



Computer Engineering Department

Reinforcement Learning: Advanced Policy Gradients

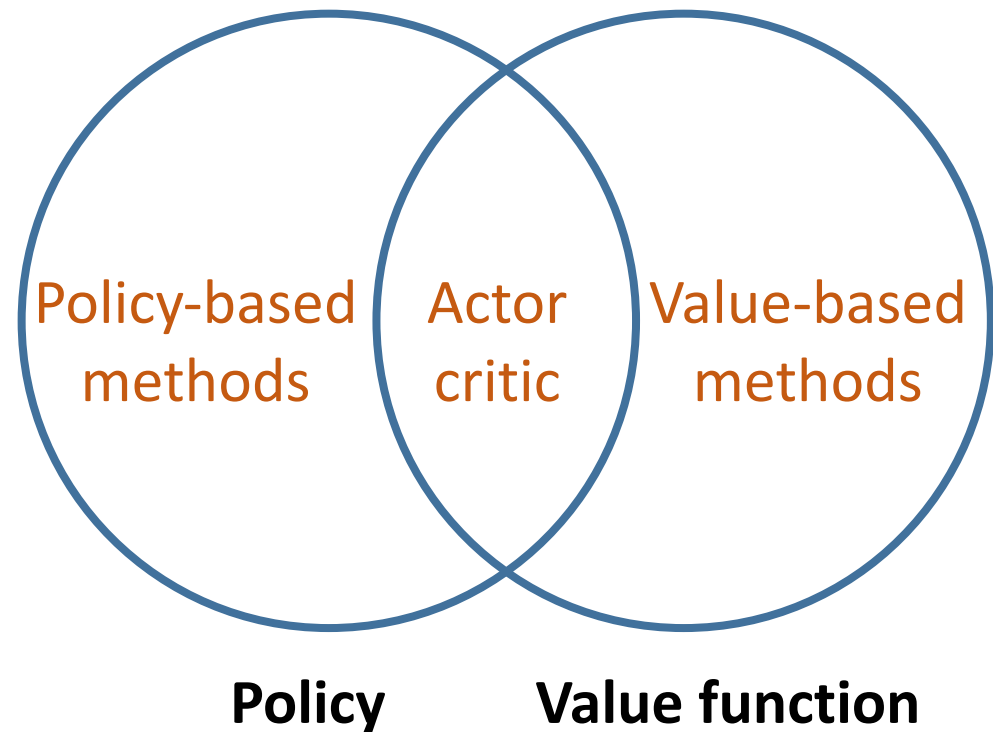
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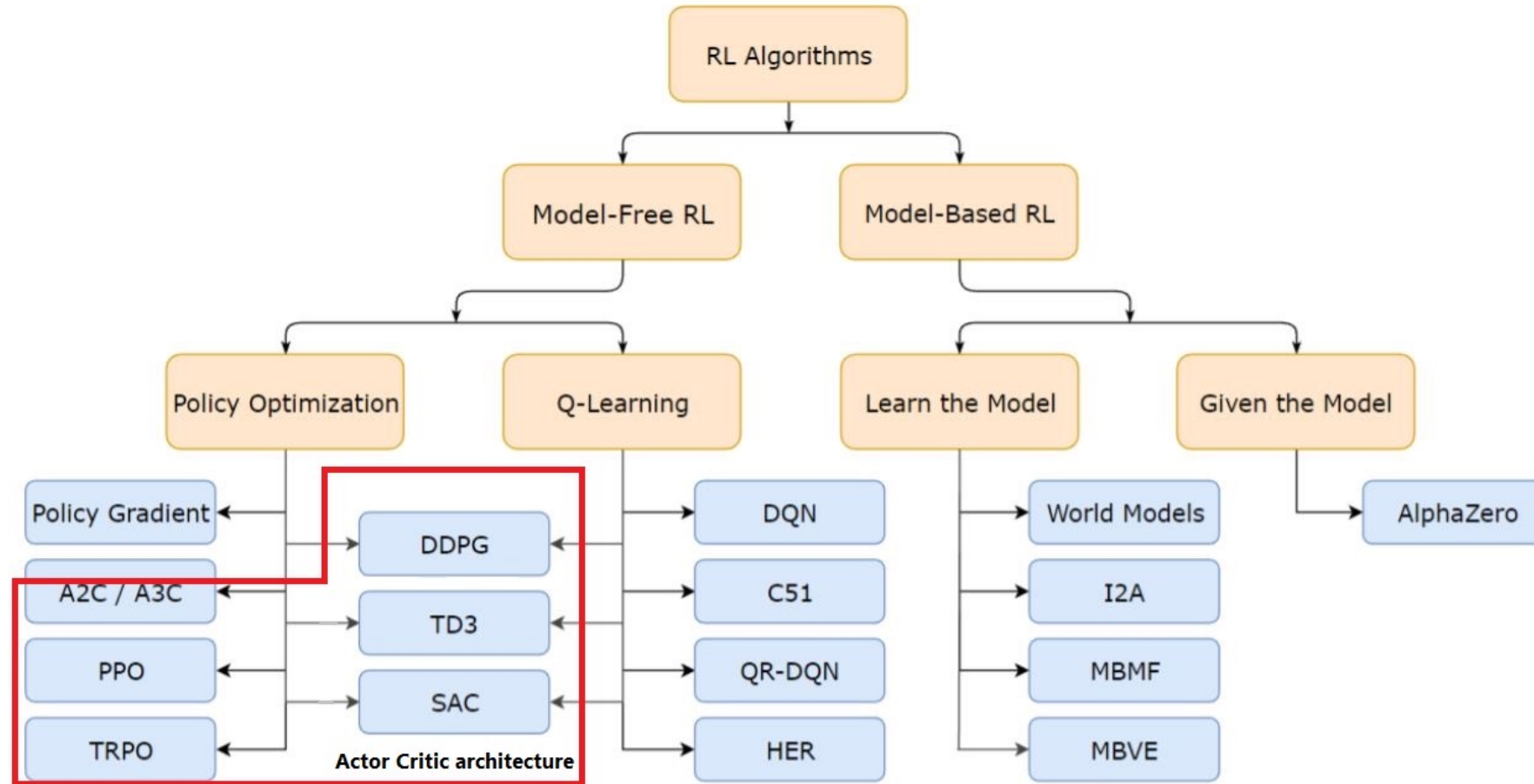
Courtesy: Most of slides are adopted from CS 285 Berkeley.

Model-Free RL

- Value-based methods
 - Learnt value function
 - Implicit policy
- Policy-based methods
 - No value function
 - Learnt policy
- Actor-critic methods
 - Learnt value function
 - Learnt policy



Overview of Modern RL Methods



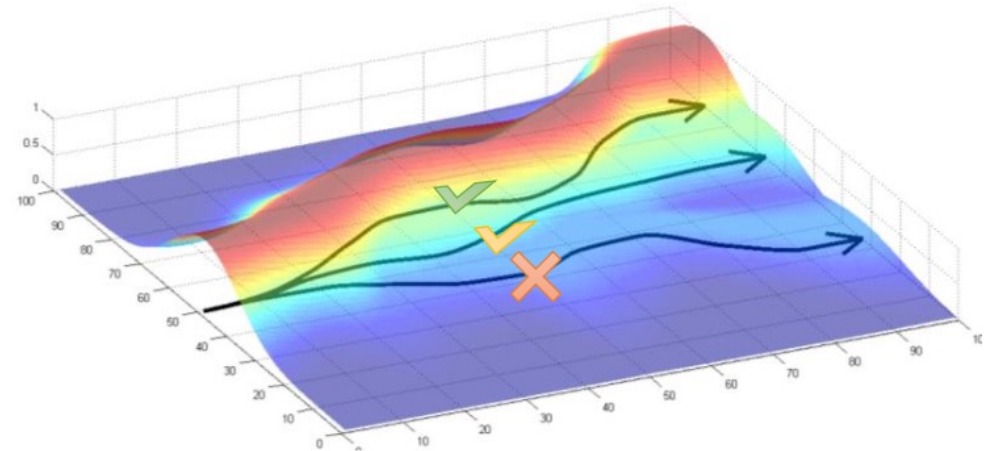
Policy Gradient Intuition

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

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

maximum likelihood: $\nabla_{\theta} J_{\text{ML}}(\theta) \approx \frac{1}{N} \sum_{i=1}^N \nabla_{\theta} \log \pi_{\theta}(\tau_i)$

- Good stuff is made more likely
- Bad stuff is made less likely
- Simply formalizes the notion of “trial and error”!



Bias and Variance of Policy Gradient

$$\nabla_{\theta} J(\theta) \approx \frac{1}{N} \sum_{i=1}^N \nabla_{\theta} \log \pi_{\theta}(\tau_i) \boxed{r(\tau_i)}$$

The main source
of high variance



- Unbiased estimation:

$$E \left[\frac{1}{N} \sum_{i=1}^N \nabla_{\theta} \log \pi_{\theta}(\tau_i) r(\tau_i) \right] = \nabla_{\theta} J(\theta)$$

- But suffers from **high variance**!

Reducing Variance

- Everything in the gradient whose **expected is zero** could be removed, without affecting the optimization, but could lead to **lower gradient variance!**
- Causality trick
- Discount factor
- Baseline
- Actor-critic
- Optimization techniques:
 - Natural gradient
 - Trust region

Reducing Variance: Causality

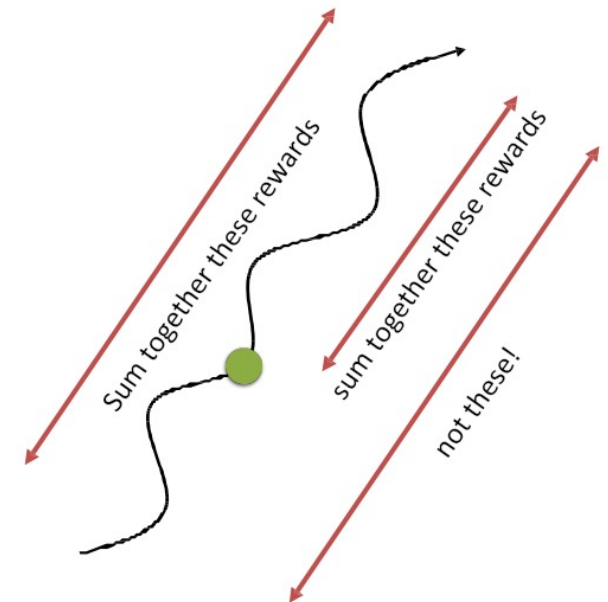
$$\nabla_{\theta} J(\theta) \approx \frac{1}{N} \sum_{i=1}^N \left(\sum_{t=1}^T \nabla_{\theta} \log \pi_{\theta}(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^T r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$$

Causality: policy at time t' cannot affect reward at time t when $t < t'$

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

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

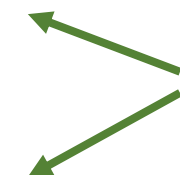
“reward to go” $\hat{Q}_{i,t}$



Reducing Variance: Discount Factor

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

option 2:
$$\nabla_{\theta} J(\theta) \approx \frac{1}{N} \sum_{i=1}^N \left(\sum_{t=1}^T \nabla_{\theta} \log \pi_{\theta}(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^T \gamma^{t-1} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$$



Not the same

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

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

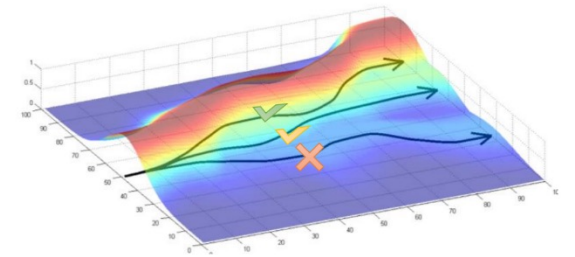
Reducing Variance: Baselines

$$\nabla_{\theta} J(\theta) \approx \frac{1}{N} \sum_{i=1}^N \nabla_{\theta} \log p_{\theta}(\tau) [r(\tau) - b]$$

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

a convenient identity

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



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

subtracting a baseline is *unbiased* in expectation!

average reward is *not* the best baseline, but it's pretty good!

Analyzing Variance

$$\text{Var}[x] = E[x^2] - E[x]^2$$

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

$$\text{Var} = E_{\tau \sim p_{\theta}(\tau)} [\underbrace{(\nabla_{\theta} \log p_{\theta}(\tau) (r(\tau) - b))^2}_{g(\tau)}] - E_{\tau \sim p_{\theta}(\tau)} [\underbrace{\nabla_{\theta} \log p_{\theta}(\tau) (r(\tau) - b)}_{\text{this bit is just } E_{\tau \sim p_{\theta}(\tau)} [\nabla_{\theta} \log p_{\theta}(\tau) r(\tau)]}]^2$$

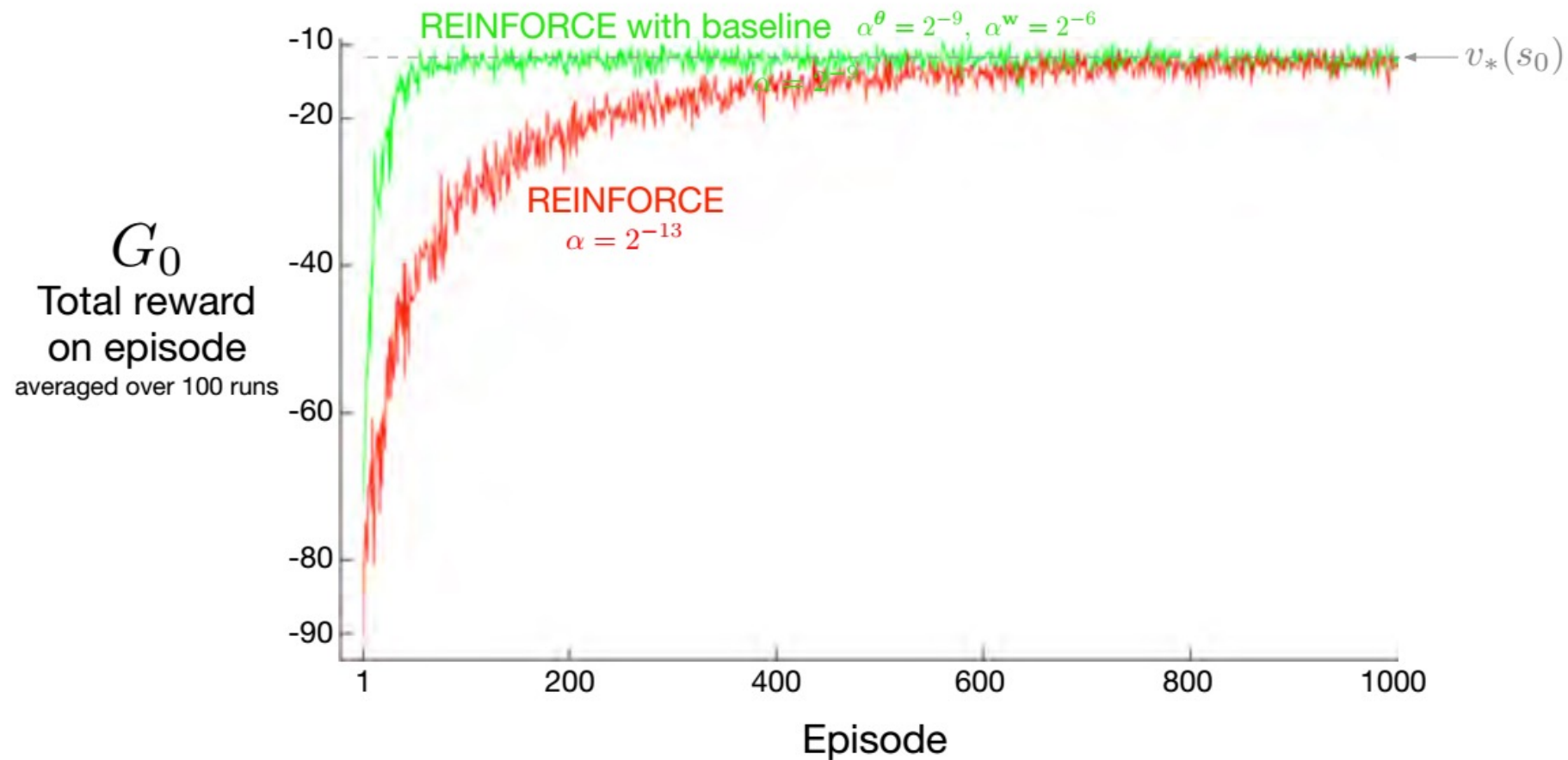
(baselines are unbiased in expectation)

$$\begin{aligned} \frac{d\text{Var}}{db} &= \frac{d}{db} E[g(\tau)^2 (r(\tau) - b)^2] = \frac{d}{db} (E[\cancel{g(\tau)^2 r(\tau)^2}] - 2E[g(\tau)^2 r(\tau) b] + b^2 E[g(\tau)^2]) \\ &= -2E[g(\tau)^2 r(\tau)] + 2bE[g(\tau)^2] = 0 \end{aligned}$$

$$b = \frac{E[g(\tau)^2 r(\tau)]}{E[g(\tau)^2]} \quad \longleftarrow \quad \text{This is just expected reward, but weighted by gradient magnitudes!}$$

Reducing Variance: Baselines

Faster convergence:

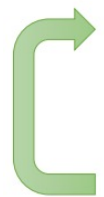


Reducing Variance: Review

- Exploiting causality
 - Future doesn't affect the past
- Discount factor
 - Two different version
- Baselines
 - Analyzing variance for deriving optimal baselines
- Now: Introducing actor-critic methods!

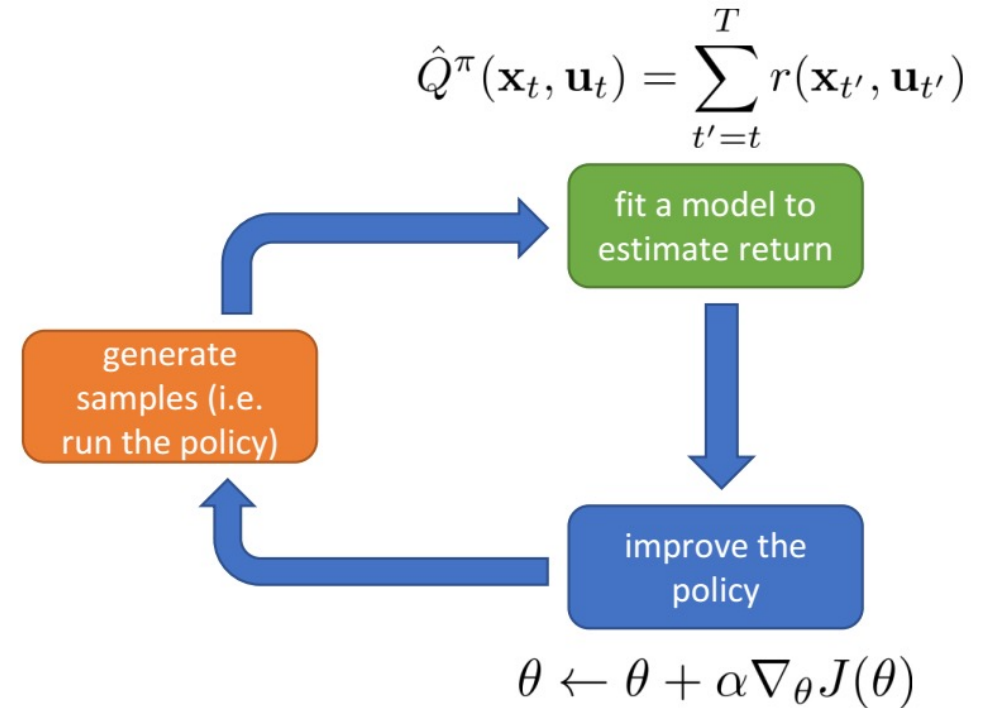
Policy Gradients so Far

REINFORCE algorithm:

- 
1. sample $\{\tau^i\}$ from $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$ (run the policy)
 2. $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_{t=1}^T \nabla_\theta \log \pi_\theta(\mathbf{a}_t^i|\mathbf{s}_t^i) \left(\sum_{t'=t}^T r(\mathbf{s}_{t'}^i, \mathbf{a}_{t'}^i) \right) \right)$
 3. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^N \sum_{t=1}^T \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \underbrace{\hat{Q}_{i,t}^\pi}_{\text{"reward to go"}}$$

“reward to go”



Improving Estimation of Reward to Go

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

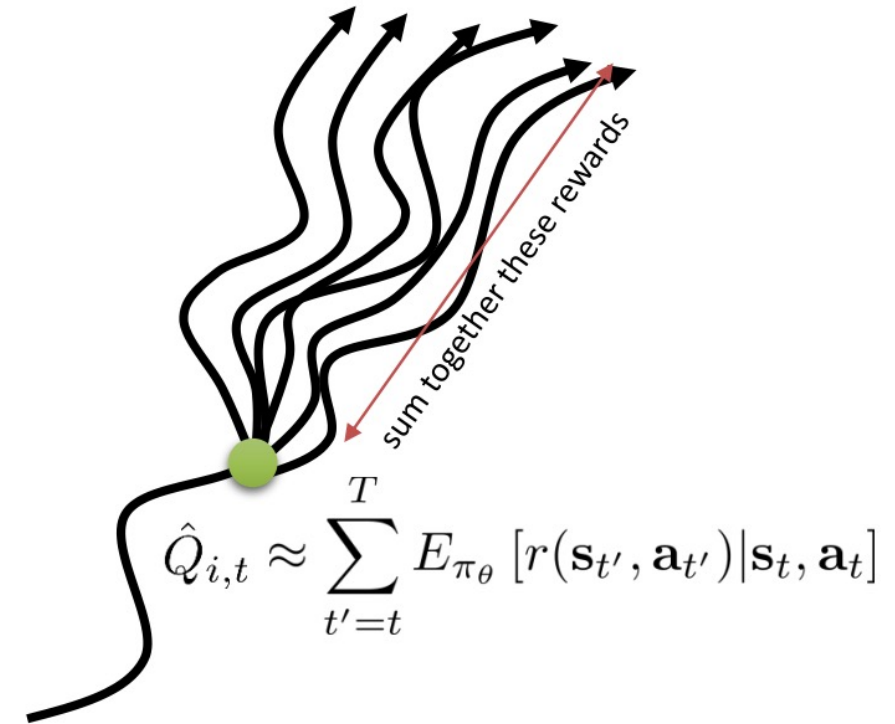
$\hat{Q}_{i,t}$: estimate of expected reward if we take action $\mathbf{a}_{i,t}$ in state $\mathbf{s}_{i,t}$

How to make a better estimate?

$Q(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^T E_{\pi_{\theta}} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t]$: true *expected* reward-to-go

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

much lower variance!



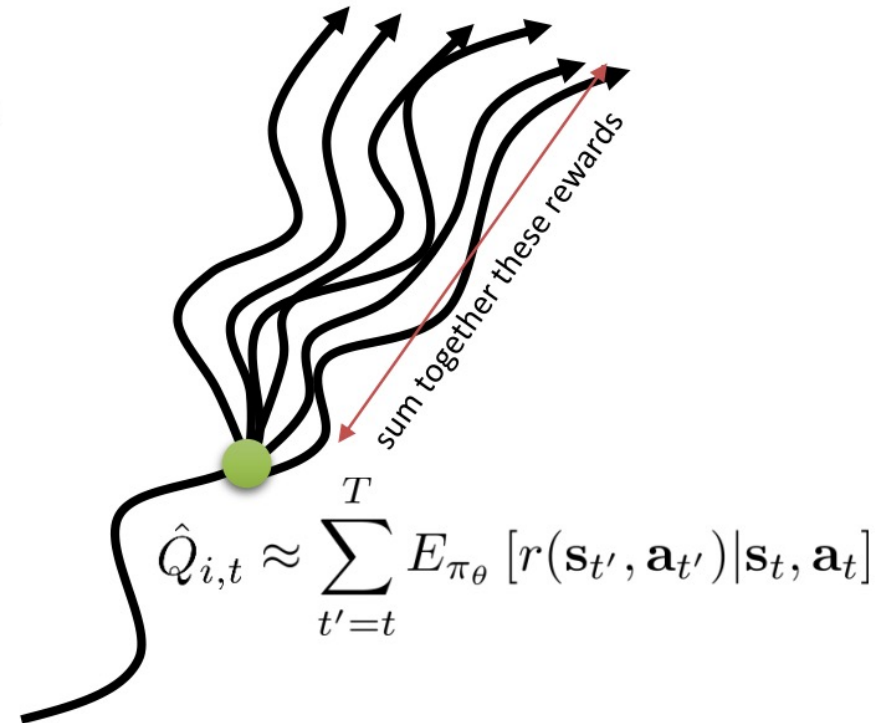
Improving Estimation of Reward to Go

Further improvement: Adding a baseline!

$Q(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t]$: true *expected* reward-to-go

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

$$b_t = \frac{1}{N} \sum_i Q(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})$$



Improving Estimation of Reward to Go

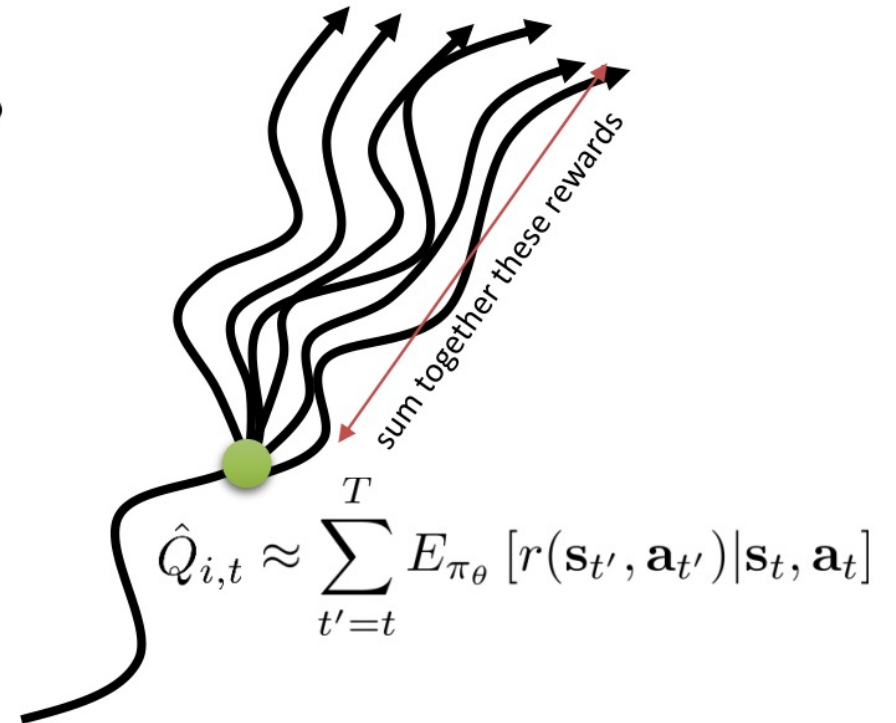
Further improvement: Adding a baseline!

$Q(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t]$: true *expected* reward-to-go

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

$$b_t = \frac{1}{N} \sum_i Q(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})$$

$$\downarrow$$
$$V(\mathbf{s}_t) = E_{\mathbf{a}_t \sim \pi_\theta(\mathbf{a}_t | \mathbf{s}_t)} [Q(\mathbf{s}_t, \mathbf{a}_t)]$$



Advantage Value

$Q^\pi(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t]$: total reward from taking \mathbf{a}_t in \mathbf{s}_t

$V^\pi(\mathbf{s}_t) = E_{\mathbf{a}_t \sim \pi_\theta(\mathbf{a}_t | \mathbf{s}_t)} [Q^\pi(\mathbf{s}_t, \mathbf{a}_t)]$: total reward from \mathbf{s}_t

$A^\pi(\mathbf{s}_t, \mathbf{a}_t) = Q^\pi(\mathbf{s}_t, \mathbf{a}_t) - V^\pi(\mathbf{s}_t)$: how much better \mathbf{a}_t is

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



the better this estimate, the lower the variance

Advantage Value Approximation

$$Q^\pi(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t]$$

$$V^\pi(\mathbf{s}_t) = E_{\mathbf{a}_t \sim \pi_\theta(\mathbf{a}_t | \mathbf{s}_t)} [Q^\pi(\mathbf{s}_t, \mathbf{a}_t)]$$

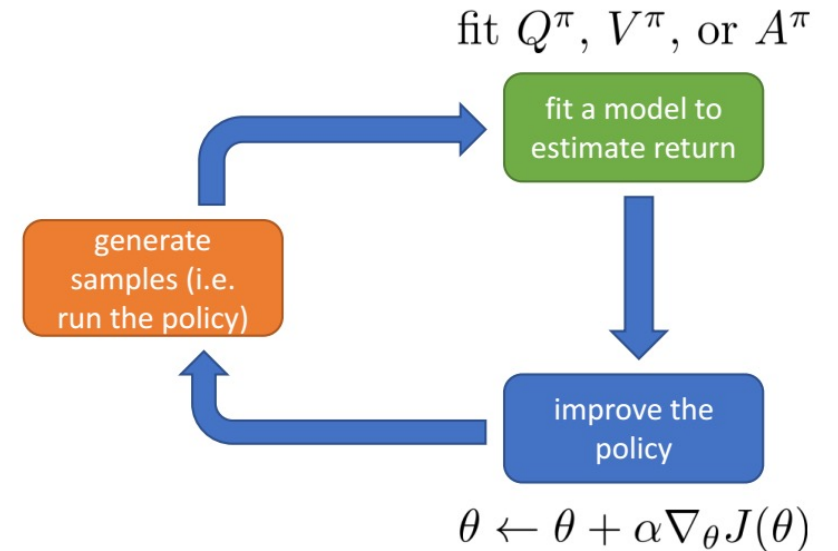
$$A^\pi(\mathbf{s}_t, \mathbf{a}_t) = Q^\pi(\mathbf{s}_t, \mathbf{a}_t) - V^\pi(\mathbf{s}_t)$$

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

$$Q^\pi(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t]$$

$$= r(\mathbf{s}_t, \mathbf{a}_t) + \underbrace{\sum_{t'=t+1}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t]}$$

$$\approx V^\pi(\mathbf{s}_{t+1})$$

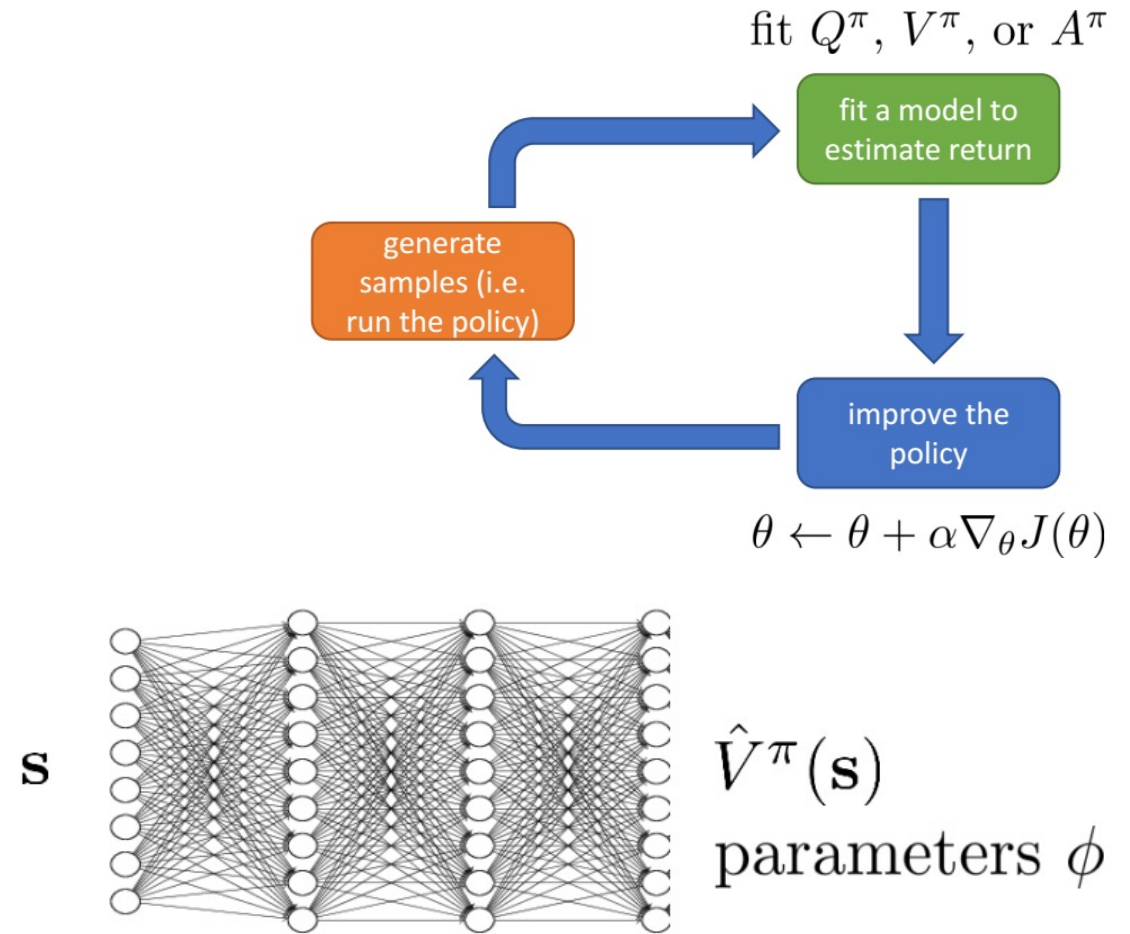


Advantage Value Approximation

$$Q^\pi(\mathbf{s}_t, \mathbf{a}_t) \approx r(\mathbf{s}_t, \mathbf{a}_t) + V^\pi(\mathbf{s}_{t+1})$$

$$A^\pi(\mathbf{s}_t, \mathbf{a}_t) \approx r(\mathbf{s}_t, \mathbf{a}_t) + V^\pi(\mathbf{s}_{t+1}) - V^\pi(\mathbf{s}_t)$$

let's just fit $V^\pi(\mathbf{s})$!



Policy Evaluation

$$V^\pi(\mathbf{s}_t) = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t]$$

$$J(\theta) = E_{\mathbf{s}_1 \sim p(\mathbf{s}_1)} [V^\pi(\mathbf{s}_1)]$$

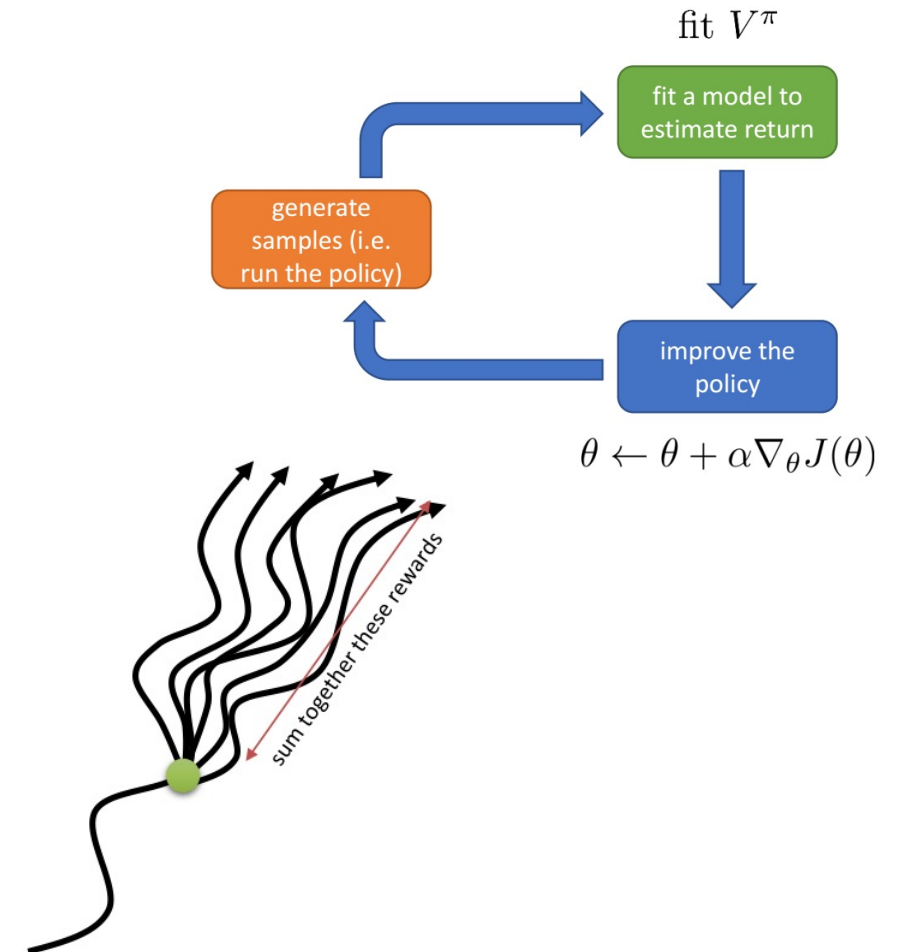
how can we perform policy evaluation?

Monte Carlo policy evaluation (this is what policy gradient does)

$$V^\pi(\mathbf{s}_t) \approx \sum_{t'=t}^T r(\mathbf{s}_{t'}, \mathbf{a}_{t'})$$

$$V^\pi(\mathbf{s}_t) \approx \frac{1}{N} \sum_{i=1}^N \sum_{t'=t}^T r(\mathbf{s}_{t'}, \mathbf{a}_{t'})$$

(requires us to reset the simulator)



Policy Evaluation

Monte Carlo estimation with function approximator:

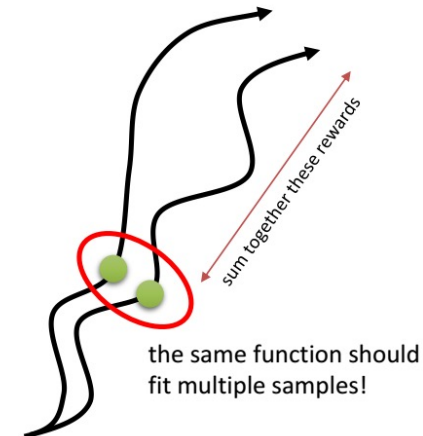
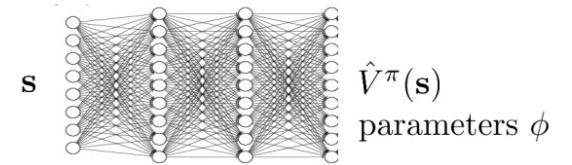
$$V^\pi(\mathbf{s}_t) \approx \sum_{t'=t}^T r(\mathbf{s}_{t'}, \mathbf{a}_{t'})$$

not as good as this: $V^\pi(\mathbf{s}_t) \approx \frac{1}{N} \sum_{i=1}^N \sum_{t'=t}^T r(\mathbf{s}_{t'}, \mathbf{a}_{t'})$

but still pretty good!

training data: $\left\{ \left(\mathbf{s}_{i,t}, \underbrace{\sum_{t'=t}^T r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'})}_{y_{i,t}} \right) \right\}$

supervised regression: $\mathcal{L}(\phi) = \frac{1}{2} \sum_i \left\| \hat{V}_\phi^\pi(\mathbf{s}_i) - y_i \right\|^2$



Policy Evaluation

How to make a better estimate?

$$\text{ideal target: } y_{i,t} = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_{i,t}] \approx r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) + V^\pi(\mathbf{s}_{i,t+1}) \approx r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) + \underbrace{\hat{V}_\phi^\pi(\mathbf{s}_{i,t+1})}$$

$$\text{Monte Carlo target: } y_{i,t} = \sum_{t'=t}^T r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'})$$

directly use previous fitted value function!

Policy Evaluation

Bootstrap Estimation with Function Approximator

ideal target: $y_{i,t} = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_{i,t}] \approx r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) + \hat{V}_\phi^\pi(\mathbf{s}_{i,t+1})$

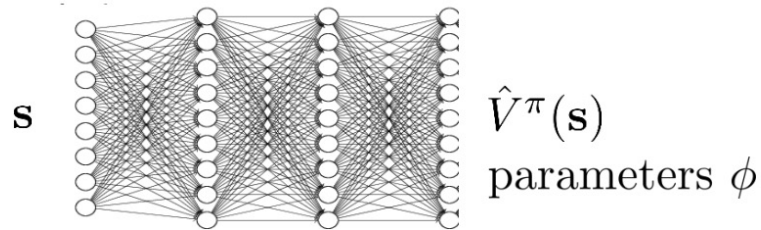
training data: $\left\{ \left(\mathbf{s}_{i,t}, \underbrace{r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) + \hat{V}_\phi^\pi(\mathbf{s}_{i,t+1})}_{y_{i,t}} \right) \right\}$

supervised regression: $\mathcal{L}(\phi) = \frac{1}{2} \sum_i \left\| \hat{V}_\phi^\pi(\mathbf{s}_i) - y_i \right\|^2$

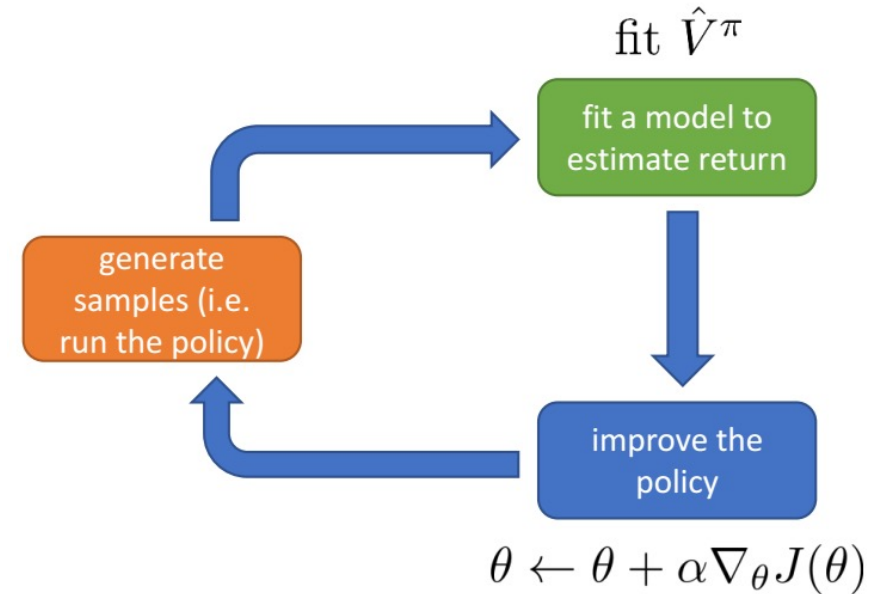
Batch Actor-Critic Algorithm

batch actor-critic algorithm:

1. sample $\{\mathbf{s}_i, \mathbf{a}_i\}$ from $\pi_\theta(\mathbf{a}|\mathbf{s})$ (run it on the robot)
2. fit $\hat{V}_\phi^\pi(\mathbf{s})$ to sampled reward sums
3. evaluate $\hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i) = r(\mathbf{s}_i, \mathbf{a}_i) + \hat{V}_\phi^\pi(\mathbf{s}'_i) - \hat{V}_\phi^\pi(\mathbf{s}_i)$
4. $\nabla_\theta J(\theta) \approx \sum_i \nabla_\theta \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i) \hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i)$
5. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$




$$V^\pi(\mathbf{s}_t) = \sum_{t'=t}^T E_{\pi_\theta} [r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t]$$

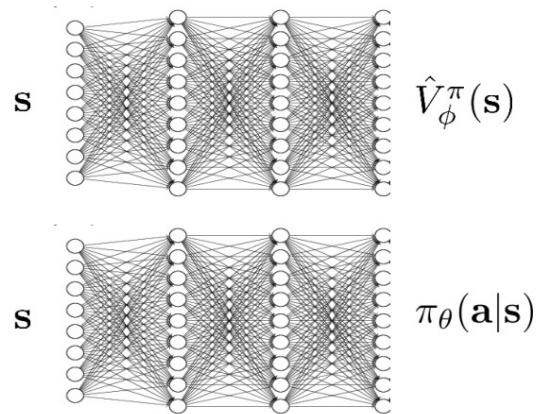


Actor-Critic Algorithm: Architecture Design

batch actor-critic algorithm:

- 
1. sample $\{\mathbf{s}_i, \mathbf{a}_i\}$ from $\pi_\theta(\mathbf{a}|\mathbf{s})$ (run it on the robot)
 2. fit $\hat{V}_\phi^\pi(\mathbf{s})$ to sampled reward sums
 3. evaluate $\hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i) = r(\mathbf{s}_i, \mathbf{a}_i) + \hat{V}_\phi^\pi(\mathbf{s}'_i) - \hat{V}_\phi^\pi(\mathbf{s}_i)$
 4. $\nabla_\theta J(\theta) \approx \sum_i \nabla_\theta \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i) \hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i)$
 5. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

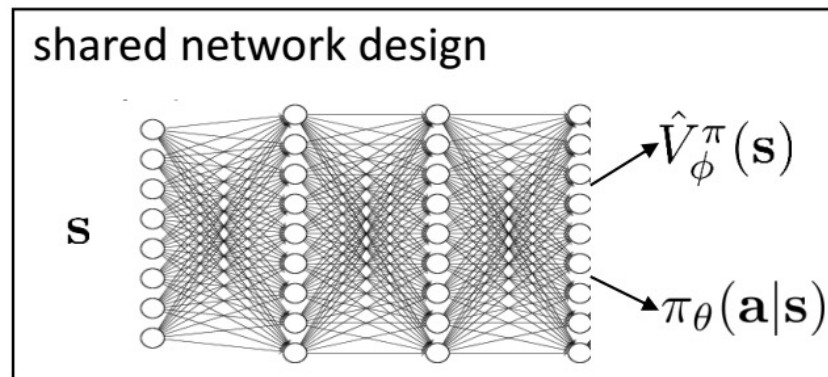
two network design



+ simple & stable


- no shared features between actor & critic

shared network design




Actor-Critic Algorithm: Batch vs. Online

batch actor-critic algorithm:

- 
1. sample $\{\mathbf{s}_i, \mathbf{a}_i\}$ from $\pi_\theta(\mathbf{a}|\mathbf{s})$ (run it on the robot)
 2. fit $\hat{V}_\phi^\pi(\mathbf{s})$ to sampled reward sums
 3. evaluate $\hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i) = r(\mathbf{s}_i, \mathbf{a}_i) + \gamma \hat{V}_\phi^\pi(\mathbf{s}'_i) - \hat{V}_\phi^\pi(\mathbf{s}_i)$
 4. $\nabla_\theta J(\theta) \approx \sum_i \nabla_\theta \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i) \hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i)$
 5. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

online actor-critic algorithm:

- 
1. take action $\mathbf{a} \sim \pi_\theta(\mathbf{a}|\mathbf{s})$, get $(\mathbf{s}, \mathbf{a}, \mathbf{s}', r)$
 2. update \hat{V}_ϕ^π using target $r + \gamma \hat{V}_\phi^\pi(\mathbf{s}')$
 3. evaluate $\hat{A}^\pi(\mathbf{s}, \mathbf{a}) = r(\mathbf{s}, \mathbf{a}) + \gamma \hat{V}_\phi^\pi(\mathbf{s}') - \hat{V}_\phi^\pi(\mathbf{s})$
 4. $\nabla_\theta J(\theta) \approx \nabla_\theta \log \pi_\theta(\mathbf{a}|\mathbf{s}) \hat{A}^\pi(\mathbf{s}, \mathbf{a})$
 5. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

Proximal Policy Optimization

- We don't want the new policy to change a lot in an iteration.
Why?

$$D_{KL}(\pi_{\theta'}(.|s) || \pi_{\theta}(.|s)) \leq \epsilon$$

- What is the effect of the constraint?
- Recall KL-Divergence:

$$D_{KL}(\pi_{\theta'}(.|s) || \pi_{\theta}(.|s)) = \sum_a \pi_{\theta'}(a|s) \log \frac{\pi_{\theta'}(a|s)}{\pi_{\theta}(a|s)}$$

We are effectively constraining the ratio $\frac{\pi_{\theta'}(a|s)}{\pi_{\theta}(a|s)}$

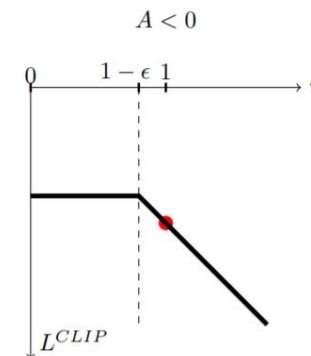
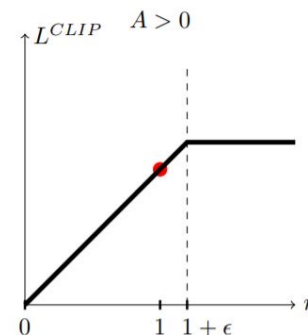
Proximal Policy Optimization

- Let's design a simpler objective that directly constrains $\frac{\pi_{\theta'}(a|S)}{\pi_{\theta}(a|S)}$

$$\operatorname{argmax}_{\theta'} E_{\{s \sim \mu_{\theta}, a \sim \pi_{\theta}\}} \min \begin{cases} \frac{\pi_{\theta'}(a|s)}{\pi_{\theta}(a|s)} A^{\pi_{\theta}}(s, a), \\ \text{clip}\left(\frac{\pi_{\theta'}(a|s)}{\pi_{\theta}(a|s)}, 1 - \epsilon, 1 + \epsilon\right) A^{\pi_{\theta}}(s, a) \end{cases}$$

could be easily implemented with auto-diff packages

$$\text{where } \text{clip}(x, 1 - \epsilon, 1 + \epsilon) = \begin{cases} 1 - \epsilon & \text{if } x < 1 - \epsilon \\ x & \text{if } 1 - \epsilon \leq x \leq 1 + \epsilon \\ 1 + \epsilon & \text{if } x > 1 + \epsilon \end{cases}$$



Proximal Policy Optimization (cont.)

Algorithm 1 PPO-Clip

- 1: Input: initial policy parameters θ_0 , initial value function parameters ϕ_0
- 2: **for** $k = 0, 1, 2, \dots$ **do**
- 3: Collect set of trajectories $\mathcal{D}_k = \{\tau_i\}$ by running policy $\pi_k = \pi(\theta_k)$ in the environment.
- 4: Compute rewards-to-go \hat{R}_t .
- 5: Compute advantage estimates, \hat{A}_t (using any method of advantage estimation) based on the current value function V_{ϕ_k} .
- 6: Update the policy by maximizing the PPO-Clip objective:

$$\theta_{k+1} = \arg \max_{\theta} \frac{1}{|\mathcal{D}_k|T} \sum_{\tau \in \mathcal{D}_k} \sum_{t=0}^T \min \left(\frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_k}(a_t|s_t)} A^{\pi_{\theta_k}}(s_t, a_t), \quad g(\epsilon, A^{\pi_{\theta_k}}(s_t, a_t)) \right),$$

typically via stochastic gradient ascent with Adam.

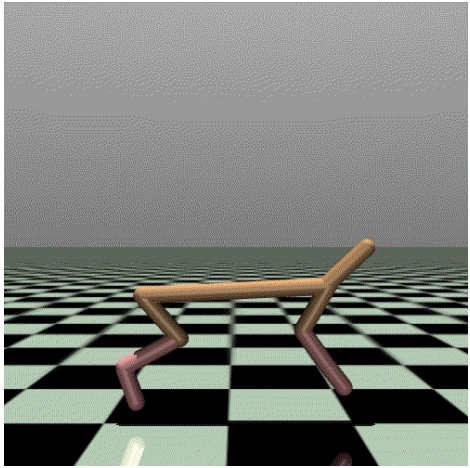
- 7: Fit value function by regression on mean-squared error:

$$\phi_{k+1} = \arg \min_{\phi} \frac{1}{|\mathcal{D}_k|T} \sum_{\tau \in \mathcal{D}_k} \sum_{t=0}^T \left(V_{\phi}(s_t) - \hat{R}_t \right)^2,$$

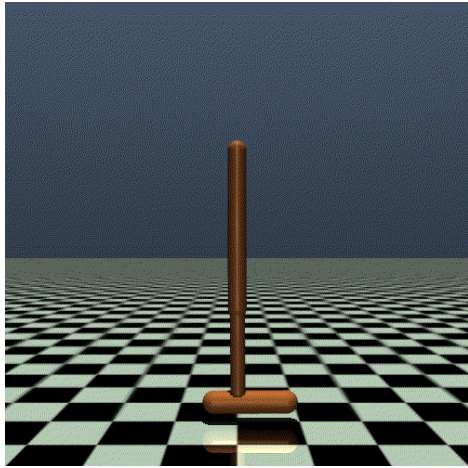
typically via some gradient descent algorithm.

- 8: **end for**
-

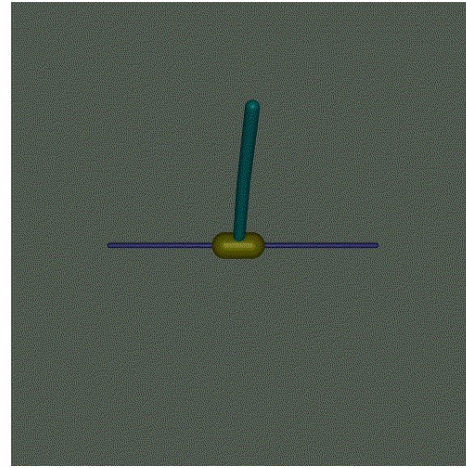
Environments



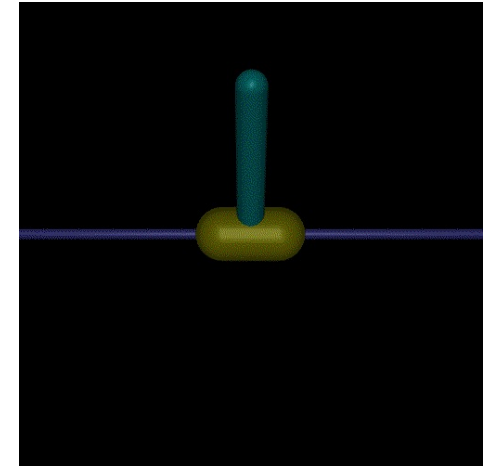
Half Cheetah



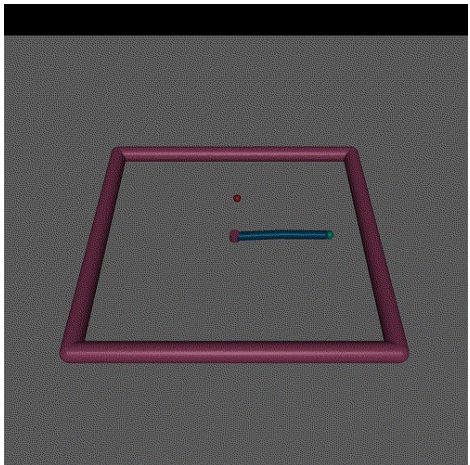
Hopper



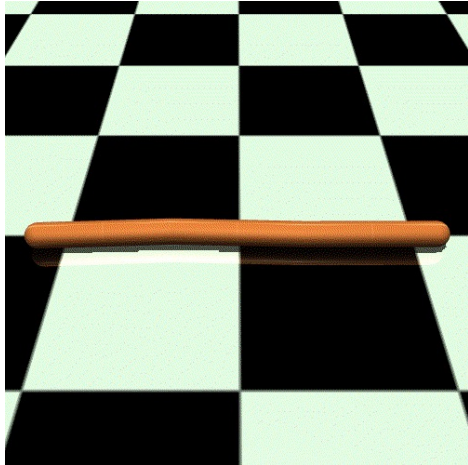
Inverted Double Pendulum



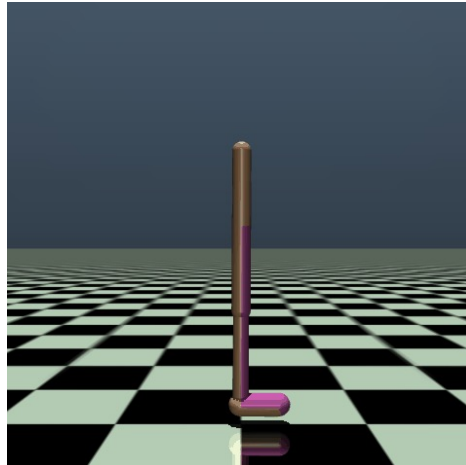
Inverted Pendulum



Reacher

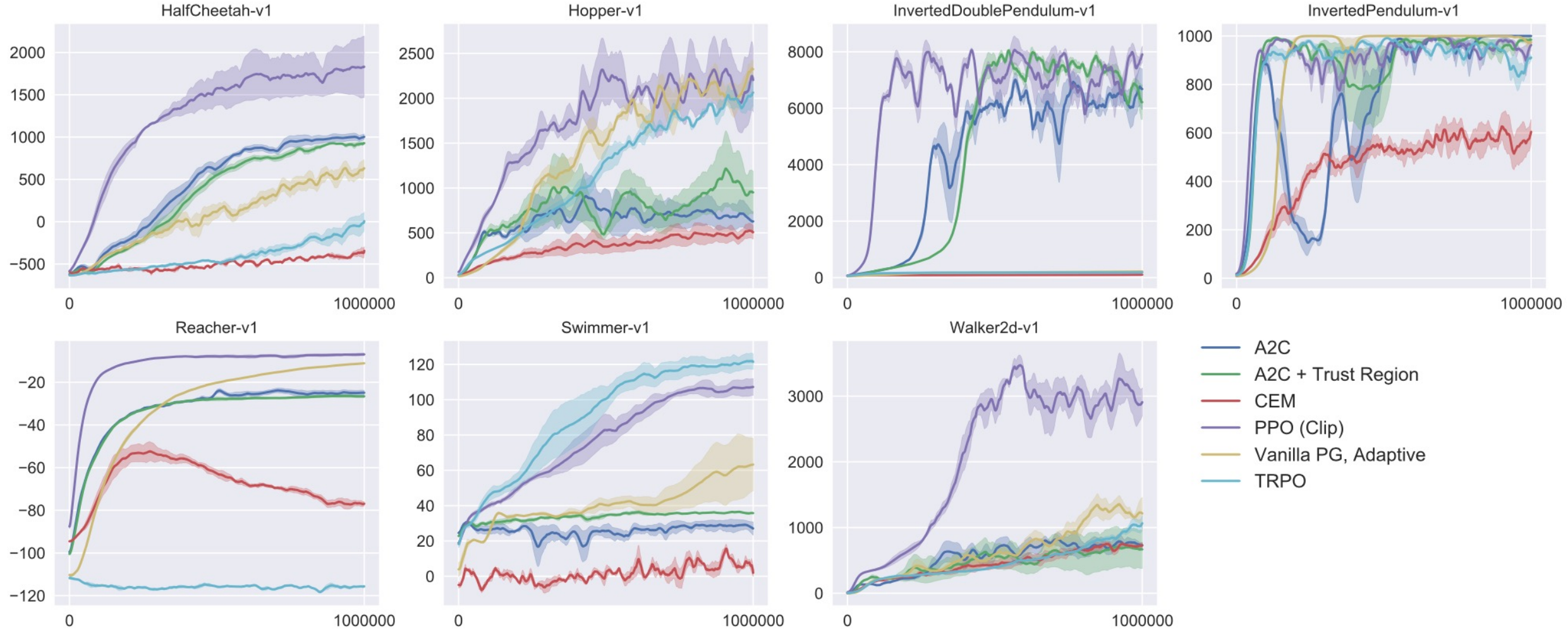


Swimmer



Walker 2D

PPO Results



Soft Actor Critic

One cause for the poor sample efficiency of deep RL methods is on-policy learning: some of the most commonly used deep RL algorithms, such as TRPO (Schulman et al., 2015), PPO (Schulman et al., 2017b) or A3C (Mnih et al., 2016), require new samples to be collected for each gradient step.

ture parameter (Haarnoja et al., 2017). More importantly, the maximum entropy formulation provides a substantial improvement in exploration and robustness: as discussed by Ziebart (2010), maximum entropy policies are robust in the face of model and estimation errors, and as demonstrated by (Haarnoja et al., 2017), they improve exploration by acquiring diverse behaviors. Prior work has proposed

Soft Policies

$$J(\pi) = \sum_{t=0}^T \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t) \sim \rho_\pi} [r(\mathbf{s}_t, \mathbf{a}_t) + \alpha \mathcal{H}(\pi(\cdot | \mathbf{s}_t))].$$

How does the Bellman equation change?

$$\mathcal{T}^\pi Q(\mathbf{s}_t, \mathbf{a}_t) \triangleq r(\mathbf{s}_t, \mathbf{a}_t) + \gamma \mathbb{E}_{\mathbf{s}_{t+1} \sim p} [V(\mathbf{s}_{t+1})], \quad (2)$$

where

$$V(\mathbf{s}_t) = \mathbb{E}_{\mathbf{a}_t \sim \pi} [Q(\mathbf{s}_t, \mathbf{a}_t) - \log \pi(\mathbf{a}_t | \mathbf{s}_t)] \quad (3)$$

Soft Policies

Lemma 1 (Soft Policy Evaluation). *Consider the soft Bellman backup operator \mathcal{T}^π in Equation 2 and a mapping $Q^0 : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ with $|\mathcal{A}| < \infty$, and define $Q^{k+1} = \mathcal{T}^\pi Q^k$. Then the sequence Q^k will converge to the soft Q -value of π as $k \rightarrow \infty$.*

Optimal Soft Policy

- The optimal soft policy (optimizing entropy augment objective) is:

$$\pi^*(a|s) = \frac{\exp Q(s, a)}{\sum_{a'} \exp Q(s, a')}$$

Soft actor-critic

1. Q-function update

Update Q-function to evaluate current policy:

$$Q(\mathbf{s}, \mathbf{a}) \leftarrow r(\mathbf{s}, \mathbf{a}) + \mathbb{E}_{\mathbf{s}' \sim p_{\mathbf{s}}, \mathbf{a}' \sim \pi} [Q(\mathbf{s}', \mathbf{a}') - \log \pi(\mathbf{a}'|\mathbf{s}')]]$$

This converges to Q^π .

2. Update policy

Update the policy with gradient of information projection:

$$\pi_{\text{new}} = \arg \min_{\pi'} D_{\text{KL}} \left(\pi'(\cdot | \mathbf{s}) \parallel \frac{1}{Z} \exp Q^{\pi_{\text{old}}}(\mathbf{s}, \cdot) \right)$$

In practice, only take one gradient step on this objective

3. Interact with the world, collect more data

Haarnoja, et al. **Soft Actor-Critic Algorithms and Applications**. '18

Soft actor-critic

Algorithm 1 Soft Actor-Critic

Inputs: The learning rates, λ_π , λ_Q , and λ_V for functions π_θ , Q_w , and V_ψ respectively; the weighting factor τ for exponential moving average.

- 1: Initialize parameters θ , w , ψ , and $\bar{\psi}$.
 - 2: **for** each iteration **do**
 - 3: *(In practice, a combination of a single environment step and multiple gradient steps is found to work best.)*
 - 4: **for** each environment setup **do**
 - 5: $a_t \sim \pi_\theta(a_t|s_t)$
 - 6: $s_{t+1} \sim \rho_\pi(s_{t+1}|s_t, a_t)$
 - 7: $\mathcal{D} \leftarrow \mathcal{D} \cup \{(s_t, a_t, r(s_t, a_t), s_{t+1})\}$
 - 8: **for** each gradient update step **do**
 - 9: $\psi \leftarrow \psi - \lambda_V \nabla_\psi J_V(\psi)$.
 - 10: $w \leftarrow w - \lambda_Q \nabla_w J_Q(w)$.
 - 11: $\theta \leftarrow \theta - \lambda_\pi \nabla_\theta J_\pi(\theta)$.
 - 12: $\bar{\psi} \leftarrow \tau\psi + (1 - \tau)\bar{\psi}$.
-

Loss functions

$$J_V(\psi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}} \left[\frac{1}{2} \left(V_\psi(\mathbf{s}_t) - \mathbb{E}_{\mathbf{a}_t \sim \pi_\phi} [Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - \log \pi_\phi(\mathbf{a}_t | \mathbf{s}_t)] \right)^2 \right] \quad (5)$$

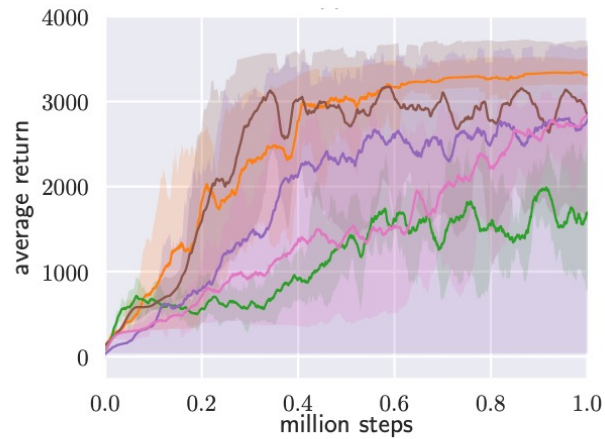
$$J_Q(\theta) = \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t) \sim \mathcal{D}} \left[\frac{1}{2} \left(Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - \hat{Q}(\mathbf{s}_t, \mathbf{a}_t) \right)^2 \right], \quad (7)$$

with

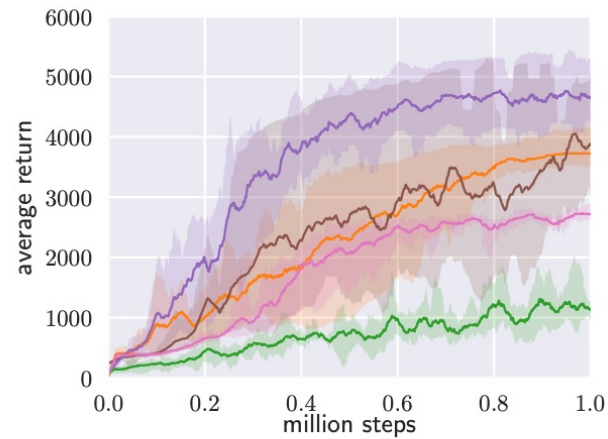
$$\hat{Q}(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + \gamma \mathbb{E}_{\mathbf{s}_{t+1} \sim p} [V_{\bar{\psi}}(\mathbf{s}_{t+1})], \quad (8)$$

$$J_\pi(\phi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}} \left[D_{\text{KL}} \left(\pi_\phi(\cdot | \mathbf{s}_t) \parallel \frac{\exp(Q_\theta(\mathbf{s}_t, \cdot))}{Z_\theta(\mathbf{s}_t)} \right) \right]. \quad (10)$$

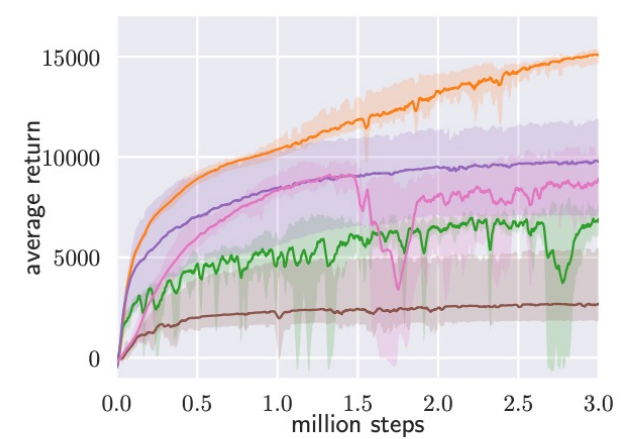
SAC Results



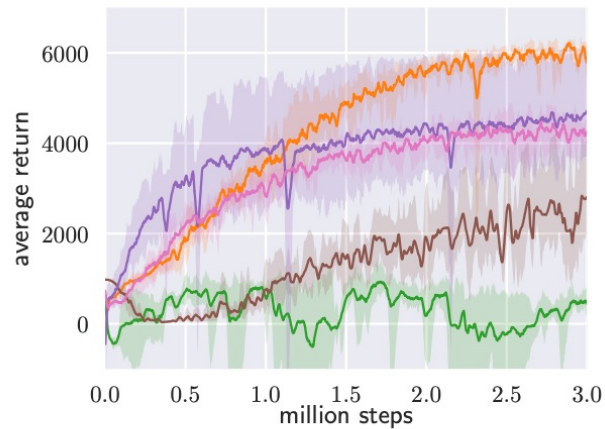
(a) Hopper-v1



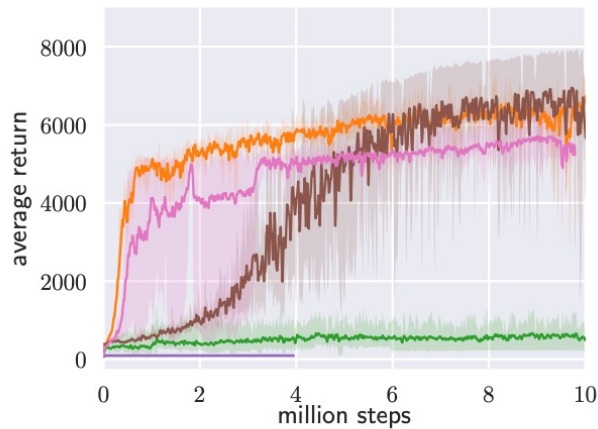
(b) Walker2d-v1



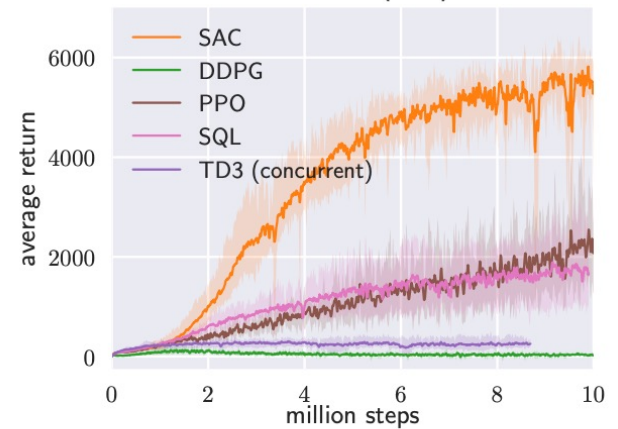
(c) HalfCheetah-v1



(d) Ant-v1

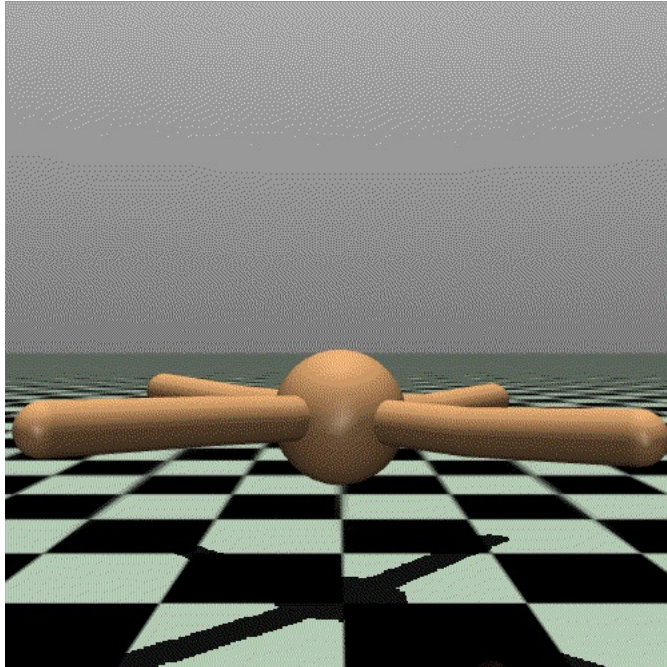


(e) Humanoid-v1

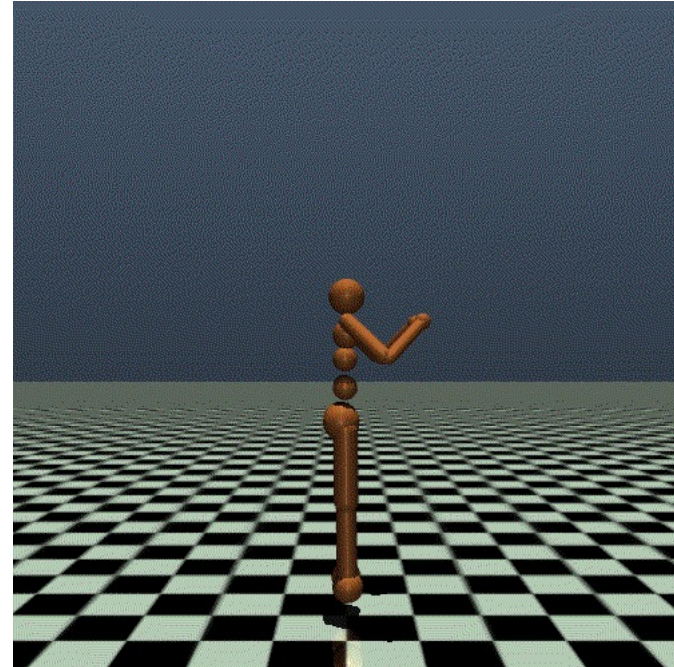


(f) Humanoid (rllab)

Environments



Ant



Humanoid

Related Papers

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- Sutton, McAllester, Singh, Mansour (1999). Policy gradient methods for reinforcement learning with function approximation: [actor-critic algorithms with value function approximation](#)
- Mnih, Badia, Mirza, Graves, Lillicrap, Harley, Silver, Kavukcuoglu (2016). Asynchronous methods for deep reinforcement learning: [A3C, parallel online actor-critic](#)
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Related Papers

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- Schulman, L., Moritz, Jordan, Abbeel (2015). Trust region policy optimization: [TRPO](#)
- Schulman, Wolski, Dhariwal, Radford, Klimov (2017). Proximal policy optimization algorithms: [PPO](#)