Sequential Decision Making
WARNING 1
Do not use this stuff because it’s cool, or it seems fancy or because you think it works better.

It doesn’t work better.

It’s worse. It’s provably worse.

You use these methods when you don’t have any other options.
WARNING 2
We only have time to cover the high level intuition of these methods in one lecture, so a lot of this will be incomplete.

The goal is to give you a flavor for the kinds of things you need to pay attention to when using RL.
Sequential Decision Making

Environment
Sequential Decision Making

Observation (x)

Environment
Sequential Decision Making

Observation (x) \rightarrow Policy (\pi) \rightarrow Action (u)

Environment
Sequential Decision Making

Observation ($x$) $\rightarrow$ Policy ($\pi$) $\rightarrow$ Action ($u$) $\rightarrow$ Environment
Sequential Decision Making

Observation ($x$) $\xrightarrow{\text{Policy (}\pi\text{)}}$ Action ($u$)

Environment
Sequential Decision Making

Environment

Policy (π)

Action (u)

Observation (x)

Reward (r)
Sequential Decision Making

\[ x_1, a_1, x_2, a_2, x_3, a_3, \ldots \]
Two High Level Categories

Imitation Learning (covered briefly last time)
- Learn from advice/instructions
- Learn from a knowledgeable teacher

Reinforcement Learning (today)
- Learn from a reward signal that tells us how well we did
- Learn by trial and error
Reinforcement Learning
Mnih et al. 2013 “Playing Atari with Deep Reinforcement Learning”
Silver et al. 2016 “Mastering the game of Go with deep neural networks and tree search”
OpenAI et al. 2019 “Solving Rubik's Cube with a Robot Hand”
Vinyals et al. 2019 “Grandmaster level in StarCraft II using multi-agent reinforcement learning”
Berner et al. 2019 “Dota 2 with large scale deep reinforcement learning”
What is Common About These Domains?
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1. Difficult to provide direct instruction
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2. Search methods may not be tractable
What is Common About These Domains?

1. Difficult to provide direct instruction
2. Search methods may not be tractable
3. May not even know how good optimal performance can be (AlphaGo)
Policy Gradient
(REINFORCE aka Vanilla Policy Gradient)
(Ancestor of A2C, A3C, TRPO, PPO)
Policy Gradient

- States/Observations : $x$
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$

This is what we are trying to learn.
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$

This is what we are trying to learn
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

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Policy Gradient

- States/Observations : \( x \)
- Policy : \( \pi \)
- Actions Space : \( u \)
- Transition Probabilities : \( p(x'|u,x) \)
- Reward Function : \( r(x,u) \)

**Idea 1:** If \( r_2 \) is kind of the opposite of a loss function (something we want to maximize rather than minimize), can we just backprop through this chain of operations?
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

This is what we are trying to learn

\[
p(u_1=A|x_1) \quad \quad p(u_1=B|x_1) \quad \quad p(u_1=C|x_1)
\]

Idea 1: If $r_2$ is kind of the opposite of a loss function (something we want to maximize rather than minimize), can we just backprop through this chain of operations?

Unfortunately, we don’t know the reward function or state-transition probabilities…
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

This is what we are trying to learn

$Idea 1$: If $r_2$ is kind of the opposite of a loss function (something we want to maximize rather than minimize), can we just backprop through this chain of operations?

Unfortunately, we don’t know the reward function or state-transition probabilities, so we can’t backprop through the reward function.
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

This is what we are trying to learn:

$\pi$

$p(u_1=A|x_1)$
$p(u_1=B|x_1)$
$p(u_1=C|x_1)$

State Transition

Reward Function

$r_2$

$x_2$

Sampling is also not differentiable* so we can't backprop this step either.

Idea 1: If $r_2$ is kind of the opposite of a loss function (something we want to maximize rather than minimize), can we just backprop through this chain of operations?

Unfortunately, we don't know the reward function or state-transition probabilities, so we can't backprop through the reward function.

*there are hacks around this though
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

This is what we are trying to learn

$\pi$

| $p(u_1=A|x_1)$ |
| $p(u_1=B|x_1)$ |
| $p(u_1=C|x_1)$ |

Idea 1: If $r_2$ is kind of the opposite of a loss function (something we want to maximize rather than minimize), can we just backprop through this chain of operations?

Unfortunately, we don't know the reward function or state-transition probabilities, so we can't backprop through the reward function.

Sampling is also not differentiable* so we can't backprop this step either.

*we may see a way around this in a later lecture
Policy Gradient

- States/Observations: \( x \)
- Policy: \( \pi \)
- Actions Space: \( u \)
- Transition Probabilities: \( p(x'|u,x) \)
- Reward Function: \( r(x,u) \)

This is what we are trying to learn:

\[
p(u_1 = A|x_1) \\
p(u_1 = B|x_1) \\
p(u_1 = C|x_1)
\]

Idea 2: Can we just increase or decrease the probability of the sampled action based on how good \( r_2 \) is?
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

This is what we are trying to learn:

- $p(u_1 = A|x_1)$
- $p(u_1 = B|x_1)$
- $p(u_1 = C|x_1)$

**Idea 2:** Can we just increase or decrease the probability of the sampled action based on how good $r_2$ is?

Remember that this is one action in a large sequence though! What if $x_2$ is terrible?
States/Observations: \( x \)
- Policy: \( \pi \)
- Actions Space: \( u \)
- Transition Probabilities: \( p(x'|u,x) \)
- Reward Function: \( r(x,u) \)

**Policy Gradient**

- This is what we are trying to learn

\[
p(u_1 = A|x_1),
p(u_1 = B|x_1),
p(u_1 = C|x_1)
\]

**State Transition**

**Reward Function**

Idea 2: Can we just increase or decrease the probability of the sampled action based on how good \( r_2 \) is?

Remember that this is one action in a large sequence though! What if \( x_2 \) is terrible?

So we also need to think about future rewards as well.
Policy Gradient

- States/Observations: \( x \)
- Policy: \( \pi \)
- Actions Space: \( u \)
- Transition Probabilities: \( p(x' | u, x) \)
- Reward Function: \( r(x, u) \)

This is what we are trying to learn

\[ p(u_1 = A | x_1) \]
\[ p(u_1 = B | x_1) \]
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- States/Observations: $x$
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This is what we are trying to learn

$$p(u_1=A|x_1)$$
$$p(u_1=B|x_1)$$
$$p(u_1=C|x_1)$$

Idea 2.5: Can we just increase or decrease the probability of the sampled action based on how good the sum of future rewards is?
Policy Gradient

- States/Observations: \( x \)
- Policy: \( \pi \)
- Actions Space: \( u \)
- Transition Probabilities: \( p(x'|u,x) \)
- Reward Function: \( r(x,u) \)

This is what we are trying to learn

\[
\begin{align*}
\Pr(u_1 = A|x_1) \\
\Pr(u_1 = B|x_1) \\
\Pr(u_1 = C|x_1)
\end{align*}
\]

Idea 2.5: Can we just increase or decrease the probability of the sampled action based on how good the sum of future rewards is?

YES! This is the rough intuition behind policy gradients.
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
  - Transition Probabilities: $p(x'|u,x)$
  - Reward Function: $r(x,u)$

One more thing to say about this though.
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

This is what we are trying to learn.

One more thing to say about this though. We just saw what can happen if $x_2$ is bad…
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

One more thing to say about this though. We just saw what can happen if $x_2$ is bad, but there’s another thing that can cause $r_3$ to be bad...
Policy Gradient

- States/Observations: \( x \)
- Policy: \( \pi \)
- Actions Space: \( u \)
- Transition Probabilities: \( p(x'|u,x) \)
- Reward Function: \( r(x,u) \)

This is what we are trying to learn:

One more thing to say about this though. We just saw what can happen if \( x_2 \) is bad, but there's another thing that can cause \( r_3 \) to be bad and it's us!
If someone offers you $10 million to jump this ramp on a skateboard do you take it?
If someone offers you $10 million to jump this ramp on a skateboard do you take it?

If you are Tony Hawk:

YES!
If someone offers you $10 million to jump this ramp on a skateboard do you take it?

If you are Aaron Walsman with grad student health insurance:

**NO!**
Policy Gradient

- States/Observations: $x$
- Policy: $\pi$
- Actions Space: $u$
- Transition Probabilities: $p(x'|u,x)$
- Reward Function: $r(x,u)$

The point is that $r_3$ depends not only on the physical environment, but also the capability of our current model $\pi$! This will come back to haunt us later!
Policy Gradient

How do we adjust the probability based on the sum of rewards?
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We will look at two ways:

Policy Gradient
Policy Gradient

How do we adjust the probability based on the sum of rewards?

We will look at two ways:

1. Derivation!
How do we adjust the probability based on the sum of rewards?

We will look at two ways:

1. Derivation!
2. Simple-ish Intuition!
Policy Gradient

How do we adjust the probability based on the sum of rewards?

We will look at two ways:

1. Derivation!
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Policy Gradient

So the derivation... I was actually going to walk through all of this, but then realized we wouldn’t have time.

Here’s a blog post on it though, it’s actually not that bad:
Policy Gradient

So the derivation... I was actually going to walk through all of this, but then realized we wouldn’t have time. This is the important part though, this is the “answer.”

\[
J(\theta) = \mathbb{E}\left[ \sum_{t=0}^{T-1} r_{t+1} \right]
\]

\[
\theta \leftarrow \theta + \frac{\partial}{\partial \theta} J(\theta)
\]

Here’s a blog post on it though, it’s actually not that bad:
Policy Gradient

What does it mean?

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The objective function

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Model parameters (NN weights)

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The objective function

Model parameters (NN weights)

Expectation is with respect to unknown transition dynamics and our own action distribution

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The objective function
Model parameters (NN weights)
Expectation is with respect to unknown transition dynamics and our own action distribution

The sum of future rewards

Here's a blog post on it though, it's actually not that bad:
Policy Gradient

What does it mean?

There is often a discount factor in here, but we will ignore it for now.

$$J(\theta) = \mathbb{E}\left[ \sum_{t=0}^{T-1} r_{t+1} \right]$$

The sum of future rewards

The objective function

Model parameters (NN weights)

Expectation is with respect to unknown transition dynamics and our own action distribution

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Policy Gradient

What does it mean?

\[ J(\theta) = \mathbb{E} \left[ \sum_{t=0}^{T-1} r_{t+1} \right] \]

So what we want is to maximize this thing, which is the expected sum of future rewards

Here's a blog post on it though, it's actually not that bad:
Policy Gradient

What does it mean?

\[ J(\theta) = \mathbb{E}\left[ \sum_{t=0}^{T-1} r_{t+1} \right] \]

And what we want is the gradient of this objective function...

\[ \nabla_\theta J(\theta) \]

...so we can adjust our network parameters in the direction that increases this objective.

\[ \theta \leftarrow \theta + \frac{\partial}{\partial \theta} J(\theta) \]

Here's a blog post on it though, it's actually not that bad:
Policy Gradient

What does it mean?

\[
J(\theta) = \mathbb{E}\left[ \sum_{t=0}^{T-1} r_{t+1} \right]
\]

\[
\nabla_\theta J(\theta) = \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta (a_t | s_t) G_t
\]

This is the “answer” that we highlighted earlier.

Here’s a blog post on it though, it’s actually not that bad:
Policy Gradient

What does it mean?

\[
J(\theta) = \mathbb{E}\left[ \sum_{t=0}^{T-1} r_{t+1} \right]
\]

\[
\nabla_\theta J(\theta) = \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t|s_t) G_t
\]

What it says is that the gradient is the sum over all steps in a trajectory... ...of the log of the probability of taking whichever action was taken... ...times the empirical return (the sum of future rewards).

Here’s a blog post on it though, it’s actually not that bad: https://medium.com/@thechrisyoon/deriving-policy-gradients-and-implementing-reinforce-f887949bd63
Policy Gradient

How do we adjust the probability based on the sum of rewards?

We will show this two ways:

1. Derivation!
2. Simple-ish Intuition!
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

Unnormalized Log Probabilities

\[ \sum_{i=0}^{9} e^{x_i} \]

Normalized Probabilities \( (p_{xi}) \)
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

\[
\begin{align*}
\text{Unnormalized Log Probabilities} & : e^{x_i} \\
\text{Normalized Probabilities (p}_{x_i} & : \frac{e^{x_i}}{\sum_{i=0}^{9} e^{x_i}} \\
\text{Target (q}_{x_i} & :
\end{align*}
\]
How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

Unnormalized Log Probabilities

\[ \sum_{i=0}^{9} e^{x_i} \]

Normalized Probabilities (\( p_{xi} \))

\[ \frac{e^{x_i}}{\sum_{i=0}^{9} e^{x_i}} \]

Target (\( q_{xi} \))

\[ -\sum_{i=1}^{9} \log(p_{xi}) q_{xi} \]
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

Unnormalized Log Probabilities

Normalized Probabilities ($p_{xi}$)

Target ($q_{xi}$)

Cross Entropy

$$\sum_{i=0}^{9} e^{x_i}$$

$$-\log(p_{x6})$$

$$-\log(p_{x7})$$

$$-\log(p_{x8})$$
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

Unnormalized Log Probabilities

Normalized Probabilities ($p_{xi}$)

Target ($q_{xi}$)

Cross Entropy

$$\sum_{i=0}^{9} e^{xi}$$

$$-\log(p_{x7})$$
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

\[-\log(p_{x_7}) \]
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization: 

\[-\log(p_{x+})\]
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

\[ \nabla \theta J(\theta) = \sum_{t=0}^{T-1} \nabla \theta \log \pi_\theta(a_t | s_t) G_t \]

Cross Entropy

\[-\log(p_{x^+}) 1\]
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

\[ \nabla_\theta \log \pi_\theta (a_t | s_t) G_t \]

Cross Entropy

\[ -\log(p_{x^+}) \]
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

\[ \nabla_\theta \log \pi_\theta(a_t|s_t)G_t \]

Cross Entropy Gradient

\[ \nabla_\theta - \log(p_{x^+}) 1 \]
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Cross Entropy Minimization:

\[ \nabla_{\theta} \log p_{\theta}(a_t|s_t) G_t \]

This is the cross entropy gradient scaled by the return

Policy Gradient

Cross Entropy Gradient

\[ \nabla_{\theta} - \log (p_{x^+}) 1 \]

Policy Distribution

Class Distribution
Policy Gradient

How do we adjust the probability based on the sum of rewards?

Take the update you would make to the network if the action you took was “correct” according to a standard classification objective and scale it by the return:

$$\nabla_\theta \log \pi_{\theta}(a_t | s_t) G_t$$
One Caveat:

What is the optimal policy for both of these environments?

Policy Gradient

Reward:
Crashing: -1
Making the first turn: +1

Reward:
Crashing: -10
Making the first turn: +10
Policy Gradient

One Caveat:

What about these two?

Reward:
Crashing: -1
Making the first turn: +1

Reward:
Crashing: +4
Making the first turn: +5
Policy Gradient

One Caveat:
The “ordering” of policies is invariant to linear transformations of reward!

Reward:
Crashing: -1
Making the first turn: +1

Reward:
Crashing: +4
Making the first turn: +5
Policy Gradient

One Caveat:
The “ordering” of policies is invariant to linear transformations of reward!

But our learning rule is definitely sensitive to these transformations!

\[ \nabla_\theta \log \pi_\theta(a_t|s_t)G_t \]
Policy Gradient

The simplest fix:

Subtract the mean and divide by the standard deviation before using returns for training.

Encourages above average actions while discouraging below-average actions.

\[ \nabla_\theta \log \pi_\theta(a_t|s_t) \left( \frac{G_t - \text{mean}}{\text{std}} \right) \]

Reward:
Crashing: -0.707
Making the first turn: +0.707

Reward:
Crashing: -0.707
Making the first turn: +0.707
Policy Gradient

Second Caveat:
Some states are actually better than others.
Policy Gradient

Second Caveat:
Some states are actually better than others.
Imagine our episode only lasts for a certain number of steps.
Policy Gradient

Second Caveat:

Some states are actually better than others.

Imagine our episode only lasts for a certain number of steps.

And you get reward for making progress along the way.
Policy Gradient

Second Caveat:

Some states are actually better than others.

Imagine our episode only lasts for a certain number of steps.

And you get reward for making progress along the way.

What happens?
Policy Gradient

Second Caveat:

Some states are actually better than others.

Imagine our episode only lasts for a certain number of steps.

And you get reward for making progress along the way.

What happens?
Policy Gradient

Second Caveat:
Some states are actually better than others.

Imagine our episode only lasts for a certain number of steps.

And you get reward for making progress along the way.

What happens?
Policy Gradient

The simplest fix:

Train a second “baseline” network to estimate future returns of each state.

Subtract the baseline from returns.

\[ \nabla \theta \log \pi_\theta (a_t | s_t) \left( \frac{G_t - \text{mean}}{\text{std}} - \text{baseline}(s_t) \right) \]
Policy Gradient

Ok, so everything we’ve done so far has only shown us how to do a single update. How do we turn this into an entire algorithm?
Policy Gradient

1. Collect data by letting the agent drive in the environment
Policy Gradient

1. Collect data by letting the agent drive in the environment
2. Compute returns from the rewards in the trajectories
Policy Gradient

1. Collect data by letting the agent drive in the environment
2. Compute returns from the rewards in the trajectories
3. Normalize the returns using the mean, and std
Policy Gradient

1. Collect data by letting the agent drive in the environment
2. Compute returns from the rewards in the trajectories
3. Normalize the returns using the mean, and std
4. Update the baseline by training it to match the current returns at each of the states visited
Policy Gradient

1. Collect data by letting the agent drive in the environment
2. Compute returns from the rewards in the trajectories
3. Normalize the returns using the mean, and std
4. Update the baseline by training it to match the current returns at each of the states visited
5. Update the Policy using the policy gradient and the returns from step 3 offset by the baseline
Policy Gradient

1. Collect data by letting the agent drive in the environment
2. Compute returns from the rewards in the trajectories
3. Normalize the returns using the mean, and std
4. Update the baseline by training it to match the current returns at each of the states visited
5. Update the Policy using the policy gradient and the returns from step 3 offset by the baseline
6. Repeat
Policy Gradient

1. Collect data by letting the agent drive in the environment
2. Compute returns from the rewards in the trajectories
3. Normalize the returns using the mean, and std
4. Update the baseline by training it to match the current returns at each of the states visited
5. Update the Policy using the policy gradient and the returns from step 3 offset by the baseline
6. Repeat

In the basic policy gradient algorithm, these two parts only train on the most recent data, can we somehow keep data around from the past like we did with DAgger and keep training on that too?
In the basic policy gradient algorithm, these two parts only care on the most recent data, can we somehow keep data around from the past like we did with DAgger and keep training on that too?

Policy Gradient

1. Collect data by letting the agent drive in the environment
2. Compute returns from the rewards in the trajectories
3. Normalize the returns using the mean, and std
4. Update the baseline by training it to match the current returns at each of the states visited
5. Update the Policy using the policy gradient and the returns from step 3 offset by the baseline
6. Repeat
Policy Gradient

Why not?
Policy Gradient

Why not?

Let’s consider the trajectory that crashed.
Policy Gradient

Why not?

Let’s consider the trajectory that crashed.

And let’s assume that after training for a while, we would learn from our mistakes and perform better from these intermediate states.
Policy Gradient

Why not?

Let’s consider the trajectory that crashed.

And let’s assume that after training for a while, we would learn from our mistakes and perform better from these intermediate states.

But if we keep around the old data and keep training on it, the return values no longer reflect how well we would do if we take this action.

We would get completely different better numbers if we took similar actions now.
Why not?

Let’s consider the trajectory that crashed.

And let’s assume that after training for a while, we would learn from our mistakes and perform better from these intermediate states.

But if we keep around the old data and keep training on it, the return values no longer reflect how well we would do if we take this action.

For this reason, we call these algorithms “On Policy” because they only work when training from data generated by the **CURRENT** policy.
Correlated Data!
Policy Gradient

What is good about this?
Policy Gradient

What is good about this?

- Doesn’t require expert advice!
Policy Gradient

What is good about this?

- Doesn’t require expert advice!
- Can potentially learn a model better than any performance level you’re aware of
Policy Gradient

What is bad about this?
Policy Gradient

What is bad about this?

- So slow!
Policy Gradient

What is bad about this?

- So slow!
  - Only get feedback on one action at a time (scales with size of action space)
Policy Gradient

What is bad about this?

- So slow!
  - Only get feedback on one action at a time (scales with size of action space)
  - Combining feedback from the future may be confusing (depends on horizon)
Policy Gradient

What is bad about this?

- So slow!
  - Only get feedback on one action at a time (scales with size of action space)
  - Combining feedback from the future may be confusing (depends on horizon)
  - Have to constantly throw away your data (reuse data 100x in other settings)
Off-Policy Methods
(DQN, DDPG, SAC)
The Problem With On-Policy Methods

We discovered that we cannot train on old data when using policy gradient.

If we have some data from the beginning of training...
The Problem With On-Policy Methods

We discovered that we cannot train on old data when using policy gradient.

If we have some data from the beginning of training and then improve our performance...
The Problem With On-Policy Methods

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If we have some data from the beginning of training and then improve our performance, the return information that we collected when we gathered the data is no longer relevant. The data is stale.
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If we have some data from the beginning of training and then improve our performance, the return information that we collected when we gathered the data is no longer relevant. The data is stale.

We said that this is called “On-Policy” because we can only train on data collected with the current policy.

We would get completely different better numbers if we took similar actions now.

\[ \gamma = 0.9 \]
The Problem With On-Policy Methods

Why is this bad?

If your environment is a really fast simulator that’s very cheap to run, it’s not that bad.
The Problem With On-Policy Methods

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If your environment is a really fast simulator that’s very cheap to run, it’s not that bad.

But if your environment is an expensive robot that can break if you do something wrong, then it’s a huge burden.
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Your main loop is:

1. Collect data on the robot (Manual labor!)
2. Train the robot using the data
The Problem With On-Policy Methods

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But if your environment is an expensive robot that can break if you do something wrong, then it’s a huge burden.

Your main loop is:

1. Collect data on the robot (Manual labor!)
2. Train the robot using the data

It’s also very inconvenient if you have to keep switching back and forth frequently.
The Problem With On-Policy Methods

It is common to measure the performance of RL algorithms using “Sample Complexity” or the amount of interactions you have need to have with an environment in order to reach a certain performance level.
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On-Policy methods usually have very high Sample Complexity because you need to interact with the environment every time you want to improve your model.
The Problem With On-Policy Methods

It is common to measure the performance of RL algorithms using “Sample Complexity” or the amount of interactions you have need to have with an environment in order to reach a certain performance level.

On-Policy methods usually have very high Sample Complexity because you need to interact with the environment every time you want to improve your model.

We can also measure how many training steps we need, but in almost all applications, training steps are much cheaper than interacting with the environment to collect data.

The x-axis is environment steps, not training steps!
What We Would Like

Program Sketch:
What We Would Like

Program Sketch:

1. initialize an empty dataset
What We Would Like

Program Sketch:

1. initialize an empty dataset
2. for some number of rounds:
What We Would Like

Program Sketch:

1. initialize an empty dataset
2. for some number of rounds:
   a. for m steps:
      i. Do one step of interaction with the environment
What We Would Like

Program Sketch:

1. initialize an empty dataset
2. for some number of rounds:
   a. for m steps:
      i. Do one step of interaction with the environment
   b. Add the data to a growing dataset (like DAgger)
What We Would Like

Program Sketch:

1. initialize an empty dataset
2. for some number of rounds:
   a. for m steps:
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   b. Add the data to a growing dataset (like DAgger)
   c. for n steps:
      i. Do one training step on a randomly sampled batch from the dataset
What We Would Like

Program Sketch:

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   b. Add the data to a growing dataset (like DAgger)
   c. for n steps:
      i. Do one training step on a randomly sampled batch from the dataset

Saving old data into a large dataset and sampling random batches has the additional advantage of providing data diversity in each batch.
What We Would Like

Program Sketch:

1. **initialize an empty dataset**
2. for some number of rounds:
   a. for m steps:
      i. Do one step of interaction with the environment
   b. **Add the data to a growing dataset** (like DAgger)
   c. for n steps:
      i. Do one training step on a randomly sampled batch from the dataset

And just to reiterate, in Policy Gradient and other On-Policy methods, we can’t store a large dataset and have to train only on the most recent data.
How do we get what we want?

Let’s unpack our previous illustration:
How do we get what we want?

Let’s unpack our previous illustration:

We showed that the returns captured early on...
How do we get what we want?

Let’s unpack our previous illustration:

We showed that the returns captured early on may not reflect the returns we will see after our policy has improved if we were to visit a similar state.
How do we get what we want?

Let’s unpack our previous illustration:

Let’s label the actions that we took originally as $a_i^{\text{old}}$...
How do we get what we want?

Let’s unpack our previous illustration:

Let’s label the actions that we took originally as $a_i^{\text{old}}$ and the actions we would take in the future as $a_i^{\text{new}}$. 

How do we get what we want?
How do we get what we want?

Let’s unpack our previous illustration:

Next note that the first step of this experience is actually still fine. If I take action $a_1^{\text{old}}$ the reward that I originally got does not depend on the shift in policy distributions.
How do we get what we want?

Let’s unpack our previous illustration:

Next note that the first step of this experience is actually still fine. If I take action $a_1^{old}$ the reward that I originally got does not depend on the shift in policy distributions.

It might be true that even the first step would be different under the new policy, BUT if I take the $a_1^{old}$ I can expect similar results to what I saw last time. The problem is with the part that comes afterward.
How do we get what we want?

Let’s unpack our previous illustration:

But what if we replaced the empirical returns with an estimate of my value in this second state?
How do we get what we want?

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If that estimate is -1 early in training...
How do we get what we want?

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But what if we replaced the empirical returns with an estimate of my value in this second state?

If that estimate is -1 early in training, but 4 later then we can train on $r + \gamma \text{estimate}(s_{i+1})$ and everything is fine.
How do we get what we want?

Let’s unpack our previous illustration:

But what if we replaced the empirical returns with an estimate of my value in this second state?

If that estimate is -1 early in training, but 4 later then we can train on $r + \gamma \text{estimate}(s_{i+1})$ and everything is fine.

So what we can do is keep the old data around, but use NEW estimates of future return.
How do we get what we want?

We could use these estimated returns \((r + \gamma \text{ estimate}(s_{i+1}))\) in a policy gradient framework, which would lead to something like the actor-critic framework we talked about last time. We’re actually going to go a bit further, but to do so, we need some new tools.
How do we get what we want?

We could use these estimated returns \((r + \gamma \text{estimate}(s_{i+1}))\) in a policy gradient framework, which would lead to something like the actor-critic framework we talked about last time. We’re actually going to go a bit further, but to do so, we need some new tools.

Also, I am so sorry guys, I really tried to avoid this, but I’m going to pass along some generational trauma in the form of grinding through some math over the next few slides. This is how most people teach RL and I hate it, but it’s kind of necessary to get where we need to be.
How do we get what we want?

New Tool 1:

1. policy (π): some agent capable of acting in the environment. Often written as πθ when it is a network with parameters θ.
2. states/observations (sᵢ or xᵢ or occasionally oᵢ): the states or observations used to make decisions at step i.
3. actions (aᵢ or uᵢ): the actions an agent takes at step i.
4. reward (rᵢ): the reward returned from the environment at step i.
5. discount (γ): a scalar constant describing how much we care about short term vs. long term reward.
6. return (gᵢ = Σᵢ≤t≤T γ(t-i)rᵢ): the discounted empirical sum of future rewards after taking an action.
7. value (v₇(sᵢ) = Eᵦᵢ…T~π gᵢ): the expected return of being in state sᵢ and acting using the policy π until the end of an episode.
8. action value (q₇(π(sᵢ, aᵢ)) = Eᵦᵢ~r(sᵢ,aᵢ)ᵢ rᵢ + γ v₇(π(sᵢ+1))): the expected value of taking action aᵢ in state sᵢ then following π until the end.
How do we get what we want?

\[
q_{\pi}(s_i, a_i) = E_{r_i \sim r(s_i, a_i)} r_i + \gamma v_{\pi}(s_{i+1})
\]
How do we get what we want?

\[ q_\pi(s_i, a_i) = E_{r_i \sim r(s_i, a_i)} r_i + \gamma V_\pi(s_{i+1}) \]

In our next algorithm DQN, we’re going to be learning this
How do we get what we want?

New Tool 2: Bellman Equation:

\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} g_i \] expand
How do we get what we want?

New Tool 2: Bellman Equation:

\[ v_\pi(s_i) = \mathbb{E}_{a_i \ldots T \sim \pi} g_i \quad \text{expand} \]

\[ v_\pi(s_i) = \mathbb{E}_{a_i \ldots T \sim \pi} r_i + \gamma r_{i+1} + \gamma^2 r_{i+2} \ldots \quad \text{Factor out } \gamma \]
How do we get what we want?

New Tool 2: Bellman Equation:

$$v_{\pi}(s_i) = E_{a_i \ldots T \sim \pi} g_i \quad \text{expand}$$

$$v_{\pi}(s_i) = E_{a_i \ldots T \sim \pi} r_i + \gamma r_{i+1} + \gamma^2 r_{i+2} \ldots \quad \text{Factor out } \gamma$$

$$v_{\pi}(s_i) = E_{a_i \ldots T \sim \pi} r_i + \gamma \left( r_{i+1} + \gamma r_{i+2} \ldots \right) \quad \text{Substitute}$$
How do we get what we want?

New Tool 2: Bellman Equation:

\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} r_i \]  
expand

\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} r_i + \gamma r_{i+1} + \gamma^2 r_{i+2} \ldots \]  
Factor out \( \gamma \)

\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} r_i + \gamma (r_{i+1} + \gamma r_{i+2} \ldots) \]  
Substitute

\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} r_i + \gamma g_{i+1} \]  
Separate the Expectation
How do we get what we want?

New Tool 2: Bellman Equation:

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\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} r_i + \gamma (r_{i+1} + \gamma r_{i+2} \ldots) \quad \text{Substitute} \]

\[ v_\pi(s_i) = E_{a_i \sim \pi} r_i + \gamma g_{i+1} \quad \text{Separate the Expectation} \]

\[ v_\pi(s_i) = E_{a_i \sim \pi} r_i + E_{a_{i+1} \ldots T \sim \pi} \gamma g_{i+1} \quad \text{Move } \gamma \text{ outside the expectation} \]
How do we get what we want?

New Tool 2: Bellman Equation:

\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} g_i \]  
--- expand

\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} r_i + \gamma r_{i+1} + \gamma^2 r_{i+2} \ldots \]  
--- Factor out \( \gamma \)

\[ v_\pi(s_i) = E_{a_i \ldots T \sim \pi} r_i + \gamma (r_{i+1} + \gamma r_{i+2} \ldots) \]  
--- Substitute

\[ v_\pi(s_i) = E_{a_i \sim \pi} r_i + \gamma g_{i+1} \]  
--- Separate the Expectation

\[ v_\pi(s_i) = E_{a_i \sim \pi} r_i + E_{a_i+1 \ldots T} \gamma g_{i+1} \]  
--- Move \( \gamma \) outside the expectation

\[ v_\pi(s_i) = E_{a_i \sim \pi} r_i + \gamma E_{a_i+1 \ldots T} g_{i+1} \]  
--- Substitute
How do we get what we want?

New Tool 2: Bellman Equation:

\[ v_\pi(s_i) = E_{a_i \sim \pi} g_i \]

\[ v_\pi(s_i) = E_{a_i \sim \pi} r_i + \gamma r_{i+1} + \gamma^2 r_{i+2} \ldots \]

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\[ v_\pi(s_i) = E_{a_i \sim \pi} r_i + \gamma v_\pi(s_{i+1}) \]

The Bellman Equation
Let’s say we’re trying to play Mario, and we already have a really good Q estimator.

$$q_{\pi}(s_i, a_i) = \mathbb{E}_{r_i \sim r(s_i, a_i)} r_i + \gamma v_{\pi}(s_{i+1})$$

How do we get what we want?

Our Q estimator takes an observation in and produces q values for all possible actions.
Let's say we're trying to play Mario, and we already have a really good Q estimator.

$$q_{\pi}(s_i, a_i) = E_{r_i \sim r(s_i, a_i)} r_i + \gamma v_{\pi}(s_{i+1})$$

If I have this information, how should I act? (What should my policy be?)

How do we get what we want?
How do we get what we want?

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\[ \pi(s_i) = \arg\max_{a_i} q_\pi(s_i, a_i) \]
How do we get what we want?

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If I have this information, how should I act? (What should my policy be?)

\[ \pi(s_i) = \arg\max_{a_i} (q_\pi(s_i, a_i)) \]

So if my policy is to take the maximum \( q \), what is \( v_\pi(s_{i+1}) = E_{a_{i+1}, \ldots, T \sim \pi} g_{i+1} \)?
How do we get what we want?

Let’s say we’re trying to play Mario, and we already have a really good Q estimator.

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\[ \pi(s_i) = \text{argmax}_{a_i} (q_{\pi}(s_i, a_i)) \]

So if my policy is to take the maximum \( q \), what is \( v_{\pi}(s_{i+1}) = \mathbb{E}_{a_{i+1} \sim \pi \, r_{i+1} + \gamma v_{\pi}(s_{i+2})} \)?

\[ v_{\pi}(s_{i+1}) = \mathbb{E}_{a_{i+1} \sim \pi \, r_{i+1} + \gamma v_{\pi}(s_{i+2})} \]

Bellman

Expand Expectation
How do we get what we want?

Let’s say we’re trying to play Mario, and we already have a really good Q estimator.

\[ q_\pi(s_i, a_i) = E_{r_i \sim r(s_i, a_i)} r_i + \gamma v_\pi(s_{i+1}) \]

If I have this information, how should I act? (What should my policy be?)

\[ \pi(s_i) = \arg\max_{a_i} (q_\pi(s_i, a_i)) \]

So if my policy is to take the maximum of a Q, what is \[ v_\pi(s_{i+1}) = E_{a_{i+1} \sim \pi} r_{i+1} + \gamma v_\pi(s_{i+2}) \]?
Let’s say we’re trying to play Mario, and we already have a really good Q estimator.

$$q_\pi(s_i,a_i) = E_{r_i \sim r(s_i,a_i)} r_i + \gamma v_\pi(s_{i+1})$$

If I have this information, how should I act? (What should my policy be?)

$$\pi(s_i) = \text{argmax}_{a_i} (q_\pi(s_i,a_i))$$

So if my policy is to take the maximum q, what is $$v_\pi(s_{i+1}) = E_{a_{i+1} \sim \pi} \sum_{t=i+1}^{T} g_t$$ ?

$$v_\pi(s_{i+1}) = E_{a_{i+1} \sim \pi} g_{i+1} + \gamma v_\pi(s_{i+2})$$

$$v_\pi(s_{i+1}) = \sum_{a_{i+1}} \pi(a_{i+1}) E_{r_{i+1} \sim r(s_{i+1},a_{i+1})} r_{i+1} + \gamma v_\pi(s_{i+2})$$

How do we get what we want?

$$v_\pi(s_{i+1}) = \sum_{a_{i+1}} \pi(a_{i+1}) q_\pi(s_{i+1},a_{i+1})$$
How do we get what we want?

Let’s say we’re trying to play Mario, and we already have a really good Q estimator.

$$q_{\pi}(s_i, a_i) = \mathbb{E}_{r_i \sim r(s_i, a_i)} r_i + \gamma v_{\pi}(s_{i+1})$$

If I have this information, how should I act? (What should my policy be?)

$$\pi(s_i) = \arg\max_{a_i} (q_{\pi}(s_i, a_i))$$

So if my policy is to take the maximum $q$, what is $v_{\pi}(s_{i+1}) = \mathbb{E}_{a_{i+1} \sim \pi} g_{i+1}$?

$$v_{\pi}(s_{i+1}) = \mathbb{E}_{a_{i+1} \sim \pi} r_{i+1} + \gamma v_{\pi}(s_{i+2})$$

$$v_{\pi}(s_{i+1}) = \sum_{a_{i+1}} \pi(a_{i+1}) \mathbb{E}_{r_{i+1} \sim r(s_{i+1}, a_{i+1})} r_{i+1} + \gamma v_{\pi}(s_{i+2})$$

$$v_{\pi}(s_{i+1}) = \sum_{a_{i+1}} \pi(a_{i+1}) q_{\pi}(s_{i+1}, a_{i+1})$$

$$v_{\pi}(s_{i+1}) = \max_{a_{i+1}} q_{\pi}(s_{i+1}, a_{i+1})$$
How do we get what we want?

\[ q_{\pi}(s_i, a_i) = E_{r_i \sim r(s_i,a_i)} r_i + \gamma v_{\pi}(s_{i+1}) \]

\[ v_{\pi}(s_{i+1}) = \max_{a_{i+1}} q_{\pi}(s_{i+1}, a_{i+1}) \]

From our definition

We just showed
How do we get what we want?

\[ q_\pi(s_i,a_i) = E_{r \sim r(s_i,a_i)} r_i + \gamma v_\pi(s_{i+1}) \]  
From our definition

\[ v_\pi(s_{i+1}) = \max_{a_{i+1}} q_\pi(s_{i+1},a_{i+1}) \]  
We just showed

\[ q_\pi(s_i,a_i) = E_{r \sim r(s_i,a_i)} r_i + \gamma \max_{a_{i+1}} q_\pi(s_{i+1},a_{i+1}) \]  
Substitution

Now we have a recursive definition of Q.

What if our Q function is bad and we want to improve it?
How do we get what we want?

\[ q_\pi(s_i, a_i) = E_{r_i \sim r(s_i, a_i)} r_i + \gamma \max_{a_{i+1}} q_\pi(s_{i+1}, a_{i+1}) \]

Now we have a recursive definition of Q.
What if our Q function is bad and we want to improve it?
How do we get what we want?

$q_{\pi}(s_i, a_i) = E_{r_i \sim r(s_i, a_i)} r_i + \gamma \max_{a_{i+1}} q_{\pi}(s_{i+1}, a_{i+1})$

Now we have a recursive definition of Q. What if our Q function is bad and we want to improve it?

We can act in the environment and collect $(s_i, a_i, r_i, s_{i+1})$ tuples for each step.
How do we get what we want?

\[ q_\pi(s_i, a_i) = E_{r_i \sim r(s_i, a_i)} r_i + \gamma \max_{a_{i+1}} q_\pi(s_{i+1}, a_{i+1}) \]

Now we have a recursive definition of Q.
What if our Q function is bad and we want to improve it?

We can act in the environment and collect \((s_i, a_i, r_i, s_{i+1})\) tuples for each step.

Then we update \(q_\pi(s_i, a_i)\) in the direction of:

\[ q_\pi(s_i, a_i) := r_i + \gamma \max_{a_{i+1}} q_\pi(s_{i+1}, a_{i+1}) \]

Our current best estimate of the future
Finally we got what we want!

DQN:
1. initialize an empty dataset
2. for some number of rounds:
   a. for m steps:
      i. Do one step of interaction with the environment using ε-greedy
   b. Add \((s,a,r,s')\) to a growing dataset (like DAgger)
   c. for n steps:
      i. Do one training step on a randomly sampled batch from the dataset according to:

\[
q_\pi(s_i, a_i) := r_i + \gamma \max_{a_{i+1}} q_\pi(s_{i+1}, a_{i+1})
\]

ε-greedy:
- Sample a random number between 0 and 1.
- If the number is less than \(\varepsilon\) take a random action
- Otherwise take the max q action
Finally we got what we want!

Caveats!
- We need to explore, so when generating data we use $\epsilon$-greedy:
  - Sample a random number between 0 and 1.
  - If the number is less than $\epsilon$ take a random action
  - Otherwise take the max q action
Finally we got what we want!

Caveats!
- We need to explore, so when generating data we use $\epsilon$-greedy:

$$ q_\pi(s_i, a_i) = \mathbb{E}_{r_i \sim r(s_i, a_i)} r_i + \gamma \max_{a_{i+1}} q_\pi(s_{i+1}, a_{i+1}) $$

This is super biased! If our q function starts wrong, it can really screw up our learning.

Furthermore the max, makes this even worse
- Use “Double-Q” trick
- Also use slowly moving target network for the second part of the equation

$$ q_\pi^{\text{target}}(s_{i+1}, a_{i+1}) = \alpha q_\pi^{\text{target}}(s_{i+1}, a_{i+1}) + (1-\alpha) q_\pi(s_{i+1}, a_{i+1}) $$
Finally we got what we want!

Caveats!
- We need to explore, so when generating data we use $\epsilon$-greedy:
  $$q_\pi(s_i, a_i) = E_{r_i \sim r(s_i, a_i)} r_i + \gamma \max_{a_{i+1}} q_\pi(s_{i+1}, a_{i+1})$$

This is super biased! If our q function starts wrong, it can really screw up our learning. Furthermore the max, makes this even worse.
- The max means we can only do this for discrete action spaces!
Continuous Action Spaces

Idea:
- Before our network produced q estimates for all actions $q(s) -> [q_{s_1}, q_{s_2}, q_{s_3}, ...]$
- Now our q network will take a state and action and produce a single estimate $q(s,a) -> q_{sa}$
- We will also add an “actor” network that produces an estimate of the current best action
  - We train our q network using the actor: $q(s,a) = r + q(s, actor(s'))$
- We train our actor using a gradient that tries to increase the q values. Compute:
  $q(s, actor(s)) -> q_{s,actor(s)}$ and use $-q_{s,actor(s)}$ as a loss.
- DDPG/SAC
References

DQN:
Playing Atari with Deep Reinforcement Learning [Mnih et al. ‘13]

DPG:
Deterministic Policy Gradient Algorithms [Sliver et al. ‘14]

DDPG:
Continuous control with deep reinforcement learning [Lillicrap et al. ‘15]

SAC:
Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor [Haarnoja et al. ‘18]
Last Thoughts

Imitation Learning:
- Online data helps!
- DAgger will perform better than Behavior Cloning if you can afford it

Reinforcement Learning:
- Learning from rewards can be very powerful
- But is hard to get right
- On-Policy methods are not very data efficient
- Off-Policy methods are better but can have a lot of moving parts and require care to get right