



Lecture 1: Introduction to RL

王志 南京大学

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What we will cover

- Preliminaries of machine learning
 - Supervised learning: Regression, classification
 - Unsupervised learning: clustering, dimensionality reduction
- Finite Markov decision process (MDP)
- Tabular RL algorithms
 - Dynamic programming
 - Monte-Carlo methods
 - Temporal-difference learning
- Deep RL algorithms
 - Policy gradients
 - Actor-critics
 - Value function-based methods
- State-of-the-arts
 - Lifelong/continual RL
 - Transfer RL
 - Meta-RL, multi-task RL
 - Evolutionary RL

Pre-requisite

- Probability theory (概率论)
 - Probability distribution (概率分布), random variable (随机变量), expectation (期望), variance (方差)
 - probability density (概率密度) , conditional probability (条件概率), Bayes rule (贝叶斯公式)
- Linear algebra
 - Matrix multiplication (矩阵乘法), eigen-vector (特征向量)
 - Inverse matrix (逆矩阵), Hessian matrix (海赛矩阵)
- Basic programming
 - Python

Grading

- Homework: 40%
 - Policy gradient (20%)
 - DDPG (20%)
- Final project: 60%
 - Make a presentation (with slides in English) of one research paper selected from a given list
- Teaching assistant: Zican Hu (胡紫灿)
 - All homeworks and final projects should be submitted to huzican0419@gmail.com

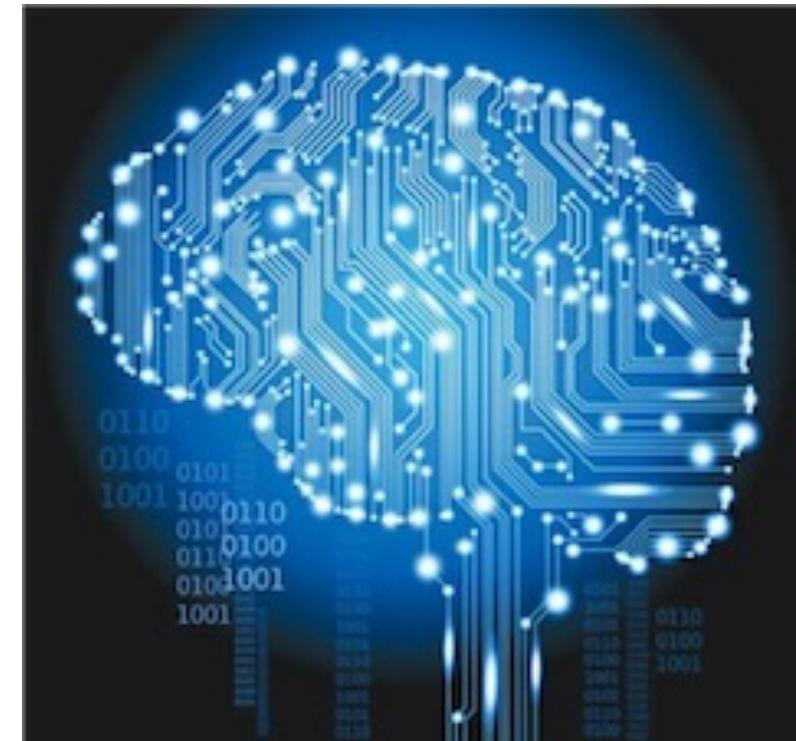
Useful links and references

- Course website
 - Heyuanmingong.github.io/teaching.html
- Books
 - Richard S. Sutton and Andrew G. Barto, *Reinforcement Learning: An Introduction*, 2nd Edition.
 - <http://www.incompleteideas.net/book/the-book-2nd.html>
- Famous open classes
 - CS 295 at UC Berkeley, *Deep Reinforcement Learning* (<http://rail.eecs.berkeley.edu/deeprlcourse/>)
 - CS 234 at Stanford, *Reinforcement Learning* (<http://web.stanford.edu/class/cs234/>)

1. Artificial Intelligence (AI)
2. Reinforcement Learning (RL)
3. Why should we care about (deep) RL?
4. How to build intelligent machines?
5. Beyond learning from reward

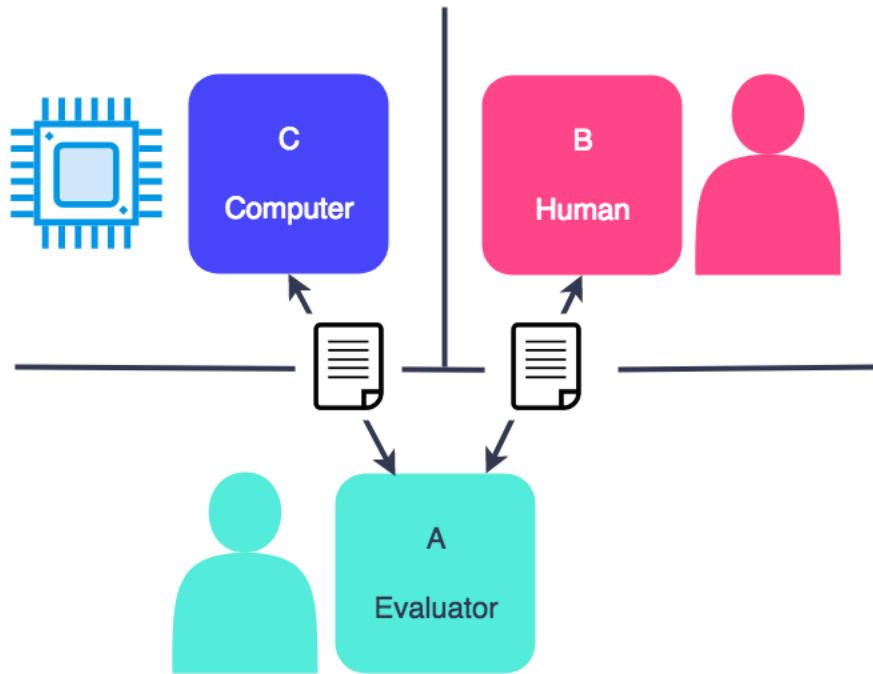
Artificial Intelligence (AI, 人工智能)

- The simulation of human intelligence processes by machines, especially **computer systems**
- The ability to **learn**, **understand**, and **think about** things in a **logical** way
- Artificial intelligence is a type of technology that mimics the human thought, empowering machines to act on their own and to perform functions similar to human intelligence, such as the ability to perceive, learn, reason, and act

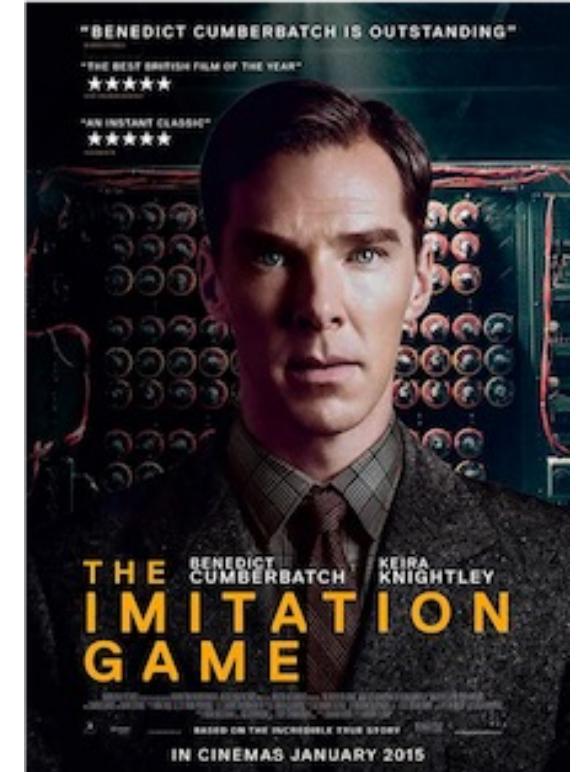


Birth of AI

Turing test (图灵测试)



Alan Turing
(1912~1954)



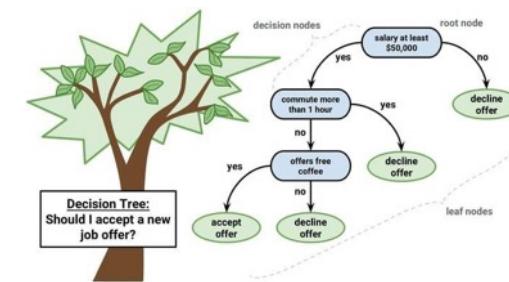
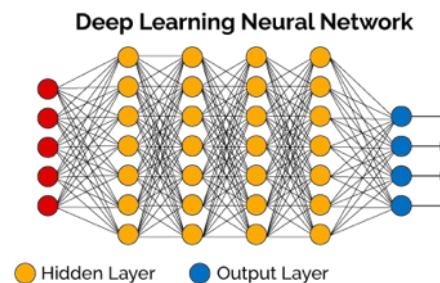
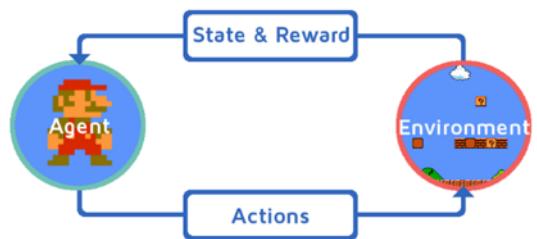
Beyond Turing: AI may **exceed** human intelligence

Reasons for Rise of AI

- **Exponential growth of computing power**



- **Rapid development of AI algorithms**



- **Massive data collection from connection of things**

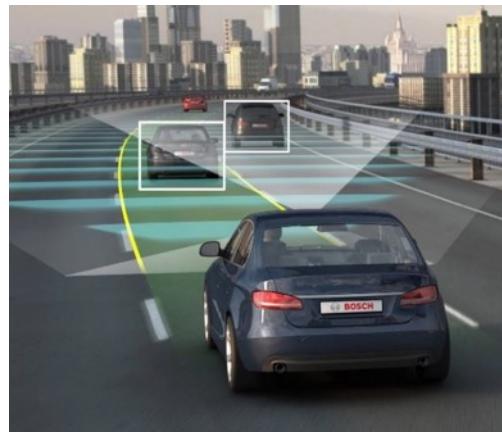


Applications of AI

Natural language processing



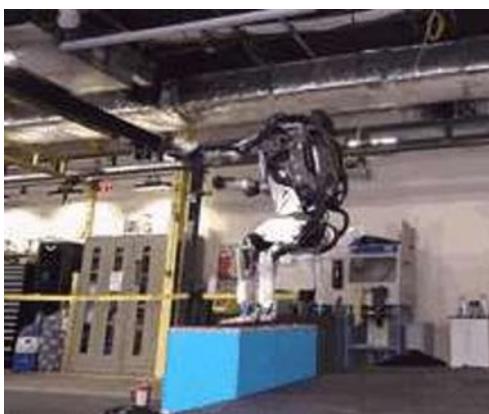
Autonomous driving



Medical diagnosis



Robotics



E-commerce



Public security



Content

1. Artificial Intelligence (AI)
2. Reinforcement Learning (RL)
3. Why should we care about (deep) RL?
4. How to build intelligent machines?
5. Beyond learning from reward

Machine Learning (机器学习)

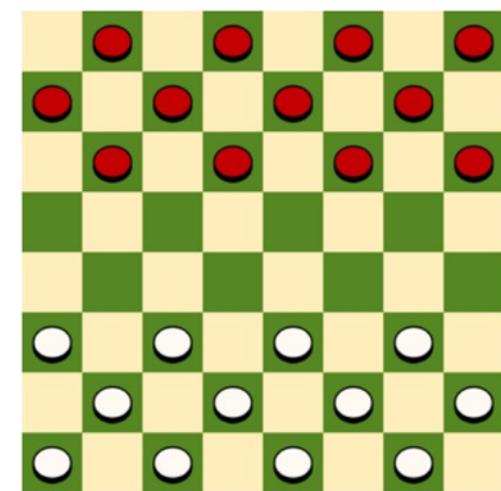
Arthur Samuel (1959):

Machine Learning is the field of study that gives the computer the ability to learn without being explicitly programmed.



A. L. Samuel*

**Some Studies in Machine Learning
Using the Game of Checkers. II—Recent Progress**



Machine Learning

Machine Learning



what society thinks I
do

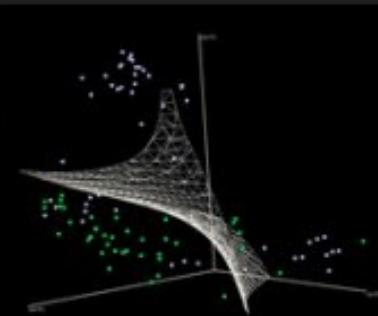


what my friends think
I do



what my parents think
I do

$$\begin{aligned}L_p &= \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^n \alpha_i y_i (\mathbf{x}_i \cdot \mathbf{w} + b) + \sum_{i=1}^n \alpha_i \\ \alpha_i &\geq 0, \forall i \\ \mathbf{w} &= \sum_{i=1}^n \alpha_i y_i \mathbf{x}_i, \sum_{i=1}^n \alpha_i y_i = 0 \\ \nabla g(\theta_t) &= \frac{1}{n} \sum_{i=1}^n \nabla \ell(x_i, y_i; \theta_t) + \nabla r(\theta_t), \\ \theta_{t+1} &= \theta_t - \eta_t \nabla \ell(x_{i(t)}, y_{i(t)}; \theta_t) - \eta_t \cdot \nabla r(\theta_t) \\ E_{i(t)} [\ell(x_i, y_i; \theta_t)] &= \frac{1}{n} \sum_i \ell(x_i, y_i; \theta_t).\end{aligned}$$



```
>>> from sklearn import svm
```

what other programmers
think I do

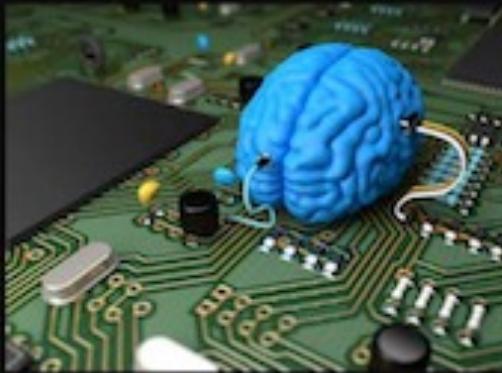
what I think I do

what I really do

Deep Learning



What society thinks I do



What my friends think I do



What other computer
scientists think I do



What mathematicians think I do



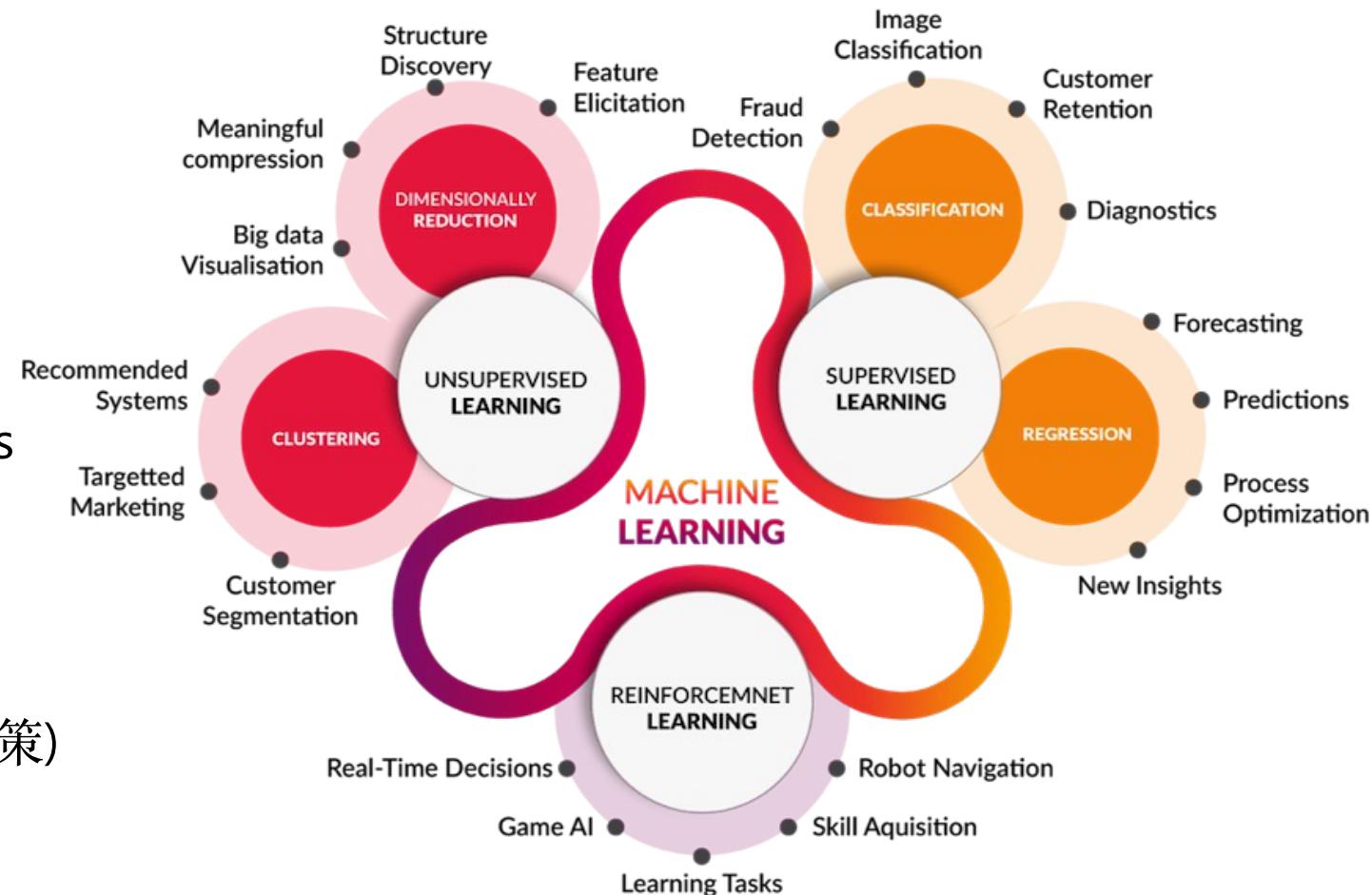
What I think I do

```
from theano import *
```

What I actually do

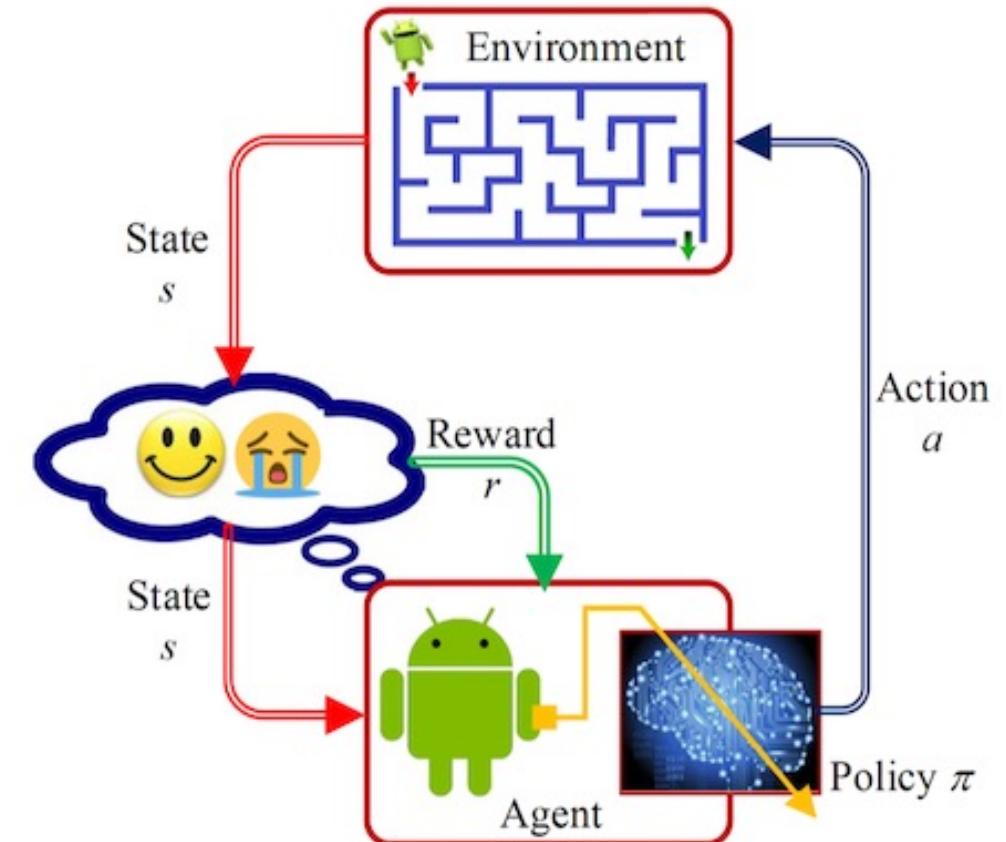
Taxonomy of Machine Learning

- Supervised learning (监督)
 - A mapping from **input** to **label**
 - Regression, classification
- Unsupervised learning (非监督)
 - Learn hidden patterns without labels
 - Clustering, dimension reduction
- Reinforcement learning (强化)
 - sequential decision-making (序贯决策)



Reinforcement Learning (RL, 强化学习)

- Mathematical formalism for learning-based decision-making
- Reinforce behaviors through rewards received from interacting with the world in a **trial-and-error** way
- Approach for sequential decision-making and control **from experience**



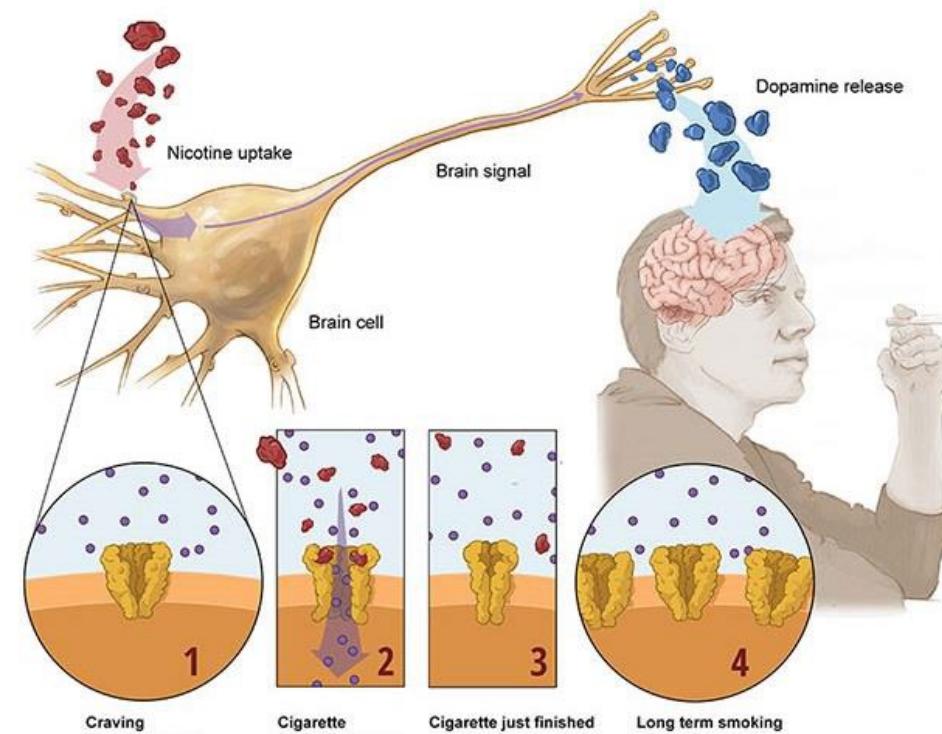
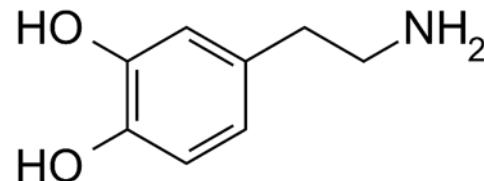
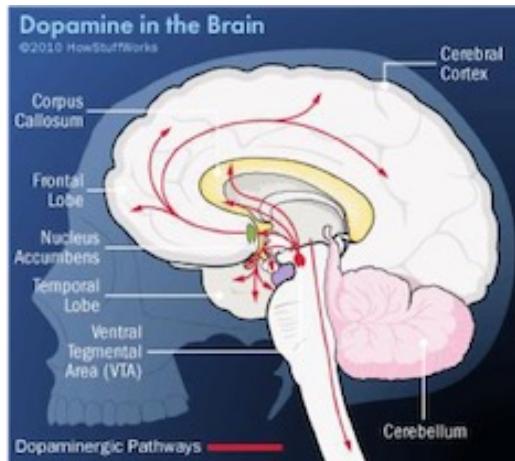
Inspiration of RL

- A **biologically inspired** training method
 - Originate from mimicking learning behaviors of animals
 - Repeat behaviors that are rewarded, avoid behaviors that are punished



Inspiration of RL

- Animal behavior is rewarded by brain dopamine (多巴胺)
 - Dopamine is neurotransmitter (神经递质)
 - Responsible for reward-motivation, motor control, and arousal

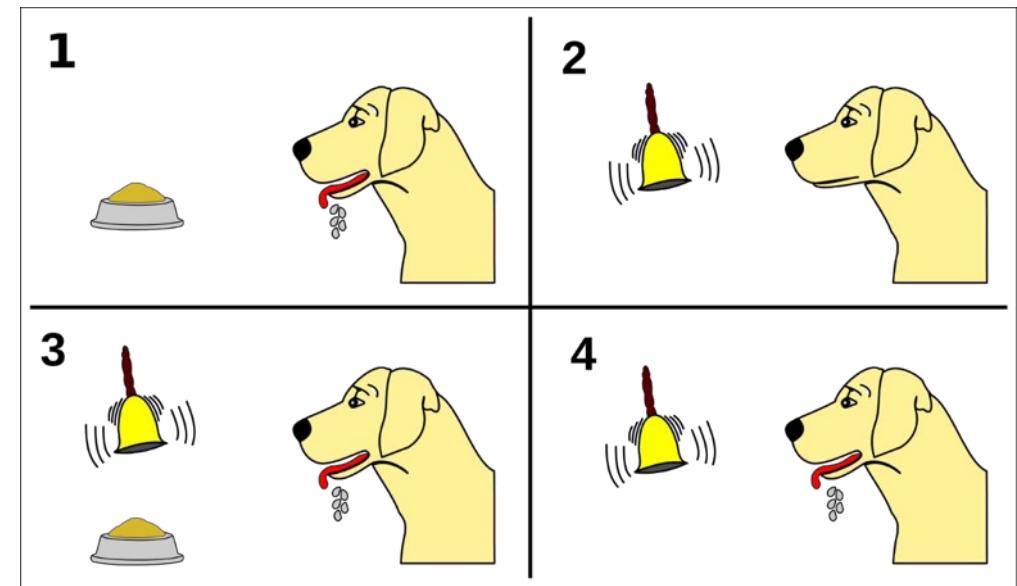


Inspiration of RL

- Pavlov's dog experiment
 - Ivan Pavlov, Russian physiologist, 1901
 - Humans and animals learn through rewards

Training: Bell → Food

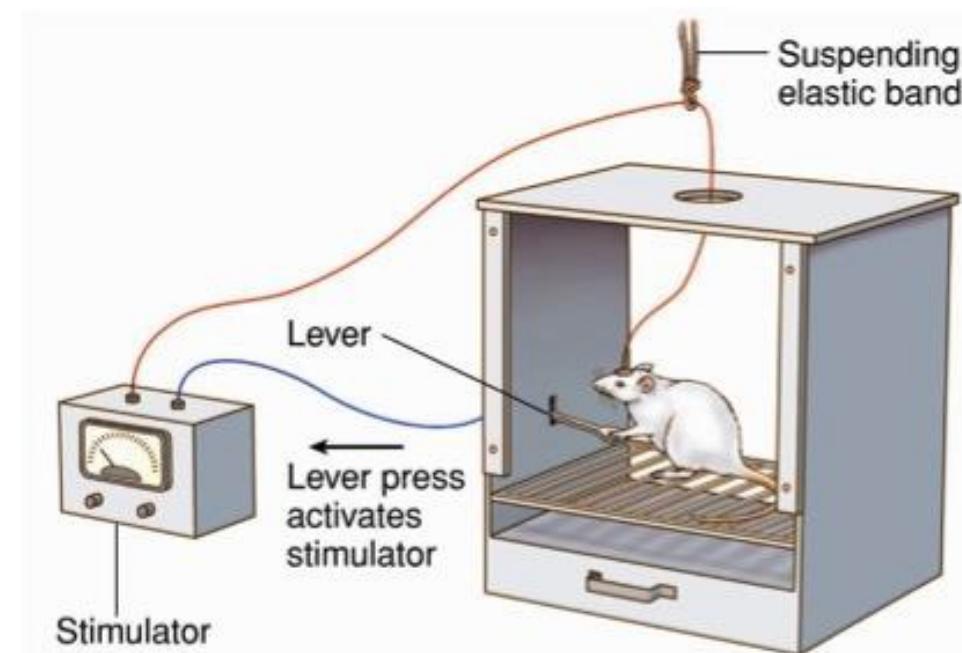
Testing: Bell → Salivate (分泌唾液)



Inspiration of RL

- Brain stimulation reward experiment
 - J Olds & P Milner, McGill University, 1954
 - Rats would continually press a lever in return for receiving a brief pulse of electrical stimulation in **a particular region of rat's brain**

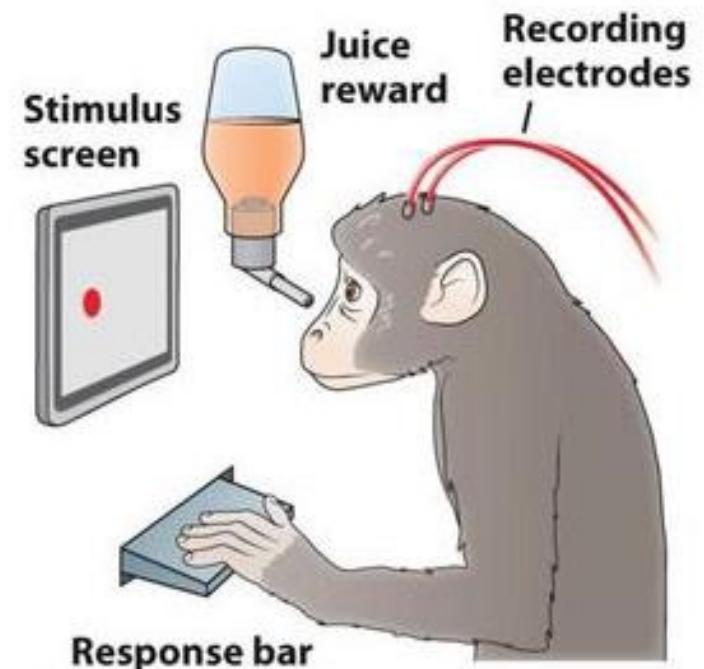
Result: Existence of a reward center in the brain



Inspiration of RL

- Dopamine releasing mechanism experiment
 - Schultz et al., Cambridge University, 1997

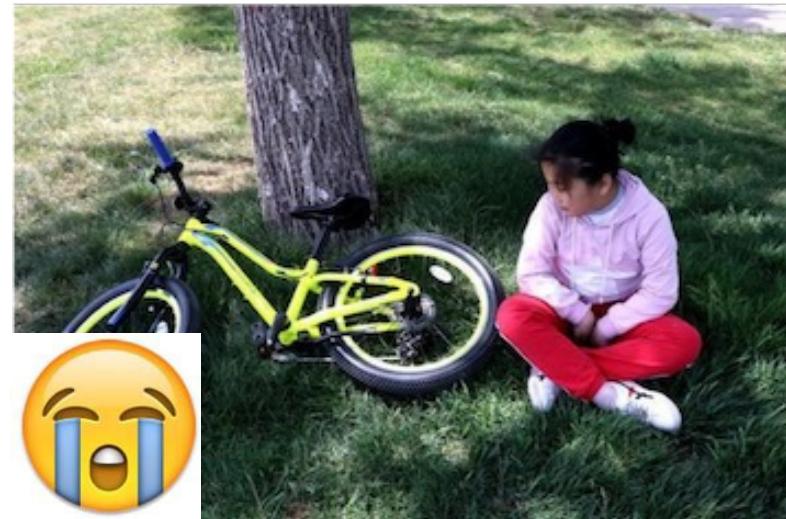
Num	Predicted reward	Actual reward	Error	Dopamine release
1	No	Yes	+	↑
2	Yes	Yes	0	→
3	Yes	No	-	↓



- Result: Dopamine release comes from the difference or error between actual reward and predicted reward

Inspiration of RL

- How a child learns to ride a bicycle
 - Initially, an adult will show how to ride (imitation learning, 模仿学习)
 - Then, the child should **try it by herself** from the **reward** or **penalty**
 - By learning from **trial and errors**, she finally masters it



Markov Decision Process (MDP, 马尔科夫决策过程)

$$M = \langle S, A, T, R \rangle$$

S : State space

State $s \in S$ (discrete/continuous)

A : Action space

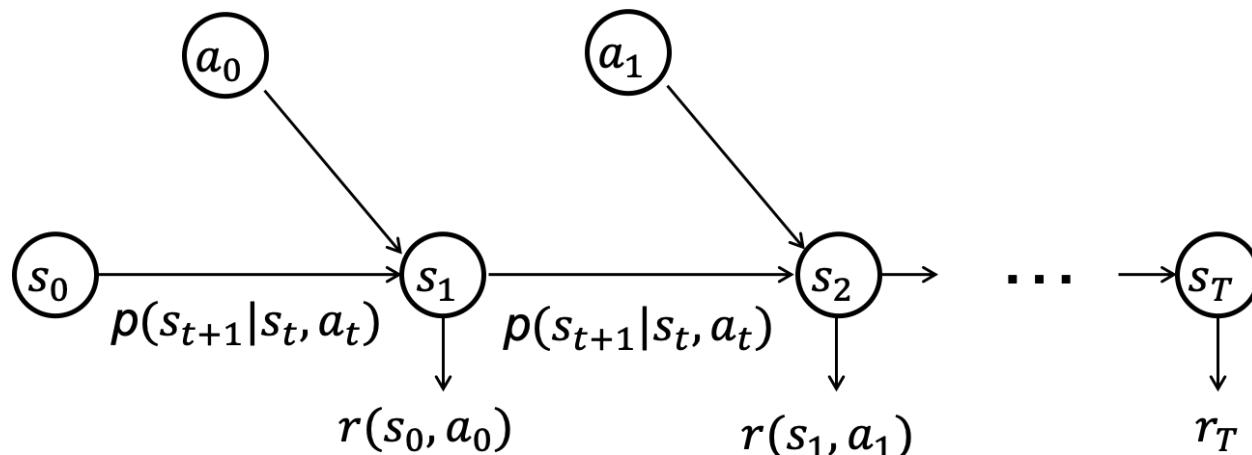
Action $a \in A$ (discrete/continuous)

T : Transition operator

$$T_{i,j,k} = p(s_{t+1} = j | s_t = i, a_t = k)$$

R : Reward function

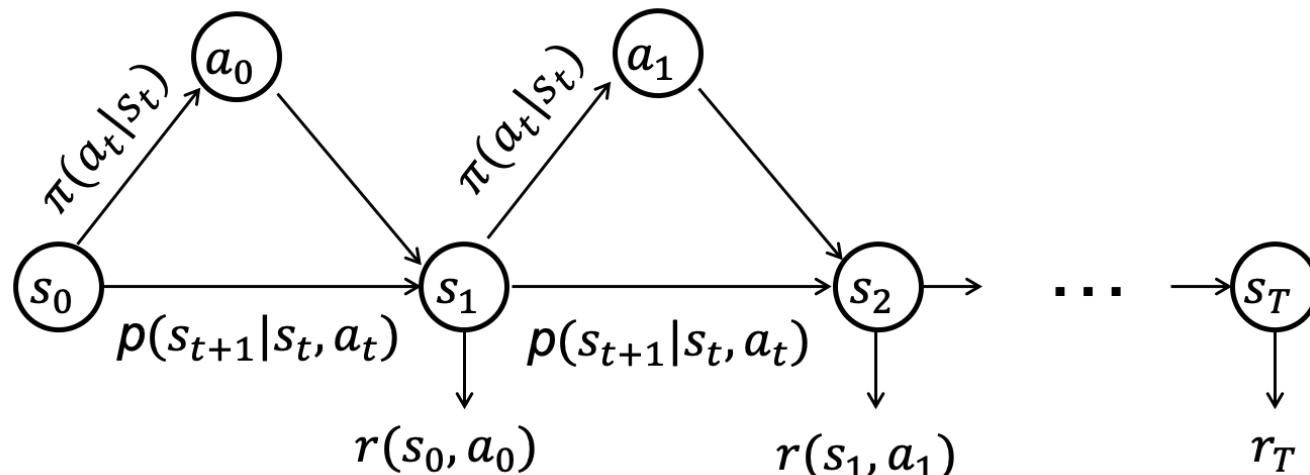
$$R_{i,j,k} = r(s_{t+1} = j | s_t = i, a_t = k)$$



The goal of RL

- Find **optimal policies** to maximize cumulative reward
 - In a **trial-and-error** manner
 - A general **optimization framework** for sequential decision-making

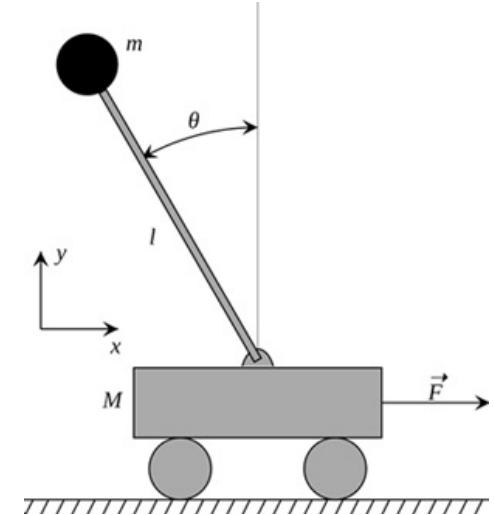
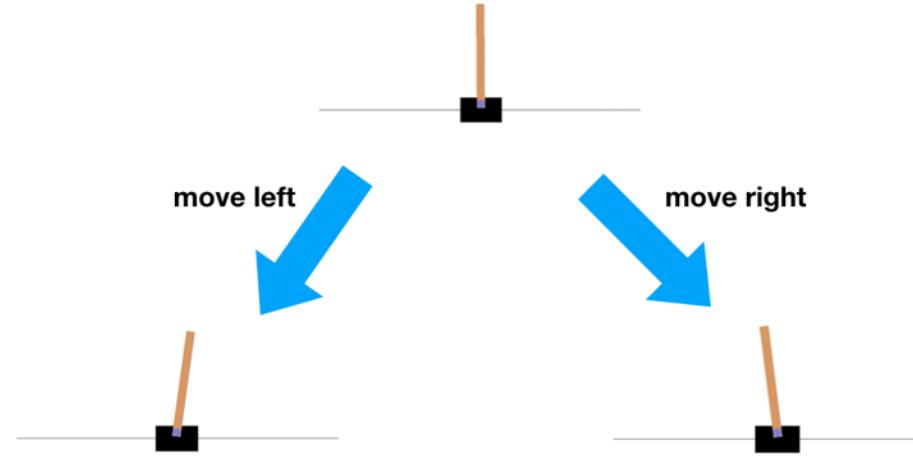
$$\pi^* = \arg \max_{\pi} \mathbb{E} \left[\sum_t r(s_t, a_t) \right]$$



How is RL different from other machine learning topics?

- Standard supervised learning:
 - given $D = \sum_i(x_i, y_i)$
 - learn to predict y from x , $f(x) \approx y$
- Usually assumes:
 - Independent and identically distributed (i.i.d., 独立同分布)
 - Known ground truth outputs in training
- RL
 - Data is not i.i.d., previous outputs influence future inputs
 - Ground truth answer is not known, only known if we succeed or failed
(more generally, we know the reward)

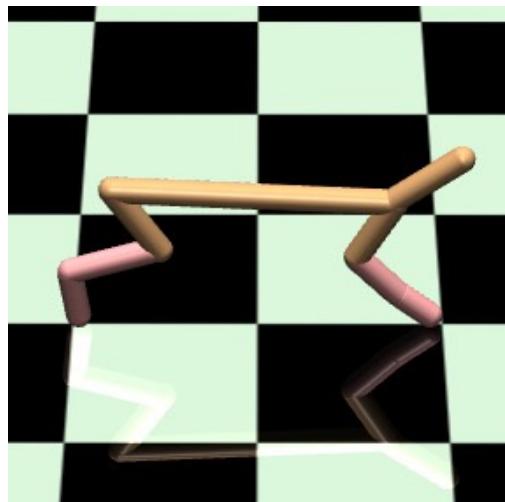
Example: Inverted pendulum (倒立摆)



- x : position along the x -axis
- θ : angle of the pendulum

- State: $(x, \dot{x}, \theta, \dot{\theta})$
- Action: $\{-1, 0, +1\}$
- Reward: +1 if stand up, -0.01 otherwise

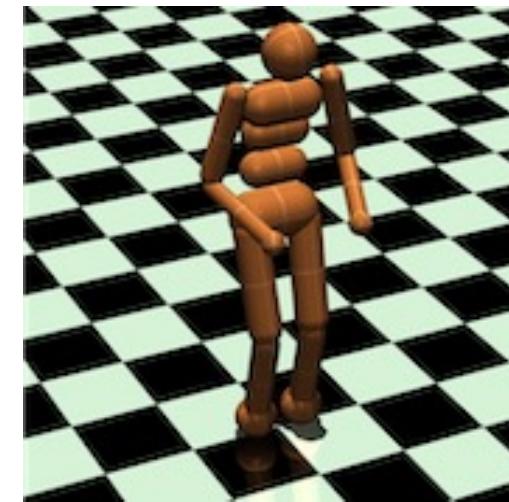
Example: Robot locomotion (机器人运动学)



Half Cheetah



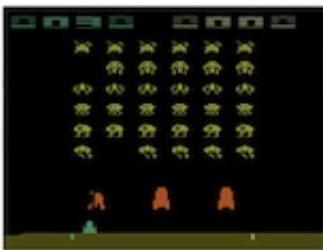
Ant



Humanoid

- Make the robots run forward, or navigation
 - Observations/states: positions, velocities, angular velocities
 - Actions: torques at the joint
 - Rewards: velocities, goal

Example: Atari games



Space Invaders



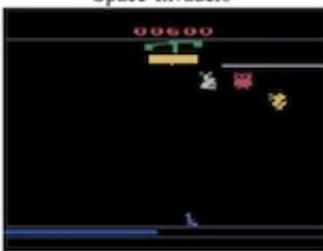
Boxing



Skiing



Alien



Breakout



Kung-Fu Master



River Raid



Ms. Pac-Man

- Observations/states: raw images
- Actions: control signals
- Rewards: win/lose

In general...



States: sight, smell
Actions: muscle contractions
Rewards: food



States: camera images
Actions: motor torque
Rewards: task success measure

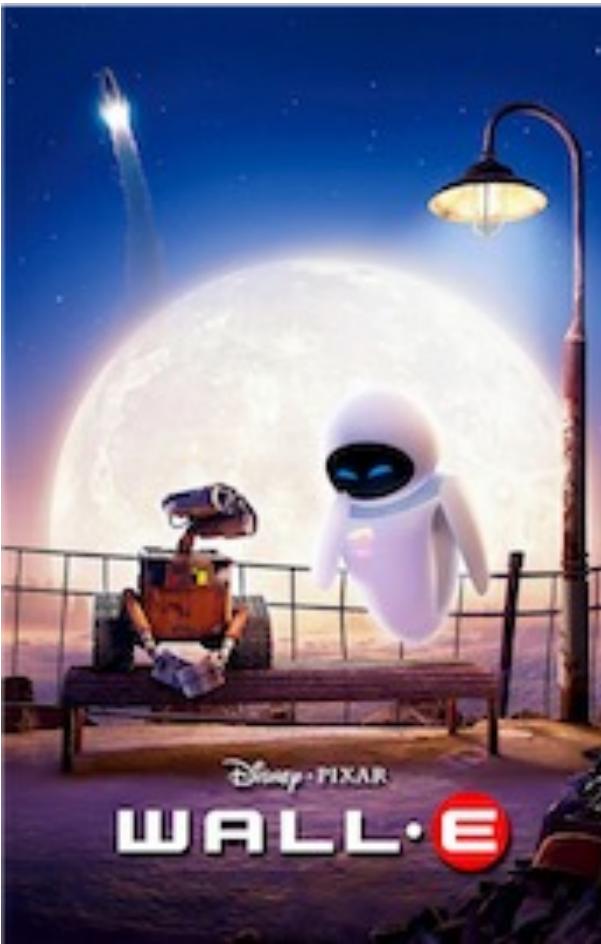


States: inventory (库存) level
Actions: what to purchase
Rewards: profit

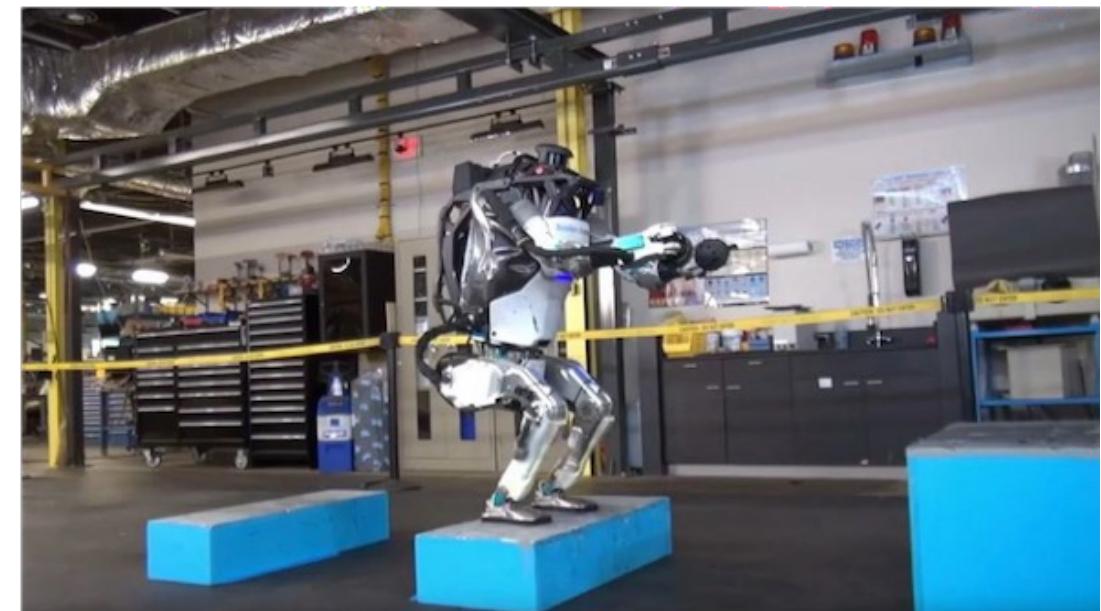
Content

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Intelligent machines

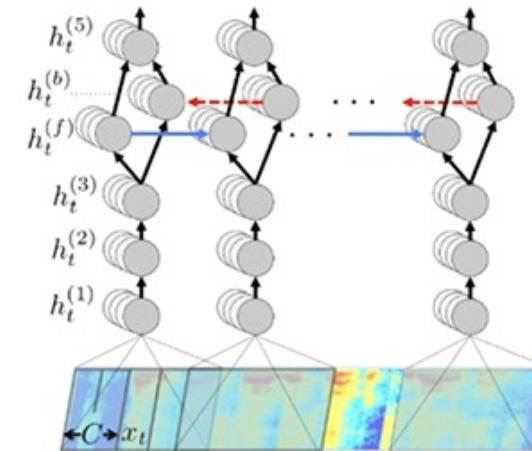
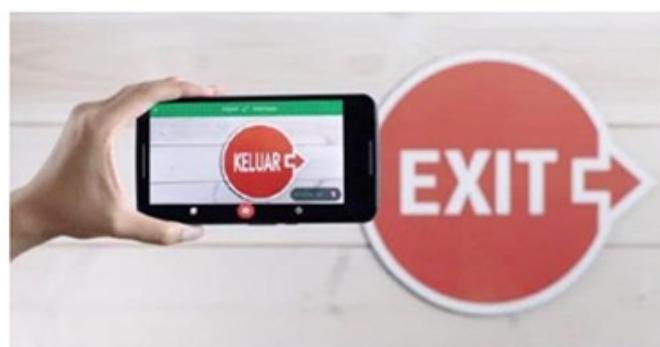
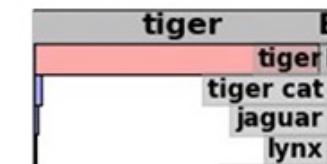
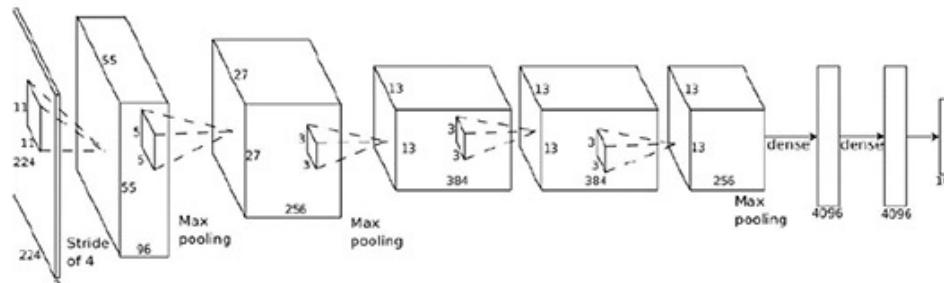


Intelligent machines must able to adapt

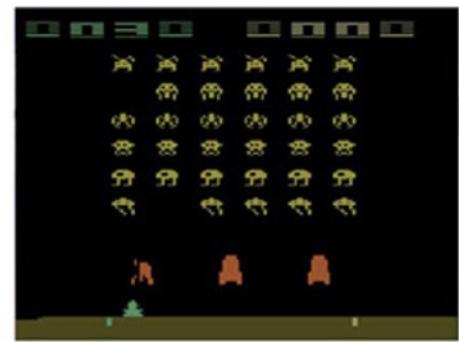
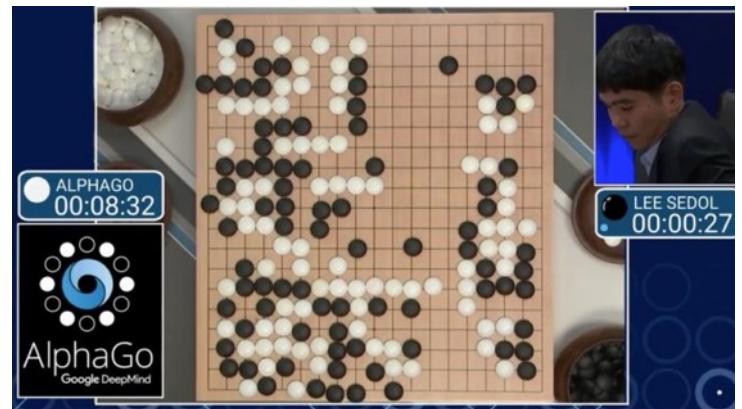
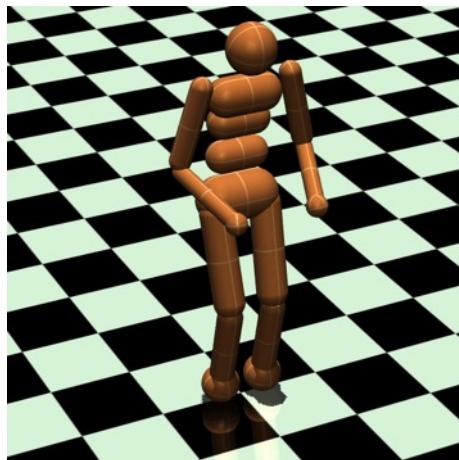
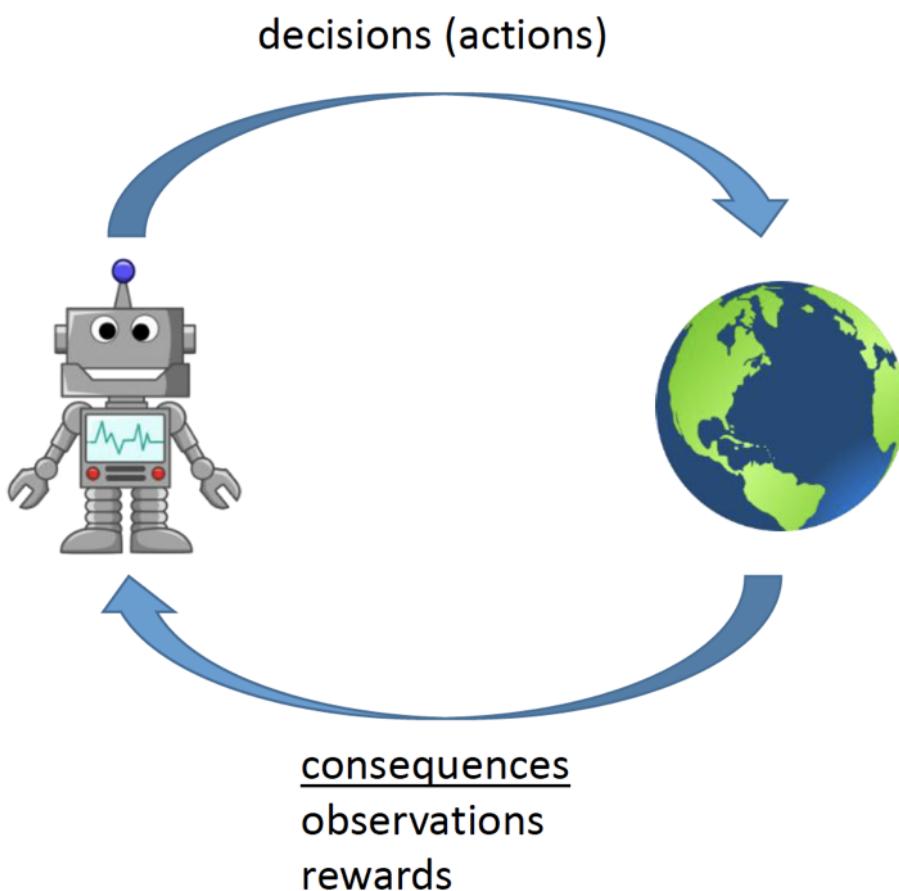


Deep learning

- Deep learning helps us handle **unstructured environments**

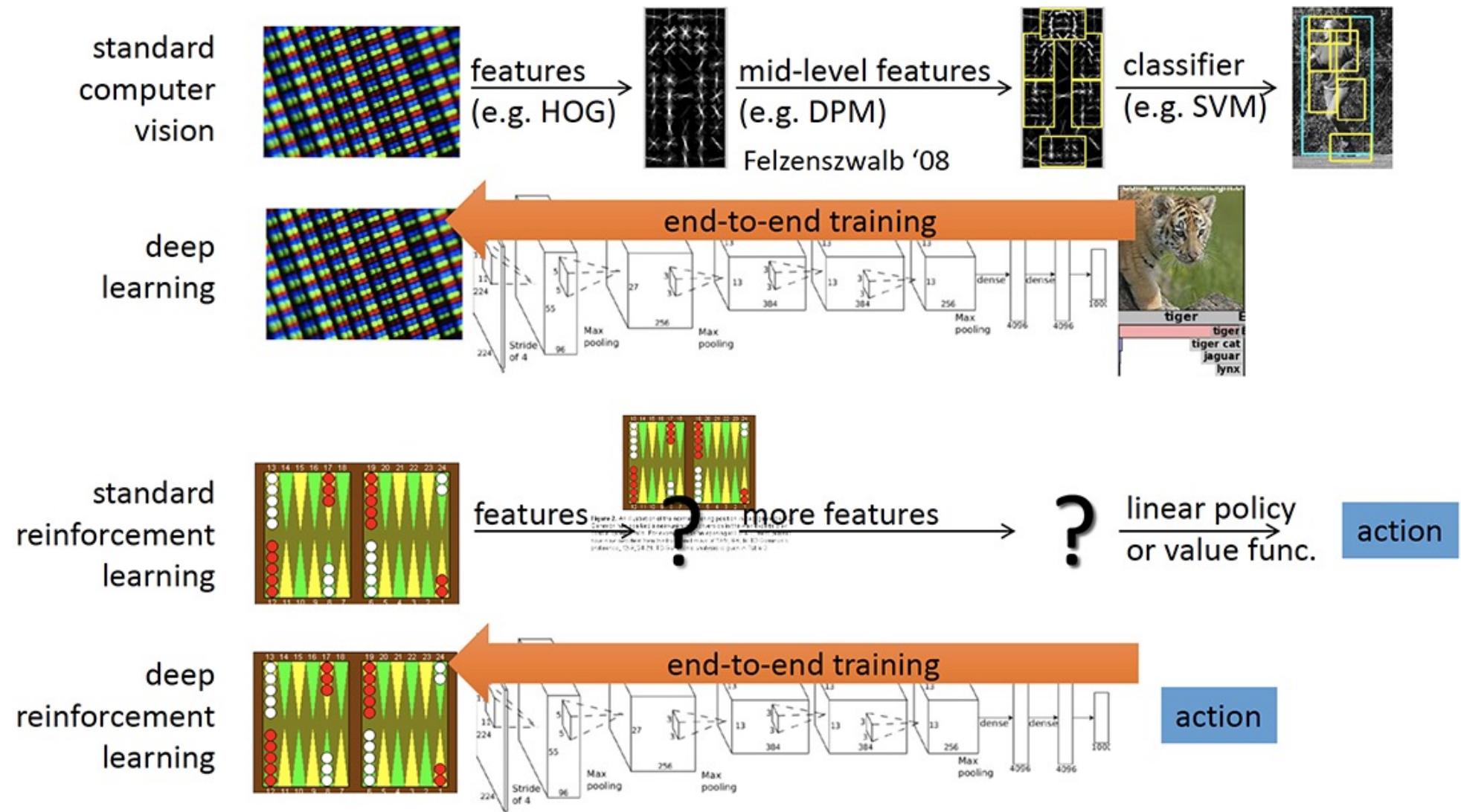


- RL provides a formalism for behavior/decision-making

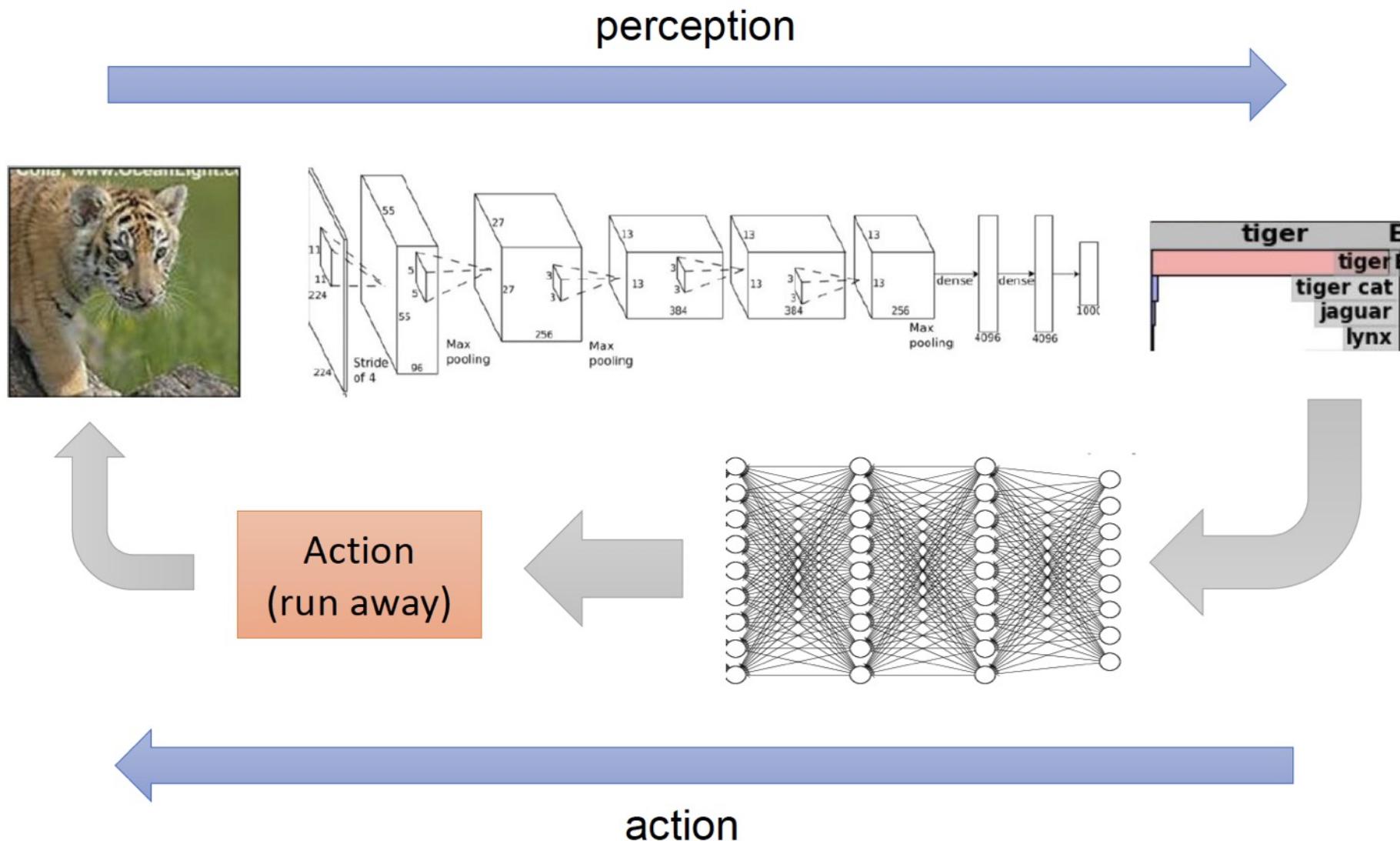


Space Invaders

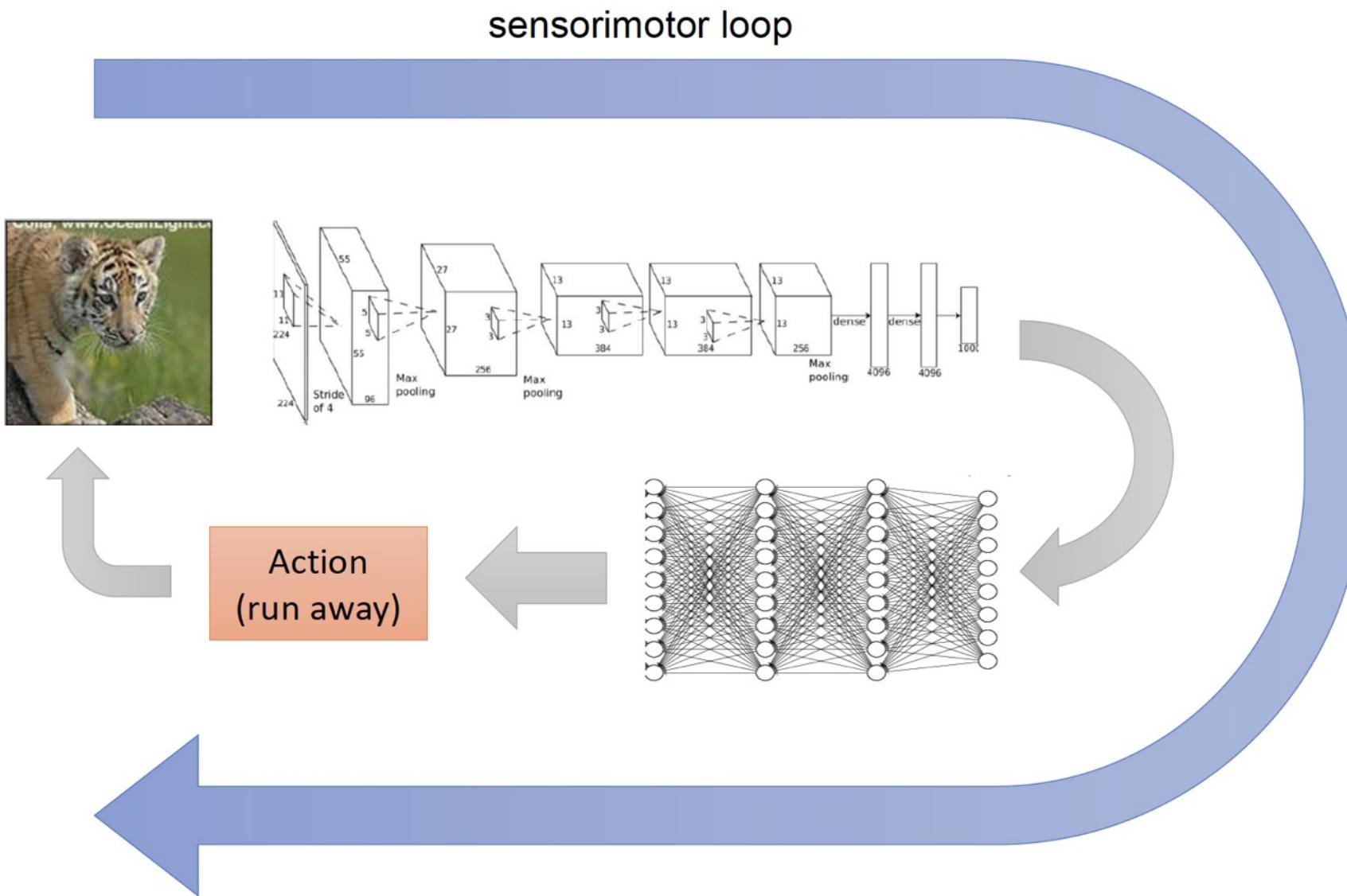
Deep RL = Deep learning + RL



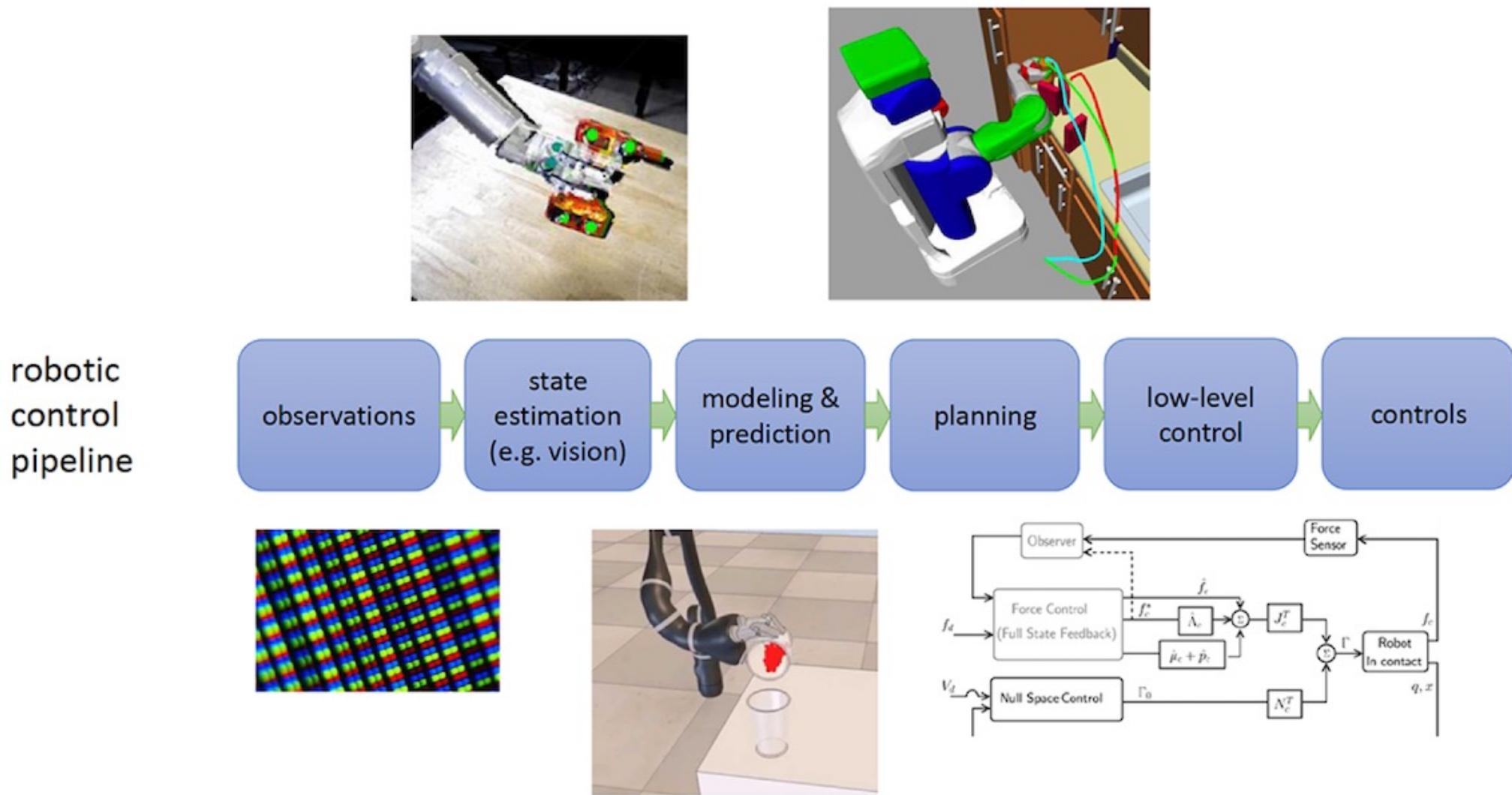
End-to-end learning for sequential decision-making



End-to-end learning for sequential decision-making

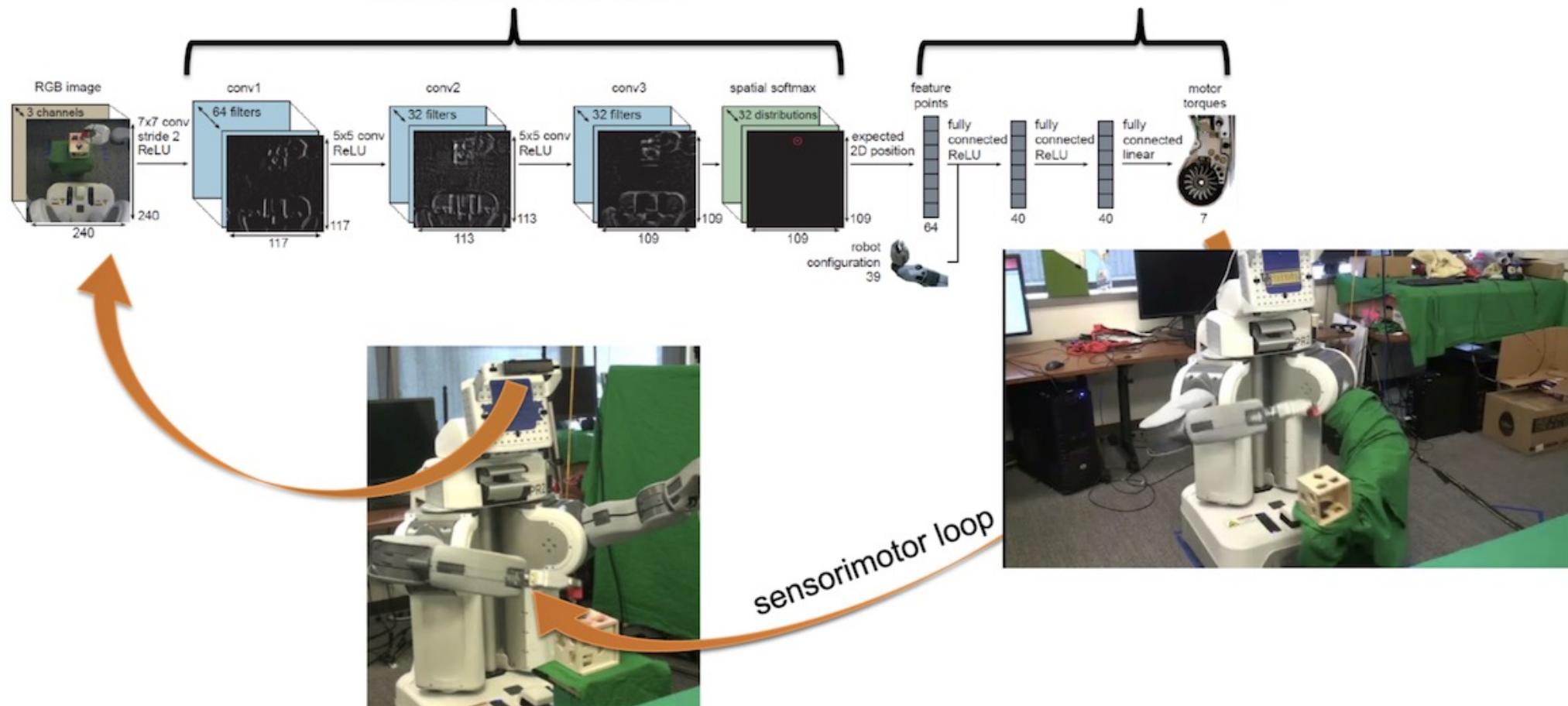


Example: Robotics



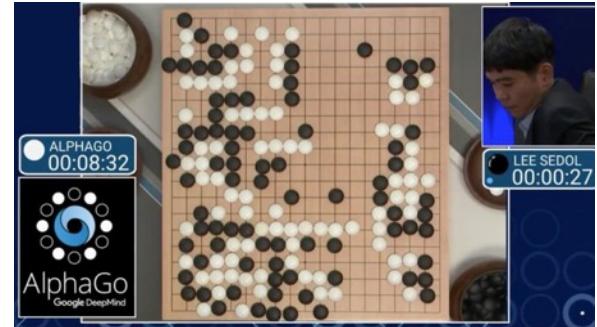
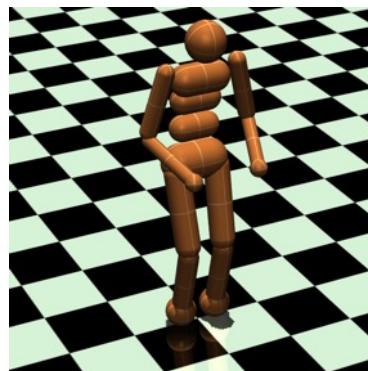
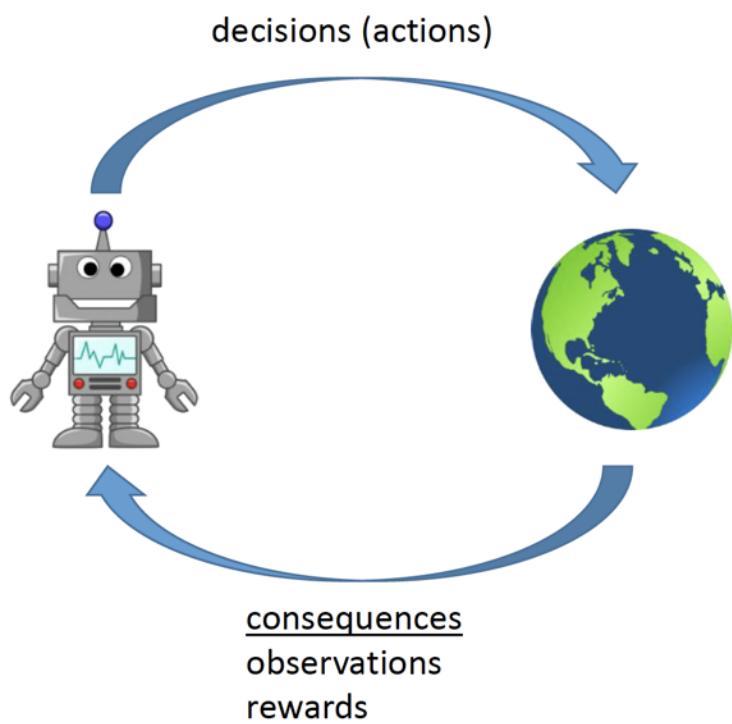
End-to-end learning

tiny, highly specialized
“visual cortex” tiny, highly specialized
“motor cortex”



The RL problem is the AI problem

- Deep models allow RL algorithms to solve complex problems end-to-end
 - Deep learning: **perception**, handle unstructured environments
 - RL: **decision**, optimize its behavior



Space Invaders

The RL problem is the AI problem

- Advances in deep learning
- Advances in RL
- Advances in computational capability

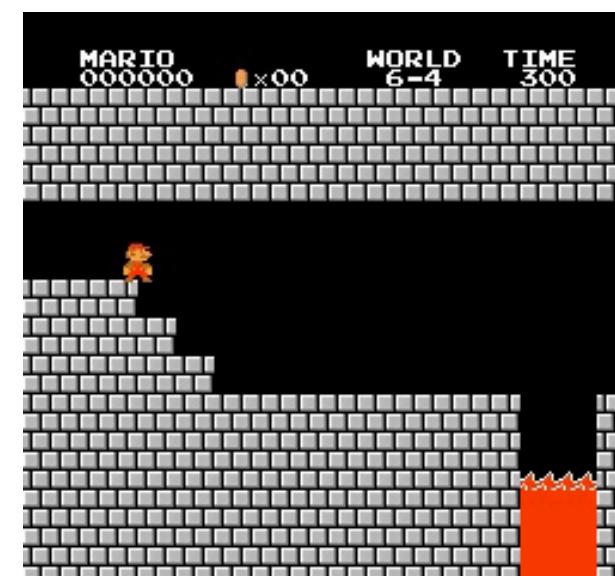
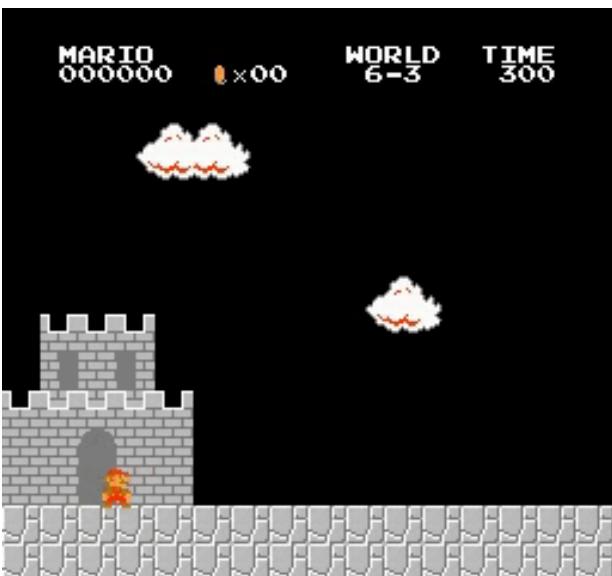
The image displays four separate cards, each representing a published article from the journal 'nature'. Each card has a dark blue header with the word 'nature' in white, followed by a light blue navigation bar with links like 'Explore our content', 'Journal information', etc. The main content area on each card includes the publication date, the title of the article in bold black text, and a brief description below it.

- Human-level control through deep reinforcement learning**
Published: 25 February 2015
- Mastering the game of Go without human knowledge**
Published: 19 October 2015
- Grandmaster level in StarCraft II using multi-agent reinforcement learning**
Published: 30 October 2019
- Discovering faster matrix multiplication algorithms with reinforcement learning**
Open Access | Published: 05 October 2022

The Era of RL

- Video games: Human-level control through DRL, Nature 2015 (视频游戏)
- AlphaGo, Nature 2016; AlphaGo Zero, Nature 2017 (围棋)
- AlphaStar in StarCraft II, Nature 2019 (星际争霸II)
- DRL for legged robots, Science Robotics 2019 (机器人学习)
- Superhuman AI for multiplayer poker, Science 2019 (德州扑克, 多人非完全信息博弈)
- Discovering faster matrix multiplication algorithms, Nature 2022 (矩阵相乘算法发现, 基础数学)
- Magnetic control of tokamak plasmas, Nature 2022 (可控核聚变控制)
- Outracing champion Gran Turismo drivers, Nature 2022 (赛车模拟控制)
- Safety validation of autonomous vehicles, Nature 2023 (无人驾驶安全验证)
- Faster sorting algorithms discovering, Nature 2023 (排序算法发现, 基础信息科学)
- Champion-level drone racing, Nature 2023 (无人机竞速)
- Avoiding fusion plasma tearing instability, Nature 2024 (可控核聚变)
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The Era of RL



The Era of RL



The Era of RL



Generative adversarial imitation learning (GAIL)

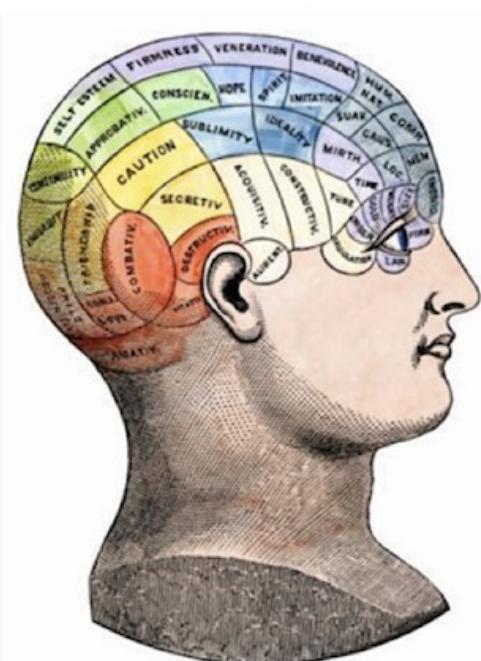
Learning **biomimetic** behaviors

Content

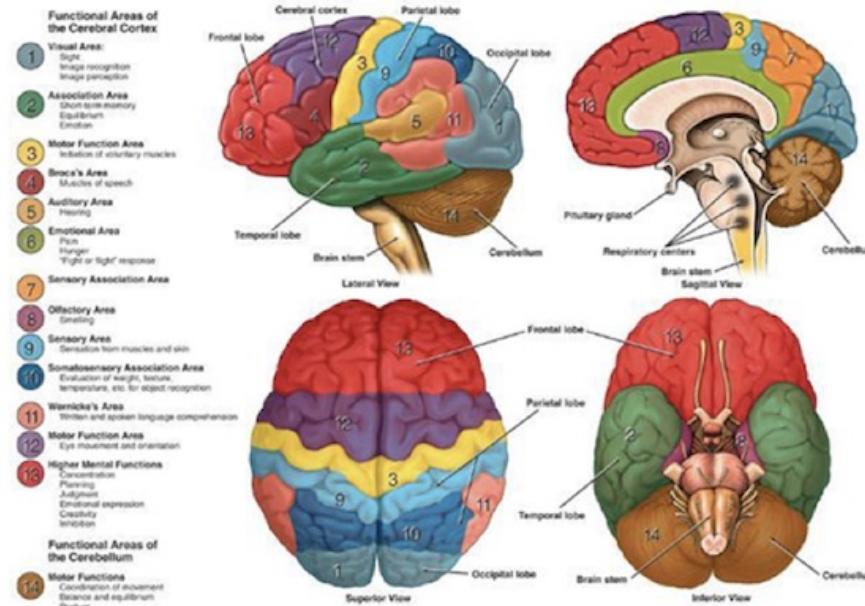
1. Artificial Intelligence (AI)
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How do we build intelligent machines?

- Imagine you have to build an intelligent machine, where do you start?



Anatomy and Functional Areas of the Brain

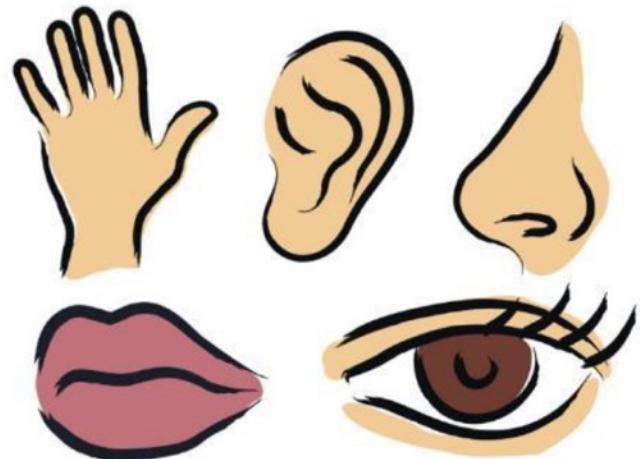


“Learning” as the basis of intelligence

- Some things we can all do (e.g., walking)
- Some things we can only learn (e.g. driving a car)
- We can learn a huge variety of things, including very difficult things
- Therefore, our **learning mechanisms** are likely powerful enough to do everything we associate with **intelligence**
 - But it may still be very convenient to “hard code” a few really important bits

What must a single algorithm do?

- Interpret (rich) sensory inputs
- Choose (complex) actions



Why (deep) RL?

- Deep = can process complex sensory inputs
 - Compute really complex functions
- RL = can choose complex actions
 - Reinforce its behaviors by rewards



Reinforcement learning in the brain

Yael Niv

Psychology Department & Princeton Neuroscience Institute, Princeton University

- Basal ganglia (基底神经节) appears to be related to reward system
- Model-free RL-like adaptation is often a good fit for experimental data of animal adaptation (but not always)

Quantum reinforcement learning during human decision-making

Ji-An Li, Daoyi Dong, Zhengde Wei, Ying Liu, Yu Pan, Franco Nori & Xiaochu Zhang 

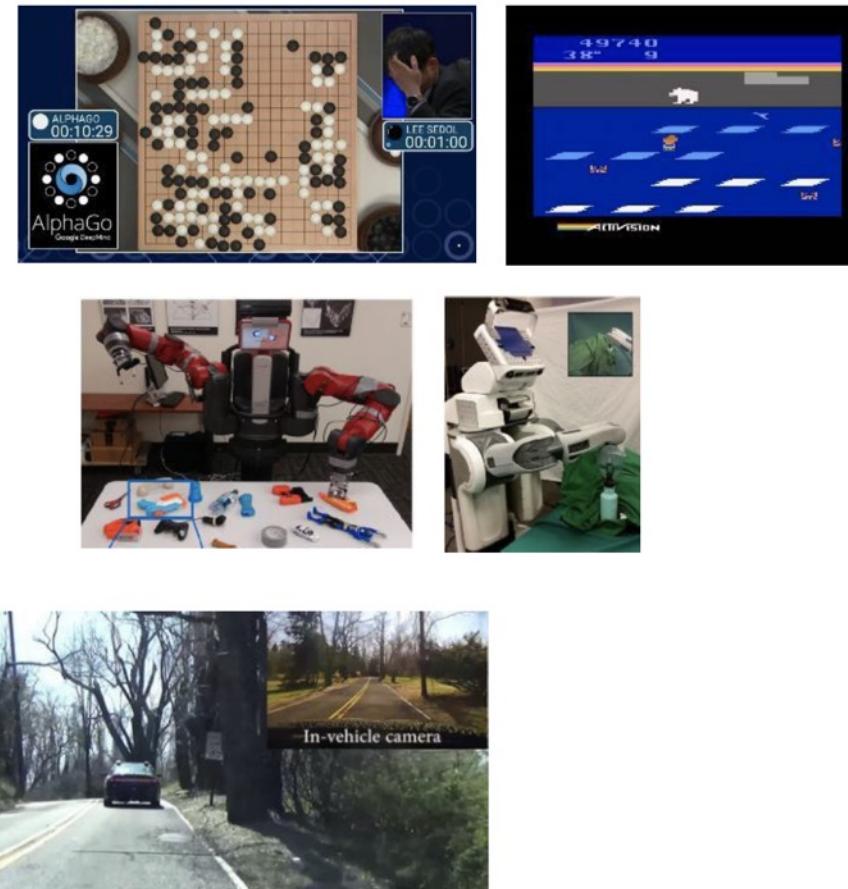
Nature Human Behaviour 4, 294–307(2020) | Cite this article

- RL has been widely applied in neuroscience (神经科学) and psychology (心理学)
- Value-based decision-making can be illustrated by quantum RL (量子强化学习) at both the behavioral and neural levels

What can (deep) RL do?

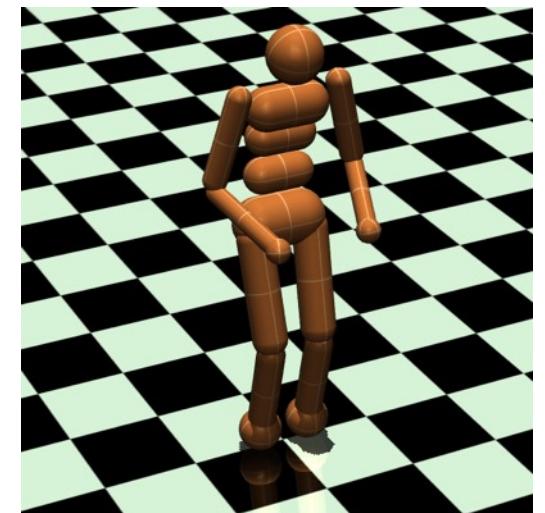
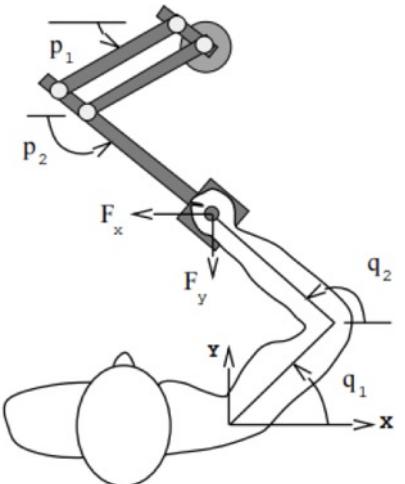
- Acquire high degree of proficiency in domains governed by **simple, known rule**
- Learn **simple** skills with raw sensory input given **enough experience**
- Learn from **imitating** enough human provided expert behavior (模仿学习)

Still in the infancy, and a promising future!



What has proven challenging so far?

- Humans can learn incredibly quickly
 - (Deep) RL methods are usually slow
- Humans can reuse past knowledge
 - Transfer learning in (deep) RL is an open problem
- Not clear what the **reward** function should be
- Not clear what the role of **prediction** should be

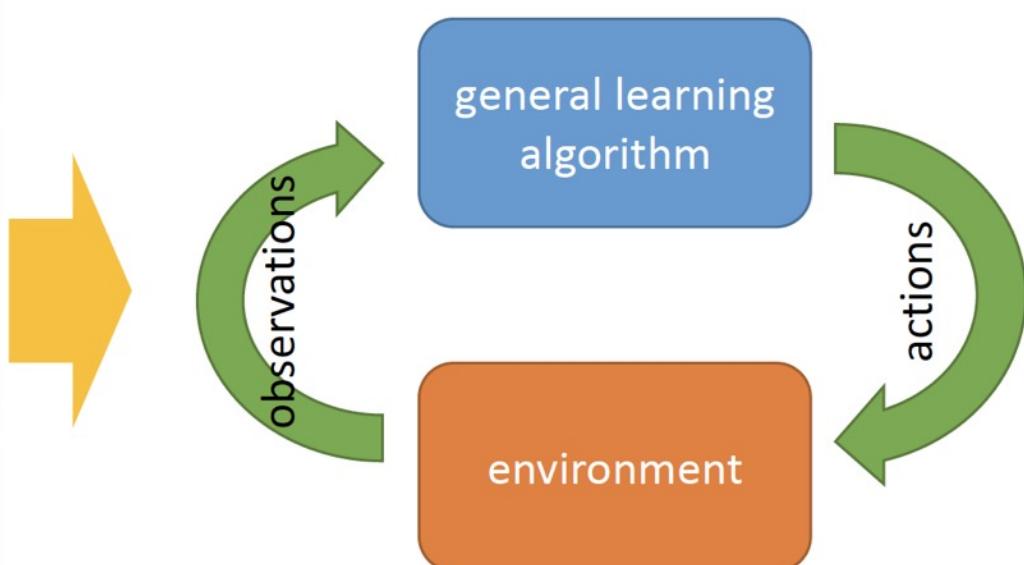
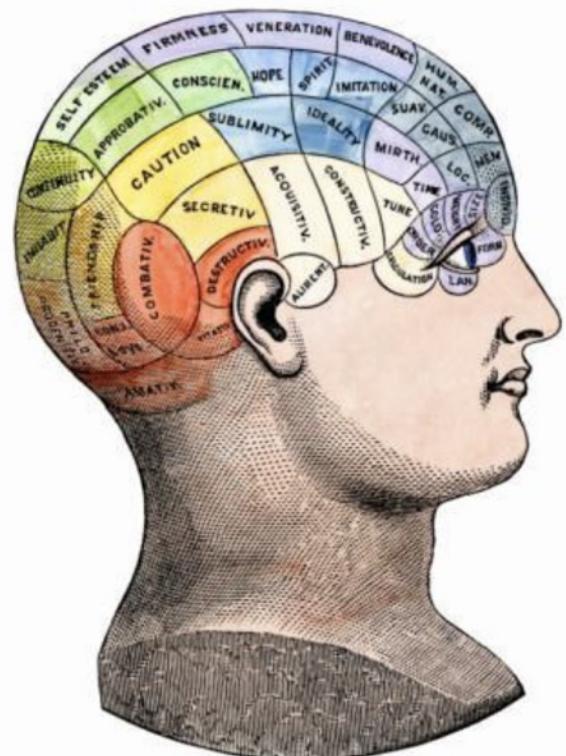


RL, decision-making, human behavior

Instead of trying to produce a program to simulate the adult mind, why not rather try to produce one which simulates the child's? If this were then subjected to an appropriate course of education one would obtain the adult brain.



- Alan Turing



Content

1. Artificial Intelligence (AI)
2. Reinforcement Learning (RL)
3. Why should we care about (deep) RL?
4. How to build intelligent machines?
5. Beyond learning from reward

Enabling real-world sequential decision-making

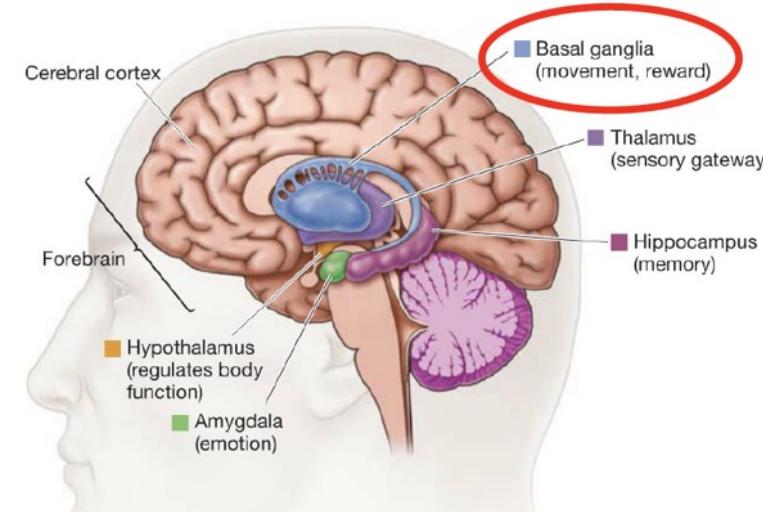
- Basic RL deals with **maximizing rewards**
- This is not the only problem that matters for sequential decision-making!
- More advanced topics
 - Transferring knowledge between domains (transfer learning, meta-learning)
 - Learning to predict and using prediction to act (model-based RL)
 - Learning reward functions from example (inverse RL)

What do rewards come from?



Mnih et al. '15

reinforcement learning agent



- As human beings, we are accustomed to operating with rewards that are so sparse that we only experience them once or twice in a lifetime, if at all.

Are there other forms of supervision?

- Learning from demonstrations
 - Directly copying observed behavior (imitation learning)
 - Inferring rewards from observed behavior (inverse RL)
- Learning from observing the reward
 - Learning to predict
 - Unsupervised learning, self-supervised learning
- Learning from other tasks
 - Transfer learning
 - Meta-learning: learning-to-learn

Learning objectives of this lecture

- You should be able to...
 - Understand the basic concepts about sequential decision-making, the differences between supervised learning and RL
 - How RL provides a formalism for behavior and decision-making

THE END