

9 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?

9.1 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. 9.1) 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 [9.1]. 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 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



Fig. 9.1. Aigeus, king of Athens, asking the Oracle at Delphi about his future (Greek bowl: 440–430 B.C.)

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 [9.2]. 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 im-

pact. 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 nonlinearly 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 compu-

tation 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 [9.3]. 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 Silybian books to the Roman king Tarquinius Superbus.

Indeed, SIBYL is a knowledge-based system (cf. Sect. 6.1) for a computerized package of forecasting methods [9.4]. 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. 9.2). 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 system with periodic trajectories of prey and predator populations modeled by nonlinear Lotka–Volterra equations. The divergence or

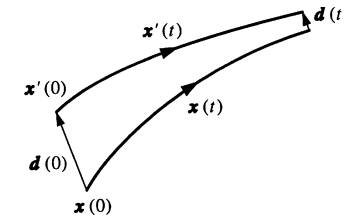


Fig. 9.2. Predictable system with stable point attractor or limit cycle and convergence of nearby trajectories [9.5]

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 $\Lambda(x(0), d(0)) = \lim_{t \rightarrow \infty} \lim_{d(0) \rightarrow 0} [(1/t) \ln(d(t)/d(0))]$. If it is positive, the Lyapunov exponent gives the rate of divergence. In Fig. 9.2, 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 demoscropy.

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. 6.14a,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 [9.6]. 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 discoveries, 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.

9.2 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 [9.7]. 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. 9.3), 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 increas-

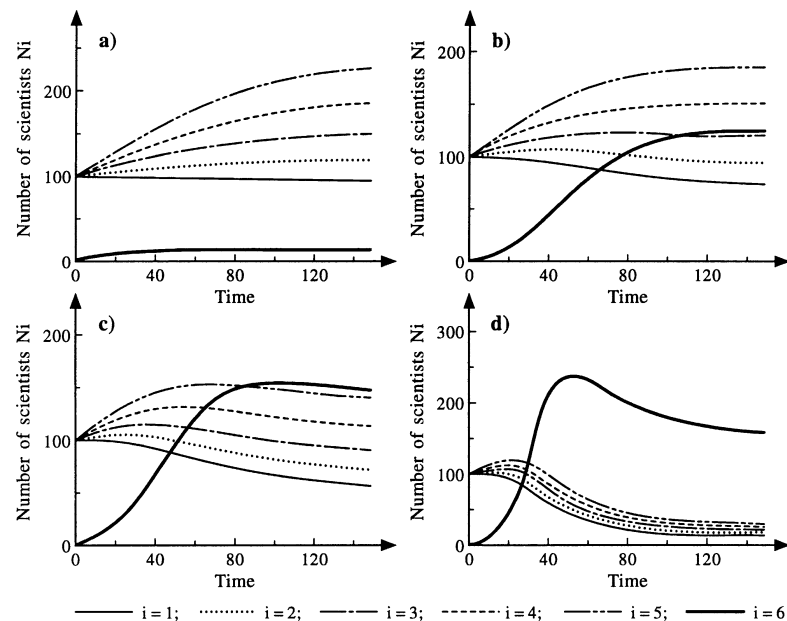


Fig. 9.3. Influence of the self-reproduction rate of a new scientific field on the growth curves of neighboring fields [9.8]

ing 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. 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 keywords ("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 described by a vector corresponding to a research problem (Fig. 9.4a). 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 working 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. 9.4b).

Thus the research fields may correspond to more or less closely connected point clouds in the problem space. Single points between these areas of greater density correspond to scientists working on isolated research problems which may represent possible nuclei of new research fields. History of science shows that it may take decades before a cluster of research problems grows up into a research field. In the continuous model, field mobility processes are reflected by density change: If a scientist changes from problem 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

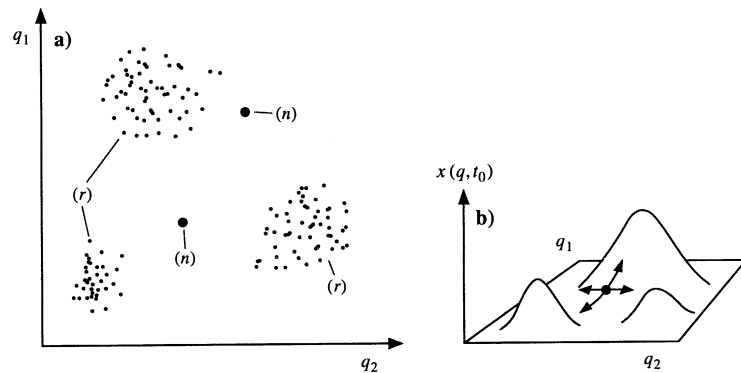


Fig. 9.4a,b. A two-dimensional problem space (a) with research fields (r) as clouds of related problems, possible nuclei (n) of new research fields, and a potential landscape (b) of research activities $x(q, t)$ in problem $q = (q_1, q_2)$ of the problem space at time t [9.9]

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. 9.4b).

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. 7.2, 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. 9.1) 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 achievement 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.

9.3 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 selfreferentiality 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 [9.10]. 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 [9.11]. 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 [9.12]. Historically, the word “ethics” stems back to the Greek word *ἠθικός*, 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 transitory and continuously changing world of matter [9.13].

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 rational is referred to the political society (*polis*), the family, and the interaction of single persons [9.14]. 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 concept 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 analogy 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 [9.15]. But how to justify individual freedom in a mechanistic world with deterministic causality? Every natural event is the effect of a linear chain of causes which in principle can be derived by mechanistic equations 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 freedom”.

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 [9.16].

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 estimation 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 natural 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 greatest welfare for the majority of people. The principles of utilitarianism have become the ethical framework of welfare economics [9.17].

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 [9.18]. From a methodological point of view, the ethical, political, and economic model of utilitarianism corresponds to a self-organizing complex 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 attracted 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 the 20th century. Nevertheless, he is another example to show that concepts from the natural sciences have influenced political and ethical ideas [9.19].

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 [9.20].

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 *interdisciplinary 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 [9.21]. 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, even though 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 [9.22]. 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 [9.23] 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 global 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 globalization 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 transition 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) [9.24]. After the 1st World War, pres-

ident 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 United 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 [9.25]. 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 [9.26]:



*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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Chapter 2

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