Machine Learning

Lecture 14: Policy-Based Deep Reinforcement Learning

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This set of notes is based on the references listed at the end and internet resources.

Outline

Value-Based RL vs Policy-Based RL

- **Value-based RL**:

$$\{(s, a, r, s')\} \Rightarrow Q(s, a : \theta) \Rightarrow \pi^*(s) = \arg\max_a Q(s, a : \theta)$$

  where π^* is a deterministic policy.

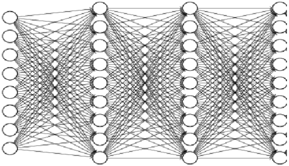
- **Policy-based RL**

$$\{(s, a, r, s')\} \Rightarrow \pi(a|s)$$

  where $\pi(a|s)$ is a stochastic policy.

- For a given s, $\pi(a|s)$ is a distribution over actions, and is represented as a neural network:

$\mathbf{s}$



$\pi_\theta(\mathbf{a}|\mathbf{s})$

Acting according to Stochastic Policy

$$\begin{array}{ccccccccc} & p(s) & & \pi_\theta(a|s_0) & & p(s'|s_0,a_0) & & \pi_\theta(a|s_1) & & p(s'|s_1,a_1) \\ & \wr & & \wr & & \wr & & \wr & & \wr \\ \tau: & s_0 & & \xrightarrow[r_0]{a_0} & & s_1 & & \xrightarrow[r_1]{a_1} & & s_2 \longrightarrow \cdots \end{array}$$

Trajectory

prob of τ: $\pi_\theta(\tau) = p(s_0)\, \pi_\theta(a_0|s_0)\, p(s_1|s_0,a_0)\, \pi_\theta(a_1|s_1)\, p(s_2|s_1,a_1) \cdots$

$$= p(s_0) \prod_t \pi_\theta(a_t|s_t)\, p(s_{t+1}|s_t,a_t)$$

Reward: $r(\tau) = r_0 + \gamma r_1 + \gamma^2 r_2 + \cdots$

$$J(\theta) = E_{\tau \sim \pi_\theta(\tau)}[r(\tau)]$$

Expected cumulative reward for following $\pi_\theta(a|s)$

Learning: $\max_\theta J(\theta)$

$$\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$$

Acting according to Stochastic Policy

- Suppose an agent interacts with its environment by following a stochastic policy $\pi_\theta(a|s)$ until an episode ends:
  - Experience trajectory τ: $s_0, a_0, r_0, \ldots, s_T, a_T, r_T$
  - At each time point t, an action a_t is sampled from the distribution $\pi_\theta(a|s_t)$
  - The probability of an experience trajectory is:

$$\pi_\theta(\tau) = p(s_0) \prod_{t=0}^{T} \pi_\theta(a_t|s_t) p(s_{t+1}|s_t, a_t) \tag{1}$$

Objective of the Policy Gradient Method

- Because of stochasticity in environment $p(s_{t+1}|s_t)$ and in action selection $\pi_\theta(a_t|s_t)$, the trajectory, and hence the total reward, will be different in different runs of the process.
- The expected total reward is:

$$J(\theta) = E_{\tau\sim\pi_\theta(\tau)}[r(\tau)] = E_{\tau\sim\pi_\theta(\tau)}[\sum_t \gamma^t r_t]$$

- The objective of policy gradient is to maximize $J(\theta)$:

$$\theta^* = \arg\max_\theta J(\theta)$$

- This is done via gradient ascent, and the output is (an approximation of) the optimal policy $\pi_{\theta^*}(a|s)$:

$$\theta \leftarrow \theta + \alpha\nabla_\theta J(\theta)$$

Policy Gradients

$$
\begin{aligned}
\nabla_\theta J(\theta) &= \nabla_\theta E_{\tau \sim \pi_\theta(\tau)}[r(\tau)] \\
&= \nabla_\theta \int r(\tau)\pi_\theta(\tau) d\tau \\
&= \int r(\tau)\nabla_\theta \pi_\theta(\tau) d\tau \\
&= \int r(\tau)\pi_\theta(\tau)\nabla_\theta \log \pi_\theta(\tau) d\tau \qquad \text{(the log-gradient trick)} \\
&= E_{\tau \sim \pi_\theta(\tau)}[\nabla_\theta \log \pi_\theta(\tau) r(\tau)]
\end{aligned}
$$

Policy Gradients

- Because of Equation (1), we have

$$\log \pi_\theta(\tau) = \log p(s_0) + \sum_t \log \pi_\theta(a_t|s_t) + \sum_t \log p(s_{t+1}|s_t)$$

- Hence,

$$\begin{aligned}
& E_{\tau\sim\pi_\theta(\tau)}[\nabla_\theta \log \pi_\theta(\tau) r(\tau)] \\
= \quad & E_{\tau\sim\pi_\theta(\tau)}[\nabla_\theta (\log p(s_0) + \sum_t \log \pi_\theta(a_t|s_t) + \sum_t \log p(s_{t+1}|s_t)) r(\tau)] \\
= \quad & E_{\tau\sim\pi_\theta(\tau)}[\sum_t \nabla_\theta \log \pi_\theta(a_t|s_t) r(\tau)] \\
\approx \quad & \frac{1}{N}\sum_{i=1}^{N}\sum_t \nabla_\theta \log \pi_\theta(a_t^i|s_t^i) r(\tau^i)
\end{aligned}$$

where $\{\tau^i = \{s_0^i, a_0^i, r_0^i, s_1^i, a_1^i, r_1^i, \ldots\}_{i=1}^N$ is a collection of N sample trajectories.

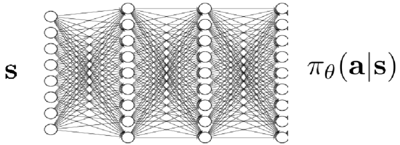
The REINFORCE Algorithm

- REINFORCE algorithm (Williams 1992):

  Repeat:

  1. sample $\{\tau^i\}_{i=1}^N$ from $\pi_\theta(a_t|s_t)$ (run the current policy)
  2. $\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_i \sum_t \nabla_\theta \log \pi_\theta(a_t^i|s_t^i) r(\tau^i)$
  3. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

- The term $\nabla_\theta \log \pi_\theta(a_t|s_t)$ is calculated on the policy network:



Supervised Learning, Imitation Learning, and RL (REINFORCE)

supervised learning $\{x_i, y_i\}_{i=1}^{N} \Rightarrow p(y|x,\theta)$

$$\theta \leftarrow \theta + \alpha \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \log p(y_i | x_i, \theta)$$

max likelihood of model / prob of data

---

current setting: $\{(s_t^i, a_t^i) \mid i=1,\dots,N,\ t=1,\dots,T\}$

$$\theta \leftarrow \theta + \alpha \frac{1}{N} \sum_i \sum_t \nabla_\theta \log p(a_t^i | s_t^i)$$

max prob of data / prob of actions

Imitation learning: learn from expert demo

REINFORCE

$$\theta \leftarrow \theta + \alpha \frac{1}{N} \sum_i \sum_t \nabla_\theta \log p(a_t^i | s_t^i)\, r(\tau^i)$$

$r(\tau^i) > 0$, increase the prob of action in τ^i

$r(\tau^i) < 0$ decrease the prob of actions in τ^i

Interpretation of the REINFORCE Update Rule

$$\theta \leftarrow \theta + \alpha \sum_i \sum_t \nabla_\theta \log \pi_\theta(a_t^i|s_t^i) r(\tau^i)$$

- Changing θ in the direction of $\nabla_\theta \log \pi_\theta(a_t^i|s_t^i)$ would increase the probability of the action a_t^i.
- If $r(\tau^i) < 0$, we change θ in the opposite direction and hence reduce the probability of a_t^i
  - So, **the update rule makes bad experiences less likely**.
- If $r(\tau^i) > 0$, we change θ so as to increase the probability of a_t^i
  - So, **the update rule makes good experiences more likely**
- So, the REINFORCE update formalizes the notion of "trial and error".

On-Policy vs Off-Policy

- REINFORCE is an **on-policy** algorithm because all the data used to improve the current policy are collected using the policy itself.

REINFORCE algorithm:

1. sample $\{\tau^i\}$ from $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$ (run the policy)
2. $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_t \nabla_\theta \log \pi_\theta(\mathbf{a}_t^i|\mathbf{s}_t^i)\right) \left(\sum_t r(\mathbf{s}_t^i, \mathbf{a}_t^i)\right)$
3. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

On-Policy vs Off-Policy

- DQN is an **off-policy** algorithm because some of the data used to improve the current policy are collected using other policies.

Repeat:

- Take action a in current state s, observe r and s'; add experience tuple (s, a, s', r) to a buffer D; $s \leftarrow s'$
- Sample a minibatch $B = \{s_j, a_j, s'_j, r_j\}$ from D.
- Update the parameters

$$\theta \leftarrow \theta - \alpha \nabla_\theta \sum_j ([r(s_j, a_j) + \gamma \max_{a'_j} Q(s'_j, a'_j; \theta^-)] - Q(s_j, a_j; \theta))^2$$

- $\theta^- \leftarrow \theta$ in every C steps.

On-Policy vs Off-Policy

- Q-learning is off-policy even without experience replay because the agent does not necessarily take the action $a' = \arg\max_{a'} Q(s', a')$ in the next step
  - The action a' used for update is chosen using the current Q, but
  - The next action is chosen using the updated Q.

- Initialize $Q(s, a)$ arbitrarily.
- Repeat (for each episode)
  - Pick initial state s.
  - **Repeat**
    - Choose a for the state s (ϵ-greedy with $\arg\max_a Q(s, a)$)
    - Take action a, observe r and s'
    - Update:

$$
\begin{aligned}
Q(s, a) &\leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)] \\
s &\leftarrow s'
\end{aligned}
$$

  - **until** s is terminal

Policy Gradient has High Variance

$$\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t}\nabla_\theta \log \pi_\theta(a_t^i|s_t^i)r(\tau^i)$$

- The policy gradient is estimated using N trajectory samples.
- N cannot be large because running a policy is costly.
- Because we can use only a small number of trajectory samples, the variance is high.

Reducing Variance using Causality

$$\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}\nabla_\theta \log \pi_\theta(a_t^i|s_t^i) r(\tau^i)$$
$$\approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}[\nabla_\theta \log \pi_\theta(a_t^i|s_t^i)\sum_{t'=0}^{T}\gamma^{t'} r_{t'}^i]$$

- An action a_t^i taken at time point t does not affect only rewards at earlier time points.
- Hence, rewards before time t should not be considered when optimizing a_t.
- So, we use the following gradient instead:

$$\frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}[\nabla_\theta \log \pi_\theta(a_t^i|s_t^i)\sum_{t'=t}^{T}\gamma^{t'} r_{t'}^i]$$

- The variance of $\sum_{t'=t}^{T}\gamma^{t'} r_{t'}^i$ is smaller than that of $\sum_{t'=0}^{T}\gamma^{t'} r_{t'}^i$ because it is influenced by less stochasticity.

Reducing Variance using Baselines

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t^i | s_t^i) r(\tau^i)$$

- Another way to reduce the variance is to use

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t^i | s_t^i) (r(\tau^i) - b)$$

  where the **baseline** b is given by:

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

Reducing Variance using Baselines: Analogy

- Let $x_1, x_2, \ldots, x_n$ be i.i.d random variables and b be another random variable.

$$
\begin{aligned}
V(\sum_{i=1}^{n}(x_i - b)) &\approx \sum_{i=1}^{n} V(x_i - b) \quad \text{(strictly true if independent)} \\
&= \sum_{i=1}^{n}(E[(x_i - b)^2] - (E[x_i - b])^2) \\
&= \sum_{i=1}^{n} E[(x_i - b)^2] - \sum_{i=1}^{n}(E[x_i - b])^2
\end{aligned}
$$

- The first term is minimized when $b = \frac{1}{n}\sum_{i=1}^{n} x_i$
- The second term is also minimized when $b = \frac{1}{n}\sum_{i=1}^{n} x_i$.

Baseline does not Make the Estimation Unbiased

- This is the policy gradient

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

- Subtracting a baseline $b = E_{\tau\sim\pi_\theta(\tau)}[r(\tau)]$, we get

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

- This does not introduce bias because

$$\begin{aligned}
E_{\tau\sim\pi_\theta(\tau)}[\nabla_\theta \log \pi_\theta(\tau) b] &= \int \pi_\theta(\tau)\nabla_\theta \log \pi_\theta(\tau) b d\tau \\
&= \int \nabla_\theta \pi_\theta(\tau) b d\tau \\
&= b\nabla_\theta \int \pi_\theta(\tau) d\tau \\
&= 0
\end{aligned}$$

Advanced Policy Gradient Methods

- Problems with policy gradient:
  - The parameters θ are changed only a little bit at each gradient step because it does not make efficient use of the sampled trajectories $\{\tau^i\}$.
  - Large learning rate can lead to performance collapse, while small learning rate implies slow learning.
- Advanced policy gradient methods:
  - Purpose: Make efficient use of data and find an update rule that is just right.
  - Methods: Natural policy gradient (Peters and Schall 2008); Trusted region policy optimization (Schulman et al. 2015); Proximal policy optimization (Schulman et al. 2017).

Outline

1 Policy Gradients

2 Actor-Critic Algorithms

Optimal Value Functions and Value Functions of Policy

- Optimal value functions:
  - $V^*(s)$: Total reward for acting optimally from state s.
  - $Q^*(s,a)$: total reward for, starting from s, taking action a and acting optimally after that.

$$V^*(s) = \max_a Q^*(s,a).$$

- Value functions of a policy π:
  - $V^\pi(s)$: Total reward for following π from state s.
  - $Q^\pi(s,a)$: total reward for, starting from s, taking action a and then following π.

$$V^\pi(s) = E_{a \sim \pi(a|s)}[Q^\pi(s,a)].$$

- Actor-Critic Algorithms: Policy gradient with policy evaluation, i.e., $Q^\pi(s,a)$.

Key Idea of Actor-Critic Algorithms

- The **advantage function**:

$$A^{\pi}(s_t, a_t) = Q^{\pi}(s_t, a_t) - V^{\pi}(s_t)$$

  tells us how good the action a_t is relative to the average.

- Using the advantage function, we can write our policy gradient estimate as follows:

$$\nabla_{\theta} J(\theta) \quad \approx \quad \frac{1}{N} \sum_{i=1}^{N} \sum_{t=0}^{T} [\gamma^t \nabla_{\theta} \log \pi_{\theta}(a_t^i | s_t^i) A^{\pi}(s_t^i, a_t^i)],$$

  - Increase probabilities of actions that are better than average,
  - Decrease probabilities of actions worse than average.

Key Idea of Actor-Critic Algorithms

REINFORCE

Actor: $s \rightarrow \boxed{\theta} \rightarrow \pi_\theta(a|s)$

$$\theta \leftarrow \theta + \alpha \sum_i \sum_t \nabla_\theta \log \pi_\theta(a_t^i | s_t^i) \underline{r(\tau^i)}$$

Actor-Critic

$$\theta \leftarrow \theta + \alpha \sum_i \sum_t \nabla_\theta \log \pi_\theta(a_t^i | s_t^i) \underline{A^\pi(s_t^i, a_t^i)}$$

$A^\pi(s_t^i, a_t^i) > 0$, a_t^i better than average, prob of a_t^i increased

$A^\pi(s_t^i, a_t^i) < 0$, a_t^i worse than average, prob of a_t^i decreased

$$A^\pi(s_t^i, a_t^i) \approx r_t^i + \gamma V^\pi(s_{t+1}^i) - V^\pi(\underline{s_t^i})$$

How to Estimate the Advantage Function?

- In general, we have

$$Q^{\pi}(s,a) = r(s,a) + \gamma \sum_{s'} V^{\pi}(s')P(s'|s,a).$$

- Estimating $Q^{\pi}(s_t, a_t)$ using one sample (s_{t+1}) of s',

$$Q^{\pi}(s_t, a_t) \approx r(s_t, a_t) + \gamma V^{\pi}(s_{t+1}).$$

- Hence we can estimate $A^{\pi}(s_t, a_t)$ using

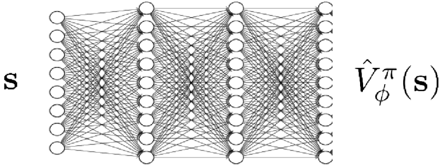
$$A^{\pi}(s_t, a_t) \approx r(s_t, a_t) + \gamma V^{\pi}(s_{t+1}) - V^{\pi}(s_t)$$

  where $s_{t+1} \sim P(s_{t+1}|s_t, a_t)$, which can be obtained by letting agent act for one step.

- If we can estimate $V^{\pi}(s_t)$, then we can get $A^{\pi}(s_t, a_t)$ and perform gradient asent.

How to Estimate the Value Function $V^{\pi}(s_t)$?

- This is called the **policy evaluation** problem.
- To learn the function from data, we use a neural network with parameters ϕ to represent it. The output for input s is denoted by $\hat{V}^{\pi}_{\phi}(s)$.



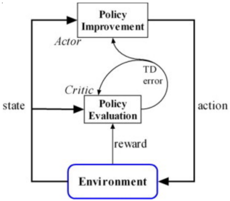
- After obtaining a collection of experience tuples $\{(s_i, a_i, s_i', r_i)\}$, we update ϕ via backprop based on the following training set:

$$\{(s_i, r_i + \gamma \hat{V}^{\pi}_{\phi}(s_i')\}$$

Online Actor-Critic algorithm

Repeat:

1. Take action $a \sim \pi_\theta(a|s)$, get (s, a, s', r).
2. Update Critic parameters ϕ using L2 loss and training data:
$$\{(s, r + \gamma \hat{V}^\pi_\phi(s')\}$$
3. $\hat{A}^\pi(s, a) \leftarrow r + \gamma \hat{V}^\pi_\phi(s') - \hat{V}^\pi_\phi(s)$
4. Update actor parameters:
$$\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(a|s) \hat{A}^\pi(s, a)$$



Batch Actor-Critic algorithm

Repeat:

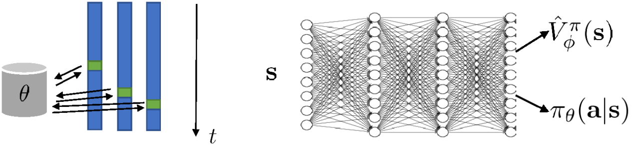
1. Sample experiences $\{(s_i, a_i, s'_i, r_i)\}$ by following π_θ for multiple steps.
2. Update Critic parameters ϕ using L2 loss and training data

$$\{(s_i, r_i + \gamma \hat{V}^\pi_\phi(s'_i))\}$$

3. $\hat{A}^\pi(s_i, a_i) \leftarrow r_i + \gamma \hat{V}^\pi_\phi(s'_i) - \hat{V}^\pi_\phi(s_i) \qquad \forall i$
4. Update actor parameters:

$$\theta \leftarrow \theta + \alpha \sum_i \nabla_\theta \log \pi_\theta(a_i|s_i) \hat{A}^\pi(s_i, a_i)$$

Asynchronous Advantage Actor-Critic (A3C)

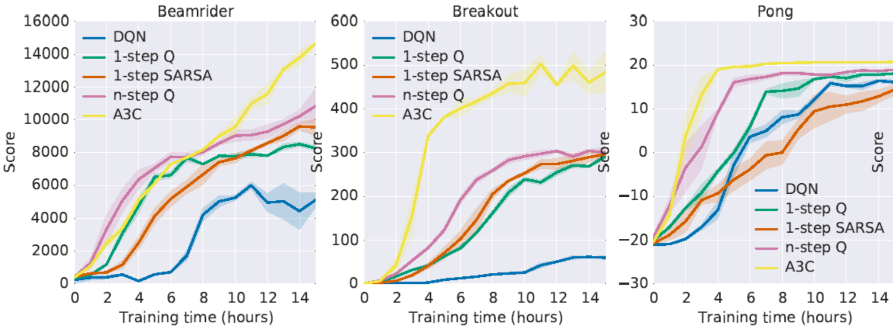


- Run multiple learners in parallel and let them take turns to update parameters .
- Decorrelates data used in learning. (Alternative to experience relay).
- Different learners explore different parts of environment.
- Actor and Critic share the same network

https://www.youtube.com/watch?v=Ajjc08-iPx8&sns=tw&

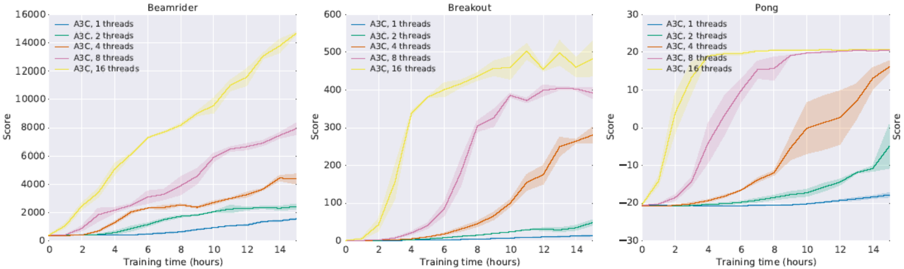
Comparisons on Atari Games: Learning Speed

- DQN on single GPU
- Asynchronous methods use 16 CPU cores



Comparisons on Atari Games: Learning Speed

- More cores mean faster learning



Comparisons on Atari Games: Performance [1]

Method	Training Time	Mean	Median
DQN	8 days on GPU	121.9%	47.5%
Gorila	4 days, 100 machines	215.2%	71.3%
D-DQN	8 days on GPU	332.9%	110.9%
Dueling D-DQN	8 days on GPU	343.8%	117.1%
Prioritized DQN	8 days on GPU	463.6%	127.6%
A3C, FF	1 day on CPU	344.1%	68.2%
A3C, FF	4 days on CPU	496.8%	116.6%
A3C, LSTM	4 days on CPU	623.0%	112.6%

Table 1. Mean and median human-normalized scores on 57 Atari games using the human starts evaluation metric.

[1] `github.com/vmayoral/basic_reinforcement_learning/blob/master/tutorial12/README.md`

Proximal Policy Optimization Algorithms (PPO) [2]

- Recall Actor-Critic Algorithm:

$$\begin{aligned}\nabla_\theta J(\theta) &\approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}[\gamma^t \nabla_\theta \log \pi_\theta(a_t^i|s_t^i) A^\pi(s_t^i, a_t^i)] \\ &= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}[\gamma^t \frac{\nabla_\theta \pi_\theta(a_t^i|s_t^i)}{\pi_\theta(a_t^i|s_t^i)} A^\pi(s_t^i, a_t^i)]\end{aligned}$$

- To get PPO, replace π_θ in the denominator with an old policy

$$\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}[\gamma^t \nabla_\theta \frac{\pi_\theta(a_t^i|s_t^i)}{\pi_{old}(a_t^i|s_t^i)} A^\pi(s_t^i, a_t^i)]$$

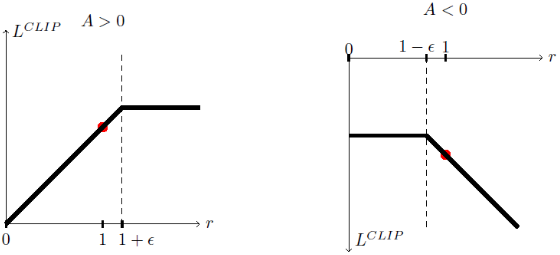
- The idea of PPO is keep $r_t^i = \frac{\pi_\theta(a_t^i|s_t^i)}{\pi_{old}(a_t^i|s_t^i)}$ close to 1 so that the gradient update step does not introduce too much change in the policy, and hence make the training more **stable**. Often used.

[2] Schulman et al. "Proximal policy optimization algorithms." arXiv preprint arXiv:1707.06347 (2017).

Proximal Policy Optimization Algorithms (PPO)

- Let $\hat{r}_t^i = min(r_t^i, clip(r_t^i, 1-\epsilon, 1+\epsilon))$. PPO uses

$$\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T}[\gamma^t \nabla_\theta \hat{r}_t^i A^\pi(s_t^i, a_t^i)]$$



$\nabla_\theta L^{CLIP} = 0$ when $r_t^i \notin (1-\epsilon, 1+\epsilon)$, where $L^{CLIP} = clip(r_t^i, 1-\epsilon, 1+\epsilon)$

Soft Actor-Critic [3]

- Policy gradient and Actor-Critic:

$$\pi^* = \arg\max_{\pi} E_{\tau\sim\pi}[\sum_{t=0}^{\infty}\gamma^t r(s_t, a_t, s_{t+1})]$$

- **Soft Actor-Critic (SAC)**:

$$\pi^* = \arg\max_{\pi} E_{\tau\sim\pi}[\sum_{t=0}^{\infty}\gamma^t (r(s_t, a_t, s_{t+1}) + \alpha H(\pi(\cdot|s_t)))]$$

where $H(\pi(\cdot|s_t))$ is the entropy of the policy, and α is the temperature parameter.

  - SAC prefers policies with high entropy, which results in better exploration performance.
  - Consequently, SAC is more stable and more sample efficient than others algorithms such as DDPG and A3C.

[3] https://spinningup.openai.com/en/latest/algorithms/sac.html

Haarnoja *et al*, 2018. Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor

Sample Complexity (Sergey Levine)

gradient-free methods
(e.g. NES, CMA, etc.)

10x

fully online methods
(e.g. A3C)

10x

policy gradient methods
(e.g. TRPO)

10x

replay buffer value estimation methods
(Q-learning, DDPG, NAF, SAC, etc.)

10x

model-based deep RL
(e.g. PETS, guided policy search)

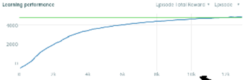
10x

model-based "shallow" RL
(e.g. PILCO)

Evolution Strategies as a Scalable Alternative to Reinforcement Learning

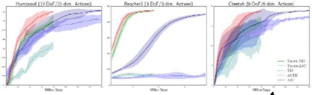
Tim Salimans[1] Jonathan Ho[1] Xi Chen[1] Ilya Sutskever[1]

half-cheetah (slightly different version)



TRPO+GAE (Schulman et al. '16)

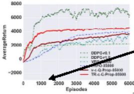
10,000,000 steps
(10,000 episodes)
(~ 1.5 days real time)



Wang et al. '17

100,000,000 steps
(100,000 episodes)
(~ 15 days real time)

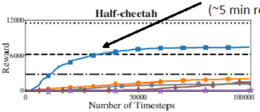
half-cheetah



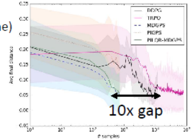
Gu et al. '16

1,000,000 steps
(1,000 episodes)
(~3 hours real time)

30,000 steps
(30 episodes)
(~5 min real time)



Chua et a. '18: Deep Reinforcement Learning in a Handful of Trials



Chebotar et al. '17 (note log scale)

about 20 minutes of experience on a real robot

Value-Based RLvs Policy-Based RL

- Value-based RL:
  - Pros: Can be off-policy, can use experience reply, more sample efficient
  - Cons: Indirect, accuracy estimation of Q is difficulty, might lead to unstable policy.
- Policy-based RL:
  - Pros: Directly optimize policy, more stable.
  - Cons: It is on-policy, not sample efficient.
- Recent Trends: Combine the best of two worlds.