Actor-Critic Methods (A2C, A3C)

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*Slides are adopted from Deep Reinforcement Learning by Sergey Levine & Policy Gradients by David Silver

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Types of RL algorithms

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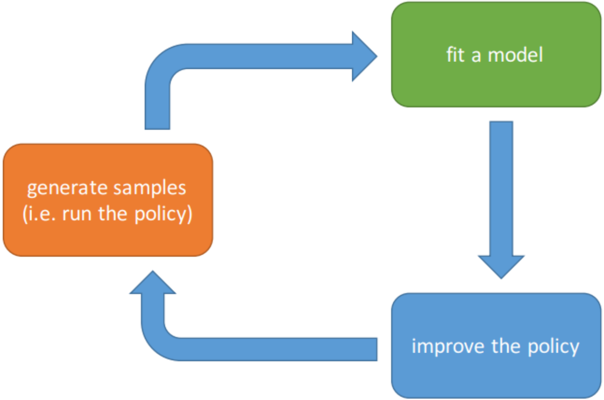
Model-based Algorithms

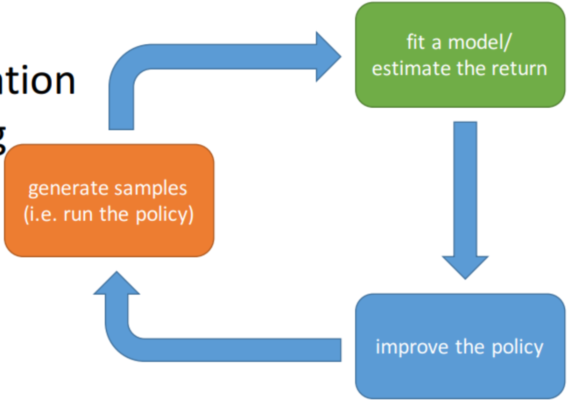


learn $p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$

a few options

Examples:

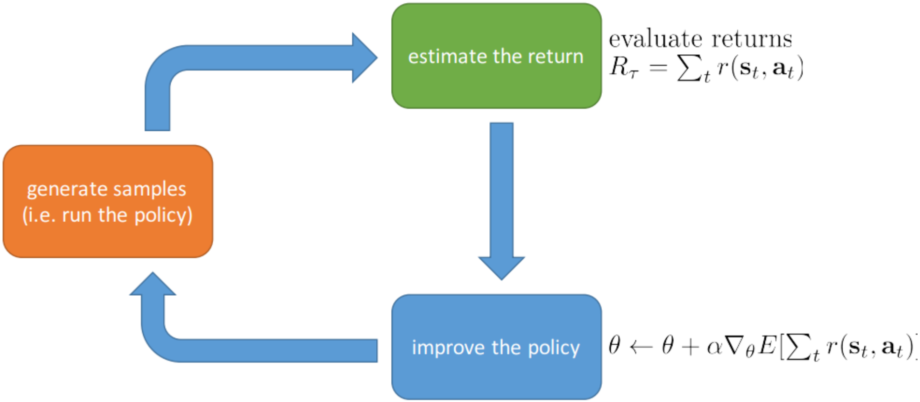
- Value-Iteration
- Q-Learning
- DQN



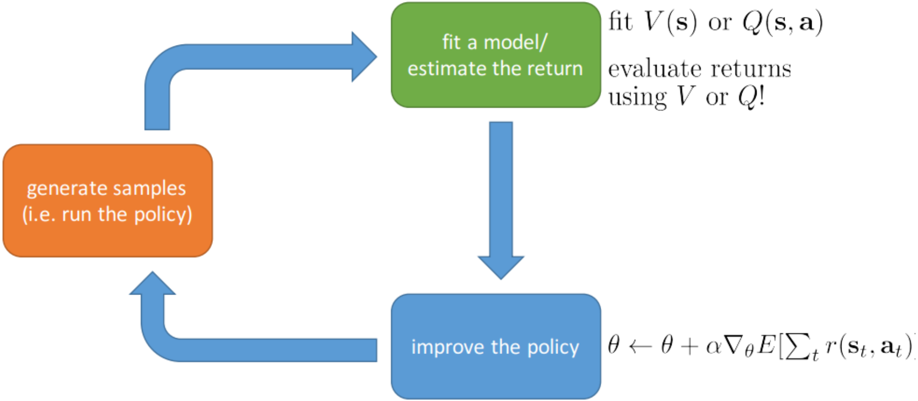
fit $V(\mathbf{s})$ or $Q(\mathbf{s},\mathbf{a})$

set $\pi(\mathbf{s}) = \arg\max_{\mathbf{a}} Q(\mathbf{s},\mathbf{a})$

Direct Policy Gradient



Actor-critic: Value Function + Policy Gradients



Comparison: Sample Efficiency

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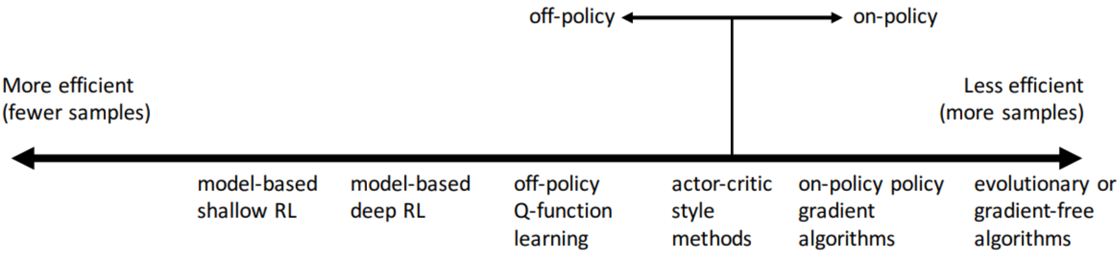
- **Sample efficiency:** How many samples do we need to get a good policy?
- Most important questions: Is the algorithm off policy?
  - Off policy: able to improve the policy without generating new samples from that policy
  - On policy: each time the policy is changed, even a little bit, we need to generate new samples

Comparison: Sample Efficiency



REINFORCE (Monte-Carlo Policy Gradient)

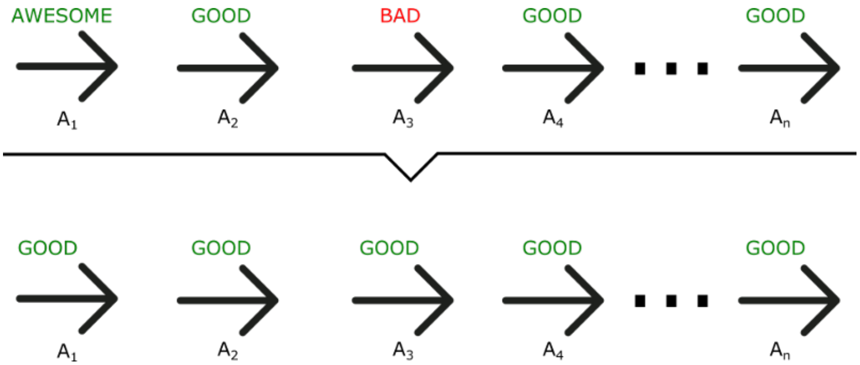
- Update parameters by stochastic gradient ascent
- Using policy gradient theorem
- Using return G_t as an unbiased sample of $Q^{\pi_\theta}(s_t, a_t)$

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

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

Input: a differentiable policy parameterization $\pi(a|s, \boldsymbol{\theta}), \forall a \in \mathcal{A}, s \in \mathcal{S}, \boldsymbol{\theta} \in \mathbb{R}^n$
Initialize policy weights $\boldsymbol{\theta}$
Repeat forever:
    Generate an episode $S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T$, following $\pi(\cdot|\cdot, \boldsymbol{\theta})$
    For each step of the episode $t = 0, \ldots, T-1$:
        $G_t \leftarrow$ return from step t
        $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha\gamma^t G_t \nabla_{\boldsymbol{\theta}} \log \pi(A_t|S_t, \boldsymbol{\theta})$

REINFORCE: Problem



Solution

Policy Update: $$\Delta\theta = \alpha * \nabla_\theta * (log\, \pi(S_t, A_t, \theta)) * R(t)$$

New update: $$\Delta\theta = \alpha * \nabla_\theta * (log\, \pi(S_t, A_t, \theta)) * \boxed{Q(S_t, A_t)}$$

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  - Critic Updates action-value function parameters w

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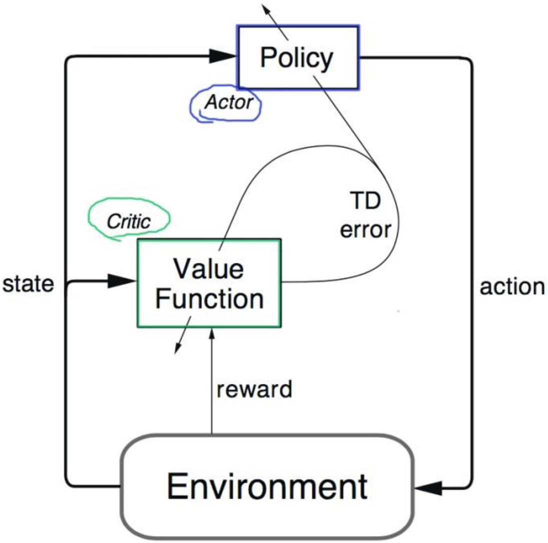
- The critic computes value functions to help assist the actor in learning. These are usually the state value, state-action value, or advantage value, denoted as $V(s)$, $Q(s, a)$, and $A(s, a)$, respectively.

Actor-Critic



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- How good is policy π_θ for current parameters θ?
- To estimate, use any policy evaluation method:
  - Monte-Carlo policy evaluation
  - Temporal-Difference learning
  - Least-squares policy evaluation

Estimating the TD Error

- For the true value function $V_{\pi_\theta}(s)$, the TD error δ_{π_θ}

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- In practice we can use an approximate TD error, that requires one set of parameters w

$$\delta_w = r + \gamma V_w(s') - V_w(s)$$

Actor-Critic: Critic (Linear TD(0)) + Actor (policy gradient)

One-step Actor–Critic (episodic), for estimating $\pi_{\boldsymbol{\theta}} \approx \pi_*$

Input: a differentiable policy parameterization $\pi(a|s, \boldsymbol{\theta})$
Input: a differentiable state-value function parameterization $\hat{v}(s,\mathbf{w})$
Parameters: step sizes $\alpha^{\boldsymbol{\theta}} > 0$, $\alpha^{\mathbf{w}} > 0$
Initialize policy parameter $\boldsymbol{\theta} \in \mathbb{R}^{d'}$ and state-value weights $\mathbf{w} \in \mathbb{R}^d$ (e.g., to $\mathbf{0}$)
Loop forever (for each episode):
  Initialize S (first state of episode)
  $I \leftarrow 1$
  Loop while S is not terminal (for each time step):
    $A \sim \pi(\cdot|S, \boldsymbol{\theta})$
    Take action A, observe S', R
    $\delta \leftarrow R + \gamma \hat{v}(S',\mathbf{w}) - \hat{v}(S,\mathbf{w})$ (if S' is terminal, then $\hat{v}(S',\mathbf{w}) \doteq 0$)
    $\mathbf{w} \leftarrow \mathbf{w} + \alpha^{\mathbf{w}} \delta \nabla \hat{v}(S,\mathbf{w})$
    $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha^{\boldsymbol{\theta}} I \delta \nabla \ln \pi(A|S, \boldsymbol{\theta})$
    $I \leftarrow \gamma I$
    $S \leftarrow S'$

REINFORCE with Baseline (episodic), for estimating $\pi_{\boldsymbol{\theta}} \approx \pi_*$

Input: a differentiable policy parameterization $\pi(a|s, \boldsymbol{\theta})$
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  Loop for each step of the episode $t = 0, 1, \ldots, T-1$:
    $G \leftarrow \sum_{k=t+1}^{T} \gamma^{k-t-1} R_k$ $\qquad (G_t)$
    $\delta \leftarrow G - \hat{v}(S_t,\mathbf{w})$
    $\mathbf{w} \leftarrow \mathbf{w} + \alpha^{\mathbf{w}} \delta \nabla \hat{v}(S_t,\mathbf{w})$
    $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha^{\boldsymbol{\theta}} \gamma^t \delta \nabla \ln \pi(A_t|S_t, \boldsymbol{\theta})$

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- And updating *both* value functions by e.g. TD learning

Summary of Policy Gradient Algorithms

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$$= \mathbb{E}_{\pi_\theta}[\nabla_\theta \log \pi_\theta(s,a) A_w(s,a)] \quad \text{Advantage Actor-Critic (A2C)}$$
$$= \mathbb{E}_{\pi_\theta}[\nabla_\theta \log \pi_\theta(s,a) \delta]$$

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&= \mathbb{E}_{\pi_\theta}[\nabla_\theta \log \pi_\theta(s,a) A_w(s,a)] && \text{Advantage Actor-Critic (A2C)} \\
&= \mathbb{E}_{\pi_\theta}[\nabla_\theta \log \pi_\theta(s,a) \delta] && \text{TD Actor-Critic}
\end{aligned}$$

- Each leads a stochastic gradient ascent algorithm
- Critic uses policy evaluation (e.g. MC or TD learning) to estimate $Q_\pi(s,a)$, $A_\pi(s,a)$ or $V_\pi(s)$.

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- **Advantage**: the policy gradient updates are done using the advantage function $A(s, a)$
- **Actor:** this is an actor-critic method which involves a policy that updates with the help of learned state-value functions.

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- Even one can explicitly use different exploration policies in each actor-learner to maximize diversity
- Asynchronism can be extended to other update mechanisms (SARSA, Q-learning, etc) but it works better in Advantage Actor critic setting

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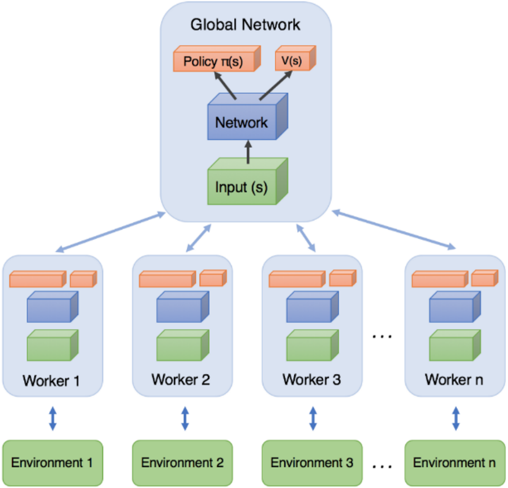

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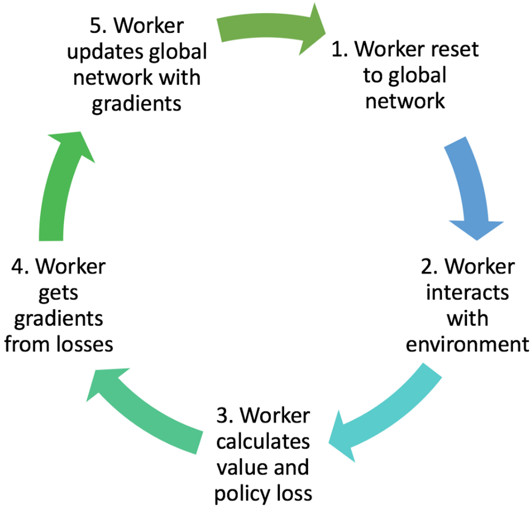

Asynchronous Advantage Actor Critic (A3C)

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

// Assume global shared parameter vectors θ and θ_v and global shared counter $T = 0$
// Assume thread-specific parameter vectors θ' and θ'_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}
        $t \leftarrow t + 1$
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    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 θ': $d\theta \leftarrow d\theta + \nabla_{\theta'} \log \pi(a_i|s_i;\theta')(R - V(s_i;\theta'_v))$
        Accumulate gradients wrt θ'_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 θ using $d\theta$ and of θ_v using $d\theta_v$.
until $T > T_{max}$