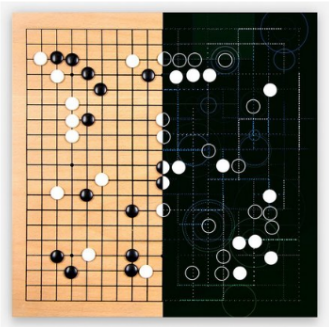
Introduction to Artificial Intelligence

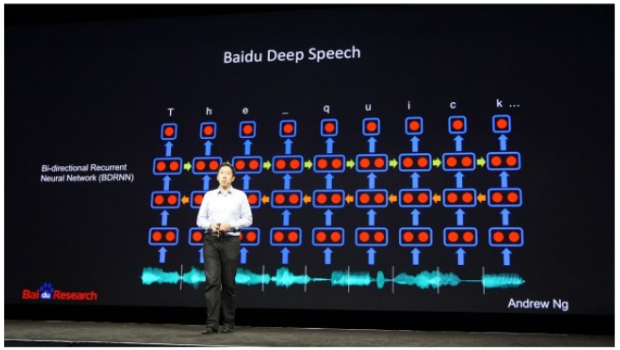
Lecture 10: Artificial General Intelligence

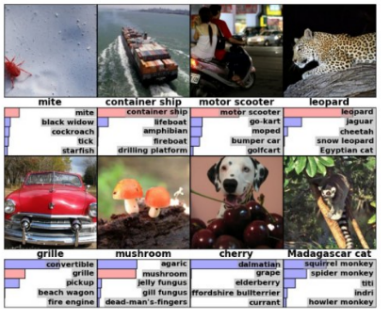
LIÈGE université

From technological breakthroughs...



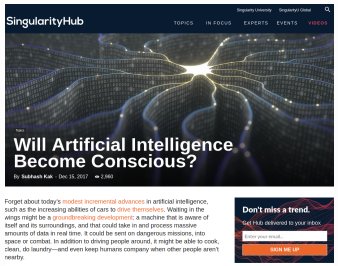
IBM Watson

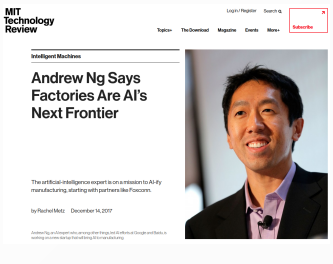


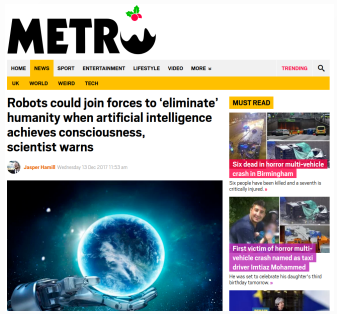


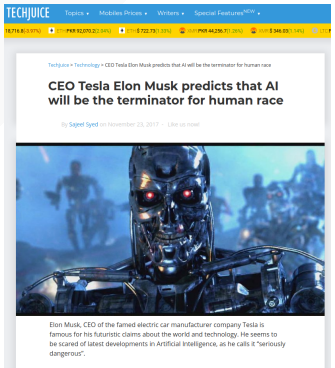
Credits: Andrej Karpathy, Where will AGI come from?

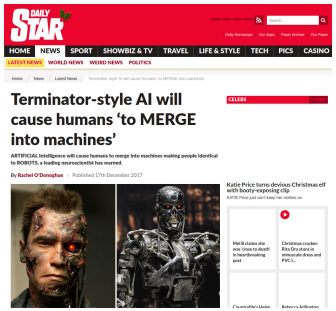
… to popular media











Artificial narrow intelligence

- Artificial intelligence today is still very narrow.
  - Modern 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.

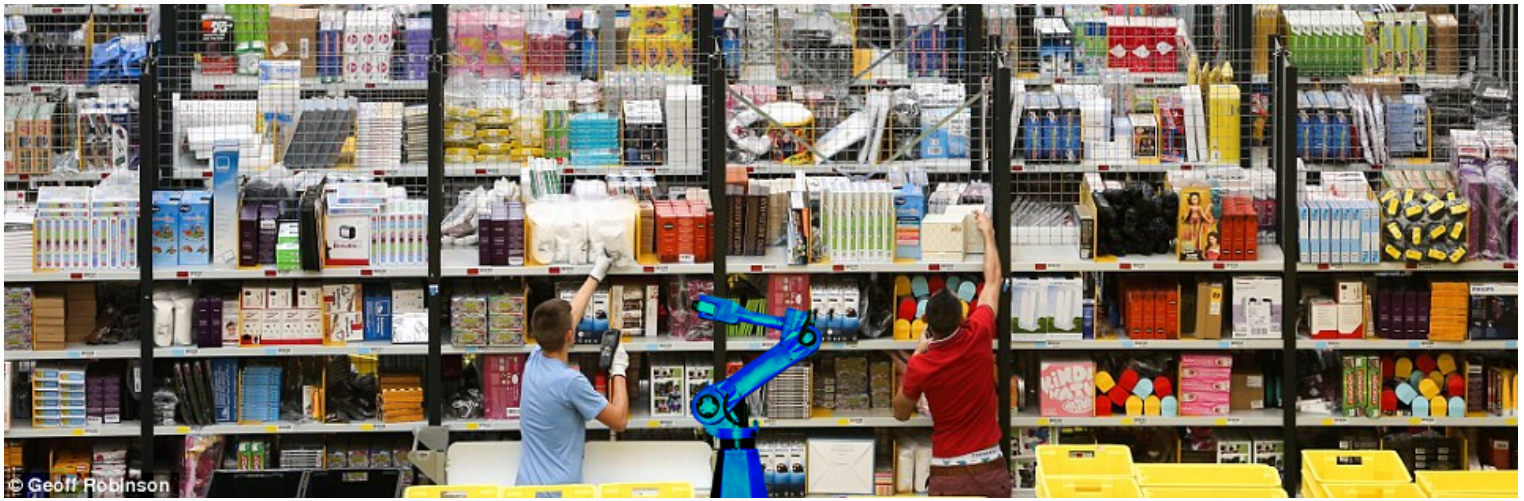
AlphaGo

Convenient properties of AlphaGo:

- 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)

Credits: Andrej Karpathy, Where will AGI come from?

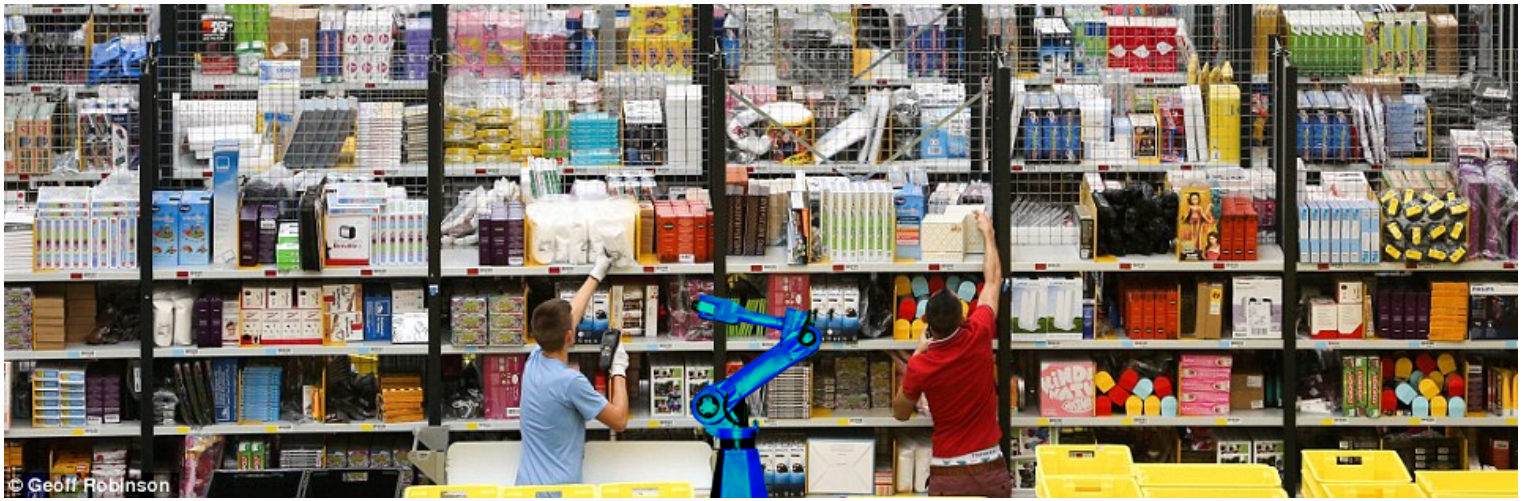
Picking challenge



Can we run AlphaGo on a robot for the Amazon Picking Challenge?

Credits: Andrej Karpathy, Where will AGI come from?

Picking challenge



- Deterministic: OK
- Fully observed: OKish
- Discrete action space: OK
- Perfect simulator: TROUBLE
- Short episodes: challenge
- Clear and fast evaluation: not good
- Huge dataset available: challenge

Credits: Andrej Karpathy, Where will AGI come from?

Artificial general intelligence

- Artificial general intelligence (AGI) is the intelligence of a machine that could successfully perform any intellectual task that a human being can.
- No clear definition, but there is an agreement that AGI is required to do the following:
  - reason, use strategy, solve puzzle and make judgments under uncertainty,
  - represent knowledge, including commonsense knowledge,
  - plan,
  - learn,
  - communicate in natural language,
  - integrate all these skills towards common goals.

Singularity

Irving John Good (1965):

- Let an ultraintelligent machine be defined as a machine that can far surpass all the intellectual activities of any man however clever.
- Since the design of machines is one of these intellectual activities, an ultraintelligent machine could design even better machines.
- There would then unquestionably be an 'intelligence explosion', and the intelligence of man would be left far behind.
- Thus the first ultraintelligent machine is the last invention that man need ever make, provided that the machine is docile enough to tell us how to keep it under control.

Superintelligence

What happens when our computers get smarter than we are? Nick Bostrom

How to build AGI?

Several working hypothesis:

- Supervised learning: "It works, just scale up!"
- Unsupervised learning: "It will work, if we only scale up!"
- AIXI: "Guys, I can write down an equation for optimal AI."
- Brain simulation: "This will work one day, right?"
- Artificial life: "Let just do what Nature did."

Or maybe something else?

Credits: Andrej Karpathy, Where will AGI come from?

AIXI

Start with an equation

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

- $\Upsilon(\pi)$ 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.
    - Intuitively, $K(\mu)$ measures the complexity of the shortest Universal Turing Machine program that describes the environment μ.

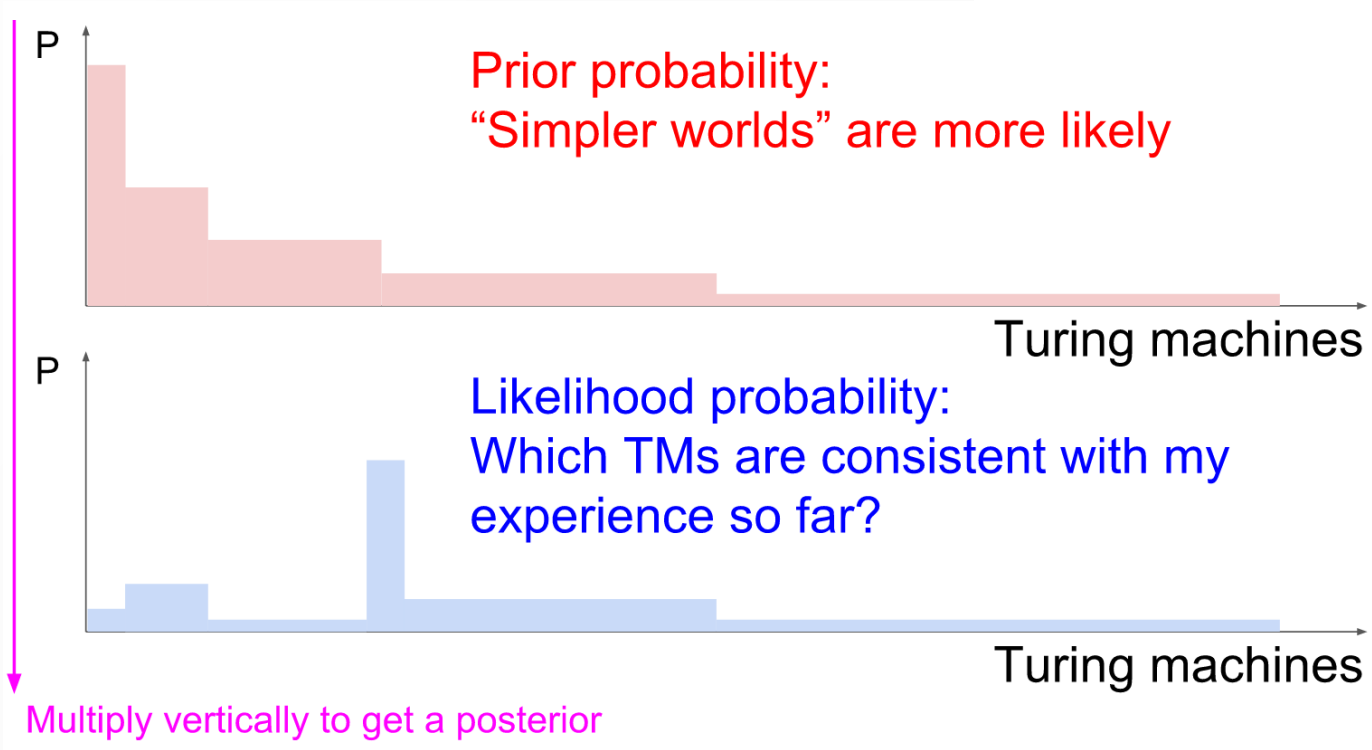
AIXI

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

- π^{AIXI} is a perfect theoretical agent.
- It 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.
  - Evaluate how likely they are.
  - Then select the action that maximizes the expected future reward.

System identification

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



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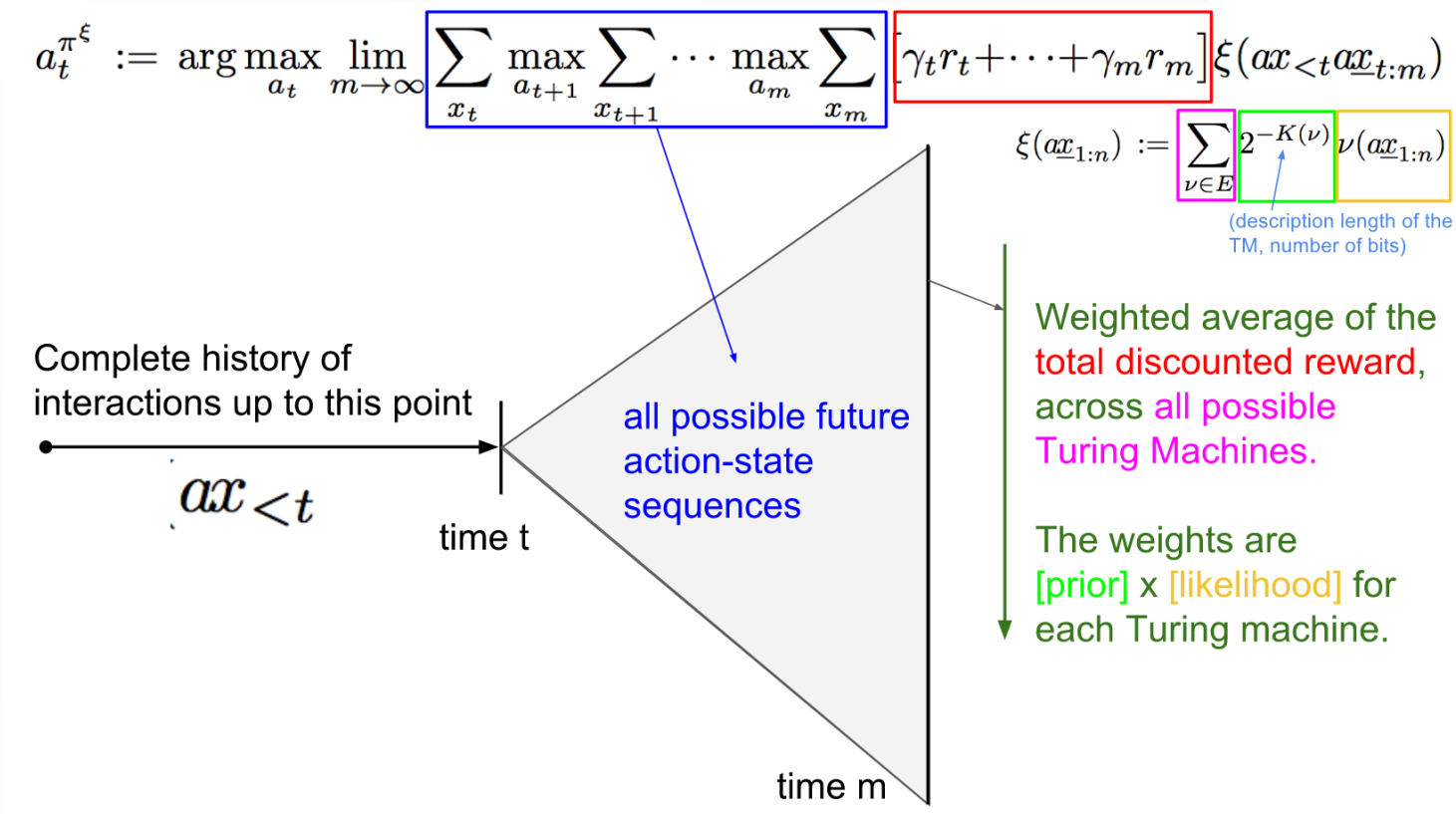
Optimal actions



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Incomputability

!!! !!!

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

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

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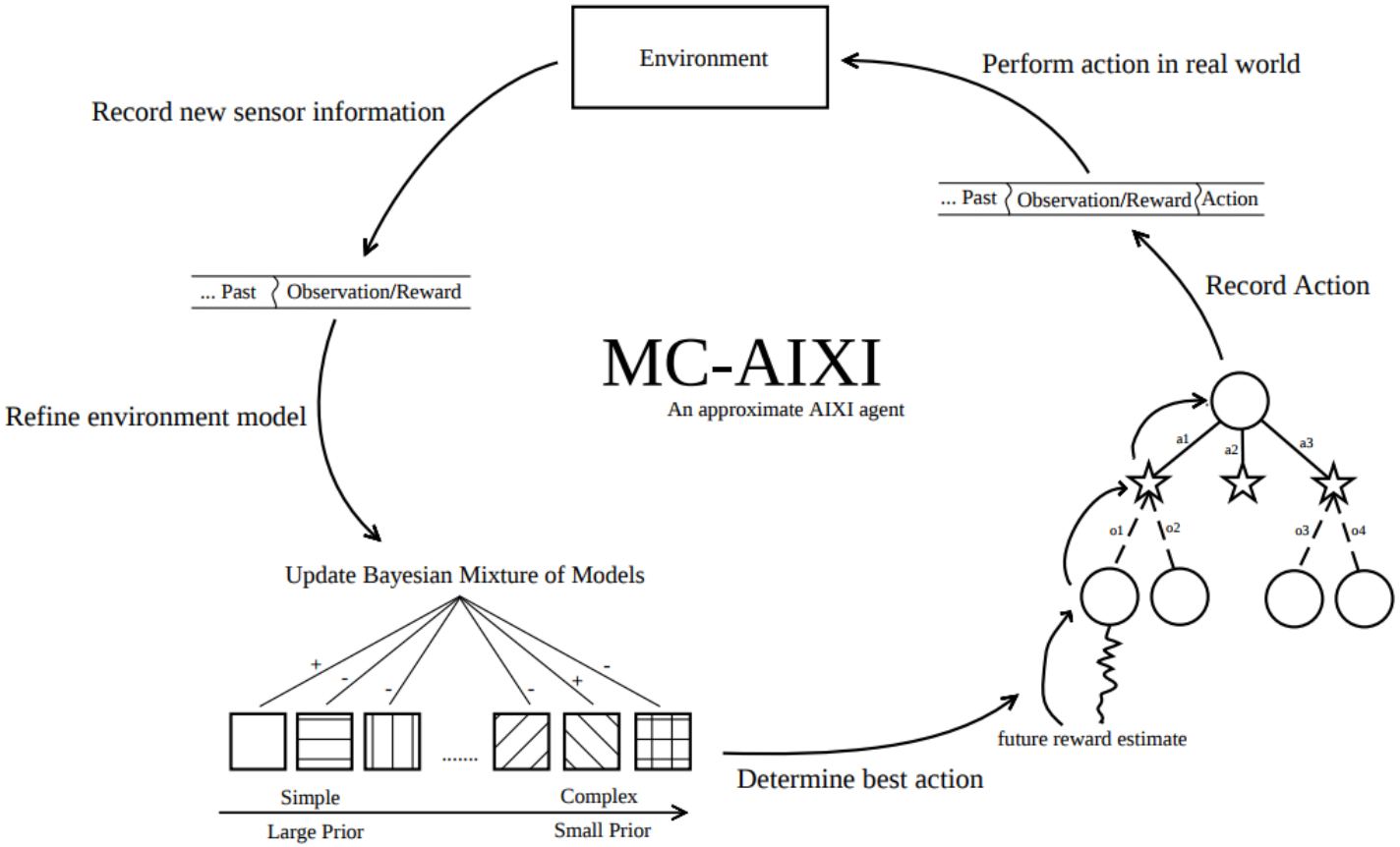
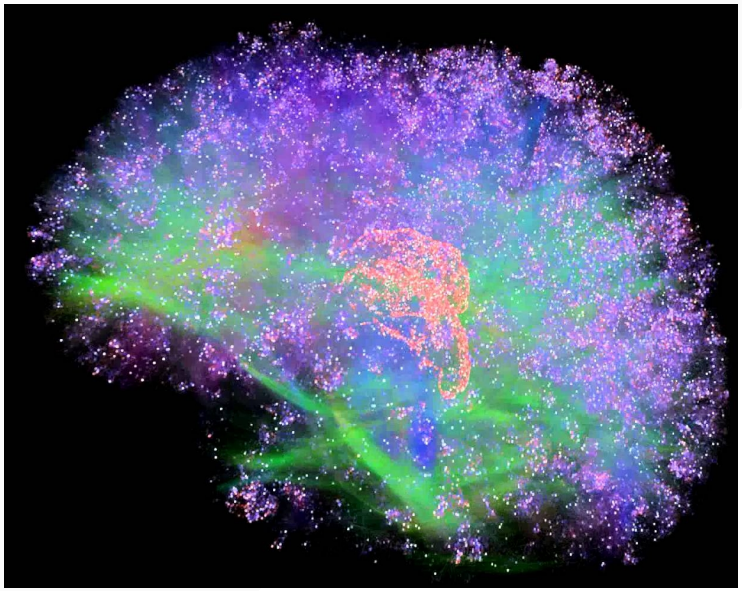
Monte Carlo approximation



Brain simulation

Whole brain emulation



- A hypothesis for AGI is whole brain simulation.
  - A low-level brain model is built by scanning and mapping a biological brain in detail and copying its state into a computer system.
  - The simulation is so faithful that it would behave in the same way as the original.
  - Therefore, the computer-run model would be as intelligent.
- Initiatives: Blue Brain Project, Human Brain Project, NeuraLink, etc.

Obstacles

- How to measure a complete brain state?
- At what level of abstraction?
- How to model the dynamics?
- How do you simulate the environment to feed into senses?
- Various ethical dilemmas.

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Mind upload

- Hypothetically, whole brain emulation would enable mind upload.
  - The mental state of a particular brain substrate could be scanned and copied into a computer.
  - The computer could then run a simulation of the brain's information processing, such that it responds in the same way as the original brain.
- That is, simulation would be indistinguishable from reality.

ARE YOU LIVING IN A COMPUTER SIMULATION?

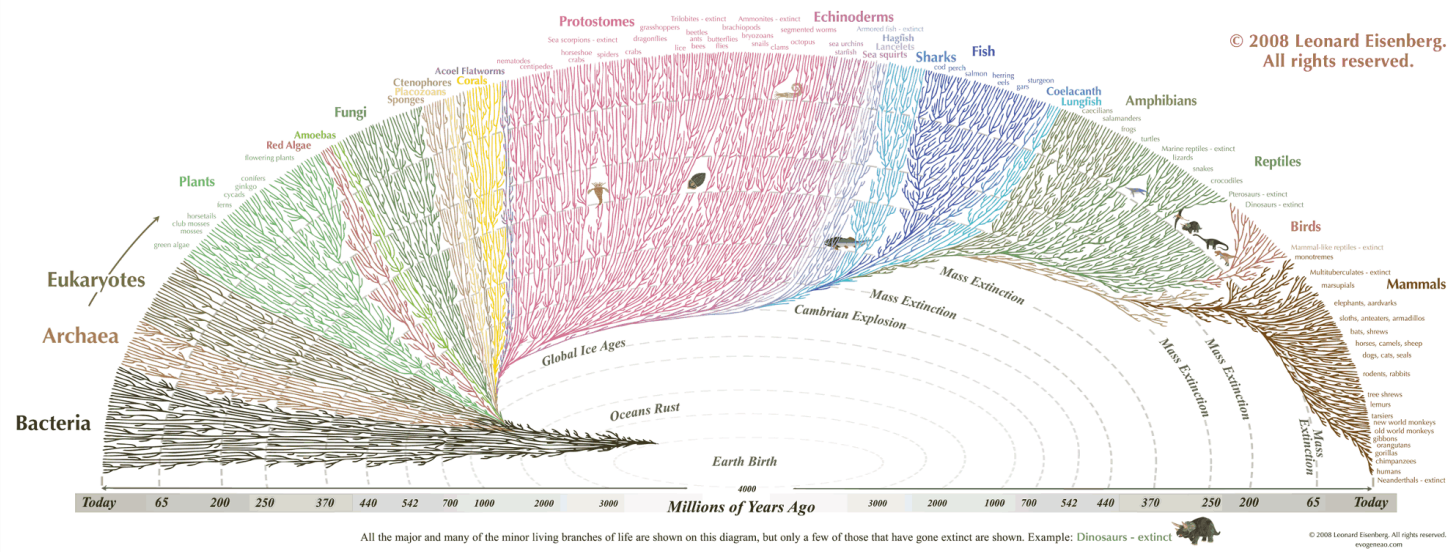
BY NICK BOSTROM

[Published in *Philosophical Quarterly* (2003) Vol. 53, No. 211, pp. 243-255. (First version: 2001)]

This paper argues that *at least one* of the following propositions is true: (1) the human species is very likely to go extinct before reaching a "posthuman" stage; (2) any posthuman civilization is extremely unlikely to run a significant number of simulations of their evolutionary history (or variations thereof); (3) we are almost certainly living in a computer simulation. It follows that the belief that there is a significant chance that we will one day become posthumans who run ancestor-simulations is false, unless we are currently living in a simulation. A number of other consequences of this result are also discussed.

Artificial life

How did intelligence arise in Nature?



Artificial life

- Artificial life is the 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.
- There are three main kinds of artificial life, named after their approaches:
  - Software approaches (soft)
  - Hardware approaches (hard)
  - Biochemistry approaches (wet)
- Artificial life is related to AI since synthesizing complex life forms would, hypothetically, induce intelligence.
- The field of AI has traditionally used a top down approach. Artificial life generally works from the bottom up.

Evolution for AGI

- Evolution may hypothetically be interpreted as an (unknown) algorithm.
- This algorithm gave rise to AGI.
  - e.g., it induced humans.
- Can we simulate the evolutionary process to reproduce life and intelligence?
- Note that we can work at a high level of abstraction.
  - We don't have to simulate physics or chemistry to simulate evolution.
  - We can also bootstrap the system with agents that are better than random.

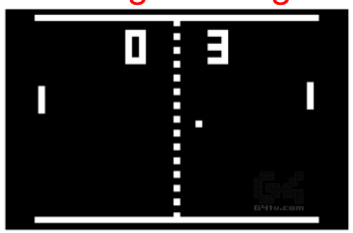
Evolutionary algorithms

- Start with a random population of creatures.
- Each creature is tested for their ability to perform a given task.
  - e.g., swim in a simulated environment.
  - e.g., stay alive as long as possible (without starving or being killed).
- The most successful survive.
- Their virtual genes containing coded instructions for their growth are copied, combined and mutated to make offspring for a new population.
- The new creatures are tested again, some of which may be improvements on their parents.
- As this cycle of variation and selection continues, creatures with more and more successful behaviors may emerge.

Environments for AGI?

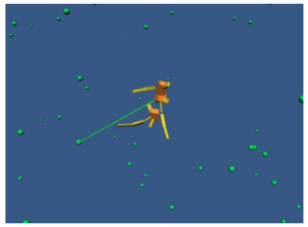
- For the emergence of intelligent creatures, we presumably need environments that incentivize the emergence of a cognitive toolkit.
  - attention, memory, knowledge representation, reasoning, emotions, forward simulation, skill acquisition, ...

Doing it wrong:



Incentives a lookup table of correct moves.

Doing it right:



Incentivises cognitive tools.

- 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.

Credits: Andrej Karpathy, Where will AGI come from?

Conclusions

A note of optimism

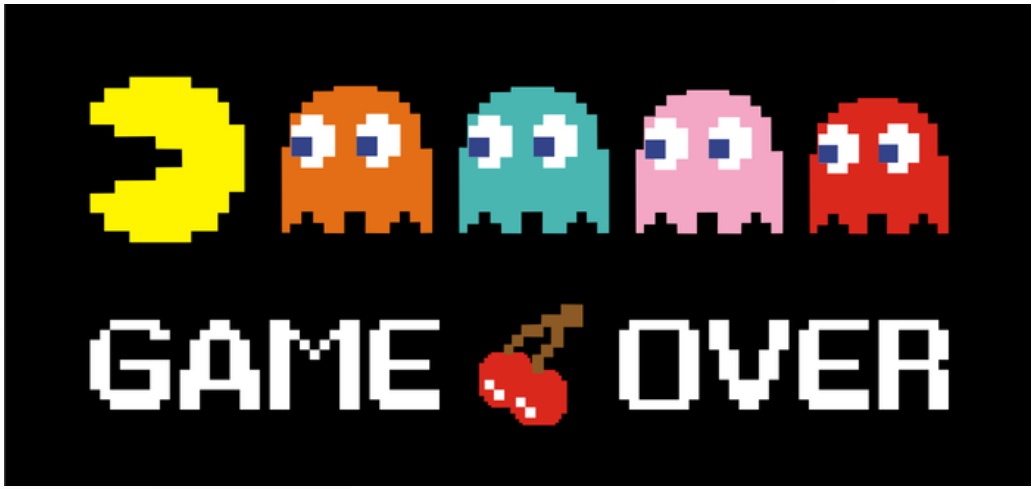
Don't fear intelligent machines, work with them. Garry Kasparov

Summary

- Lecture 1: Foundations
- Lecture 2: Solving problems by searching
- Lecture 3: Adversarial search
- Lecture 4: Constraint satisfaction problems
- Lecture 5: Representing uncertain knowledge
- Lecture 6: Inference in Bayesian networks
- Lecture 7: Reasoning over time
- Lecture 8: Learning
- Lecture 9: Communication
- Lecture 10: Artificial General Intelligence

Going further

- ELEN0062: Introduction to Machine Learning
- INFO8004: Advanced Machine Learning
- INFOXXXX: Deep Learning (Spring 2019)
- INFO8003: Optimal decision making for complex problems
- INFO0948: Introduction to Intelligent robotics
- INFO0049: Knowledge representation
- ELEN0016: Computer vision



Thanks for following Introduction to AI!

Readings

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- Sims, Karl. "Evolving 3D morphology and behavior by competition." Artificial life 1.4 (1994): 353-372.
- Kasparov, Garry. Deep Thinking: Where Machine Intelligence Ends and Human Creativity Begins, 2017.