Carnegie Mellon

School of Computer Science

Deep Reinforcement Learning and Control

REINFORCE, Actor-critic methods

Spring 2021, CMU 10-403

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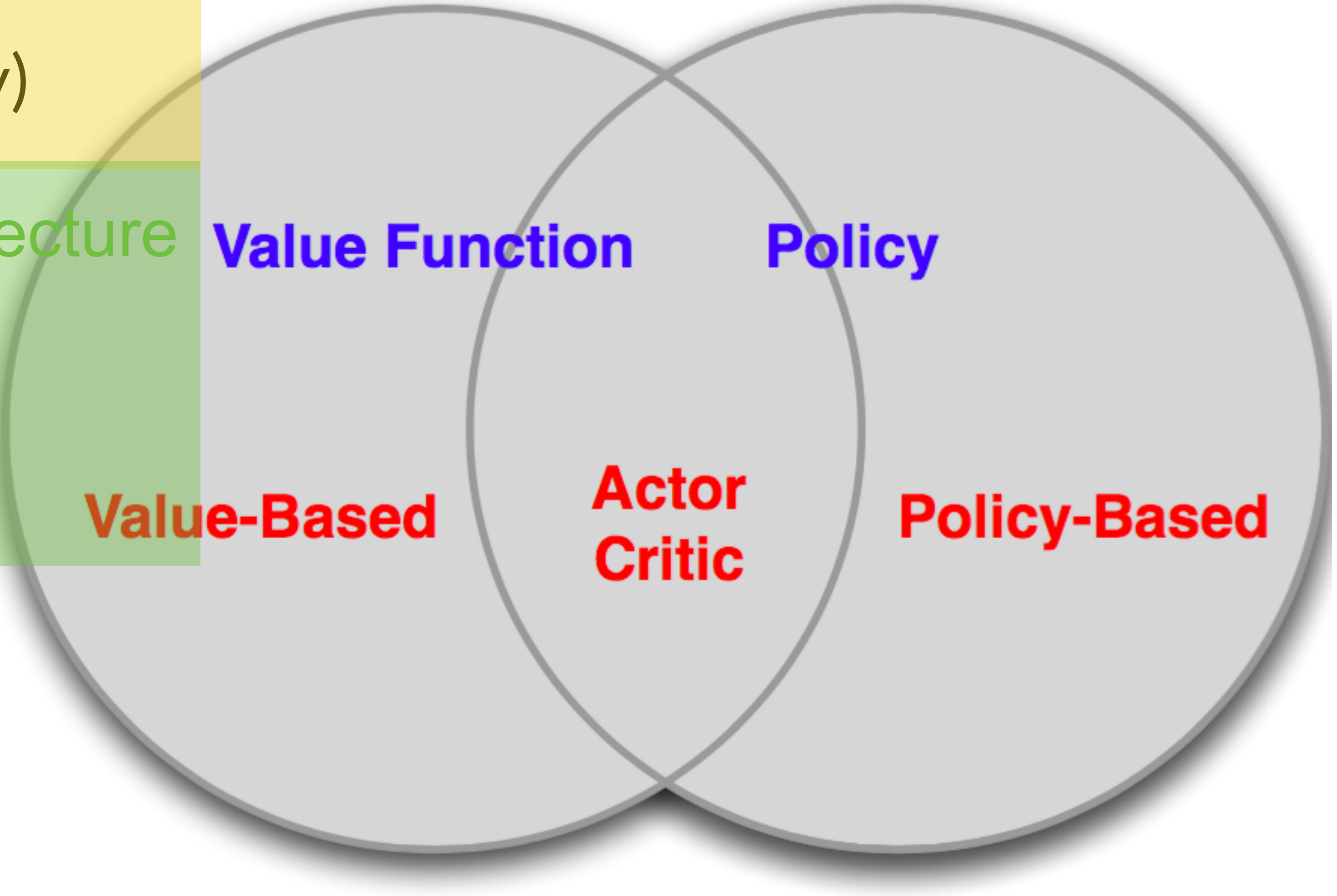
Value-Based and Policy-Based RL

- Value Based
  - Learned Value Function
  - Implicit policy (e.g. ε-greedy)
- Policy Based
  - No Value Function
  - Learned Policy
- Actor-Critic
  - Learned Value Function
  - Learned Policy

We have covered those

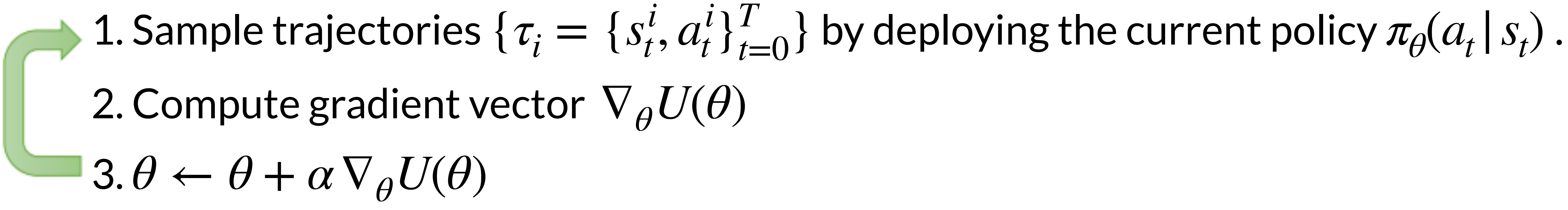
this lecture



Policy Optimization

- Let $U(\theta)$ be any policy objective function

0. Initialize policy parameters θ



1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{t=0}^{T}\}$ by deploying the current policy $\pi_\theta(a_t \mid s_t)$.

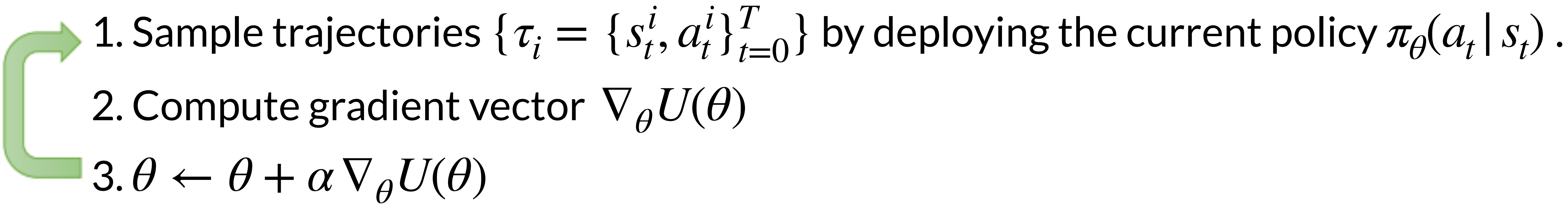
2. Compute gradient vector $\nabla_\theta U(\theta)$

3. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$

- Policy based reinforcement learning is an optimization problem: Find θ that maximizes $U(\theta)$
- General alternatives: gradient free optimization
  - Hill climbing
  - Genetic algorithms. We have seen this! Today we will learn different policy gradient estimators.

Policy Optimization

0. Initialize policy parameters θ



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2. Compute gradient vector $\nabla_\theta U(\theta)$

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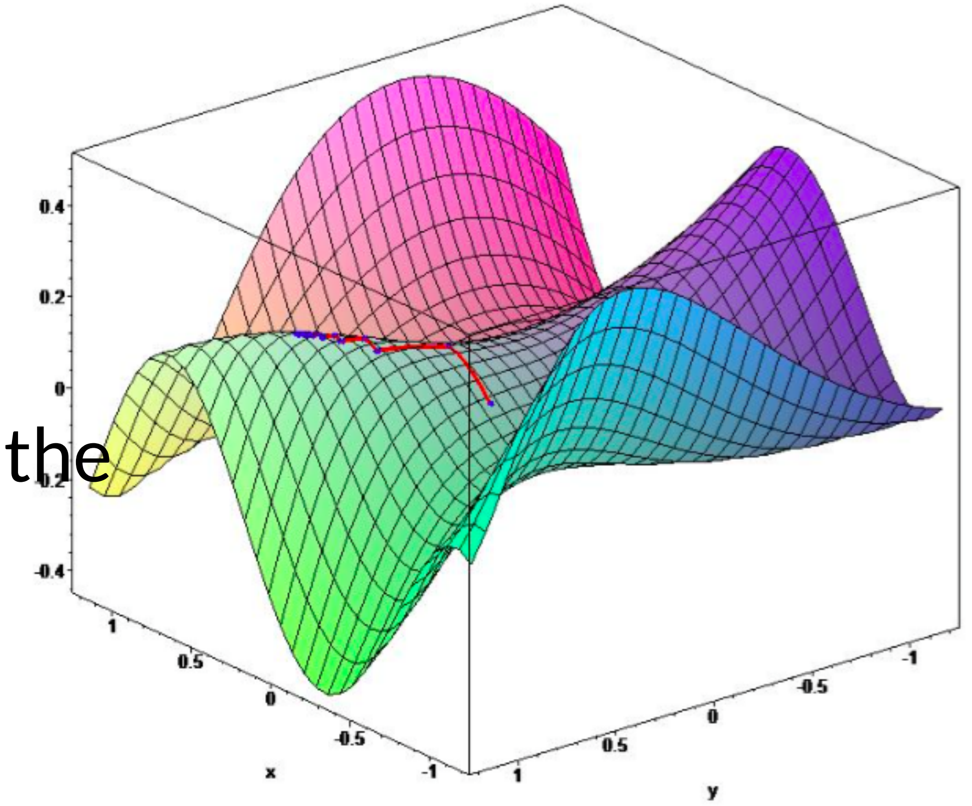
- Advantages over value based methods:
  - Effective in high-dimensional or continuous action spaces
  - Can learn stochastic policies

Policy Gradient



- Let U(θ) be any policy objective function

- Policy gradient algorithms search for a local maximum in U(θ) by ascending the gradient of the policy, w.r.t. parameters θ

$$\theta_{new} = \theta_{old} + \Delta\theta$$

$$\Delta\theta = \alpha \nabla_{\theta} U(\theta)$$

α is a step-size parameter (learning rate)

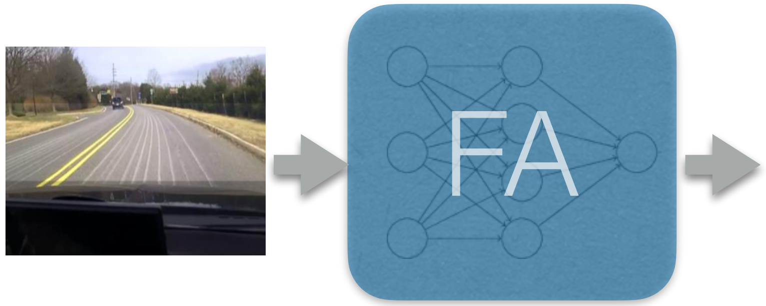
is the policy gradient

$$\nabla_{\theta} U(\theta) = \begin{pmatrix} \frac{\partial U(\theta)}{\partial \theta_1} \\ \vdots \\ \frac{\partial U(\theta)}{\partial \theta_n} \end{pmatrix}$$

Policy gradient: the gradient of the policy objective w.r.t. the parameters of the policy

Policy functions

deterministic continuous policy

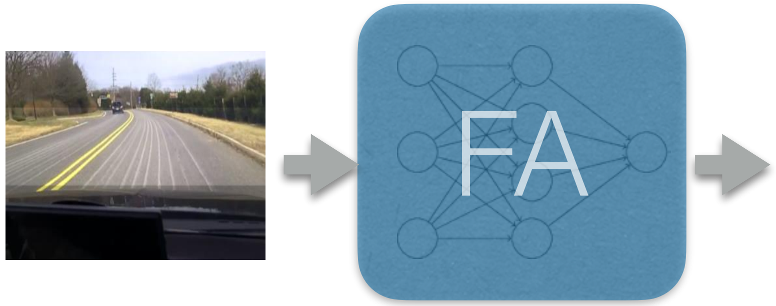


a

$$a = \pi_\theta(s)$$

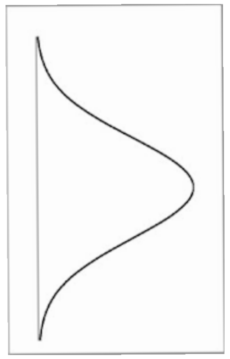
e.g. outputs a steering angle directly

stochastic continuous policy



$\mu_\theta(s)$

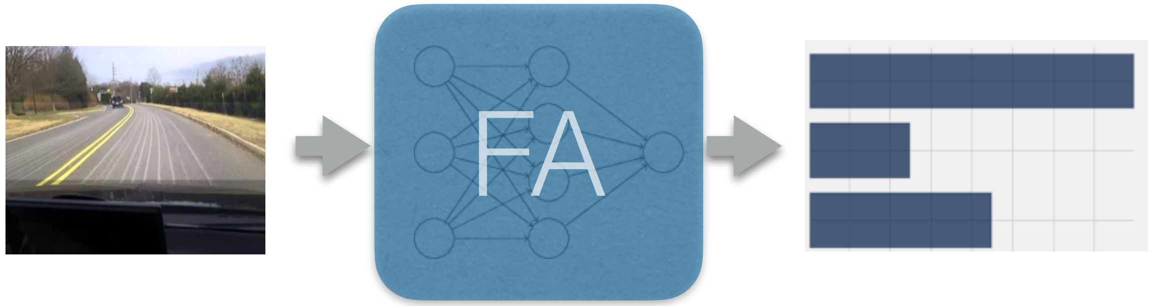
$\sigma_\theta(s)$



$$a \sim \mathcal{N}(\mu_\theta(s), \sigma_\theta^2(s))$$

FA for stochastic multimodal continuous policies is an active area of research

(stochastic) policy over discrete actions



go left

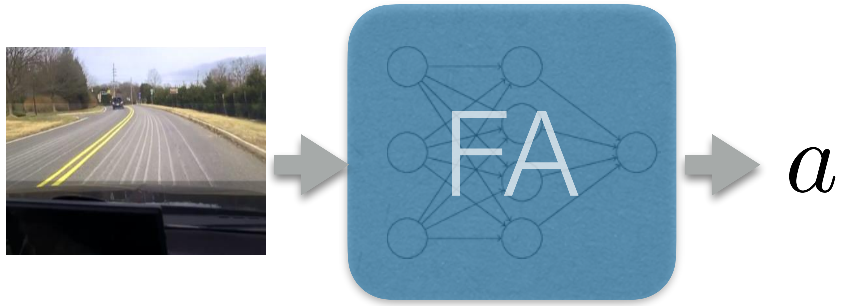
go right

press brake

Outputs a distribution over a discrete set of actions

Policy functions

deterministic continuous policy



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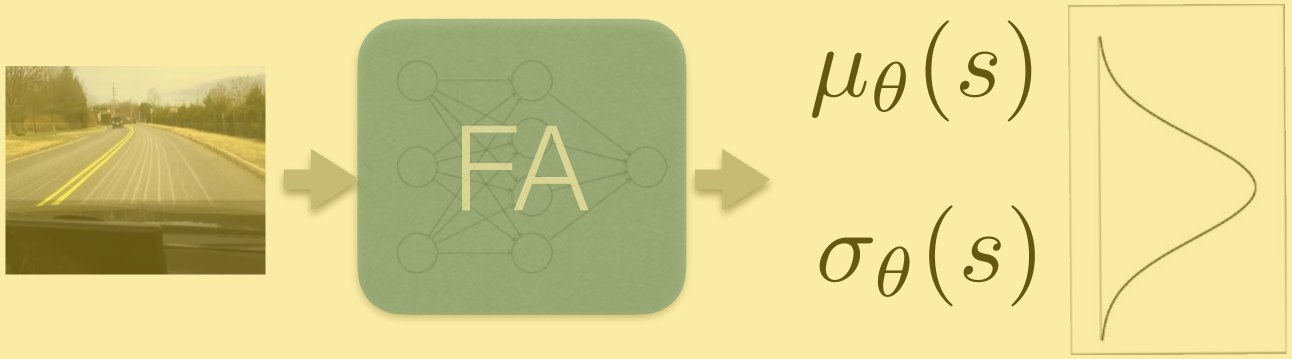

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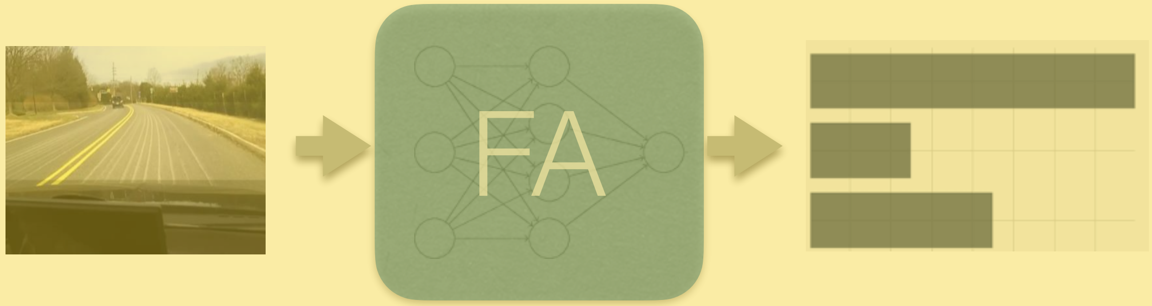

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Outputs a distribution over a discrete set of actions

Policy objective

Trajectory τ is a state action sequence $s_0, a_0, s_1, a_1, \ldots s_H, a_H$

Trajectory reward: $R(\tau) = \sum_{t=0}^{H} R(s_t, a_t)$

A reasonable policy objective then is:

$$\max_{\theta} . \quad U(\theta) = \mathbb{E}_{\tau \sim P(\tau;\theta)}[R(\tau)] = \sum_{\tau} P(\tau;\theta)R(\tau)$$

Probability of a trajectory: $P(\tau;\theta) = \prod_{t=0}^{H} \underbrace{P(s_{t+1} \mid s_t, a_t)}_{\text{dynamics}} \cdot \underbrace{\pi_\theta(a_t \mid s_t)}_{\text{policy}}$

Our problem is to compute $\nabla_\theta U(\theta) = \nabla_\theta \mathbb{E}_{\tau \sim P(\tau;\theta)}[R(\tau)]$

Policy objective

$$U(\theta) = \mathbb{E}_{\tau \sim P(\tau;\theta)}[R(\tau)]$$

Computing derivatives of expectations w.r.t. variables that parametrize the distribution, not the quantity inside the expectation

$$\max_{\theta} . \quad \mathbb{E}_{x \sim P(x;\theta)} f(x)$$

Assumptions:

- P is a probability density function that is continuous and differentiable
- P is easy to sample from

Derivatives of expectations

$$\nabla_\theta \mathbb{E}_x f(x) = \nabla_\theta \mathbb{E}_{x \sim P_\theta(x)} \left[f(x) \right]$$

Derivatives of expectations

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\begin{aligned}
\nabla_\theta \mathbb{E}_x f(x) &= \nabla_\theta \mathbb{E}_{x \sim P_\theta(x)} \left[f(x) \right] \\
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Why?

Derivatives of expectations

$$\begin{aligned}\nabla_\theta \mathbb{E}_x f(x) &= \nabla_\theta \mathbb{E}_{x\sim P_\theta(x)}\left[f(x)\right]\\ &= \nabla_\theta \sum_x P_\theta(x) f(x)\\ &= \sum_x \nabla_\theta P_\theta(x) f(x)\end{aligned}$$

What is the problem here?

Derivatives of expectations

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What have we achieved?

Derivatives of expectations

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I can obtain an unbiased estimator for the gradient $\nabla_\theta \mathbb{E}_x f(x)$ by sampling!

From the law of large numbers, it will converge to the right gradient with infinite number of samples

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Derivatives of the policy objective

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Approximate the gradient with empirical estimate from N sampled trajectories:

$$\nabla_\theta U(\theta) \approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)}) R(\tau^{(i)})$$

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From trajectories to actions

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$$= \sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t^{(i)} \mid s_t^{(i)})$$

$$\nabla_\theta U(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)}) R(\tau^{(i)})$$

➡

$$\nabla_\theta U(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) R(\tau^{(i)})$$

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Let's call $\hat{g}$ the approximate gradient vector

$$\nabla_\theta U(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)}) R(\tau^{(i)})$$

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&= \nabla_\theta \left[\sum_{t=0}^{T} \underbrace{\log P(s_{t+1}^{(i)} \mid s_t^{(i)}, a_t^{(i)})}_{\text{dynamics}} + \underbrace{\log \pi_\theta(a_t^{(i)} \mid s_t^{(i)})}_{\text{policy}} \right] \\
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\end{aligned}
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$$
\nabla_\theta U(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)}) R(\tau^{(i)}) \quad \Longrightarrow \quad \nabla_\theta U(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) R(\tau^{(i)})
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$\nabla_\theta \log \pi_\theta(a)$ for Gaussian policy

Variance may be fixed, or can also be parameterized, for now let's fix it.

- For univariate Gaussian $\mathcal{N}(\mu, \sigma^2) = \dfrac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\frac{(a-\mu)^2}{\sigma^2}}$

$$\nabla_\theta \log \pi_\theta(a \mid s) = \text{const.} \cdot \frac{(a - \mu_\theta(s))}{\sigma^2} \nabla_\theta \mu_\theta(s)$$

- For multivariate Gaussian $\mathcal{N}(\mu, \Sigma) = \dfrac{1}{\sqrt{(2\pi)^k \det \Sigma}} e^{-\frac{1}{2}(\mathbf{a}-\mu)^\top \Sigma^{-1}(\mathbf{a}-\mu)}$

$$\nabla_\theta \log \pi_\theta(a \mid s) = \text{const.} \cdot \Sigma^{-1}(\mathbf{a} - \mu_\theta(s)) \frac{\partial(\mu_1 \ldots \mu_k)}{\partial(\theta_1 \ldots \theta_n)}$$

Two-dimensional Gaussian $P_\theta(x)$

$$\begin{aligned}
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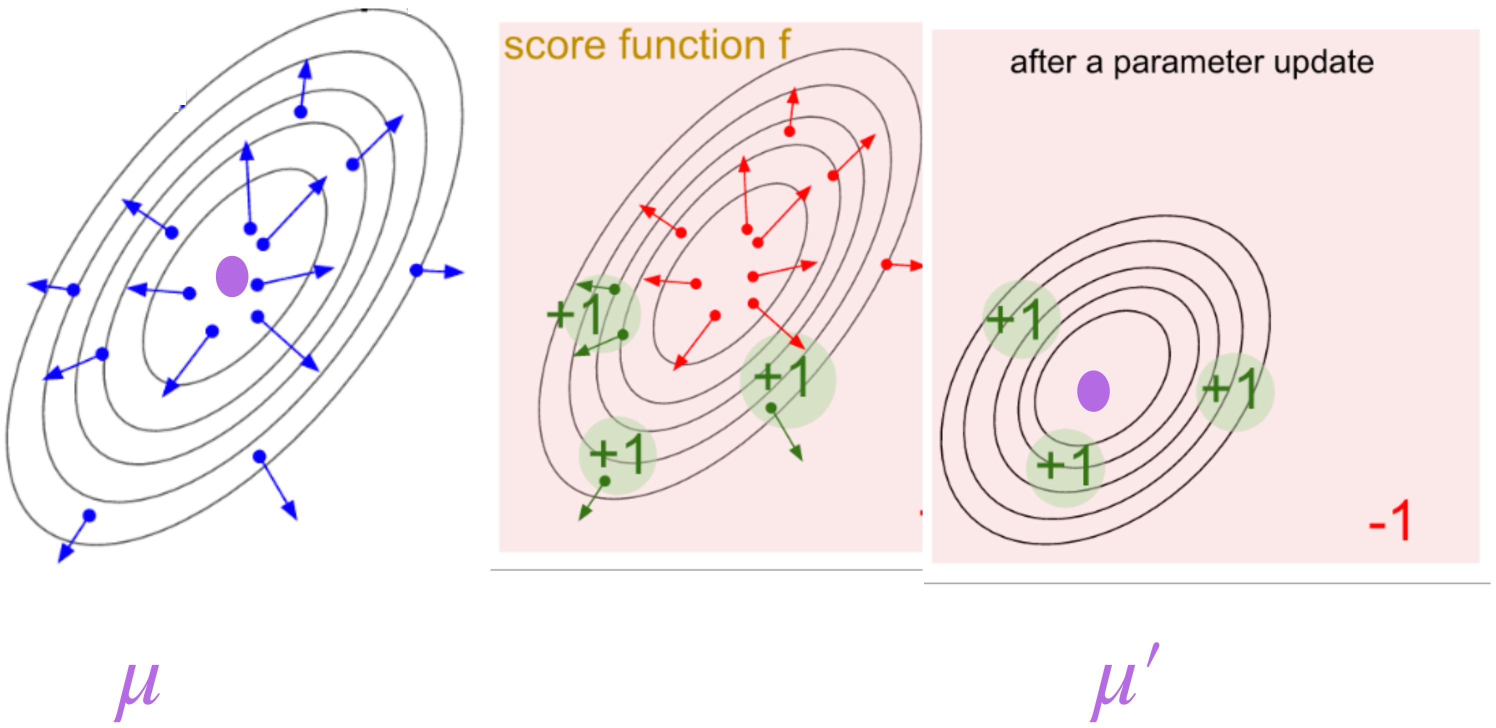
&= \sum_x P_\theta(x)\, \nabla_\theta \log P_\theta(x) f(x) \\
&= \mathbb{E}_{x\sim P_\theta(x)}\left[\nabla_\theta \log P_\theta(x) f(x)\right] \\
&\approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log P_\theta(x^{(i)}) f(x^{(i)}) \\
&\approx \frac{1}{N}\sum_{i=1}^{N} \text{const.}\Sigma^{-1}\cdot(\mathbf{a}^{(i)}-\mu)\begin{bmatrix}1&0\\0&1\end{bmatrix} f(x^{(i)})
\end{aligned}$$

Imagine I am optimizing over these two parameters:

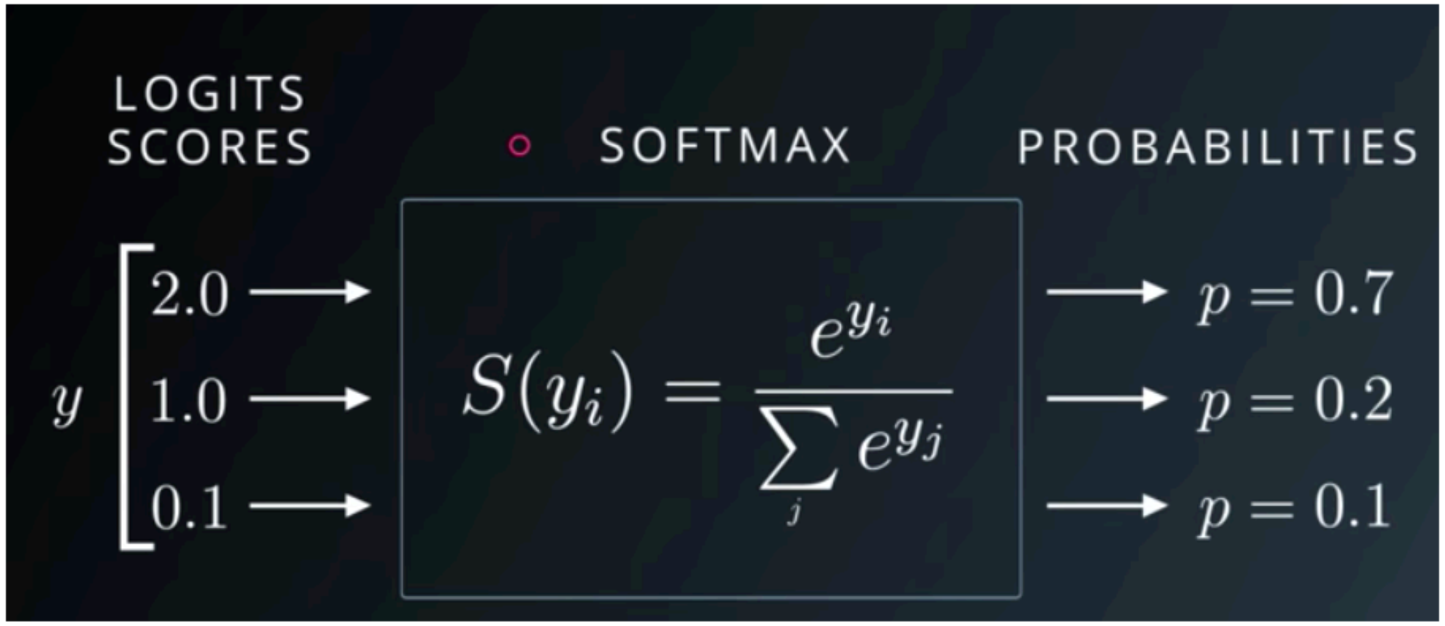
$$\mu = [\theta_1, \theta_2]^\top$$

- $\mathbf{a}^{(i)}$

→ $\Sigma^{-1}(\mathbf{a}^{(i)} - \mu) \propto \nabla_\theta \log P_\theta(\mathbf{a})$

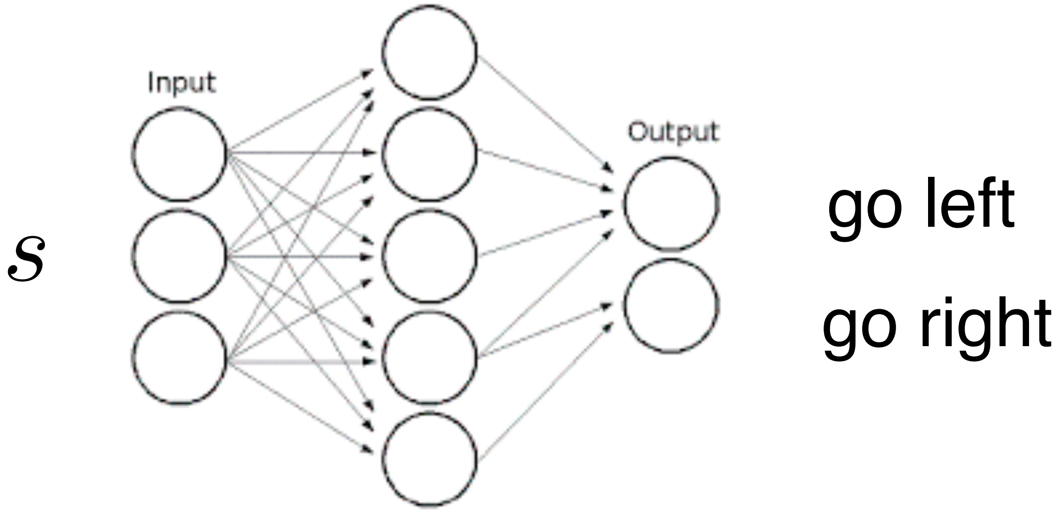


Softmax



$$\pi(a \mid s, \theta) \doteq \frac{e^{h(s,a,\theta)}}{\sum_b e^{h(s,b,\theta)}}$$

discrete actions



Output is a distribution over a discrete set of actions

$\nabla_\theta \log \pi_\theta(a)$ for softmax policy

$$\pi_\theta(a \mid s) = \frac{e^{h_\theta(s,a)}}{\sum_b e^{h_\theta(s,b)}}$$

$$\nabla_\theta \log \pi_\theta(a) =$$

$\nabla_\theta \log \pi_\theta(a)$ for softmax policy

$$\pi_\theta(a \mid s) = \frac{e^{h_\theta(s,a)}}{\sum_b e^{h_\theta(s,b)}}$$

$$\nabla_\theta \log \pi_\theta(a) = \nabla_\theta h_\theta(s,a) - \nabla_\theta \log \sum_b e^{h_\theta(s,b)}$$

$\nabla_\theta \log \pi_\theta(a)$ for softmax policy

$$\pi_\theta(a \mid s) = \frac{e^{h_\theta(s,a)}}{\sum_b e^{h_\theta(s,b)}}$$

$$\nabla_\theta \log \pi_\theta(a) = \nabla_\theta h_\theta(s, a) - \nabla_\theta \log \sum_b e^{h_\theta(s,b)}$$

$$\nabla_\theta h_\theta(s, a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \nabla_\theta \sum_b e^{h_\theta(s,b)}$$

$\nabla_\theta \log \pi_\theta(a)$ for softmax policy

$$\pi_\theta(a \mid s) = \frac{e^{h_\theta(s,a)}}{\sum_b e^{h_\theta(s,b)}}$$

$$\begin{aligned}
\nabla_\theta \log \pi_\theta(a) = \ & \nabla_\theta h_\theta(s,a) - \nabla_\theta \log \sum_b e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \nabla_\theta \sum_b e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \sum_b \nabla_\theta e^{h_\theta(s,b)}
\end{aligned}$$

$\nabla_\theta \log \pi_\theta(a)$ for softmax policy

$$\pi_\theta(a \mid s) = \frac{e^{h_\theta(s,a)}}{\sum_b e^{h_\theta(s,b)}}$$

$$\begin{aligned}
\nabla_\theta \log \pi_\theta(a) = {} & \nabla_\theta h_\theta(s,a) - \nabla_\theta \log \sum_b e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \nabla_\theta \sum_b e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \sum_b \nabla_\theta e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \sum_b e^{h_\theta(s,b)} \nabla_\theta h_\theta(s,b)
\end{aligned}$$

$\nabla_\theta \log \pi_\theta(a)$ for softmax policy

$$\pi_\theta(a \mid s) = \frac{e^{h_\theta(s,a)}}{\sum_b e^{h_\theta(s,b)}}$$

$$\begin{aligned}
\nabla_\theta \log \pi_\theta(a) = {} & \nabla_\theta h_\theta(s,a) - \nabla_\theta \log \sum_b e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \nabla_\theta \sum_b e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \sum_b \nabla_\theta e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \sum_b e^{h_\theta(s,b)} \nabla_\theta h_\theta(s,b) \\
& \nabla_\theta h_\theta(s,a) - \sum_b \frac{e^{h_\theta(s,b)}}{\sum_b e^{h_\theta(s,b)}} \nabla_\theta h_\theta(s,b)
\end{aligned}$$

$\nabla_\theta \log \pi_\theta(a)$ for softmax policy

$$\pi_\theta(a \mid s) = \frac{e^{h_\theta(s,a)}}{\sum_b e^{h_\theta(s,b)}}$$

$$\begin{aligned}
\nabla_\theta \log \pi_\theta(a) = \; & \nabla_\theta h_\theta(s,a) - \nabla_\theta \log \sum_b e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \nabla_\theta \sum_b e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \sum_b \nabla_\theta e^{h_\theta(s,b)} \\
& \nabla_\theta h_\theta(s,a) - \frac{1}{\sum_b e^{h_\theta(s,b)}} \sum_b e^{h_\theta(s,b)} \nabla_\theta h_\theta(s,b) \\
& \nabla_\theta h_\theta(s,a) - \sum_b \frac{e^{h_\theta(s,b)}}{\sum_b e^{h_\theta(s,b)}} \nabla_\theta h_\theta(s,b) \\
& \nabla_\theta h_\theta(s,a) - \sum_b \pi_\theta(s,b) \nabla_\theta h_\theta(s,b)
\end{aligned}$$

Temporal structure

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) R(\tau^{(i)})$$

Temporal structure

$$\begin{aligned}\hat{g} &= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_{\theta}\log\pi_{\theta}(\alpha_t^{(i)}\,|\,s_t^{(i)})R(\tau^{(i)}) \\ &= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_{\theta}\log\pi_{\theta}(\alpha_t^{(i)}\,|\,s_t^{(i)})\left(\sum_{k=0}^{T}R(s_k^{(i)}, a_k^{(i)})\right)\end{aligned}$$

Each action takes the blame for the full trajectory!

Temporal structure

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) R(\tau^{(i)})$$

$$= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(\sum_{k=0}^{T} R(s_k^{(i)}, a_k^{(i)})\right)$$

$$= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(\sum_{k=0}^{t-1} R(s_k^{(i)}, a_k^{(i)}) + \sum_{k=t}^{T} R(s_k^{(i)}, a_k^{(i)})\right)$$

Each action takes the blame for the full trajectory!

These rewards are not caused by actions that come after t

Can we do better than assigning the cumulative trajectory reward to every action in the trajectory?

Temporal structure

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) R(\tau^{(i)})$$

$$= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(\sum_{k=0}^{T} R(s_k^{(i)}, a_k^{(i)})\right)$$

$$= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(\sum_{k=0}^{t-1} R(s_k^{(i)}, a_k^{(i)}) + \sum_{k=t}^{T} R(s_k^{(i)}, a_k^{(i)})\right)$$

Each action takes the blame for the full trajectory!

Consider instead:

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(\sum_{k=t}^{T} R(s_k^{(i)}, a_k^{(i)})\right)$$

Each action takes the blame for the trajectory that comes after it

Temporal structure

$$\begin{aligned}
\hat{g} &= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) R(\tau^{(i)}) \\
&= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(\sum_{k=0}^{T} R(s_k^{(i)}, a_k^{(i)})\right) \\
&= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(\sum_{k=0}^{t-1} R(s_k^{(i)}, a_k^{(i)}) + \sum_{k=t}^{T} R(s_k^{(i)}, a_k^{(i)})\right)
\end{aligned}$$

Each action takes the blame for the full trajectory!

Consider instead:

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(\sum_{k=t}^{T} R(s_k^{(i)}, a_k^{(i)})\right)$$

Each action takes the blame for the trajectory that comes after it

We can call this the return from t onwards G_t

Likelihood ratio gradient estimator

- Let’s analyze the update:

$$\Delta\theta_t = \alpha G_t \nabla_\theta \log \pi_\theta \left(s_t, a_t\right)$$

- Let’s us rewrite is as follows:

move most in the directions that favor actions that yield the highest return

$$\boldsymbol{\theta}_{t+1} \doteq \boldsymbol{\theta}_t + \alpha\gamma^t G_t \frac{\nabla_{\boldsymbol{\theta}} \pi \left(A_t | S_t, \boldsymbol{\theta}\right)}{\pi \left(A_t | S_t, \boldsymbol{\theta}\right)}$$

Update is inversely proportional to the action probability to fight the fact that actions that are selected frequently are at an advantage (the updates will be more often in their direction)

REINFORCE (or Monte Carlo Policy Gradient)

0. Initialize policy parameters θ

1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{t=0}^{T}\}$ by deploying the current policy $\pi_\theta(a_t \mid s_t)$.

2. Compute gradient vector $\nabla_\theta U(\theta) \approx \hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(a_t^{(i)} \mid s_t^{(i)}) G_t^{(i)}$

3. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$

Policy Gradients

$$\max_{\theta}.\ U(\theta) = \mathbb{E}_{\tau \sim P_\theta(\tau)}\left[R(\tau)\right]$$

$$\begin{aligned}
\nabla_\theta U(\theta) &= \nabla_\theta \mathbb{E}_{\tau \sim P_\theta(\tau)}\left[R(\tau)\right] \\
&= \nabla_\theta \sum_{\tau} P_\theta(\tau) R(\tau) \\
&= \sum_{\tau} \nabla_\theta P_\theta(\tau) R(\tau) \\
&= \sum_{\tau} P_\theta(\tau) \frac{\nabla_\theta P_\theta(\tau)}{P_\theta(\tau)} R(\tau) \\
&= \sum_{\tau} P_\theta(\tau) \nabla_\theta \log P_\theta(\tau) R(\tau) \\
&= \mathbb{E}_{\tau \sim P_\theta(\tau)}\left[\nabla_\theta \log P_\theta(\tau) R(\tau)\right]
\end{aligned}$$

Sample estimate:

$$\nabla_\theta U(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)}) R(\tau^{(i)})$$

Evolutionary Methods

$$\max_{\mu} .\ U(\mu) = \mathbb{E}_{\theta \sim P_\mu(\theta)} \left[F(\theta) \right]$$

$$\begin{aligned}
\nabla_\mu U(\mu) &= \nabla_\mu \mathbb{E}_{\theta \sim P_\mu(\theta)} \left[F(\theta) \right] \\
&= \nabla_\mu \int P_\mu(\theta) F(\theta) d\theta \\
&= \int \nabla_\mu P_\mu(\theta) F(\theta) d\theta \\
&= \int P_\mu(\theta) \frac{\nabla_\mu P_\mu(\theta)}{P_\mu(\theta)} F(\theta) d\theta \\
&= \int P_\mu(\theta) \nabla_\mu \log P_\mu(\theta) F(\theta) d\theta \\
&= \mathbb{E}_{\theta \sim P_\mu(\theta)} \left[\nabla_\mu \log P_\mu(\theta) F(\theta) \right]
\end{aligned}$$

Sample estimate:

$$\nabla_\mu U(\mu) \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\mu \log P_\mu(\theta^{(i)}) F(\theta^{(i)})$$

Policy gradients VS Evolutionary methods

Considers distribution over actions

$$\max_{\theta}.\; U(\theta) = \mathbb{E}_{\tau \sim P_\theta(\tau)}\left[R(\tau)\right]$$

$$\begin{aligned}
\nabla_\theta U(\theta) &= \nabla_\theta \mathbb{E}_{\tau \sim P_\theta(\tau)}\left[R(\tau)\right] \\
&= \nabla_\theta \sum_\tau P_\theta(\tau) R(\tau) \\
&= \sum_\tau \nabla_\theta P_\theta(\tau) R(\tau) \\
&= \sum_\tau P_\theta(\tau) \frac{\nabla_\theta P_\theta(\tau)}{P_\theta(\tau)} R(\tau) \\
&= \sum_\tau P_\theta(\tau) \nabla_\theta \log P_\theta(\tau) R(\tau) \\
&= \mathbb{E}_{\tau \sim P_\theta(\tau)}\left[\nabla_\theta \log P_\theta(\tau) R(\tau)\right]
\end{aligned}$$

Sample estimate:

$$\nabla_\theta U(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)}) R(\tau^{(i)})$$

Considers distribution over policy parameters

$$\max_{\mu}.\; U(\mu) = \mathbb{E}_{\theta \sim P_\mu(\theta)}\left[F(\theta)\right]$$

$$\begin{aligned}
\nabla_\mu U(\mu) &= \nabla_\mu \mathbb{E}_{\theta \sim P_\mu(\theta)}\left[F(\theta)\right] \\
&= \nabla_\mu \int P_\mu(\theta) F(\theta) d\theta \\
&= \int \nabla_\mu P_\mu(\theta) F(\theta) d\theta \\
&= \int P_\mu(\theta) \frac{\nabla_\mu P_\mu(\theta)}{P_\mu(\theta)} F(\theta) d\theta \\
&= \int P_\mu(\theta) \nabla_\mu \log P_\mu(\theta) F(\theta) d\theta \\
&= \mathbb{E}_{\theta \sim P_\mu(\theta)}\left[\nabla_\mu \log P_\mu(\theta) F(\theta)\right]
\end{aligned}$$

Sample estimate:

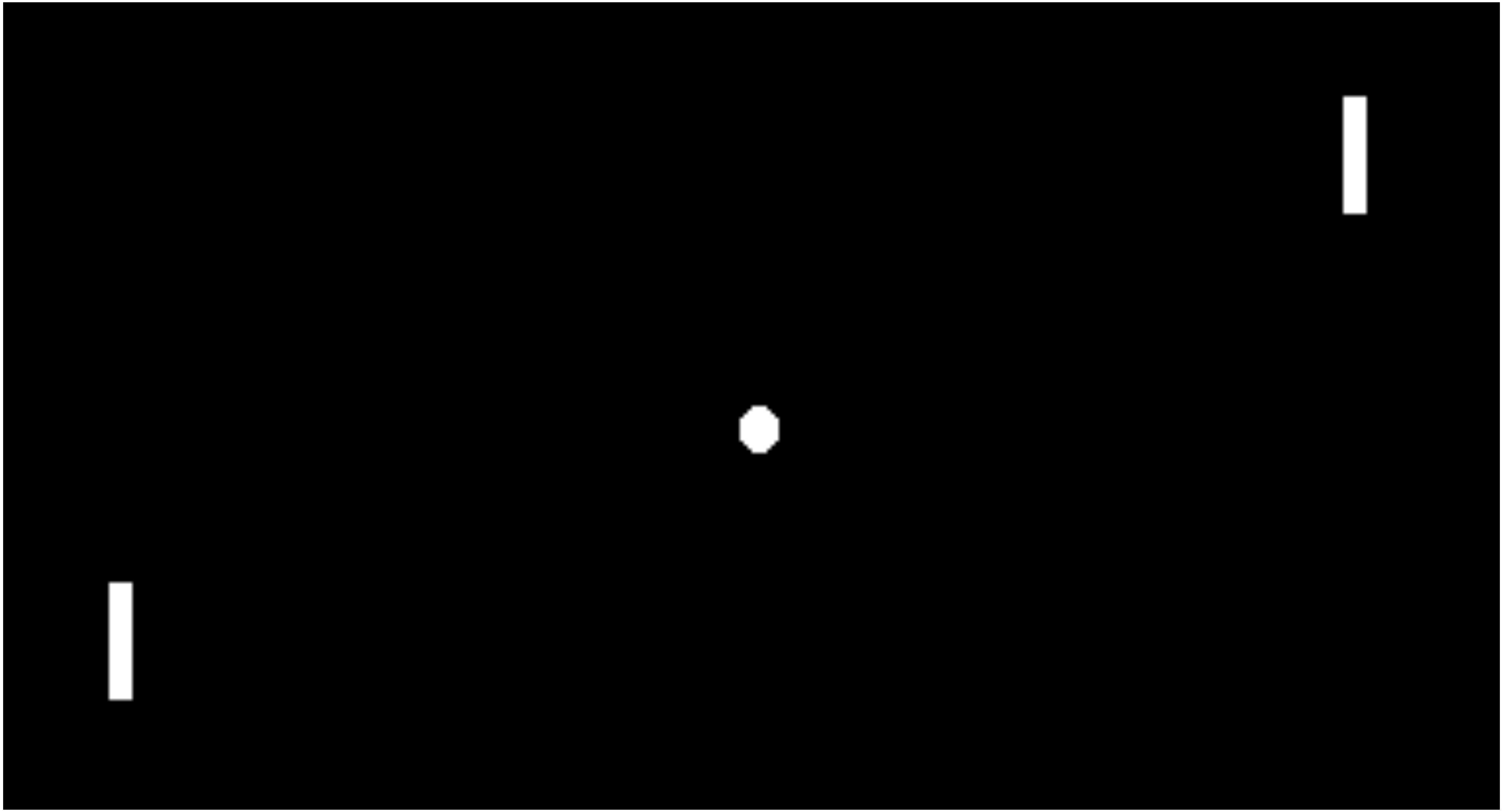
$$\nabla_\mu U(\mu) \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\mu \log P_\mu(\theta^{(i)}) F(\theta^{(i)})$$

Policy gradients VS Evolutionary methods

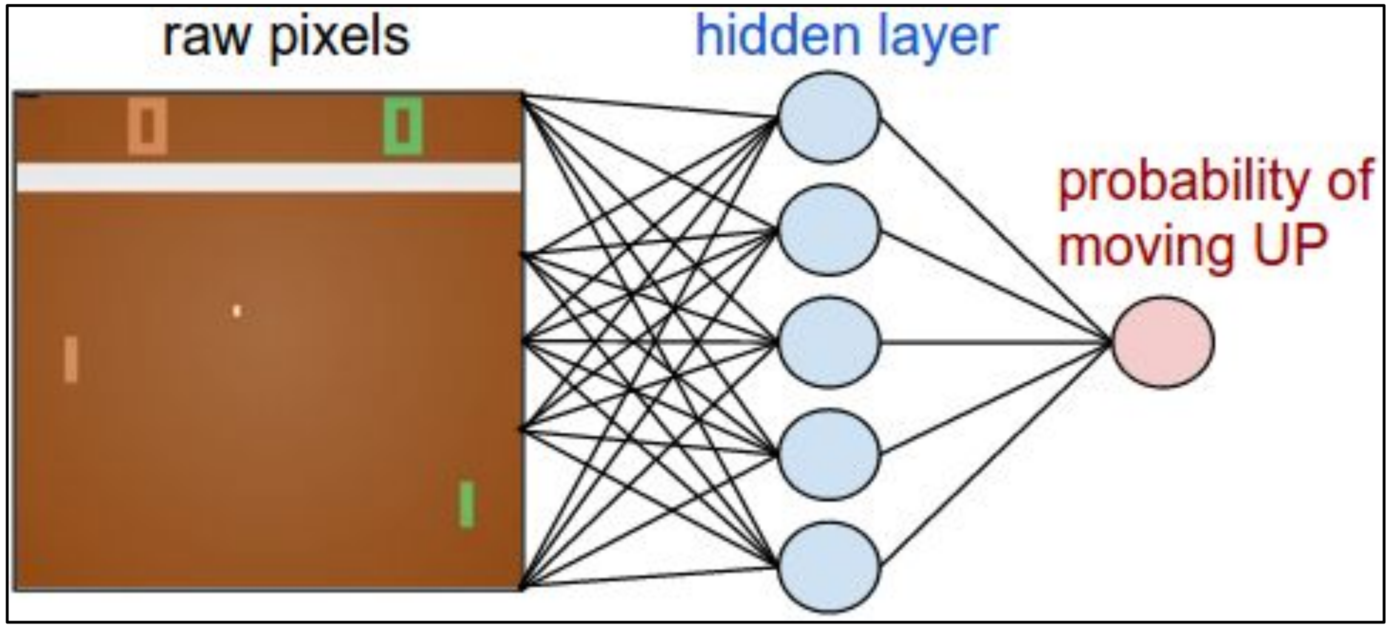
- We are sampling in both cases…
  - PG: sampling in action space
  - ES: sampling in parameter space

Pong from Pixels

Slides from Andrei Karpathy



Policy network

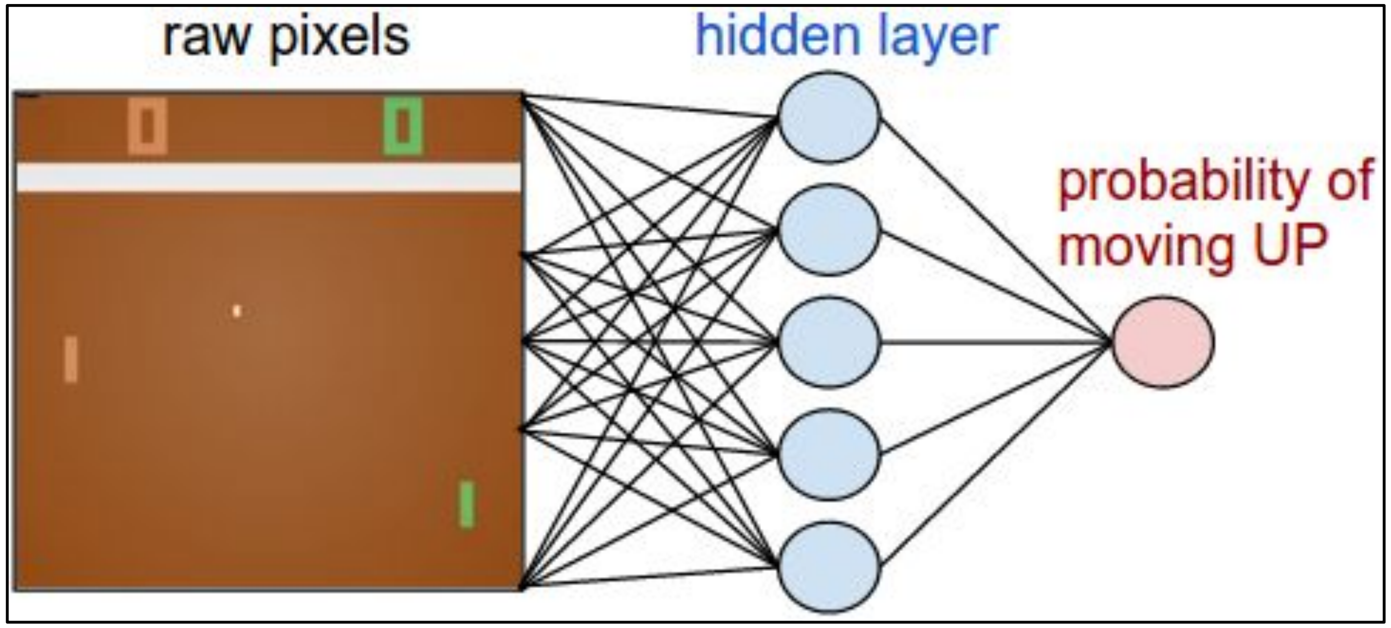


Policy network

e.g.,

height width

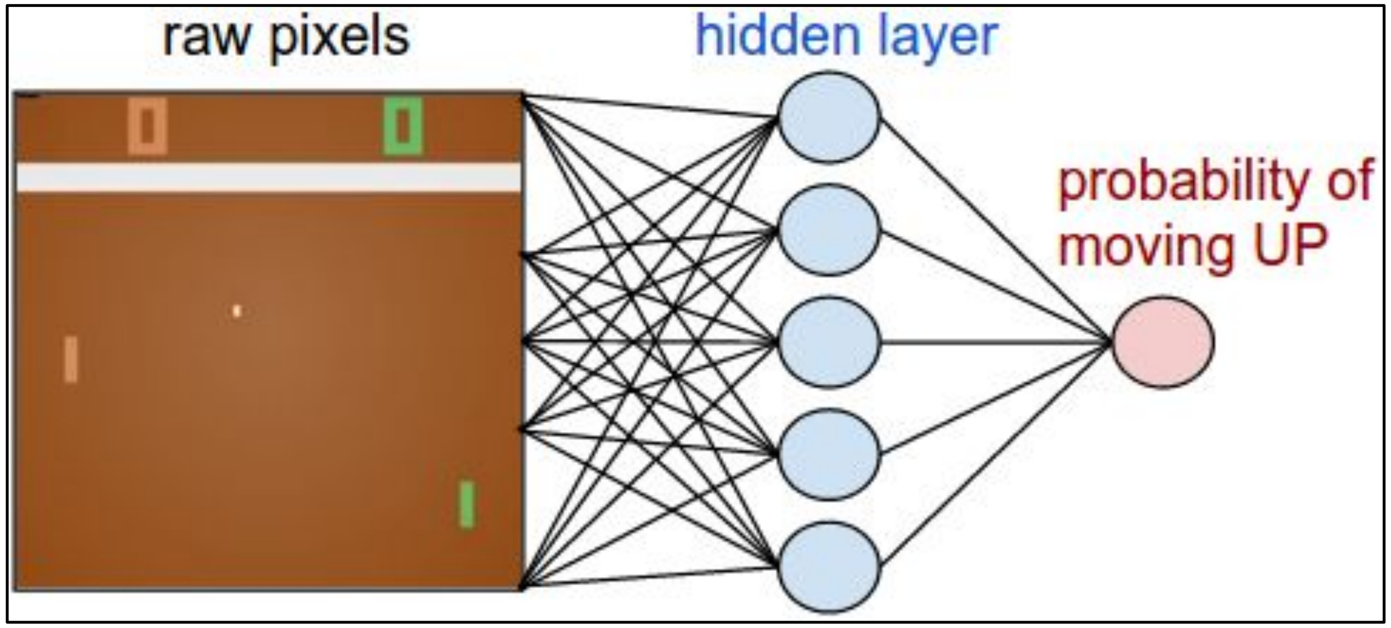
[80 x 80]
array



Policy network

height width

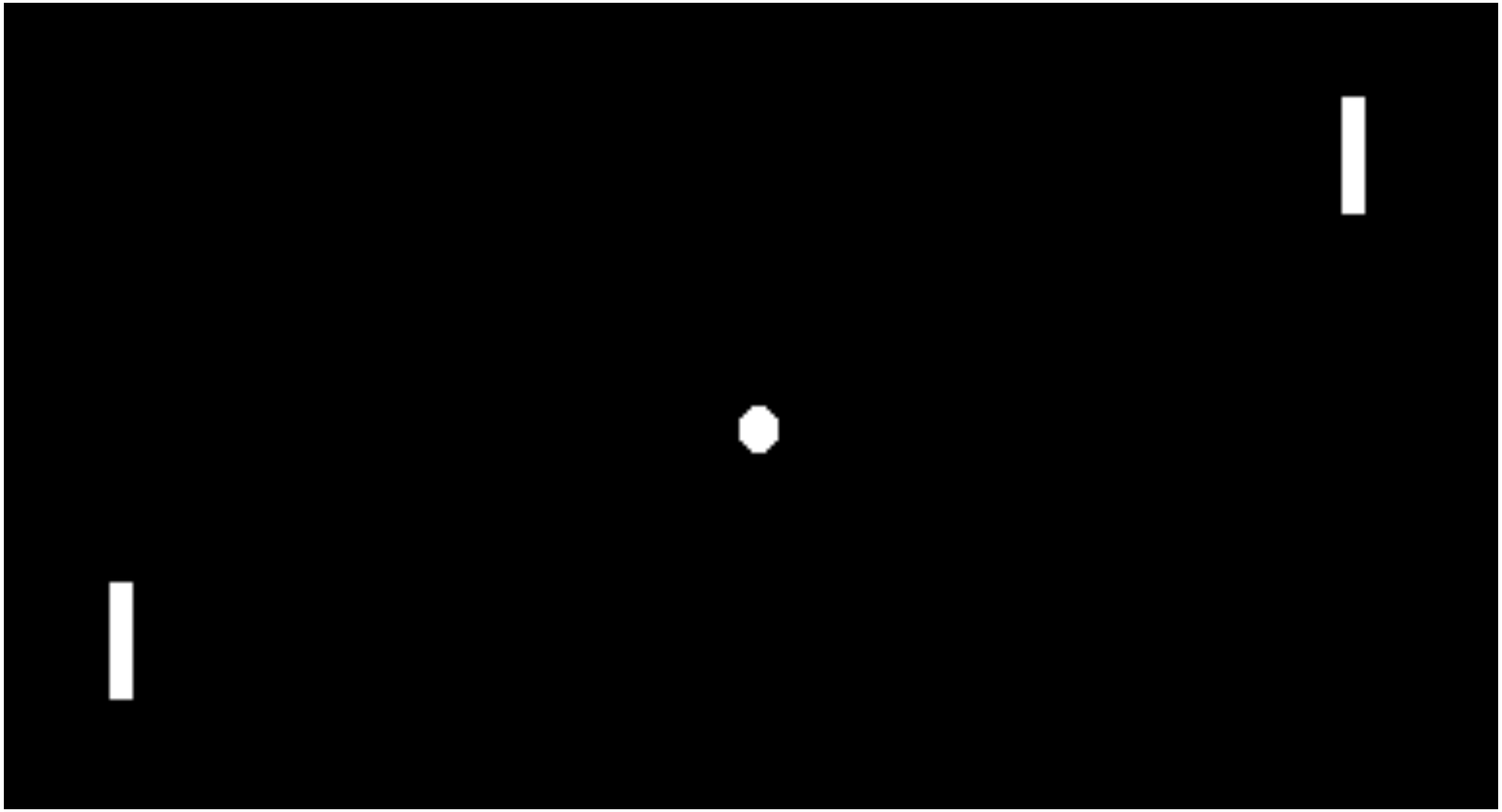
[**80** x **80**]
array



E.g. 200 nodes in the hidden network, so:

[(80*80)*200 + 200] + [200*1 + 1] = **~1.3M parameters**

Layer 1 Layer 2



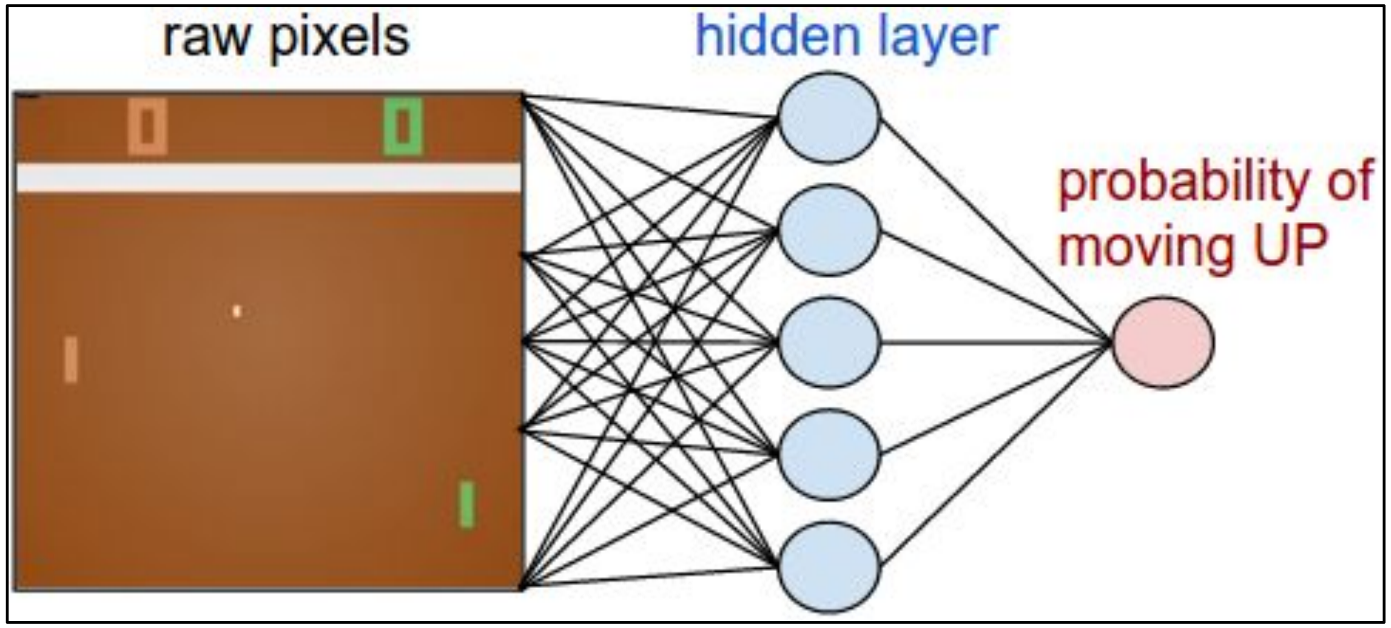
Network does not see this. Network sees 80*80 = 6,400 numbers.
It gets a reward of +1 or -1, some of the time.
Q: How do we efficiently find a good setting of the 1.3M parameters?

Suppose we had the training labels…
(we know what to do in any state)

(x1,UP)
(x2,DOWN)
(x3,UP)
...

Suppose we had the training labels…
(we know what to do in any state)

(x1,UP)
(x2,DOWN)
(x3,UP)
...

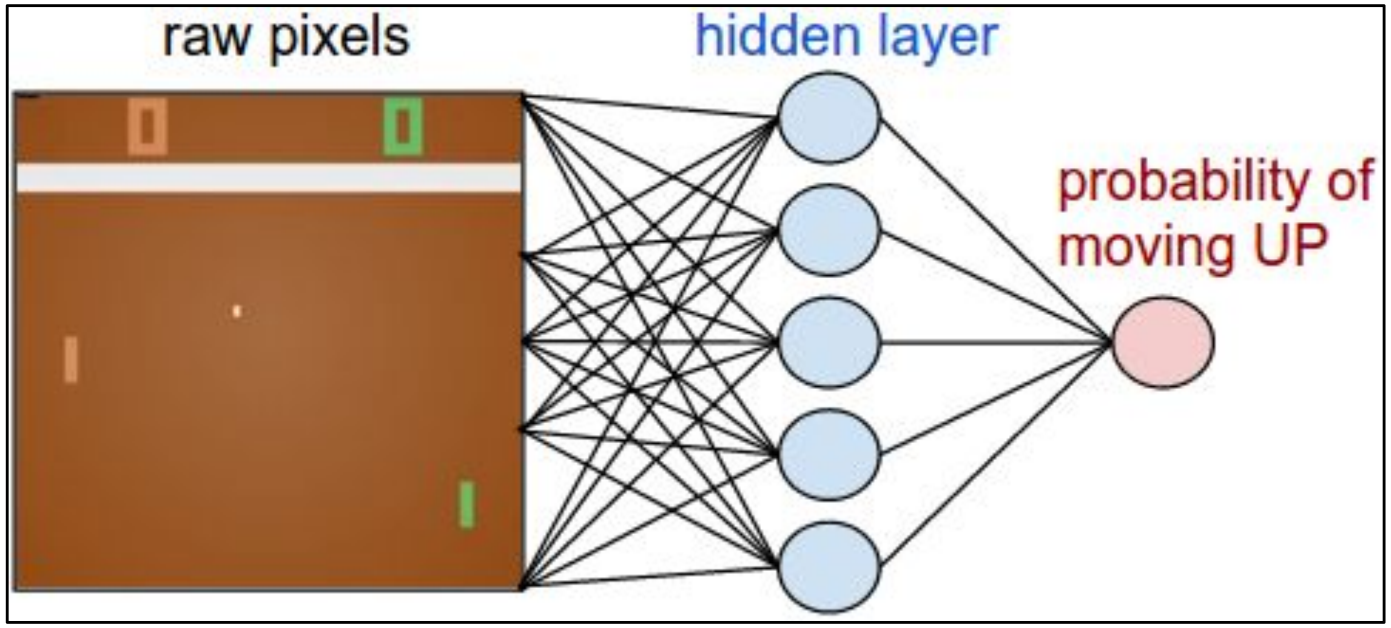


Suppose we had the training labels…
(we know what to do in any state)

(x1,UP)
(x2,DOWN)
(x3,UP)
...

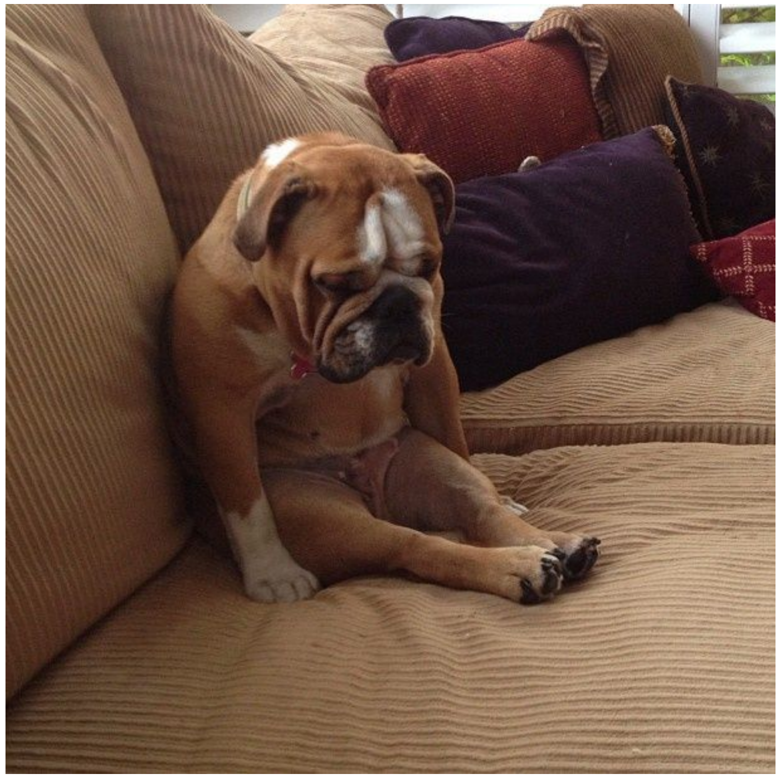
maximize:

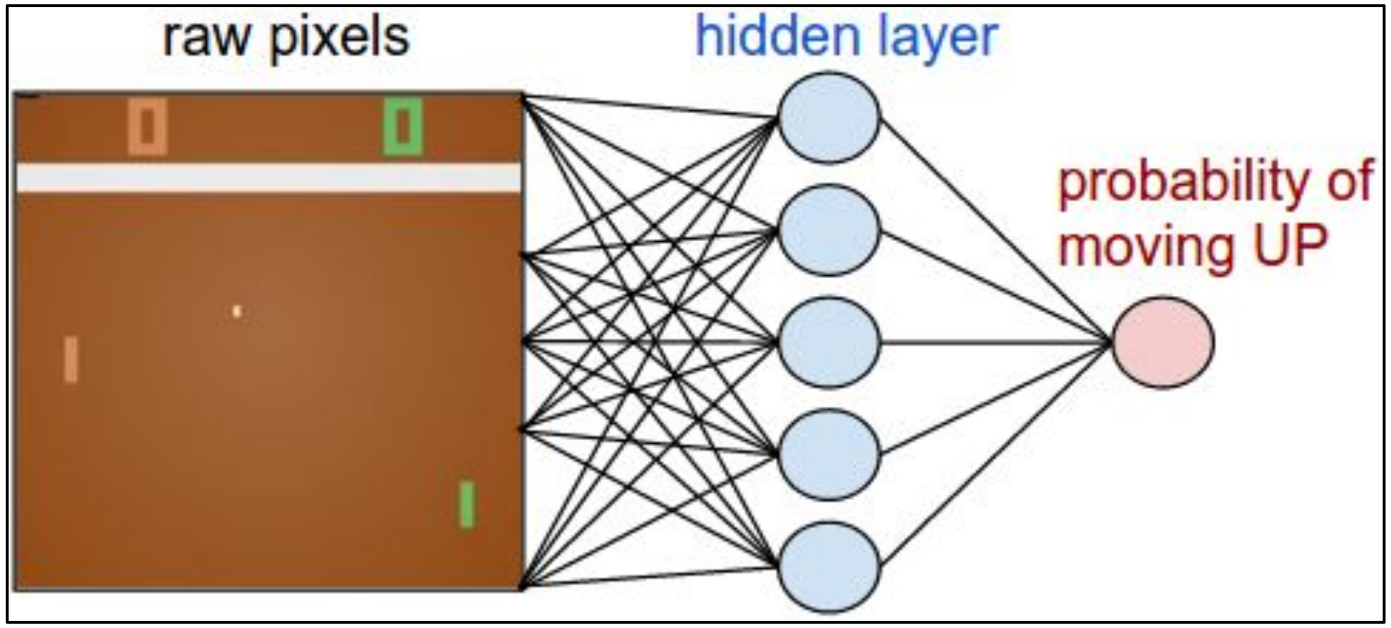
$$\sum_i \log p(y_i \mid x_i)$$



supervised learning

Except, we don’t have labels...





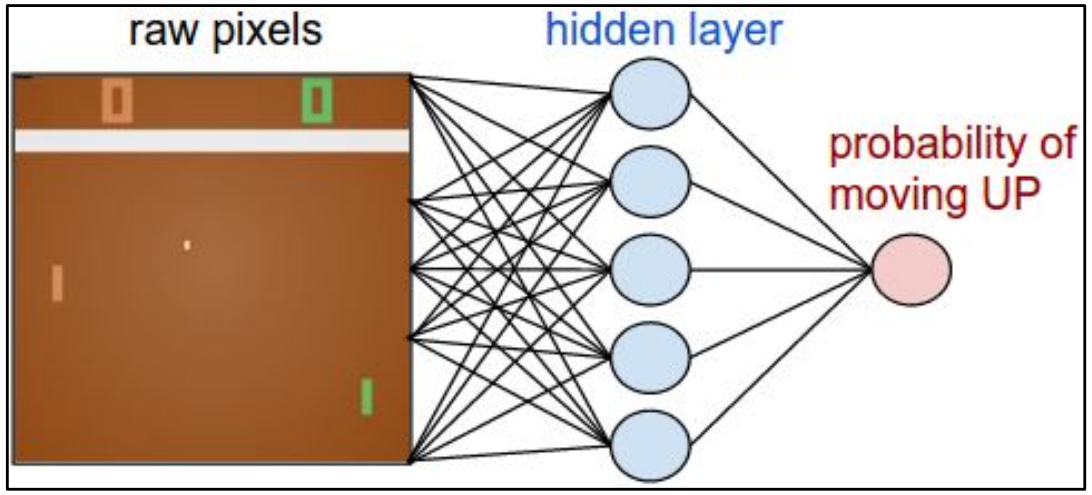
Should we go UP or DOWN?

Except, we don’t have labels...

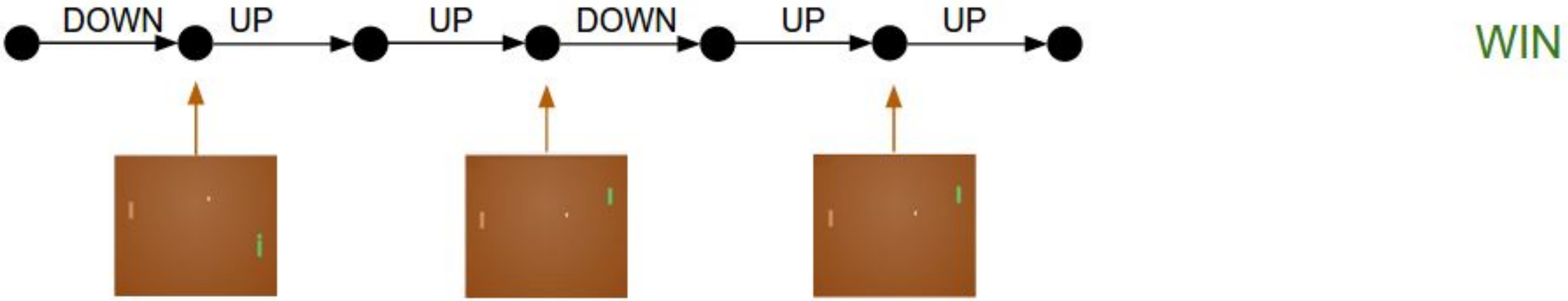
> *“Try a bunch of stuff and see what happens. Do more of the stuff that worked in the future.”*
>
> -RL

trial-and-error learning

Let’s just act according to our current policy...

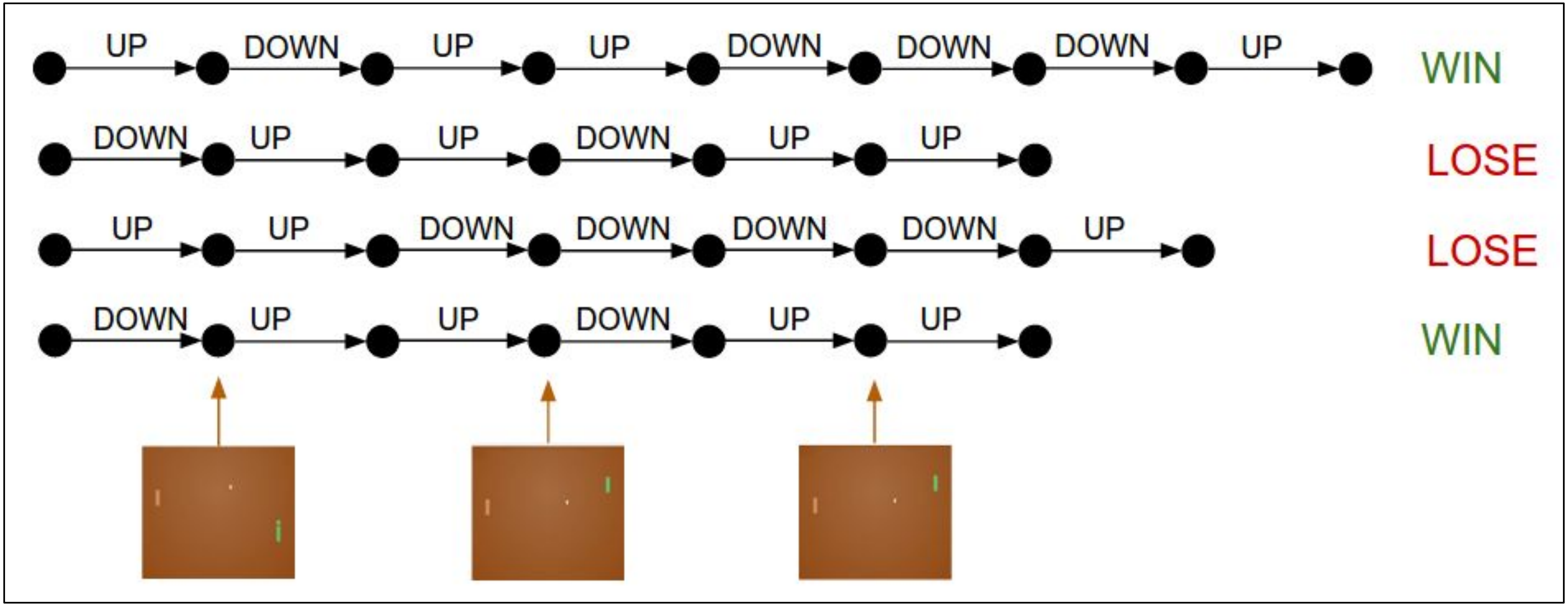


Rollout the policy and collect an episode

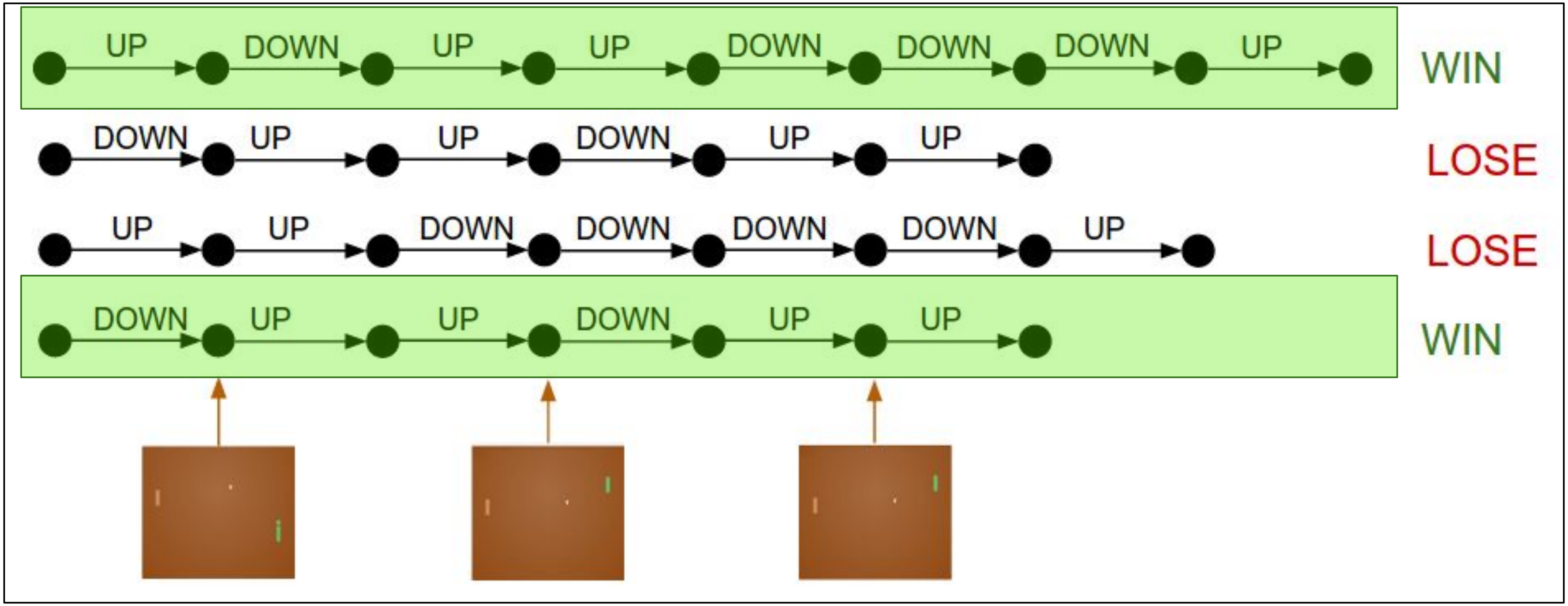


Collect many rollouts...

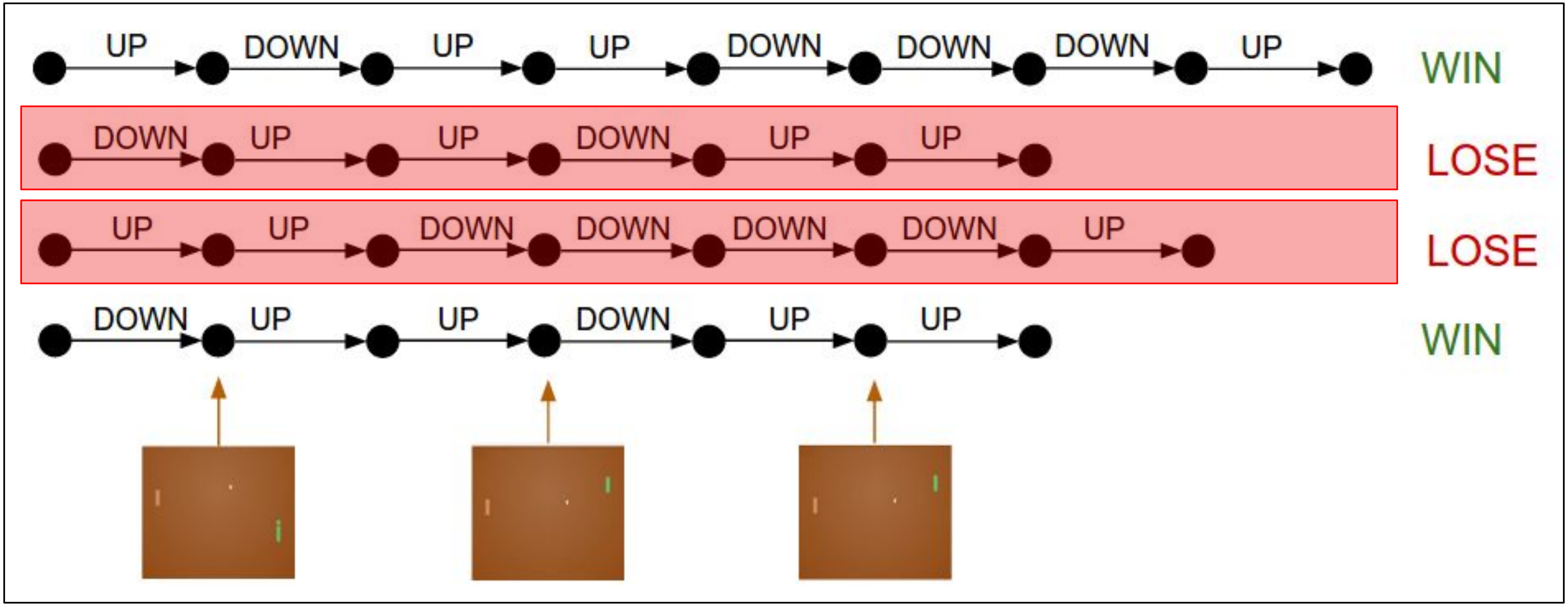
4 rollouts:



Not sure whatever we did here, but apparently it was good.



Not sure whatever we did here, but it was bad.

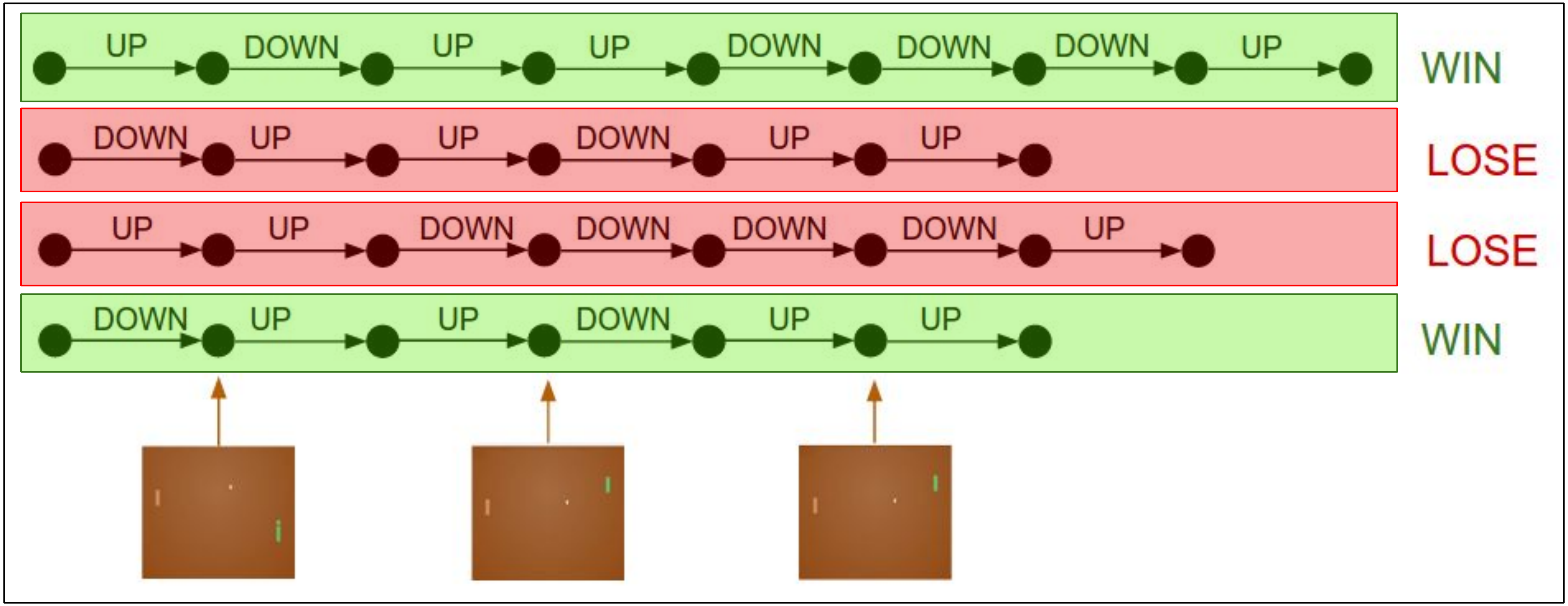


Pretend every action we took here was the correct label.

maximize: $\log p(y_i \mid x_i)$

Pretend every action we took here was the wrong label.

maximize: $(-1) * \log p(y_i \mid x_i)$



$$\nabla_\theta U(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)})R(\tau^{(i)})$$

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i | x_i)}$$

For images x_i and their labels y_i.

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i \mid x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i | x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot | x_i)}$$

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i \mid x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot \mid x_i)}$$

2) once we collect a batch of rollouts:

maximize:

$$\boxed{\sum_i A_i * \log p(y_i \mid x_i)}$$

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i | x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot | x_i)}$$

2) once we collect a batch of rollouts: maximize:

$$\boxed{\sum_i A_i * \log p(y_i | x_i)}$$

We call this the **advantage**, it’s a number, like +1.0 or -1.0 based on how this action eventually turned out.

Advantage is the same for all actions taken during a trajectory, and depends on the trajectory return (episode return)

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i | x_i)}$$

For images x_i and their labels y_i.

$$\nabla_\theta U(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} | s_t^{(i)}) R(\tau^{(i)})$$

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot | x_i)}$$

2) once we collect a batch of rollouts:
maximize:

$$\boxed{\sum_i A_i * \log p(y_i | x_i)}$$

+ve advantage will make that action more likely in the future, for that state.
-ve advantage will make that action less likely in the future, for that state.

Variance

Here is our gradient estimator:

$$\hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) G_t^{(i)}$$

It is unbiased, i.e., with large N it will accurately approximate the true gradient.

Problem: Unfortunately, usually a very large N is required.

Can we improve the variance of our estimator?

Variance

Here is our gradient estimator:

$$\hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \,|\, s_t^{(i)}) G_t^{(i)}$$

Variance is the trace of the covariance matrix:

$$\mathrm{Var}(\hat{g}) = \mathrm{tr}\left(\mathbb{E}\left[(\hat{g} - \mathbb{E}[\hat{g}])(\hat{g} - \mathbb{E}[\hat{g}])^T\right]\right) = \sum_{k=1}^{n} \mathbb{E}\left[\left(\hat{g}_k - \mathbb{E}[\hat{g}_k]\right)^2\right]$$

Our goal is to minimize the variance of our estimator.

Reducing variance by subtracting a baseline

What if we subtract a constant b from the rewards:

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)})(R(\tau^{(i)}) - b)$$

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)})R(\tau^{(i)}) - \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)})b$$

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original formulation

new term

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original formulation

new term

$$\begin{aligned}\sum_\tau P(\tau;\theta)\nabla_\theta \log P_\theta(\tau)b &= \sum_\tau P(\tau;\theta)\frac{\nabla_\theta P_\theta(\tau)}{P(\tau;\theta)}b \\ &= \sum_\tau \nabla_\theta P_\theta(\tau)b \\ &= b\left(\sum_\tau \nabla_\theta P_\theta(\tau)\right) \\ &= b\left(\nabla_\theta \sum_\tau P_\theta(\tau)\right) \\ &= 0\end{aligned}$$

Reducing variance by subtracting a baseline

What if we subtract a constant b from the rewards:

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)})(R(\tau^{(i)}) - b)$$

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)})R(\tau^{(i)}) - \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log P_\theta(\tau^{(i)})b$$

original formulation

new term

$$\begin{aligned}\sum_\tau P(\tau;\theta)\nabla_\theta \log P_\theta(\tau)b &= \sum_\tau P(\tau;\theta)\frac{\nabla_\theta P_\theta(\tau)}{P(\tau;\theta)}b \\ &= \sum_\tau \nabla_\theta P_\theta(\tau)b \\ &= b\left(\sum_\tau \nabla_\theta P_\theta(\tau)\right) \\ &= b\left(\nabla_\theta \sum_\tau P_\theta(\tau)\right) \\ &= 0\end{aligned}$$

- new term equals to 0 in expectation
- We are still unbiased

Baseline choices

Constant Baseline (single scalar): $b = \mathbb{E}[R(\tau)]$

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)})\left(G_t^{(i)} - b\right)$$

Time-dependent Baseline (a vector length T): $b_t = \sum_{i=1}^{N} G_t^{(i)}$

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)})\left(G_t^{(i)} - b_t\right)$$

State-dependent Baseline (a function):

$$b(s) = \mathbb{E}\left[r_t + r_{t+1} + r_{t+2} + \ldots + r_{T-1} \,\middle|\, s_t = s\right] = V_\pi(s)$$

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}\nabla_\theta \log \pi_\theta(a_t^{(i)} \mid s_t^{(i)})(G_t^{(i)} - b(s_t^{(i)}))$$

Variance

Subtracting a state-dependent Baseline:

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}\nabla_\theta \log \pi_\theta(a_t^{(i)} \mid s_t^{(i)})G_t^{(i)}$$

$$\mathrm{Var}(\hat{g}) = \mathrm{tr}\left(\mathbb{E}\left[(\hat{g} - \mathbb{E}[\hat{g}])(\hat{g} - \mathbb{E}[\hat{g}])^T\right]\right) = \sum_{k=1}^{n}\mathbb{E}\left[\left(\hat{g}_k - \mathbb{E}[\hat{g}_k]\right)^2\right]$$

- Imagine in some state S_1 the rewards of all actions are ~3000 and in some state S_2 the rewards of all actions are~ -4000.

Action advantages Versus Action returns

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}\nabla_\theta \log \pi_\theta(a_t^{(i)} | s_t^{(i)})\underbrace{(G_t^{(i)} - b(s_t^{(i)}))}_{\text{advantage}}$$

$G(a_1) = 3030$

$v(s_1) = 3000$ s_1

$G(a_2) = 2970$

$G(a_1) = -3970$

s_2 $v(s_2) = -4000$

$G(a_2) = -4030$

- Imagine in some state s_1 the rewards of all actions are ~3000 and in some state s_2 the rewards of all actions are~ -4000. Bad actions in s_1 will much influence the gradient way more than good actions in s_2. But our goal is to select the right actions across both bad and good states!

- Now imagine you have $b(s_1) = 3000$ and $b(s_2) = -4000$ and you subtract those values from the sample returns.

Action advantages Versus Action returns

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}\nabla_\theta \log \pi_\theta(a_t^{(i)} \mid s_t^{(i)})\underbrace{(G_t^{(i)} - b(s_t^{(i)}))}_{\text{advantage}}$$

$G(a_1) = -3970$

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- Now imagine you have $b(s_1) = 3000$ and $b(s_2) = -4000$ and you subtract those values from the sample returns.

- We want to encourage an action not when it has high return, but when it has higher return than the other actions from that state, i.e., when it has an *advantage* over other actions. It may well be that a state is bad and all actions have low returns in that state, we care to find the actions that have higher returns that the rest, and we need to calibrate for the goodness of state using state dependent baselines.

Estimate state dependent baseline $V_\phi^\pi(s_t)$

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \Big(G_t^{(i)} - V_\phi^\pi(s_t^{(i)}) \Big)$$

- Monte Carlo estimation

1. Initialize ϕ
2. Collect trajectories: $\tau_1, \ldots, \tau_N$
3. Regress against empirical return, e.g., using gradient descent:

$$\phi \leftarrow \arg\min_{\phi} \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T-1}\left(V_\phi^\pi\left(s_t^{(i)}\right) - \left(\sum_{k=t}^{T-1} R\left(s_k^{(i)}, a_k^{(i)}\right) \right) \right)^2$$

Estimate state dependent baseline $V_\phi^\pi(s_t)$

$$\hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)})\left(G_t^{(i)} - V_\phi^\pi(s_t^{(i)})\right)$$

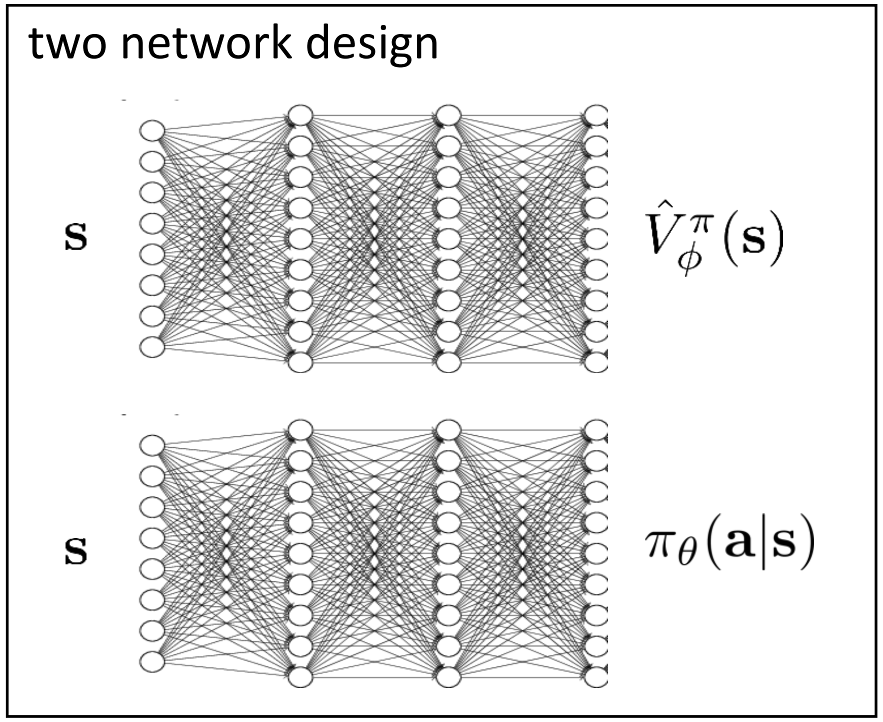
- TD estimation

1. Initialize ϕ
2. Collect data for: s, a, s', r
3. Fitted V iteration

$$\phi_{\ell+1} \leftarrow \arg\min_\phi \sum_{(s,a,s',r)} \left\| (r + V_{\phi_\ell}^\pi(s')) - V_\phi(s) \right\|_2^2$$

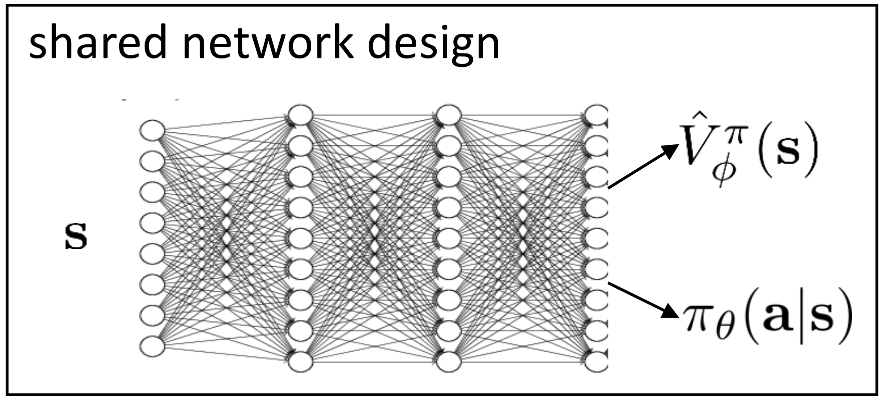
Actor-Critic

- Actor-critic algorithms maintain two sets of parameters
  - Critic Updates action-value function parameters w
  - Actor Updates policy parameters θ, in direction suggested by critic

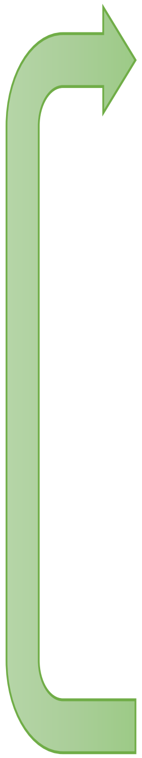

two network design

+ simple & stable

- no shared features between actor & critic


shared network design

Actor-Critic



0. Initialize policy parameters θ and critic parameters ϕ .

1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{i=0}^{T}\}$ by deploying the current policy $\pi_\theta(a_t \mid s_t)$.

2. Fit value function $V_\phi^\pi(s)$ by MC or TD estimation (update ϕ)

3. Compute action advantages $A^\pi(s_t^i, a_t^i) = G_t^{(i)} - V_\phi^\pi(s_t^i)$

4. $\nabla_\theta U(\theta) \approx \hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^i \mid s_t^i) A^\pi(s_t^i, a_t^i)$

5. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$

Sample returns are Q estimates!

Whether we use a baseline:

$$\hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) \left(G_t^{(i)} - V_\phi^\pi(s_t^{(i)}) \right)$$

or not:

$$\hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^{(i)} \mid s_t^{(i)}) G_t^{(i)}$$

returns $G_t^{(i)} = \sum_{k=t}^{T} R(s_k^{(i)}, a_k^{(i)})$ are trying to estimate Q values from a single rollout:

$$Q^\pi(s, a) = \mathbb{E}[R_0 + R_1 + \cdots \mid S_0 = s, A_0 = a]$$

Sample returns are Q estimates!

Returns $G_t^{(i)} = \sum_{k=t}^{T} R(s_k^{(i)}, a_k^{(i)})$ are trying to estimate Q values from a single rollou

$$Q^{\pi}(s, a) = \mathbb{E}[R_0 + R_1 + \cdots \mid S_0 = s, A_0 = a]$$

Minimize variance of such Q estimates by:

- discounting
- introducing a learnt approximation for the Q, as opposed to returns from single rollouts

By definition of the Q function

$$Q^{\pi,\gamma}(s,a) = \mathbb{E}[R_0 + \gamma R_1 + \gamma^2 R_2 \cdots \mid S_0 = s, A_0 = a]$$

By definition of the Q function

$$\begin{aligned} Q^{\pi,\gamma}(s,a) &= \mathbb{E}[R_0 + \gamma R_1 + \gamma^2 R_2 \cdots \mid S_0 = s, A_0 = a] \\ &= \mathbb{E}[R_0 + \gamma V^{\pi}(S_1) \mid S_0 = s, A_0 = a] \end{aligned}$$

By definition of the Q function

$$
\begin{aligned}
Q^{\pi,\gamma}(s,a) &= \mathbb{E}[R_0 + \gamma R_1 + \gamma^2 R_2 \cdots \,|\, S_0 = s, A_0 = a] \\
&= \mathbb{E}[R_0 + \gamma V^{\pi}(S_1) \,|\, S_0 = s, A_0 = a] \\
&= \mathbb{E}[R_0 + \gamma R_1 + \gamma^2 V^{\pi}(S_2) \,|\, S_0 = s, A_0 = a]
\end{aligned}
$$

By definition of the Q function

$$\begin{aligned} Q^{\pi,\gamma}(s,a) &= \mathbb{E}[R_0 + \gamma R_1 + \gamma^2 R_2 \cdots \mid S_0 = s, A_0 = a] \\ &= \mathbb{E}[R_0 + \gamma V^{\pi}(S_1) \mid S_0 = s, A_0 = a] \\ &= \mathbb{E}[R_0 + \gamma R_1 + \gamma^2 V^{\pi}(S_2) \mid S_0 = s, A_0 = a] \\ &= \mathbb{E}[R_0 + \gamma R_1 + \gamma^2 R_2 + \gamma^3 V^{\pi}(S_3) \mid S_0 = s, A_0 = a] \\ &= \cdots \end{aligned}$$

If I have estimated $V^{\pi}_{\phi}(S)$, I can use it to estimate the Q values, I do not need a separate Q function approximate!

Advantage Actor-Critic

0. Initialize policy parameters θ and critic parameters ϕ .

1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{t=0}^{T}\}$ by deploying the current policy $\pi_\theta(a_t \,|\, s_t)$.

2. Fit value function $V_\phi^\pi(s)$ by MC or TD estimation (update ϕ)

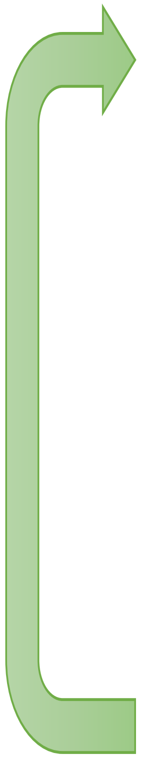
3. Compute action advantages $A^\pi(s_t^i, a_t^i) = R(s_t^i, a_t^i) + \gamma V_\phi^\pi(s_{t+1}^i) - V_\phi^\pi(s_t^i)$

4. $\nabla_\theta U(\theta) \approx \hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^i \,|\, s_t^i) A^\pi(s_t^i, a_t^i)$

5. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$

Advantage Actor-Critic

0. Initialize policy parameters θ and critic parameters ϕ .



1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{t=0}^{T}\}$ by deploying the current policy $\pi_\theta(a_t \mid s_t)$.
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4. $\nabla_\theta U(\theta) \approx \hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^i \mid s_t^i) A^\pi(s_t^i, a_t^i)$
5. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$

How can we compute this in automatic differentiation packages, such us Tensor flow?

We need to write the expression that when differentiated will give that gradient.

$$\hat{U} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \log \pi_\theta(\alpha_t^i \mid s_t^i) A^\pi(s_t^i, a_t^i)$$

REINFORCE/Actor-critic training

- Stability of training neural networks requires the **gradient updates to be de-correlated**

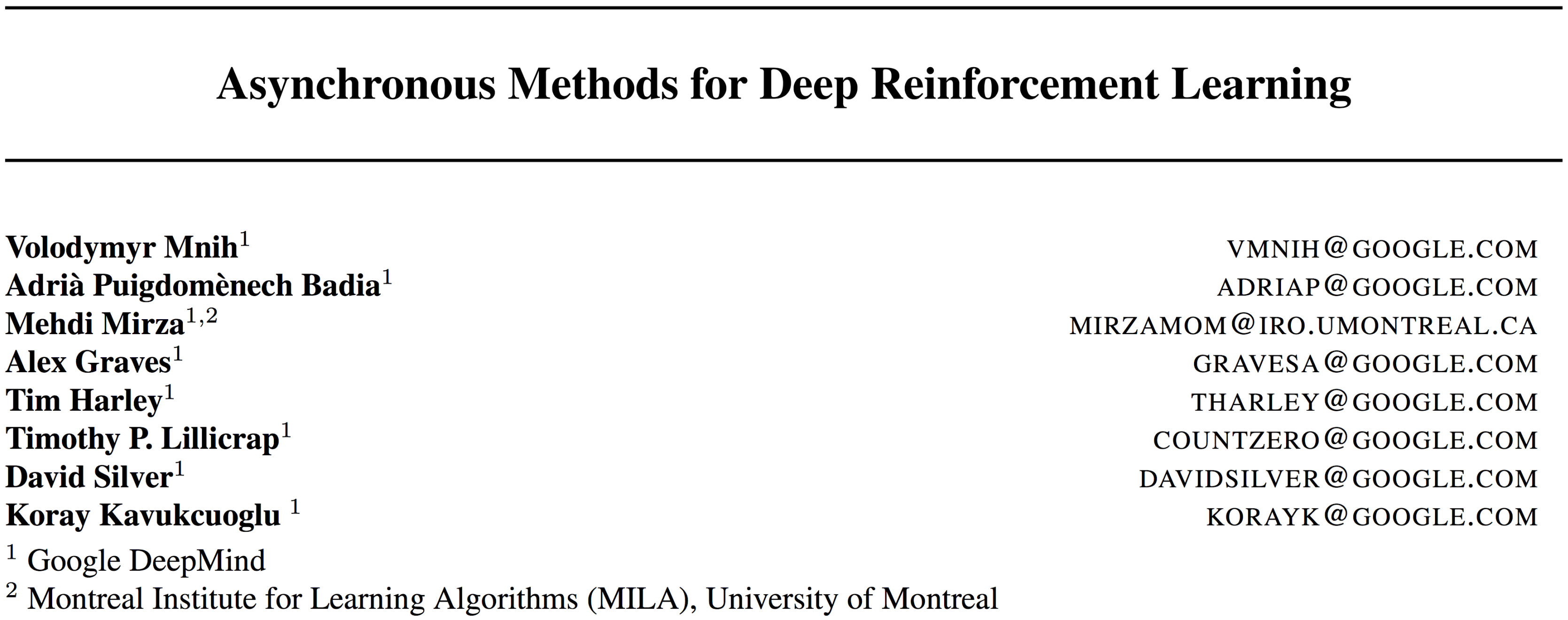
- This is not the case if data arrives **sequentially**

- Gradient updates computed from some part of the space can cause the value (Q) function approximator to **oscillate**

- Our solution so far has been: **Experience buffers** where experience tuples are mixed and sampled from. Resulting sampled batches are more stationary that the ones encountered online (without buffer)

- This limits deep RL to **off-policy** methods, since data from an older policy are used to update the weights of the value approximator (critic) (except if we take care and weight such data under our current stochastic policy->importance sampling)

Asynchronous Deep RL for on policy learning



Asynchronous Methods for Deep Reinforcement Learning

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[1] Google DeepMind
[2] Montreal Institute for Learning Algorithms (MILA), University of Montreal

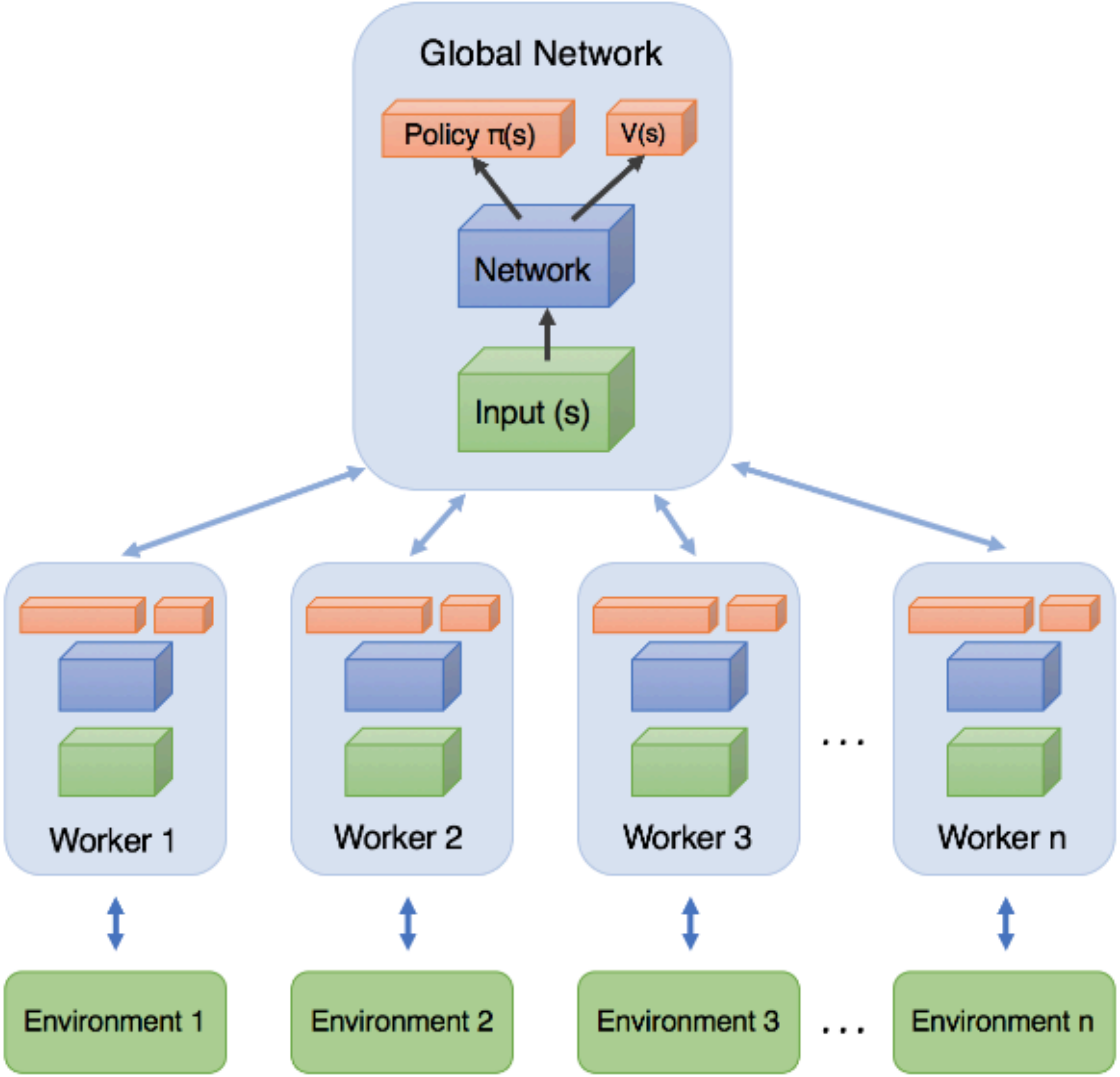
- Alternative: parallelize the collection of experience and stabilize training **without experience buffers**

- **Multiple threads of experience**, one per agent, each exploring in different part of the environment contributing experience tuples

- **Different exploration strategies** (e.g., various ϵ values) in different threads increase diversity

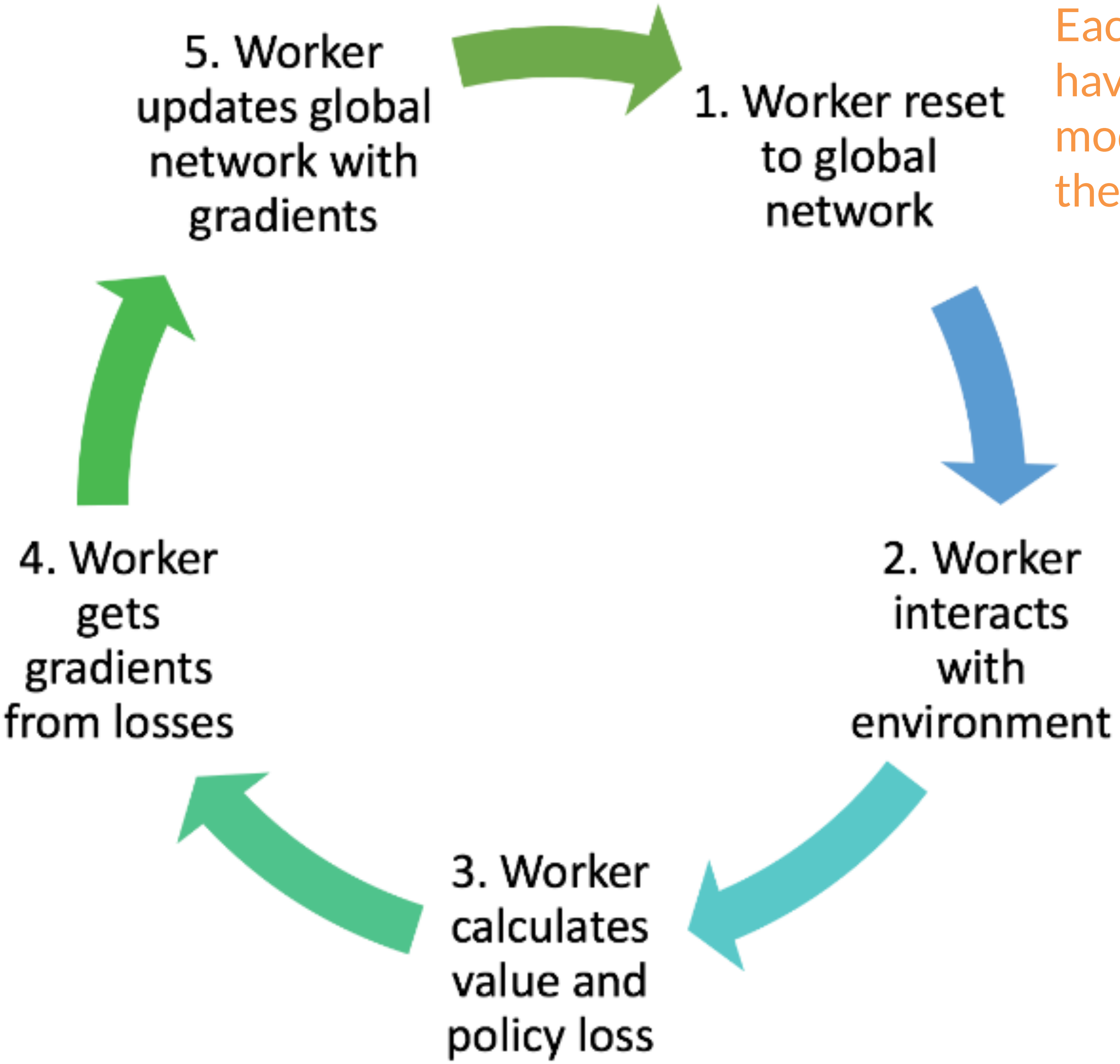
- Now you can train on-policy using any of our policy gradient methods

Distributed RL



Distributed Asynchronous RL-A3C

No locking



5. Worker updates global network with gradients

1. Worker reset to global network

2. Worker interacts with environment

3. Worker calculates value and policy loss

4. Worker gets gradients from losses

Each worker may have slightly modified version of the policy/critic

A3C

Algorithm S3 Asynchronous advantage actor-critic - pseudocode for each actor-learner thread.

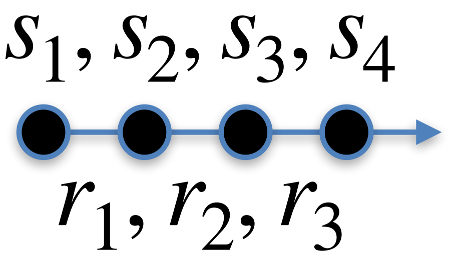
```
// Assume global shared parameter vectors $\theta$ and $\theta_v$ and global shared counter $T = 0$
// Assume thread-specific parameter vectors $\theta'$ and $\theta'_v$
Initialize thread step counter $t \leftarrow 1$
repeat
    Reset gradients: $d\theta \leftarrow 0$ and $d\theta_v \leftarrow 0$.
    Synchronize thread-specific parameters $\theta' = \theta$ and $\theta'_v = \theta_v$
    $t_{start} = t$
    Get state $s_t$
    repeat
        Perform $a_t$ according to policy $\pi(a_t|s_t;\theta')$
        Receive reward $r_t$ and new state $s_{t+1}$
        $t \leftarrow t + 1$
        $T \leftarrow T + 1$
    until terminal $s_t$ or $t - t_{start} == t_{max}$
    $R = \begin{cases} 0 & \text{for terminal } s_t \\ V(s_t, \theta'_v) & \text{for non-terminal } s_t \text{// Bootstrap from last state} \end{cases}$
    for $i \in \{t-1, \ldots, t_{start}\}$ do
        $R \leftarrow r_i + \gamma R$
        Accumulate gradients wrt $\theta'$: $d\theta \leftarrow d\theta + \nabla_{\theta'} \log \pi(a_i|s_i;\theta')(R - V(s_i;\theta'_v))$
        Accumulate gradients wrt $\theta'_v$: $d\theta_v \leftarrow d\theta_v + \partial\left(R - V(s_i;\theta'_v)\right)^2 / \partial\theta'_v$
    end for
    Perform asynchronous update of $\theta$ using $d\theta$ and of $\theta_v$ using $d\theta_v$.
until $T > T_{max}$
```

Copying the weights

Rollout

Advantage

Learning the critic



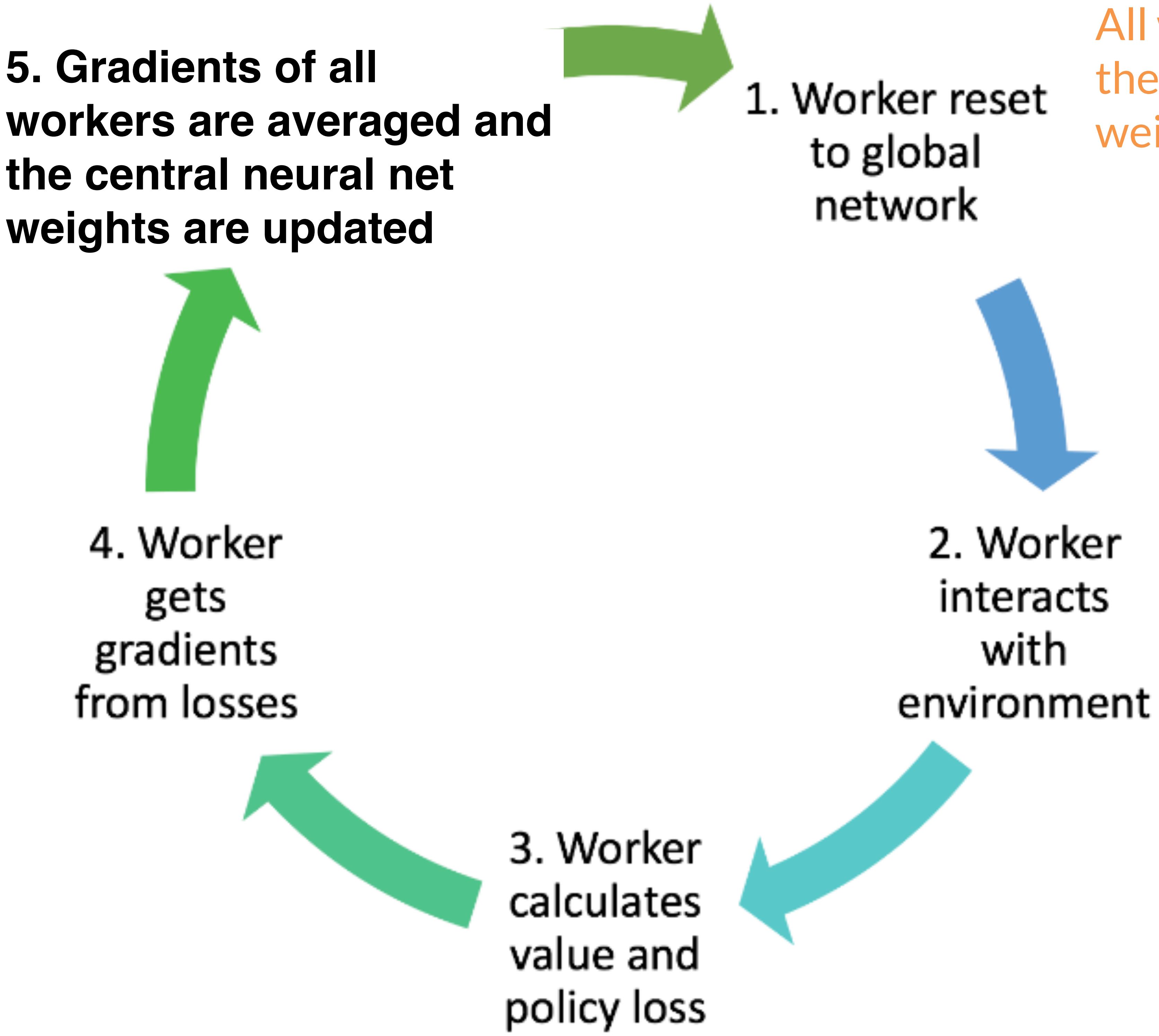
$R_3 - V(s_3)$

What is the approximation used for the advantage?

$R_3 = r_3 + \gamma V(s_4, \theta'_v)$ $\quad A_3 = R_3 - V(s_3; \theta'_v)$

$R_2 = r_2 + \gamma r_3 + \gamma^2 V(s_4, \theta'_v)$ $\quad A_2 = R_2 - V(s_2; \theta'_v)$

Distributed Synchronous RL-A2C



5. Gradients of all workers are averaged and the central neural net weights are updated

1. Worker reset to global network

2. Worker interacts with environment

3. Worker calculates value and policy loss

4. Worker gets gradients from losses

All worker may have the same actor/critic weights

Algorithm S3 Asynchronous advantage actor-critic - pseudocode for each actor-learner thread.

```
// Assume global shared parameter vectors $\theta$ and $\theta_v$ and global shared counter $T = 0$
// Assume thread-specific parameter vectors $\theta'$ and $\theta'_v$
Initialize thread step counter $t \leftarrow 1$
repeat
    Reset gradients: $d\theta \leftarrow 0$ and $d\theta_v \leftarrow 0$.
    Synchronize thread-specific parameters $\theta' = \theta$ and $\theta'_v = \theta_v$
```

``We also found that adding the entropy of the policy π to the objective function improved exploration by discouraging premature convergence to suboptimal deterministic policies." So you need to add to the policy gradient: $+\beta \nabla_\theta \mathrm{H}(\pi_\theta(a_t | s_t; \theta))$

We will look into the entropy as part of the reward in later lecture

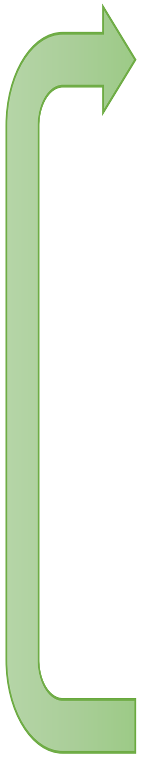
```
    Perform asynchronous update of $\theta$ using $d\theta$ and of $\theta_v$ using $d\theta_v$.
until $T > T_{max}$
```

What is the approximation used for the advantage?

$R_3 = r_3 + \gamma V(s_4, \theta'_v)$ $\qquad$ $A_3 = R_3 - V(s_3; \theta'_v)$

$R_2 = r_2 + \gamma r_3 + \gamma^2 V(s_4, \theta'_v)$ $\qquad$ $A_2 = R_2 - V(s_2; \theta'_v)$

Actor-Critic



0. Initialize policy parameters θ and critic parameters ϕ .

1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{i=0}^{T}\}$ by deploying the current policy $\pi_\theta(a_t \mid s_t)$.

2. Fit value function $V_\phi^\pi(s)$ by MC or TD estimation (update ϕ)

3. Compute action advantages $A^\pi(s_t^i, a_t^i) = R(s_t^i, a_t^i) + \gamma V_\phi^\pi(s_{t+1}^i) - V_\phi^\pi(s_t^i)$

4. $\nabla_\theta U(\theta) \approx \hat{g} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\alpha_t^i \mid s_t^i) A^\pi(s_t^i, a_t^i)$

5. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$

Actor-Critic as Policy Iteration

0. Initialize policy parameters θ and critic parameters ϕ .

1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{i=0}^T\}$ by deploying the current policy $\pi_\theta(a_t \mid s_t)$.

2. Fit value function $V_\phi^\pi(s)$ by MC or TD estimation (update ϕ)

3. Compute action advantages $A^\pi(s_t^i, a_t^i) = R(s_t^i, a_t^i) + \gamma V_\phi^\pi(s_{t+1}^i) - V_\phi^\pi(s_t^i)$

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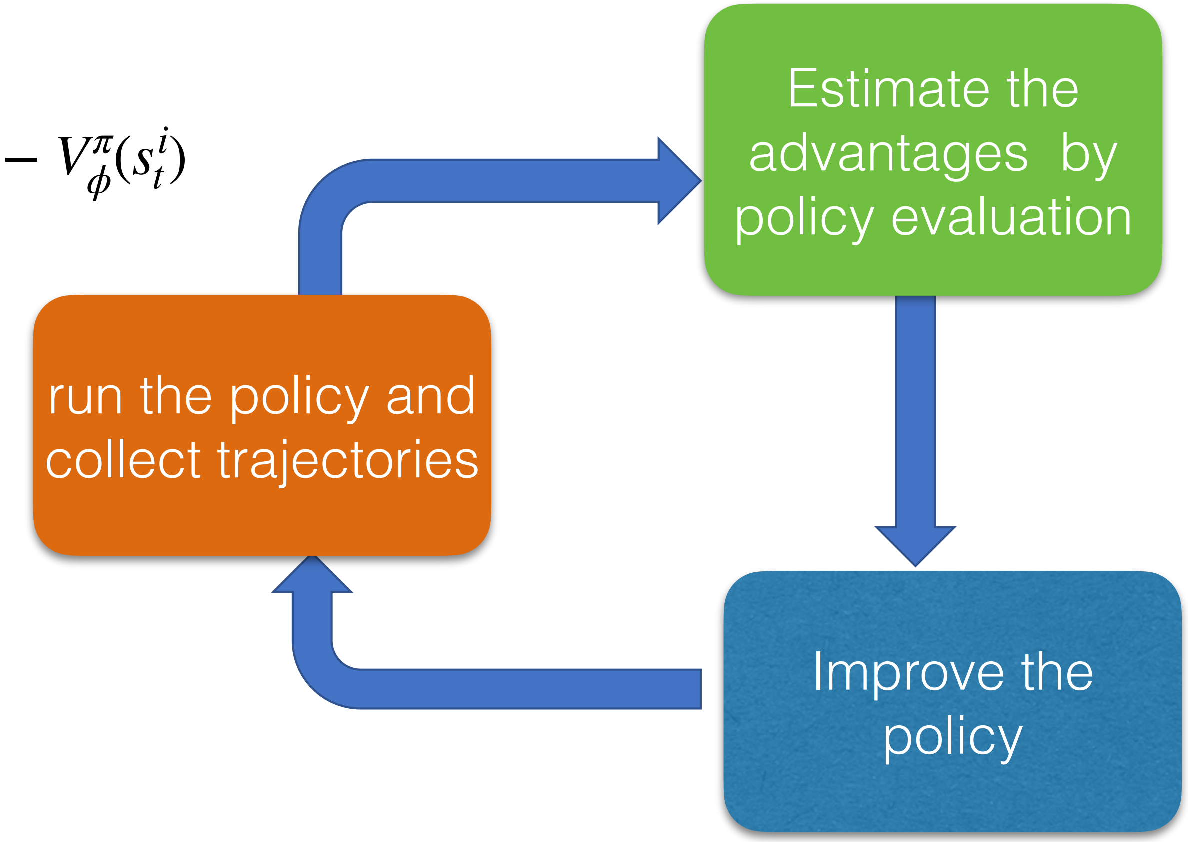
5. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$



Estimate the advantages by policy evaluation

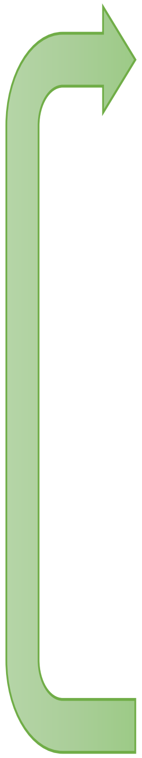
Improve the policy

run the policy and collect trajectories

Policy iteration:

1. Initialize policy π.
2. Deploy policy in the environment
3. Estimate and identify advantages A^π: actions whose $Q_\pi(s, a)$ value is higher than the state $V_\pi(s)$ value.
4. Change the policy to switch to those actions (or to make them more probable), resulting in π_{new}.
5. $\pi \rightarrow \pi_{new}$

Actor-Critic is on policy



0. Initialize policy parameters θ and critic parameters ϕ .

1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{i=0}^T\}$ by deploying the current policy $\pi_\theta(a_t \mid s_t)$.

2. Fit value function $V_\phi^\pi(s)$ by MC or TD estimation (update ϕ)

3. Compute action advantages $A^\pi(s_t^i, a_t^i) = R(s_t^i, a_t^i) + \gamma V_\phi^\pi(s_{t+1}^i) - V_\phi^\pi(s_t^i)$

4. $\nabla_\theta U(\theta) \approx \hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t^i \mid s_t^i) A^\pi(s_t^i, a_t^i)$

5. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$

The actor critic methods we have described are on policy methods: they use data of the current policy to improve the policy.

This lecture

When we have guarantees that we have policy improvement in AC methods?
What should be our stepwise in AC methods?
Can we use older data, data from previous versions of the policy, and train off-policy?

It runs out these are related:
To guarantee improvement we need the policy not to change too much from iteration to iteration.

Can we use older data, data from previous versions of the policy?

Off-policy Policy Gradients with Importance Sampling

$$\begin{aligned} U(\theta) &= \mathbb{E}_{\tau \sim \pi_\theta(\tau)} \left[R(\tau) \right] \\ &= \sum_\tau \pi_\theta(\tau) R(\tau) \end{aligned}$$

Off-policy Policy Gradients with Importance Sampling

$$\begin{aligned} U(\theta) &= \mathbb{E}_{\tau \sim \pi_\theta(\tau)} \left[R(\tau) \right] \\ &= \sum_\tau \pi_\theta(\tau) R(\tau) \\ &= \sum_\tau \pi_{\theta_{old}}(\tau) \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} R(\tau) \\ &= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} R(\tau) \end{aligned}$$

Off-policy Policy Gradients with Importance Sampling

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$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\nabla_\theta \pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} R(\tau)$$

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Off-policy Policy Gradients with Importance Sampling

$$\begin{aligned} U(\theta) &= \mathbb{E}_{\tau \sim \pi_\theta(\tau)}\left[R(\tau)\right] \\ &= \sum_\tau \pi_\theta(\tau) R(\tau) \\ &= \sum_\tau \pi_{\theta_{old}}(\tau) \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} R(\tau) \\ &= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} R(\tau) \end{aligned}$$

$$\begin{aligned} \nabla_\theta U(\theta) &= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\nabla_\theta \pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} R(\tau) \\ &= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\pi_\theta(\tau)}{\pi_\theta(\tau)} \frac{\nabla_\theta \pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} R(\tau) \\ &= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} \frac{\nabla_\theta \pi_\theta(\tau)}{\pi_\theta(\tau)} R(\tau) \\ &= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} \nabla_\theta \log \pi_\theta(\tau) R(\tau) \end{aligned}$$

Gradient evaluated at θ_{old} is unchanged:

$$\nabla_\theta U(\theta)\,|_{\theta=\theta_{old}} = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \nabla_\theta \log \pi_\theta(\tau)\,|_{\theta=\theta_{old}} R(\tau)$$

Off-policy Policy Gradients with Importance Sampling

$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau\sim\pi_{\theta_{old}}} \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} \nabla_\theta \log \pi_\theta(\tau) R(\tau)$$

$$\pi_\theta(\tau) = p(s_0)\prod_{t=1}^{T} p(s_{t+1} \,|\, s_t, a_t) \cdot \pi_\theta(a_t \,|\, s_t) \quad \Rightarrow \quad \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} = \frac{p(s_0)\prod_{t=1}^{T} p(s_{t+1} \,|\, s_t, a_t) \cdot \pi_\theta(a_t \,|\, s_t)}{p(s_0)\prod_{t=1}^{T} p(s_{t+1} \,|\, s_t, a_t) \cdot \pi_{\theta_{old}}(a_t \,|\, s_t)} = \prod_{t=1}^{T} \frac{\pi_\theta(a_t \,|\, s_t)}{\pi_{\theta_{old}}(a_t \,|\, s_t)}$$

$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau\sim\pi_{\theta_{old}}} \prod_{t=1}^{T} \frac{\pi_\theta(a_t \,|\, s_t)}{\pi_{\theta_{old}}(a_t \,|\, s_t)} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t \,|\, s_t) \sum_{t=1}^{T} R(s_t, a_t)$$

$$= \mathbb{E}_{\tau\sim\pi_{\theta_{old}}} \sum_{t=1}^{T} \left[\nabla_\theta \log \pi_\theta(\alpha_t \,|\, s_t) \left(\prod_{t=1}^{T} \frac{\pi_\theta(a_t \,|\, s_t)}{\pi_{\theta_{old}}(a_t \,|\, s_t)} \right) \left(\sum_{t=1}^{T} R(s_t, a_t) \right) \right]$$

Off-policy Policy Gradients with Importance Sampling

$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} \nabla_\theta \log \pi_\theta(\tau) R(\tau)$$

$$\pi_\theta(\tau) = p(s_0) \prod_{t=1}^{T} p(s_{t+1} \mid s_t, a_t) \cdot \pi_\theta(a_t \mid s_t)$$

⇨

$$\frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} = \frac{p(s_0) \prod_{t=1}^{T} p(s_{t+1} \mid s_t, a_t) \cdot \pi_\theta(a_t \mid s_t)}{p(s_0) \prod_{t=1}^{T} p(s_{t+1} \mid s_t, a_t) \cdot \pi_{\theta_{old}}(a_t \mid s_t)} = \prod_{t=1}^{T} \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)}$$

$$\begin{aligned}\nabla_\theta U(\theta) &= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \prod_{t=1}^{T} \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t \mid s_t) \sum_{t=1}^{T} R(s_t, a_t) \\ &= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \sum_{t=1}^{T} \left[\nabla_\theta \log \pi_\theta(\alpha_t \mid s_t) \left(\prod_{t=1}^{T} \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)} \right) \left(\sum_{t=1}^{T} R(s_t, a_t) \right) \right]\end{aligned}$$

Causal temporal structure?

$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \sum_{t=1}^{T} \left[\nabla_\theta \log \pi_\theta(\alpha_t \mid s_t) \left(\prod_{t'=1}^{t} \frac{\pi_\theta(a_{t'} \mid s_{t'})}{\pi_{\theta_{old}}(a_{t'} \mid s_{t'})} \right) \left(\sum_{t'=t}^{T} R(s_{t'}, a_{t'}) \right) \right]$$

Off-policy Policy Gradients with Importance Sampling

$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} \nabla_\theta \log \pi_\theta(\tau) R(\tau)$$

$$\pi_\theta(\tau) = p(s_0) \prod_{t=1}^{T} p(s_{t+1} | s_t, a_t) \cdot \pi_\theta(a_t | s_t)$$

⇨

$$\frac{\pi_\theta(\tau)}{\pi_{\theta_{old}}(\tau)} = \frac{p(s_0) \prod_{t=1}^{T} p(s_{t+1} | s_t, a_t) \cdot \pi_\theta(a_t | s_t)}{p(s_0) \prod_{t=1}^{T} p(s_{t+1} | s_t, a_t) \cdot \pi_{\theta_{old}}(a_t | s_t)} = \prod_{t=1}^{T} \frac{\pi_\theta(a_t | s_t)}{\pi_{\theta_{old}}(a_t | s_t)}$$

$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \prod_{t=1}^{T} \frac{\pi_\theta(a_t | s_t)}{\pi_{\theta_{old}}(a_t | s_t)} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\alpha_t | s_t) \sum_{t=1}^{T} R(s_t, a_t)$$

$$= \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \sum_{t=1}^{T} \left[\nabla_\theta \log \pi_\theta(\alpha_t | s_t) \left(\prod_{t=1}^{T} \frac{\pi_\theta(a_t | s_t)}{\pi_{\theta_{old}}(a_t | s_t)} \right) \left(\sum_{t=1}^{T} R(s_t, a_t) \right) \right]$$

Causal temporal structure?

These terms can explode or vanish! Not very useful due to the large variance they cause in the estimator.

$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \sum_{t=1}^{T} \left[\nabla_\theta \log \pi_\theta(\alpha_t | s_t) \left(\prod_{t'=1}^{t} \frac{\pi_\theta(a_{t'} | s_{t'})}{\pi_{\theta_{old}}(a_{t'} | s_{t'})} \right) \left(\sum_{t'=t}^{T} R(s_{t'}, a_{t'}) \right) \right]$$

Approximate Off-policy Policy Gradients with Importance Sampling

$$U(\theta) = \mathbb{E}_{\tau \sim \pi_\theta(\tau)} \left[R(\tau) \right]$$

Let’s write the objective w.r.t. expectations for each time step using per-timestep state marginal distributions:

$$U(\theta) = \sum_{t=1}^{T} \mathbb{E}_{(s_t, a_t) \sim p_\theta(s_t, a_t)} R(s_t, a_t) = \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_\theta(s_t)} \left[\mathbb{E}_{a_t \sim \pi_\theta(a_t | s_t)} R(s_t, a_t) \right]$$

We define the state marginal distribution as the probability that the policy visits state s:

$$p_\theta(s) = \mathbb{E}_{s_1 \sim p_0(s), a \sim \pi(\cdot | s), s_{t+1} \sim p(S | s_t, a_t)} \frac{1}{T} \sum_{t=1}^{T} \mathbf{1}(s_t = s)$$

Approximate Off-policy Policy Gradients with Importance Sampling

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Now let’s use importance sampling for state and action sampling:

$$U^{IS}(\theta) = \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_{\theta_{old}}(s_t)} \frac{p_\theta(s_t)}{p_{\theta_{old}}(s_t)} \left[\mathbb{E}_{a_t \sim \pi_{\theta_{old}}(a_t | s_t)} \frac{\pi_\theta(a_t)}{\pi_{\theta_{old}}(a_t)} R(s_t, a_t) \right]$$

Approximate Off-policy Policy Gradients with Importance Sampling

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Do we know those quantities?

Approximate Off-policy Policy Gradients with Importance Sampling

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Let’s write the objective w.r.t. expectations for each time step using per-timestep state marginal distributions:

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Approximation!

$$U^{IS}(\theta) = \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_{\theta_{old}}(s_t)} \cancel{\frac{p_\theta(s_t)}{p_{\theta_{old}}(s_t)}} \left[\mathbb{E}_{a_t \sim \pi_{\theta_{old}}(a_t|s_t)} \frac{\pi_\theta(a_t)}{\pi_{\theta_{old}}(a_t)} R(s_t, a_t) \right]$$

$$U^{IS}(\theta) \approx \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_{\theta_{old}}(s_t)} \left[\mathbb{E}_{a_t \sim \pi_{\theta_{old}}(a_t|s_t)} \frac{\pi_\theta(a_t)}{\pi_{\theta_{old}}(a_t)} R(s_t, a_t) \right]$$

Approximate Off-policy Policy Gradients with Importance Sampling

$$U(\theta) = \mathbb{E}_{\tau \sim \pi_\theta(\tau)} \left[R(\tau)\right]$$

Let's write the objective w.r.t. expectations for each time step using per-timestep state marginal distributions:

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Approximation!

$$U^{IS}(\theta) = \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_{\theta_{old}}(s_t)} \cancel{\frac{p_\theta(s_t)}{p_{\theta_{old}}(s_t)}} \left[\mathbb{E}_{a_t \sim \pi_{\theta_{old}}(a_t|s_t)} \frac{\pi_\theta(a_t)}{\pi_{\theta_{old}}(a_t)} R(s_t, a_t)\right]$$

Do you know how to optimize this objective?

$$\boxed{U^{IS}(\theta) \approx \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_{\theta_{old}}(s_t)} \left[\mathbb{E}_{a_t \sim \pi_{\theta_{old}}(a_t|s_t)} \frac{\pi_\theta(a_t)}{\pi_{\theta_{old}}(a_t)} R(s_t, a_t)\right]}$$

Approximate Off-policy Policy Gradients with Importance Sampling

$$U(\theta) = \mathbb{E}_{\tau \sim \pi_\theta(\tau)} \left[R(\tau) \right]$$

Let's write the objective w.r.t. expectations for each time step using per-timestep state marginal distributions:

$$U(\theta) = \sum_{t=1}^{T} \mathbb{E}_{(s_t,a_t)\sim p_\theta(s_t,a_t)} R(s_t, a_t) \; = \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_\theta(s_t)} \left[\mathbb{E}_{a_t \sim \pi_\theta(a_t|s_t)} R(s_t, a_t) \right]$$

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Approximation!

$$U^{IS}(\theta) = \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_{\theta_{old}}(s_t)} \cancel{\frac{p_\theta(s_t)}{p_{\theta_{old}}(s_t)}} \left[\mathbb{E}_{a_t \sim \pi_{\theta_{old}}(a_t|s_t)} \frac{\pi_\theta(a_t)}{\pi_{\theta_{old}}(a_t)} R(s_t, a_t) \right]$$

Do you know how to optimize this objective? Yes, we will sample trajectories from π_{old} and use likelihood ratio estimator.

$$\boxed{U^{IS}(\theta) \approx \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_{\theta_{old}}(s_t)} \left[\mathbb{E}_{a_t \sim \pi_{\theta_{old}}(a_t|s_t)} \frac{\pi_\theta(a_t)}{\pi_{\theta_{old}}(a_t)} R(s_t, a_t) \right]}$$

Approximate Off-policy Policy Gradients with Importance Sampling

Do you know how to optimize this objective? Yes, we will sample trajectories from π_{old} and use likelihood ratio estimator.

$$\boxed{\hat{U}^{IS}(\theta) = \sum_{t=1}^{T} \mathbb{E}_{s_t \sim p_{\theta_{old}}(s_t)} \left[\mathbb{E}_{a_t \sim \pi_{\theta_{old}}(a_t|s_t)} \frac{\pi_\theta(a_t)}{\pi_{\theta_{old}}(a_t)} R(s_t, a_t) \right]}$$

$$\nabla_\theta \hat{U}^{IS}(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \sum_{t=1}^{T} \left[\nabla_\theta \log \pi_\theta(\alpha_t \,|\, s_t) \left(\frac{\pi_\theta(a_t \,|\, s_t)}{\pi_{\theta_{old}}(a_t \,|\, s_t)} \right) \left(\sum_{t'=t}^{T} R(s_{t'}, a_{t'}) \right) \right]$$

Compare to the exact IS gradient:

$$\nabla_\theta U(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta_{old}}} \sum_{t=1}^{T} \left[\nabla_\theta \log \pi_\theta(\alpha_t \,|\, s_t) \left(\prod_{t'=1}^{t} \frac{\pi_\theta(a_{t'} \,|\, s_{t'})}{\pi_{\theta_{old}}(a_{t'} \,|\, s_{t'})} \right) \left(\sum_{t'=t}^{T} R(s_{t'}, a_{t'}) \right) \right]$$