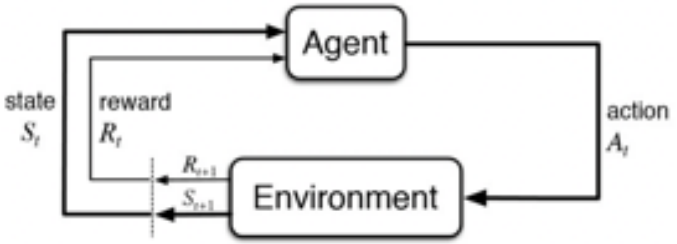
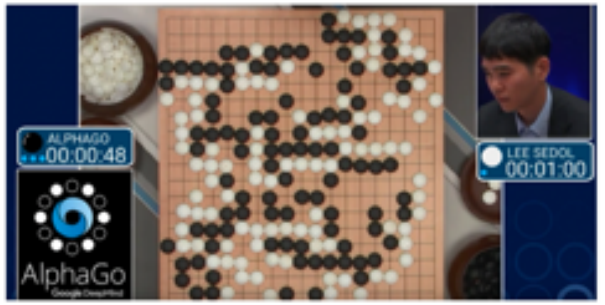



# IERG 5350
# Reinforcement Learning

## Lecture 1: Course Overview

Bolei Zhou

The Chinese University of Hong Kong

# Outline

- Course logistics
- RL overview and examples

# Course Logistics

- Instructor: Bolei Zhou
- TAs:

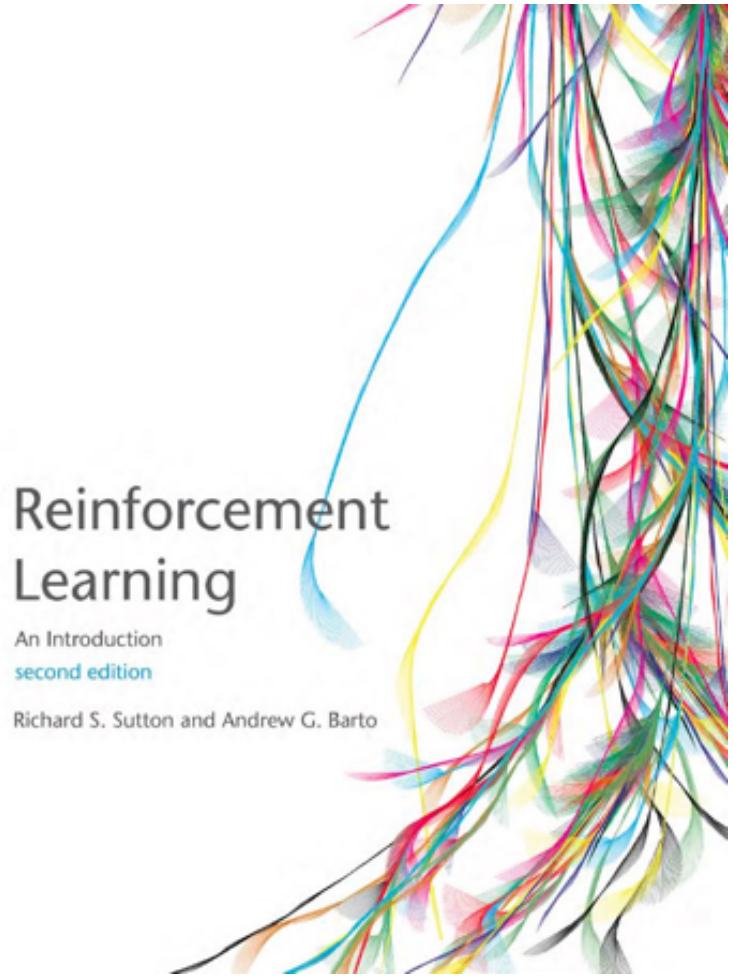

Zhenghao Peng

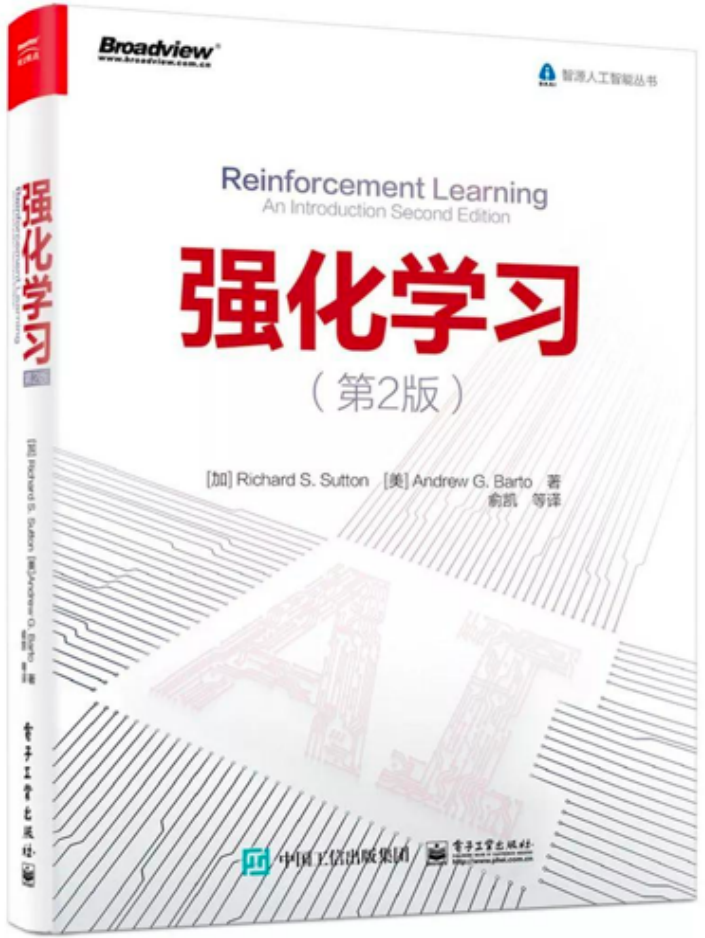

Sun Hao


Xiaohang Zhan

- Time:
  - Monday 10:30 am – 11:15 am : one 45-min session
  - Tuesday 10:30 am – 12:15 pm: two 45-min sessions
  - Course website: https://cuhkrlcourse.github.io/
  - Piazza: http://piazza.com/cuhk.edu.hk/fall2020/ierg5350
  - ZOOM virtual: link sent, please keep confidential
- Office hour: Monday 5:00 pm – 6:00 pm, ZOOM virtual
- TA office hour: Tuesday 5:00 pm – 6:00 pm, ZOOM virtual

# Optional Textbook: Sutton and Barton: http://incompleteideas.net/book/the-book-2nd.html



# Optional Textbook with more flavor of control theory

- By Dimitri P. Bertsekas
- https://web.mit.edu/dimitrib/www/RLbook.html

# Prerequisites & Enrollment

- This is IERG-5XXX course, which means it is a graduate level course
- All enrolled students must have taken the Linear Algebra course and Probability course, and one machine learning relevant course (data mining, pattern recognition, deep learning, etc).
- Coding experience with python

# What we will cover

- Key elements of RL: state, reward, action, Markov decision process, exploration and exploitation, etc.
- RL algorithms: Q-learning, policy gradients, actor-critic.
- Others advanced topics: inverse RL, imitation learning, game AI.
- Case studies: Projects in DeepMind, projects at OpenAI, and others.
- Two guest lectures:
  - Researcher from Didi Research on RL in transportation
  - Researcher from Facebook AI Research on RL in game AI

# Course Objective

- Know the difference between reinforcement learning, machine learning, and deep learning.
- Knowledge on the foundation and practice of RL
- Given your research problem (e.g. from computer vision, NLP, IoT, etc) decide if it should be formulated as a RL problem, if yes be able to define it formally (in terms of the state space, action space, dynamics and reward model), state what RL algorithm is best for addressing it, and make it work!

# Grading

- Attendance: 10%
- 5 assignments: 50%
- Course Project : 40%

# Course project

- Relevant to RL or the application of RL
- Suggested projects will be posted in the coming week, but feel free to work on your own project relevant to RL.
- Expected workload of the project: 7 weeks.
- Course projects from last year: https://cuhkrlcourse.github.io/2019spring/project.html
- Deliverables:
  - Proposal due (by the end of Week 3)
  - Mid-term presentation (Week 8): 3-min video recording
  - A github repo containing your work (commits, readme, human-understandable code)
  - Final presentation  (Week 14): 5-min video recording and peer-review
  - Course report (in NIPS LaTex Template), due by the end of semester

# Course Schedule: https://cuhkrlcourse.github.io/schedule.html

Part 1: Tabular methods, RL foundation

Part 2: Approximate methods

Part 3: Policy optimization

Part 4: Advanced topics

| Week | Time | Topic | Materials |
|---|---|---|---|
| Week 1 | Mon | Course overview | |
| | Tue | Introduction of RL and coding examples | |
| Week 2 | Mon | Markov decision process | |
| | Tue | Policy iteration and value iteration | HW1 out |
| Week 3 | Mon | Model-free prediction | |
| | Tue | Model-free control | |
| Week 4 | Mon | On-policy learning and off-policy learning | |
| | Tue | Connection to optimal control | HW1 due, HW2 out |
| Week 5 | Mon | Value function approximation | |
| | Tue | Deep Q Learning | |
| Week 6 | Mon | Policy optimization I | |
| | Tue | Policy optimization II | HW2 due, HW3 out |
| Week 7 | - | Chung Yeung Holiday | |
| | Tue | Policy optimization III: variants of actor-critic and code | |
| Week 8 | Mon | Policy optimization IV: state of the arts 1 | |
| | Tue | Policy optimization IV: state of the arts 2 | HW3 due, HW4 out |
| Week 9 | Mon | Imitation learning | |
| | Tue | **Student project mid-term review** | |
| Week 10 | Mon | Guest Lecture by Tony Qin (Didi Research): RL in transportation | |
| | Tue | Model-based Reinforcement Learning | HW4 due, HW5 out |
| Week 11 | Mon | Exploration and exploitation | |
| | Tue | Distributed computing and RL system design | |
| Week 12 | Mon | Guest Lecture by Yuandong Tian (Facebook AI Research): Game AI | |
| | Tue | Inverse RL and Realworld RL | HW5 due |
| Week 13 | Mon | Course Summary | |
| | Tue | Course Summary | |
| Week 14 | Mon | **Student project final presentation** | |
| | Tue | **Student project final presentation** | |

# 5 Assignments: all programming driven

| Week | Time | Topic | Materials |
|---|---|---|---|
| Week 1 | Mon | Course overview | |
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HW1: MDP, Policy and value iterations

HW2: on-policy and off-policy learning in tabular setting

HW3: policy gradient methods

HW4: SOTA methods, PPO, TD3, SAC

HW5: imitation learning/offline RL

open-ended tournament

*HW4 and HW5 will be based on Google Colab

# Open-end Competition in Assignment 5

**Competitive Pong Tournament**

**Reinforcement Learning Course@CUHK**

**Spring Semester, 2020**

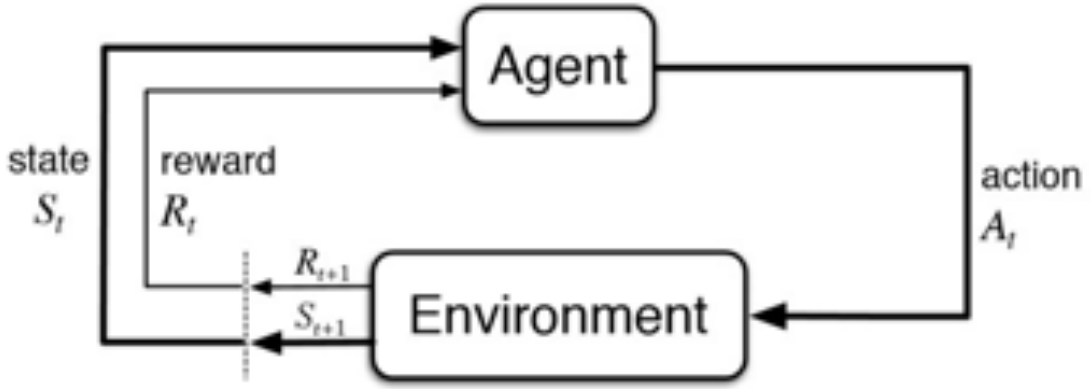
Lecturer: Bolei Zhou
TA: Zhenghao Peng

https://github.com/cuhkrlcourse/competitive-rl

# Open-end Competition in Assignment 5

- Another possible choice: Competitive car-racing (in development)

# What is reinforcement learning and why we care




a computational approach to learning whereby an agent tries to maximize the total amount of reward it receives while interacting with a complex and uncertain environment.

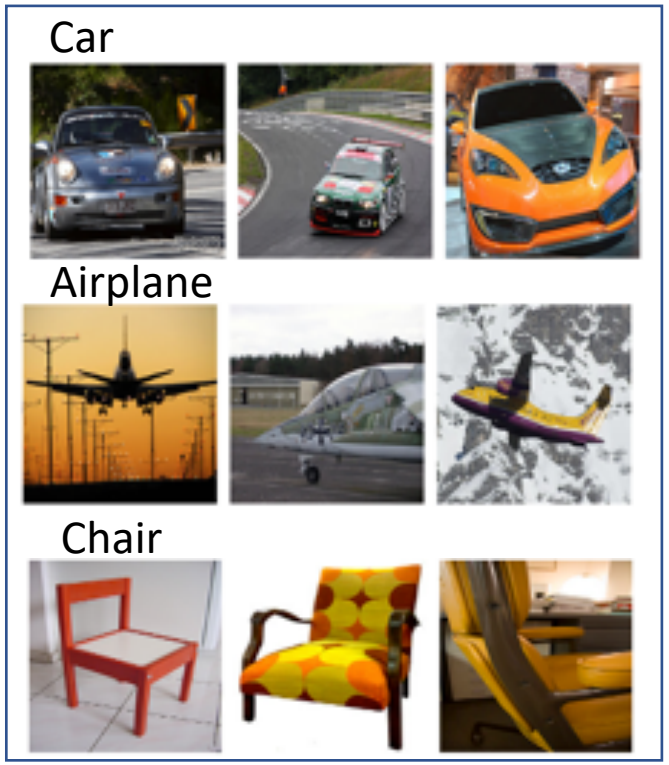
- Sutton and Barto

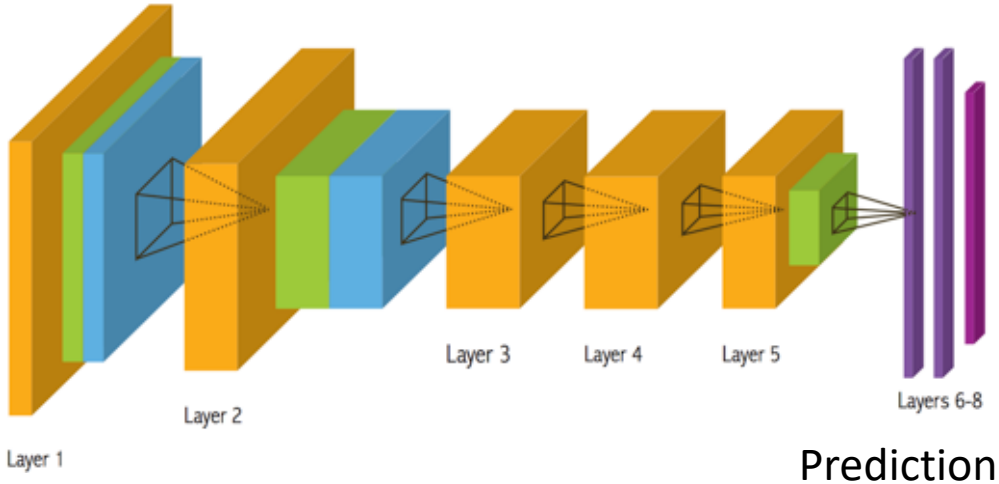
# Supervised Learning

## Learn to classify object

- Annotated images, data follows i.i.d distribution.
- Learners are told what the labels are.

Training annotated data




Prediction: Airplane

Prediction is wrong
Correct label: Car

Back-propagation

# Reinforcement Learning

Learn to play Breakout

- Data are not i.i.d. Instead, a correlated time series data
- No instant feedback or label for correct action

Action: Move LEFT or Right


Atari Game: Breakout

# Reinforcement Learning

Training data

Step1

Step2

Step3

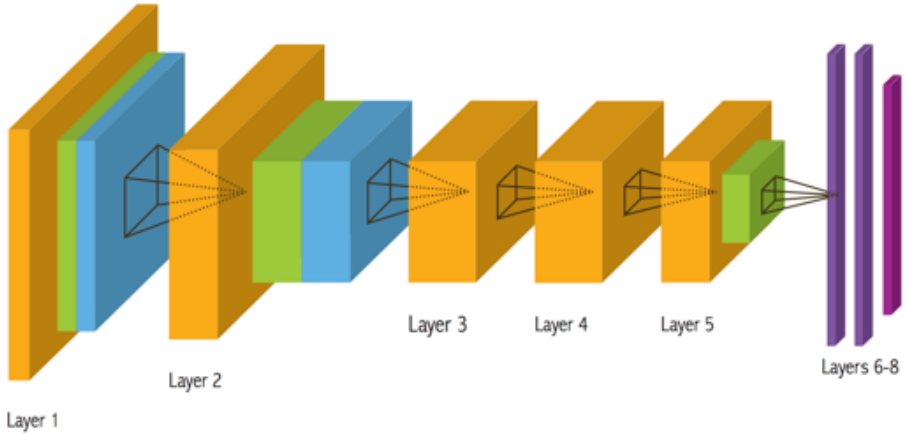
Step4

Step5

. . .

Human playing?

Step3




Action:
Move LEFT

Correct or Wrong???
Don't know for now, until game is over
Delayed reward

Backpropagation?

# Difference between Reinforcement Learning and Supervised Learning

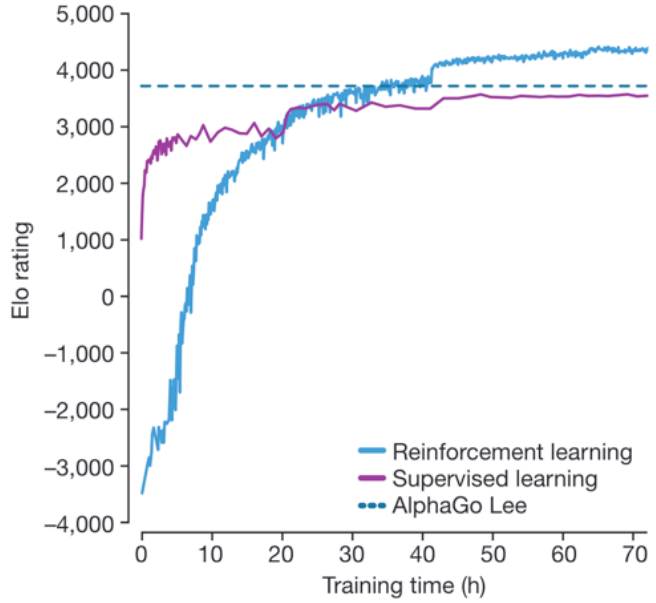
- Sequential data as input (not i.i.d)
- The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them.
- Trial-and-error exploration (balance between exploration and exploitation)
- There is no supervisor, only a reward signal, which is also delayed

# Properties of reinforcement learning

- Trial-and-error exploration
- Delayed reward
- Time matters (sequential data, non i.i.d data)
- Agent’s actions affect the subsequent data it receives (agent’s action changes the environment)

# Why we care about RL

- Learn to control something via trial-and-error in model-free setting
- May achieve super-human performance
  - Upper bound for supervised learning is human-performance.
  - Upper bound for reinforcement learning?

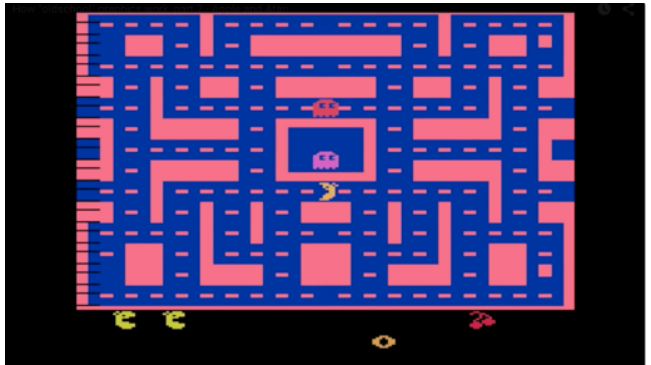



AlphaGo vs. AlphaGo Zero

Silver and Schrittwieser, et al. Mastering the game of Go without human knowledge, Nature'17

# Examples of reinforcement learning

- A chess player makes a move: the choice is informed both by planning-anticipating possible replies and counterreplies.
- A gazelle calf struggles to stand, 30 min later it is able to run 36 kilometers per hour.
- Portfolio management.
- Playing Atari game

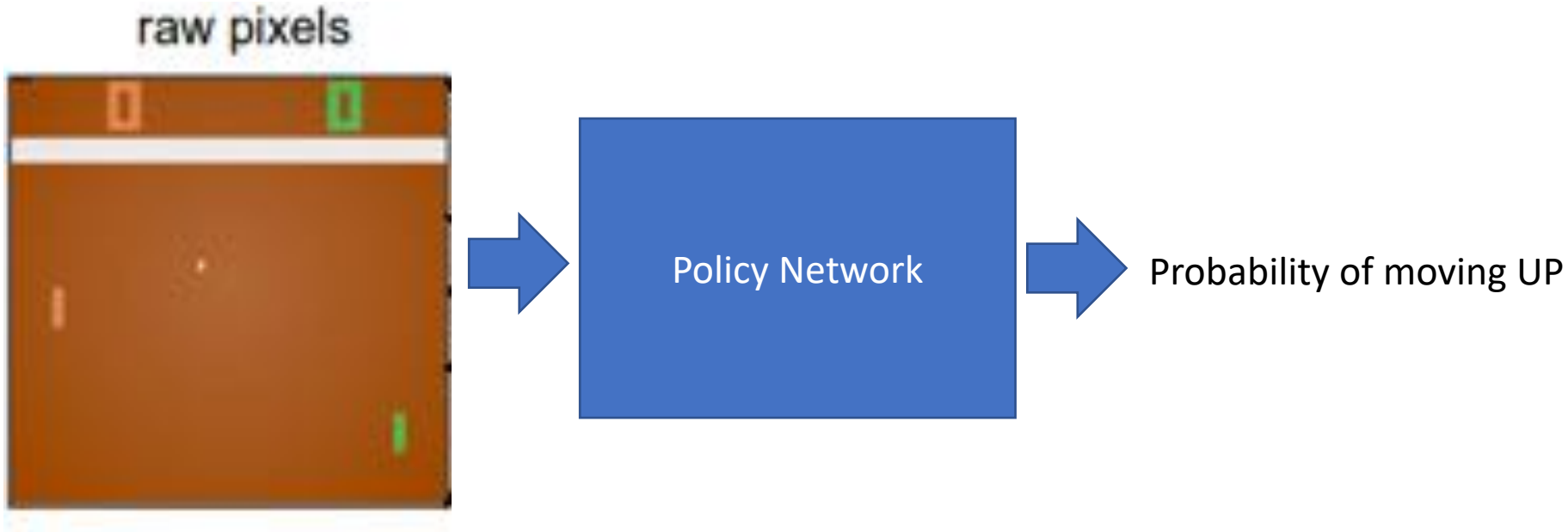
# RL example: Pong

Action: move UP or DOWN

From Andrej Karpathy blog: http://karpathy.github.io/2016/05/31/rl/

# RL example: Pong

Action: move UP or DOWN

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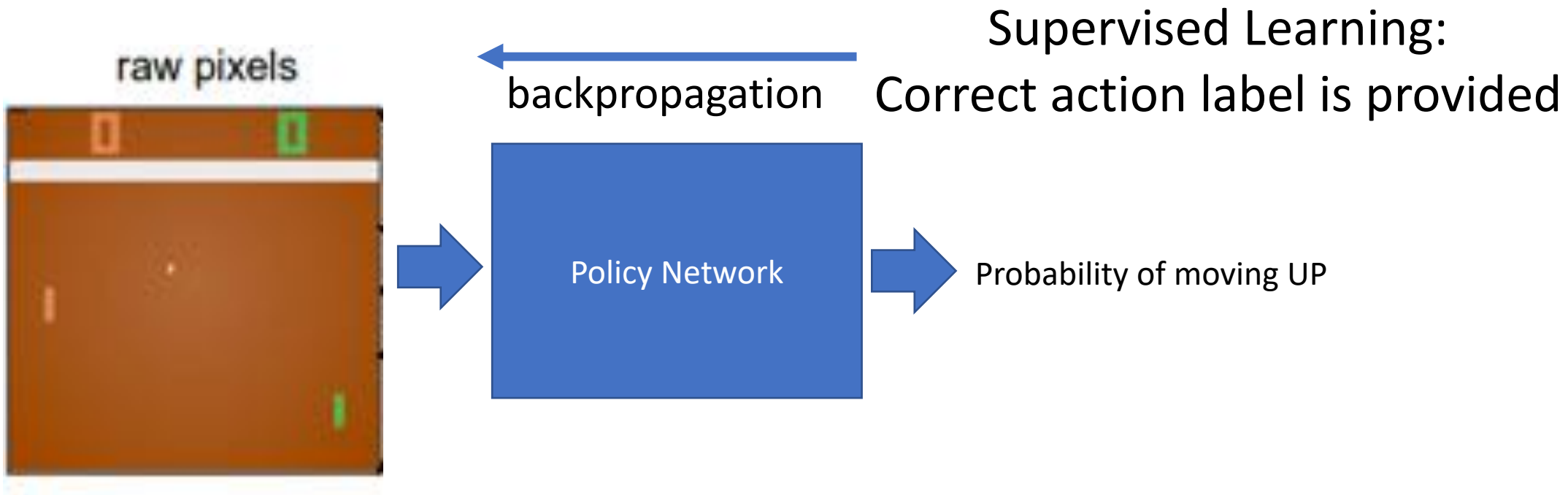
# RL example: Pong

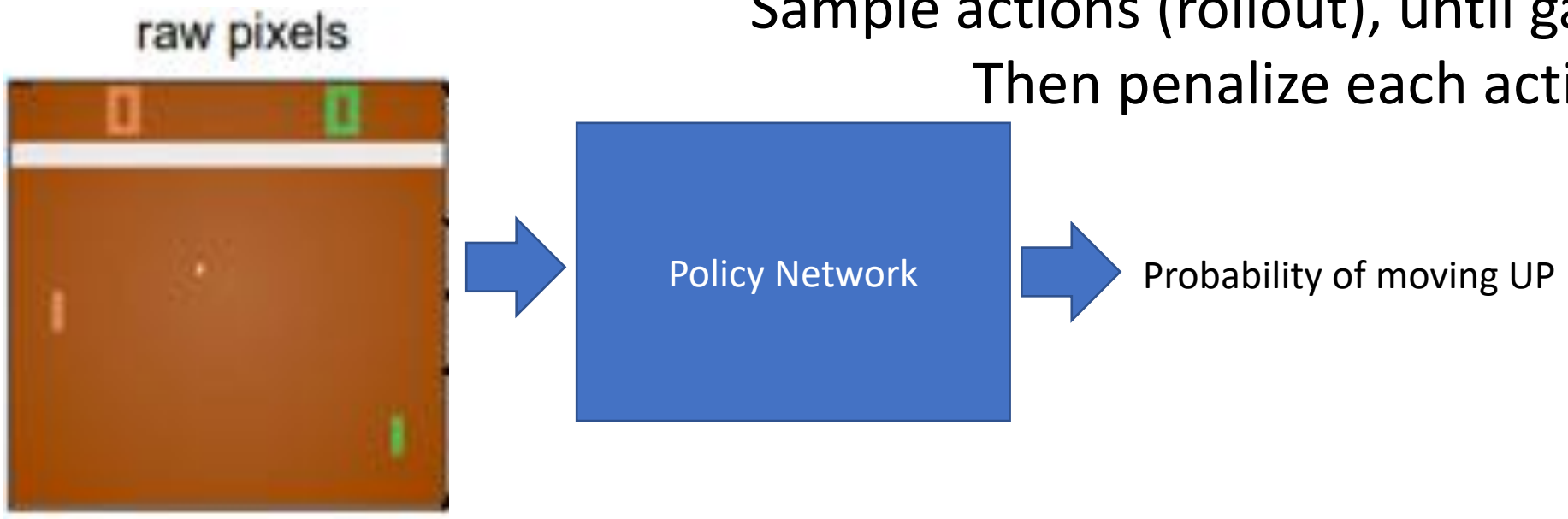
- Action: move UP or DOWN



# RL example: Pong

- Action: move UP or DOWN

Reinforcement Learning:
Sample actions (rollout), until game is over,
Then penalize each action



# RL example: Pong

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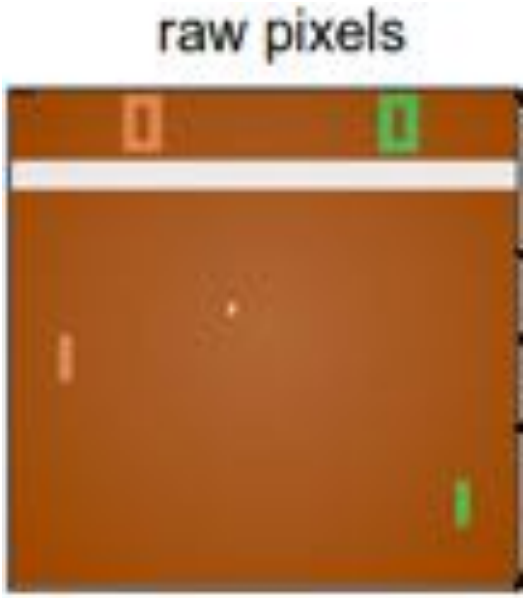
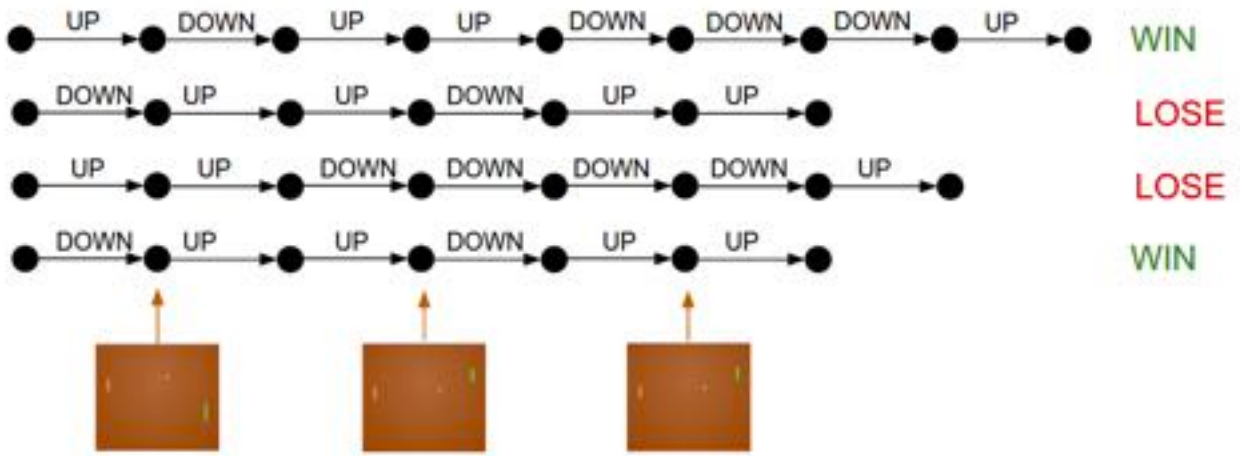



Reinforcement Learning:
Sample actions (rollout), until game is over,
Then penalize each action

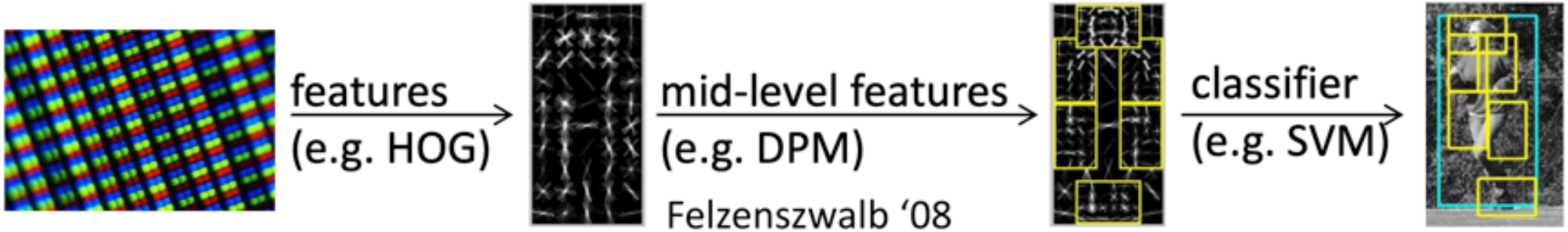
Possible rollout sequence:

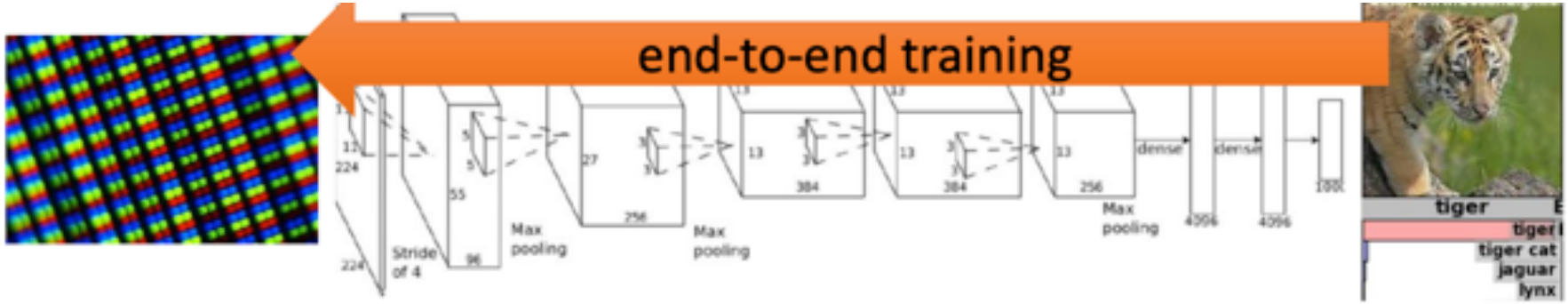
Eventual Reward:



# Why deep reinforcement learning?

- Analogy to traditional CV and deep CV

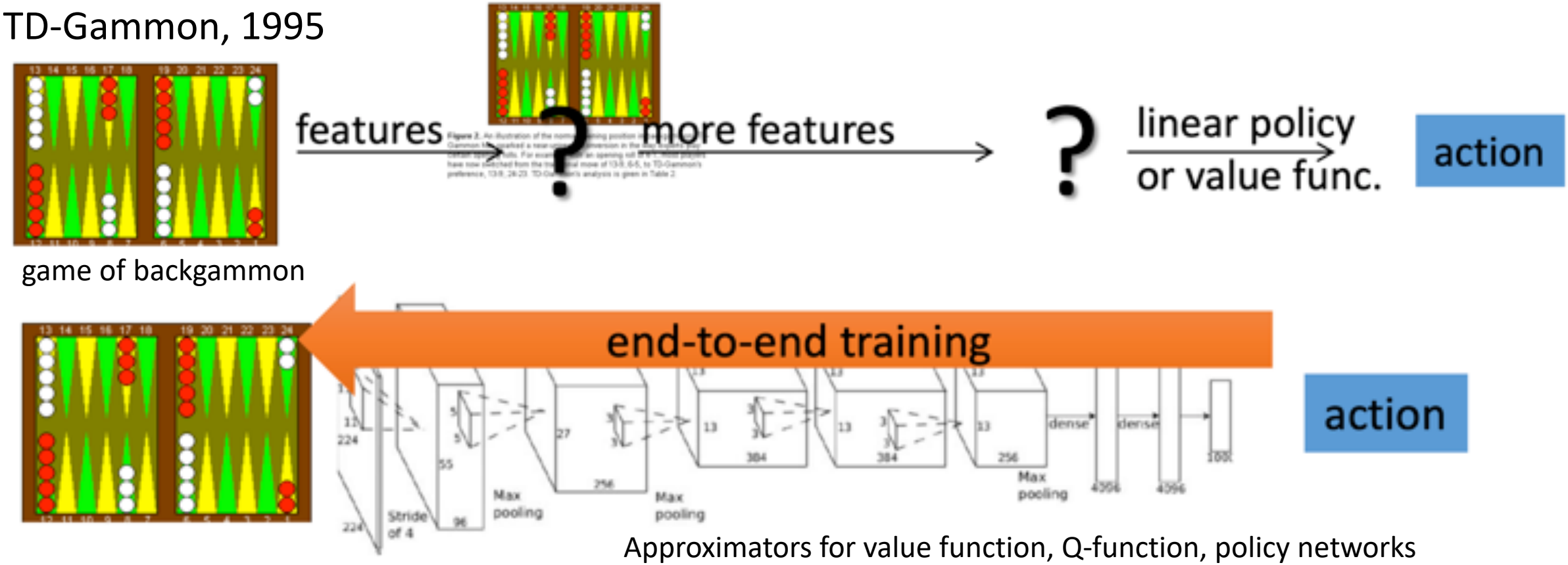


# Why deep reinforcement learning?

- Standard RL and deep RL

TD-Gammon, 1995



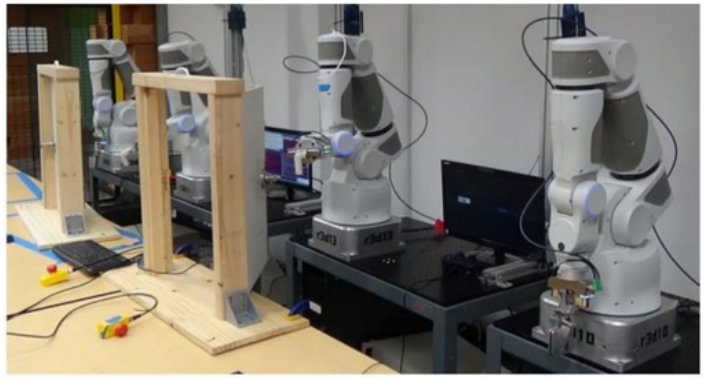

Approximators for value function, Q-function, policy networks

# Why RL works now?

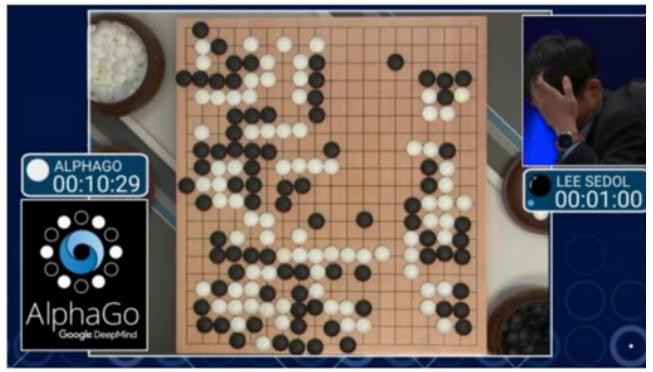
- One of the most exciting areas in machine learning



Game playing



Robotics




Beating best human player

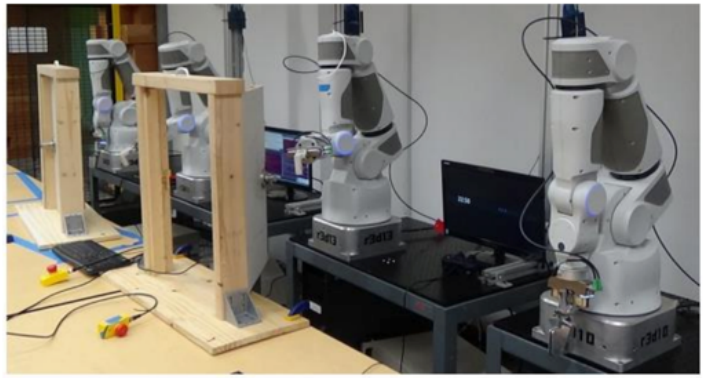
[Playing Atari with Deep Reinforcement Learning]
[Mastering the game of Go without Human Knowledge]

# Why RL works now?

- Computation power: many GPUs to do trial-and-error rollout
- End-to-end training, features and policy are jointly optimized toward the end goal
  - Acquire the high degree of proficiency in domains governed by simple, known rules



Game playing



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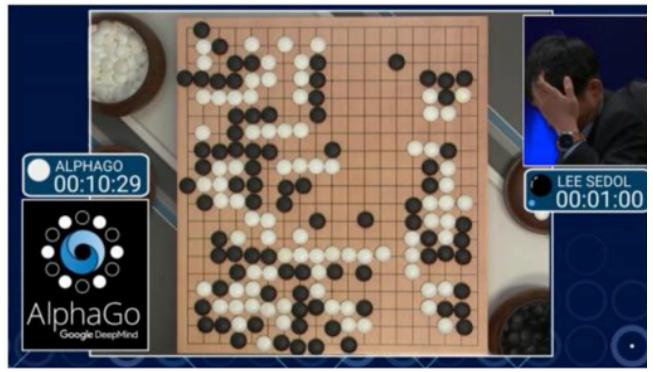
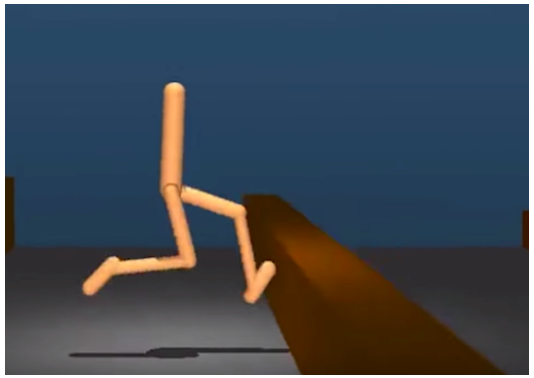



Beating best human player

# What are the applications of RL?

Some interesting examples:

Learning to walk

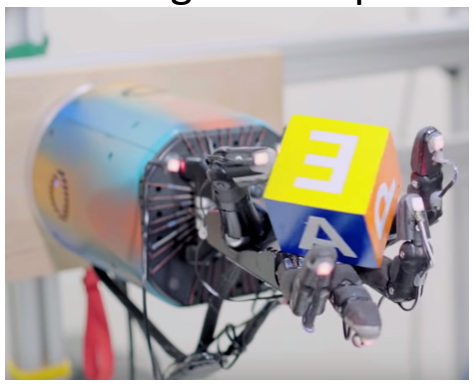


https://www.youtube.com/watch?v=gn4nRCC9TwQ

Learning to grasp

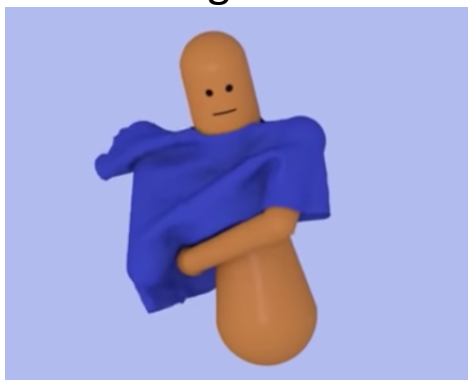

https://ai.googleblog.com/2016/03/deep-learning-for-robots-learning-from.html

Learning to manipulate



https://www.youtube.com/watch?v=jwSbzNHGflM

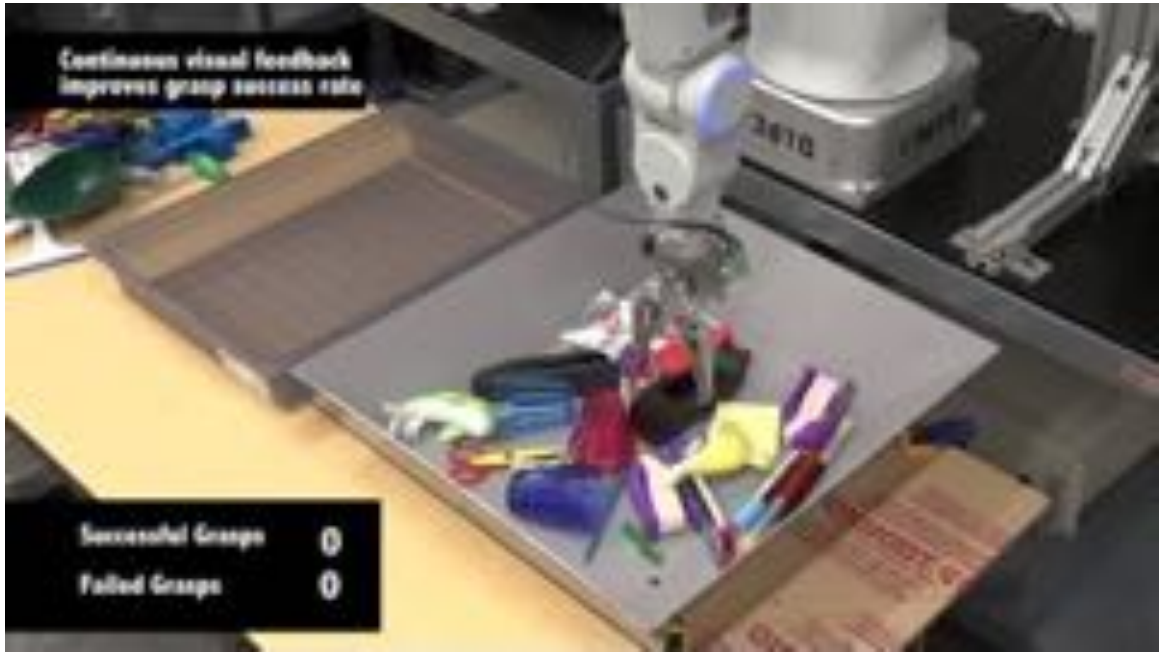
Learning to dress



https://www.youtube.com/watch?v=ixmE5nt2o88

# Learning to walk

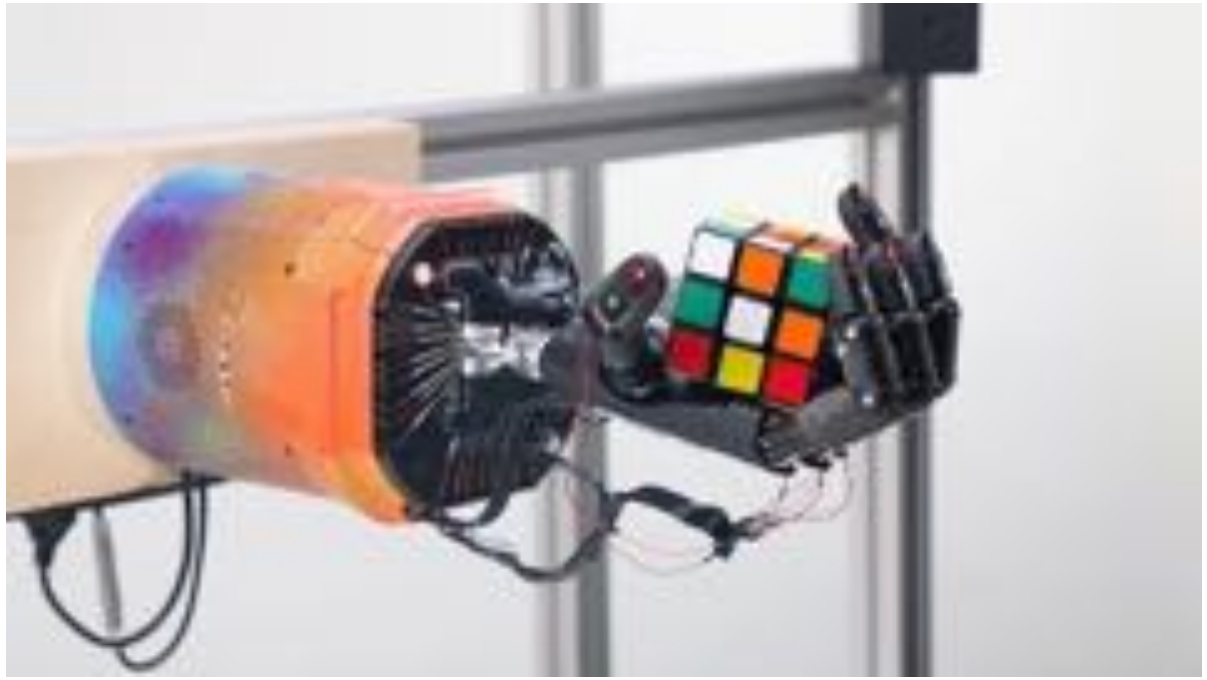
# Learning to grasp



# Learning to move fingers

2018


2019



OpenAI

# Learning to dress

Learning to dress: synthesizing human dressing motion via deep reinforcement learning.
https://ckllab.stanford.edu/learning-dress-synthesizing-human-dressing-motion-deep-reinforcement-learning

# Learning to race


Super-Human Performance in Gran Turismo Sport Using Deep Reinforcement Learning. https://arxiv.org/pdf/2008.07971.pdf

# Break

- Next lecture:
  - RL basics
  - coding with RL