SAMPO Mills: Neocybernetic Grounding of Ontogenesis

Heikki Hyötyniemi
neocybernetics.com

Abstract

This paper presents a framework for modeling and *understanding* real-life scale complex systems. *Neocybernetics* is generalized to all domains where one can recognize *generalized diffusion,* meaning that the *emergent model structures* with their *degrees of freedom* become a universal basis for understanding Nature.

1 Introduction

What is there beyond everything that exists? Are there some common principles underlying all of those forms that we can recognize? — It seems that, indeed, *metaphysics* can perhaps someday change into a science.

In prior publications, *neocybernetics* has already been studied extensively [1]. The universality of this approach has been hypothesized, but there have been more or less severe holes in the reasonings. Here, those discussions are put in a consistent framework, starting from very basic assumptions; perhaps it is already possible to sketch the converged guidelines through the jungle of complexity. Now these guidelines for thinking about complex systems are presented in the form of *SAMPO mills*[1].

In cybernetic systems one always employs the idea of *feedback* — there is a self-referential loop blurring the causality chains and making it challenging to apply traditional analyses. In the neocybernetic framework this dynamical, cyclic structure is taken to its logical conclusion: feedback signals take a loop after another indefinitely, the signal flows finally finding some equilibrium levels — this must happen in all physically meaningful systems. The qualitative notion of feedback is changed to quantitative analysis. Thus, the "whirls" constitute stable attractors in a *phenosphere* (see Fig. 1).

Tensions between the system and its environment cause flows. Here we let the flows loose, letting them follow their natural dynamics, trusting that the underlying structures implement self-regulation, and the system can finally reach stability. Individuals are "drowned" into the flows, and only the relevant net effects remain visible. When all feedbacks are taken into account, the system becomes *pancausal,* all parts of the system affecting the others. Counterintuitively, in this final dynamic balance, after all conflicting pressures have become compensated, detailed analyses become simpler: the behaviors in equilibrium are typically smooth and linear, and mathematical tools can efficiently be applied.

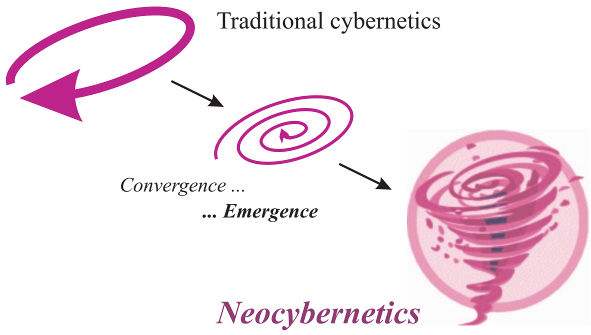

Figure 1: What is special to (this interpretation of) neocybernetics — the loop structure is taken to its logical extreme applying system theoretical tools

How do the whirls originate to begin with? It seems that some minor fluctuations get boosted because of the properties of the environment, they become amplified, and soon they characterize the whole system. Further, the turbulence around the whirls is like a "cooker" of new candidate whirls ... This all is closely related to *evolution* in its simplest form. As the whirls continuously change form, expand or contract, etc., their *essence* somehow remains, whereas

[1] Short for "Stable Attractors Maintaining Proper Ontologies", or "Self-Adapting Machinery Processing Observations", or "Simple Autogenous Mappings Producing Order", etc. — interpretation depending on the point of view

in some directions there can exist faster development and change of form. It turns out that SAMPO mills may help in understanding development of systems in general terms. — Indeed, the etymological studies have shown that the word evolution comes from Latin "evolutio", meaning *unrolling* — or opening up the whirls!

— Do you feel uneasy about counting so much on the intuitive appeal? But when facing truly complex systems, intuition *must* have the key role. In mathematics there is too much freedom, too many open ends — one must have additional guidelines for selecting the direction where to proceed. Justification for manipulations has to be found from nature, and it is intuition that helps us here: human cognition machinery has always been tackling with the complex world, and one can utilize the magnificent human pattern recognition capacity for detecting what is truly essential. One can recognize the essence even though one cannot explicitly define it.

2 Assumptions and terminology

It has been claimed that neocybernetics does not study all mathematically possible systems, but only the really existing, the physically relevant ones. What then *are* the characteristics of physical relevance? Which are the appropriate concepts to discuss them? — Next, to approach such issues, things are *seen from the nature's viewpoint.* Let us see what happens when we try to be such *empathetic* (the prefix "em" becoming familiar later).

2.1 Extreme naturalism

The basics of the "streamlined" approach to neocybernetics can perhaps best be crystallized in the terms *complete subjugation, generalized diffusion*, and *universal evolution.* Now, we start from very physical-sounding considerations; however, the principles are general, and later these discussions can be extended to non-physical domains.

Here, "complete subjugation" means that the systems are *at the mercy of their environments:* no internal "will" of the systems needs to be assumed nor taken into account. The system consists of "stupid" (or "humble") actors that know nothing about the big picture, they just follow the very local nudges. From the point of view of an individual actor, also neighboring actors belong to its local environment. To assure the humbleness, the system is divided in small enough (ϵ-sized) elements so that a lumped parameter representation applies to sufficient degree; it is assumed that everything that is relevant, all properties of the system can finally be expressed in terms of some (sets of) elementary scalar variables. Thus, there is a huge number of variables to start with.

This environment-orientedness means extreme trust on observations (when using system-centric terminology) and the emphasis can be concentrated on quantifiable global-level phenomena. — In retrospect, it is this inversion of emphasis, or concentration on the environment rather than on the system itself that makes it possible to anticipate the behaviors of systems in general terms and create models for them: everything relevant is in the data if that data is collected appropriately.

The low-level actions are stochastic and beyond any reasonable analysis. Only in the statistical perspective, when a large number of actors is considered, something "coordinated-looking" or consistent behaviors can emerge as a net effect: the random walks on the low level generally result in *diffusion.* Here, *generalized* diffusion means extension from strictly physical to other domains, too: whenever there are density differences, whatever are their interpretations and units (not only *concentrations* or *temperatures*), they tend to smoothen out — where there is more, there will be less, and vice versa, or, as it is sometimes said, "nature abhors a gradient".

As this generalized diffusion (or "generalized entropy (or *emtropy*) growth principle") is the only action-reaction mechanism assumed, behaviors are totally distributed and there is no need for central control. As seen from the higher level, the diffusion process can be interpreted as *gross flow* between *potentials,* or specially high (or low) densities. In a still wider perspective one can see "forces" driving the process; but these forces are purely virtual. Even so, it seems that such causality-based interpretations are natural and unavoidable for the human perception machinery. Specially, when looking at more complex systems, one easily sees something teleological taking place, as actors are seemingly active, "pulling" resources from their environment — but, again, it is the environment pushing its excess, the system passively just having to absorb it.

The third issue to be discussed here is *universal evolution* (or perhaps *emolution* to avoid the biology-bound connotations). Expanding the idea of Theodosius Dobzhansky, one could say that *nothing in complex systems makes sense except in the light of emolution.* The claim here is that even physics is evolutionary: we only can see net effects that have survived in the competition of behaviors. If there is no consistent boost for emerging complexity, the atoms of order get drowned in the chaos. In physical systems there is natural selection in its crudest form, but, of course, the mechanisms for implementing the emolution and for storing the evolved information are very different as compared to the mechanisms of biological evolution. For example, as there is no genetic code, the emerged structure can be stored in internal *inertias* (as illustrated in Sec. 5.1).

The surviving species (or behaviors) are assumedly the best possible; optimality can be seen as a general modeling principle. But what behavior *is* optimal — this is not always clear (see Sec. 2.3). As the criteria vary, there is not necessarily only one winner in an ecosystem.

Emolution is to be understood here not only in the wide but also in the narrow scale. It is not only the biological species-level that evolves; there are developmental processes taking place at all levels of systems, biological and physical. To reach the qualitative developments, instantiation of huge numbers of subprocesses has to be carried out in an orchestrated manner; such evolutionary processes cannot be "extremely improbable". The "blind watchmaker" metaphor is simply too incredible. Somehow the beneficial behaviors become magnified, outperform other behaviors, and finally become visible. There must be some structure behind the developments, it cannot be just randomness, and in the neocybernetic perspective the key point is the existence of dynamic attractors as determined by the environment.

It should be recognized that universal emolution can be thought of as being a (very) special case of (very) generalized diffusion. In such an abstract process, *fitness* that can be seen (see semiosis in Sec. 2.3) as the key quantity determining behaviors, spreading (and increasing) in the space of life forms (life being defined as is done in neocybernetics). This interpretation helps to understand that in emolution there is not pulling but *pushing* towards arenas of no life yet. Nature does not know where it is aiming at, life just expands; understanding the current state and constraints can tell us something about the future and how this future is approached.

2.2 Weak emergence

As observed above, individual events cannot be traced reasonably — but it does not matter really: if something is hardly recognizable, it cannot make a *difference.* Nature is slow, it cannot respond immediately. Something that better characterizes the overall behaviors has to *emerge* and become visible. Indeed, all visible phenomena emerge of some lower-level ones, and one should be speaking of *layers of emergence.* What is characteristic to all observables, then?

Formalization of the abstraction over individuals, to "see the forest for the trees", can easiest be accomplished through concentrating on *average behaviors,* statistical net effects over a large number of time points or over a large number of actors. Such *coarsening,* or reducing the number of variables, is traditionally seen as the key to a higher-level view. But the claim here is that averaging, or just filtering out the assumed noise, is not yet real *emergence.*

The other key intuition concerning true emergence is *interaction.* On the most fundamental level, one can only observe interactions, and the same applies also to nature. However, real "co-operation" can hardly be quantified, and it is only the *possibility* of interaction that is elaborated on here; that is, *co-existence* will only be studied. Assuming that there are two variables ξ and ζ, the "atom of interaction" can be based on the product $\xi\zeta$, and, when combined with the above idea of averaging, this changes to (uncentered and unnormalized) *correlation,* meaning that weak emergence in this context is defined as

$$\begin{array}{rcl} \mathcal{E}(\xi,\zeta) & = & \lim_{T\to\infty}\left\{\frac{1}{t-T}\int_{-T}^{t}\xi\zeta\,d\tau\right\} \\ & \approx & \mathrm{E}\left\{\xi\zeta\right\}, \end{array}$$

where t is the current time (time indices of variables are dropped for brevity). Thus, the emergence operator changes to *expectation,* as interpreted in a somewhat loose sense: for example, rather than extending to infinity, the integration typically takes place only within the "visibility horizon". The definition above should not be interpreted in a rigid formal sense, the key idea being an integral over elementary interactions; thus, in some cases, one can also define the set of involved variables not temporally but spatially for some volume element V as

$$\mathcal{E}'(\xi,\zeta) = \frac{1}{V}\int_V \xi\zeta\,dV.$$

Such "emergent coupling between variables" is now called *emformation.* It is evident that mutual emformations can be captured in (unscaled) covariances or covariance matrices, so that there is strong connection to *Fisher information* and corresponding information matrices. However, term emformation rather than information is here used to avoid inappropriate information theoretical connotations. For example, very unlikely sample is now *not* important; in this context, statistical *relevance* rather than novelty is emphasized.

It is constructs of such emformation that are the elementary basis of the *system memory,* offering the framework for changes in structures, or emolution. Later it is shown how the cumulated emformation structures act as *filters* affecting the further emformation cumulation, so that the past determines the future.

This definition of emergence means that, even though averages of actors (particles, molecules, ants, humans, etc.) only are concentrated on, so that the temporal (or spatial) axis is collapsed and "summarized", the number of emerged variables *increases* rather than decreases. By some means the chaos of signals has to become simplified to become manageable. It turns out that emformation carries relevance only among special variables. How emolution finds those atoms of interaction that are the "atoms of meaning"?

2.3 System semiosis

It is generally accepted that man-made models are not unique but their structures have to reflect their intended usage, that is, model construction is directed by some kind of *meaning* or semantic considerations. But this simple observation can be inverted in the spirit of the adopted extreme naturalism: *also nature needs some reason to do something.* Indeed, nature first had to motivate itself why there should be something instead of nothing! In practice, these "reasons" for complexification are assumedly very down-to-earth, being focused on emolutionary benefit, but the human-centric retrospective interpretation about nature's "intentions", its quest for relevance and meaning, turns out to carry the appropriate connotations here[2]. Without emphasis on *natural semantics,* mathematical analyses become too hollow to be able to "emulate" relevant behaviors. The searched-for *emantics* needs not be something as fancy and intractable as it is when speaking of cognitive models and human's intentions; again, on the lowest level everything is based on direct observations and their properties.

There exists a pragmatic branch of semantics that exactly fulfills our needs, or *pragmatism.* It turns out that there *relevance* is seen as a more useful starting point than the unaccessible *truth* itself. In pragmatism, semantics is determined by *functioning,* an actor's relevance being determined by its role among other actors. Truly, this all could even be called *cybernetic semantics,* as cybernetics traditionally studies "differences that make difference", actions that affect the world. In concrete terms, in neocybernetics one concentrates on *variations that give rise to further variations.* This means that semantics cannot be subjective, but it has to be shared among others, becoming a concrete system-level concept.

It needs to be remembered that the seemingly goal-directed behavior is an illusion, an anthropomorphic interpretation when looking the emolutionary processes from above. Specially, the emerging structure of *causality* (actors acting, environment adapting) is virtual: it is the environment rather than the actors that is the *primus motor* causing all behaviors.

The appropriate formal framework for discussing system semantics is offered by *semiotics.* Semiotics in general studies *signs,* "something that stands for something", being discrete units of some meaning. Whereas semiotic signs are traditionally studied in human life, where signs are used for information communication between human minds, there are subfields, like *biosemiotics,* where the role of external signals is studied in biological organisms in general. Still more generally, one could speak of *system semiotics* (or perhaps *emiotics*) when studying how a system sees its environment.

It is this emiosis that makes all the difference: the variables have differing roles, and only some of their emformation is relevant. The chaos of signals becomes structured, as the emiosis defines the *interior* and the *exterior,* or some kind of a kernel and its environment. The external variables, or actual signs, are now seen as some kind of a *resources,* and the internal variables are some kind of *activities* caused by the resources. In some domains they can be seen, for example, as concrete *pressures* and *yields,* or generally as *actions* and *reactions,* or *causes* and *effects.* From now on those ξ and ζ variables in the previous section that are interpreted as resources are denoted as $\bar{u}_j$, where $1 \leq j \leq m$, and variables that are interpreted as activities are denoted as $\bar{x}_i$, where $1 \leq i \leq n$. Typically, as the chaotic environment is more complex than the assumedly more organized interior, there holds $n < m$. Of course, also flows can cause accumulation of potential: distinction between causes and effects depends on the point of view. — Again, it needs to be observed that these distinctions can be validated only in retrospect: there are many interpretations, but successful emiosis becomes rewarded, resulting behaviors having emolutionary advantage, and finally determining the dominant behaviors in the environment.

Emiosis determines how the external world is seen.

[2] Later, indeed, it turns out that in the neocybernetic perspective, nature can also be seen as searching for a "model" for its "observations" to implement "control" in a distributed manner

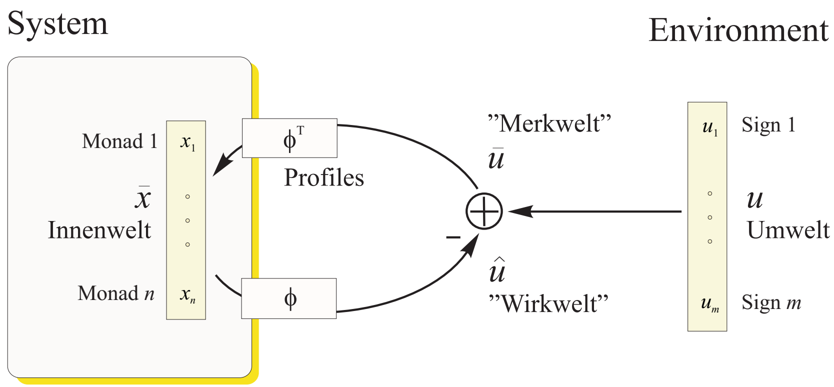

Figure 2: The neocybernetic model structures can be interpreted in terms of semiotics

As it will turn out, *selection* of the signs, or variables in the vector $\bar{u}$ and their *weighting* considerably affects the outcomes of emolutionary processes. That is why, it is reasonable to define the entities that will be concentrated on:

> (Emiotic) system = set of activities $\bar{x}$ that share the same view $\bar{u}$ of the world.

This can be interpreted so that "system is a measure of its subjective world". It seems that the most appropriate connotations about the "measurement units", or the activities $\bar{x}_i$, get captured in the framework of *monads,* as discussed originally by Gottfried Wilhelm Leibniz. Monads are *granules of existence,* dynamic atomary entities that form the basis of everything that can be seen. However, as comparing to traditional monads, it turns out that there exist now many differences. For example, monads are not eternal, they emerge from non-existence but only in a correct environment. Their manifestation is determined by the environment, so that their outlook varies; only their functioning remains invariant, looking always the same (see Sec.4.3). Monads are now not independent but under a constant competition that modifies them. They are irreducible what comes to the current level of abstraction as they are the basis of basic constructs or "emergent concepts" at that level; indeed, they implement the coupling among levels.

As seen in the semiotics framework, Fig. 2 summarizes the loop structure of the neocybernetic model being discussed later (see Sec. 3). Following Jakob von Uexküll's notations, one can distinguish between *innenwelt* and *umwelt* of a system. Further, a "forage profile" determines the *mapping* between the signs and a monad, if adopting another appropriate concept this time from *ecology.*

Generally, monads are attractors capturing the domain field dynamics, and, as it turns out, this applies also to the *ideasphere.* All fields of science and philosophy tackle with complex systems, so it is no wonder that beyond the differing paradigms there are similarities and overlaps. Concepts employed within paradigms are "probes" that try to capture the appropriate monads. To locate and anchor neocybernetic ideas appropriately in the mental domain, it is sometimes reasonable not only to refine established concepts but to employ fresh ones[3]. Here, various provisional concept candidates (like "emformation" and "emiosis") have been proposed; one of such ideas that probably deserves a term of its own is *emergy.*

2.4 Emergy concept — the key forward

Combining the above discussions, *emergy is emformation among relevant variables,* that is, it emerges (as defined in Sec. 2.2) from variables that are seen as "resources" and "activities". Emformation in general is expectation of the product of variables, but emergy connects this with semantics. The meaning of this definition can be understood through the following analogy, where the intuition of mechanical concepts is extended now to emergy:

energy = deformation $\times$ force (tension) causing it
power = flow $\times$ potential giving raise to that flow
$\downarrow$
emergy = activity $\times$ resource inducing the activity.

That is, variables ξ and ζ in the emergence formula are selected so that one has $\mathcal{E}(\bar{x}_i, \bar{u}_j) = \mathrm{E}\{\bar{x}_i\bar{u}_j\}$.

[3] The same applies also to the name "neocybernetics" itself: how the term is used here differs much from the today's discussions on *new cybernetics,* still carrying the key idea of multi-level cybernetic system interconnections. Perhaps some new name, like "uuscybernetics", would be in place

Also emformation among two activity variables can be relevant, and the same holds for a combination of two resource variables. Specially, *self-emergy,* or "localized" emformation within an individual variable, is the *simplest* form of emergy. Perhaps it is because of this extreme simplicity that self-emergy has typically even some global-level interpretation. For example, if the induced variable $\bar{x}_i$ (or $\bar{u}_j$) is some velocity, then $\mathrm{E}\left\{\bar{x}_i^2\right\}$ (or $\mathrm{E}\{\bar{u}_j^2\}$) is proportional to average *kinetic energy;* if the variable is some deformation, its self-emergy *can* be proportional to average *potential energy* (as in springs), and if the variable is electric current (or voltage), then the self-emergy is proportional to the average *electric power,* etc. However, emergies and self-emergies do NOT generally have some physically meaningful energy dimension; for example, in a cognitive system emformations are just some kind of *information* pushing the developments.

The claim here is that emergy is the key concept that makes it possible to build a bridge between signals and the corresponding emergent-level constructs. Because of its upfront visibility, self-emergy has a pivotal role: again, nature can only see those phenomena *that can make a difference,* and self-emergy seems to be the power, the necessary fuel, that is needed to make these differences. The emolutionary relevance of a "resource" and an "activity" is measured in emergy units. It is as it is with Lagrangian mechanics as compared to Newtonian mechanics: as movements of individual mass bodies are abstracted to summable energies, a higher-level view of the system is reached.

In all observations-based environments, the warning due to David Hume applies: one cannot observe causalities, only correlations. But this applies only to external observers, not to the subjects and objects themselves — they directly experience the turmoil.

It turns out that the emolutionary objective is *maximum average emergy transfer* between the environment and the system, or maximum emergy dissipation, $\bar{x}_i\bar{u}_j$ being the momentary "throughput" of the monad. This all resembles Ilya Prigogine's ideas of far-from-equilibrium systems that can produce a higher degree of order (note that in this context such constant flow, however rapid, is still considered *homeostatic* when variables are selected appropriately, including time derivatives among them). The more there is emergy available, the more the system structure can further be modified to enhance emergy capture from the environment (see next section). Even though everything is based on competition among dissipation modes, finalistic arguments seem to become quite appropriate, as seen from above: *will* of systems is a useful abstraction. What is this emergy flow then — assumedly it is *élan vital*!

The emergy pursuit principle makes it possible to make predictions concerning emolution, too. The eternal search for fresh emformation helps to understand also qualitative enhancements: for example, one can introduce new input variables, and hopefully new emergy, by augmenting the space of signs — that is, by employing new sensors or senses. The appropriate system structure can also change: new $\bar{x}_i$'s can be found when closer analysis is applied (tighter coupling); new $\bar{u}_j$'s enter when new "innovations" are made; an external $\bar{u}_j$ changes to $\bar{x}_i$ when a wider scale analysis is done, external signals forming higher-level feedbacks; existing $\bar{x}_i$ can vanish, if the *coupling* becomes too weak (see later), etc.

Concentrating on the energy variables and flow variables is a standard approach to modeling of dynamic systems, being exploited, for example, under the name *bond graphs.* Now, too, as the structures converge and find their balance, it turns out that the monads change to *models,* mirror images of the environment, as shown below.

3 Functionalization of ideas

Given the above starting points, the systems start rolling *autonomously.* The detailed theory of neocybernetics [1] is not repeated here, it is only shown how the old discussions fit the current more general framework.

3.1 Trying to prosper — *feedforward*

All system emergy and activity comes from outside, the environment is the "master" and the system is the "slave". The nice thing about the assumed activation spreading mechanism, or diffusion, is that it is a strictly *linear* phenomenon. So, if $\bar{u}_j$ is some resource (potential, or excess of actors) and $\bar{x}_i$ is some activity (net flow, or spreading of actors), in "abstract diffusion" they are coupled as

$$\bar{x}_{ij} = a_{ij}\,\bar{u}_j, \tag{1}$$

for the indices ranging between $1 \leq i \leq n$ and $1 \leq j \leq m$. Here, a_{ij} is some kind of *diffusion coefficient*, determining the level of interaction between the system and its environment. As compared to traditional diffusion, this generalized diffusion must be thought in a wider perspective. Whenever one can write some *mass balance* (or *heat balance,* etc.), the above formulation applies (the left-hand-side variable often being some derivative of another quantity; see Sec. 6.3). Also, the behaviors need not be of first-order type (exponential); oscillatory transients also belong to this category when *complex numbers* are employed (see Sec. 6.5).

But there are typically many resources that contribute to an internal phenomenon. Because of the simple scalar nature of the activity variable, the contributions can be added together, so that

$$\bar{x}_i = a_{i1}\bar{u}_1 + \cdots + a_{im}\bar{u}_m = \sum_{j=1}^{m} a_{ij}\,\bar{u}_j. \qquad (2)$$

It does not matter if the resources u_j have different dimensions or interpretations, or if the mechanisms differ, as long as they are reflected internally in the same way, increasing (or possibly decreasing) the monad activity.

To understand the emolutionary success of the monad $\bar{x}_i$, its self-emergy needs to be analyzed. Multiplying both sides in (2) by $\bar{x}_i$ and taking expectation gives

$$\mathrm{E}\left\{\bar{x}_i^2\right\} = \sum_{j=1}^{m} a_{ij}\,\mathrm{E}\left\{\bar{x}_i\bar{u}_j\right\}. \qquad (3)$$

This should assumedly be maximized. How is the possibility of optimization, or emolution (in its basic form) reflected in the formulas, what are the structural changes that can take place here? — It has to be assumed that the coefficients a_{ij} can vary; in practice, it is best to think of a_{ij} as reflecting some kind of *proximity* between the sign $\bar{u}_j$ and the monad $\bar{x}_i$. The system can (more or less knowingly!) move itself nearer to those resources that seem like most promising ones; the lucky strategies outperform the inferior ones, becoming rewarded in emolution.

To define a sound emergy optimization task, one needs to assume that there is some cost for increasing the parameters a_{ij}, because otherwise a bounded solution does not exist. It is reasonable to assume that to maintain proximity and better coupling, emergy has to be invested. How many units of emergy is needed for one unit of proximity, then?!

To approach this dilemma, one can recognize that by raising both sides in (1) to second power and applying expectation, one has

$$\mathrm{E}\left\{\bar{x}_{ij}^2\right\} = a_{ij}^2\,\mathrm{E}\left\{\bar{u}_j^2\right\}. \qquad (4)$$

That is, if all (or certain proportion) of the acquired emergy is invested in increasing proximities, it is the squares of the a_{ij} parameters that should be compared to evaluate the investment. If one knows the total emergy available for maintaining proximity, this emergy equals the sum of squares of a_{ij}'s.

The optimization problem now becomes: given the constraints, reach towards the maximum dissipation. The weighting factors a_{ij} should be selected so that the internal emergy $\mathrm{E}\left\{\bar{x}_i^2\right\}$ becomes maximized when the "length" of the a_i parameter vector (square root of available emergy) is some constant b_i, so that $a_{i1}^2 + \cdots + a_{im}^2 = b_i^2$:

$$\begin{array}{ll} \text{Maximize} & \sum_{j=1}^{m} a_{ij}\,\mathrm{E}\left\{\bar{x}_i\bar{u}_j\right\} \\ \text{when} & \sum_{j=1}^{m} a_{ij}^2 = b_i^2. \end{array} \qquad (5)$$

This constrained optimization problem can be solved applying the method of Lagrange multipliers, so that one can write

$$\max_{a_{i1},\ldots,a_{im}} \left\{ \sum_{j=1}^{m} a_{ij}\,\mathrm{E}\left\{\bar{x}_i\bar{u}_j\right\} + \lambda_i \left(b_i^2 - \sum_{j=1}^{m} a_{ij}^2 \right) \right\},$$

with maximization to be carried out for each a_{ij}. Now, these are unconstrained problems and, having a unique maximum, it can be optimized for each a_{ij} separately by setting the partial derivative to zero — this means, for example, that

$$\frac{d\,(\cdots)}{da_{ij}} = \mathrm{E}\left\{\bar{x}_i\bar{u}_j\right\} - 2\lambda_i(b_i)\,a_{ij} = 0.$$

Here the notation $\lambda_i(b_i)$ means that the Lagrange multiplier, if it were solved, would be dependent of b_i. When all derivatives are set to zero and a_{ij}'s are solved, one has

$$\left\{ \begin{array}{lcl} a_{i1} & = & \frac{1}{2\lambda_i(b_i)}\mathrm{E}\left\{\bar{x}_i\bar{u}_1\right\} = q_i\,\mathrm{E}\left\{\bar{x}_i\bar{u}_1\right\} \\ & \vdots & \\ a_{im} & = & \frac{1}{2\lambda_i(b_i)}\mathrm{E}\left\{\bar{x}_i\bar{u}_m\right\} = q_i\,\mathrm{E}\left\{\bar{x}_i\bar{u}_m\right\}, \end{array} \right.$$

where a new constant parameter q_i is employed. Thus, from (2) it can be seen that if the monad is optimally coupled to its environment, for some *coupling factor* q_i, there holds

$$\bar{x}_i = q_i \sum_{j=1}^{m} \mathrm{E}\left\{\bar{x}_i\bar{u}_j\right\}\,\bar{u}_j. \qquad (6)$$

This is the local principle for a local entity between $\bar{u}_j$ and $\bar{x}_i$ to reach for in emolution, whatever is the physical implementation of the coupling mechanism. The same reasoning applies to all available monads in the system, so that the set of n similar equations (6) can be expressed as

$$\begin{pmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_n \end{pmatrix} =$$
$$\begin{pmatrix} q_1 \mathrm{E}\left\{\bar{x}_1\bar{u}_1\right\} & \cdots & q_1 \mathrm{E}\left\{\bar{x}_1\bar{u}_m\right\} \\ \vdots & \ddots & \vdots \\ q_n \mathrm{E}\left\{\bar{x}_n\bar{u}_1\right\} & \cdots & q_n \mathrm{E}\left\{\bar{x}_n\bar{u}_m\right\} \end{pmatrix} \begin{pmatrix} \bar{u}_1 \\ \vdots \\ \bar{u}_m \end{pmatrix}$$

or in a compact matrix form as

$$\bar{x} = Q\,\mathrm{E}\left\{\bar{x}\bar{u}^T\right\}\,\bar{u}, \tag{7}$$

where the vectors $\bar{x}$ and $\bar{u}$ contain the variables $\bar{x}_i$ and $\bar{u}_j$, respectively, and the diagonal matrix Q contains the individual q_i's on its diagonal. The mapping matrix $\mathrm{E}\left\{\bar{x}\bar{u}^T\right\}$ is the *covariance matrix,* but without the traditional mean-centering or normalization. It needs to be remembered that even though the matrix representation is employed, all the operations in the system are still completely local. The system can be truly distributed and ubiquitous.

This formula (7) was the starting point when studying the Hebbian neural networks in [1] — but in the emergy framework this all can be extended to very different domains.

3.2 Paying the toll — *feedback*

It is hard to believe that something interesting could come out from emergy capture alone, and, indeed, to see this, closer analysis of matter flow is needed. The key point is to observe that there is negative feedback as exploitation means exhaustion: emergy that is invested in some specific monad, is no more available to others. This feedback is an implicit consequence of the nonideality of the world, there are no pure information flows. The feedback signal does not have a physical channel of its own, even though it is shown as a separate path in an information flow graphs (as in Fig. 2). Seen from above, this feedback means competition among monads, resulting in self-regulation and self-organization.

Monads are distinct dissipation structures, and this structure is determined by the environment (for concrete examples on what this means in practice, see Sec. 5.1). Once the monad activity has been started, it is the proximity structure that determines the interaction probabilities, dictating where the needed resources are fetched from. When following the learned structure, the monad seems to be selective and active, sucking the resources it wants. In this sense, the *systemic diffusion* is not simple dispersion of resources, but there exists intricate structure in the flows.

When the monad i has activity $\bar{x}_i$, it sucks from resource j such an amount of emergy that is proportional to the proximity α_{ij} or $q_i\mathrm{E}\{\bar{x}_i\bar{u}_j\}$. This means that the change in the resource j because of the monads can be written as

$$\begin{aligned} \Delta u_j &= c_1 a_{1j}\bar{x}_1 + \cdots + c_n a_{nj}\bar{x}_n \\ &= \textstyle\sum_{i=1}^n c_i a_{ij}\,\bar{x}_i \\ &= \textstyle\sum_{i=1}^n c_i q_i \mathrm{E}\left\{\bar{x}_i\bar{u}_j\right\}\,\bar{x}_i. \end{aligned} \tag{8}$$

The factors $c_i > 0$ are some proportionality factors. For the whole grid of resources one can write

$$\begin{aligned} &\Delta u \\ &= \begin{pmatrix} c_1 q_1 \mathrm{E}\left\{\bar{x}_1\bar{u}_1\right\} & \cdots & c_n q_n \mathrm{E}\left\{\bar{x}_n\bar{u}_1\right\} \\ \vdots & \ddots & \vdots \\ c_1 q_1 \mathrm{E}\left\{\bar{x}_1\bar{u}_m\right\} & \cdots & c_n q_n \mathrm{E}\left\{\bar{x}_n\bar{u}_m\right\} \end{pmatrix} \bar{x} \\ &= \begin{pmatrix} \mathrm{E}\left\{\bar{x}_1\bar{u}_1\right\} & \cdots & \mathrm{E}\left\{\bar{x}_n\bar{u}_1\right\} \\ \vdots & \ddots & \vdots \\ \mathrm{E}\left\{\bar{x}_1\bar{u}_m\right\} & \cdots & \mathrm{E}\left\{\bar{x}_n\bar{u}_m\right\} \end{pmatrix} \\ &\qquad \cdot \begin{pmatrix} c_1 q_1 & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & c_n q_n \end{pmatrix} \bar{x} \\ &= \mathrm{E}\left\{\bar{x}\bar{u}^T\right\}^T Q^T C\,\bar{x}, \end{aligned}$$

where matrices Q and C both are diagonal, C containing the parameters c_i on its diagonal. This expression can still be simplified. Because one can multiply $\bar{x}$ with an arbitrary C, so that

$$C\bar{x} = CQ\,\mathrm{E}\left\{\bar{x}\bar{u}^T\right\}\,\bar{u} = Q\,\mathrm{E}\left\{C\bar{x}\bar{u}^T\right\}\,\bar{u},$$

the expression (7) must hold also for the linearly transformed system where $\bar{x}$ has been substituted with $C\bar{x}$ as well. One can also alter the system state vector without essentially changing the system properties; thus, without loss of generality, from now on assume that "unit conversions" and scalings have been carried out beforehand so that this vector has been modified as

$$x \quad \longleftarrow \quad Cx, \tag{9}$$

giving the feedback mapping in the simple form that is the *transpose* of that in (7):

$$\Delta u = \mathrm{E}\left\{\bar{x}\bar{u}^T\right\}^T Q^T\,\bar{x}. \tag{10}$$

According to the above discussion, either x or u can have arbitrary scaling, but thereafter the scaling of the other is fixed — this makes it possible to wonder whether there are some *natural unit systems* in nature.

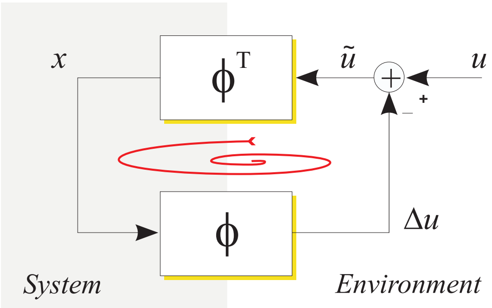

Figure 3: The basic monad structure

Further, assume that systems are interconnected subsystems, or there are *trophic layers,* so that the acquired emergy gets shared. If the loss is proportional to the activity, what remains of $\bar{x}$ is only $\bar{x}' = \bar{x} - A\bar{x}'$, where A represents the loss. It is this $\bar{x}'$ only that remains visible; if it is this effective $\bar{x}'$ that the system uses also for proximity adaptation, *variable x can be ignored altogether,* when one formally writes $\bar{x}' = Q\mathrm{E}\{\bar{x}'\bar{u}^T\}\bar{u}$. Also in feedback: only the actualized activity $\bar{x}'$ affects the environment. Substituting now $\bar{x}$ for $\bar{x}'$ in all formulas, everything in the derivations remains unchanged, even though the convergence to the balance in the deeply nested system may take a longer time.

There are some more words that need to be said about the internal convergent processes and signal visibility. Above, symbols like $\bar{u}$ and $\bar{x}$ have been used; they are the final, effective, visible variables, dynamic balance values that result after underlying interactions have converged. The original undisturbed resource vector u is *invisible* for the local actors, because in reality it is disturbed by the systems (this can be called here, too, *observer effect*). Only visible values can make a difference; only outcomes remain, as one cannot trace the underlying details. When the feedback is taken into account, one has

$$\tilde{u} = u - \Delta u, \tag{11}$$

as illustrated in Fig. 3. After convergence (the feedback loop is always asymptotically stable) the remaining visible resource level becomes

$$\bar{u} = \lim_{t \to \infty} \tilde{u}. \tag{12}$$

This $\bar{u}$ could thus be characterized as the remaining error, or *residual,* representing what is left of the original resource u. Similarly, final $\bar{x}$ is available only after the signal-level convergence of $x = Q\mathrm{E}\{\bar{x}\bar{u}^T\}\tilde{u}$. In practice, one only needs to wait until a time has elapsed that is considerably longer than what are the time constants in the loop, so that the *virtually* stationary value has been reached. Indeed, there are various different time scales and "different infinities". In the Heraclitean spirit, everything changes, only time scales differ. To capture the "momentary nature" of these changings, one has to concentrate on the following scales separately:

- Fastest, system's internal time scale: relevant to momentary signals like x
- Moderate, environmental time scale: relevant to signals like u, $\bar{u}$ and $\bar{x}$
- Slowest, "ecosystem scale": models of emergy, for example $\mathrm{E}\{\bar{u}\bar{u}^T\}$, $\mathrm{E}\{\bar{x}\bar{x}^T\}$, and $\mathrm{E}\{\bar{x}\bar{u}^T\}$.

In the environmental time scale, for example, the system state can be seen as a static function of its inputs, its dynamics being too fast to be observed, and when studying the time scales relevant to the system state, the environment remains practically constant, being too slow to change considerably during the system's time constant. This means that when concentrating on a specific time scale, signals from other scales look like constants. The co-existence of various time scales reflects the structure of nature: there are emergent layers everywhere, and the hierarchy of such layers does not always remain detached.

3.3 Putting the system on wheels

Signals traverse through the system, "feed-in" and "feed-out" looping between the system and its environment, searching for equilibrium that would satisfy the constraints. The underlying dynamics supplies the machinery to reach and maintain the asymptotic dynamic balance. When seen in the mathematical perspective, finding equilibrium corresponds to "solving" an algebraic structure of constraint expressions through implicit iteration (see also Sec. 6.3).

There is always the trivial solution $\bar{x} \equiv 0$; to find a non-trivial solution, emergy needs to be invested. When studying the feedback structure (see [1]), it turns out that the environmental "resource modes" become separated so that one distinct monad represents each of the most relevant correlation structures among the signs; some emergy is lost in this feedback process, so that one can write a formula for inheritance of emformation (also see Fig. 19):

$$\mathrm{E}\left\{\bar{x}_i^2\right\} = \sqrt{\frac{\lambda_j}{q_i}} - \frac{1}{q_i}. \tag{13}$$

Here j represents the index of the input data mode with variance λ_j that has been coupled with the monad i.

Self-emergy must always have a positive value. Thus, as seen in the formula (13), activity in a monad does not necessarily start at all. There is "static friction" that is not caused by physical non-idealities, but by the sophisticated structure of the feedback loop itself, emerging (astonishingly) in a strictly linear structure. There is a *threshold* to get the "mills running", or a *tipping point* where "the momentum for change becomes unstoppable", a monad changing from not-being into existence (one can also speak of the "hundredth-monkey effect"). In very concrete terms, *quantitative* changes to *qualitative* when the *bifurcation point* is reached and the coupling parameter fulfills

$$q_i > \frac{1}{\lambda_j}. \tag{14}$$

Otherwise what is *potential* never becomes *actual.* — Later it turns out that the system is forced to detect some *patterns* in the input data by matching the data against learned *features.* The monad model does not exactly match the observed world; when the system is put "face to face" with the environment, bargaining can be started, matching the views about the "merchandise" (the offered pattern) between the "buyer" (the system) and the "seller" (the environment). When the pressure (coupling) is strong enough, a compromise is always found.

Such *strong coupling* has so special effects on the environment that one could perhaps introduce yet another term, or *emmersion.* When all monads are active and have the same coupling q, *equalization* in the environment takes place, so that $\bar{\lambda}_j = 1/q$ for all i, that is, variation in the *visible* environment after feedback effects becomes suppressed, its variances in all directions becoming constant[4]. There is a nice paradox here: even though the seemingly invariant environment as seen by the local actors (in the time scale of the system) is volatile in the wider scale, after coupling, the environment (in a certain sense) *becomes* invariant (for more paradoxes, see Sec. 6.6). Because of the structured diffusion, system moulds its visible environment, or the vectors $\bar{u}$: it is not only so that the system (the observer) would reflect its environment, but the environment (the observed) is also modified by the system. The system and its environment essentially become one.

[4]In practice, when all variances in the system become equal then, modes can get blurred, because, if one selects Q_{opt}, one has $Q = q\,I$, and there holds $Q\text{E}\{\bar{x}\bar{x}^T\} = \text{E}\{\bar{x}\bar{x}^T\}Q^T$ also for non-diagonal $\text{E}\{\bar{x}\bar{x}^T\}$ — to learn why, see [1]

There is now one free parameter q_i for each monad that effectively determines the faith of that monad. Assumedly there have to exist some external mechanisms to automatically adjust those control parameters: the goal is that there would exist no parameters to be tuned whatsoever, because only when the subsystems are truly autonomous real scalability can be achieved. In practice, an adaptive selection of the coupling parameters as

$$q_i = \frac{1}{\text{E}\left\{\bar{x}_i^2\right\}} \tag{15}$$

can do the trick, effectively implementing variance compensation of the monad activation. This selection makes that monad emerge for any complex enough data, pushing the coupling so tight that even the weakest resources become visible. Such adaptation is completely local and can be implemented in each monad separately. There are other ways to motivate this choice, too:

- It promises fast and robust (second-order) convergence of signals and models (see Sec. 6.3)
- There is also maximum system excitation, meaning emolutionary advantage (see Fig. 19)
- Additionally, *symmetry* between the system and its environment is reached (see below)
- Last but not least: such activity adaptation has been observed in neuron systems where active neurons become less sensitive.

The term symmetry (or "emmetry"?) that was used above means here that the system and the visible environment become *balanced,* meaning that $\text{E}\{\bar{x}_i^2\} = \bar{\lambda}_j$, that is, their variation levels become equalized. Indeed, one can write a simple formula that connects the standard deviations of the system activation, visible input, and the original input:

$$\sqrt{\text{E}\left\{\bar{x}_i^2\right\}}_{\max} = \sqrt{\bar{\lambda}_j} = \frac{\sqrt{\lambda_j}}{2}. \tag{16}$$

This means that in optimum only one fourth of the resource is exploited, and maximum emergy transfer is reached even before that (see Fig. 19).

Thus, to reach the emolutionary optimality, the matrix Q_{opt} implementing the maximum system emergy as defined as the objective in Sec. 3.1 should be selected as

$$\begin{pmatrix} q_1 & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & q_n \end{pmatrix} = \begin{pmatrix} \frac{1}{\text{E}\{\bar{x}_1^2\}} & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & \frac{1}{\text{E}\{\bar{x}_n^2\}} \end{pmatrix}.$$

In practice, however, strict optimality in couplings is not always desirable: equalization of variances tends to make modes harder distinguishable, and the emergence of clusters can suffer.

In practice, when emulating monads, in some cases there can emerge convergence problems, and some *nonlinearity* can help. It turns out that the *cut-form nonlinearity* or *rectification* has some practical and theoretical benefits; that is, during iteration apply for all monads

$$x_i = f_{\text{cut}}\left(q_i \mathrm{E}\{\bar{x}_i \bar{u}^T\}\, \tilde{u}\right), \tag{17}$$

where

$$f_{\text{cut}}(x_i) = \begin{cases} x_i, & \text{if } x_i > 0, \\ 0, & \text{otherwise,} \end{cases} \tag{18}$$

so that the activity value can only be non-negative. It needs to be recognized that the model linearity is not completely lost: the inactive modes are temporarily pruned out from the model as they cannot have any effect whatsoever, and the model with the remaining ones is linear. In some cases, it may also be reasonable to restrict $\tilde{u}$ to have only non-negative values.

The world of stable monad attractors must be started from the bottom, always assuring the next layer of monads only contains convergent processes, so that the emerging complexity, or the bundles of activity manage to stick together maintaining their integrity. From here on, the story continues as presented in [1][5] — only the main results (and fresh interpretations!) are summarized below.

4 Analyses and interpretations

Here, the resulting *view from above* is briefly presented — how the monads contribute to the *model.*

4.1 Summary: mathematical properties

Even though everything in complex systems is based on elementary operations, the system properties can best be understood in terms of multivariate linear theory and as mappings between spaces. Interactions between a system and its environment are mappings between the space of signs and the space of monad activities, and resources are just input data. When the dynamic equilibrium is found not only on the signal level but also on the statistical level, the emergy-maximizing mapping from the signs to monads is

$$\phi^T = Q\, \mathrm{E}\left\{\bar{x}\bar{u}^T\right\}, \tag{19}$$

according to (7), presenting the explicit operation of the underlying actors, as studied above, in a compact form. This means that the feedback (10) can be expressed as $\Delta u = \phi \bar{x}$. Further, when the effective mapping from the original, undisturbed u to the system state $\bar{x}$ is solved, one has the following formulation for this *implicit* mapping

$$\varphi^T = \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}\right)^{-1} \mathrm{E}\left\{\bar{x}\bar{u}^T\right\}, \tag{20}$$

exploiting the "sparse linearity" of the loop structure ($\bar{x}$ perhaps containing only a subset of the all n variables, only the active ones), so that $\bar{x} = \varphi^T u$. The two mappings are related so that

$$\varphi^T = \left(I_n + Q\mathrm{E}\left\{\bar{x}\bar{x}^T\right\}\right)^{-1} \phi^T. \tag{21}$$

It needs to be recognized that the formula for φ in (20), or the implicit feedback mapping $(\varphi^T)^T = \varphi$, coincides with the well-known formulation of *ridge regression* from the lower-dimensional $\bar{x}$ to the estimate of the higher-dimensional $\bar{u}$. Similarly, as it turns out, the explicit feedback mapping ϕ, when it is appropriately transformed by solving $\bar{u}$ in terms of u, implements ridge regression from $\bar{x}$ back to the *original* resource vector u, giving out its estimate $\hat{u}$; this means that there holds $\Delta u = \hat{u}$. Thus, the negative feedback, or $u - \Delta u$, maximally exhausts the input. Note, however, that as ridge regression gives *robust* and rather conservative estimates, the input elimination is still far from complete: if the modes have been separated, so that $\mathrm{E}\{\bar{x}\bar{x}^T\}$ is diagonal, the estimates are *half* of what they theoretically should be[6].

This all can be presented as shown in Fig. 4. Intuitively, the emergent strange dual symmetry as depicted in the figure *cannot* be a coincidence — it is a "proof" that we are heading in the right direction![7]

Local level maximization results in global level modeling — these issues deserve emphasis here. In the sense of emergy (emformation) representation, the neocybernetic model is the *best possible*:

- The feedforward implements optimal (robust) modeling of the input data in terms of variance preservation.
- The feedback implements optimal (robust) estimation (or "generative modeling") of the input data in terms of variance preservation.

[5] Specially, check the paper "Hebbian-Style Feature Extraction – From Neural Systems to Neocybernetics" (2008) in Publications section therein

[6] But doing right things is more important than doing them exactly right — this "sloppy" exploitation, not exhausting all of the available resources, is perhaps one key to the sustainability of natural systems?

[7] Another, perhaps more plausible, but still debatable "proof": *Applying the neocybernetic approach, one achieves maximum number of consequences with minimum number of assumptions*

- Thus, the closed loop with negative feedback implements optimal (robust) "statistical level control" of the input.

Here, *optimality* in estimation is to be interpreted in the linear regression framework, and in modeling it means *principal component (subspace) analysis* perspective, so that the orthonormal basis axes spanning the subspace of maximum emergy in the environmental data are the rows in the matrix

$$\theta^T = \sqrt{Q}\,\sqrt{\mathrm{E}\left\{\bar{x}\bar{x}^T\right\}^{-1}}\;\mathrm{E}\left\{\bar{x}\bar{u}^T\right\}. \qquad (22)$$

If the system covariance $\mathrm{E}\{\bar{x}\bar{x}^T\}$ becomes diagonal, and if one uses Q_{opt}, the orthonormal axes of the "system subspace" are determined directly by the *forage profiles* or vectors ϕ_i, implementing "reconcentration" of distributed emformation in data.

On the other hand, *robustness* in regression means reduced sensitivity to *colinearity of variables.* In traditional regression, one has to invert the data covariance matrix $\mathrm{E}\{\bar{x}\bar{x}^T\}$, and if this is singular, estimates become badly behaving. Now, however, as Q is positive definite, the matrix to be inverted, for example, in (20) always has full rank. Specially, if the coupling factors are selected as in (15), this matrix becomes

$$\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + \mathrm{diag}\left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\}\right). \qquad (23)$$

that is, the diagonal elements of the covariance matrix are doubled. This matrix is always invertible, assuming that the environment is complex enough, that is, if there exist at least n behavioral modes in the data.

In the modeling part, robustness means *sparse coding.* Because of (13), as the losses try to suffocate the monad activity, system has to struggle; this becomes manifested as *rotation* of the subspace basis axes as determined by the profile vectors in $\mathrm{E}\{\bar{x}\bar{u}^T\}^T$. The most beneficial directions in the resource space are *sparse components* within the principal subspace: the goal is to make the monads that are active at a certain moment *maximally* active, "winners" surpassing the threshold, simultaneously damping the "loser monads". Thus, a *feature representation* of the environmental data becomes implemented, where a pattern is decomposed into a low number of clearly distinguishable features that have different degrees of relevance, revealed by the corresponding monad activities.

The cut-form nonlinearity further enhances sparsity, putting some activities explicitly to zero: this means the simultaneously active monad combinations define different "subworlds" in the same model, or in the "cybernetic multiverse" (there are maximally $2^n - 1$ submodels). Within each subworld linearity applies. The subworlds "communicate" with each other only through the shared features.

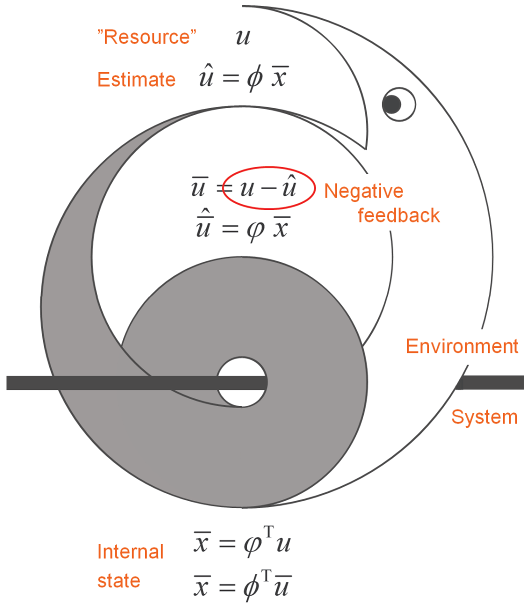

Figure 4: *Ouroboros* eating its own tail: exploitation means exhaustion, and good modeling results eventually in starvation. As the "snake" infinitely loops between the system and its environment, searching for balance, it simultaneously defines the behaviorally relevant axis between the opposite extremes

According to the above discussion, it is not only humans that do modeling: *nature tries to detect its own model.* As seen from outside, it seems that nature tries to compress the chaos by employing all its "submodels", like different species, etc. When natural processes are seen in such modeling perspective, new horizons open up: for example, one can speak of *interobjectivity,* or the possibility of *sharing the common world view with nature* (see Sec. 6.1).

As seen in the mathematical perspective, it is the *cost criterion* that determines the nature of the system in the most compact form. It turns out that in the neocybernetic framework the criterion to be minimized is

$$J(x) = \frac{1}{2}\, x^T \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}\right) x - x^T \mathrm{E}\left\{\bar{x}\bar{u}^T\right\} u.$$

This criterion also connects the time scales: it can be used for determining $\bar{x}$ (when minimizing $J(x)$), and for determining the model itself (when minimizing $\mathrm{E}\{J(x)\}$). The criterion can be decomposed as $J = J_{\mathrm{int}} + J_{\mathrm{ext}}$, with the *internal emergy* and the *external emergy flow* being defined as

$$\begin{aligned} J_{\mathrm{int}}(\bar{x}) &= \tfrac{1}{2}\,\bar{x}^T \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}\right) \bar{x} \\ J_{\mathrm{ext}}(\bar{x}) &= -\bar{x}^T \mathrm{E}\left\{\bar{x}\bar{u}^T\right\} u. \end{aligned}$$

It turns out that for a given data the model size $n_{\rm opt}$ can be found when $\mathrm{E}\{J(x)\}$ becomes minimized. This makes it perhaps posssible to get rid of the final global control parameter. For some reason it seems that often this $n_{\rm opt}$ is found in the vicinity of the magical number 7 ± 2.

In the spirit of *deformation energy* in mechanics, the neocybernetic criterion could be seen to define *emformation energy,* the system trying to minimize it. — Such compact mathematical patterns help to see connections, as shown below.

4.2 Step aside: *Hopfield nets,* etc.

The above cost criterion can be expressed in different ways. After some manipulations, it can be written, for example, as

$$\begin{aligned} J(x) = &-\tfrac{1}{2}\, x^T \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} - Q^{-1}\right) x \\ &- u^T \mathrm{E}\left\{\bar{x}\bar{u}^T\right\}^T \left(I_n + Q\mathrm{E}\left\{\bar{x}\bar{x}^T\right\}\right)^{-1} x. \end{aligned}$$

As it turns out, such formulation is familiar from *Hopfield networks* — maximum of emergy can be seen as *minimum of pattern representation effort*[8].

A Hopfield net is a form of recurrent artificial neural networks proposed by John Hopfield. Hopfield nets serve as content-addressable memory systems; the main application of a Hopfield net is the storage and recognition of patterns. It consists of a set of neurons x_i, where $1 \leq i \leq n$. Each neuron is connected to each other neuron (not to itself), and reciprocal connections have identical weights. This means that the coupling matrix (weight matrix) W has to be symmetric, so that $W_{ij} = W_{ji}$, and its diagonal has to be zero. The Hopfield net has traditionally no inputs: it is the steady-state pattern of x values that is searched for starting from some initial state (the disturbed pattern) $x[0]$, hoping that this associative search process converges to some preprogrammed attractor pattern. The state adaptation towards the balance takes place as

$$x[k+1] = f\left(Wx[k] + V\right),$$

where some kind of bias values are collected in the vector V, and f is some nonlinearity, typically giving out only binary values. What is special about Hopfield nets is that they are based on explicit energy considerations, so that their behaviors can be understood in the top-down perspective, too. It is the *Lyapunov function* that captures the total energy:

$$E = -\frac{1}{2}\, x^T W x - V^T x.$$

Comparing this to the neocybernetic criterion, it turns out that $J(x)$ can be seen as a Lyapunov function, because for a fixed input u one can define the vector $V = (I_n + Q_{\rm opt}\mathrm{E}\{\bar{x}\bar{x}^T\})^{-1}\mathrm{E}\{\bar{x}\bar{u}^T\}\, u$ and the matrix $W = \mathrm{E}\{\bar{x}\bar{x}^T\} - Q_{\rm opt}^{-1}$. Indeed, the weight matrix W with this selection of Q is now symmetric and its diagonal is zero. This means that there are many connections between these differing approaches.

There exists a plenty of analysis directly available for Hopfield nets, and this material can be employed for gaining intuition on the properties of neocybernetic models, too.

First, the Hopfield net experience promises that very strong nonlinearities can be introduced in the system and there still is convergence to (local) minimum. It is not only the proposed cut-form nonlinearity, but, for example, upper bounds can also be introduced. Even an extreme nonlinearity, binary "on/off" thresholding is evidently possible.

Another intuition gained for free is that in the nonlinear system there can coexist various stable attractors in the data space (different stored patterns in the Hopfield net), so that the final state $\bar{x}$ is dependent of the initial state. There is "memory" not only in the structures, but also in the system state; so, assuming that the state is not reset between runs, *continuums among successive data can be modeled.* Location of the attractors is not only dependent of the environment but also of the system dynamics. Not having to reset the state between the input vectors also makes convergence faster if the successive inputs are correlated; what is more, omission of such higher level initialization and synchronization makes the approach still more plausible.

In the Hopfield net, explicit "programming", or off-line storing of patterns is needed. If the vectors s_i, where $\eta < n$, are the samples to be stored, the weight matrix is, in principle, defined as

$$W = s_1 s_1^T + \cdots + s_\eta s_\eta^T,$$

with the diagonal being additionally zeroed (and some further modifications perhaps being carried out). In the neocybernetic case, too, the eigenvectors of the covariance matrix assumedly carry some information of the "natural patterns" of the system? — It needs to be remembered that in the Hopfield net with the state vector x simultaneously being the "input", no abstraction or actual model construction

[8] There are other neural network structures that could be mentioned, too — for example, the neocybernetic model works like a distributed version of *Kohonen's self-organizing maps,* when the matrix Q is used as a *non-diagonal* (but still symmetric) "neighborhood matrix", so that there is some interaction among neighboring nodes. This interpretation gives a clue of how the set of n model elements could be automatically organized

takes place. The system is just an associative pattern memory there, whereas in the neocybernetic model the system is a storage for associative *features,* components for constructing the actual patterns. For example, visual patterns (like handwritten digits) are decomposed into *strokes.* One can assume that now there exist less spurious stable points as the system dimension n is much lower than the pattern size m.

Looking once more at the signals, it is the error between the environment and its estimate, $\bar{u} = u - \hat{u}$, that is used as the effective input for modeling. If the vector u already can be represented, then $\bar{u} = 0$, and it does not have effect. Refine the boundary region between the model and the input patterns, concentrating on the key points — intuitively, this makes learning more efficient. Such low-level "attention control", or emphasis on the hardest cases, resembles the operation of yet another approach that is studied in the field of neural networks, namely *support vector machines.*

As discussed by Geoffrey Hinton, many unsupervised layers can work conditioning the patterns: iterative modification of the observed "virtual world" or "reality-directed phantasy" can enhance the adaptation process. Now all layers are collapsed onto a single recurrent layer. Relevant features are first extracted, and only after their relevance is assessed, they are adapted in appropriate directions. The features are the common structures in the whole multiverse, becoming updated much more often than the subworlds themselves, making the model adaptation a feasible task.

The Hopfield nets, however, turned out to have their own deficiencies. Later, the similar ideas were polished in *Boltzmann machines,* where a simple local learning principle was proposed. Still further on, in *restricted Boltzmann machines* there was feedback only through the environment, and real variables were employed instead of binary. Active development work is still taking place — one could almost say that the stochastic emolution is getting nearer towards the neocybernetic model!

4.3 "Whirls" made concrete

The basic monad structure, or the elementary loop, is similar in all environments. But according to Leibniz's *monadology,* monads go in all scales. Now we have been studying monads only on the most elementary level — how to widen our views? What are the common characteristics beyond the ever-changing reality? Have we learnt something this far?

The key characteristic in neocybernetics is feedforward and feedback that together constitute a loop whose outlook is determined by the underlying realm. The above discussions were necessary to understand how the seeds of order emerge from chaos, but, hereafter, when stability has been reached, it is easy to see why the models and controls become more sophisticated: more efficient control of resources means emolutionary advantage. As the loops become more complex, implicit controls become more and more explicit, and the structures of *circular causality* become visible. And, in the neocybernetic spirit, it is a control loop if it helps to maximize dissipation. For example, in metabolic systems the behaviors are governed by a multitude of general chemical laws — but only those reactions turn out to be relevant that constitute a proper functional chain (see Fig. 5). There are homeostatic control loops within a cell, and more complicated ones like the *cell cycle.*

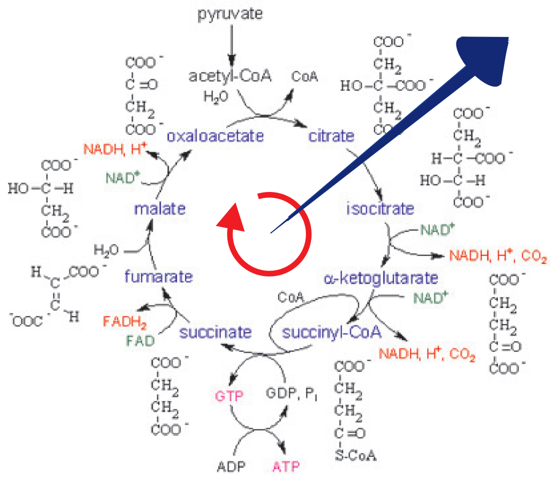

Figure 5: An example of more complex monads: the metabolic *citric acid cycle* (or *Krebs cycle*), a series of enzyme-catalysed chemical reactions, which is of central importance in all living cells that use oxygen as part of cellular respiration

As Stuart Kauffman argues, loops of *auto-catalysis* emerge in complex enough chemical mixtures. His claim is that such self-organization (together with evolution) would be enough for life to emerge in the primordial sea. However, mindless loops cannot accomplish very much — as discussed above, it is the self-regulation that is the third key ingredient, boosting and modifying the appropriate autocatalytic loops. All of this can be understood only in terms of dynamic balances using mathematical tools.

Because of the system *pancausality* (see [1]), all variables are interconnected, and the system is assumedly full of loops. Each independent cycle defines a new monad (if loops are locked together, there is just one degree of freedom). The same intuition and methodology still applies: covarying variables along the longer cycles are collapsed into the one freedom-oriented variable $\bar{x}$ when aplying the principal components based methodologies, either implicitly or explicitly. This degree of freedom on top of the constraints, or the mathematical construct, can easily be made intuitive: the monad activity is the "loop rate" or "rotation speed" in the loop. Applying the intuition from physics, one could say that when the constraints are written down, the remaining freedom points out in a new direction (note that in abstract loops, as in Fig. 5, the "right hand rule" becomes obsolete). Of course, the loop radius can also be infinite in the case of pure forward flows, when one has too narrow scope, or when feedbacks have not yet been implemented. The data-oriented analysis methodology can still model such partial structures — a subset of variables are missing, but probably the key covariations are still visible in the remaining ones. In more complex systems, the loops can be *allogenous* rather than autogenous (see Sec. 5).

For physical reasons, often the loops cannot be run in reverse direction, so that the minimum speed is zero, whereas there is no theoretical limitation from above. When emulating such irreversible processes, the cut-form nonlinearity is again well motivated.

Monads emerge as "pathways" through the underlying jungle of constraints, defining degrees of freedom. They compress the overall effects of the underlying realm, thus offering new abstracted ways to see the world to a system. Finding such new views can be called *low-level creativity.* As it has been said, *the universe is characterized by a "persistent creativity" operating on all scales and in all contexts, but especially where there is life.* Finding degrees of freedom can be seen as *exploration* — thereafter, when the enhanced view of the world is applied for implementing further controls, there is *exploitation* of the freedoms. Quantitative adaptations change to qualitative steps in development as new monads pass the threshold.

Depending on the situation, a monad can be characterized in different ways. The monads are the *system freedoms*; simultaneously they are the *basic activity patterns.* Or, putting it in a more intuitive way: monads are the *mills producing order and structure.*

In the dynamic setting, when systems are seen as processes (see *process philosophy* in the following section) the surface patterns and the *deep patterns* become equal. Indeed, one is getting nearer and nearer to the Heraclitean vision: *panta rhei,* and it is a *river*

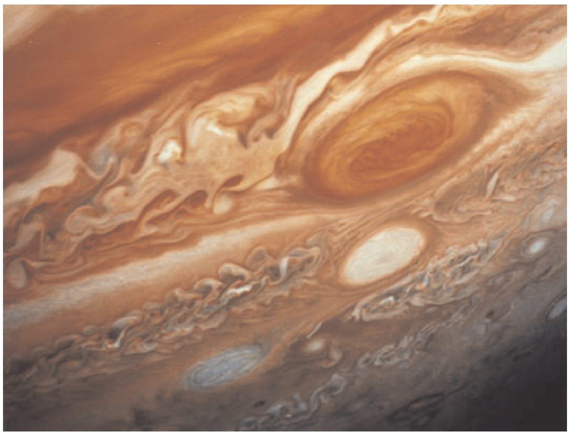

Figure 6: The "red spot" on Jupiter has been there for hundreds of years

that can be used as a metaphor to describe the nature of all things. One can propose a *river analogue*: there are flow patterns, whirls and eddies that are determined by the environmental constraints, they may disappear but re-emerge when the time is right. Such river is filled with *élan vital,* constituting the flow of life! — Self-sustaining whirls can perhaps tell something about the underlying realm (see Fig. 6). Similarly, "fluid analogies" have been coined by Douglas Hofstadter to describe cognition.

Everything is patterns, and the cybernetic pattern structure can be assumed to be always the same. This is a very deep philosophical claim — and there are other philosophically oriented consequences, too.

4.4 Consilience of philosophies?

Edward Wilson's idea of *consilience,* or the unity of all knowledge, is not restricted only to the "two cultures", or to natural sciences and human sciences. All branches of human knowing are also natural systems, following the same principles of emolution, and, indeed, this applies to all branches of human *living.* In Fig. 7, the neocybernetic perspective is applied to *natural philosophy,* but the same structure can be extended to the metaphysical basis of *all* philosophies. It is mathematics that offers the *language* for discussions; the domain area offers their *semiosis* and *semantics* — and the *narrative,* or the story outline, with the initial rise and eventual downfall, is offered by the engineering experience concerning *adaptive control systems* (see [1]). Everything can then be seen as branches of "abstract physics".

It is interesting to study how the neocybernetic

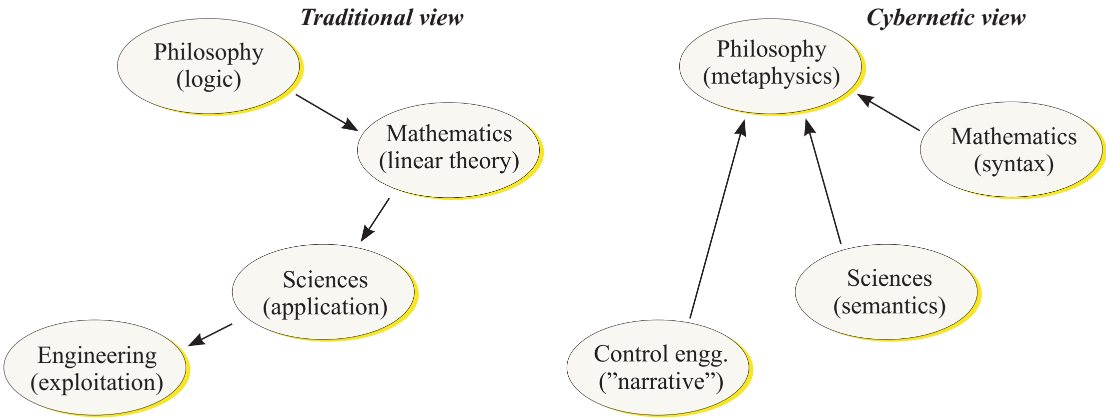

Figure 7: The hierarchy of scientific endeavors being put upside down

"mental attractors" are related to concepts in traditional philosophies. One key idea with dozens of reincarnations is that of *dialectics,* or the study of opposing tensions forming some kind of patterns in their dynamic balance. In Eastern philosophy they have *yin* and *yang,* Heraclitus speaks of the *unity of opposites,* and, later, in the writings of Hegel and Marx, dialectics again has a central role, being recycled in the form of *thesis* and *antithesis* by Kuhn. Now, in the neocybernetic setting, a monad defines an axis, simultaneously making the opposite directions along that axis visible. There are new nuances, though: now there is *continuity* between the extremes, as $\bar{x}_i$ is real-valued. The traditional Aristotelian thinking claims that there cannot exist an intermediate between contradictories; only recently the fuzzy logics, etc., have shown that continuity can be possible and beneficial. Neocybernetics uses calculus rather than logics to evaluate the balances along the continuums.

However, things are not so straightforward. Neocybernetic models also propose need for discontinuity in world models: granularity there emerges in the form of sparsity. Convergent continuous processes (monads) determine discrete constructs. Further, dichotomies in those models emerge on the most fundamental level when structuring the world; one could even speak of *new dualism*: it is reasonable to distinguish between *information* and *matter,* and the models implement the coupling between this information (as stored in the emergent structures, or expressions of emergy $\mathrm{E}\{\bar{x}\bar{u}^T\}$) and matter (as manifested in the actual signals u and x). It seems that there is new hope — when trying to understand the world, perhaps it is not only about structureless energy and its Hamiltonians (see also Fig. 20).

Yet another key to combining neocybernetics with today's paradigms is through *process philosophy,* or the "ontology of becoming". Truly, this branch of philosophy promotes the Heraclitean spirit: what exists is result of processes, the metaphysical basis being dynamic rather than static.

On the other hand, the general framework of neocybernetic emulations can be seen as a branch of *computationalism,* implementing the application and functionalization of the process philosophical framework. It operates more through *synthesis* than through *analysis,* always starting from the bottom. One tries to understand the *existing* life forms by creating *new* ones. Properties of the world emerge from low-level computations. To reach a view of "universal life", it cannot be whatever iterations: the neocybernetics reveals (so is claimed here) how to implement semantics and emulate emolution in terms of convergent (computer) processes, capturing the *essence* of natural systems.

Returning to consilience: it is usually assumed that the "equalization" among sciences means *downgrading,* as scientific communities, too, are vulnerable to societal randomness, and the domination of paradigms perverts the neutral scientific progress. Now, however, when there is the computational common basis for all sciences, natural and humanistic alike, the level can be *upgraded.* To be regarded as a science, there must be repeatability, and, thus, possibility of verification or falsification of claims. A science cannot be based on unique successions of behaviors, because then one cannot determine whether the observed developments are just extremely improbable coincidences, or whether there does exist some general rule, or pattern of attractors. For example, *evolution* cannot be "proven" as the history cannot be repeated and verified in the classical sense. Now, neocybernetic computationalism (or "emputationalism"?) starts from hermeneutic/cybernetic semiosis, the valuation of signs (of course) remaining debatable, semantics being grounded in converging iterations. When the mills are grinding, fresh monads emerge, producing new data material, or spectra of alternative scenarios. Rather than having a case with chaotic divergence, one finds stable attractors where the activity concentrates. When there are many case samples available, relevant models can be found by cleverly abstracting over individual details.

The classical starting point of new cybernetics, or "radical constructivism", seems to be outdated. Relativism has to give way to relevance, meaning that things are no more negotiable but they have to be based on real attractors in their domains. This means that even *ethics* can someday become a subject of theoretical study.

Having "in silico" data on alternative scenarios, the Hegelian Geist can perhaps be captured in social sciences and in history. And biology can change from studying taxonomies towards understanding general principles of "abstract biology". Indeed, there perhaps emerge higher categories over the contemporary paradigms; one will have *abstract philosophy* or *metaphilosophy,* and there will be *metascience.* — But how to detect and recognize the appropriate signs and monads in practice? This will be studied next.

5 Examples of monads

In this section, real systems are seen through "neocybernetic eye-glasses", actively putting things in that framework, showing how the assumptions can be motivated in different domains, and what the "low-level monads" can look like. The examples are unpolished, and, in some sense, this cavalcade is more like a "reality show and tell".

5.1 Physical systems

When facing a mindless system, like systems in basic physics, there are challenges when applying the presented framework: what is the "memory" there, or the assumed model where emergy is stacked; how does it adapt, and how can this memory act as a signal filter?

In elementary level mechanical systems, the memory is implemented through *mass inertia,* so that there is emergy storage in the system dynamics. How the filtering through such memory becomes implemented is dependent of the physical domain — below, two cases are studied, namely, that of *surface waves,* and that of *Bénard cells.*

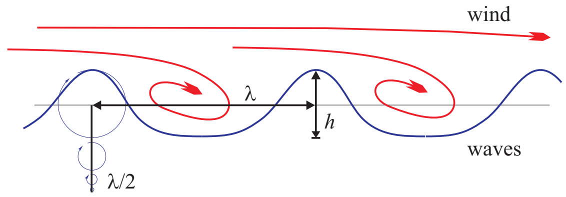

Figure 8: Surface waves are emolutionary, too

The **surface waves** in the sea are manifestations of the interaction between wind and water. In this case, water is the "system" that tries to get coupled to the wind to capture some of its emergy (or, in this case, mere energy). This situation is illustrated in Fig. 8.

The molecules within a wave are in a circular movement; there is no net translation of the molecules, the propagation of the wave front being an emergent phenomenon. The molecules are the actors doing random walk, turbulence providing "innovations" in their realm, some of the paths become magnified, resonating with other similar behaviors, constituting the visible effects. All this is difficult to quantify. When everything is abstracted to global energies (emergies), as in *Lagrange mechanics,* assuming that the emolutionarily successful system maximizes the "throughput", one can apply the top-down view and ignore the details.

The wind energy is assumedly present in its kinetic energy, average energy density being proportional to the wind speed squared, or $\mathrm{E}\{v^2\}$, and the average energy density of surface waves is proportional to the wave height squared, or $\mathrm{E}\{h^2\}$, according to *linear wave theory.* Now, assuming that it is the interplay between these self-emergies only, one can write the (scalar) resource as $u = v$ and the (scalar) system state or activity as $x = h$. Assumedly the coupling between the wind and the waves is then proportional to $\mathrm{E}\{xu\} = \mathrm{E}\{hv\}$. How can this be interpreted?

It is the *wave height* that summarizes the experienced wind, being the manifestation of the system memory $\mathrm{E}\{hv\}$, kinetic energy becoming in this way visible and effective. It is this wave height that determines the degree of coupling: when the wave is higher, the wind blow is resisted more by the wave, and the energy capture from the wind is more effective. This kind of analyses can give new ways to reach qualitative understanding — for quantitative results, different kinds of losses, etc., should also be taken care of in analyses.

Another example of simple physical systems with emergent behaviors is the case of **Bénard cells**. Assume that there is a layer of liquid that is heated from below. When the temperature is not high enough, one can only detect thermal conduction, or diffusion of heat through the liquid; but when a threshold temperature gradient is reached, a qualitative change in the system takes place, and *convection cells* emerge, that is, there is an organized-looking structure of flows upward and downward in the system (see Fig. 9). If the temperature is further increased, chaos takes over.

Again, this organized behavior is difficult to understand within the traditional theories. When one observes that in the case of structured convection, there is *maximum dissipation,* or transfer of heat through the liquid layer, one is again approaching the key point: the system tries to exhaust the available resource, or heat difference, as efficiently as possible.

In principle, there are (at least) two alternatives when system semiosis is studied:

1. If one selects $u = \Delta\, 1/T$ and $x = dW/dt$, or if the system sees the difference of *inverted* temperatures as the resource and the heat flow as the activity (Case 1 in Fig. 10), the "cross-emergy" is

$$\mathrm{E}\{xu\} = \mathrm{E}\left\{\frac{dW}{dt}\left(\frac{1}{T_2} - \frac{1}{T_1}\right)\right\},$$

so that it is the *average entropy growth* that becomes maximized in emolution.

2. If one selects $u = \Delta T$ and $x = dV/dt$, or if the system sees the temperature difference as the resource and the volume (mass) flow as the activity (Case 2), on the other hand, one has

$$\mathrm{E}\{xu\} = \mathrm{E}\left\{\frac{dV}{dt}\,(T_1 - T_2)\right\},$$

so that it is the *average heat transfer* that becomes maximized.

It is questionable whether entropy *per se* would be the explicit maximization goal; on the other hand, it is easy to assume that heat (power) maximization offers emolutionary benefit. The principle of *maximum entropy production* is probably too simple: entropy production qualifies as a Lyapunov function for the system, yes, but it is not the most efficient of the alternatives. Also the resource dimensions raise questions:

1. In the former case, the "inverted temperature", indeed, can in special cases be seen as a natural system input. Assume that a system of chemical balance reactions is modeled by first taking logarithms (see [1]); then, what one has from the Arrhenius equation is exactly this $1/T$.

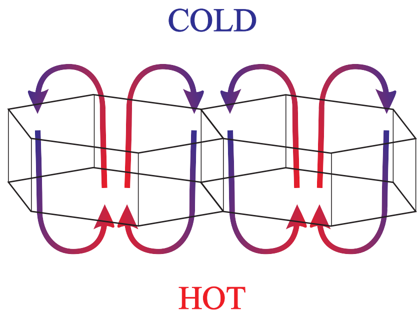

Figure 9: Structure of Bénard cells

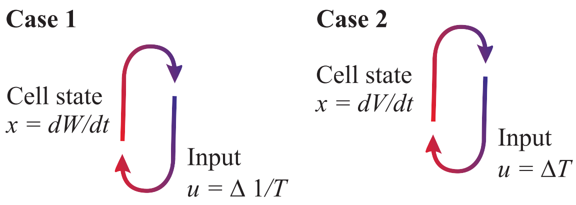

Figure 10: Two possibilities for "system semiosis"

2. In the latter case, T^2 should be proportional to some energy quantity; however, heat content in objects is only proportional to their temperature T. Perhaps one just has to remember that emergy is not always energy, not even in physical systems!

It is clear that the wave system and the Bénard cell system are nonlinear, thus conflicting the ideal neocybernetic starting points; however, qualitatively, there is perhaps something to learn. Does the neocybernetic starting point offer some fresh intuitions for analyses? The claim here is that *there is no other theory that can explain the sudden qualitative transitions.* In the wave system, there is a threshold wind speed that only is enough to actuate the wave formation, and in the Bénard cell case, there is a threshold temperature difference that is needed to change heat transfer from conductive to convective.

Why do such wave systems, etc., never emolve further, producing more complex structures, or even some kind of "ecosystems"? One key point seems to be that there are no appropriate *side effects* now. Compare to a system of electrons in neocybernetic orbitals [1]: as the electrons find their "electronical lockers", they simultaneously give raise to *charge vibrations* in the molecular system. These vibrations interact, making it possible to have coordination among separate molecules in solids and in tissues, so that on the higher level new round of cybernetic modeling can take place with new rules of the game (see Sec. 6.5).

Or more complex structures can emerge also if there is *somebody* making the qualitative difference.

5.2 Allocybernetic systems

Here, *allocybernetic* means a system where the actors are *not* themselves part of the system. In *autocybernetic* systems, as in the physical examples above, the memory is in the actors; now, actors are outside the "memory" that is getting constructed. Of course, memory alone is dead, and the actors are needed to see the *signs* there.

Here, two very different allocybernetic cases are studied: from the bottom, we take *ants,* and from the top, we take *humans.*

First, study the case of **ant paths**. The actors, or the ants, have no understanding of the big picture; their role is that of *signal carriers* only (Fig. 11). Still, the outcomes of their uncoordinated local operation look marvelous in the global scale. How can they accomplish this?

In an ant hill, assume that there are n different types of "workers" or actors, differentiated by the *pheromone* they use for communication (as has been shown, it is the pheromones that attract ants to follow other's footsteps). Further, assume that an ant of type i, where $1 \leq i \leq n$, behaves so that when it has found a food resource j, where $1 \leq j \leq m$, it secretes its pheromone; the amount of pheromone is higher if that resource is specially good (u_j denoting the value of the resource). If x_i is the number of type i ants that have passed a certain location along a path from a resource j, then the total amount of pheromone along the path is proportional to $x_i u_j$.

It turns out that, as seen from above, it is the expression $\mathrm{E}\{x_i u_j\}$ that "tries" to become maximized in each location because of the ants' mindless actions. And there is negative feedback, or exhaustion of resources, so that each spatial location seems to compete for pheromones. This all means that the neocybernetic model applies, and one can directly jump to conclusions: there emerge "eigenpaths", or "highways" between the ant hill and the resources. The "wisdom" of the ants is distributed in their pheromone map.

Furthermore, of course, there should hold $x_{ij} = q_i \mathrm{E}\{x_i u_j\} u_j$, or the number of ants should be linearly proportional to the pheromone amount on the path. The bilinearity, or simultaneous dependency of $\mathrm{E}\{x_i u_j\}$ and the resource value u_j is not such a challenge if the resource remains constant as is normally

Figure 11: The signal carrier

the case.

Ants wander randomly, but if there is a strong pheromone scent along some path, that path becomes selected more probably. This randomness means that there is emolution: shortcuts become employed when they are found, and paths become optimized. Popular routes tend to become even more popular, and "sparsity" of ant paths emerges. As the pheromones evaporate, old model gets gradually forgotten, and the model adapts continuously. — Similar ideas could be applied also for design of human-scale roads.

It is interesting to note a similarity: as the photons (or gravitons) that have travelled the distance r get distributed on an area r^2 in the three-dimensional space, the pheromone at radius r gets distributed on an area that is proportional to r^2 in the planar case. This means that one can apply an electrostatical analogy and visualization: resources define a force field around them, the "charge" being proportional to $\mathrm{E}\{u_j^2\}$. In this case, the force field is distorted by the roughness of the terrain.

Yet another similarity, again related to photons, deserves to be mentioned: the operation of the optimizing agents, the ants, resembles the operation of individual photons, yet in a very different temporal and spatial scale. There seems to be some kind of general "sparsity pursuit" what comes to their interaction with observers (or other systems). While the effects of such systems are only relevant on the emergent level (as studied statistically), snapshots collapse the "wave function", and only samples of the underlying probability distribution remain to be seen (sparsity pursuit visible here, too). Always when you look at the ant colony, you do not see the flow of food into the nest, the relevant thing, you only see the randomwalking individual ants!

What comes to **systems of humans**, both of the two alternatives are possible: the systems can be either autocybernetic or they can be allocybernetic.

Autocybernetic human systems are the object of social sciences: human is seen as a member of its group only. In a society of humans, too, there are the "ecological lockers" or niches, determined by the resource variation structure in the environment.

The human semiosis is not very complex thing really, indeed, it seems to be simpler than among animals: at least for some people, *money* or the *prices of things* is the valid measure for everything, together with *fashions.* Of course, some stubborn people still value the *respect* or cumulating social appreciation and gratefulness that can be earned through seemingly irrational action (as seen from the utility theory point of view). As the resources in different sources are limited, there is competition and negative feedback (everybody just cannot be fashionable!), and self-organization emerges in the form of "eigenbehaviors". Of course, one could claim that humans do not behave in such a trivial way — but note that the human motivation works, at least quantitatively, as presented in Sec. 3.1: one is even encouraged to go where one is good at and where there are available possibilities, this activity amplification resulting in neocybernetic adaptation. The "free will" is exceptional, and usually it does not affect the statistically relevant big picture, but it is needed to bring variation in behaviors, making emolution possible.

But humans are more than animals: *culture* in general consists of a variety of allocybernetic systems, with humans acting as the signal-carrying actors, taking care of their construction, development, and maintenance.

The *memetic systems* are most characteristic to humans: more and more complex concept networks become constructed. Perhaps the most (neo)cybernetic of all human systems is *science,* as claimed by the scientific community itself: The unique goal of science is the absolute "goodness" of theories what comes to their match with reality. All assumptions should be transparent to make them debatable, thus enabling fast emolution (however, the cybernetic thresholds are immense in today's highly coupled science). If x_i is the number of researchers within a community i, and u_j is the potential of the paradigm j, it seems that the system efficiently follows the assumed changes in those potentials. Potential here means the possibility of reaching a breakthrough; that is why, there is a negative feedback effect when some paradigms become *too* popular. The "paradigm semiosis" in the abstract ideasphere, or the evaluation of the potential, can become rather random, for example in hermeneutic social sciences, where the contact with the real world has become somewhat faint — and also in natural sciences, the choice of what is *interesting,* how the evidence should be weighted and what is to be ignored altogether (!), is determined in far-from-optimal ways.

When studying allocybernetic systems with humans as actors, it is advantageous to invert the point of view now: Human-made systems must be seen as the active entities, whereas humans with differing capabilities supply for their resources. Rather than being anything concrete, resources are now the *functionalities* and *capabilities* available among people. And it is the society that tries to lubricate the wheels for the systems, educating people and enhancing their mobility, so that there would be maximum transparency and resource availability. Of course, the society itself, or the highest-level system, does this to utilize the sub-cultures as its own resources to reach prosperity, or self-emergy. Long and intertwined monad loops here, too!

As seen from the perspective of average individual humans, or the allocybernetic actors, it is again the money (and respect) that keeps them active. Arrogant humans can even think they have the control over their systems — but this is just an illusion caused by the missing understanding of the big picture: systems follow their own dynamics, and humans had better comply with it. The role of us *is* to go round and round in the monadic squirrel-wheels, keeping the loops in motion.

In practice, there are always competing objectives and limited possibilities. Different goals compete for both human resources and economical resources. The needs, desires, and potential benefits are opposed by physical and economical constraints, and when the tensions get balanced, the compressed space of "design freedoms" becomes instantiated.

A good example of humans-powered allocybernetic emolutionary iterations is the on-going development of the *Internet system.*

5.3 Case study: *Internet*

Information retrieval has experienced tremendous quantitative and also qualitative emolution in a very short time: not so long time ago, it was the *physical* structure that was the key issue, or the actual location of the library collections; then, in early Internet, it was the *logical* structure, meaning that you just needed to find the address or follow the links. After that, enhancements have proceeded to capture *semantics*: the search engines try to find *relevant* pages. There is still plenty to do, as one is here facing the age-old challenges of artificial intelligence.

How could our understanding of systems in general be applied for enhancing the existing search strategies? And, specially, can we anticipate the direction of emolution? What can we say about the "semantics capture" in Internet?

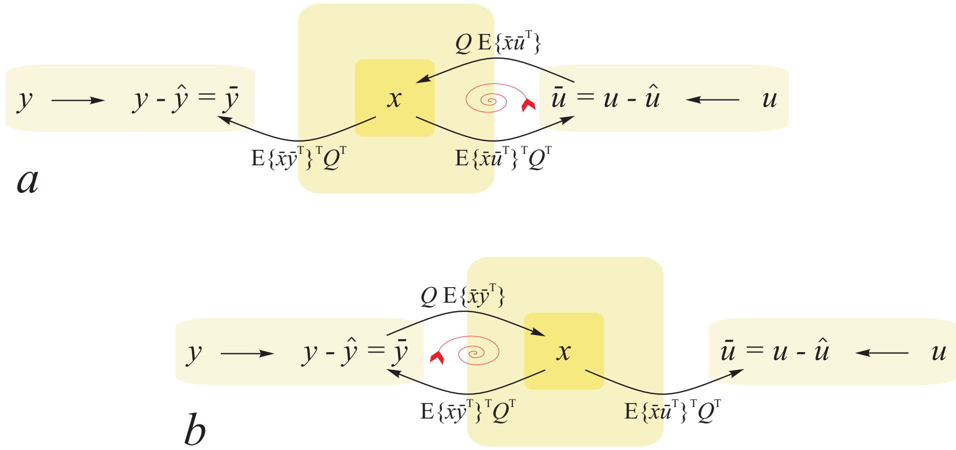

Figure 12: Regression structure mapping between two spaces u and y through latent variables x. The case *a* above shows how the regression can be implemented if the latent structure is determined by the variables in u alone, searching for common features among all patterns; when *a* is alternated with *b,* the latent structure is balanced between the patterns in both input and output, assumedly trying to detect *distinguishing features*

Just a few years ago, the World Wide Web seemed incredible; later, the operation of the modern search engines was amazing. There is always a threshold: only after the infrastructure has developed enough, it is possible to start thinking of yet higher-level platforms. Similarly, now, as the possibilities of the contemporary systems have been seen, it is perhaps the time for new leaps.

To understand where the today's *avant-garde* in the field is, one has to know what there is behind the success of the Google search engine. Beyond all the surface-level sophistication, the key factor there is the PageRank algorithm that evaluates the candidate pages in the web. The algorithm works as follows: first, the traffic among pages in the whole web is simulated, assuming that *outlinks* to the accessible "next pages" on any individual page are selected equally probably; the resulting Markov chain (see Sec. 6.5) can be used to analyze the steady state probability distribution among the pages, because (ignoring the *dangling nodes,*, etc.) it is the *most significant of the link matrix eigenvectors whose elements reveal the "relevance" of each page.* This means that a huge off-line iteration to find "the \$25,000,000,000 eigenvector" is needed in the m dimensional space, m here denoting the total number of web pages.

Again, speaking of eigenvectors rings a bell. Indeed, the neocybernetic model can be used to streamline and extend the PageRank approach. There are now *various* alternative eigenvectors, assumedly representing different compressed "traffic features" for different cases, and the whole latent model is available for matching the data against them. What is more, there is a more sophisticated model structure available, and it is not only the determination of the relevance vectors but the whole search process that can be compactly implemented in this framework.

First, note that the neocybernetic regression is not only capable of estimating the input, as shown in Sec. 4.1, but a complete regression chain from input space to output space through a latent basis can be written as shown in Fig. 12. In this case, u is the vector of search words, and y is the vector of web pages, m_u being the number of search words and m_y being the number of pages. Both of these vector dimensions are huge, but the latent structure dimension n can have a reasonable size, so that on-line iterations are feasible. Each query can then be matched against the "web eigenstructure", so that a form of *collaborative filtering* becomes implemented.

This was the top-down view — but the key point in neocybernetics is emergence. How can the global effects be motivated in terms of local actions now? There are no physical energies, but "web semiosis" for some reason dictates that *each node tries to maximize incoming traffic.* If x_i is the activity on one's own page i, then self-emergy is $\mathrm{E}\{x_i^2\}$ (for the probability interpretation, see Sec. 6.5). If u_j is the traffic on some external page j, one tries to persuade this traffic to the page i if the traffics are correlated, that is, if there is common interest. Thus, the page owner's urge to increase connection is assumedly proportional to $\mathrm{E}\{x_i u_j\}$ again, this proportion being invested to persuasiveness. The increase in activity can be assumed to be the product of page activity and link temptation, or $x_{ij} = q_i \mathrm{E}\{x_i u_j\} u_j$. The rest is straightforward as the attractor is there (because each page is others' possible resource, the variables u and x need to be restructured as shown above). Negative feedback is caused by the fact that successful coupling decreases the activity flow to competing pages. As a page cannot affect its inlinks, its only tool for increasing the coupling is through being somehow *attractive.*

In practice, behaviors predicted by the neocybernetic model have truly been observed: there is sparse coding, pages getting more and more specialized (and some portals specializing in generality!). Assumedly the web would finally automatically evolve towards being more and more structured, the chaos of pages giving way to order, but without specialized tools such emolution process would be extremely slow.

When trying to match user's intentions ever better, one has to study *semantics.* Google is based on strictly formal *contextual semantics,* studying merely the link structure[9]. The proposed neocybernetic model is based on the observed traffic, on the functioning of the web as a reaction of user needs — that is, one can speak of *pragmatic semantics.* Of course, it is the *user satisfaction* that should be used as a criterion rather than the number of hits; how to monitor this satisfaction is an open question (use some voting mechanism, or observe how long a visit lasts, etc.?).

When trying to capture semantics even better, one can propose true *cybernetic semantics*; this could also be called *Heraclitean semantics* or *equilibrium semantics.* The idea here is to capture the *balances* in the domain: when there are no more tensions or tendencies, one has found the "hermeneutic meaning". In the case of search processes this means that when the query has converged to the final balance, or when the user is satisfied and the search process is interrupted, the user's intent is captured. The "flow of search" towards (assumedly) more accurate search words is buried in the *search derivatives* within the query session, that is, in the difference between successive searches. These derivatives can be included among the data in different ways — a promising approach is to employ phase shifts in terms of complex variables (see Sec. 6.5).

The future Internet is a nice example of how a truly complex system looks like when seen from above. Everything is seen through an intermediate level, or, in this case, through the search engine. As individuals themselves are invisible, there is an illusion of co-operation, the whole net acting as one entity. As the "net effect", one could say that there is a transition from a traditional net to a "safety net": loads are distributed in the net, and disturbances extend over the whole system. Equalization means homogeneity: whatever is the pattern of disturbances (queries), their average "penetration" into the system (or the average search path length, or "search emergy") is minimized. The system yields along the degrees of freedom that could be called "web features". And as this interface to information reaches maturity, it will be included in other yet higher-level systems, finally becoming truly ubiquitous, offering the platform for yet higher-level information systems to emerge.

[9] *Semantic webs* with static, hand-written ontologies are also examples of contextual semantics only, reflecting one person's view of the world

6 "Ways up and down the same"

Ontology is the study of what there exists in the world; the "opposite" of this is *epistemology,* making hypotheses about what we can *know* about it, concentrating on the mental domain. In a way, epistemology is the "ontology of knowing": the key question again is how the concept attractors emerge in the mind, or *epistemogenesis.* — What Heraclitus once observed is that "the way up and the way down are the one and the same", and, indeed, ontology and epistemology are perhaps both based on the same dynamic principles — as discussed in what follows.

6.1 Reconstructing the world

The motivation for the development of the cognitive system is again emolutionary, and it has the same origin as other (neo)cybernetic systems. The objective is to acquire more resources, and this is accomplished through neurons acting as actors. Resources are exploited through controlling the environment more or less knowingly. The fine structure of the loop can be very complicated, but the control is always there: one tries to put the world into the "reference state", or reach the goal. To make differences, world is an essential part in the mental monads, closing the main loops (see Fig. 13). As Ross Ashby has observed: mind is not mainly a *thinking* machine, it is an *acting* machine.

As compared to earlier control structures, the mental system is more complicated, because it has to implement explicit controls for all kinds of environments with all kinds of real-life complexities. First, separate observation and actuation is often needed; then, because of the delays, one has to *anticipate* to "emplement" control in real time, so that memory is

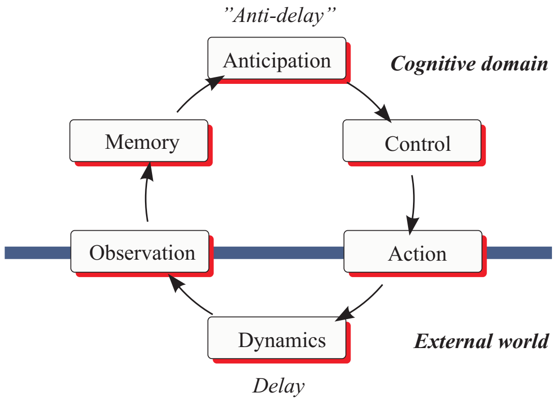

Figure 13: When seen in a wide enough perspective, the cognitive machinery is part of a loop, too, thus helping to determine the goals of cognitive faculties

needed; higher level pattern recognition is necessary to detect the "big picture", etc. There are different levels of world views that are needed to reach different performance levels:

1. *Implicit control* for a "simple world": the neocybernetic basic strategy of selfish actors suffices

2. *Explicit control* to tackle with the real world dependencies: separate muscles, etc., are needed

3. *Prediction* to handle dynamicity and delays in the world: it is necessary to estimate the future

4. *Scenarios* because of the world uncertainty: Alternative possibilities need to be observed

5. *Imagination* to fully exploit the "inner world": turn the analysis machinery into a synthesis engine, *construct* a view of the better world!

Of course, to change one's subjective world, there are various strategies. If the environment cannot be affected, it is enough to change one's view of it: for example, the easiest way to change the immediate resources u offered by the environment is to *move* to another environment.

The claim here is that it is the same motivation for complexification of mental systems as it is with other natural systems. Why cognition seems so special is perhaps only because of its such a deeply nested structure — and because it is the "seat of soul", our most intimate essence. As loops and subloops become intertwined, there being no limit for the number of loops, some emergent limit becomes surpassed. Each loop can be seen to consist of a controller and a model; thus, successive layers of loops implement some kind of *higher-level models.* Indeed, the system starts modeling its own models: in this sense, there is a succession of *homunculi,* and, in the limit, it can be claimed that *consciousness* emerges. Higher-level models distinguishing between actual world models and "model-models" detached from the direct world data can witness the emergence of *self.* What about feelings and *qualia*: such "concepts" are not only connected to the hermeneutic closure, but also to chemical levels, like adrenaline, etc. Intelligence is just another name for the versatility of the machinery, reflecting the many-faceted challenges of the real world. Understanding is the way to better resource management. Even *arts* may help in world mastery — new viewpoints, or new models perhaps give raise to further control loops, or new cognitive monads.

Everything is based on good models. Specially, deep-level associative understanding (without the need of explicit "thinking") means that essentially the *same* attractors get implemented in the mental domain as in the outside domain. How is this possible, as (in the Humean spirit) one can only observe the *interactions* of systems, or data, never the system itself? — Here, one has to remember that it is the system itself, too, that is a "slave" obeying the environmental pressures as becoming visible in data. Then it can be the same data that drives the emolution of the natural system and the mental model, and, as a result of co-emolution, *interobjectivity* among domains can be reached. Attractors must be instantiated one by one in both cases. Remember that neither system, the experiencing one or the observing one, has direct access to the actual u_j, both only see $\bar{u}_j$, so that the system state and the *perception* can, in principle, both contain the identical $\bar{x}_i$ variables[10].

Here it is assumed that it is the Hebbian neurons that are the building blocks in the cognitive systems, all physical phenomena, etc., being emulated in terms of neuronal activities. Neuron nets can be combined, so that previous level emergy is valid resource for successive neuron layers — but what is the added value when various layers of neurons are connected?

Assume that all senses are *logarithmic,* so that not the observed values are used as input signals but their logarithms (at least visual and auditory channels seem to work this way). Sums of logarithms corresponds to multiplication of the original variables. The operation of the net becomes then clearer if the variables have *probability interpretation,* or, more appropriately, some kind of *relevance interpretation*: the

[10] However, the observing system outside the arena cannot experience the actual tensions: to really "käsittää" (*to understand* in Finnish) something, one needs to have a grip of it with one's hand ("käsi" in Finnish)

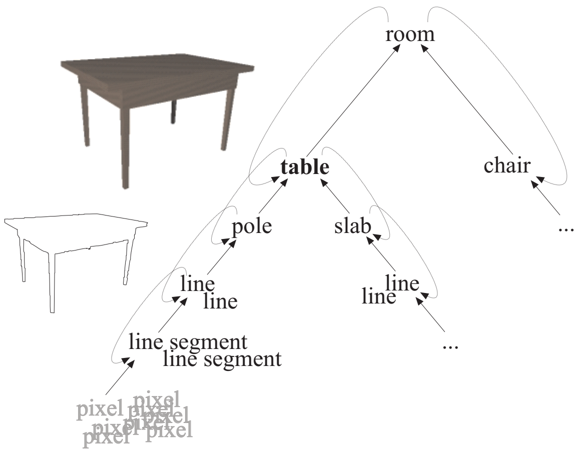

Figure 14: Various layers of neuron grids — making it possible to have multiple interacting mental monads, each refining a concept from below and from above. Here, the visual components for perceiving a *table* are illustrated (all coordination of the spatial structure among constructs is ignored)

sum of variables does not need to sum up to one, and, to make the system adaptible, the probabilities are raised to some power (after taking the logarithms, this corresponds to linear scaling carried out by the synaptic weights). Because the adaptation mechanism tries to make the variables uncorrelated, one can see the value $\bar{x}$ as "and" operation being carried out to the inputs. On the other hand, the alternative submodels in the sparse model can be seen as an "or" — this all means that layers of neural nets constitute an *and/or graph* that can implement descriptions of complex objects. The key point here is that each sub-loop is a self-organizing and self-regulating entity, so that increased number of loops does not increase system complexity. In Fig. 14 it is shown how a visual concept is based on lower-level concepts and higher-level concepts, inaccurate evidence being shuffled in the loops in the two-way connections, finally converging to produce the most probable interpretation (an another kind of probability network is studied Sec. 6.5).

Still, a succession of neural layers is only a data filter; intuitively, to explain the cognitive functionalities, this is not enough. Hebbian neurons constitute a universal medium capable of simulating interconnected monads, but is there possibility of somehow *escaping* the neuronal associative realm, to reach something more? Indeed, there are new functionalities and new physical domains available; for example, below, two extensions to the basic view perhaps offering at least partial answers are presented:

- New nonlinear functionality can be reached through the *collapse of emergent levels* and through *sequentiality* (see Sec. 6.2)
- Higher-level interaction among constructs can be reached through *exploitation of phase information* (see Sec. 6.4).

6.2 Back towards logics?

The presented neocybernetic model can be used to explain the quantitative and associative representations and functionalities in the brain, but how about the non-associative ones, the traditional field of human intelligence and *thinking*? How to integrate brittle logic with fluid computation — are additional functionalities necessary? Or, what kind of additional functionalities can be proposed in the presented framework?

When one searches for $\min\{J\}$, it is the *variables*, or $\bar{x}$, that become determined; when one searches for $\min\{\mathrm{E}\{J\}\}$, on the other hand, it is the *model* on the emergent level that gets determined. In both cases, it is the same vectors that are being optimized on — somehow the state changes to model when seen in the higher-level perspective. Let us assume here that in a wide neural net there is no coordination or any standardized clock, and the time scales can get blurred. The emergent level time scale in some loops can be the signal time scale in some others, meaning that *some subsystem's $\bar{x}_i$ is included in some other subsystem's profile vector.*

How does it look like when the models are "collapsed" in such way? Instead of being linear, the filter becomes *bilinear.* The system can be seen as a *controllable switching circuit* with dynamically changeable information flow structures, higher-level categorizations redirecting lower-level analyses, signals being "modulated" by other signals. One could speak of "pattern-based transistor"; such *emristor* could be the basic element in "em(e)tronics". Thus, the computer metaphor can be applied again, so that *universality* is achieved in such systems: all computable functions can be implemented on such a platform (and universality seems to be such a common phenomenon among nonlinear systems that some other extension could also be proposed, if those "emristors" do not exist in the brain).

Building a complex computer program starting from transistors — this is an impossible task. To implement high-level program-like functionalities, one needs conceptual tools to master the complexity, or, indeed, one needs a *programming language.* But this time there are very special demands what comes

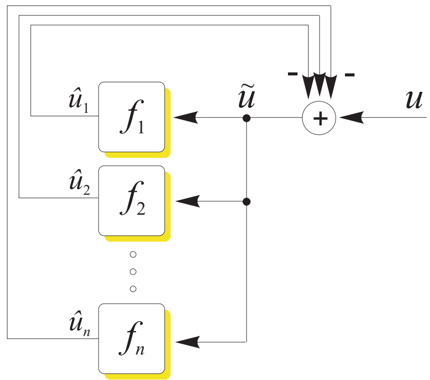

Figure 15: General principle of neocybernetic division of labor, searching for "task patterns", no matter how complex the internal functions are in the blocks

to such language to comply with the underlying realm: particularly, how this higher-level formalism could inherit the key property, self-organized self-regulating self-learning based on observations?

First of all, the new formalism framework has to support the monads, as everything has to be based on dynamically balanced loops. And to facilitate learning, there has to be continuity of representations. The programmer is not to explicitly predestinate the attractors, but all monads need to automatically get instantiated from non-existence. Then, how to control emergence in synthetic domains, and how to control sparsity so that the relevant concepts only emerge? The key point to recognize is that systems are determined by their environments. Monads and systems emerge in a *correct environment* with *appropriate semiosis.* The environment has to be defined, together with the appropriate viewpoint so that the object world can be emulated; after that, truly *ubiquitous processing,* ultimate distribution of control, can take place. Debugging takes place on the high level: does the behavior of the estimate correspond to that of the observed real world? Amusingly, this all resembles Douglas Adams' view of Earth as a simulator for completing a huge computation.

Individual attractors need not be unique (see below), and only the top level behavior, or the capability of reproducing the inputs, is relevant. To select one of the alternatives, the wire frame of the solution can be preprogrammed. The inner structure of computations can be altered, for example, by using predefined subprograms that determine monads of their own, so that all emulation need not continue always to the very basics. In Fig. 15, ready-to-use modules, or encapsulated "(sub)pattern recognition units", to be included in emulations, supplying for special functionalities, compete for input. Coordination of such agents is trivial, based on exhaustion of the input; agents emolve to still better match the local data, self-organizing and finding their niches, or "functional features". Here object-orientation is taken to extreme, the system being agents-based, operation being controlled by the modules themselves.

To implement the above scheme, tasks to be carried out must be *quantifiable* and *decomposable.* Indeed, *mathematical algorithms* manipulate numbers, and many of them are even, at least to some degree, parallelizable. What is more, they naturally consist of monads, or of convergent iteration loops (even though there is typically just a single program counter). Specially interesting algorithms are those that are designed for *optimization.* It seems that many real-life problems, too, can be seen in the optimization perspective, so that perhaps optimization could offer the underlying basic machinery for the general programming language, to exploit computationalistic emulation also outside basic physics.

It is optimization what the neocybernetic monads do. In addition to those observations that were shown in Sec. 4.1, one can say more: at each level *neocybernetic networks implement fastest possible optimization (in the second-order sense).*

6.3 Example: "emergent algorithms"

Monads are not unique: there can be the same surface pattern even if there are different underlying attractors. To match a real world pattern, some combination of monads can be more efficient than others. It is interesting to study whether natural emolution has found the best solutions. The end result is that in some cases *algorithms can be not only solution quadratures but emulations of reality.*

Because neocybernetic systems are characterized by tensions, one can assume that the role of a basic monad is that of finding solution to differential equations. For example, one possibility for finding the steady state $\bar{x}$ (in addition to the trivial iteration of (7)) is by following the negative gradient of $J(x)$

$$\frac{dJ}{dx}(x) = \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}\right) x - \mathrm{E}\left\{\bar{x}\bar{u}^T\right\} u,$$

so that the corresponding iteration loop implements the *steepest descent* algorithm. However, there are different ways to make this iteration faster by introducing more loops: for example, as the steady state of the iteration can (in linear case) be expressed explicitly using matrix inverses, one can invest the loops there, implementing a matrix inversion algorithm.

If there are nonlinearities in the loop, the matrix inversion approach is not available, and one would need another efficient approach. Here, study another iterative optimization scheme. Assume that one wants to find x so that J would be minimized for given u and ϕ; applying convergent iterations, x should finally converge in $\bar{x}$. To reach such an algorithm, first observe that

$$\frac{d^2 J}{dx dx^T}(x) = \mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}.$$

Now, the familiar *Newton's method* for optimization assuring *quadratic convergence,* being faster in the vicinity of the optimum than the steepest descent algorithm, can be written (with κ being the iteration index) as

$$x[\kappa+1] = x[\kappa] - \left(\frac{d^2 J}{dx dx^T}(x[\kappa])\right)^{-1} \frac{dJ}{dx}(x[\kappa]),$$

giving in this case

$$\begin{aligned}
x[\kappa+1] & \\
&= x[\kappa] + \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}\right)^{-1} \cdot \\
&\qquad \left(\mathrm{E}\left\{\bar{x}\bar{u}^T\right\} u - \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}\right) x[\kappa]\right) \\
&= x[\kappa] + \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}\right)^{-1} \mathrm{E}\left\{\bar{x}\bar{u}^T\right\} \cdot \\
&\qquad \Big(u - \mathrm{E}\left\{\bar{x}\bar{u}^T\right\}^T Q^T \mathrm{E}\left\{\bar{x}\bar{x}^T\right\}^{-1} \cdot \\
&\qquad\qquad \left(\mathrm{E}\left\{\bar{x}\bar{x}^T\right\} + Q^{-1}\right) x[\kappa]\Big)
\end{aligned}$$

because $I_n = \mathrm{E}\{\bar{x}\bar{u}^T\}\mathrm{E}\{\bar{x}\bar{u}^T\}^T Q^T \mathrm{E}\{\bar{x}\bar{x}^T\}^{-1}$, as shown in [1]. Further, when one uses Q_{opt} so that there holds $\mathrm{E}\{\bar{x}\bar{x}^T\} + Q_{\text{opt}}^{-1} \approx 2Q_{\text{opt}}^{-1}$ (because the activity covariance is diagonally dominant), the final update rule can be written as

$$x[\kappa+1] = x[\kappa] + \frac{1}{2}\phi^T \left(u - 2\phi x[k]\right)$$

or, when defining $x' = 2x$,

$$x'[\kappa+1] = x'[\kappa] + \phi^T \left(u - \phi x'[k]\right),$$

giving the familiar form of mappings (however, remember that it is x that is the variable to be used in other circumstances). One can select the initial guess as $x[0] = \mathbf{0}$, or $x[0] = \bar{x}$ of the previous iteration run if the initialization is omitted, as discussed in Sec. 4.2. The above algorithm is very fast: for the quadratic cost criterion, it is, in principle, a "one-step algorithm", jumping immediately to the (linear) optimum (remember the properties of quadratic convergence). However, the nonlinear cases are more challenging, and convergence can be enhanced by tuning down the adaptation rate in the above update law.

The algorithm changes the cumulated value of x' in each step, so that what one effectively has is an *integrator.* It is interesting to note that here the *static* definition (7) has changed to *dynamic,* asymptotic expression where the *right-hand-side is essentially identical.* Thus, in a way, the mapping formula combines the asymptotic and the immediate time scales.

To get rid of the final external control structures, to avoid sampling, etc., one can express the discrete-time integrator in continuous time without affecting the final outcome. Regardless of anything that happens outside, the following dynamics governs the behavior of the local monad:

$$\frac{dx'}{dt} = \frac{1}{\tau_x}\phi^T \left(u(t) - \phi x'(t)\right),$$

where the parameter τ_x is (proportional to) the *time constant* of the system dynamics. The accurate (matrix-form) time constant, or the time it takes for the step response to reach $1 - 1/e \approx 63.2\%$ of its final value, would then be

$$\tau_x \left(\phi^T \phi\right)^{-1} = \tau_x \left(Q_{\text{opt}} \mathrm{E}\left\{\bar{x}\bar{x}^T\right\}\right)^{-1}.$$

Linearity assumption was used above; yet, the cut-form nonlinearity can be applied, preventing x from becoming negative (case of *limited integration*). However, because $\bar{x}_i$ are now always positive, $\mathrm{E}\{\bar{x}\bar{x}^T\}$ cannot become diagonal!

Similarly, on the higher level, there is another optimization problem. Above, the challenge was that of fitting the observed pattern against existing features, to find the state; next, there is the challenge of fitting the features against *all* observed patterns, to find the model. The former task is deterministic as the model is given and new "samples" are computed, but the latter task is *nondeterministic,* iteration steps being dependent of the stochastic flow of measurements. Indeed, what one is here facing, is an *identification problem.*

Now the matrix ϕ is seen as an estimator; to put this into the standard identification framework, the model has to be studied vector by vector. So, assume that there should hold $u_j = (\phi^T)_j^T \bar{x}$, where $\bar{x}$ is seen as the regressor data and u_j as the scalar output, and $(\phi^T)_j$ is the j'th column of ϕ^T, and optimize the parameters applying the traditional methods, having fixed sequences of $\bar{x}$ and u_j data available.

For minimization of the squared reconstruction error $\frac{1}{2}\,\bar{u}_j^T \bar{u}_j$, with errors $\bar{u}_j = u_j - \hat{u}_j = u_j - (\phi^T)_j^T \bar{x}$, one can first find the gradient $dJ_j/d(\phi^T)_j = -\bar{x}(u_j - (\phi^T)_j^T \bar{x})$, and from this one can write the *stochastic gradient algorithm* as

$$\begin{aligned}(\phi^T)_j[k] &= (\phi^T)_j[k-1] \\ &\quad + \gamma\, \bar{x}[k](u_j[k] - \hat{u}_j[k]) \\ &= (\phi^T)_j[k-1] + \gamma\, \bar{x}[k]\bar{u}_j[k],\end{aligned}$$

now having k as the time index in the discrete-time parameter update process. Parameter γ is the *step size factor* determining the length of the update step.

Similarly as in the previous case, one can proceed from the steepest descent approach to second order stochastic Newton algorithm, when the inverse of the approximated *Hessian* $\mathrm{E}\{\bar{x}\bar{x}^T\}$ is included in front of the gradient. Again, a more robust approach is reached if only the diagonal elements are included, meaning that one can add Q_{opt} instead, resulting in the adaptation law

$$\phi^T[k] = \phi^T[k-1] + \gamma'\, Q_{\text{opt}}[k]\bar{x}[k]\bar{u}^T[k].$$

Here, it has been observed that the m separate update rules can be combined because of the common structures, so that one has a matrix-form adaptation formula. This is an integrator again.

It is interesting to note that the straightforward covariance update, with the monad sensitivity taken into account, again assures the best possible (in the quadratic sense) convergence of parameters: in principle, the nearer you get to the optimum, the faster the convergence is (however, remember that the nature of the problem is stochastic). Parameter adaptation is "lazier" if the monad is more active, so that it is not only the signal-level activity adaptation that gets slower; in general, one could say that *more activity means slower clocks.*

As in the case of signal-level adaptation, one can get rid of the final part of global control, or that of maintaining the coordination of update campaigns in the actors: the adaptation can take place in a continuous fashion without upper-level synchronization. Assuming that $\tau_x \ll \tau_u \ll \tau_\phi$, the intermediate τ_u being the "environmental time constant", so that one does not need to explicitly wait for signal convergence, one can write the model update formulas as

$$\left\{\begin{aligned}
\frac{d\hat{\mathrm{E}}\{x_1^2\}}{dt} &= \frac{1}{\tau_\phi}\left(x_1^2(t) - \hat{\mathrm{E}}\{x_1^2\}\right) \\
&\vdots \\
\frac{d\hat{\mathrm{E}}\{x_n^2\}}{dt} &= \frac{1}{\tau_\phi}\left(x_n^2(t) - \hat{\mathrm{E}}\{x_n^2\}\right) \\
\frac{d\hat{\phi}^T}{dt} &= \frac{1}{\tau_\phi} \overbrace{\begin{pmatrix} \frac{1}{\hat{\mathrm{E}}\{x_1^2\}(t)} & & \\ & \ddots & \\ & & \frac{1}{\hat{\mathrm{E}}\{x_n^2\}(t)} \end{pmatrix}}^{\hat{Q}_{\text{opt}}(t)} x(t)\tilde{u}^T(t).
\end{aligned}\right.$$

Inclusion of integration also results in fastest convergence of signals and fastest convergence of models, meaning fastest overall follow-up of the environment — assumedly resulting in best exploitation of resources, and emolutionary benefit. Is it not reasonable to assume that nature, too, has detected such strategies? As seen from above, can we interpret this all so that *nature has implemented its models using the best possible computational tools*?

6.4 Further analogies and intuitions

The above section already returned from mental spheres back to the physical realms: indeed, there is again a loop, now from ontology to epistemology and back, each nourishing the other. In some sense, *rationalism* is back — or one can use what one knows for making hypotheses about what exists. For example, one can make an assumption that there *is* an integrator in the loop: the goal, implementing the static expression (7), is done through integration. What are the consequences, then?

The key point is that one gets from static models back to dynamic ones, from the asymptotic behaviors to the ever-changing (truly Heraclitean) reality. And it is only through dynamics that the magnificent transient structure of the real world can be captured, making it possible to understand the interactions among systems.

As observed in Sec. 3.2, systems can be chained, so that the former system variable is the resource of the latter one, and, when coupling is complete, input and state variances become equalized. All system variables x_i can be interpreted simultaneously as resource variables u_i, resources and activities having the same dimension, so that mere redistribution of potential takes place. There is a symmetry between systems, either of them can be the emergy donor.

An interesting special case is a long chain of identically behaving systems that constitute a medium where signals can traverse from system to system perhaps long distances. Finally, as all stiffnesses have been equalized, there is the same coupling through the whole sequence. Such chain of successive integrators can best be understood through an electrical *RC circuit analogy* (see Fig. 16, with capacitors acting as integrators; "empedances" in the system can be based on selecting $R = (Q_{\text{opt}}\mathrm{E}\{xx^T\})^{-1}$, being the inverse of conductance, and $C = \tau_x\, I_n$). Here, the succession of internal variable vectors x has changed to external vectors u_x, with each u_x having the dimension n; variable x is used as a spatial coordinate only. It has to be remembered that these u's are now

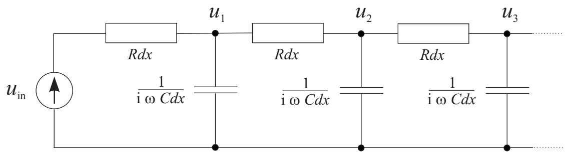

Figure 16: RC circuit analogy

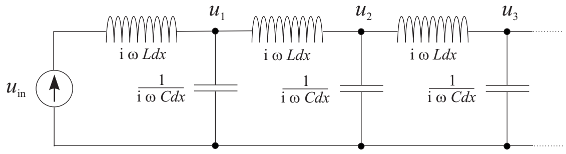

Figure 17: LC circuit analogy

essentially internal, or *coupled* variables. Note that it is the voltage differences over the resistors that are the driving forces in the electronic systems; this corresponds to $\tilde{u}$ that drives the neocybernetic model.

The presented *lumped parameter model* can be made ever more accurate by introducing smaller and smaller elements, so that the "system width" dx becomes smaller; at the limit, when $dx \to 0$, one reaches continuum with a *distributed parameter model* that can be described using a *partial differential equations* (PDE). In this case, as shown in *circuit theory,* the dynamics of the chain of (damped) integrators can be expressed in the parabolic PDE form

$$\frac{\partial u(t,x)}{\partial t} = D\,\frac{\partial^2 u(t,x)}{\partial x^2}$$

that corresponds to standard *diffusion equation* with diffusion coefficient D (compare to the "abstract diffusion" in Sec. 3.1!). This expression holds in each location x along the continuum of subsystems. Looking at this formula, it seems that a higher-level view at the systems, ignoring the actual loop structure of the underlying signal paths, is again neocybernetic, with the integration added, now with different semiosis: physically, the driving force (or "resource") is the spatial imbalance what comes to the distribution of some quantity u, and the local activity is the temporal change of that quantity. The new differential formulation of general diffusion is more natural when representing activity, making it possible to attack "system systems".

The "heat equation" above offers a top-down view to highly coupled systems. The internal variables are no more of interest; key point is how the system of systems as a whole responds to incoming signals, and, specially, how emergy in the systems becomes conveyed. For example, when some disturbance enters the system, or when some variation becomes coupled, so that $\bar{u}_x$ gets disturbed from its balance, there is *spreading of activation* that gets attenuated in a somewhat "sluggish" way, never overreacting, the neighbors (somewhat reluctantly) sharing the load. The temporary deviations get "swallowed" and "digested" in the net. — Of course, the diffusion analogy can be extended from the one-dimensional case to higher dimensions, when the spatial second derivative is substituted with the Laplacian operator ∇^2.

The diffusion equation motivates other analogies, too. If one assumes that there is *double integration* in the nested systems, so that the structure can be presented as in Fig. 17, it is the following PDE that applies:

$$\frac{\partial u^2(t,x)}{\partial t^2} = v^2\,\frac{\partial^2 u(t,x)}{\partial x^2}.$$

This is the *wave equation* that characterizes an unattenuated relaying succession of disturbances in either direction, with v being the speed of the wave. Again, for electrically oriented, this can best be seen as a *transmission line analogy.* If one again selects $L = (Q_{\text{opt}}\mathrm{E}\{xx^T\})^{-1}$ and $C = \tau_x\, I_n$, one has the following matrix expressions for the *characteristic empedance* and the *wave velocity,* respectively:

$$\left\{\begin{array}{lcl} Z_0 = \sqrt{\frac{L}{C}} & \overset{now}{=} & \sqrt{\frac{1}{\tau_x}\left(Q_{\text{opt}}\mathrm{E}\left\{xx^T\right\}\right)^{-1}} \\ v = \frac{1}{\sqrt{LC}} & \overset{now}{=} & \sqrt{\frac{1}{\tau_x}Q_{\text{opt}}\mathrm{E}\left\{xx^T\right\}}. \end{array}\right.$$

The transmission line analogy gives intuition about the nature of coupled systems: only if there is *matched load,* empedances being equal, the emergy transfer among systems can be carried out losslessly, without reflections (or "ringing"), as shown in Fig. 18. Again, one can apply the principle of emolutionary benefit — one can assume that systems try to become better and better matched, or, as seen from above, the platform for signals tries to become more and more homogeneous to maximize the emergy throughput.

The above two analogies visualize the two extreme behavioral modes in "pancausal" neocybernetic nets. The other end with the transmission line type behavior is like a *trampoline,* a vibrating membrane, and the other end with pure diffusive behavior is like a *quagmire* with no sturdiness. In between, different levels of attenuation are possible between the strictly imaginary and strictly real transfer function poles.

Whereas the diffusion analogy is reasonable in "normal" cases, in some systems double integration is motivated. For example, if a change in some field

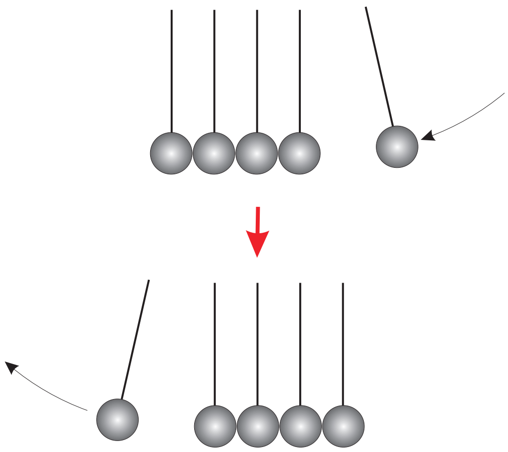

Figure 18: Perfect matching of subsystems

gives raise to another field, and the change of this field causes the other field, two alternating fields push each other, as in the case of *electromagnetic waves.* Indeed, the neocybernetic model offers an interesting interpretation of *photons* as wave fronts in *aether,* effects traveling as disturbances in a *cell-structured universe.*

The neocybernetic model may offer the key to explaining the coupling between the quantum world and the classical realm: the *observing system* has to couple to the *observed system,* resulting in *quantum decoherence* or collapse of wave function. And, again, remember the role of neocybernetic-like eigenproblems, etc., in modern quantum mechanics! Further, those *string theories* and their "collapsed dimensions" are well compatible with the monadic resonators and their more or less controlled degrees of freedom. The equalization of empedances, or uniform "stiffening" of the observed environment, finally results in the whole universe becoming coupled; perhaps this gives a mechanism how the global can affect the local, so that the mystical *Mach's principle* can also be addressed.

What are *natural constants*? Natural constants connect quantities together, so that when signal interacts with matter, they couple the numeric values of the cause and the effect. Now, it can be proposed that the couplings between signals and matter take place in the neocybernetic setting, and the coupling factors, or the natural constants reflect empedances. This would mean that the constants change when the world changes; for example, can it be assumed that the *speed of light* changes when the universe expands and the system stiffness increases?

The nature of *phonons* have been studied in the neocybernetic framework, observing that the molecules can act as *antennas,* emitting differing vibration patterns in different directions [1]. The transmission line analogy further extends this view: crystals (and solids in general) are characterized by standing waves, directed vibration fields, where individual atoms match and further amplify the pattern. The vibration patterns determine the emergent forms and the macroscale properties of the substance.

6.5 Complexity — reflected in numbers!

When differential equations are integrated as an integral part in the neocybernetic model, it seems that the possibility of simple static calculations is lost. However, this is not the case, when one steps up to *frequency domain,* where it is assumed that individual signals are, again, irrelevant, and it is the resultant group behaviors or wave fronts that are relevant; in steady state, then, it is *frequencies* and their *phases* that count — this all matching again well with the monadic loop rates as manifestations of activity.

The mathematical tool to manipulate and analyze systems with linear differential equations is the *Laplace transform.* Applying this transformation, differential equations change back to static algebraic equations, but the signal-domain variables become substituted with frequency-domain ones. In a way, a separate model is constructed for each frequency, and signals are thought to be superpositions of those frequencies. After the system has been solved in frequency-domain, the dynamic trajectories in time-domain can be solved (if this is needed) applying the inverse Laplace transform. But *vibration patterns* can best be studied directly in Laplace domain. In a special sense, the *steel plate analogy* in [1] has a reincarnation when studying systems on yet higher levels: as there are differing tensions, the vibration modes are modified, skipping the analyses to the auditory realm; and, similarly, the *river analogy* can be reemployed, as the whirls become manifested in the auditory world as *noise of rapids.*

In Laplace domain, systems look different (again, see Fig. 16). Resistances R look the same for each frequency, but capacitor C acts like an integrator, and its impedance is $1/sC$ where s is the Laplace-domain variable $s = \mathrm{i}\,2\pi f$, where f is the signal frequency. The interpretation of this is that the impedance is frequency-dependent: the higher the frequency is, the more of it gets through, whereas for direct current, with $f \to 0$, the impedance becomes infinite. Additionally, symbol i is the *imaginary unit.* Indeed, *complex numbers* become crucial in frequency-domain;

for example, the step input from zero to level A is $A/s = A/\mathrm{i}\,2\pi f$ in Laplace domain, being purely imaginary. In complex domain, different kinds of nonlinearities can thus be proposed instead of the cut-form one: it seems that limiting variables to be strictly imaginary (or strictly real), for example, can efficiently direct the convergence process.

Complex numbers can readily be used in the neocybernetic models[11]. However, there is one essential change: *all transposed expressions are substituted with Hermitean ones,* that is, formulas like $\mathrm{E}\{xu^T\}$ change to $\mathrm{E}\{xu^H\}$, etc. In Hermitean matrices, in addition to transposition, all complex values of the form $x + y\mathrm{i}$ (or $r\,e^{\mathrm{i}\psi}$) are changed to complex conjugates $x - y\mathrm{i}$ (or $r\,e^{-\mathrm{i}\psi}$). This change in formulas can be motivated so that the symbol ψ in $r\,e^{\mathrm{i}\psi}$ represents the *phase difference*; if the mapping ϕ conveys some phase-lead, it is only natural that in the matching balance the backward mapping ϕ^H conveys the corresponding phase-lag.

Exploitation of such phase information between neural subsystems can be the key to get onto the next-level neural models. At least, it has been observed that there are some kind of rhythmic interactions between brain regions, and in some situations their momentary synchronizations take place. The frequency-domain models are necessary tools to understand such phenomena. Similarly, the phase-based approach can be a key towards implementing some kind of Heraclitean semantics (compare to Sec. 5.3): the difference between successive patterns can be coded as the complex component in inputs without introducing excessive variables.

When studying the case of complex molecules with neocybernetic orbitals (see [1]), it seems that modeling of solids changes to *frequency pattern recognition,* that is, the "resources" are the frequency bands with orbitals-determined emergies.

How can the observations in the previous section be now expressed in this more concrete frequencies-oriented way of thinking? — For example, study the coupling between different kinds of systems, where the characteristic empedances must match to reach maximum emergy flow. As a concrete example of this, study a higher-level intuition concerning complex industrial systems: one should not directly combine "fast" and "slow" subsystems with higher-frequency vs. lower-frequency internal (control) loops (or monads). Otherwise there will be unnecessary control activity and emergy/energy loss, or "ringing", between the subsystems.

Another vision that can be boosted by the introduction of complex variables is the **probability interpretation** of the effective variables.

As it was assumed (in Sec. 2.2), the underlying behaviors are assumed to be intractable — pushing this interpretation still further, it can be assumed that the actual signals are *truly unreal* (or imaginary!), as only the emergent variables are relevant for the observer. According to what has been said before, these self-emergies are always non-negative, their sum is fixed (scalable to 1), and the structure of their relative relevance is optimized in the neocybernetic modeling process. In other words, the relevant variables are of the form $\mathrm{E}\{x_i^H x_i\} = \mathrm{E}\{|x_i|^2\}$, and the goal of the system is maximization of these $\mathrm{E}\{x_i^H x_i\}$ when the total $\sum_i \mathrm{E}\{x_i^H x_i\}$ is some fixed constant. The variables $\mathrm{E}\{x_i^H x_i\} / \sum_i \mathrm{E}\{x_i^H x_i\}$ can be seen as having a probability interpretation; these probabilities compete in some environment, resulting in a neocybernetically self-organized *probability structure.*

Looking at the essence of neocybernetic adaptations, or the cost criterion J, one can see that it can be written in the following form, too, using the system's internal variables alone (now taking the complexity of the variables and their time scales into account):

$$J = -\frac{1}{2}\, x^H \left(\mathrm{E}\left\{xx^H\right\} + Q^{-1}\right) x.$$

There are present only square forms $x^H M x$, where matrix M is symmetric, never the signals themselves, and it is essentially the *fourth powers* that are emphasized in model construction — or "squares" of probabilities. Thus, analyses can be carried out for a system of probabilities, ignoring the underlying machinery that maintains those probability structures.

The theoretical framework for studying dynamic probability distributions is that of *Markov chains.* Given the individual transition probabilities, one can resolve the long-term average, or balance among probabilities (or "probability of probabilities"), by finding the eigenvector of the link matrix corresponding to the most significant eigenvalue. Assuming pancausality, this is exactly what the neocybernetic approach tries to model — with a few extensions: note that now there are various eigenvector candidates, and a sparse structure among them, whatever this means!

Probabilities-based models can naturally be used in the ant systems (see Sec. 5.2), and also the PageRank algorithm in Sec. 5.3 is based on the analysis of Markov chains. But specially relevant such emergent probabilities become in elementary quantum systems where the "signal carriers" are modeled as truly complex. Remember the Feynman's *path integrals*: the

[11] Emulations with complexified algorithms have been carried out by Mr. Petri Lievonen, showing that convergence typically becomes *faster* and *more robust* in complex domain

probability for an event is given by the squared length of a complex number called the *probability amplitude.*

Another branch of research where probabilities are heavily studied is *game theory.* This field is full of paradoxical examples: for example, the game theoretic solution to the *prisoner's dilemma* ("you should always deceive") is clearly against common sense. Indeed, only when studying *iterated* prisoner's dilemma, correct answers are found. This is the neocybernetic approach, truly: as the time axis is collapsed, when individual "games" are of no interest and the long-term survival is concentrated on, one can explain *altruism,* etc. — It seems that when looking things from the new perspective, some paradoxes vanish, but new ones emerge.

6.6 Emerging paradoxes

Applying (generalized) diffusion of information, and eternal increase in the coupling factor q_i, one would assume that it is only the heat death with infinitely stiff structures that would result from such neocybernetic evolutionary processes continued *ad infinitum* — or, putting it poetically: *finally there would only stand deserted ruins in the fiendish dark space.* However, things need not be so simple. Here, study examples that oppose the straightforward reasoning.

1. *Keeping stability means loss of balance.* Ever better adaptive control finally loses the necessary excitation, resulting in some kind of collapse at some stage.

2. *Diffusion results in extreme gradients.* Whereas diffusion (as studied above) apparently tries to reach a situation where emformation is distributed equally, the reality is very different.

3. *Increasing coupling means decreasing emergy.* It would seem that more efficient emergy capture would be a winning strategy, but *after a certain point* things change.

The item 1 above, or the problems with simultaneous estimation and control, has been studied already in [1], but items 2 and 3 are discussed below.

The above case 2, or **emergence of extreme dichotomies**, is based on the neocybernetic sparse coding and differentiation of monads on *each* level. The most developed systems suck information from other systems; when this continues across a multitude of emergent levels, the resulting "information landscape" can become extremely rugged.

Sparse coding is truly universal. The general sparsity pursuit is illustrated by the emerging granularity and structure in the universe. Why structures emerge from continuum — this, however, cannot be explained merely in terms of local dynamic attractors; indeed, a higher-level view is again appropriate. One could say that *emergent structures facilitate maximum emformation dispersal in terms of best knowledge.* For example, applying the river analogy again: first the obstacles are being eliminated to reach unrestricted flow in rapids, but, after all this smoothening of water flow, a dam will be erected, where the energy of the flow is maximally concentrated, all potential drops being collected in one huge gradient. This concentrated emergy can then be exploited to smoothen flows *elsewhere,* in some other systems, increasing emformation diffusion in the global scale.

And this sparsity-oriented thinking can be brought to still higher levels: one could even say that when trying to explain nature in its simplest terms, one should proceed from the *Heraclitean pantheism* towards "sparse-coded deity". And, specially, then the emolutionary avantgarde is assumedly directed by some conscious and creative mastermind!

The claim 3 in the above list, or **optimization turning to suffering**, can to some extent be explained so that neocybernetic competition among actors always finds the balance where nobody is fully satisfied. But there is still more fundamental issue that deserves to be mentioned: *even the winner with no competition that could do what it likes is bound to suffer.* When the actors are clever enough, special internal mechanisms come to play. Indeed, one could say that this is a deeply *human tragedy*: if you are clever enough to reach for better, and if you are arrogant enough to do it, you and your society will be punished.

As studied in Sec. 3.3, there is a threshold: before a monad can emerge, its *coupling* to the environment must be strong enough — but this is not the whole story. In Fig. 19, the whole behavior of the formula (13) is illustrated: in addition to the era of "nonexistence", there is the era of "unlimited growth" and after that the rest is miserable decay. What is this emolution running the coupling factor q_i to ever higher values, or *cybernetization*?

In systems involving humans, closer coupling comes from better understanding; the increasing knowledge is applied to increasing efficiency in measurement and in control. This is unavoidable, this is what humans always do, stagnation seems like nobody's benefit. The dilemma here is that system emolution is based on individual actions: improve-

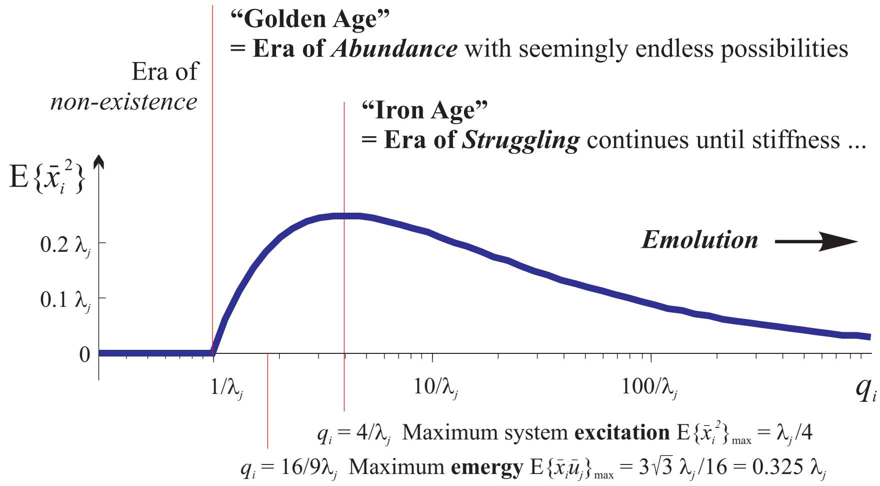

Figure 19: Illustration of the behavior of the formula (13), and its interpretation

ments are *always* beneficial to the individual, assuring higher share of the available emergy (see formula (6)), but as the winning strategies finally penetrate through the whole society (we are interested in the steady states), the whole system moves forward: everybody is to follow the better strategy, but nobody can benefit of it any more. This inevitable emolution goes first beyond the *ecosystem optimum* where the transferred emergy is maximized, and then beyond the *system optimum* where the system's share of the available emergy would be maximum (value $q_{i,\text{opt}} = 1/\mathrm{E}\{\bar{x}_i^2\}_{\text{max}}$ with the peak in Fig. 19), towards a situation where stiffness and system rigidity is immense. There is nothing that an individual human could do to resist this, everybody suffering after the "hill top". Only catastrophes can reduce the system back to an ecologically sustainable level.

There are direct applications of the above view — serving also as examples of how difficult it is to be reasonable. For example, study the *taxation system,* where government (the higher level) collects money from the individual people (the lower level). That is, u variables are the money available in differing income classes, and x variables are the money collected (see Fig. 20). Because the total sum of money is fixed, it is reasonable to interpret the money-variables as being squares of some more elementary factors (as in the case of the probability interpretation in Sec. 6.5). Ignoring the details, one can claim that it is the $1/4 = 25\%$ taxation level that is optimum when one wants to maximize the collected money; but if one wants to reach the "econosystem optimum", the tax level should be only $3/16 = 18.75\%$ (compare to *Laffer curve* and *Hauser's law*). What is more, from the model one can also directly observe that there is a threshold: there should be zero tax for low enough income! In a too low-level society, a (self-sustained) government cannot exist.

Of course, the above mechanism of increasing the coupling is only one possibility of implementing emolution. It is the straightforward approach: investing more effort, developments in this way can always be reached. More *qualitative* emolution steps are difficult, because it takes a "wider view". Indeed, finding structurally new perspectives means new semiosis — typically one can introduce new resources, where there are fresh degrees of freedom available. Such innovation can perhaps start a new Golden Age. For example, when looking at the family trees of living species, one can observe such steps, and between the steps there are minor modifications of structures; this is called *saltationistic evolution.*

As the neocybernetic approach can perhaps serve as a basis of the "new science" of complex systems, something more is still needed: to understand emolution, the processes of *innovation* have to be elaborated on. What are the general properties of the freedoms in abstract domains, and how the loops determined by the constraints can be escaped? More thorough understanding of self-reference, or, more ambitiously, general study of *self* is needed.

Further, to understand the nature of emolution, and the *élan vital* that perpetually drives it, one should also address the high-level general driving principles beneath the emolutionary processes in scientific terms. It is not the entropy growth principle that qualifies here alone: first, entropy is too much limited to the physical realm, but there are other problems, too.

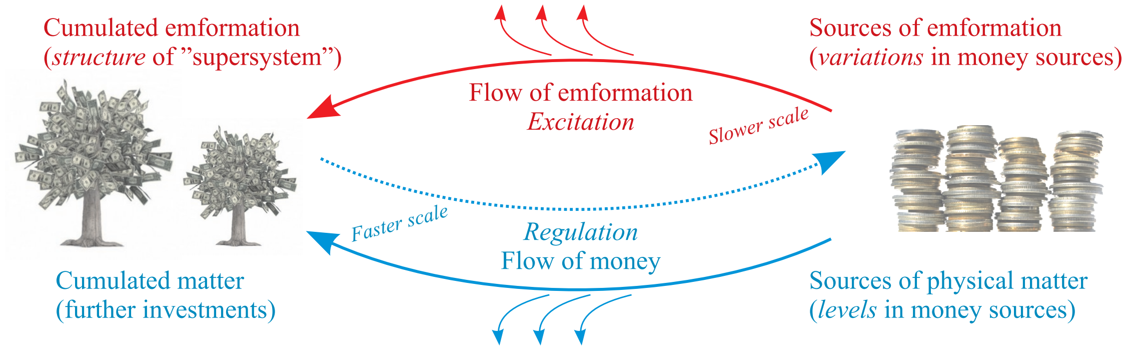

Figure 20: Dualism between matter and emformation: case of *money* being collected and invested

Entropy is too much associated with structureless decay and information loss; however, as was studied above, it is about *restructuring* of emformation, or sparse coding that takes place. There are different "containers" of emformation, the other containers being exploited and further enhanced to better evacuate emformation from some other containers. The idea of entropy should be expanded in the direction of "abstract control" and *coding of emformation.*

Paradoxes and other counterintuitive observations are nourishment to imagination and they give a possibility of escaping the constrained thinking patterns of established scientific paradigms. As Pablo Picasso has said: "In arts and in humor the same laws apply — only the unexpected makes you laugh."

7 Conclusion

What does this all have to do with artificial intelligence? — In the cybernetic spirit, complex systems cannot be studied one subfield at a time, and this certainly applies to the cognitive system, too. Sometimes it is easier to attack a wider-ranging problem than a specific problem case. To escape the human-centered view, to reach wider perspectives of what universal intelligence truly is, *understanding the world* is the key also to *knowing.* Or, rather than *knowing* something, it is about knowing *something.*

As artificial intelligence is a subfield in artificial life, real intelligence can only be understood through *real life.* Intelligence and life both are emergent-level phenomena, and it is this emergence that deserves main emphasis. Fundamentally, emergence does not make sense without reference to semantics, and the grounding of semantics is supplied here by the mills grinding of everything that exists.

Neocybernetics implements the Heraclitean spirit: everything flows, everything affects everything else, etc. The famous *aporias* provide nourishment to imagination — but in addition to Heraclitus, there are other mythical recitations to learn from, too.

In the Finnish national epic *Kalevala* the heroes have complete mastery of any system as these wise men are capable of *presiding over the births* of those systems (that is, they know their emergence). Further, this might culminated in their construction of *Sampo,* a magic mill where all this wisdom was automated. The Sampo mill indefinitely produced "syötäviä ja myötäviä", or *things to eat and things to sell.*

In the case of SAMPO mills, the things to eat are *nourishment for intellect,* turning into understanding and imagination, innovation and application, finally producing things to sell.

Kalevala tells us further that in a certain fight, Sampo was accidentally dropped from a boat, and it was a wave ("Aalto" in Finnish) that billowed over, so that Sampo was lost forever, leaving only some whirls (assumedly!) on the surface. — On the other hand, the faith of SAMPO could be different. The idea of SAMPO mills, the ubiquitous information refineries, is today still in our hands. I hope the new SAMPO is recognized before it is lost again.

Acknowledgement

I am grateful to Mr. Petri Lievonen for his comments, and for his deep involvement in making neocybernetics hopefully reach the *scientific threshold.*

Bibliography

1. *More material on neocybernetics (and also links to further references) can be found in Internet at* `http://neocybernetics.com`.