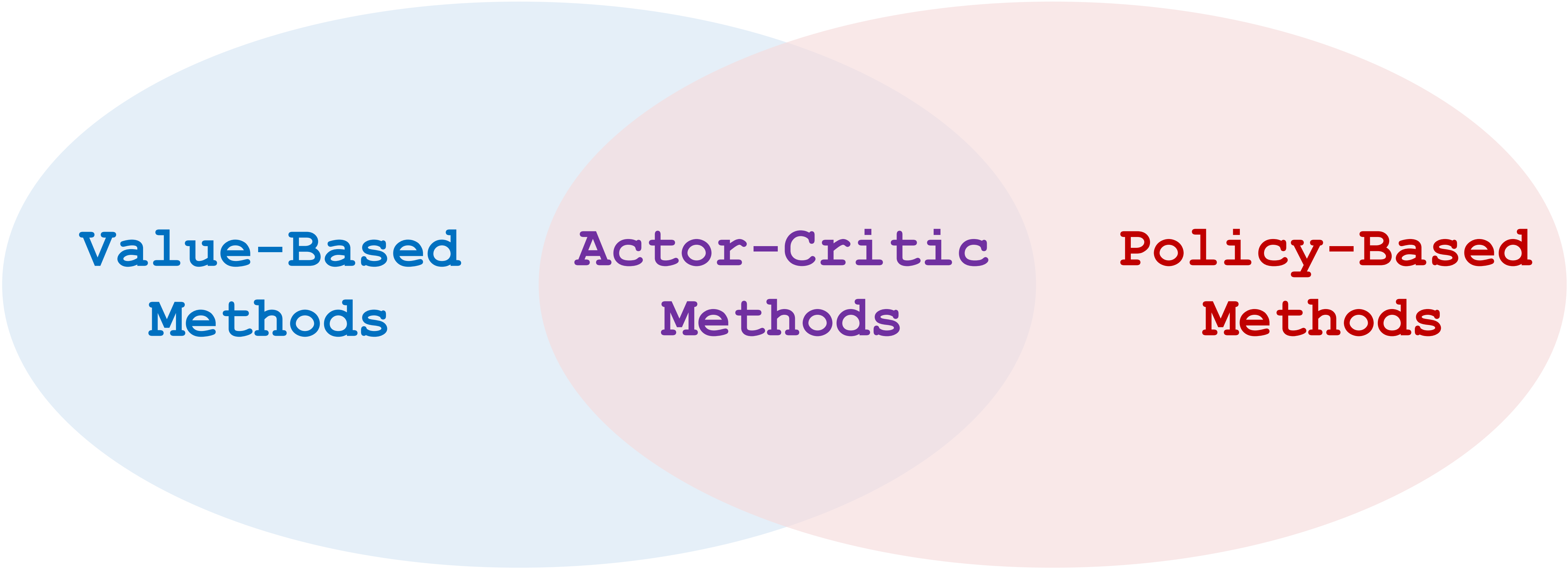
Actor-Critic Methods

Shusen Wang


Value-Based Methods
Actor-Critic Methods
Policy-Based Methods

Value Network and Policy Network

State-Value Function Approximation

Definition: State-value function.

- $V_\pi(s) = \sum_a \pi(a|s) \cdot Q_\pi(s, a)$.

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Policy network (actor):

- Use neural net $\pi(a|s; \boldsymbol{\theta})$ to approximate $\pi(a|s)$.
- $\boldsymbol{\theta}$: trainable parameters of the neural net.

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- Use neural net $\pi(a|s; \boldsymbol{\theta})$ to approximate $\pi(a|s)$.
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Value network (critic):

- Use neural net $q(s, a; \mathbf{w})$ to approximate $Q_\pi(s, a)$.
- $\mathbf{w}$: trainable parameters of the neural net.

State-Value Function Approximation

Definition: State-value function.

- $V_\pi(s) = \sum_a \pi(a|s) \cdot Q_\pi(s,a)$ $\approx \sum_a \pi(a|s;\boldsymbol{\theta}) \cdot q(s,a;\mathbf{w})$.

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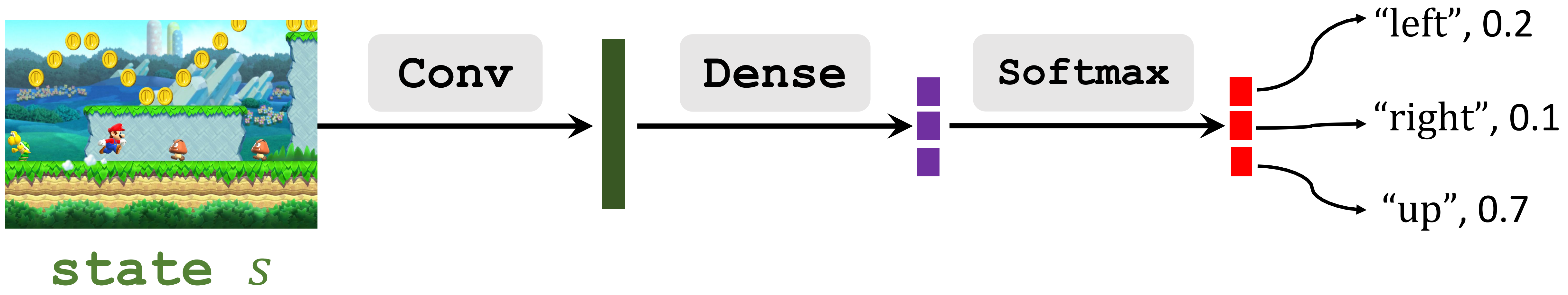
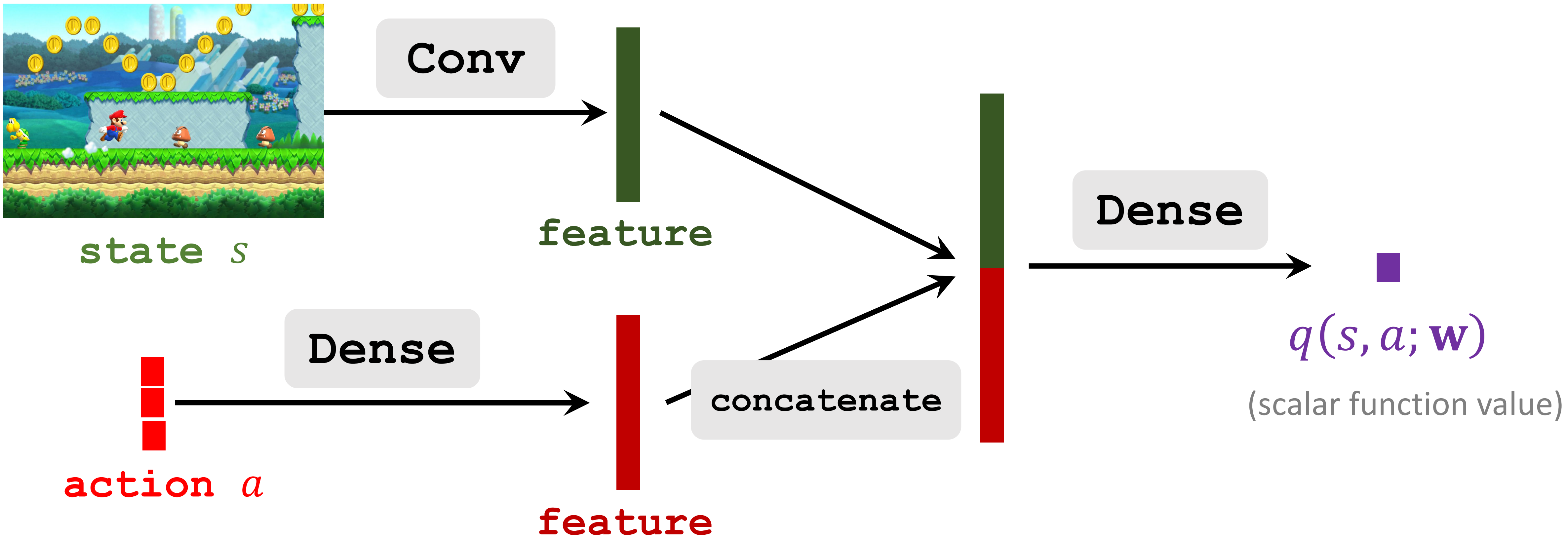
Policy Network (Actor): $\pi(a|s, \boldsymbol{\theta})$

- Input: state s, e.g., a screenshot of Super Mario.
- Output: probability distribution over the actions.
- Let $\mathcal{A}$ be the set all actions, e.g., $\mathcal{A} = \{\text{"left"}, \text{"right"}, \text{"up"}\}$.
- $\sum_{a \in \mathcal{A}} \pi(a|s, \boldsymbol{\theta}) = 1$. (That is why we use softmax activation.)



Value Network (Critic): $q(s, a; \mathbf{w})$

- Inputs: state s and action a.
- Output: approximate action-value (scalar).



Actor-Critic Method

policy network (actor)

value network (critic)

Train the Neural Networks

Train the networks

Definition: State-value function approximated using neural networks.

- $V(s; \boldsymbol{\theta}, \mathbf{w}) = \sum_a \pi(a|s; \boldsymbol{\theta}) \cdot q(s, a; \mathbf{w})$.

Training: Update the parameters $\boldsymbol{\theta}$ and $\mathbf{w}$.

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- Update policy network $\pi(a|s; \boldsymbol{\theta})$ to increase the state-value $V(s; \boldsymbol{\theta}, \mathbf{w})$.
  - Actor gradually performs better.
  - Supervision is purely from the value network (critic).

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- Update policy network $\pi(a|s;\boldsymbol{\theta})$ to increase the state-value $V(s;\boldsymbol{\theta},\mathbf{w})$.
  - Actor gradually performs better.
  - Supervision is purely from the value network (critic).
- Update value network $q(s,a;\mathbf{w})$ to better estimate the return.
  - Critic's judgement becomes more accurate.
  - Supervision is purely from the rewards.

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Training: Update the parameters $\boldsymbol{\theta}$ and $\mathbf{w}$.

1. Observe the state s_t.
2. Randomly sample action a_t according to $\pi(\cdot \mid s_t; \boldsymbol{\theta}_t)$.
3. Perform a_t and observe new state s_{t+1} and reward r_t.
4. Update $\mathbf{w}$ (in value network) using temporal difference (TD).
5. Update $\boldsymbol{\theta}$ (in policy network) using policy gradient.

Update value network q using TD

- Compute $q(s_t, a_t; \mathbf{w}_t)$ and $q(s_{t+1}, a_{t+1}; \mathbf{w}_t)$.
- TD target: $y_t = r_t + \gamma \cdot q(s_{t+1}, a_{t+1}; \mathbf{w}_t)$.

Update value network q using TD

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- TD target: $y_t = r_t + \gamma \cdot q(s_{t+1}, a_{t+1}; \mathbf{w}_t)$.

- Loss: $L(\mathbf{w}) = \frac{1}{2}[q(s_t, a_t; \mathbf{w}) - y_t]^2$.
- Gradient descent: $\mathbf{w}_{t+1} = \mathbf{w}_t - \alpha \cdot \frac{\partial\, L(\mathbf{w})}{\partial\, \mathbf{w}} \Big|_{\mathbf{w}=\mathbf{w}_t}$.

Update policy network π using policy gradient

Definition: State-value function approximated using neural networks.

- $V(s;\boldsymbol{\theta},\mathbf{w}) = \sum_a \pi(a|s;\boldsymbol{\theta}) \cdot q(s,a;\mathbf{w})$.

Policy gradient: Derivative of $V(s_t;\boldsymbol{\theta},\mathbf{w})$ w.r.t. $\boldsymbol{\theta}$.

- Let $\mathbf{g}(a,\boldsymbol{\theta}) = \frac{\partial \log \pi(a|s,\boldsymbol{\theta})}{\partial\, \boldsymbol{\theta}} \cdot q(s_t,a;\mathbf{w})$.
- $\frac{\partial\, V(s;\boldsymbol{\theta},\mathbf{w}_t)}{\partial\, \boldsymbol{\theta}} = \mathbb{E}_A[\mathbf{g}(A,\boldsymbol{\theta})]$.

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- $\frac{\partial \, V(s; \boldsymbol{\theta}, \mathbf{w}_t)}{\partial \, \boldsymbol{\theta}} = \mathbb{E}_A[\mathbf{g}(A, \boldsymbol{\theta})]$.

Algorithm: Update policy network using stochastic policy gradient.

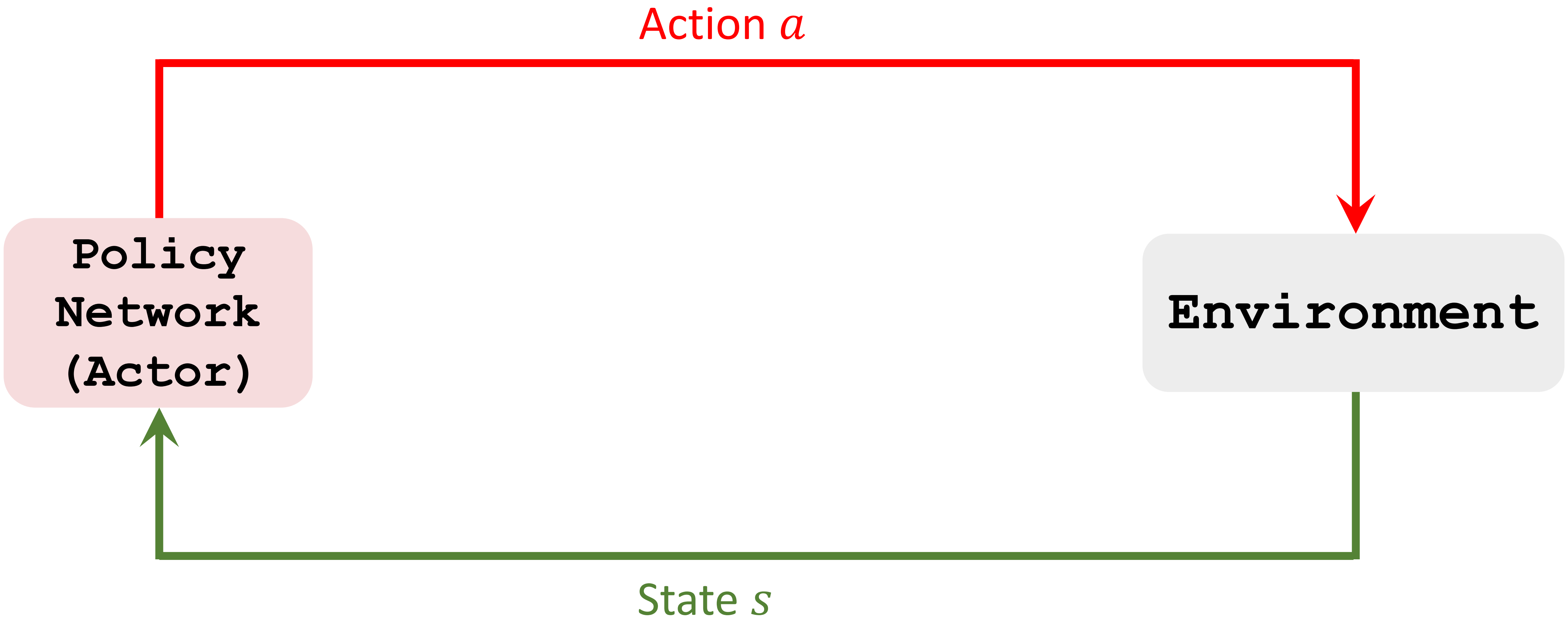
- Random sampling: $a \sim \pi(\cdot \, | s_t; \boldsymbol{\theta}_t)$. (Thus $\mathbf{g}(a, \boldsymbol{\theta})$ is unbiased.)
- Stochastic gradient ascent: $\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \beta \cdot \mathbf{g}(a, \boldsymbol{\theta}_t)$.

Actor-Critic Method

policy network (actor)

value network (critic)

Actor-Critic Method



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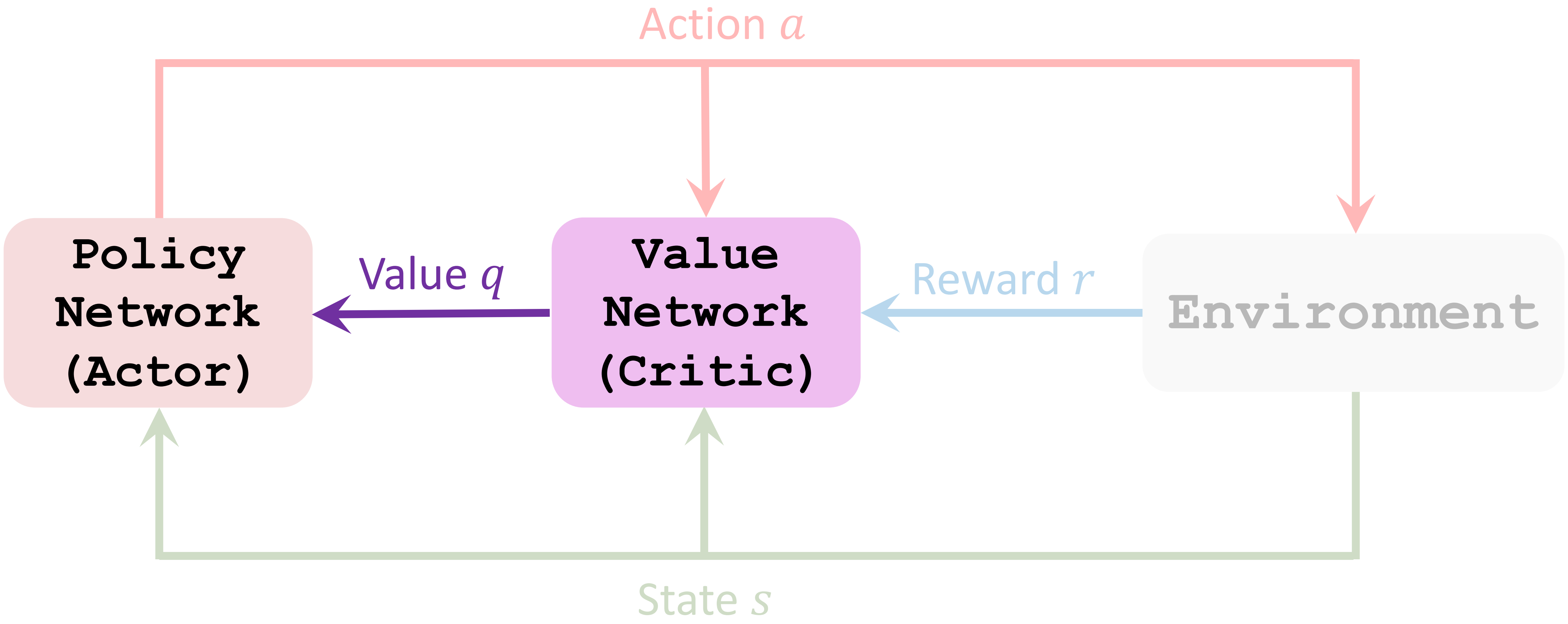
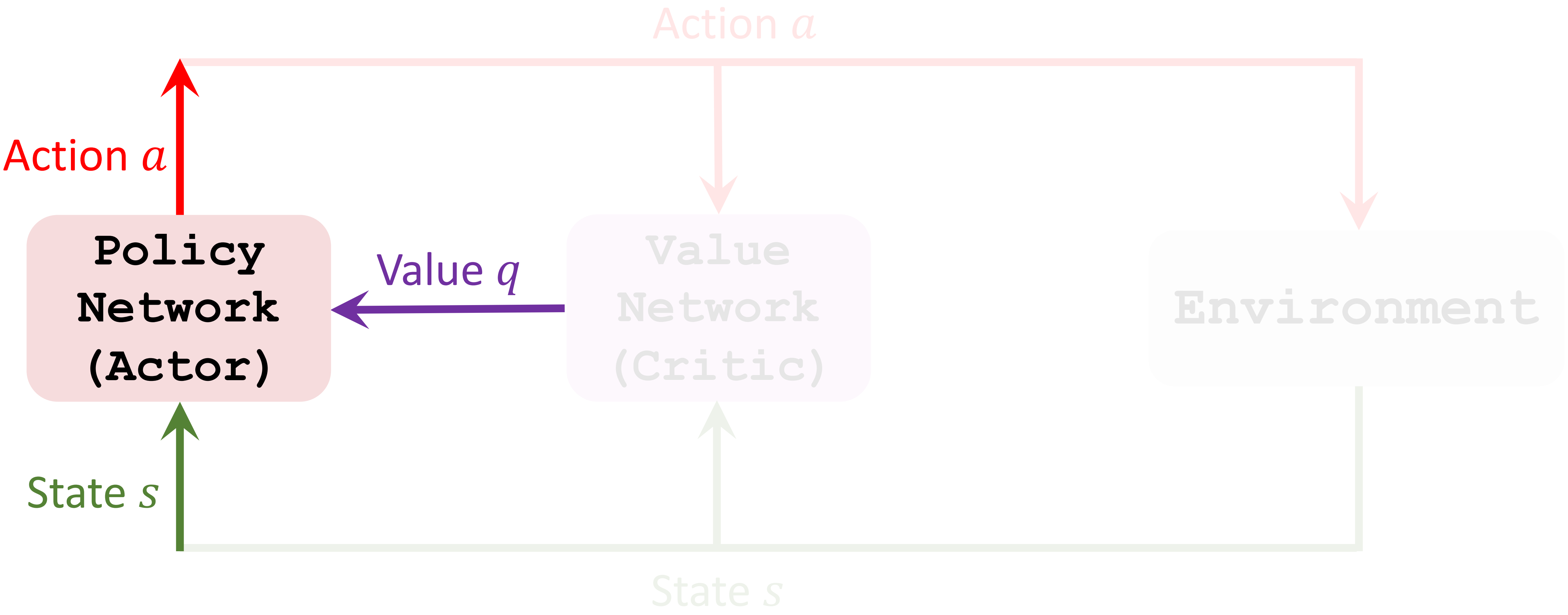
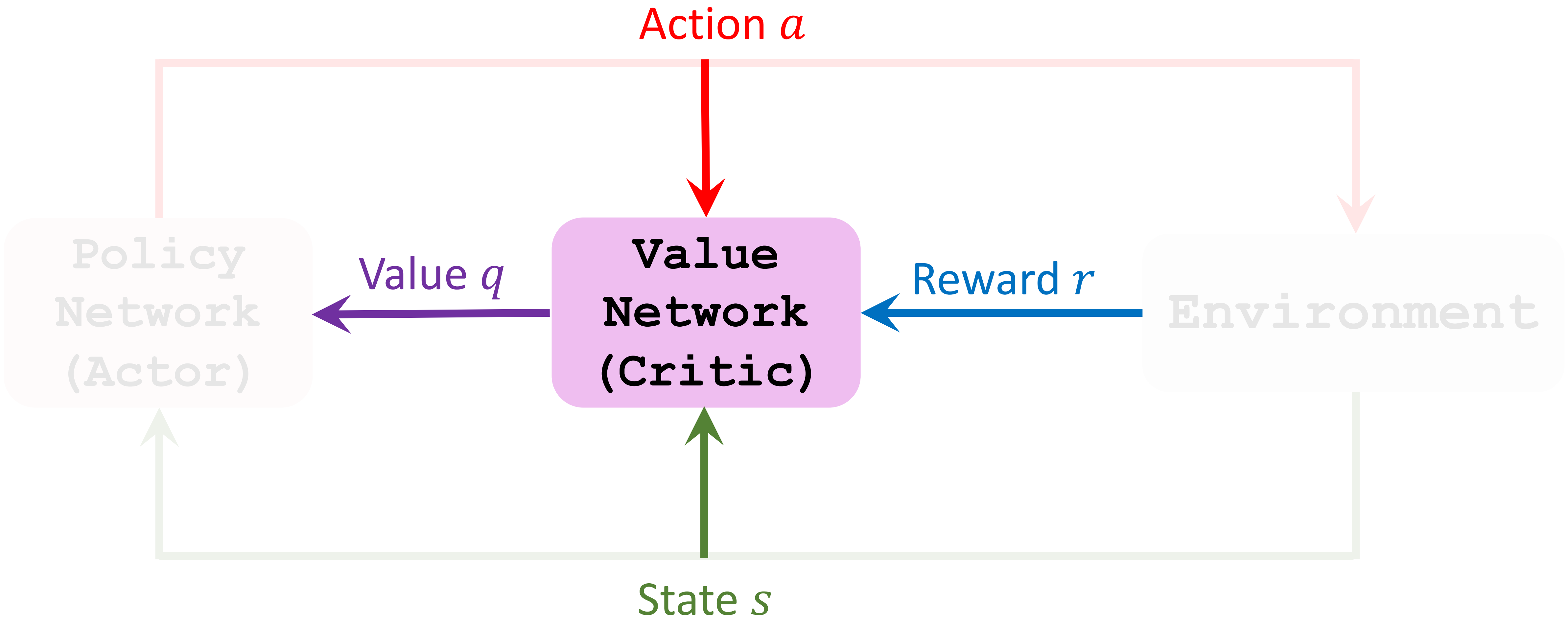


Actor-Critic Method: Update Actor



Actor-Critic Method: Update Critic



Summary of Algorithm

1. Observe state s_t and randomly sample $a_t \sim \pi(\cdot \,|s_t; \boldsymbol{\theta}_t)$.
2. Perform a_t; then environment gives new state s_{t+1} and reward r_t.
3. Randomly sample $\tilde{a}_{t+1} \sim \pi(\cdot \,|s_{t+1}; \boldsymbol{\theta}_t)$. (Do not perform $\tilde{a}_{t+1}$!)

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4. Evaluate value network: $q_t = q(s_t, a_t; \mathbf{w}_t)$ and $q_{t+1} = q(s_{t+1}, \tilde{a}_{t+1}; \mathbf{w}_t)$.
5. Compute TD error: $\delta_t = q_t - \underbrace{(r_t + \gamma \cdot q_{t+1})}_{\text{TD Target}}$.

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Policy Gradient with Baseline

1. Observe state s_t and randomly sample $a_t \sim \pi(\cdot\,|s_t; \boldsymbol{\theta}_t)$.
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4. Evaluate value network: $q_t = q(s_t, a_t; \mathbf{w}_t)$ and $q_{t+1} = q(s_{t+1}, \tilde{a}_{t+1}; \mathbf{w}_t)$.
5. Compute TD error: $\delta_t = q_t - \underbrace{(r_t + \gamma \cdot q_{t+1})}_{\text{Baseline}}$.
6. Differentiate value network: $\mathbf{d}_{w,t} = \frac{\partial q(s_t, a_t, \mathbf{w})}{\partial \mathbf{w}} \Big|_{\mathbf{w}=\mathbf{w}_t}$.
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Summary

Policy Network and Value Network

Definition: State-value function.

- $V_\pi(s) = \sum_a \pi(a|s) \cdot Q_\pi(s, a)$.

Definition: function approximation using neural networks.

- Approximate policy function $\pi(a|s)$ by $\pi(a|s; \boldsymbol{\theta})$ (actor).
- Approximate value function $Q_\pi(s, a)$ by $q(s, a; \mathbf{w})$ (critic).

Roles of Actor and Critic

During training

- Agent is controlled by policy network (actor): $a_t \sim \pi(\cdot\,|s_t;\boldsymbol{\theta})$.
- Value network q (critic) provides the actor with supervision.

Roles of Actor and Critic

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- Agent is controlled by policy network (actor): $a_t \sim \pi(\cdot \mid s_t; \boldsymbol{\theta})$.
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After training

- Agent is controlled by policy network (actor): $a_t \sim \pi(\cdot \mid s_t; \boldsymbol{\theta})$.
- Value network q (critic) will not be used.

Training

Update the policy network (actor) by policy gradient.

- Seek to increase state-value: $V(s;\boldsymbol{\theta},\mathbf{w}) = \sum_a \pi(a|s;\boldsymbol{\theta}) \cdot q(s,a;\mathbf{w})$.
- Compute policy gradient: $\frac{\partial\, V(s;\boldsymbol{\theta})}{\partial\, \boldsymbol{\theta}} = \mathbb{E}_A\left[\frac{\partial \log \pi(A|s,\boldsymbol{\theta})}{\partial\, \boldsymbol{\theta}} \cdot q(s,A;\mathbf{w})\right]$.
- Perform gradient ascent.

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- Compute policy gradient: $\frac{\partial\, V(s;\boldsymbol{\theta})}{\partial\, \boldsymbol{\theta}} = \mathbb{E}_A\left[\frac{\partial \log \pi(A|s,\boldsymbol{\theta})}{\partial\, \boldsymbol{\theta}} \cdot q(s,A;\mathbf{w})\right]$.
- Perform gradient ascent.

Update the value network (critic) by TD learning.

- Predicted action-value: $q_t = q(s_t, a_t; \mathbf{w})$.
- TD target: $y_t = r_t + \gamma \cdot q(s_{t+1}, a_{t+1}; \mathbf{w})$
- Gradient: $\frac{\partial (q_t - y_t)^2/2}{\partial\, \mathbf{w}} = (q_t - y_t) \cdot \frac{\partial\, q(s_t,a_t;\mathbf{w})}{\partial\, \mathbf{w}}$.
- Perform gradient descent.

Thank you!

Policy Gradient with Baseline

Policy Gradient with Baseline

Definition: Approximated state-value function.

- $V(s;\boldsymbol{\theta}) - b = \sum_a \pi(a|s;\boldsymbol{\theta}) \cdot [Q_\pi(s,a) - b]$.
- Here, the baseline b must be independent of $\boldsymbol{\theta}$ and a.

Policy Gradient with Baseline

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- $V(s;\boldsymbol{\theta}) - b = \sum_a \pi(a|s;\boldsymbol{\theta}) \cdot [Q_\pi(s,a) - b]$.
- Here, the baseline b must be independent of $\boldsymbol{\theta}$ and a.

Policy gradient: Derivative of $V(s;\boldsymbol{\theta})$ w.r.t. $\boldsymbol{\theta}$.

- $\frac{\partial\, V(s;\boldsymbol{\theta})}{\partial\, \boldsymbol{\theta}} = \frac{\partial\, [V(s;\boldsymbol{\theta}) - b]}{\partial\, \boldsymbol{\theta}} = \mathbb{E}_{a \sim \pi(\cdot|s;\boldsymbol{\theta})}\left[\frac{\partial \log \pi(a|s,\boldsymbol{\theta})}{\partial\, \boldsymbol{\theta}} \cdot [Q_\pi(s,a) - b]\right]$.
- The baseline b does not affect correctness.
- A good baseline b can reduce variance.
- We can use $b = r_t + \gamma \cdot q_{t+1}$ (TD target) as the baseline.

Actor Critic Update (without baseline)

1. Observe the state s_t; randomly sample action a_t according to $\pi(\cdot\,|s_t;\boldsymbol{\theta}_t)$.
2. Perform a_t; observe new state s_{t+1} and reward r_t.
3. Randomly sample a_{t+1} according to $\pi(\cdot\,|s_{t+1};\boldsymbol{\theta}_t)$. (Do not perform a_{t+1}.)
4. Evaluate value network: $q_t = q(s_t, a_t; \mathbf{w}_t)$ and $q_{t+1} = q(s_{t+1}, a_{t+1}; \mathbf{w}_t)$.
5. Compute the TD error: $\delta_t = q_t - (r_t + \gamma \cdot q_{t+1})$.
6. Differentiate value network: $\mathbf{d}_{w,t} = \frac{\partial q(s_t, a_t; \mathbf{w})}{\partial\, \mathbf{w}} \Big|_{\mathbf{w}=\mathbf{w}_t}$.
7. Update value network: $\mathbf{w}_{t+1} = \mathbf{w}_t - \alpha \cdot \delta_t \cdot \mathbf{d}_{w,t}$.
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Actor Critic Update (with baseline)

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4. Evaluate value network: $q_t = q(s_t, a_t; \mathbf{w}_t)$ and $q_{t+1} = q(s_{t+1}, a_{t+1}; \mathbf{w}_t)$.
5. Compute the TD error: $\delta_t = q_t - \underbrace{(r_t + \gamma \cdot q_{t+1})}_{\text{Baseline}}$.
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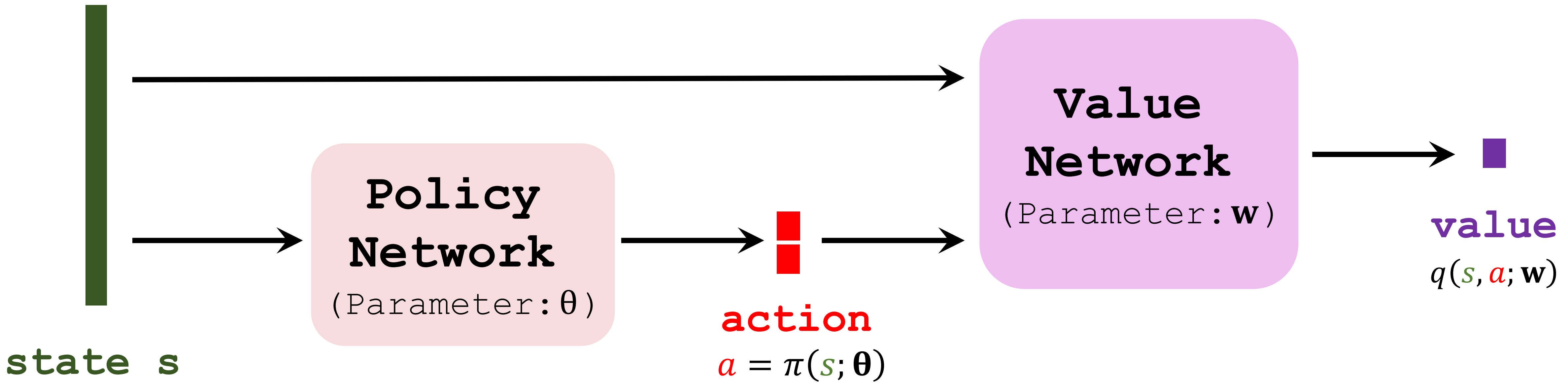
Deterministic Policy Gradient (DPG)

Reference

- Silver and others: Deterministic Policy Gradient Algorithms. In *ICML*, 2014.
- Lillicrap and others: Continuous control with deep reinforcement learning. arXiv:1509.02971. 2015.

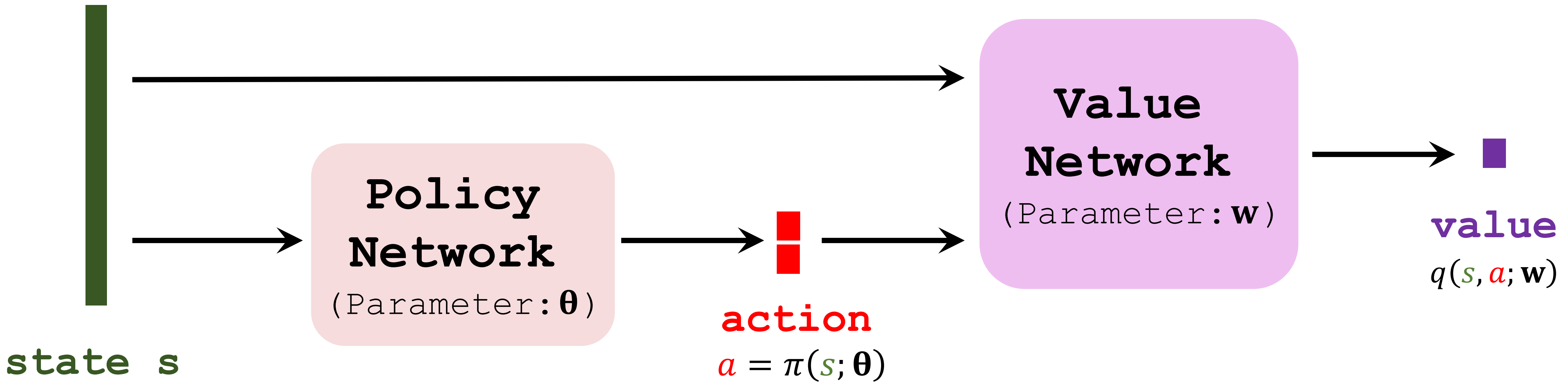
Deterministic Policy Gradient (DPG)

- DPG is a actor-critic method.
- The policy network is deterministic: $a = \pi(s; \boldsymbol{\theta})$.



Deterministic Policy Gradient (DPG)

- DPG is a actor-critic method.
- The policy network is deterministic: $a = \pi(s; \boldsymbol{\theta})$.
- Trained value network by TD learning.
- Train policy network to maximize the value $q(s, a; \mathbf{w})$.



Train Policy Network

- Train policy network to maximize the value $q(s, a; \mathbf{w})$.
- Gradient: $\frac{\partial\, q(s,a;\mathbf{w})}{\partial\, \boldsymbol{\theta}} = \frac{\partial\, a}{\partial\, \boldsymbol{\theta}} \cdot \frac{\partial\, q(s,a;\mathbf{w})}{\partial\, a}$.
- Update $\boldsymbol{\theta}$ using gradient ascent.