Wstęp do modelowania procesów sensorycznych i percepcyjnych

Iwo Błądek, Konrad Miazga

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Informacje organizacyjne

Prowadzący

- mgr inż. Iwo Błądek (*iwo.bladek@cs.put.poznan.pl*)
- mgr inż. Konrad Miazga (*konrad.miazga@.cs.put.poznan.pl*)

Plan semestru

1. ACT-R (Konrad Miazga)
   modelowanie symboliczne
2. Nengo (Iwo Błądek)
   modelowanie koneksjonistyczne
3. Sztuczne sieci neuronowe (Iwo Błądek)
   sztuczna inteligencja $\longleftrightarrow$ modelowanie mózgu
4. Framsticks (Konrad Miazga)
   symulacja ewolucji percepcji / mózg + ciało

Zasady zaliczenia

Obecności

- Dopuszczalne są dwie nieobecności nieusprawiedliwione w czasie semestru.
- Każda kolejna nieusprawiedliwiona nieobecność oznacza obniżenie oceny końcowej o pół oceny.
- Znaczne spóźnienie traktowane jest jak połowa nieobecności.
- 30% nieobecności (zarówno usprawiedliwionych, jak i nieusprawiedliwionych) stanowi *podstawę* do niezaliczenia przedmiotu.
- Usprawiedliwienia (lekarskie) należy dostarczyć w ciągu dwóch tygodni od nieobecności (później nieobecność będzie uważana za nieusprawiedliwioną).

Zasady zaliczenia

Oceny

- Aby zaliczyć przedmiot trzeba uzyskać co najmniej 50% z każdego zadania/projektu realizowanego w trakcie semestru.
- Ocena końcowa wyliczona zostanie na podstawie punktów uzyskanych w trakcie semestru.

Introduction to modeling

Different types of systems

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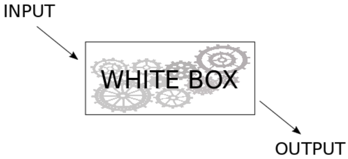

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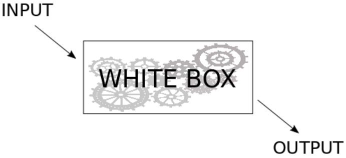

- **Grey Box** (combination of both)

Why are we creating models?

- A tool for devising a theory
- A tool for testing a theory
- Predictions
- Freedom of manipulation
- Precision of analysis

A tool for devising a theory

- Theories can be created on the basis of models.
- Models can be used to provide data and intuitions regarding the process.
- Machine learning is able to create a working efficient models for processes, for which we don't have a (single and widely accepted) theory (e.g. recognition of emotion).
- Such models, even when not necessarily consistent with the modeled process, can give us some intuitions.

A tool for testing a theory

- Theories are usually high level and omit implementation details.
- Sometimes those details prove to be troublesome enough to invalidate the whole theory.
- A working model with good predictions, build on the basis of such a theory, demonstrates the soundness of that theory.
- The more such a model is similar to the workings of the real brain, the more reliable is the connected theory.

Predictions

- Accurate model allows to “predict future”, that is to have a good approximation of what will happen.
- Correct predictions are the main concern of *machine learning*.
- Important for practical applications of knowledge.

Freedom of manipulation

- Having a (computer) model allows for much easier and faster testing of hypotheses.
- Especially useful for testing rare conditions and impairments.
- We can consider many parameters and variants of both the modeled system (brain) and the stimuli.
- We can temporarily disturb certain element of the model and observe effects.
- And we don't need the ethics committee approval. :)

Precision of analysis

- We can "look inside" the model while it is running and analyze the behavior of all of its elements.
- Example: real time tracking of the state of every neuron in the network.
- Because of this we can possibly find some interesting patterns, which we would otherwise miss.
- Example: in deep neural networks (AI), we can get the information about the pattern which a particular neuron is specialized to detect.

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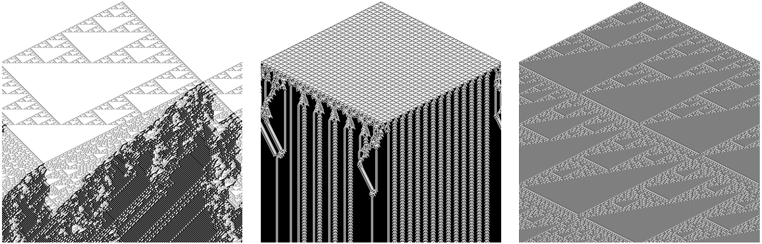

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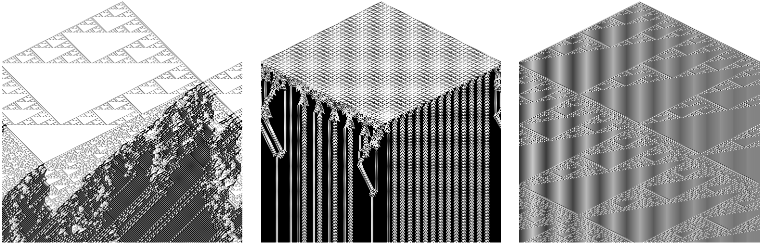

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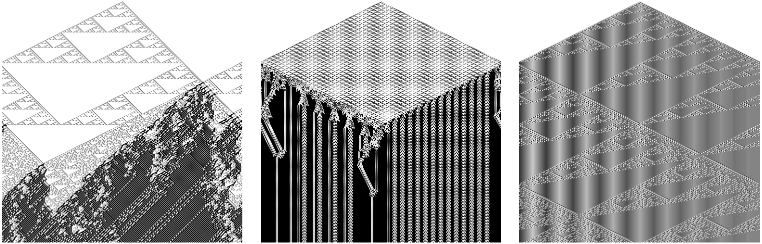


- It is easy to overestimate the complexity of the system.
- Ockham's razor – presented with several equivalent hypothesis, one should choose the simplest one (with the fewest assumptions)

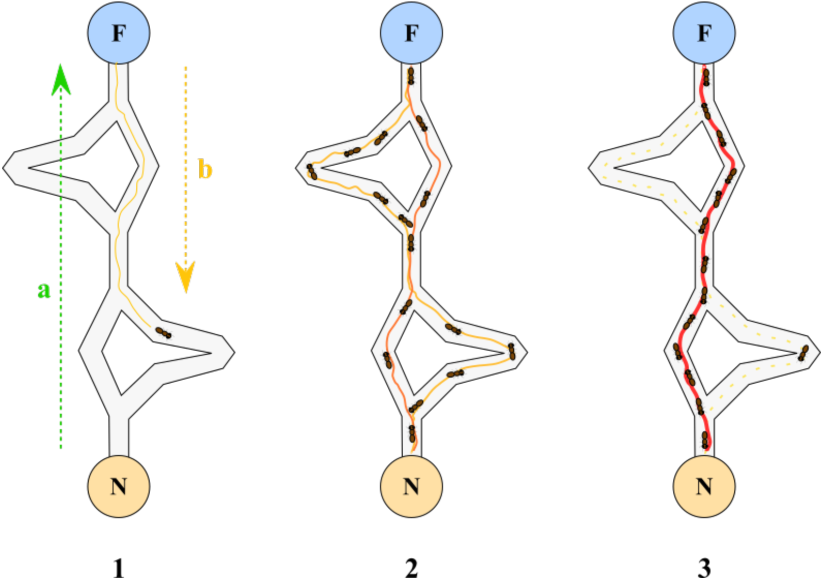
Apparent complexity

Example #1: How ants find the shortest way to the food

- Ants are able to find short paths to food.
- How do they determine this fact?
- How do they share this knowledge?
- Are ants more intelligent then we thought?

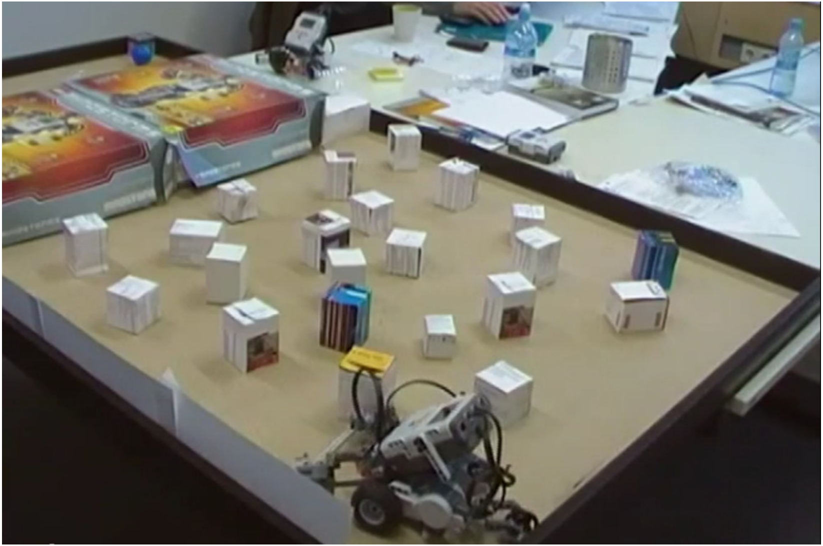
Apparent complexity

Example #1: How ants find the shortest way to the food



Apparent complexity

Example #2: "Swiss robots"



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- https://www.youtube.com/watch?v=B0wM-eKSxhk
- Created in 1990s in the Artificial Intelligence Laboratory at Zurich University by M. Maris & R. te Boekhorst.
- Two sensors at the front, directed at a certain angle to left and right.

  "The world, as seen by a Swiss robot, only consists of sensory stimulation on the right and on the left."

Simple working principle:

- If no object is detected, the robot goes forward.
- If one of the sensors detects an object, the robot turns in the opposite direction.

Apparent complexity

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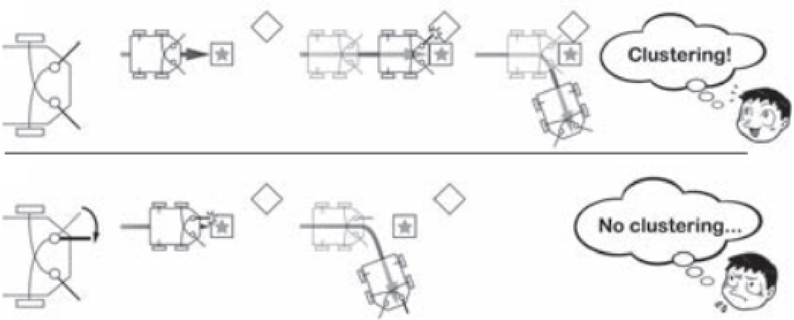


Source: *How the Body Shapes the Way We Think*, Rolf Pfeifer, Josh Bongard

Apparent complexity

Example #3: Navigation of the *Cataglyphis* ant

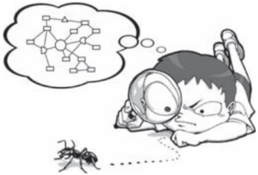
- *Cataglyphis* ant, living on the Sahara Desert, can return to the anthill after moving away from it on the distances of 200 meters.
- Does she learn and creates a mental map of the terrain?

Apparent complexity

Example #3: Navigation of the *Cataglyphis* ant

- Cartright and Collett (1983) suggested simpler model.
- The ant has two navigation systems: short-distance and long-distance.
- *Short-distance*: after leaving anthill, the ant creates visual snapshot of the area (it's sight spans nearly 360°). When she wants to go back home, she goes in the direction of maximizing the visual similarity to this snapshot.
- *Long-distance*: the ant uses estimations of distance and direction (based on the polarization of light) to approximately select the direction she should go.

Apparent complexity



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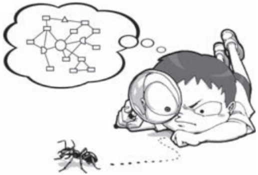

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Approaches to the modeling of the brain

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- Symbolic approaches
- Connectionism approaches

Symbolic approaches:

- "Moving symbols" according to some rules

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- Cooperation of many simple agents realizing simple functions

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- Generally sequential
- High level of abstraction
- Data structures and schemes of behaviors must be manually created
- Transparent, knowledge representations easy to interpret
- Not resistant to failure of some parts

Connectionism approaches:

- Cooperation of many simple agents realizing simple functions
- Distributed
- Level of biological implementation
- Systems can learn
- Knowledge representations hard to interpret
- Resistant to failure of some parts

Cognitive science

Symbolic approaches:

- E.g. **ACT-R***, Soar, ...
- Focused on high-level mental processes

Connectionism approaches:

- E.g. **Nengo***, Emergent, ...
- Focused on reflecting the real structure of the brain

* In this course we will present in greater detail **ACT-R** and **Nengo**.

Artificial Intelligence

Symbolic approaches:

- GOFAI (Good Old Fashioned AI)
- General Problem Solver (Simon, Shaw, Newell, 1959)
- Production (rule) systems (*pol. systemy regułowe*)
- Focused on knowledge representation.

Connectionism approaches:

- **ANN (Artificial Neural Networks)***
- Focused on incremental learning and adaptation.

* In this course we will present in greater detail **Artificial Neural Networks**.

Artificial Intelligence vs. modeling of the brain

- The aim of *AI* is to solve a certain problem in the most effective way possible.
- The aim of *modeling* is obtaining some knowledge about the workings of a particular system.
- AI takes some inspiration in modeling and vice versa.

Big simulation projects

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Simulations of human brain or its parts *in silico*:

- BRAIN Initiative (USA)
- Human Brain Project (European Union)

Simulations of brain of other creatures *in silico*:

- OpenWorm (C. Elegans worm)

BRAIN Initiative

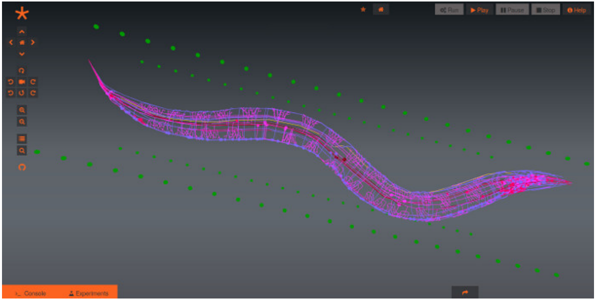
- Brain Research through Advancing Innovative Neurotechnologies
- Website: https://www.humanbrainproject.eu
- 2016–2020: technology development and validation
- 2020–2025: application of those technologies

Human Brain Project

- Website: https://www.humanbrainproject.eu
- Duration: October 2013 – October 2023
- Budget: ~ 1 billion €

OpenWorm

- Website of the project: `openworm.org`, demo: `live.geppetto.org`
- Simulation of the whole C. Elegans worm, the only organism with fully mapped connectome (302 neurons).
- Open source, still work in progress.



Reflection on the methods of biology/neuroscience

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- "Can a biologist fix a radio? – Or, what I learned while studying apoptosis" Yuri Lazebnik, 2002
- "Could a neuroscientist understand a microprocessor?" Eric Jonas, Konrad Kording, 2017