Policy Gradient

CMPUT 366: Intelligent Systems

S&B §13.0-13.3

Lecture Overview

1. Recap
2. Parameterized Policies
3. Policy Gradient Theorem
4. REINFORCE Algorithm

Recap: Parameterized Value Functions

- A **parameterized value function**'s values are set by setting the values of a **weight vector** $\mathbf{w} \in \mathbb{R}^d$:

$$\hat{v}(s, \mathbf{w}) \approx v_\pi(s)$$

  - $\hat{v}$ could be a **linear function**: $\mathbf{w}$ is the feature weights
  - $\hat{v}$ could be a **neural network**: $\mathbf{w}$ is the weights, biases, kernels, etc.
- Many fewer weights than states: $d \ll |\mathcal{S}|$
  - Changing **one weight** changes the estimated value of **many states**
  - Updating a single state **generalizes** to affect many other states' values

Recap:
Stochastic Gradient Descent

- **Stochastic Gradient Descent:** After each example $(S_t, v_\pi(S_t))$, adjust weights a tiny bit in **direction** that would most **reduce error** on **that example**:

target

$$\mathbf{w}_{t+1} \doteq \mathbf{w}_t - \frac{1}{2}\alpha \nabla \left[\boxed{v_\pi(S_t)} - \hat{v}(S_t, \mathbf{w}_t)\right]^2$$

$$= \mathbf{w}_t + \alpha \left[\boxed{v_\pi(S_t) - \hat{v}(S_t, \mathbf{w}_t)}\right] \nabla \hat{v}(s, \mathbf{w}_t)$$

error

- We don't know $v_\pi(S_t)$, so we update toward an **approximate target** U_t:

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \alpha \left[U_t - \hat{v}(S_t, \mathbf{w}_t)\right] \nabla \hat{v}(s, \mathbf{w}_t)$$

Approaches to Control

1. **Action-value methods** (all previous approaches)
   - Learn the value of **each action** in **each state**: $q_\pi(s, a)$
   - Pick the **max-value action** (usually): $\arg\max_a q_\pi(s, a)$
2. **Function approximation** (last lecture)
   - **Prediction:** Learn the **parameters** $\mathbf{w}$ of state-value function $\hat{v}(s, \mathbf{w})$
   - **Control:** Learn the **parameters** $\mathbf{w}$ of action-value function $\hat{q}(s, \mathbf{w})$
3. **Policy-gradient methods** (today)
   - Learn the **parameters** θ of a policy $\pi(a \mid s, \theta)$
   - Update by **gradient ascent** in performance

Parameterized Policies

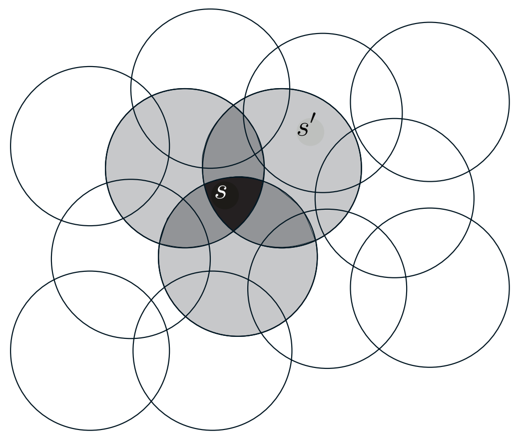
- The action probabilities of a **parameterized policy** $\pi(a \mid s, \theta)$ are set by setting the values of a **parameter vector** $\theta \in \mathbb{R}^{d'}$
- Common approach: **softmax in action preferences**
  - Learn an **action preference function** $h(s, a, \theta)$
  - **Softmax** over action preferences gives action probabilities:

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

Action Preferences

- **Question:** What functional forms can we use for action preferences?
- Anything we could have used for $\hat{v}$:
  - **Linear approximations:**

$$h(s, a, \theta) \doteq \theta^T \mathbf{x}(s) = \sum_{i=1}^{d} \theta_i x_i(s)$$



    - Including coarse coding, tile coding
  - **Neural network:** θ are weights, offsets, kernels, etc.

Parameterized Policies Advantage: Deterministic Action

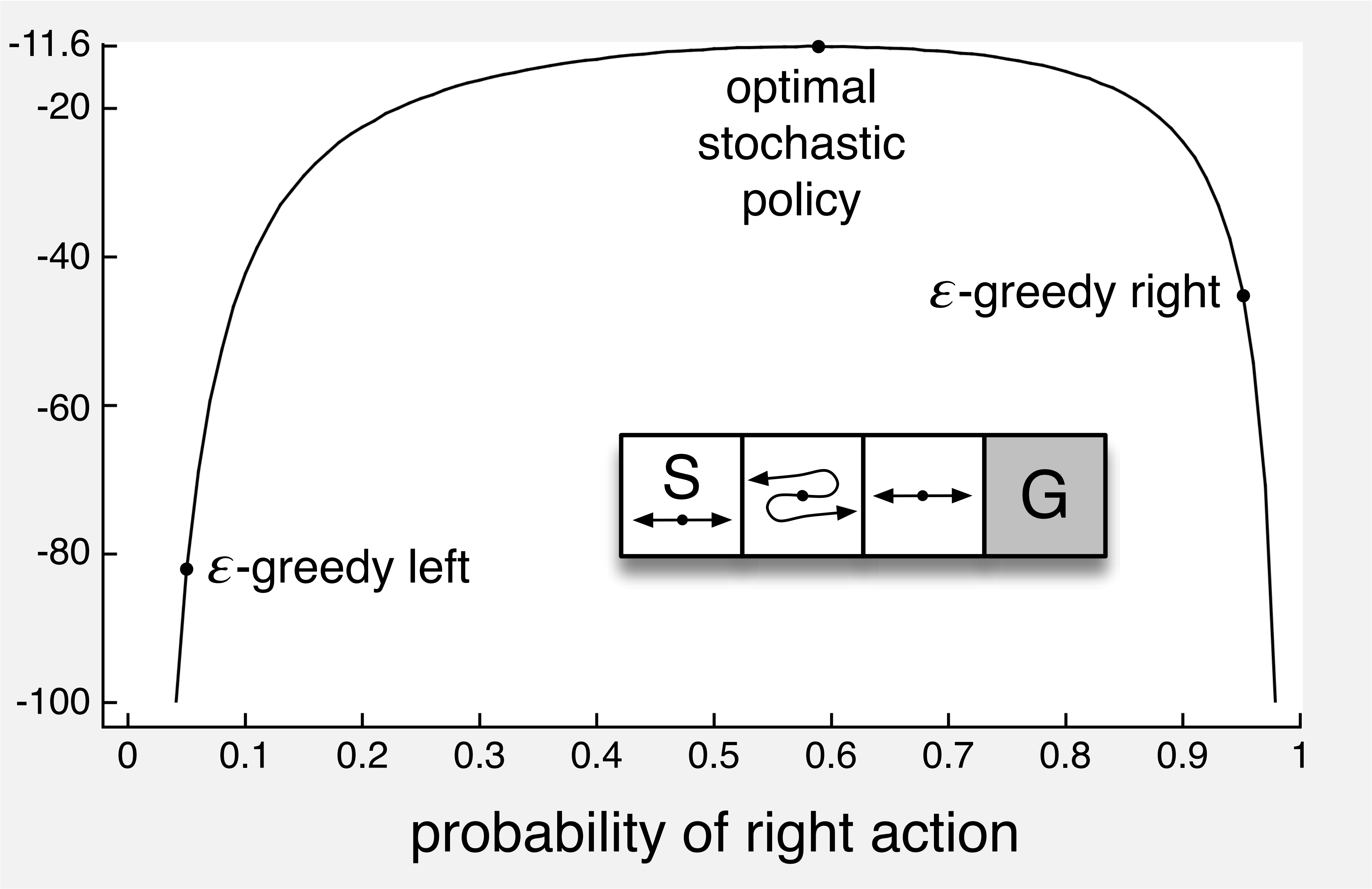
- The **optimal policy** $\pi^*(a \mid s) = \arg\max_a q^*(s, a)$ is typically **deterministic**
- If we run an ε-soft policy, we cannot get to an optimal policy
  - **Every action** is played either with probability ε or (1-ε)
- Softmax in **action preference policies** can learn **arbitrary probabilities**, because $h(s, a, \theta)$ is completely **unconstrained**:

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

- **Question:** How can a softmax in action preferences policy converge to a deterministic policy?
- **Question:** Can you get the same results with $h(s,a,\theta) = \hat{q}(s,a,\theta)$? (**why?**)

Example: Switcheroo Corridor

- Actions `left` and `right` have usual effect
- Except in one state they are **reversed**!
- Function approximation makes all the states **look identical**
- **Optimal policy** is **stochastic**, with Pr(`right`) ≈ 0.59
- But ε-greedy policies can only pick Pr(`right`) of ε or (1-ε)!



(Image: Sutton & Barto, 2018)

Parameterized Policies Advantage: Stochastic Actions

- Optimal policies are **deterministic**, but only when there is no **state aggregation**
- When **function approximation** makes states look the same, or when states are **imperfectly observable**, the optimal policy might be an **arbitrary probability distribution**
- Parameterized policies can represent **arbitrary** distributions
    - Although not necessarily arbitrary distributions in **every possible state** (**why not?**)

Policy Performance

- We choose the policy parameters θ in order to maximize the **performance** of the policy: $J(\theta)$
- **Question:** What should $J(\theta)$ be in epsiodic cases?
- **Expected returns** to the policy specified by θ:

$$J(\theta) \doteq \mathbb{E}_{\pi_\theta}\left[G_0\right]$$

- With special **single starting state** s_0:

$$J(\theta) \doteq v_{\pi_\theta}(s_0)$$

Policy Gradient Ascent

1. Want to **maximize performance**: $J(\theta) = v_{\pi_\theta}(s_0)$
2. Gradient gives direction that **J increases**: $\nabla J(\theta)$
3. Update parameters in **direction of the gradient**:

$$\theta_{t+1} \leftarrow \theta_t + \alpha \nabla J(\theta_t)$$

$$= \theta_t + \alpha \boxed{\nabla v_{\pi_\theta}}(S_t)$$

Oops!

Policy Gradient Theorem

- The **gradient of the policy** $\nabla J(\theta)$ is just the gradient of the value function with respect to the policy $v_{\pi_\theta}(s_0)$
- But we **don't know** the gradient of the **value function**!

Policy Gradient Theorem:

$$\nabla J(\theta) \propto \sum_s \mu(s) \sum_a q_\pi(s, a) \nabla \pi(a \mid s, \theta)$$

on-policy stationary distribution

true action values

gradient of policy

Monte Carlo Policy Gradient

$$
\begin{aligned}
\nabla J(\theta) &\propto \sum_s \mu(s) \sum_a q_\pi(s, a) \nabla \pi(a \mid s, \theta) \\
&= \mathbb{E}_\pi \left[\sum_a q_\pi(S_t, a) \nabla \pi(a \mid S_t, \theta) \right] \\
&= \mathbb{E}_\pi \left[\sum_a q_\pi(S_t, a) \nabla \pi(a \mid S_t, \theta) \frac{\pi(a \mid S_t, \theta)}{\pi(a \mid S_t, \theta)} \right] \\
&= \mathbb{E}_\pi \left[\sum_a \pi(a \mid S_t, \theta) q_\pi(S_t, a) \frac{\nabla \pi(a \mid S_t, \theta)}{\pi(a \mid S_t, \theta)} \right] \\
&= \mathbb{E}_\pi \left[q_\pi(S_t, A_t) \frac{\nabla \pi(A_t \mid S_t, \theta)}{\pi(A_t \mid S_t, \theta)} \right] \\
&= \mathbb{E}_\pi \boxed{\left[G_t \frac{\nabla \pi(A_t \mid S_t, \theta)}{\pi(A_t \mid S_t, \theta)} \right]}
\end{aligned}
$$

Monte Carlo Policy Gradient Algorithm: REINFORCE

REINFORCE Update: $\theta_{t+1} \leftarrow \theta_t + \alpha \boxed{G_t \frac{\nabla \pi(A_t \mid S_t, \theta_t)}{\pi(A_t \mid S_t, \theta_t)}}$

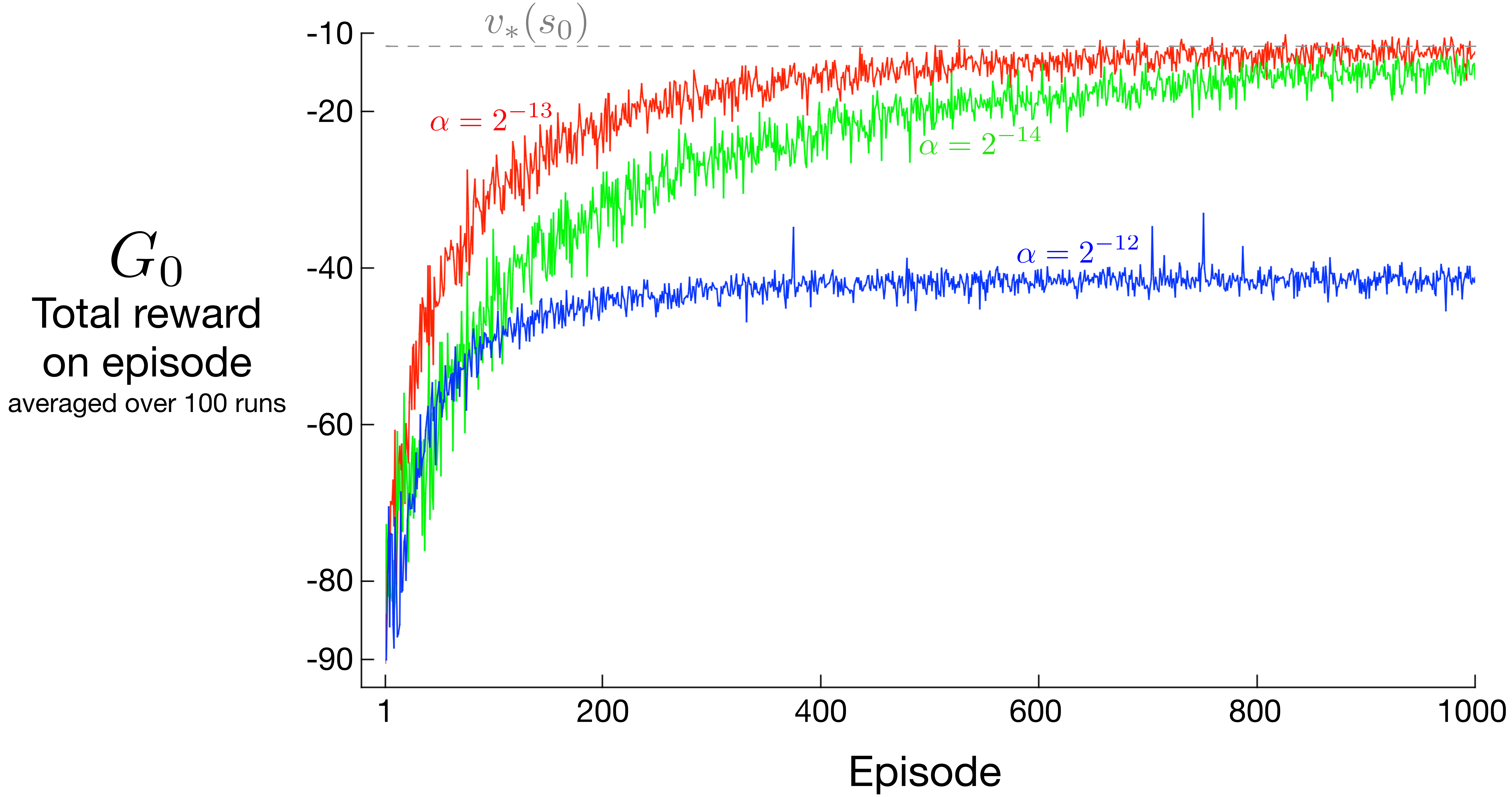
REINFORCE: Monte-Carlo Policy-Gradient Control (episodic) for π_*

Input: a differentiable policy parameterization $\pi(a|s, \boldsymbol{\theta})$
Algorithm parameter: step size $\alpha > 0$
Initialize policy parameter $\boldsymbol{\theta} \in \mathbb{R}^{d'}$ (e.g., to $\mathbf{0}$)

Loop forever (for each episode):
  Generate an episode $S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T$, following $\pi(\cdot|\cdot, \boldsymbol{\theta})$
  Loop for each step of the episode $t = 0, 1, \ldots, T-1$:
    $G \leftarrow \sum_{k=t+1}^{T} \gamma^{k-t-1} R_k$ $\quad (G_t)$
    $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha \gamma^t G \underbrace{\nabla \ln \pi}(A_t|S_t, \boldsymbol{\theta})$

$\frac{\nabla \pi(A_t \mid S_t, \theta)}{\pi(A_t \mid S_t, \theta)}$ "eligibility function" $\left(\nabla \ln x = \frac{\nabla x}{x} \right)$

REINFORCE Performance in Switcheroo Corridor



(Image: Sutton & Barto, 2018)

Summary

- All our previous control algorithms were **action-value** methods
  1. Approximate the action-value $q^*(s, a)$
  2. Choose maximal-value action at every state
- **Policy gradient** methods:
  1. Represent policies using parametric policy $\pi(s \mid a, \theta)$
  2. Directly optimize performance $J(\theta)$ by adjusting θ
- **Policy Gradient Theorem** lets us restate $J(\theta)$ in terms of quantities that we know ($\nabla \pi$) or can approximate (q_π)
- REINFORCE uses a particular estimation scheme for policy gradients