Policy Gradient Methods

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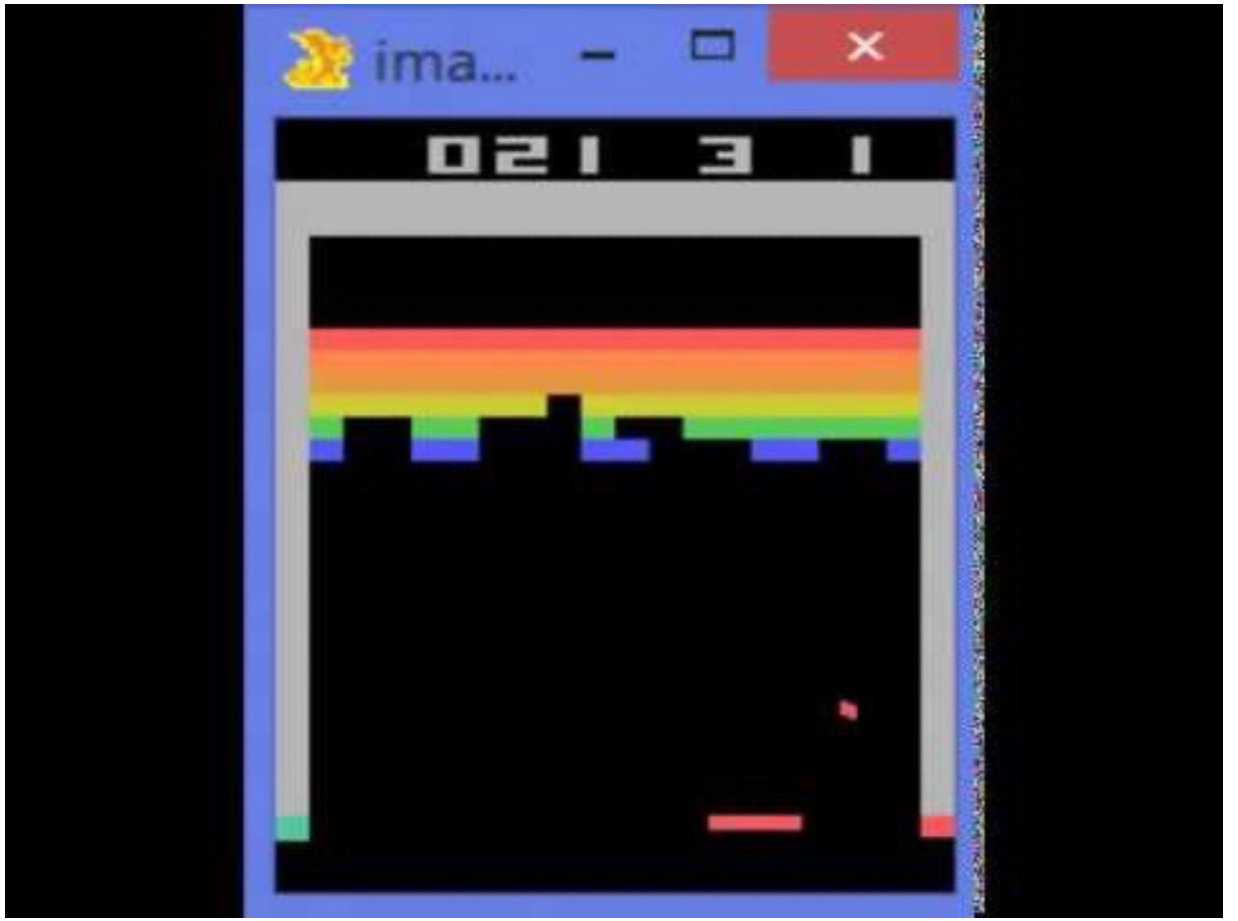
CSCI 410

Serena Booth

Deep-Q Networks



Video Source: https://www.youtube.com/watch?v=V1eYniJ0Rnk

Q-Values to Policy

What do we do after we learn Q? We need to turn them into a policy.

For a given state, take the action associated with the best Q-value.

$$\pi(s) = argmax_a \, Q(s, a)$$

Policies

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Use Softmax activation function:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

Output i

Vector of intermediate features z

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$$\pi = \text{argmax}_{\pi} \left(V(s_0) \right)$$

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Find a policy π such that the value of the start state is maximized:

$$\pi = \text{argmax}_{\pi} \left(V(s_0) \right)$$

How can we maximize $V(s_0)$?

Let $J(\theta)$ be our objective function:

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Probability of a trajectory occurring

Returns of a specific trajectory

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State transition Probability

Probability of taking an action for a given state

Log-Derivative Trick

We can rewrite the derivative of a function using the derivative of the natural log function:

$$\nabla \ln f(x) = \frac{\nabla \mathrm{f}(x)}{f(x)}$$

$$\nabla f(x) = f(x) \nabla \ln \mathrm{f}(\mathrm{x})$$

When applied to $\Pr(\tau|\theta)$:

$$\nabla_\theta \Pr(\tau|\theta) = \Pr(\tau|\theta)\, \nabla_\theta \ln \Pr(\tau|\theta)$$

Log Probability Trick

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Log of product -> sum of logs

$$\nabla_\theta \ln \Pr(\tau \mid \theta) = \nabla_\theta \sum_{t=0}^{T} \ln[\mathrm{P}(\mathrm{s_{t+1}}|\mathrm{s_t}, \mathrm{a_t})\pi_\theta(\mathrm{a_t}|\mathrm{s_t})]$$

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Derivative of sum -> sum of derivative

$$\nabla_\theta \ln \Pr(\tau \mid \theta) = \sum_{t=0}^{T} \nabla_\theta \ln(\mathrm{P}(\mathrm{s_{t+1}}|\mathrm{s_t}, \mathrm{a_t})) + \nabla_\theta \ln(\pi_\theta(\mathrm{a_t}|\mathrm{s_t}))]$$

Gradient of a trajectory

$$\nabla_\theta \ln \Pr(\tau \mid \theta) = \sum_{t=0}^{T} \nabla_\theta \ln(P(s_{t+1}|s_t, a_t)) + \nabla_\theta \ln(\pi_\theta(a_t|s_t))]$$

State transition function does not depend on θ!

$$\nabla_\theta \ln \Pr(\tau \mid \theta) = \sum_{t=0}^{T} \nabla_\theta \ln \pi_\theta(at|st)$$

Policy Gradient Derivation

Putting it all back together:

$$J(\theta) = \sum_{\tau} \Pr(\tau|\theta) G(\tau)$$

Our Objective

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$$\nabla_\theta J(\theta) = \mathbb{E}\left[G_0 \sum_{t=0}^{T} \nabla_\theta \ln(\pi_\theta(s_t|a_t)) \right]$$ As an expectation

Policy Gradient

Bigger step if better returns

Direction to move in to increase probability of trajectory

$$\nabla_\theta J(\theta) = \mathbb{E}\left[G_0 \sum_{t=0}^{T} \nabla_\theta \ln(\pi_\theta(s_t|a_t))\right]$$

We will never be able to sum over all possible trajectories…

How do we get around this?

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Sampling!

1. Collect n trajectories following policy π_θ
2. $\Pr(\tau|\theta) = 1/n$ for each trajectory
3. Calculate the total return for each trajectory $G(\tau)$

Reward-To-Go Policy Gradient

You can also do the policy gradient derivation such that the gradient does not depend on G_0, but on G_t

$$\nabla_\theta J(\theta) = \mathbb{E}\left[\sum_{t=0}^{T} G_t \nabla_\theta \ln(\pi_\theta(s_t|a_t))\right]$$

Or

$$\nabla_\theta J(\theta) = \mathbb{E}\left[\sum_{t=0}^{T} Q(st, a_t) \nabla_\theta \ln(\pi_\theta(s_t|a_t))\right]$$

REINFORCE (Policy Gradient Learning)

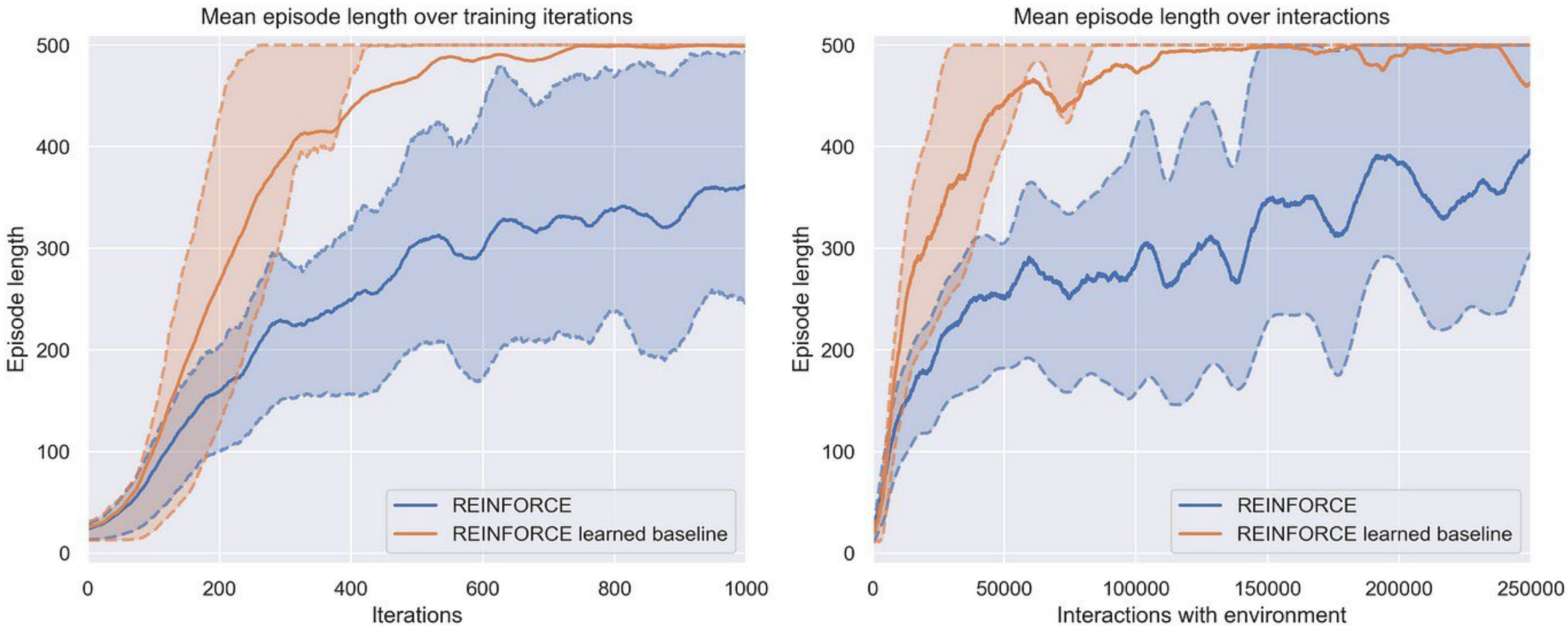
REINFORCE, A Monte-Carlo Policy-Gradient Method (episodic)

Input: a differentiable policy parameterization $\pi(a|s, \boldsymbol{\theta})$
Initialize policy parameter $\boldsymbol{\theta} \in \mathbb{R}^{d'}$
Repeat forever:
  Generate an episode $S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T$, following $\pi(\cdot|\cdot, \boldsymbol{\theta})$
  For each step of the episode $t = 0, \ldots, T-1$:
    $G \leftarrow$ return from step t
    $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha \gamma^t G \nabla_{\boldsymbol{\theta}} \ln \pi(A_t|S_t, \boldsymbol{\theta})$

Source: Sutton and Barto, Reinforcement Learning: An Introduction

REINFORCE Variance

If we could calculate $\nabla_\theta J(\theta)$ exactly (not just for single trajectory/sample), then Policy Gradient would be a great algorithm! (with some minor flaws)



Results on Cartpole

Image Source: https://medium.com/@fork.tree.ai/understanding-baseline-techniques-for-reinforce-53a1e2279b57

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Actor-Critic Algorithm: Learn Q^{π} and $\pi(a|s)$

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Policy network has parameters θ
Q network has parameters w

Initialize π_θ, Q_w, α_θ, α_w

Repeat forever:

Take action a, get new state s' and reward r

Sample next action $a' \sim \pi_\theta(a|s)$

update $\theta \leftarrow \theta + \alpha_\theta Q_w(s,a) \nabla_\theta \ln \pi_\theta(a|s)$

Calculate TD Error: $\delta = r + \gamma Q_w(s', a') - Q_w(s,a)$

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

$a \leftarrow a', s \leftarrow s'$

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Like Q-learning and REINFORCE at the same time

Variations on a Theme…

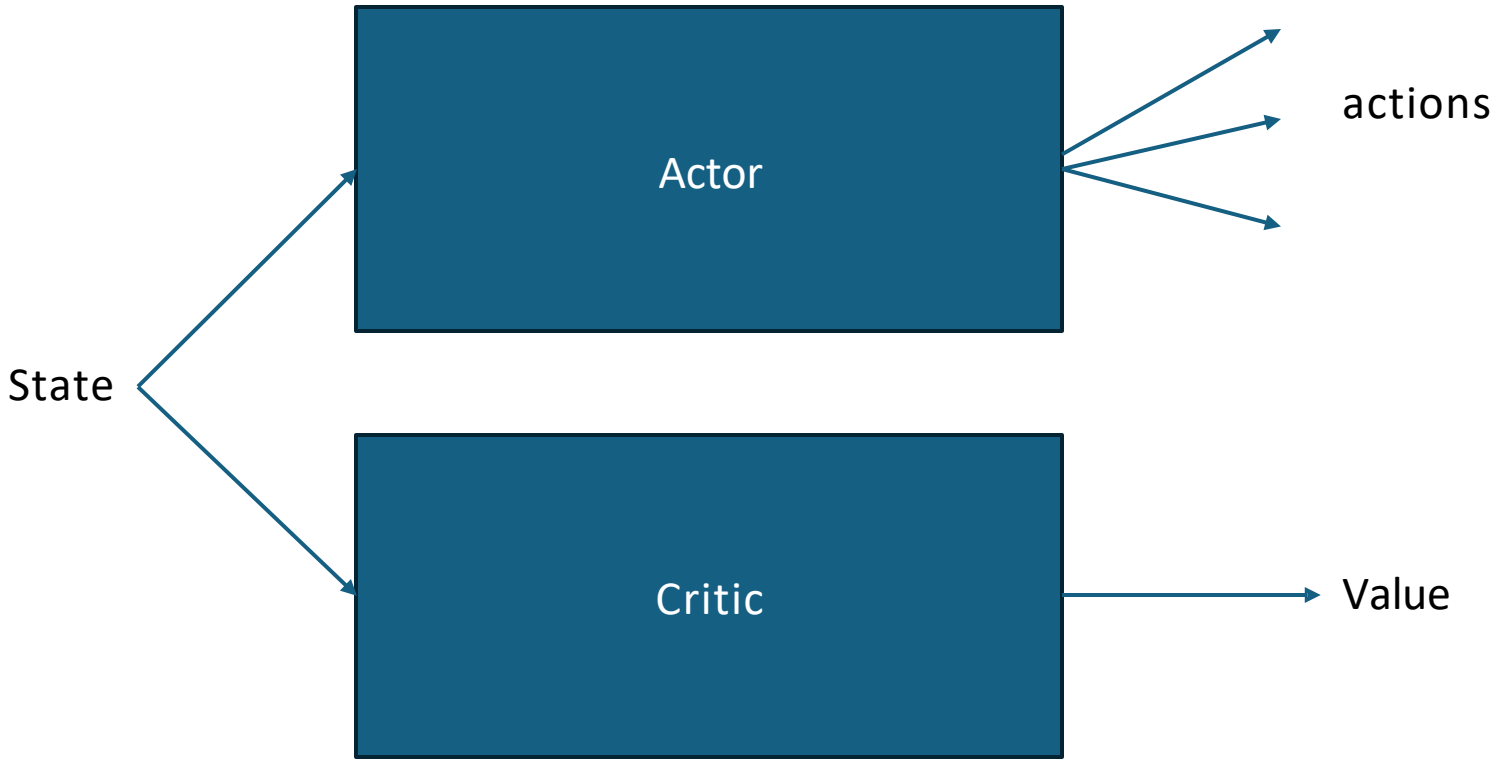
How to estimate $J(\theta)$

(Wikipedia uses R_t instead of G_t)

- $\sum_{0 \leq i \leq T} (\gamma^i R_i)$.
- $\gamma^j \sum_{j \leq i \leq T} (\gamma^{i-j} R_i)$: the **REINFORCE** algorithm.
- $\gamma^j \sum_{j \leq i \leq T} (\gamma^{i-j} R_i) - b(S_j)$: the **REINFORCE with baseline** algorithm. Here b is an arbitrary function.
- $\gamma^j \left(R_j + \gamma V^{\pi_\theta}(S_{j+1}) - V^{\pi_\theta}(S_j)\right)$: TD(1) learning.
- $\gamma^j Q^{\pi_\theta}(S_j, A_j)$.
- $\gamma^j A^{\pi_\theta}(S_j, A_j)$: **Advantage Actor-Critic (A2C)**.[3]
- $\gamma^j \left(R_j + \gamma R_{j+1} + \gamma^2 V^{\pi_\theta}(S_{j+2}) - V^{\pi_\theta}(S_j)\right)$: TD(2) learning.
- $\gamma^j \left(\sum_{k=0}^{n-1} \gamma^k R_{j+k} + \gamma^n V^{\pi_\theta}(S_{j+n}) - V^{\pi_\theta}(S_j)\right)$: TD(n) learning.
- $\gamma^j \sum_{n=1}^{\infty} \frac{\lambda^{n-1}}{1-\lambda} \cdot \left(\sum_{k=0}^{n-1} \gamma^k R_{j+k} + \gamma^n V^{\pi_\theta}(S_{j+n}) - V^{\pi_\theta}(S_j)\right)$: TD(λ) learning, also known as **GAE (generalized advantage estimate)**.[4] This is obtained by an exponentially decaying sum of the TD(n) learning terms.

Source: https://en.wikipedia.org/wiki/Actor-critic_algorithm

Actor-Critic Networks



Actor-Critic Networks

Just make sure you use the correct activation function for the different outputs

Deep Q-Learning Revisited

Compute TD-Error: $\delta = r + \gamma \max_{a'} Q(s', a') - Q(s, a)$

Loss Function: $L = \delta^2$

Update model with Gradient Descent

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Q-Learning is learning *Optimal Q-values*

Actor-Critic Uses:

$$\delta = r + \gamma Q(s', a') - Q(s, a)$$

Actor-Critic is learning the Q-values for following a specific policy Q^{π}

On-Policy Vs. Off-Policy Learning

RL algorithms collect experiences and learn from these experiences

On-Policy Algorithms have to collect experiences with the policy they are learning

Off-Policy Algorithms can use **any** policy to collect experiences

DQNs Are Off-Policy

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In Q-Learning, we typically collect experiences using an ϵ-greedy policy in training

With probability ϵ, take random action.

Else, take action $\text{argmax}_a\ Q(s, a)$

At test time, we should take the best actions, not the ϵ-greedy actions

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These are different policies! DQNs can be trained with any data collection policy at training time

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Initialize π_θ, Q_w, α_θ, α_w

Repeat forever:

Take action a, get new state s' and reward r

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On Policy: Have to take actions according to π_θ

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Disadvantages of Off-Policy Learning:

- Slower…

Off-Policy Learning

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So far, we've looked at an example, learned from it, and discarded it.

In all our other problems, we always learned from data multiple times (i.e., epochs)

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In all our other problems, we always learned from data multiple times (i.e., epochs)

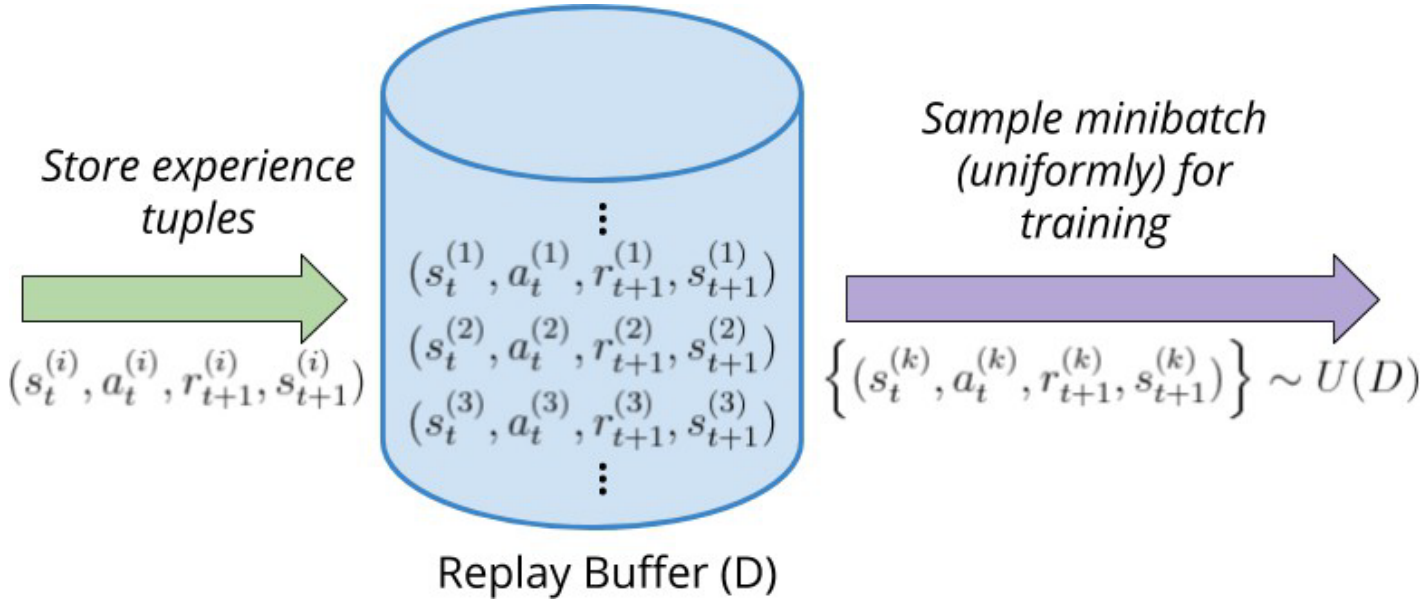
Maybe we shouldn't throw away useful data immediately…

Experience Replay and Replay Buffers

Keep a memory of experiences (state, action, reward, next_state)

As you collect new experiences, remove oldest experiences from buffer

To train model, sample batch of data from buffer



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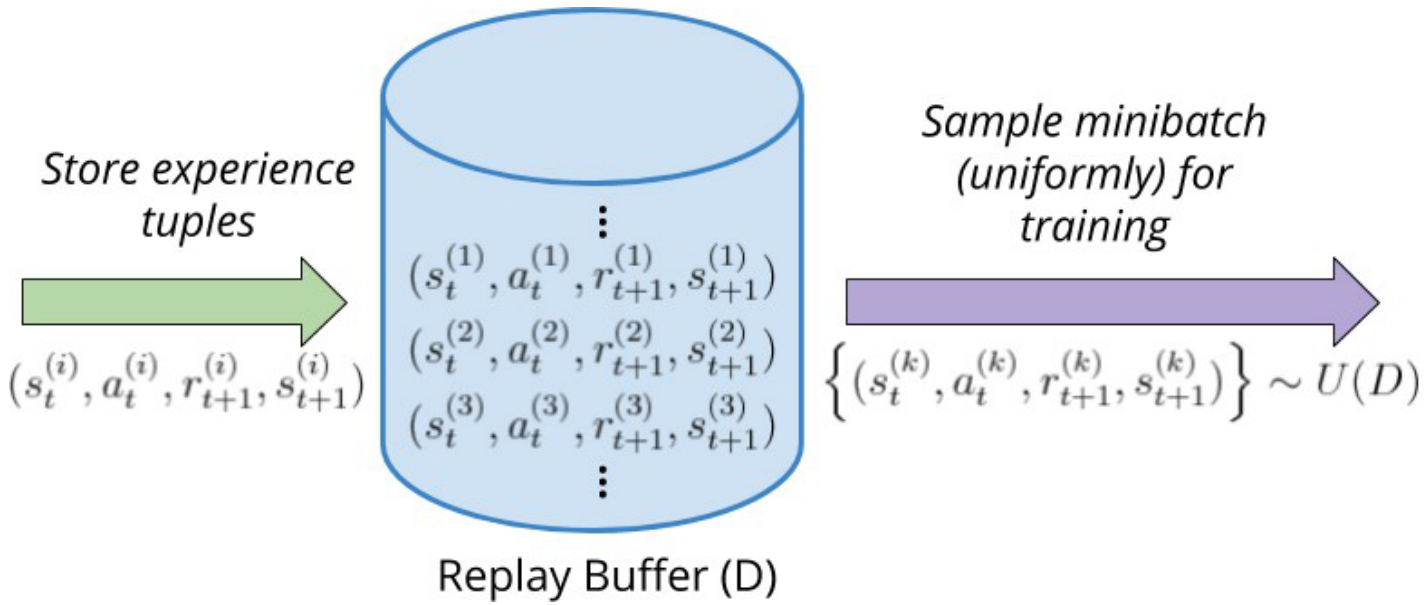

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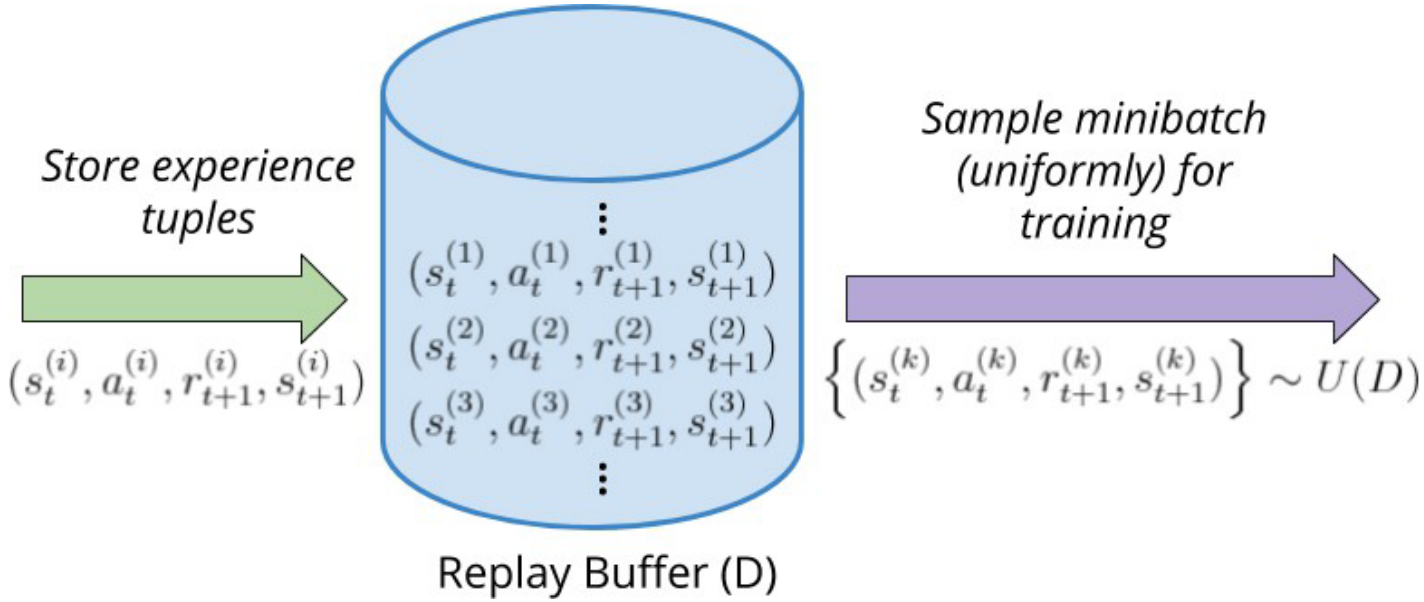

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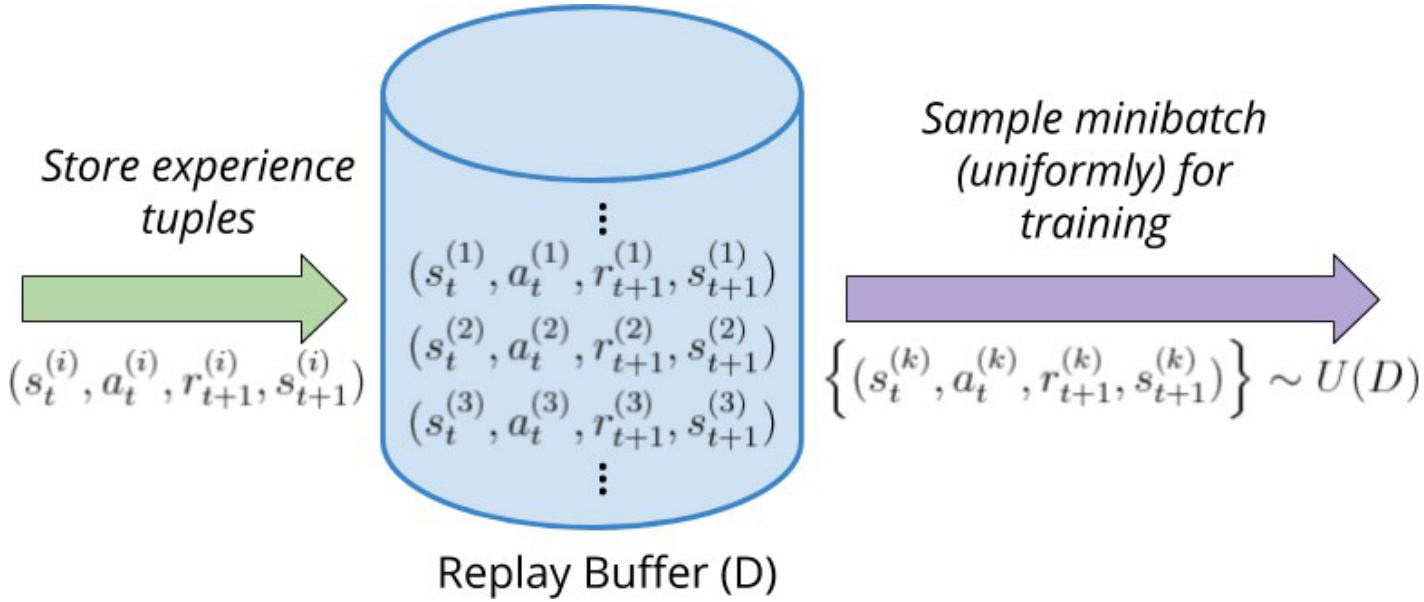

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On-Policy Learning

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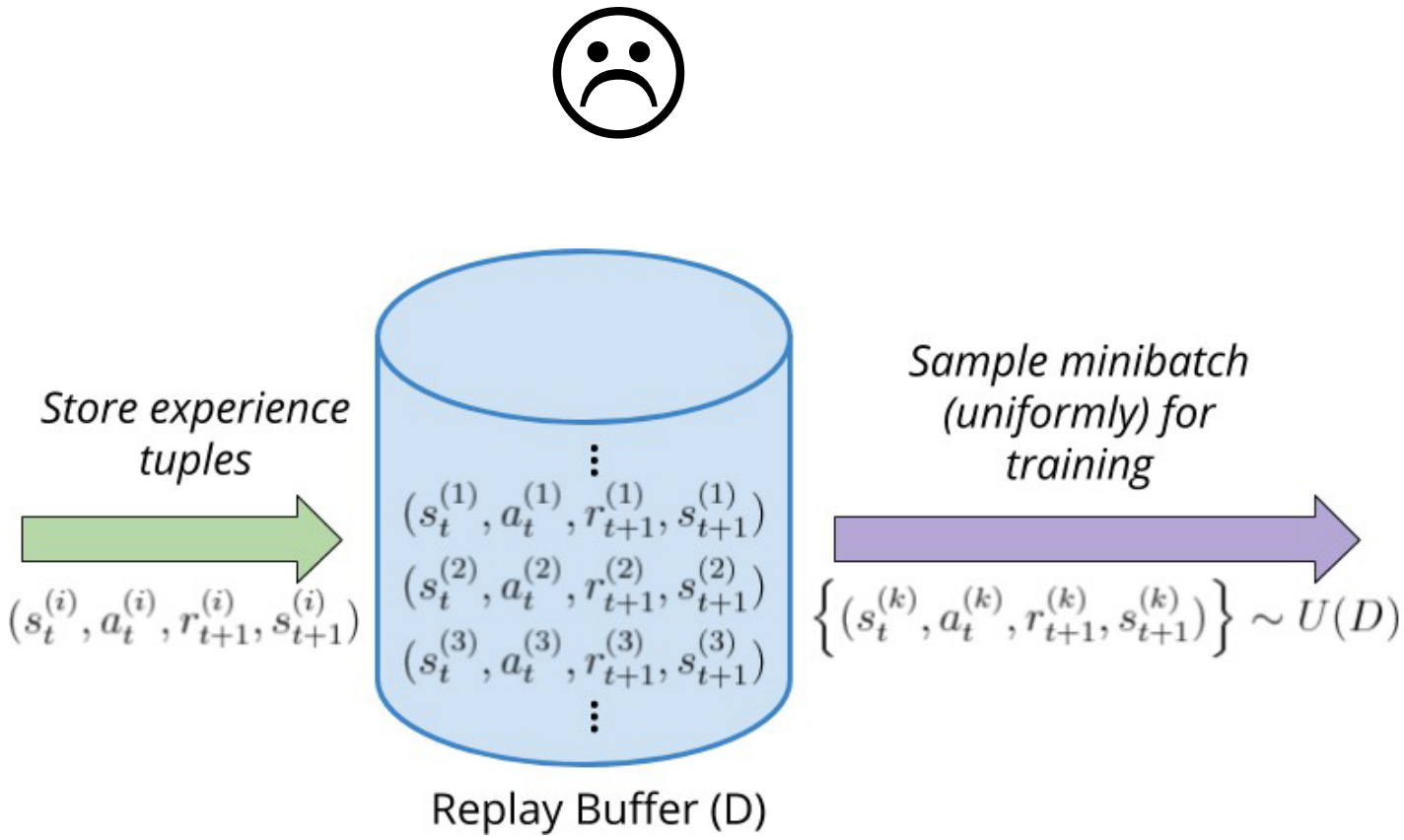

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But what if we actually could…

Off-Policy Policy Gradient:

Data collected under policy $\beta(a|s)$ (i.e., older version of policy)

We can re-weight our gradient according to the old policy:

$$\rho = \frac{\pi(a|s)}{\beta(a|s)}$$

$$\nabla_\theta J(\theta) = \sum_{(\mathrm{s,a}) \in batch} \rho \cdot Q^\pi(\mathrm{s,a}) \nabla_\theta \ln \pi(s, a)$$

Actor-Critic with Importance Sampling

Off-Policy Actor Critic: https://arxiv.org/pdf/1205.4839

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Actor-Critic with Importance Sampling

Store action probabilities $\beta(a|s)$ in replay buffer

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Trust Region Policy Optimization

Insight: the reason that variance is bad is that it can cause large updates to π_θ

Add a constraint to how large of an update can be applied:

KL-Divergence between old and new policy must be below some hyperparameter Δ

$$\mathrm{D}_{\mathrm{KL}}\left(\pi_\theta^{\mathrm{new}}\left(.|\mathrm{s}\right)||\pi_\theta^{\mathrm{old}}\left(.|\mathrm{s}\right)\right)\leq\Delta$$

$$\rho=\frac{\pi^{new}(a|s)}{\pi^{old}(a|s)}$$

$$J^{TRPO}(\theta)=\mathbb{E}\left[\rho*\left(r+\gamma\mathrm{V}^{\pi^{old}}\left(s'\right)-\mathrm{V}^{\pi^{old}}(s)\right)\right]$$

Paper: https://arxiv.org/pdf/1502.05477

Proximal Policy Optimization

TRPO is complicated…

What if instead of constraining the update with KL-Divergence, we clipped the update if it's too big…

$$\rho_{clipped} = clip[\frac{\pi^{new}(a|s)}{\pi^{old}(a|s)}, 1-\epsilon, 1+\epsilon]$$

$$J^{PPO}(\theta) = \mathbb{E}[\min(\rho_{clipped} \cdot \left(r + \gamma V^{\pi^{old}}(s') - V^{\pi^{old}}(s)\right), \rho\left(r + \gamma V^{\pi^{old}}(s') - V^{\pi^{old}}(s)\right)]$$

Spinning Up PPO: https://spinningup.openai.com/en/latest/algorithms/ppo.html

PPO

Final phase of training ChatGPT