AS-74.4192 Elementary Cybernetics

Lecture 3:

Towards Modeling of Emergence

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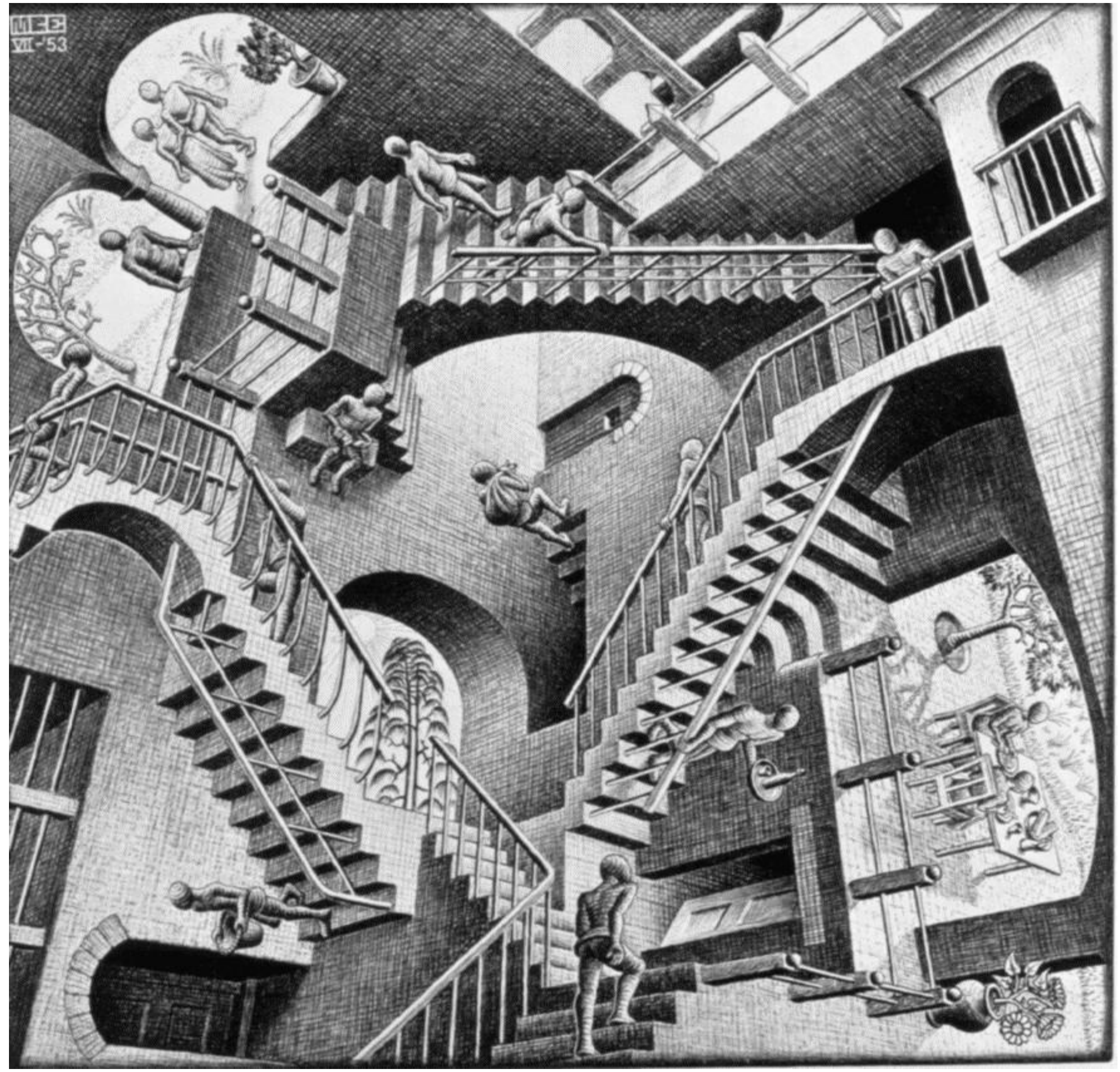
Where to go?

- First: mindstorming, apply the intuitions!
- Then: select the directions where one can proceed
- Vision + mission:

  Holistic problems, but reductionistic methods
- First:

  "Model of modeling"



Typical evolution of models: “Bottom up”

- Models tend to become more and more sophisticated
- For example, in bioprocess modeling, using the basic bricks

Exponential

$$\frac{dx}{dt} = \mu x$$

Logistic

$$\frac{dx}{dt} = \mu x - kx^2$$

Monod model

$$\frac{dx}{dt} = \frac{\eta s}{k+s} \cdot x$$

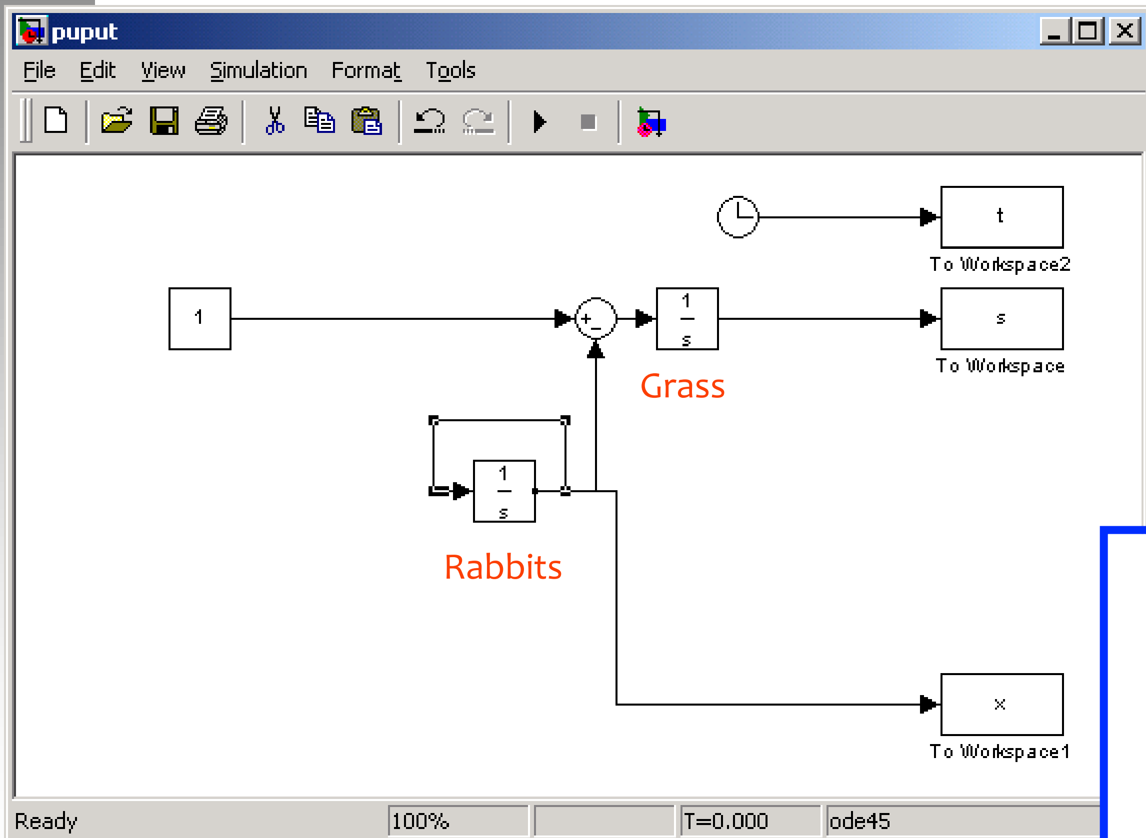
one can construct:

$$\begin{cases} \dfrac{dx}{dt} = \mu x - k_1 xb & \text{Biomass} \\[2ex] \dfrac{ds}{dt} = -k_2 sx - k_3 \dfrac{s}{k_4 + s} x & \text{Substrate} \\[2ex] \dfrac{da}{dt} = k_5 s \dfrac{1}{k_6 + b} x - k_7 \dfrac{a}{k_8 + a} x & \text{Acid} \\[2ex] \dfrac{db}{dt} = k_9 sx - k_{10} \left(k_5 s \dfrac{1}{k_6 + b} x - k_7 \dfrac{a}{k_8 + a} x \right) & \text{Alcohol} \end{cases}$$

Fiddler’s paradise!

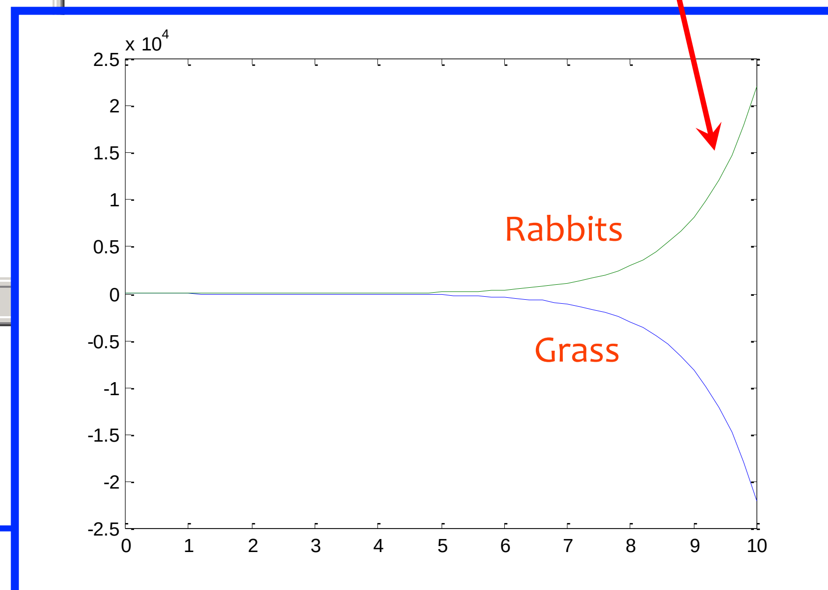
Models unanalyzable & hardly useful

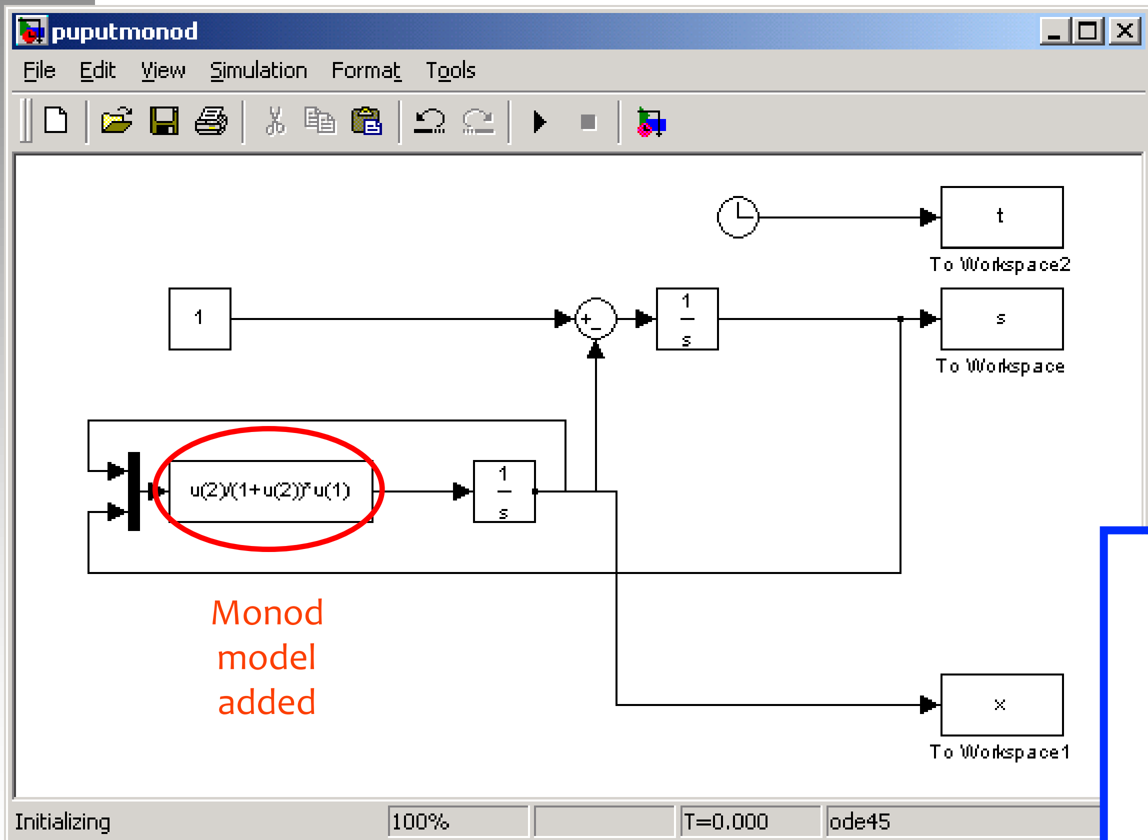
Example: Model of Grass vs. Rabbits



First try

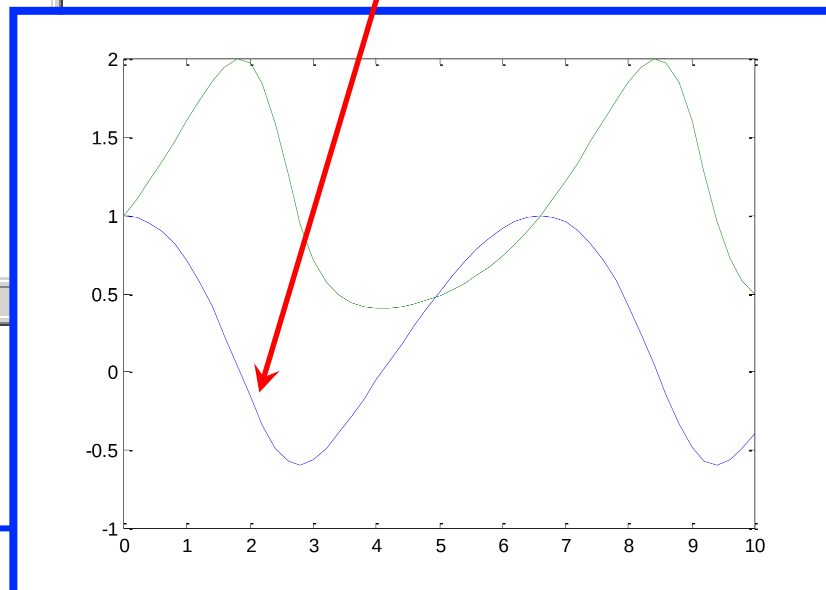
- Needs fixing: unlimited growth





Still needs fixing ...

- Negative biomass!



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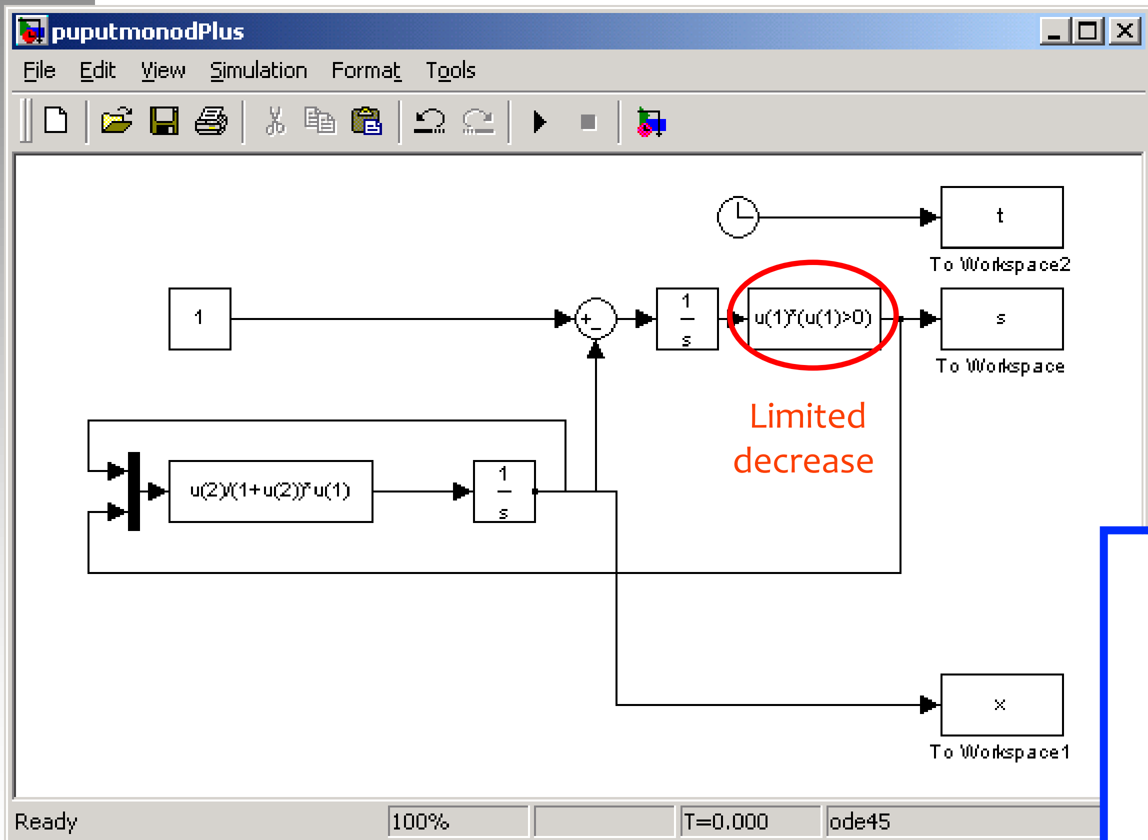
... and still ...



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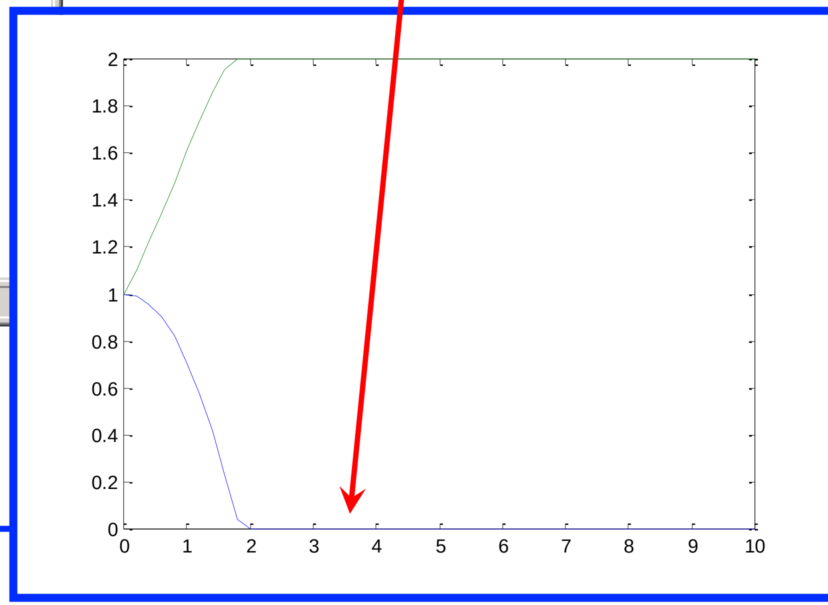

2
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1.4
1.2
1
0.8
0.6
0.4
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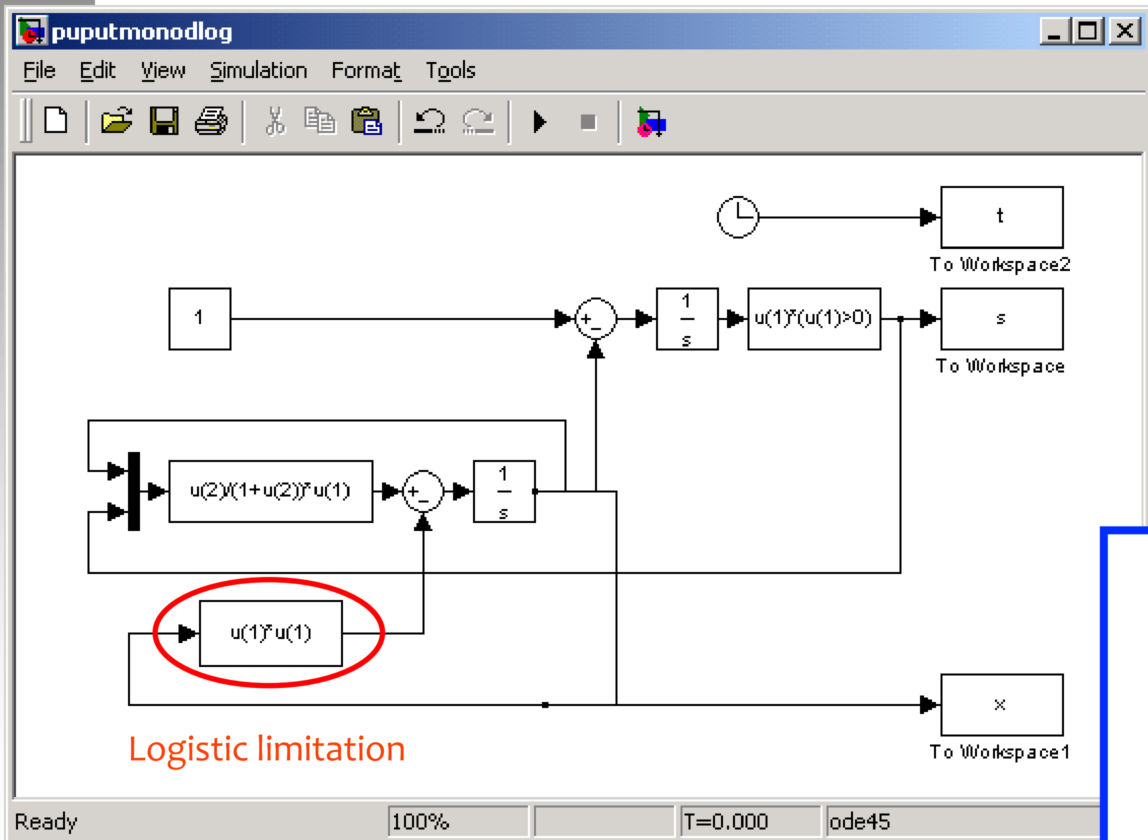
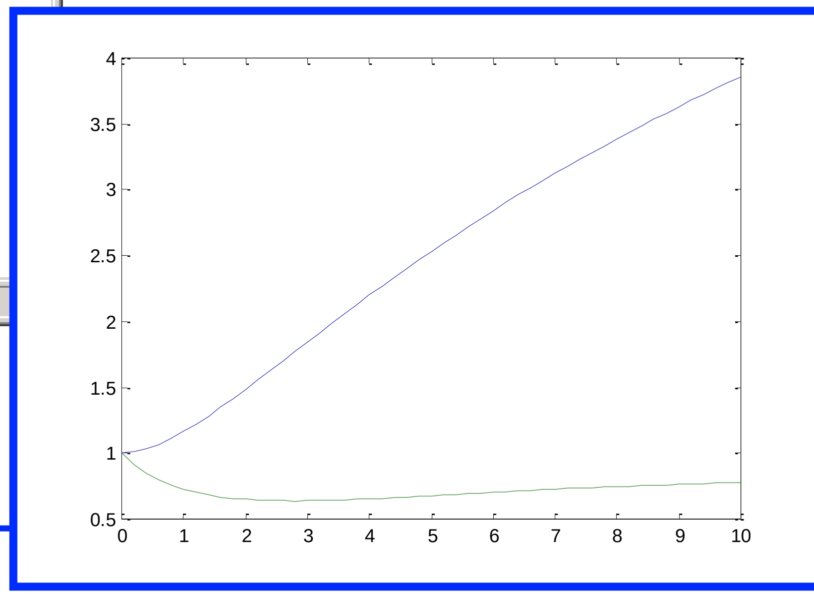
0
0 1 2 3 4 5 6 7 8 9 10

... An endless task!





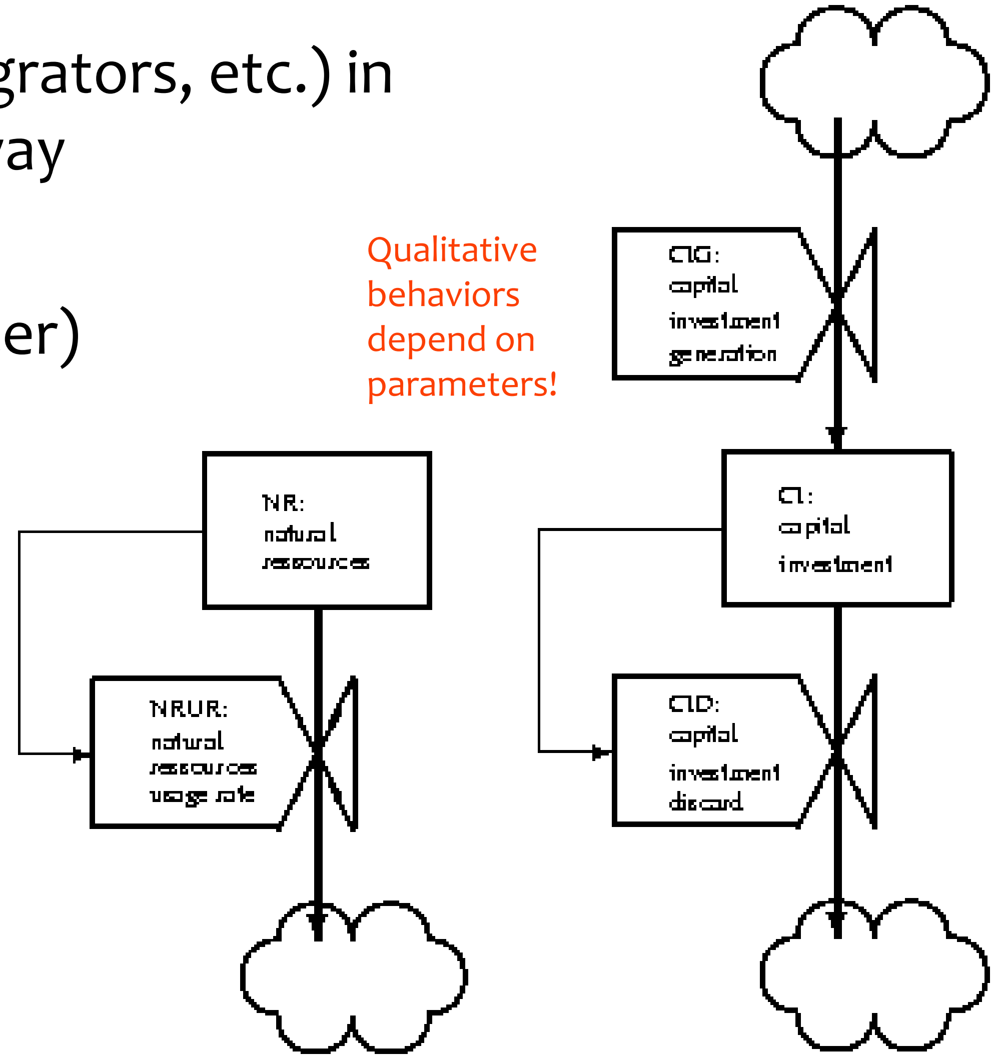
Similarly in all complex environments ...

- Combine basic blocks (integrators, etc.) in an intuitively appropriate way
- Example: *System dynamics*
- World models, etc. (Forrester)
- However:

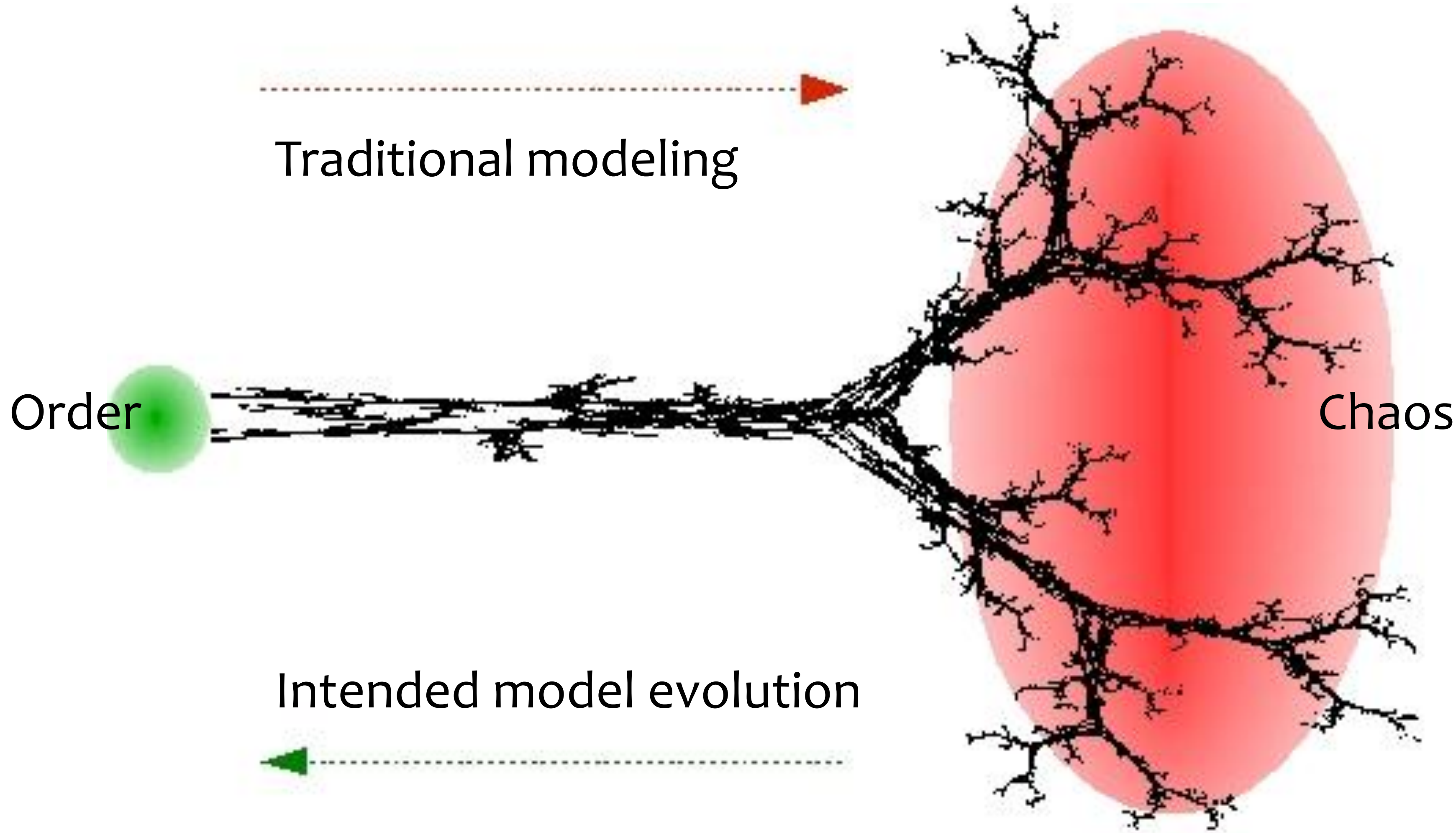
  Simulation exactly reveals what was explicitly modeled!

  Are there other alternatives for finding models?

Qualitative behaviors depend on parameters!



Are there alternative approaches?



“Top down”: Power of systemic thinking

Assume that the door of a refrigerator (1 kW, $\eta = 30\%$) is left open. How will the room temperature behave?

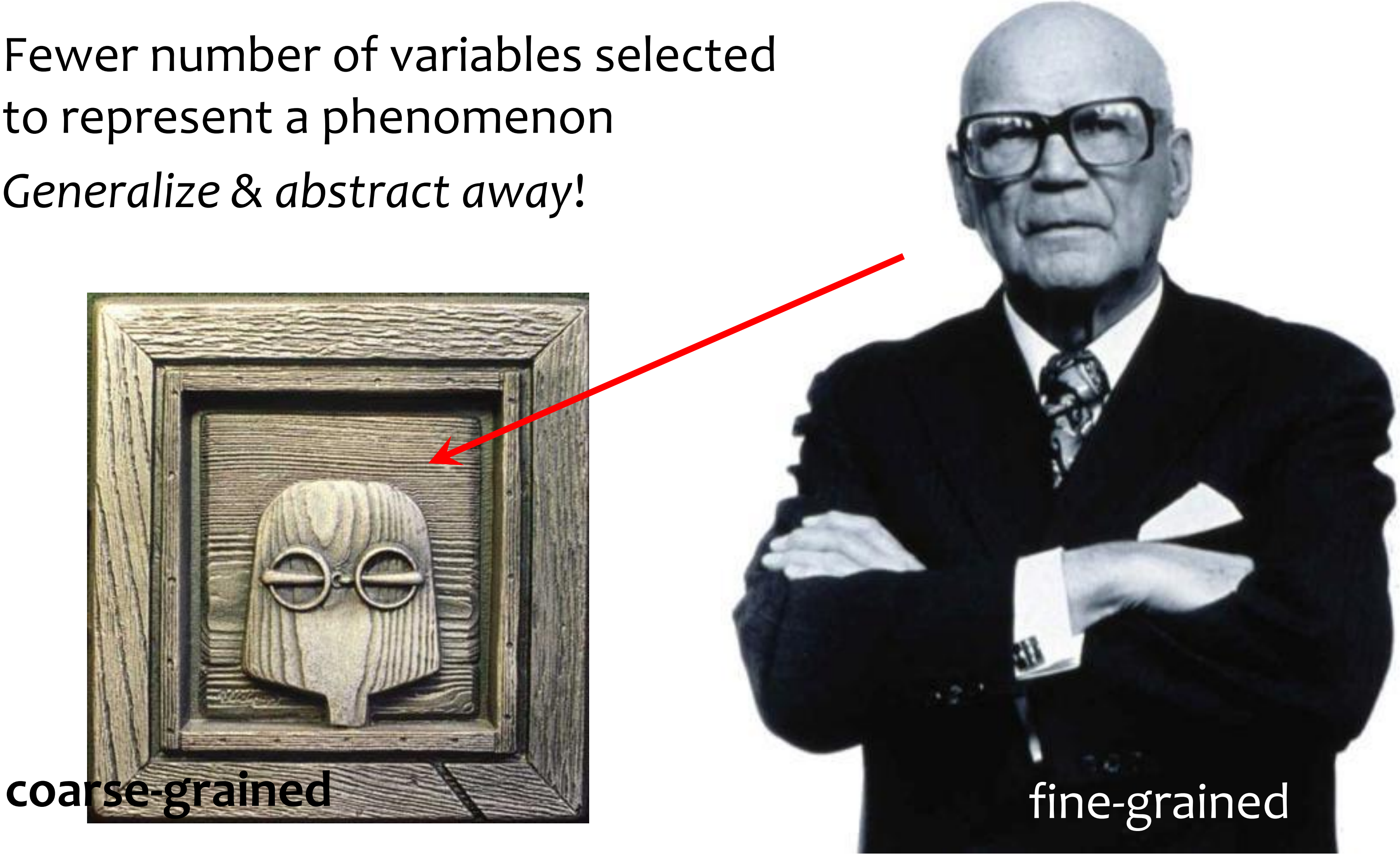
1. It will decrease.
2. It will increase.

– But *what is the power*?

- Appropriately defining the system boundaries makes this simple!

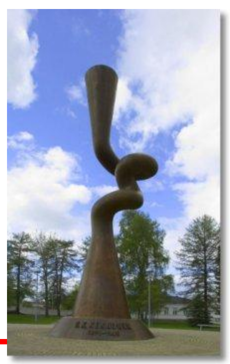
"Granularization"

- Fewer number of variables selected to represent a phenomenon
- *Generalize* & *abstract away*!



Warning

- Ideal of holism: The whole is larger than the sum of the parts
- Risk of holism: The “hole” is larger than the sum of the parts:



The temptation of loose hypothesizing has to be avoided, abstractions must not be too wild

Key question – link among levels = *emergence*

1. What do *you* think is an emergent phenomenon?

2. How would you approach and model it?

Complex systems: Science in the making

- The field of complex systems research is far from mature
- No paradigmatic guidelines yet exist: There are no generally approved approaches, common concepts, methodologies or tools, typical application domains or problem settings

- **Neocybernetics** is an approach to capturing the essence of complexity in a simple framework
- Now: The concepts and underlying assumptions are defined
- Note: The developments were not originally so straightforward – only “highway through the jungle” is shown
- Note: There always exist many ways where to proceed; here, alternative branches also need to be considered ...

Opposite intuitions #1

- Traditionally, in complex systems research emphasis is on *surface patterns*, visible formations
  - For example, Wolfram's sea shells
  - Fractal intuitions, etc.
- However, remember Alan Turing: "The zebra stripes are simple – I am more concerned of the *horse* behind"

Compare to shallow vs. deep views to AI

- **Now:** key point in complex systems is not the surface patterns but *deep structures*

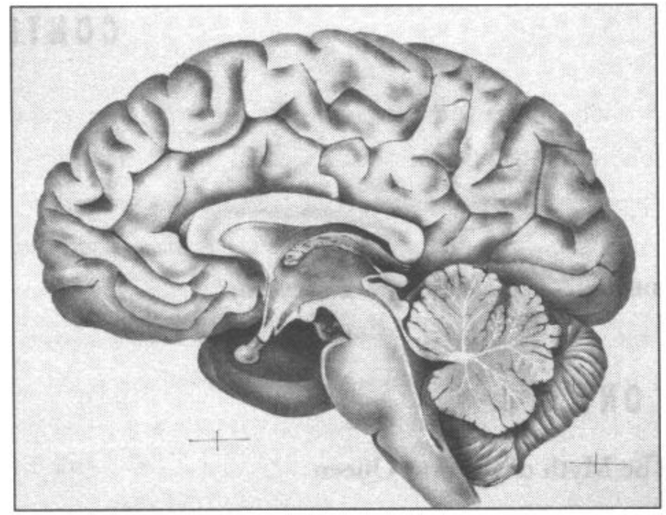
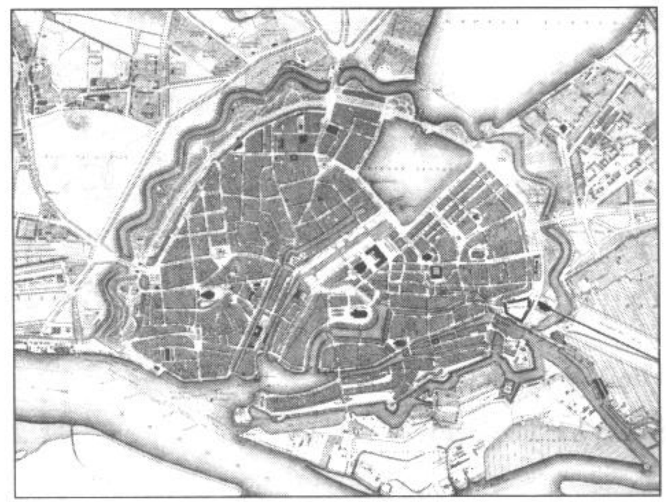


Diagram of the human brain *(Courtesy of Mittermeier)*



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

from S. Johnson: "Emergence"

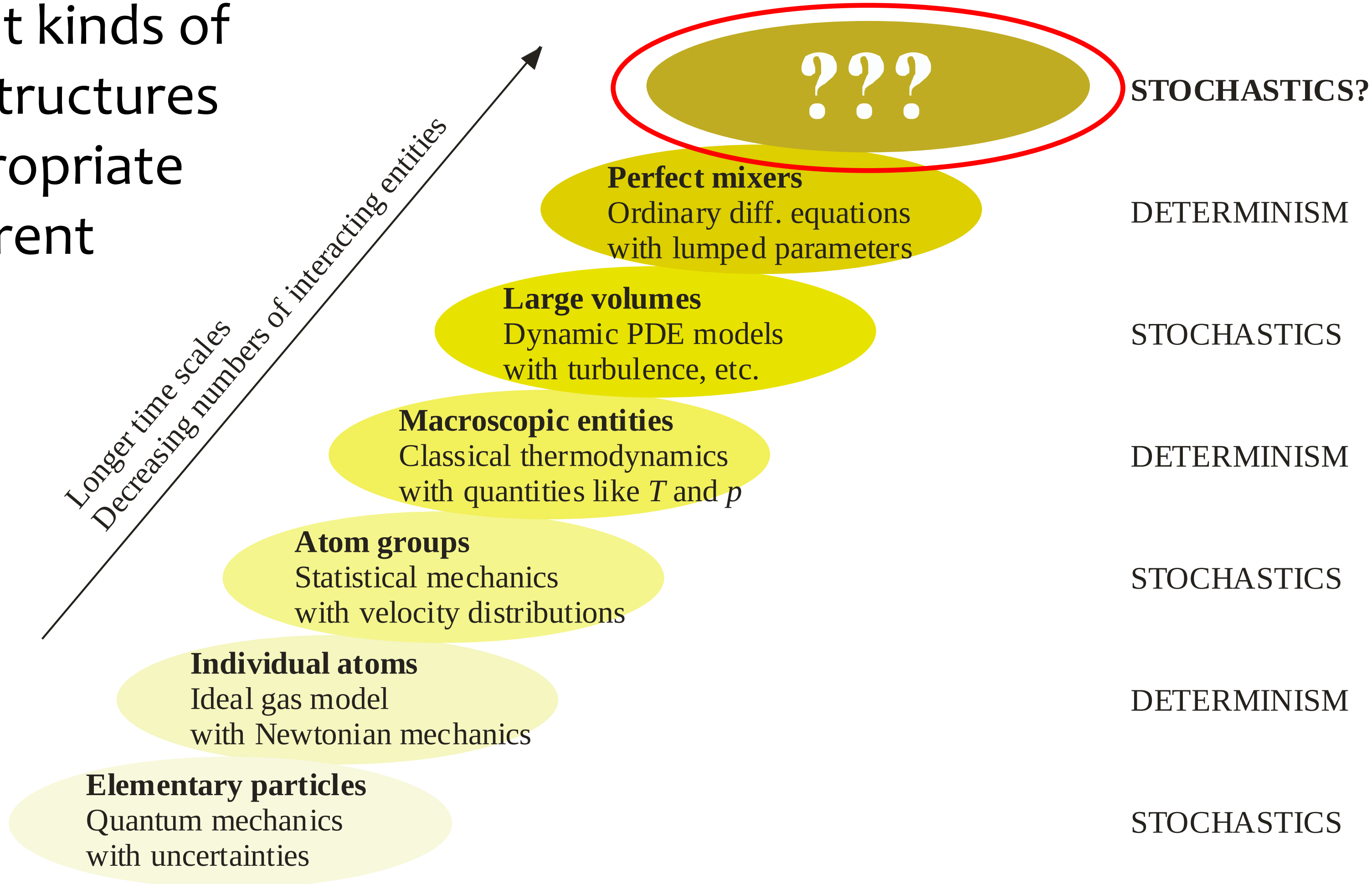
- Assume: *Deep structures = underlying emergent patterns* meaning *functionalities* where the system is attracted to
- How to model emergence (a *holistic* phenomenon) in a reductionistic way ...?!
- Indeed, apply the very traditional modeling ideas:
  - First: Studying explicit examples, construct an intuitive understanding of what emergence is
  - After that: Find the common features and represent them in an explicit mathematical framework
- Sounds like nonsense? However, this *can be done*.

... There are many ways to interpret the evidence ...

"Definition" of Emergence: "Phenomenon that cannot be defined"!

Emergence? – Seen it before!

- Different kinds of model structures are appropriate on different levels



"Emergence" taking place between each layer!

- Today, the level of deterministic first-principles models is already fully exploited
- Now one should reach for the highest, stochastic level

  (Note: Stochastic and deterministic levels alternating is no coincidence: Otherwise the levels could be “collapsed”)

- Higher level: *Time scales longer + number of functional entities lower* (granularizing lots of faster parallel interactions)
- Abstractions in emergent models:
  - Time axis has to be eliminated!
  - Individual realizations have to be ignored!
- This must be done in an appropriate way, so that the properties relevant on the higher level are not compromized

“Weak emergence”: Higher-level variables = functions of statistical distribution properties

Towards formalizing the intuitions

- ... You have one grain of sand, then you have two, then three – at what point do you have a *pile* of sand?
- Two concepts that are intuitively close to each other: emergence and infinity
- Abstracting details away along the time axis *or* spatial axis:

$$\mathrm{E}\left\{ quantity \right\} \overset{\text{def}}{=} \lim_{t \to \infty} \left\{ \frac{1}{t} \int_{-t}^{0} quantity(\tau)\, d\tau \right\}$$

- Here, *expectation* "E" can be interpreted as "emergence"
- Individual instances have no relevance whatsoever any more; time-domain behaviors become represented by end results

See the forest for the trees!

- **Is emergence only averaging?!**
- Appropriate nonlinearity is here needed – then, *effective theories* can be found (standard view)
- For example, *gas temperature* follows weak emergence:

$$T \quad \sim \quad \bar{E}_{\mathrm{kin}} \quad \sim \quad \mathrm{E}\left\{v^2\right\}$$

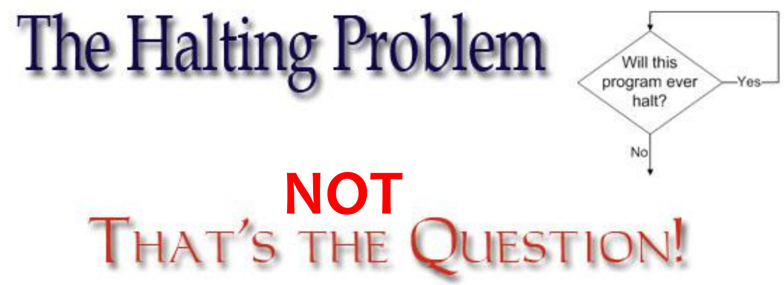
- What is needed for (more intuitively appealing) emergence is *interaction of underlying components* (new view!)
- In its simplest form, such *coupling* can be modeled as

$$\mathrm{E}\left\{x_i x_j\right\}$$

Note that covariances can still be modeled in linear terms!

- This all is captured in *covariances* (next time!)

- Traditional computability theory has only studied cases where algorithms stop – in the Greek spirit truly!



- Such theory cannot study emergence because all computations with E are *infinite* (at least in principle)
- In practice, relevant data typically behaves nicely, iterations converging towards final values also for finite sample sizes
- Rather than studying formal algorithms or other structures, emphasis and starting point now is on data properties!

Opposite intuitions #2

- Traditionally, one concentrates on individual actors and distinct time points
- Now one abstracts *from individuals to groups or populations*, *from distinct anomalies to averages or expectations*
- Consequences – some examples:
  - The "selfish gene" and game theoretic individualistic approaches cannot explain *altruism*, etc., that become reasonable only at the population level
  - "Survival of the fittest" is not the key point – matching the whole terrain, finding the outlook of "fitness landscape" is the goal of a population
  - Family of good solutions and modeling their spectrum – this is assumedly what nature also does: It does not know how to solve NP hard problems!
- Disadvantage: The resulting models cannot then simulate individual actors or processes

NEW

- Paradoxes are like "super colliders" of traditional thinking: problems and new horizons are momentarily exposed
  - For example, study the "prisoner's dilemma". There are two prisoners, A and B, who are accused of the same crime. If they co-operate and do not deceive each other, the penalty is not very bad … on the other hand, if either one deceives the other, he will walk free, while the other will have the maximum penalty – long sentences are given also if both deceive.
  - Traditional game theory says that one should always deceive.
  - Co-operation emerges as a winning strategy only in "iterated prisoner's dilemma" case, where – again – the time axis is eliminated.

Payoff to player A

		Player B	
		C	D
Player A	C	2	0
	D	3	1

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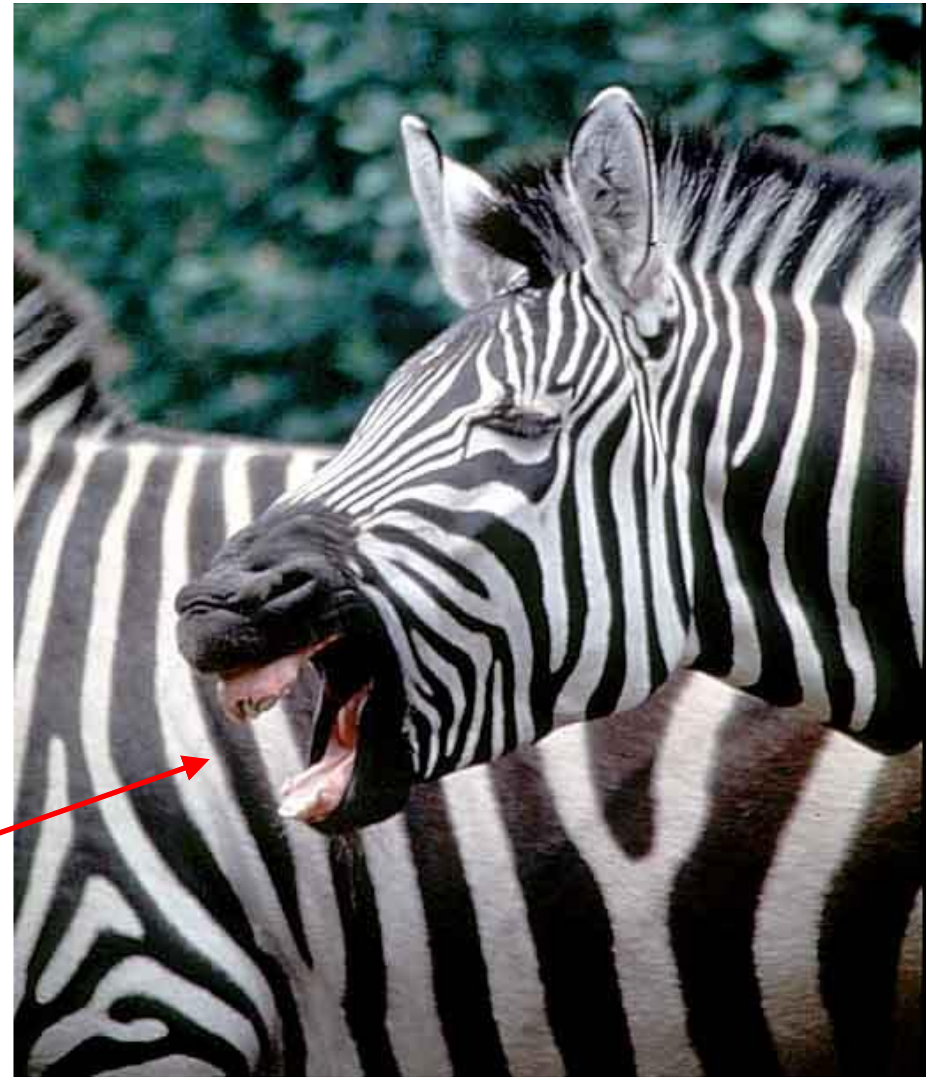
Opposite intuitions #3

- Phenomena can be represented in terms of *processes* or in terms of *patterns* (Herbert Simon 1969)
- When describing complex systems, process view dominates:
  - Individual (inter)actions and explicit time structure is emphasized; no doubt because such causal structures are easier to grasp
  - For example, traditional cybernetic models are based on actual realizations of sequential, more or less one-at-a-time interactions
  - Thinking in terms of programs; for example, the *agents* today are software constructs
    - And all AI techniques are today seen in such agent perspective (for example, Russell, Norvig: "Artificial Intelligence: A Modern Approach" states that "... The unifying theme of the book is the concept of an *intelligent agent*. ...")
- **Now:** *Patterns* are determined using *statistical properties* Counterintuitively, one can address *process philosophies*

... Process view (cont'd)

- Why process view rules? Some intuitions:

1. Because computer is used as a general modeling tool, algorithmic view dominates
2. Specially, the chaos theory defines iteration as the route to complexity
3. Also: There is more to the phenotype than there is information in the genotype



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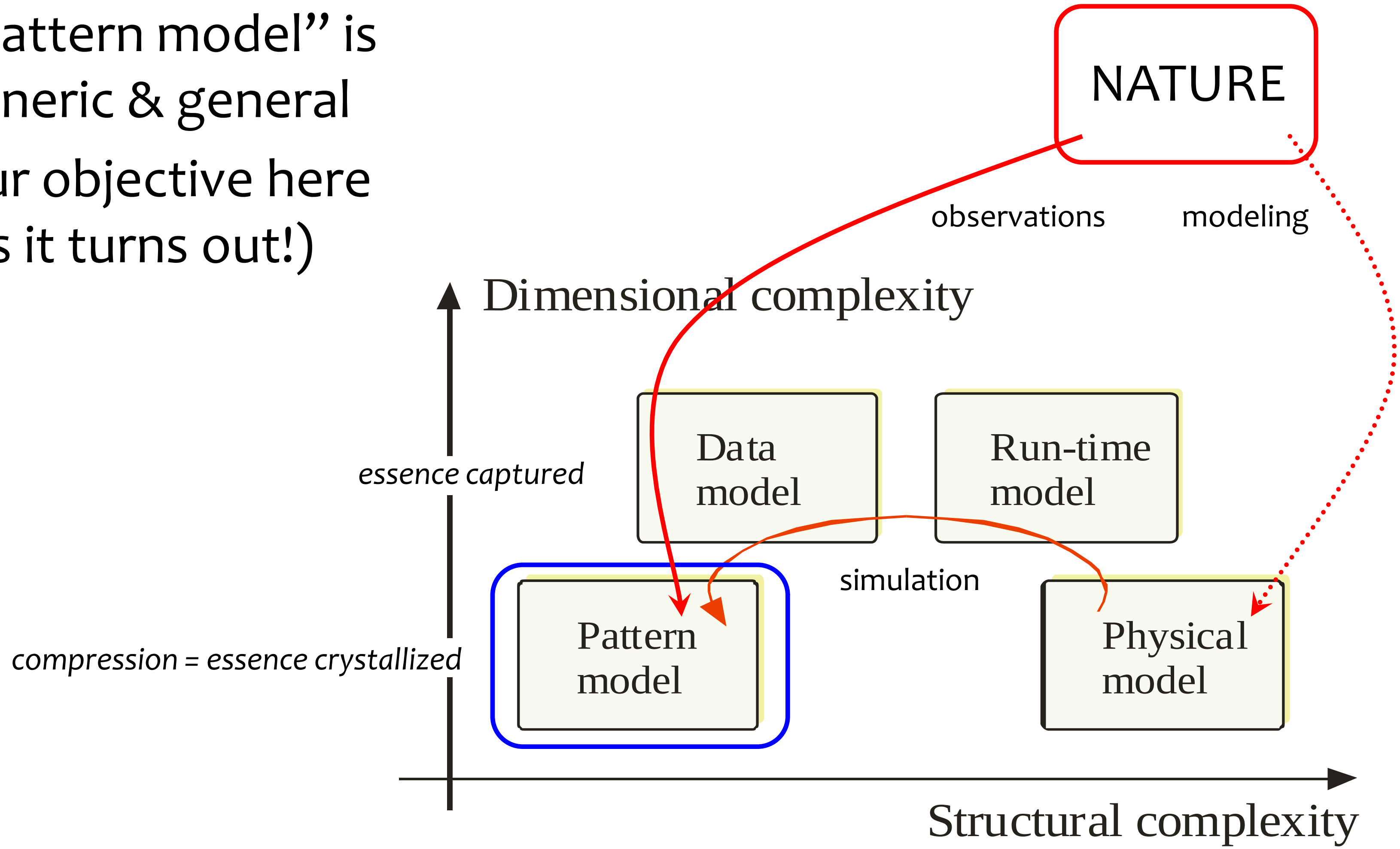
Vision now / Technical view

- "Pattern model" is generic & general
- Our objective here (as it turns out!)

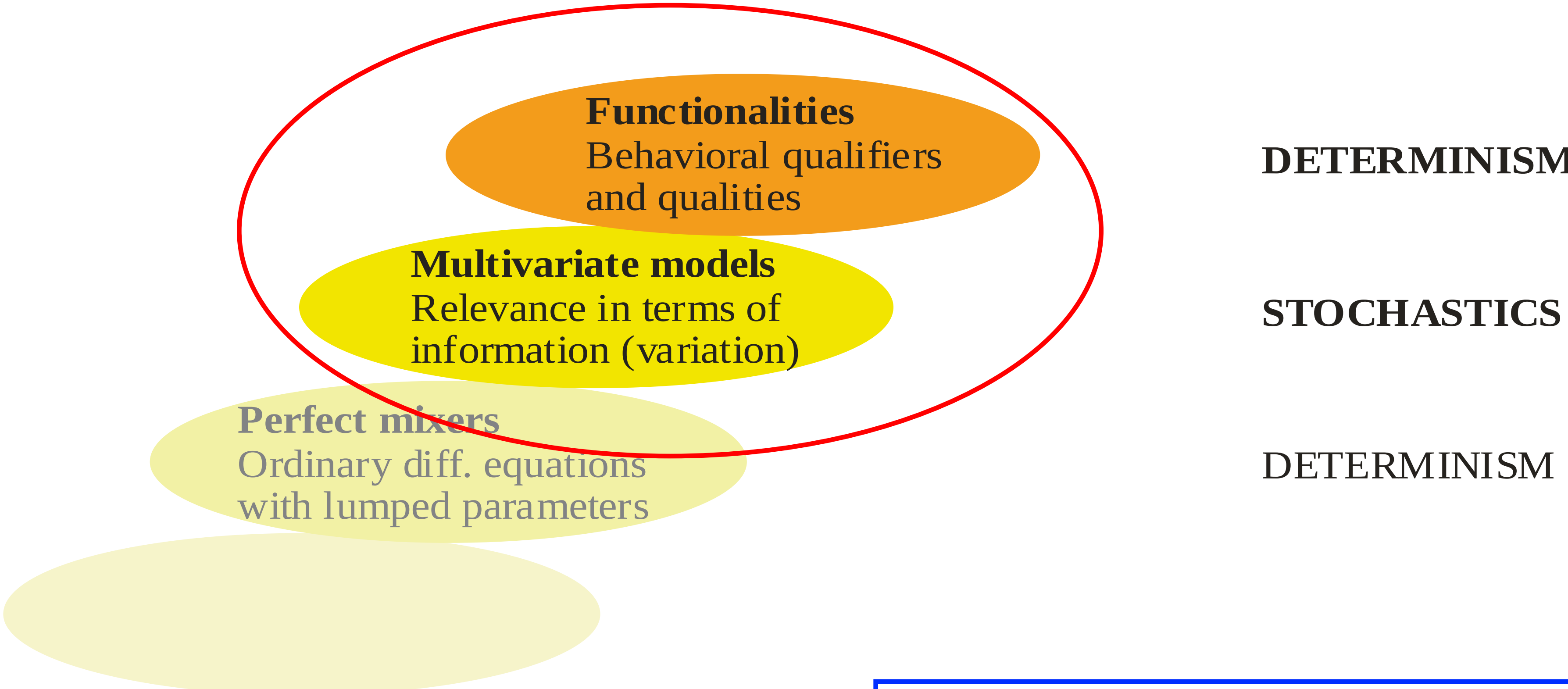


Opposite intuitions #4

- Traditionally, physical model tries to capture one system, one phenomenon in isolation
- Purely syntactical fixed model structure as the starting point – a priori assumptions about the system are needed
- "TRUTH" = system behavior with no disturbances

- Now, pattern model integrates the system and its environment
- System is in interaction with the surroundings; this reveals its role in the environment, giving a "semantical" representation
- RELEVANCE = System with "disturbances", typical auxiliary effects, resulting in the *essence* of the system

- New levels in the emergence hierarchy (to be seen later)
- Highest level consists of semantically meaningful patterns



Kantian-style compromize:
Structure of the patterns theory driven
Contents of the patterns data defined!

Importance of *stationarity* and *stability*

- Many problems fade away when the actual dynamic processes are abstracted using statistical system properties (these problems are tackled with in control engineering)
- When can such abstractions be carried out?
  - To have statistical measures emerge, the signals have to be *stationary*
  - To have stationary signals, underlying system has to be *stable* in the large
- However, there are tensions in a system: The cybernetic balance is a *dynamic equilibrium* (in the large)
- Heuristics: Stability constitutes a “cooker” of complexity
- Truly, how could one assume stability in natural processes?
  – The other alternatives are *explosion* (resulting in exhaustion of resources) or *extinction*

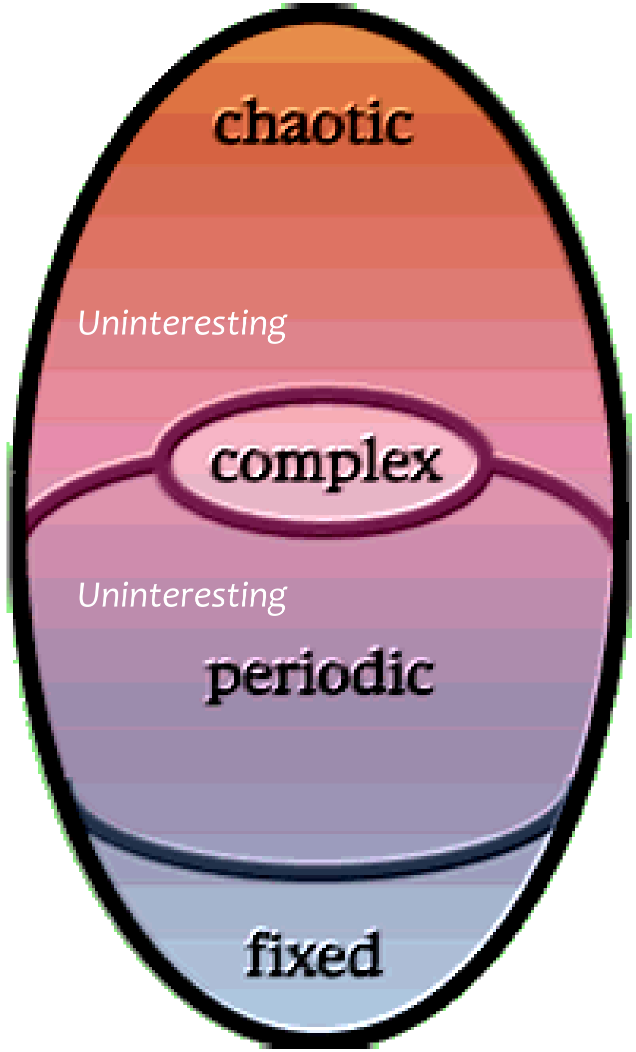
- Note that there is a big difference between momentary patterns and dynamic equilibria

  Static form can be characterized as $f(x) = 0$; *balance* means zero gradient $df(x)/dx = 0$. In *dynamic balance* underlying flows compensate each other; *thermodynamic balance* (or *death*) means that all flows have ceased.

- Even though the visible system may seem to consist of algebraic dependencies among variables, underneath there are (fast) dynamic processes
- These are typically (generalized) diffusion processes
- Otherwise, finding the balance cannot be explained in decentralized terms

Opposite intuitions #5

- The traditional intuition concerning complex systems says they are extremely unstable, always being at the "edge of chaos"
- "Steady state means death"
    - Erwin Schrödinger: Life is as far as possible from balance
    - Ilya Prigogine: The essence of life is in dissipative processes
- **Now:** The *static* and *dynamic* balances are different things!



- Non-balance thinking, emphasizing change, is very Western style
- Eastern wisdom takes harmony = balance as the underlying goal and ideal (philosophy, medicine, ...)
- The essence is in more or less fixed patterns, or *attractors* of dynamics

气

Chinese symbol for *air* or *vapor*; also meaning the mystical *ordering principle*

Cybernetic model – Intermediate summary

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

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

Physically meaningful or mathematically possible?

- In theory, stability extremely rarely is encountered in arbitrary systems
  - The probability of a "completely random" n'th order linear continuous system to be stable is $1/2^n$
- Indeed: The neocybernetic model is limited to a very narrow class of all possible dynamics – to those that are *relevant* in nature
- It is assumed that stability is caused by some internal mechanisms; in cybernetic system these causal structures are constituted by *negative feedback loops* (*see later*)
- The negative feedbacks are *control structures*; the different dynamic equilibria result from changing inputs ("reference signals") – thus …

Systems of *thermodynamic consistency* ...

- The neocybernetic model is a model-based (adaptive) controller trying to compensate the disturbances coming from the environment; further, this can be extended:

- The neocybernetic model is a means of reaching maximum entropy (or "heat death") of the environment! (These things are all discussed *later*)

- In addition, there are also other views available that contradict traditional intuitions; indeed:

- The neocybernetic model is a model of inverse thinking: For example, the relationships are "pancausal" rather than unidirectional; it is *freedoms* rather than *constraints* that are modeled, etc.

... Intuitions applicable in different fields!

- Intuitions can efficiently be exploited: **Analogues** can be extended to partial differential equation models
- First, a *mechanical analogue*:
- The neocybernetic model is an elastic system, where the internal tensions compensate the external forces. The deformations are proportional to the forces (behaving like a *steel plate*) whatever is their physical manifestation
- Then, an *electrical analogue*:
- The neocybernetic model is a model where neighboring cybernetic systems can be managed: There is maximum power transfer among the systems when they are matched so that their input and output impedances are equal

"Pallas Athene Hypothesis"

Compare to "Gaia Hypothesis"

- It is by no means self-evident that mathematics can be used to explain nature; however, this far, it has been astonishingly efficient
- Here this optimistic belief is taken as the starting point: The *end of science* is not yet there; complex systems **can** be modeled

Is this justified?

- *If it is*, there exist strong modeling guidelines to be followed ...

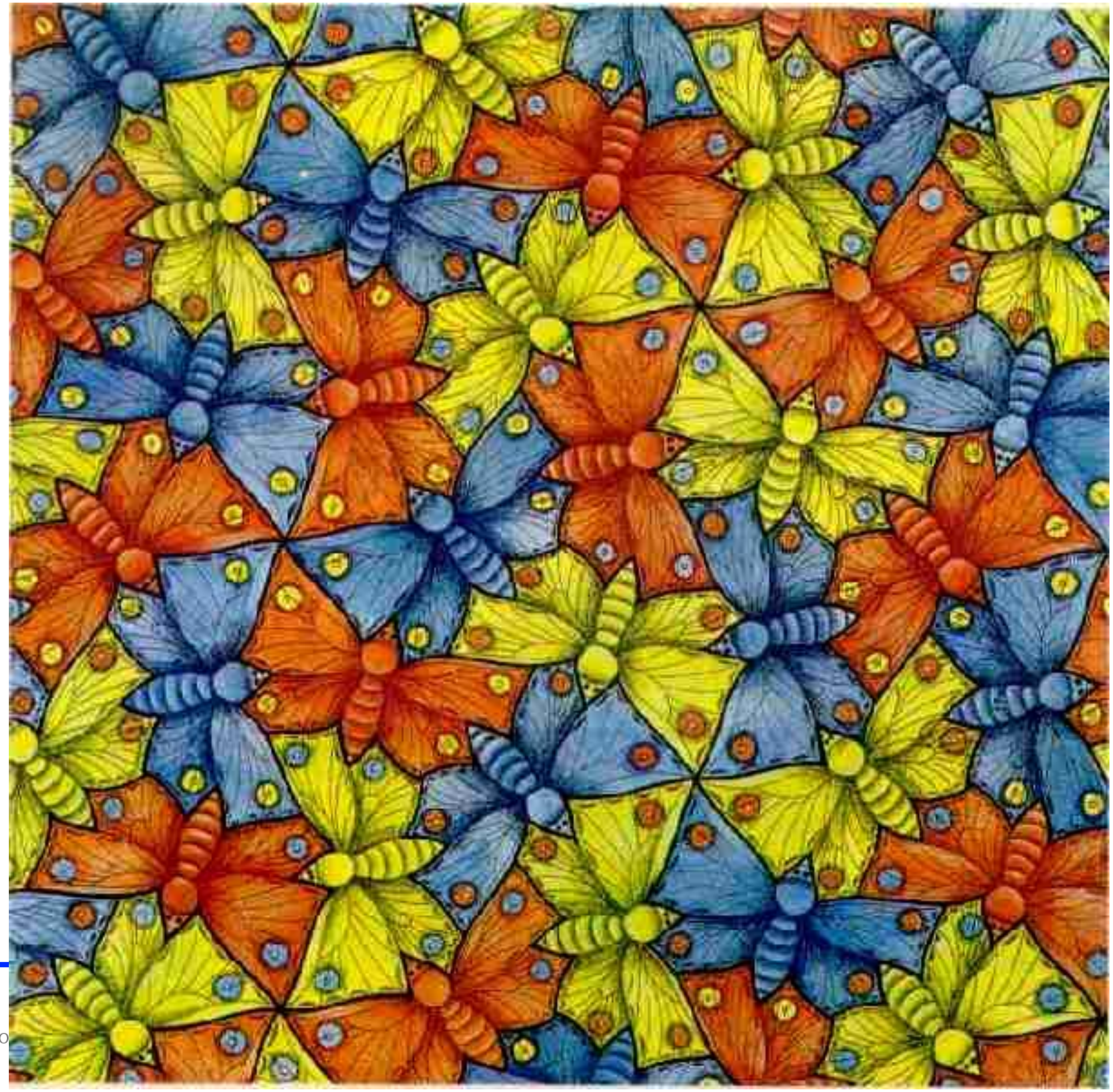
Compare also to the Parallel Postulate!

Additional intuition #1: *Determinism*

- The above stability studies did not yet give guidelines to select the model structure – how to get forward?
- Here – apply the "Pallas Athene Hypothesis": Theory of complex systems **does** exists, so that systems have to be qualitatively more or less uniquely determined in each case ("free will" is a fallacy!)
- The parameters are to be optimized in some sense, so that the representation is unique within that model framework
- The neocybernetic model is (as it turns out) a "mirror image" of its environment, being itself a model of the environment, capturing relevant behavioral patterns as manifested in data (in a more or less unique manner).

Symmetry – and beauty?

- A system is surrounded by other systems
- Symmetricity: Environment and a system have to be interchange-able in the models



Additional intuition #2: *Linearity*

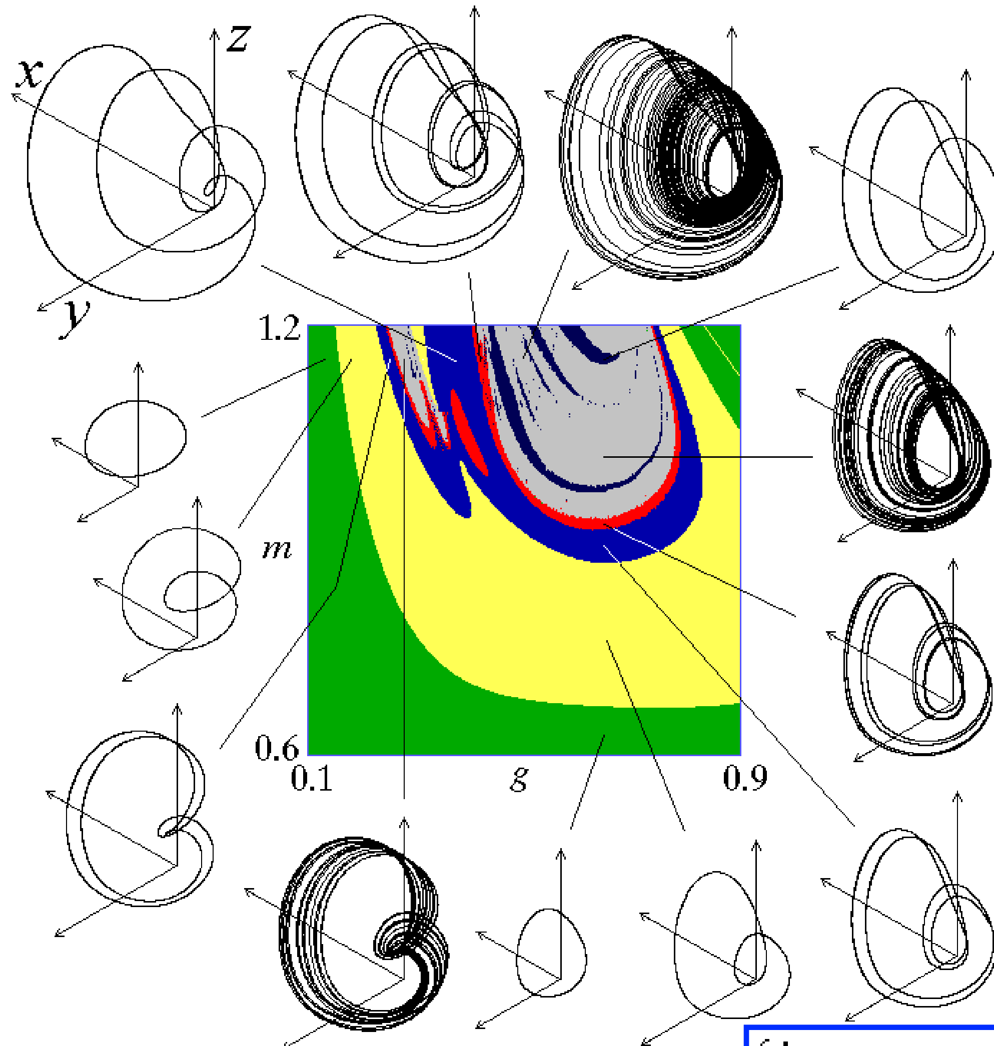
- System theoretic intuition: Linearity is essential in large-scale models – otherwise, no scalability and no predictability, etc. – that is, no general theory of complex systems could exist!
- Here – again apply the "Pallas Athene Hypothesis": Theory of complex systems **does** exists, so that models to be created have to be *basically linear*
- Deficiencies in expressional power are compensated by high-dimensionality and interactions, resulting in stochastic, high-dimensional, dynamic feedback models
- Linearity can be motivated in cybernetic steady-state models when it is assumed that only minor deviations take place around the balance of a smooth nonlinear dynamics

Opposite intuitions #6

- Nonlinearity = always the basic starting point in all studies of chaos and complexity theory!
- Without nonlinearity qualitatively new phenomena cannot emerge – this IS true

  $$"f(a+b) = f(a) + f(b)"$$

- **Now:** The *final state* can be studied without process nonlinearities



$$\begin{cases} \dot{x} = mx + y - xz \\ \dot{y} = -x \\ \dot{z} = -gz + 1(x)x^2 \end{cases}$$

Conclusion – to be utilized ...

- Intuition #1: Balance pursuit
  - Theoretical understanding: In steady state one can directly attack the emergent pattern and forget about the details of complex processes
  - Pragmatic understanding: Only in stable conditions, when fast phenomena have ceased, something fragile can emerge
- Intuition #2: Linearity pursuit
  - Theoretical understanding: Natural processes are smooth, and around the equilibrium (locally) linear
  - Pragmatic understanding: Linearity is the only way to scalability and out from toy worlds

- Motivations for both approaces
  - Heuristics: There is evolutionary advantage!?
  - Theory: Stronger tools are available for analysis and synthesis
  - Practice: It is clever to first study what can be reached with simple approaches – the assumptions can be relaxed (see later)

Can a "model of balances" be interesting in the linear case?!

NEW

Opposite intuitions #7

- Philosophically speaking, traditional science is based on *Cartesian dualism*, or the distinction between the observing **subject** and the observed **object** (or *mind* and *matter*)
- Now, on the other hand, subjects and objects get mixed, as all entities are active – and because of pancausality, observation disturbs the observed
- However, there will be *another kind of dualism* introduced: it turns out that "emformation" (free information or energy) determines the structure wherein the matter is manifested
- Later on, when signals are analyzed in *frequency domain*, also Kantian *transcendental idealism* becomes challenged, as observations are not spatially and temporally determined.

Why linearity? – Bonus example

- System theoretic intuition also is: "To find scalable models for truly large systems, the model structure must be linear" (however, this constraint can be relaxed *later*)
- Why? Let us study an example – assume that

$$s(k+1) = f\,(As(k))$$

where
$$f_i(s) = \begin{cases} s_i, & \text{when } s_i > 0 \\ 0, & \text{when } s_i \le 0. \end{cases}$$

- This is almost linear ... it even looks simpler than a linear model (only the first quadrant is employed)
- What kind of dynamics is possible here?

- Computability theory: Any algorithm can be constructed using only increment and decrement operations and conditional branches
- Each of these commands can be implemented using the given dynamic model!
- Matrix A represents the program structure, and s represents the program "snapshot" (program counter + variable values)

- Initial state (variable values) given in $s(0)$
- One program step takes one to two steps in the system
- If the program halts, the system state converges; the resulting variable values can be read in s

- For example, the *parity function* can be coded as corresponding to

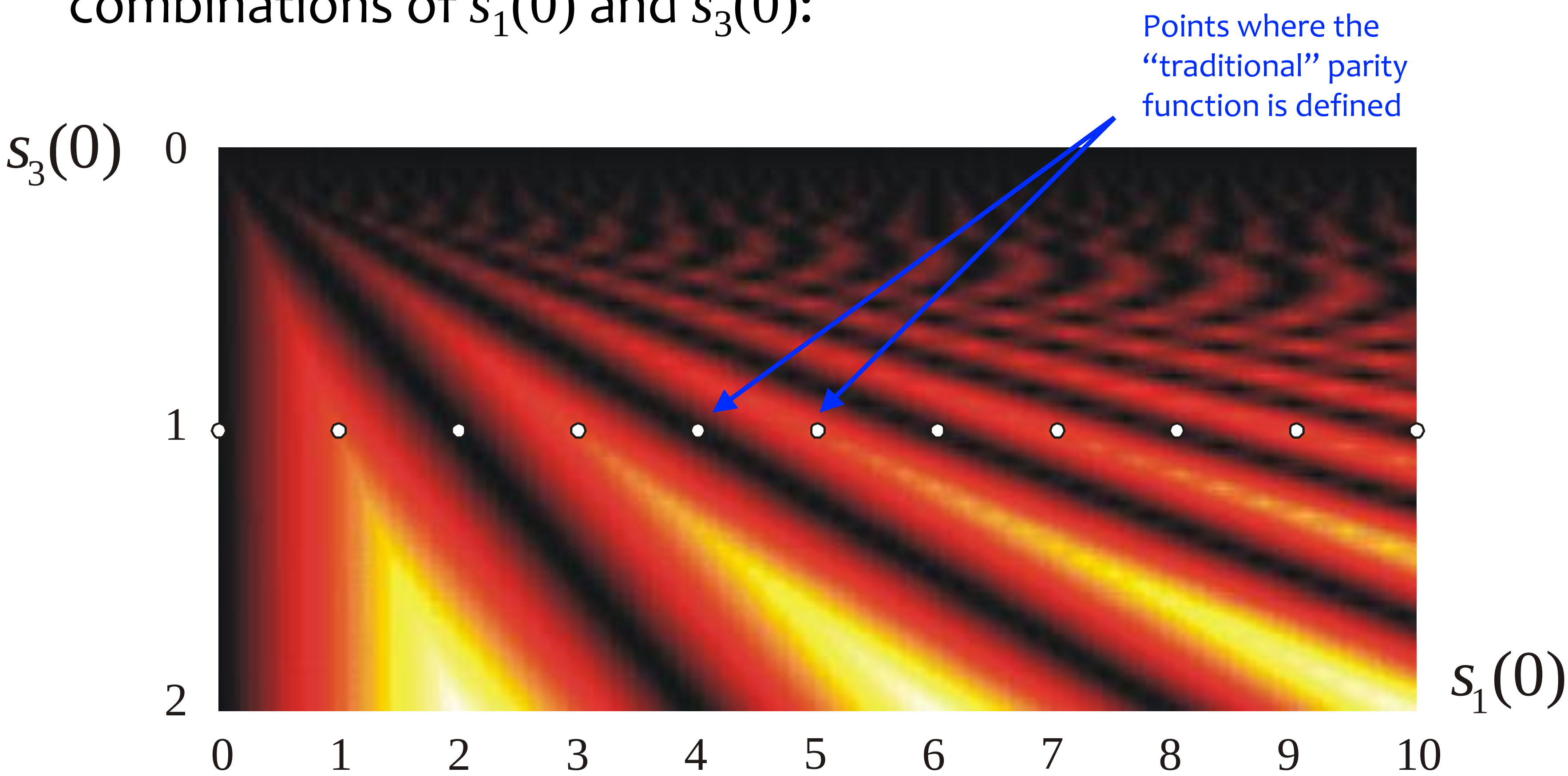
```
1   VAR X = x          input
2   VAR Y = 0          output
3   IF X > 0           entry point
    THEN X SUB 1 Y ADD 1 GOTO 6
    ELSE GOTO END
6   IF X > 0
    THEN X SUB 1 Y SUB 1 GOTO 3
    ELSE GOTO END
```

$$A_{\texttt{parity}} = \begin{pmatrix} + & & & - & + & & - & + \\ & + & & + & - & & - & + \\ & & & & & & + & - \\ & & + & & & & & \\ - & & + & & & & & \\ & & & + & - & & & \\ & & & & & + & & \\ - & & & & & + & & \end{pmatrix} \qquad s(0) = \begin{pmatrix} x \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}.$$

A compiler from program to system exists for Matlab

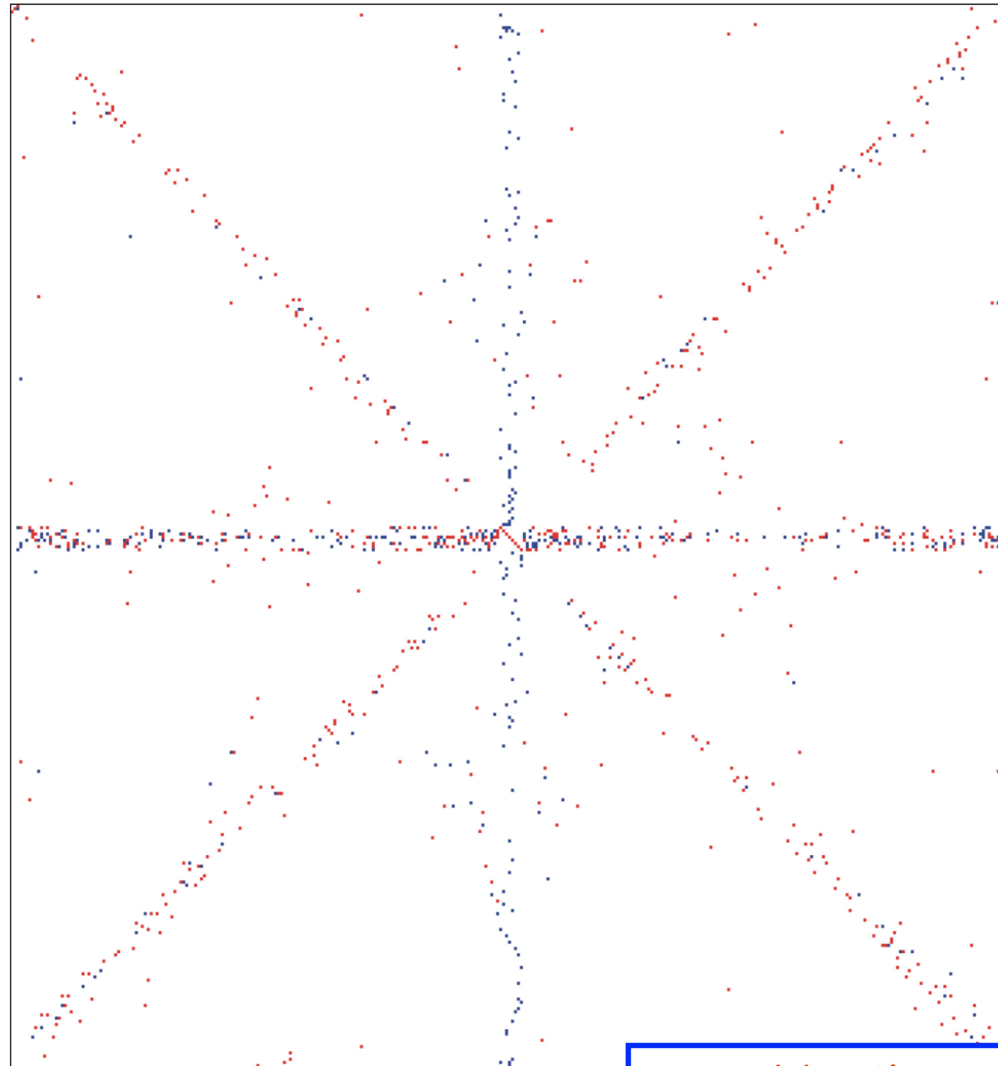
"Generalized parity function"

- Eventual steady state values of s_2 corresponding to different combinations of $s_1(0)$ and $s_3(0)$:



Universal machine implemented

- If the system is selected as shown here, there is no algorithm to say for all inputs $s(0)$ whether the system is stable ...

$A =$ 

- "If the algorithm claims that the iteration would remain bounded, it will not, and vice versa" ...!

Red dots 1's,
blue dots -1's,
other 0's

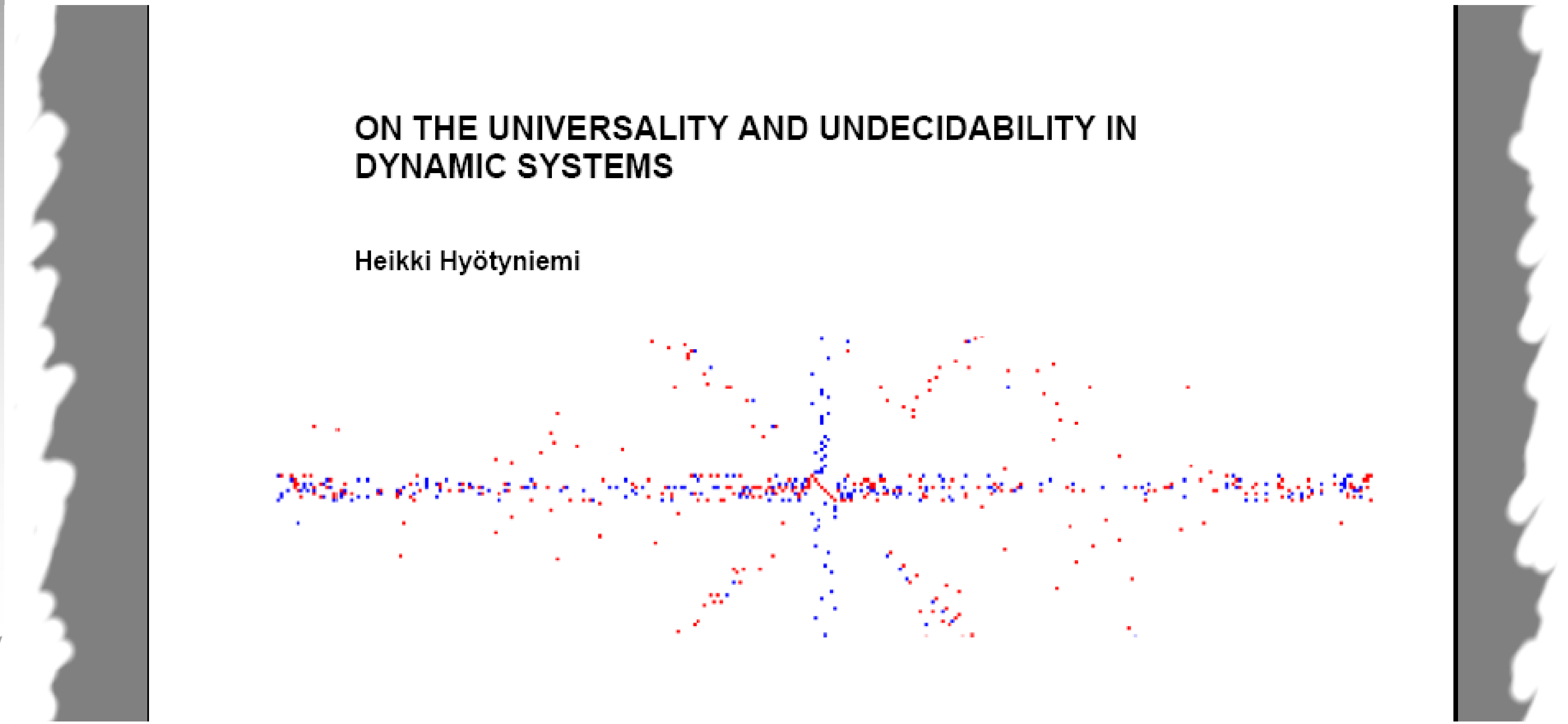
Universality and undecidability

- A nonlinear high-dimensional system can implement any imaginable algorithm
- Gödel's *incompleteness theorem* applies
- There will never exist a general theory of nonlinear systems!

- When searching for a general model structure for complex systems, only for (essentially) linear systems one has hope.

Report 133

- Illustrates the problems encountered in nonlinear systems



ON THE UNIVERSALITY AND UNDECIDABILITY IN DYNAMIC SYSTEMS

Heikki Hyötyniemi

http://neocybernetics.com/report133/

NEW

- This example also illustrated that infinity can be addressed in finite space
- It showed, too, that structured representations can be implemented through iteration with minor *a priori* complexity
- So, there is motivation for cybernetic approaches: *Loops (proper feedback) can do wonders*

- To what extent is the expressional power caused by the *nonlinearity*, and to what extent by the *dynamic nature* alone?!

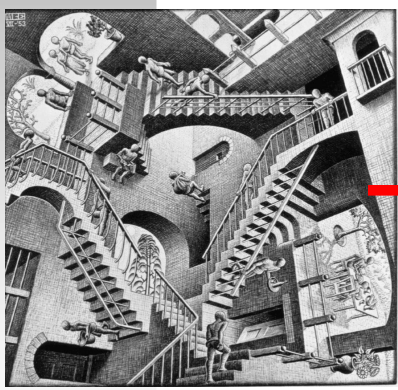
HELSINKI UNIVERSITY OF TECHNOLOGY
Department of Automation and Systems Technology
Cybernetics Group

Modeling strategy – applied next time

- Linear models are traditionally regarded as deficient, inferior, models for pragmatic uses – where does that come from?
  - The typical engineering-like route: Construct the model as exactly as possible, applying nonlinearities where appropriate
  - After that, locally linearize the model to boost applications; unfortunately, in this process the connections to the real system are lost
- Now: Again, apply first physical principles exactly, never going to approximations
  - The application domain must not include explicit nonlinearities! – Yes, there exist such complex domains
  - Modeling strategy to be followed: Avoid introducing nonlinearities if it is not *absolutely* necessary

Instead, apply understanding of dynamic systems and control + engineering intuitions about real life constraints and non-idealities

- Stairs to step deeper are now available?



Iterate after the course!