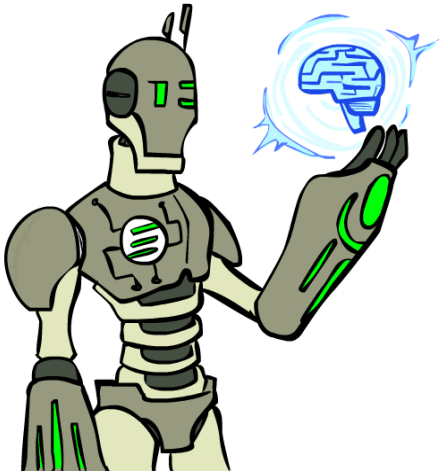
Introduction to Artificial Intelligence

Lecture: Artificial General Intelligence

Prof. Gilles Louppe
g.louppe@uliege.be

Today*



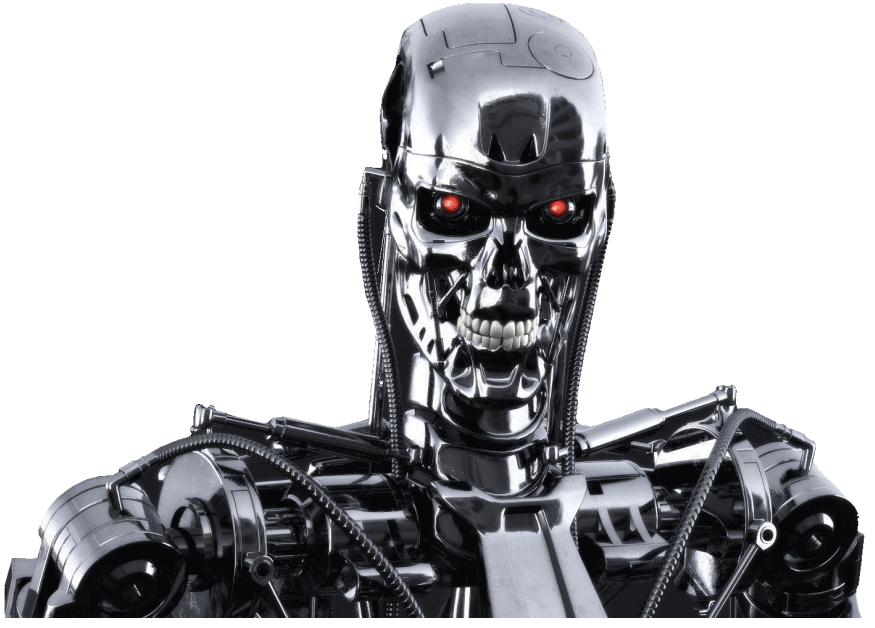
Towards generally intelligent agents?

- Artificial general intelligence
- AIXI
- Artifical life

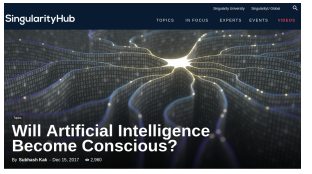
---

* : Take today's lecture with a grain of salt. Image credits: CS188, UC Berkeley.

From technological breakthroughs...



... to press coverage.



Artificial narrow intelligence

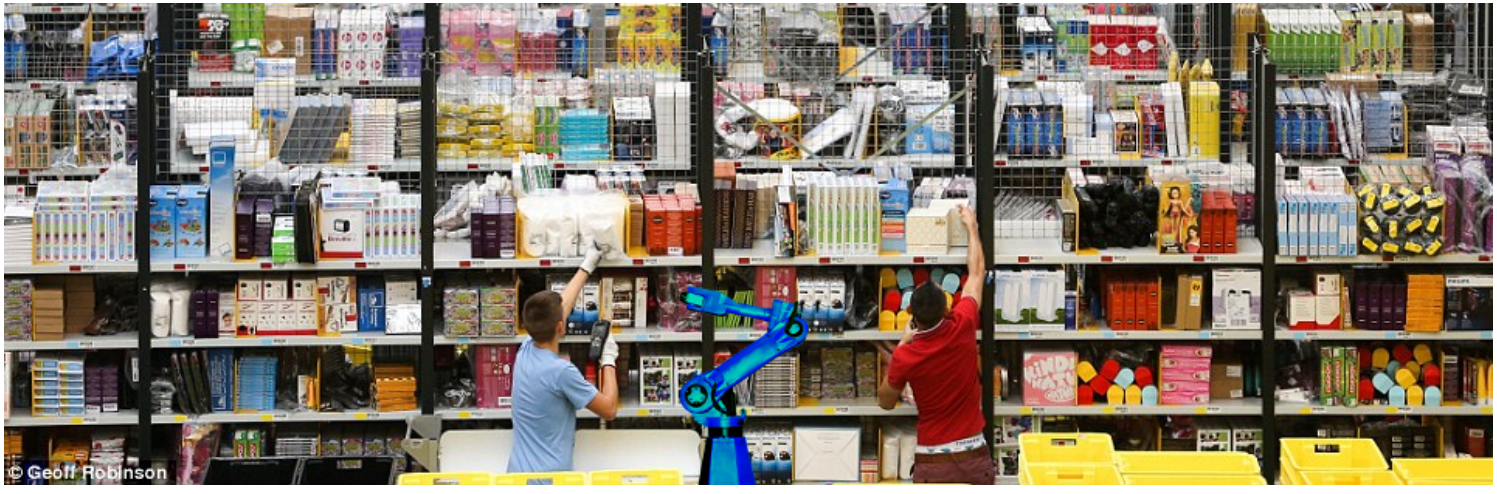
Today's artificial intelligence remains narrow:

- AI systems often reach super-human level performance, ... but only at very specific problems!
- They do not generalize to the real world nor to arbitrary tasks.

The case of AlphaGo

Convenient properties of the game of Go:

- Deterministic (no noise in the game).
- Fully observed (each player has complete information)
- Discrete action space (finite number of actions possible)
- Perfect simulator (the effect of any action is known exactly)
- Short episodes (200 actions per game)
- Clear and fast evaluation (as stated by Go rules)
- Huge dataset available (games)



Can we run AlphaGo on a robot?

AGI

Artificial general intelligence, or AGI, is the intelligence of a machine that could successfully perform any intellectual task that a human being can perform.

The scientific community agrees that AGI would be required to do the following:

- reason, use strategy, solve puzzle, plan,
- make judgments under uncertainty,
- represent knowledge, including commonsense knowledge,
- improve and learn new skills,
- communicate in natural language,
- be creative,
- integrate all these skills towards common goals.

This is similar to our definition of thinking rationally, but applied broadly to any set of tasks.

Roads towards AGI

Several working hypothesis:

1. Learning (supervised, unsupervised, reinforcement)
2. AIXI
3. Artificial life

... or probably something else?

Learning

Reward is Enough

Abstract

In this paper we hypothesise that the objective of maximising reward is enough to drive behaviour that exhibits most if not all attributes of intelligence that are studied in natural and artificial intelligence, including knowledge, learning, perception, social intelligence, language and generalisation. This is in contrast to the view that specialised problem formulations are needed for each attribute of intelligence, based on other signals or objectives. The reward-is-enough hypothesis suggests that agents with powerful reinforcement learning algorithms when placed in rich environments with simple rewards could develop the kind of broad, multi-attribute intelligence that constitutes an artificial general intelligence.

David Silver et al, 2021.

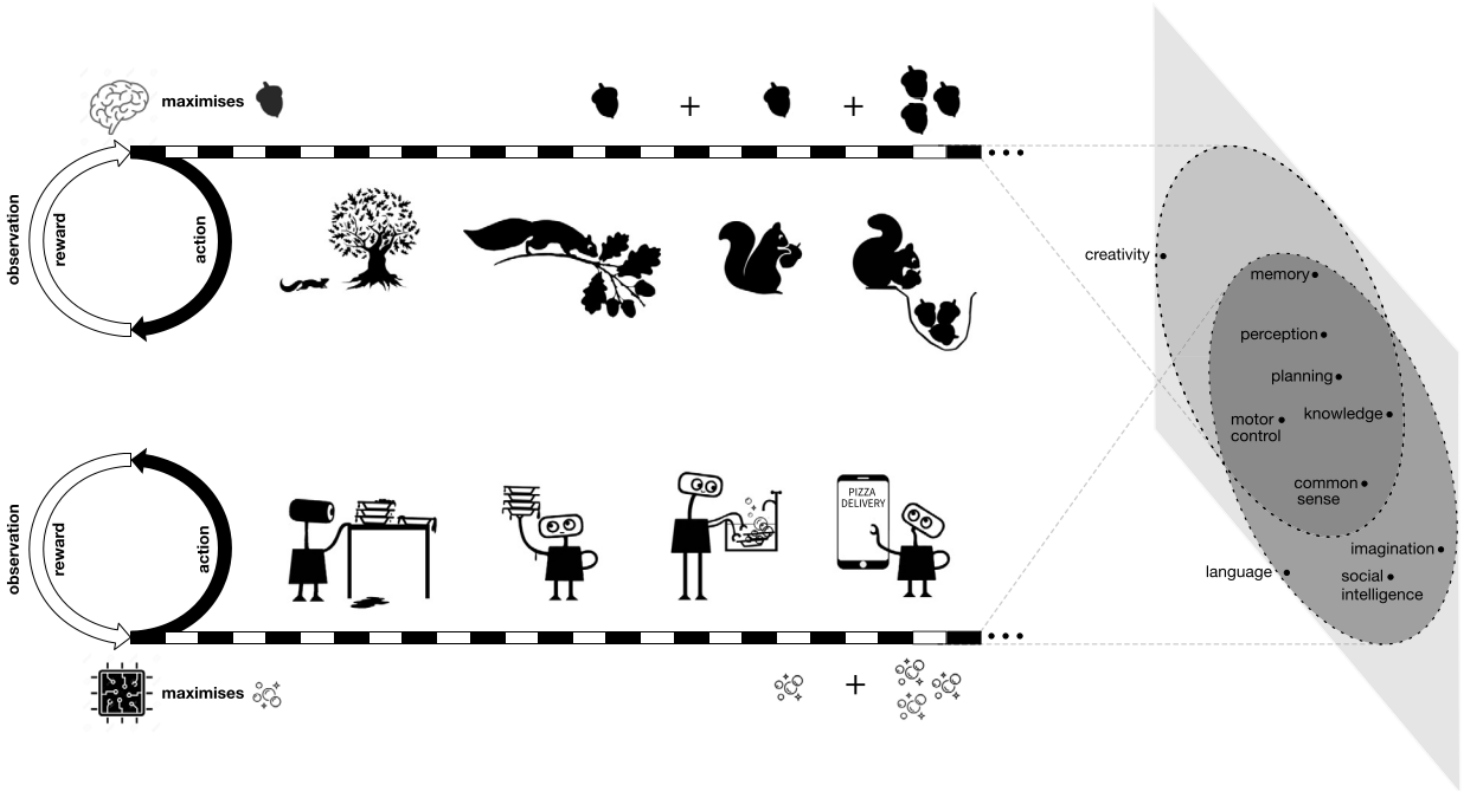


Fig. 1. The *reward-is-enough* hypothesis postulates that intelligence, and its associated abilities, can be understood as subserving the maximisation of reward by an agent acting in its environment. For example, a squirrel acts so as to maximise its consumption of food (top, reward depicted by acorn symbol), or a kitchen robot acts to maximise cleanliness (bottom, reward depicted by bubble symbol). To achieve these goals, complex behaviours are required that exhibit a wide variety of abilities associated with intelligence (depicted on the right as a projection from an agent's stream of experience onto a set of abilities expressed within that experience).

—

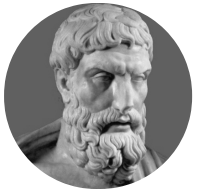
Image credits: David Silver et al, "Reward is enough", 2021.

Could AI be perceived as creative? (Jürgen Schmidhuber)

AIXI

AIXI (Hutter, 2005) is a theoretical mathematical formalism of artificial general intelligence.

Occam: Prefer the simplest consistent hypothesis.



Epicurus: Keep all consistent hypotheses.

Bayes: $P(h|d) = \frac{P(d|h)P(h)}{P(d)}$

Turing: It is possible to invent a single machine which can be used to compute any computable sequence.

Solomonoff: Use computer programs μ as hypotheses/environments.

AIXI defines a measure of universal intelligence as

$$\Upsilon(\pi) := \sum_{\mu \in E} 2^{-K(\mu)} V_{\mu}^{\pi}$$

where

- $\Upsilon(\pi)$ formally defines the universal intelligence of an agent π.
- μ is the environment of the agent and E is the set of all computable reward bounded environments.
- $V_{\mu}^{\pi} = \mathbb{E}[\sum_{i=1}^{\infty} R_i]$ is the expected sum of future rewards when the agent π interacts with environment μ.
- $K(.)$ is the Kolmogorov complexity, such that $2^{-K(\mu)}$ weights the agent's performance in each environment, inversely proportional to its complexity.

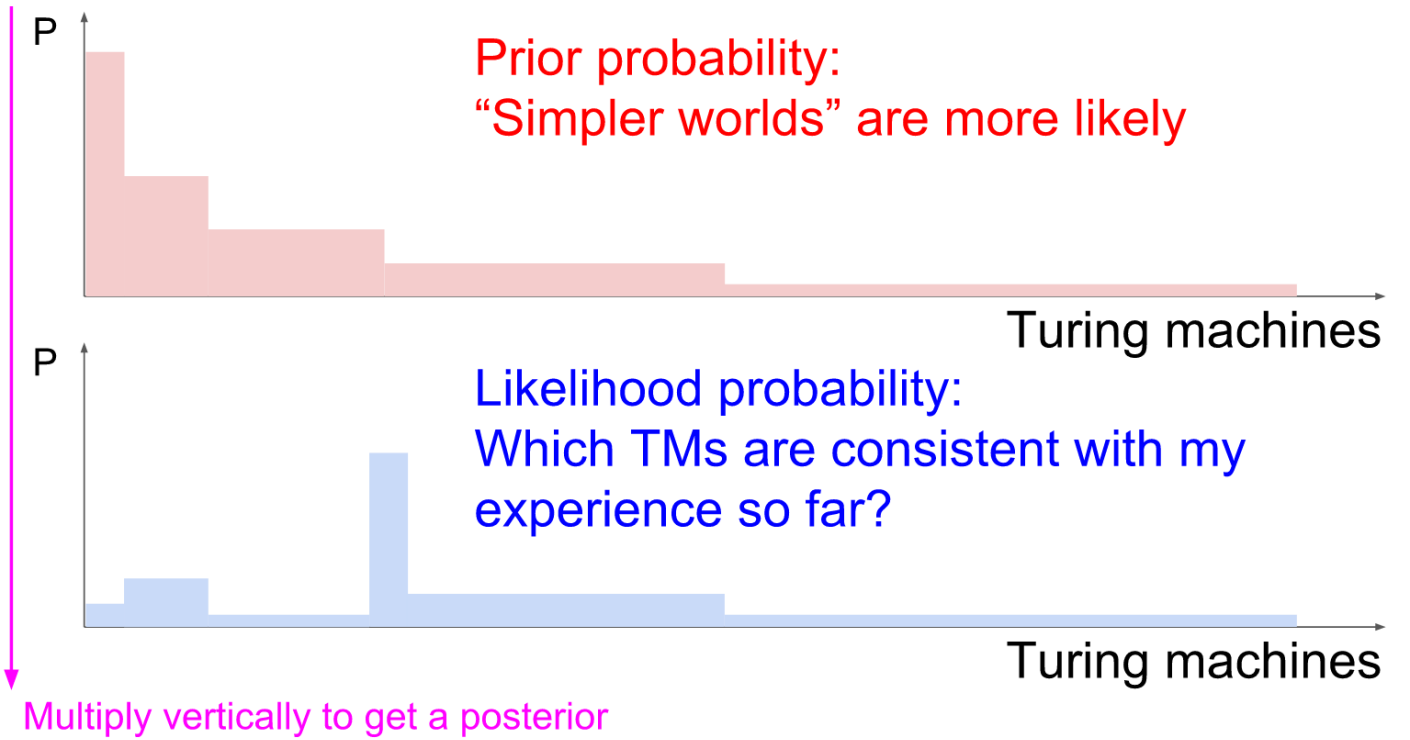
AIXI

$$\bar{\Upsilon} = \max_{\pi} \Upsilon(\pi) = \Upsilon(\pi^{\mathrm{AIXI}})$$

π^{AIXI} is a perfect theoretical agent.

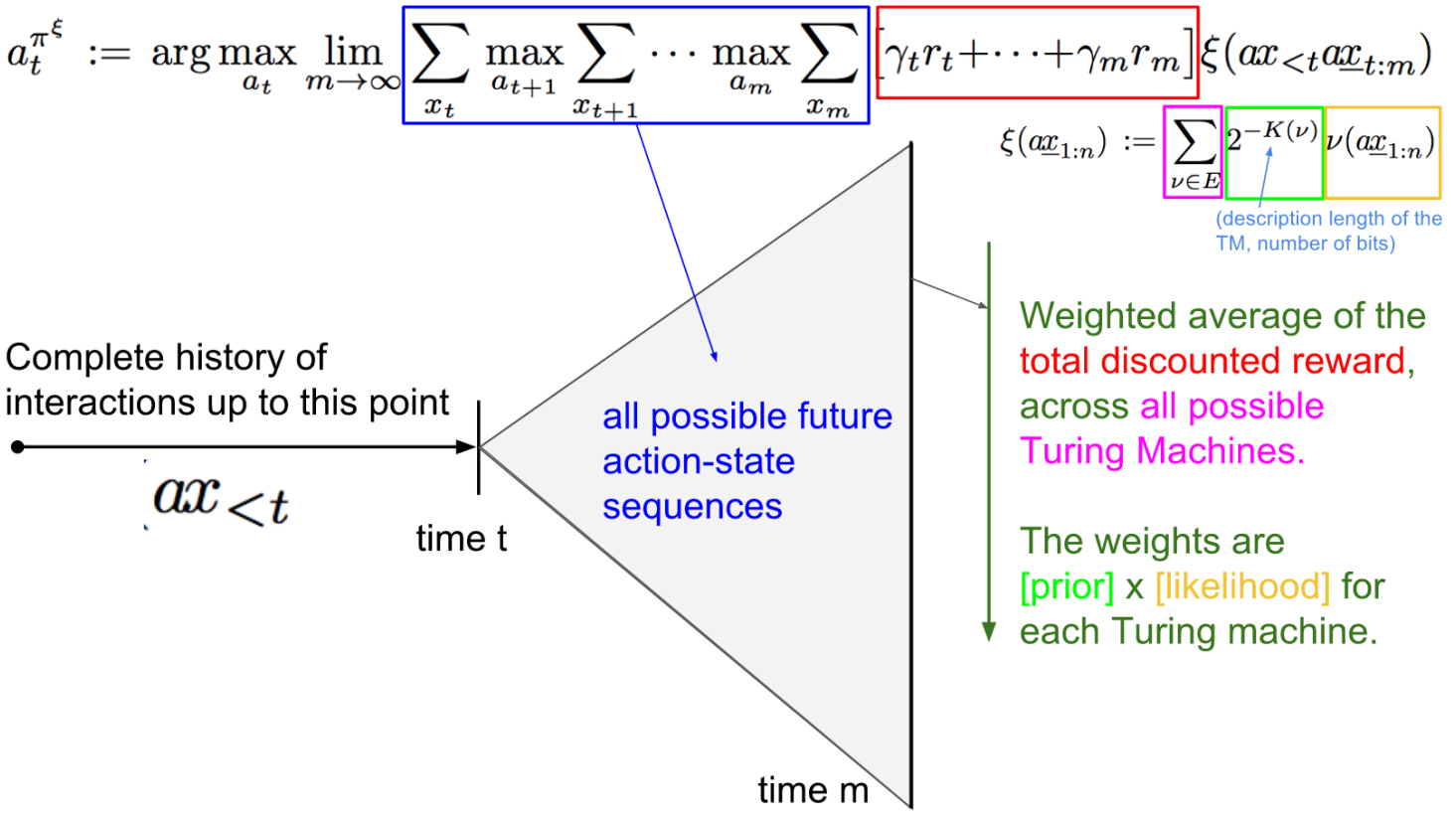
System identification

- Which Turing machine is the agent in? If it knew, it could plan perfectly.
- Use the Bayes rule to update the agent beliefs given its experience so far.



Acting optimally

- The agent always picks the action which has the greatest expected reward.
- For every environment $\mu \in E$, the agent must:
  - Take into account how likely it is that it is facing μ given the interaction history so far, and the prior probability of μ.
  - Consider all possible future interactions that might occur, assuming optimal future actions.
  - Evaluate how likely they are.
  - Then select the action that maximizes the expected future reward.


$a_t^{\pi^\xi} := \arg\max_{a_t} \lim_{m\to\infty} \sum_{x_t} \max_{a_{t+1}} \sum_{x_{t+1}} \cdots \max_{a_m} \sum_{x_m} [\gamma_t r_t + \cdots + \gamma_m r_m] \xi(ax_{<t} a\underline{x}_{t:m})$
$\xi(a\underline{x}_{1:n}) := \sum_{\nu\in E} 2^{-K(\nu)} \nu(a\underline{x}_{1:n})$
(description length of the TM, number of bits)
Complete history of interactions up to this point
$ax_{<t}$
time t
all possible future action-state sequences
time m
Weighted average of the total discounted reward, across all possible Turing Machines.
The weights are [prior] x [likelihood] for each Turing machine.

—

AIXI is incomputable

!!! !!!

$$a_t^{\pi^\xi} := \arg\max_{a_t} \lim_{m\to\infty} \sum_{x_t} \max_{a_{t+1}} \sum_{x_{t+1}} \cdots \max_{a_m} \sum_{x_m} \left[\gamma_t r_t + \cdots + \gamma_m r_m\right] \xi(ax_{<t} a\underline{x}_{t:m})$$

$$\xi(a\underline{x}_{1:n}) := \sum_{\nu\in E} 2^{-K(\nu)}\, \nu(a\underline{x}_{1:n})$$

—

Credits: Andrej Karpathy, Where will AGI come from?

Benefits of AIXI

The AIXI theoretical formalism of AGI provides

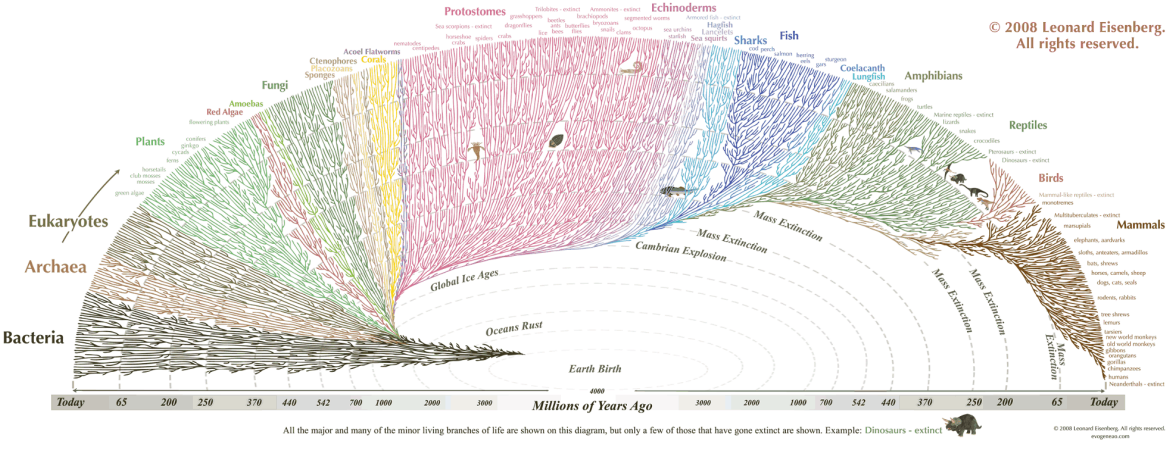
- a high-level blue-print or inspiration for design;
- common terminology and goal formulation;
- understand and predict behavior of yet-to-be-built agents;
- appreciation of fundamental challenges (e.g., exploration-exploitation);
- definition/measure of intelligence.

Artificial life

Artificial life

Study of systems related to natural life, its processes and its evolution, through the use of simulations with computer models, robotics or biochemistry.

One of its goals is to synthesize life in order to understand its origins, development and organization.



How did intelligence arise in Nature?

Approaches

There are three main kinds of artificial life, named after their approaches:

- Software approaches (soft)
- Hardware approaches (hard)
- Biochemistry approaches (wet)

The field of AI has traditionally used a top down approach. Artificial life generally works from the bottom up.

Wet artificial life: The line between life and not-life (Martin Hanczyc).

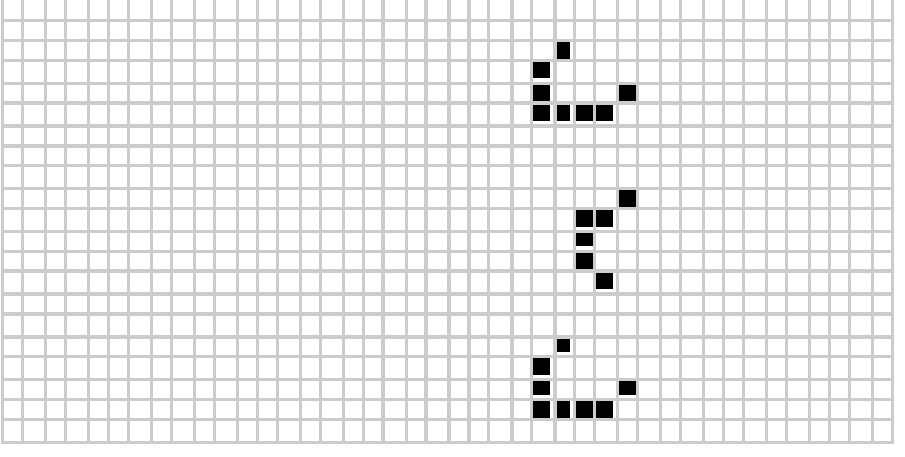
Evolutionary algorithms

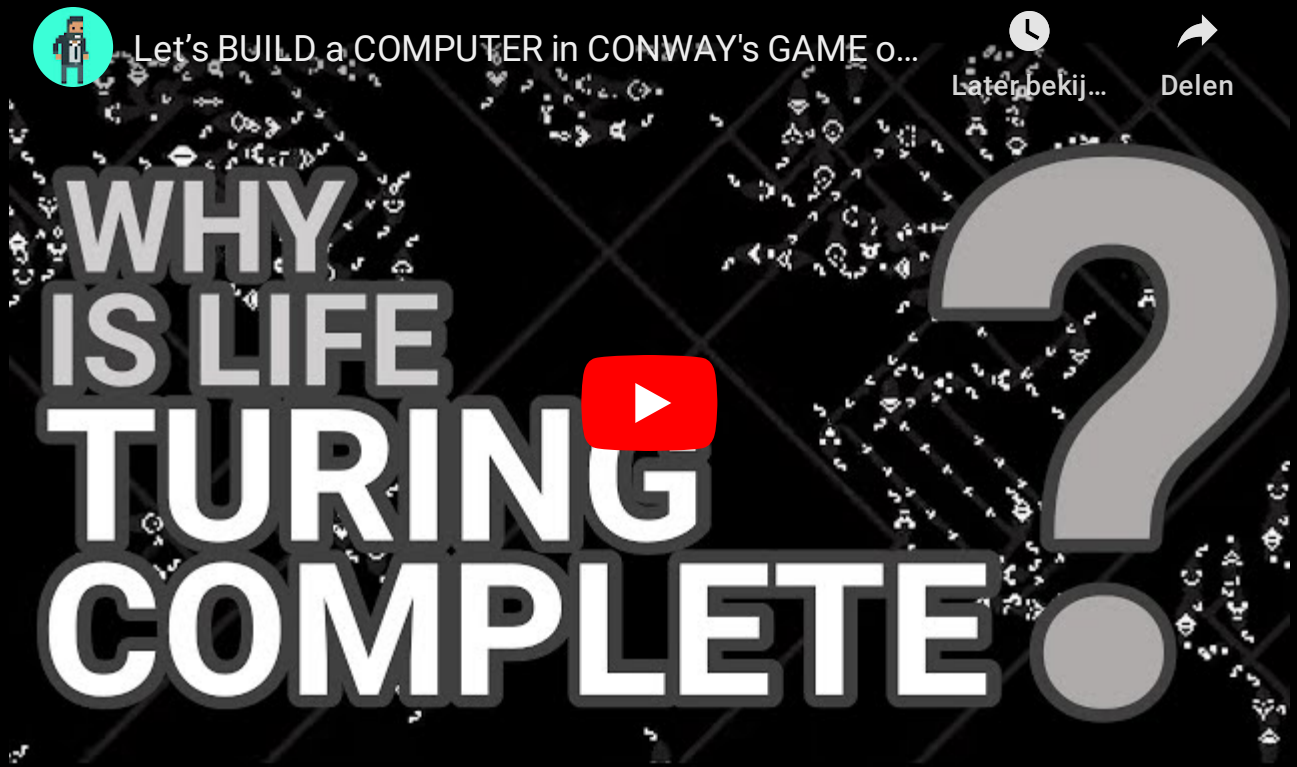
Evolution may hypothetically be interpreted as an (unknown) algorithm.

- This algorithm gave rise to AGI (e.g., it induced humans).
- Simulation of the evolutionary process should/could eventually reproduce life and, maybe, intelligence?

Conway's Game of Life

- Any live cell with two or three live neighbours survives.
- Any dead cell with three live neighbours becomes a live cell.
- All other live cells die in the next generation. Similarly, all other dead cells stay dead.



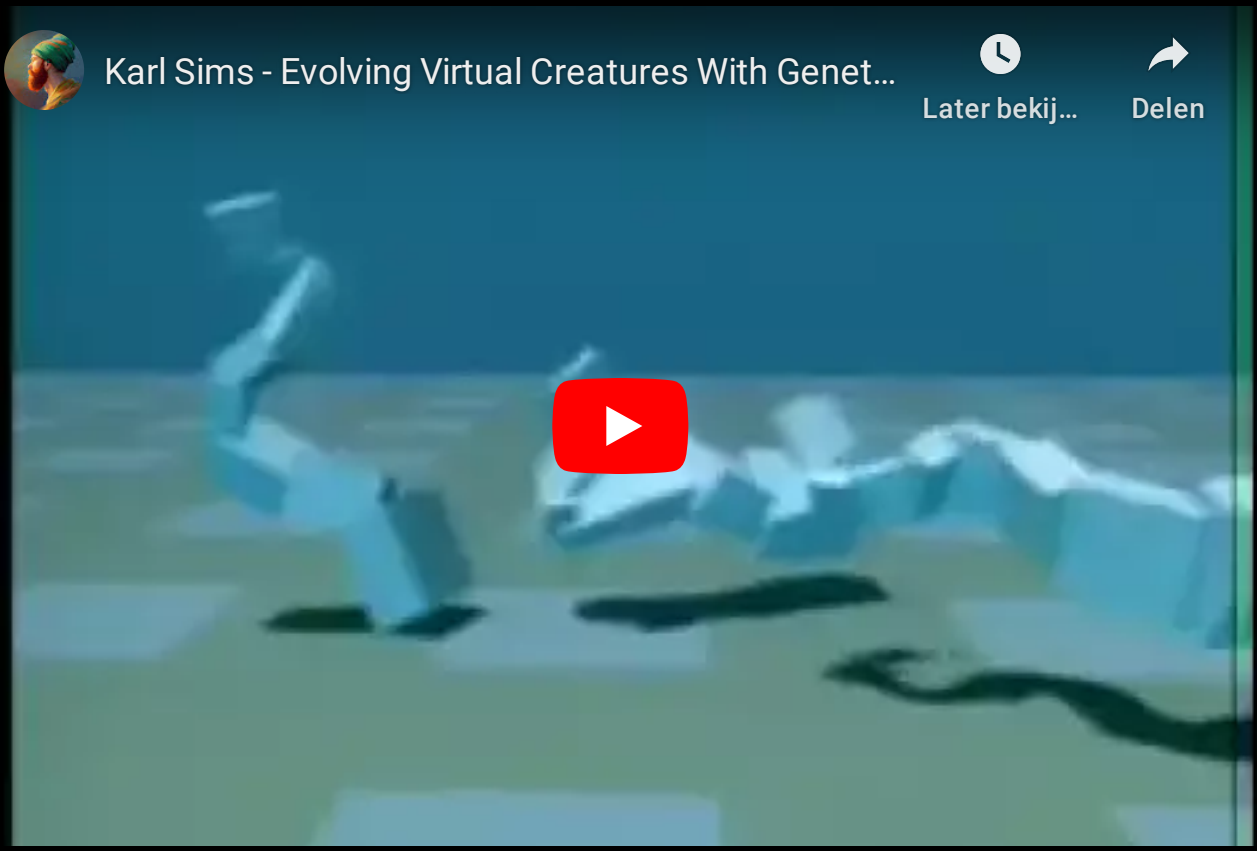


Conway's game of life

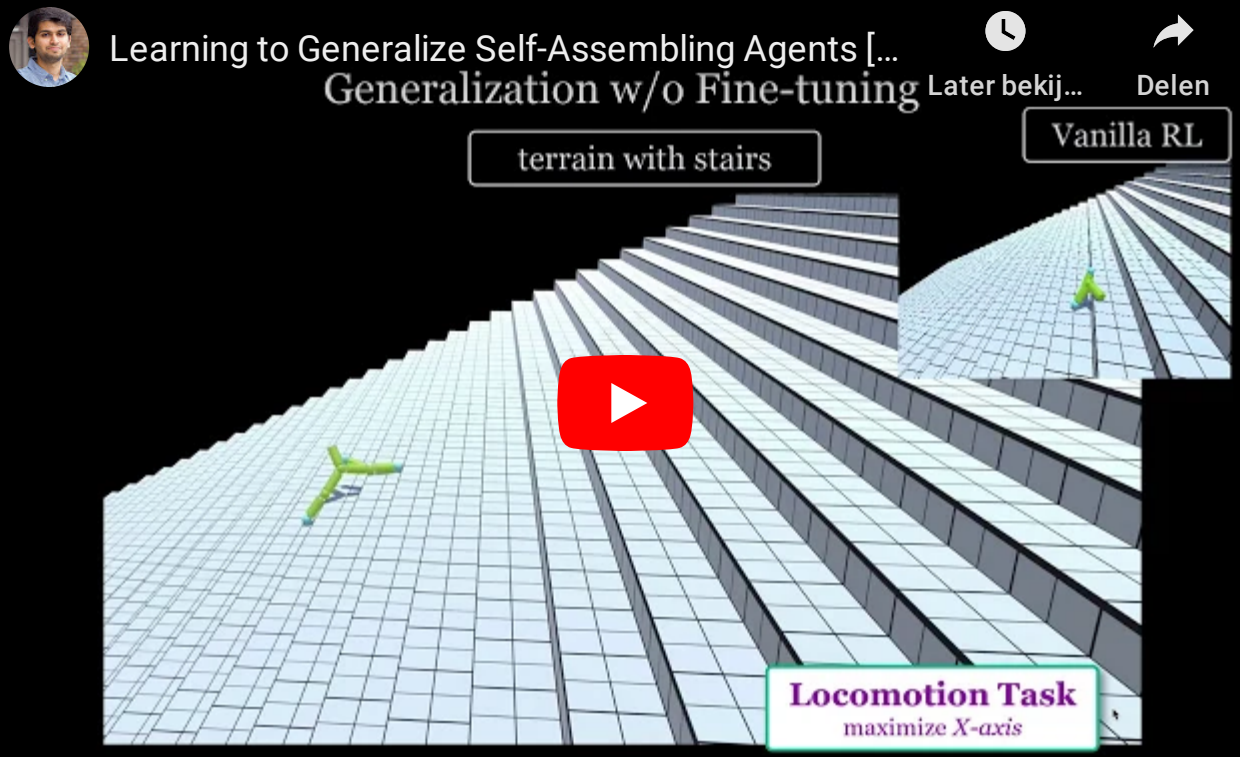
Evolutionary algorithms as metaheuristic optimization algorithms

1. Start with a random population of creatures.
2. Repeat until termination:
    1. Each creature is tested for their ability to perform a given task.
    2. Select the fittest creatures for reproduction.
    3. Breed new creatures by combining and mutating the virtual genes of their selected parents.
    4. Replace the least-fit creatures of the population with new creatures.

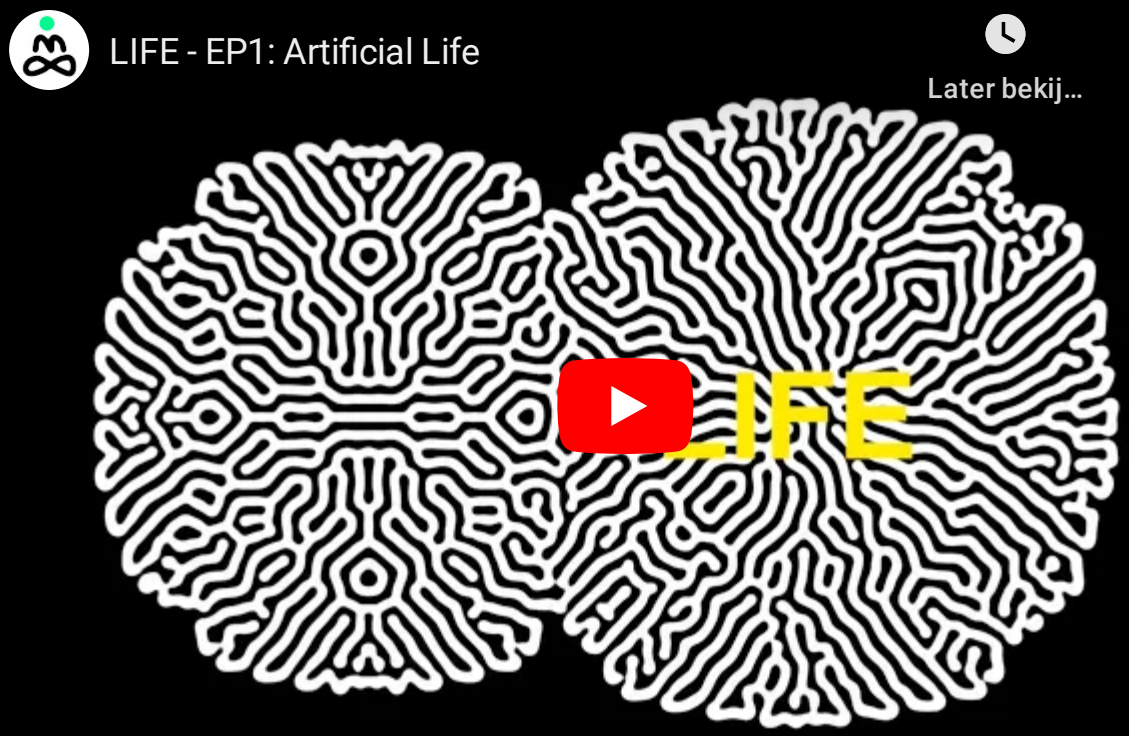
As this cycle of variation and selection continues, creatures with more and more successful behaviors may emerge.



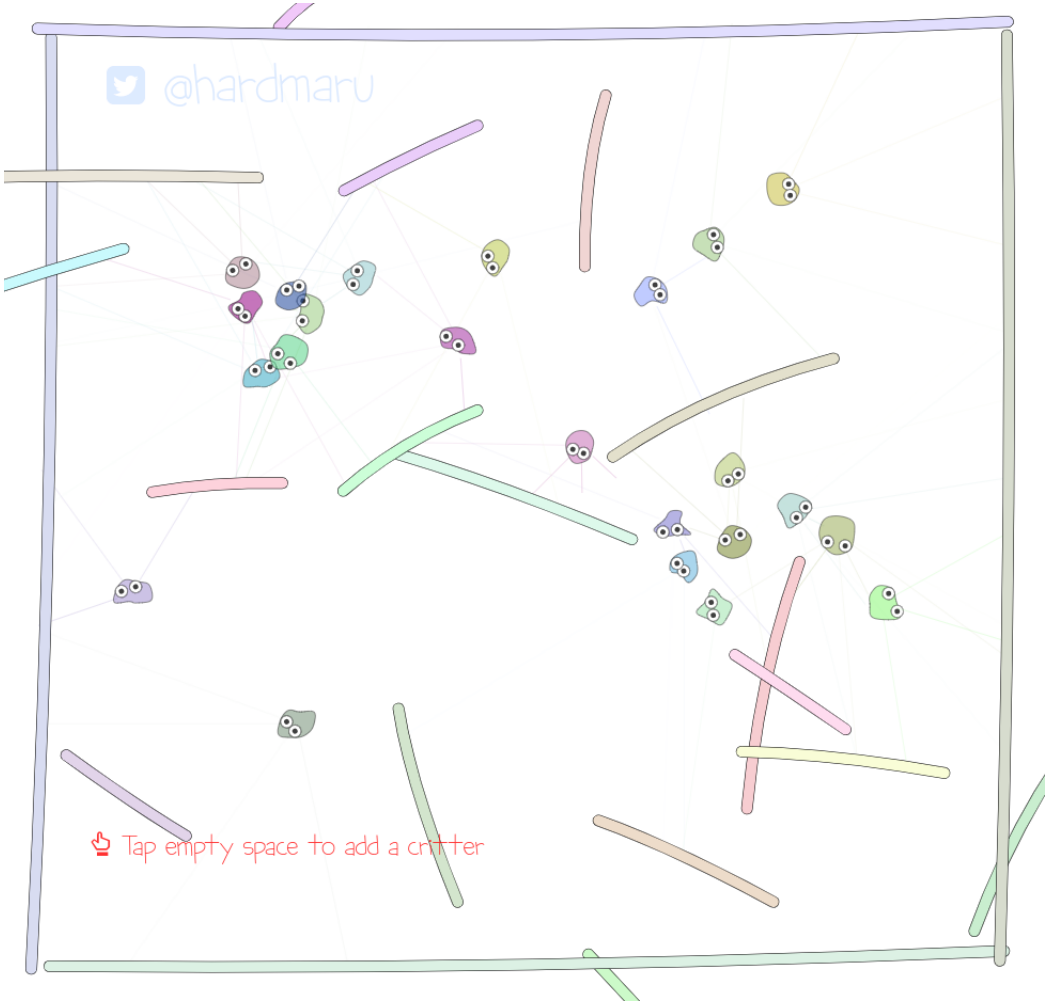
Karl Sims, 1994.



Self-assembling morphologies (Pathak et al, 2019)



Mini-documentary: Artifical life

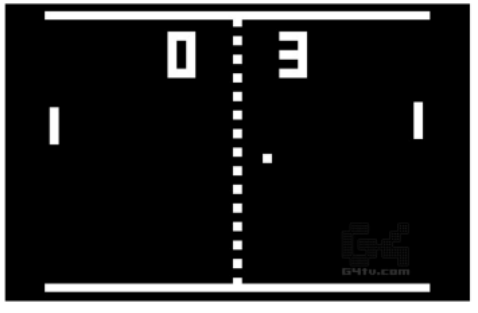


Creatures avoiding planks [demo].

Environments for AGI?

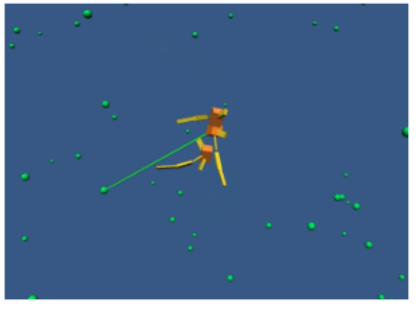
For the emergence of generally intelligent creatures, environments should incentivize the emergence of a cognitive toolkit (attention, memory, knowledge representation, reasoning, emotions, forward simulation, skill acquisition, ...).

Doing it wrong:



Incentives a lookup table of correct moves.

Doing it right:



Incentivises cognitive tools.

—

Credits: Andrej Karpathy, Where will AGI come from?

Multi-agent environments are certainly better because of:

- Variety: the environment is parameterized by its agent population. The optimal strategy must be derived dynamically.
- Natural curriculum: the difficulty of the environment is determined by the skill of the other agents.

The end.