Klaus Mainzer

Thinking in Complexity

The Computational Dynamics of Matter, Mind, and Mankind

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Das Ganze ist aber nur das durch seine Entwicklung sich vollendende Wesen. *

G. W. F. Hegel: Phänomenologie des Geistes (1807)

* *The whole, however, is merely the essential nature reaching its completeness through the process of its own development.*

G. W. F. Hegel: The Phenomenology of Mind (1807)

Last but not least, I would especially like to thank J. Andrew Ross (Springer-Verlag) for carefully reading and correcting the book as a native speaker, and Katja E. Hüther and Jutta Janßen (University of Augsburg) for typing the text.

Augsburg, June 1994 *Klaus Mainzer*

Contents

1. Introduction: From Linear to Nonlinear Thinking

The theory of nonlinear complex systems has become a successful problem solving approach in the natural sciences – from laser physics, quantum chaos, and metereology to molecular modeling in chemistry and computer-assisted simulations of cellular growth in biology. On the other hand, the social sciences are recognizing that the main problems of mankind are global, complex, nonlinear, and often random, too. Local changes in the ecological, economic, or political system can cause a global crisis. Linear thinking and the belief that the whole is only the sum of its parts are evidently obsolete. One of the most exciting topics of present scientific and public interest is the idea that even our mind is governed by the nonlinear dynamics of complex systems. If this thesis of computational neuroscience is correct, then indeed we have a powerful mathematical strategy to handle the interdisciplinary problems of the natural sciences, social sciences, and the humanities. But one of the main insights of this book is the following: Handling problems does not always mean computing and determining the future. In the case of randomness, we can understand the dynamical reasons, but there is no chance of forecasting. Understanding complex dynamics is often more important for our practical behavior than computing definite solutions, especially when it is impossible to do so.

What is the reason behind these successful interdisciplinary applications? The book shows that the theory of nonlinear complex systems cannot be reduced to special natural laws of physics, although its mathematical principles were discovered and at first successfully applied in physics. Thus it is no kind of traditional "physicalism" to explain the dynamics of laser, ecological populations, or our brain by similar structural laws. It is an interdisciplinary methodology to explain the emergence of certain macroscopic phenomena via the nonlinear interactions of microscopic elements in complex systems. Macroscopic phenomena may be forms of light waves, fluids, clouds, chemical waves, plants, animals, populations, markets, and cerebral cell assemblies which are characterized by order parameters. They are not reduced to the microscopic level of atoms, molecules, cells, organisms, etc., of complex systems.

Actually, they represent properties of real macroscopic phenomena, such as field potentials, social or economical power, feelings or even thoughts. Who will deny that feelings and thoughts can change the world?

In history the concepts of the social sciences and humanities have often been influenced by physical theories. In the age of mechanization Thomas Hobbes described the state as a machine ("Leviathan") with its citizens as cog wheels. For Lamettrie the human soul was reduced to the gear drive of an automaton. Adam Smith explained the mechanism of the market by an "invisible" force like Newton's gravitation. In classical mechanics causality is deterministic in the sense of the Newtonian or Hamiltonian equations of motion. A conservative system is characterized by its reversibility (i.e., symmetry or invariance) in time and the conservation of energy. Celestial mechanics and the pendulum without friction are prominent examples. Dissipative systems are irreversible, like Newton's force with a friction term, for instance.

But, in principle, nature was regarded as a huge conservative and deterministic system the causal events of which can be forecast and traced back for each point of time in the future and past if the initial state is well known ("Laplace's demon"). It was Henri Poincaré who recognized that celestial mechanics is no completely calculable clockwork even with the restrictions of conservation and determinism. The causal interactions of all planets, stars, and celestial bodies are nonlinear in the sense that their mutual effects can lead to chaotic trajectories (e.g., the 3-body problem). Nearly sixty years after Poincaré's discovery, A.N. Kolmogorov (1954), V.I. Arnold (1963), and J.K. Moser proved the so-called KAM theorem: Trajectories in the phase space of classical mechanics are neither completely regular nor completely irregular, but they depend very sensitively on the chosen initial states. Tiny fluctuations can cause chaotic developments (the "butterfly effect").

In this century quantum mechanics has become the fundamental theory of physics [1.1]. In Schrödinger's wave mechanics the quantum world is believed to be conservative and linear. In the first quantization classical systems described by a Hamiltonian function are replaced by quantum systems (for instance electrons or photons) described by a Hamiltonian operator. These systems are assumed to be conservative, i.e., non-dissipative and invariant with respect to time reversal and thus satisfy the conservation law of energy. States of a quantum system are described by vectors (wave functions) of a Hilbert space spanned by the eigenvectors of its Hamiltonian operator. The causal dynamics of quantum states is determined by a deterministic differential equation (the Schrödinger equation) which is linear in the sense of the superposition principle, i.e., solutions of this equation (wave functions or state vectors) can be superposed like in classical optics. The superposition or linearity principle of quantum mechanics delivers correlated ("entangled") states of combined systems which are highly confirmed by the EPR experiments (A. Aspect 1981). In an entangled pure quantum state of superposition an observable can only have indefinite eigenvalues. It follows that the entangled state of a quantum system and a measuring apparatus can only have indefinite eigenvalues. But in the laboratory the measuring apparatus shows definite measurement values. Thus, linear quantum dynamics cannot explain the measurement process.

In the Copenhagen interpretation of Bohr, Heisenberg, et al., the measurement process is explained by the so-called "collapse of the wave-packet", i.e., splitting up of the superposition state into two separated states of measurement apparatus and measured quantum system with definite eigenvalues. Obviously, we must distinguish the linear dynamics of quantum systems from the nonlinear act of measurement. This nonlinearity in the world is sometimes explained by the emergence of human consciousness. Eugene Wigner (1961) suggested that the linearity of Schrödinger's equation might fail for conscious observers, and be replaced by some nonlinear procedure according to which either one or the other alternative would be resolved out. But Wigner's interpretation forces us to believe that the linear quantum superpositions would be resolved into separated parts only in those corners of the universe where human or human-like consciousness emerges. In the history of science anthropic or teleological arguments often showed that there were weaknesses and failures of explanation in science. Thus, some scientists, like Roger Penrose, suppose that the linear dynamics of quantum mechanics is not appropriate to explain cosmic evolution with the emergence of consciousness. He argues that a unified theory of linear quantum mechanics and nonlinear general relativity could at least explain the separated states of macroscopic systems in the world. A measuring apparatus is a macroscopic system, and the measurement process is irreversible far from thermal equilibrium. Thus, an explanation could only succeed in a unified nonlinear theory. Even the generalization of Schrödinger's wave mechanics to quantum field theory is already nonlinear. In quantum field theory, field functions are replaced by field operators in the so-called second quantization. The quantum field equation with a two-particle potential, for instance, contains a nonlinear term corresponding to pair creation of elementary particles. In general the reactions of elementary particles in quantum field theory are essentially nonlinear phenomena. The interactions of an elementary particle cause its quantum states to have only a finite duration and thereby to violate the reversibility of time. Thus even the quantum world itself is neither conservative nor linear in general. In system theory, complexity means not only nonlinearity but a huge number of elements with many degrees of freedom [1.2]. All macroscopic systems like stones or planets, clouds or fluids, plants or animals, animal populations or human societies consist of component elements like atoms, molecules, cells or organisms. The behaviour of single elements in complex systems with huge numbers of degrees of freedom can neither be forecast nor traced back. The deterministic description of single elements must be replaced by the evolution of probabilistic distributions.

The second chapter analyzes *Complex Systems and the Evolution of Matter*. Since the presocratics it has been a fundamental problem of natural philosophy to discover how order arises from complex, irregular, and chaotic states of matter. Heraclitus believed in an ordering force of energy (*logos*) harmonizing irregular interactions and creating order states of matter. Modern thermodynamics describes the emergence of order by the mathematical concepts of statistical mechanics. We distinguish two kinds of phase transition (self-organization) for order states: conservative self-organization means the phase transition of reversible structures in thermal equilibrium. Typical examples are the growth of snow crystals or the emergence of magnetisation in a ferromagnet by annealing the system to a critical value of temperature. Conservative self-organization mainly creates order structures with low energy at low temperatures which are described by a Boltzmann distribution. An application of modern technology is pattern formation in the materials sciences. Complex systems of the nanoworld and self- constructing materials are challenges of key technologies in the future.

Dissipative self-organization is the phase transition of irreversible structures far from thermal equilibrium [1.3]. Macroscopic patterns arise from the complex nonlinear cooperation of microscopic elements when the energetic interaction of the dissipative ("open") system with its environment reaches some critical value. Philosophically speaking, the stability of the emergent structures is guaranteed by some balance of nonlinearity and dissipation. Too much nonlinear interaction or dissipation would destroy the structure. As the conditions of dissipative phase transitions are very general, there is a broad variety of interdisciplinary applications. A typical physical example is the laser. In chemistry, the concentric rings or moving spirals in the Belousov-Zhabotinski (BZ) reaction arise when specific chemicals are poured together with a critical value. The competition of the separated ring waves show the nonlinearity of these phenomena very clearly, because in the case of a superposition principle the ring waves would penetrate each other like optical waves.

The phase transitions of nonlinear dissipative complex systems are explained by synergetics. In a more qualitative way we may say that old structures become unstable and break down by changing control parameters. On the microscopic level the stable modes of the old states are dominated by unstable modes (Haken's "slaving principle") [1.4]. They determine order parameters which describe the macroscopic structure and patterns of systems. There are different final patterns of phase transitions corresponding to different attractors. Different attractors may be pictured as a stream, the velocity of which is accelerated step by step. At the first level a homogeneous state of equilibrium is shown ("fixed point"). At a higher level of velocity

the bifurcation of two or more vortices can be observed corresponding to periodic and quasi-periodic attractors. Finally the order decays into deterministic chaos as a fractal attractor of complex systems. Philosophically, I want to underline that in synergetics the microscopic description of matter is distinguished from the macroscopic order states. Thus the synergetic concept of order reminds me of Heraclitus" "logos" or Aristotle's "form" which produces the order states of nature in a transformative process of matter. But, of course, in antiquity a mathematical description was excluded.

In a more mathematical way, the microscopic view of a complex system is described by the evolution equation of a state vector where each component depends on space and time and where the components may denote the velocity components of a fluid, its temperature field, or in the case of chemical reactions, concentrations of chemicals. The slaving principle of synergetics allows us to eliminate the degrees of freedom which refer to the stable modes. In the leading approximation the evolution equation can be transformed into a specific form for the nonlinearity which applies to those systems where a competition between patterns occurs. The amplitudes of the leading terms of unstable modes are called order parameters. Their evolution equation describes the emergence of macroscopic patterns. The final patterns ("attractors") are reached by a transition which can be understood as a kind of symmetry breaking [1.5]. Philosophically speaking, the evolution of matter is caused by symmetry breaking, which was earlier mentioned by Heraclitus.

Understanding complex systems and nonlinear dynamics in nature seems to yield appropriate models for the evolution of matter. But how can we find correct models in practice? Physicists, chemists, biologists, or physicians start with data mining in an unknown field of research. They only get a finite series of measured data corresponding to time dependent events of an unknown dynamical system. From the time series of these data, they must reconstruct the behavior of the system in order to guess the type of its dynamical equation. Therefore, time series analysis is a challenge to modern research in chaos theory and nonlinear dynamics.

The third chapter analyzes *Complex Systems and the Evolution of Life*. In the history of science and philosophy, people believed in a sharp difference between "dead" and "living" matter. Aristotle interpreted life as a power of self-organization (entelechy) driving the growth of plants and animals to their final form. A living system is able to move by itself, while a dead system can only be moved from outside. Life was explained by teleology, i.e., by non-causal ("vital") forces aiming at some goals in nature. In the 18th century Kant showed that self-organization of living organisms cannot be explained by a mechanical system of Newtonian physics. In a famous quotation he said that the Newton for explaining a blade of grass is still lacking. In the 19th century the second law of thermodynamics describes the irreversible movement of closed systems toward a state of maximal entropy or disorder.

But how can one explain the emergence of order in Darwin's evolution of life? Boltzmann stressed that living organisms are open dissipative systems in exchange with their environment which do not violate the second law of closed systems. But nevertheless in the statistical interpretation from Boltzmann to Monod the emergence of life can only be a contingent event, a local cosmic fluctuation "at the boundary of universe".

In the framework of complex systems the emergence of life is not contingent, but necessary and lawful in the sense of dissipative self-organization. Only the conditions for the emergence of life (for instance on the planet Earth) may be contingent in the universe. In general, biology distinguishes ontogenesis (the growth of organisms) from phylogenesis (the evolution of species). In any case we have complex dissipative systems the development of which can be explained by the evolution of (macroscopic) order parameters caused by nonlinear (microscopic) interactions of molecules, cells, etc., in phase transitions far from thermal equilibrium. Forms of biological systems (plants, animals, etc.) are described by order parameters. Aristotle's teleology of goals in nature is interpreted in terms of attractors in phase transitions. But no special "vital" or "teleological" forces are necessary. Philosophically, the emergence of life can be explained in the framework of nonlinear causality and dissipative self-organization, although it may be described in a teleological language for heuristic reasons.

I remind the reader that the prebiological evolution of biomolecules was analyzed and simulated by Manfred Eigen et al. Spencer's idea that the evolution of life is characterized by increasing complexity can be made precise in the context of dissipative self-organization. It is well known that Turing analyzed a mathematical model of organisms represented as complex cellular systems. Gerisch, Meinhardt, et al. described the growth of an organism (e.g., a slime mould) by evolution equations for the aggregation of cells. The nonlinear interactions of amebas cause the emergence of a macroscopic organism like a slime mould when some critical value of cellular nutrition in the environment is reached. The evolution of the order parameter corresponds to the aggregation forms during the phase transition of the macroscopic organism. The mature multicellular body can be interpreted as the "goal" or (better) "attractor" of organic growth. Multicellular bodies, like genetic systems, nervous systems, immune systems, and ecosystems, are examples of complex dynamical systems, which are composed of a network of many interacting elements. S. Kauffman suggested studying random Boolean networks that could be programmed in a computer. In computer experiments, he found a hierarchy of dynamical behavior with fixed points and cycles of increasing complexity, which can be observed in real cells.

Even the ecological growth of biological populations may be simulated using the concepts of synergetics. Ecological systems are complex dissipative systems of plants or animals with mutual nonlinear metabolic interactions

with each other and with their environment. The symbiosis of two populations with their source of nutrition can be described by three coupled differential equations which were already used by Edward Lorenz to describe the development of weather in meteorology. In the 19th century the Italian mathematicians Lotka und Volterra described the development of two populations in ecological competition. The nonlinear interactions of the two complex populations are determined by two coupled differential equations of prey and predator species. The evolution of the coupled systems have stationary points of equilibrium. The attractors of evolution are periodic oscillations (limit cycles).

The theory of complex systems allows us to analyze the nonlinear causality of ecological systems in nature. Since the industrial revolution human society has become more and more involved in the ecological cycles of nature. But the complex balance of natural equilibria is highly endangered by the linear mode of traditional industrial production. People assumed that nature contains endless sources of energy, water, air, etc., which can be used without disturbing the natural balance. Industry produces an endless flood of goods without considering their synergetic effects like the ozone hole or waste utilization. The evolution of life is transformed into the evolution of human society.

Perhaps the most speculative interdisciplinary application of complex systems is discussed in the fourth chapter, *Complex Systems and the Evolution of Mind-Brain*. In the history of philosophy and science there have been many different suggestions for solutions to the mind-body problem. Materialistic philosophers like Democritus, Lamettrie, et al., proposed to reduce mind to atomic interactions. Idealists like Plato, Penrose, et al. emphasized that mind is completely independent of matter and brain. For Descartes, Eccles, et al. mind and matter are separate substances interacting with each other. Leibniz believed in a metaphysical parallelism of mind and matter because they cannot interact physically. According to Leibniz mind and matter are supposed to exist in "pre-established harmony" like two synchronized clocks. Modern philosophers of mind like Searle defend a kind of evolutionary naturalism. Searle argues that mind is characterized by intentional mental states which are intrinsic features of the human brain's biochemistry and which therefore cannot be simulated by computers.

But the theory of complex systems cannot be reduced to these more or less one-sided positions. The complex system approach is an interdisciplinary methodology to deal with nonlinear complex systems like the cellular organ known as the brain. The emergence of mental states (for instance pattern recognition, feelings, thoughts) is explained by the evolution of (macroscopic) order parameters of cerebral assemblies which are caused by nonlinear (microscopic) interactions of neural cells in learning strategies far from thermal equilibrium. Cell assemblies with mental states are interpreted as attractors (fixed points, periodic, quasi-periodic, or chaotic) of phase transitions.

If the brain is regarded as a complex system of neural cells, then its dynamics is assumed to be described by the nonlinear mathematics of neural networks. Pattern recognition, for instance, is interpreted as a kind of phase transition by analogy with the evolution equations which are used for pattern emergence in physics, chemistry, and biology. Philosophically, we get an interdisciplinary research program that should allow us to explain neurocomputational self-organization as a natural consequence of physical, chemical, and neurobiological evolution by common principles. As in the case of pattern formation, a specific pattern of recognition (for instance a prototype face) is described by order parameters to which a specific set of features belongs. Once some of the features which belong to the order parameter are given (for instance a part of a face), the order parameter will complement these with the other features so that the whole system acts as an associative memory (for instance the reconstruction of a stored prototype face from an initially given part of that face). According to Haken's slaving principle the features of a recognized pattern correspond to the enslaved subsystems during pattern formation.

But what about the emergence of consciousness, self-consciousness, and intentionality? In synergetics we have to distinguish between external and internal states of the brain. In external states of perception and recognition, order parameters correspond to neural cell assemblies representing patterns of the external world. Internal states of the brain are nothing other than self-referential states, i.e., mental states referring to mental states and not to external states of the world. In the traditional language of philosophy we say that humans are able to reflect on themselves (self-reflection) and to refer external situations of the world to their own internal state of feeling and intentions (intentionality). In recent neurobiological inquiries, scientists speculate that the emergence of consciousness and self-consciousness depends on a critical value of the production rate for "meta-cell-assemblies", i.e., cell-assemblies representing cell-assemblies which again represent cell-assemblies, etc., as neural realization of self-reflection. But this hypothesis (if successful) could only explain the structure of emergent features like consciousness. Of course, mathematical evolution equations of cell assemblies do not enable us to feel like our neighbour. In this sense – this is the negative message – science is blind. But otherwise – this is the positive message – personal subjectivity is saved: Calculations and computer-assisted simulations of nonlinear dynamics are limited in principle.

Anyway, the complex system approach solves an old metaphysical puzzle which was described by Leibniz in the following picture: If we imagine the brain as a big machine which we may enter like the internal machinery of a mill, we shall only find its single parts like the cog wheels of the mill and never the mind, not to mention the human soul. Of course, on the microscopic level we can only describe the development of neurons as cerebral parts of the brain. But, on the macroscopic level, the nonlinear interactions in the complex neural system cause the emergence of cell assemblies referring to order parameters which cannot be identified with the states of single cerebral cells. The whole is not the sum of its parts.

It is obvious that the complex system approach delivers solutions of the mind-body problem which are beyond the traditional philosophical answers of idealism, materialism, physicalism, dualism, interactionism, etc. Concerning the distinction between so-called natural and artificial intelligence, it is important to see that the principles of nonlinear complex systems do not depend on the biochemistry of the human brain. The human brain is a "natural" model of these principles in the sense that the cerebral complex system is a product of physical and biological evolution. But other ("artificial") models produced by human technology are possible, although there will be technical and ethical limits to their realization.

In Chap. 5 we discuss *Complex Systems and the Evolution of Computability*. Universal Turing machines and algorithmic complexity are the traditional concepts of computability. Are there limitations to the analogies of computers with human mind and brain by Gödel's and Turing's results of incompleteness and undecidability? How can the human brain be understood as both an information processing machine and a knowledge-based system? John von Neumann's concept of celluar automata refined the idea of self-organizing cellular systems. Recent computer experiments by Stephen Wolfram have shown that all kinds of nonlinear dynamics, from fixed point attractors and oscillating behavior to chaos, can be simulated by cellular automata. Even randomness can be generated by appropriate cellular automata, though their local rules of cellular interaction may be very simple and well-known. Cellular automata deliver digital approximations of complex dynamical systems that are determined by continuous differential equations.

Computational dynamics open new avenues for *Complex Systems and the Evolution of Artificial Life and Intelligence* (Chap. 6). Artificial life, as well as neural networks have their roots in the universal method of cellular automata. Self-organization and learning are main features of neural networks modeling intelligent systems. In synergetic computers, the order parameter equations allow a new kind of (non-Hebbian) learning, namely a strategy to minimize the number of synapses. In contrast to neurocomputers of the spin-glass type (for instance Hopfield systems), the neurons are not threshold elements but rather perform simple algebraic manipulations like multiplication and addition. Beside deterministic homogeneous Hopfield networks there are so-called Boltzmann machines with a stochastic network architecture of non-deterministic processor elements and a distributed knowledge representation which is described mathematically by an energy function. While Hopfield systems use a Hebbian learning strategy, Boltzmann machines favour a backpropagation strategy (Widrow-Hoff rule) with hidden neurons in a many-layered network.

In general it is the aim of a learning algorithm to diminish the information-theoretic measure of the discrepancy between the brain's internal model of the world and the real environment via self-organization. The recent revival of interest in the field of neural networks is mainly inspired by the successful technical applications of statistical mechanics and nonlinear dynamics to solid state physics, spin glass physics, chemical parallel computers, optical parallel computers, and – in the case of synergetic computers – to laser systems. Other reasons are the recent development of computing resources and the level of technology which make a computational treatment of nonlinear systems more and more feasible. Philosophically, traditional topics of epistemology like perception, imagination, and recognition may be discussed in the interdisciplinary framework of complex systems.

In electrical engineering, information theory, and computer science, the concept of cellular neural networks (CNN) is becoming an influential paradigm of complexity research, which has been realized in information and chip technology [1.6]. Analogic Cellular Computers are the technical response to the sensor revolution, mimicking the anatomy and physiology of sensory and processing organs. A CNN is a nonlinear analog circuit that processes signals in real time. Its architecture dates back to J. von Neumann's earlier paradigm of Cellular Automata (CA). Unlike conventional cellular automata, CNN host processors accept and generate analog signals in continuous time with real numbers as interaction values. The CNN universal chip is a technical realization of the CNN Universal Machine (CNN-UM), analogous to the Universal Turing machine of digital computers. It is a milestone in information technology because it is the first fully programmable, industrial-sized, brain-like, stored-program dynamic array computer. Further on, appropriate CNNs can simulate all kinds of pattern formation and pattern recognition, which have been analyzed in synergetics in the theory of nonlinear dynamics. Two great advantages of CNNs are their rigorous mathematical analysis and their technical realization. The dynamic complexity of cellular automata and their corresponding nonlinear dynamic systems can be characterized by a precise complexity index. An immense increase of computing speed, combined with significantly less electrical power in the first CNN chips, has led to the current intensive research activities on CNN since Chua and Yang's proposal in 1988.

An important application of the complex system approach is neurobionics and medicine. The human brain is not only a cerebral computer as a product of natural evolution, but a central organ of our body which needs medical treatment, healing, and curing. Neurosurgery, for instance, is

a medical discipline responsible for maintaining the health of the biological medium of the human mind. The future well-being of the brain-mind entity is an essential aim of neurobionics. In recent years new diagnostic procedures and technical facilities for transplantation have been introduced which are based on new insights into the brain from complex dynamical systems. In this context a change of clinical treatment is unavoidable. Neural and psychic forms of illness can be interpreted as complex states in a nonlinear system of high sensitivity. Even medical treatments must consider the high sensitivity of this complex organ. Another more speculative aspect of the new technology is cyberspace. Perception, feeling, intuition, and fantasy as products of artificial neural networks? Virtual reality has become a keyword in modern philosophy of culture.

After moving through matter, life, mind-brain, and artificial intelligence, the book finishes in a Hegelian grand synthesis with the seventh chapter, *Complex Systems and the Evolution of Human Society*. In social sciences one usually distinguishes strictly between biological evolution and the history of human society. The reason is that the development of nations, markets, and cultures is assumed to be guided by the intentional behavior of humans, i.e., human decisions based on intentions, values, etc. From a microscopic viewpoint we may, of course, observe single individuals with their intentions, beliefs, etc. But from a macroscopic view the development of nations, markets, and cultures is not only the sum of its parts. Mono-causality in politics and history is, as we all know, a false and dangerous way of linear thinking. Synergetics seems to be a successful strategy to deal with complex systems even in the humanities. Obviously it is not necessary to reduce cultural history to biological evolution in order to apply synergetics interdisciplinarily. Contrary to any reductionistic kind of naturalism and physicalism we recognize the characteristic intentional features of human societies. Thus the complex system approach may be a method of bridging the gap between the natural sciences and the humanities that was criticized in Snow's famous "two cultures".

In the framework of complex systems the behaviour of human populations is explained by the evolution of (macroscopic) order parameters which is caused by nonlinear (microscopic) interactions of humans or human subgroups (states, institutions, etc.). Social or economic order is interpreted by attractors of phase transitions. Allen et al. analyze the growth of urban regions. From a microscopic point of view the evolution of populations in single urban regions is mathematically described by coupled differential equations with terms and functions referring to the capacity, economic production, etc., of each region. The macroscopic development of the whole system is illustrated by computer-assisted graphics with changing centers of industrialization, recreation, etc., caused by nonlinear interactions of individual urban regions (for instance advantages and disadvantages of far and near connections of transport, communication, etc.). An essential result of the synergetic model is that urban development cannot be explained by the free will of single persons. Although people of local regions are acting with their individual intentions, plans, etc., the tendency of the global development is the result of nonlinear interactions.

Another example of the interdisciplinary application of synergetics is Weidlich's model of migration. He distinguishes the micro-level of individual decisions and the macro-level of dynamical collective processes in a society. The probabilistic macro-processes with stochastic fluctuations are described by the master equation of human socioconfigurations. Each component of a socioconfiguration refers to a subpopulation with a characteristic vector of behavior. The macroscopic development of migration in a society could be illustrated by computer-assisted graphics with changing centers of mixtures, ghettos, wandering, and chaos which are caused by nonlinear interactions of social subpopulations. The differences between human and non-human complex systems are obvious in this model. On the microscopic level human migration is intentional (i.e., guided by considerations of utility) and nonlinear (i.e., dependent on individual and collective interactions). A main result of synergetics is again that the effects of national and international migration cannot be explained by the free will of single persons. I think migration is a very dramatic topic today, and demonstrates how dangerous linear and mono-causal thinking may be. It is not sufficient to have good intentions without considering the nonlinear effects of single decisions. Linear thinking and acting may provoke global chaos, although we locally act with the best intentions.

It is a pity to say that in economics linear models are still dominant. From a qualitative point of view, Adam Smith's model of a free market can already be explained by self-organization. Smith underlined that the good or bad intentions of individuals are not essential. In contrast to a centralized economical system, the equilibrium of supply and demand is not directed by a program-controlled central processor, but is the effect of an "invisible hand" (Smith), i.e., nothing but the nonlinear interaction of consumers and producers. The recent interest of economists in nonlinear dissipative systems is inspired by the growth of knowledge-based high-tech industries with positive feedback (i.e., increasing production depending on increasing know-how, such as electronics, computer industries, etc.) in contrast to the old industries with negative feedback (i.e., decreasing production depending limited resources like coal or steel).

In a dramatic step, the complex systems approach has been expanded from neural networks to include global technical information networks like the World Wide Web. The information flow is accomplished through information packets with source and destination addresses. The dynamic of the Internet has essential analogies with CAs and CNNs. Computational and

information networks have become technical superorganisms, evolving in a quasi-evolutionary process. The information flood in a more or less chaotic Internet is a challenge for intelligent information retrieval. We could use the analogies of the self-organizing and learning features of a living brain to find heuristic devices for managing the information flood of the Internet. But the complexity of global networking isn't confined to the Internet. Below the complexity of a PC, cheap, low power, and smart chip devices are distributed throughout the intelligent environments of our everyday world. Ubiquitous computing is a challenge of global networking by wireless media access, wide-bandwidth range, real-time capabilities for multimedia over standard networks, and data packet routing. Not only millions of PCs, but also billions of smart devices are interacting via the Internet. The overwhelming flow of data and information forces us to operate at the edge of chaos.

In general, economic information processes are very complex and demand nonlinear dissipative models. Recall the different attractors from economic cycles to financial chaos which can only be explained as synergetic effects by nonlinear interactions of consumers and producers, fiscal policy, stock market, unemployment, etc. Even in management possible complex models are discussed in order to support creativity and innovation by nonlinear cooperation at all levels of management and production. But experience shows that the rationality of human decision making is bounded. Human cognitive capabilities are overwhelmed by the complexity and randomness of the nonlinear systems they are forced to manage. The concept of bounded rationality, first introduced by Herbert Simon, was a reaction to the limitations of human knowledge, information, and time.

Evidently, there are some successful strategies to handle nonlinear complex systems. We shall discuss examples of applications in quantum physics, hydrodynamics, chemistry, and biology, as well as economics, sociology, neurology, and AI. What is the reason behind the successful applications in the natural sciences and humanities? The complex system approach is not reduced to special natural laws of physics, although its mathematical principles were discovered and at first successfully applied in physics (for instance to the laser). Thus, it is an interdisciplinary methodology to explain the emergence of certain macroscopic phenomena via the nonlinear interactions of microscopic elements in complex systems. Macroscopic phenomena may be forms of light waves, fluids, clouds, chemical waves, biomolecules, plants, animals, populations, markets, neural cell assemblies, traffic congestions in street networks or the Internet, which are characterized by order parameters (Table 1.1). Philosophically, it is important to see that order parameters are not reduced to the microscopic level of atoms, molecules, cells, organisms, etc., of complex systems. In some cases they are measurable quantities (for instance the field potential of a laser). In other cases they are qualitative properties (for instance geometrical forms of patterns). Nevertheless, order

Table 1.1. Interdisciplinary applications of nonlinear complex systems

DISCIPLINE	SYSTEM	ELEMENTS	DYNAMICS	ORDER PARAMETER
cosmology	universe	matter	cosmic dynamics	cosmic pattern formation (e.g., galactic structures)
quantum physics	quantum systems (e.g., laser)	atoms photons	quantum dynamics	quantum pattern formation (e.g., optical waves)
hydrodynamics	fluids	molecules	fluid dynamics	form of fluids
meteorology	weather climate	molecules	meteorological dynamics	pattern formation (e.g., clouds, hurricanes)
geology	lava	molecules	geological dynamics	pattern formation (e.g., segmentation)
chemistry	molecular systems	molecules	chemical reaction chemical dynamics	chemical pattern formation (e.g., dissipative structures)
materials science	smart materials nano system	macromolecules	macromolecular dynamics	macromolecular pattern formation (e.g., nano forms)
biology	genetic systems	biomolecules	genetic reaction	genetic pattern formation
	organisms	cells	organic growth	organic pattern formation
	populations	organisms	evolutionary dynamics	pattern formation of species
economics	economic systems	economic agents (e.g., consumer producer)	economic interaction (e.g., mechanisms of markets)	economic pattern formation (e.g., supply and demand)
sociology	societies	individuals, institutions etc.	social interaction historical dynamics	social pattern formation
neurology psychology	brain	neurons	neural rules learning algorithms information dynamics	neural pattern formation pattern recognition
computer science	cellular automata neural networks global networking (e.g., Internet, ubiquitous computing)	cellular processors	computational rules evolutionary algorithms learning algorithms information dynamics	pattern formation of computational networks

parameters are not mere theoretical concepts of mathematics without any reference to reality. Actually they represent properties of real macroscopic phenomena, such as field potentials, social or economic power, feelings or even thoughts. Who will deny that feelings and thoughts can change the world? If we can understand their nonlinear dynamics, it could even become possible to implement them in chips, such as CNNs.

Thus, the complex systems approach is not a metaphysical process ontology. Synergetic principles (among others) provide a heuristic scheme to construct models of nonlinear complex systems in the natural sciences and the humanities. If these models can be mathematized and their properties quantified, then we get empirical models which may or may not fit the data. The slaving principle shows another advantage. As it diminishes the high number of degrees of freedom in a complex system, synergetics is not only heuristic, mathematical, empirical and testable, but economical too. Namely, it satisfies the famous principle of Ockham's razor which tells us to cut away superfluous entities. Further on, nonlinear models may be implemented in nonlinear computer chips of high speed and miniaturized size. We can also prove basic principles of computational dynamics. But, because of chaos and randomness, understanding computational dynamics does not mean predicting and determining the future in all its details. The analysis of computational systems allows us to gain experience with nonlinear dynamics, as well as insights into and feelings about what is going on in the real world. But, as life is complex and random, we have to live it in order to experience it.

In this sense, our approach suggests that physical, social, and mental realities are nonlinear, complex, and computational. This essential result of a new epistemology has severe consequences for our behavior. As we underlined, linear thinking may be dangerous in a nonlinear complex reality. Recall, as one example, the demand for a well-balanced complex system of ecology and economics. Our physicians and psychologists must learn to consider humans as complex nonlinear entities of mind and body. Linear thinking may fail to yield a successful diagnosis. Local, isolated, and "linear" therapies of medical treatment may cause negative synergetic effects. In politics and history, we must remember that mono-causality may lead to dogmatism, intolerance, and fanaticism. As the ecological, economic, and political problems of mankind have become global, complex, nonlinear, and random, the traditional concept of individual responsibility is questionable. We need new models of collective behavior depending on the different degrees of our individual faculties and insights. In short: The complex system approach demands new consequences in *epistemology* and *ethics*. Finally, it offers a chance to handle chaos and randomness in a nonlinear complex world and utilize the creative possibilities of synergetic effects.

8. Epilogue on Future, Science, and Ethics

The principles of complex systems suggest that the physical, social, and mental world is nonlinear, complex, random. This essential result of epistemology has important consequences for our present and future behavior. Science and technology will have a crucial impact on future developments. Thus this book finishes with an outlook on future, science, and ethics in a nonlinear, complex, and random world. What can we know about its future? What should we do?

8.1 Complexity, Forecasts, and the Future

In ancient times the ability to predict the future seemed to be a mysterious power of prophets, priests and astrologists. In the oracle of Delphi, for example, the seer Pythia (6th century B.C.) revealed the destiny of kings and heroes in a state of trance (Fig. 8.1) In modern times people came to believe in the unbounded capabilities of Laplace's demon: Forecasting in a linear and conservative world without friction and irreversibility would be perfect. We only need to know the exact initial conditions and equations of motion of a process in order to predict the future events by solving the equations for future times. Philosophers of science have tried to analyze the logical conditions of forecasting in the natural and social sciences [8.1]. Belief in man's forecasting power has been shaken over the course of this century by several scientific developments. Quantum theory teaches us that, in general, we can only make predictions in terms of probabilities (cf. Sect. 2.3). A wide class of phenomena is governed by deterministic chaos: Although their motions obey the laws of Newtonian physics, their trajectories depend sensitively on their initial conditions and thereby exclude predictions in the long run. In dissipative systems, such as the fluid layer of a Bénard experiment (Fig. 2.20), the emergence of order depends on microscopically small initial fluctuations. A tiny event, such as the stroke of a butterfly's wing, can, in principle, influence the global dynamics of weather. In chaotic systems, the prediction

Fig. 8.1. Aigeas, king of Athens, asking the Oracle at Delphi about his future (Greek bowl: 440–430 B.C.)

of future events is restricted, because the information flow from past to future decreases: The Kolmogorov-Sinai entropy has a finite value. But, in the case of random and noise, every correlation of past and future decays and the Kolmogorov-Sinai entropy is running to infinity: No prediction is possible. Obviously, the randomness of human fate was the challenge of ancient prophets, priests, and astrologists. In Chap. 7 we have learnt that patterns and relationships in economics, business, and society sometimes change dramatically. Going beyond the natural sciences, people's actions, which are observed in the social sciences, can and do influence future events. A forecast can, therefore, become a self-fulfilling or self-defeating prophecy that itself changes established patterns or relationships of the past. Is forecasting nothing more than staring into a crystal ball?

But nearly all our decisions are related to future events and require forecasts of circumstances surrounding that future environment. This is true for personal decisions, such as when and whom to marry or when and how to invest savings, and for complex decisions affecting an entire organization, firm, society, or the global state of the earth. In recent years increased emphasis has been placed on improving forecasting and decision making in economy and ecology, management and politics. Economic shocks, ecological catastrophes, political disasters, but also chances such as new markets, new technological trends, and new social structures, should no longer be

random and fateful events sent by the gods. People want to be prepared and have thus developed a variety of quantitative forecasting methods for different situations, e.g., in business and management. From a methodological point of view, every quantitative forecasting instrument can be characterized by a particular predictability horizon which limits its reliable application. Let us have a look at the strengths and weakness of some forecasting instruments.

The most common quantitative methods of forecasting are the time-series procedures [8.2]. They assume that some pattern in a data series is recurring over time and can be extrapolated to future periods. Thus, a time-series procedure may be appropriate for forecasting environmental factors such as the level of employment or the pattern of weekly supermarket sales where individual decisions have little impact. But time-series methods cannot explain the causes behind the data patterns. In historical times, the method was used by the Babylonian astronomers who extrapolated the data pattern of moonrise into the future without any explanation based on models of planetary motion. In the 18th century physicists knew little about the causes of sunspots. But in the observations of sunspots a pattern of frequency and magnitude was found and predictions were possible by its continuation through time-series analysis. In business and economics, there are various underlying patterns in data series. A horizontal pattern exists where there is no trend in the data (e.g., products with stable sales). A seasonal pattern exists when a series fluctuates according to some seasonal factor such as products whose sale depends on the weather. A cyclic pattern may not repeat itself at constant intervals of time, e.g., the price of metals or the gross national product. A trend pattern exists when there is a general increase or decrease in the value of the variable over time. When an underlying pattern exists in a data series, that pattern must be distinguished from randomness by averaging and weighting ("smoothing") the past data values. Mathematically, a linear smoothing method can be used effectively with data that exhibit a trend pattern. But smoothing methods make no attempt to identify individual components of the basic underlying patterns. There may be subpatterns of trend, cycle, and seasonal factors, which must be separated and decomposed in analyzing the overall pattern of the data series.

While in time-series procedures some data pattern from the past is merely extrapolated to the future, an explanatory model assumes a relationship between the ("dependent") variable y that we want to forecast and another ("independent") variable x. For example, the dependent variable y is the cost of production per unit, and the independent variable x determining the cost of production is the number of units produced. In this case, we can model the relationship in a two-dimensional coordinate system of y and x and draw a straight line that in some sense will give the best linear approximation of the relationship. Regression analysis uses the method of least squares in order to minimize the distance between the actual observations y and the corresponding points $\hat{y}$ on the straight line of linear approximation. Obviously, there are many situations in which this is not a valid approach. An example is the forecast of monthly sales varying nonlinearily according to the seasons of the year. Furthermore, every manager knows that sales are not influenced by time alone, but by a variety of other factors such as the gross national product, prices, competitors, production costs, taxes, etc. The linear interaction of two factors only is a simplification in economy similar to the two-body problems in the linear and conservative world of classical physics.

But, of course, a complex model that is more accurate requires a larger amount of effort, greater expertise and more computational time. In many decision-making situations more than one variable can be used to explain or forecast a certain dependent variable. An ordinary example is a marketing manager who wants to forecast corporate sales for the coming year and to better understand the factors that influence them. Since he has more than one independent variable, his analysis is known as multiple regression analysis. Nevertheless, the dependent variable he wishes to forecast is expressed as a linear function of the independent variables. The computation of the coefficients in the regression equation is based on the use of a sample of past observations. Consequently the reliability of forecasts based on that regression equation depends largely on the specific sample of observations that were used. Therefore degrees of reliability must be measured by tests of statistical significance. While multiple regression involves a single equation, econometric models can include any number of simultaneous multiple regression equations [8.3]. In the case of linear equations, the mathematical methods of solution are based on linear algebra and linear optimization methods (e.g., simplex method). In spite of their linearity, the econometric models may be highly complicated with many variables which can only be mastered by computer programs and machines. The solution strategy of nonlinear programming in economics often decomposes complex problems into subproblems which can be approximately treated as linear.

An implicit assumption in using these methods is that the model best fitting the available historical data will also be the best model to predict the future beyond these data. But this assumption does not hold true for the great majority of real-world situations. Furthermore, most data series used in economics and business are short, measurement errors abound, and controlled experimentation is not possible. It is therefore necessary to understand how various forecasting methods succeed when changes in the established patterns of the past take place. The predictions are different at the various forecasting horizons characterizing each method. Obviously, there is no unique method that can forecast best for all series and forecasting horizons. Sometimes there is nothing in the past data to indicate that a change will be forthcoming. Thus, it may be impossible to anticipate a pattern change without inside knowledge. Pattern shifts or the "change of paradigms" is an everyday experience of business people and managers and by no means an extraordinary insight of some philosophers of science in the tradition of Kuhn et al.

Are there quantitative procedures for determining when a pattern or relationship in a data series has changed? Such methods indeed exist and use a tracking signal to identify when changes in the forecasting errors indicate that a nonrandom shift has occurred. In a quality control chart of, e.g., a production series of cars, the output of the equipment is sampled periodically. As long as that sample mean is within the control limits, the equipment is operating correctly. When this is not the case, the production is stopped and an appropriate action is taken to return it to correct operation. In general, automatic monitoring of quantitative forecasting methods follows the concept of a quality control chart. Every time a forecast is made, its error (i.e., actual minus predicted value) is checked against the upper and lower control limits. If it is within an acceptable range, the extrapolated pattern has not changed. If the forecasting error is outside the control limits, there has probably been some systematic change in the established pattern. Automatic monitoring through tracking signals may be appropriate when large numbers of forecasts are involved. But in the case of one or only a few series, one must still play a waiting game to discover whether changes in the trends of business data are occurring.

Forecasting the future of technological trends and markets, the profitability of new products or services, and the associated trends in employment and unemployment is one of the most difficult, but also most necessary tasks of managers and politicians. Their decisions depend on a large number of technological, economic, competitive, social, and political factors. Since the emergence of commercial computers in the 1950s there has been hope that one might master these complex problems by increasing computational speed and data memory. Indeed, any quantitative forecasting method can be programmed to run on a computer. As no single forecasting method is appropriate for all situations, computer-based multiple forecasting systems have been developed in order to provide a menu of alternative methods for a manager. An example is the forecasting system SIBYL which is named after the ancient seer Sibyl. The story goes that Sibyl of Cumae sold the famous Sibylian books to the Roman king Tarquinius Superbus.

Indeed, SIBYL is a knowledge-based system (cf. Sect. 5.3) for a computerized package of forecasting methods [8.4]. It provides programs for data preparation and data handling, screening of available forecasting methods, application of selected methods, and comparing, selecting, and combining of forecasts. In screening alternative forecasting techniques, the inference component of the knowledge-based system suggests those methods that most closely match the specific situation and its characteristics based on a broad sample of forecasting applications and decision rules. The final function of SIBYL is that of testing and comparing which method provides the best results. The interface of user and system is as friendly and efficient as possible, in order to suit a forecasting expert as well as a novice. Nevertheless, we must not forget that SIBYL can only optimize the application of stored forecasting methods. In principle, the predictability horizon of forecasting methods cannot be enlarged by the application of computers. Contrary to the learning ability of a human expert, forecasting systems such as SIBYL are still program-controlled with the typical limitations of knowledge-based systems.

In general, the computer-based automation of forecasting followed along the lines of linear thinking. On the other hand, the increasing capability of modern computers encouraged researches to analyze nonlinear problems. In the mid-1950s meteorologists preferred statistical methods of forecasting based on the concept of linear regression. This development was supported by Norbert Wiener's successful predicting of stationary random processes. Edward Lorenz was sceptical about the idea of statistical forecasting and decided to test its validity experimentally against a nonlinear dynamical model (cf. Sect. 2.4). Weather and climate is an example of an open system with energy dissipation. The state of such a system is modeled by a point in a phase space, the behavior of the system by a phase trajectory. After some transient process a trajectory reaches an attracting set ("attractor") which may be a stable singular point of the system (Fig. 2.14a or 3.11c), a periodic oscillation called a limit cycle (Fig. 3.11d) or a strange attractor (Fig. 2.21). If one wants to predict the behavior of a system containing a stable singular point or a limit cycle, one may observe that the divergence of nearby trajectories appears not to be growing and may even diminish (Fig. 8.2). In this case, a whole class of initial conditions will be able to reach the steady state and the corresponding systems are predictable. An example is an ecological

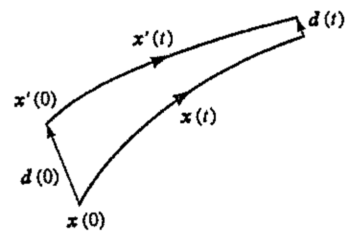

Fig. 8.2. Predictable system with stable point attractor or limit cycle and convergence of nearby trajectories [8.5]

system with periodic trajectorties of prey and predator populations modeled by nonlinear Lotka–Volterra equations. The divergence or convergence of nearby trajectories can be measured numerically by the so-called Lyapunov exponent:

Let us consider two nearby trajectories $x(t)$ and $x'(t)$ with the initial states $x(0)$ and $x'(0)$ at time $t = 0$ and the length $d(t) = |x'(t) - x(t)|$ of the vector $d(t)$. If the trajectories converge, then $d(t) \approx e^{\Lambda t}$ and $\Lambda < 0$. The quantity Λ is called Lyapunov exponent and defined as $\Lambda(x(0), d(0)) = \lim_{t\to\infty} \lim_{d(0)\to 0} [(1/t)\ln(d(t)/d(0))]$. If it is positive, the Lyapunov exponent gives the rate of divergence. In Fig. 8.2, the model process $x'(t)$ delivers reliable predictions of the real process $x(t)$, because the system is assumed to have converging trajectories independent of their initial conditions.

A phase portrait of a nonlinear system may have a number of attractors with different regions ("separatrices") of approaching trajectories (cf. Fig. 2.10). For forecasting the future of the evolving system it is not sufficient to know all possible attractors and the initial state $x(0)$. What we need to know in addition are the separatrices for attraction basins of the different attractors. If the initial state of a system happens to be far away from the basin of a certain attractor, the final state of the corresponding attractor cannot be predicted.

In Fig. 2.22a-c, the nonlinear logistic map describes a transition from order to chaos depending on an increasing control parameter. Figure 2.23a,b illustrates the corresponding sequence of bifurcations with the chaotic regime occurring beyond a critical threshold. If the corresponding Lyapunov exponent is positive, the behavior of the system is chaotic. If it is zero, the system has a tendency to bifurcate. If it is negative, the system is in a stable state or branch of the bifurcation tree. In this case the system is predictable. In the other cases the sensitivity to initial conditions comes into play. It is remarkable that a nonlinear system in the chaotic regime is nonetheless not completely unpredictable. The white stripes or "windows" in the grey veil of a chaotic future (Fig. 2.23b) indicate local states of order with negative Lyapunov exponents. Thus, in a sea of chaos we may find predictable islands of order. In this case the system is at least predictable for characteristic short intervals of time.

In general, the degree of predictability is measured by a statistical correlation between the observed process and the model at the particular time since the start of the observation. Values close to unity correspond to a satisfactory forecast, while small values indicate a discrepancy between observation and prediction. Every forecasting model has a certain time of predictable behavior after which the degree of predictability decreases more or less rapidly to zero. With improvement of the model the time of predictable behavior may be enlarged to some extent. But the predictability range depends upon fluctuational parameters. Weak microscopic perturbations of locally unstable chaotic systems can reach a macroscopic scale in a short time. Thus, local instabilities reduce the improvement of predictable behavior drastically. The predictability horizon of a forecasting system means a finite timespan of predictable behavior that cannot be surpassed by either improved measuring instruments or a refined prediction model. When we remember that the atmosphere is modeled, following Lorenz, by nonlinear systems with local and global instabilities, we realize the difficulties encountered by meteorologists in obtaining efficient long- or even medium-term forecasting. The belief in a linear progress of weather forecasting by increasing computational capacities was an illusion of the 1950s.

As nonlinear models are applied in different fields of research, we gain general insights into the predictable horizons of oscillatory chemical reactions, fluctuations of species, populations, fluid turbulence, and economic processes. The emergence of sunspots, for instance, which was formerly analyzed by statistical methods of time-series is by no means a random activity. It can be modeled by a nonlinear chaotic system with several characteristic periods and a strange attractor only allowing bounded forecasts of the variations. In nonlinear models of public opinion formation, for instance, we may distinguish a predictable stable state before the public voting ("bifurcation") when neither of two possible opinions is preferred, the short interval of bifurcation when tiny unpredictable fluctuations may induce abrupt changes, and the transition to a stable majority. The situation reminds us of growing air bubbles in turbulently boiling water: When a bubble has become big enough, its steady growth on its way upward is predictable. But its origin and early growth is a question of random fluctuation. Obviously, nonlinear modeling explains the difficulties of the modern Pythias and Sibyls of demoscopy.

Today, nonlinear forecasting models do not always deliver better and more efficient predictions than the standard linear procedures. Their main advantage is the explanation of the actual nonlinear dynamics in real processes, the identification and improvement of local horizons with short-term predictions. But first of all an appropriate dynamical equation governing an observation at time t must be reconstructed, in order to predict future behavior by solving that equation. Even in the natural sciences, it is still unclear whether appropriate equations for complex fields such as earthquakes can be derived. We may hope to set up a list in a computer memory with typical nonlinear equations whose coefficients can be automatically adjusted for the observed process. Instead, to make an exhaustive search for all possible relevant parameters, a learning strategy may start with a crude model operating over relatively short times and then specify a smaller number of parameters in a relatively narrow range of values. An improvement of short-term forecasting has been realized by the learning strategies of neural networks. On the basis of learned data, neural nets can weight the input data and minimize the forecasting errors of short-term stock quotations by self-organizing procedures (Fig. 6.4 a, b). So long as only some stock market advisors use this technical support, they may do well. But if all agents in a market use the same learning strategy, the forecasting will become a self-defeating prophecy.

The reason is that human societies are not complex systems of molecules or ants, but the result of highly intentional acting beings with a greater or lesser amount of free will [8.6]. A particular kind of self-fulfilling prophecy is the Oedipus effect in which people like the legendary Greek king try, in vain, to change their future as forecasted to them. From a macroscopic viewpoint we may, of course, observe single individuals contributing with their activities to the collective macrostate of society representing cultural, political, and economic order ("order parameters"). Yet, macrostates of a society, of course, do not simply average over its parts. Its order parameters strongly influence the individuals of the society by orientating ("enslaving") their activities and by activating or deactivating their attitudes and capabilities. This kind of feedback is typical for complex dynamical systems. If the control parameters of the environmental conditions attain certain critical values due to internal or external interactions, the macrovariables may move into an unstable domain out of which highly divergent alternative paths are possible. Tiny unpredictable microfluctuations (e.g., actions of very few influential people, scientific dicoveries, new technologies) may decide which of the diverging paths in an unstable state of bifurcation society will follow.

One of the deepest insights into complex systems is the fact that even complete knowledge of microscopic interactions does not guarantee predictions of the future. In this book, we have learnt that simple rules of physical, genetic, neural, or social dynamics can generate very complex and even random patterns of material formation, organic growth, mental recognition, and social behavior. Randomness, in a practical sense, only means that future formation or behavior cannot be detected by familiar and well-known patterns or programs. In this case, the computability of the future is not reducible relative to certain patterns and programs. Randomness, in principle, implies computational irreducibility: Then, there is no finite method of predicting how the system will behave except by going through nearly all the steps of actual development. In the case of randomness, there is no shortcut to evolution. Mathematical systems like cellular automata (CA) or technical systems like cellular neural/nonlinear networks (CNN) can achieve exactly the same level of complexity and randomness of nature and society. Thus, the traditional view of science – that precise knowledge of laws allows precise forecasting – fails in the case of nonlinear and random dynamics.

8.2. Complexity, Science, and Technology

Despite the difficulties referred to above, we need reliable support for short-, medium-, and long-term forecasts of our local and global future. A recent demand from politics is the modeling of future developments in science and technology which have become a crucial factor of modern civilization. Actually, this kind of development seems to be governed by the complex dynamics of scientific ideas and research groups which are embedded in the complex network of human society. Common topics of research groups attract the interest and capacity of researchers for longer or shorter periods of time. These research "attractors" seem to dominate the activities of scientists like the attractors and vortices in fluid dynamics. When states of research become unstable, research groups may split up into subgroups following particular paths of research which may end with solutions or may bifurcate again, and so forth. The dynamics of science seems to be realized by phase transitions in a bifurcation tree with increasing complexity. Sometimes scientific problems are well-defined and lead to clear solutions. But there are also "strange" and "diffuse" states like the strange attractors of chaos theory.

Historically, quantitative inquiries into scientific growth started with statistical approaches such as Rainoff's work on "Wave-like fluctuations of creativity in the development of West-European physics in the 18th and 19th century" (1929). From a sociological point of view Robert Merton discussed "Changing foci of interest in the sciences and technology", while Pitirim Sorokin analyzed the exponential increase of scientific discoveries and technological inventions since the 15th century. He argued that the importance of an invention or discovery does not depend on subjective weighting, but on the amount of subsequent scientific work inspired by the basic innovation. As early as 1912 Alfred Lotka had the idea of describing true epidemic processes like the spread of malaria and chemical oscillations with the help of differential equations. Later on, the information scientist William Goffman applied the epidemic model to the spread of scientific ideas. There is an initial focus of "infectious ideas" infecting more and more people in quasi-epidemic waves. Thus, from the viewpoint of epidemiology, the cumulation and concentration in a scientific field is modeled by so-called Lotka- and Bradford-distributions, starting with a few articles of some individual authors which are the nuclei of publication clusters [8.7]. The epidemic model was also applied to the spread of technical innovations. In all these examples we find the well-known S-curve of a logistic map (Fig. 2.22a) with a slow start followed by an exponential increase and then a final slow growth towards saturation. Obviously a learning process is also described in the three phases of an S-curve with slow learning success of an individual in the beginning,

then a rapid exponential increase and finally a slow final phase approaching saturation.

The transition from statistical analysis to dynamical models has the great methodological advantage that incomprehensible phenomena such as strange fluctuations or statistical correlations of scientific activities can be illustrated in computer-assisted simulation experiments with varying dynamical scenarios. The epidemic model and Lotka–Volterra equation were only a first attempt to simulate coupled growth processes of scientific communities. However, essential properties of evolutionary processes like creation of new structural elements (mutation, innovation, etc.) cannot be reflected. Evolutionary processes in social systems have to be pictured through unstable transitions by which new ideas, research fields, and technologies (like new products in economic models) replace already existing ones and thereby change the structure of the scientific system. In a generalization of Eigen's equation of prebiotic evolution (cf. Sect. 3.3), the scientific system is described by an enumerable set of fields (i.e., subdisciplines of a scientific research field), each of which is characterized by a number of occupying elements (i.e., scientists working in the particular subdiscipline). Elementary processes of self-reproduction, decline, exchange, and input from external sources or spontaneous generation have to be modeled. Each self-replication or death process changes only the occupation of a single field. For simple linear self-reproduction processes without exchange, the selection value of a field is given by the difference between the "birth" and "death" rates of the field. When a new field is first populated, it is its selection value that decides whether the system is stable or unstable with respect to the innovation. If its selection value is larger than any other selection value of existing fields, the new field will outgrow the others, and the system may become unstable. The evolution of new fields with higher selection values characterizes a simple selection process according to Darwinian "survival of the fittest".

But we must not forget that such mathematical models do not imply the reduction of scientific activities to biological mechanisms. The variables and constants of the evolution equation do not refer to biochemical quantities and measurements, but to the statistical tables of scientometrics. Self-reproduction corresponds to young scientists joining the field of research they want to start working in. Their choice is influenced by education processes, social needs, individual interest, scientific schools, etc. Decline means that scientists are active in science for a limited number of years. The scientists may leave the scientific system for different reasons (e.g., age). Field mobility means the process of exchange of scientists between research fields according to the model of migration. Scientists might prefer the direction of higher attractiveness of a field expressed by a higher self-reproduction rate. When processes include exchange between fields with nonlinear growth functions of self-reproduction and decline, then the calculation of selection values of an innovation is a rather complicated mathematical task. In general, a new field with higher selection value is indicated by the instability of the system with respect to a corresponding perturbation.

Actually, scientific growth is a stochastic process. When, for example, only a few pioneers are working in the initial phase of a new field, stochastic fluctuations are typical. The stochastic dynamics of the probable occupation density in the scientific subfields is modeled by a master equation with a transition operator which is defined by transition probabilities of self-reproduction, decline, and field mobility. The stochastic model provides the basis for several computer-assisted simulations of scientific growth processes. The corresponding deterministic curves, as average over a large number of identical stochastic systems, are considered for trend analysis, too. As a result, the general S-shaped growth law for scientific communities in subdisciplines with a delayed initial phase, a rapid growth phase, and a saturation phase has been established in several simulations. In a series of simulations (Fig. 8.3), a research field was assumed to comprise about 120–160 members. For five fields, 100 scientists were chosen as initial condition with the saturation domain near the initial conditions. A sixth field is not yet set up (with the initial condition of zero members). In a first example, the influence of the self-reproduction process on the growth curve of the new field was simulated for several cases. With increasing self-reproduction rates the new field grows ever more rapidly at the expense of neighboring fields.

The emergence of a new field may have a tendency to more coexistence or selection. The growth of the initial phase may be more or less rapid or can also be delayed. A famous example of delayed growth in the history of science is chaos theory itself, which was treated by only very few scientists (e.g., Poincaré) in its initial phase. Although the mathematical principles of the new field were quite clear, its exponential growth began only some years ago when computational technology could handle nonlinear equations. Sometimes an emerging field cannot expand to a real domain of science, because it has only a weak selection advantage in comparison with mighty surrounding fields. It is a pity that some technological fields such as alternative energies (e.g., wind, solar) are still in such a poor state, surrounded by the powerful industries of traditional or nuclear energy. If a new attractive field emerges, a strong influx of scientists from the surrounding fields can be observed. These people are adapting to the style and problem solving pattern of the new field. This kind of directed field mobility sometimes leads to the phenomena of fashion in science.

It is well-known that the S-shaped nonlinear logistic map gives rise to a variety of complex dynamical behaviors such as fixed points, oscillations, and deterministic chaos, if the appropriate control parameters increase beyond certain critical values (Fig. 2.22). Obviously, both the stochastic and the deterministic models reflect some typical properties of scientific growth.

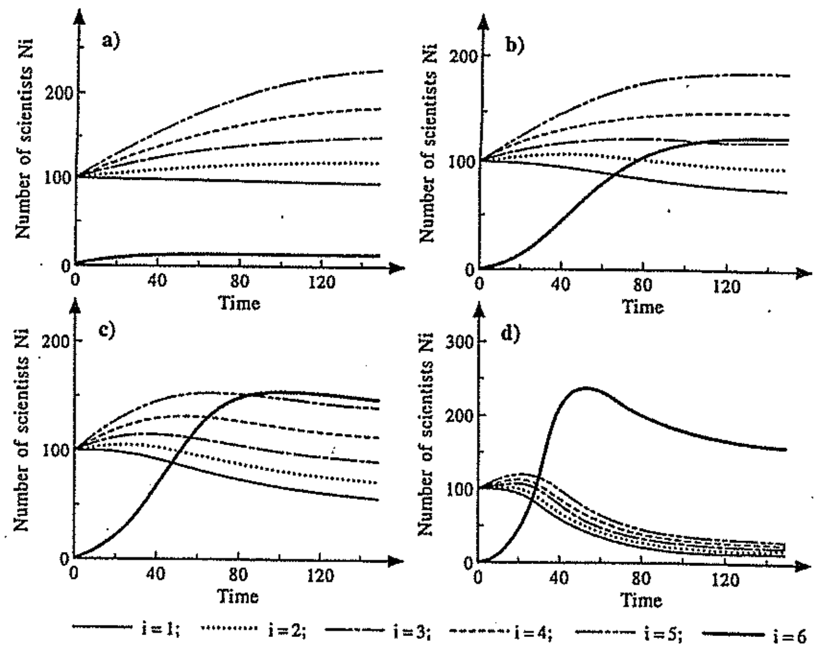

Fig. 8.3. Influence of the self-reproduction rate of a new scientific field on the growth curves of neighboring fields [8.8]

Such effects are structural differentiation, deletion, creation, extension of new fields with delay, disappearance, rapid growth, overshooting fashions, and regression. The computer-assisted graphic simulations of these dynamical effects allow characterization by appropriate order parameters which are testable on the basis of scientometric data. Possible scenarios under varying conditions can be simulated, in order to predict the landmarks and the scope of future developments.

But so far, the evolution of scientific research fields has been considered in the model only in terms of changes of the scientific manpower in the selected fields. A more adequate representation of scientific growth must take account of the problem-solving processes of scientific endeavors. But it is a difficult methodological problem to find an adequate state space representing the development of problem solving in a scientific field. In the mathematical theory of biological evolution, the species can be represented by points in a high-dimensional space of biological characters (Fig. 3.4). The evolution of a species corresponds to the movement of a point through the phenotypic character space. Analogously, in the science system, a high-dimensional character space of scientific problems has to be established. Configurations of scientific articles which are analyzed by the technique of multidimensional scaling in co-citation clusters can be represented by points in a space of two or three dimensions. Sometimes research problems are indicated by sequences of key-words ("macro-terms") which are registered according to the frequency of their occurrence or co-occurrence in a scientific text.

In a continuous evolution model each point of the problem space is de- scribed by a vector corresponding to a research problem (Fig. 8.4a). The problem space consists of all scientific problems of a scientific field, of which some are perhaps still unknown and not under investigation. This space is metric, because the distance between two points corresponds to the degree of thematic connection between the problems represented. The scientists work- ing on problem q at time t distribute themselves over the problem space with the density $x(q, t)$. In the continuous model $x(q, t)\,dq$ means the number of scientists working at time t in the "problem element" dq (Fig. 8.4b).

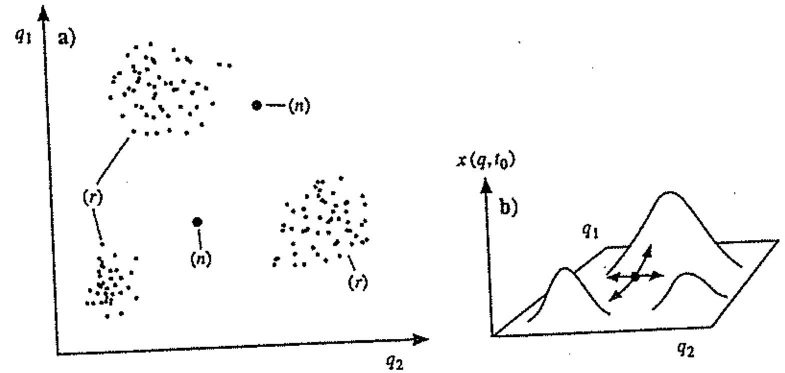

Fig. 8.4a,b. A two-dimensional problem space (a) with research fields (r) as clouds of related problems, possible nuclei (n) of new research fields, and a potential landscape (b) of research activities $x(q, t)$ in problem $q = (q_1, q_2)$ of the problem space at time t [8.9]

Thus the research fields may correspond to more or less closely con- nected point clouds in the problem space. Single points between these areas of greater density correspond to scientists working on isolated research prob- lems which may represent possible nuclei of new research fields. History of science shows that it may take decades before a cluster of research prob- lems grows up into a research field. In the continuous model, field mobility processes are reflected by density change: If a scientist changes from prob- lem q to problem q', then the density $x(q, t)$ will get smaller and $x(q', t)$ will

increase. The movement of scientists in the problem space is modeled by a certain reproduction–transport equation. A function $a(q)$ expresses the rate at which the number of scientists in field q is growing through self-reproduction and decline. Thus, it is a function with many maxima and minima over the problem space, expressing the increasing or decreasing attractiveness of the problems in a scientific field. In analogy to physical potentials (e.g., Fig. 4.10), one may interpret $a(q)$ as a potential landscape of attractiveness with hills and valleys, representing the attractors and deadlocked areas of a research field (Fig. 8.4b).

Dynamical models of the growth of knowledge become testable by scientometrics. Thus, they may open a bridge between philosophy of science with its conceptual ideas of scientific growth and history of science with its evaluation of scientific documents. In cognitive scientometrics an attempt has recently been made to quantify the concept of research problems and to represent them in appropriate problem spaces by bibliometric, cognitive, and social characteristics. The simplified schemes of the history of science which have been suggested by Popper, Kuhn, and others, could perhaps be replaced by testable hypotheses. Kuhn's discontinuous sequence with phases of "normal" and "revolutionary" science is obviously not able to tackle the growth of knowledge. On the other hand, the naive belief of some historians that the growth of science is a continuous cumulation of eternal truths is not appropriate to the complex dynamics of research in any way. Even Popper's sophisticated late philosophy that science does not grow through a monotonic increase of the number of indubitably established laws but through learning strategies of hypotheses and criticism needs more precision and clarification with reference to the changing historical standards of methodology, institutionalization, and organization. The increasing computational capacities of modern computers enable a new quantitative approach with simulation experiments in social sciences. The great advantage of dynamical models is their computer-assisted graphic illustration of several scenarios with varying parameters. These scenarios may confirm, restrict, or refute the chosen model. Last but not least, we need reliable support for decisions in science policy. Different scenarios of future developments may help us to decide where to invest our limited resources of research budget and how to realize desirable future states of society.

Thus nonlinear modeling and computer-assisted simulation may enable us to derive multiple futures, but provides no algorithm to decide between them. Normative goals must be involved in order to realize desirable future states of society. Since the 1960s the reports of the Club of Rome have tried to initiate international debates about the goals and alternative futures of mankind, supported by quantitative long-term forecasts. In Sect. 7.1, we saw the limitations of quantitative long-term forecasting in a nonlinear world. Consequently, scientific ideas and technological innovations cannot be forced into being by political decisions. But they must no longer be fateful random events which may or may not happen. We need instruments to evaluate desirable goals and their chance of realization.

A nonquantitative approach is the so-called Delphi method, used to prepare decisions and forecasts of scientific and technological trends by a panel of experts. The name "Delphi" is a reference to the legendary Pythia (Fig. 8.1) who was said to prepare her prophecies by gathering information about her clients. The Delphi method of today uses the estimates of scientific experts. The individual experts are kept apart so that their judgement is not influenced by social pressure or group behavior. The experts were asked in a letter to name and to weight inventions and scientific breakthroughs that are possible and/or desirable in a certain period of time. Sometimes they are not only asked for the probability of each development: Additionally, they are asked to estimate the probability that the occurrence of any one of the potential developments will influence the likelihood of occurrence of each of the others. Thus one gets a correlated network of future developments which can be represented by a matrix of subjective conditional probabilities. In the next phase the experts are informed about the items with general consensus. When they are asked to state the reasons for their disagreement with the majority, several of the experts re-evaluate their time estimates, and a narrower range for each breakthrough may be arranged.

The Delphi method, of course, cannot deliver a single answer. But the spread of expert opinions gathers considerable information about potential major breakthroughs. The average deviations from the majority should be narrowed down without pressuring the experts with extreme responses. But the Delphi method therefore cannot predict the unexpected. Sometimes the Delphi method is supported by the relevance-tree method, in order to select the best actions from alternatives by constructing decision trees. The relevance-tree method uses the ideas of decision theory to assess the desirability of a certain future and to select those areas of science and technology whose development is necessary for the achievment of those goals.

Obviously there is no single method of forecasting and deciding in a complex nonlinear world. We need an integrative ("hybrid") network of quantitative and qualitative methods. Finally, we need ethical landmarks to guide us in applying these instruments and in mastering the future.

8.3 Complexity, Responsibility, and Freedom

In recent years, ethics has become a major topic attracting increasing interest from a wide variety of professionals including engineers, physicians, scientists, managers, and politicians. The reasons for this interest are the growing problems with the environment, the economy, and modern technologies,

questions of responsibility, increasing alarm, and decreasing acceptance of critical consequences in a highly industrialized world. But we must be aware that our standards of ethical behavior have not fallen to Earth from Heaven and have not been revealed by some mysterious higher authority. They have changed and they will continue to change, because they are involved in the evolution of our sociocultural world.

In modeling human society we must not forget the highly nonlinear self-referentiality of a complex system with intentionally acting beings. There is a particular measurement problem in social sciences arising from the fact that scientists observing and recording behavior of society are themselves members of the social system they observe. Well-known examples are the effects of demoscopic opinion-polling during political elections. Furthermore, theoretical models of society may have a normative function influencing the future behavior of its agents. A well-known example was the social Darwinism of the 19th century which tried to explain the social development of mankind as a linear continuation of biological evolution. Actually, that social theory initiated a brutal ideology legitimating the ruthless selection of the social, economic, and racial victors of history. Today, it is sometimes fashionable to legitimate political ideas of basic democracy and ecological economy by biological models of self-organization [8.10]. But nature is neither good nor bad, neither peaceful nor militant. These are human evaluations. Biological strategies over millions of years have operated at the expense of myriads of populations and species with gene defects, cancer, etc., and have, from a human point of view, perpetrated many other cruelties. They cannot deliver the ethical standards for our political, economic, and social developments.

In this book we have seen that the historical models of life, mind, and society often depend on historical concepts of nature and historical standards of technology. Especially the linear and mechanistic view of causality was a dominant paradigm in the history of natural, social, and technical sciences. It also influenced ethical norms and values which cannot be understood without the epistemic concepts of the historical epochs in which they arose. The historical interdependence of epistemology and ethics does not mean any kind of relativism or naturalism. As in the case of scientific theories and hypotheses we have to distinguish their context of historical and psychological invention and discovery from their context of justification and validity. Even human rights have a historical development with changing meanings [8.11]. Hegel once mentioned that the history of mankind can be understood as a "development to freedom". Thus, before we discuss possible ethical consequences in a complex, nonlinear, and random world, we should take a short glance at the historical development of ethical standards.

Ethics is a discipline of philosophy like logic, epistemology, philosophy of science, language, law, religion, and so on [8.12]. Historically, the word "ethics" stems back to the Greek word ἦθος, which means custom and practice. Originally, ethics was understood as a doctrine of moral customs and institutions teaching people how to live. The central problem of ethics has become that of finding a good moral code with advice on how to live well, how to act justly, and how to decide rationally. Some essential concepts of ethics were already discussed in Greek philosophy following Socrates. His student Plato generalized the Socratic quest for a good life to the universal idea of the greatest good, which is eternal and independent of the historical life behind the transistory and continously changing world of matter [8.13].

Aristotle criticized his teacher's doctrine of eternal values as ignorant of real human life. For Aristotle the validity of the good, the just, and the ratio- nal is referred to the political society (*polis*), the family, and the interaction of single persons [8.14]. Justice in the polis is realized by the proportionality or the equilibrium of natural interest of free men. The greatest good of man is happiness, which is realized by a successful life according to the natural customs and practice in the polis and the family. Obviously, Aristotle's con- cept of ethics corresponds to his organic view of a nature filled with growing and maturing organisms like plants, animals, and humans.

After the dissolution of the Greek polis, ethics needed a new framework of standards. In Epicurean ethics, the internal equality of individual life, action, and feeling was emphasized, while the ethics of the Stoics underlined the external equality of all people achieved by nature. In the Christian Middle Ages a hierarchy of eternal values was guaranteed by the divine order of the world. At the beginning of modern times the theological framework as a universally accepted foundation of ethics was ripe for dissolution.

Descartes not only suggested a mechanistic model of nature but also demanded a moral system founded upon scientific reason. Baruch Spinoza derived an axiomatized system of rationalist morality corresponding to the deterministic and mechanistic model of nature. As the laws of nature are believed to be identical with the laws of rationality, human freedom only could mean acting according to deterministic laws which were recognized as rational. The greatest good meant the dominance of rationality over the affects of the material human body. Hobbes defended a mechanistic view of nature and society, but he doubted human rationality. Political laws and customs can only be guaranteed by the centralized power of "Leviathan". The greatest good is peace as a fixed and final equilibrium in an absolutist state.

The liberal society of Locke, Hume, and Smith was understood by anal- ogy with Newton's model of separable forces and interacting celestial bodies. In the American and French revolutions, individual freedom was proclaimed as a natural right [8.15]. But how to justify individual freedom in a mechanis- tic world with deterministic causality? Every natural event is the effect of a linear chain of causes which in principle can be derived by mechanistic equa- tions of motion. Only humans are assumed to be capable of spontaneous and

free decisions initiating causal chains of actions without being influenced by outer circumstances. Kant called this human feature the "causality of free- dom".

As nobody's opinions and desires are privileged, only advice which is acceptable for everybody is justified as reasonable. In the words of Kant, only those generally accepted "maxims" can be justified as universal moral laws. This formal principle of moral universality is Kant's famous categorical imperative of reason: we should act according to imperatives which can be justified as general laws of morality. The freedom of a person is limited by the freedom of his or her neighbor. In another famous formulation, Kant said that humans as free beings should not be misused as instruments for the interests of other humans. Thus, besides the mechanistic world of nature, which is ruled by deterministic laws, there is the internal world of reason with the laws of freedom and morality. Kant's ethic of freedom has been incorporated in the formal principles of every modern constitutional state [8.16].

But how can the laws of freedom be realized in the real world of politics and economics? During the initial process of industrialization the ethics of Anglo-American utilitarianism (due to Bentham and Mill) required an esti- mation of personal happiness. The happiness of the majority of people was declared to be the greatest good of ethics. While Kant suggested a formal principle of individual freedom, the utilitarian principle of happiness can be interpreted as its material completion. It was explicitly demanded as a natu- ral human right in the American constitution. The utilitarian philosophers and economists defined the demand for happiness as an utility function that must be optimized with as few costs as possible in order to realize the great- est welfare for the majority of people. The principles of utilitarianism have become the ethical framework of welfare economics [8.17].

Modern philosophers like John Rawls have argued that the utilitarian principle in combination with Kant's demand for ethical universality can help to realize the demand for a just distribution of goods in modern welfare politics [8.18]. From a methodological point of view, the ethical, political, and economic model of utilitarianism corresponds to a self-organizing com- plex system with a single fixed point of equilibrium which is realized by an optimization of the utility function of a society and which is connected with a just distribution of goods to the majority of people.

Obviously, Kant's ethics as well as Anglo-American utilitarianism are normative demands to judge our actions. They may be accepted or not by individuals. Hegel argued that the subjective ethical standards of individuals were products of objective historical processes in history which were realized by the institutions of a society. Thus, he distinguished between the subjective morality and subjective reason of individuals and the objective morality and objective reason of institutions in a society. Historically, Hegel's foundation of ethics in the actual customs and morality of a civil society reminds the reader of Aristotle's realistic ethics of the Greek polis. But Aristotle's order of society was static, while Hegel assumed a historical evolution of states and their institutions.

From a methodological point of view, it is remarkable that Hegel already distinguished between the micro-level of individuals and a macro-level of societies and their institutions which is not only the sum of their citizens. Furthermore, he described an evolution of society which is not determined by the intentions and the subjective reason of single individuals, but by the self-organizing process of a collective reason. Nevertheless, Hegel believed in a rather simplified model of evolution with sequential states of equilibrium leading to a final fixed point which is realized by the attractor of a just civil society. Actual history after Hegel showed that his belief in the rational forces of history driving human society to a final state of justice by self-organization was a dangerous illusion. It is well known that his model was modified and misused by totalitarian politicians of the political right and left.

Friedrich Nietzsche attacted the belief in objective reason as well as in eternal ethical values as idealistic ideologies which were contrary to the real forces of life. Nietzsche's philosophy of life was influenced by Darwin's biology of evolution, which had become a popular philosophy in the late 19th century. Although Nietzsche had criticized nationalism and racism in his writings, his glorification of life and the victors in the struggle of life was terribly misused in the politics of our century. Nevertheless, he is another example to show that concepts from the natural sciences have influenced political and ethical ideas [8.19].

Nietzsche's nihilism and his critique of modern civilization were continued by Martin Heidegger in our century. In Heidegger's view, the technical evolution of mankind is an automatism without orientation which has forgotten the essential foundation of man and humanity. A philosopher like Heidegger cannot and will not change or influence this evolution. He only has the freedom to bear this fate with composure. But in what way is Heidegger's attitude against technology and civilization more than resignation, fatalism, and an escape into an idyllic utopia without technology which has never existed in history? It seems to be the extreme counterposition to the Laplacean belief in an omnipotent planning and controlling capacity in nature and society [8.20].

What are the ethical consequences of the complex system approach which has been discussed in this book? First, we must be aware that the theory of complex systems is not a metaphysical process ontology. It is not an epistemic doctrine in the traditional sense of philosophy. The principles of this methodology deliver a heuristic scheme for constructing models of nonlinear complex systems in the natural and social sciences. If these models can be mathematized and their properties quantified, then we get empirical

models which may or may not fit the data. Moreover, it tries to use a minimum of hypotheses in the sense of Ockham's razor. Thus it is a *mathematical, empirical, testable*, and *heuristically economical methodology*. Furthermore, it is an *interdisplinary research program* in which several natural and social sciences are engaged. However, it is not an ethical doctrine in the traditional sense of philosophy.

Nevertheless, our models of complex, nonlinear, and random processes in nature and society have important consequences for our behavior. In general, linear thinking may be dangerous in a nonlinear complex reality. We have seen that traditional concepts of freedom were based on linear models of behavior. In this framework every event is the effect of a well defined initial cause. Thus, if we assume a linear model of behavior, the responsibility for an event or effect seems to be uniquely decidable. But what about the global ecological damage which is caused by the local nonlinear interactions of billions of self-interested people? Recall, as one example, the demand for a well balanced complex system of ecology and economics. As ecological chaos can be global and uncontrollable, some philosophers like Hans Jonas have proposed that we stop any activity which could perhaps have some unknown consequences [8.21]. But we can never forecast all developments of a complex system in the long run. Must we therefore retire into a Heidegger-like attitude of resignation? The problem is that doing nothing does not necessarily stabilize the equilibrium of a complex system and can drive it to another metastable state. In chaotic situations, short-term forecasting is possible in complex systems, and attempts are being made to improve it in economics, for instance. But in the case of randomness and information noise, any kind of forecasting fails, eventhough we may be completely informed about the local rules of interaction in a complex system.

In a linear model, the extent of an effect is believed to be similar to the extent of its cause. Thus, a legal punishment of a punishable action can be proportional to the degree of damage effected. But what about the butterfly effect of tiny fluctuations which are initiated by some persons, groups, or firms, and which may result in a global crisis in politics and economics? For instance, consider the responsibility of managers and politicians whose failure can cause the misery of thousands or millions of people [8.22]. But what about responsibility in the case of random events? Information noise in the Internet, for example, must be prevented beforehand. If random happens, it is too late.

As the ecological, economic, and political problems of mankind have become global, complex, nonlinear, and random, the traditional concept of individual responsibility is questionable. We need new models of collective behavior depending on the different degrees of our individual faculties and insights. Individual freedom of decision is not abolished, but restricted by collective effects of complex systems in nature and society which cannot be forecast or controlled in the long run. Thus, it is not enough to have good individual intentions. We have to consider their nonlinear effects. Global dynamical phase portraits deliver possible scenarios under certain circumstances. They may help to achieve the appropriate conditions for fostering desired developments and preventing evil ones.

The dynamics of globalization is surely the most important political challenge of complexity for the future of mankind. After the fall of the Berlin wall, politicians believed in the linear assumption that coupling the dynamics of free markets and democracy would automatically lead to a community of modernized, peace-loving nations with civic-minded citizens and consumers. This was a terrible error in a complex world! From our point of view, complexity is driven by multi-component dynamics. Politicians and economists forgot that there are also ethnic and religious, psychological and social forces which can dominate the whole dynamics of a nation at a critical point of instability. As we all know from complex dynamical systems, we must not forget the initial and secondary conditions of dynamics. Instability emerges if free markets and elections are implemented under conditions of underdevelopment.

Recent studies [8.23] demonstrate that in many countries of Southeast Asia, South America, Africa, Southeast Europe, and the Middle East the coupling of laissez-faire economics and electoral freedom did not automatically lead to more justice, welfare, and peace, but tipped the balance in these regions toward disintegration and strife. One reason is that these countries mainly have no broad majority of well educated people. Thus, minorities of clever ethnic groups, tribes, and clans come to power and dominate the dynamics of markets and politics. In the terminology of complex dynamics, they are the order parameters dominating ("enslaving") the whole dynamics of a nation. Again, the good intentions of democracy and free markets are not sufficient. We must consider the local conditions of countries and regions.

In classical philosophy, the transition from an intended development to a development contrary to the spirit of the philosophy has become famous as a contradiction of dialectics (e.g., Hegel). Good intentions may lead to bad effects. But sometimes human agents are driven by history to good effects without their subjective intentions. Hegel called it a "stratagem of reason" (List der Vernunft). Actually, it is a well-known effect of nonlinear dynamics. Therefore, market-dominant minorities are not a priori evil. Minorities are also the driving forces of activity. If they are open-minded and flexible, they prevent narrow-minded "enslaving" which may be successful only for a short time. In their own interest, they must try to stabilize the whole system in the long run. Therefore they should help dampening the social effects of free markets, bridging social cleavages, and transcending class division during a phase transition to democracy and welfare for the majority of the people.

But these phase transitions may be different from region to region in the world. Responsible decisions require sensativity to local conditions in light of the butterfly effect.

There are not only local minorities in regions and countries. During the process of globalization, a minority of nations, institutions, and companies can come to power and dominate the whole dynamics of global economics and politics. Recent discussions on globalization show that a lot of people are not happy with the results of globalization. But it is necessary to understand that globalization means nothing more than the gobal dynamics of political and economic systems in the world. So, in a first run, it is neither good nor evil like the dynamics of weather. But contrary to weather, the dynamics of globalization is generated by the interactions of humans and their institutions. Thus, there will be a chance to influence globalization if we take into account the dynamical laws of complexity and nonlinearity.

It is a hard fact that the order parameters of globalization have been defined by a minority of nations. They are the world's preeminent political, economic, military, and technological powers whether we like it or not. Philosophers, mathematicians, and systems scientists have no power. But, again, we should use Hegel's "stratagem of reason": Minorities are also the centers of driving power which enables chances for change. Concepts and ideas without political power have no chance. If the dominating minorities of globilization are open-minded and flexible, they will prevent narrow-minded "enslaving" which may be successful only for a short time. In their own interest, they must try to stabilize the whole system in the long run. Therefore they should help dampening the social effects of global free markets, bridging social cleavages, and transcending class division during a phase transition to global democracy and welfare for the majority of the people.

Globalization means the critical phase transion to global governance in the world. We need new global structures to manage the political, economic, military, and technological power in the world according to the interests of the majority of people on earth. Global structures emerge from the nonlinear interactions of peoples, nations, and systems. At the end of the 18th century, Kant already demanded a law of nations leading "To Eternal Peace" (1795) [8.24]. After the 1st World War, president Wilson of the United States strongly influenced the foundation of the League of Nations. After the 2nd World War, the United Nations (UN) presented a new chance to handle international conflicts, but they often fail because of their lack of power. The dilemma of international law is that law needs power to enforce rights and ethical norms. Therefore nations have to give up parts of their sovereignty, in order to be dominated by commonly accepted "order parameters". After September 11 2001, a global network of terrorism threatens the preeminent political and economic nations of the world. This is the reason why especially the United States, which historically helped found the League of Nations as well as the

Unitied Nations, now hesitates to restrict its national sovereignty and prefers to organize its own national security through global military defense.

Clearly it is a long way to global governance among autonomous nations. On the other hand, we must not forget the practical progress made by new social and humanitarian institutions of the UN. New economic, technological, and cultural networks of cooperation emerge and let people grow slowly together in spite of reactions and frictions in political reality. On the way to "eternal peace", Kant described a federal (multi-component) community of autonomous nations self-organizing their political, economic, and cultural affairs without military conflicts. But an eminent working condition of his model is the demand that states organize their internal affairs according to the civil laws of freedom. It is a hard fact of historical experience that civic-mindedness and humanization have sometimes not only be defended, but also enforced by military power. As long as the demand for civil laws of freedom is not internationally fulfilled, the organization of military power is an urgent challenge to globalization.

Globalization and international cooperation is accelerated by the growth of global information and computational networks like the internet and wireless mobile communication systems. On the other hand, the electronic vision of a global village implies a severe threat to personal freedom. If information about citizens can easily be gained and evaluated in large communication networks, then the danger of misuse by interested institutions must to be taken in earnest. As in the traditional economy of goods, there may arise information monopolies acting as dominating minorities prejudicing other people, classes, and countries. For instance, consider the former "Third World" or the "South" with its less developed systems for information services which would have no fair chance against the "North" in a global communication village.

Our physicians and psychologists must learn to consider humans as complex nonlinear entities of mind and body. Linear thinking may fail to yield a successful diagnosis. Local, isolated, and "linear" therapies of medical treatment may cause negative synergetic effects. Thus, it is noteworthy that mathematical modeling of complex medical and psychological situations advises high sensitivity and cautiousness, in order to heal and help ill people. The complex system approach cannot explain to us *what* life is. But it can show us *how* complex and sensitive life is. Thus, it can help us to become aware of the value of our life.

But what about the value of our life if it is computable? One of the most essential insights of this book is that the dynamics of nature and society are not only characterized by nonlinearity and chaos, but by randomness, too. Only in randomness can human free will have a real chance [8.25]. In the completely deterministic and computational world of a mechanical nature, Kant had to postulate a transcendental world in order to make free will,

ethical duties, and responsibility possible. In random states of nature and society, the behavior of a system is not determined in any way. Random dynamics can be generated even if all rules of interaction of the elements in a dynamical system are known. In this case, the dynamics of a system correspond to irreducible computation, which means that there is no chance of forecasting. The only way to learn anything about the future of the system is to perform the dynamics. The macrobehavior of a brain, for example, could correspond to an irreducible computation, although we know all the rules of synaptic interactions. In this case, there is no shortcut or finite program for our life. We have to live our life in order to experience it. It is amazing that human free will seems to be supported just by the mathematical theory of computability.

Obviously, the theory of complex systems has consequences for the ethics of politics, economics, ecology, medicine, and biological, computational, and information sciences. These ethical consequences strongly depend on our knowledge about complex nonlinear dynamics in nature and society, but they are not derived from the principles of complex systems. Thus, we do not defend any kind of ethical naturalism or reductionism. Dynamical models of urban developments, global ecologies, human organs, or information networks only deliver possible scenarios with different attractors. It is a question for us to evaluate which attractor we should prefer ethically and help to realize by achievement of the appropriate conditions. Immanuel Kant summarized the problems of philosophy in the three famous questions [8.26]:

What can I know?
What must I do?
What may I hope?

The first question concerns epistemology with the possibilities and limitations of our recognition. The theory of complex systems explains what we can know and what we cannot know about nonlinear dynamics in nature and society. In general, the question invites a demand for scientific research, in order to improve our knowledge about complexity and evolution.

The second question concerns ethics and the evaluation of our actions. In general, it invites a demand for sensitivity in dealing with highly sensitive complex systems in nature and society. We should neither overact nor retire, because overaction as well as retirement can push the system from one chaotic state to another. We should be both cautious and courageous, according to the conditions of nonlinearity and complexity in evolution. In politics we should be aware that any kind of mono-causality may lead to dogmatism, intolerance, and fanaticism.

Kant's last question "What may we hope?" concerns the Greatest Good, which has traditionally been discussed as *summum bonum* in the philosophy of religion. At first glance, it seems to be beyond the theory of complex systems, which only allows us to derive global scenarios in the long run and short-term forecasts under particular conditions. But when we consider the long sociocultural evolution of mankind, the greatest good that people have struggled for has been the dignity of their personal life. This does not depend on individual abilities, the degree of intelligence, or social advantages acquired by the contingencies of birth. It has been a free act of human self-determination in a stream of nonlinearity and randomness in history. We have to project the Greatest Good on an ongoing evolution of increasing complexity.

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