we saw that usually the iteration of the rules leads to attractors, in particular point attractors and attractors with only small periods. The question now is whether the iterative application of meta rules to interaction rules and topologies also leads to attractors, i.e., to rule ensembles and specific topologies that the application of the meta rules does not change any more, although the meta rules are still applied. This is one of the most important questions, e.g., in the field of machine learning and of the adaptation of complex systems in general.

Holland (1975) has constructed a mathematical model of biological evolution, the so called genetic algorithm (GA). It is basically nothing else than an optimization algorithm that uses the operators of biological evolution, namely mutation and recombination (crossover). In this case Michalewicz (1994) has given a proof that a certain form of GAs indeed has attractors in the sense just described: by iteratively applying the genetic operators on an artificial "genotype", i.e., different vectors consisting of symbols for specific rules, the vectors converge and do not change any more.[2] This convergent characteristic of the GA gives a mathematically expressed explanation for the fact that most biological species do not change any more after some time of evolution although their environment may change. For the same general problem it was demonstrated that artificial neural networks, formal models for the simulation of individual learning processes, converge under specific conditions, in particular if the networks are "recurrent" (cf. McLeod et al., 1998). In a literal sense we may speak here of "meta attractors" that can be defined just the way attractors are defined:

Let F be the ensemble of meta rules that regulate the rule and topology variations of a system at a certain time t and let f_t be the ensemble of rules of interaction and topology at this time.[3] Then a meta point attractor f_A is obviously defined as

$$(5) \qquad F^n(f_A) = f_A,$$

for all n. An attractor with larger periods is accordingly defined; we leave it to the imagination of the readers if there is anything like strange meta attractors in the domain of rule changing.

It is rather unfortunate that the concept of attractor is often used for both cases, namely the "one-dimensional dynamics" considered above and the adaptive dynamics, which is some kind of optimization process. In the first case the states of the system reach an attractor by the iterative application of the rules of interaction, in the second case the rules and topology of the system reach an attractor by the iterative application of the meta rules. The concept of "meta attractor" is more precise, but this term is not frequently used. To avoid confusion we shall speak of attractors only in the first case, i.e., an attractor of the system's states; in the second case we shall use the terms "meta attractor", "local optimum", "point of convergence" or in the case of individual learning processes "learning goal".

It is also possible to analyze the adaptive processes in regard to the efficiency of their optimization as a formal parallel to the ordering parameters described above. One can introduce so called "meta parameters" (Klüver, 2000) that measure different degrees of rule variations. Apparently the meta parameters regulate the adaptive optimization processes in a formal similar way as do the ordering parameters in regard to non-adaptive dynamics.

For the sake of brevity we designate non-adaptive dynamics as *first order dynamics* and adaptive dynamics as *second order dynamics*. The evolution of complex systems is in some special cases determined by still another type of dynamics that we call *third order dynamics*. (Klüver, 2002). Third order dynamics is characterized by its ability to change its own initial structural conditions, in

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[2] The proof of Michalewicz uses a famous theorem from the theory of metrical spaces, i.e. the Banach fix point theorem, and is valid only for so called elitistic GAs.

[3] Over a longer period of time the meta rules may vary also, as is the case for example with social systems where the change of social rules can be obtained in different ways-civil wars versus democratic legitimatized reforms etc.

particular its topology, without the selective force of an environment. In this sense third order dynamics has the capability of structural change like second order dynamics, but it is in important aspects independent from the environment of the system – like first order dynamics. Processes of third order dynamics seem to occur only in cases of sociocultural evolution and ontogenetic learning (Klüver, 2002); because we shall later deal with these processes in some detail these remarks are enough for the moment.

To be sure, a lot more could and should be said about the dynamics of complex systems. However, our purpose is not a treatise on the research on complex systems but the unfolding of that theoretical framework that we shall use for a theoretical analysis of communicative processes. Therefore we now shall sketch some methodical consequences.

2.2. UNIVERSAL MODELING SCHEMAS AND MODELS OF SOFT COMPUTING

In the introduction we remarked that we shall use computer simulations as a methodical tool for our research. Unfortunately neither in the natural nor in the social and cognitive sciences the concept of computer simulation is unambiguously used. In particular in the natural sciences the tradition of constructing formal models and computer programs by the use of the classical differential equations of physics is still dominant; the same can be said about many computer simulations in biology where for example variants of the Lotka-Volterra equations are applied when simulating eco-systems (e.g. Pimm, 1991).

Because we use the theoretical frame of complex systems dynamics it seems appropriate to look for modeling schemas and formal tools, i.e., classes of formal models, that are immediately applicable to the task of the modeling of communicative complex systems. In consequence of our theoretical considerations of the last subchapter we therefore use a modeling schema that is a direct methodical transfer from our theoretical frame and that is, for reasons given below, universally applicable (cf. Klüver et al., 2003):

Consider any empirical domain, for instance social groups, whose members communicate according to certain rules, or a learning system with certain elements that interact – neurons in the case of the brain, concepts in the case of the mind. Then the construction of a formal model of this domain is its representation as a formal complex system just defined in subchapter 2.1. We saw already that such systems are characterized by rules of local interactions and a certain topology, i.e., a structure that defines which elements are interacting with which others. It is now an empirical question which kind of dynamics the model of our system should have. Social groups for example do not change their rules and/or topology over short times of observation; in this case first order dynamics is enough for the construction of an adequate model. In the case of learning systems obviously second order dynamics has to be introduced into the model, and sometimes even third order dynamics is necessary.

A little example may illustrate this procedure. It is well known in the analysis of social groups that their "structure" may be characterized by a so called sociomatrix or Moreno matrix (cf. Freeman, 1989). In many cases the sociomatrix describes the mutual feelings of the group members towards the others, i.e., the matrix contains different values v, say 1, 0 and -1. $v(a,b)=1$ means that a has positive emotions towards b; 0 means neutrality, -1 means negative feelings. Apparently these values can be defined as the topology of this social group. As each member has particular feelings towards all other members the topological relations of one group member must be modeled as a (n–1)-dimensional vector if the group has n members. Now we have to introduce specific rules of interaction which are in this case simply that a group member interacts frequently with those members he likes, that he interacts only sometimes with members neutral for him and that he avoids to interact with members he does not like. In addition we have to determine if all members can interact with all others or if only with certain members; then we have a formal model of that particular group and its probable dynamics.

Before we sketch the formal tools that are especially suited for this kind of modeling we have to make a methodical *caveat:* it is a *methodical decision* which "level" one wants to take as the system level and accordingly it is a methodical decision whether the elements of the respective system are just represented by their states – scalars, vectors or other symbols. For instance, in many social cases it is sociologically sufficient to represent the elements of social systems, i.e., the social actors, by simple states and to concentrate just on the social level. In this case, of course, one neglects the obvious fact that social actors are not simple finite state automata but are themselves complex systems that should be modeled the same way as the systems on the social level. This is a methodical reduction every sociologist is aware of (cf. Luhmann, 1984). The theoretical and methodical reason for this often justified abstraction is the knowledge that in many cases the differences between the individual elements, in this case social actors, dissolve in the statistical average. In the case of social systems there is the additional theoretical reason that via the process of socialization individuals tend to act rather uniformly according to the specific social rules that are valid in particular situations of action. However, in certain cases this reduction is not valid, and the analysis of communication is such a case where the participants of communicative processes must be represented as complex systems themselves. The reason for this is the mentioned fact that communicative processes in general are determined by both social rules of interaction and the cognitive processes of the communicators. Therefore, we have to model communication as a complex system whose elements are complex systems themselves.

In this sense communication as the core of social reality mirrors the dual character of society: on the one hand a society can be characterized by its social *structure*, i.e. the social rules of interaction and the respective topology; on the other hand a society is defined by a certain *culture*, i.e., the sum of the knowledge that is hold to be valid in that society (cf. Habermas, 1981; Geertz, 1973). That is why communication as the basic generating principle of societies has to be analyzed in just that dual manner (see below).

Because we shall deal with this problem in the next chapter we may for the moment return to the modeling schema in its simple version, i.e., single elements are just represented by the value of the finite states they have obtained at certain times.

Why is this schema universal? The answer is grounded in a mathematical characteristic of the formal models we use when we transfer the models of empirical domains into formal systems and according computer programs. Take for example the formal model of cellular automata (CA) that has been mentioned above and which is frequently used in the social and some natural sciences (cf. Wolfram, 2002; Klüver, 2000).

A CA is an algorithm that generates a grid of cells, usually visualized as squares. The cells are in particular states – scalars or vectors. In the logically simplest case the cells just have two possible states: 1 or 0, on or off, dead or alive. Each cell has eight adjacent cells, i.e. on its sides and at its edges. The topology of this formal system is usually that a cell interacts with these eight cells in its neighborhood – the so called Moore neighborhood – or only with the four adjacent cells at its sides – the so called von Neumann neighborhood. The rules of interaction, in the terminology of CAs the rules of transition, are simply that the next state of a cell depends on the states of the four or eight adjacent cells in the respective neighborhood and on its own previous state. A classical rule of a famous CA, the Game of Life by Conway, is that the state s of a cell becomes or stays $s = 1$ if exactly three adjacent cells in its Moore neighborhood are in the state 1.

CAs and their generalization in form of Boolean networks (BN) are obviously rather simple systems, at least with respect to their basic logic. Therefore, on a first view it is quite astonishing that they are logically equivalent to universal Turing machines (Rasmussen et al., 1992), which means that it is possible to model literally all complex systems by using these formal models.[4] There is little doubt that this assumption is valid for all empirical systems. The modeling schema we present in this subchapter is universal because it is always possible to construct a model according to this schema and to map the model onto a suited formal system like a CA or a BN. To be sure, this general proof of the universality of our schema says nothing about the task how to capture the peculiarities of a specific empirical domain in such a model; that is up to the creativity of the constructors. But the decisive point is that the application of the modeling schema will always yield a model that is suited to capture *in principle* each characteristic of the empirical domain one wishes.

[4] To be more exact, universal Turing machines are able to compute any computable function and by this it is possible to model every system by such a formal system that is computable in the abstract sense of mathematical logic. No scientist seriously believes that there are physically real systems that cannot be modeled by a suited universal Turing machine or some logical equivalent (the so called physical Church-Turing hypothesis).