CONVERSATIONAL AI LAB

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Talk: “Giving Agents Agency with : An Introduction to Augmenting LLMs with LangChain”

The power LLMs and Gen AI can be dramatically amplified by giving them access to computational tools and the capacity to reason at each step whether to use its generative capacities or one of the tools.

Speaker: Bradley Marx, Masters student in DSI, Brown

Location and Time: Friedman Hall, 102; Wednesday, April 24, 6-7 pm

Reinforcement Learning: Actor-Critic

Deep Learning

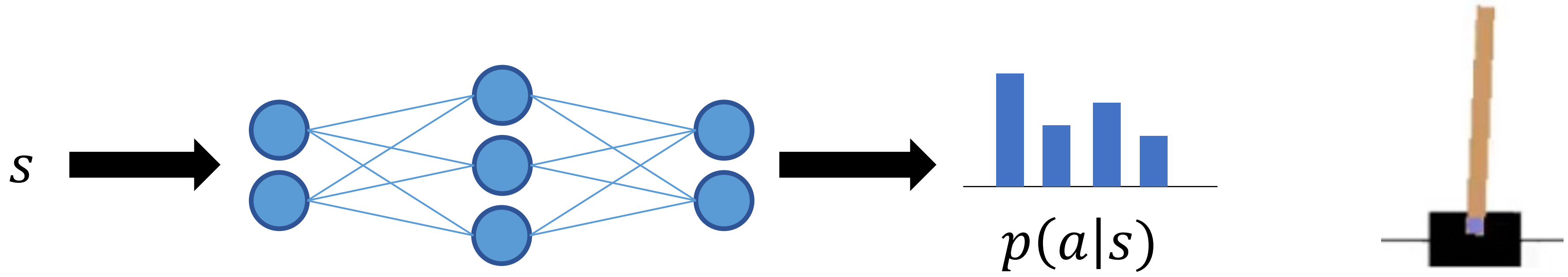
CSCI 1470/2470
Spring 2024

Ritambhara Singh

April 24, 2024
Wednesday

ChatGPT prompt “minimalist landscape painting of a deep underwater scene with a blue tang fish in the bottom right corner”

Review: Policy Network for Cart Pole



Policy Gradient: $-\sum_{t=1}^{T} \nabla \log p(a_t|s_t)\, D(s_t, a_t)$

Review: REINFORCE: Pseudo Code

Initialize model weights θ

Repeat until done (converge, time limit expired, etc.):

Run N episodes of environment simulation, each for T timesteps

For each episode

For $t = 1$ to $t = T$

$$\theta \leftarrow \theta + \boxed{\mathrm{OptimizerStep}}(\nabla \log p(a_t|s_t) D\ (s_t, a_t))$$

Your favorite optimizer (SGD, Adam, …)

Return θ

Reinforce vs DQN

Pros

- Policy often easier to learn than Q function
- Automates explore vs. exploit tradeoff
  - Policy network starts off random and gradually becomes better as it is trained for more and more episodes
- Can learn stochastic policies
  - More naturalistic behavior
- In practice, can converge faster than DQN

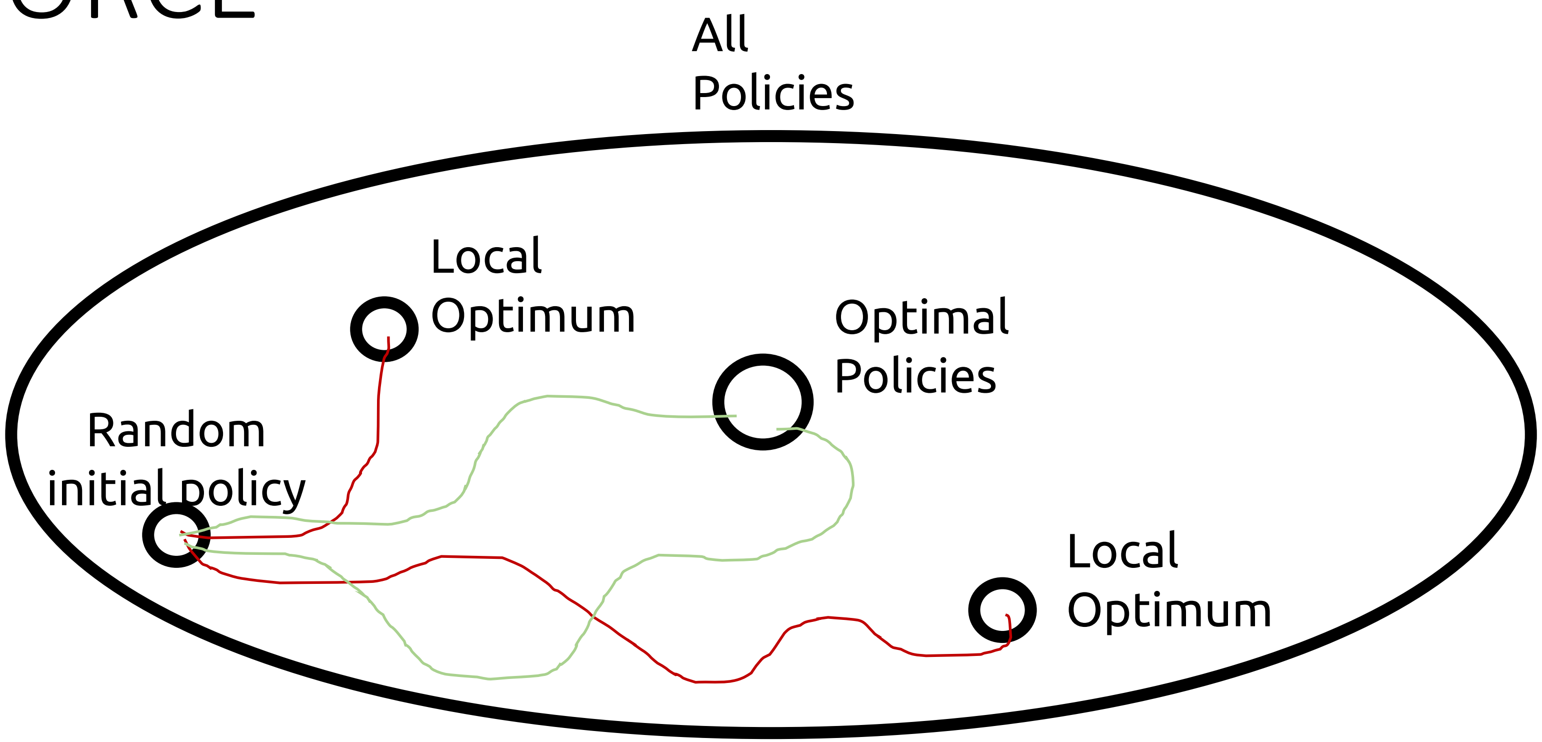
Cons

- Finds local optima more often than DQN...
- Unstable training
- Gradient updates only at end of each game (DQN updates after every step)

We'll see how to fix these two issues in the next lecture...

Issues with REINFORCE

- **High Variance**
  - Multiple runs of training an agent with REINFORCE can yield very different results
  - Susceptible to local optima



First, going to address this problem…

- **High “sample complexity”**
  - Must play an entire episode to get gradient, takes many episodes to learn

…which will actually give us a solution for this problem via a simple extension

The Solution:
Looking at Policy Gradient through a different "lens"

Organizing RL problems/algorithms

	Know T and R	Don't know T and R
Simple/discrete	Value iteration	Q-Learning
Complex/continuous		Deep Q-Networks REINFORCE Actor-Critic

For a more complete taxonomy of RL algorithms, see https://spinningup.openai.com/en/latest/spinningup/rl_intro2.html#citations-below

The “Actor Critic” Framework

Consider the REINFORCE gradient:

$$-\sum_{t=1}^{T} \nabla \log p(a_t|s_t) D(s_t, a_t)$$

The “Actor Critic” Framework

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Actor:
Specifies how to (probabilistically) choose actions for a given state

The "Actor Critic" Framework

Consider the REINFORCE gradient:

$$-\sum_{t=1}^{T} \nabla \log p(a_t|s_t) D(s_t, a_t)$$

Actor:
Specifies how to (probabilistically) choose actions for a given state

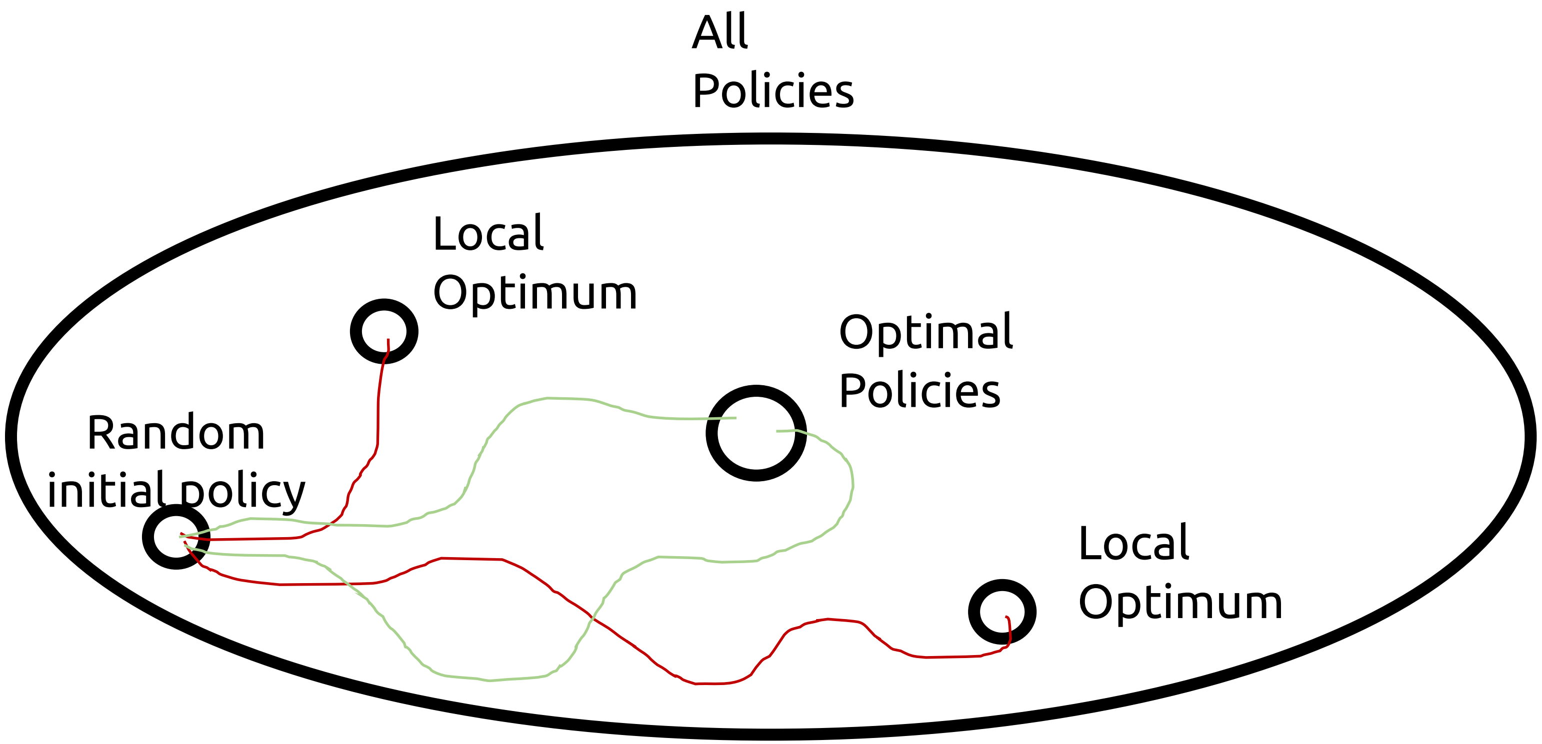
Critic:
"Scores" the goodness/badness of taking an action

Different critics are possible

- E.g. $Q(s_t, a_t)$, if we knew it
- **Recall that $D(s_t, a_t)$ is our single-episode estimate of $Q(s_t, a_t)$**

The trick to solving our problems:
Coming up with a better critic function…

The Problem: High Variance



- To understand why this happens, have to dig into the math a little bit

High Variance

- For a random variable X: $Var[X] = E[(X - E[X])^2]$
  - The expected squared difference from the expected value
  - "The average distance from the average"

High Variance in REINFORCE

Out of the two terms, which is more likely produce high variance?

- The REINFORCE gradient: $-\sum_{t=1}^{T} \nabla \log p(a_t|s_t) D(s_t, a_t)$
- $D(s_t, a_t)$ is a random variable, because it depends on following a stochastic policy (and a potentially stochastic transition function)
- Assertion: $D(s_t, a_t)$ is high variance
- ***Why?***
  - $D(s_t, a_t)$ can be very low ***or*** very high depending on subsequent actions
  - Especially for actions taken early in the episode
  - Especially early in training, when the policy is mostly random

High Variance Rewards: Frozen Lake

- Frozen Lake
  - S: Starting Point
  - F: Frozen
  - H: Hole, ends episode
  - G: Goal

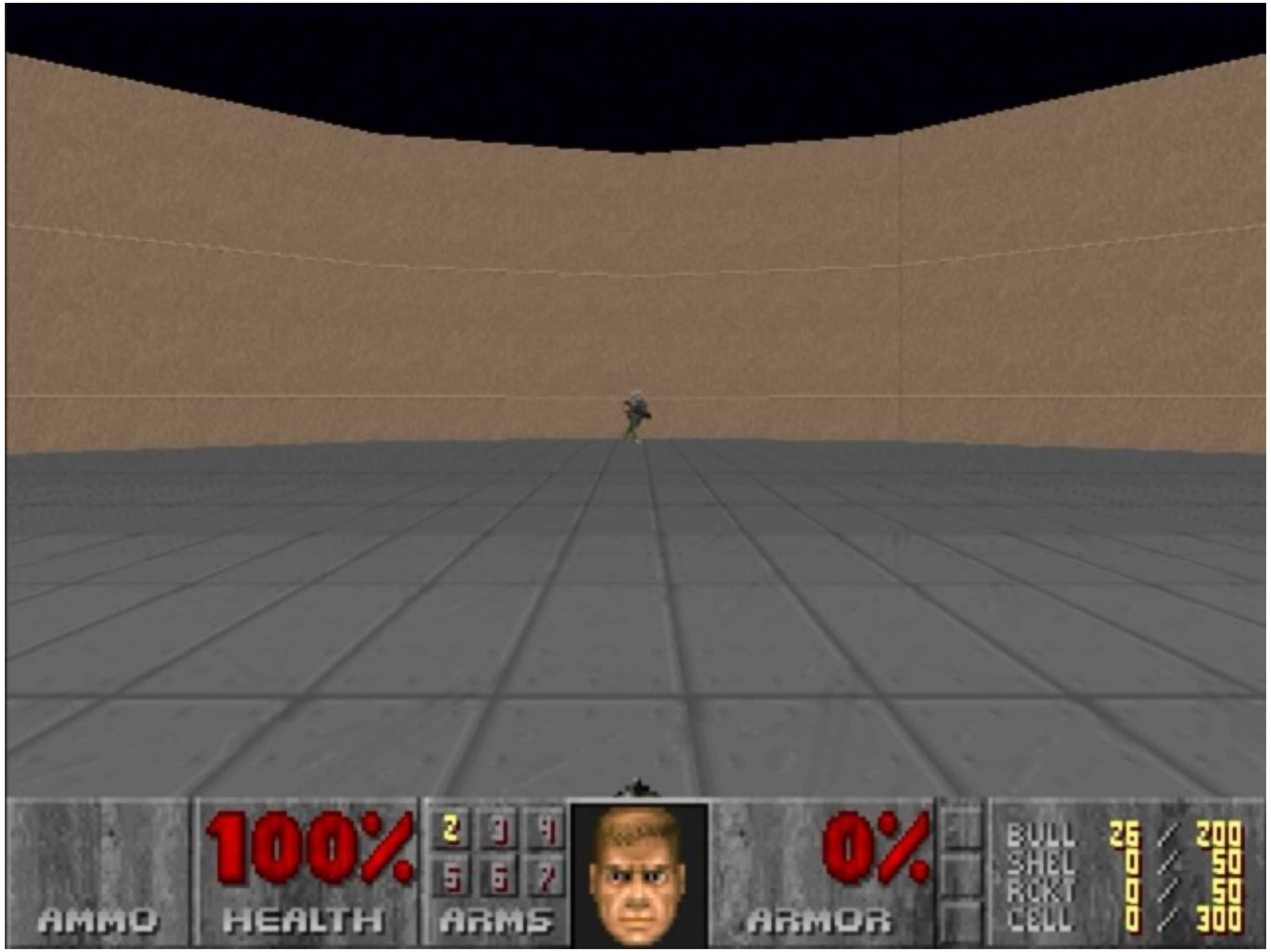
- S F F F
F H F H
F F F H
H F F G

Very Low Reward

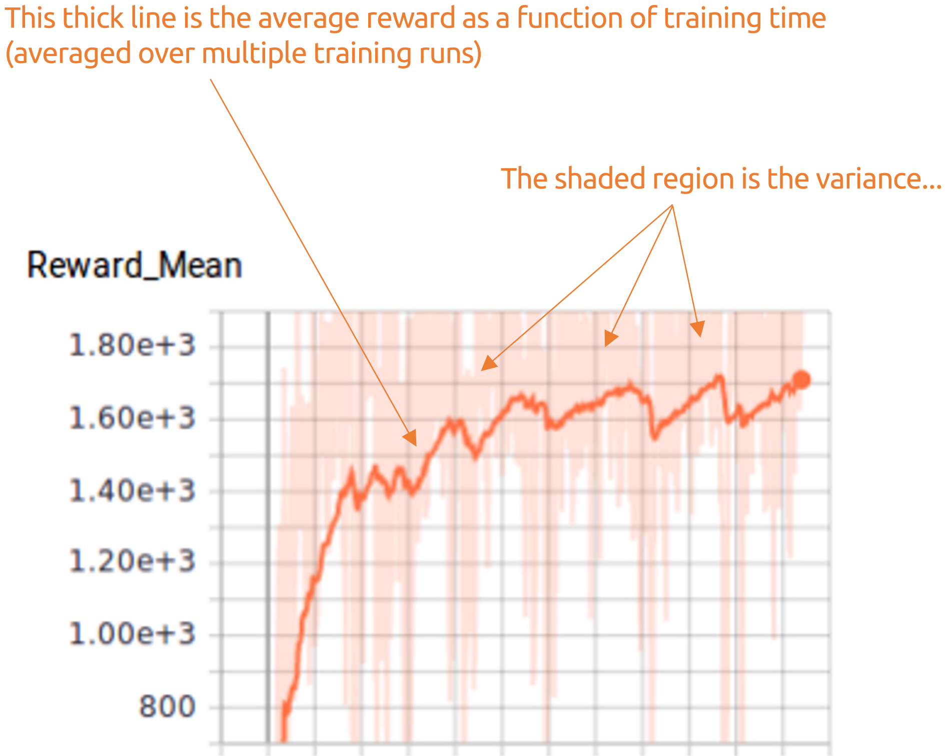
Very High Reward

- Look at $D(s_0 = S, a_0 = \text{down})$

High Variance Rewards: VizDoom



https://www.youtube.com/watch?v=93TrfMZ2Dqs



https://www.oreilly.com/ideas/reinforcement-learning-with-tensorflow

High Variance in REINFORCE

- $D(s_t, a_t)$ is high variance
- This in turn makes $-\sum_{t=1}^{T} \nabla \log p(a_t|s_t) D(s_t, a_t)$ have high variance
- ***What's the consequence of high variance gradients?***
  - Magnitude and direction of gradients is unstable
  - Need very low learning rate to keep training from blowing up
  - Low learning rate → need ***lots*** of training episodes to converge

High Variance in REINFORCE

- Naïve solution: if the gradients fluctuate too much, just scale them so they don't fluctuate as much
  - $-\sum_{t=1}^{T} \nabla \log p(a_t|s_t) D(s_t, a_t) \rightarrow -\boldsymbol{\beta} \sum_{t=1}^{T} \nabla \log p(a_t|s_t) D(s_t, a_t)$

- ***Why won't this work?***
  - Scaling the gradients is equivalent to scaling the learning rate, which is exactly what we're trying to avoid!

Solving High Variance: A Better Critic

- A better critic function:

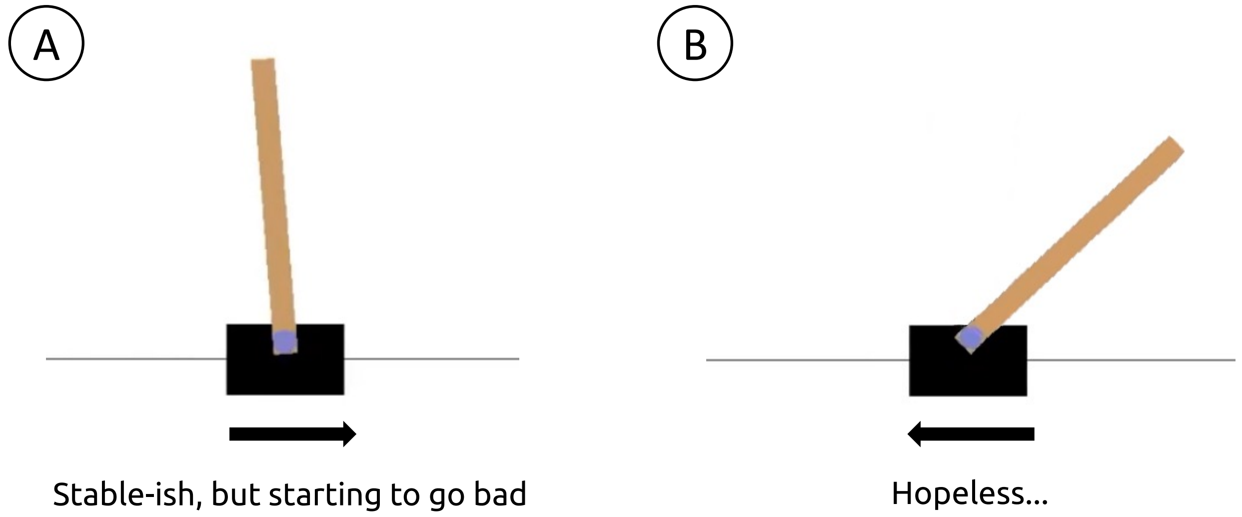
$$\begin{aligned} A(s_t, a_t) &= Q(s_t, a_t) - V(s_t) \\ &= Q(s_t, a_t) - \max_{a_t} Q(s_t, a_t) \end{aligned}$$

- This is called the ***advantage function***
  - The "advantage" of taking action a_t vs. taking the best possible action in state s_t, under the current policy

- **Claim:** $A(s_t, a_t)$ has lower variance than $Q(s_t, a_t)$ (or $D(s_t, a_t)$)

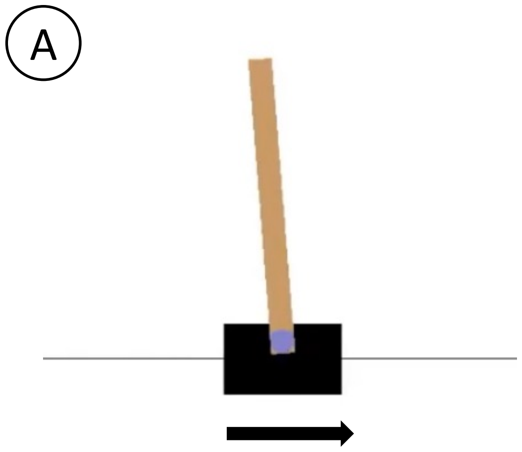
Why $A(s_t, a_t)$ has lower variance

- Consider these two states in Cart Pole

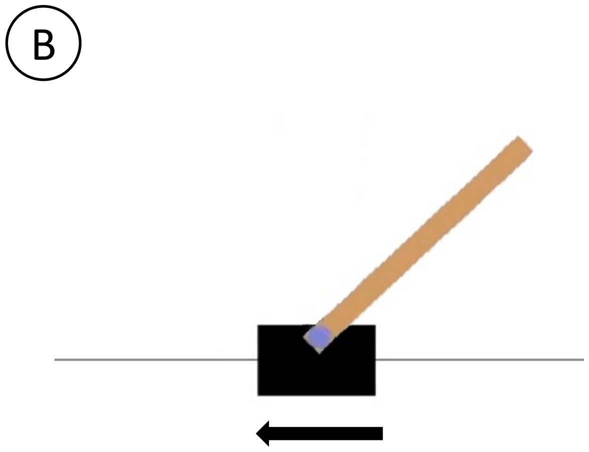


Why $A(s_t, a_t)$ has lower variance

- What would be the Q value of taking the ← action in either state?



Stable-ish, but starting to go bad



Hopeless...

$Q(S_A, \leftarrow)$: Good! (helps stabilize)

$Q(S_B, \leftarrow)$: Bad... (tipping over and this isn't helping)

$\boldsymbol{Q(S_A, \leftarrow) - Q(S_B, \leftarrow)}$: **Large, i.e. high variance...**

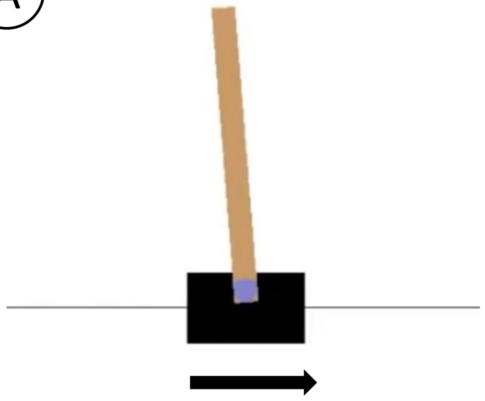
Why $A(s_t, a_t)$ has lower variance

What will be the A values for situation A and B (conceptually)?

- Now consider the A value of taking the ← action in either state:

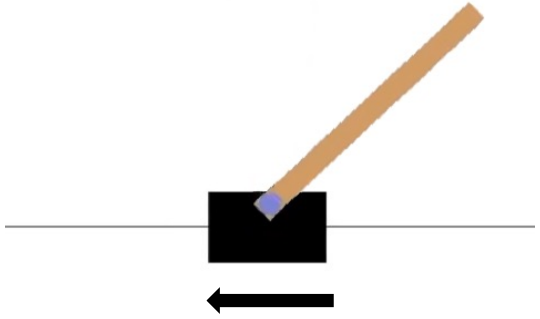
$$A(s_t, a_t) = Q(s_t, a_t) - V(s_t)$$
$$= Q(s_t, a_t) - \max_{a_t} Q(s_t, a_t)$$

A



Stable-ish, but starting to go bad

B



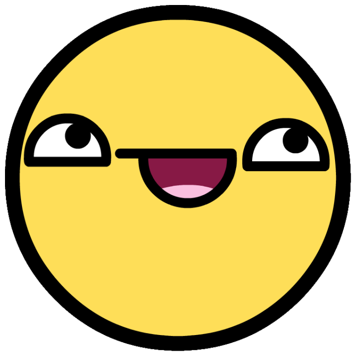
Hopeless...

$A(S_A, \leftarrow)$: Zero (this is the best action)

$A(S_B, \leftarrow)$: Tiny negative number (not the best action, but state is already bad)

$\boldsymbol{A(S_A, \leftarrow) - A(S_B, \leftarrow)}$: **Small difference! Lower variance**

The Advantage of Using Advantage



- **The main idea:** to learn a policy, it doesn't matter whether some states are better than others. All that matters is which *actions* are better for a given state.
- ***Factor out*** the difference in state value and just look at the difference in action value
- $|A(s_1, a_1) - A(s_2, a_2)| < |Q(s_1, a_1) - Q(s_2, a_2)|$

Using Advantage in REINFORCE

- Substitute in the advantage function for the critic:

$$-\sum_{t=1}^{T} \nabla \log p(a_t|s_t) A(s_t, a_t)$$

- Of course, in practice, we don't have Q, so we use D instead:

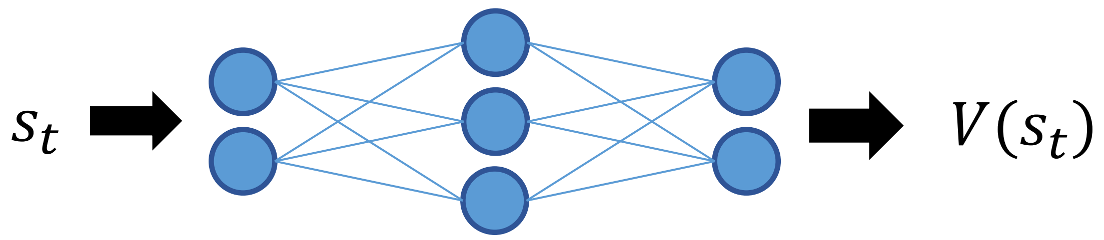
Are we done?

$$-\sum_{t=1}^{T} \nabla \log p(a_t|s_t) \big(D(s_t, a_t) - \boxed{V(s_t)}\big)$$

Wait a minute…we *also* don't have V…

Value Networks

- Use another neural net, the ***Value Network***, to learn an approx. of V
- Like Policy Network, architecture depends on the MDP being solved (i.e. what data representation its state uses)
- For Cart Pole, state is a 4D vector of real numbers
  - [Cart pos, cart vel, pole ang, pole tip vel]
- Fully connected net is appropriate here:



How to Train a Value Network

- Recall the definition of the Value Function
  - Expected future return from being in a given state
  - $V(s_t) = \max_{a_t} Q(s_t, a_t)$
- ***What data do we get from each episode that we might use for training?***
  - The discounted future reward that we got in that episode, from each timestep
  - $D(s_t, a_t) = \sum_{i=t}^{T} \gamma^{i-1}\, r(s_i, a_i, s_{i+1})$
- Idea: just as we used D as an approximation for Q, let's also use it to approximate V
  - i.e. train the Value Network with (input, output) pairs of the form $\left(s_t, D(s_t, a_t)\right)$
  - When trained with many such pairs obtained over many episodes, the network will learn to output a good estimate of the future reward that can be expected starting from the input state—**in other words, the Value Function!**

Any questions?

How to Train a Value Network

- Training loss: $L(s_t) = \left(D(s_t, a_t) - V(s_t)\right)^2$, where V is the Value Network
- ***Does this look familiar?***
- This is exactly the "advantage" term in our gradient update!

$$-\sum_{t=1}^{T} \nabla \log p(a_t|s_t)\left(D(s_t, a_t) - V(s_t)\right)$$

- In other words: training the value network == minimizing the advantage
  - Which is exactly what we want in order to lower the variance!
- The $V(s_t)$ term in the gradient update is also called a "baseline," which gives this algorithm the name ***REINFORCE with Baseline (RwB)***

Modify the code to RL w/ baseline

REINFORCE: Pseudo Code

Initialize policy net weights θ

Repeat until done (converge, time limit expired, etc.):

Run N episodes of environment simulation, each for T timesteps

For each episode

For $t = 1$ to $t = T$

$$\theta \leftarrow \theta + \mathrm{OptimizerStep}(\nabla \log p(a_t|s_t) D\,(s_t, a_t))$$

Return θ

RwB: Pseudo Code

Initialize policy net ***and*** value net weights θ

Repeat until done (converge, time limit expired, etc.):

Run N episodes of environment simulation, each for T timesteps

For each episode

For $t = 1$ to $t = T$

$L_{\text{actor}} = -\log p(a_t|s_t)(D(s_t, a_t) \; - V(s_t))$

$L_{\text{critic}} = \left(D(s_t, a_t) - V(s_t)\right)^2$

$\theta \; \leftarrow \; \theta + \text{OptimizerStep}(\nabla(L_{\text{actor}} + L_{\text{critic}}))$

Return θ

RwB: Pseudo Code

Initialize policy net ***and*** value net weights θ

Repeat until done (converge, time limit expired, etc.):

Run N episodes of environment simulation, each for T timesteps

For each episode

In practice, batch episodes and/or timesteps rather than looping over them

For $t = 1$ to $t = T$

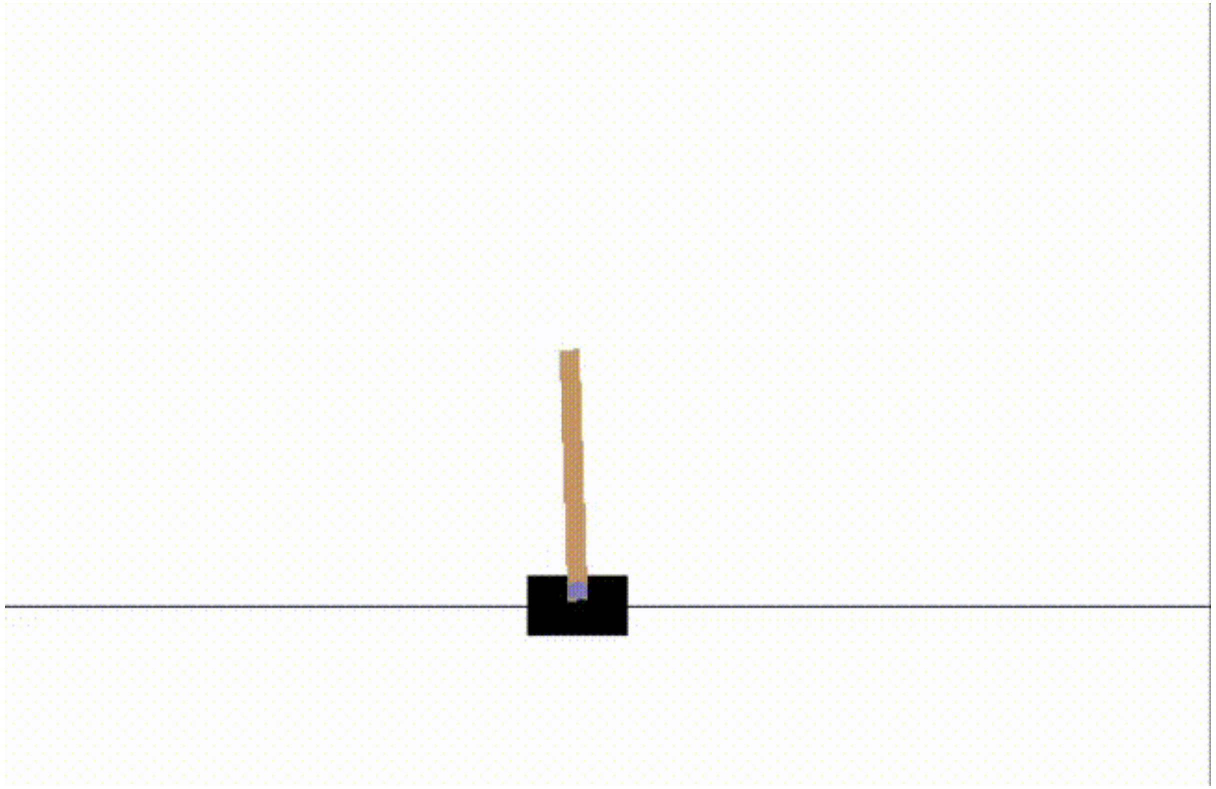
$$L_{\text{actor}} = -\log p(a_t | s_t)(D(s_t, a_t) - V(s_t))$$

$$L_{\text{critic}} = \left(D(s_t, a_t) - V(s_t)\right)^2$$

$$\theta \leftarrow \theta + \text{OptimizerStep}(\nabla(L_{\text{actor}} + L_{\text{critic}}))$$

Return θ

Cart pole with Actor-Critic



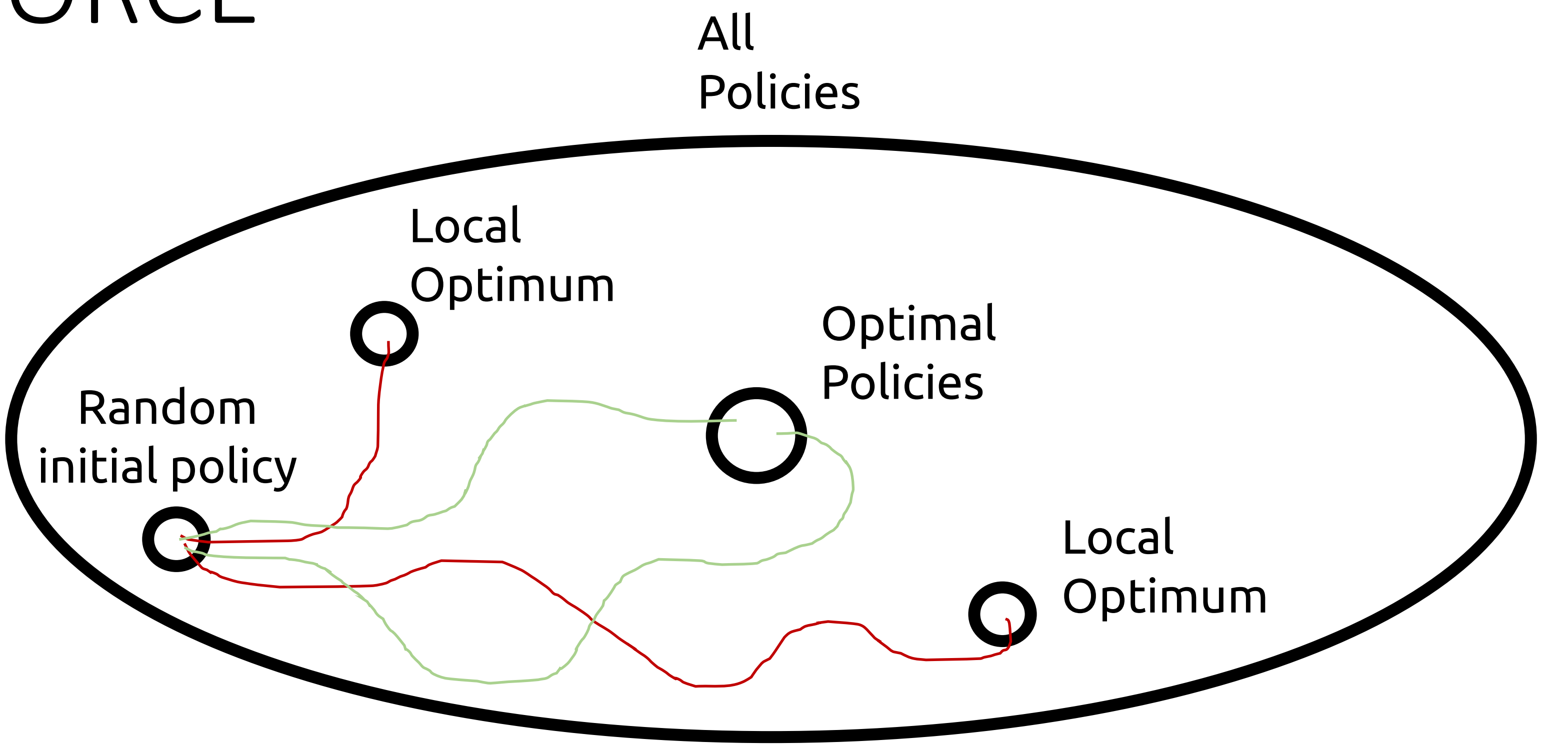
The number of episodes needed to obtain maximum reward << than that for REINFORCE

https://medium.com/nerd-for-tech/policy-gradients-reinforce-with-baseline-6c871a3a068

Issues with REINFORCE

- **High Variance**
  - Multiple run… ning an agent with… ORCE can yield ve… rent results
  - …sc… to local optima

First, go… s this problem…



- **High "sample complexity"**
  - Must play an entire episode to get gradient, takes many episodes to learn

…which will actually give us a solution for this problem via a simple extension

Dealing with Sample Complexity

Enabling more frequent gradient updates

- In REINFORCE, we have to wait until the end of an episode to make a gradient update
- That's because our gradient is $-\sum_{t=1}^{T} \nabla \log p(a_t|s_t) D(s_t, a_t)$
  - To calculate $D(s_t, a_t)$, we need to know everything that happens up to the end of the episode
- You could cut the episode off early, but then $D(s_t, a_t)$ would be biased
- ***What would happen if we did this while training on Frozen Lake?***
  - The only nonzero reward comes on the very last step of the episode
  - If we cut the episode off early, we'd never see this reward, and the agent would never learn anything!

Enabling more frequent gradient updates

- RwB gives us a way to cut the episode off early (or pause it) and take a gradient update *without introducing bias*
- Recall the definition of $D(s_t, a_t)$:

$$D(s_t, a_t) = \sum_{i=t}^{T} \gamma^{i-1} \, r(\, s_i, a_i, s_{i+1})$$

- Write it as a recurrence relation:

$$D(s_T, a_T) = 0$$
$$D(s_t, a_t) = r(s_t, a_t, s_{t+1}) + \gamma D(s_{t+1}, a_{t+1})$$

Enabling more frequent gradient updates

- At any point, we can choose to stop expanding this recurrent relation and instead use our value network to estimate the remainder of D:

$$D(s_t, a_t) = r(s_t, a_t, s_{t+1}) + \gamma D(s_{t+1}, a_{t+1})$$

$$\Downarrow$$

$$D(s_t, a_t) = r(s_t, a_t, s_{t+1}) + \gamma V(s_{t+1})$$

- **Fun fact:** this strategy is how AlphaGo trained itself to play Go without having to explore the (massive) search tree of a Go game: it could terminate the search early and use a trained value network to estimate the value of being in a particular board state

Reducing the number of episodes needed

- Simulating episodes can be very compute-intensive
- More intensive, in fact, than training the networks!
    - AlphaGo used 64 GPUs and 19 CPUs for its model updates...
    - ...but it used ~5,500 TPUs for its Go simulations to create training episodes
- Idea: get more out of the training episodes we've already simulated by periodically re-using them
    - Not a crazy idea: we iterate multiple epochs over the same training set in supervised learning, after all
- Known as ***Experience Replay***

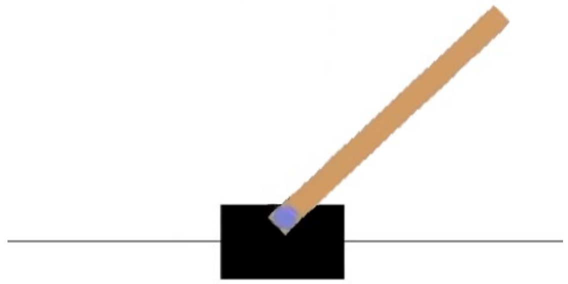
Experience Replay can also stabilize training!

- Recall from way back at the beginning of the class: SGD assumes that the training data is **IID (independent, identically distributed)**
- Time steps taken from a simulated MDP episode are definitely ***not*** independent
  - $(s_0, a_0), (s_1, a_1), \dots, (s_n, a_n)$ → successive time steps are highly correlated
- By training on this data, agent could overfit to patterns in one episode, then have to un-learn when presented with a different episode
- Experience replay mixes up timesteps from past/present episodes, making the data “more IID”
  - Think of it like the agent ‘teleporting’ around to different timesteps of different episodes during training

Any questions?

Experience Replay: Caveat

- As the agent gets better over time, episodes from earlier in training become less valuable (even useless)
- ***Why?***
  - Those mostly explore bad parts of the state space from when the agent was flailing around randomly
  - Now it knows not to go to those states anymore, so why bother learning what to do in them?



Experience Replay: Caveat

- Solution: only keep a limited-size buffer of episodes

Ep 1	Ep 2	Ep 3	•••	Ep 500

- Train on randomly-sampled timesteps from these episodes, for some number of training steps

Experience Replay: Caveat

- Solution: only keep a limited-size buffer of episodes

~~Ep 1~~ | Ep 2 | Ep 3 | ••• | Ep 500 | Ep 501

- Train on randomly-sampled timesteps from these episodes, for some number of training steps
- Then, sample a new episode, add to the buffer, and remove the oldest episode in the buffer
  - i.e. the buffer is a **queue**

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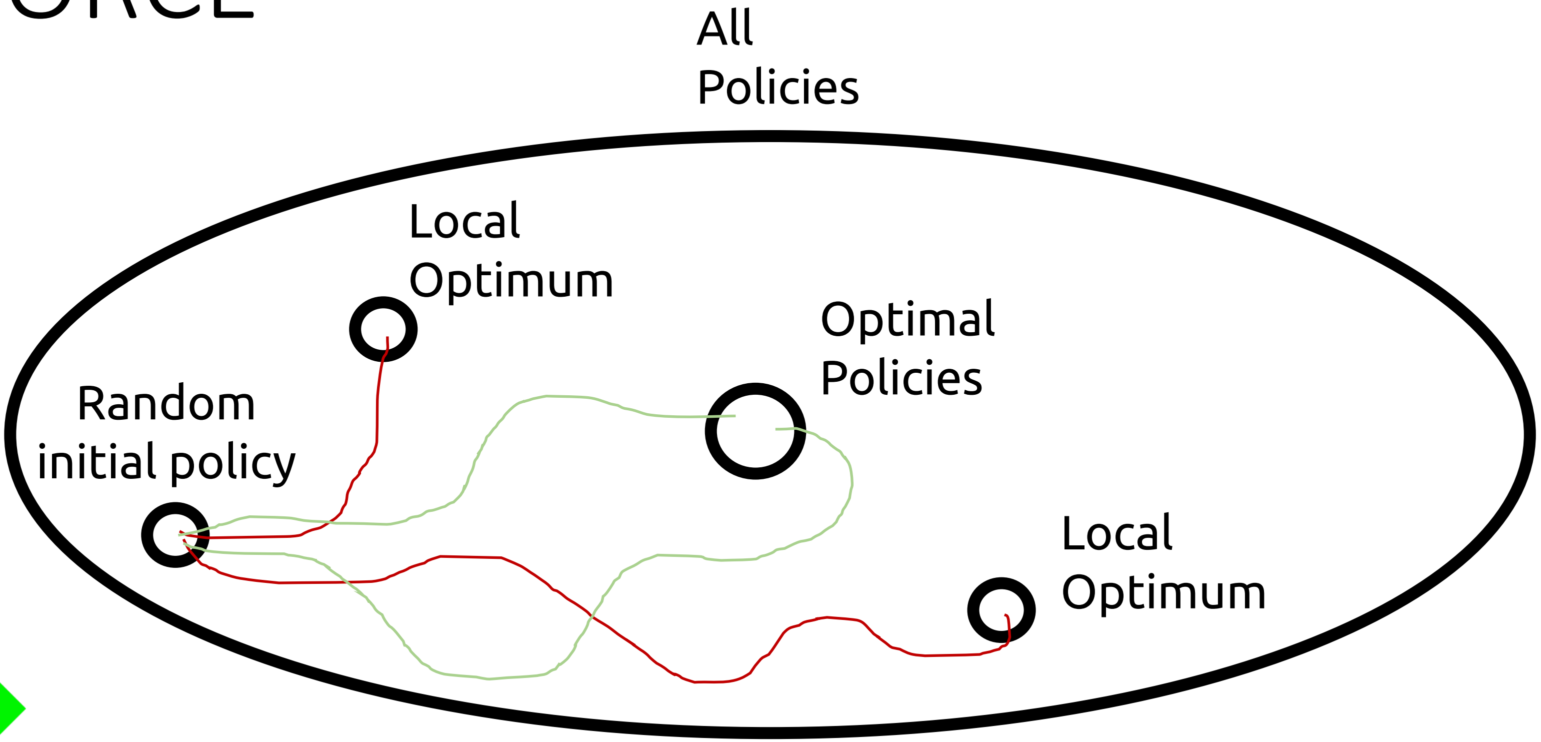

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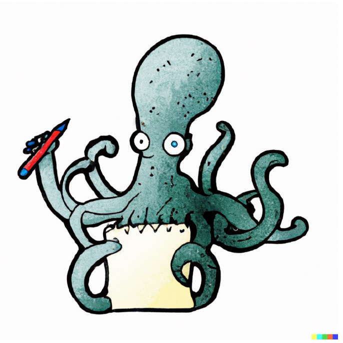

For a more complete taxonomy of RL algorithms, see https://spinningup.openai.com/en/latest/spinningup/rl_intro2.html#citations-below