

Artificial Life and Swarm Intelligence

bottom-up modelling,
multi-agent simulations
and algorithms

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Artificial life

- What is life?
 1. Self-Reproduction
 2. Exchange of energy, substances and information with the environment
 3. Export of entropy
 4. Storage of information
 5. Reaction to environmental stimuli, homeostasis
 6. Growth of form (including patterns)
 7. Self-boundedness (every organism has a boundary)
 8. Adaptation

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What is self-organization?

- A system shows self-organisation if it tends towards achieving a higher level of order (by itself).
- This order-generating behavior has to come from within the system not from outside.
- It is the interactions between positive and negative feedback that achieves this system behavior.

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It is often the case in such systems

- ... that the single system components are rather simple (dumb)
- ... but together many of these components can solve complex problems
- ... self-organization works only if enough of such components are present. → 3 grains of sand will never form a dune, but 3 millions will do so

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What is order?

- More order → less entropy
- More order → less information content
- More order → higher compressability
- More order → higher predictability
- More order → less complexity

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Information theory was founded by C.E. Shannon.

Claude Elwood Shannon (April 30, 1916 – February 24, 2001) was an American mathematician, electronic engineer, and cryptographer known as "the father of information theory". Shannon is famous for having founded information theory with one landmark paper published in 1948. But he is also credited with founding both digital computer and digital circuit design theory in 1937, when, as a 21-year-old masters student at MIT, he wrote a thesis demonstrating that electrical application of Boolean algebra could construct and resolve any logical, numerical relationship. It has been claimed that this was the most important master's thesis of all time. Shannon contributed to the field of cryptanalysis during World War II and afterwards, including basic work on code breaking.



Claude Elwood Shannon (1916–2001)

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... but he also had humor

What did he want to express?

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He mixed arts, science and comedy

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But he was victim of the "Fall of A.I."

- Between the 60's and the late 80's the field of **Artificial Intelligence** (A.I.) was hyped a lot (raise of computers, cold war, ...)
- The consumed vast amounts of money.
- They claimed to produce thinking machines.
- Most work was based on logic & reasoning.
- They did not deliver at all.
- The became discredited in the 90's.
- This is known as "old-AI" or "classic AI".
- But: Neural networks & Genetic algorithms

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Overstatements

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The raise of the phoenix

- Since the mid of the 90's but gaining momentum after 2000 there emerged new fields.
- They are not based on logic & reasoning, they are based on self-organization, decentralization & parallelism:
 - Swarm intelligence, swarm robotics, evolutionary robotics, modular robotics, artificial immune systems, ...
- Look at google, amazon and others: They exploit the "wisdom of the crowd"

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New approaches

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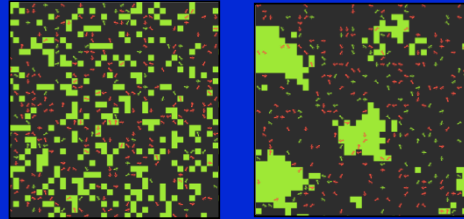
And there are many others ...

- Particle swarm optimization:
 - Inspired by the motion of flocks of birds
- Ant colony optimization algorithms:
 - Inspired by ant trails
- Beehive optimization algorithms
 - Inspired by honeybees
- Evolutionary computation:
 - Genetic Algorithms, Evolutionary Strategies, Genetic Programming
- Artificial Immune Systems:
 - Inspired by vertebrate immune cells
- Artificial Hormone Systems
 - Inspired by hormones and cell signals
- Artificial Neural Networks
 - Inspired by networks of neurons
- ... many more ...

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Back to the question: "What is order?"

- But: In our common-sense understanding it is absolutely the other way around:



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What is order?

- But: In our common-sense understanding it is absolutely the other way around:
- Compare these sequences of symbols:
 - A: "100100"
 - B: "100100100100100100100100100100"
 - C: "10010011110100"
- According to Shannon the information content is ranked like this: $A=B$ and $A,B < C$

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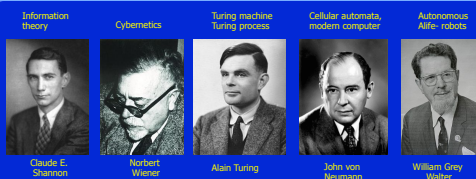
Some faces of Artificial life



And many, many more

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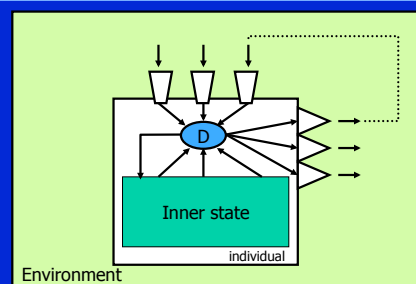
They build upon the work of these people



- Within 25 years 1940-1965, these people laid the foundation of Artificial Life, although they worked on real-world applications like inventing computers, rockets and weapons.
- Today's big names in Artificial life made their groundbreaking work based on the foundations these people have laid after WWII.

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How I see one individual



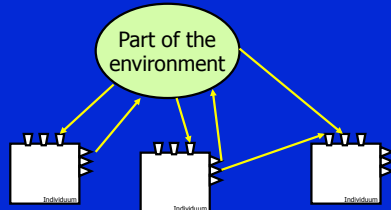
Decision making subsystem

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The role of the environment

The environment can act as:

- Information center
- Information filter
- Collective memory



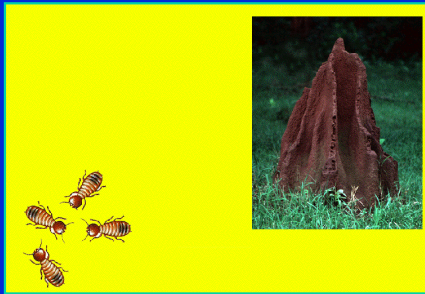
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It is often the case

- That the self-organizing process is running as a
 - distributed,
 - parallel & sequential
 - decentralized (no central control unit!) process !

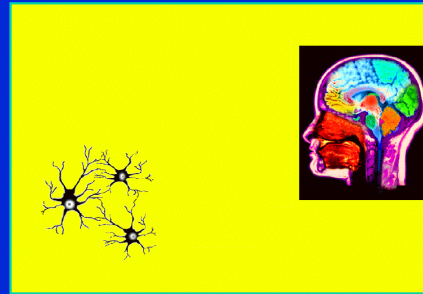
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The simple form the complex



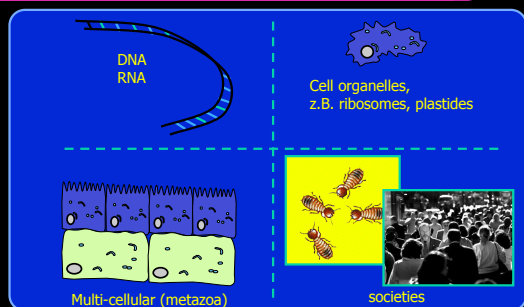
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The simple form the complex



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We see „levels of cooperation“:



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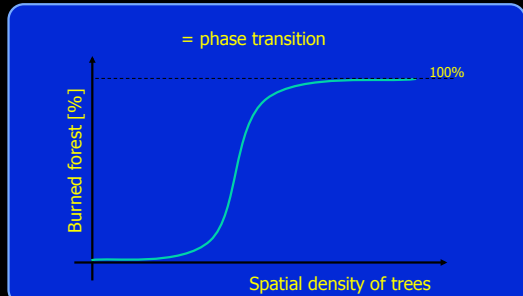
An evolutionary trend:

“[the cooperation of simple units to achieve higher functionality] ... is a major transition in evolution ... and happened several times ... [and always emerge very suddenly].” (E. Szathmari and J. Maynard-Smith)

- Genetic code (bases → info)
- Cell organelles (simple cells become complex ones)
- Metazoa (cells → organisms)
- Brain development (neurons → brain)
- Language (words/sounds → language)
- Society (people → society)
- Social insects (workers → colony)

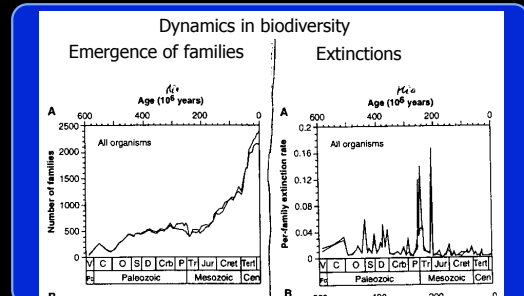
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Example for a phase transition



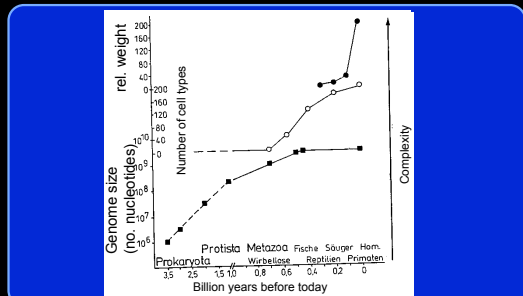
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Some interesting facts



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Some interesting facts



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This pattern is found frequently

- What is the „principle“ behind it?
- Is there a pattern of processes that favours such sudden phase transition?
- Can we make models that demonstrate this principle?

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Interesting study cases

- Birds, fish, insects form flocks, swarms, shoals:
 - Stay together
 - Avoid each other
- Many animals tend to aggregate at specific places
- Highly self-regulated insect colonies:
 - Building
 - Foraging for food
 - Process and share food
 - Inner climate of the colony, homeostasis
- Biological pattern formation
 - skin and fur patterns
 - Aggregation patterns of animals

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Other mechanisms of building order

- Something is ordered „by lead“:
 - A „pre-programmed recipe“ is executed which produces order. No feedback involved, that means the order does not adaptive to environmental changes.
 - „Blueprint“: An environmental, pre-given template is exploited. Again, non self-adaptive as there are no feedbacks involved. Blueprint can be even the own body shape.
- By „seed“: e.g.; flies aggregate where the cadaver lies in the desert.

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Emergence

- In philosophy, systems theory, science, and art, **emergence** is the way complex systems and patterns arise out of a multiplicity of relatively simple interactions.
- Emergence is central to the theories of integrative levels and of complex systems.
- The simple saying "**the whole is more than the sum of its parts**" is already referring to emergent properties. (Aristotle)
- Konrad Lorenz called it "**fulguration**".

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Strong emergence

Strong emergence says that if systems can have qualities not directly traceable to the system's components, but rather to how those components **interact**, and one is willing to accept that a system supervenes on its components, then it is difficult to account for an emergent property's cause. These new qualities are irreducible to the system's constituent parts. (Laughlin 2005) The whole is greater than the sum of its parts. This view of emergence is called strong emergence. Strong emergence is a view not widely held in the physical sciences but proposed as a philosophical theory of etiology, epistemology and ontology.

Source: wikipedia

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also

- **Macroscopic** observable phenomena cannot be fully explained by just looking at the **microscopic** mechanisms observed at the single component:
- Example:
 - Honeybee colony vs. Single bee
 - Brain vs. neuron cell
 - Snow-flake vs. H₂O molecule
 - ...



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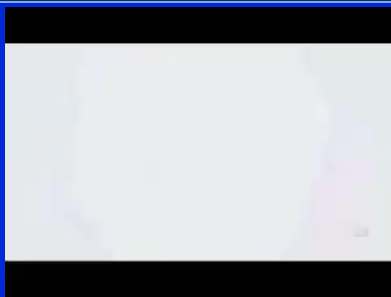
Weak emergence

A high-level phenomenon is **weakly emergent** with respect to a low-level domain when truths concerning that phenomenon are **unexpected** given the principles governing the low-level domain. **Weak emergence is the notion of emergence that is most common in recent scientific discussion** of emergence, and is the notion that is typically invoked by proponents of emergence in complex systems theory. (See Bedau 1997 for a nice discussion of the notion of weak emergence.)

Source: <http://consc.net/papers/granada.html>

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emergence movie part 1



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emergence movie part 2



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Examples of biological patterns

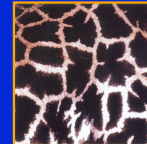
For every one of the following patterns there exists a model for explaining its emergence.

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Patterns in biology



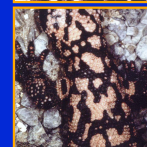
zebra



giraffe



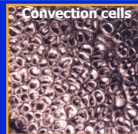
tiger



gila-monster

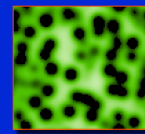
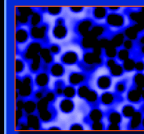
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Other patterns



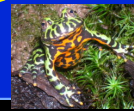
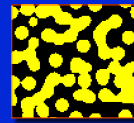
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An example of a model of biological pattern formation



Here:
A reaction-diffusion
model, AKA a
„Turing process“

...more of that kind
will follow later.



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Cellular automata
Monte-Carlo simulations
Multiagent models

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Alan Turing (1912-1954)

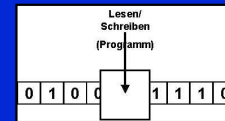
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Major breakthroughs:

- 1936: "Turing machine"
- in WW2: Code of the Enigma encryption machine broken
- 1950: The "Turing test"
- 1952: The "Turing process"

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The Turing-machine



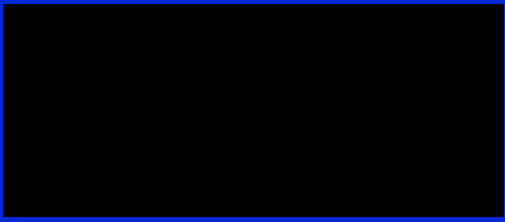
Answer:

- 1.) For each elementary mathematical operation one can invent a Turing machine..
- 2.) A Turing machine consists mainly of its rule table
- 3.) The outputs of one Turing machine can be the rule table of another, yet different Turing machine
- 4.) An endless number of Turing machines can result
- 5.) Thus the Turing machine is universal.

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A Turing-machine in action

- It was a hypothetical model that helped to invent today's computer. But:



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In parallel

- John von Neumann, who later invented our modern computer's architecture, investigated **cellular automata**.
- Such automata can be seen as a **set of interlinked Turing machines**.
- It seems like that Turing and von Neumann **did never personally meet**, although their ideas were quite similar.

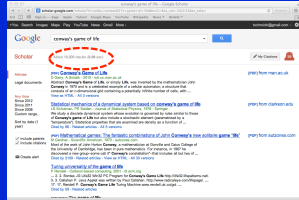


John von Neumann

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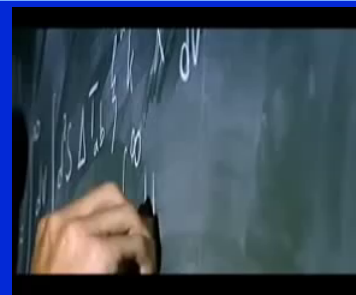
The game of life

- The world's most famous cellular automaton is the **"Game of life"** invented by John Horton Conway in 1970.



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Cellular automata



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An example: The Game Of Life

The simple rule set:

- Discrete grid-world that consists of cells
- Each cell can be either living (1) or dead (0)

Classical "Characters" to appear

+ many other creatures, including creatures that produce creatures that produce creatures ...

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This is the Emerging Behavior

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The rules are "fragile"

- Die only if 5 or more neighbors, other rules stay the same:

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This is a cellular automaton

Monte-Carlo simulations:

- Instead of fixed rules use probabilities
- Make these probabilities depend on the status of the local neighbors and/or of the cells own history.

In both ways, the space becomes often structured in some way.

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Cellular automaton

Grid

Neighborhood

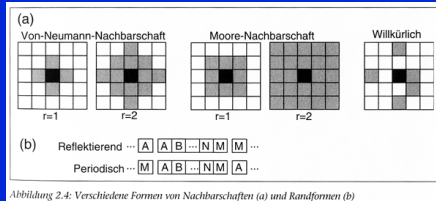
P

N

If Monte-Carlo:
Probability of the growth of a new cell depends on the local density of neighboring cells.

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Neighborhood types



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And in terms of mathematics:

Grid:

$$G = \{(i, j) \mid i, j \in N, 0 \leq i \leq n, 0 \leq j \leq n\}$$

Neighborhood:

$$N_{ij} = \{(k, l) \in G \mid (|k - i| \leq 1) \vee (|l - j| \leq 1)\}$$

States:

$$Z \in \{0, 1\}$$

Rules:

$$Z_{ij}(t+1) = \begin{cases} 1 & \text{if } \sum_{(k,l) \in N_{ij}} Z_{kl}(t) = 3 \\ 1 & \text{if } \sum_{(k,l) \in N_{ij}} Z_{kl}(t) = 4 \vee Z_{ij}(t) = 1 \\ 0 & \text{else} \end{cases}$$

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In Sociology

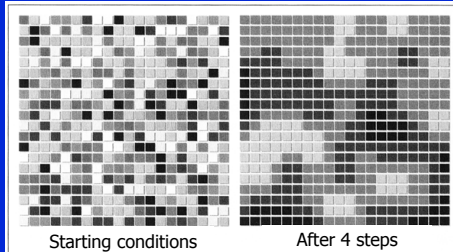
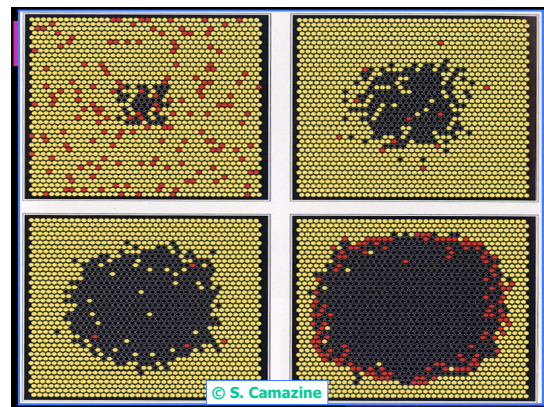


Abbildung 2.5: Zustände eines Modells zur Propagierung von Meinungen

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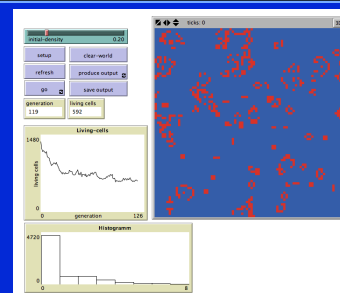


Summary

- **Cellular automata are very useful for:**
 - Models of localized events.
 - Model of systems in which „neighborhood“ is important.
 - For reducing complex processes down to simple mechanisms.
- **Monte-Carlo simulations:**
 - Are superior to other models as stochasticity is included and non-robust solutions (artefacts) are avoided.
 - Stochastic component is a surrogate for all factors that exist in reality but are excluded from being explicitly modelled.
 - Results are not so clear. Often statistics is needed.

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Let's do our own game of life



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Analysis 1

- It is often said that the game of life is a simple model of biological populations.
- Do you know ecological models that follow similar lines of thought?
- Compare the results you obtain with the GOL to the results of the "Verhulst model" of populations!

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Analysis 2

- Try to predict the density of cells at which populations should be stabilizing. Try to infer this "equilibrium density" from the rule set.
- Do your GOL results converge to these predicted population densities?

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Analysis 3

- Make a parameter sweep to analyze whether or not the result depends on the initial number of cells.

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More experiments (new automata)

- Find your own rule set. Try at to find at least 3 other interesting cellular automata by changing the rules in the model.
- Describe how the density of the population develops over time, like we did it check also for the original GOL model
- Does your models converge to your predicted population densities?

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MICRO-MACRO PROBLEM

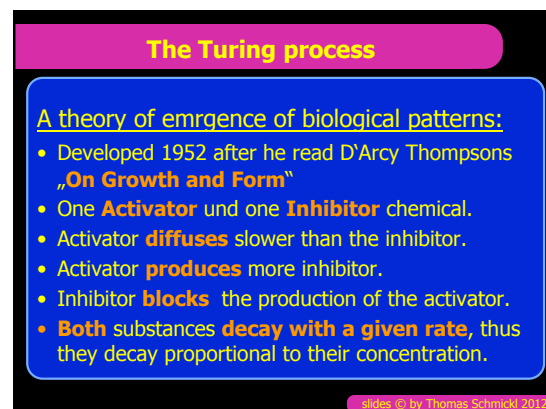
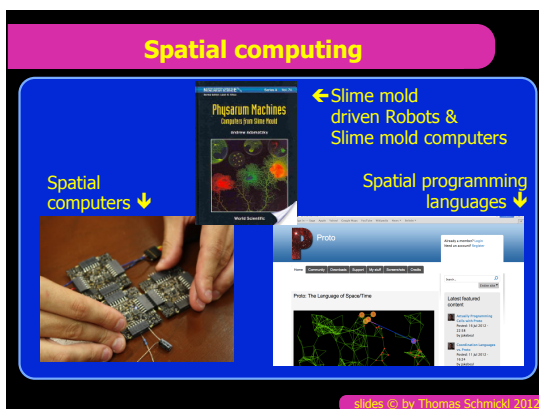
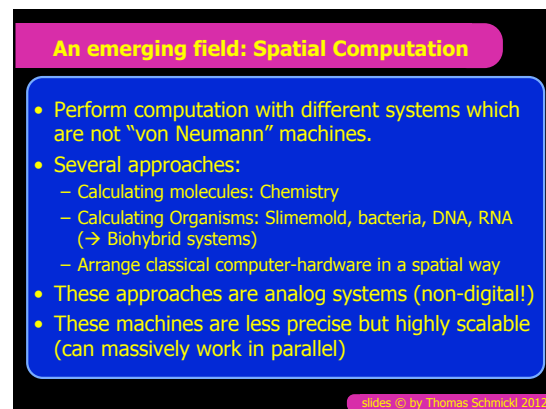
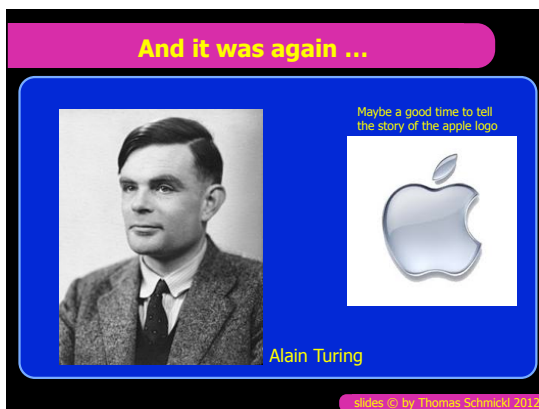
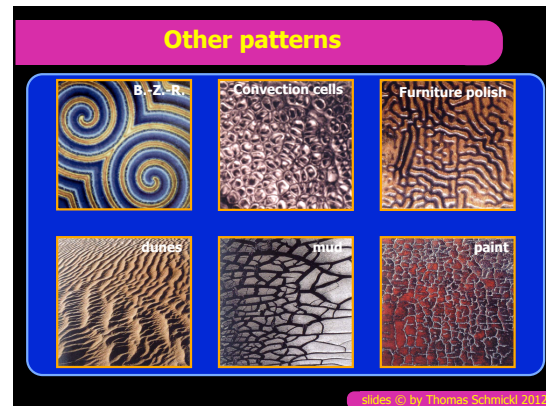
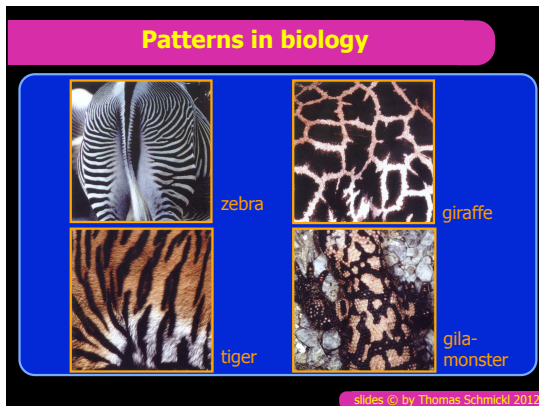
- Obviously the original rule set of the GOL is a very special one.
- Also other rules easily produce patterns but only in the GOL is it not possible to infer from the microscopic rules to macroscopic properties (like the equilibrium density).
- How does a model have to look like to capture these discrepancies?
 - Discuss mesoscopic models (hybrids of micro and macro), this is an example of strong emergence

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Other spatial patterns

- So far we had cellular automata that contained cells of only a few discrete steps.
- Neighbor interaction was also very simple.
- Now we go a step further:
 - Continuous states of every cell (chemical concentrations)
 - More complex non-linear interaction
 - Real diffusion process.

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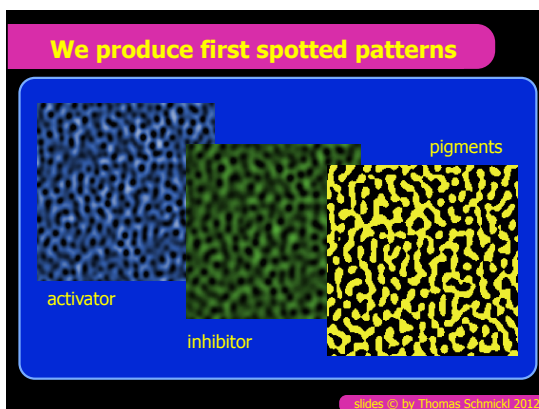
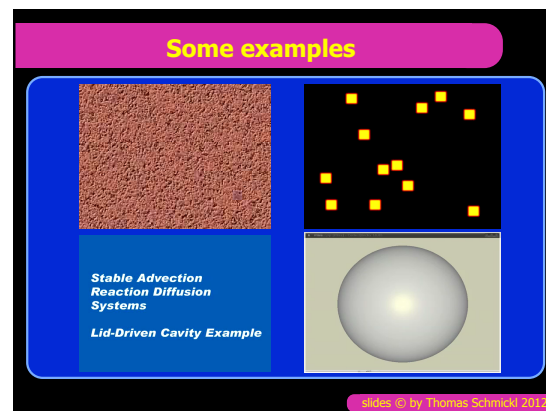
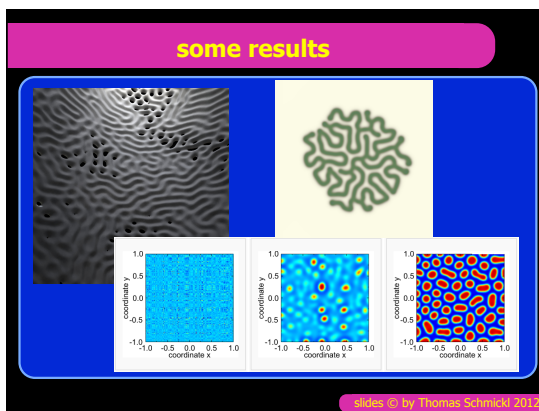
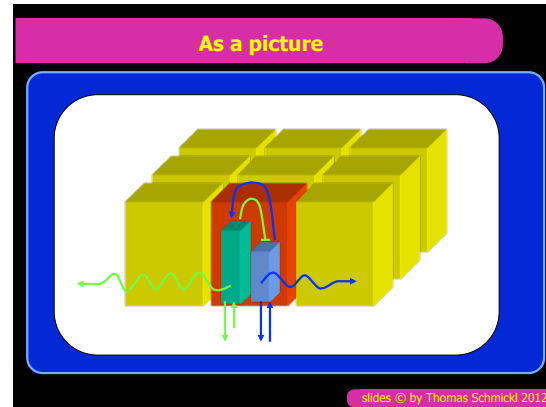
In mathematical terms

$$\frac{\partial A}{\partial t} = \frac{k_1 A^2}{H} - k_2 A + k_1 k_3 + D_A \frac{\partial^2}{\partial x^2} A$$

$$\frac{\partial H}{\partial t} = k_4 A^2 - k_5 H + k_6 + D_H \frac{\partial^2}{\partial x^2} H$$

$$k_1 \approx k_2 \approx k_5 ; k_6 \approx k_1 k_3 ; D_A < D_H ; k_4 \ll k_1$$

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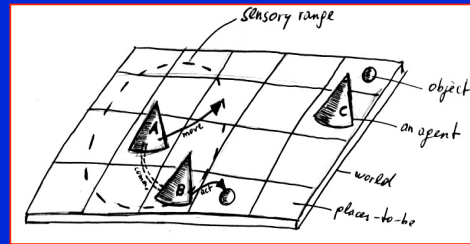


Next section

**Now we start with
mobile agents**

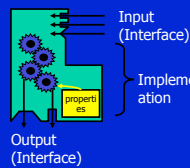
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One step further: „Agents“



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Agent



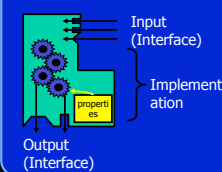
After J. Ferber 2001

- Situated
- Perception
- Decision
- Egoism & needs
- Own „will“
- Services
- Action is locally restricted
- Self-reproduction
- (local) communication

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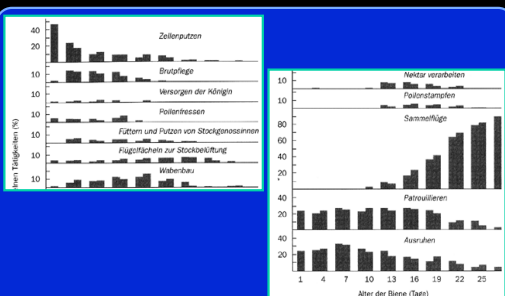
Polymorphism & inheritance

- Spaghetti code
- Functions (libraries)
- Object-oriented programming
- Agent-based systems



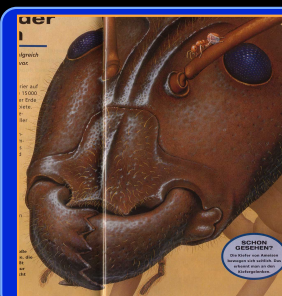
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Is similar in social insects in biology



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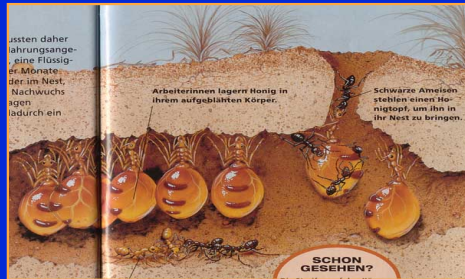
Division of labour & polymorphy



The biggest and the
smallest ant in
comparison

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specialization



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cooperation



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cooperation



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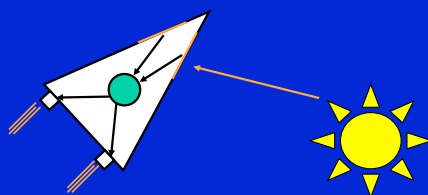
Agent types

- Situated/non-situated:
 - Is there „space“ playing a role in the system?
- Communicating/non-communicating.
- Sub-Cognitive architectures:
 - Reactive agents / reflex agents (with/without inner state)
 - Reactive planners
 - Utility-based agents
- Cognitive architectures:
 - BDI systems (Belief-Desire-Intention)

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Braitenberg vehicle (reaktive agent)

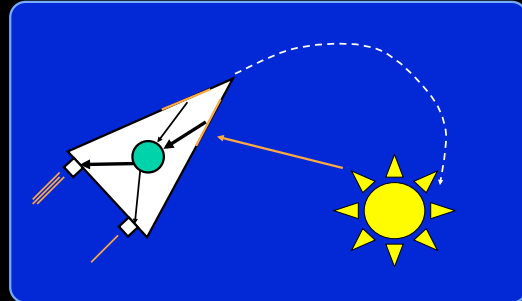
Valentino Braitenberg (1926-2011) was an Italian neuroscientist and cyberneticist. He was most famous for the book *Vehicles: Experiments in Synthetic Psychology*, in which he described how hypothetical analog vehicles (a combination of sensors, actuators and their interconnections), though simple in design, can exhibit behaviors akin to aggression, love, foresight and optimism.



Source: wikipedia

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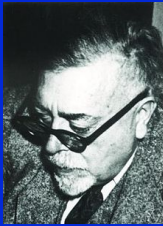
Braitenberg vehicle (reaktive agent)



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Early work was done 50 years ago

Cybernetics



Norbert Wiener

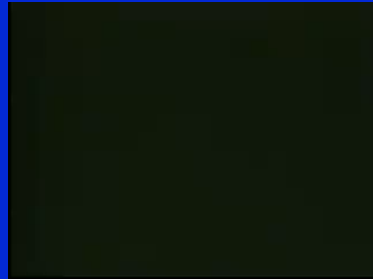
inspired →

Autonomous
Alife- robots

William Grey Walter

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Early work was done 50 years ago



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Next section

- Statistical interpretation of agents' properties (e.g., their motion).
- Statistical interpretation of the overall system's properties (e.g., the distribution of motion steps of all the agents that form the system).

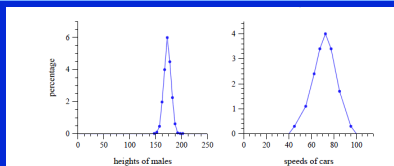
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Isometry Allometry

- **Allometry** is the study of the relationship of body size to shape, anatomy, physiology and finally behavior, first outlined by Otto Snell in 1892, D'Arcy Thompson in 1917 and Julian Huxley in 1932.
- **Allometry** is a well-known study, particularly in statistical shape analysis for its theoretical developments, as well as in biology for practical applications to the differential growth rates of the parts of a living organism's body.
- One application is in the study of various insect species (e.g., the Hercules Beetle), where a small change in overall body size can lead to an enormous and disproportionate increase in the dimensions of appendages such as legs, antennae, or horns. The relationship between the two measured quantities is often expressed as a power law:

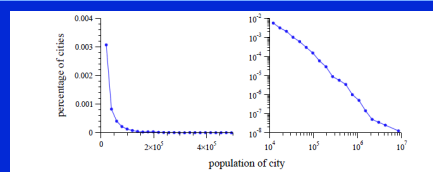
$$y = kx^a \text{ or in a logarithmic form: } \log y = a \log x + \log k$$

Normal distribution

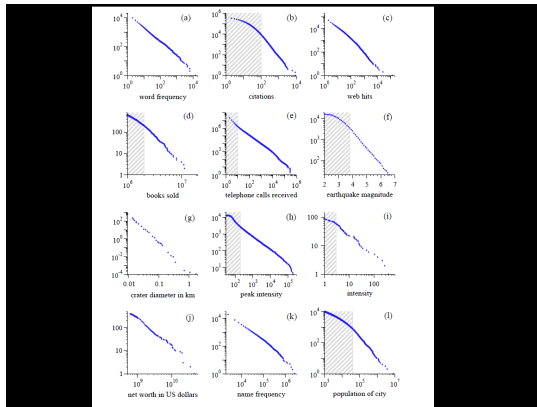


- Left: histogram of heights in centimeters of American males. Data from the National Health Examination Survey, 1959–1962 (US Department of Health and Human Services).
- Right: histogram of speeds in miles per hour of cars on UK motorways. Data from Transport Statistics 2003 (UK Department for Transport).

Distributions with long tails



- Left: histogram of the populations of all US cities with population of 10 000 or more. Right: another histogram of the same data, but plotted on logarithmic scales. The approximate straight-line form of the histogram in the right panel implies that the distribution follows a power law. Data from the 2000 US Census

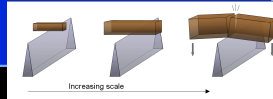


Why this is interesting?

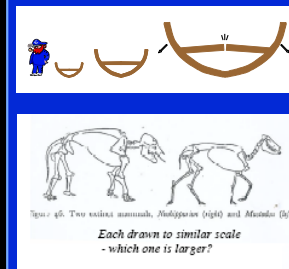
- One: Lot of very different things looks the same
- The same thing is behave differently if we study on a linear scale.

History

- The physicist Galileo Galilei (1564-1642) had the basic insight how natural phenomena behave differently on different scales.
- His observations were about mechanical structures, but he later extended his insights to living things.
- As we increase the size of the wooden plank isometrically, ultimately, it will break and collapse due to its own weight.



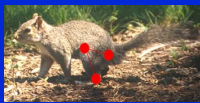
Physics and biology



- The same situation is found in ship building: a larger boat needs much thicker bracing
- Galileo's original drawing: larger animals need much thicker bones

How biology solve the physical problem?

- What we have here is nature's "design principle" for mainstream skeletons: all have evolved to have a safety factor of three to five while range of body size is about 25,000 folds.
- By changes in posture. Small mammals run with their limbs bent; large mammals always run with their limbs straight.
- By changes in behavior. Small mammals jump high up or jump down from high places. Large mammals do not jump



- Large mammals do not jump



<http://farhoom.lh.uchicago.edu/a/arp0757/>

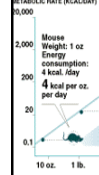
Scaling relates to metabolism

From the Small to the Huge

Three scientists have proposed a novel theory to explain how characteristics like body size and energy consumption differ from species to species along fixed scales. Their theory derives from analysis of the circulatory system.

An Example of Scaling:

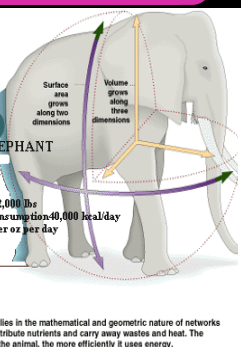
Metabolic Rate



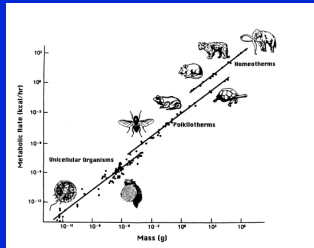
Size and Efficiency

The average elephant weighs 220,000 times as much as the average mouse, but requires only about 10,000 times as much energy in the form of food calories to sustain itself. The

reason lies in the mathematical and geometric nature of networks that distribute nutrients and carry away wastes and heat. The bigger the animal, the more efficiently it uses energy.



Metabolic rate seems to scale with mass fairly independently from other factors

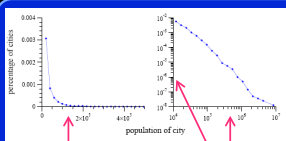


A log-log plot of metabolic rate versus body mass. Even though body mass undergoes a 21 order of magnitude difference, we see that the metabolic rate scales quite nicely with mass. (Reproduced from "Scaling in Biology", edited by Brown and West)

Doing the Math

- Quantitative means relating different variables
 - Involves variables x and y
 - Measuring different quantities that may be related
 - Like width and height, or volume and surface area
 - Involves parameters k, p (recall that a parameter is a constant whose value is not yet determined)
- Allometry corresponds to curves of the form $y = kx^p$
 - x and y are *allometrically related* if there are parameters k and p such that $y = kx^p$
 - Isometry occurs if the curve has a power of $p = 1$
 - Isometric means $y = kx$
 - Isometric means y is proportional to x

Log-Log plots



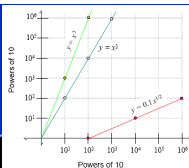
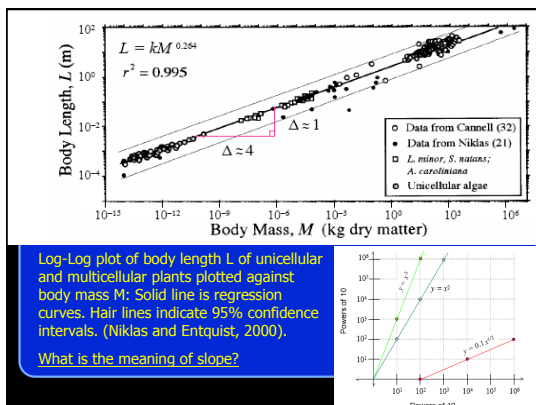
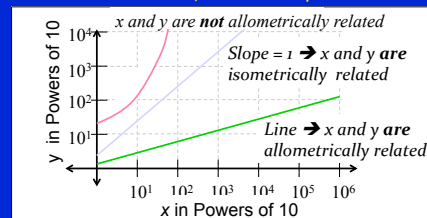
Normal Units

Both axes are marked off in powers of 10!!

- Left: histogram of the populations of all US cities with population of 10 000 or more.
- Right: another histogram of the same data, but plotted on logarithmic scales.
- The approximate straight-line form of the histogram in the right panel implies that the distribution follows a power law. Data from the 2000 US Census.

Seeing the Math

- Log-Log plots (Log = logarithm)
 - Use powers of 10 (or some other number) on axes
 - Lines are *allometries*; Line with slope=1 is *isometry*



$$y = kx^p$$

Quarter rule:

- the exponent, p , takes on a limited set of values, which are typically simple multiples of $1/4$.
- Examples that obey these simple quarter-power allometric scaling laws (usually with respect to mass M) are nearly all biological rates, times, and dimensions ($p=$):
 - metabolic rate ($3/4$)
 - Lifespan ($1/4$),
 - growth rate ($-1/4$),
 - heart rate ($-1/4$),
 - DNA nucleotide substitution rate ($-1/4$),
 - lengths of aortas ($1/4$),
 - heights of trees ($1/4$),

Metabolic rate dictated by surface area. Rubner (1883)

- **Body temperature is related to body size**
- **Heat loss takes place at the surface**

For geometrically similar structures
Volume, $V = s^3 V_0$
Area, $A = s^2 A_0$
 which in turn implies that $s = (V/V_0)^{1/3}$ and consequently that

$$A = \left(\frac{V}{V_0} \right)^{2/3} A_0 = \frac{A_0}{V_0^{2/3}} V^{2/3} \quad A \propto V^{2/3} \propto M^{2/3}$$

Small animals have a higher surface to volume ratio.

- Must produce heat that is lost to surface to maintain a constant temp.
- Small animals should have a higher mass specific metabolic rate to make up for constraints of Euclidean geometry (lost heat due to increased surface area)



Brody 1945: Bioenergetics and Growth

Was Rubner correct? - surface area?

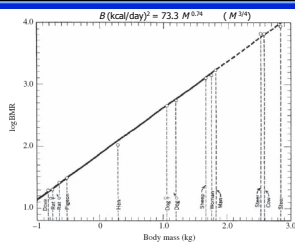
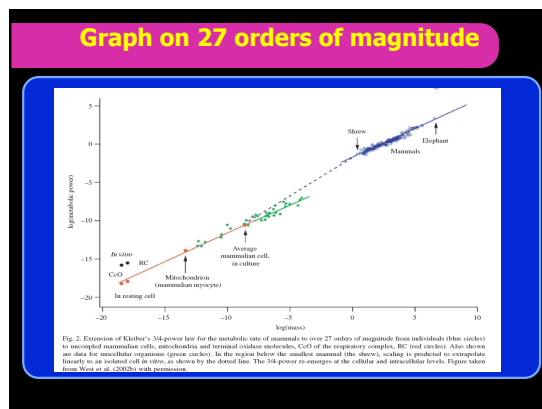
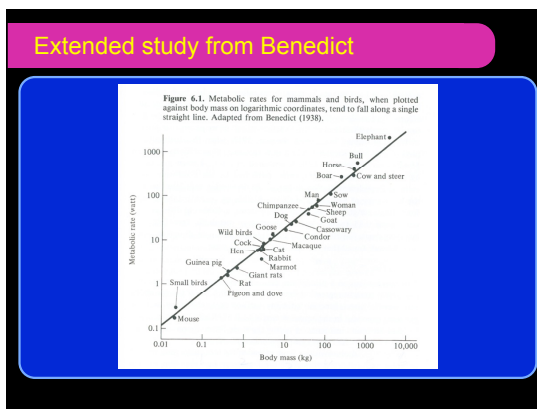


Fig. 1. Kleiber's original 1932 plot of the basal metabolic rate of mammals and birds (in kcal/day) plotted against mass (M , in kg) on a log-log scale (Kleiber, 1975). The slope of the best straight-line fit is 0.74, illustrating the scaling of metabolic rate as $M^{0.74}$. The diameters of the circles represent his estimated errors of 10% in the data.

- The best-known of these scaling laws is for basal metabolic rate, which was first shown by Kleiber (1932) to scale approximately as $M^{3/4}$ for mammals and birds
- Subsequent researchers showed that whole-organism metabolic rates also scale as $M^{3/4}$ in nearly all organisms, including animals (endotherms and ectotherms, vertebrates and invertebrates; Peters, 1986), plants (Niklas, 1994), unicellular microbes and even intracellular levels (mitochondria).



What about other attributes of organismal structure and function???

During the 1950s -> 1980 much accumulation of allometric information.

Numerous attributes of organismal structure and function scale with body size. Peters (1983) compiled much information

Exponents are not all 3/4 but are instead unique

and some are paradoxical

Some examples

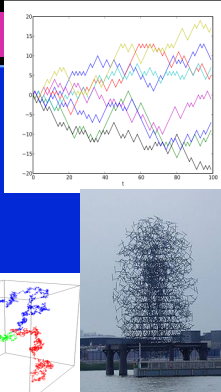
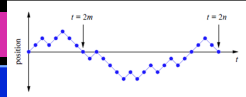
Some examples of allometric laws:

- Kleiber's law, metabolic rate q_0 is proportional to body mass M raised to the $3/4$ power:
 $q_0 \sim M^{3/4}$
- breathing and heart rate f are both proportional to body mass M raised to the $1/4$ power:
 $f \sim M^{1/4}$
- mass transfer contact area A and body mass M :
 $A \sim M^{2/3}$
- the proportionality between the optimal cruising speed V_{opt} of flying bodies (insects, birds, airplanes) and body mass M raised to the power $1/6$:
 $V_{opt} \sim 30 \cdot M^{1/6} [m \cdot s^{-1}]$

Random walk

- The term random walk was first introduced by Karl Pearson in 1905.
- A random walk is a mathematical formalization of a path that consists of a succession of random steps.
- For example, the path traced by a molecule as it travels in a liquid or a gas, the search path of a foraging animal, the price of a fluctuating stock and the financial status of a gambler can all be modeled as random walks, although they may not be truly random in reality.

<http://lab.infotech.monash.edu.au/simulations/swarms/random-walk/demo/>

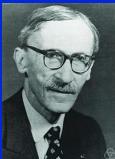



- Many properties of random walks are distributed according to power laws, and this could explain some power-law distributions observed in nature. In particular, a randomly fluctuating process that undergoes "gambler's ruin", that ends when it hits zero, has a power-law distribution of possible lifetimes.
- Consider a random walk in one dimension, in which a walker takes a single step randomly one way or the other along a line in each unit of time. Suppose the walker starts at position 0 on the line and let us ask what the probability is that the walker returns to position 0 for the first time at time t (i.e., after exactly t steps). This is the so-called first return time of the walk and represents the lifetime of a gambler's ruin process.

- As an example application, the random walk can be considered a simple model for the lifetime of biological taxa. A taxon is a branch of the evolutionary tree, a group of species all descended by repeated speciation from a common ancestor.
- If a taxon gains and loses species at random over time, then the number of species performs a random walk, the taxon becoming extinct when the number of species reaches zero for the first (and only) time. (This is one example of "gambler's ruin".) Thus the time for which taxa live should have the same distribution as the first return times of random walks.
- In fact, it has been argued that the distribution of the lifetimes of genera in the fossil record does indeed follow a power law. The best fits to the available fossil data put the value of the exponent at $\alpha = 1.7 \pm 0.3$, which is in agreement with the simple random walk model.

Special "random walk"

- A **Lévy flight** is a random walk in which the step-lengths have a probability distribution that is heavy-tailed. When defined as a walk in a space of dimension greater than one, the steps made are in isotropic random directions. The name "Lévy flight" refers to the French mathematician Paul Pierre Lévy.



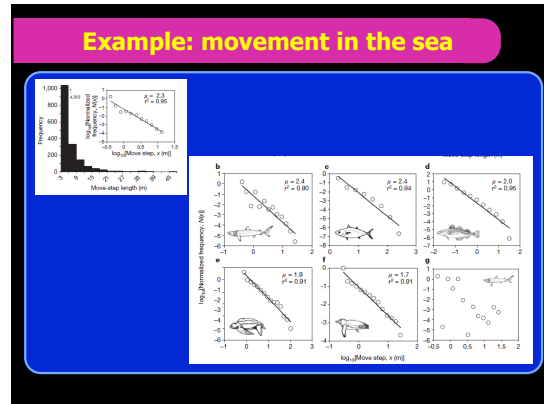
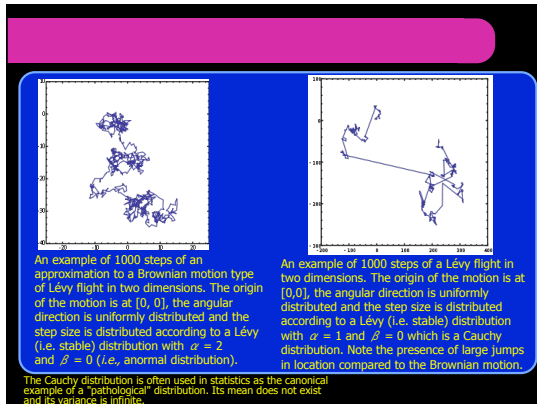
Paul Pierre Lévy

Levy did not give the name

- The term "Lévy flight" was coined by Benoît Mandelbrot, who used this for one specific definition of the distribution of step sizes.
- He used the term **Cauchy flight** for the case where the distribution of step sizes is a Cauchy distribution, and **Rayleigh flight** for when the distribution is a normal distribution (which is not an example of a heavy-tailed probability distribution).
- Later researchers have extended the use of the term "Lévy flight" to include cases where the random walk takes place on a discrete grid rather than on a continuous space

- A Lévy flight is a random walk in which the steps are defined in terms of the step-lengths, which have a certain probability distribution, with the directions of the steps being isotropic and random.
- The particular case for which Mandelbrot used the term "Lévy flight" is defined by the survivor function (commonly known as the survival function) of the distribution of step-sizes, U , being

$$\Pr(U > u) = \begin{cases} 1 & : u < 1 \\ u^{-D} & : u \geq 1 \end{cases}$$
 where D is a parameter related to the fractal dimension and the distribution is a particular case of the Pareto distribution. Later researchers allow the distribution of step sizes to be any distribution for which the survival function has a power-like tail.



Levy walks / Levy flights

Science

AAAS

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Several variants of "Random walk"

- In nature, Brownian motion is important.
 - Thermodynamics, chemistry, biology: diffusion, reaction rates, ...
- Pure random walk:
 - Agent can rotate in any direction with the same probability. Leads to wiggling around, like in Brownian motion.
- Correlated random walk:
 - Agent turns $\pm X$ degrees from current heading.
- Walks with straight-motion phases:
 - Not turn in every time step, just sometimes.
- Levy walk:
 - unequal distribution of long and short straight walks.
- In discrete space often: Jump to random neighbor patches

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Practical work

- Let's do some Netlogo models of random walks

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Your tasks:

- Implement step-by-step several variants of random walk:
 - Brownian motion without collision detection
 - Correlated random walk w/o coll. detect.
 - Correlated random walk with coll. detect.
 - Correlated random walk with collision avoidance
 - Levy walk

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Schwarm intelligence

What is „Intelligence“
and what is
„Swarm-Intelligence“?

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Intelligence

Intelligence: in latin: intellegere = 'understanding', but by the two words 'inter' and 'legere' it means to „lay something in between“, maybe „read between the lines“.

- It is a scientific term in psychology for the cognitive abilities of humans.
- no clear well-accepted definition.
- Intelligence tests are very much criticized as they very often favour people with specific background
- My personal working definition: „Intelligence is the ability to solve problems in ways that were unknown before.“

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Swarm intelligence

Swarm intelligence is:

Ability to solve a problem **collectively**:

- The path to solutions have to be **flexible**.
- solutions should be **robust**.
- Individuals should be „**simple**“.
- The swarm should **scale** well. Thus: The bigger the swarm, the better it should work (within bounds)
- There is a **critical minimum density**.
- It is often an **emergent** phenomenon observed.
- The problems are solved **without a global decision making component (no boss)**.

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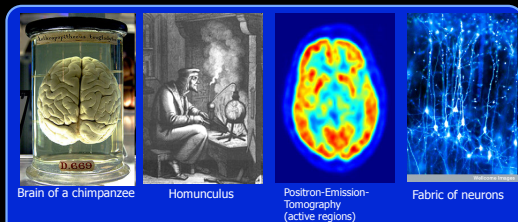
Swarm intelligence

Swarm intelligence in nature:

- social insects
- naked mole rats.
- non-social insects (e.g., fireflies).
- Humans, dolphins, ...
- Fish (schoaling)
- Birds (flocks)
- Sheep, cattle, chicken (herds)

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Intelligence+ Cognition



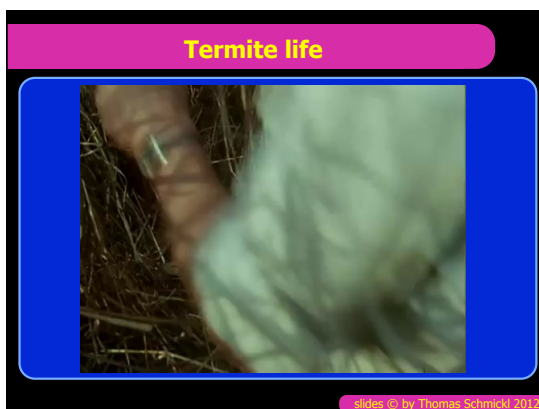
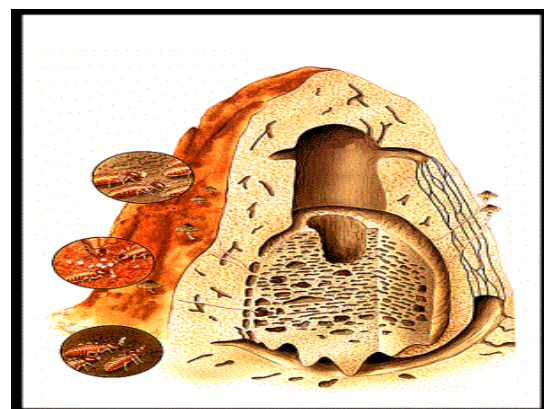
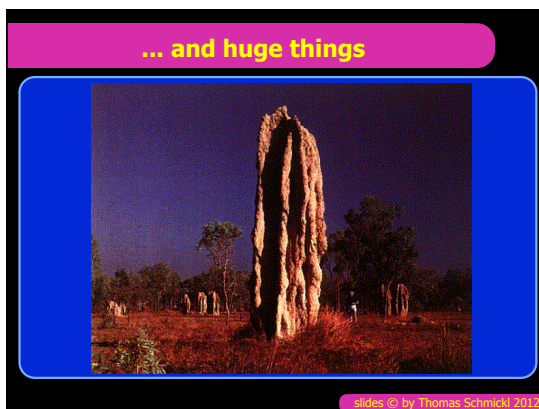
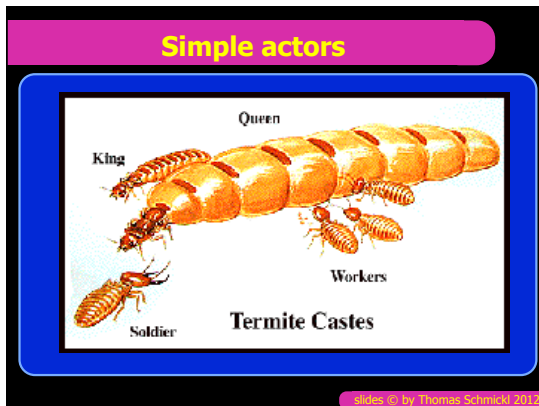
- How does the brain produce cognition and self-awareness?
- Could this also be an **emergent phenomenon**?

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Building by termites

Some models of collective intelligence
(over the course of the examples,
the collective gets smarter and smarter)

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They tend to self-organize



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They tend to self-organize



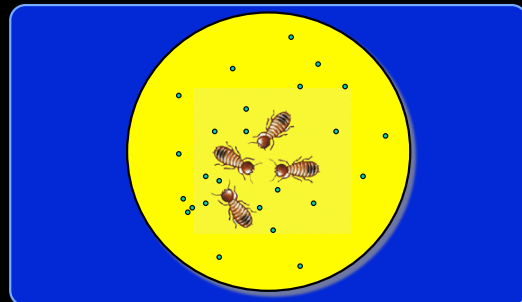
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But we skip this for the moment

- We will investigate models of such pheromone trails later, when we will model ants.
- Thus we consider their motion so far to be almost random motion.
- But they show other ways of interacting which we will consider in our next model.

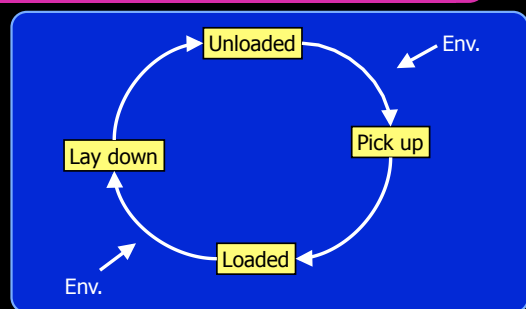
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a laboratory experiment



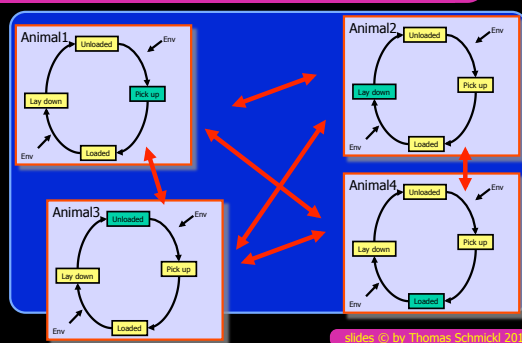
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Termite behavior as finite state machine



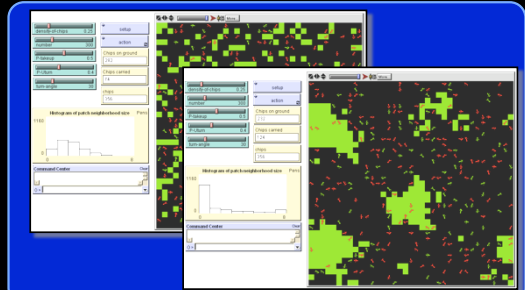
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Many of such machines



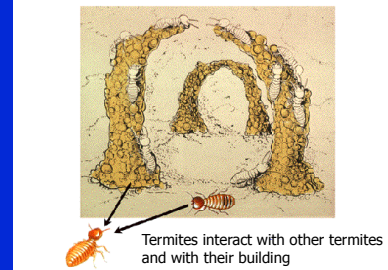
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Resulting behavior



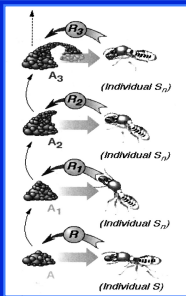
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Where is the plan?



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Stigmergy



„Stigmergy“ means that the product/result of a behavior is triggering or modulating another behavior..

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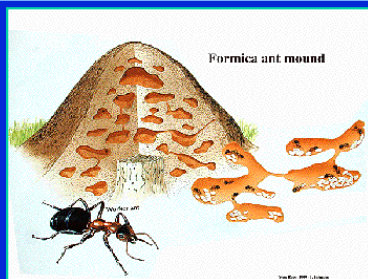
Steps of self organization

- 1.) **Random** work, because there is nowhere a strong stimulus (e.g., random walk).
- 2.) Amplification of these random inhomogeneities through a **positive** feedback.
- 3.) Focussing work/channelization of work by „**stigmergy**“.
- 4.) **Negative** feedback stabilizes the achieved work.



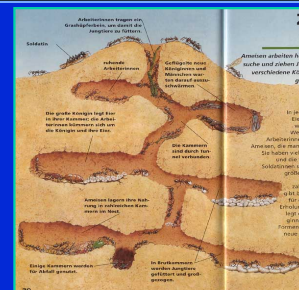
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Building by ants: similar



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They often carve material out instead of piling it up.



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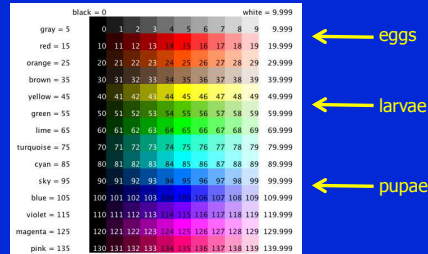
Further modeling steps:

- In similar ways, ants often organize their brood, their food and their cemeteries.
- Similar things become sorted together
- Often humidity and temperature are used as templates in this process.

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We color code our brood stages

- Now, the "chips" became "brood items"



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New stochastic rules

- The better an item locally fits:

- The lower is the probability of pick-up
- The higher is the probability of drop-down

If all neighboring patches are empty:
 $local_similarity_i = 0$
 else:

$$local_similarity_i = \frac{1}{s^2} \sum_{j \in \text{neigh}(s_i)} 1 - \frac{|color_i - color_j|}{\alpha}$$

$$P_{take}_i = \left(\frac{k_1}{k_1 + local_similarity_i} \right)^2$$

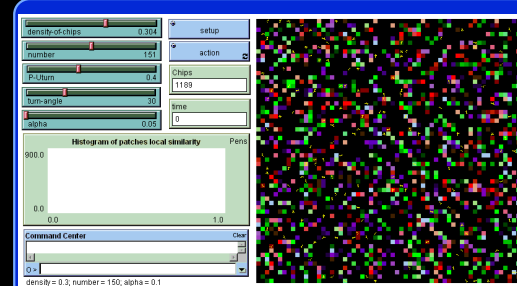
$$P_{drop}_i = \begin{cases} 2 \cdot local_similarity_i, & \text{if } local_similarity_i < k_2 \\ 1, & \text{if } local_similarity_i \geq k_2 \end{cases}$$

$$k_1 = 0.15, k_2 = 0.3$$

Images from: Swarm Intelligence: From Natural to Artificial Systems by
 Eric Bonabeau, Marco Dorigo and Guy Theraulaz. (1999)

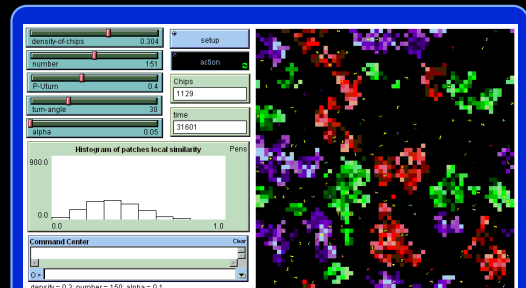
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From randomness



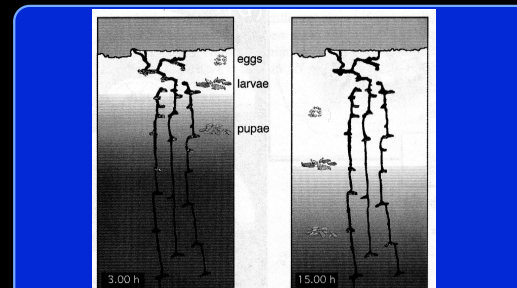
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To orderedness



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Environmental templates

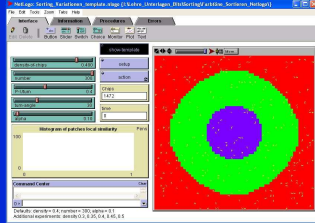


Images from: Swarm Intelligence: From Natural to Artificial Systems by
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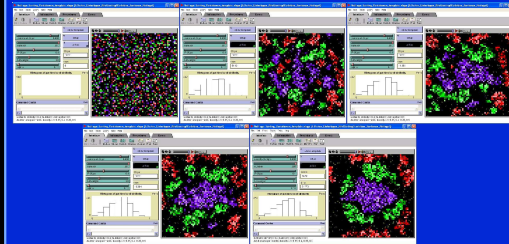
Type-specific sorting

- Change the probability of dropping/pick-up of these types of items:



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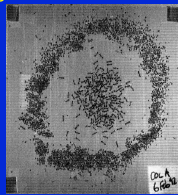
Type specific sorting



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"Centralized" but still self-organized building

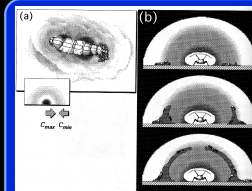
- In many colonies the queen's diffusing pheromones provide a centralized template.
- The building itself is still self-organized.



Images From: Swarm Intelligence: From Natural to Artificial Systems by Eric Bonabeau, Marco Dorigo and Guy Theraulaz. (1999)

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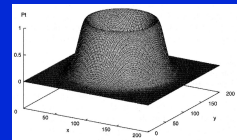
Pheromone gradients



Queen chamber:
The building is constructed around the queen's body. It is automatically adapted when the queen grows.

Leptothorax ants:

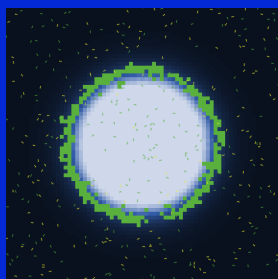
Also here the queen sits in the center and emits a radial pheromone gradient field.



Images From: Swarm Intelligence: From Natural to Artificial Systems by Eric Bonabeau, Marco Dorigo and Guy Theraulaz. (1999)

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The resulting chamber



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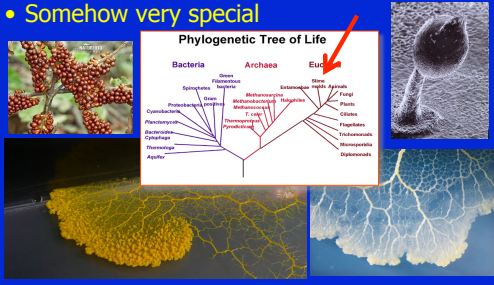
Slime mold

Models of collective intelligence

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Slime molds

- Somehow very special



Phylogenetic Tree of Life

The tree shows three main domains: Bacteria, Archaea, and Eukarya. A red arrow points to the Eukarya domain. Various groups are listed under each domain, including Eukaryotes, Plants, Fungi, and others.

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Slime mold amoebae aggregate



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Some more impressions of this aggregation



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7 phases of this process

The "swarm" of 100,000 amoebas shows:

1. Random walk
2. Aggregation
3. Nested Trails
4. A rotating spiralic cycle
5. A „snail like“ creature/colony emerges
6. This "snail" moves and reacts
7. Reassembly to a fruiting body (plant like)

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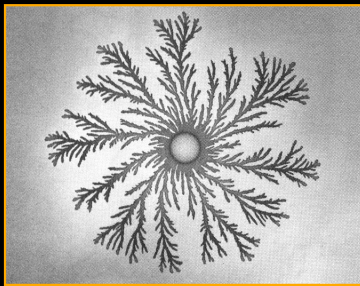
Spiral waves

- Looking through "optical density microscope":



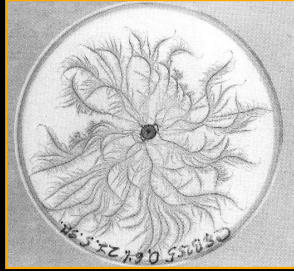
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Schleimpilze und Bakterien bei der Aggregation



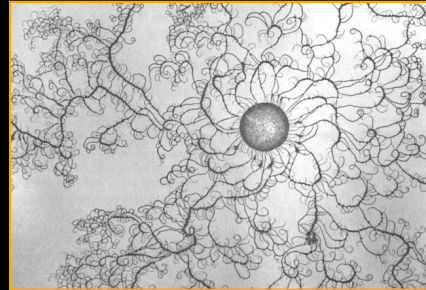
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Schleimpilze und Bakterien bei der Aggregation



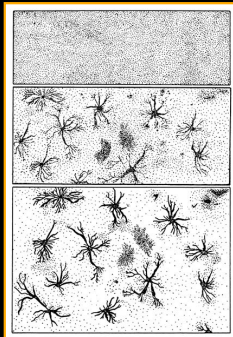
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Schleimpilze und Bakterien bei der Aggregation



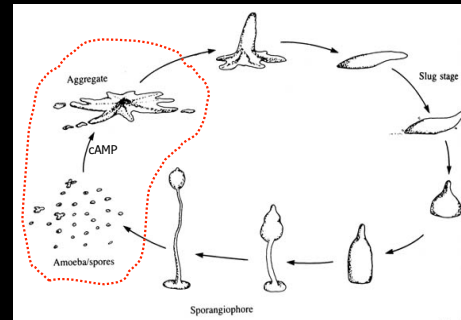
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Ziel: Ein Modell



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The life cycle of „dictyostelium discoideum“



Step 1: Random walk

- Amoebas change their orientation randomly.

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Step 2: A chemical signal is excreted

- Each amoeba emits a small portion of a chemical substance to the outside environment: cAMP
- This substance diffuses and decays
→ a gradient emerges
- Amoebas tend to move uphill in this gradient: positive chemotaxis

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Step 2: random walk & cAMP emission

- We only emit the chemical so far
- We change the model so that the chemical gradient is shown, and see: lines!

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Step 3: add diffusion & decay

- Now the chemicals should reach an upper boundary (due to decay) and spread in the environment (due to diffusion)

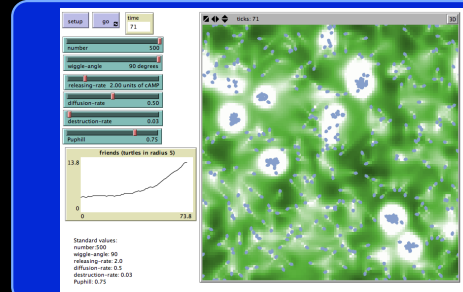
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Step 4: add uphill motion

- We add phototaxis and the amoebas should move uphill and thus aggregate.
→ More amoebas → more cAMP → steeper gradient → attracts even more amoebas → leads to even more cAMP → ...
- This is a behavioural positive feedback!
- But look: That works really badly
- Find a numeric metric that expresses the quality of the collective aggregation.
- Investigate how uphill-motion perfectness affects the global performance!

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This is what you should finally get



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Metrics

- Why is a metric so important?
 - In the termite model we were satisfied after the final spatial pattern of "chips" resembled qualitatively natural observations.
 - But qualitatively is nice but is not enough.
 - We cannot compare/express the effect of parameter changes without a numerical (quantitative) metric.
 - A quantitative metric can work on the individual level or on the collective level.
 - The collective metrics are often hard to define, as they have to compare the results of behaviors of many agents over many time steps into one single number.

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Now let's try to model the spirals

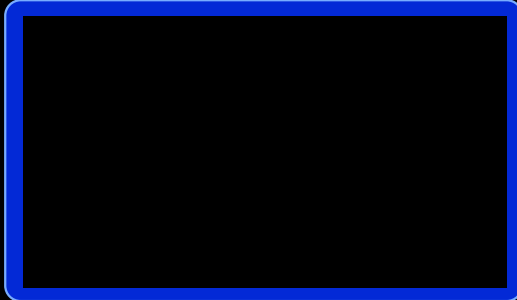


Belousov-Zhabotinsky reaktion

- 2 chemical substances are a mixed.
- The interact and show a change of their colour (= reaction)
- After such a color-change they are in a refractory period for some time (they do not react anymore), after that they can react again with the other chemical.
- Result: **circular and spirelic waves**

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Movie of the B.Z. reaction



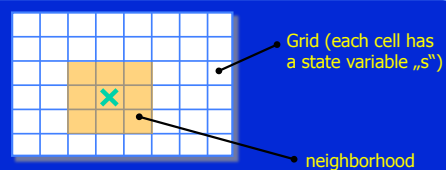
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Movie of the BZ reaction



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B.-Z. reaktion as a cellular automaton

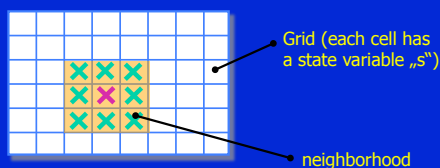


Rules:

- If one neighbor is active and focal cell is reactive ($s=0$) -> then the focal cell becomes also active ($s=10$)
- Then be refractory -> (decrement $s \rightarrow 9,8,\dots,1$)
- Then be reactive again ($s=0$)

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B.-Z. reaktion as a cellular automaton

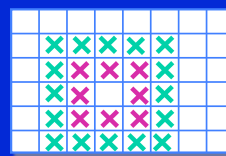


Rules:

- If one neighbor is active and focal cell is reactive ($s=0$) -> then the focal cell becomes also active ($s=10$)
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- Then be reactive again ($s=0$)

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B.-Z. reaktion as a cellular automaton

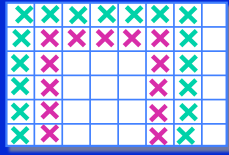


Rules:

- If one neighbor is active and focal cell is reactive ($s=0$) -> then the focal cell becomes also active ($s=10$)
- Then be refractory -> (decrement $s \rightarrow 9,8,\dots,1$)
- Then be reactive again ($s=0$)

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B.-Z. reaction as a cellular automaton



Rules:

- If one neighbor is active and focal cell is reactive ($s=0$) $\rightarrow$ then the focal cell becomes also active ($s=10$)
- Then be refractory $\rightarrow$ (decrement $s \rightarrow 9, 8, \dots, 1$)
- Then be reactive again ($s=0$)

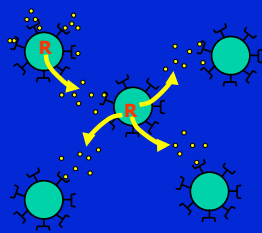
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Also the slime mold reacts similar:

- Whenever an amoeba senses a very high concentration of cAMP in its local environment (**triggering threshold**), then the amoeba is reacting with a sudden high emission of cAMP. $\rightarrow$ This is a **pulsed positive feedback!**
- As the amoeba has spent here cAMP, it becomes insensitive for some time (**refractory period**).
- The amoeba takes up cAMP from the environment.
- This process is noisy: **spiral waves**.
- The centers of such waves are very stable and attract more and more amoebas. This way the system establishes its own self-organizing coordinate system.

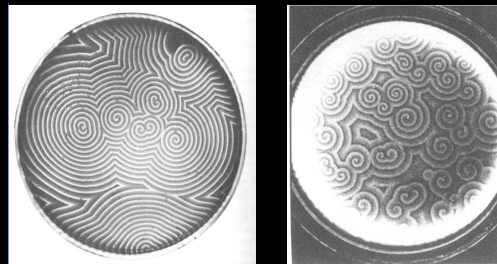
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Chain reaction



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Comparison of B.Z. reaction and slime mold spiral waves



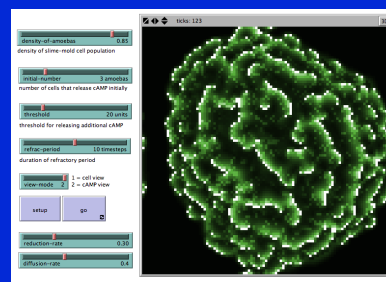
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Why did we choose a cellular automaton approach?

- Amoebas move much slower than the spread of the wave.
- Thus the amoebas can be assumed to be stationary.
- „keep it simple“ approach!

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This is how it should look like



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Analysis

- Generate your own metric!
- It should tell you whether or not the signal reaches all (or enough) amoebas in case that some amoebas start the process.
- Note: The process should only start if the local density of the amoebas is high.
- No "false starts" because of some few crazy guys.
- Analyze: Is this signal a "honest signal", that is can the swarm rely on the fact that the spirals emerge and everyone gets triggered?

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Now we have 2 different models

- In one model we see the aggregation.
- In the other we see the spiral waves.

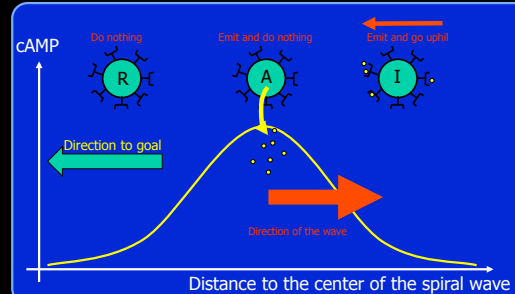
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Let's combine these two models

- Amoebas react with a pulsed emission of CAMP like in the second model (spiral waves).
- Amoebas move uphill in the gradient like in the first model (aggregation).
- Amoebas that are refractory do nothing: no walk, no emission, nothing.
- Not-emitting amoebas walk either not or move randomly.

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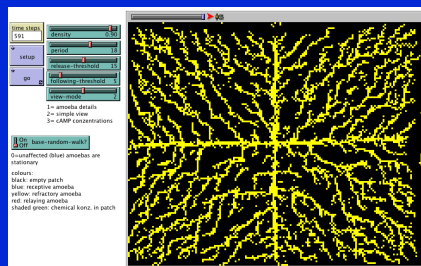
Here is the trick:



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This is how it looks like

http://zool33.uni-graz.at/schmickl/models/slimemold_moving.html



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Conclusions

- None of the simple models could predict the global behavior alone.
- Each model showed only specific aspects of the overall system.
- We had to fuse the modelled subsystems to observe the expected global behavior. It came from the interplay between these subsystems.
- → This is emergence!

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But the slime mold is even capable of more complex and intelligent things:

- Some (much bigger) slime mold species can form tubes that connect food stocks.
- They do it in a smart way, finding the shortest distance between these food places.
- This way they solve mazes, solve "Steiner trees" & "travelling salesman problems".
- Computer science found that these problems are NP hard, thus among the toughest problems to solve.

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Connecting points in a smart way

- Optimizing transportation networks in a self-organizing process:

Rules for Biologically Inspired Adaptive Network Design

Atsushi Tera,^{1,2} Seiji Takagi,¹ Tetsu Saigusa,² Rintaro Ito,² Dan P. Bebber,⁴ Mark D. Fricker,⁴ Kenji Yamaki,^{1,2} Ryo Kobayashi,^{2,4} Toshiyuki Nakagaki^{1,2,4}

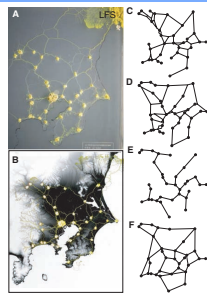
Transport networks are ubiquitous in both social and biological systems. Robust network performance involves a complex trade-off involving cost, transport efficiency, and fault tolerance. Biological networks have been honed by many cycles of evolutionary selection pressure and are likely to yield reasonable solutions to such combinatorial optimization problems. Furthermore, they develop without centralized control and may represent a readily scalable solution for growing networks in general. We show that the slime mold *Physarum polycephalum* forms networks with comparable efficiency, fault tolerance, and cost to those of real-world infrastructure networks—in this case, the Tokyo rail system. The core mechanisms needed for adaptive network formation can be captured in a biologically inspired mathematical model that may be useful to guide network construction in other domains.

www.sciencemag.org SCIENCE VOL 327 22 JANUARY 2010

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Connecting points in a smart way

Fig. 2. Comparison of the *Physarum* networks with the Tokyo rail network. (A) In the absence of illumination, the *Physarum* network resulted from even exploration of the available space. (B) Geographical constraints were imposed on the developing *Physarum* network by means of an illumination mask to restrict growth to more shaded areas corresponding to low-altitude regions. The ocean and inland lakes were also given strong illumination to prevent growth. (C and D) The resulting network (C) was compared with the rail network in the Tokyo area (D). (E and F) The minimum spanning tree (MST) connecting the same set of city nodes (E) and a model network constructed by adding additional links to the MST (F).



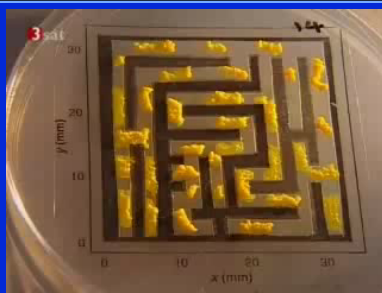
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Network growth



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Solving the maze



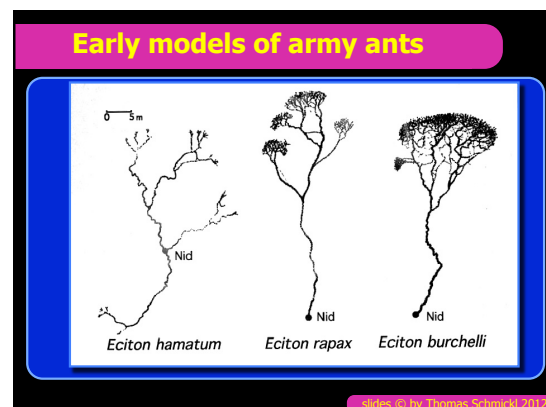
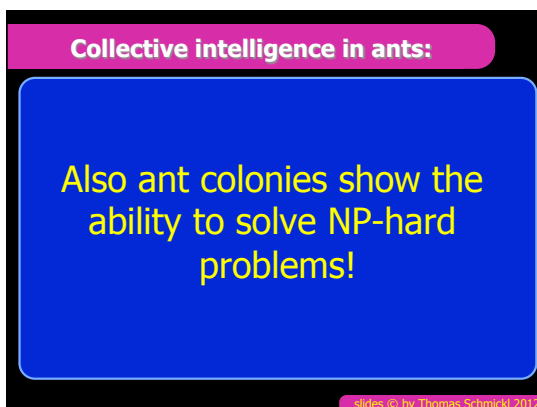
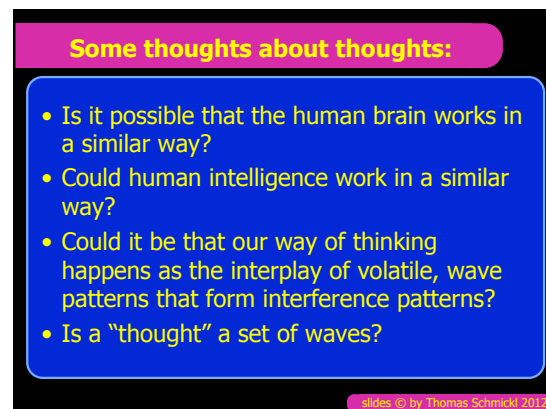
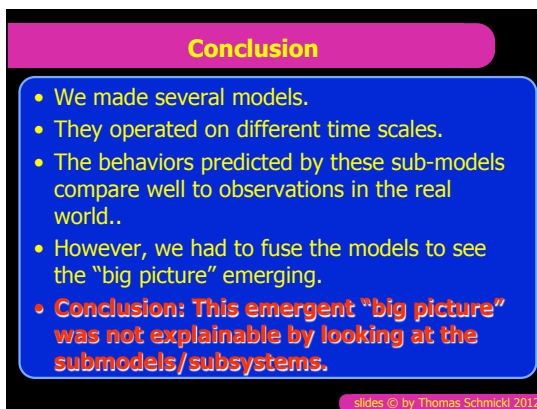
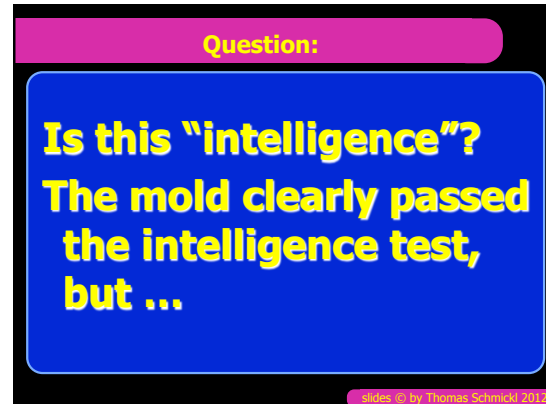
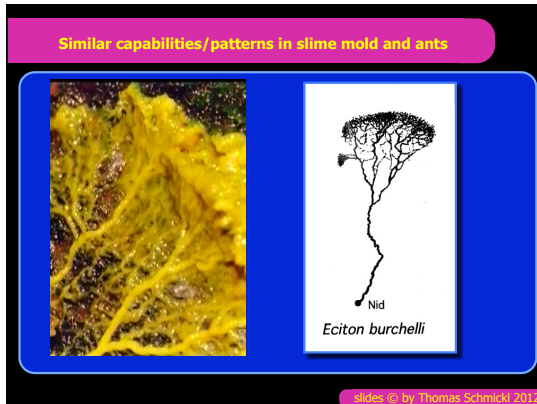
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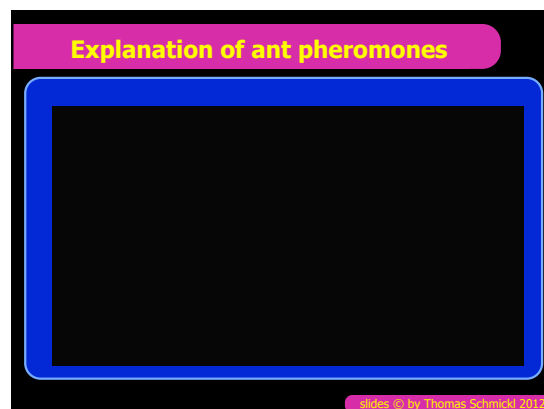
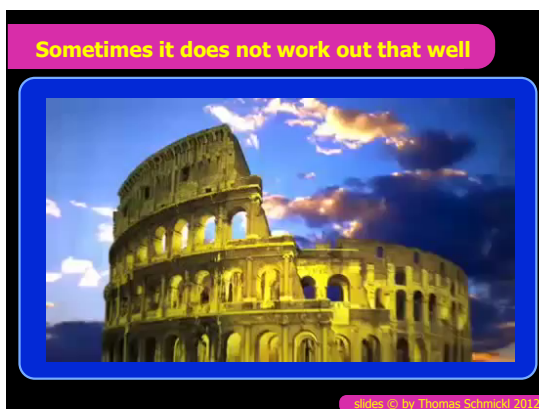
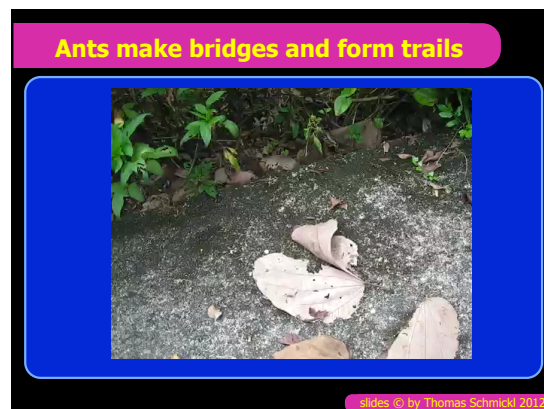
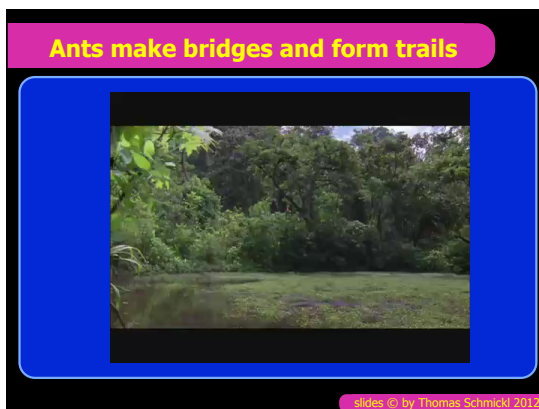
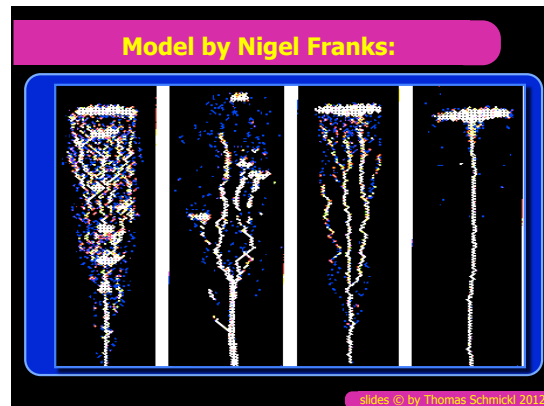
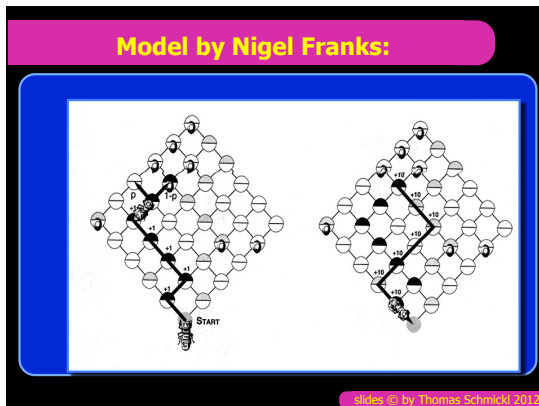
Solving a maze (think about it!)



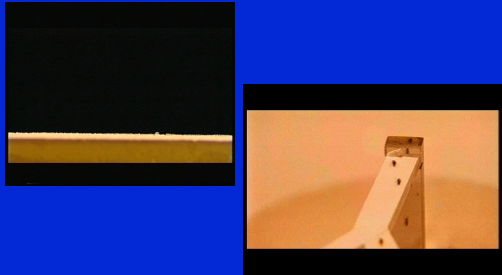
Is this a fair comparison?

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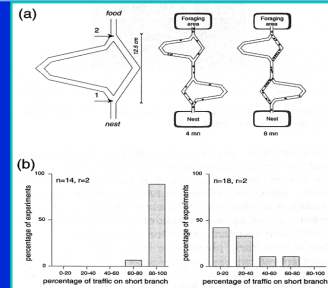


Movies of ground-breaking experiments



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Double bridge experiments



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A simple model derived:

$$P_A = \frac{(k + A_i)^n}{(k + A_i)^n + (k + B_i)^n} = 1 - P_B$$

A_i, B_i : Numbers of ants on branches after i ants in total
 n : degree of non-linearity
 k : degree of attraction of an unmarked branch

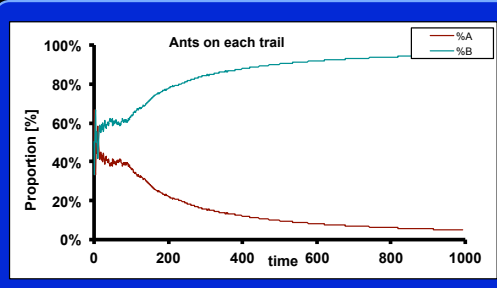
$$A_{i+1} = \begin{cases} A_i + 1 & \text{...if } \delta \leq P_A; \\ A_i & \text{...if } \delta > P_A; \end{cases}$$

$$B_{i+1} = \begin{cases} B_i + 1 & \text{...if } \delta > P_B; \\ B_i & \text{...if } \delta \leq P_B; \end{cases}$$

δ = uniform random number between 1 and 0
 $A_i + B_i = 1$

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See EXCEL simulation of this model



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Assumptions of our next model step:

- Each naive ant moves randomly (exploration).
- If food was found she moves back to the nest (directly) and lays down pheromones.
- If an unloaded ant finds such pheromones she will follow it.
- The shorter the path is, the more often ants will follow it up and down (pos. feedback)
- Too much pheromones prevent the chemotaxis (neg. feedback)

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Ant trails will emerge



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Analysis:

- Ants could exploit the food sources in parallel or in a serial way.
- Create a numerical metric that allows to discriminate these strategies.
- Ideally it should scale between 0 and 1, or between 0% and 100%
- You should be able to describe the extremes of your metric!
- Pick one parameter and investigate its effect on the ants' strategy by using your metric.

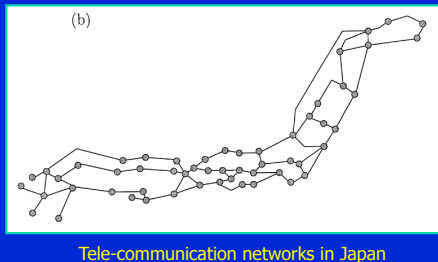
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Ant colony optimization:



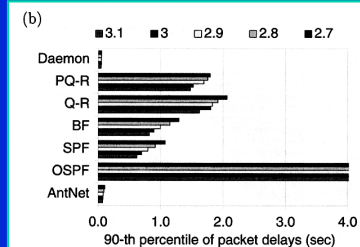
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Successful application of ant-derived algorithms



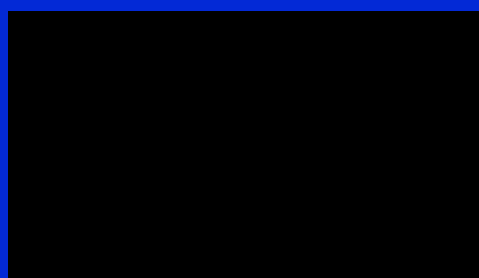
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Successful application of ant-derived algorithms



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Ant robots



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Decision making in other animals:

- Honeybees are the world champions in choosing their foraging targets.
- They operate in a changing environment.
- They choose the energetically most profitable food source.
- They cannot lay down pheromone trails because they fly to their food.
- They are able to revert decisions.
- Most sophisticated collective decision making system that is known (dance language)

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The honeybee dance language

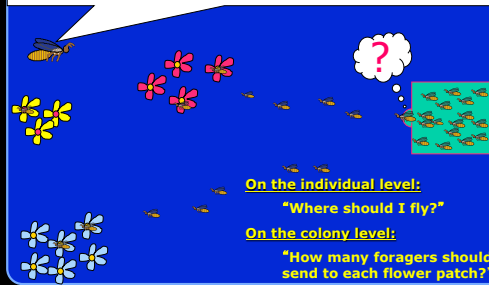
- Points other bees to the food-source (vector)
- Motivates other bees to forage for nectar.

- Motivates other bees to work as nectar storer.
- Demotivates bees to become a forager.

... and there are many more dances !

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Hmm, what does he mean by “foraging decision”?



On the individual level:

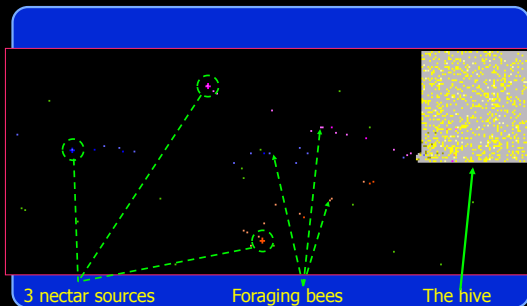
“Where should I fly?”

On the colony level:

"How many foragers should we send to each flower patch?"

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The simulation HoFo(Re)Sim



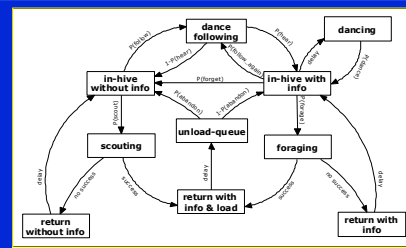
3 nectar sources

Foraging bees

The hive

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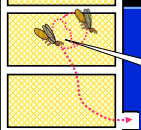
Possible states of agents (bees)



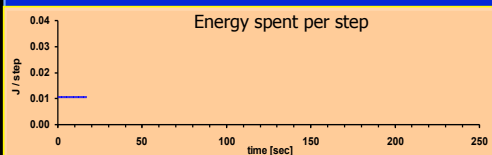
- Each bee is in a behavioral state and behaves corresponding to it.
- State transitions are induced by: threshold curves, events or fixed delays

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Energy spent for foraging

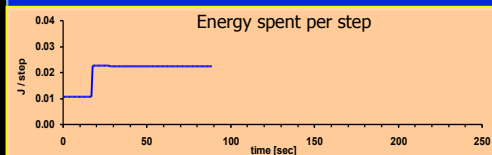
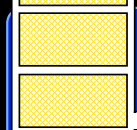


O.k., let's go ...

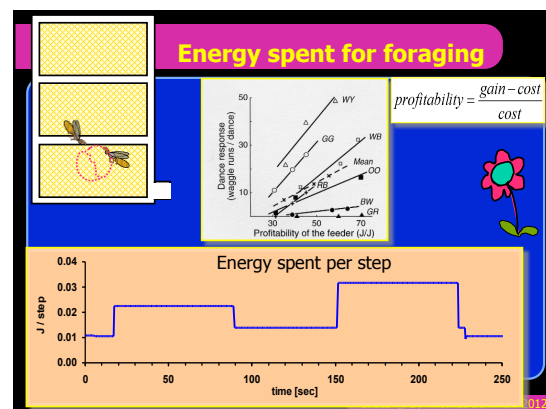
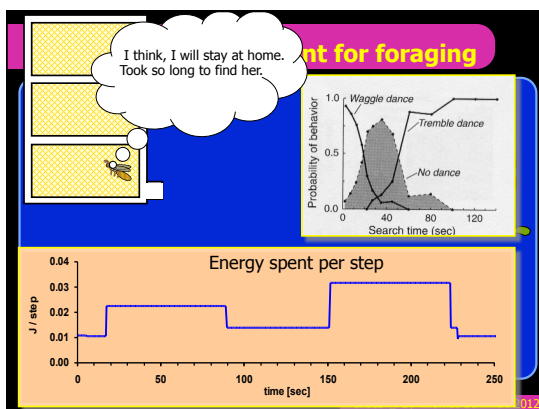
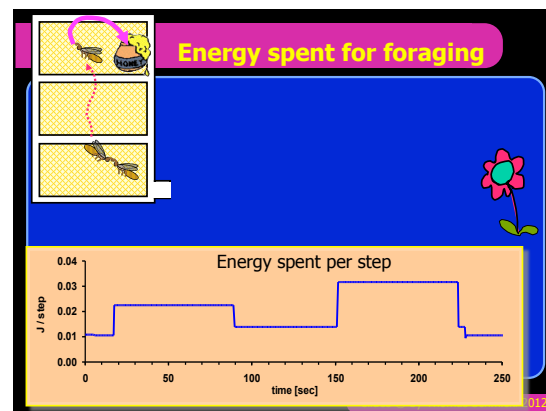
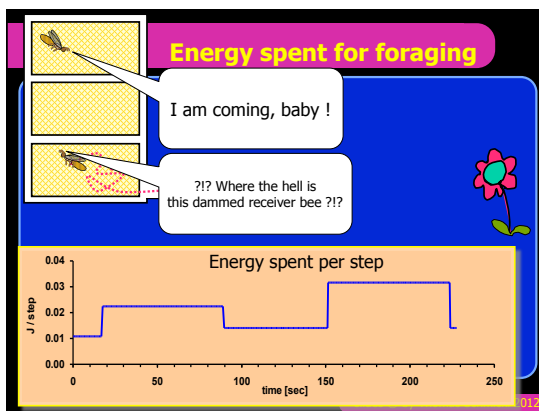
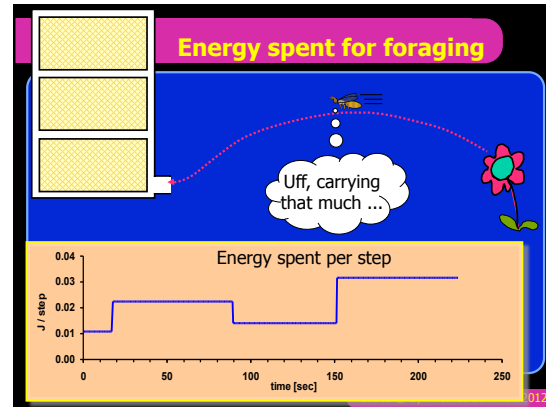
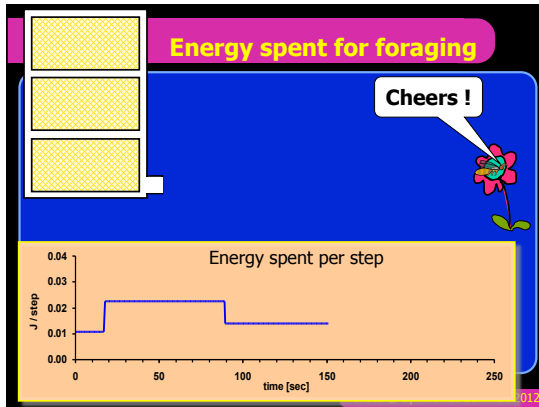


2012

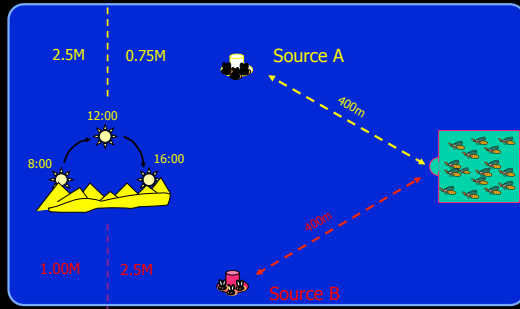
Energy spent for foraging



2012

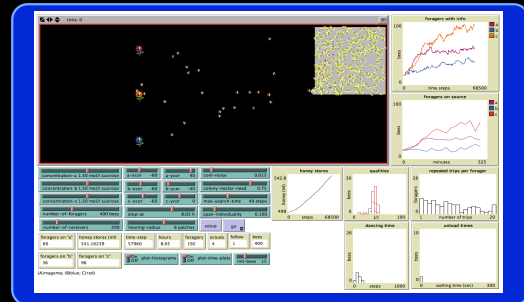


Setup of T. Seeley et al. 1991



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The model at runtime:



Note: The quality of food sources can be changed at runtime but not their positions!

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Use the simulation to find out:

- Do the bees decide in a smart way?
- Did this experiment impose costs to the colony?
- Was it important to model the energetic costs of the foragers to answer these questions?
- It takes 3 simulation runs to answer:
 - 1x undisturbed, 1x Seeley-Experiment, 1x only bad choice in the environment.

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Other topics in Artificial Life:

- We did not show all aspects of Artificial Life.
There is also:
 - Models of the primordial soup
 - “Wet Artificial life”. (Craig Venter)
 - A lot of bio-mimetic robotics
 - Evolutionary robotics
 - Bio-inspired machine learning algorithms
 - A vast of “artificial worlds”: sugarworld, poyworld, bubbleworld, framesticks, ...

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Tierra/Avida: The first artificial worlds



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Early beginnings: Karl Sims

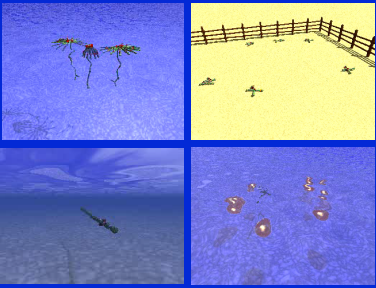
- Evolutionary models

**Evolved Virtual
Creatures**

**Examples from
work in progress**

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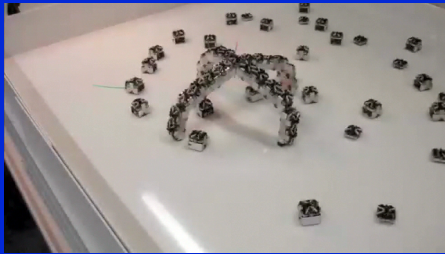
Framesticks: a modern approach



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Symbion/Replicator

- Modular robotics



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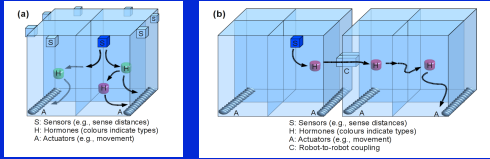
Artificial Homeostatic Hormone System

- Ein Modell eines Stoffwechsel-Netzwerkes treibt Roboter an:
 - Sensorwerte in Produktion von chemischen Stoffen übersetzt
→ Signalkaskaden.
 - Virtuelle Hormone verfallen mit der Zeit.
 - Virtuelle Hormone diffundieren.
 - Masse-Erhalt!
 - In Zukunft: Echte chemische Reaktionen.



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The AHHS (hormone controller)



S: Sensors (e.g., sense distances)
H: Hormones (colours indicate types)
A: Actuators (e.g., movement)
C: Robot-to-robot coupling

$$\frac{\Delta H_h^c}{\Delta t} = \alpha_h + D_h \nabla^2 H_h^c(t) - \mu_h H_h^c(t) + \sum_i S_i(t) + \mathcal{L}_i(t) + \mathcal{N}_i(t),$$

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Artificial hormone systems 1

Hormone dynamics

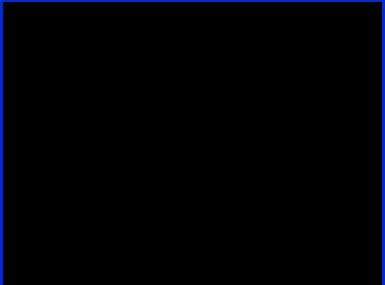
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Artificial hormone systems 2

Scalability

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Artificial hormone systems 3



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Artificial hormone systems 4

SYMBRION  REPLICATOR

Grand Challenge I:

The quest for robustness



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Artificial hormone systems 5

SYMBRION  REPLICATOR

Grand Challenge II:

The quest for diversity



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And finally:

Thank you for
attending, listening,
thinking & working

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