Reinforcement Learning

CS6960 MultiModal LLM Agents

Kenneth Marino

Slide credits: Daniel Brown, Dan Klein and Pieter Abbeel, Chelsea Finn, others

Quick Announcements

- Add/Drop Course
  - Class is pretty much at capacity
  - If you already know you will drop, please do that ASAP so people can get in off the waiting list
- HW0 due next week
  - It’s really short and easy
  - Basically just asking you to read the intro unit to the HF Agents tutorial and write some boilerplate code

Recommended Readings

- Reinforcement Learning an Introduction - Sutton & Barto
  - It's all good but for introduction to RL Ch1&3 are helpful
  - http://incompleteideas.net/book/RLbook2020.pdf
- Reinforcement Learning Courses
  - Stanford Deep RL Class: https://cs224r.stanford.edu/
  - Berkeley Deep RL Course: https://rail.eecs.berkeley.edu/deeprlcourse/
  - If you need to understand particular topic/algorithm, notes from these courses are really useful

Warning

- I can’t possibly cover everything about RL in a single lecture
- Goal: give the high-level overview of RL and how it can be used in agents
- If you took e.g. Daniel Brown’s course, this will be mostly review
- You probably don’t need to know everything about RL to understand VLM agents
- For papers/project, if you need to know more details
  - E.g. details of algorithms like PPO
  - See recommended readings/resources

Any Questions

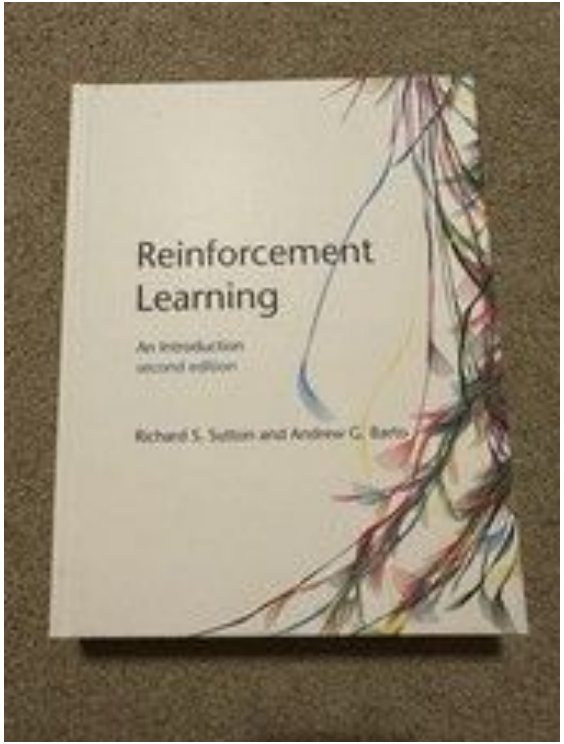
Recall: What are Agents?

- VLM Agents

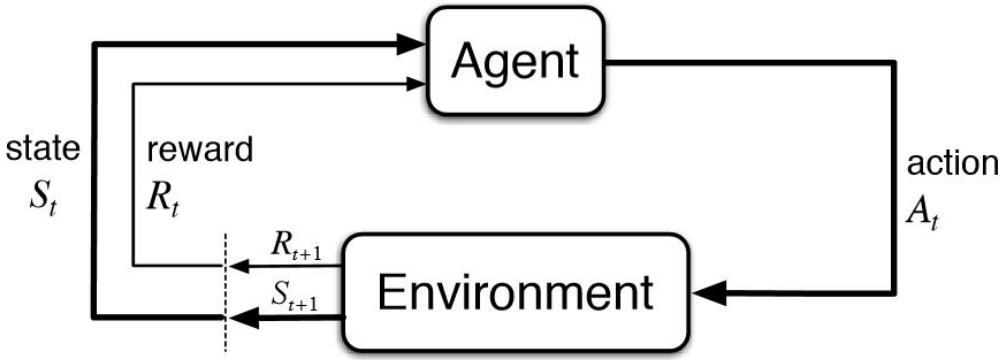
What Even is an Agent?

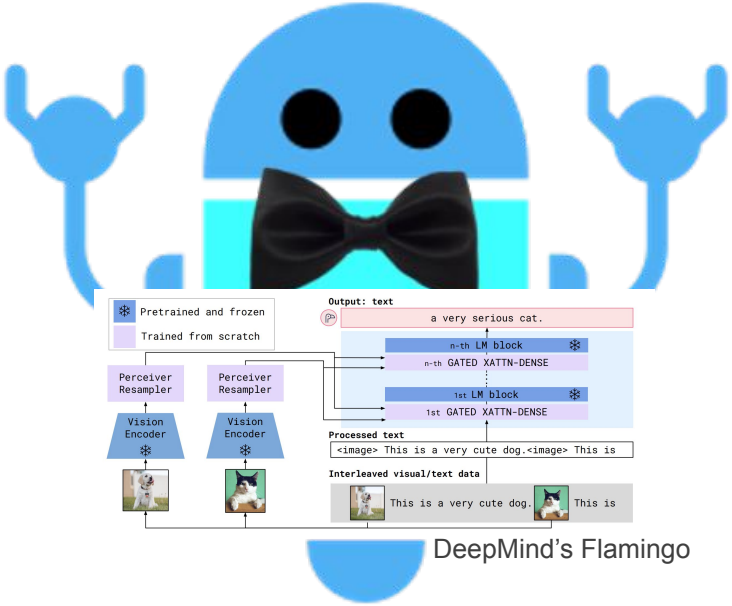
Recall: Classical Definition

- Sutton and Barto: "The learner and decision maker is called the agent. The thing it interacts with, comprising everything outside the agent, is called the environment."



Recall: VLM Agents

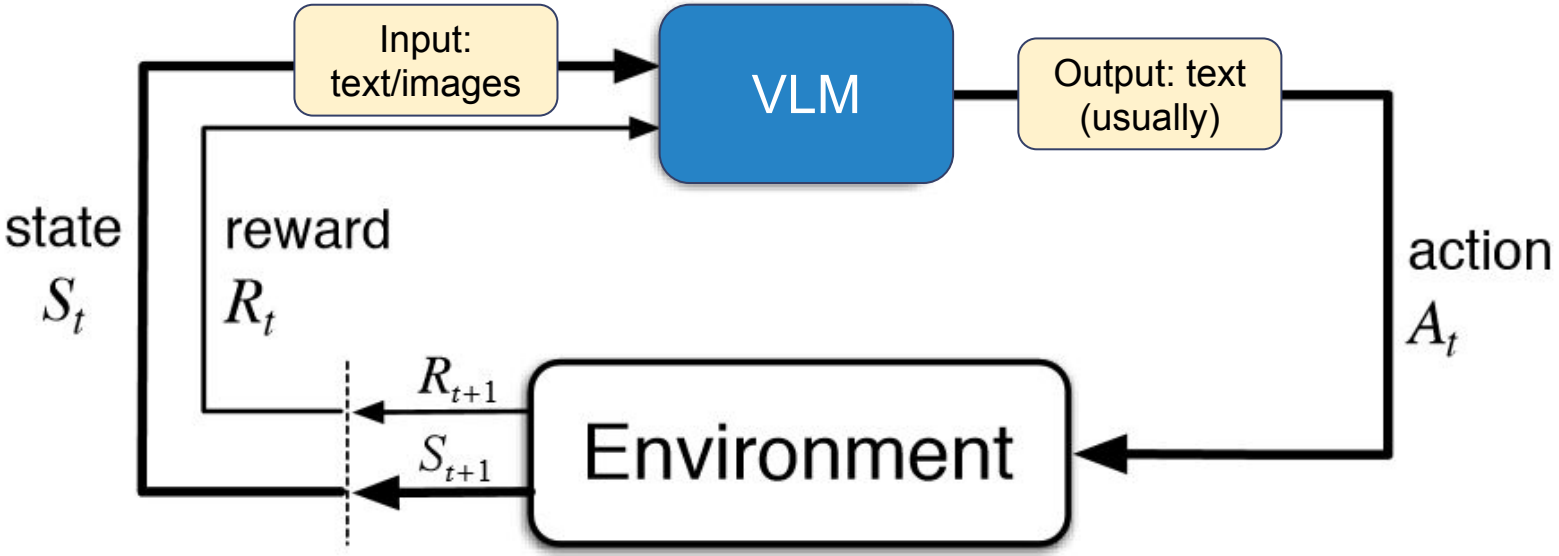




DeepMind's Flamingo

Agent

Recall: VLM Agents



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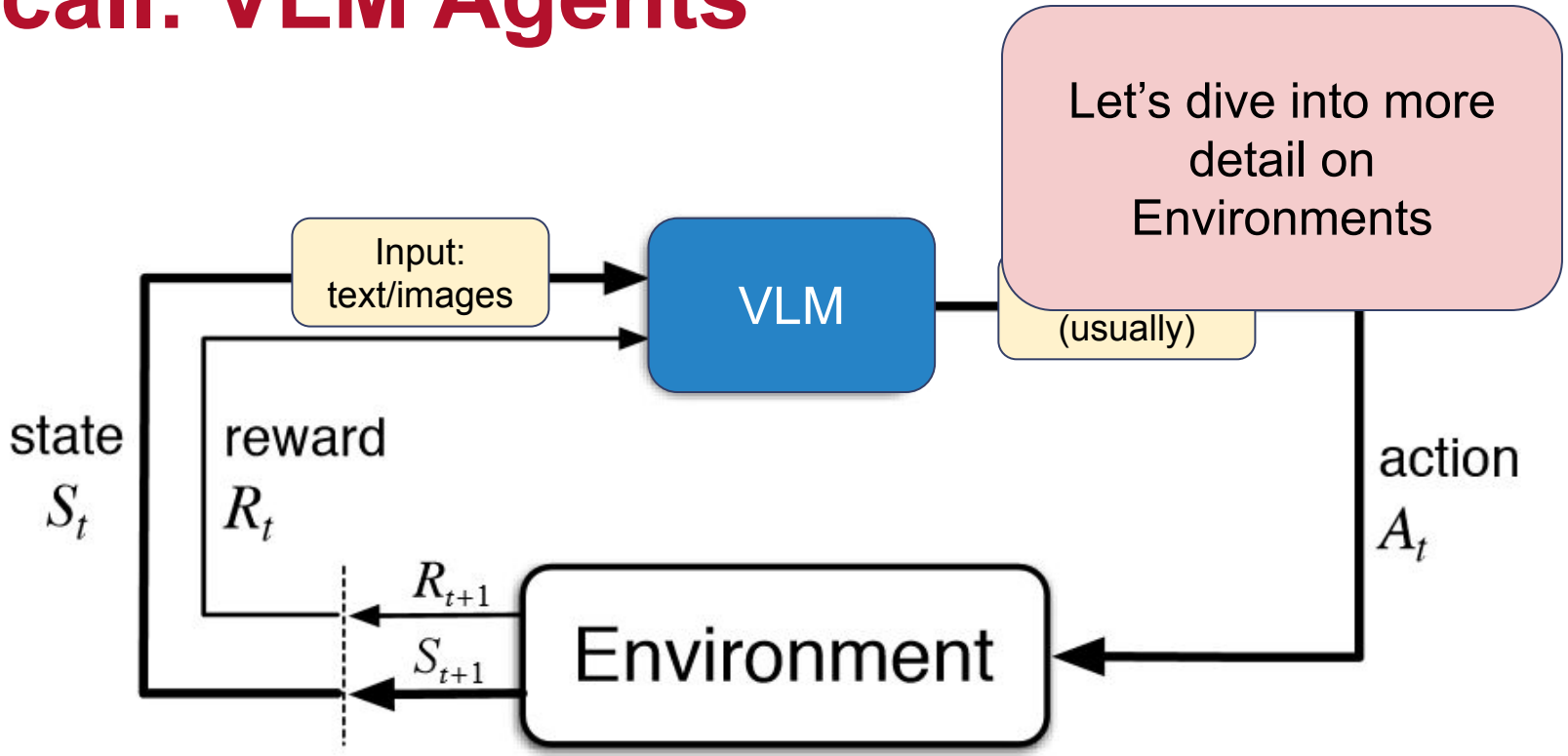


Clarifying Terms

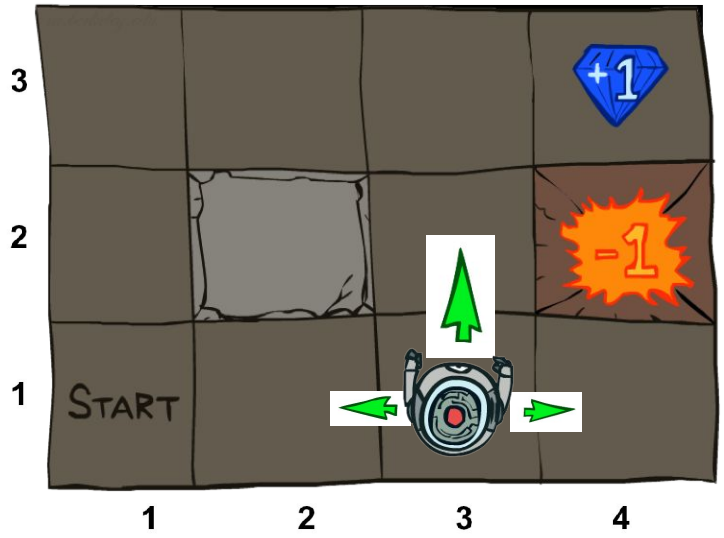
- When I say RL sometimes I mean
  - The science of understanding decision making agents in environments
- Sometime it means, a specific set of algorithms for maximizing reward from experience
  - E.g. REINFORCE, Q-Learning, PPO are RL algorithms
  - Behavior cloning is not technically an RL algorithm, but we often talk about it in RL classes because it's an algorithm for training decision making agents
- VLM Agents require an understanding of the first (it is about decision making)
- VLM Agents may not use RL algorithms (can use BC or even just prompting)

Slide credit: Daniel Brown

[Demo – gridworld manual intro (L8D1)]

Environments Defined by MDPs

- An MDP is defined by:
  - A set of states $s \in S$
  - A set of actions $a \in A$
  - A transition function $T(s, a, s')$
    - Probability that a from s leads to s', i.e., $P(s'| s, a)$
    - Also called the model or the dynamics
  - A reward function $R(s, a, s')$
    - Sometimes just R(s), R(s,a), or R(s')
  - A start state
  - Maybe a terminal state



Slide credit: Daniel Brown

[Demo – gridworld manual intro (L8D1)]

What is Markov about MDPs?

- "Markov" generally means that given the present state, the future and the past are independent. Conditional Independence!

- For Markov decision processes, "Markov" means action outcomes depend only on the current state

$$P(S_{t+1} = s' | S_t = s_t, A_t = a_t, S_{t-1} = s_{t-1}, A_{t-1}, \ldots S_0 = s_0)$$

$$=$$

$$P(S_{t+1} = s' | S_t = s_t, A_t = a_t)$$

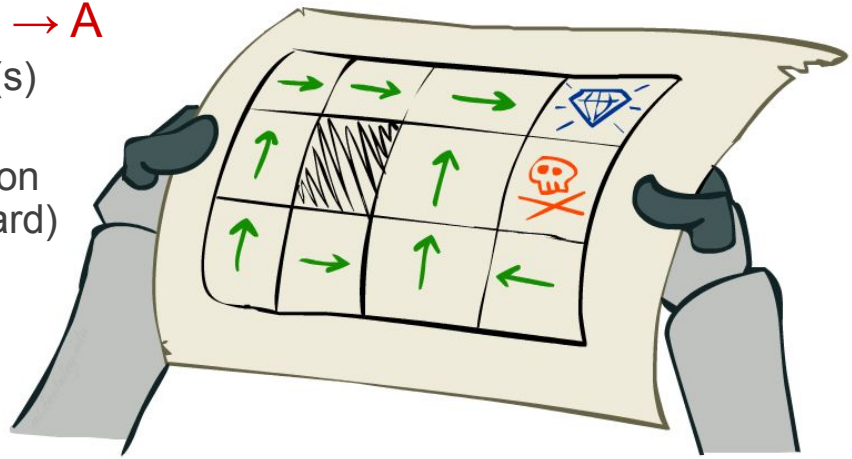
Andrey Markov
(1856-1922)

Slide credit: Daniel Brown

Policies

- For MDPs, we want an optimal policy $\pi^*: S \rightarrow A$
  - A policy π gives an action for each state: $a = \pi^*(s)$
  - Depends only on the current state (not past states)
  - In an optimal policy, at every state, taking the action given by our policy leads to the most utility (reward)

- How do we learn this policy?



Optimal policy when R(s, a, s') = -0.03
for all non-terminals s

Slide credit: Daniel Brown

How do we learn a policy?

- Old-school Tabular RL
  - Given the full MDP and a discrete state/action space, calculate the optimal actions/values at each state
  - Essentially a DP problem
  - Sutton/Barto book goes into a lot of details about this

Try to figure out what each state "is worth"

Slide credit: Daniel Brown

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- Model-Free Methods
  - No access to underlying MDP, can't solve it with just computation
  - State/action spaces not necessarily discrete/finite
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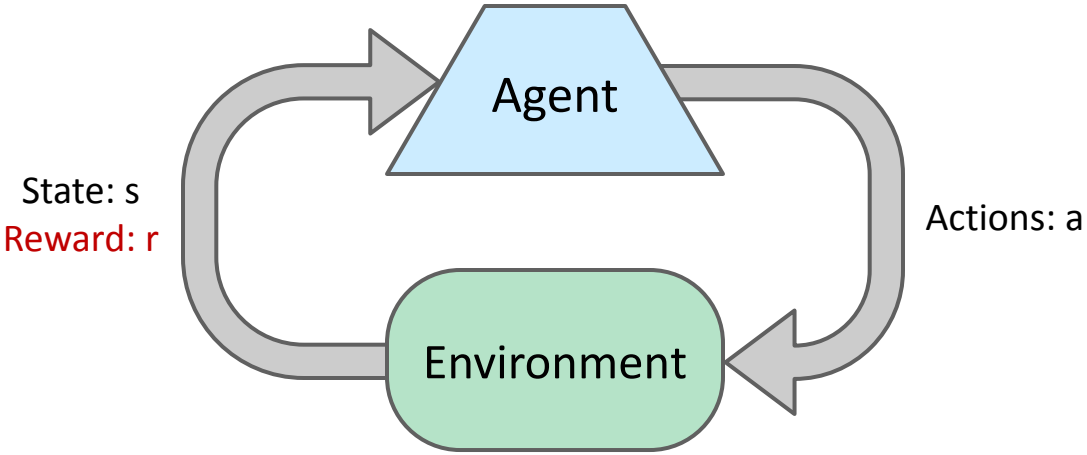
- Model-Free Methods
  - No access to underlying MDP, can't solve it with just computation
  - State/action spaces not necessarily discrete/finite
  - You needed to actually act to figure it out
- Important ideas in reinforcement learning that come up
  - Exploration: you have to try unknown actions to get information
  - Exploitation: eventually, you have to use what you know
  - Regret: even if you learn intelligently, you make mistakes
  - Sampling: because of chance, you have to try things repeatedly
  - Difficulty: learning can be much harder than solving a known MDP

Slide credit: Daniel Brown

Reinforcement Learning



- Basic idea:
  - Receive feedback in the form of rewards
  - Agent's utility is defined by the reward function
  - Must (learn to) act so as to maximize expected rewards
  - All learning is based on observed samples of outcomes!

Slide credit: Daniel Brown

Goal: Maximize Return/Utility

- Return: sum of all future rewards $G_t = R_{t+1} + R_{t+2} + R_{t+3} + \cdots + R_T$
- Often we care about *discounted Return
  - Idea, reward later isn't as good as reward sooner
  - Want to get to goal/reward sooner ideally
  - Discount factor 0 > γ >= 1

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

- Utility (sometimes used interchangeably with return) is just expected utility

$$E[G_t] = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1}\right]$$

Goal: Maximize Return/Utility

- Return: sum of all future rewards $G_t = R_{t+1} + R_{t+2} + R_{t+3} + \cdots + R_T$
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  - Idea, rewa
  - Want to g
  - Discount
- Utility (sometir

In agents, utility is often just 0/1 at the end if we completed a task*

* But not always. E.g. you might want your agent to minimize things like cost, or give negative rewards for unsafe behavior

R_{t+k+1}

y

$\left[\sum_{k=0}$

Example: Learning to Walk

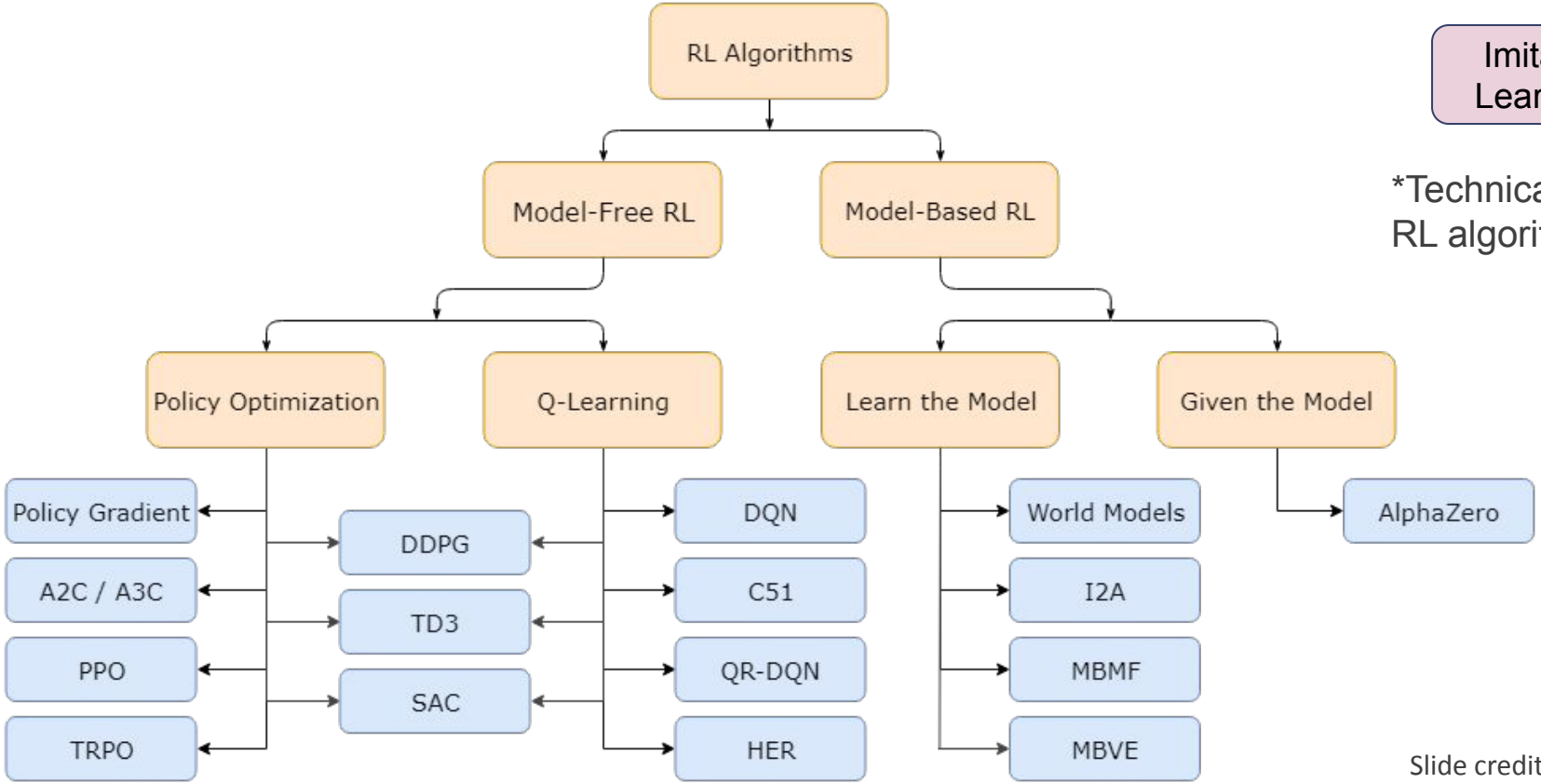
Initial

A Learning Trial

After Learning [1K Trials]

[Kohl and Stone, ICRA 2004]

Rough Taxonomy of RL Algorithms

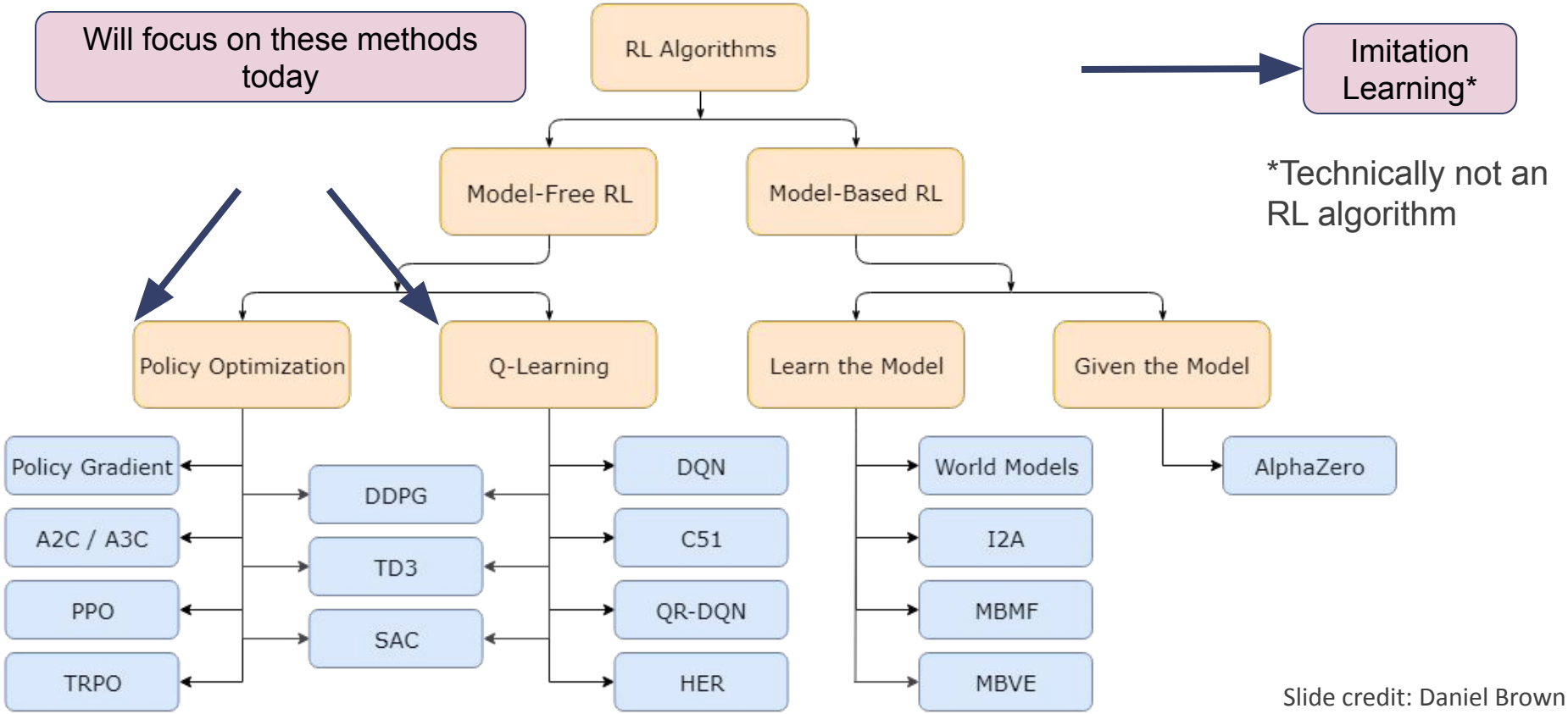


Imitation Learning*

*Technically not an RL algorithm

Slide credit: Daniel Brown

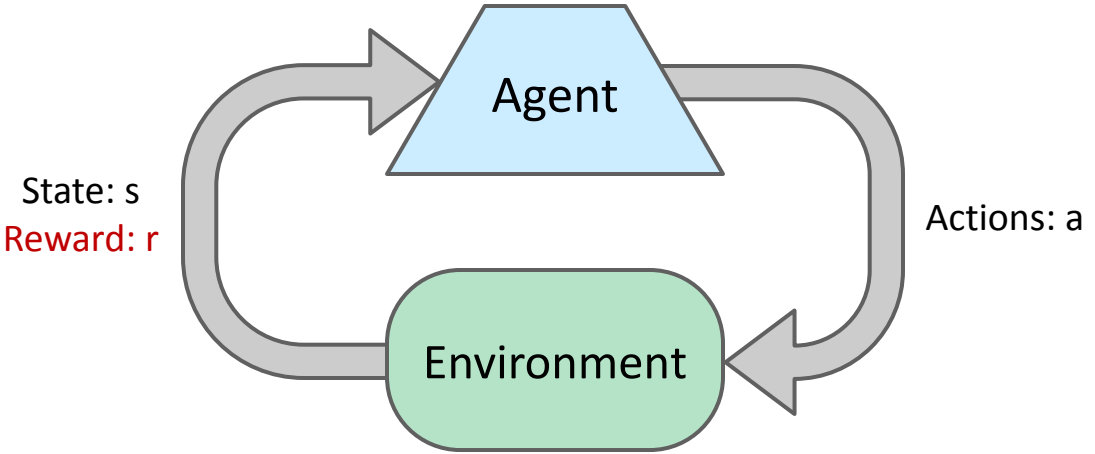
Rough Taxonomy of RL Algorithms



Slide credit: Daniel Brown

Reinforcement Learning

- Still assume there exists a Markov decision process (MDP):
  - A set of states $s \in S$
  - A set of actions (per state) A
  - A model T(s,a,s')
  - A reward function R(s,a,s')
- Still looking for a policy $\pi(s)$



Slide credit: Daniel Brown

Option 1: Imitation Learning

Common algorithm: Behavioral Cloning

Slide credit: Chelsea Finn

Goal of Imitation Learning

Data: Given trajectories collected by an expert

"*demonstrations*" $\mathcal{D} := \{(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T)\}$

(sampled from some unknown policy π_{expert})

Goal: Learn a policy π_θ that performs at the level of the expert policy, by mimicking it.

Example

- Dataset from human drivers
- Sensor readings + steering commands

Slide credit: Chelsea Finn

Imitation Learning - v1

0. Given demonstrations collected by an expert $\mathcal{D} := \{(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T)\}$

1. For deterministic policy, supervised regression to the expert's actions

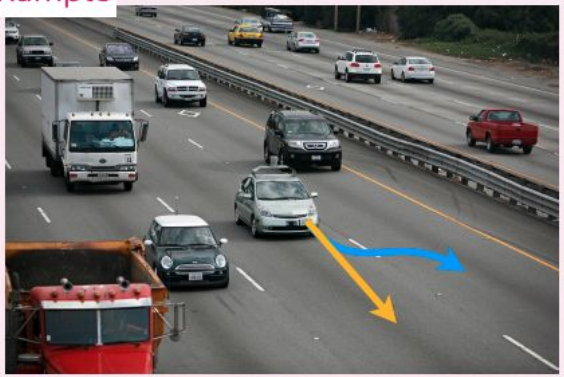
$$\min_{\theta} \frac{1}{|\mathcal{D}|} \sum_{(\mathbf{s},\mathbf{a})\in\mathcal{D}} \|\mathbf{a} - \hat{\mathbf{a}}\|^2 \qquad \text{where } \hat{\mathbf{a}} = \pi_\theta(\mathbf{s})$$

2. Deploy learned policy π_θ

Slide credit: Chelsea Finn

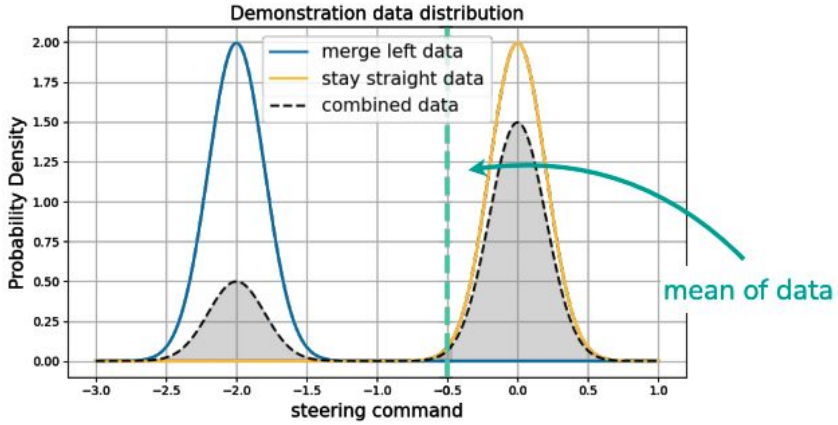
What can go wrong?

Example



- Dataset from human drivers
- Sensor readings + steering commands

Question: what might policy trained with ℓ_2-regression do?



How can we represent more than the mean?

How often does this happen in practice? All the time!

Esp. when data collected by multiple people.

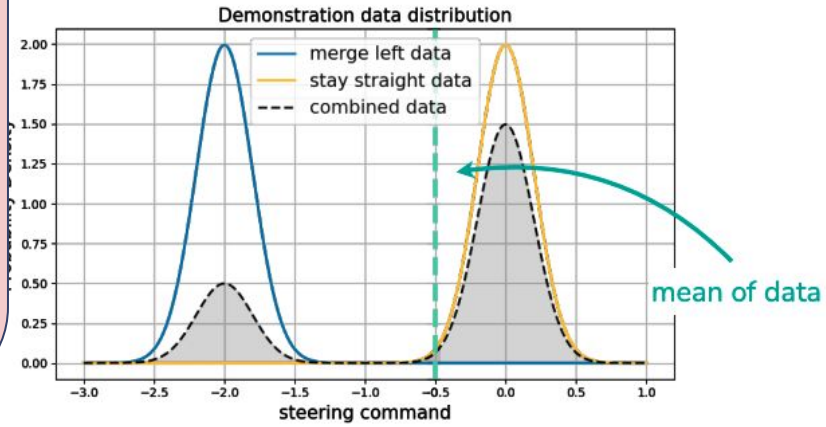
Slide credit: Chelsea Finn

What can go wrong?

Confusingly for this class, often this is called a multimodal distribution (because it has multiple modes)
But we often mean, multiple modes of input (e.g. vision and language)
Hopefully from context its clear which one I mean

- Sensor readings + steering commands

n: what might policy trained with ℓ_2-regression do?



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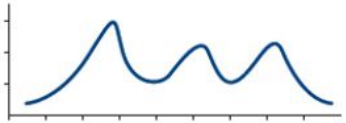
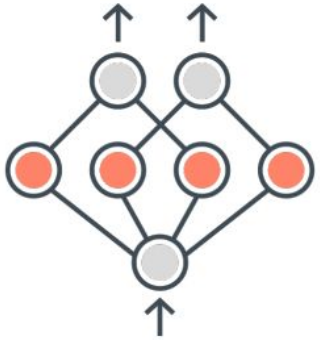
Learning Distributions with NNs



parameters of distribution

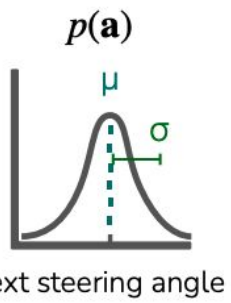


1D discrete actions

Neural net outputs $p(\text{up}), p(\text{down}), \ldots$ represent categorical distribution.

Maximally expressive

Continuous actions



Neural net outputs μ, σ to represent Gaussian distribution.

Not very expressive!

Slide credit: Chelsea Finn

Imitation Learning v2

Expressive policies

0. Given demonstrations collected by an expert $\mathcal{D} := \{(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T)\}$

1. Train **generative model** of the expert's actions

$$\min_\theta - \mathbb{E}_{(\mathbf{s},\mathbf{a})\sim\mathcal{D}}[\log \pi_\theta(\mathbf{a}\,|\,\mathbf{s})]$$ with expressive distribution $\pi(\cdot\,|\,\mathbf{s})$

maximize the log probability of the demo actions under the policy

2. Deploy learned policy π_θ

Slide credit: Chelsea Finn

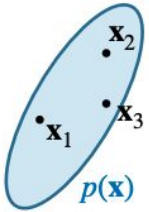
How this connects to agents

- v1
  - Works well for discrete actions
  - Works well for VLM agents where our action space is text
  - Most common way of learning policies in this course
  - Is actually just another way of doing SFT (we'll discuss how we do SFT on VLMs next lecture)
- v2
  - Matters most when output is something continuous like robotics actions
  - Will cover this more on Robotics unit

What can still go wrong?

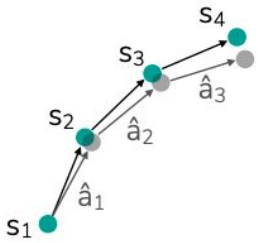
Compounding errors

Supervised learning



Inputs independent of predicted labels $\hat{\mathbf{y}}$

Supervised learning of behavior



Predicted actions affect next state.

Errors can lead to drift away from the data distribution!

Errors can then compound!

$$p_{expert}(\mathbf{s}) \neq p_{\pi}(\mathbf{s})$$

states visited by expert

states visited by learned policy π

"covariate shift"

Slide credit: Chelsea Finn

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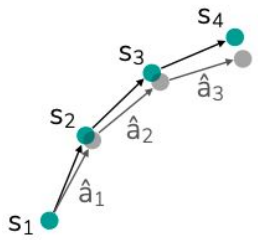
Compounding errors

Supervised learning of behavior



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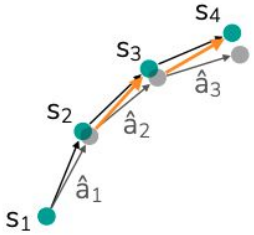
Solutions?

1. Collect A LOT of demo data & hope for the best.
2. Collect corrective behavior data



Slide credit: Chelsea Finn

Other problems with IL

- Can only learn from positive data
  - Only have positive examples of what the agent should do
  - Can we learn from mistakes?
- Covariate drift
  - Discussed above (compounding errors, veering out of our data distribution)
  - Ideally we have some way to update our policy ***online*** (i.e. update the policy live in the actual environment)

Other problems with IL

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Need true RL

Reinforcement Learning

- We still assume an MDP:
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  - A model T(s,a,s')
  - A reward function R(s,a,s')
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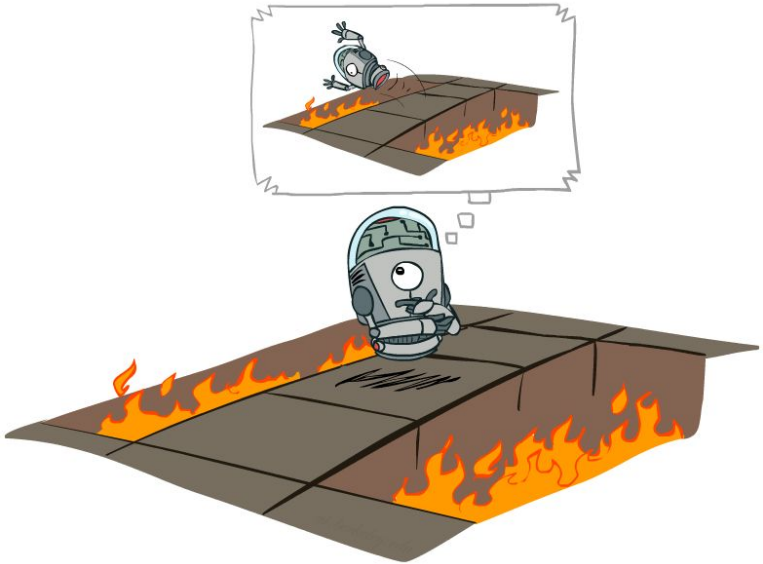
Slide credit: Daniel Brown

Idea: Learn how good an action is

- In state s
- We want to know how good an action a is
- Let's write this as a function



Value = Q(s, a)

How much return we think we'll get

Given take action a in state s

Idea: Learn how good an action is

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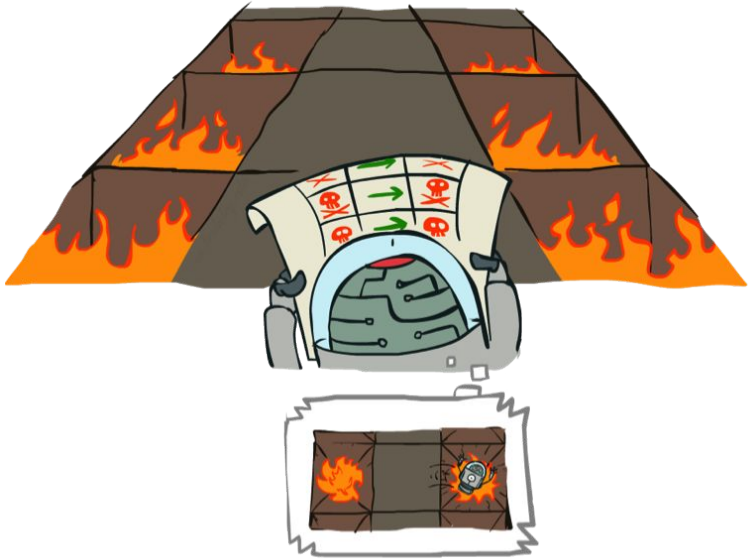
At each state s, choose action that gives best Q value



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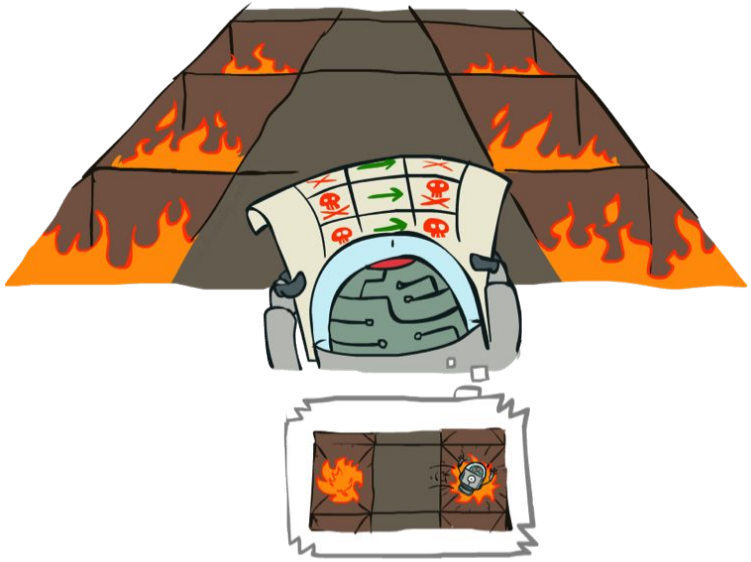


How do we learn Q?

$$\text{Value} = Q(s, a)$$

How much return we think we'll get

Given take action a in state s

Tabular Q learning

- Make a table for all possible values s&a and set Q = 0
- Update Q function using formula below (Bellman Equation)

$$Q_{k+1}(s,a) \leftarrow \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma \max_{a'} Q_k(s',a') \right]$$

- Tells you, what's the expected sum of rewards if you take action in state
- Guaranteed convergence
- See Sutton/Barto for more details
- Problems
  - Assumes we know world model (we usually don't)
  - Only works for discrete and small state/action space

Updated Q learning

- Q function is now a neural network (like a VLM)
  - Takes in state/action as input
  - No longer constrained to tabular environments
- Approximate Q update

$$Q_{k+1}(s,a) \leftarrow \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma \max_{a'} Q_k(s',a') \right]$$

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \max_{a'} Q(s',a') - Q(s,a))$$

- We can treat the Q-learning problem as a regression problem

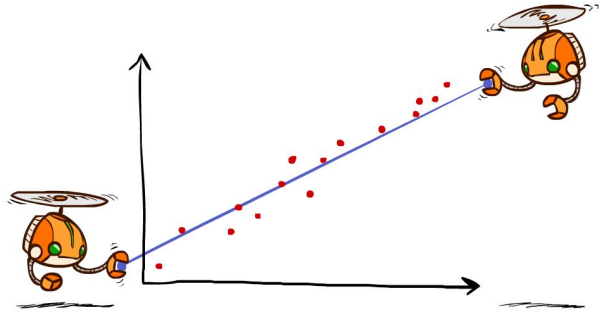
Update Q with gradient descent

Imagine we had only one point x, with features f(x), target value y, and weights w:

$$\text{error}(w) = \frac{1}{2}\left(y - \sum_k w_k f_k(x)\right)^2$$

$$\frac{\partial\ \text{error}(w)}{\partial w_m} = -\left(y - \sum_k w_k f_k(x)\right) f_m(x)$$

$$w_m \leftarrow w_m + \alpha\left(y - \sum_k w_k f_k(x)\right) f_m(x)$$



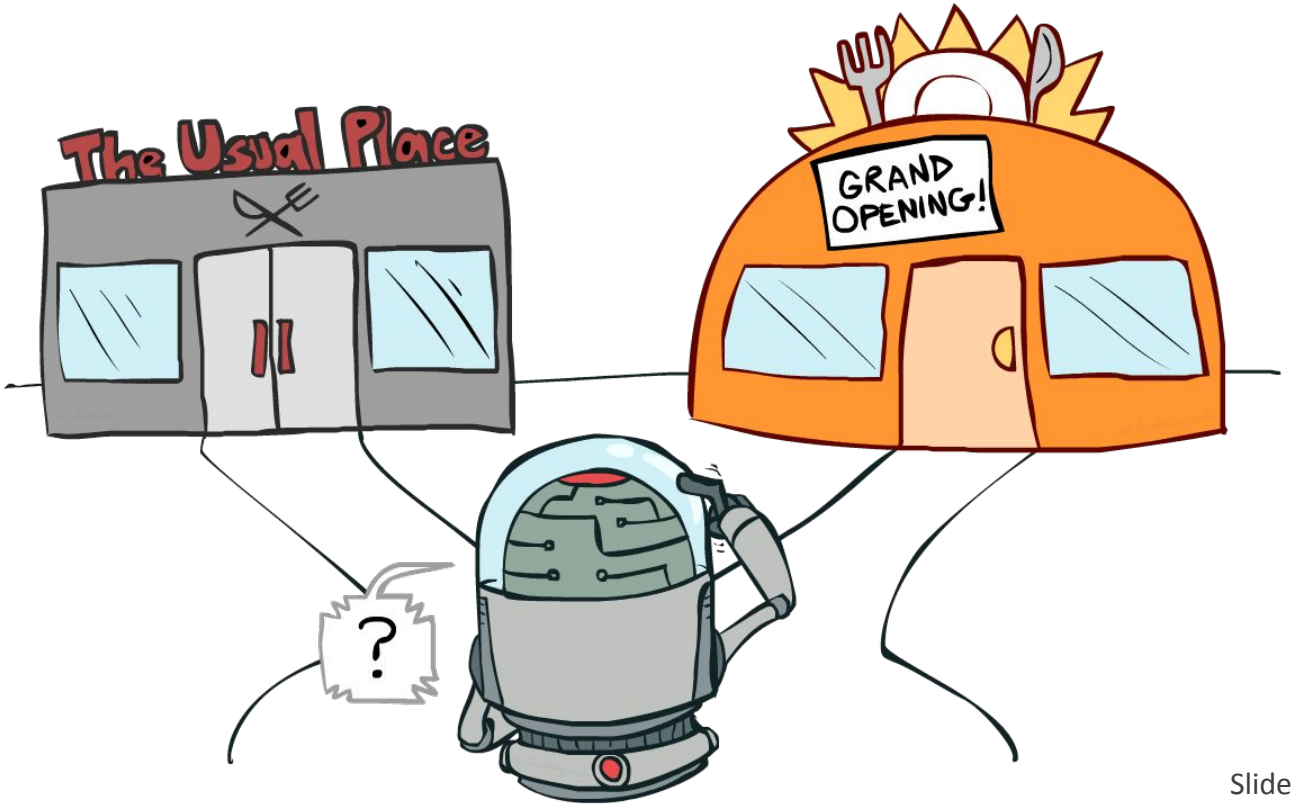
Approximate q update explained:

$$w_m \leftarrow w_m + \alpha\left[r + \gamma \max_a Q(s', a') - Q(s, a)\right] f_m(s, a)$$

"target" "prediction"

Slide credit: Daniel Brown

Exploration vs. Exploitation



Slide credit: Daniel Brown

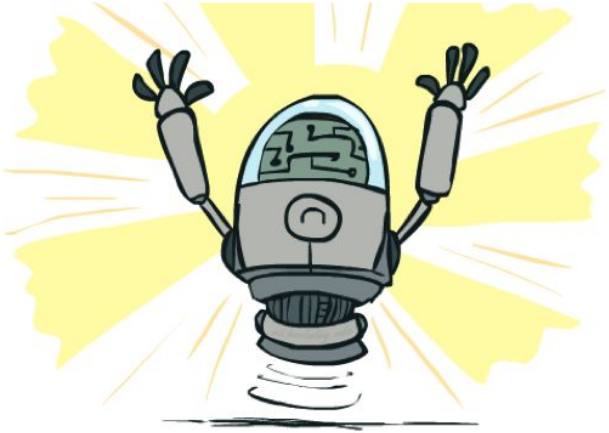
How to Explore

- We want to visit many states/actions so we can learn a good Q function
- Several schemes for forcing exploration
  - Simplest: random actions (ε-greedy)
    - Every time step, flip a coin
    - With (small) probability ε, act randomly
    - With (large) probability 1-ε, act on current policy

Slide credit: Daniel Brown

Q Learning Properties

- Amazing result: Q-learning converges to optimal policy -- even if you're acting suboptimally!
- This is called off-policy learning
- Caveats:
  - You have to explore enough
  - You have to eventually make the learning rate small enough
  - … but not decrease it too quickly
  - Basically, in the limit, it doesn't matter how you select actions (!)



Slide credit: Daniel Brown

Problems with Q Learning

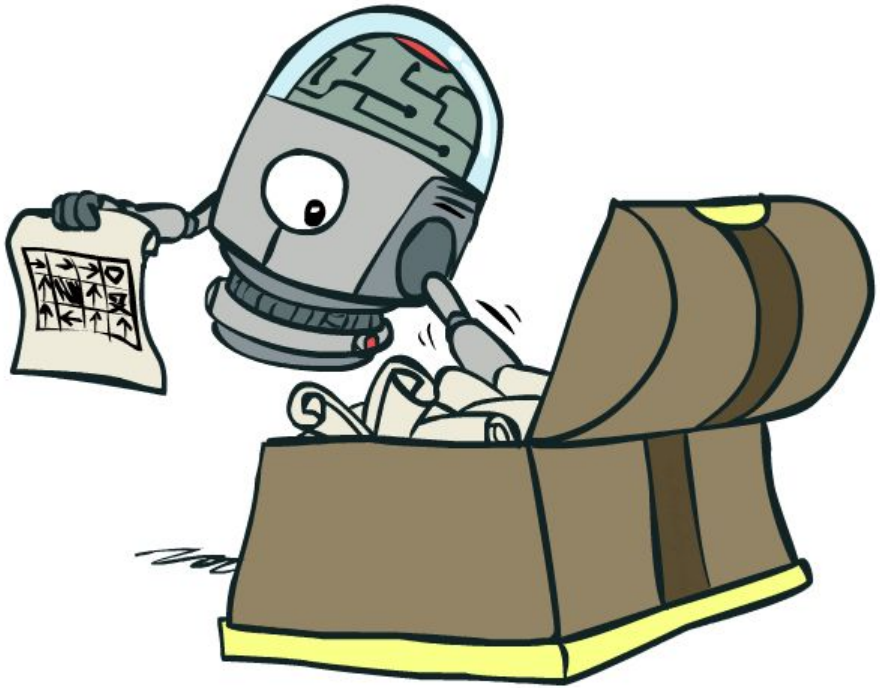
- Only works for discrete action space
  - Useless for continuous actions like in e.g. robotics
  - Can also be tricky for very large action spaces (like in many agent problems)
- Off-policy
  - Great when we have a lot of off-policy data to use (e.g. trajectories collected from people)
  - Need to do a lot of random exploration to efficiently explore to find the optimal policy

Two approaches to model-free RL

- Learn Q-Values
  - Train Q values to be consistent
  - Does not *directly optimize performance
  - Uses an objective based on Bellman Equation
- Learn Policy Directly
  - Instead, just learn a parameterized function π_θ
  - Update weights of policy network to directly optimize policy

Slide credit: Daniel Brown

Policy Search



Slide credit: Daniel Brown

Preliminaries

- Trajectory (rollout, episode) $\tau = (s_0, a_0, s_1, a_1, \dots)$
  - $s_0 \sim \rho_0(\cdot), \quad s_{t+1} \sim P(\cdot\,|s_t, a_t)$
- Rewards $r_t = R(s_t, a_t, s_{t+1})$
- Finite-horizon undiscounted return of a trajectory

$$R(\tau) = \sum_{t=0}^{T} r_t$$

- Actions are sampled from a parameterized policy π_θ

$$a_t \sim \pi_\theta(\cdot\,|s_t)$$

Slide credit: Daniel Brown

Preliminaries

- Probability of a trajectory (rollout, episode) $\tau = (s_0, a_0, s_1, a_1, \dots)$

$$P(\tau|\pi) = \rho_0(s_0) \prod_{t=0}^{T-1} P(s_{t+1}|s_t, a_t)\pi_\theta(a_t|s_t)$$

- Expected Return of a policy $\mathrm{J}(\pi)$

$$J(\pi) = \sum_{\tau} P(\tau|\pi)\, R(\tau) = E_{\tau\sim\pi}[R(\tau)]$$

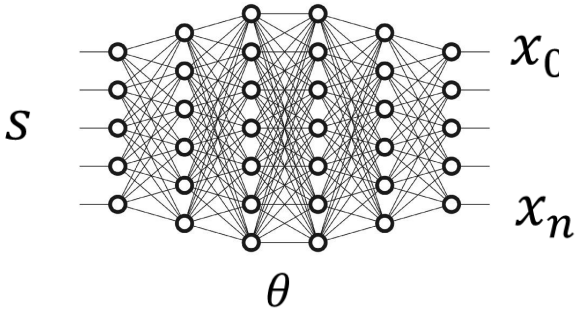
- Goal of RL: Solve the following optimization problem

$$\pi^* = \underset{\pi}{\operatorname{argmax}}\, J(\pi)$$

Slide credit: Daniel Brown

How should we parameterize our policy?

- We need to be able to do two things:
  - Sample actions $a_t \sim \pi_\theta(\cdot|s_t)$
  - Compute log probabilities $\log \pi_\theta(a_t|s_t)$
- Categorical (classifier over discrete actions)
  - Typically, you output a value x_i for each action (class) and then the probability is given by a softmax equation



$$\pi_\theta(a_i|s) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

Slide credit: Daniel Brown

How should we parameterize our policy?

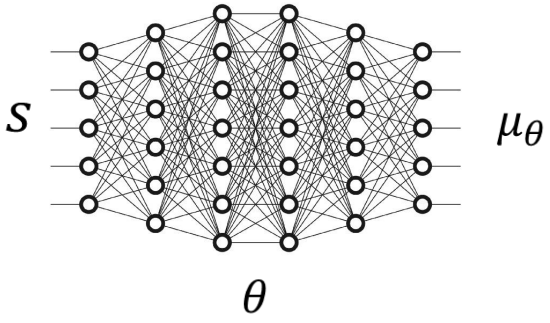
- Diagonal Gaussian (distribution over continuous actions)

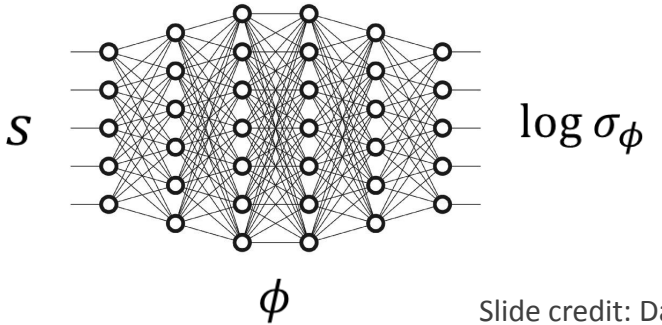
$$a \sim N(\mu, \Sigma)$$

where Σ has non-zero elements only on the diagonal.

Thus, an action can be sampled as

$$a = \mu_\theta(s) + \sigma_\phi(s) \odot z, \qquad z \sim N(0, I)$$





Slide credit: Daniel Brown

Goal: Update Policy via Gradient Ascent

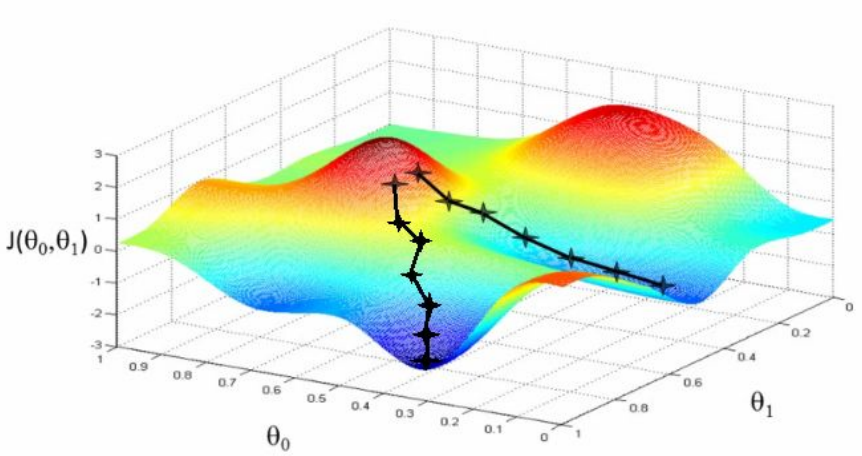
- We have a parameterized policy and we want to update it so that it maximizes the expected return.
- We want to find the gradient of the return with respect to the policy parameters and step in that direction.

$$\theta_{k+1} \leftarrow \theta_k + \alpha \nabla_\theta J(\pi_\theta) \Big|_{\theta_k}$$

Policy gradient

Slide credit: Daniel Brown

Optimization: Max a function by “climbing” a hill



$$\theta_{k+1} \leftarrow \theta_k + \alpha \nabla_\theta J(\pi_\theta)\Big|_{\theta_k}$$

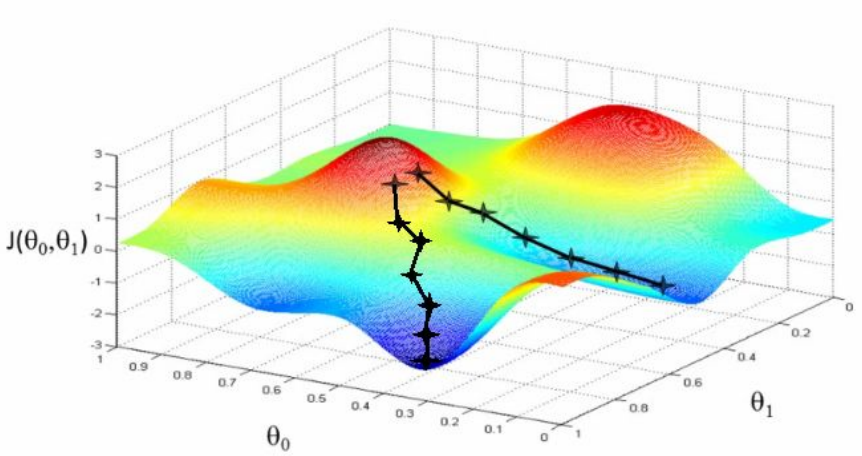
Policy gradient

Image via: https://blog.datumbox.com/tuning-the-learning-rate-in-gradient-descent/

Slide credit: Daniel Brown

Optimization: Max a function by “climbing” a hill

Use gradient to move in the direction of highest values



$$\theta_{k+1} \leftarrow \theta_k + \alpha \nabla_\theta J(\pi_\theta)\Big|_{\theta_k}$$

Policy gradient

Image via: https://blog.datumbox.com/tuning-the-learning-rate-in-gradient-descent/

Slide credit: Daniel Brown

Derivation of Policy Gradient

$$
\begin{aligned}
\nabla_\theta J(\pi_\theta) &= \nabla_\theta E_{\tau\sim\pi_\theta}[R(\tau)] \\
&= \nabla_\theta \sum_\tau P(\tau|\theta) R(\tau) \\
&= \sum_\tau \nabla_\theta P(\tau|\theta) R(\tau) \\
&= \sum_\tau P(\tau|\theta) \nabla_\theta \log P(\tau|\theta)\, R(\tau) \\
&= E_{\tau\sim\pi_\theta}[\nabla_\theta \log P(\tau|\theta)\, R(\tau)] \\
&= E_{\tau\sim\pi_\theta}[\textstyle\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t)\ \ R(\tau)]
\end{aligned}
$$

See https://cs229.stanford.edu/notes2020fall/notes2020fall/cs229-notes14.pdf for details of derivation

Slide credit: Daniel Brown

The Policy Gradient (REINFORCE)

- We can now perform gradient ascent to improve our policy!

$$\theta_{k+1} \leftarrow \theta_k + \alpha \nabla_\theta J(\pi_\theta) \Big|_{\theta_k}$$

$$\nabla_\theta J(\pi_\theta) = E_{\tau \sim \pi_\theta} \left[\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t) \; R(\tau) \right]$$

Estimate with a sample mean over a set D of policy rollouts given current parameters

$$\approx \frac{1}{|D|} \sum_{\tau \in D} \sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t) \; R(\tau)$$

Slide credit: Daniel Brown

How would you implement this?

1. Start with random policy parameters θ_0
2. Run the policy in the environment to collect N rollouts (episodes) of length T and save returns of each trajectory.

$$a_t \sim \pi_\theta(\cdot|s_t) \Rightarrow (s_0, a_0, r_0, s_1, a_1, r_1, \ldots, r_T, s_{T+1})$$

$$D = \{\tau_1, \ldots \tau_N\}, \qquad R = \{R(\tau_1), \ldots R(\tau_N)\}$$

3. Compute policy gradient

$$\nabla_\theta J(\pi_\theta) = E_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t)\ R(\tau)\right]$$

4. Update policy parameters

$$\theta_{k+1} \leftarrow \theta_k + \alpha \nabla_\theta J(\pi_\theta)\Big|_{\theta_k}$$

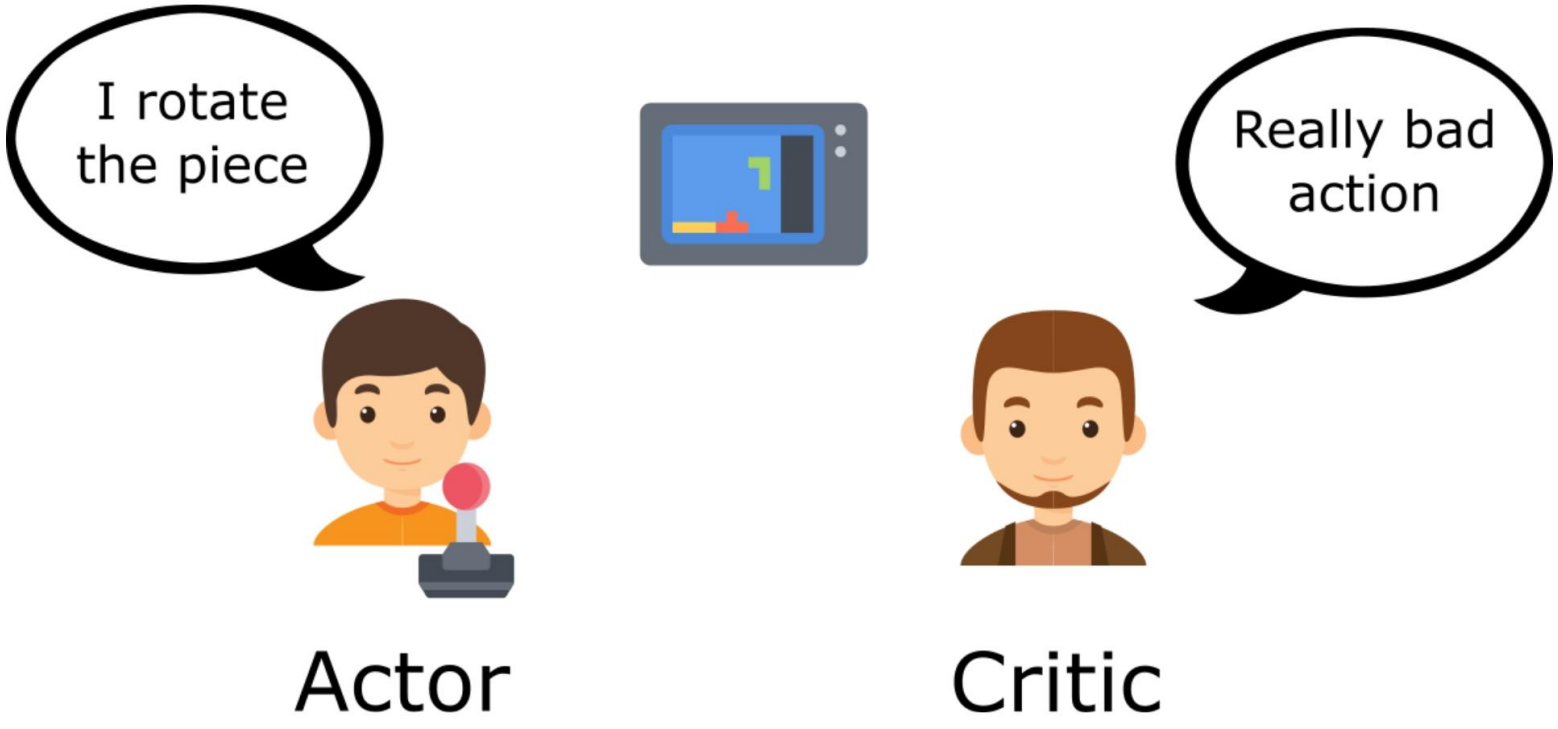
Slide credit: Daniel Brown

Policy Gradient RL Algorithms

- We can directly update the policy to achieve high reward.
- Pros:
  - Directly optimize what we care about: Utility!
  - Naturally handles continuous action spaces!
  - Can learn specific probabilities for taking actions.
  - Often more stable than value-based methods (e.g. DQN).
- Cons:
  - On-Policy -> Sample-inefficient we need to collect a large set of new trajectories every time the policy parameters change.
  - Q-Learning methods are usually more data efficient since they can reuse data from any policy (Off-Policy) and can update per sample.

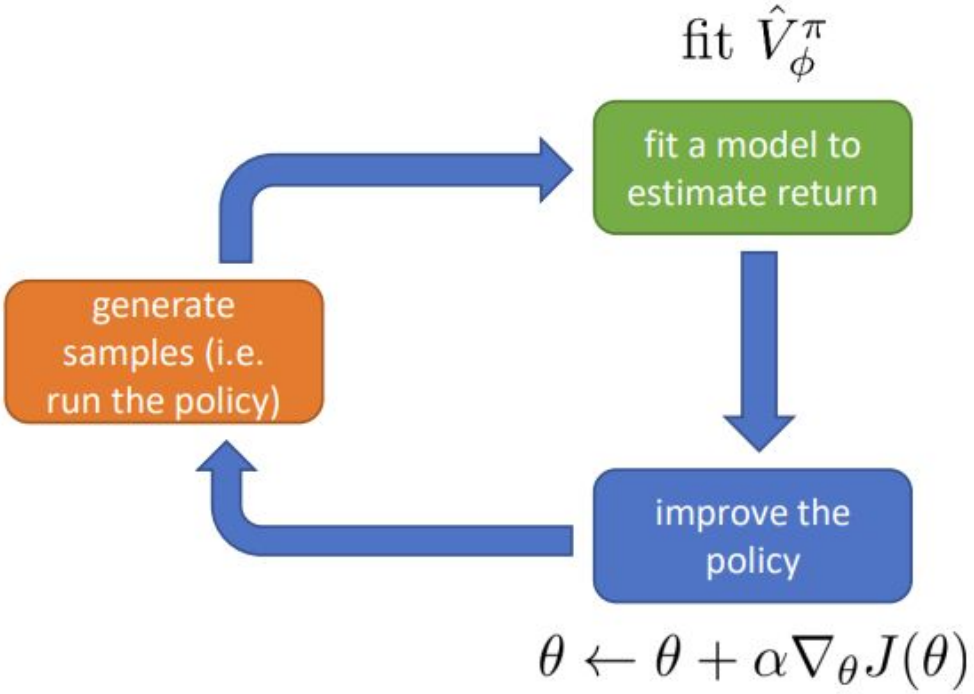
Slide credit: Daniel Brown

Actor Critic



Slide credit: Daniel Brown

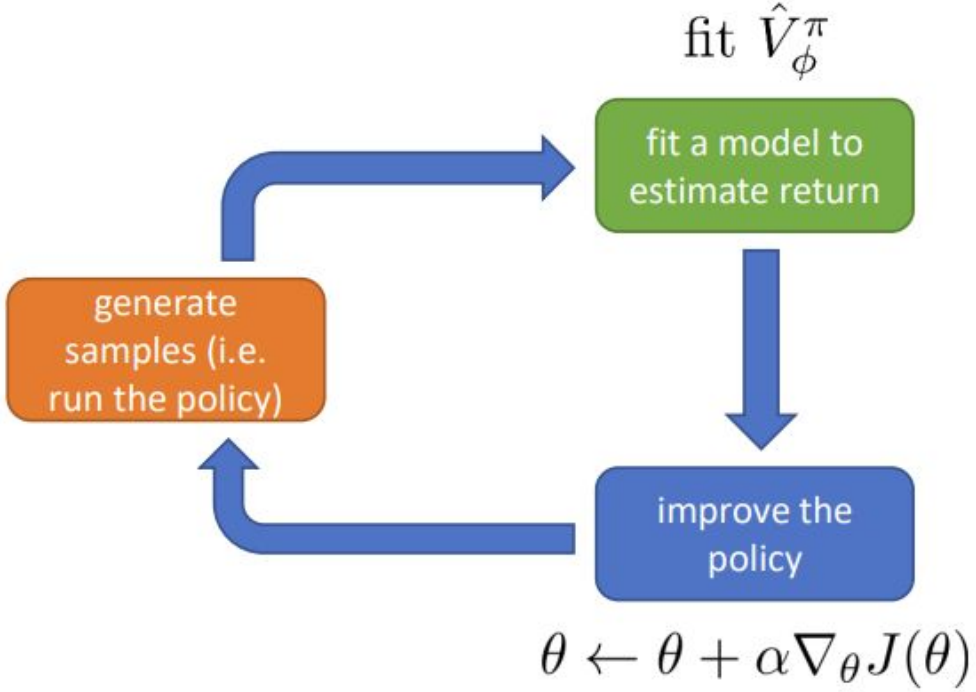
Actor Critic



Slide credit: Daniel Brown

Actor Critic

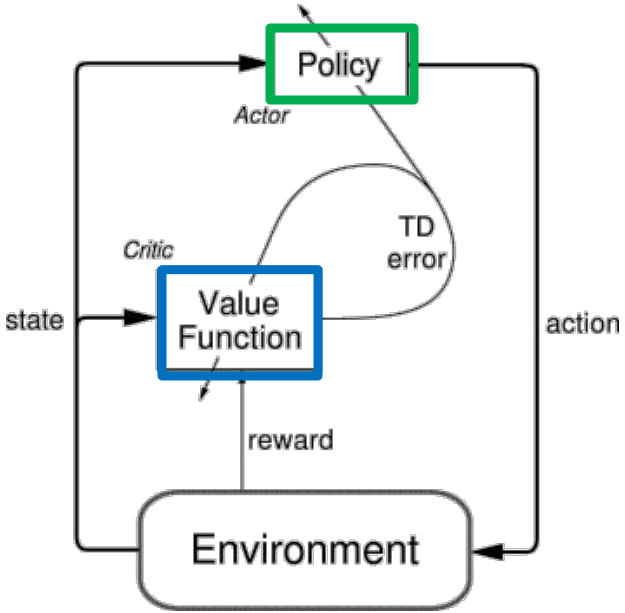
Combination of the two ideas of RL we've seen so far



Slide credit: Daniel Brown

Actor Critic Algorithms

- Combining value learning with direct policy learning
  - One example is policy gradient using the advantage function



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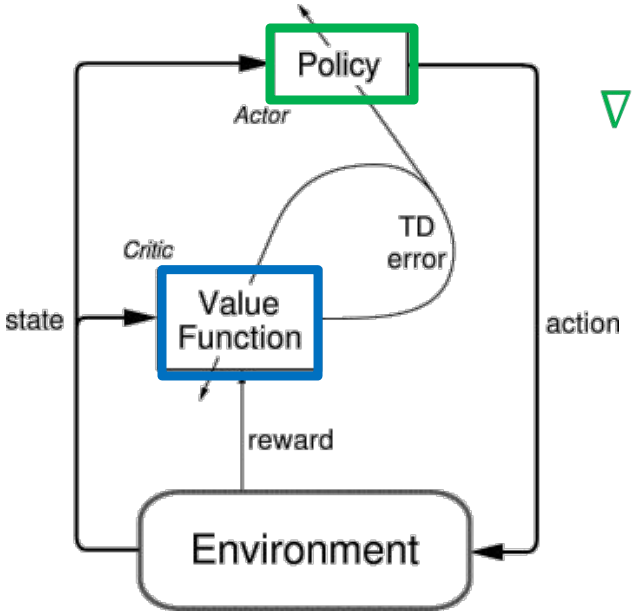

$$\nabla_\theta J(\pi_\theta) = E_{\tau \sim \pi_\theta}\left[\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t)\, Q_w^{\pi_\theta}(s_t, a_t)\right]$$

Slide credit: Daniel Brown

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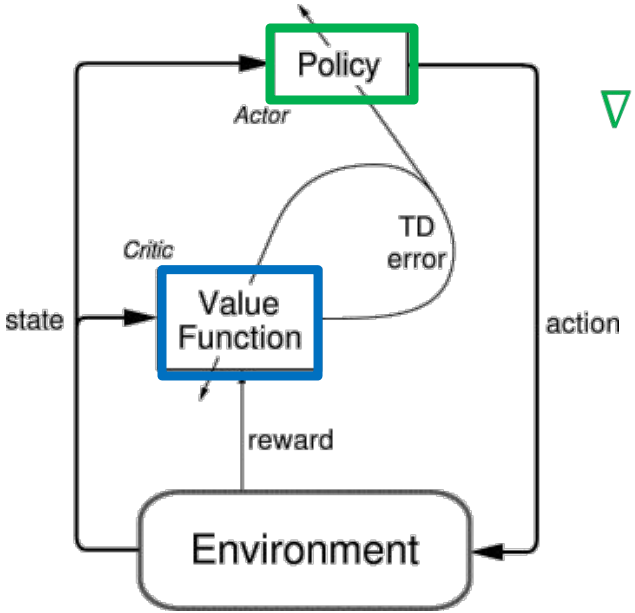

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Recall, before we directly used reward here

$$\nabla_\theta J(\pi_\theta) = E_{\tau \sim \pi_\theta}\left[\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t)\; R(\tau)\right]$$

Slide credit: Daniel Brown

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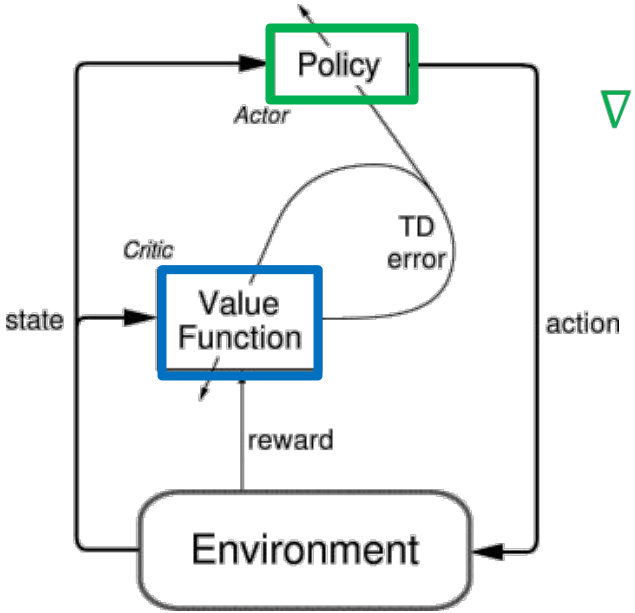

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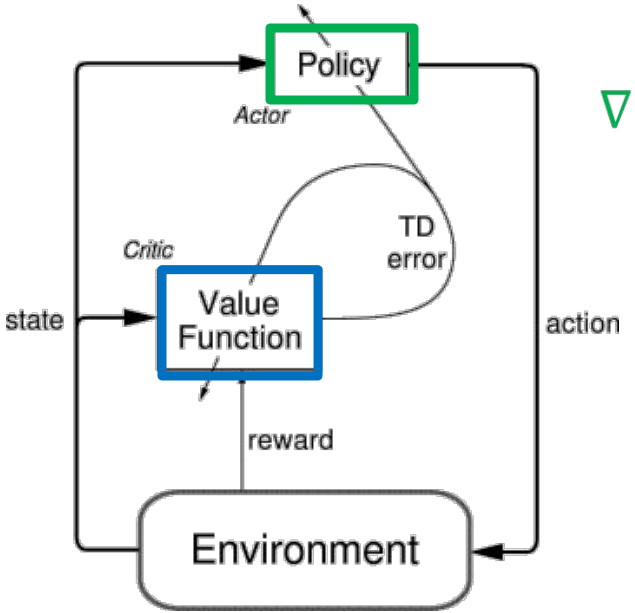

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$$\theta_{k+1} \leftarrow \theta_k + \alpha \nabla_\theta J(\pi_\theta)\Big|_{\theta_k}$$

$$\delta = (r_t + \gamma Q_w^{\pi_\theta}(s_{t+1}, a_{t+1}) - Q_w^{\pi_\theta}(s_t, a_t))$$

$$w_{k+1} \leftarrow w_k + \alpha \delta_t \nabla_\theta Q_w^{\pi_\theta}$$

Slide credit: Daniel Brown

Q Actor Critic Algorithm Pseudo Code

Algorithm 1 Q Actor Critic

Initialize parameters s, θ, w and learning rates α_θ, α_w; sample $a \sim \pi_\theta(a|s)$.

for $t = 1 \dots T$: **do**

Sample reward $r_t \sim R(s, a)$ and next state $s' \sim P(s'|s, a)$

Then sample the next action $a' \sim \pi_\theta(a'|s')$

Update the policy parameters: $\theta \leftarrow \theta + \alpha_\theta Q_w(s, a) \nabla_\theta \log \pi_\theta(a|s)$; Compute the correction (TD error) for action-value at time t:

$$\delta_t = r_t + \gamma Q_w(s', a') - Q_w(s, a)$$

and use it to update the parameters of Q function:

$$w \leftarrow w + \alpha_w \delta_t \nabla_w Q_w(s, a)$$

Move to a $\leftarrow a'$ and s $\leftarrow s'$

end for

Adapted from Lilian Weng's post "Policy Gradient algorithms"

Slide credit: Daniel Brown

Why Do This?

- Vanilla Policy Gradients has high variance
  - Directly uses return in updates which can have very high variance
  - Learning a value function instead greatly reduces noise in gradient updates
- Often faster convergence
  - Can update every few steps, not just at end of episodes when we get full return
- Separately estimating an estimate of how good a state/action pair is may help with policy learning

Proximal Policy Optimization (PPO)

Proximal Policy Optimization Algorithms

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, Oleg Klimov
OpenAI
{joschu, filip, prafulla, alec, oleg}@openai.com

Slide credit: Daniel Brown

Proximal Policy Optimization (PPO)

- One of the most popular deep RL algorithms
- Used to train ChatGPT and other LLMs

Motivation:

- Many Policy Gradient algorithms have stability problems.
- This can be avoided if we avoid making too big of a policy update.

https://huggingface.co/blog/deep-rl-ppo

Algorithm 1 PPO-Clip

1: Input: initial policy parameters θ_0, initial value function parameters ϕ_0
2: **for** $k = 0, 1, 2, \ldots$ **do**
3: Collect set of trajectories $\mathcal{D}_k = \{\tau_i\}$ by running policy $\pi_k = \pi(\theta_k)$ in the environment.
4: Compute rewards-to-go $\hat{R}_t$.
5: Compute advantage estimates, $\hat{A}_t$ (using any method of advantage estimation) based on the current value function V_{ϕ_k}.
6: Update the policy by maximizing the PPO-Clip objective:

$$\theta_{k+1} = \arg\max_{\theta} \frac{1}{|\mathcal{D}_k|T} \sum_{\tau \in \mathcal{D}_k} \sum_{t=0}^{T} \min \left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_k}(a_t|s_t)} A^{\pi_{\theta_k}}(s_t, a_t), \quad g(\epsilon, A^{\pi_{\theta_k}}(s_t, a_t)) \right),$$

typically via stochastic gradient ascent with Adam.
7: Fit value function by regression on mean-squared error:

$$\phi_{k+1} = \arg\min_{\phi} \frac{1}{|\mathcal{D}_k|T} \sum_{\tau \in \mathcal{D}_k} \sum_{t=0}^{T} \left(V_\phi(s_t) - \hat{R}_t \right)^2,$$

typically via some gradient descent algorithm.
8: **end for**

Slide credit: Daniel Brown

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typically via some gradient descent algorithm.
8: **end for**

Note: too many details to get into in such a short time

See https://huggingface.co/blog/deep-rl-ppo for full details

Slide credit: Daniel Brown

Lots of other tricks used

- Additional advantage normalization
- Early stopping with KL-divergence
- Etc.

The 37 Implementation Details of Proximal Policy Optimization: https://iclr-blog-track.github.io/2022/03/25/ppo-implementation-details/

Slide credit: Daniel Brown

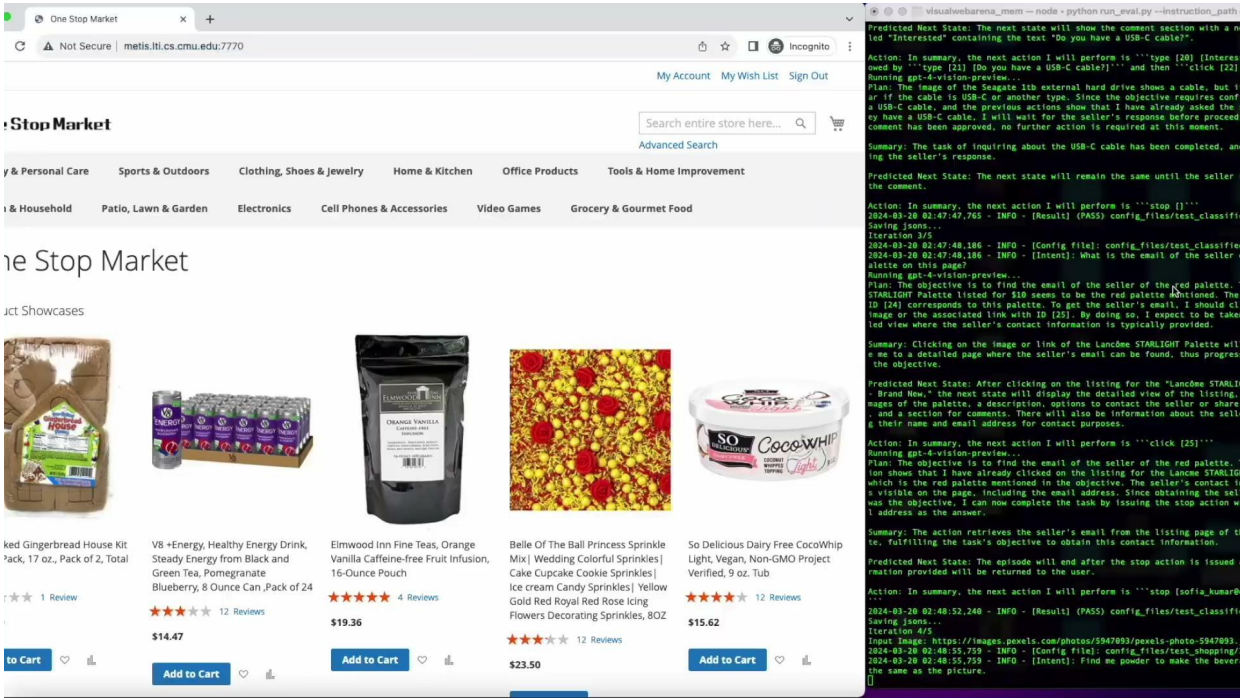
Review: How to learn the policy

- Imitation Learning
  - Is especially effective / used in VLM agent problems
  - IL == BC == SFT
- Offline methods / Q learning
  - Learn the “goodness” of a state, action pair w/ Bellman updates
  - Follow highest Q values
- Policy Gradient Methods
  - Directly optimize policy network
  - Improve with actor and critic
  - Improve further with more tricks (PPO)
  - PPO is most common RL algorithm for LLMs

Assumptions we've made

- Markov Assumption
  - For environment - only your current state matters, not how you got there
  - For policy - you only need to look at your current state
- Fully Observable
  - Everything about the environment is full observed and captured in your state s

Example: Computer Use



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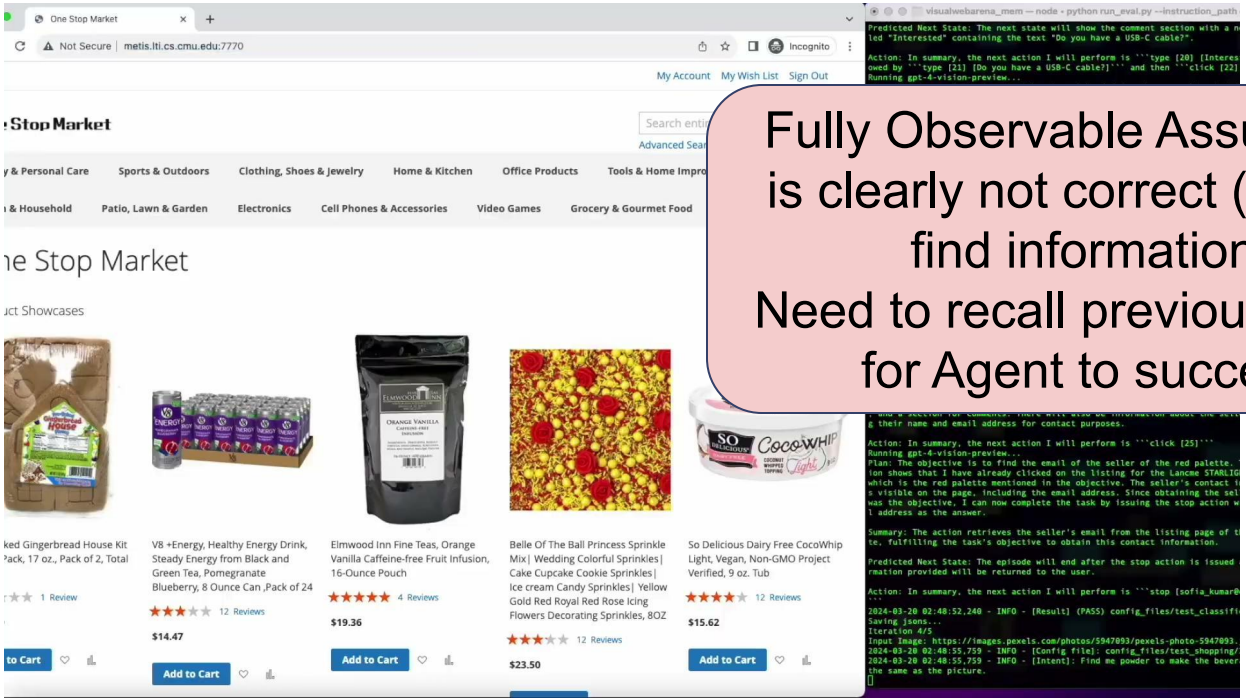
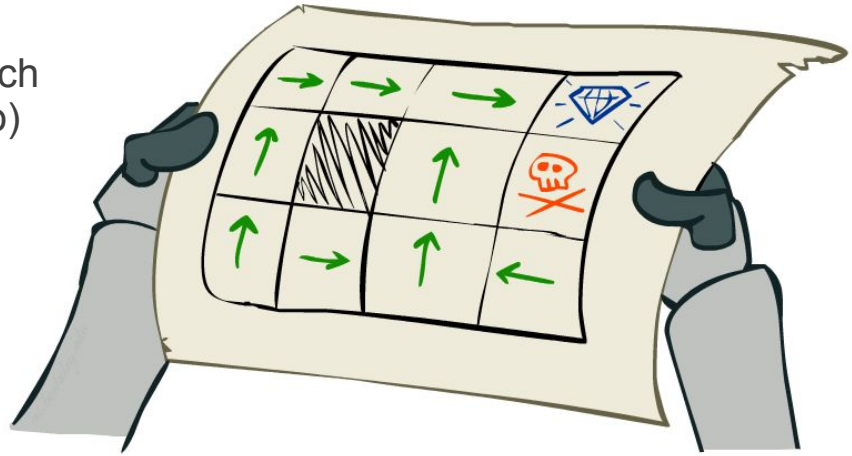


LLM Policies In Practice

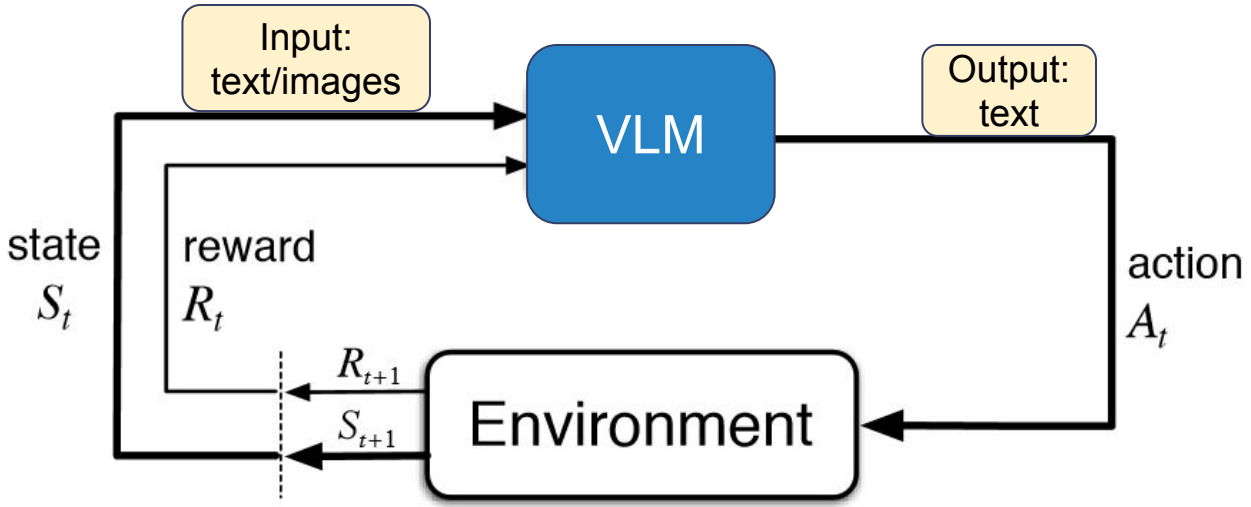
- $\pi(o_t, \text{history}(o_{0:t-1}, a_{0:t-1}), i)$
  - VLM policy takes the current observation o_t (which doesn't necessarily contain all relevant state info)
  - Some (usually condensed) history of past observations and actions the agent took
  - Possibly other information (may depend on your problem)
- Fortunately
  - VLMs are transformer based and quite good at handling sequential information



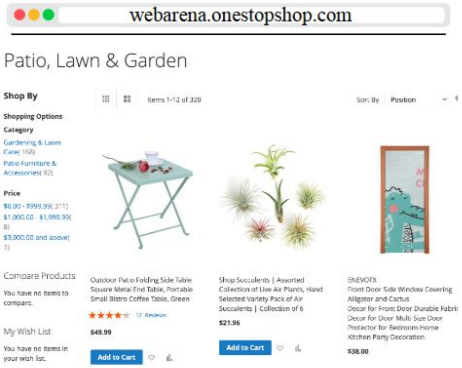
Optimal policy when R(s, a, s') = -0.03 for all non-terminals s

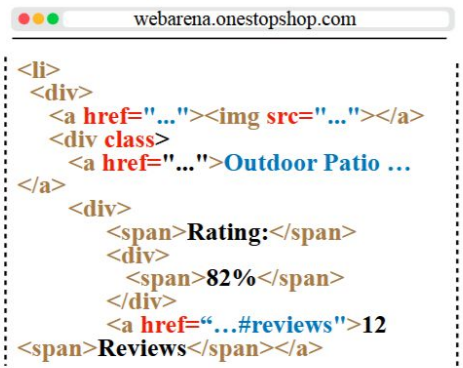
What this means for VLM Agents

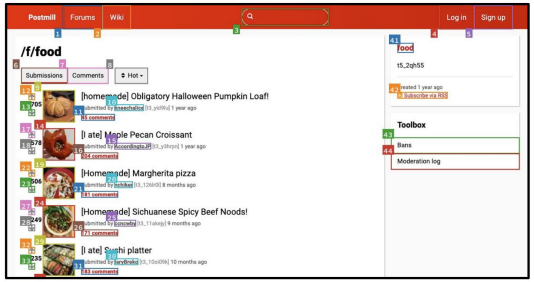
- Basics of environment, maximizing reward, policies, all apply
  - State/observation given by text image tokens
  - Output is text (then interpreted as environment actions)
  - Want to maximize some reward (answer a query, fill out a web form, do some action in the environment)



Recall: Obs/Action Space of CU Agent







Webpage with SoM of Interactable Elements

```
...
[7] [A] [Comments]
[8] [BUTTON] [Hot]
[9] [IMG] [description: picture of a pumpkin]
[10] [A] [kneechalice]
...
```

SoM Elements and Text Content

Action Type a	Description
`click [elem]`	Click on element `elem`.
`hover [elem]`	Hover on element `elem`.
`type [elem] [text]`	Type `text` on element `elem`.
`press [key_comb]`	Press a key combination.
`new_tab`	Open a new tab.
`tab_focus [index]`	Focus on the i-th tab.
`tab_close`	Close current tab.
`goto [url]`	Open `url`.
`go_back`	Click the back button.
`go_forward`	Click the forward button.
`scroll [up|down]`	Scroll up or down the page.
`stop [answer]`	End the task with an output.

What this means for VLM Agents

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  - Output is text (then interpreted as environment actions)
  - Want to maximize some reward (answer a query, fill out a web form, do some action in the environment)
- Most useful algorithms to know
  - Imitation learning probably most common
    - When we talk about LLMs, this is exactly the same as Supervised Fine Tuning (SFT)
  - When we do RL with agents, PPO is most commonly used

What this means for VLM Agents

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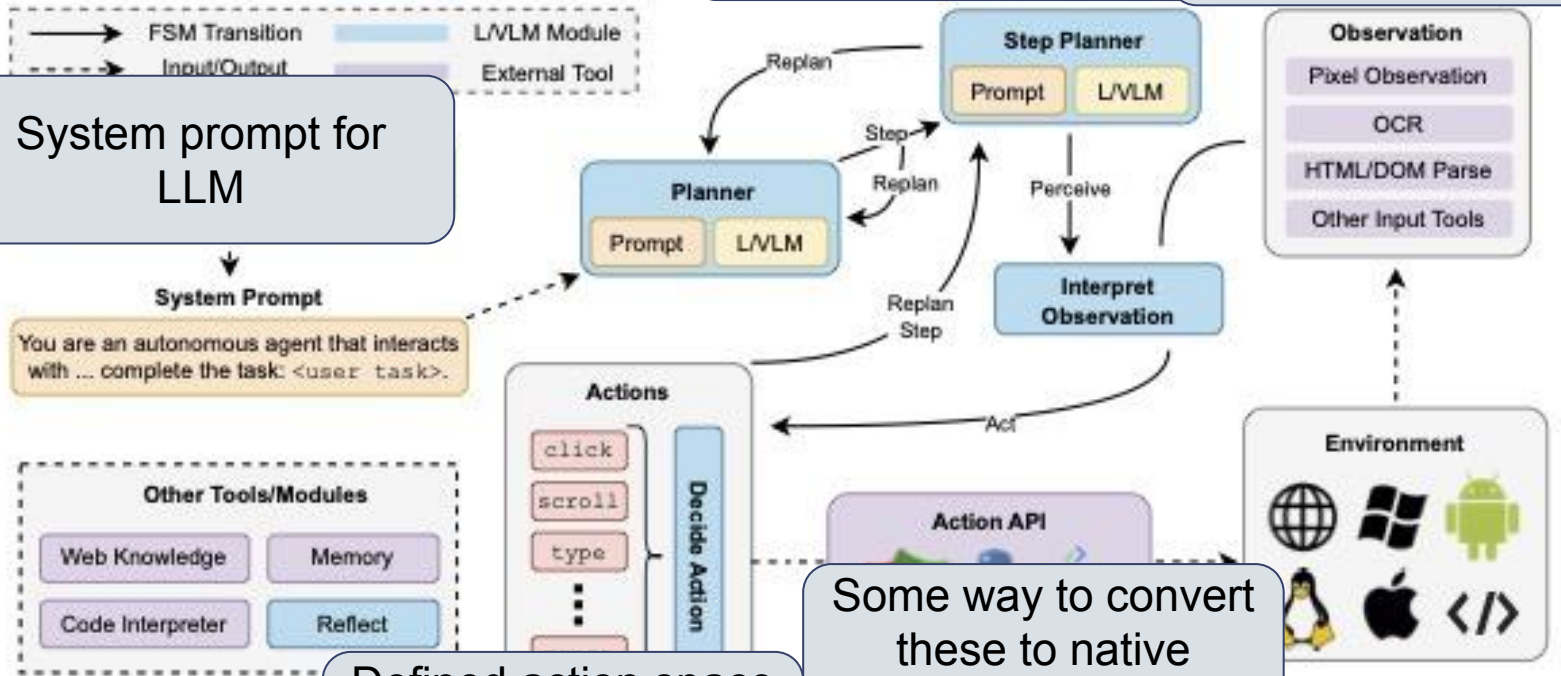
  - When we do RL with agents, PPO is most commonly used
- VLM agents also often work without any training!
  - Through prompting frameworks and other methods
  - Just relies on general ability of the base models!

Recall: Firmament

Frameworks for LLMs be better at actions (reflect, plan, replan, e

Hand-crafted observations useful for VLM



System prompt for LLM

Some way to convert these to native actions in env

Tools VLM can i that do different t

Defined action space that can be expressed in text

Image credit: Farhan Ishmam

What this means for VLM Agents

- Basics of environment, maximizing reward, policies, all apply
  - State/observation given by text image tokens
  - Output is text (then interpreted as environment actions)
  - Want to maximize some reward (answer a query, fill out a web form, do some action in the environment)
- Most useful algorithms to know
  - Imitation learning probably most common
    - When we talk about LLMs, this is exactly the same as Supervised Fine Tuning (SFT)
  - When we do RL with agents, PPO is most commonly used
- VLM agents also often work without any training!
  - Through prompting frameworks and other methods
  - Just relies on general ability of the base models!

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  - Just relies on general ability of the base models!
  - **There will always be a limit on how good this will be / no way to make it better**

Recommended Readings

- Reinforcement Learning an Introduction - Sutton & Barto
  - It's all good but for introduction to RL Ch1&3 are helpful
  - http://incompleteideas.net/book/RLbook2020.pdf
- Reinforcement Learning Courses
  - Stanford Deep RL Class: https://cs224r.stanford.edu/
  - Berkeley Deep RL Course: https://rail.eecs.berkeley.edu/deeprlcourse/
  - If you need to understand particular topic/algorithm, notes from these courses are really useful
- This was a very brief overview of topics
  - Some/none of details might matter depending on your project/application
  - Goal: get a 10,000 foot view so that when an RL topic comes up again, you know where to start looking

Any Questions

Questions