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Intelligent Systems

Chapter 12: Self-organised Order

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About this Chapter

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Content

- A first example: water temples in Bali
- A second example: ants
- Emergence
- Term definition
- Quantification of emergence
- A refined approach to emergence quantification
- Conclusion
- Further readings

Goals

Students should be able to:

- explain the relation between self-organisation and emergence.
- briefly summarise the term emergence.
- give examples for emergent phenomena, e.g. in nature.
- quantify emergence in technical systems based on discrete attributes.
- outline how emergence detection is done for systems with continuous attributes.

Agenda

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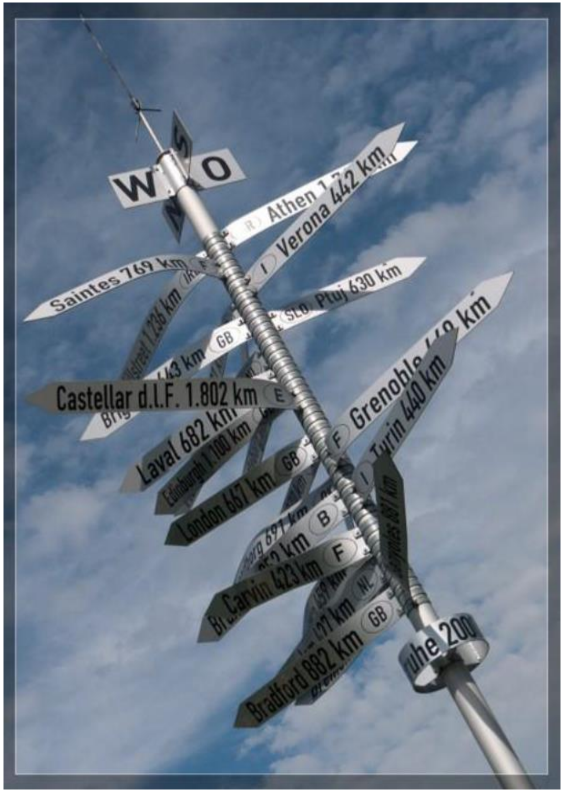
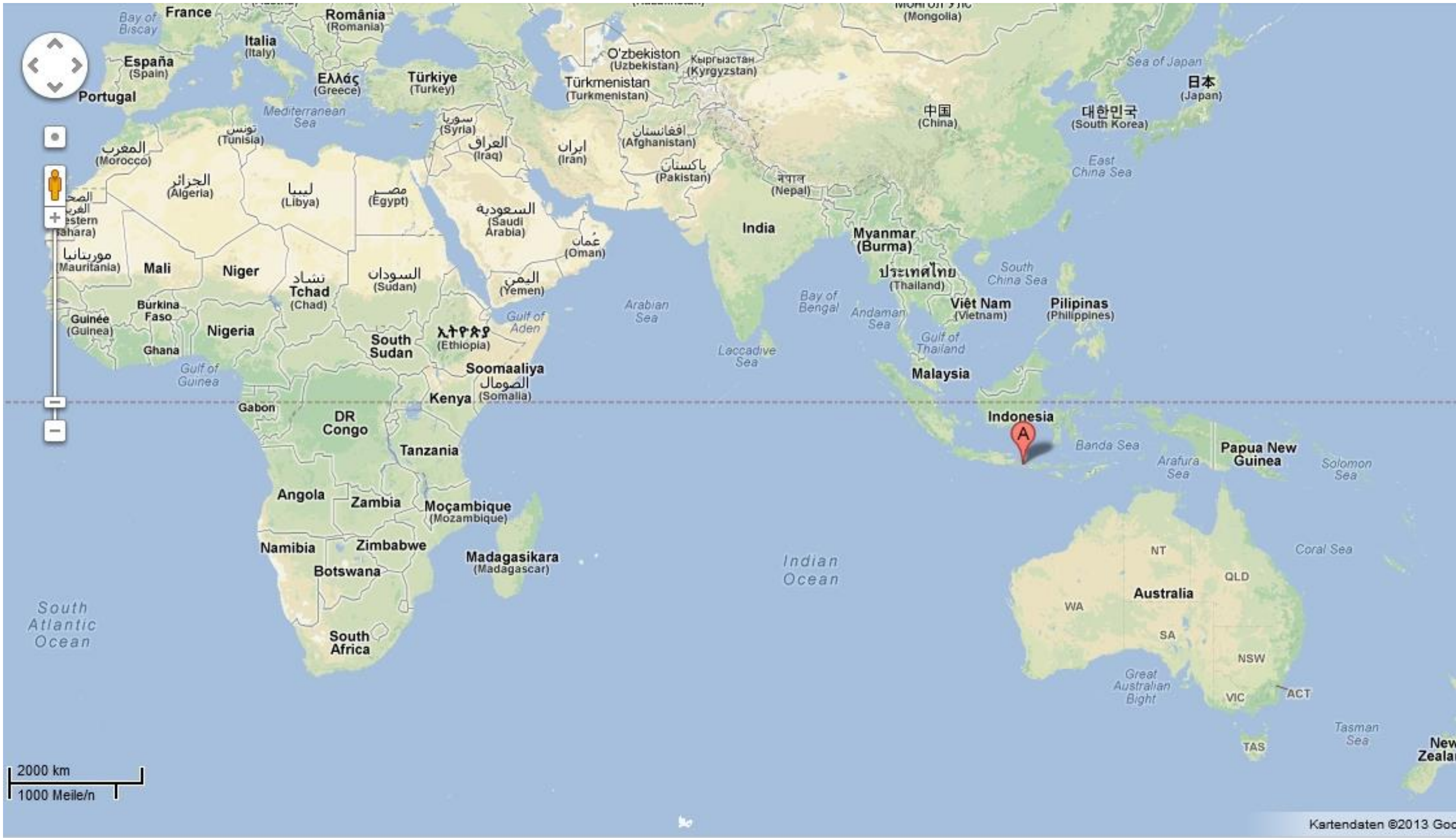


A journey to Bali



Water temples in Bali

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Water temples in Bali (2)

Water temples in Bali (3)

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Watering system for the cultivation of rice

- Main factors:
  - Water circulation
  - Alternation between dry and wet periods
- Objectives
  - PH-values
  - Activity of micro-organisms
  - Distribution of mineral nutrient
  - Herbicide
  - Pest control (for large areas)
  - Stabilisation of temperature
- Problem: Synchronous watering leads to peak demand of water!

Water temples in Bali (4)

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Problem for each farmer:

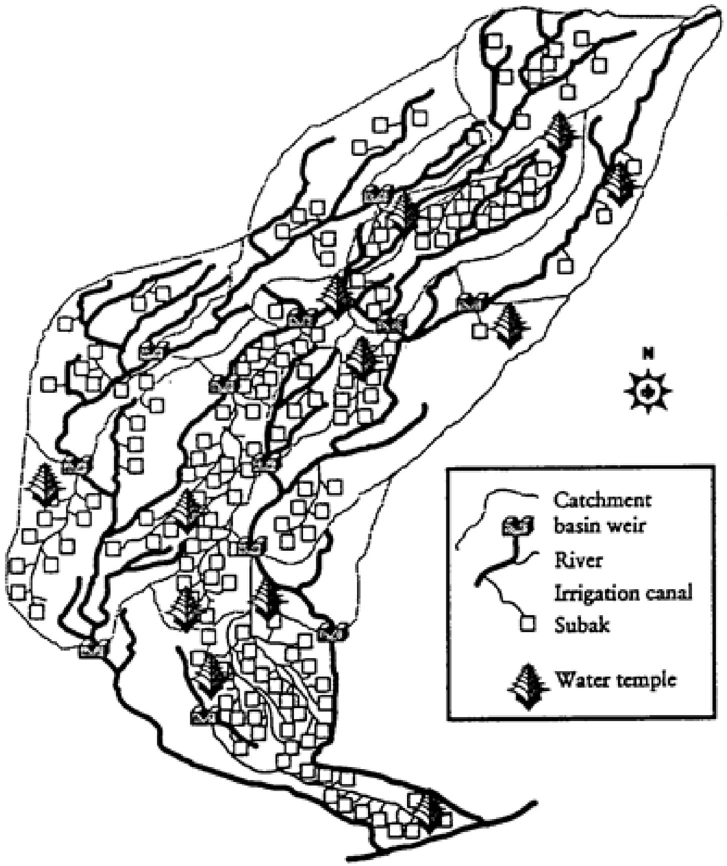
- Determine cultivation sequence

Goal:

- Maximise crop

Attributes of cultivation sequence:

- Phases of cropping (date)
- Cultivar (kind of plant)
- Watering
- Drying



The Oos and Petanu rivers in south-central Bali (not to scale).[16]

Source: Lansing and Kremer

Water temples in Bali (5)

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How to determine the optimal sequence?

- Trial and error vs. planning
- Coordination: global or local?
- Is the solution suitable for the local problem?
- Is the solution adaptable?

Hypothesis:

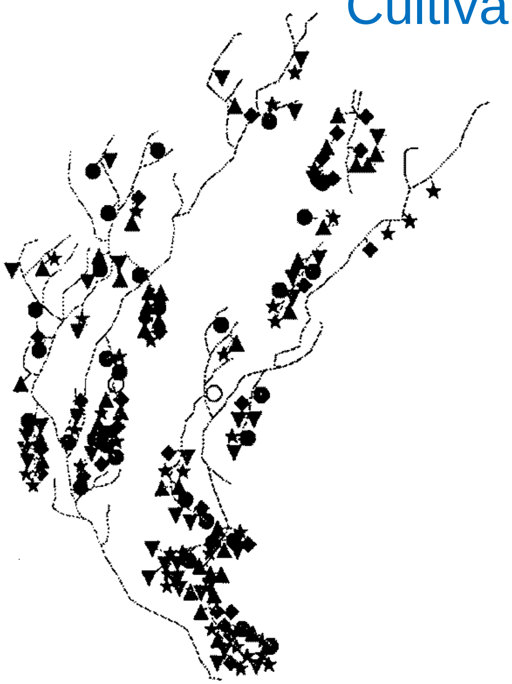
- Coordination algorithm
- Synchronous, local, like the best neighbour
- Co-adaptation

Verification of hypothesis: simulation

- Crop is modelled as a function of cultivation sequence and environment.
- Start: randomised initialisation

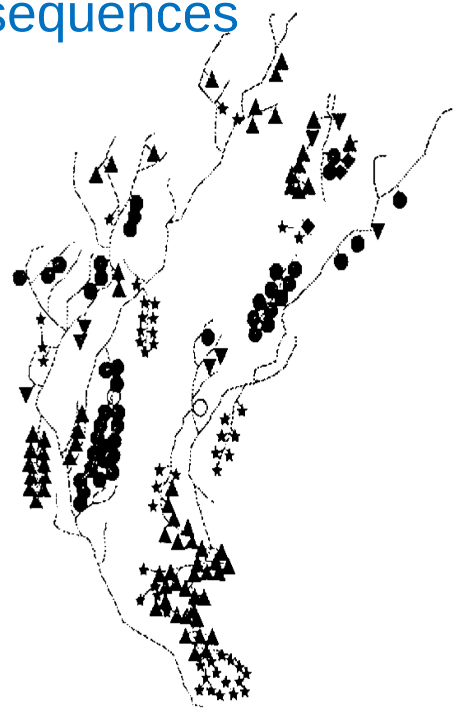
Water temples in Bali (6)

Cultivation sequences



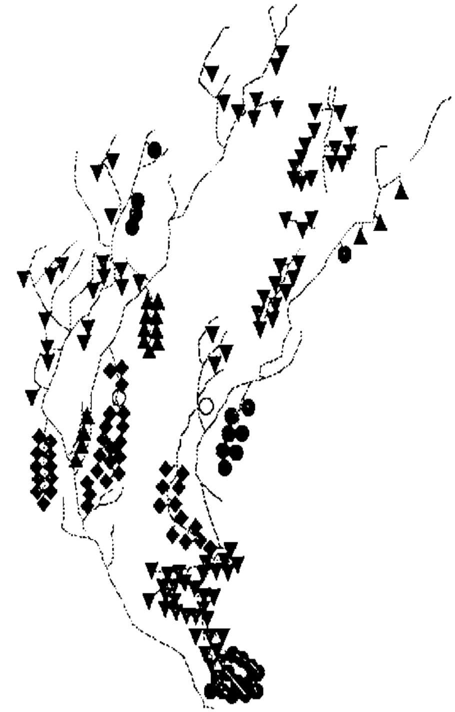
Randomised distribution at start-up

4.9 tons/ha



Simulated pattern after co-adaptation cycles

8.6 tons/ha



Traditional system of cave temples at Bali

Water temples in Bali (7)

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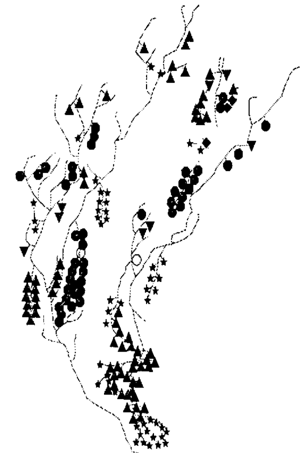
Conclusions to be drawn from the water temple networks:

- Contains locally behaving and self-motivated farmers (nodes, agents).
- Cooperation leads to globally optimal (or ”good enough“) patterns.
  → An emergent effect.
- Bottom-up evolved problem-solving networks are adaptive: react to changing environmental conditions (e.g. reduced rainfall).
- Success of the networks depends on: (1) ability of local nodes to collect local information and (2) react to it locally.
- There is no central authority needed, the system is decentralised.
- There is no external authority needed, the system is self-organised.
- Co-adaptation requires large populations of interacting agents.
- Agents decide on their own but in close and regular coordination with their neighbours. They are semi-autonomous.
- The system learns and adapts in evolutionary cycles.
- Evolutionary steps are subject to random variations.

Self-organised Order

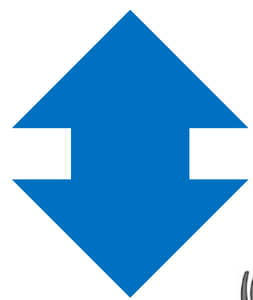
Insight: self-organised order

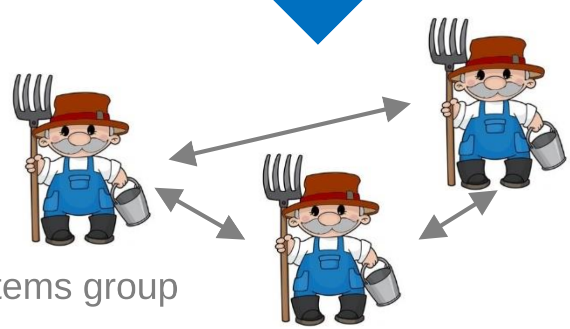
- A global pattern emerges
- System is structured
- Nobody is in charge
- Nobody has a global view
- Nothing is planned externally
- Distinguish between micro- and macro-level
  → actions at micro-level, effects at macro-level
  → “good enough” solutions at macro-level



Macro-level:

- Global view
- Pattern
- Structure





Micro-level:

- Interaction
- Local view

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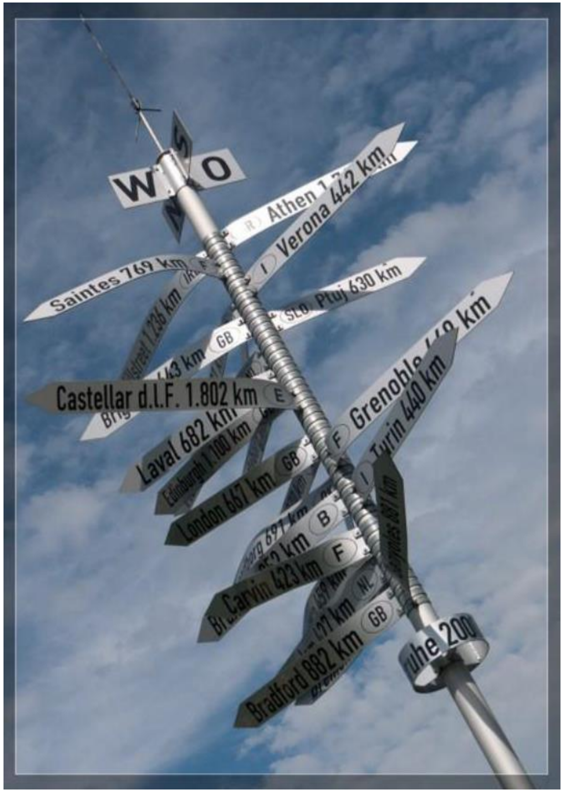

Ants

- Related to wasps and bees
- About 100 million years old
- Extremely successful:
  - About 30% of bio mass in the Amazonas are (with termites)
  - About 9% of bio mass world-wide
  - Comparable to bio mass of humans
- No or only limited vision
- Distribution of labour:
  - soldiers,
  - construction workers,
  - gardeners,
  - reproduction
  - …

Source: Ants at Work (1999) by Deborah Gordon

Ants (2)

Abilities of ants

- Find shortest paths
- Build bridges
- Sort
- Efficient logistics
- Farming / food production
- Construction of complex structures
- Caring about brood and offspring
- Caring about useful entities
- Distribution of labour
- ...

Ants (3)

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Building bridges

- Chains of ants clamping together
- To bridge gaps in path
- Other ants use these chains as path
- E.g. to better reach food
- Chains of ants to pull leaves down
- Alternative: use silk from larvae as material to build bridges

Ants (4)

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Food production

- Ant species that cultivate fungi
- Ground and substrate is processed for fungi.
- "Gardens" are laid out and cultivated.
- Fungal spores are planted.
- Competing fungi (i.e. light or water) is eliminated.
  → Like weeding the garden!
- Fertilisation of chewed larval cases.

Ants (5)

Distribution of labour

- Different types of ants in a colony:
  - Worker
  - Medium-sized ants
  - Small ants
  - Queen
  - Male ants
- Workers search for food (leaves) in the surroundings (up to hundreds of meters from nest).
- Workers organise ant trails for transport of food.
- Medium-sized ants carry leaves.

Ants (6)

Symbiosis

- Ants cannot digest cellulose.
- But fungus can!
  → Eat hyphal tips
- Ants provide leaves as breeding ground for fungus.

Gardens

- Sculptured with many furrows and caves for brood.
- System of lower passages to drain wet chambers.
- Other tunnels for temporary control
- Ants swab floor clean.
- If foreign fungus develops, it is removed.
- Garden lasts 3-4 weeks / in various stages
- Founding queen brings fungal spores from old colony.

Alternative: Some ant species (e.g. Lasius niger, common black ant in Britain) herd aphids (“ant cattle”), protecting and even constructing them shelters.

Ants (7)

Protection

- Problem: large ants are victims of parasites.
- I.e. small flies try to deposit their eggs at head or neck of ants.
- Causes illness.
- Solution: small ants “ride“ piggy-back and chase attackers.

Ants (8)

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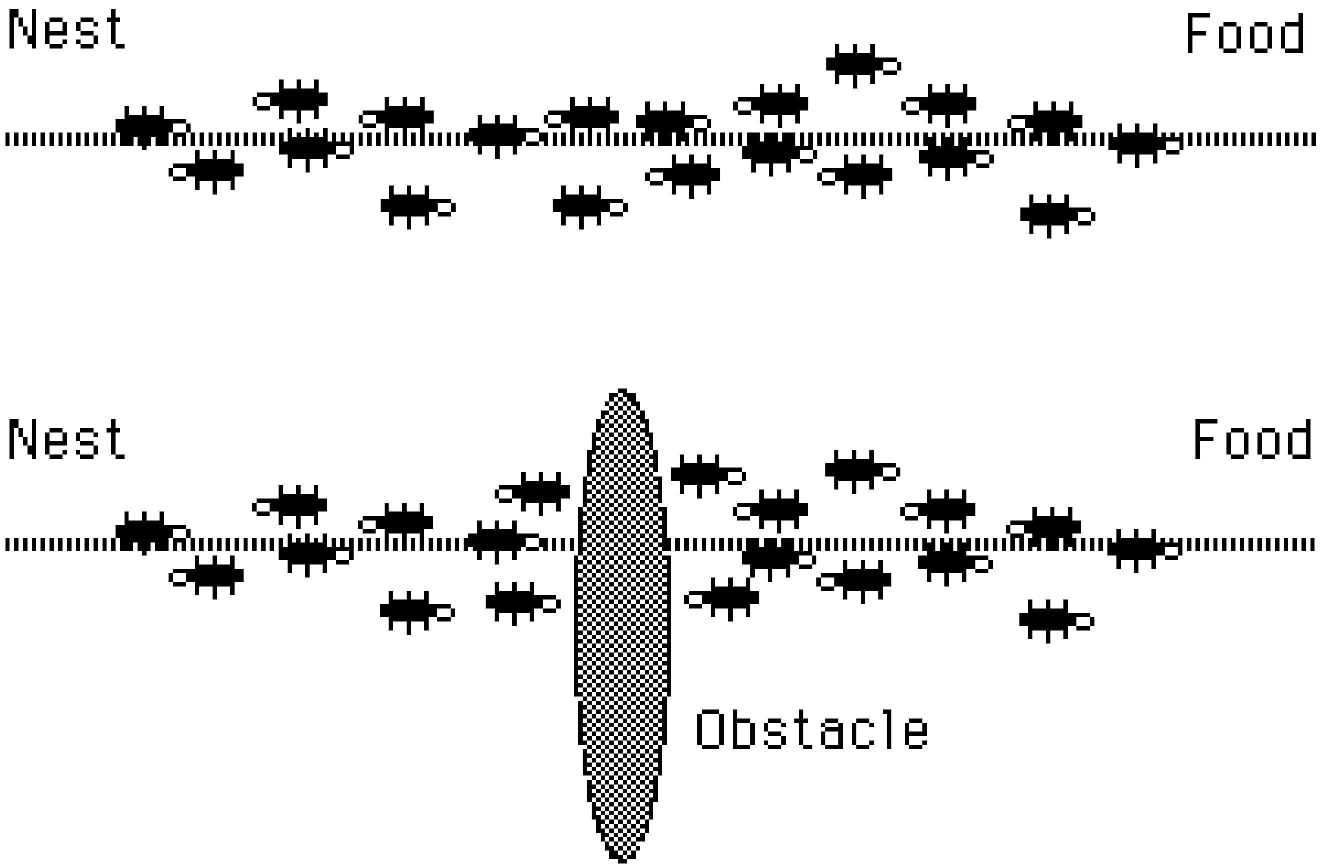
Finding shortest paths:

- Prioritisation of food sources based on distance and reachability
- Dynamic adaption of participating ants, e.g. depending on:
  - Size of colony (in number of ants)
  - Amount of stored food
  - Available food sources in vicinity
  - Other colonies and their location

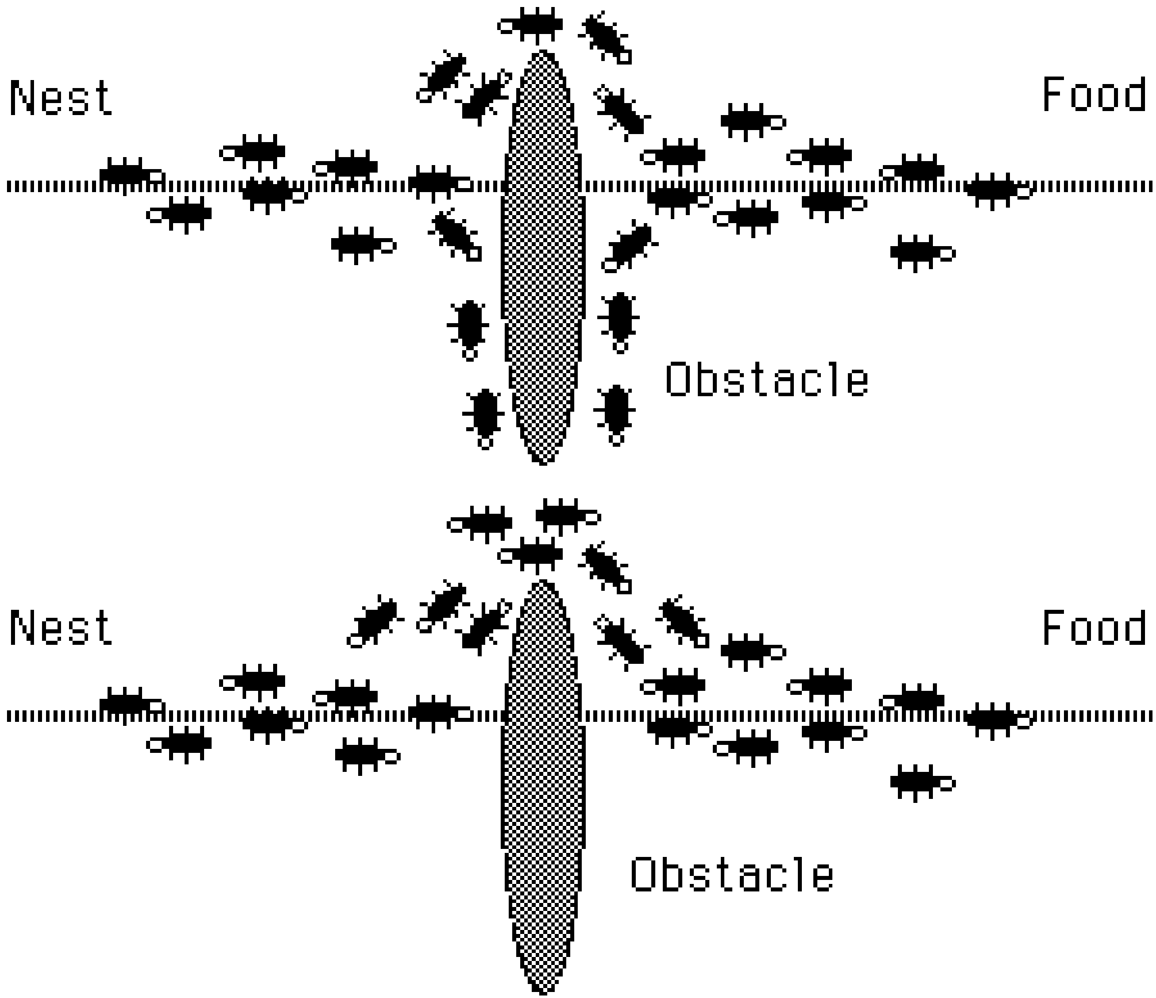
Ants (9)

Adaptive path optimisation



[Source: iridia.ulb.ac.be/~mdorigo]

Ants (10)



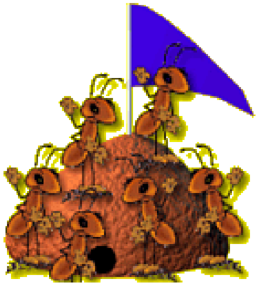
Ants (11)

Behaviour of ants (foraging)

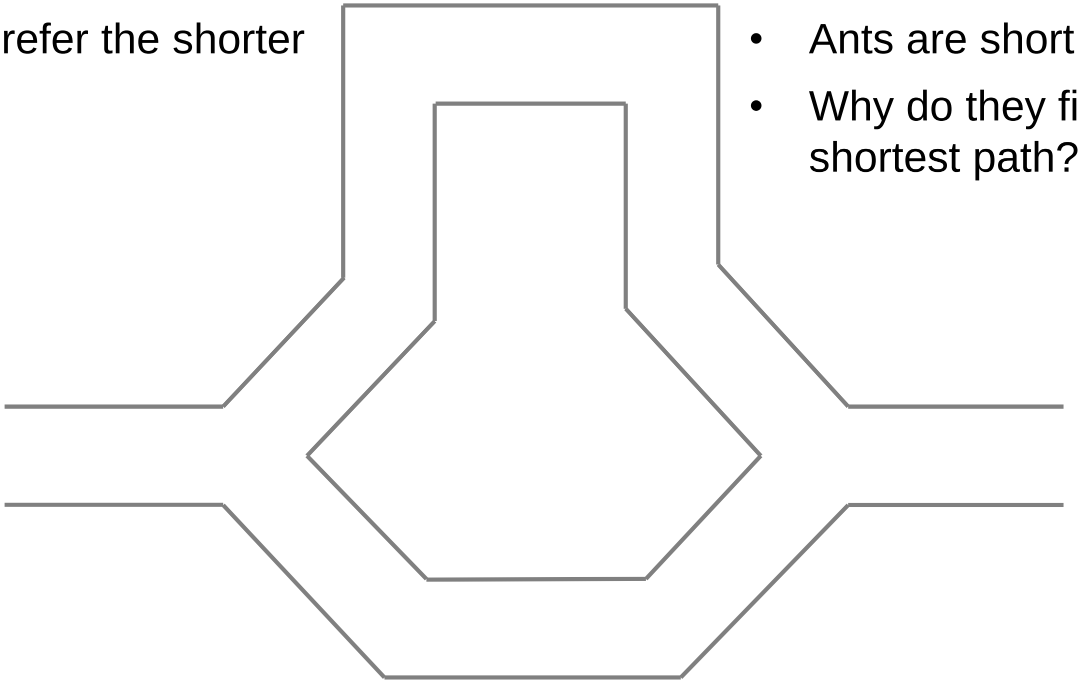
[Deneubourg et al., Dorigo, around 1990]

- Ants explore both paths.
- They find and prefer the shorter path.

- Distances are unknown!
- Ants are short sighted!
- Why do they find the shortest path?



Net

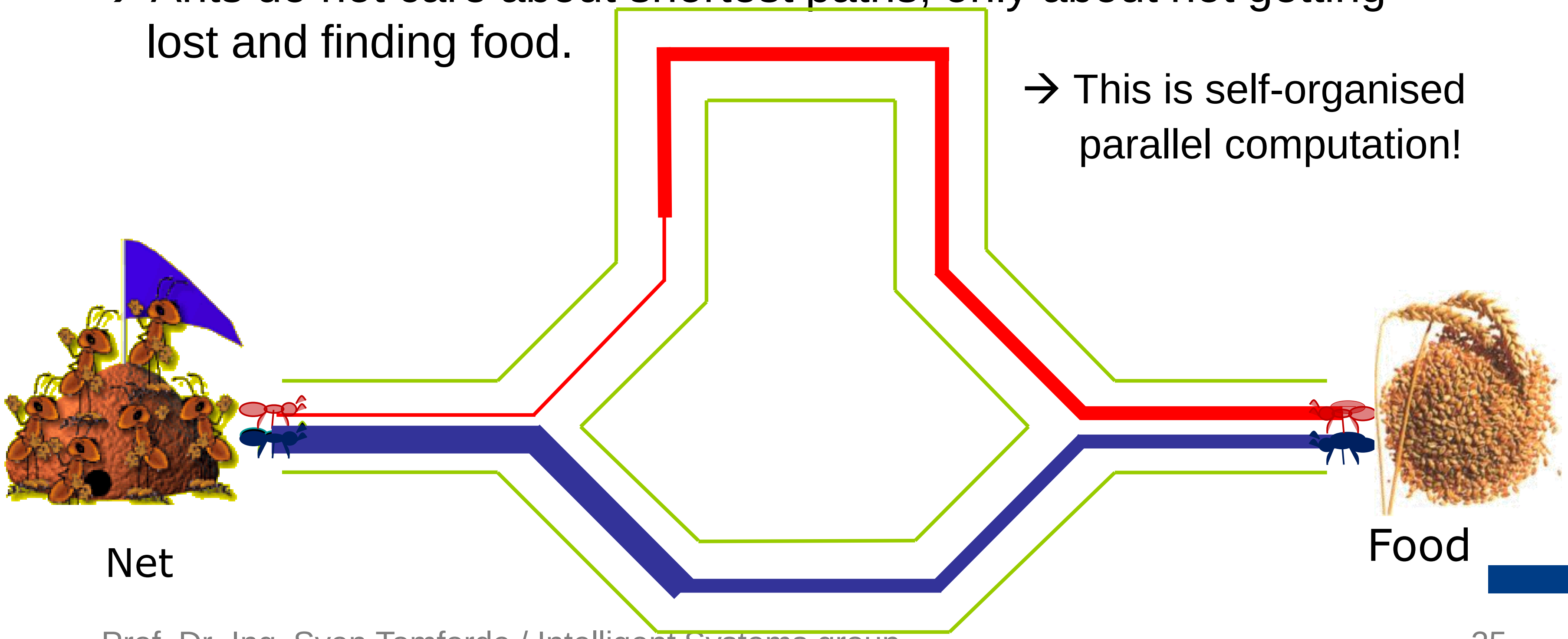


Food

Ants (12)

- Ants deposit pheromones on their path.
- Ants prefer paths having higher pheromone concentration.
- Pheromones evaporate.
  → Ants do not care about shortest paths, only about not getting lost and finding food.

→ This is self-organised parallel computation!



Ants (13)

Characteristics

- Colony size ~ 8∗10^6
- Without central authority:
  no one is “in charge”!
- Colony lifetime ~ 15 years (about the lifetime of one queen)
- Colonies have a “life cycle”
- Older ants behave differently from younger:
  - Older are more fixed in ways.
  - Younger are more responsive to environmental conditions.
  - Younger, though smaller, are more persistent & aggressive.
- But ants live no longer than one year!
  - Males live one day (fight & mate).
  - Colonies in an area (which may be as large as Southern England) coordinate their Nuptial Flight to one single evening.

Question: What governs here?

→ Centralised control is impossible!

Emergence

Insight: Emergence

- Something just appears:
  - A shortest path
  - Protection
  - Role assignment
  - Gardens
- Not predictable from individual entities
- Ingredients
  - Self-organisation
  - Autonomous decisions
  - Interaction

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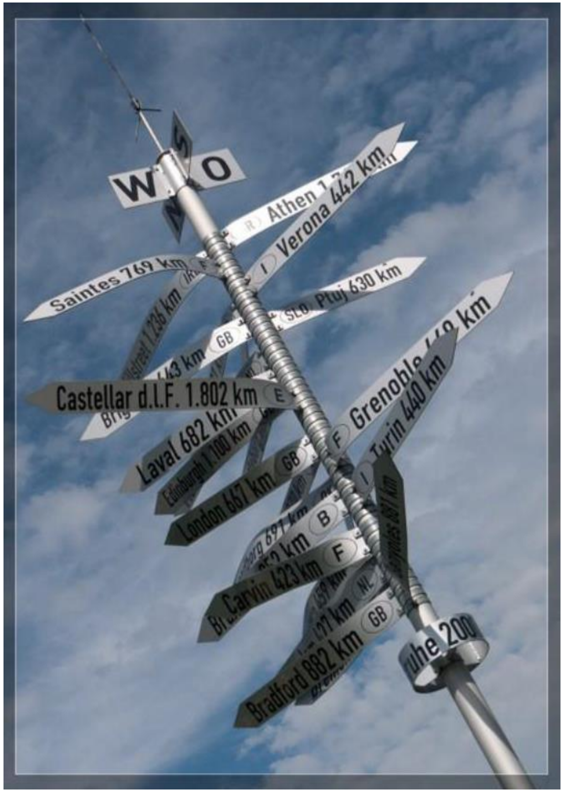

Example: Intersection behaviour

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Traffic behaviour at an intersection

- Youtube video, duration 2:13 min

- https://www.youtube.com/watch?v=RjrEQaG5jPM

Emergence

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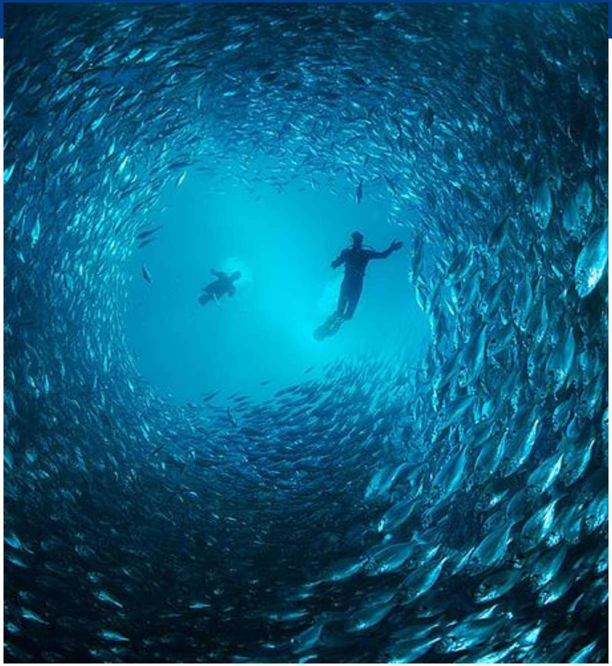
- Emergence is a phenomenon that can be observed in various systems (especially in nature).
- In principle, it can be found if the following “ingredients“ exist:
  - A set of multiple (homogeneous) individuals
  - Individuals are self-motivated and self-organised
  - Individuals interact with each other
  - No centralised authority controls the process
- “The whole is more than the sum of its parts!”
- Let‘s have a look at some examples:
  1. From nature
  2. From technical systems
  3. From social systems

Examples from nature: swarms

Swarms
- Flock of birds
- School of fish

Observations
- Behave as a unified organism
- No leader, no control
- Very simple rules

Advantageous for participants:
- Avoid attackers (appear as huge fish)
- Highly resource efficient (wind for birds)



Examples from nature: swarms (2)

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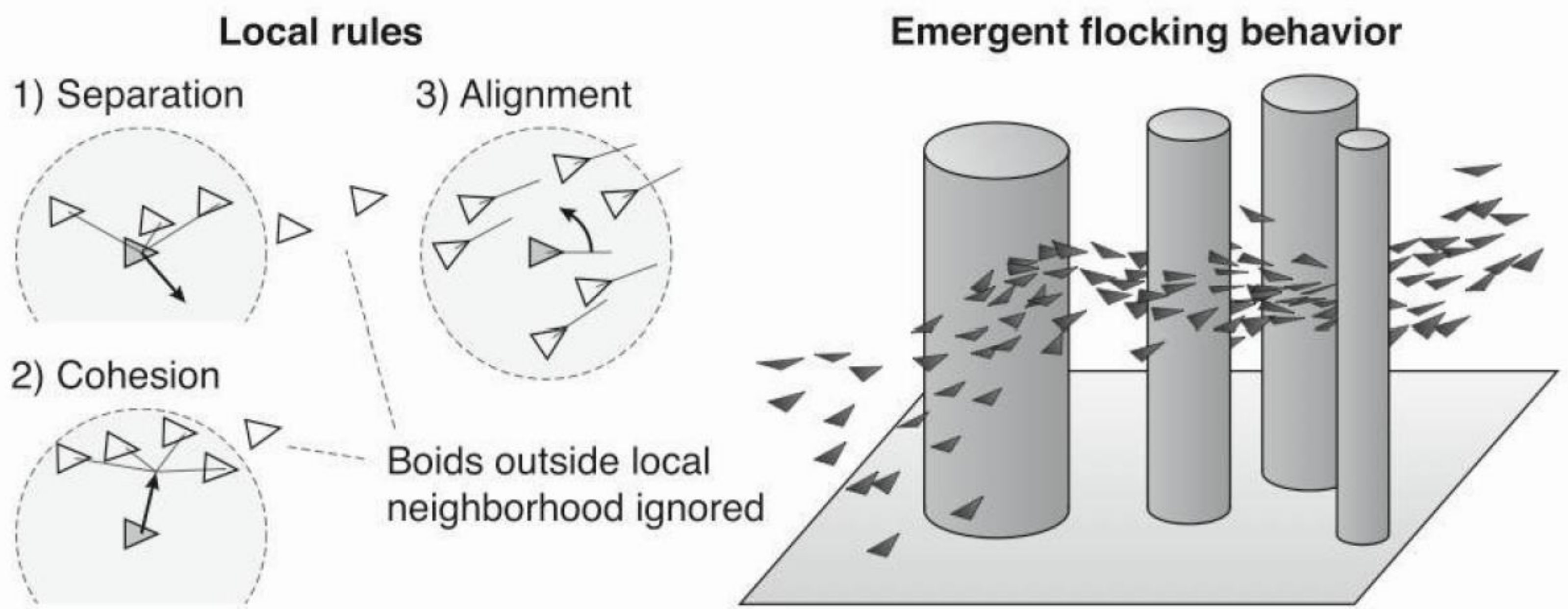
Also called “urges“



1. **Separation:** Boid maintains a given distance from other boids
2. **Cohesion:** Boid moves towards center of mass of neighboring boids
3. **Alignment:** Boid aligns its angle along those of neighboring boids

Examples from nature: termites

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Termite colonies

- Are able to build large “cathedral” structures.
- Structures consist of cone-shaped outer walls and ventilation ducts (“channels“).
- Brood chambers are situated in central hive.
- Spiral cooling vents (“openings“), support pillars.

Characteristics

- No central plan!
- No intelligence required from the individual termites, just simple individual behaviours.
- Local and global interaction between termites achieve emergence.
- To ensure that the “cathedral” adapts to local conditions, a randomness to the individual’s behaviour is necessary.
- Central, top-down control would actually suppress the positive effect of emergence in termite cathedrals.

Examples from nature: alpine meadows

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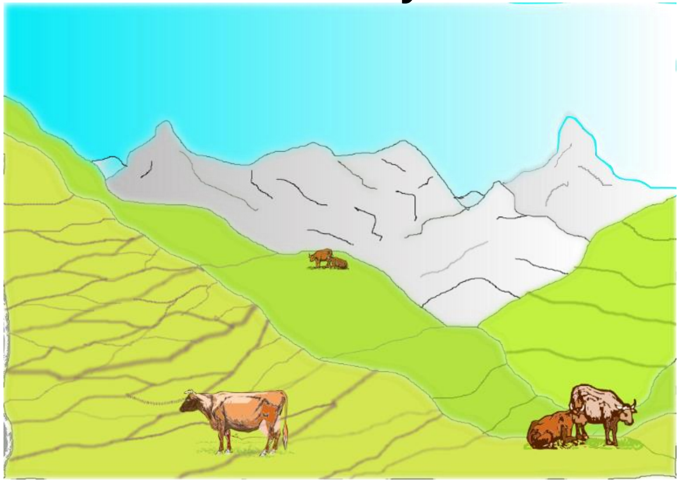
Alpine meadows

- Cows use the same paths
- A pattern of way structures appears over time
- Although there is no normative system like in human traffic operation, cows seem to build ways on their own!



Examples from nature: the human brain

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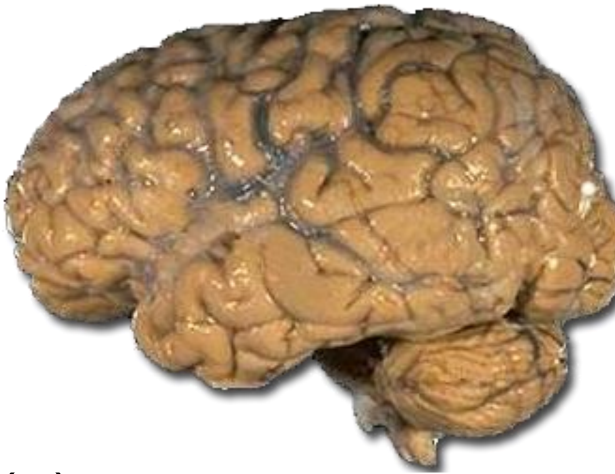
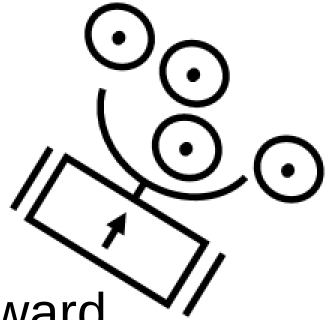


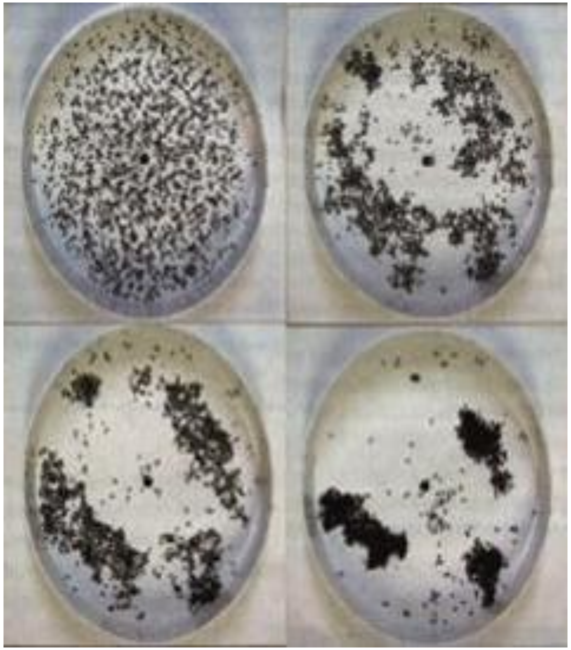
The human brain:

- Micro-level: the neuron
  - exhibits very simple behaviour
  - equals single-bit memory
  - has some stochastic characteristics
- Macro-level: the brain
  - About 1.5 kg, volume of around 1130 (f) / 1260 (m) cm^3
  - Consists of billions of neurons
  - Displays an infinitely sophisticated and complicated behaviour
  - I.e. language, visual, aural, and tactile I/O, the arts, culture, emotions, as well as logical thought and processing
  - Is robust, adaptive, innovative
- An examination of individual neurons cannot predict the behaviour of billions of them working together!

“Candle Mover”

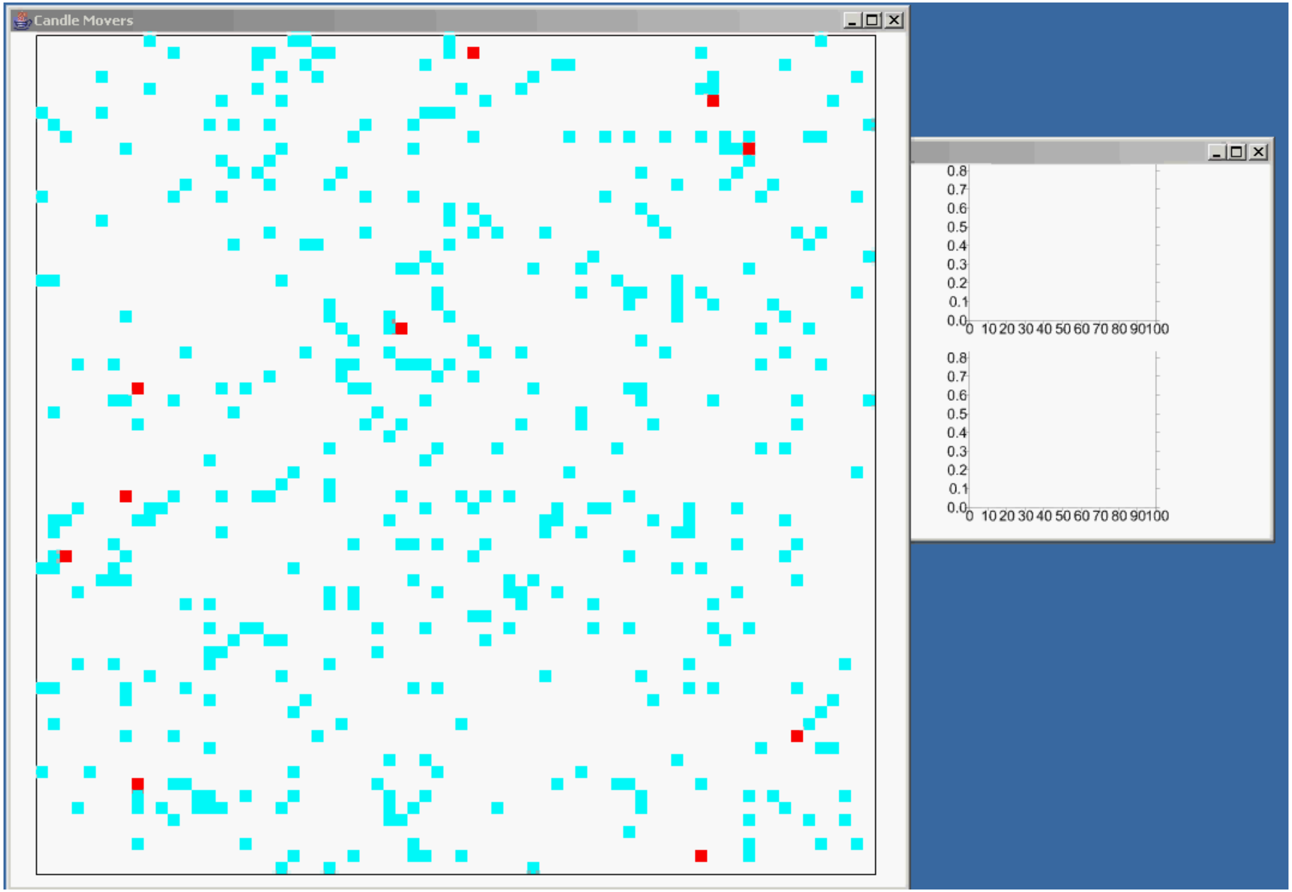


- 1 sensor (pressure)
- 1 actuator (direction)
- In case of 2 candles: move backward, turn, continue to move forward



Technical examples: the candle mover (2)

- What happens?



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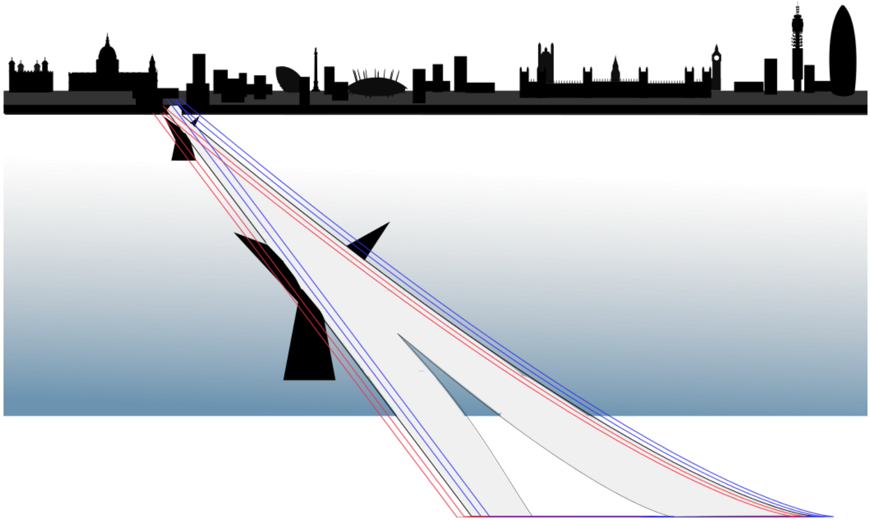
London Millennium Foot Bridge

- Built according to classical engineering.
- Analysis showed that the bridge was sufficiently strong and rigid.
- Immediately after opening, it had to be closed due to strong lateral swinging caused by a number of walking pedestrians.



Technical examples: London Millennium Bridge (2)

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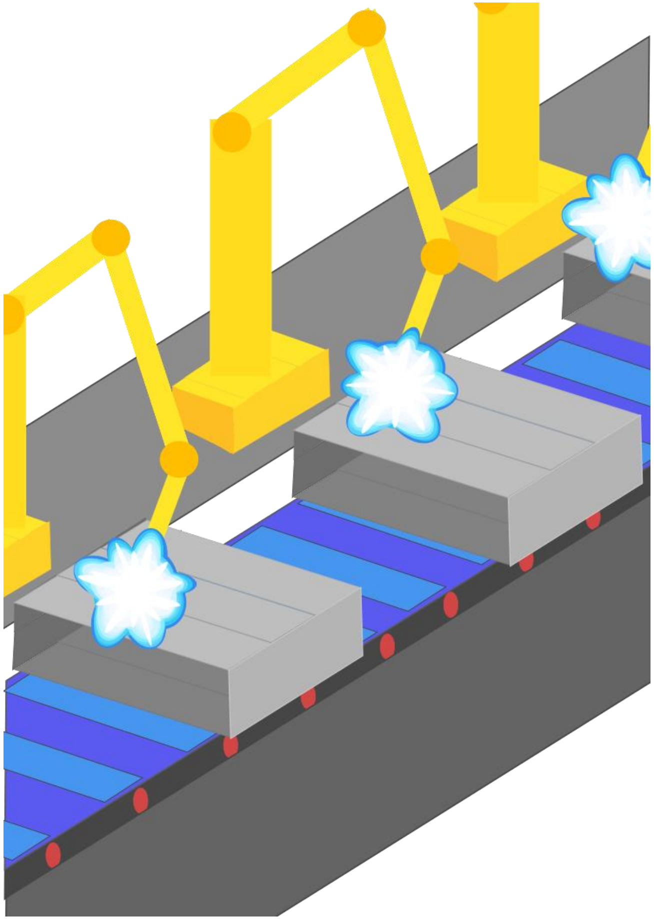
- Analysis of the emergent swinging effect
  - Natural lateral frequency of the bridge was close to the normal walking frequency of pedestrians.
  - Pedestrians were becoming synchronised in phase and frequency to each other.
    → Humans on a swaying surface tend to subconsciously synchronise their footsteps to the sway.
  - The bridge designers did not anticipate this phenomenon.
- Individual behaviour responded to the common network (the swaying bridge), thereby resulting in an unexpected top-level system behaviour.
  → This is communication, not control!

Automotive Welding Robots

- The weld's quality depends upon the line voltage.
- Set of robots were installed in a factory.
- Random irregularities/defects were observed.
- Quality management techniques did not work.



Technical examples: welding robots (2)

Failures

- Caused by line voltage drops.
- Due to simultaneous welds from several robots.
- Design assumed random (non-synchronised) operation.
- All robots share the same networked voltage line.

Approach to alleviate the problem:

- Robot monitors the line voltage and waits until it is high enough.
  → Problem became worse: increased synchronisation.
- Result: No synchronisation due to random delays.
  → Note the importance of stochastic behaviour.

Technical examples: hard drives

“Enterprise” Server Disk Drives

- Sensitive to vibration
- Especially in case of synchronised seek activity
- Set of disk drives mounted together
  → Data faults were experienced.
- I.e. computer system database searches caused several disk drives to seek simultaneously, thereby building up synchronised vibration that disturbed each other’s operation.

Simultaneous disk drive seek operations are inherent to large enterprise servers – inducing emergent behaviour among multiple disk drives.

Freeway Traffic Jams

- Drivers act egoistically (avoid traffic jams).
- Observation: Minor perturbation in high traffic periods cause traffic jams.
  - Areas of light and areas of jammed traffic appear periodically.
  - Especially at fast lanes.
  - Total effective flow rate of cars is significantly reduced.
- Example: https://www.youtube.com/watch?v=7wm-pZp_mi0

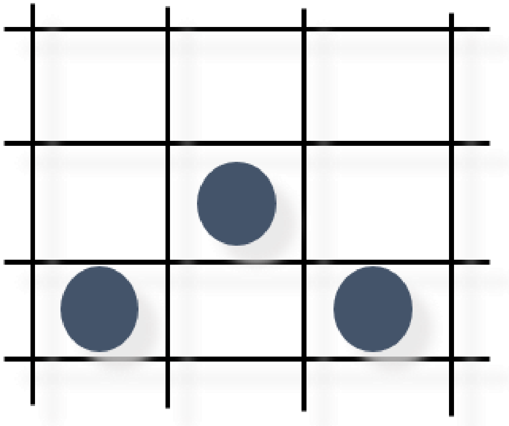
v=const 85km/h
-> full stop

v=const 85km/h
-> break hard

v=const 85km/h
-> break

v=const 85km/h
-> slow down

v=const 80km/h



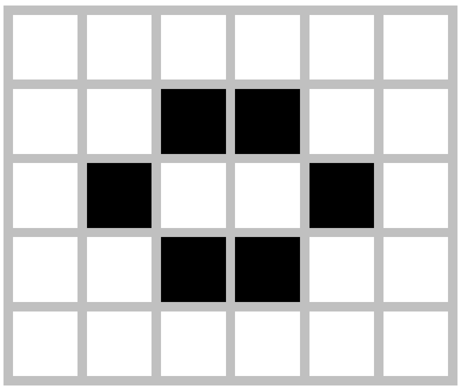
- Field of Finite State Machines (FSM)
- Automaton changes its state depending on the states of its neighbours
- Example: Game of Life (John Conway) http://www.bitstorm.org/gameoflife/

- Example rule set:

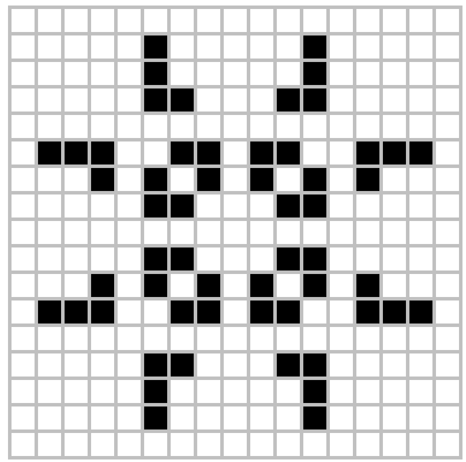
≤ 1	neighbour	dead
2	neighbours	const
3	neighbours	alive
≥ 4	neighbours	dead

Technical examples: Cellular Automata (2)

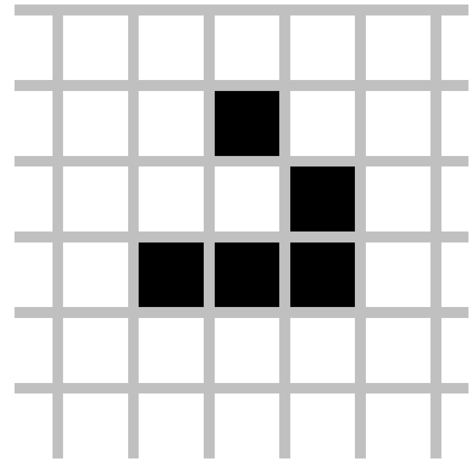
The "Game of Life"



Static



Oscillating

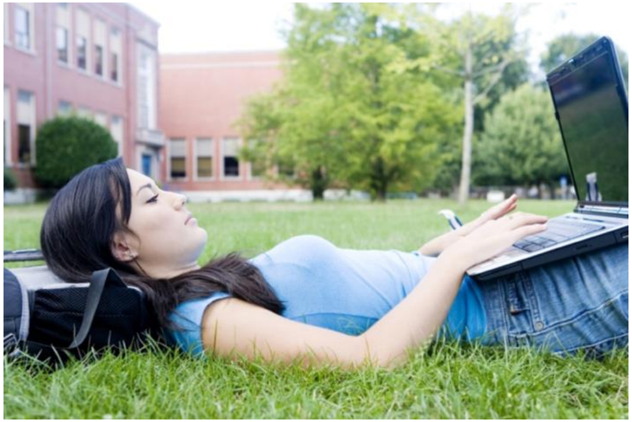


Moving

- Generalisation based on: form, position, colour, communication, etc.
  → Used to simulate united cell structures.

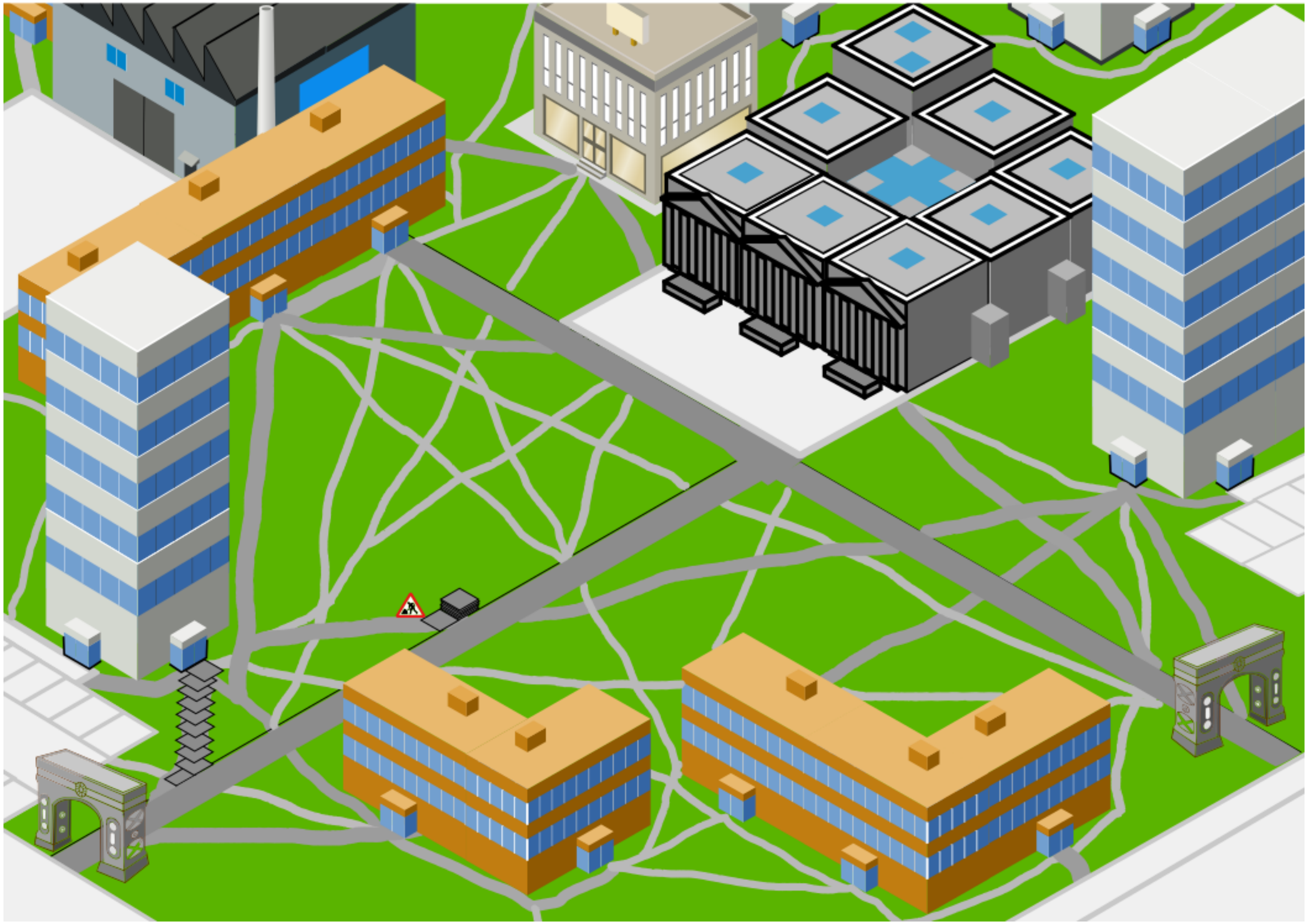
Source: http://en.wikipedia.org/wiki/Conway%27s_Game_of_Life

Social examples: sidewalk structures



- Optimised sidewalk structure
  - University of Michigan built a new campus.
  - Concrete sidewalks were to be placed in the Quad between buildings, but how to design?
  - Once installed they are difficult to change.
  - Previous approaches turned out to be not useful.
- Concept:
  - Plant grass and allow students to walk as they want.
  - Concrete sidewalks were installed according to emerging patterns.
  - Students and faculty are cognitive and adaptive elements in a larger system.
  - At a system level, their patterns of walking could not be accurately predicted.
  - Later analysis showed that as a group, an optimum sidewalk structure was derived.

Social examples: sidewalk structures (2)



Social examples: social networks

Social network:

- Nodes = people
- Edges = relations between people
  → E.g.: friends, relatives, colleagues
- Paths:
  - Chain of people
  - E.g.: friend of my friend of my friend

Interesting properties:

- Decentralised, self-organising, robust, scalable network
  → E.g.: people are born, die, get to know new people
- Efficient (short) communication paths & decentralised routing
  - See Milgram’s Experiment

Social examples: Milgram‘s experiment

- Analysis of paths in social networks
  - Conducted in the 1960s by Stanley Milgram
  - Stanley Milgram (1933 –1984) was an American social psychologist.
- Milgram sends a letter to 160 randomly selected persons from Omaha and Nebraska (USA).
- Letter contains task: Deliver letter to a certain stock broker in Boston, Massachusetts, USA.
- Constraints: Persons must only send letter to someone they know at a “first name basis” (i.e.: friends, colleagues).
- Results:
  - 44 letters reached the target
  - Average number of “hops”: 6
    I.e., short paths in network of 200 million US citizens!

Further examples for small world networks:

- Network derived from movie database
  - Nodes: actors
  - Edge between two actors if they have acted in same movie
- Bacon number of actor:
  Shortest path between an actor and Kevin Bacon
  - Average bacon number: 2.9
  - Via Kevin Bacon, any actor can be linked to any other in 6 “hops”
- 6 is a typical distance between pairs of nodes in such networks.
  → 6 degrees of separation

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- "Die Zeit" linked a Turkish Kebab-shop owner in Frankfurt, Germany, to his favorite actor Marlon Brando in 6 hops:
  - Shop owner has a friend in California who works together with the boyfriend of a woman who is in the same student's union of the daughter of the producer of the movie "Don Juan" starring Marlon Brando.
- Erdös number: distance in graph of paper (co-) authors
  - Paul Erdös: famous mathematician (> 1500 papers with > 500 co-authors)
  - Average Erdös number: 4.7
  - Average distance between authors: 7.3

Paul Erdös Brendan D. McKay Peter Eades Jürgen Branke Sven Tomforde

Agenda

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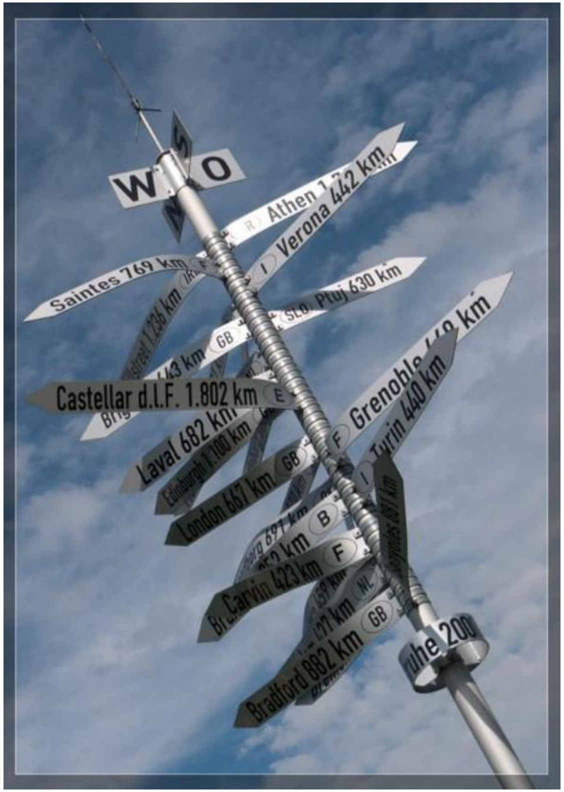
- A first example: water temples in Bali
- A second example: ants
- Emergence
- **Term definition**
- Quantification of emergence
- A refined approach to emergence quantification
- Conclusion
- Further readings



Term definition: “emergence”

- How macroscopic behaviour arises from microscopic behaviour.
- Emergent entities (properties or substances) ‘arise’ out of more fundamental entities and yet are ‘novel’ or ‘irreducible’ with respect to them.
  [Stanford Encyclopedia of Philosophy: http://plato.stanford.edu/entries/properties-emergent/]

- “It is unlikely that a topic as complicated as emergence will submit meekly to a concise definition, and I have no such definition to offer.“
  [John Holland: „*Emergence: From Chaos to Order*“]

Emergence (2)

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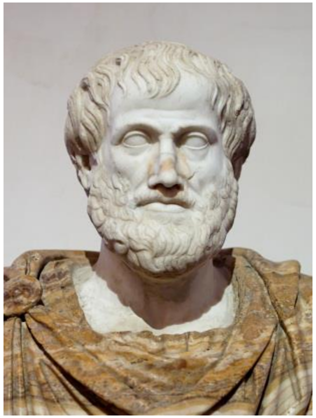

Emergence

- Comes from “*to emerge” (in German: „auftauchen“)*
- Verbal description:
  - “A system is more than the sum of its parts.“
  - From Aristotle (384 BC – 322 BC); Greek philosopher and polymath.
- Is a characteristic of the whole system, not part of the subsystems.

Definition:

- „An emergent system characteristic is a property, which is not only defined by the elements contained in the system, but by the interaction between these elements.“
- Emergent system characteristics are not computable by *summarising* the characteristics of the contained parts.
- Emergent behaviour is the result of interactions between processes.

Emergence (3)

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Management of emergent behaviour

- Prevent or mitigate the sources of emergence.
- Design limits into systems to lessen the negative effects of emergence.
- Add **extra stability and robustness** to the system.
- Use simulations to detect and design for emergence (caution, very sophisticated simulations required; beware of chaos theory).
- Reduce non-linearity.
- Increase scarce resources to minimise thrashing.

- Goal: Promote its positive effects and suppress its negative effects!

Emergence in Organic Computing / intelligent systems

- Why do we have to consider emergence in OC systems?
- Do we want do explicitly design emergent effects?
  → This is hardly impossible…
- Emergence is **not** something we want to design, but something that will appear automatically!
  - Emergence is the result of interactions between a set of self-organised entities.
  - OC systems consist of a set of self-organised interacting entities.
    → We have to be aware of emergence: positive and negative!
  - In technical systems: How to be aware of something?
    → We need to measure it!

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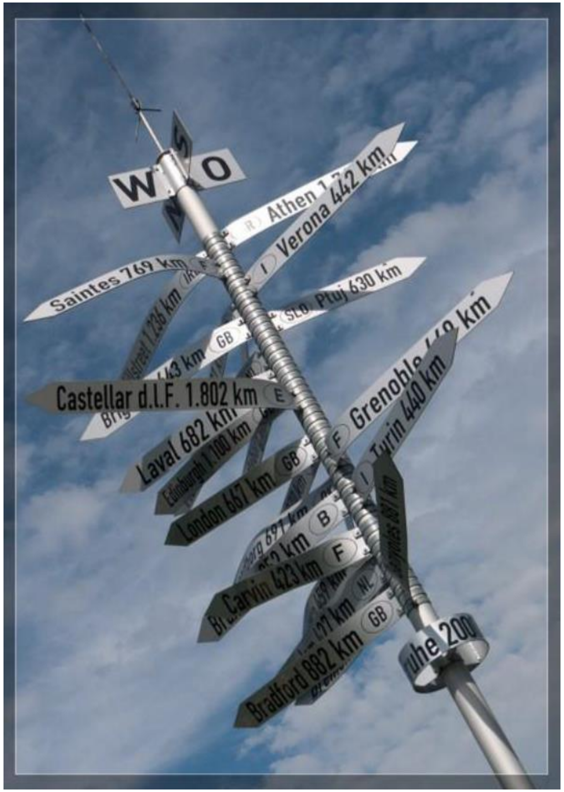


Emergence in intelligent systems

- Structural emergence in the sense of collective self-organisation shows as:
  - patterns in time and/or space
  - patterns (order) at the system level (macro level).
- Patterns at system level are realised by:
  - interaction
  - of (a large number of) similar individuals.
- These patterns have properties not existent in the individuals.

- How can we measure emergence?
  - Emergence measures the result (in terms of ”order“) of some unknown process.
  - Order per se says nothing about self-organisation.
  - Entropy is a measure of order. How is emergence related to entropy?

Quantification of emergence

Goal:

- Assign a high emergence value to a system, which is perceived as emergent!
- Quantification of emergence in OC systems.

Approach:

- Basis: verbal definitions
- Emergence is always associated with patterns (symmetry breaks).
- This corresponds to structural emergence.
- Patterns represent order.
- Order can be measured in terms of entropy.
- Therefore, we must: 1) define entropy and 2) relate it to emergence!

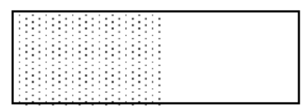
What is order?

Dissipative structures (Prigogine)

Where is more order? Left or right?

Right: Higher entropy

Left: More structure



Gas molecules: distribution with low probability

Gas molecules: thermodynamic equilibrium

higher entropy

What is order? (2)

Order is subjective!

- The perception of order depends on the view of the observer.
- The purpose and the sensory equipment of the observer determine the view.
- A system can be rated as orderly or disorderly dependent on the utility.

Views and order

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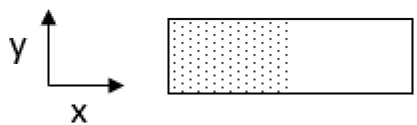
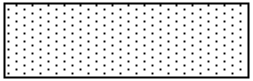
- „Order“ or „disorder“ depends on
  - the purpose and
  - the view (aspect).
- A view is determined by the selection of certain attributes (or a group of attributes / also called features) of an object.
- Example:

View	x position	colour
	higher order	same order
	lower order	same order

- The view is influenced by the pre-processing of sensory data.

- Definition from information theory (Shannon):
  - Entropy is a measure of information.
  - Message source M, alphabet Z:

$$\boxed{EntropyH(M) = -K \cdot \sum_{j=1}^{|Z|} p_j \cdot ld\, p_j}$$

  - p_j = probability for occurrence of symbol $z_j \in Z$ in message source M
  - Entropy H is a measure for random information in a system (or a message source M).
  - K is a constant (can be neglected).
  - High content of random information $\Rightarrow$ low predictability $\Rightarrow$ low probability $\Rightarrow$ high information content.

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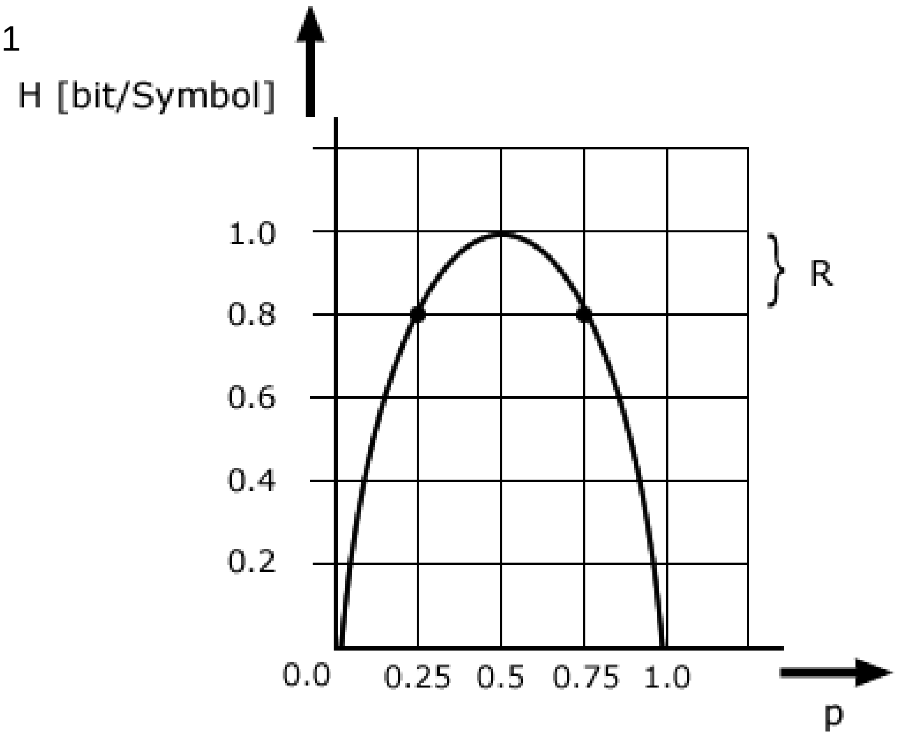
- Example:
  - 2 symbols (0 and 1)
  - with probabilities p_0 and p_1
  - $H = - p_0 \text{ ld } p_0 - p_1 \text{ ld } p_1$



Shannon's entropy (3)

- $H = H_{max}$ is desirable, if a channel must transport the maximal "newness" value per (physical) step.

- In case of: $H < H_{max}$: $R = H_{max} - H$
  - The channel transports useless information (redundancy R).
  - Known information burdens the channel but does not increase the knowledge of the receiver.

- A Shannon channel is "good", if it transports the maximum amount of information:

  $\rightarrow R = 0$!

Approach: Use the statistical definition of entropy!

- Procedure:
  - Select an attribute A of the system (discrete, enumerable) with values a_j.
  - Observe all elements e_i and assign a value a_i to each e_i.
  - Transform into a probability distribution over the attribute values a_j.
  - Determine:

$$\boxed{\text{entropy } H_A = -\sum_j p_j \text{ ld } p_j}$$

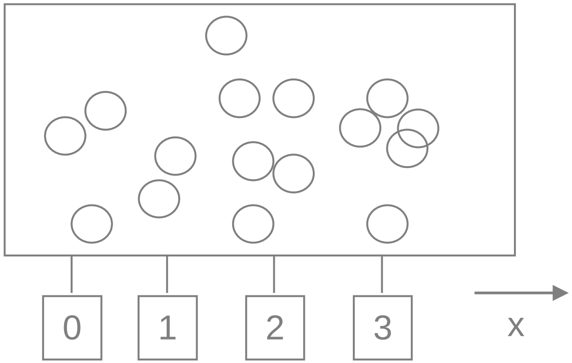
- Each attribute X has its entropy H_X.
- System entropy:

$$\boxed{H_S = \sum_X H_X}$$

- Characterisation of a system by:
  a) System entropy (low specificity)
  b) Vector of attribute entropies („fingerprint“): (HA, HB, HC...)

Example for the quantification of emergence

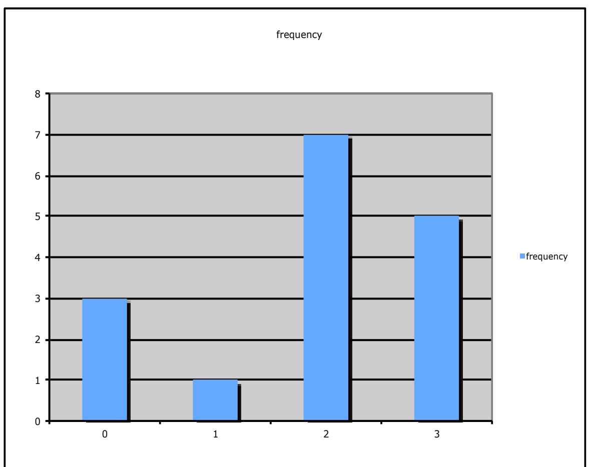
- Discrete values of x coordinate: 0, 1, 2, 3



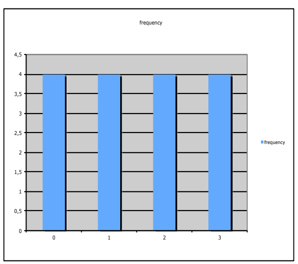
N = 16

Position:	0	1	2	3
Frequency:	3	2	6	5
p	3/16	2/16	6/16	5/16

$$H_{xcoordinate} = -\left(\frac{3}{16}\ ld\frac{3}{16}+\frac{2}{16}\ ld\frac{2}{16}+\frac{6}{16}\ ld\frac{6}{16}+\frac{5}{16}\ ld\frac{5}{16}\right)$$
$$= 1{,}88\ bit\ /\ element$$



Uniform distribution:



$$H_{xcoordinate} = -\left(\frac{4}{16}\ ld\frac{4}{16}+\frac{4}{16}\ ld\frac{4}{16}+\frac{4}{16}\ ld\frac{4}{16}+\frac{4}{16}\ ld\frac{4}{16}\right)$$
$$= 2\ bit\ /\ element$$

Emergence: definition

- Entropy ≠ Emergence!
- First try of a definition: Emergence M is the decrease of entropy H from a start state to an end state:

  $M = \Delta H = H_{Start} - H_{End}$
- This is a necessary, not a sufficient condition for a process to be called emergent. Emergence manifests itself by an increase of order,

  i.e. $H_{End} < H_{Start}$ and $\Delta H > 0$.
- In addition, the process that leads to the increase of order must be self-organised (not e.g. human-induced).
- Problem:
  The observation of emergent phenomena frequently involves a change of abstraction level.

Emergence: definition (2)

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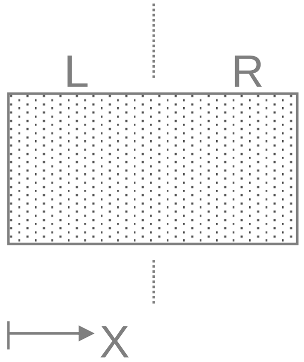
- A change of view to a higher abstraction level leads to a positive ΔH, which is **not** due to an emergent process.
- $\Delta H = \Delta H_{view} + \Delta H_{emergence}$
- Emergence $M = \Delta H_{emergence} = \Delta H - \Delta H_{view}$
- If the two observations (start, end) are made on different abstraction levels, the increase of order due to the change of view (ΔH_{view}) must not be counted as entropy stemming from emergence.
- Or: the entropies H_{Start} and H_{End} are only comparable if they are observed at the same abstraction level ($\Delta H_{view} = 0$).

- Example:



Observation 1 of x coordinate:
32-bit floating point

Observation 2 of x coordinate:
quantisation to 256 values (8 bit integer)

- Quantisation:
  - $\Delta H = 24 \frac{bit}{element}$
  - $\Delta H = \Delta H_{view}$
  - $Emergence\ M = \Delta H_{emergence} = 0$

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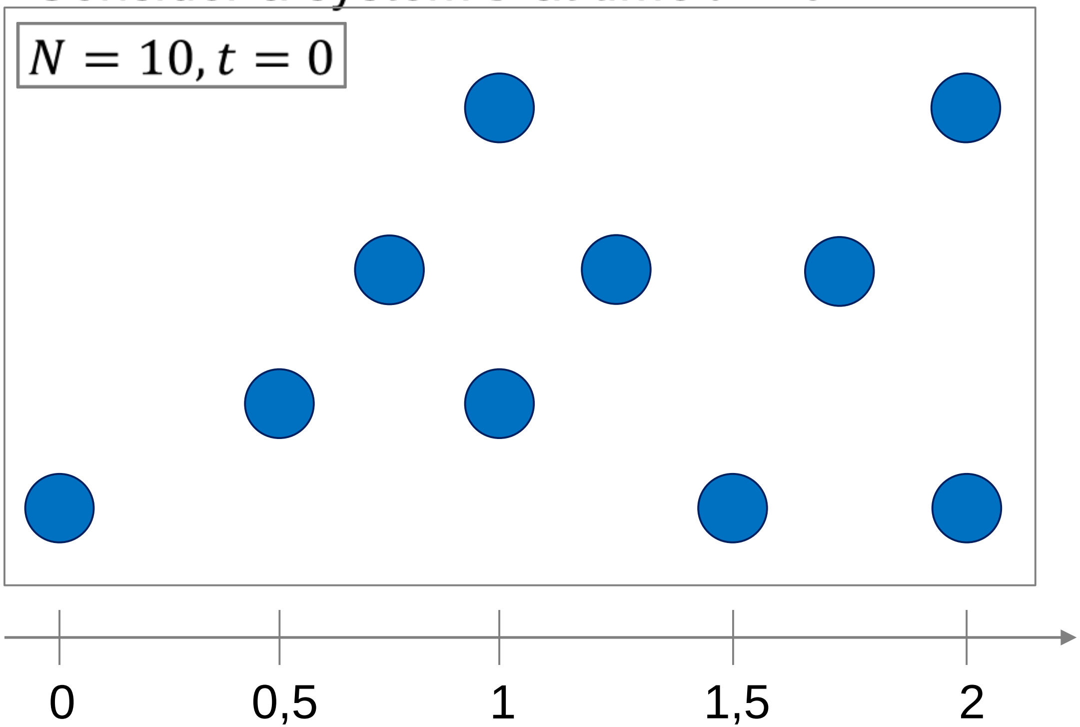
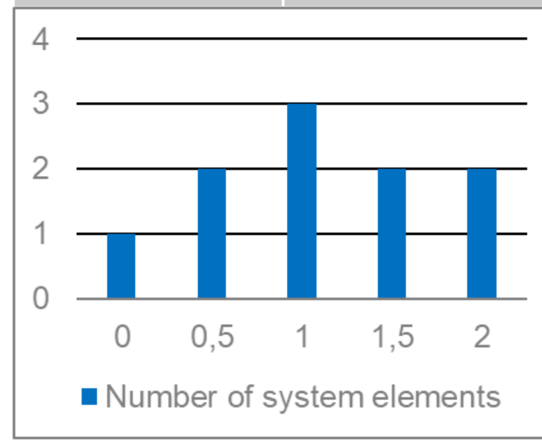
Consider a system S at time $t = 0$



Attribute value	Frequency
0	1
0,5	2
1	3
1,5	2
2	2

x

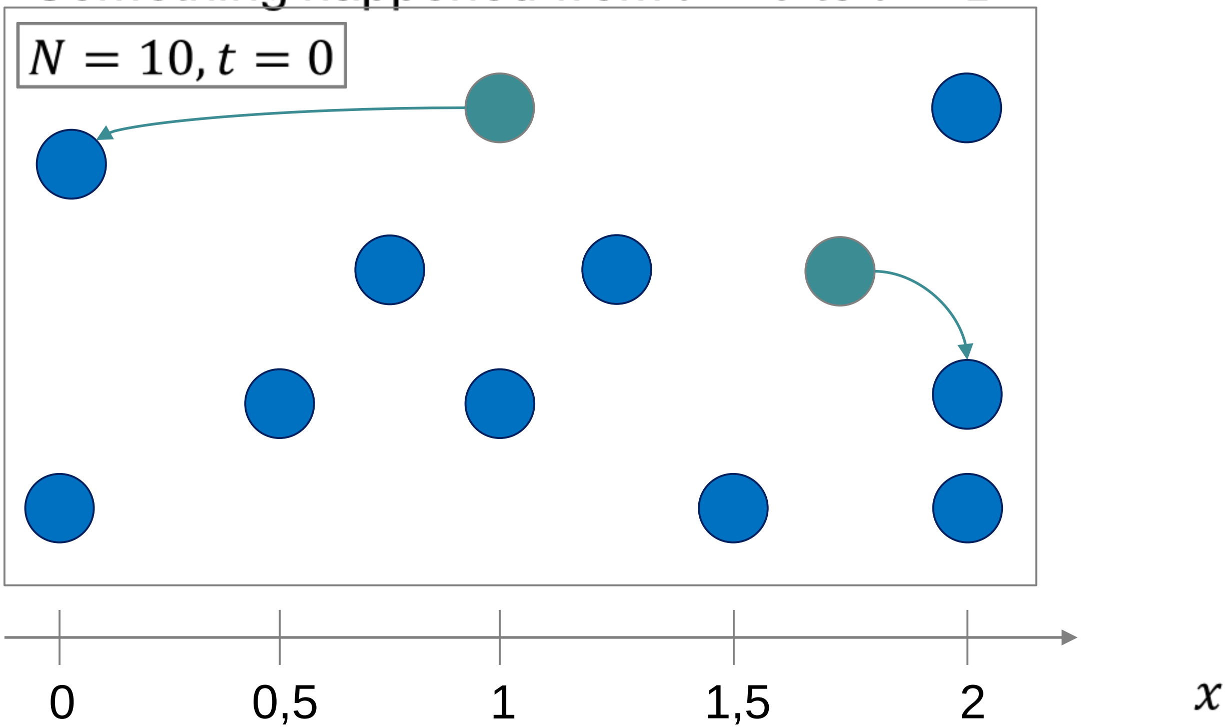


$$H_x^0 = -\left(\frac{1}{10} * ld\,\frac{1}{10} + 3 * \left(\frac{2}{10} * ld\,\frac{2}{10}\right) + \frac{3}{10} * ld\,\frac{3}{10}\right)$$

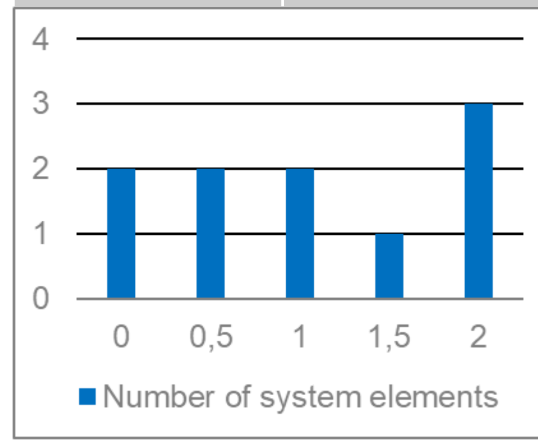
$$H_x^0 = 2{,}24643934467$$

Quantification of abstraction change (2)

Something happened from $t = 0$ to $t = 1$



Attribute value	Frequency
0	2
0,5	2
1	2
1,5	1
2	3



Different state due to self-organised process!

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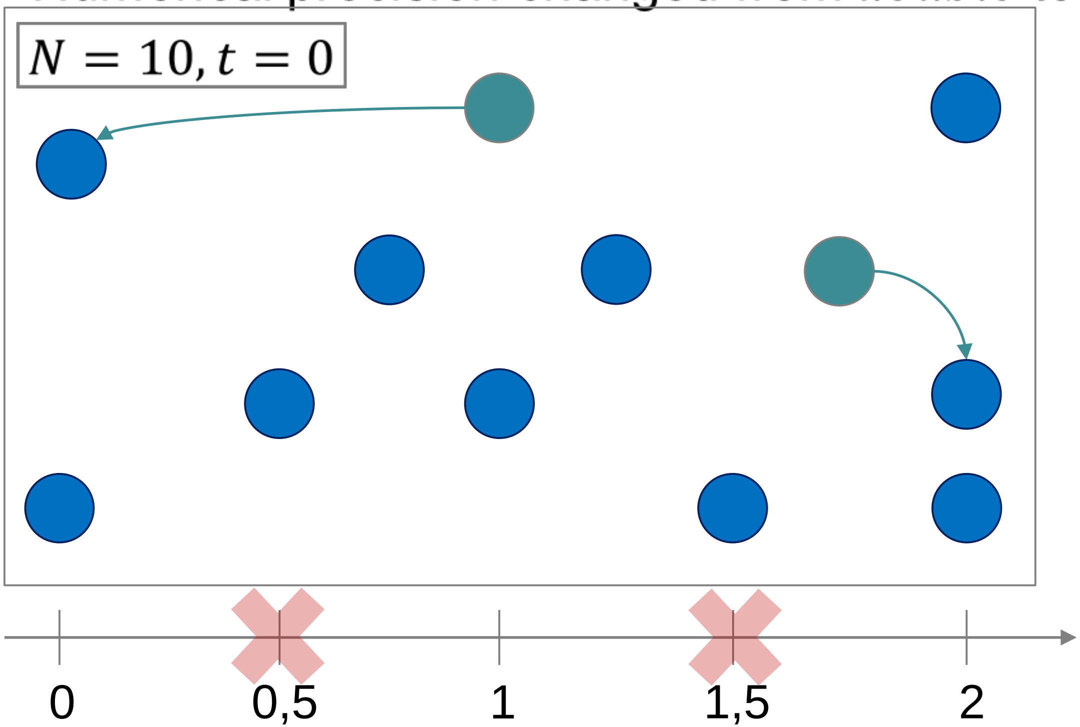
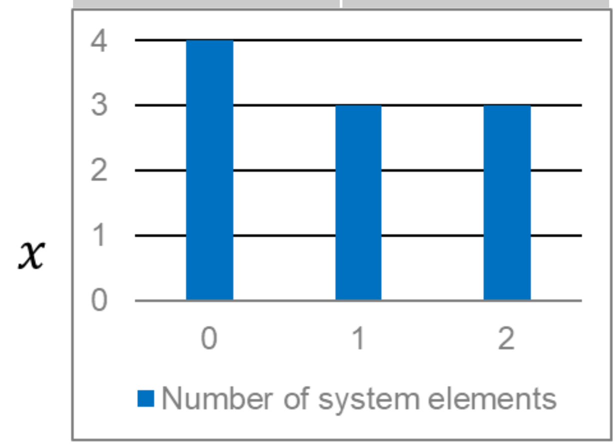
Numerical precision changed from $double$ to int



Attribute value	Frequency
0	4
~~0,5~~	
1	3
~~1,5~~	
2	3



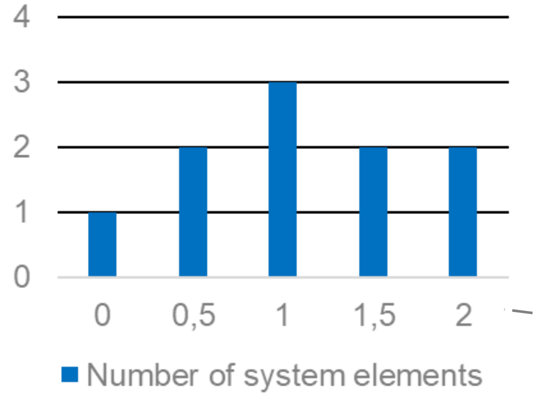
Different state (self-organisation) AND abstraction level

$$H_x^1 = -\left(\frac{4}{10} * ld\,\frac{4}{10} + \frac{3}{10} * ld\,\frac{3}{10} + \frac{3}{10} * ld\,\frac{3}{10}\right)$$

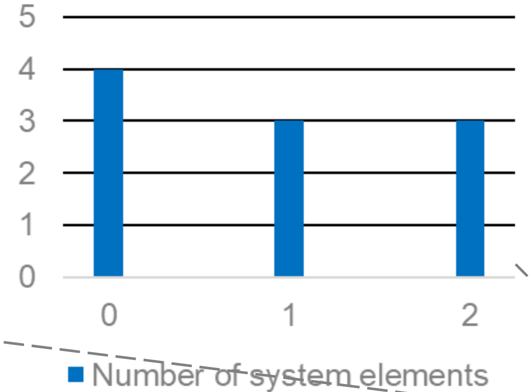
$$H_x^1 = 1{,}57095059445$$

Quantification of abstraction change (4)

What happened? Do we have a higher degree of order?



S at $t = 0$



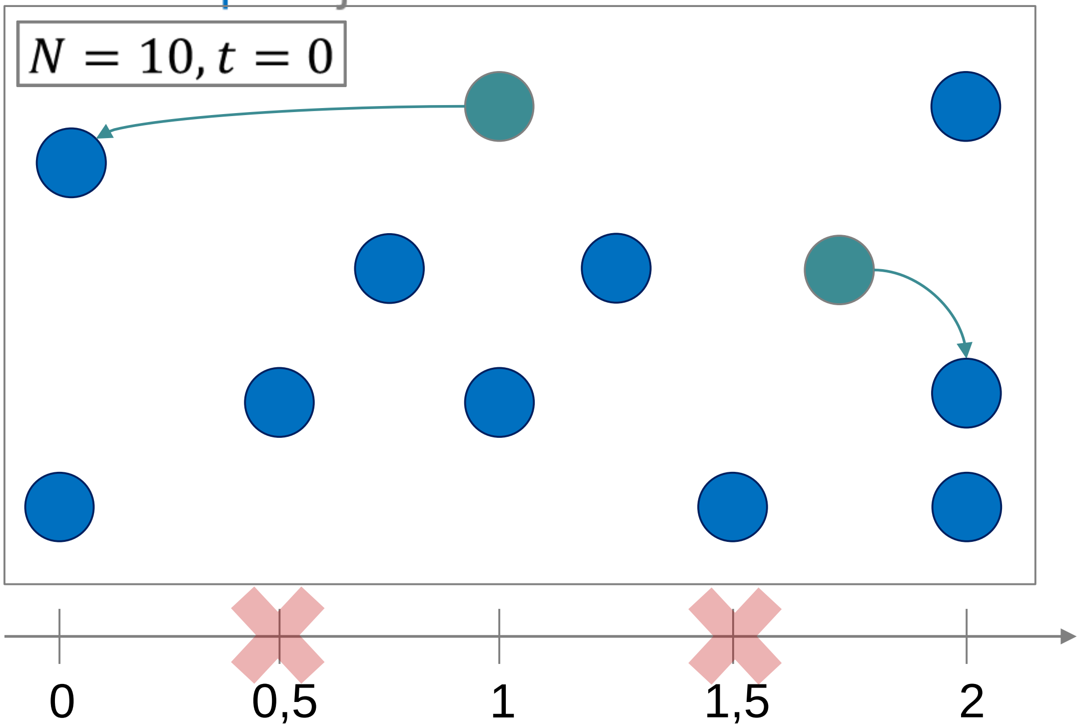
S at $t = 1$

Let's calculate the emergence M:

$$M = H_x^0 - H_x^1$$
$$M = 2{,}24643934467 - 1{,}57095059445$$
$$M = 0{,}67548875022$$

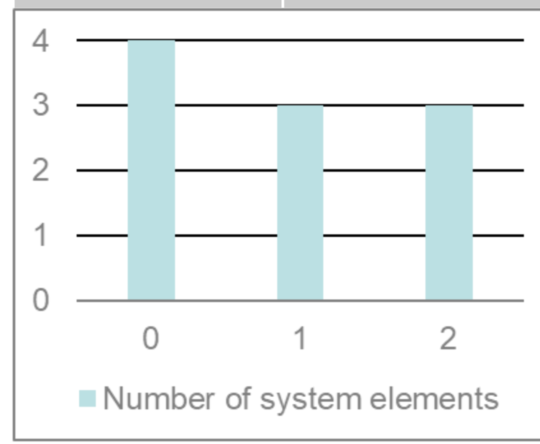
Result: *increase* in terms of *order* (*decrease* of *entropy*)!
But: Subtract influence of ΔH_{view} (i.e. abstraction change)!

First step: adjust the abstraction at time $t = 0$:



Attribut-wert	Frequenz
0	4
~~0,5~~	
1	3
~~1,5~~	
2	3

x



Change of abstraction level (double → int)

$$H'^{0}_{x} = -\left(\frac{3}{10} * ld\,\frac{3}{10} + \frac{5}{10} * ld\,\frac{5}{10} + \frac{2}{10} * ld\,\frac{2}{10}\right)$$

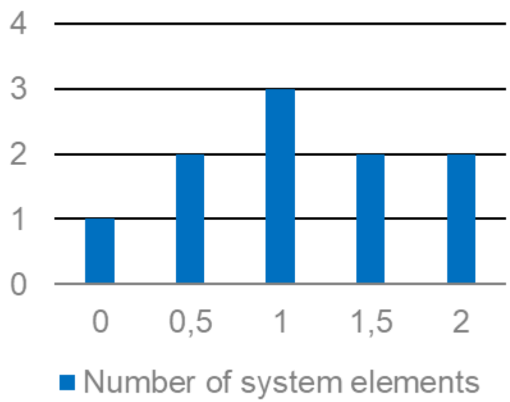
$$H'^{0}_{x} = 1{,}48547529723$$

Quantification of ΔH_{view}

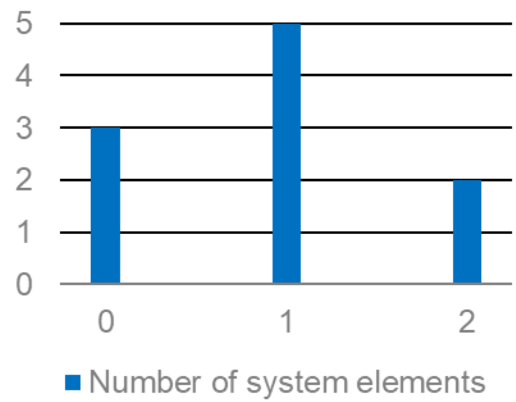
Now, ΔH_{view} calculates:

- $\Delta H_{view} = H_x^0 - H_x'^0$
- $\Delta H_{view} = 2{,}24643934467 - 1{,}48547529723$
- $\Delta H_{view} = 0{,}76096404744$

- Thus, we have an *increase* in terms of *order*, caused by the abstraction level change (less uniformly distributed)!

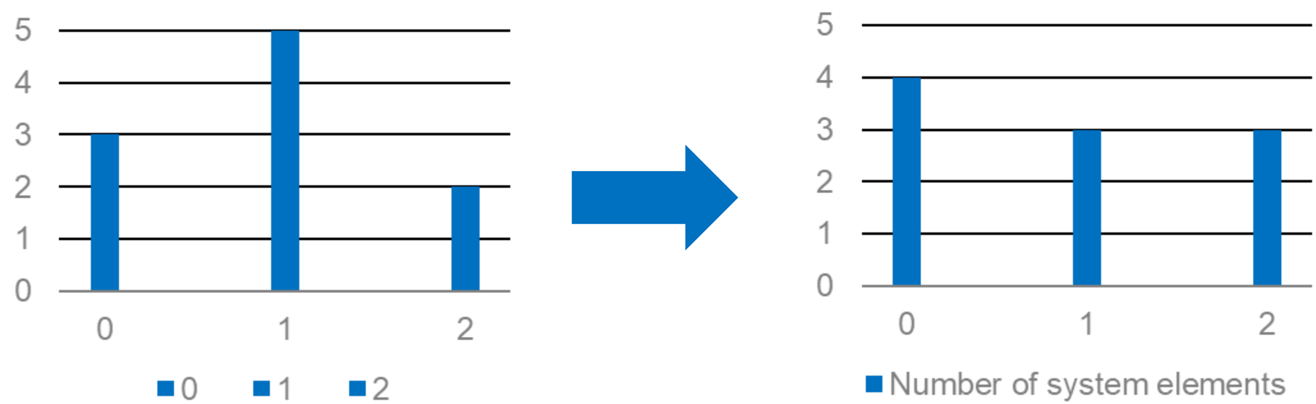


S at $t = 0$



S at $t = 0$

- If we compare the states at $t = 0$ and $t = 1$ on the same level of abstraction, we see a *decrease of order*, due to a *higher degree* of *uniform distribution*!



S at $t = 0$ S at $t = 1$

Quantification of ΔH_{view} (3)

Final step: subtract ΔH_{view} from the emergence M calculated before:

- $M = H_x^0 - H_x^1 - \Delta H_{view}$
- $M = 2{,}24643934467 - 1{,}57095059445 - 0{,}76096404744$
- $M = -0{,}08547529722$

- And \`Ta-da‘!

- Now, we get a negative emergence value M which indicates an *increase* in terms of *entropy* from time $t = 0$ to $t = 1$, given the change in the level of abstraction.

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Emergence and order

- Emergence $M = \Delta H_{emergence}$ is a measure of the (self-organised) increase of order from start to end of a process.
- Is there an absolute indicator of order?
- We can define order as the difference between the entropy at maximum disorder (H_{max}) and at a certain system state (H):

  $M = \Delta H = H_{max} - H = \Delta H_{emergence} - \Delta H_{view}$

  with $\Delta H_{view} = 0$:

  $$\text{Emergence } M = \Delta H_{emergence} = H_{max} - H$$

- H_{max} is the system or attribute entropy for the case of a uniform probability distribution.

Term definition

- Emergence is the increase of order due to self-organised processes between the elements of a system.
- Higher order is measured in terms of a lower description complexity, i.e. in terms of lower information content.
- The more structure a system displays, the less explicit information is necessary to describe it: Kolmogoroff complexity.
- Any entropy decrease due to a change to a higher abstraction level (ΔH_{view}) must be subtracted.
- Emergence $M = \Delta H_{emergence} = H_{max} - H - \Delta H_{view}$
- Relative Emergence m (for $\Delta H_{view} = 0$):

$$m = \frac{H_{max} - H}{H_{max}}$$

Information theory:

- Redundancy $R = H_{max} - H$
- Relative redundancy: $r = \frac{H_{max} - H}{H_{max}}$

- Why is M = R (or $\Delta H_{emergence} = R$)?
- Answer: Different notions of utility
  - Information theory: A channel should be used only for the transmission of relevant (= new) information.
  - Max. information content if $H = H_{max} \rightarrow R = 0$
  - Newness or unpredictability of messages increase their value (information content).
  - The physical steps (light pulses, current levels, voltage levels) should be used economically only to transport relevant information.
  - Living (self-organising) systems are ”better“ if they display higher order, lower newness, higher predictability

Redundancy (2)

Redundancy conclusions:

- Communication engineer:
  Redundant information should not be transmitted over a channel.
  → Redundancy is ”bad“.

- Nature, living systems:
  The existence of predictable information about a system means that no (or little) new information has to be sent via the channel.
  → High predictability (= emergence = redundancy) is ”good“.

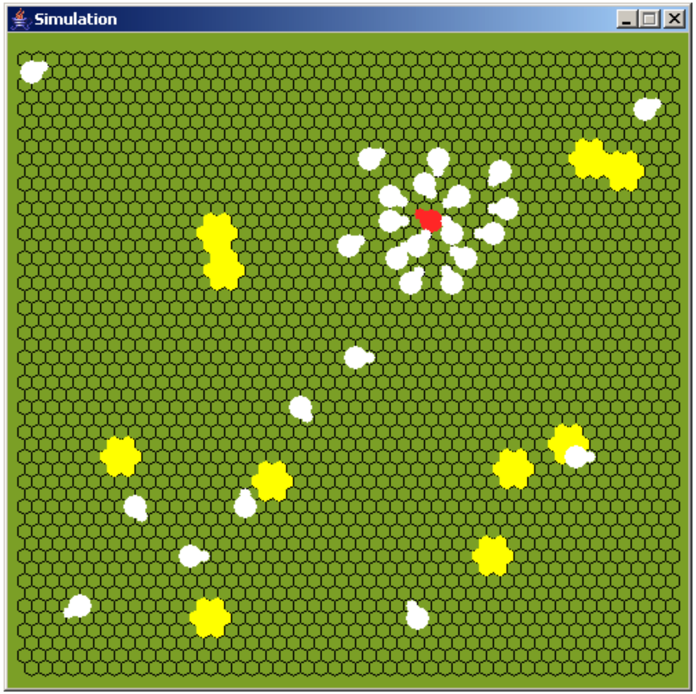
How to utilise emergence information?

- Emergence can be calculated for a given system for different attributes.
- It can be used as an early indicator of (emergent) ordering processes.
- System emergence (the total of all attribute emergence values) is not selective enough.
- More interesting: Emergence fingerprint for all relevant attributes.
- Open questions:
  - Which attributes are relevant?
  - What is positive (wanted) and negative (unwanted) emergence?
  - How can we identify results of self-organised processes?

Example: cannibalistic behaviour of chicken

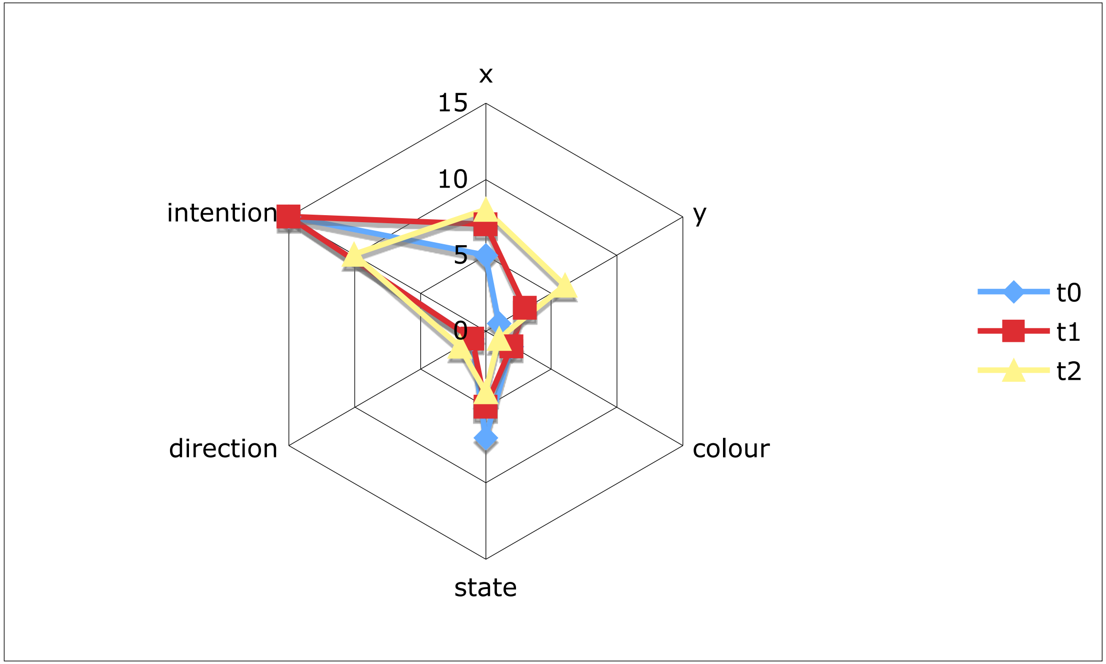
Problem

- TiHo Hannover
- Chicken stock in large farms
- Thousands of chicken in one shed
- Injured chicken:
  - Other chicken start to hurt injured chicken.
  - Do not stop until chicken is dead.
  - Even a small scratch causes dead!
  - Bad for chicken (→ dead) and owner (→ cost)
- What to do?
  - Noise disturbs chicken, they let up from injured chicken.
    → Activate horn.
  - But: noise is bad (stress level)

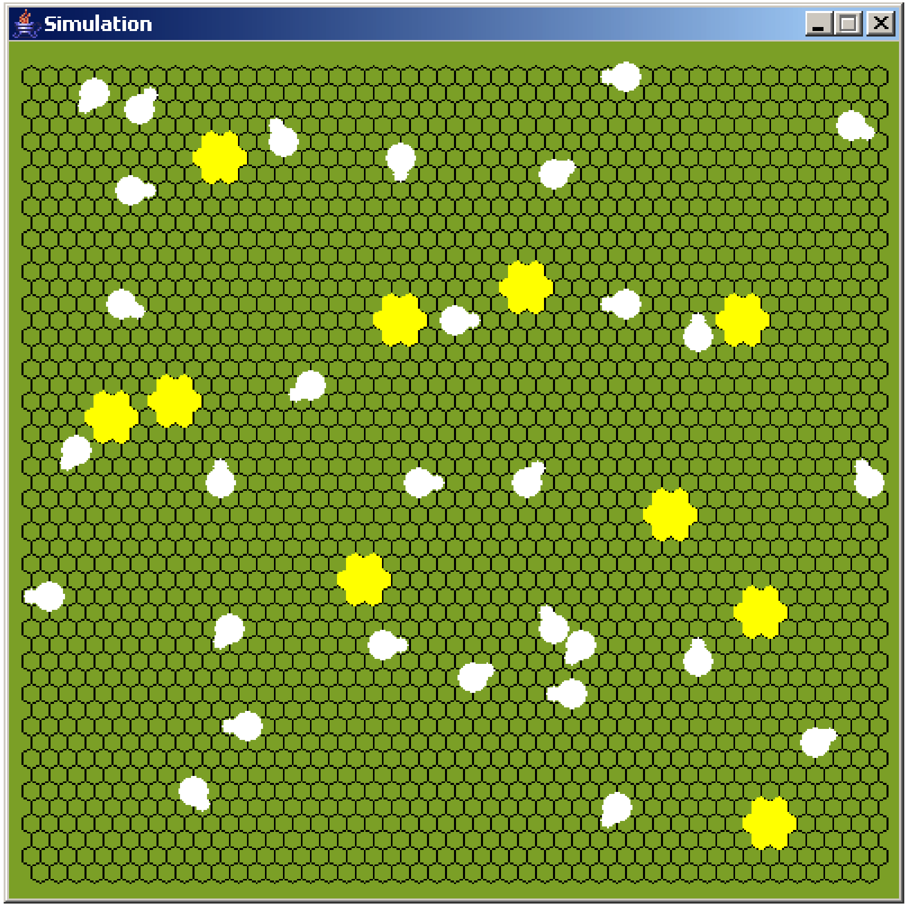


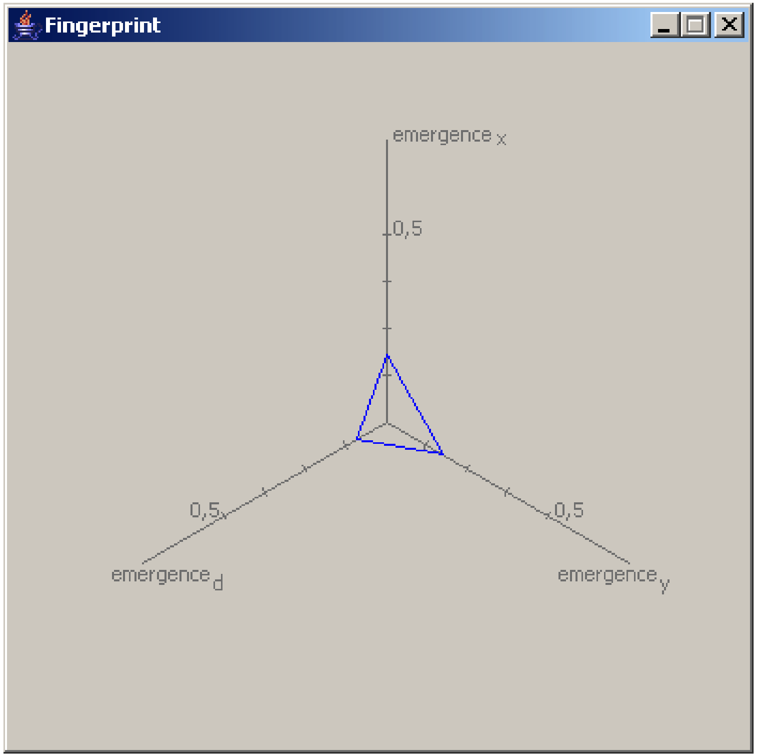
Yellow: food source
White: chicken with heading
Red: injured chicken

- Emergence fingerprint = visualisation of all (relevant) attribute emergence values of a system.
  - Visualisation as *n*-dimensional Kiviat graph
- Example
  - x-position
  - y-position
  - colour
  - state
  - direction
  - intention



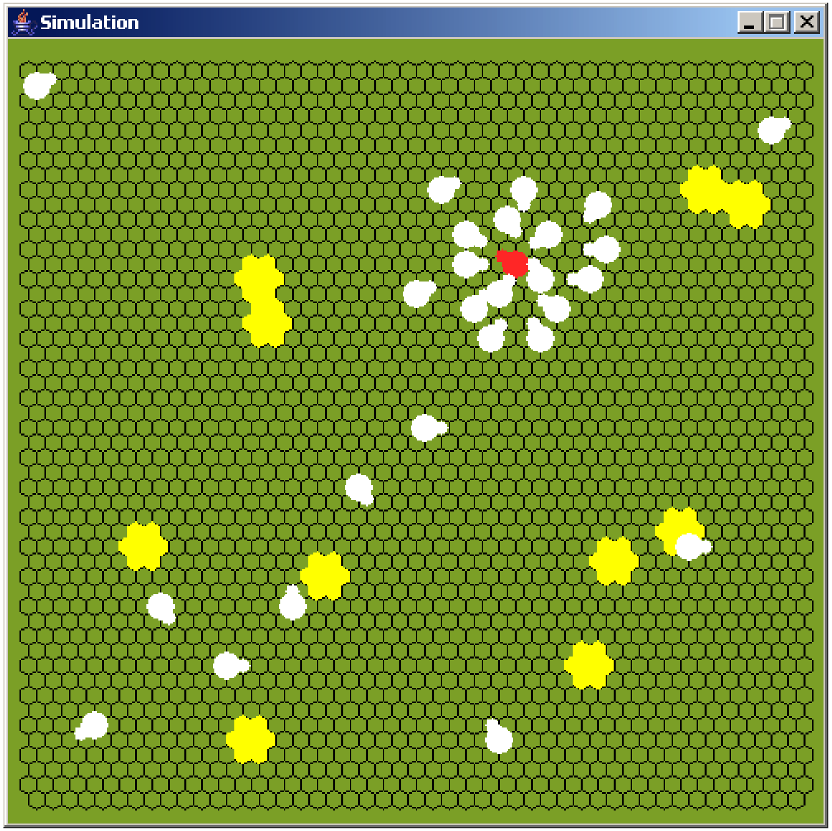
Emergence fingerprint (2)

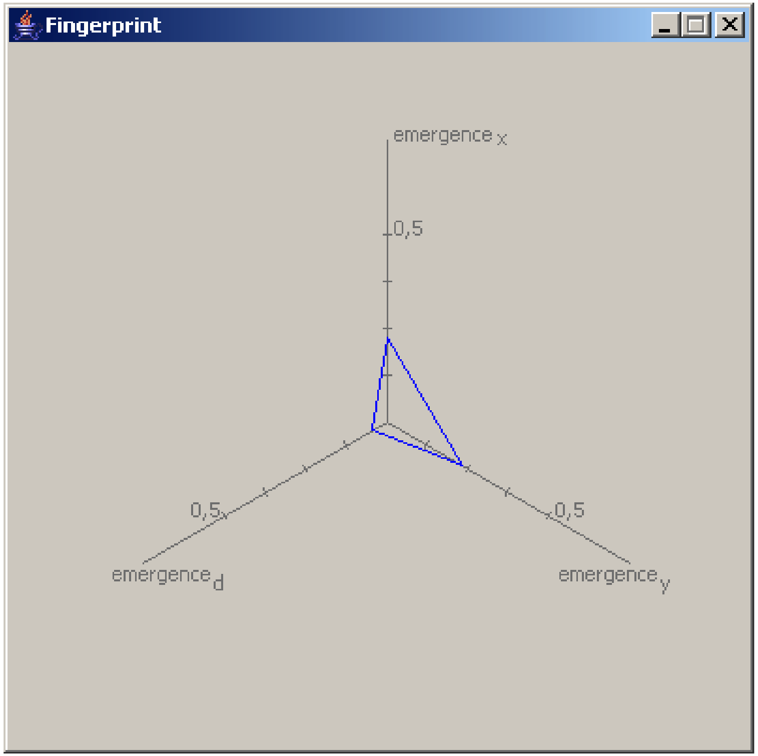




Pattern 1: $M_x = 0.181$, $M_y = 0.177$, $M_{direction} = 0.091$

Emergence fingerprint (3)





Pattern 2: $M_x = 0.226$, $M_y = 0.237$, $M_{direction} = 0.046$

Emergence fingerprint (4)

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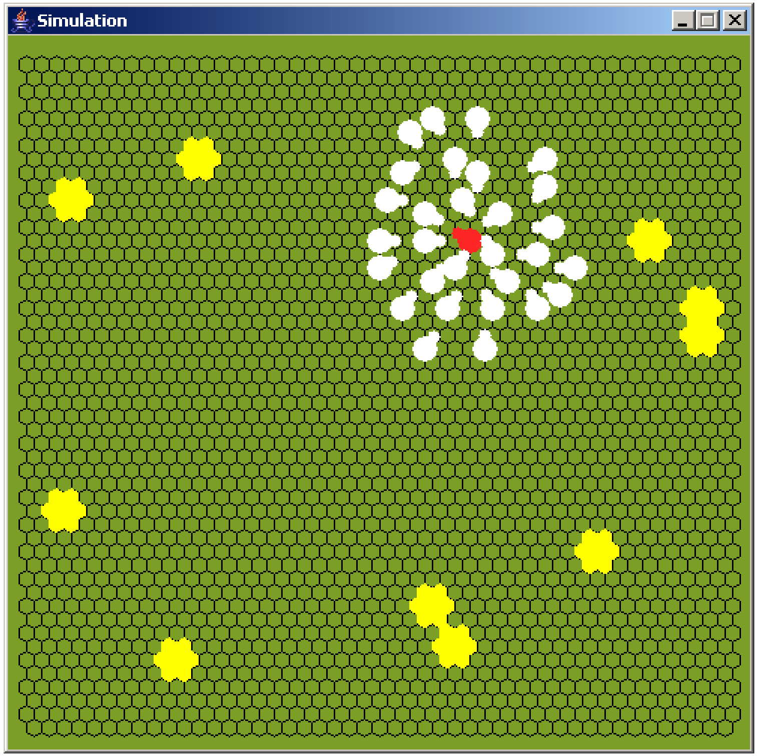
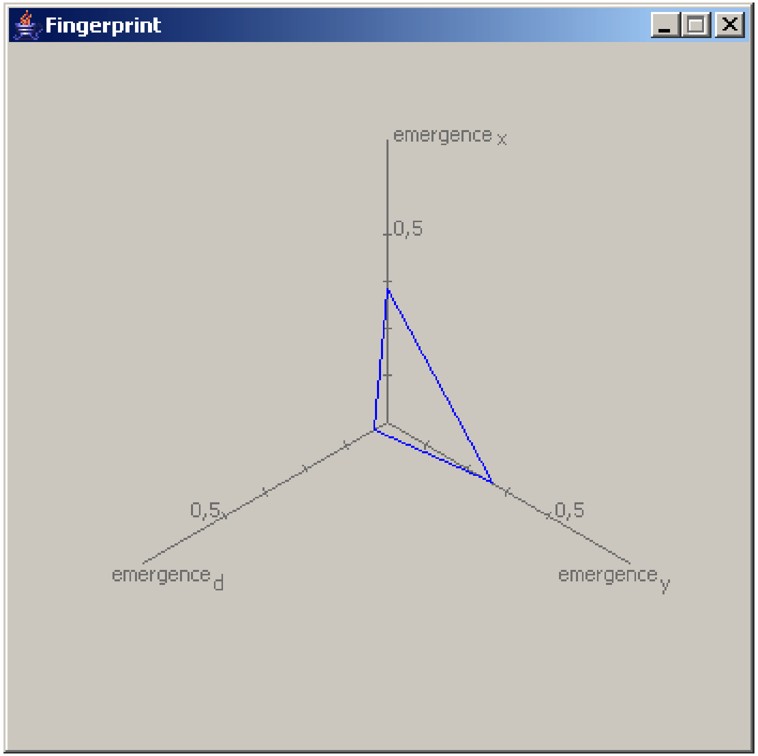
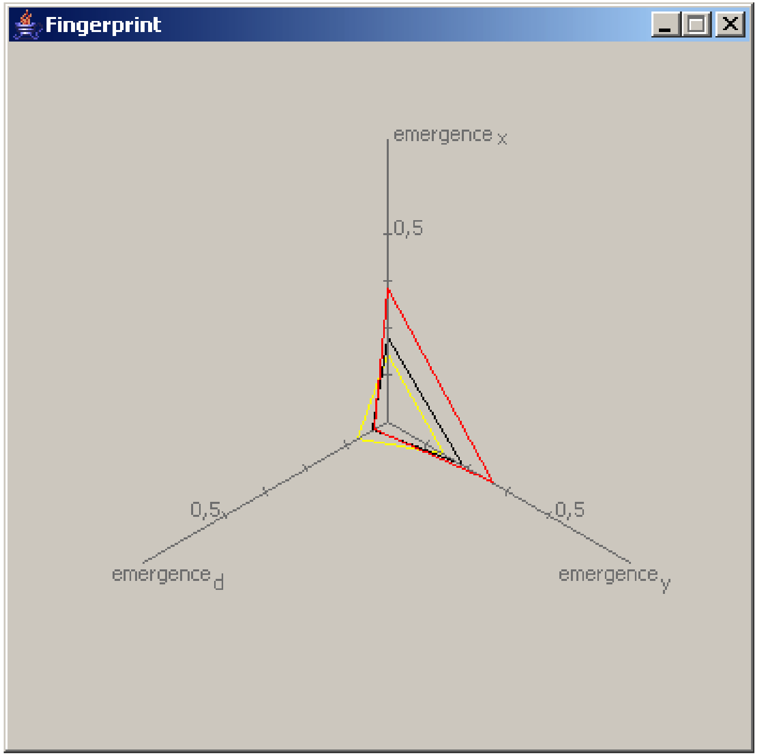
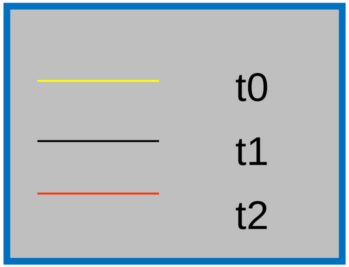




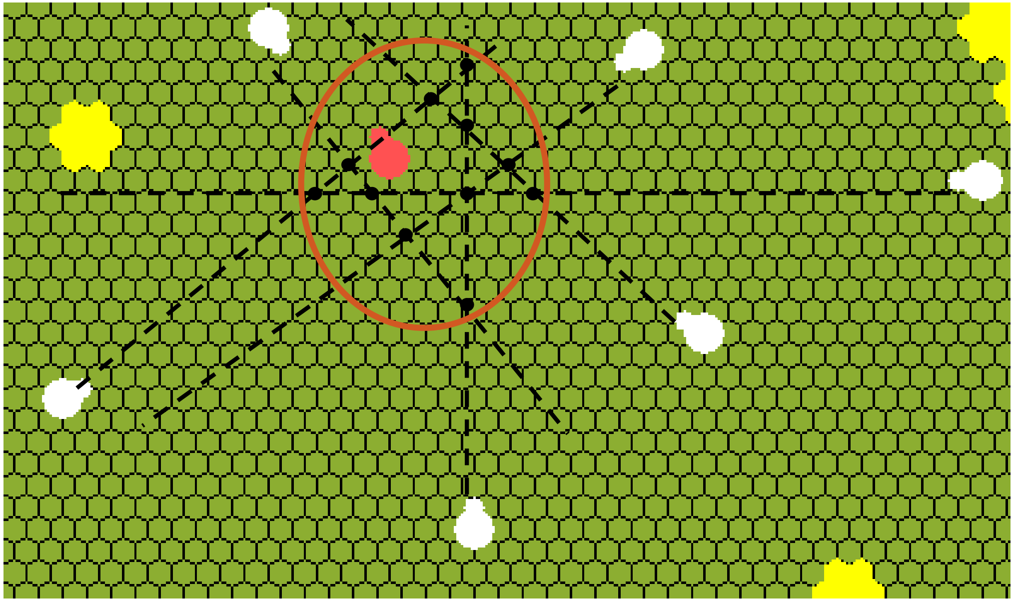
Pattern 3: $M_x = 0.359$, $M_y = 0.328$, $M_{direction} = 0.041$

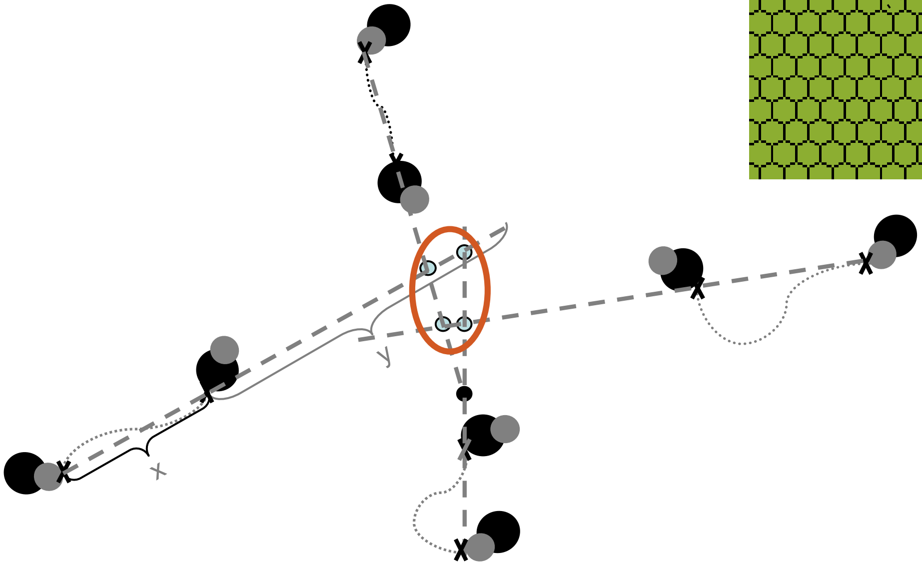
Emergence fingerprint (5)





Emergence fingerprint (6)





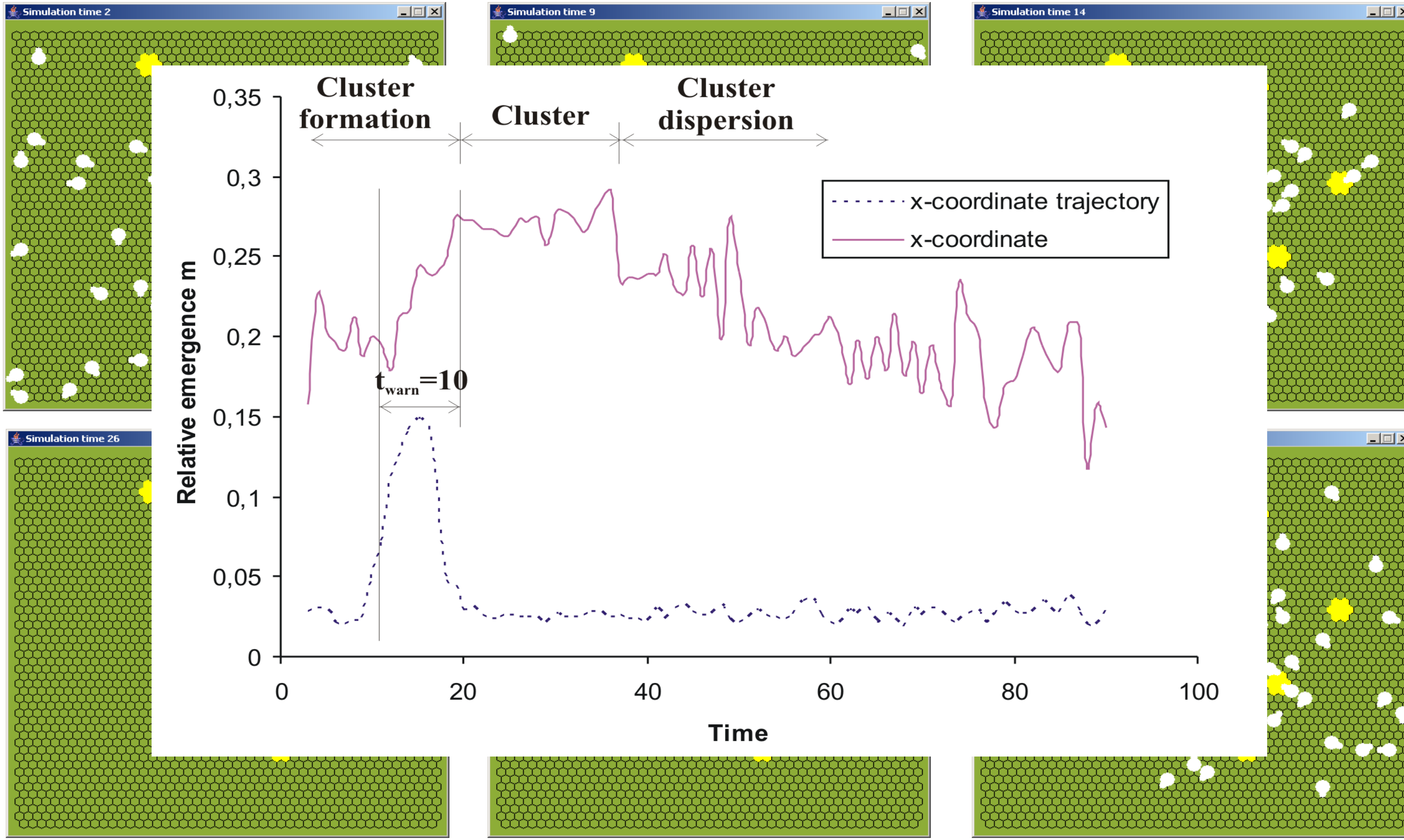
$$v = \frac{x}{\Delta t}$$

$$y = v \times \tau$$

Δt Observation period

τ Prediction period

Cluster formation



Summary: quantification of emergence

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Process

1. Quantify entropy for each attribute.
2. Calculate emergence (M) for each attribute:
$M = \Delta H = H_{Start} - H_{end} - \Delta H_{view}$
3. ΔH_{view} is the (possible) change of abstraction when observing H_{Start} and H_{end} , e.g. converting *float* to *int* values.
4. a) Determine the system emergence as sum over all attributes.
b) Illustrate as "fingerprint".
5. Is this due to self-organisation?

Agenda

- A first example: water temples in Bali
- A second example: ants
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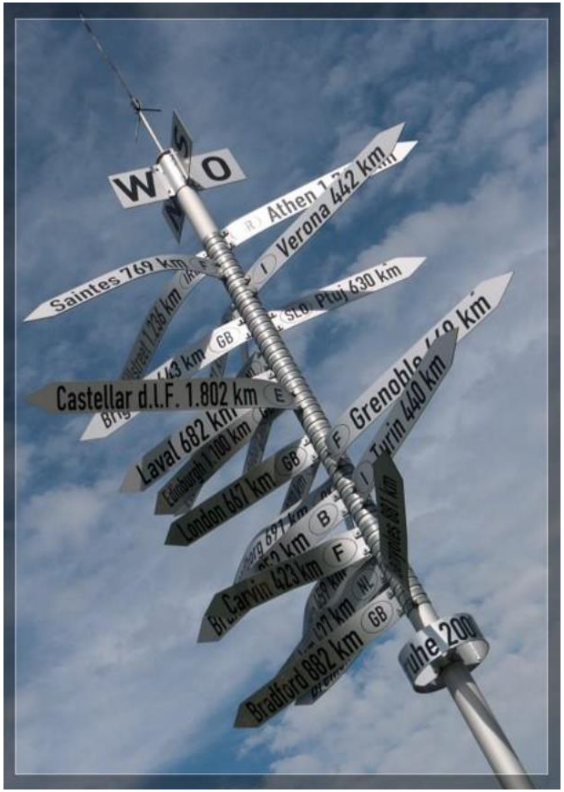
- Conclusion
- Further readings



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Until now:

- Regarded emergence as the difference between an entropy at the beginning of some process and at the end.
- Discrete entropy difference (DED):

$$DED[x] = H_{start}[x] - H_{end}[x]$$

- A process is called emergent if DED[x] > 0 and the process is self-organised.
- What if we do not know if self-organisation is in place?
- Entropy values are computed for different attributes – which leads to a so-called emergence fingerprint – and this fingerprint serves as basis for certain decisions, e.g., concerning interactions with the system S.

Approach:

- We want to measure the amount of information that we gain, when we know that a categorical variable x has value i'.
- In a probabilistic framework: probability $p(x = i')$.
- Another unrelated, categorical attribute y and a value j': $p(y = j')$.
- This information measure has to be additive: If we knew the values of both attributes, the two information values are added.
- Hence: Use $-\ln p(x = i')$ and $-\ln p(y = j')$ (which are always non-negative)
- If we observe both values, the amount of information for this observation of statistically independent variables gets:
$$-\ln\left(p(x = i', y = j')\right) = -\ln p(x = i') - \ln p(y = j')$$

Entropy again

From probabilities to entropy

- We are not interested in specific values of an attribute.
- Instead: We are interested in expected values.
- Hence: Determine the expectation of the information with respect to the corresponding distribution.
- This is exactly the entropy, i.e., for a variable x with a corresponding distribution $p(x)$ we get:

$$H[x] = -\sum_{x} p(x) \ln p(x)$$

- Then: sum up over all possible values of x again.
- Entropy describes the expected amount of information which we gain when we observe x.

Limitations of the previous approach

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Measure may be unsatisfying in some applications due to:

1. There are many attributes with continuous values in practical applications.
2. Many applications are multi-variate, i.e., based on several (categorical and continuous) attributes.

- The former problem (1) is solved by categorisation of continuous attributes.
→ Could be problematic as entropy measurements depend on size and position of the chosen “bins”.
- The latter (2) is solved by analysing the fingerprints.
→ If this analysis is conducted automatically, the different entropy values must be combined at some time.

An extended model

Approach:

- Multivariate entropy measure for continuous variables.
- Combine all attributes into a vector x.
  Then: continuous entropy (also known as differential entropy) is:

$$H[x] = -\int p(x) \ln p(x) \, dx$$

- where p is the joint density of x.
- p combines all attributes, i.e. several continuous random variables.
- For simplicity: assume that we only have continuous variables.
  →Hybrid (categorical/continuous) approaches are possible.
- Please note: A continuous entropy (in contrast to a categorical one) may have negative values.

Density

- Approach relies on estimating the density of a continuous variable.
- Neglect (by now) the functional form of the density function (e.g. to assume that it is Gaussian).
- Then: a non-parametric density estimation approach can be used.
- Assume: given a set X of N observations of x (i.e., samples): $x_0, \ldots, x_{N-1}$.
- Goal: estimate $p(x')$ for arbitrary x' (not necessarily $x \in X$).
- Idea: count all samples in a certain environment around x' and divide this number by the size of the environment.

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Alternative (smoother):

- Use Parzen window approach, i.e. a kernel density estimator based on a Gaussian kernel:

$$p(x') \approx \frac{1}{N} \sum_{x_n \in X} \frac{1}{(2\pi h^2)^{\frac{D}{2}}} \exp(-\frac{1}{2} \frac{||x' - x_n||^2}{h^2})$$

- where D is the dimensionality of x and h is a user-defined parameter.
- h depends on the data set X – there are a number of heuristics to estimate h (e.g. h is set to the average distance of the ten nearest neighbours from each sample, averaged over the entire data set).

Evaluation of the integral

- Continuous entropy model contains integral.
  → How to evaluate this?
- Remember: data set X contains samples x_n distributed according to p (i.e., $x_n \sim p$).
- Hence: Entropy can be approximated

$$\widehat{H}[x] \approx -\frac{1}{N} \sum_{x_n \in X} \ln p(x_n)$$

- where the $p(x_n)$ are estimated using the Parzen approach.
- Note: this discrete approximation of the entropy does not sum up over discrete points in the input space situated on a regular grid.
- Hence: take their non-uniform distribution into account by a correcting factor $\frac{1}{P(x_n)}$.
  → Corresponds to the concept of importance sampling.

- The static approach defines emergence using a difference of entropy values.
  → Emergence is considered as a change of order within a system.
- Here, we define emergence as an unexpected or unpredictable change of the distribution underlying the observed samples.
- Then: use divergence measure to compare two density functions,
  i.e. p(x) at t_0 and $q(x)$ at t_1.
- Possible measure is Kullback-Leibler (KL) divergence $KL(p||q)$.
- Also known as relative entropy.
- Compares two probability density functions.

$$KL(p||q) = - \int p(x) \ln \frac{q(x)}{p(x)} dx$$

Limitations of Kulback-Leibler

- KL divergence is not a true metric since it is not symmetric.
- However:
  - $KL(p||q) \geq 0$ and
  - $KL(p||q) = 0$ only if $q(x) = p(x)$.

- We measure the expected amount of information contained in a new distribution with respect to the original distribution of samples and not with respect to the new distribution:

$$KL(p||q) = -\int p(x) \ln q(x)\ dx + \int p(x) \ln p(x)\ dx$$

- There are concepts for symmetric variants (neglected here).

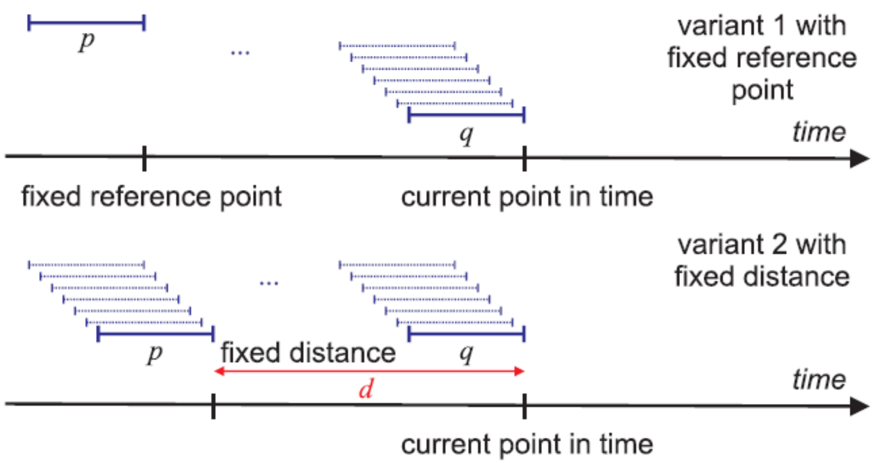
Application of the measures

Measures are applicable to emergence quantification:

- Abstraction from the technical system.
- Consider only distributions of samples in the attribute space.
- Assumption: observation of a number of processes “generating” samples.
- Goal: comparison of the distributions underlying the observed samples.
- Concept: estimation of the distributions at two different points in time, an earlier one (p) and a later one (q).
- Instead of assuming that we get a set of observations at each (discrete) point in time: one single observation at each point in time (these points are considered as equidistant in time).

Sliding window: Estimate p and q in sliding data windows.

- Windows have fixed length, must be:
  - long enough to estimate p and q with sufficient reliability.
  - short enough to allow for the assumption that the observed processes are nearly time-invariant in these windows.
- Distinguish:
  - First (earlier) time interval is fixed at a certain point in time, whereas the second interval moves along the time axis with the current point in time.
    → Online application.
  - Both windows move along the time axis in a fixed temporal distance.
    → Distance d is important parameter of the measure-



Application of the measures (3)

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- Estimation of densities p and q: non-parametric or model-based approaches.
→ Depending on application.
- Hybrid approaches are possible as well.
- If both densities are estimated in a non-parametric approach:
→ Either using the sampling points in the first set of observations ($x_n \sim p$) or those given in the second ($x_n \sim q$).
- Suggestion: Evaluate both intervals and average measures.
→ Get more robust estimates.
- Comparison leads to 'degree' of emergence. In addition:
  - Detection of processes that disappear (i.e., components become obsolete).
  - Detection of newly emerging processes (i.e., new components are required).
  → Novelty detection.
  - Detection of components that change their characteristics (i.e., components change their parameters such as centre or mixing coefficients).
  → Concept drift.

Emergence detection

- Based on probabilistic (or information-theoretic) considerations.
- May be used to determine ‘degree‘ of emergence.
- Contrast to previous approach:
  - Applicable in cases with continuous attributes,
  - Applicable if several attributes have to be combined,
  - Applicable if application allows for model-based density estimates.
- Measures can assess emergence gradually.
- Can further be used to detect novel situations or phenomena such as concept drift.
- In organic systems:
  - Monitor the overall distribution by combining measures for different components.
  - Supervise components individually.

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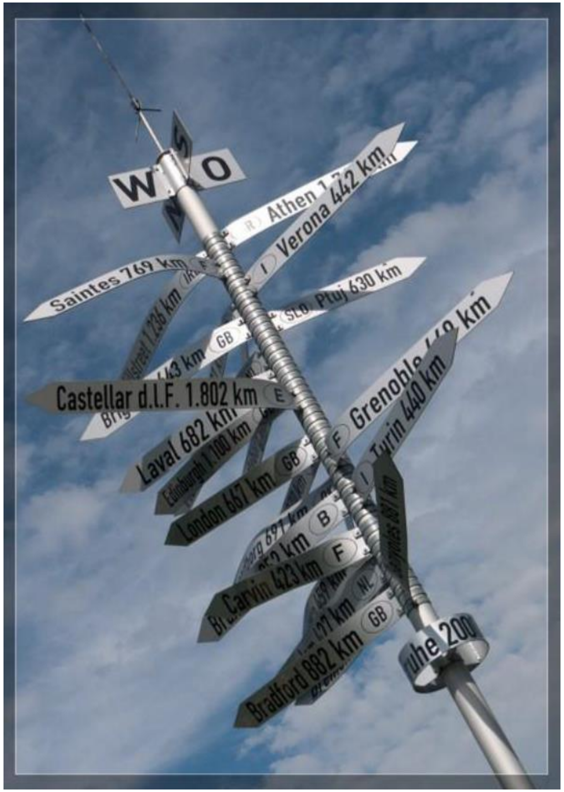

From self-organised order to emergence

- Nature as inspiration: Complexity is handled by self-organised order.
- Order is observer- and goal-dependent!
- Self-organised order consists of purposeful self-organisation processes and additional emergent phenomena.
- Same ingredients in organic systems → same processes expected!
- Consequence: We have to measure and master emergence.
- Approach:
  - Observe behaviour of system
  - Measure order (i.e. based on entropy)
  - Compare measures at different points.

Conclusion (2)

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This chapter:

- Demonstrated how self-organised order appears in natural, technical and social systems.
- Highlighted the control of complexity by self-organisation and emergence.
- Defined the term 'emergence' and its relation to self-organisation.
- Explained how emergence is quantification for systems with discrete attributes.
- Refined this quantification concept to be applicable to continuous attributes and their combinations.

By now, students should be able to:

- Explain the relation between self-organisation and emergence.
- Briefly summarise the term emergence.
- Give examples for emergent phenomena, e.g. in nature.
- Quantify emergence in technical systems based on discrete attributes.
- Outline how emergence detection is done for systems with continuous attributes.

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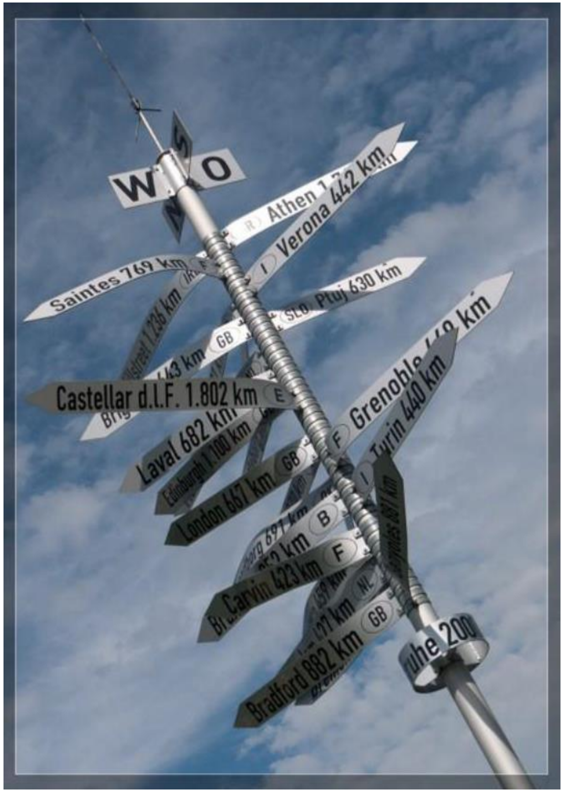

Further readings

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- Nelson Fernandez, Carlos Maldonado, Carlos Gershenson: „Information Measures of Complexity, Emergence, Self-organisation, Homeostasis, and Autopoiesis“, online available at: http://arxiv.org/pdf/1304.1842v1.
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- Dominik Fisch, Martin Jänicke, Bernhard Sick and Christian Müller-Schloer, "Quantitative Emergence - A Refined Approach Based on Divergence Measures," 2010 Fourth IEEE International Conference on Self-Adaptive and Self-Organizing Systems, Budapest, 2010, pp. 94-103. DOI: 10.1109/SASO.2010.31
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End

- Questions….?