

Level 0

Chaotic Complexity vs. *Homeostasis*

The deepest intuitions concerning real-life complex systems date back already to Heraclitus (about 540 B.C.):

- *Everything changes, everything remains the same.* Cells are replaced in an organ, staff changes in a company – still the *functions* and *essence* therein remain the same.
- *Everything is based on hidden tensions.* Species compete in ecology, companies in economy – the opposing tensions resulting in *balance* and *diversity*.
- *Everything is steered by all other things.* There is no centralized control in economy, or in the body – but the interactions result in *self-regulation* and *self-organization*.

However, after Heraclitus the mainstream philosophies developed in other directions: For example, Plato emphasized the eternal *ideas*, regarding the change as ugly and noninteresting. And still today, the modern approaches cannot satisfactorily answer (or even formulate) the Heraclitus' observations. What is the nature of the “stable attractors” characterizing complex systems? There have been no breakthroughs, and there will be no breakthroughs if the fundamental nature of complex systems is ignored. There now exists a wealth of novel conceptual tools available — perhaps it is the time to take another look.

0.1 Facing the new challenges

The ideas are intuitively appealing but they are vague, and there are many approaches to looking at them. Truly, it is a *constructivistic challenge* to try to explain a novel approach: Everybody already knows something about complex systems, and everybody has heard of cybernetics, but few people share the same views, and misunderstandings are unavoidable. That is why, there is need to briefly survey the history — or, as Gregory Bateson (1966) has put it:

I think that cybernetics is the biggest bite out of the fruit of the Tree of Knowledge that mankind has taken in the last 2000 years. But most such bites out of the apple have proven to be rather indigestible – *usually for cybernetic reasons.*

0.1.1 Lure of cybernetics

The term *cybernetics* was coined by Norbert Wiener in 1948, when he published his book *Cybernetics, or Control and Communication in the Animal and the Machine* [86]. The underlying idea in cybernetics is the assumption that it is the dynamics caused by the interactions and feedback structures among actors that result in observed complex behaviors. According to one definition, cybernetics is the study of *systems and control in an abstracted sense*. Indeed, intuitively, cybernetics directly addresses the Heraclitus’ challenge.

Because of its intuitiveness, cybernetics was thought to be a panacea — indeed, it was one of the first “isms” to become *hype*. Since its introduction, there has been a long history of false interpretations, not only in Western countries, but also in the East, where cybernetics was seen as (another!) “scientific” motivation for communism: *How to steer the society in an optimal way?* There still exists a wide spectrum of more or less appropriate connotations; perhaps the term is today mostly associated with “cyberspaces”, and “cyborgs”, or cybernetic organisms combining biological and non-biological organs. In biological and ecological sciences cybernetics gained a bad reputation as the hypotheses were too wild: Evolutionary processes simply do not take place on the level of systems.

Perhaps cybernetics is today free of incorrect associations. Anyhow, it turns out to be an excellent framework for combining control theory, information theory, and communication theory with application domains (biology, ecology, economy, etc.).

Cybernetics has already had its impact on today’s scientific world. For example, being a framework for studies on clever interactions among agents cybernetics was one of the starting points beyond Artificial Intelligence. Similarly, as a framework of complicated feedback structures, cybernetics boosted the developments in the field of modern control theory.

However, the total potential of cybernetic ideas has not yet been fully exploited in control theory. At Wiener’s time, control theory was still very classical, and even the most straightforward ideas sufficed, but during the years control field has considerably matured. It seems that the field of traditional, centralized control theory has by now been exhausted – it is time to implement the deepest cybernetic insights and *get distributed*.

0.1.2 Theories of complexity

In fact, cybernetics is just one view to understanding complex systems in general. There are also other approaches to attacking the challenges, all of them being basically based on the conviction: *Clearly, there exist similarities among complex systems.* Different kinds of intuitions are exploited, for example, in

[14], [38], [43], and [91].

Whereas today’s control theory concentrates on the individual feedback loops, being too reductionistic, *general system theory* explicitly emphasizes *holism*. The original contribution in this field was given by Ludwig von Bertalanffy [9]. However, trying to attack all systems at the same time, the approaches easily become too holistic without concrete grounding. There is need to find ways to combine the wider perspectives with the concrete substance.

An opposite approach is to start from the bottom, from simple formulas or data, and hope for some order to emerge when some kind of manipulations are applied. This kind of “computationalism” is the mainstream approach in complexity theory today — indeed, the trust on the power of the increasing capacity of computers seems overwhelming: “In 20 years, computer will be more intelligent than a human”! Introduction to *computational biology* is given, for example, in [84]. But what if the iterations are chaotic, the results are sensitive to the initial conditions, and the simulations have no more correspondence with reality? Mindless thrashing of data only gives trash out. And the more challenging goal — how can computation make non-trivial phenomena emerge? How to sieve the *essence* out from the data?

The field of complex systems research is far from mature. No paradigmatic guidelines yet exist: There are no generally approved approaches, common concepts, methodologies and tools, typical application domains or problem settings. It has also been claimed that this “chaoplexity” is a form of *ironic science* where there are unsubstantiated promises, buzzwords, etc., more than there are hard results [40].

There are also more striking views. It has been claimed that the vagueness in the field is not due to the inadequacy of the theories, but we are facing the end of traditional science. For example, Stephen Wolfram who proposes the use of *cellular automata* for representing natural systems, proves that such a model family is too strong, and cannot be analyzed by traditional means [91]. From this he deduces that a New Science is needed — but he gives no hints of what that science would look like.

But there are also other ways to escape the deadlock: Perhaps the cellular automata was not the correct model family for representing complex systems after all. The unanalyzability is a property of the model, not of the system itself. If a more appropriate model structure is selected, perhaps old mathematics still works?

0.1.3 Return to basic mathematics

As observed by Eugene Wigner [87], in the past mathematics has been astonishingly efficient when explaining nature. Why should we be unlucky, why should it all end now?

It is clear that today’s conceptual tools are insufficient when explaining the complex diversity. New concepts and structures need to be defined, and one needs an appropriate language for presenting and defining these concepts: As Ludwig Wittgenstein observed in his *Tractatus*: “What you cannot express, that you cannot think of”. Wittgenstein spoke of natural languages — but it is mathe-

Syntax		Semantics
Scalar t	Free variable	Time, axis of evolution
Scalar i	Index	Agent identifier
Scalar $J(x, u)$	Positive-valued function	Cost criterion
Vector ϕ_i	Latent basis vector	“Forage profile”
Scalars q_i, γ	Adjustable parameters	(Inverse) “system impedance”; time axis contraction factor
Vectors x, u	States, latent variables; input signals	Agent (population) activities; set of resources
Matrices A, B	System matrices	Feedback interaction factors; interactions with environment
$\frac{dx}{dt} = -\gamma Ax + \gamma Bu$	Linear dynamic model	Matching with environment
$\bar{x}(u) = A^{-1}Bu = \phi^T u$	Asymptotic behavior	Dynamic equilibrium
$E\{uu^T\} \approx \frac{1}{t} \int_{t_0}^t uu^T d\tau$	Covariance matrix	Mutual information structure
$E\{uu^T\} \theta_i = \lambda_i \theta_i$	Eigenvectors θ_i ; eigenvalues λ_i	Directions of information; corresponding relevances

Figure 1: Key symbols and definitions to be studied later. Simple mathematics, yes, but appropriate interpretations make a difference

matics that is the natural language of nature! Development of mathematics has always been directed by applications, so that the logical structures and concepts have evolved to appropriately and compactly describe real-life phenomena; and, when looking at complex systems, there are some special benefits:

- In mathematics, syntax and semantics are separated; it is possible to generalize and find analogues among systems.
- In mathematics, real numbers naturally capture fuzziness, non-crispness and continuity.
- In mathematics, parallelity of phenomena is transformed into high dimensionality, and there are efficient tools available for operating on high-dimensional data structures.
- In mathematics, time-bound phenomena, dynamics and inertia can efficiently be mastered and manipulated, and asymptotic behaviors can be captured.

And, of course, the clarity and unambiguity of mathematical expressions is invaluable — as compared to natural languages, this helps to avoid hand-waving.

It turns out that no new mathematics is needed to model complex systems, it is just new interpretations that are needed (see Fig. 1). Mastering some basic mathematical grammar is necessary: Specially, linear algebra and matrix calculus, and understanding of dynamic systems is essential. No New Science is needed, the Old Science still suffices — but as new interpretations are applied, there will be a New World, new ways of seeing the environment!

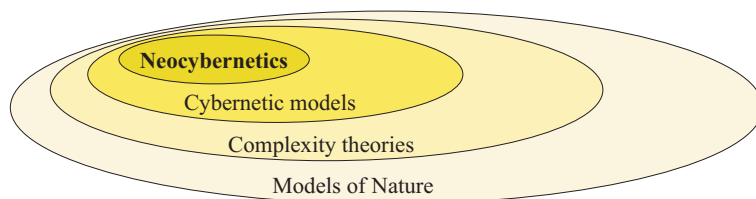


Figure 2: Neocybernetics offers a fresh view to studying real-life systems

0.2 Principles of neocybernetics

Cybernetics is a special view to look at complex systems, emphasizing dynamics induced by internal interactions and feedbacks. Further, *neocybernetics* is a special view to look at cybernetic systems (see Fig. 2). There always exist many ways where to proceed; it seems that neocybernetics combines mathematical compactness and expressional power in a consistent framework.

0.2.1 Capturing “emergence”

The key concept in complexity theory is *emergence* — some qualitatively new, unanticipated functionality pops up from accumulation of simple operations. There is a challenge here: If analysis of some higher-level phenomena cannot be reduced to analysis of their components, the traditional reductionistic modeling approaches collapse: The “whole” is more than the sum of the parts. This means that emergence is a somewhat notorious concept, emergent phenomena (like “life”, “intelligence”, or “consciousness”) remaining outside the range of engineering-like “good” sciences. One could say that *emergent phenomenon is something that by definition defies definitions* — and what can you do then?

However, as emergence is indeed the *essence* of complex systems, it is necessary to attack this challenge. To reach good compact models, at each level one should employ the most appropriate concepts valid at that level — this means that emergence has to be “domesticated” somehow. The first objective here also is to *make emergence a well-defined, scientifically reasonable concept*.

When trying to formalize the idea of emergence, one can apply the very traditional modeling ideas: First, study explicit examples and construct an intuitive understanding of what the phenomenon is all about, and after that, find the common features and represent them in an explicit mathematical framework. And, indeed, there are many examples available where emergence is demonstrated in a very clear form. See Fig. 3, where the appropriate levels of abstraction are shown when modeling (gaseous) systems in different scales. Between each level, “emergence” takes place: Appropriate concepts, variables, and model structures change altogether.

At the lowest level, it is the elementary particles that determine the properties of matter, the models on orbitals, etc., being stochastic. At the atom level, however, the Newtonian approximate ideal gas model with atoms as “billiard balls” becomes quite accurate, the appropriate concepts like velocities and moments being determinis-

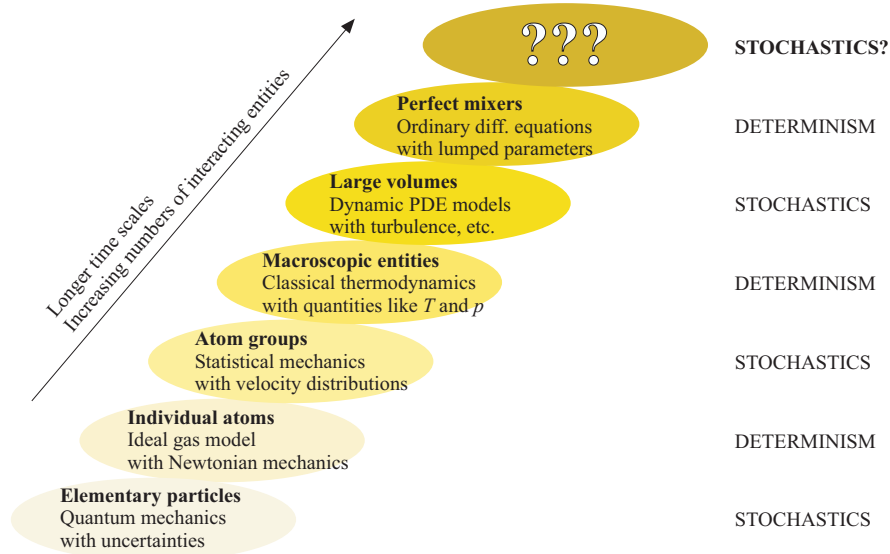


Figure 3: Different levels of abstraction are needed for modeling interactions of particles in different cases

tic. When there are millions of atoms, individual collisions cannot be tracked, and statistical mechanics becomes the modeling framework of choice. In still larger volumes, it is the deterministic macroscopic quantities like temperatures, pressures, and entropies that best characterize the system state. However, in still larger volumes, the temperature distributions cause convection and turbulence that can best be characterized in statistical terms. Assuming complete turbulence, the deterministic level of lumped parameters is again reached, where it is concentrations that only need to be studied.

Today, the level of deterministic first-principles models is already fully exploited. But to understand large systems consisting of such ideal mixers (like cells) one should reach for the still higher level of abstraction. Are there any lessons to be learned from the above hierarchy?

- First, it seems that one has stochastic and deterministic levels alternating in the hierarchy. Actually, this is no coincidence: For example, two successive deterministic levels could be “collapsed” into one.
- Second, it seems that on the higher levels the volumes (or number of constituents) is larger, and time scales become longer and longer.

How about exploiting the intuition on time scales: A higher level is reached, when the lower-level time scale is (locally) collapsed into a *singularity*, or when the time axis is abstracted away altogether. Note that at the higher (global) level, there can still exist time-related phenomena, so that still higher levels can further be defined.

Time axis is to be eliminated and individual signal realizations are to be ignored. Only the statistical properties are left there to characterize the overall signal

properties; this must be done in an appropriate way, so that the properties relevant on the higher level are not compromised. It turns out that statistical cumulants like (co)variances, or expectation values of signal squares are beneficial in this respect.

Many problems fade away when the actual dynamic processes are abstracted using statistical (and static) system cumulants. But is this kind of ignoring of the time axis justified — when can such abstractions be carried out?

To have statistical measures emerge, the signals have to be *stationary*. To have stationary signals, the underlying system essentially has to be *stable*.

However, out of all possible system models, the stable ones are rather rare: There must not exist a single unstable mode among the assumedly high number of dynamic modes. How could one assume stability in natural processes? — The motivation is simple: If the system were unstable, it would have ended in explosion (resulting in exhaustion of resources) or extinction already for a long time ago¹. In this sense, one is not trying to model all mathematically possible systems — only the physically meaningful ones!

We are now ready to present the basic ideas beyond neocybernetic modeling.

0.2.2 Key ideas

The following principles can be used more or less as guidelines for deriving neocybernetic models, as will be demonstrated in subsequent chapters: Complex-looking phenomena are interpreted through the “neocybernetic eye-glasses”. It needs to be emphasized that these principles are by no means self-evident (as becomes clear in Section 0.2.3): The proposed approach that has turned out to be advantageous is a result of iterative refinement processes, and, as it is always the case, the “highway through the jungle” without extra steps aside can be seen clearly only in retrospect.

Dynamic balance

In neocybernetic models, as presented above, the emphasis is on the final balance rather than on processes that finally lead there. In steady state one can directly attack the emergent pattern and forget about the details of complex nonlinear processes. It needs to be kept in mind that the balance here is *dynamic equilibrium*, or a balance between tensions, where external disturbances are compensated by some internal mechanisms. In practice, the compensating tensions are caused by negative feedback loops — but the implementation of these feedbacks is not of special interest, *as long as they can maintain the stability*.

¹Stability here means *marginal stability*, that is, oscillatory systems, etc., are allowed — indeed, such marginally stable behaviors are typical to fully developed cybernetic systems. Truly, the key point is *stationarity*: The signals need to have statistically well-defined properties

Cellular systems have long been characterized in terms of balance or *homeostasis*. However, it needs to be noted that the concept of balance here is to be interpreted in a wider sense: The balance is defined with respect to only the selected variables. For example, it can be *derivatives* of some other quantities that are in balance, so that there is a balanced level of *dissipation* taking place in the system. Further, the system is assumed to be stable not necessarily locally but in a wider scale; for example, there can be oscillations as long as the system can maintain its integrity and the behaviors can be characterized in statistical terms. Dynamic transients are seen as secondary phenomena, being caused by natural strivings back towards balance after a disturbance.

Environment-orientedness

Neocybernetic systems are assumed to be explicitly oriented towards their environment, constituting “embedded systems” with their environments. The underlying intuition is that there cannot exist a cybernetic system in isolation. In this sense, the traditional system theoretic thinking collapses: a subsystem cannot be studied alone, without its connections to other systems.

This emphasis on the environment means, for example, that adaptation in the system is by no means a random process. A system reflects its environment, so that somehow it has to capture the properties of this environment. The available measurement information needs to be observed and stored in a reasonable way. All this means that it is not only the more or less random competition, “selection of the fittest”, that is taking place in evolution — there are other, more consistent processes taking place, too, making such information gathering and storage more efficient.

Environment-orientedness gives another motivation for emphasis on balance: There is always scarcity of information, and the already existing structure has to be maintained while further information is gradually being acquired. Neocybernetic balance is a “kilo of emergent order”. Only in stable conditions, when fast turbulent phenomena have ceased, something fragile can emerge.

High dimensionality

In practice, environment-orientedness changes to *data-orientedness*. No structure of the environment can be assumed to be known, only “measurements” of the environmental responses are available.

To make relevant information available to the modeling machinery, appropriate coding of information, or definition of *features* is needed. In neocybernetic models, *structural complexity* is substituted with *dimensional complexity*, that is, all possibly relevant features are simultaneously captured in the information structures (data vectors), hoping that the modeling machinery can construct appropriate connections among these pieces of data. Typically, the data are highly redundant, and new kinds of problems emerge. This means that efficient multivariate methods and corresponding mathematical tools are needed to analyze the neocybernetic models.

The features should capture the essence of the system; to reach this, the *domain-*

area semantics should somehow be coded in the variables — and, specially, as it was assumed above that the neocybernetic models are extremely environment-oriented, one is speaking of appropriate coding of *contextual semantics*. To reach this kind of coding, careful analysis needs to be carried out to capture the essence of the domain field in data structures. In [92], this bottom-up analysis was carried out for Hebbian neurons, whereas here it will be carried out for metabolic systems.

To reach the intended *universality* over the spectrum of all cybernetic systems despite the very different underlying realms, however, additional assumptions have to be made. If it is assumed that the mathematical model family is very constrained, so that indeed there are more systems to be modeled than there are available model structures, the behaviors of the different systems — within that model framework — must be analogous. How to determine such a model family that would be simple enough, still capturing the essence of systems?

Simplicity pursuit

The search for simplest possible representations is the traditional goal of practical modeling, being intuitively motivated by *Ockham's razor*: Simplest explanation is the “most correct”. In a mathematical context, simplicity can often be interpreted as *linearity*.

The traditional approach to reach simpler analysis and manipulation of complex systems is to apply linear models. As a first approximation, linearity seems to offer rather good match with reality, at least if the nonlinearities are smooth and locally linearizable. The main benefit here is that for linear models one has extremely strong mathematical analysis tools available, no matter what is the system dimension; what is more, for linear model families one knows that the dynamic analogues work well, letting behavioral intuitions be transferred from a domain field to another.

In neocybernetic models, linearity is also taken as the starting point. The linearity assumption can be motivated in different ways:

1. In control engineering, it is well known that feedbacks “smoothen” nonlinearities. Specially in neocybernetic models where balance is emphasized, the deviations around the the equilibrium can be assumed to be small, and the transients can be assumed to have decayed, justifying the linear approximation.
2. High dimensionality typically makes it possible to find more linear models, at least if features are selected appropriately. For example, if the features include powers of signals, linear model can represent the terms in the Taylor expansion, approximating the nonlinearities.

But it is not only the pragmatic reasons — there also exist more fundamental motivations for taking linearity as the starting point. The belief here is that *there really exists a theory of cybernetic systems to look for* — and assuming that there will ever exist a general theory of cybernetic systems, *it must be based on essentially linear constructs*. There are no other alternatives — why? The

system of cybernetic actors can be studied from outside in the top-down way, and in the bottom-up way :

1. **Top-down view.** Assume that a truly useful theory once is found. It is the linear models that are the only ones for which *scalability* applies, so that simple “toy world” examples can be extended to real-life scales — for large-scale nonlinear structures there cannot exist a general theory.
2. **Bottom-up view.** Assume that the complex system is to be based on identical underlying “agents” that do not share high-level strategies. It is only essentially linear combinations of underlying functionalities that can be implemented by such an unorchestrated bunch of competing actors — each of the actors only thinks for itself.

As it turns out later, the neocybernetic models are *optimal* in some very specific sense. If the “bootstrapping” in the underlying structures is carried out so that they are linear, the optimally adjusted layers later in the hierarchy of subsystems will also be linear. Linearity assumption is like a parallel axiom: It can be ignored, or it can be employed. In either case, a consistent non-trivial theoretical structure can be found.

The above reasoning only applies to “simple complex systems”, and linearity is more like a guiding principle. The modeling strategy to be followed here is: Avoid introducing nonlinearities if it is not absolutely necessary, remembering that there always exist many alternative modeling approaches. Later, if extensions are necessary, the assumptions can be relaxed (such extensions are studied in the latter part of the report). Similarly, the originally static balance models can be extended towards dynamic models — but this should be done only after the basic nature of cybernetic systems is being captured.

0.2.3 Contrary intuitions

When comparing to traditional views of studying and modeling complex systems, the above neocybernetic starting points — views of emergence, role of time axis, balance, environment-orientedness, high dimensionality, and linearity — are very different, indeed contradictory.

What comes to *environment-orientedness* and *high dimensionality*, it seems that traditionally in chaos and complexity research, holism is studied in a very reductionistic ways. Typically, it is synthetic, isolated formulas that are iterated without connection to the environment, and it is hard to see how these “laboratory experiments” could be integrated in natural systems. The chaos theoretical models are extremely simple, often consisting of a single variable and a single formula. And also when explaining real-life complexity, the mysteries are often wiped under the carpet, into the twilight of the unknown: The issue of *emergence* has been “solved” by regressing it back to elementary levels. For example, Roger Penrose [63] claims that “cognition can be explained in terms of quantum-level phenomena”. Indeed – there are always the underlying atoms and cells, etc., that implement the observed functionalities, but, as was explained above, these concepts are not the most economical way to express the higher-level phenomena. Similarly, it is individual chemicals that carry out the functionalities

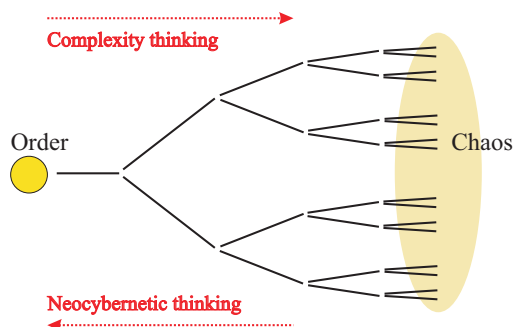


Figure 4: Complexity theory pessimism vs. neocybernetic optimism

of cells and organs; but, in the subsequent chapters, emergence is reached for by going *up*, not down.

The emphasis on *linearity* is perhaps the most radical assumption in neocybernetic studies, because nonlinearity is always taken as the starting point in studies of chaos and complexity theory — it is often thought that nonlinearity is the *essence* of a complex system. This nonlinearity view is well motivated, because theory says that linear systems are inferior to nonlinear ones: Without nonlinearity qualitatively new phenomena cannot emerge, and without nonlinearity there cannot exist chaos. But in linear systems there still can exist complexity, and, specially, there can be emergence of order. As it turns out, linear structures have not been fully exploited — or, rather, not all *interpretations* of linear models have yet been studied.

The intuitions concerning *balance* is a longer story. The idea of homeostasis has long history, indeed dating back to ancient times, but today it is regarded as a too poor starting point. Such views are formulated, for example, by Erwin Schrödinger [69] and Ilya Prigogine [64]: *The essence of life is in dissipative, non-equilibrium processes*. Static balance, steady state, is thought to mean death — interesting systems are seen to be extremely unstable, always being at the “edge of chaos”. Whereas ordered state is uninteresting and complete disorder is uninteresting, it is the boundary line between order and chaos that is regarded as being of relevance. However, such boundary lines have zero length (in mathematical terms), their probability is practically zero, especially as such boundary phenomena are assumed to be unstable with their exploding Liapunov exponents. In neocybernetic models, however, things have to be studied from a different point of view: First, it has to be remembered that static and dynamic balances are very different things, the virtual placidity of dynamic equilibria hiding the underlying turmoil. Second, as it turns out, the balances are *stable* — this means that cybernetic systems are not at all as rare or fragile as the chaos theoretical instability-oriented thinking would suggest.

Abstracting the time axis away contradicts traditional intuitions about dynamic and turbulent nature of complex systems. It is the causally structured, or even *algorithmic* view to phenomena that rules today: Complex systems are seen as being composed of sequential processes. Individual one-at-a-time (inter)actions and explicit time structures are emphasized — no doubt because such action/reaction structures are easy to grasp. Another reason for the domination of such *process view* is, of course, the role of computer programs as the main tool in the simulation analyses. For example, it is *agents* that are seen as

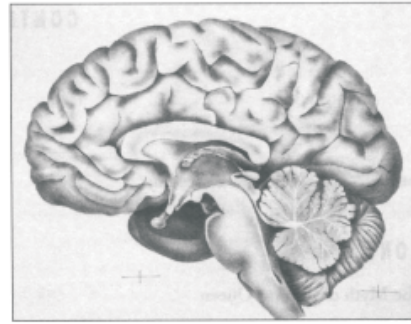


Diagram of the human brain (Courtesy of Mittermeier)



Map of Hamburg, circa 1850 (Courtesy of Princeton Architectural Press)

Figure 5: Do surface patterns reveal underlying similarities? (Adopted from [43])

the basic constructs in many complex environments, like in intelligent systems, and these agents are software constructs. On the other hand, if following the chaos theory paradigm, iteration is regarded as the paradigmatic route to complexity. The “butterfly effect” has been seen as being characteristic to complex systems, meaning that their behaviors cannot be predicted — indeed, models for them are more or less useless. In the neocybernetic setting, on the other hand, new hope is perhaps given to those who are struggling with modeling of complex systems. Because it is stable attractors that characterize the structures in cybernetic systems, there can exist consistent convergence even from differing initial conditions. Modeling *is* possible after all (see Fig. 4).

But one always has to be aware of the dynamic nature of the real systems, and the static models are dynamic ones in equilibrium. What is more, as it turns out, neocybernetic modeling itself is about balancing between dynamic and static worlds: Every now and then the static structure needs to be relaxed to escape the constraints of traditional thinking.

As explained by Herbert Simon [72], phenomena can be represented in terms of such processes or in terms of *patterns*. In neocybernetics, it is this pattern view that is pursued; these patterns are determined using statistical measures. And, further — it is not *surface patterns* but it is *deep structures*, or underlying latent patterns where the system is aiming at, when following its natural aspirations. The difference between surface patterns and deep structures needs to be emphasized: Also the traditional complexity theory is driven by patterns — Mandelbrot’s fractals, Wolfram’s sea shells, Kohonen’s maps — but these

visible formations, even though being intuitively appealing, do *not* capture the essence of systems (see Fig. 5). As Alan Turing has put it: “The zebra stripes are simple — I am more concerned of the horse behind”.

Summarizing, it can almost be said that the neocybernetic model is a *model of inverse thinking*. As it turns out, the relationships are “pancausal” rather than unidirectional; it is freedoms rather than constraints that are modeled, etc. Some additional insights are given below.

0.2.4 Neocybernetics in a nut shell

The starting points of neocybernetic modeling — linearity and balance, etc. — do not sound very intriguing. However, it is the strong mathematical tools, when letting their effects cumulate, that provide for nontrivial model properties. It needs to be noted that the presented approaches make it possible to define various consistent model families — the presented one, however, is claimed to the simplest one still giving nontrivial results. The following characterizations are studied in more detail when reaching higher levels.

The complexity theory being full of unsubstantiated promises, it turns out that *neocybernetics is the theory that puts the pieces (at least some of them) together*.

The neocybernetic model is a framework for studying variations, changes and tensions instead of immediately visible static structures. Counterintuitively, this analysis of variations is reached through the analysis of balances.

The role of dynamic balances is crucial when constructing neocybernetic models — indeed, the emergent patterns that are modeled are “structures of stability”. The neocybernetic model is a *model of balances*, or, if put in a more accurate way, it is a *balanced model of balances* (or *higher-order balance*) taking into account the properties of the environment, as determined by the statistical signal properties. The neocybernetic model is a map of the relevant behaviors corresponding to the observed environment, determining the behavioral spectrum of the system, where “behavior” means reactions to environmental excitations.

In a nonlinear system, uniqueness of the balance cannot be assumed; indeed, the neocybernetic model covers the spectrum of alternatives or potential balances, as determined by the environment. The neocybernetic model is a *model over the local minima* rather than a model of the global optimum, assuming that an appropriate cost criterion is defined. Traditionally, the single global optimum is searched for in analysis and in design: This results in theoretical deadlocks (compare to NP problems [73] — finding a large number of suboptimal solutions is typically much simpler than finding the absolute optimum). Also nature has no centralized master mind; it is facing the same optimization problems, seldom finding the strictly optimal solution: In this sense, the model over the local minima better captures the possible alternatives and essence (remember Heraclitus: “You cannot step in the same river twice”).

Because the system is optimized in a certain sense, the representations are (more or less) unique. The neocybernetic model is a “mirror image” of its environment, being itself a model of the environment, capturing relevant behavioral patterns as manifested in data. There exists certain kinds of *symmetries* between the original image and its model. This property makes it possible to draw

conclusions, for example, about such high-spirited concepts as *intersubjectivity* and *interobjectivity*.

Because of the simple structure of the models, intuitions can efficiently be exploited: For example, the idea of analogues can be extended to partial differential equation models. The neocybernetic model can be seen as an *elastic system*, where the internal tensions compensate the external forces. The deformations are proportional to the forces (behaving like a steel plate) whatever is their physical manifestation. The electrical analogue makes it possible to conceptually manage neighboring cybernetic systems: There is maximum power transfer among the systems when they are matched so that their input and output impedances are equal.

There are close connections to today's research activities: Neocybernetics gives a framework for *distributed agents and networks* where there is no centralized control. It may also offer a framework for data-based modeling approaches and *computationalism*.

The negative feedbacks constructed in the neocybernetic model are control structures. The different dynamic equilibria result from changing inputs, or "reference signals" – thus the neocybernetic model is a *model-based adaptive controller* trying to compensate the disturbances coming from the environment. Further, this can be extended: The neocybernetic model is a *means of reaching maximum entropy* (or "heat death") of the environment. This means that the modeling framework offers a means of attacking the problems of cumulating improbability, and even for *inverting the arrow of entropy*. For example, it can be said that *life is a higher-order dynamic balance in some phenosphere*.

Indeed, neocybernetics offers tools for understanding the *whirls in the flow of dissipation*. These stable attractors are information-determined structures crystallizing the dependency structures observed in the environment. These intuitions can be applied to many very different domains from biological systems to cognitive ones, even to the Theory of Mind.

As it turns out, many of the neocybernetic issues have a more or less philosophical dimension. Without concrete grounding, such discussions are hollow and void, and they lack credibility. It is necessary first to define the concepts — or "whirls in the infosphere" — and this will be done next, the application domain being that of living cells.

— How to read the subsequent texts? Different chapters characterize specific aspects of cybernetic systems from different points of view, and they are best suited for people with different backgrounds. Together they are intended to form "ladders" towards understanding the steps in evolution — for changing such discussions into real science, or, indeed, into natural philosophy (see Fig. 6). The chapters marked in blue are mathematically involved or contain detailed physics or chemistry. The red chapters are more philosophically oriented. On the left-hand side, there are the *analyses*, being based on observations, whereas on the right-hand side, there are the *syntheses*, starting from first principles. The main line of thought in the middle tries to draw balanced conclusions between the tensions. The material is not self-contained, though: In the beginning, one should (in principle) get acquainted with *complex systems theory, multivariate statistics, artificial intelligence, biochemistry, ...*

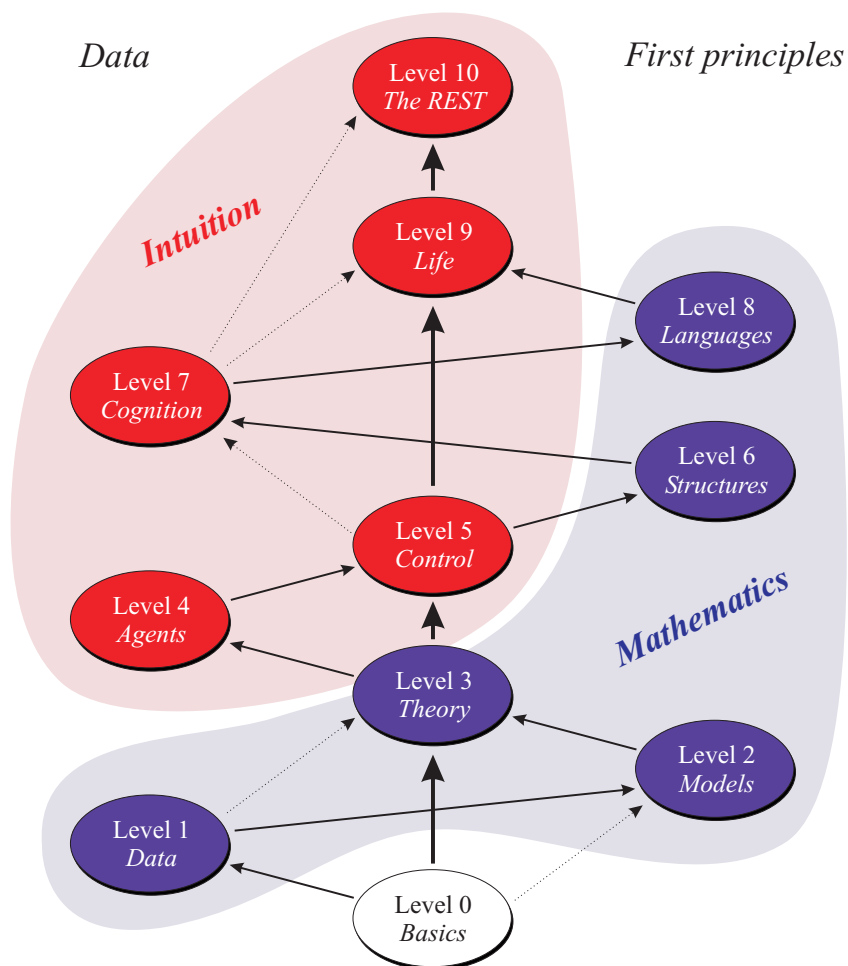


Figure 6: The chapters presented as ladders towards understanding of neocybernetic systems and emergence in them (sorry, but without some mathematical concepts there is *no route* to intuition)