

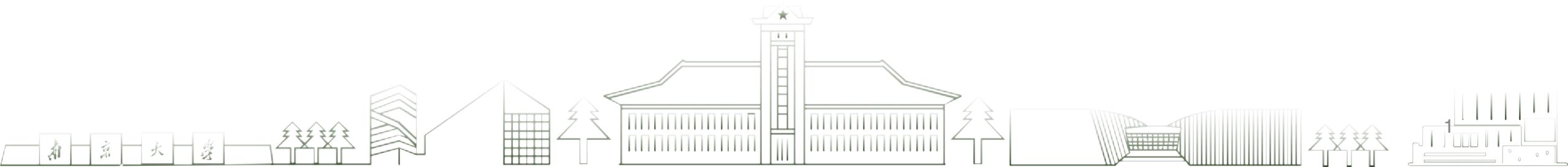


# Lecture 1: Introduction to RL

王志 南京大学

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2023-02-16



# 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: Hongyu Ding (丁泓宇)
  - All homeworks and final projects should be submitted to [hongyuding@mail.nju.edu.cn](mailto:hongyuding@mail.nju.edu.cn)

# 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/>)

# 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

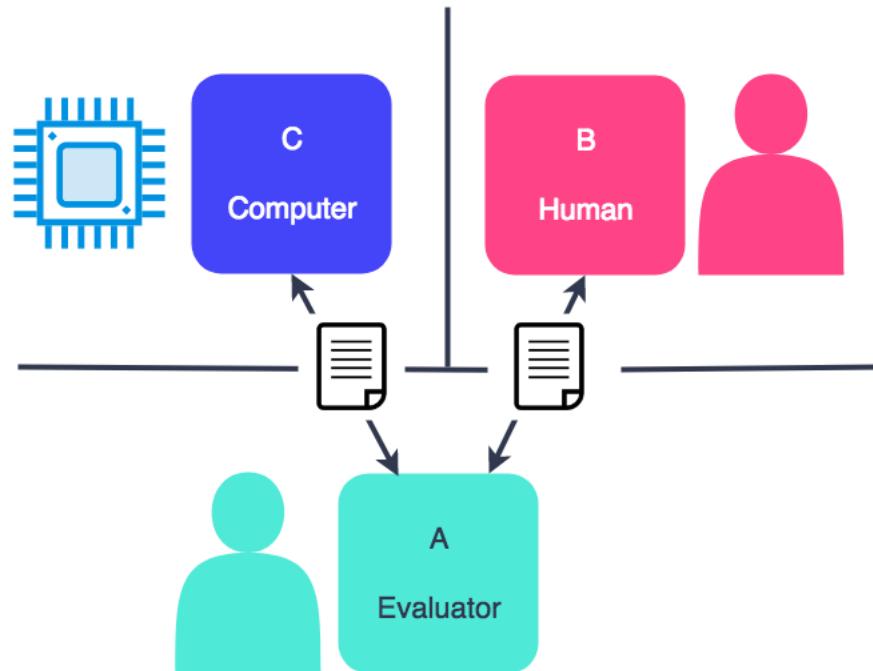
# Artificial Intelligence (AI, 人工智能)

- 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)



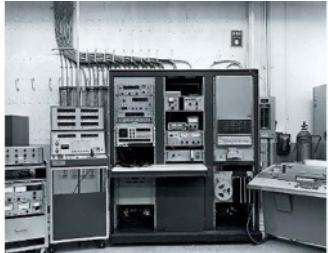
Alan Turing  
(1912~1954)



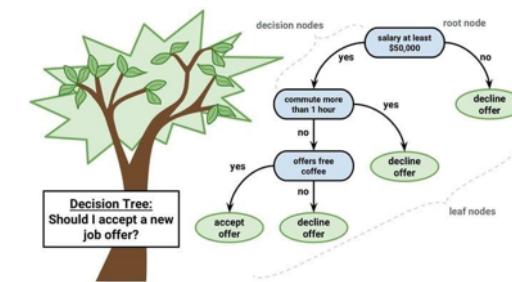
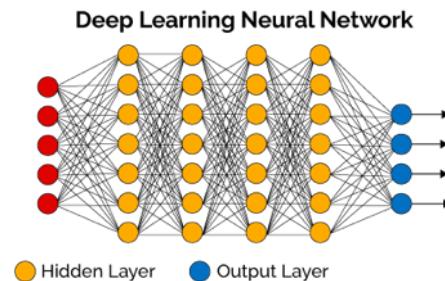
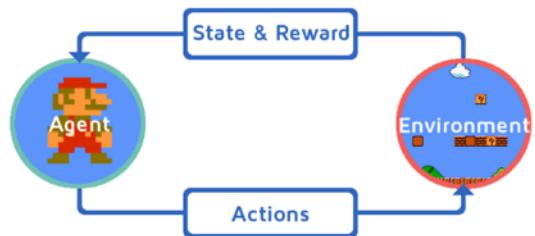
Beyond Turing: AI may exceed human intelligence

# Reasons for Rise of AI

- Exponential growth of computing power



- Rapid development of AI algorithms



- Massive data collection from connection of things

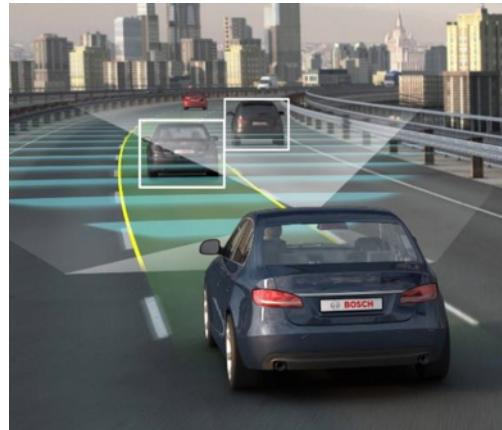


# Applications of AI

Natural language processing



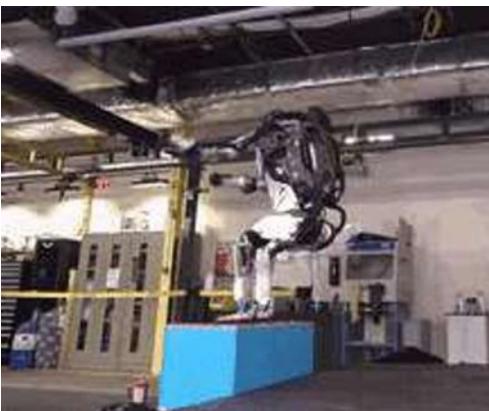
Autonomous driving



Medical diagnosis



Robotics



E-commerce



Public security



# Content

1. Artificial Intelligence (AI)
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# Machine Learning (机器学习)

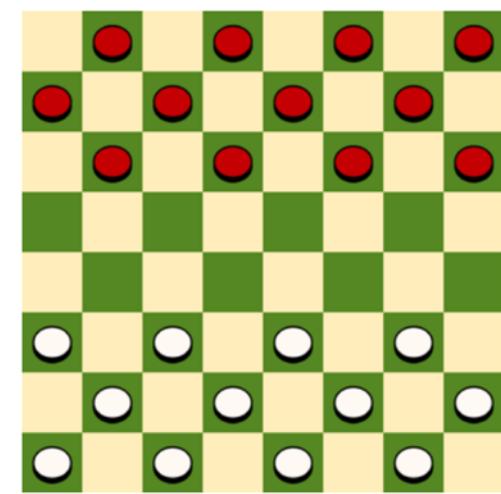
Arthur Samuel (1959):

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



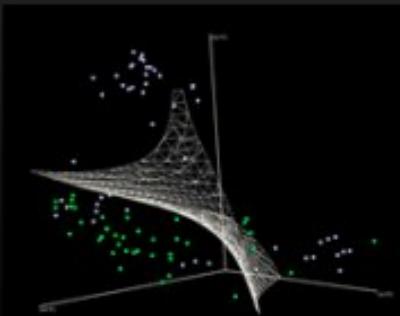
what my friends think  
I do



what my parents think  
I do

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

what other programmers  
think I do



what I think I do

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

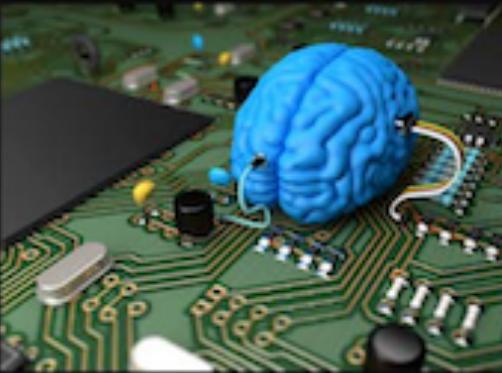
what I really do

# Machine Learning

## Deep Learning



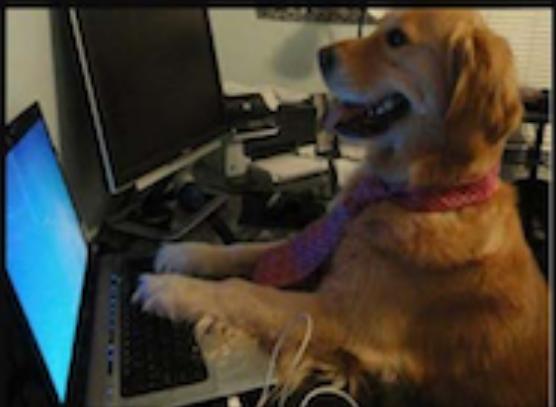
What society thinks I do



What my friends think I do



What other computer  
scientists think I do



What mathematicians think I do



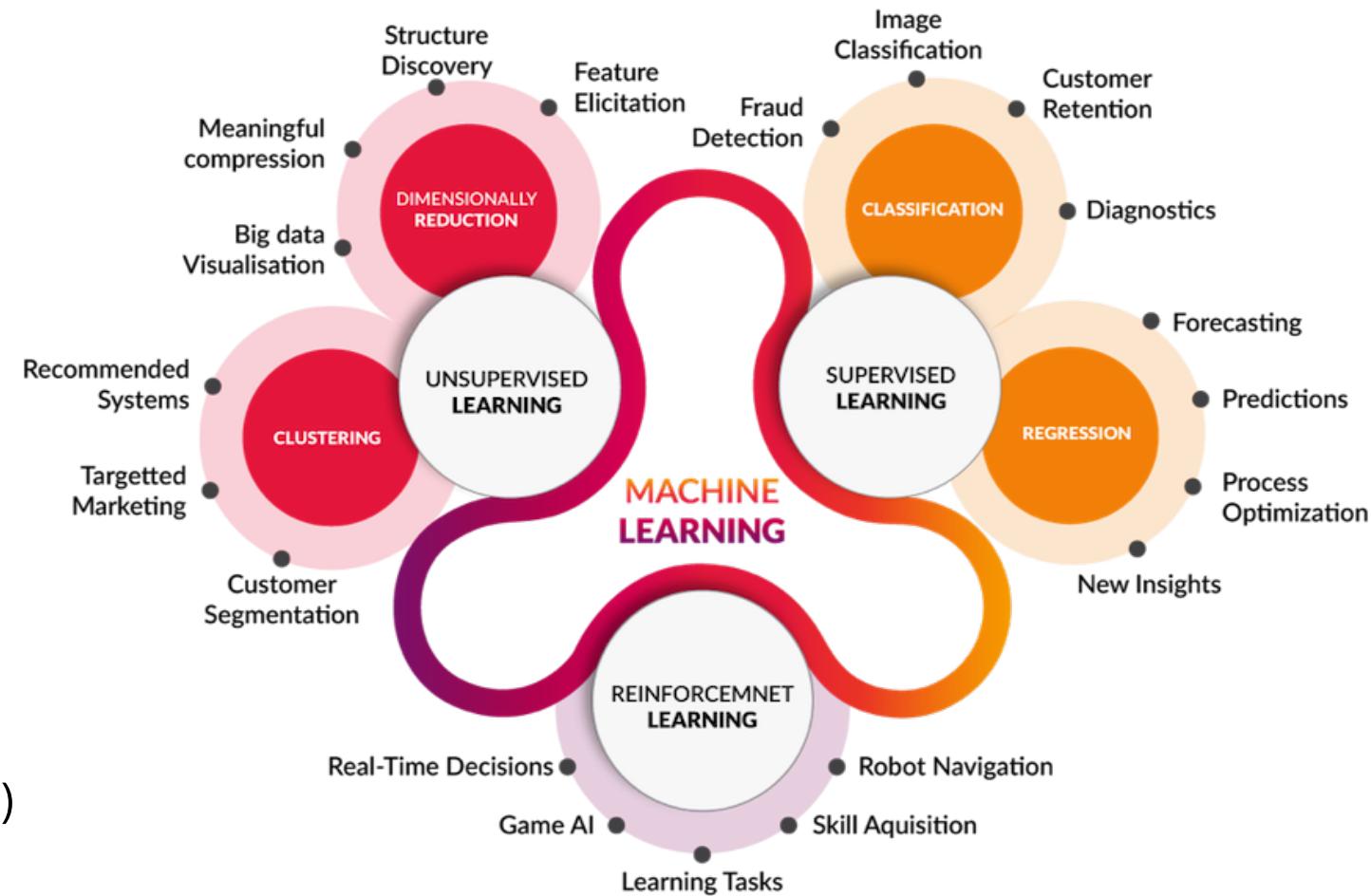
What I think I do

```
from theano import *
```

What I actually do

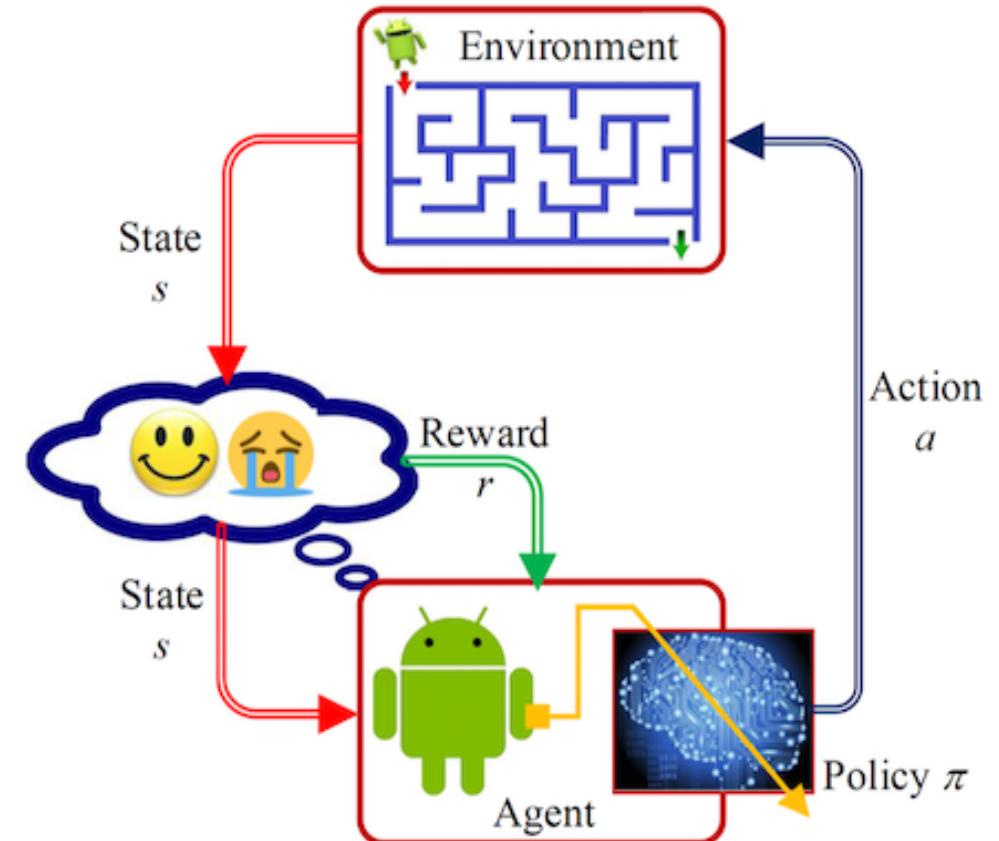
# Taxonomy of Machine Learning

- 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



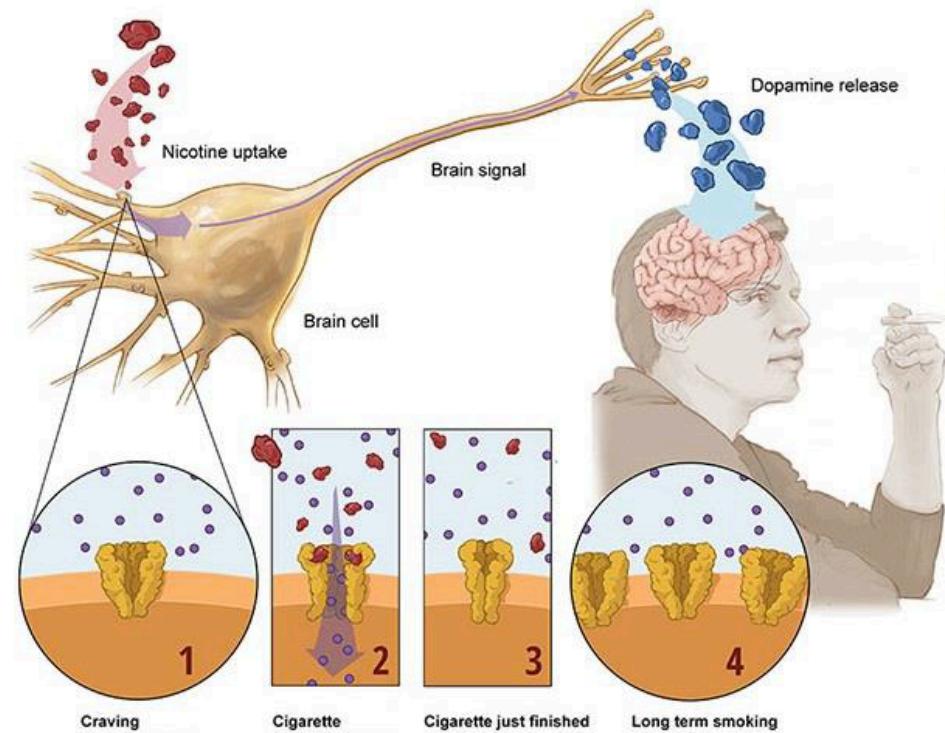
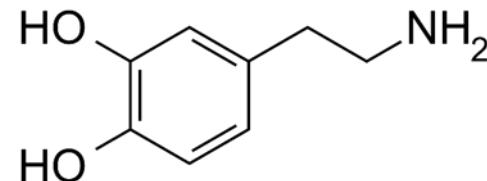
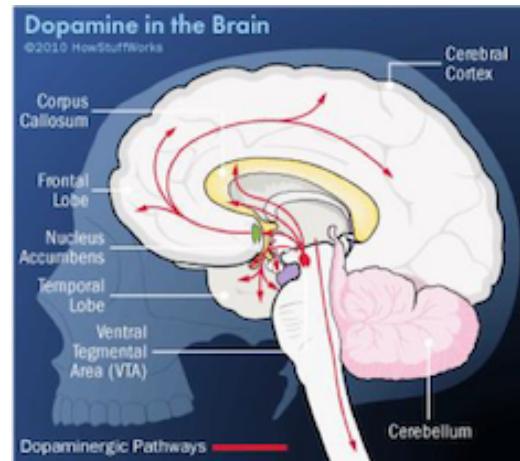
# Inspiration of RL

- 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

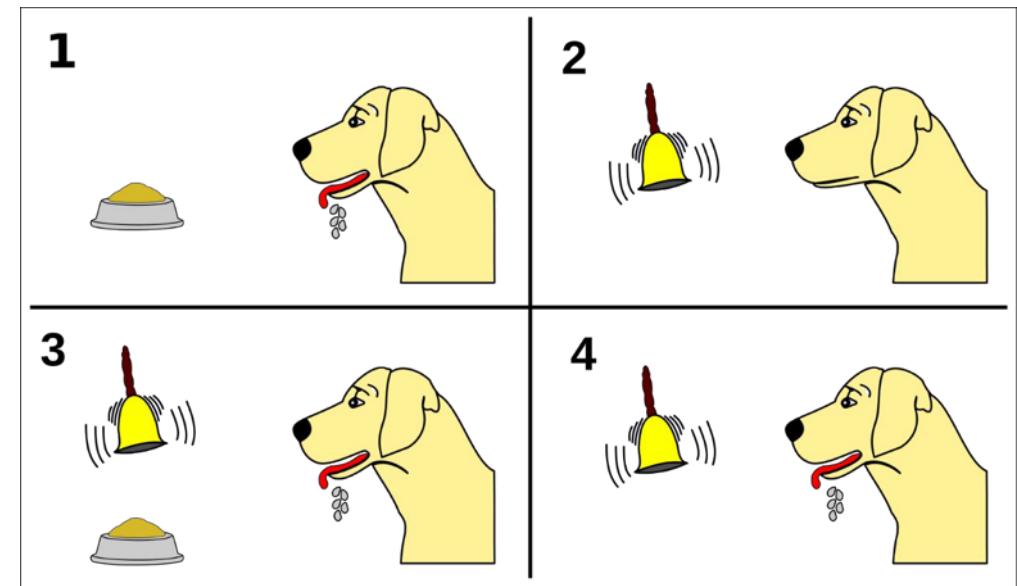


# Inspiration of RL

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

Training: Bell → Food

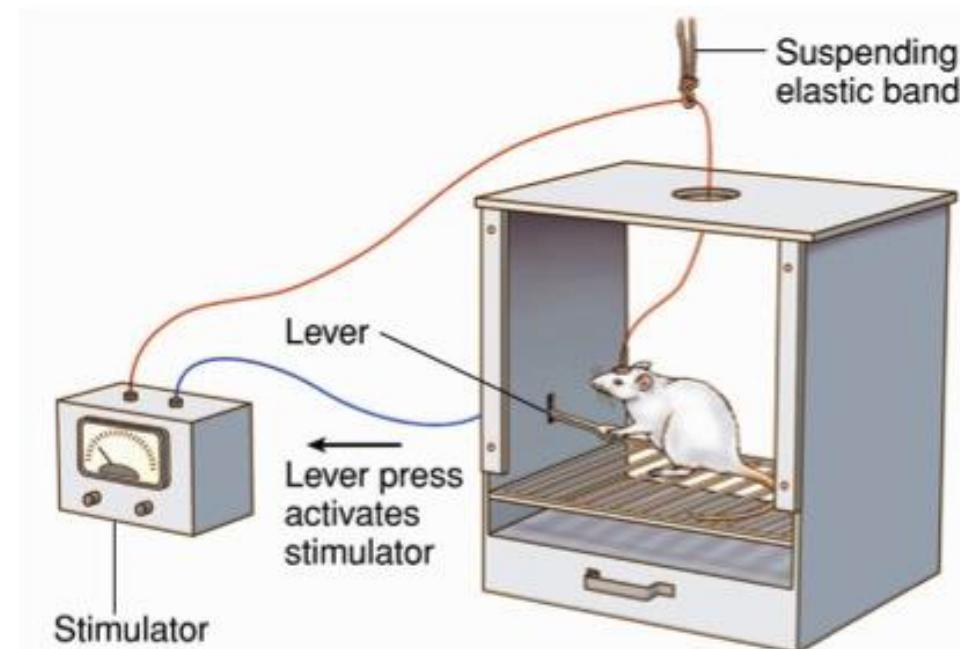
Testing: Bell → Salivate (分泌唾液)



# 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

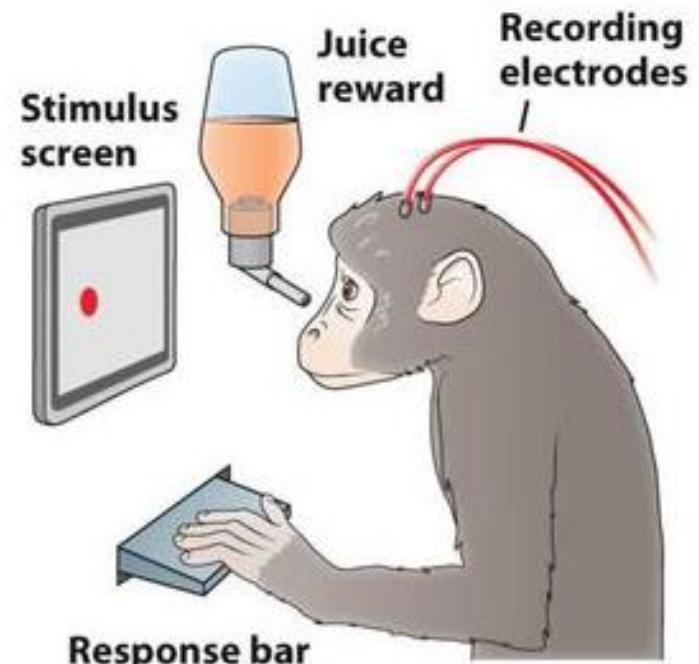
Result: Existence of a reward center in the brain



# Inspiration of RL

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

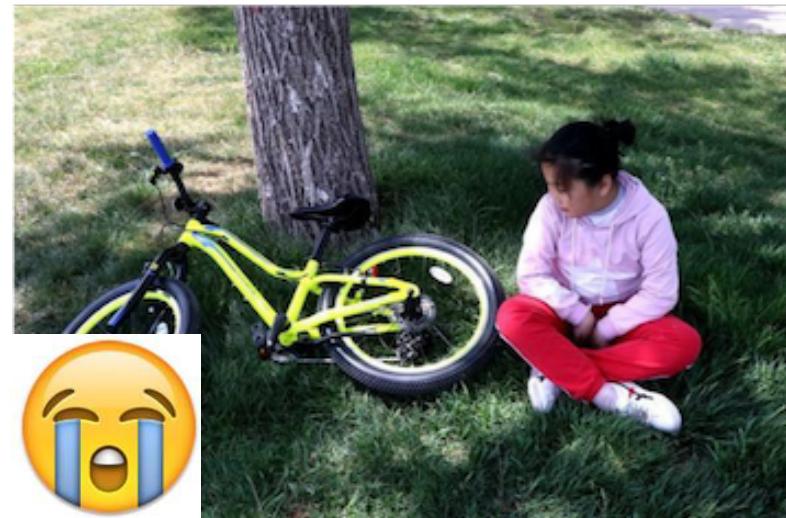
Num	Predicted reward	Actual reward	Error	Dopamine release
1	No	Yes	+	↑
2	Yes	Yes	0	→
3	Yes	No	-	↓



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

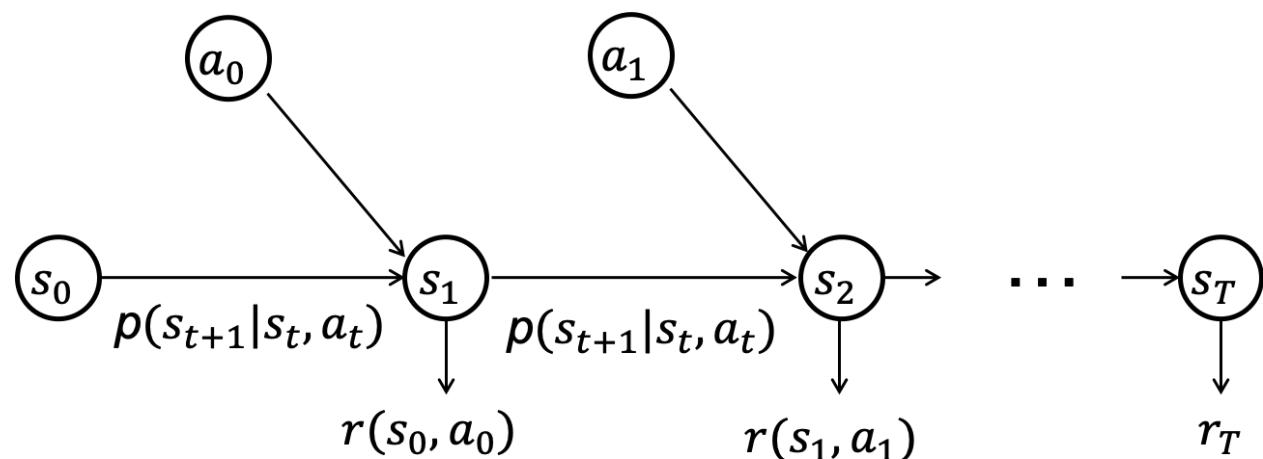
# Inspiration of RL

- 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)

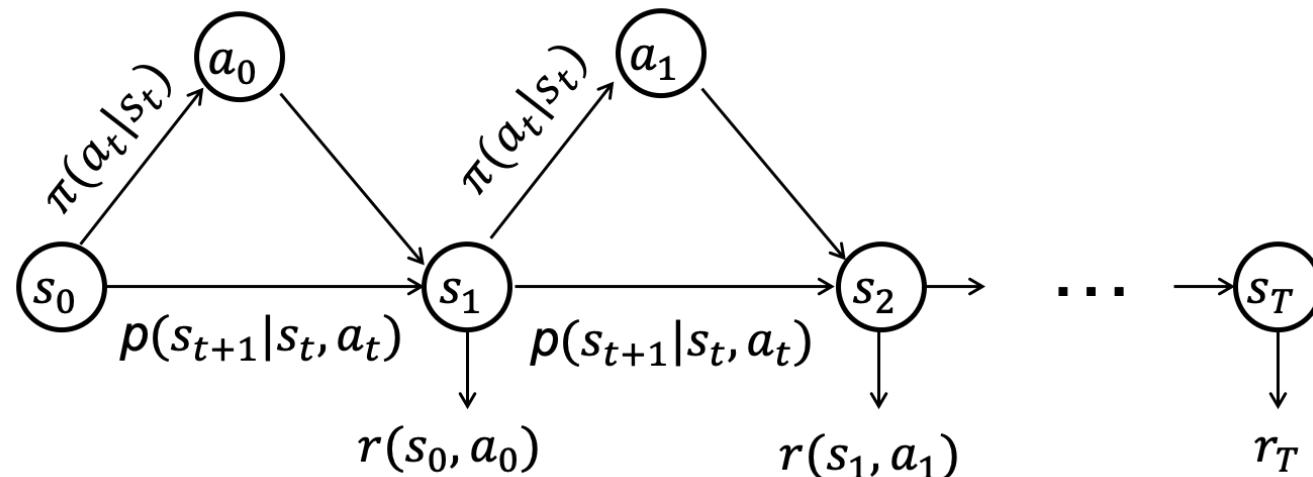
- : State space State (discrete/continuous)
- : Action space Action (discrete/continuous)
- : Transition operator
- : Reward function



# 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

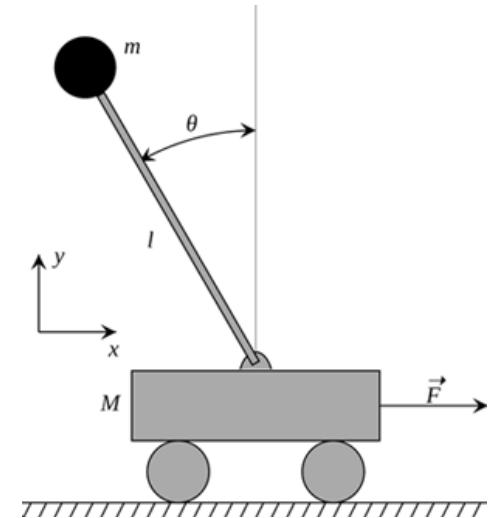
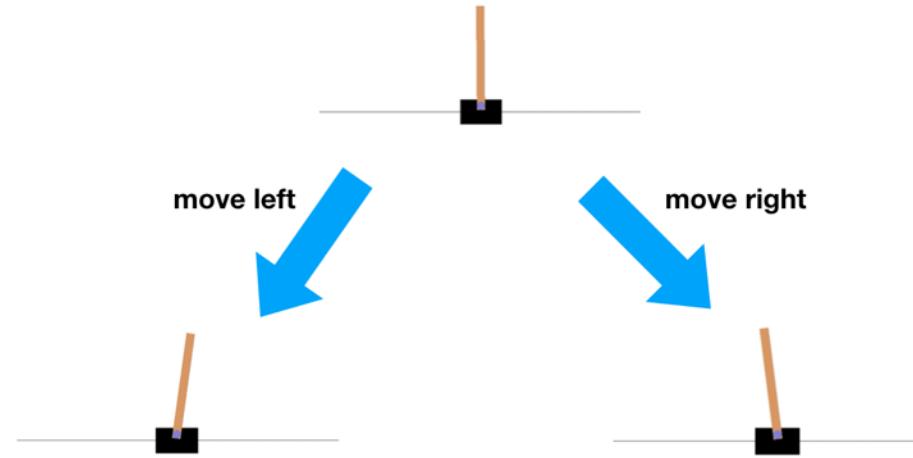
$$\pi^* = \operatorname{argmax}_{\pi} \mathbb{E} \left[ \sum_t r(s_t, a_t) \right]$$



# 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)

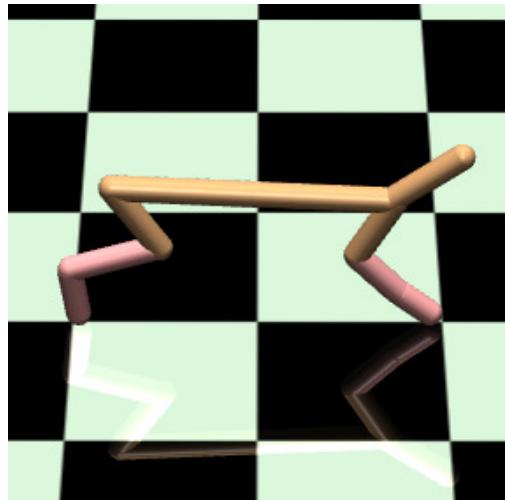
# Example: Inverted pendulum (倒立摆)



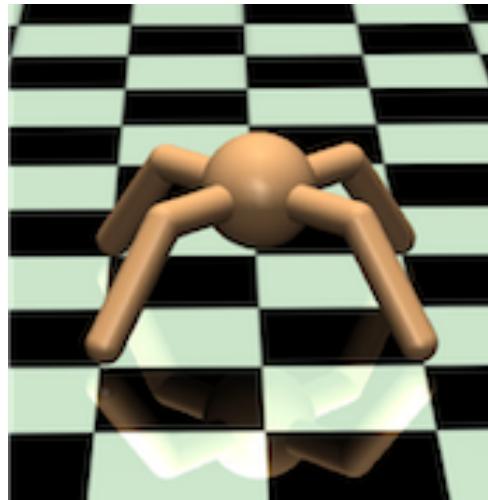
- $x$ : position along the  $x$ -axis
- $\theta$ : angle of the pendulum

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

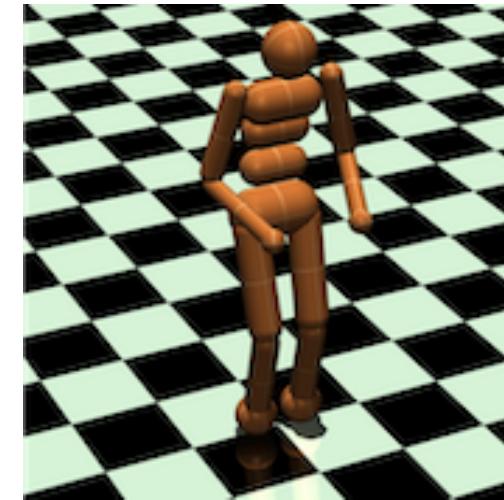
# Example: Robot locomotion (机器人运动学)



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



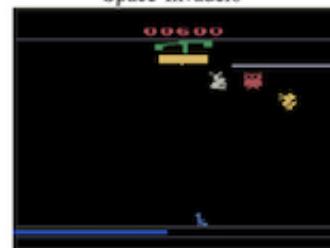
Boxing



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

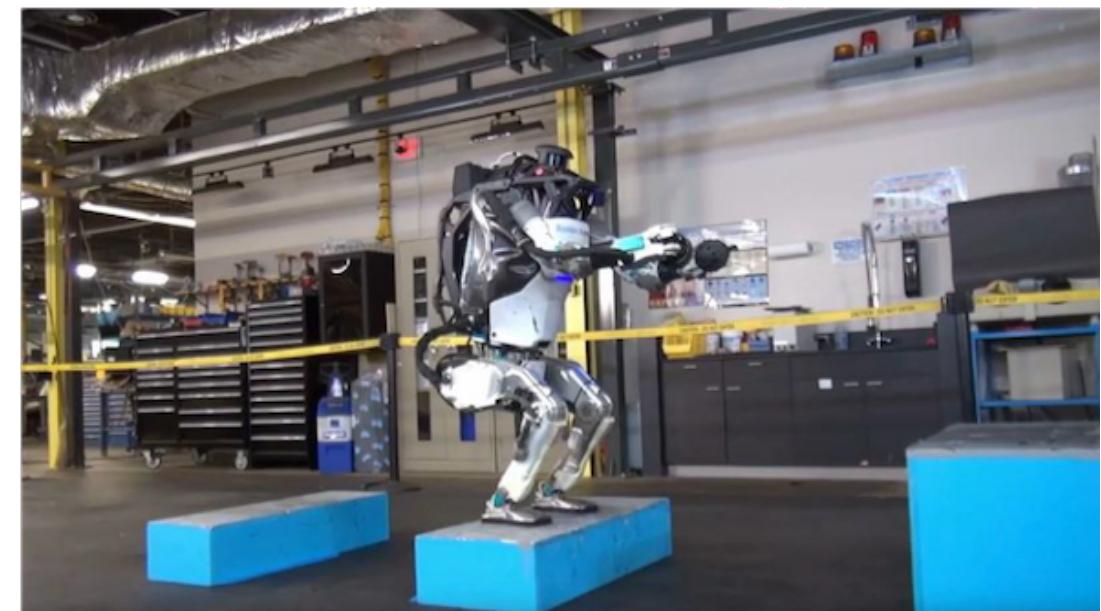
# Content

1. Artificial Intelligence (AI)
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# Intelligent machines

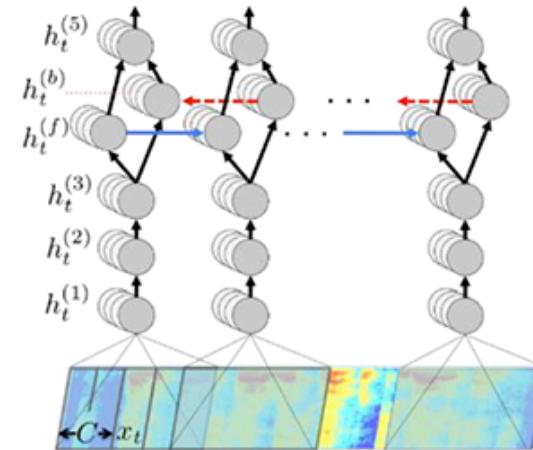
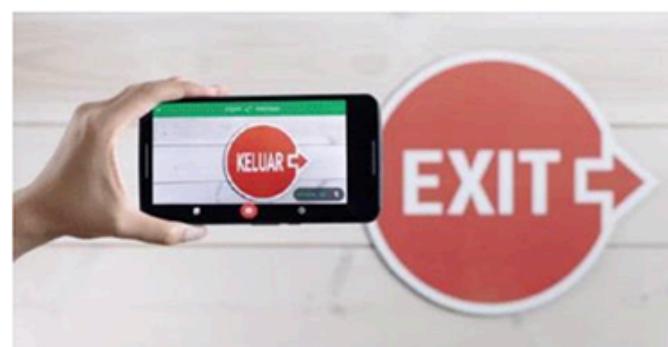
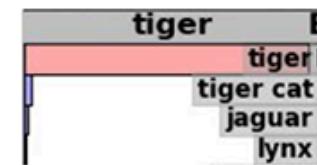
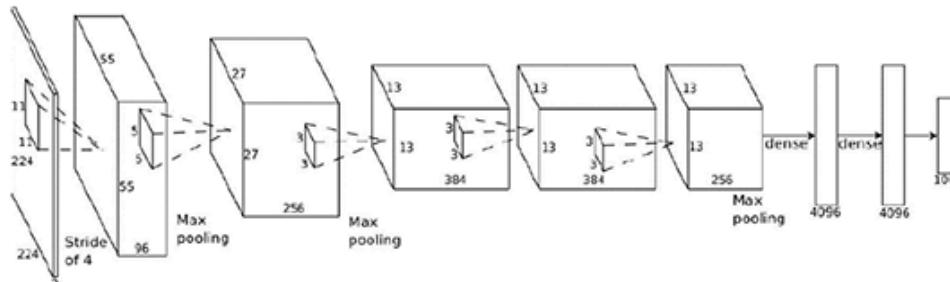


# Intelligent machines must able to adapt

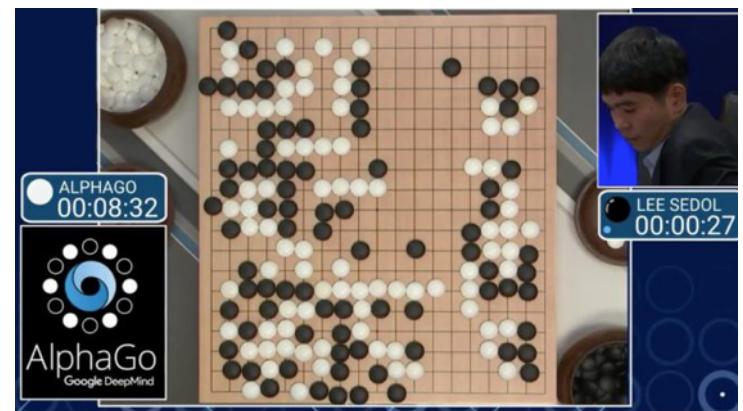
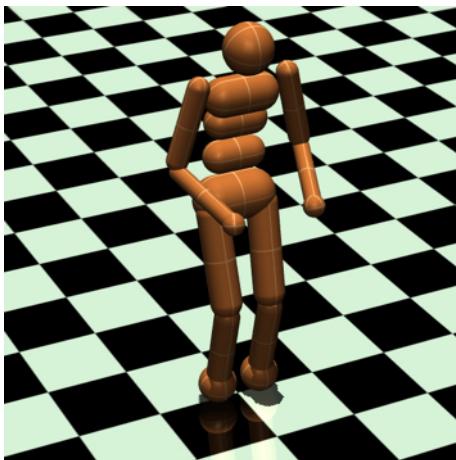
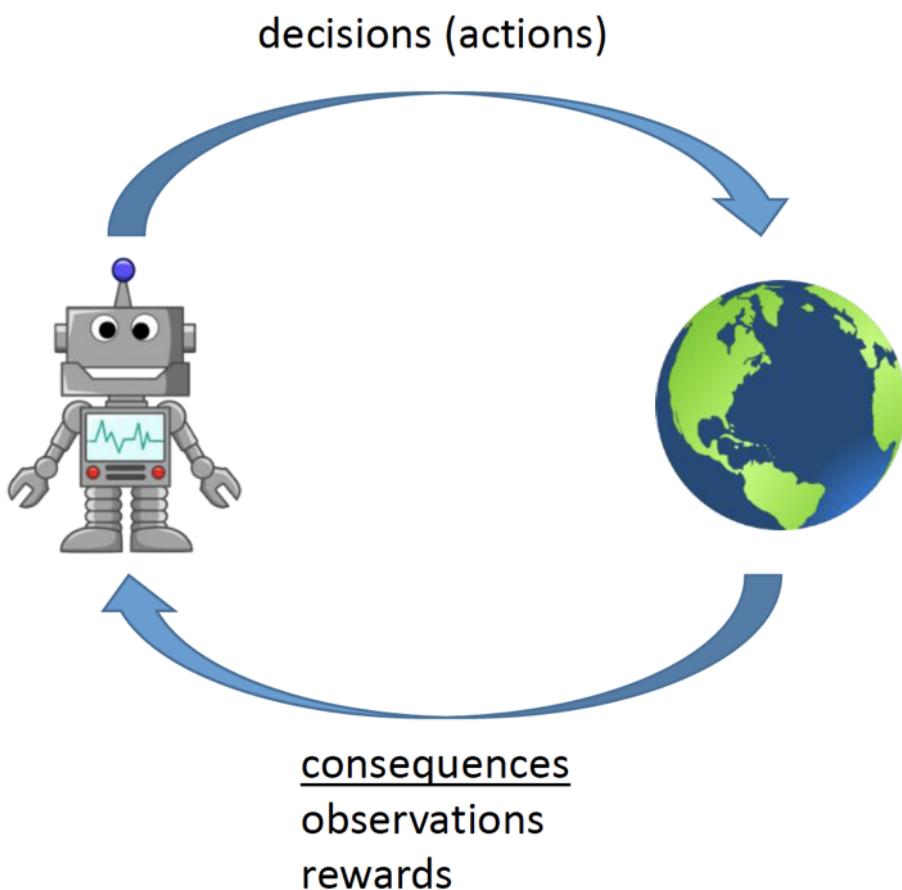


# Deep learning

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

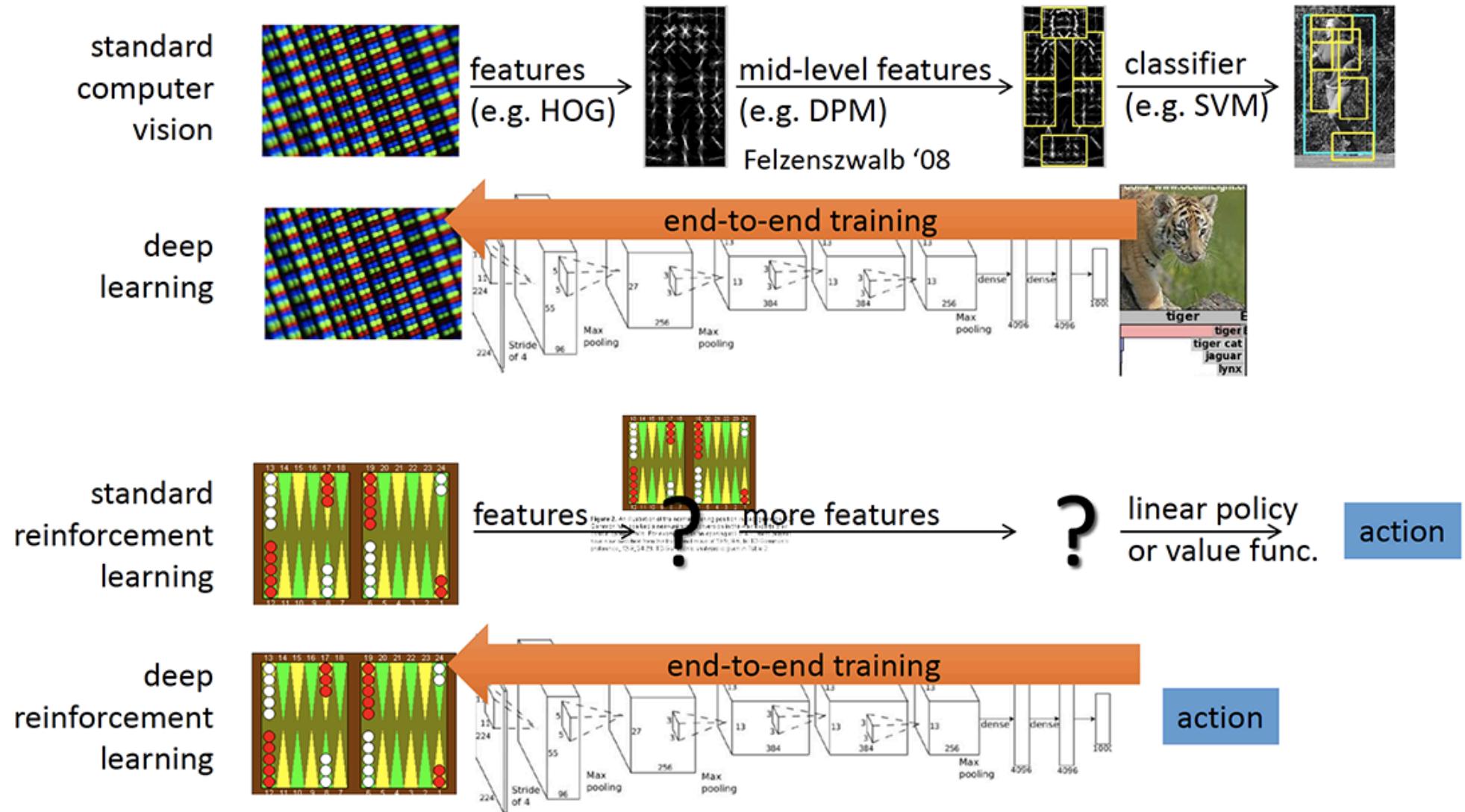


- RL provides a formalism for behavior/decision-making

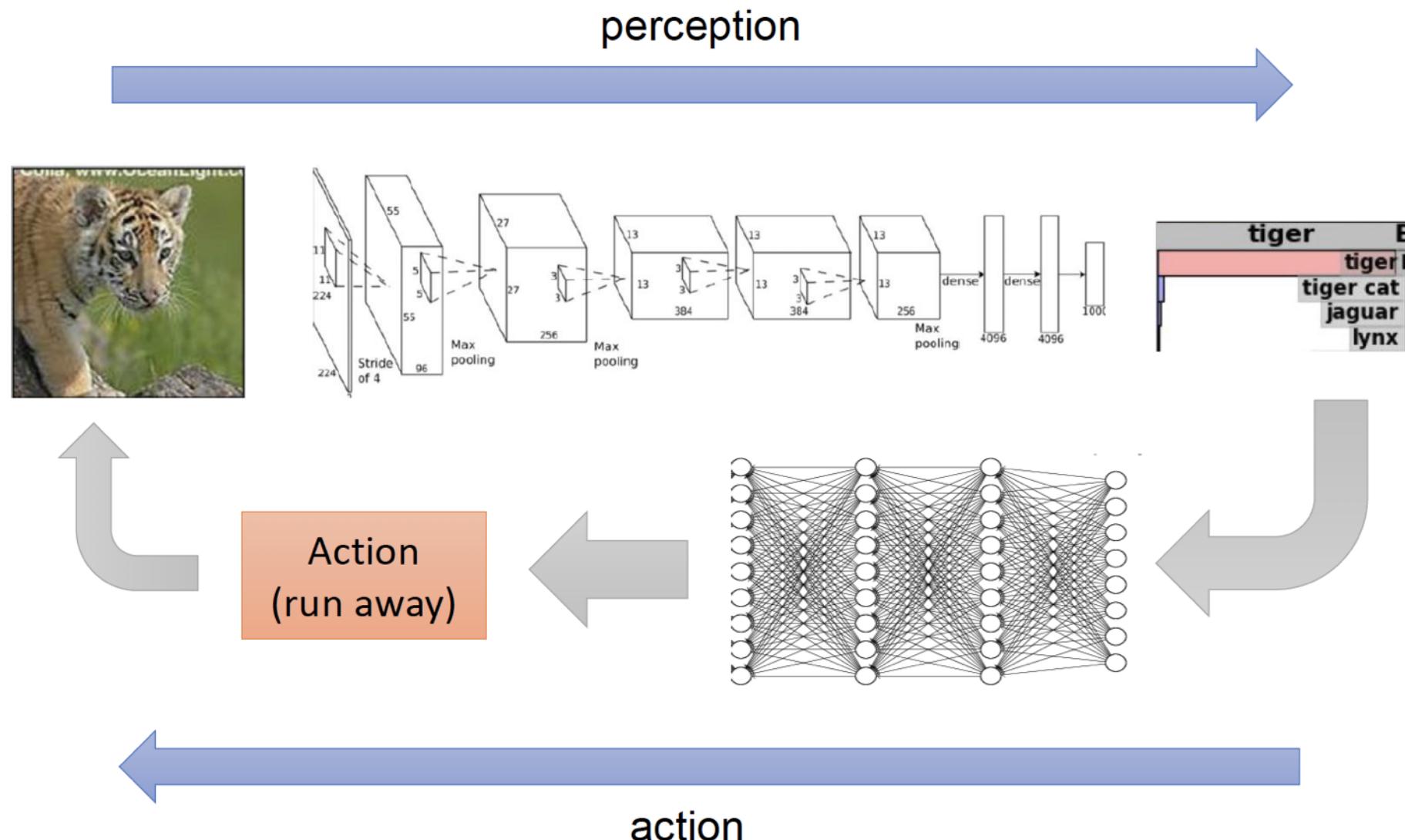


Space Invaders

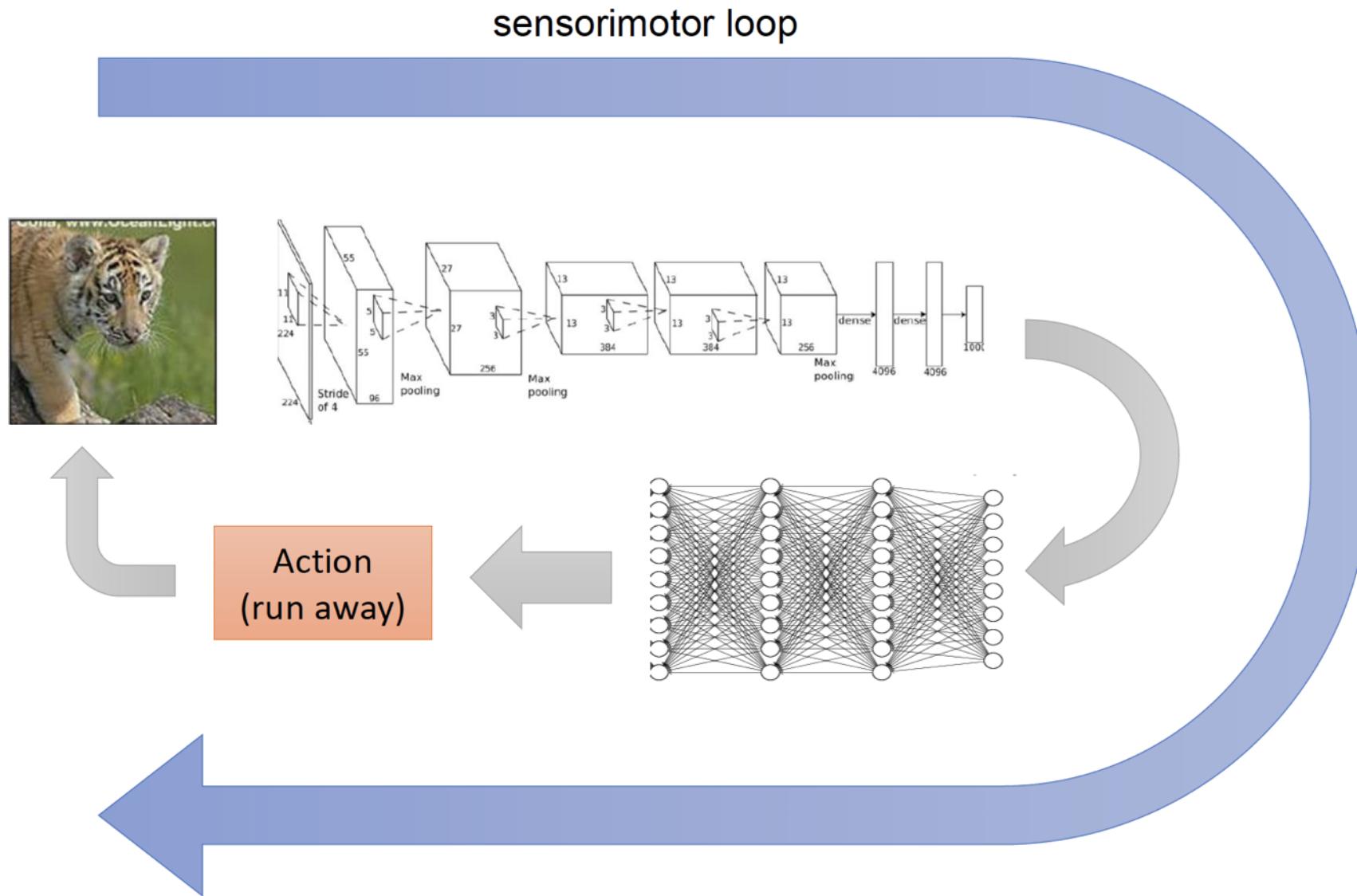
# Deep RL = Deep learning + RL



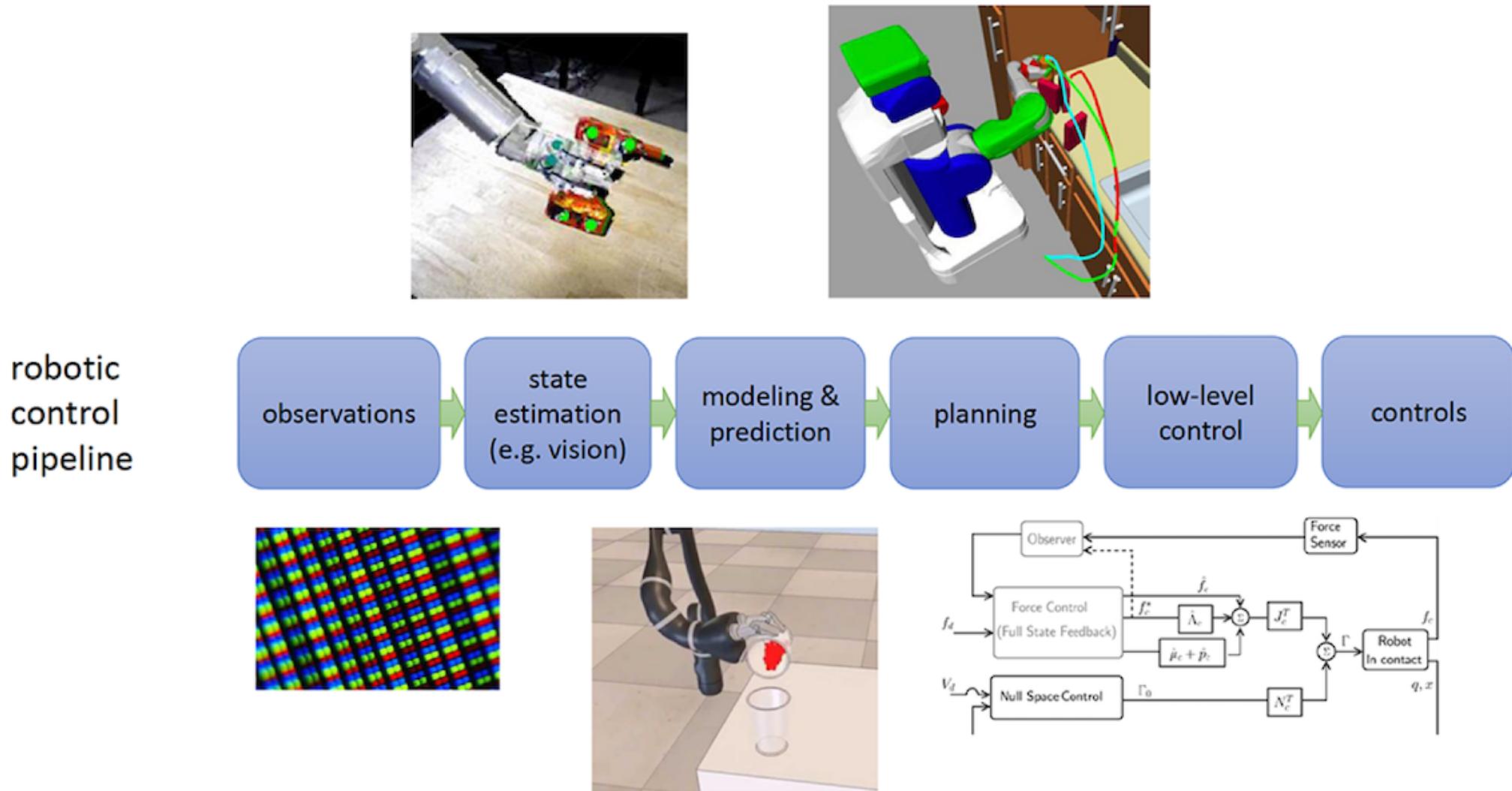
# End-to-end learning for sequential decision-making



# End-to-end learning for sequential decision-making

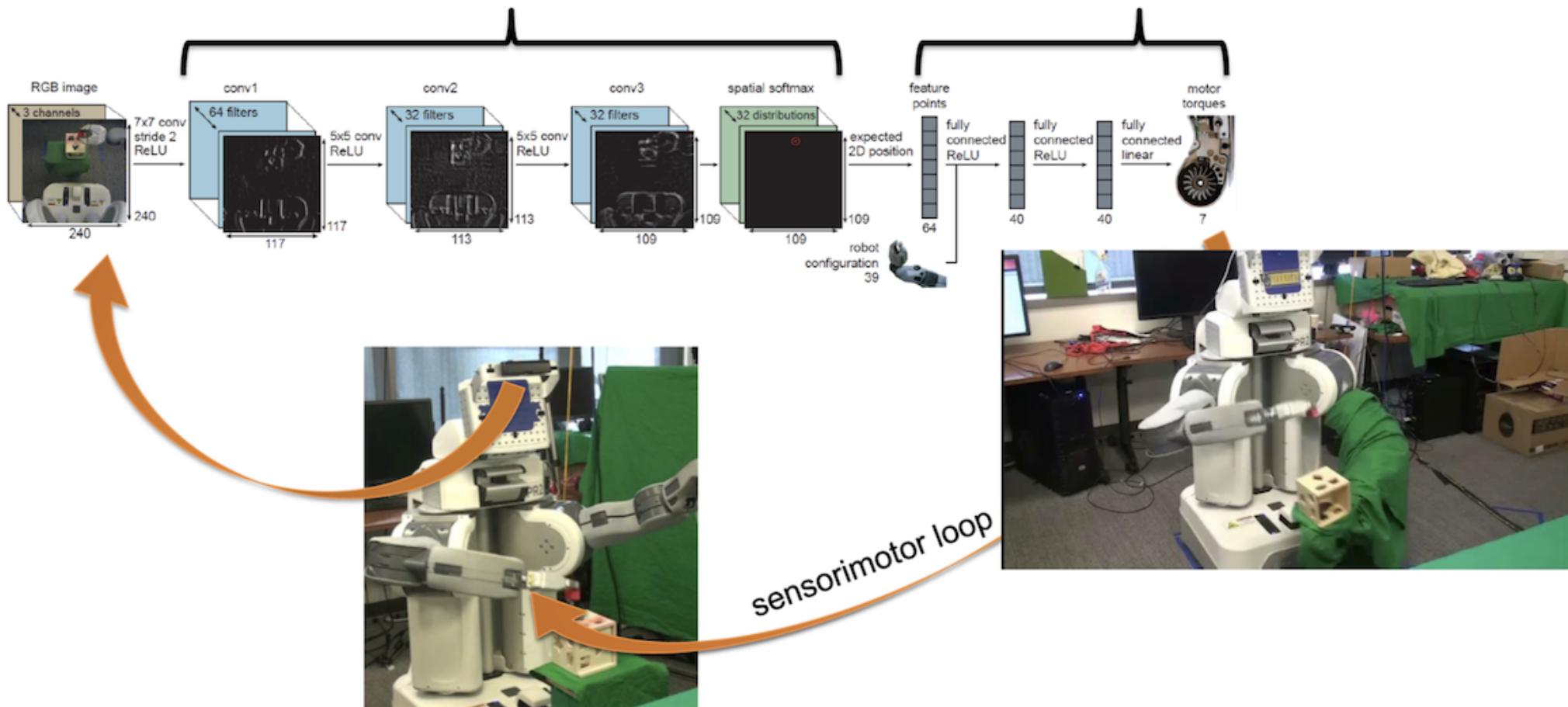


# Example: Robotics



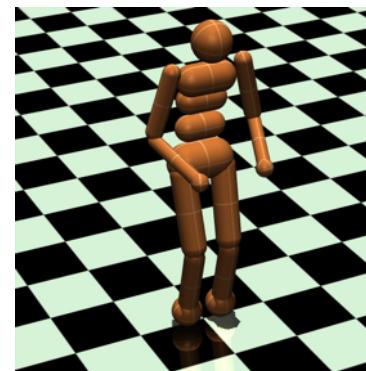
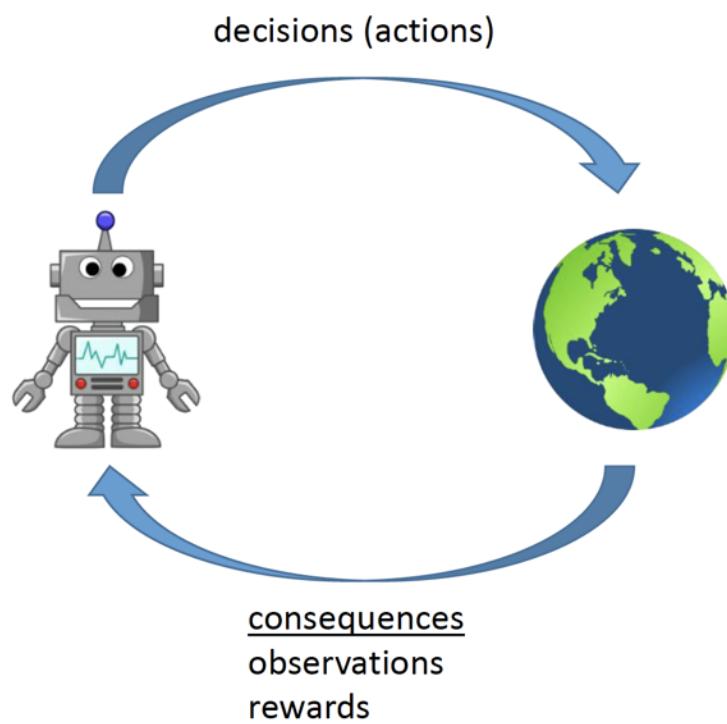
# End-to-end learning

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

**nature**

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nature > letters > article

Published: 25 February 2015

**Human-level control through deep reinforcement learning**

**nature**

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nature > articles > article

Published: 19 October 2017

**Mastering the game of Go without human knowledge**

**nature**

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**Grandmaster level in StarCraft II using multi-agent reinforcement learning**

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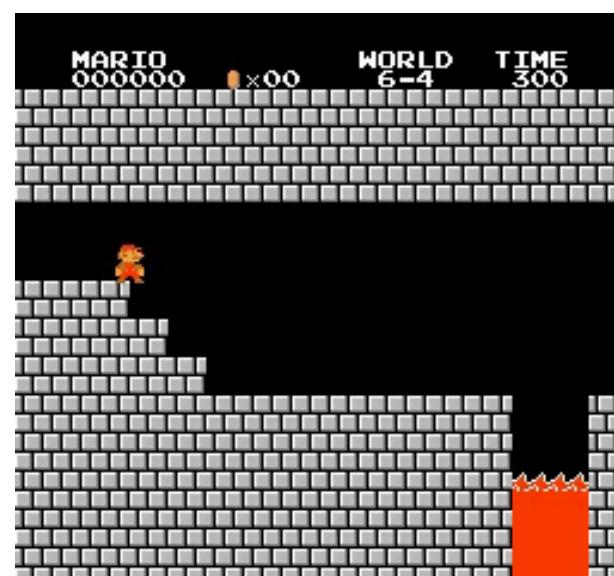
Article | Open Access | Published: 05 October 2022

**Discovering faster matrix multiplication algorithms with reinforcement learning**

# The Era of RL

- "Human-level control through DRL", Nature 2015
- AlphaGo, Nature 2016; AlphaGo Zero, Nature 2017
- AlphaStar in StarCraft II, Nature 2019
- DRL for legged robots, Science Robotics 2019
- "Superhuman AI for multiplayer poker", Science 2019
  - For the first time, AI defeated top human players in complex games containing more than two players
  - One of the ten top scientific breakthroughs in 2019, by <Science>
- "Discovering faster matrix multiplication algorithms", Nature 2022
  - Help solve challenges in fundamental mathematics, by the Cover of <Nature>
- Magnetic control (核聚变控制), Nature 2022; Simulated racing (赛车), Nature 2022
- .....

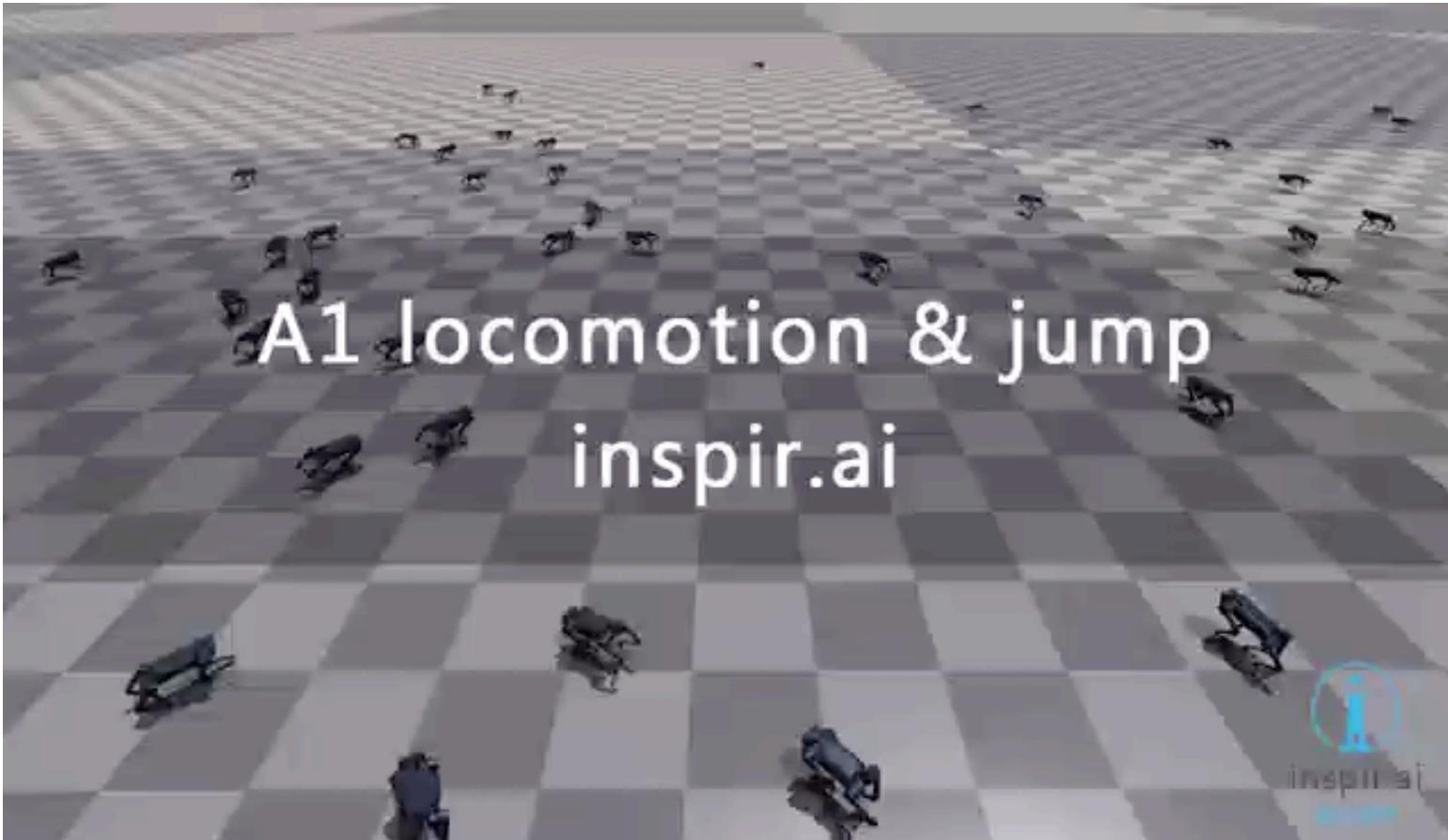
# The Era of RL



# The Era of RL



# The Era of RL



Generative adversarial imitation learning (GAIL)

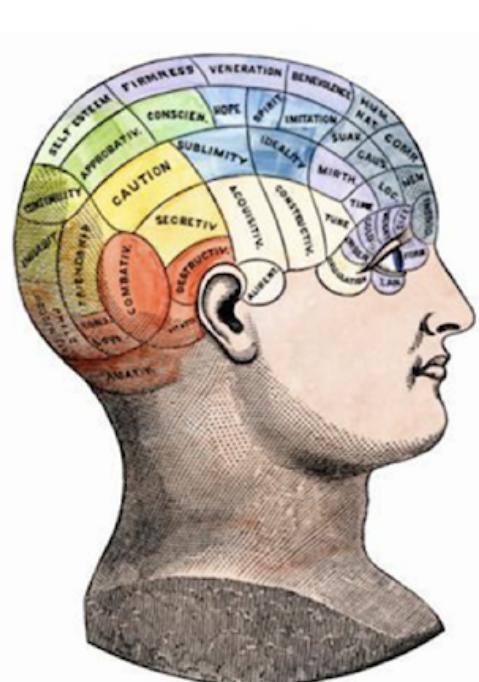
Learning **biomimetic** behaviors

# Content

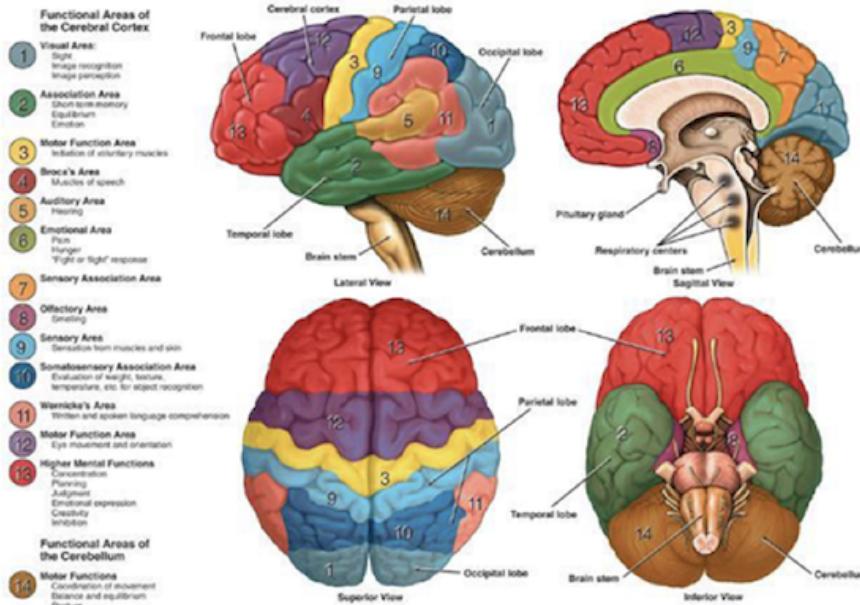
1. Artificial Intelligence (AI)
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# How do we build intelligent machines?

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



Anatomy and Functional Areas of the Brain

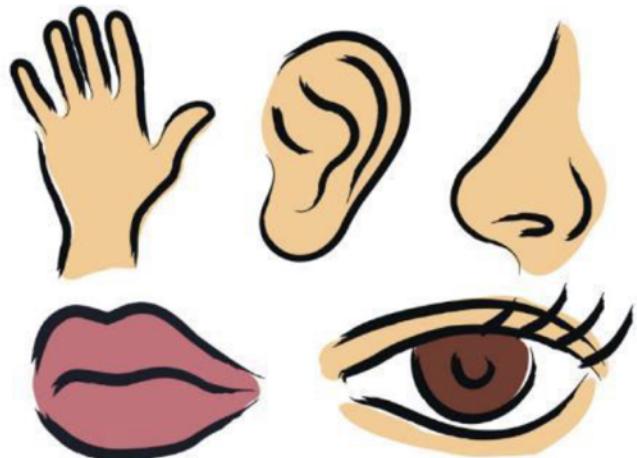


# “Learning” as the basis of intelligence

- 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

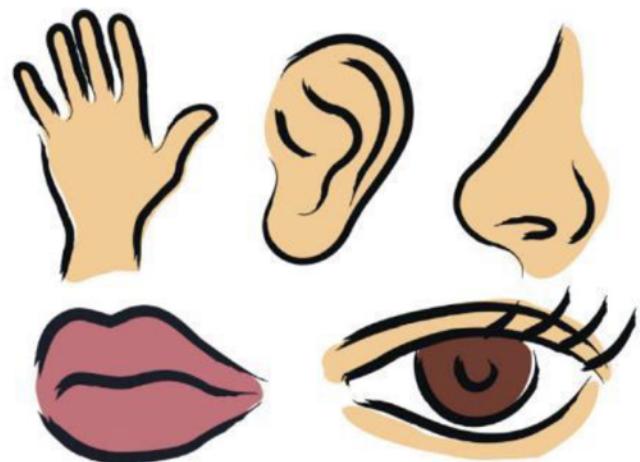
# What must a single algorithm do?

- 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

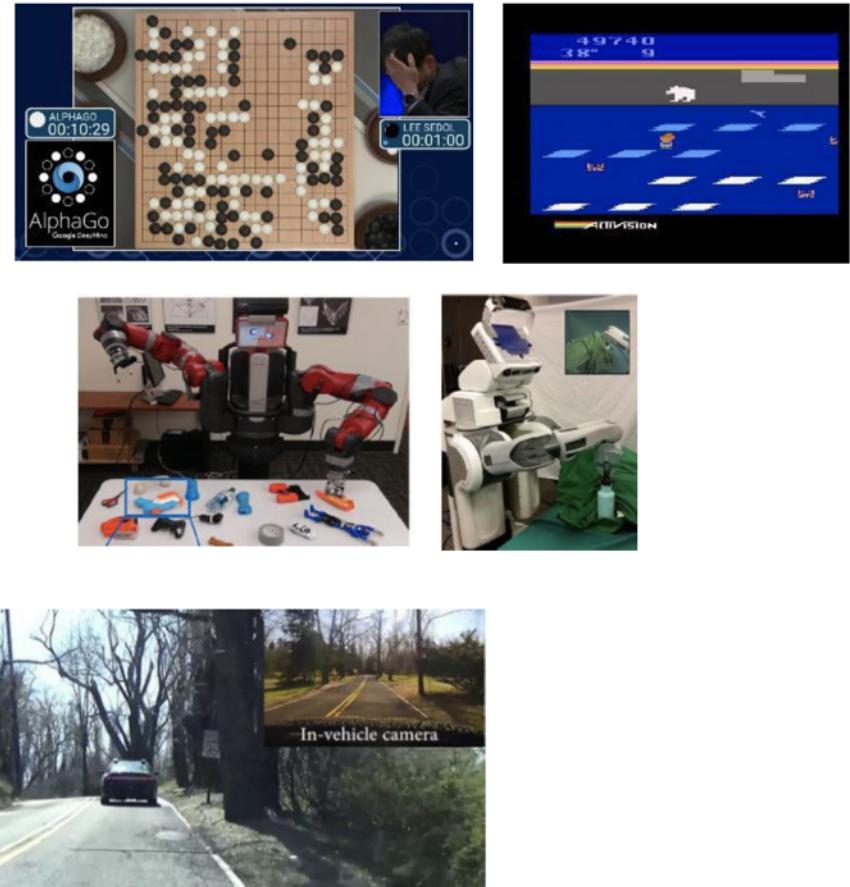
Ji-An Li, Daoyi Dong, Zhengde Wei, Ying Liu, Yu Pan, Franco Nori & Xiaochu Zhang 

*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?

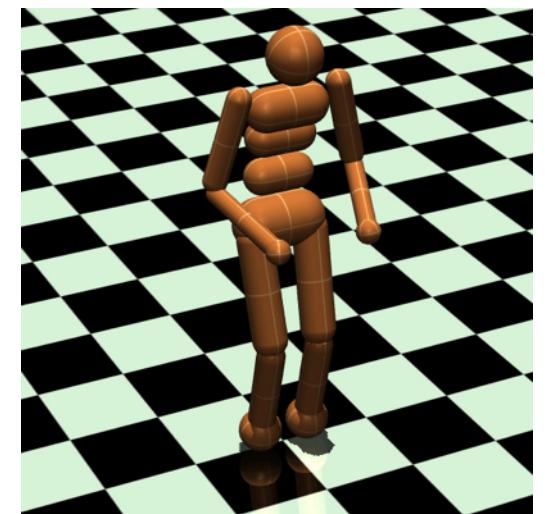
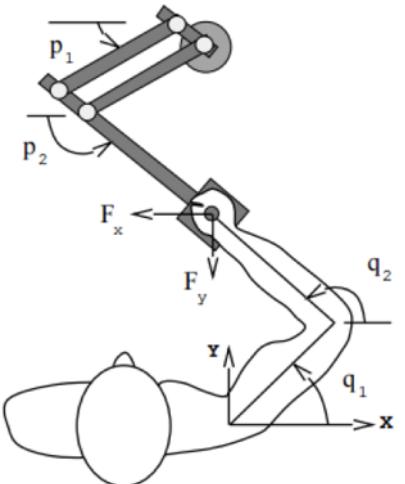
- Acquire high degree of proficiency in domains governed by **simple, known rules**
- Learn **simple** skills with raw sensory inputs, given **enough experience**
- Learn from **imitating** enough human provided expert behavior (模仿学习)



Still in the infancy, and a promising future!

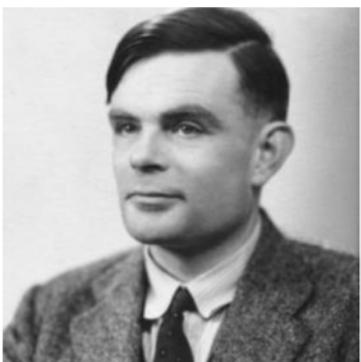
# What has proven challenging so far?

- 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

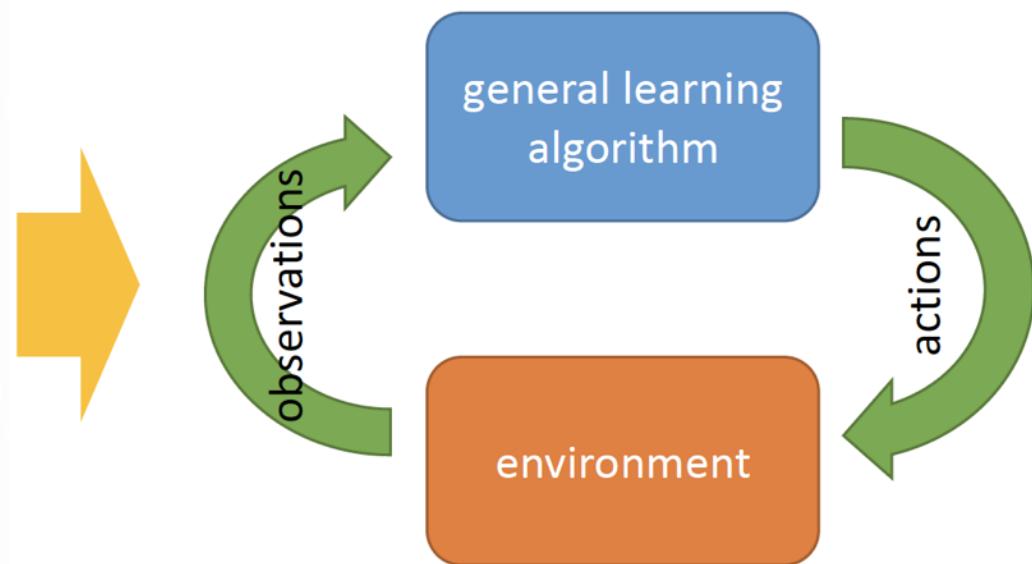
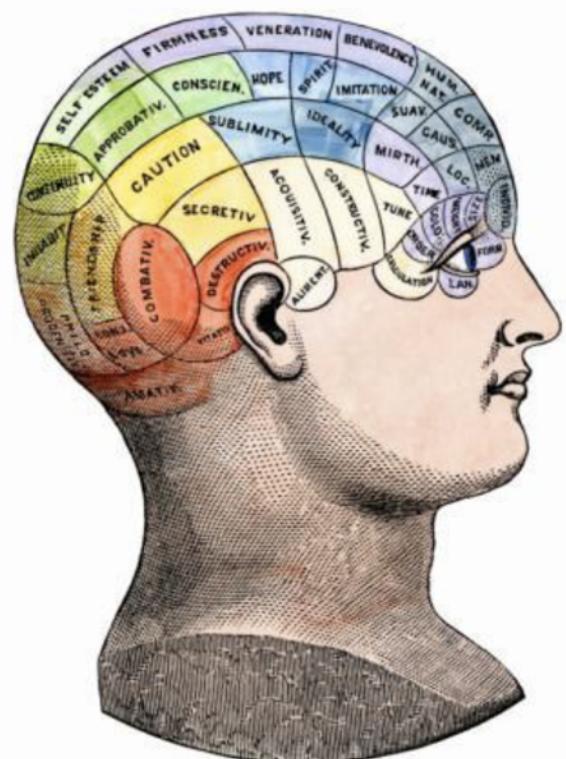


# RL, decision-making, human behavior

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

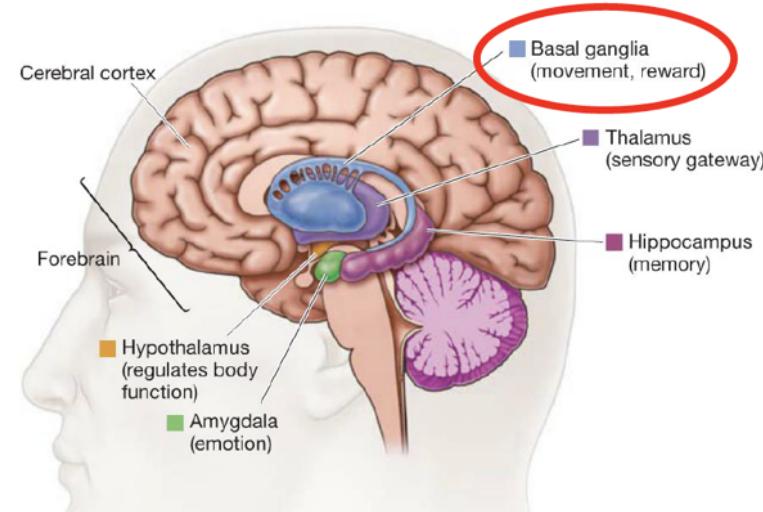
- Basic RL deals with **maximizing rewards**
- This is not the only problem that matters for sequential decision-making!
- More advanced topics
  - Transferring knowledge between domains (transfer learning, meta-learning)
  - Learning to predict and using prediction to act (model-based RL)
  - Learning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