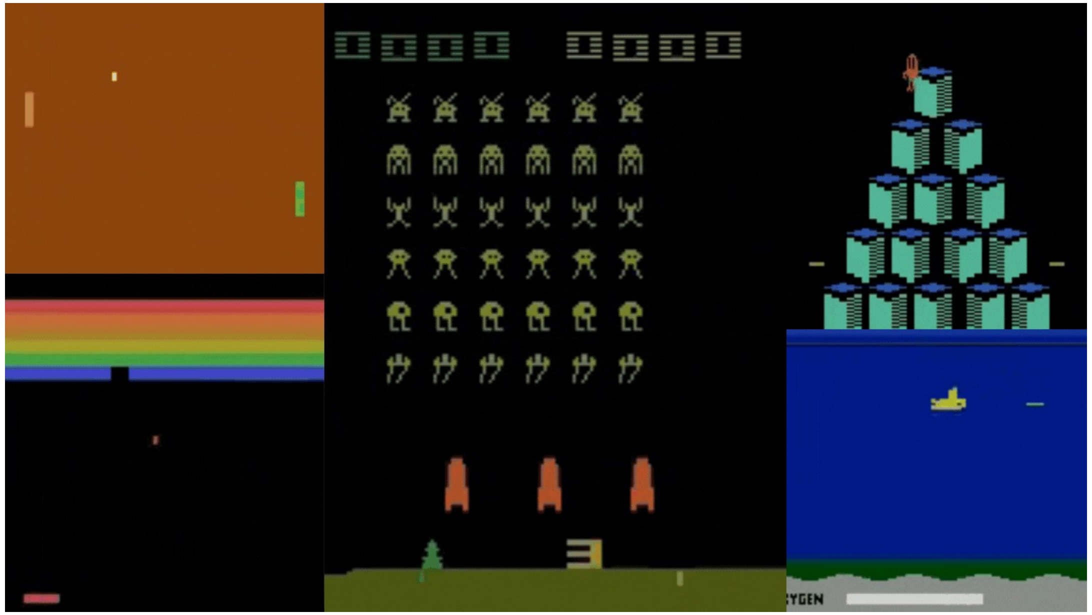
Reinforcement Learning
Spring 2024

Abhishek Gupta

TAs: Patrick Yin, Qiuyu Chen



Welcome to Reinforcement Learning – Sp 24!

Lecture Outline

Course logistics and scope

What is RL, a formal definition

Why should we care?

Going beyond RL

Course Logistics

- Where: BAG 261
- When: Tue/Thu 11:30-12:50
- Who:
  - Abhishek Gupta (Instructor)
  - Patrick Yin (TA)
  - Zoey Chen (TA)
- Office hours:
  - Abhishek: Gates 215, Wed 2-3pm
  - Patrick:
  - Zoey:

Course Logistics

- Grading: Seminar style
  - 40 % final project
  - 10% paper discussions/readings
  - 45 % for HWs – 15% for each of 3 HWs
  - 5% participation
- Communications through EdStem/e-mail
- Mix of lectures and paper readings:
- Final projects will be presented in a poster session.
  - Intermediate project proposals and milestone check ins.
- Please participate, otherwise it will be boring for all of us!

Course Logistics - Project

- Final project (40% of grade):
  - Project proposal (1 page) [Due 4/10]
  - Milestone report (3-4 pages) [Due 5/2 (subject to change)]
  - Final report (6-8 pages) [Due 6/5 (subject to change)]
- Project can be investigating any question related to reinforcement learning, imitation learning or sequential decision making
  - New algorithm
  - Performant/stable implementation
  - Empirical investigation
  - New application or domain
  - …
- Can be done in groups of 1-2 students.

Course Logistics – Discussions

- We will try out a new discussion style (many to many role playing)
  - Stolen from Alec Jacobson (Toronto), Colin Raffel (UNC), etc
- Idea is that for every paper, we will have people fulfilling many roles:
  - **Discussion leader:** Presents the overall premise of the paper, quickly goes over the key ideas in the paper and presents the basic results
  - **Paper reviewer 1 (pro):** Argues why the paper should be accepted
  - **Paper reviewer 2 (con):** Argues why the paper should NOT be accepted
  - **Archaeologist:** Identifies where this paper fits into the literature
  - **Academic researcher:** Identifies future projects that can build on this work
  - **Industry practitioner:** Identifies where exactly this work can see application and discuss the societal impact of such an application
  - **Hacker**: Implements the algorithm/tries out the code if published
- Everyone else posts commentaries about the paper on EdStem!
- For non discussion lectures, everyone is expected to post a commentary on at least one of the readings.

Course Logistics – Homework

- 3 HW assignments, each Python programming of different algorithms
- HW 1 – Imitation Learning
  - Implement and test out simple imitation learning algorithms in simulation
- HW 2 – Model-free RL
  - Implement and test out policy gradient and actor critic methods
- HW 3 – Model-based RL
  - Implement and test out model-based RL algorithms
- Submit through canvas with a small written report.

Who am I?

- Assistant professor in CSE
- Grew up in Oregon/India, last 10 years in Berkeley
- Undergrad Berkeley, Ph.D. Berkeley, Postdoc MIT.
- Interests: RL/robotics/optimization and control/robustness and generalization
- Outside of work: Tennis/soccer/sketching/dog enthusiast

Who is Patrick?

1. First-year PhD in Robotics/ML

2. Life Trajectory: Grew up in the bay area, did my undergrad at Berkeley

3. Research Interests: Robot Learning, Reinforcement Learning, Manipulation

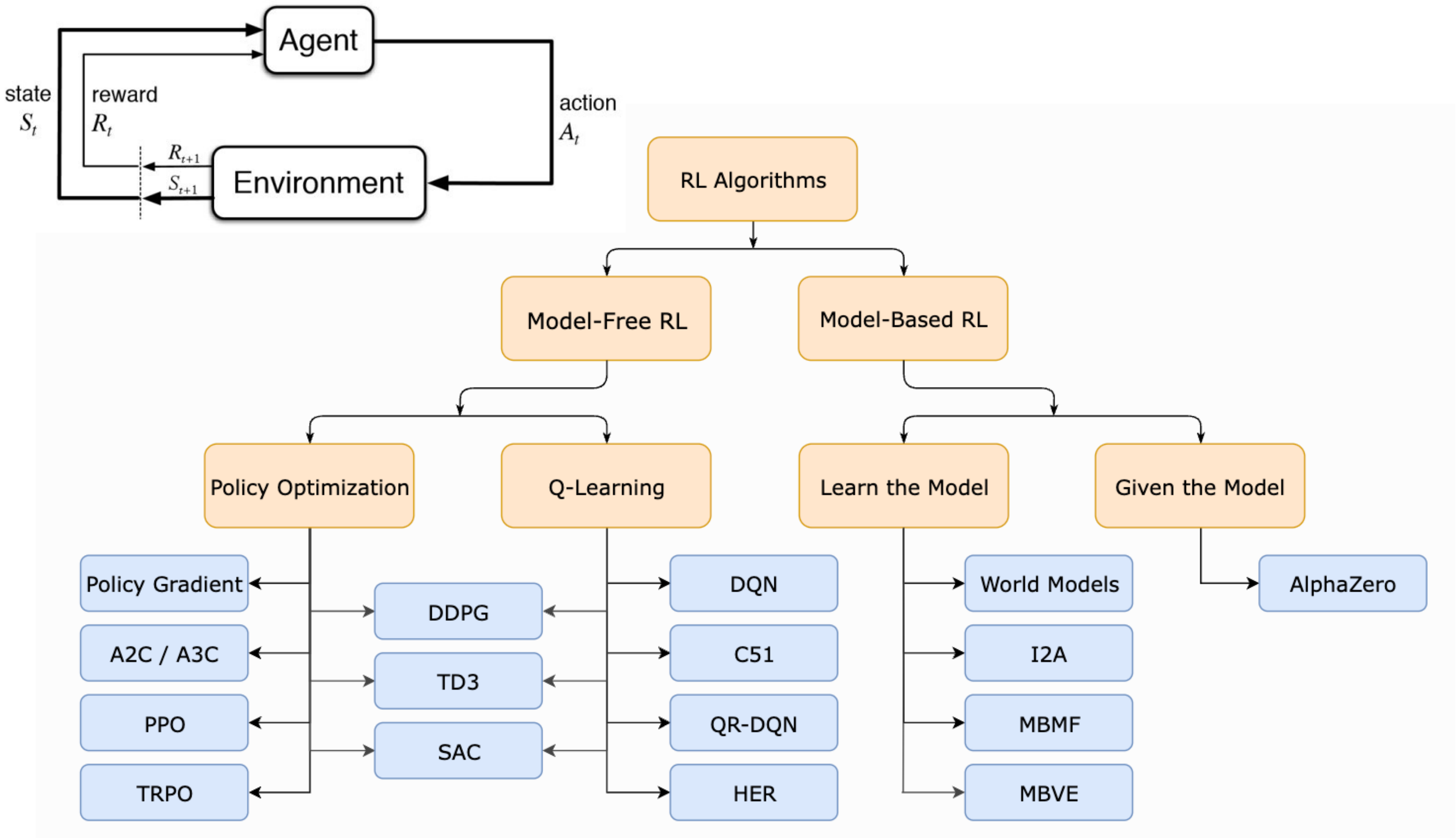
4. Outside work: baking, guitar, tennis/pickleball, hiking, gyming, reading

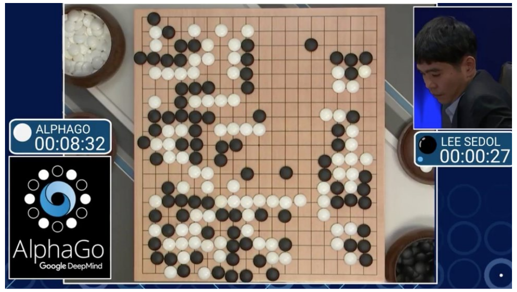
Who is Zoey?

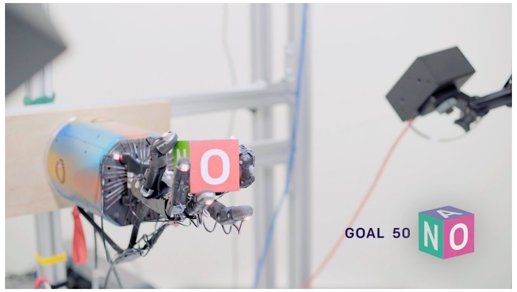
- Final Year PhD in Robotics
- Life Trajectory: grow up in China, last 10 years: Seattle->Japan->Switzerland->Seattle
- Academic Trajectory: Optics & Lasers -> Medical Image Analysis -> Robotics
- Research Interest: Imitation Learning, Robot Perception, Manipulation
- Outside work: piano, painting, board game, hiking, dog owner in 3 weeks!

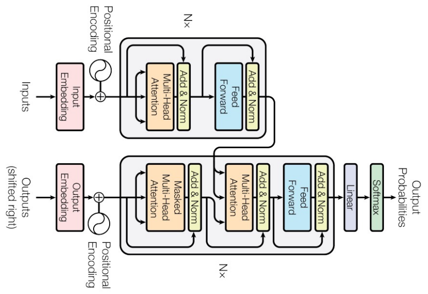
What is this course about?

- The design and **practice** of reinforcement learning algorithms



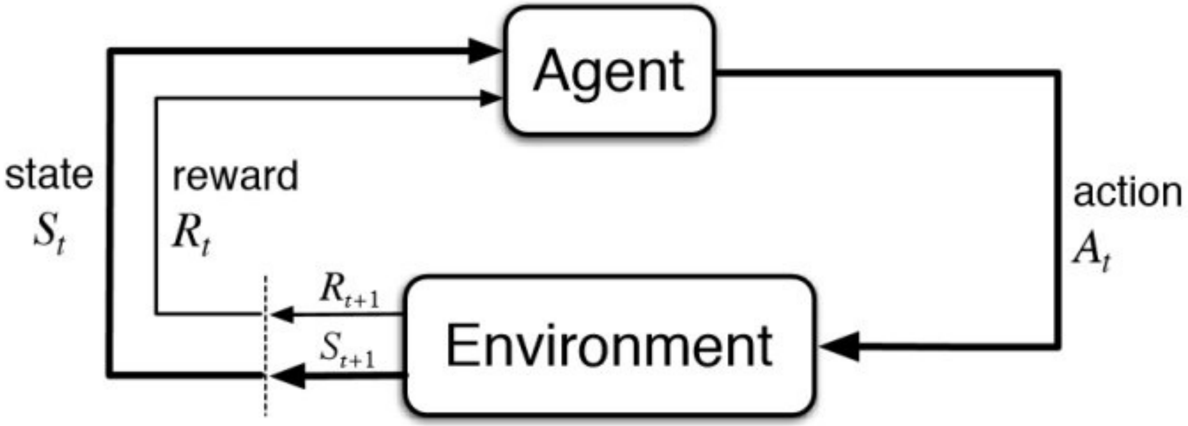




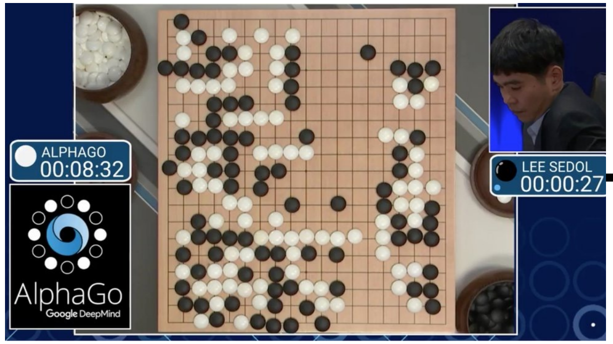


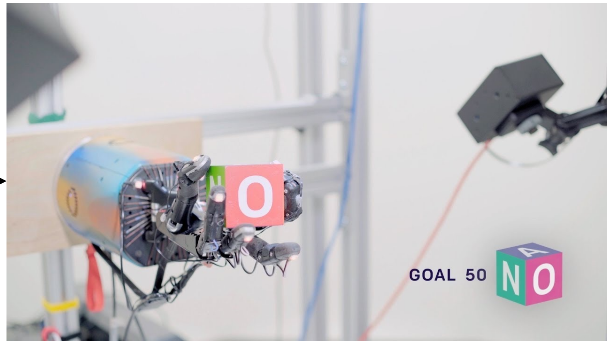
What is this course about?

- Building RL algorithms that are practical for real applications



- Sample efficient
- Operates from high-dimensional observations
- Continually improving



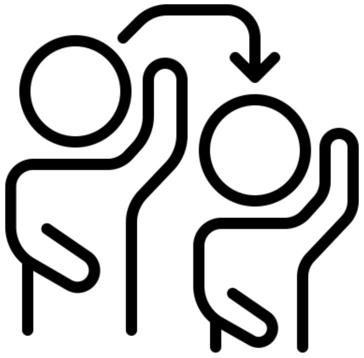


RL algorithms were not conceived to operate under practical assumptions, needs some extra work

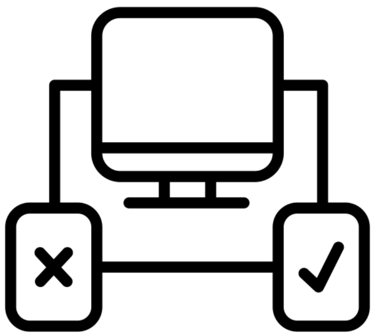
What is this course about?

- Practice implementing and **<u>tuning</u>** sequential decision making algorithms

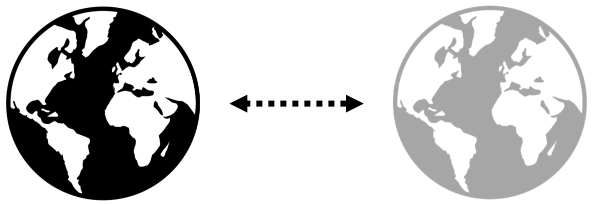
Imitation learning



Model-Free RL



Model-Based RL



....

- Most RL algorithms require tips and tricks, we will study them

What is this course not about?

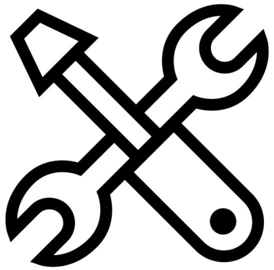
- Not a pure theory course, more an applied-RL course
  - For pure theory classes, recommend CSE 541 or Simon's CSE 542
  - RL theory book (https://rltheorybook.github.io/rltheorybook_AJKS.pdf)

Lemma 2.10. *Let $\delta > 0$. With probability greater than $1-\delta$,*

$$|(P-\widehat{P})V^\star| \le \sqrt{\frac{2\log(2|\mathcal{S}||\mathcal{A}|/\delta)}{N}}\sqrt{\mathrm{Var}_P(V^\star)} + \frac{1}{1-\gamma}\frac{2\log(2|\mathcal{S}||\mathcal{A}|/\delta)}{3N}\mathbb{1}\,.$$

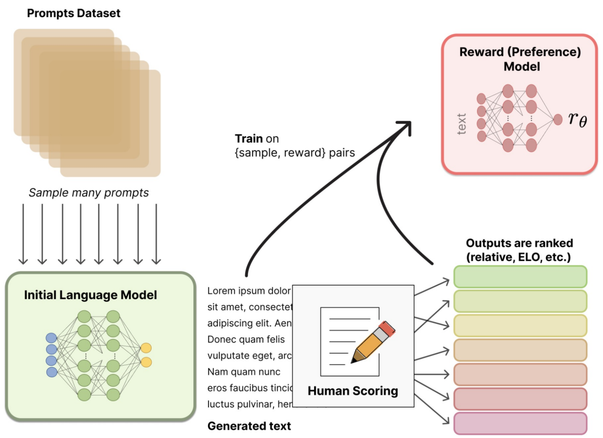
Theorem 4.3 (FQI guarantee). *Fix $K \in \mathbb{N}^+$. Fitted Q Iteration guarantees that with probability $1-\delta$,*

$$V^\star - V^{\pi^K} \le \frac{1}{(1-\gamma)^2}\left(\sqrt{\frac{22CV_{\max}^2\ln(|\mathcal{F}|^2K/\delta)}{n}} + \sqrt{20C\epsilon_{approx,\nu}}\right) + \frac{\gamma^K V_{\max}}{(1-\gamma)}$$



- Only cover the theory needed to derive algorithms

What should we be able to do post CSE 542?

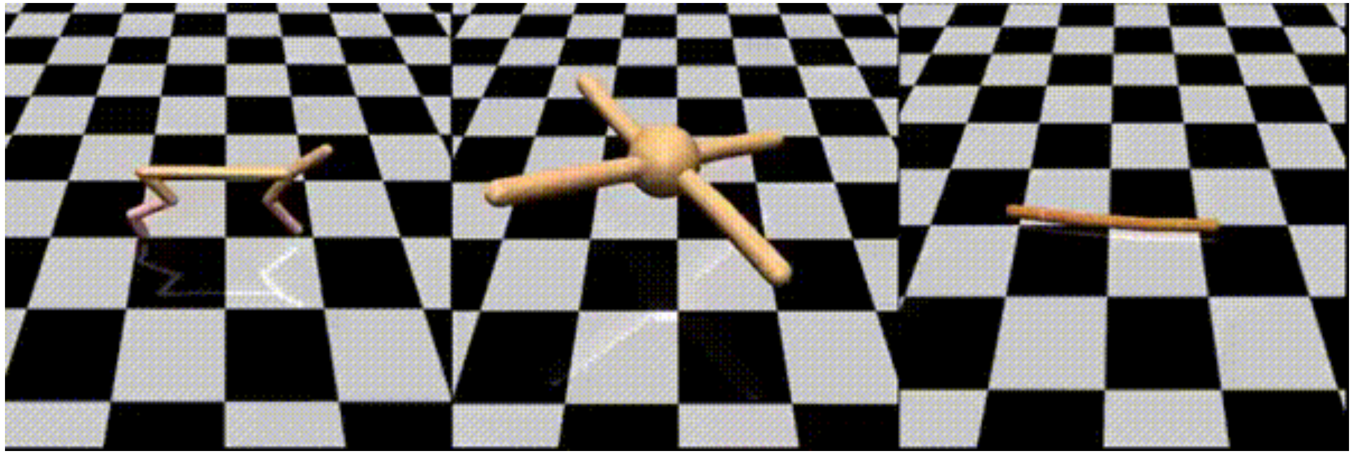


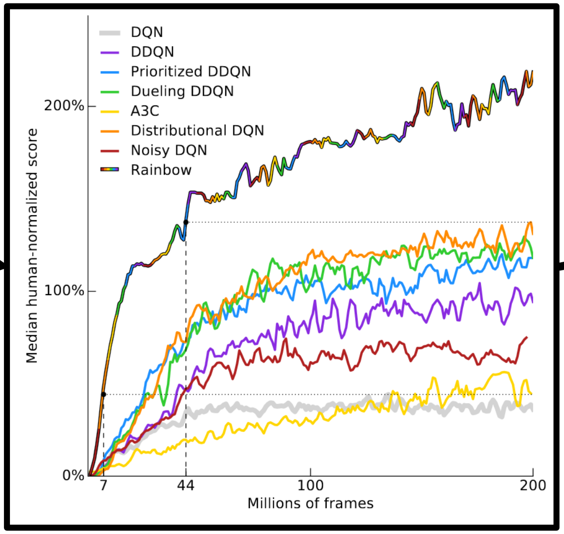
```
def update_critic(self, obs, action, reward, next_obs, not_done, logger,
                  step):
    dist = self.actor(next_obs)
    next_action = dist.rsample()
    log_prob = dist.log_prob(next_action).sum(-1, keepdim=True)
    target_Q1, target_Q2 = self.critic_target(next_obs, next_action)
    target_V = torch.min(target_Q1,
                         target_Q2) - self.alpha.detach() * log_prob
    target_Q = reward + (not_done * self.discount * target_V)
    target_Q = target_Q.detach()

    # get current Q estimates
    current_Q1, current_Q2 = self.critic(obs, action)
    critic_loss = F.mse_loss(current_Q1, target_Q) + F.mse_loss(
        current_Q2, target_Q)
    logger.log('train_critic/loss', critic_loss, step)

    # Optimize the critic
    self.critic_optimizer.zero_grad()
    critic_loss.backward()
    self.critic_optimizer.step()

    self.critic.log(logger, step)
```





Lecture Outline

Course logistics and scope

What is RL, a formal definition

Why should we care?

Going beyond RL

Ok so let's try and define Reinforcement Learning

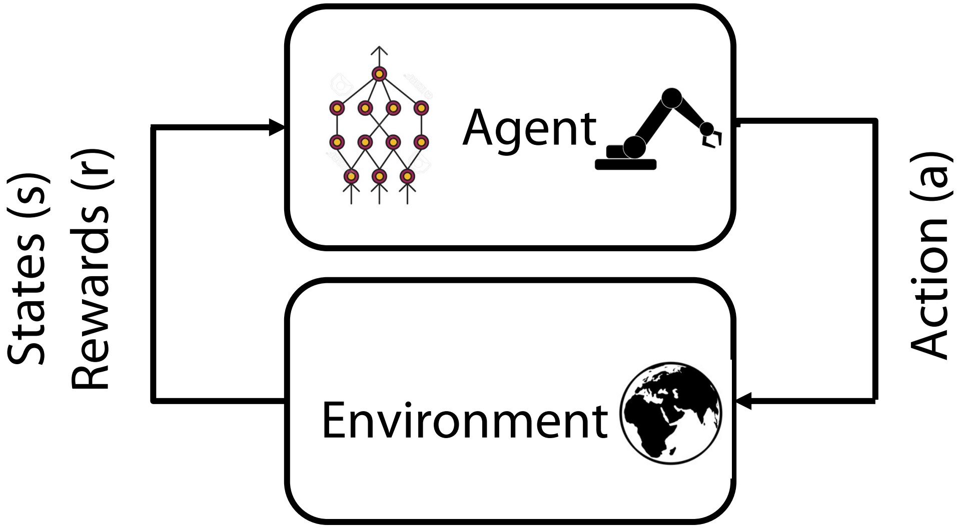
Can learn in arbitrary settings

Go from expert label → scalar measure of success

No expert corpus needed

Can generalize to new states

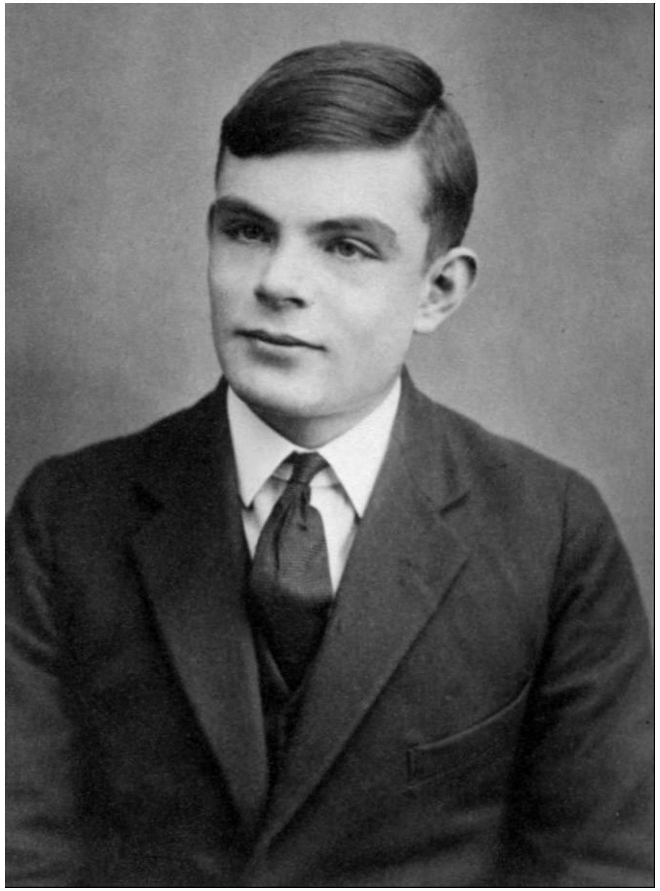
Using trial and error in an environment to learn a strategy to maximize some notion of "reward"



Easy (?) way for agents to continue improving their own behavior on deployment

Why reinforcement learning?: Philosophical

Hypothesis: By designing algorithms that can improve themselves, we can reach fully intelligent systems



"Instead of trying to produce a programme 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

⇩

Rather than try to directly replicate behaviors, try to replicate adaptative learning mechanisms

Why reinforcement learning?: Practical

A useful tool for building continually improving robots!

Robot learning is different for several reasons:

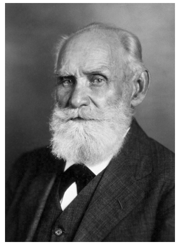
1. Sequential decision making problem (Non IID)
2. Large amounts of expert robot data may be expensive
3. Naturally multi-task and continual
4. Behaviors may be hard to pre-program

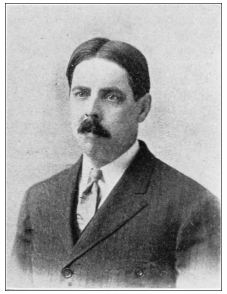
Robots that collect their own data to improve!

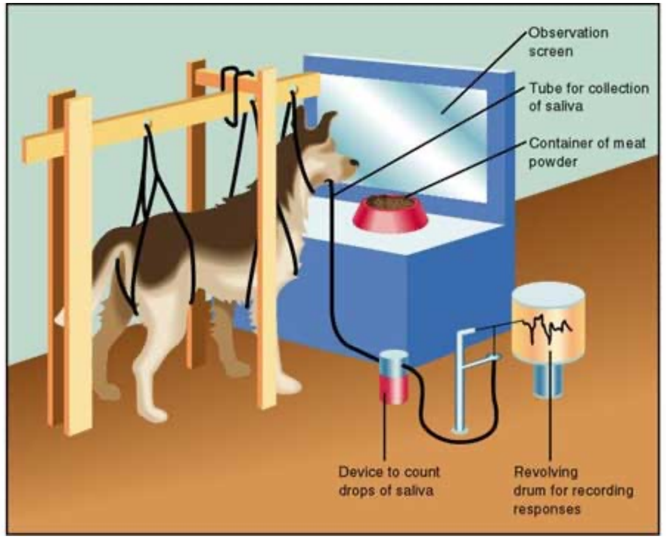
A Little History on Reinforcement Learning

Two distinct threads converged to give rise to modern RL

Animal Psychology







Optimal Control

$$\min_{x,u} \int_0^X L(t, x(t), u(t)).dx$$

w.r.t

$$x'(t) = f(x(t), u(t))$$

Ideas from temporal difference learning/dynamic programming united these fields!

Sutton and Barto

A Little History on Reinforcement Learning

Klopf/Sutton/Barto brought together ideas from psych/neuro and computational TD learning

Harry Klopf

Introduced the ideas of "generalized reinforcement" – linked together TD learning and trial and error learning from psychology

Brain Function and Adaptive Systems - A Heterostatic Theory

A. HARRY KLOPF

Sutton

Barto

AD A101476

AFWAL-TR-81-1070

LEVEL II

2

GOAL SEEKING COMPONENTS FOR ADAPTIVE INTELLIGENCE: AN INITIAL ASSESSMENT

Also had major contributions from Watkins, Shannon, Minsky, Tesauro, Michie, Sutton, Samuel, etc!

Sutton and Barto

A Little History on Reinforcement Learning

<u>Some</u> evidence about RL in the brain

Reinforcement learning in the brain

Yael Niv
Psychology Department & Princeton Neuroscience Institute, Princeton University

Shows the importance of temporal difference reward prediction error in processes in the brain

Dopamine != reward, rather dopamine corresponds strongly to errors in long term reward prediction (aka TD errors) (Montague '96, Schultz '97). Some inconsistencies, e.g. Dealing with aversive events like pain

Likely much more research needed, since decisions can be made in the absence of dopamine → multiple different RL processes in the brain

A Little History on Modern Reinforcement Learning (my view)

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih **Koray Kavukcuoglu** **David Silver** **Alex Graves** **Ioannis Antonoglou**

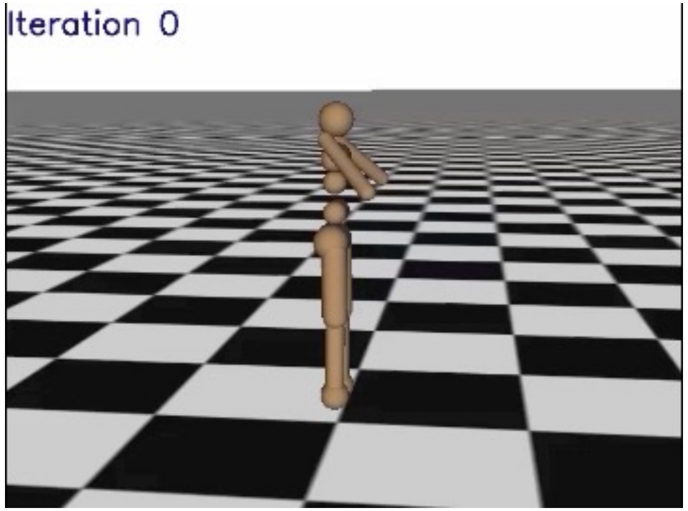
Daan Wierstra **Martin Riedmiller**

DeepMind Technologies

A Little History on Modern Reinforcement Learning (my view)

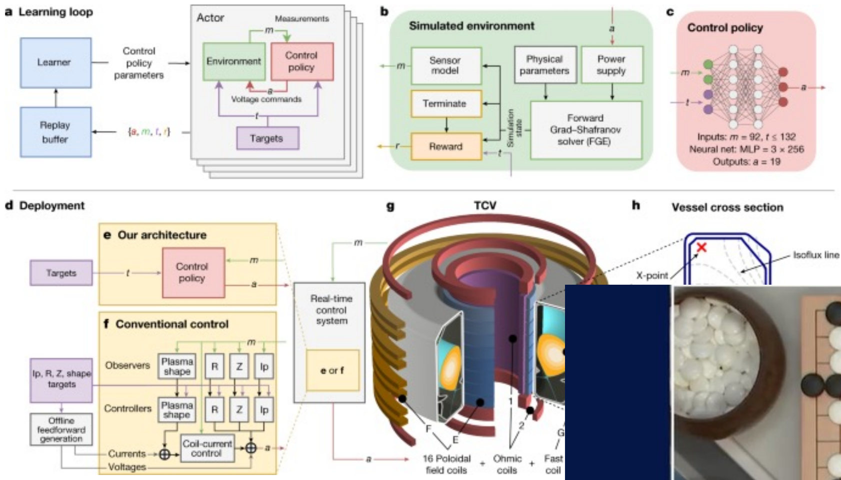
Trust Region Policy Optimization

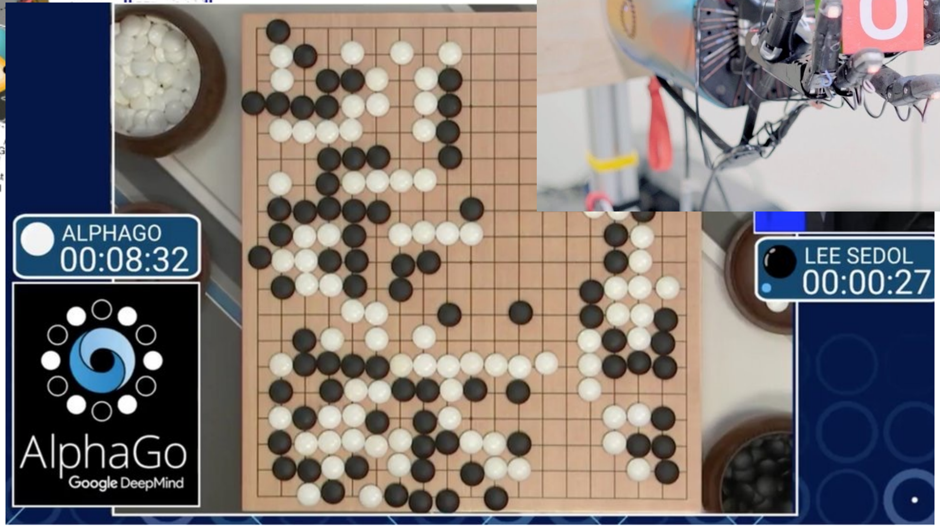
John Schulman JOSCHU@EECS.BERKELEY.EDU
Sergey Levine SLEVINE@EECS.BERKELEY.EDU
Philipp Moritz PCMORITZ@EECS.BERKELEY.EDU
Michael Jordan JORDAN@CS.BERKELEY.EDU
Pieter Abbeel PABBEEL@CS.BERKELEY.EDU
University of California, Berkeley, Department of Electrical Engineering and Computer Sciences

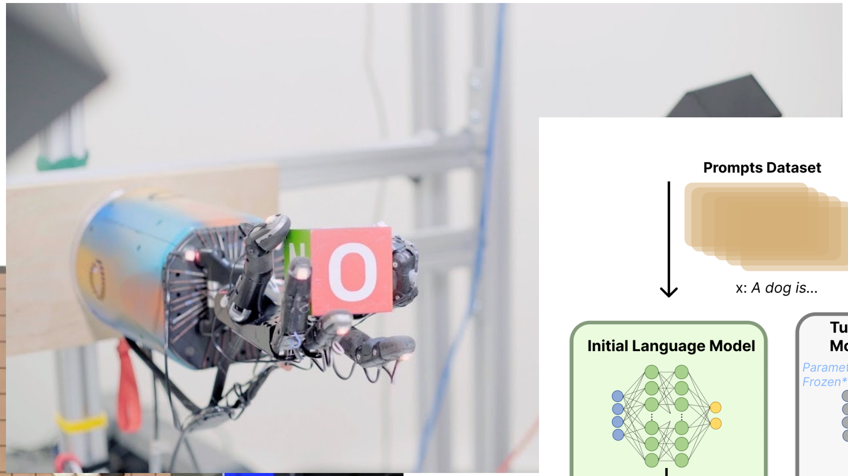


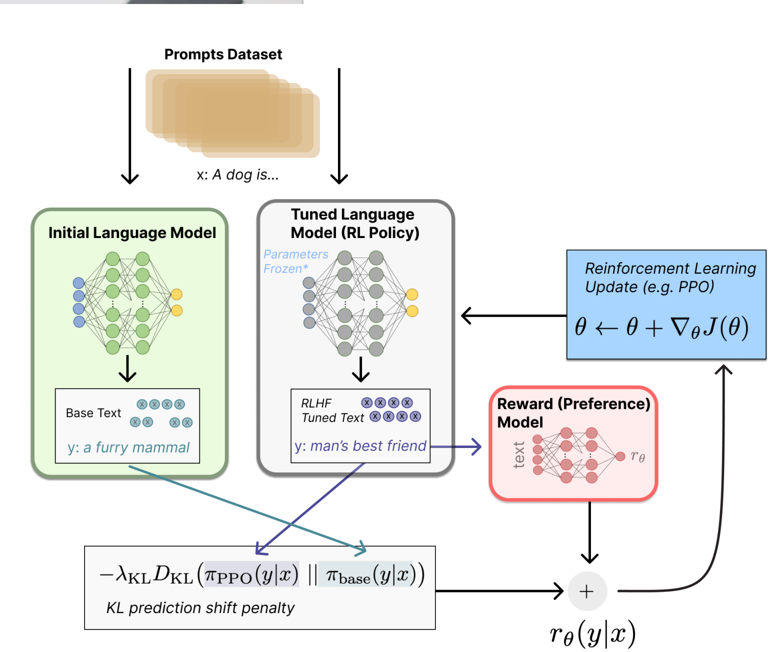
A Little History on Modern Reinforcement Learning (my view)

Since then, we have gotten RL now to power a variety of high-impact applications

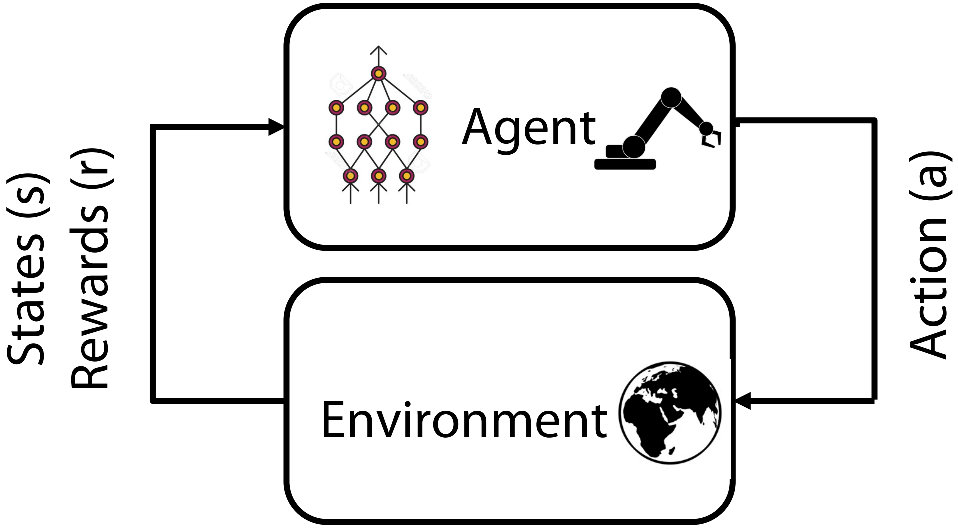




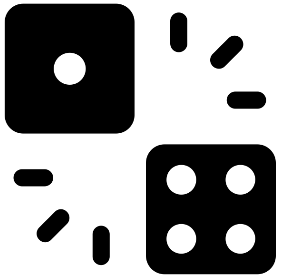




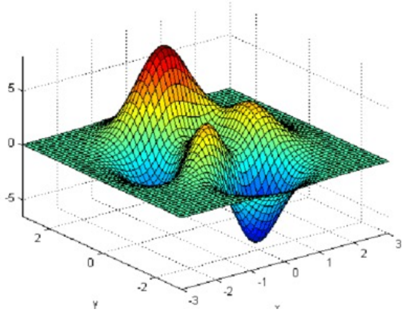
Let's define a formalism



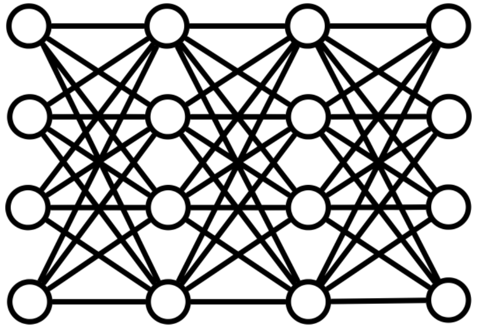
Probability theory



Optimization



Machine Learning



Preliminaries: Markov Chains

$$s_0 \to s_1 \to s_2 \to s_3$$

Initial state distribution

Transition Kernel (T)

Future is independent of past, conditioned on the present

$$p(s_1, s_2, s_3) = p(s_3|s_2)p(s_2|s_1)p(s_1)$$

Goal of Markov chain: running the Markov chain leads to sampling from stationary distribution d^{π}

Balance equation

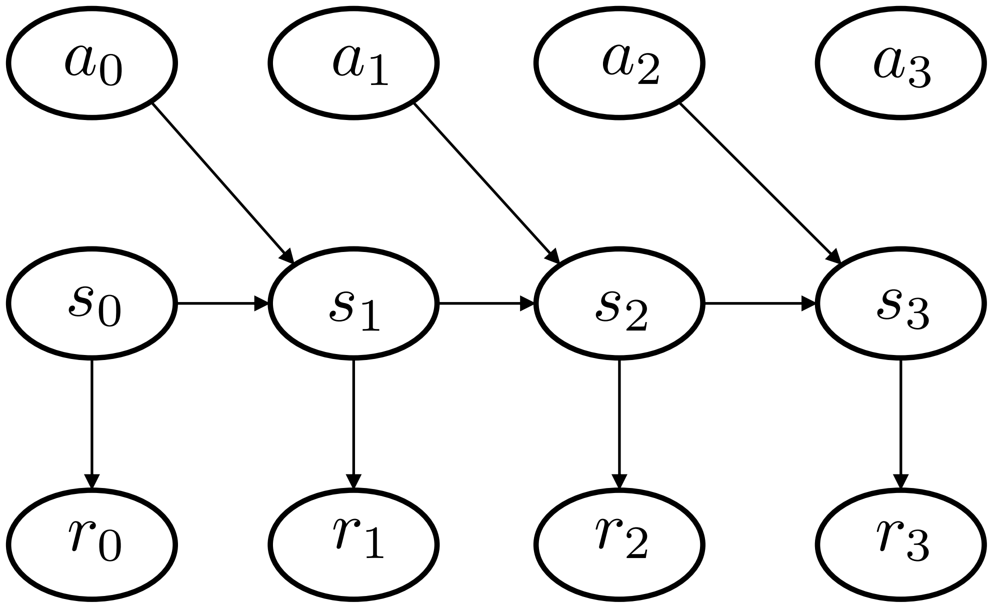
$$Td^{\pi} = d^{\pi}$$

Useful in sampling based inference eg MCMC

How can we make this useful for decision making?

Framework for RL - Markov Decision Process

Augment Markov chain with rewards and actions



States: $\mathcal{S}$

Initial state dist: $\rho_0(s)$

Actions: $\mathcal{A}$

Discount: γ

Rewards: $\mathcal{R}$

Transition Dynamics - $p(s_{t+1}|s_t, a_t)$

Markov property $\quad p(s_1, s_2, s_3) = p(s_3|s_2)p(s_2|s_1)p(s_1)$

Trajectory $\quad \tau = (s_0, a_0, r_0, s_1, a_1, r_1, \ldots, s_T, a_T, r_T)$

Mapping MDPs to the Real World

Task: Place kettle in sink

State: Camera Images / Joint Encoders

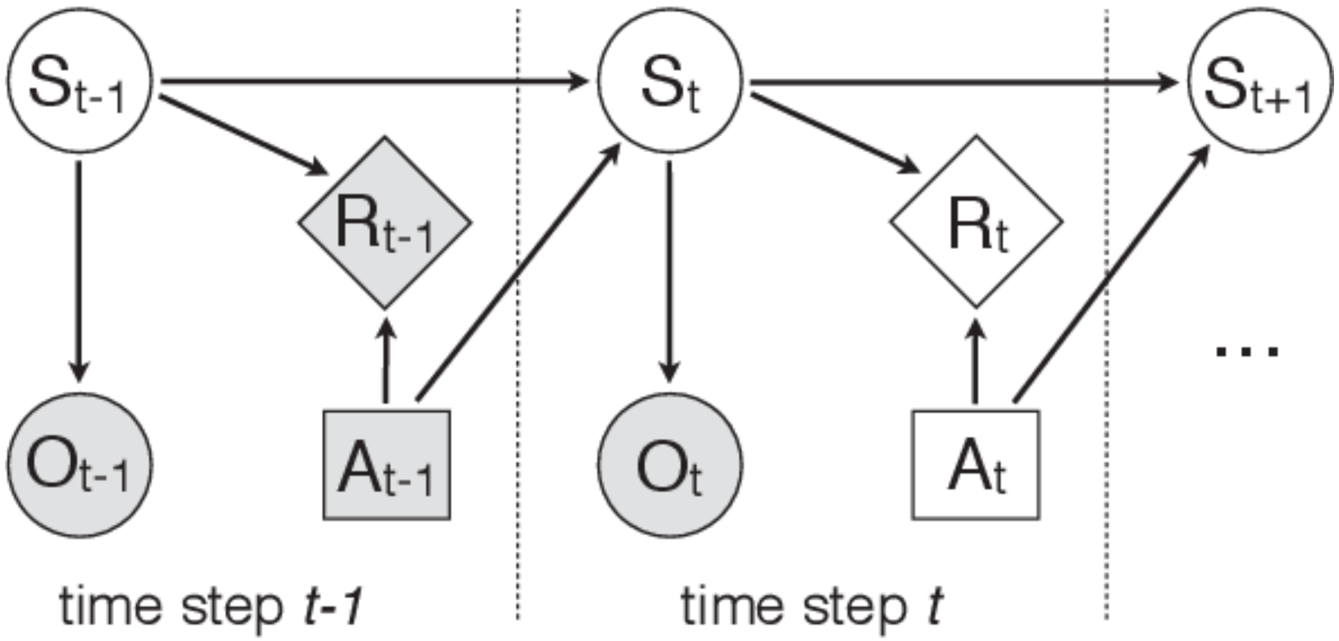
Action: Joint torques/velocities

Reward: Distance from kettle to sink

Transition: World physics

Aside: Partially Observed MDPs

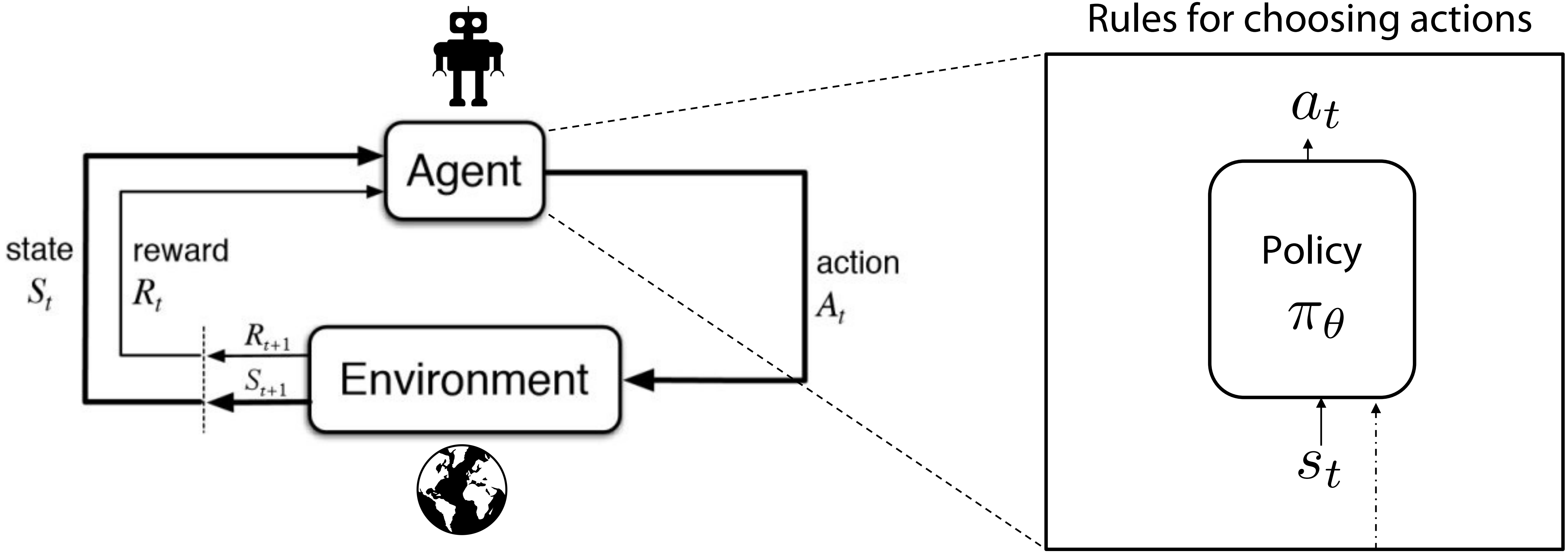
Not every environment is an MDP, in-fact most are POMDPs



POMDPs are hard, we will try to avoid them!

Reinforcement Learning Formalism

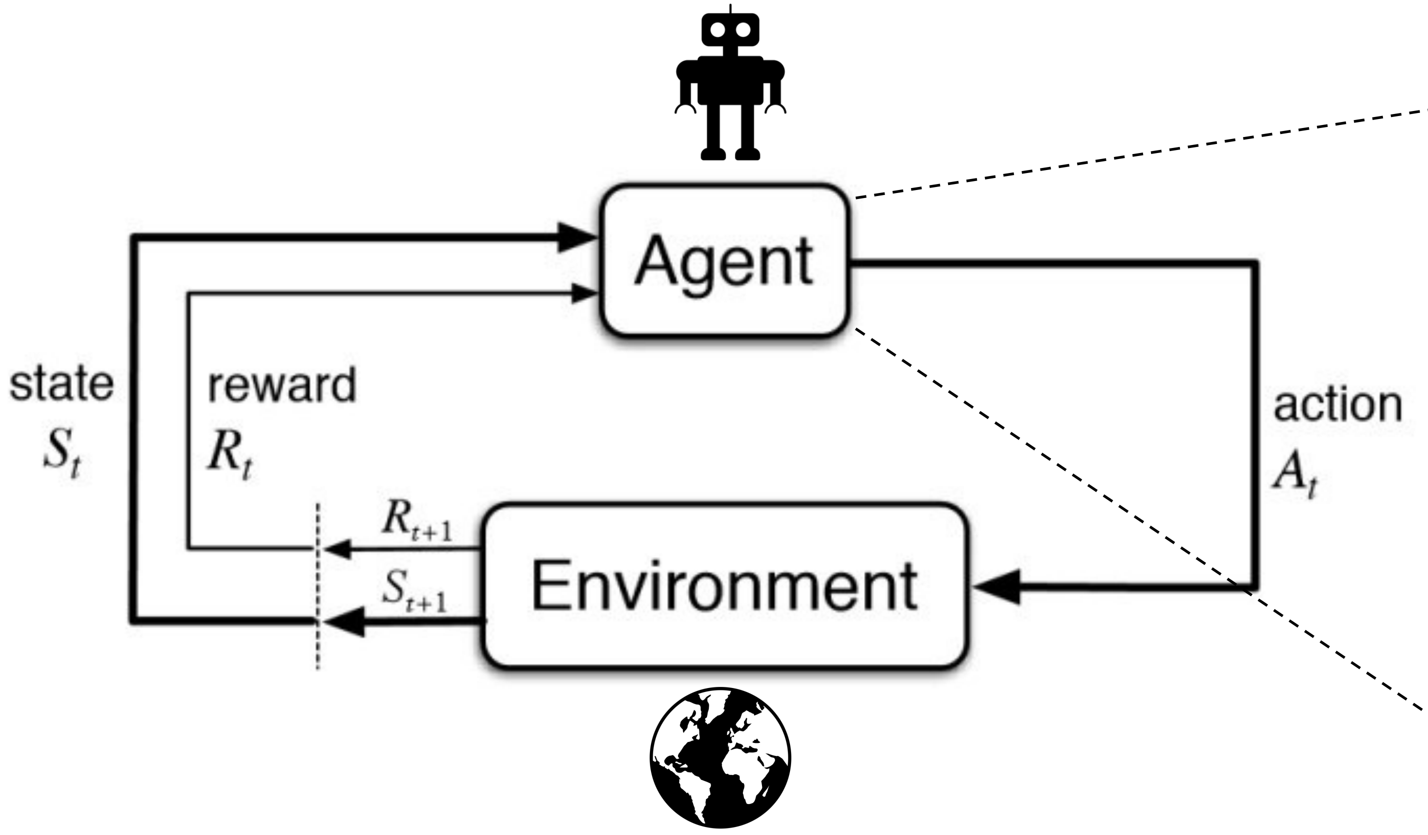
Rules for choosing actions



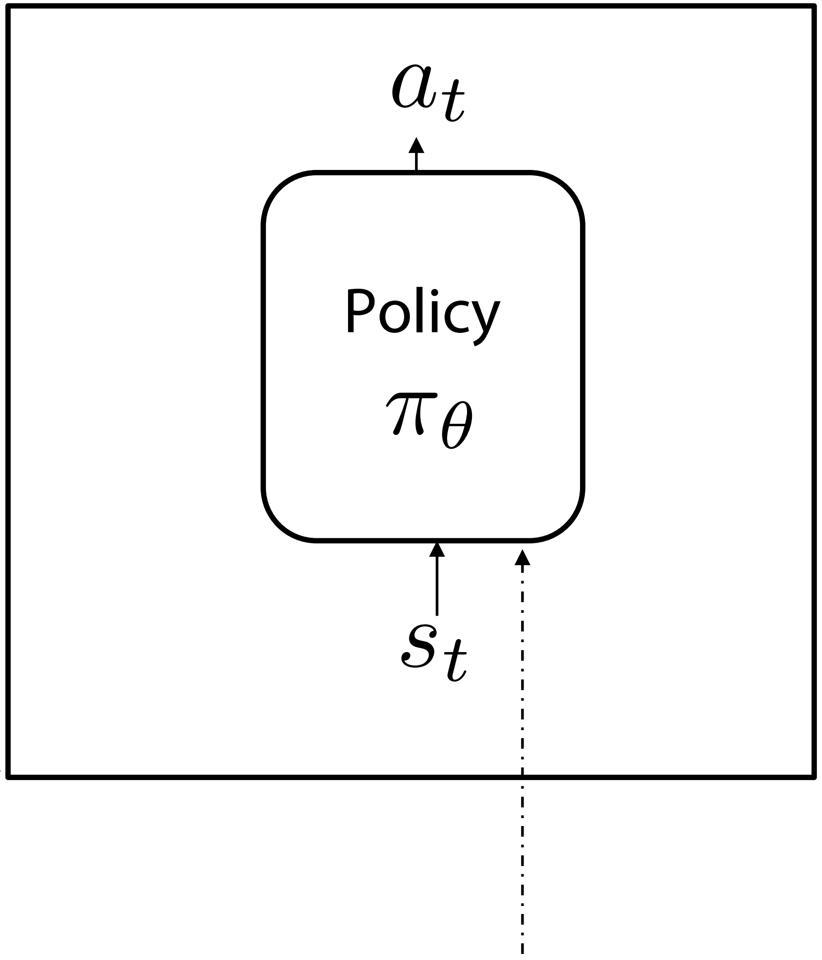
Maximize the sum of expected rewards under policy

Needs to be learned

Reinforcement Learning Formalism



Rules for choosing actions



$$\max_\theta \mathbb{E}_{\tau \sim \pi_\theta} \left[\sum_{t=0}^{T} r(s_t, a_t) \right]$$

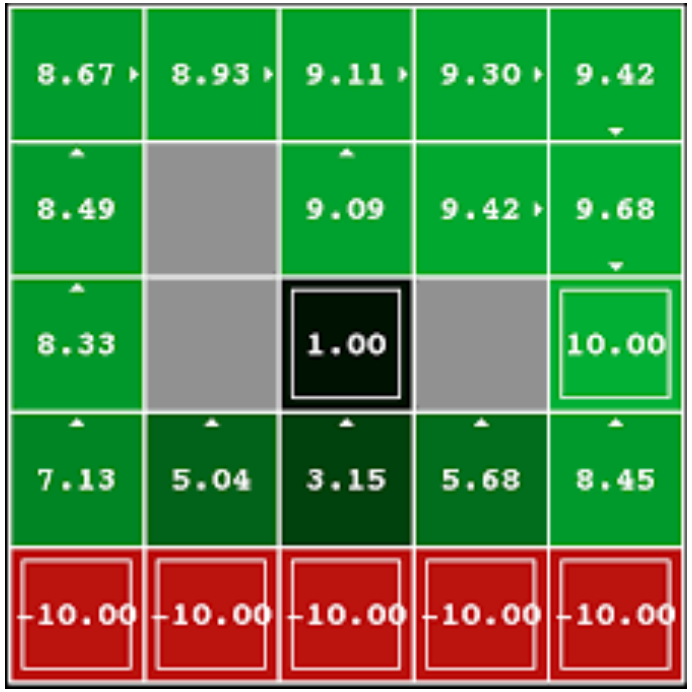
Trajectory sampled using policy

Needs to be learned

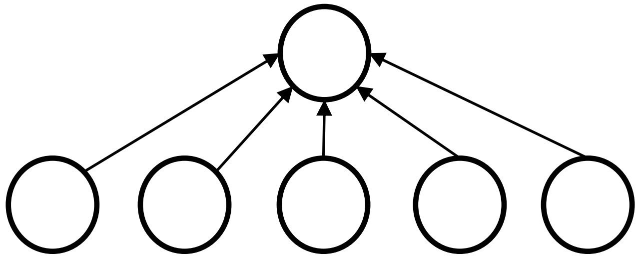
Main thing to learn - Policies

Policies are **mappings** from states to distributions over actions

Tabular

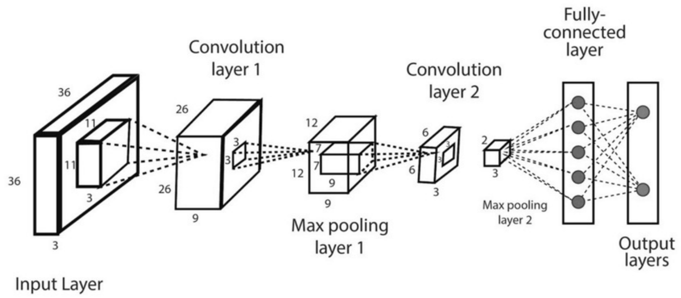


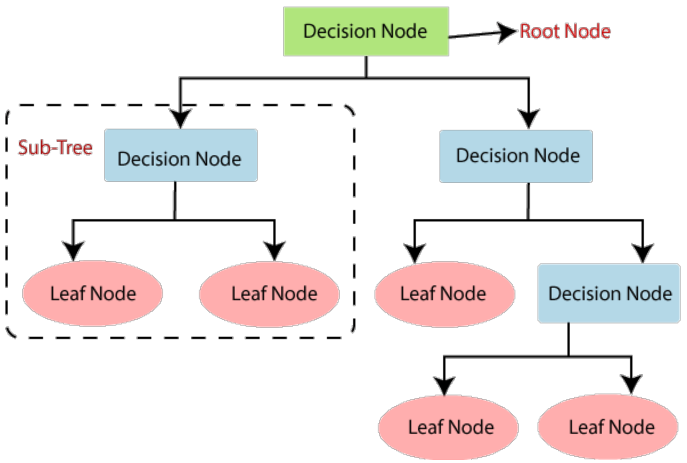
Linear



$$\pi(a|s) = \langle \phi(s,a), w \rangle$$

Arbitrary function approx

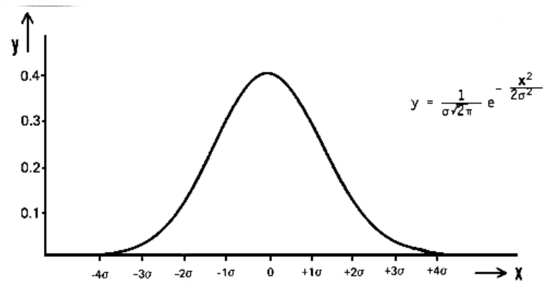




Main thing to learn - Policies

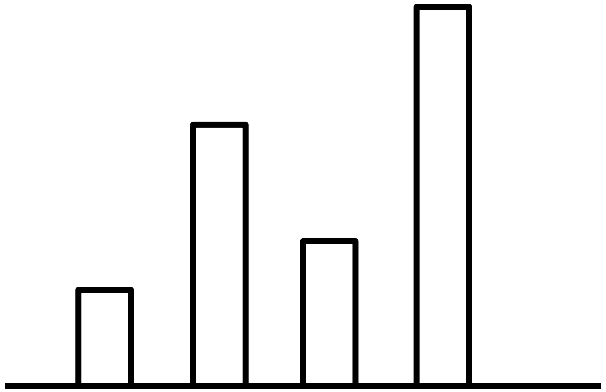
Policies are mappings from states to **distributions** over actions

Gaussian



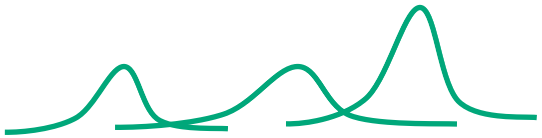
$\mu(s), \Sigma(s)$

Categorical



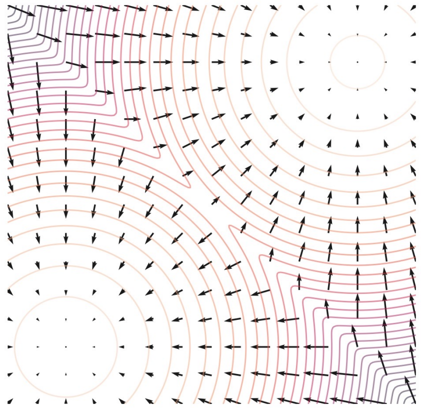
$p_1(s), p_2(s), \dots, p_k(s)$

Mixture of Gaussians



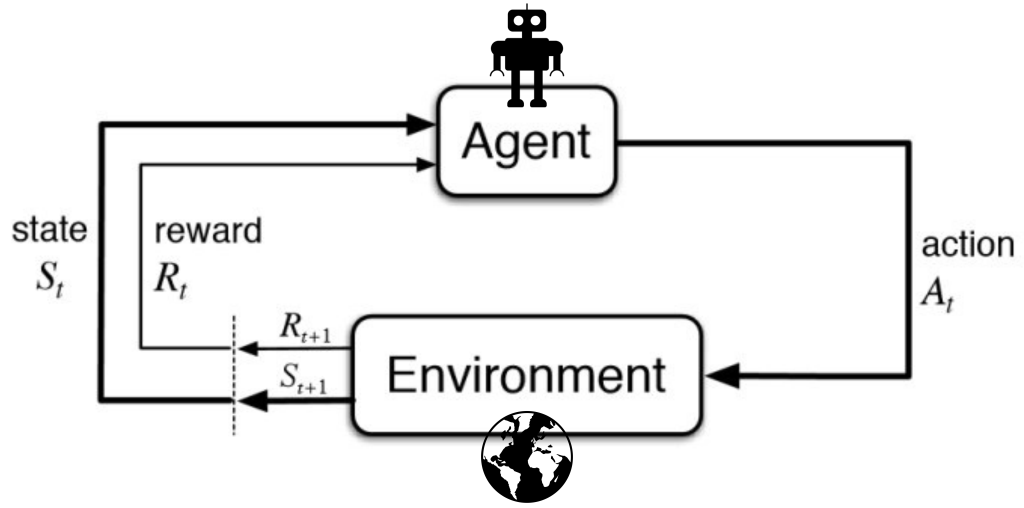
$\mu_1(s), \Sigma_1(s), w_1$
$\mu_2(s), \Sigma_2(s), w_2$
$\dots$
$\mu_N(s), \Sigma_N(s), w_N$

Diffusion Models



$\nabla_a \log \pi(a|s)$

Let’s revisit policies: stochastic vs deterministic



$$\max_{\theta} \mathbb{E}_{\tau \sim \pi_\theta} \left[\sum_{t=0}^{T} r(s_t, a_t) \right]$$

Lemma 1: Every MDP has atleast one optimal *deterministic* policy

Theorem 1.7. *Let Π be the set of all non-stationary and randomized policies. Define:*

$$V^\star(s) := \sup_{\pi \in \Pi} V^\pi(s)$$
$$Q^\star(s,a) := \sup_{\pi \in \Pi} Q^\pi(s,a).$$

which is finite since $V^\pi(s)$ and $Q^\pi(s,a)$ are bounded between 0 and $1/(1-\gamma)$.

There exists a stationary and deterministic policy π such that for all $s \in \mathcal{S}$ and $a \in \mathcal{A}$,

$$V^\pi(s) = V^\star(s)$$
$$Q^\pi(s,a) = Q^\star(s,a).$$

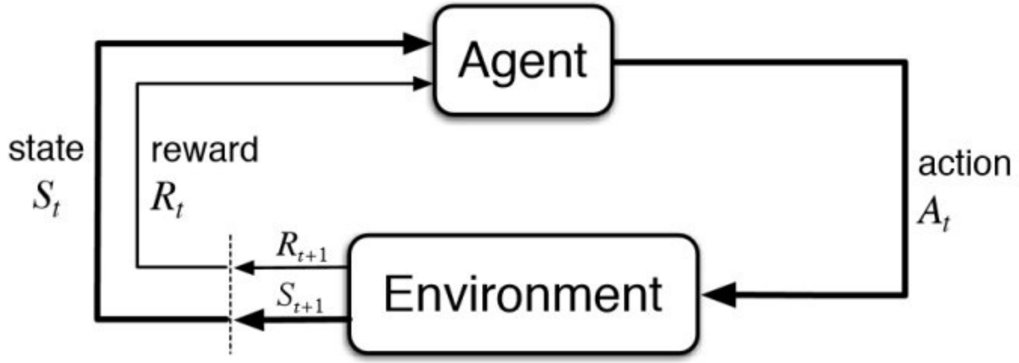
We refer to such a π as an optimal policy.

Intuition: pick the best possible action at every state

Stochastic policies will help in the search/optimization process for finding (close to) deterministic policies

Let's take a closer look at the objective: horizon

$$\max_\theta \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$



Finite horizon

$$\mathbb{E}_{\pi_\theta^t}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$

Time-dependent policy
(not stationary)

$$\mathbb{E}_{\pi_\theta^t}\left[\sum_{t=0}^{T} \gamma^t r(s_t, a_t)\right]$$

Infinite horizon discounted

$$\mathbb{E}_{\pi_\theta}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)\right]$$

Time-independent (stationary) policy
→ Need discount to prevent blow up

Lemma: there always exists a stationary optimal policy

Unpacking the Expectation

$$\max_{\theta} \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$

$$\mathbb{E}_{\pi_\theta^t}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)\right]$$

Trajectory View - Ancestral sampling along MDP

Initial state
Policy
Dynamics
Policy
Dynamics

$$\mathbb{E}_{\substack{s_0\sim\rho_0(s)\\ a_0\sim\pi_\theta(.|s_0)\\ s_1\sim p(.|s_0,a_0)\\ a_1\sim\pi_\theta(.|s_1)\\ s_2\sim p(.|s_1,a_1)\\ \dots}}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$

Compact representation

$$\mathbb{E}_{\substack{s_0\sim\rho_0(s)\\ a_t\sim\pi_\theta(.|s_t)\\ s_{t+1}\sim p(s_{t+1}|s_t,a_t)}}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$

Stationary View – sampling from stationary dist

$$d_t^\pi(s,a) = \mathbb{P}(s_t = s, a_t = a \mid s_0 \sim \rho_0, \forall i < t, a_i \sim \pi_\theta(\cdot|s_i), s_{i+1} \sim p(\cdot|s_i, a_i))$$

(Likelihood of being at state s, action a at time step t)

$$\mu_\pi^\gamma(s,a) = (1-\gamma)\sum_{t=0}^{\infty} \gamma^t d_t^\pi(s,a)$$

(Likelihood of being at state s, action a across **all** steps)

γ subsumed into E

$$\mathbb{E}_{(s,a)\sim\mu_\gamma^\pi(s,a)}\left[r(s,a)\right]$$

No sequential sampling

No sum over rewards

Some notation: Q-functions and V-functions

Estimate of how "good" a policy is – estimate of future returns under a policy π

Q-function

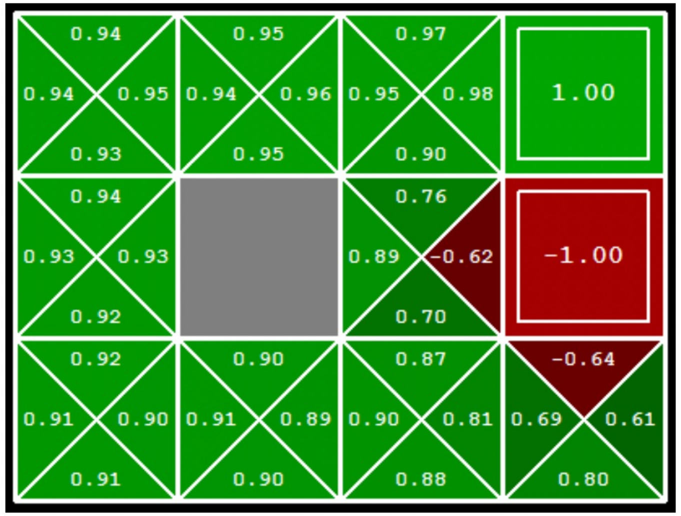
Take one action and then follow policy from s

$$Q^\pi(s,a) = \mathbb{E}_{\pi,p}\left[\sum_t r(s_t,a_t) \mid s_0 = s, a_0 = a\right]$$

V-function

Follow policy from s

$$V^\pi(s,a) = \mathbb{E}_{\pi,p}\left[\sum_t r(s_t,a_t) \mid s_0 = s\right]$$



$$V^\pi(s,a) = \mathbb{E}_{a\sim\pi(\cdot|s)}\left[Q^\pi(s,a)\right]$$

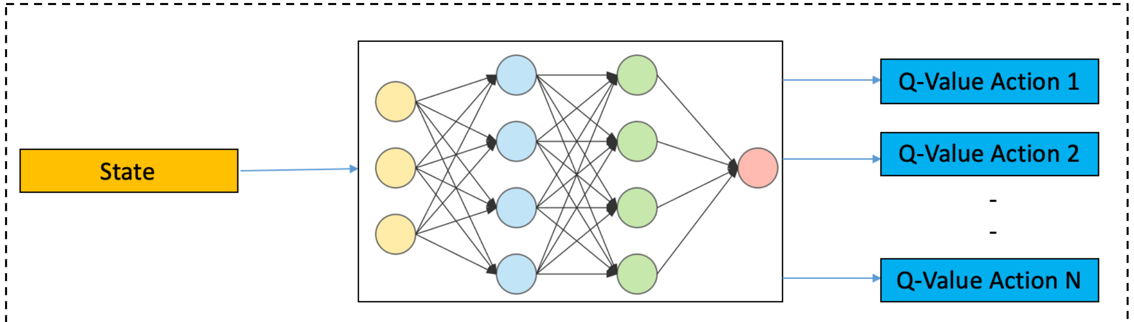
Will be useful soon!

$$J(\pi) = \mathbb{E}_{s\sim\rho_0(s)}\left[V^\pi(s)\right]$$

Average value over initial states

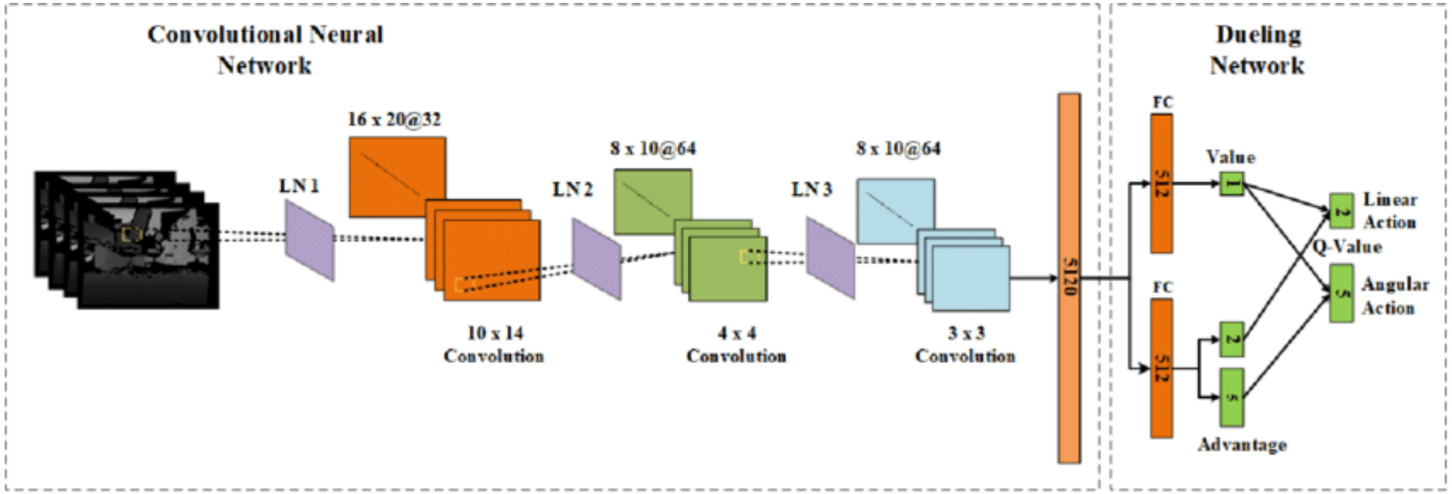
Ok so where does deep learning fit in?

Avoids expensive hand-design for adaptive agents, learn end-to-end: sensors → actions



Deep Q Learning

Policies/Q-values/model are represented as deep neural networks



Leads to non-trivial challenges in learning and optimization!

Why is deep RL important now?

Deep models have enabled the huge advances in modern AI

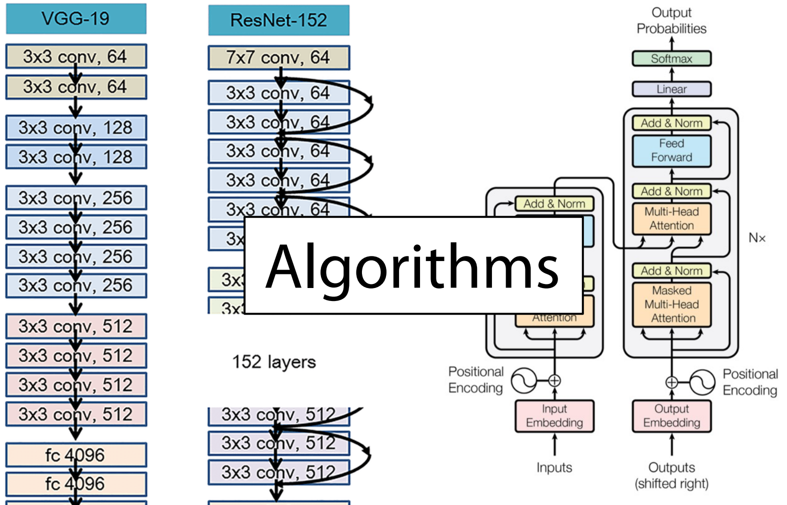
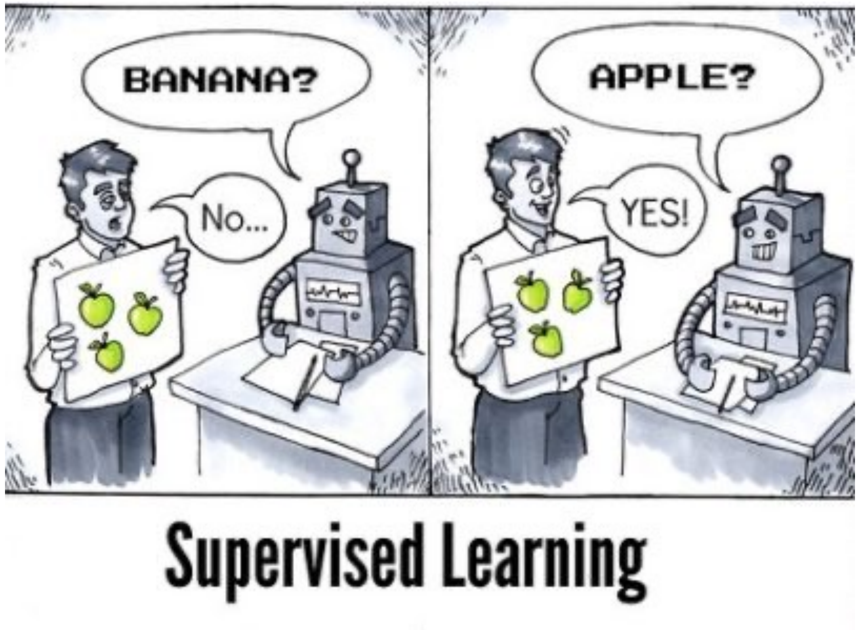


Figure 1: The Transformer - model architecture.

We are betting that the same holds for RL

Ok so is this just supervised learning?

Supervised learning aims to maximize likelihood of observed data under the model



$$\max_{\theta} \mathbb{E}_{(x,y)\sim\mathcal{D}} \left[\log \hat{p}_{\theta}(y|x)\right]$$

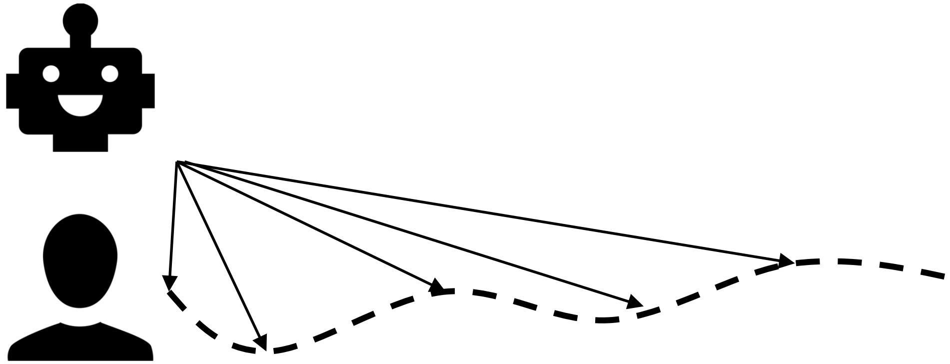
Why is this not just supervised learning?

Supervised Learning

$$\max_\theta \mathbb{E}_{(x,y)\sim\mathcal{D}}\left[\log \hat{p}_\theta(y|x)\right]$$

Sampling from expert

$D_{\mathrm{KL}}(p^* || p_\theta)$ IID

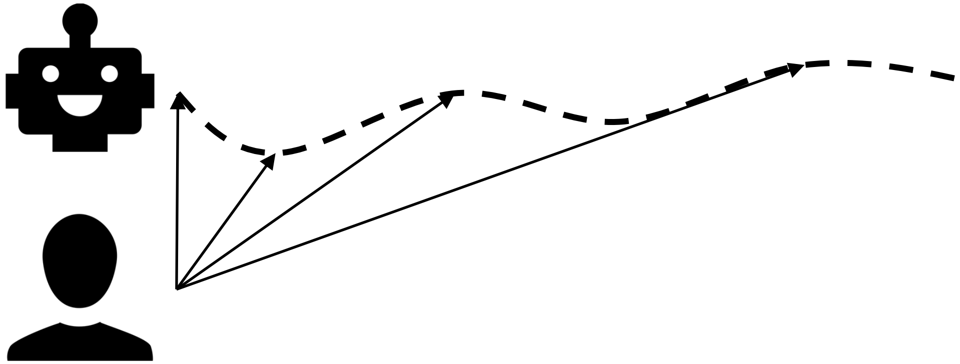


Reinforcement Learning

$$\max_\theta \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$

Sampling from policy

$D_{\mathrm{KL}}(p_\theta || p^*)$ Non-IID



Why is this not just supervised learning?

Supervised Learning

$$\max_{\theta} \mathbb{E}_{(x,y)\sim\mathcal{D}} \left[\log \hat{p}_\theta(y|x)\right]$$

Reinforcement Learning

$$\max_{\theta} \mathbb{E}_{\tau\sim\pi_\theta} \left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$

The resulting paradigms are different in many ways:

1. Optimization and learning dynamics
2. Balancing exploration and exploitation

$$\Downarrow$$

But many overlapping tools! In fact often we try to convert RL into a supervised problem

Lecture Outline

Course logistics and scope

↓

What is RL, a formal definition

↓

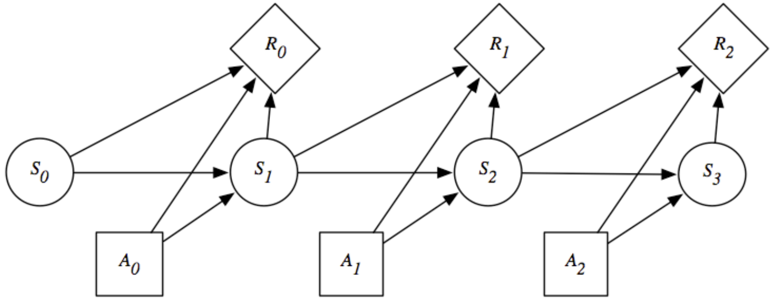
Why should we care?

↓

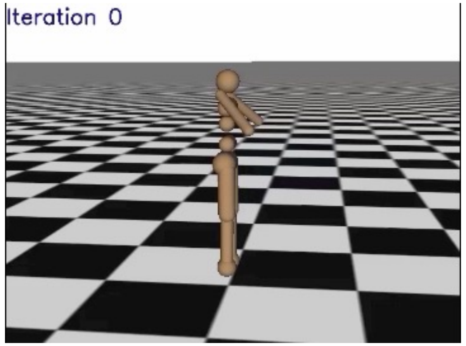
Going beyond RL

Ok so why should we care about RL?

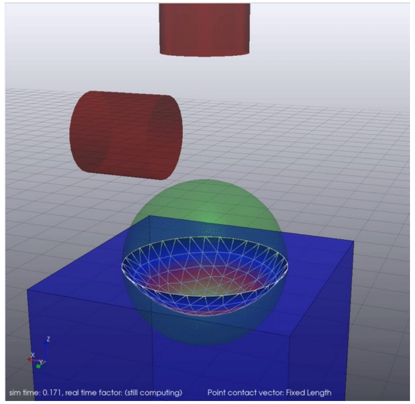
Solves sequential decision making problems



Enables continual improvement



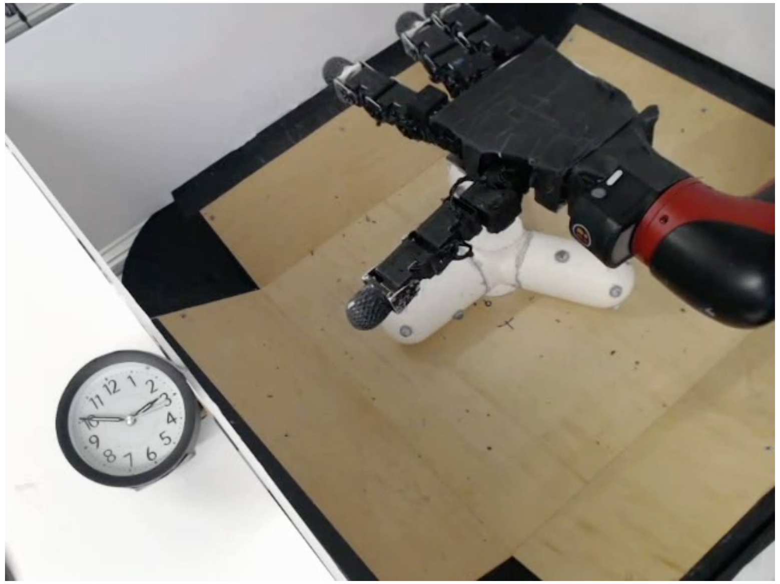
Has black-box assumptions

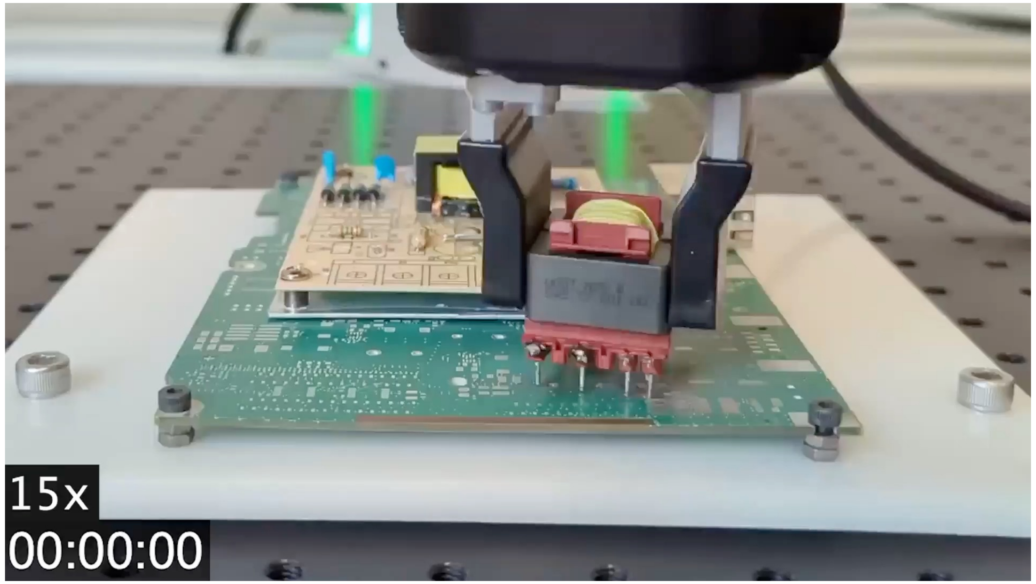


Reduces burden of human data collection

Applications of RL: Robotics

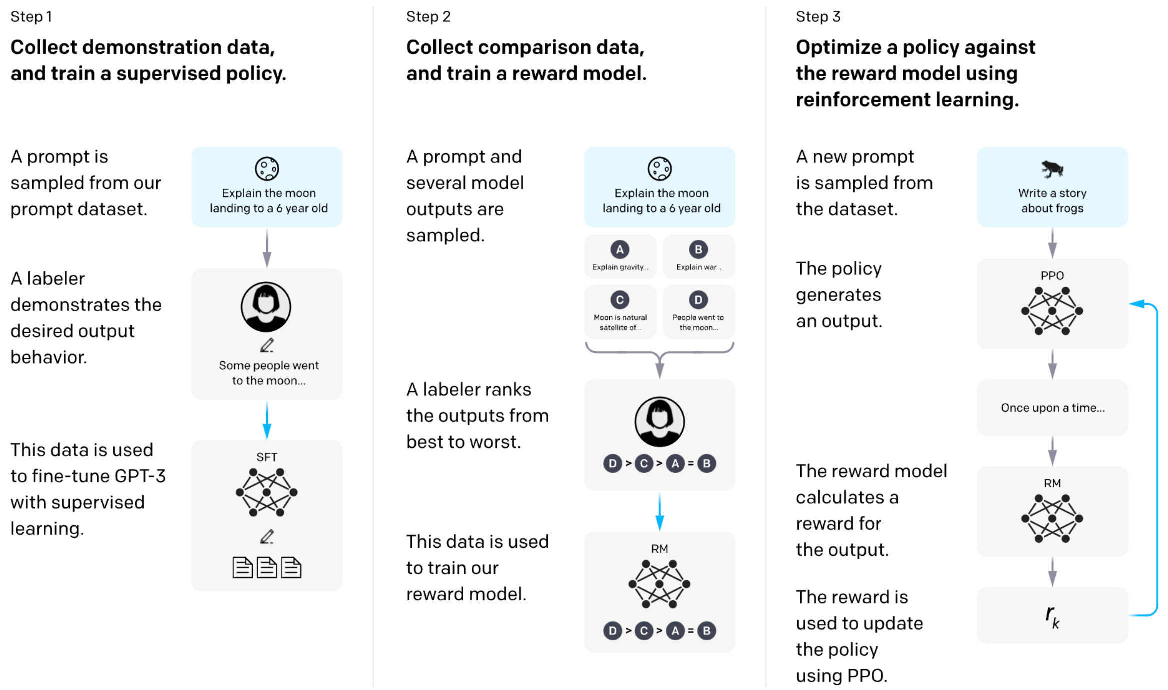
RL can enable robotic learning of hard to specify/script behaviors in the presence of contact





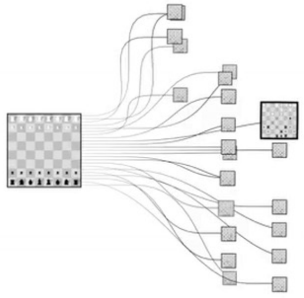
Applications of RL: Large Language Models

Systematically finds and reduces model hallucinations using RLHF



Applications of RL: Games

Both single and multi-agent RL has proven transformative for game AI

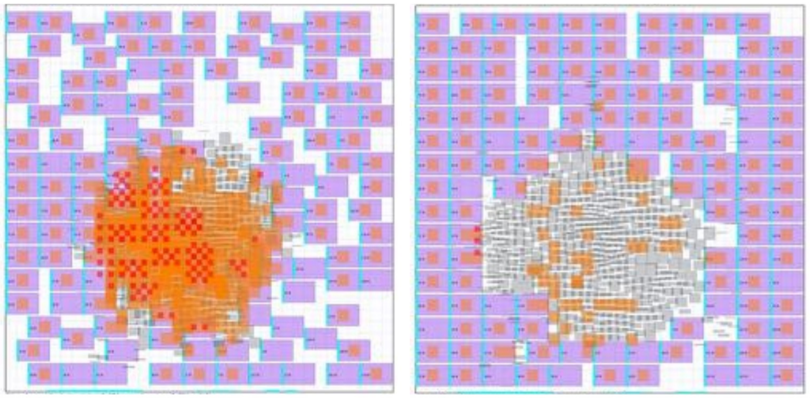


Particularly well suited to RL assumptions

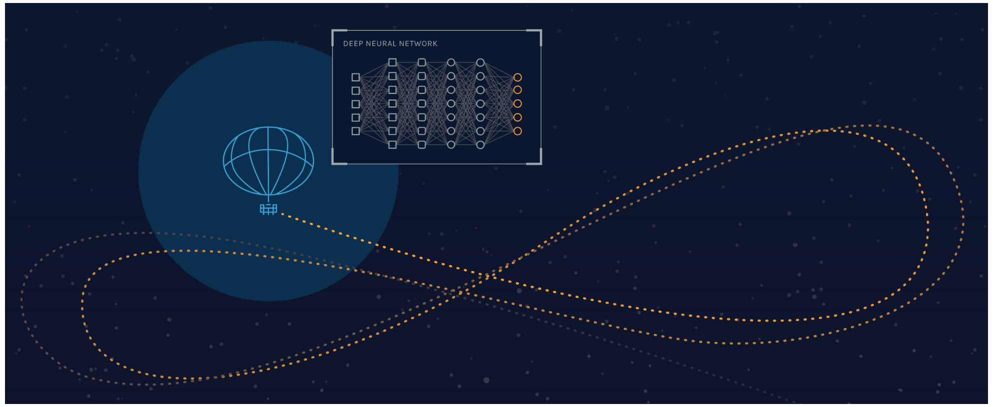
Applications of RL: Science and Engineering

RL has started to become a useful tool for engineering design

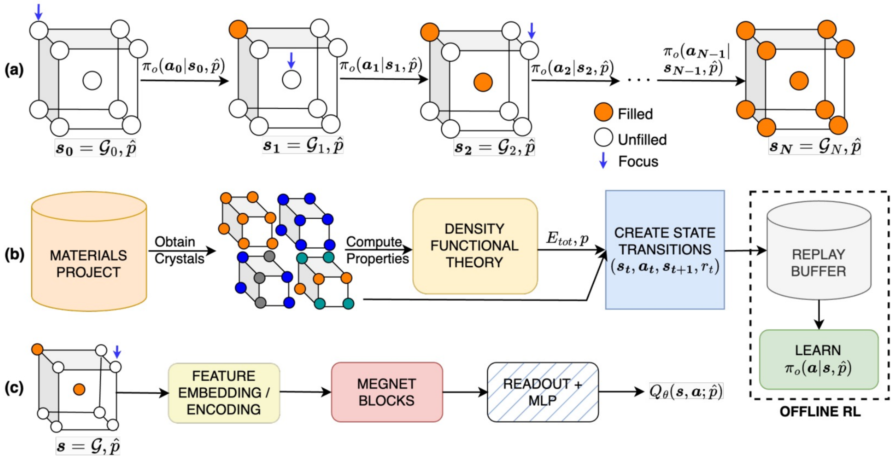
Chip Design



Weather balloon navigation

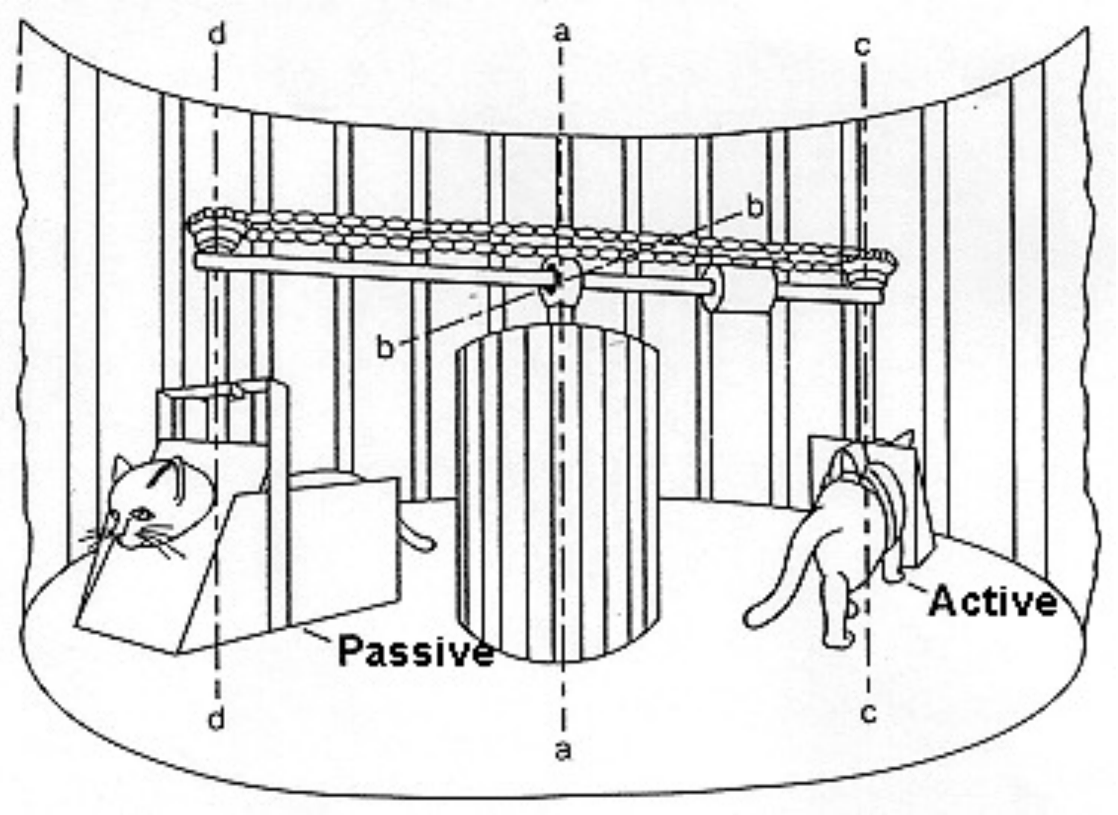


Crystal design



Zooming out – why this matters for the study of intelligence?

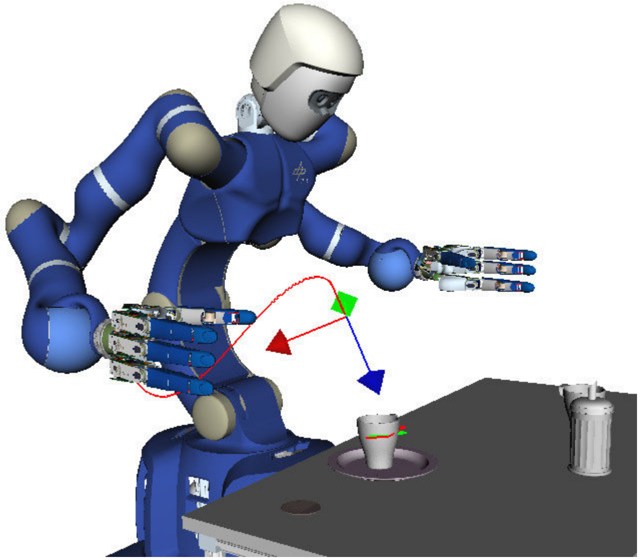
Hypothesis: Intelligence with and without embodiment looks drastically different



Elephants don't play chess!

Why must we study RL in the real world?

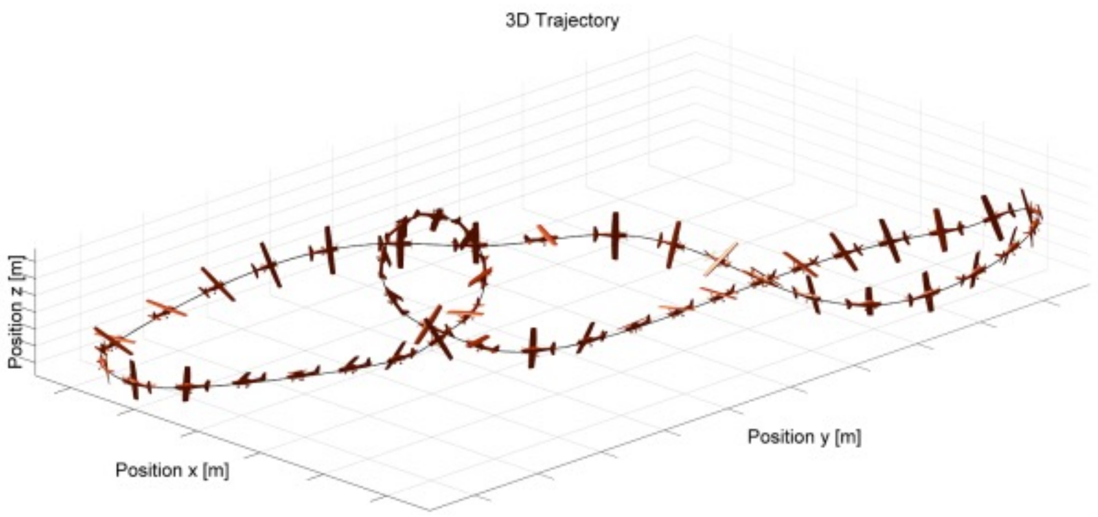
Hypothesis: Agents that learn with embodiment will have emergent complexity in complex, dynamic environments



Increasingly interesting behavior

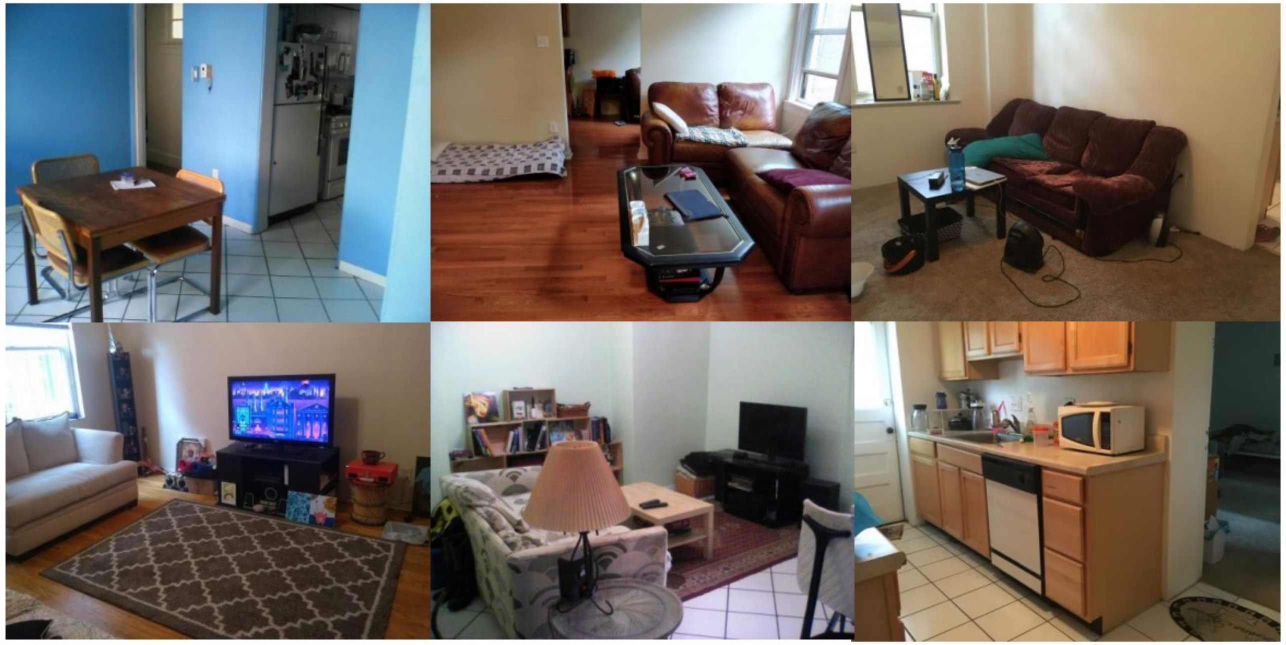
Where is Reinforcement Learning not useful?

Not the right call for very safety-critical, repetitive applications



Where is Reinforcement Learning "potentially" useful?

Domains which have high diversity, yet relatively cheap autonomous data collection



But these domains are not as simple as just running RL algorithms!

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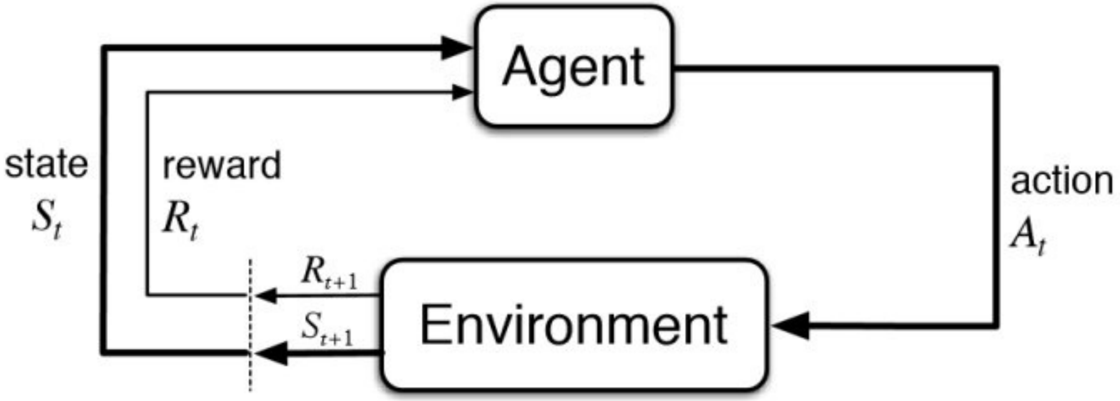
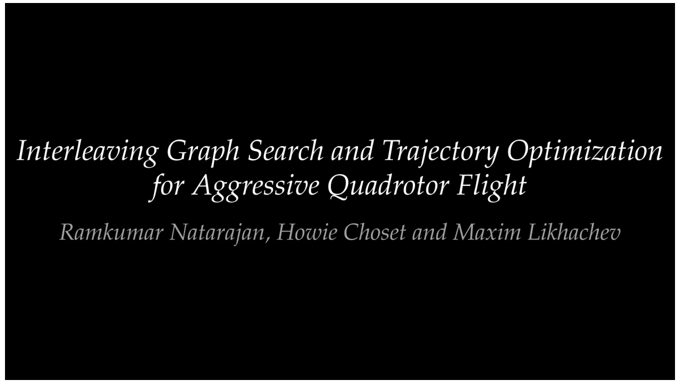
So is sequential decision making = RL?



We conflated sequential decision making and RL!

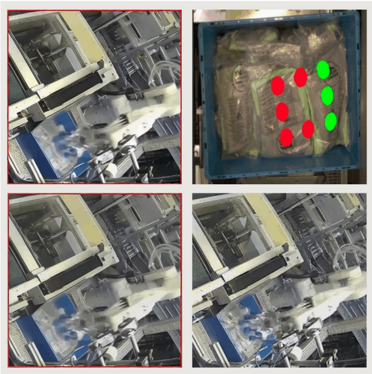
RL is sequential decision making under a particular set of assumptions:
1. Sampling access to the environment
2. Access to reward
3. Goal-directed behavior

<u>Trajectory optimization/planning</u>



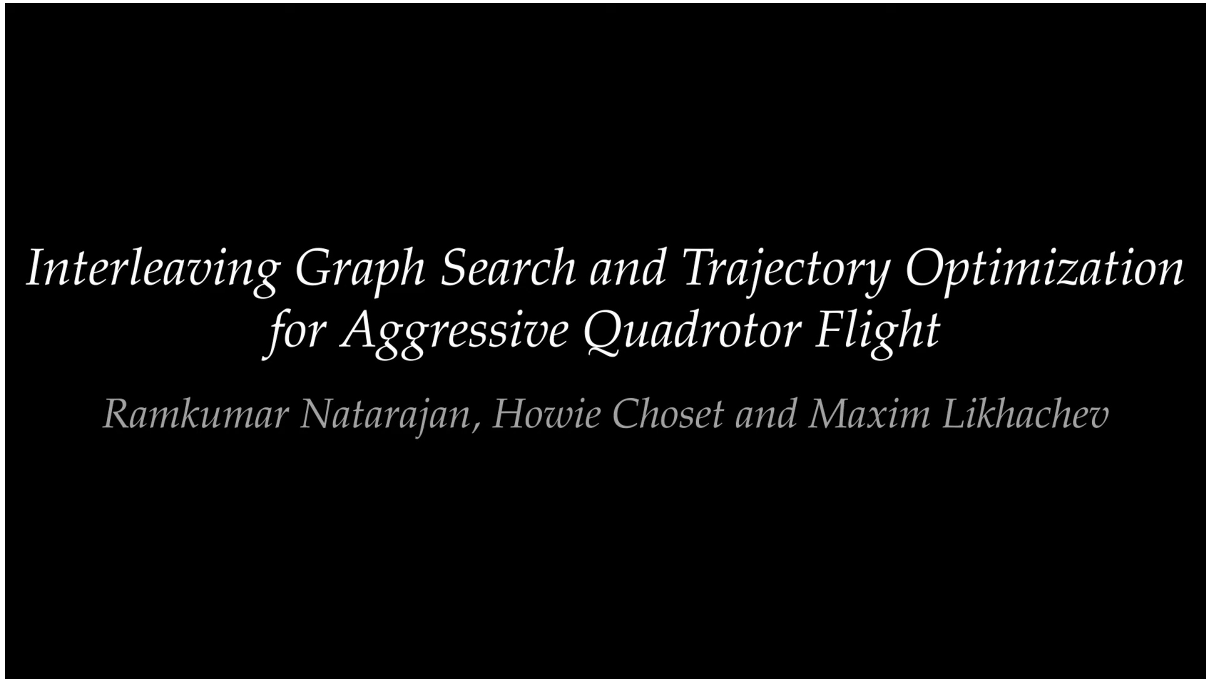
<u>Imitation Learning</u>

<u>Unsupervised Decision Making</u>



Trajectory Optimization

Sequential decision making with ”known” models



We combine RRT and local smoothing of contact dynamics to generate complex contact-rich manipulation plans.

May be hard to construct perfect, known models

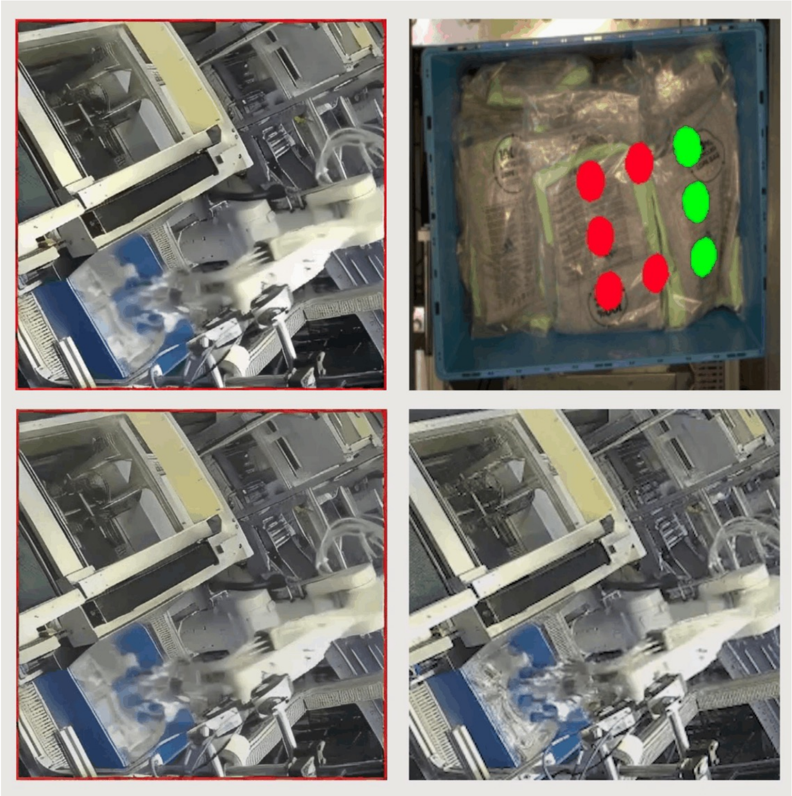
Imitation Learning

Sequential decision making provided expert data

Often called learning from demonstrations

Self-Supervised Prediction of the World

Sequential decision making without reward – self-supervised prediction



Often called model-based RL

How should we think about designing effective RL algorithms?

Easy to specify **objectives**

Stable performant **optimization** algorithms

Efficient **data** collection

Class Structure