Policy Gradients

CS 224R

Course reminders

- Start forming **final project groups** (survey due next Wednesday)
- **Homework 1** out, due Fri April 18

Recap

state $\mathbf{s}_t$ - the state of the "world" at time t

action $\mathbf{a}_t$ - the decision taken at time t

trajectory τ - sequence of states/observations and actions

$$(\mathbf{s}_1, \mathbf{a}_1, \mathbf{s}_2, \mathbf{a}_2, \ldots, \mathbf{s}_T, \mathbf{a}_T)$$

reward function $r(\mathbf{s}, \mathbf{a})$ - how good is $\mathbf{s}, \mathbf{a}$?

policy $\pi(\mathbf{a}|\mathbf{s})$ or $\pi(\mathbf{a}|\mathbf{o})$ - behavior, usually what we are trying to learn

Goal: learn policy π_θ that maximizes *expected* sum of rewards:

$$\max_\theta \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right]$$

where $p(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T) = p(\mathbf{s}_1) \prod_t \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) p(\mathbf{s_{t+1}}|\mathbf{s}_t, \mathbf{a}_t)$

Imitation learning from demonstrations $\mathscr{D}$

$$\min_{\theta} - \mathbb{E}_{(\mathbf{s},\mathbf{a})\sim\mathscr{D}}[\log \pi_\theta(\mathbf{a}\,|\,\mathbf{s})]$$

+ Simple, scalable approach for learning performant behavior

- Cannot outperform demonstrator, doesn't allow improvement from practice

Definitions.

offline: using only an existing dataset, no new data from learned policy

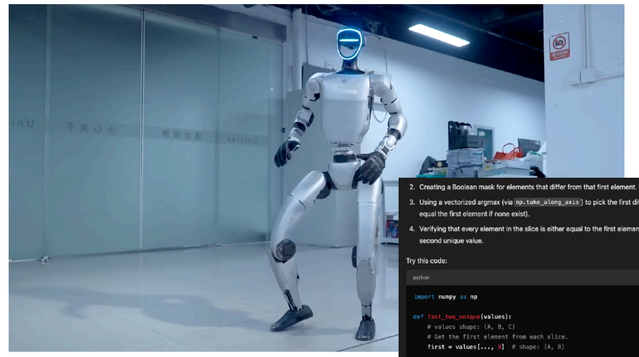
online: using new data from learned policy

The plan for today

Policy gradients: our first **online RL** algorithm

1. On-policy policy gradient
   a. Derivation and intuition of policy gradients
   b. Full algorithm
   c. How to make it better - causality and baselines
2. Off-policy policy gradients
   a. Importance sampling
   b. KL constraints

the basis for:



Source: Unitree

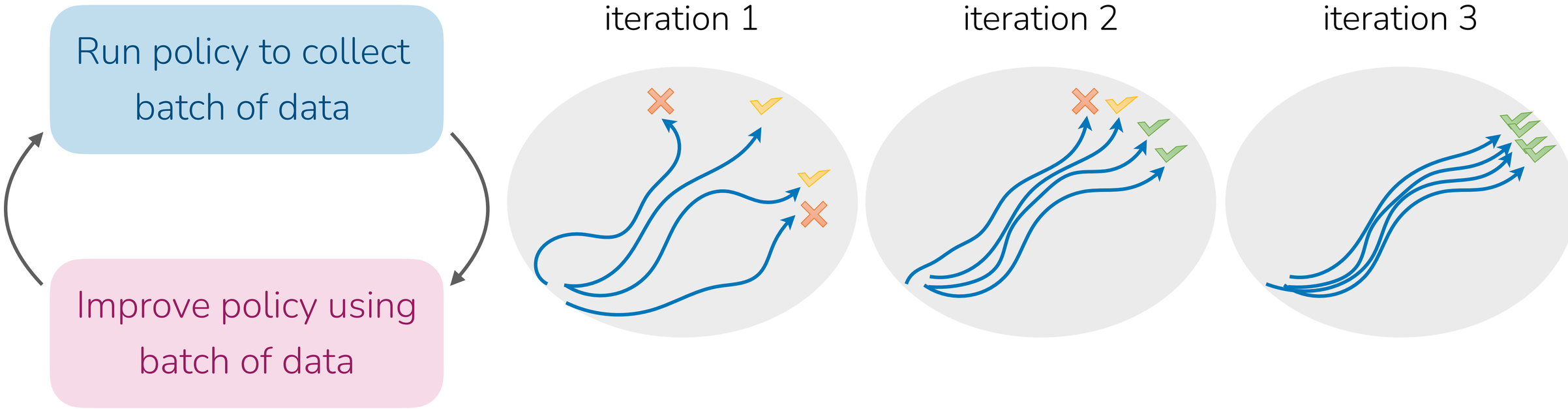
+ part of default project

Key learning goals:

- Key intuition behind policy gradients
- How to implement, when to use policy gradients

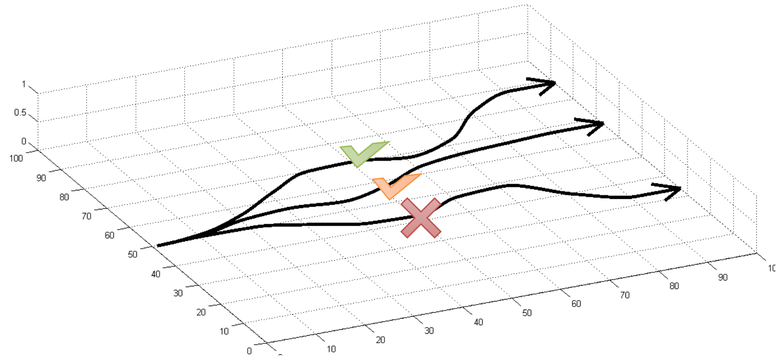
Online RL Outline

First: Initialize the policy (randomly, with imitation learning, with heuristics)



Evaluating the RL objective

$$\theta^\star = \arg\max_\theta \underbrace{E_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right]}_{J(\theta)}$$



$$J(\theta) = E_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right] \approx \frac{1}{N}\sum_i\sum_t r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})$$

sum over samples from π_θ

Slide adapted from Sergey Levine

Can we get the gradient of the RL objective?

Let's start in terms of trajectories.

$$\theta^\star = \arg\max_\theta \underbrace{E_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right]}_{J(\theta)}$$

a convenient identity

$$p_\theta(\tau)\nabla_\theta \log p_\theta(\tau) = p_\theta(\tau)\frac{\nabla_\theta p_\theta(\tau)}{p_\theta(\tau)} = \nabla_\theta p_\theta(\tau)$$

$$J(\theta) = E_{\tau\sim p_\theta(\tau)}[\underbrace{r(\tau)}_{\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)}] = \int p_\theta(\tau) r(\tau) d\tau$$

$$\nabla_\theta J(\theta) = \int \nabla_\theta p_\theta(\tau) r(\tau) d\tau = \int p_\theta(\tau)\nabla_\theta \log p_\theta(\tau) r(\tau) d\tau = E_{\tau\sim p_\theta(\tau)}[\nabla_\theta \log p_\theta(\tau) r(\tau)]$$

Slide adapted from Sergey Levine

Can we get the gradient of the RL objective?

From trajectories to final form.

$$\nabla_\theta J(\theta) = E_{\tau \sim p_\theta(\tau)}[\nabla_\theta \log p_\theta(\tau) r(\tau)]$$

$$\nabla_\theta \left[\log p(\mathbf{s}_1) + \sum_{t=1}^{T} \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) + \log p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) \right]$$

$$p_\theta(\tau) = p(\mathbf{s}_1) \prod_{t=1}^{T} \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$$

$$\log p_\theta(\tau) = \log p(\mathbf{s}_1) + \sum_{t=1}^{T} \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) + \log p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$$

$$\nabla_\theta J(\theta) = E_{\tau \sim p_\theta(\tau)} \left[\left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t) \right) \right]$$

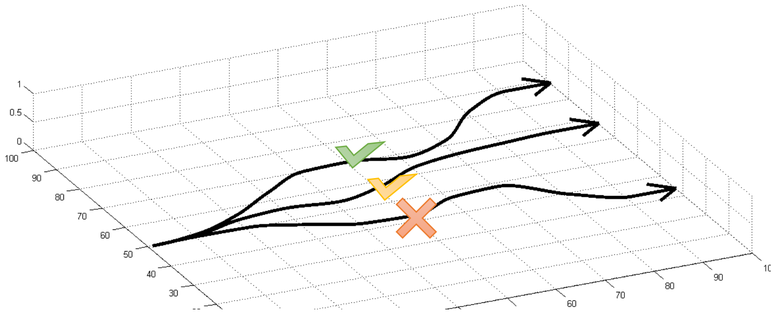
Slide adapted from Sergey Levine

Estimating the gradient

$$\nabla_\theta J(\theta) = E_{\tau \sim p_\theta(\tau)} \left[\left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t | \mathbf{s}_t) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t) \right) \right]$$

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$$

$$\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$$



Run policy to collect batch of data

Improve policy using batch of data

Full algorithm:

1. sample $\{\tau^i\}$ from $\pi_\theta(\mathbf{a}_t | \mathbf{s}_t)$
2. $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_t \nabla_\theta \log \pi_\theta(\mathbf{a}_t^i | \mathbf{s}_t^i) \right) \left(\sum_t r(\mathbf{s}_t^i, \mathbf{a}_t^i) \right)$
3. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

"REINFORCE algorithm", vanilla policy gradient

Slide adapted from Sergey Levine

What does the gradient mean?

$$\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})\right)\left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t},\mathbf{a}_{i,t})\right)$$

Imitation gradient, but weighted by reward

Recall: imitation learning

$$\min_\theta -\mathbb{E}_{(\mathbf{s},\mathbf{a})\sim\mathcal{D}}\left[\log \pi_\theta(\mathbf{a}|\mathbf{s})\right]$$

$$\nabla_\theta J_{\mathrm{BC}}(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t-1}^{T}\nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})\right)$$

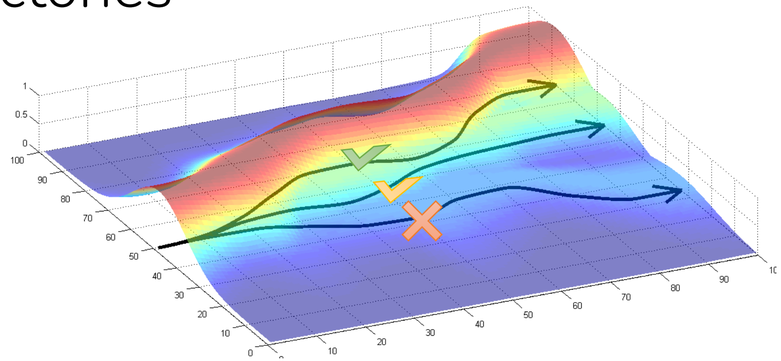
Intuition:

Increase likelihood of actions you took in high reward trajectories.

Decrease likelihood of actions you took in negative reward trajectories

i.e. do more of the good stuff, less of the bad stuff.

formalization of “trial-and-error”



What does the gradient do?

Example: learning humanoid walking in simulation

reward: $r(\mathbf{s}, \mathbf{a}) =$ forward velocity of robot

(can be negative if robot goes backwards)

1. $\text{sample } \{\tau^i\} \text{ from } \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$

τ^1: falls backwards ✗

τ^2: falls forwards ✓

τ^3: manages to stand still ✓

τ^4: one small step forward then falls backwards ✗

τ^5: one large step backwards then small step forwards ✗

2. $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_t \nabla_\theta \log \pi_\theta(\mathbf{a}_t^i|\mathbf{s}_t^i)\right) \left(\sum_t r(\mathbf{s}_t^i, \mathbf{a}_t^i)\right)$

Question: what will the gradient encourage the policy to do?

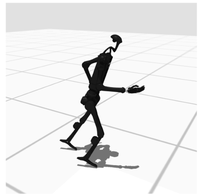
-> will encourage policy to fall forward, and not take step forward 😨

Policy gradient is noisy / high-variance

Improving the gradient

Using causality

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$$



τ^5: one large step backwards then small step forwards ✖

Policy behavior at time t does not affect rewards at time $t' < t$

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \left(\sum_{t'=t}^{T} r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'}) \right)$$

sum of *future* rewards

What does the gradient do?

Example: learning humanoid walking in simulation

reward: $r(\mathbf{s}, \mathbf{a}) =$ forward velocity of robot

(can be negative if robot goes backwards)

1. $\text{sample } \{\tau^i\} \text{ from } \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$

τ^1: falls forwards ✔

τ^2: slowly stumbles forwards ✔

τ^3: steadily walks forwards ✔

τ^4: runs forwards ✔

2. $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_t \nabla_\theta \log \pi_\theta(\mathbf{a}_t^i|\mathbf{s}_t^i)\right) \left(\sum_t r(\mathbf{s}_t^i, \mathbf{a}_t^i)\right)$

Question: what will the gradient encourage the policy to do?

-> encourages policy to fall, stumble forward some of the time 😨

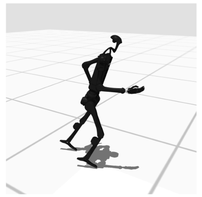
Policy gradient is noisy / high-variance

sensitive to reward scale

Improving the gradient

Introducing baselines

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\nabla_\theta \log p_\theta(\tau) r(\tau) \right]$$



τ^1: falls forwards ✔

τ^4: runs forwards ✔

Improving the gradient

Introducing baselines

a convenient identity

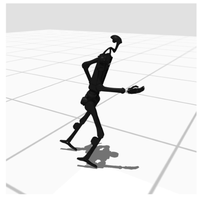
$$p_\theta(\tau)\nabla_\theta \log p_\theta(\tau) = \nabla_\theta p_\theta(\tau)$$

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau\sim p_\theta(\tau)}\left[\nabla_\theta \log p_\theta(\tau)\,(r(\tau) - b)\right]$$

$$b = \frac{1}{N}\sum_{i=1}^{N} r(\tau)$$

subtracting a constant

"baseline"



τ^1: falls forwards ✔

τ^4: runs forwards ✔

If we subtract average reward, we get negative gradients for below-average behavior. 🥳

But, can we even do that? 🤔

$$E[\nabla_\theta \log p_\theta(\tau) b] = \int p_\theta(\tau)\nabla_\theta \log p_\theta(\tau) b\, d\tau = \int \nabla_\theta p_\theta(\tau) b\, d\tau = b\nabla_\theta \int p_\theta(\tau) d\tau = b\nabla_\theta 1 = 0$$

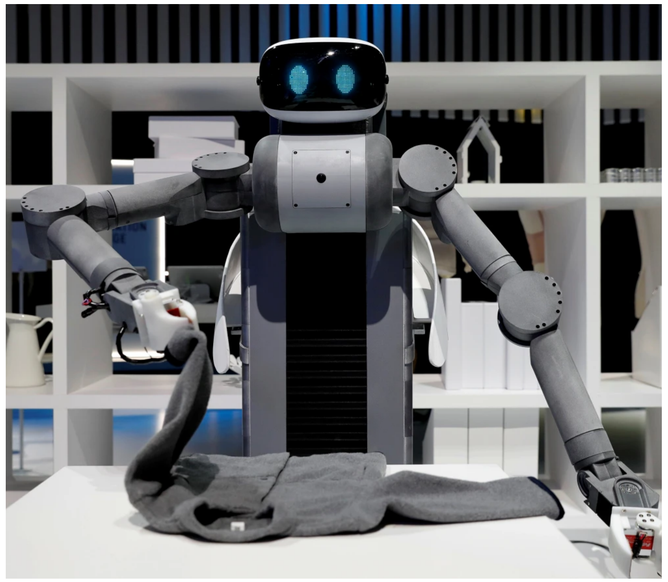
Subtracting a constant baseline does not change the gradient in expectation. It is **unbiased**.

and can reduce **variance** of the gradient

Average reward is a pretty good baseline.

What does the gradient do? (baseline edition)

Example: learning to fold a jacket



reward: $r(\mathbf{s}, \mathbf{a}) = \begin{cases} 1 & \text{neatly folded} \\ 0.5 & \text{folded with some wrinkles} \\ 0 & \text{not folded} \end{cases}$

1. sample $\{\tau^i\}$ from $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$

τ^1: doesn't touch the jacket

τ^2: folds only the sleeves

τ^3: flattens the jacket but does not fold it

τ^4: folds the jacket

2. $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_t \nabla_\theta \log \pi_\theta(\mathbf{a}_t^i|\mathbf{s}_t^i)\right)\left(\sum_t r(\mathbf{s}_t^i, \mathbf{a}_t^i) - b\right)$

Question: what will the gradient encourage the policy to do?

-> will encourage folding, but gradient is constant for all but one trajectory 😨

Policy gradient is still noisy / high-variance

Best with **dense rewards**, **large batches**.

How to implement policy gradients?

Our gradient

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \right) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'}) \right) - b \right)$$

Computing these individually is inefficient.
(N*T backwards passes)

Can we use automatic differentiation on full objective?

Implement “surrogate objective” whose gradient is the same as ∇J

$$\tilde{J}(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \right) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'}) \right) - b \right)$$

weighted maximum likelihood

Cross-entropy for discrete action policy, squared error for Gaussian policy

Summary so far

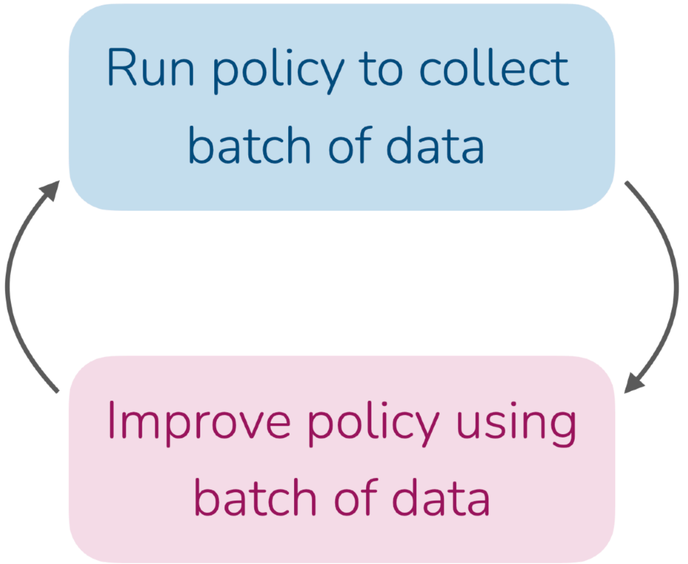
Estimating gradient of RL objective

- log gradient trick
- weigh policy likelihood by future rewards
- subtract baseline (e.g. average reward)
- even with tricks, gradient is noisy

First reinforcement learning algorithm

- collect batch of data, improve policy by applying gradient
- formalizes trial-and-error learning

Key intuition: do more high reward stuff, less low reward stuff



What else is troublesome about policy gradients?

Latest version of our gradient:

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t | \mathbf{s}_t) \right) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) - b \right) \right]$$

assumes samples from current policy π_θ

Full algorithm:

1. sample $\{\tau^i\}$ from $\pi_\theta(\mathbf{a}_t | \mathbf{s}_t)$
2. compute $\nabla_\theta J(\theta)$ using $\{\tau^i\}$
3. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$ <- we change θ right here

Need to recollect data every gradient step! 😱

Vanilla policy gradient is **on-policy**.

attribute of online RL algorithms

Definitions.

on-policy: update uses only data from current policy

off-policy: update can reuse data from other, past policies

Off-policy version of policy gradient?

Importance sampling

$$J(\theta) = E_{\tau \sim p_\theta(\tau)}[r(\tau)]$$

What if we want to use samples from $\bar{p}(\tau)$?

(e.g. previous policy)

$$J(\theta) = E_{\tau \sim \bar{p}(\tau)}\left[\frac{p_\theta(\tau)}{\bar{p}(\tau)} r(\tau)\right]$$

$$\frac{p_\theta(\tau)}{\bar{p}(\tau)} = \frac{\cancel{p(\mathbf{s}_1)} \prod_{t=1}^{T} \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) \cancel{p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}}{\cancel{p(\mathbf{s}_1)} \prod_{t=1}^{T} \bar{\pi}(\mathbf{a}_t|\mathbf{s}_t) \cancel{p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}} = \frac{\prod_{t=1}^{T} \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\prod_{t=1}^{T} \bar{\pi}(\mathbf{a}_t|\mathbf{s}_t)}$$

Importance sampling

Using proposal distribution q

$$\begin{aligned} E_{x \sim p(x)}[f(x)] &= \int p(x) f(x) dx \\ &= \int \frac{q(x)}{q(x)} p(x) f(x) dx \\ &= \int q(x) \frac{p(x)}{q(x)} f(x) dx \\ &= E_{x \sim q(x)}\left[\frac{p(x)}{q(x)} f(x)\right] \end{aligned}$$

Note: Important for q to have non-zero support for high probability $p(x)$

Off-policy version of policy gradient?

Importance sampling

$$\frac{p_\theta(\tau)}{\bar{p}(\tau)} = \frac{\prod_{t=1}^{T} \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\prod_{t=1}^{T} \bar{\pi}(\mathbf{a}_t|\mathbf{s}_t)}$$

Say we want to update our latest policy $\boldsymbol{\pi_{\theta'}}$ but we want to use samples from $\boldsymbol{\pi_\theta}$

$$\nabla_{\theta'} J(\theta') = \mathbb{E}_{\tau \sim p_{\theta'}(\tau)} \left[\left(\sum_{t=1}^{T} \nabla_{\theta'} \log \pi_{\theta'}(\mathbf{a}_t|\mathbf{s}_t) \right) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) - b \right) \right]$$

$$\nabla_{\theta'} J(\theta') = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\frac{p_{\theta'}(\tau)}{p_\theta(\tau)} \left(\sum_{t=1}^{T} \nabla_{\theta'} \log \pi_{\theta'}(\mathbf{a}_t|\mathbf{s}_t) \right) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) - b \right) \right]$$

$$\nabla_{\theta'} J(\theta') = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\prod_{t=1}^{T} \frac{\pi_{\theta'}(\mathbf{a}_t|\mathbf{s}_t)}{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)} \left(\sum_{t=1}^{T} \nabla_{\theta'} \log \pi_{\theta'}(\mathbf{a}_t|\mathbf{s}_t) \right) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) - b \right) \right]$$

This can become very small or very large, for larger $\boldsymbol{T}$

Off-policy version of policy gradient?

Importance sampling

Say we want to update our latest policy $\pi_{\theta'}$ but we want to use samples from π_θ

$$\nabla_{\theta'} J(\theta') = \mathbb{E}_{\tau \sim p_\theta(\tau)} \left[\prod_{t=1}^{T} \frac{\pi_{\theta'}(\mathbf{a}_t|\mathbf{s}_t)}{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)} \left(\sum_{t=1}^{T} \nabla_{\theta'} \log \pi_{\theta'}(\mathbf{a}_t|\mathbf{s}_t) \right) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) - b \right) \right]$$

This can become very small or very large, for larger T

What if we consider the expectation *over timesteps* instead of trajectories?

$$\nabla_{\theta'} J(\theta') \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{\pi_{\theta'}(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})}{\pi_\theta(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})} \nabla_{\theta'} \log \pi_{\theta'}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'}) \right) - b \right)$$

Much less likely to explode/vanish ...but, hard to measure $\frac{\pi_{\theta'}(\mathbf{s}_{i,t})}{\pi_\theta(\mathbf{s}_{i,t})}$

Common final form

$$\nabla_{\theta'} J(\theta') \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{\pi_{\theta'}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})}{\pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})} \nabla_{\theta'} \log \pi_{\theta'}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'}) \right) - b \right)$$

often approximated as 1

Off-policy policy gradient

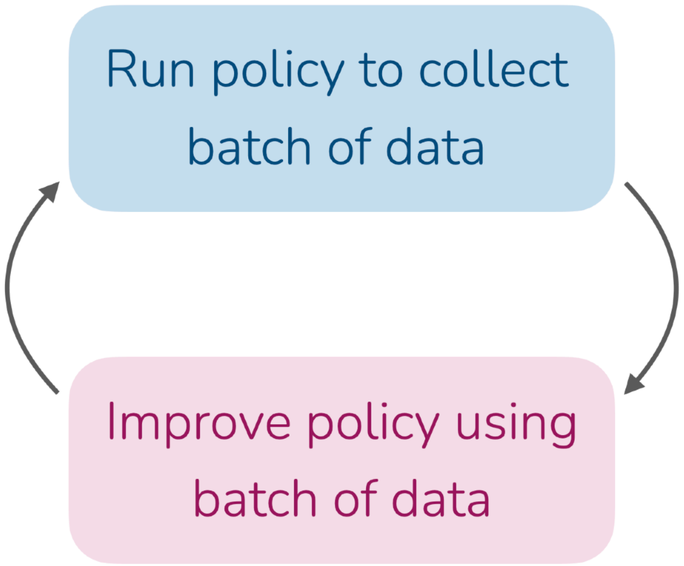
Common final form

$$\nabla_{\theta'} J(\theta') \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{\pi_{\theta'}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})}{\pi_{\theta}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})} \nabla_{\theta'} \log \pi_{\theta'}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'}) \right) - b \right)$$

Full algorithm:

1. sample $\{\tau^i\}$ from $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$
2. compute $\nabla_\theta J(\theta)$ using $\{\tau^i\}$
3. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

Can take multiple gradient steps on the same batch



What if our policy changes **a lot** before sampling new data?

Data no longer reflects states that policy will visit. Gradient estimate less accurate.

Off-policy policy gradient

Common final form

$$\nabla_{\theta'} J(\theta') \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{\pi_{\theta'}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})}{\pi_{\theta}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})} \nabla_{\theta'} \log \pi_{\theta'}(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \left(\left(\sum_{t'=t}^{T} r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'}) \right) - b \right)$$

What if our policy changes **a lot** before sampling new data?

Data no longer reflects states that policy will visit. Gradient estimate less accurate.

Can we constrain the policy to not stray too far during gradient updates?

One common choice: $\mathbb{E}_{\mathbf{s} \sim \pi_\theta} \left[D_{KL}(\pi_{\theta'}(\cdot \mid \mathbf{s}) \| \pi_\theta(\cdot \mid \mathbf{s})) \right] \leq \delta$

Review

Online RL via policy gradients

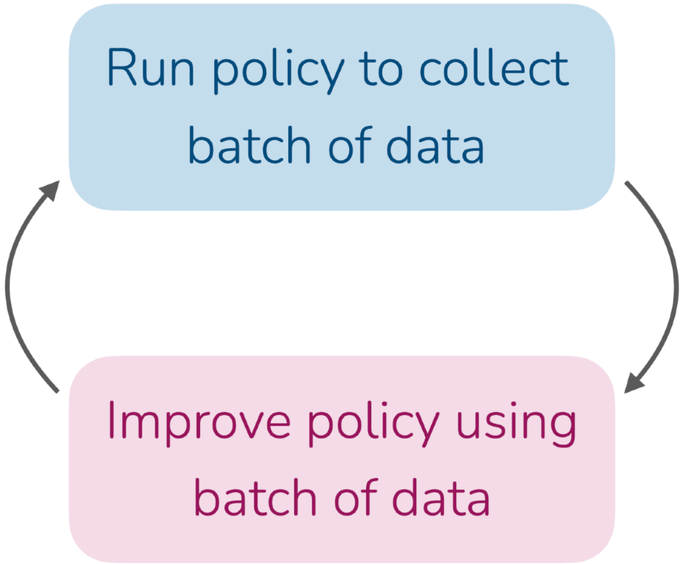
- On-policy algorithm, differentiating the RL objective
- Baselines, causality for reducing gradient variance
- collect batch of data, improve policy by applying gradient

Derived off-policy policy gradient

- importance sampling
- KL constraint on policy
- collect batch of data, apply multiple gradient updates

Intuition

- Do more high reward stuff, less low reward stuff
- Gradient still very noisy, best with large batch sizes and dense rewards

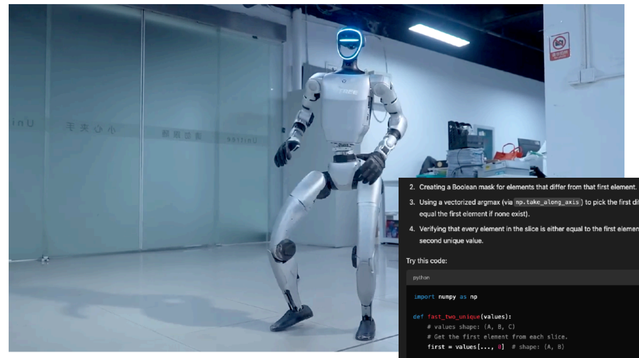


The plan for today

Policy gradients: our first **online RL** algorithm

1. On-policy policy gradient
   a. Derivation and intuition of policy gradients
   b. Full algorithm
   c. How to make it better - causality and baselines
2. Off-policy policy gradients
   a. Importance sampling
   b. KL constraints

the basis for:



Source: Unitree

+ part of default project

Key learning goals:

- Key intuition behind policy gradients
- How to implement, when to use policy gradients

Next time

Actor critic methods

—> build closely on policy gradients!

—> basis for popular algorithms like PPO

Course reminders

- Start forming **final project groups** (survey due next Wednesday)
- **Homework 1** out, due next Friday