Deep Reinforcement Learning

Overview of main articles
Part 2. Policy gradient algorithms

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MSU

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Basic policy gradient methods

Direct optimization

Recall RL goal:

$$\mathbb{E}_{\pi(\theta)}\mathbb{E}_{\mathcal{T}} R \to \max_{\theta}$$

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Options:

* Metaheurisics
* Log-derivative trick[1].

[1] aka REINFORCE

Stochasitc estimators optimization via log-derivative trick

$$\nabla_\theta \mathbb{E}_{x \sim \pi(x,\theta)} f(x) = \nabla_\theta \int \pi(x,\theta) f(x) dx$$

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$$\nabla_\theta \pi(\theta) = \pi(\theta) \nabla_\theta \log \pi(\theta)$$

$$= \int \pi(x,\theta) \nabla_\theta \log \pi(x,\theta) f(x) dx = \mathbb{E}_{x\sim\pi(x,\theta)} \nabla_\theta \log \pi(x,\theta) f(x)$$

From importance sampling point of view

Recall Importance Sampling. For arbitrary distribution $\phi(x)$:

$$\mathbb{E}_{x\sim\pi(x,\theta)} f(x) = \mathbb{E}_{x\sim\phi(x)} \frac{\pi(x,\theta)}{\phi(x)} f(x)$$

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Note: that is the same gradient as with log-derivative trick[2].

[2] really? Could it even happen otherwise?

REINFORCE

Let's apply log-derivative trick to our goal!

$$\nabla_\theta \mathbb{E}_{\pi(\theta)} \mathbb{E}_{\mathcal{T}} R = \mathbb{E}_{\pi(\theta)} \nabla_\theta \log \pi(\theta) \mathbb{E}_{\mathcal{T}} R$$

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$$\nabla_\theta \mathbb{E}_{\pi(\theta)} \mathbb{E}_{\mathcal{T}} R = \mathbb{E}_{\pi(\theta)} \nabla_\theta \log \pi(\theta) \mathbb{E}_{\mathcal{T}} R \approx$$

We can estimate this gradient using Monte-Carlo by playing, let's say, one game:

$$\approx \sum_{t}^{T} \nabla_\theta \log \pi(a_t \mid s_t, \theta) R$$

Problems of REINFORCE

- × Doesn't work.

Problems of REINFORCE

- $\times$ Doesn't work.
  - **Reason:** *high variance* of Monte-Carlo gradient estimation.

Problems of REINFORCE

× Doesn't work.

- **Reason:** *high variance* of Monte-Carlo gradient estimation.
- you can play more than one game for one gradient step, but that doesn't help much.

Baseline

Proprosition

For arbitrary distribution $\pi(\theta)$:

$$\mathbb{E}\nabla_\theta \log \pi(\theta) = \int \nabla_\theta \pi(\theta) = \nabla_\theta \int \pi(\theta) = \nabla_\theta 1 = 0$$

Baseline

Proprosition

For arbitrary distribution $\pi(\theta)$:

$$\mathbb{E}\nabla_\theta \log \pi(\theta) = \int \nabla_\theta \pi(\theta) = \nabla_\theta \int \pi(\theta) = \nabla_\theta 1 = 0$$

Adding $\mathbb{E}\nabla_\theta \log \pi(\theta) b$ for some b to gradient estimate will not lead to bias, but may change variance.

Lowest variance baseline

Theorem

$$b = \frac{\mathbb{E}(\nabla_\theta \log \pi(\theta))^2 R}{\mathbb{E}(\nabla_\theta \log \pi(\theta))^2}$$

is the baseline which leads to the lowest variance.

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is the baseline which leads to the lowest variance.

* similar to average reward, which is also a good baseline.

Careful REINFORCE

Strange thing: our gradient estimate depends on R, which includes reward in the first state $r(s_0)$, where we haven't performed any actions.[3]

[3] did we make any mistake?

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Let's untangle our goal:

$$\nabla_\theta \mathbb{E}_{p(s_1)} \left(r(s_1) + \mathbb{E}_{a_1 \sim \pi(s_1, \theta)} \mathbb{E}_{p(s_2 | s_1, a)} \left[r(s_2) + \ldots \right] \right)$$

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After carefully applying log-derivative trick:

$$= \mathbb{E} \sum_t^T \nabla_\theta \log \pi(a_t \mid s_t, \theta) \left(\sum_{t'=t+1}^T r(s_{t'}) \right)$$

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✓ that's much better!

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Actor-critic

Note: $\sum_{t'=t+1}^{T} r(s_{t'})$ is estimation of $Q^{\pi}(s_t, a_t)$!

$$\nabla = \mathbb{E} \sum_{t}^{T} \nabla_\theta \log \pi(a_t \mid s_t, \theta) \left(\sum_{t'=t+1}^{T} r(s_{t'}) \right)$$

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Better estimation of $Q^{\pi}(s, a)$
should lead to lower variance.

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$$
\begin{aligned}
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&= \mathbb{E} \sum_t^T \nabla_\theta \log \pi(a_t \mid s_t, \theta) Q^{\pi}(s_t, a_t)
\end{aligned}
$$

Better estimation of $Q^{\pi}(s, a)$
should lead to lower variance.

* π is an *actor*
* estimate of $Q^{\pi}(s, a)$ is a *critic*

Advantage Actor Critic

$$\nabla = \mathbb{E} \sum_{t}^{T} \nabla_\theta \log \pi(a_t \mid s_t, \theta) Q^\pi(s_t, a_t)$$

Let's insert some baseline:

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$$\nabla = \mathbb{E} \sum_{t}^{T} \nabla_\theta \log \pi(a_t \mid s_t, \theta) \left(Q^\pi(s_t, a_t) - b\right)$$

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Critic set up

Critic can be a second neural net!

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Options:

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✓ the least complex one! [5]

[4] can we just use Q-learning for this?
[5] why?

Critic learning

For given state s we can calculate a target $y = V^{\pi}(s) \approx \sum_{t'=t+1}^{T} r(s_{t'})$.

At the end of the game, make a step of gradient descent to teach critic.

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Alternative: $y = V^\pi(s) \approx r(s') + V^\pi(s')$

A2C: Complete algorithm

Advantage Actor-Critic (A2C) Algorithm:

- get (s, a, r, s')

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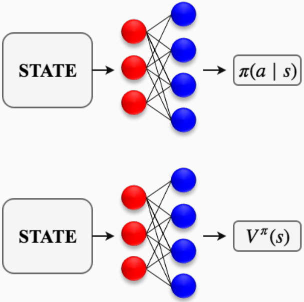
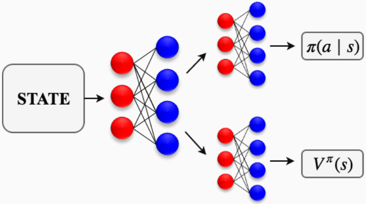
Check out this comic about A2C!

Dealing with two networks

Option 1: just two neural nets



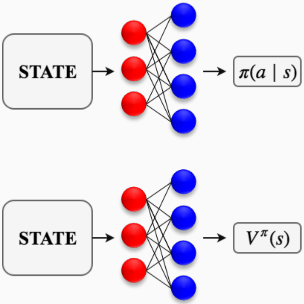


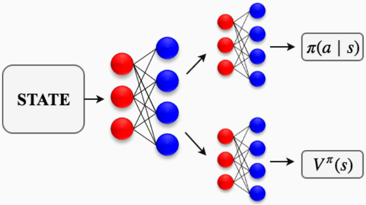
Option 2: shared feature extractor

Dealing with two networks

Option 1: just two neural nets

× obviously redundant





Option 2: shared feature extractor

× may be unstable

A2C: Resume

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- × batch_size $= 1$
    - ✓ do gradient descent step every N game steps.

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A2C: Resume

- ✓ lower variance!
- × yet policy gradient estimates are not unbiased anymore![6]
- × batch_size = 1
  - ✓ do gradient descent step every N game steps.
  - ✓ play several games in parallel.

[6] why?

Generalized Advantage Estimation (GAE) (2018)

Playing with Q and V...

$$\nabla = \mathbb{E} \sum_t^T \nabla_\theta \log \pi(a_t \mid s_t, \theta) \left(Q^\pi(s_t, a_t) - V^\pi(s_t) \right)$$

In practice we may use separate approximations for $Q^\pi(s_t, a_t)$ and baseline $b = V^\pi(s_t)$ and play with different ways to do that:

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In practice we may use separate approximations for $Q^\pi(s_t, a_t)$ and baseline $b = V^\pi(s_t)$ and play with different ways to do that:

$$\nabla = \mathbb{E} \sum_t^T \nabla_\theta \log \pi(a_t \mid s_t, \theta) \Psi_t$$

Ψ_t	**bias**	**variance**
$\sum_t^T r(s_t)$	0	very high
$Q^\pi(s_t, a_t)$	tolerant	high
$A^\pi(s_t, a_t)$	tolerant	low enough
$\sum_t^T r(s_t) - V^\pi(s_t)$	0	low

Eligibility trace

We may use critic only for baseline:

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× higher variance

Or use a compromise (for simplicity $\gamma = 1$):

$$\nabla = \mathbb{E}\sum_{t}^{T} \nabla_\theta \log \pi(a_t \mid s_t, \theta) \left(\sum_{t'=t+1}^{t+N} r(s_{t'}) + V^\pi(s_{t+N}) - V^\pi(s_t) \right)$$

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× new hyperparameter N

✓ regulates trade-off between variance and bias

GAE

So, for different N we have different advantage estimators.

GAE

So, for different N we have different advantage estimators.

Create an ensemble out of them!

GAE

So, for different N we have different advantage estimators.

Create an ensemble out of them!

Let $A^{\pi}_{(N)}(s_t, a_t)$ be a N-step advantage estimator:

$$A^{\pi}_{(N)} = \sum_{t'=t+1}^{t+N} r(s_{t'}) + V^{\pi}(s_{t+N}) - V^{\pi}(s_t)$$

GAE

So, for different N we have different advantage estimators.

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$$A^{\pi}_{(N)} = \sum_{t'=t+1}^{t+N} r(s_{t'}) + V^{\pi}(s_{t+N}) - V^{\pi}(s_t)$$

Let's take exponentially-weighted average:

$$A^{\pi}_{(\text{GAE})}(s_t, a_t) = (1-\lambda)(A^{\pi}_{(1)} + \lambda A^{\pi}_{(2)} + \lambda^2 A^{\pi}_{(3)} + \dots)$$

NEXT: TRPO