

Flappy Bird

Frame-Based Policy Gradient

Fall 2021

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Two New Knowledge


- Generalized Advantage Estimation (GAE)
 - UC Berkley CS285: Lecture 6, Part 4
 - [Video](#)
 - [Slides](#)
 - [Original paper](#)
- Proximal Policy Optimization (PPO)
 - University of Waterloo CS885: Lecture 15b
 - [Video](#)
 - [Slides](#)
 - [Original paper](#)

Outline

- Recap
- GAE
- PPO

Recap

- Policy gradient has 2 parts
 - Left part is a **log probability** of executing an action
 - Right part is an **advantage term**.

$\nabla \log \text{prob. of actions}$ 

Left part

1. $\sum_{t=0}^{\infty} r_t$: total reward of the trajectory.
2. $\sum_{t'=t}^{\infty} r_{t'}$: reward following action a_t .
3. $\sum_{t'=t}^{\infty} r_{t'} - b(s_t)$: baselined version of previous formula.

Right part: **Several formula can be chosen**

4. $Q^{\pi}(s_t, a_t)$: state-action value function.
5. $A^{\pi}(s_t, a_t)$: advantage function.
6. $r_t + V^{\pi}(s_{t+1}) - V^{\pi}(s_t)$: TD residual.

Outline

- Recap
- **GAE**
- PPO

Generalized Advantage Estimation (GAE)

Eligibility traces & n-step returns

$$\hat{A}_C^\pi(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + \gamma \hat{V}_\phi^\pi(\mathbf{s}_{t+1}) - \hat{V}_\phi^\pi(\mathbf{s}_t)$$

+ lower variance

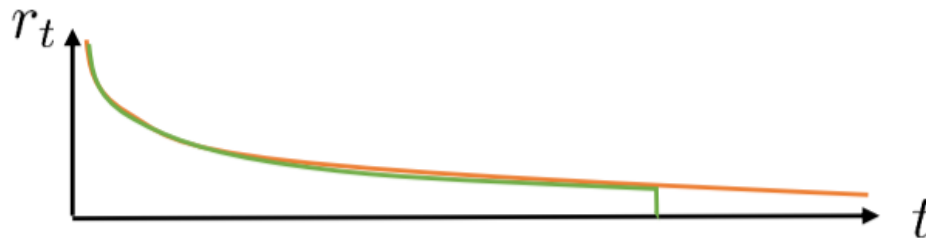
- higher bias if value is wrong (it always is)

$$\hat{A}_{MC}^\pi(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^{\infty} \gamma^{t'-t} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) - \hat{V}_\phi^\pi(\mathbf{s}_t)$$

+ no bias

- higher variance (because single-sample estimate)

Can we combine these two, to control bias/variance tradeoff?

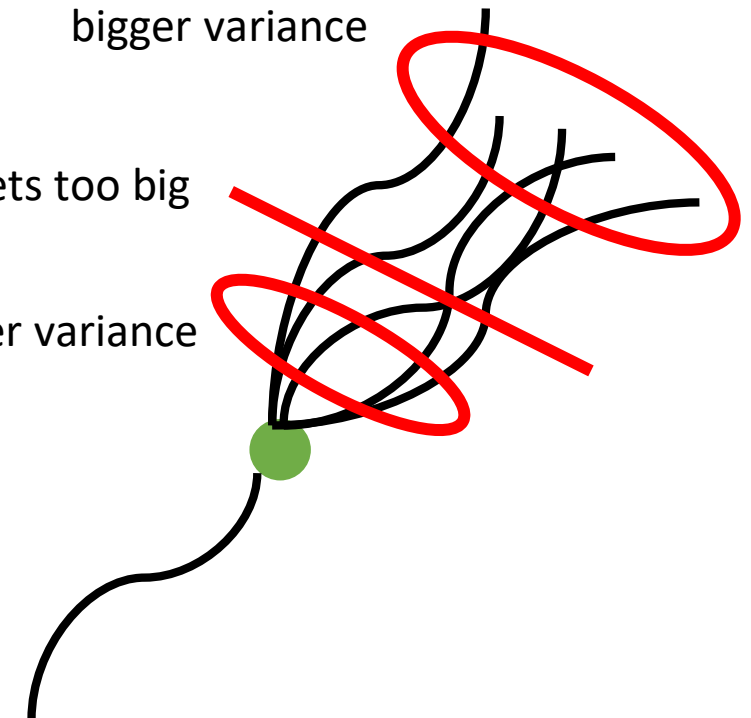


$$\hat{A}_n^\pi(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^{t+n} \gamma^{t'-t} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) - \hat{V}_\phi^\pi(\mathbf{s}_t) + \gamma^n \hat{V}_\phi^\pi(\mathbf{s}_{t+n})$$

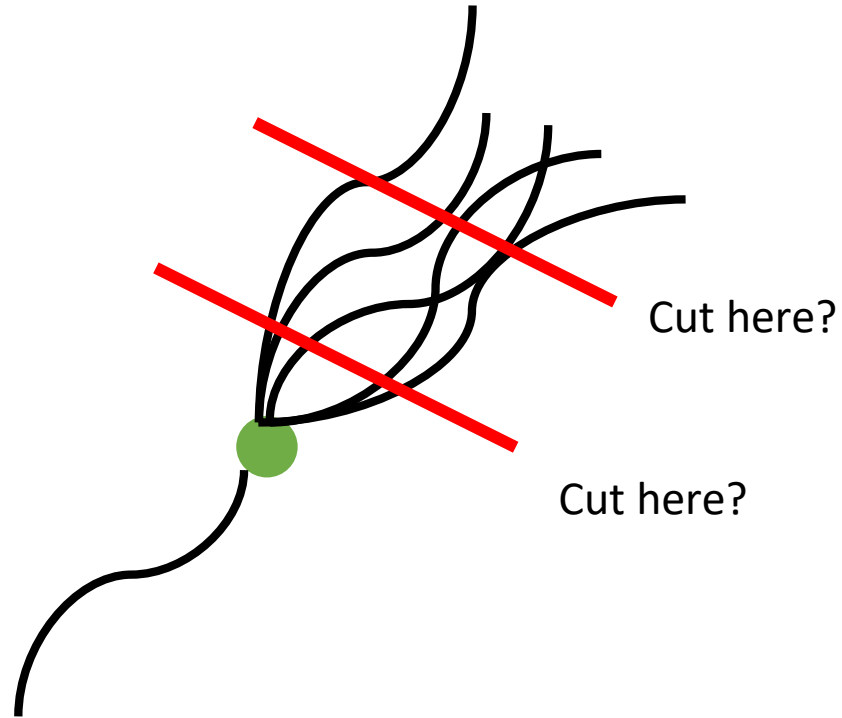
Cut here before variance gets too big

Smaller variance

bigger variance

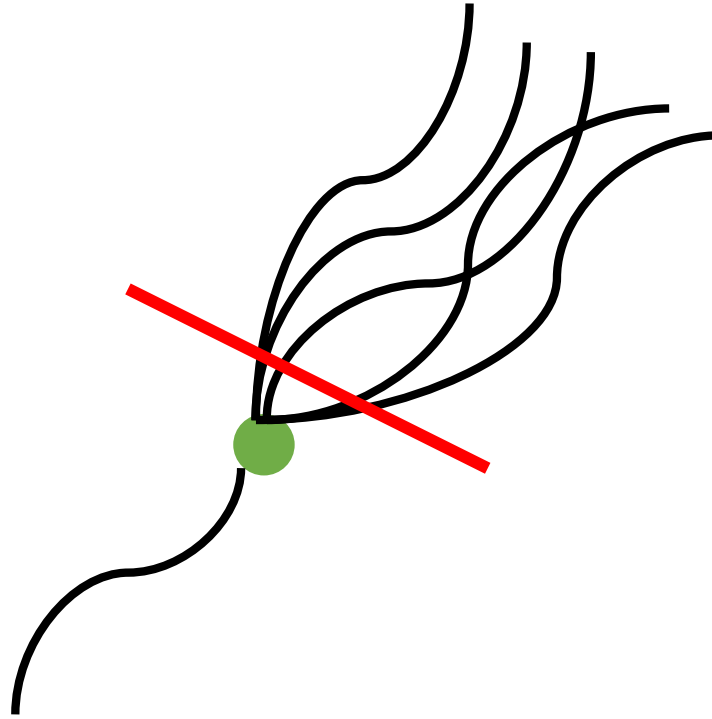


Do We Have to Choose Just One N?



Cut Everywhere All at Once

Cut everywhere all at once and use exponentially-weighted average to add up



The Derivative of GAE

$$\hat{A}_n^\pi(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^{t+n} \gamma^{t'-t} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) - \hat{V}_\phi^\pi(\mathbf{s}_t) + \gamma^n \hat{V}_\phi^\pi(\mathbf{s}_{t+n})$$



Cut at t+1: $\hat{A}_t^{(1)} := \delta_t^V = -V(s_t) + r_t + \gamma V(s_{t+1})$

Cut at t+2: $\hat{A}_t^{(2)} := \delta_t^V + \gamma \delta_{t+1}^V = -V(s_t) + r_t + \gamma r_{t+1} + \gamma^2 V(s_{t+2})$

Cut at t+3: $\hat{A}_t^{(3)} := \delta_t^V + \gamma \delta_{t+1}^V + \gamma^2 \delta_{t+2}^V = -V(s_t) + r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 V(s_{t+3})$

$$\hat{A}_t^{(k)} := \sum_{l=0}^{k-1} \gamma^l \delta_{t+l}^V = -V(s_t) + r_t + \gamma r_{t+1} + \cdots + \gamma^{k-1} r_{t+k-1} + \gamma^k V(s_{t+k})$$

$$\hat{A}_t^{(\infty)} = \sum_{l=0}^{\infty} \gamma^l \delta_{t+l}^V = -V(s_t) + \sum_{l=0}^{\infty} \gamma^l r_{t+l}, \quad \gamma^\infty V(s_{t+k}) \text{ becomes zero}$$

The Derivative of GAE (Con.)

exponential weighted average
↓

$$\begin{aligned} A_t^{\text{GAE}} &= \frac{A_t^{(1)} + \lambda A_t^{(2)} + \lambda^2 A_t^{(3)} + \lambda^3 A_t^{(4)} + \dots}{1 + \lambda + \lambda^2 + \lambda^3 + \dots} \\ &= \frac{A_t^{(1)} + \lambda A_t^{(2)} + \lambda^2 A_t^{(3)} + \lambda^3 A_t^{(4)} + \dots}{\frac{1 - (1 - \lambda^k) \approx 1}{1 - \lambda}} \\ &= (1 - \lambda) (A_t^{(1)} + \lambda A_t^{(2)} + \lambda^2 A_t^{(3)} + \lambda^3 A_t^{(4)} + \dots) \end{aligned}$$

The Derivative of GAE (Con.)

The generalized advantage estimator $\text{GAE}(\gamma, \lambda)$ is defined as the exponentially-weighted average of these k -step estimators:

$$\begin{aligned}
 \hat{A}_t^{\text{GAE}(\gamma, \lambda)} &:= (1 - \lambda) \left(\hat{A}_t^{(1)} + \lambda \hat{A}_t^{(2)} + \lambda^2 \hat{A}_t^{(3)} + \dots \right) \quad \text{Exponentially-weighted average} \\
 &= (1 - \lambda) \left(\delta_t^V + \lambda(\delta_t^V + \gamma \delta_{t+1}^V) + \lambda^2(\delta_t^V + \gamma \delta_{t+1}^V + \gamma^2 \delta_{t+2}^V) + \dots \right) \\
 &= (1 - \lambda) \left(\delta_t^V (1 + \lambda + \lambda^2 + \dots) + \gamma \delta_{t+1}^V (\lambda + \lambda^2 + \lambda^3 + \dots) \right. \\
 &\quad \left. + \gamma^2 \delta_{t+2}^V (\lambda^2 + \lambda^3 + \lambda^4 + \dots) + \dots \right) \\
 &= (1 - \lambda) \left(\delta_t^V \left(\frac{1}{1 - \lambda} \right) + \gamma \delta_{t+1}^V \left(\frac{\lambda}{1 - \lambda} \right) + \gamma^2 \delta_{t+2}^V \left(\frac{\lambda^2}{1 - \lambda} \right) + \dots \right) \\
 &= \sum_{l=0}^{\infty} (\gamma \lambda)^l \delta_{t+l}^V
 \end{aligned} \tag{16}$$

Two Special Case

There are two notable special cases of this formula, obtained by setting $\lambda = 0$ and $\lambda = 1$.

$$\text{GAE}(\gamma, 0) : \quad \hat{A}_t := \delta_t \quad = r_t + \gamma V(s_{t+1}) - V(s_t) \quad (17)$$

$$\text{GAE}(\gamma, 1) : \quad \hat{A}_t := \sum_{l=0}^{\infty} \gamma^l \delta_{t+l} = \sum_{l=0}^{\infty} \gamma^l r_{t+l} - V(s_t) \quad (18)$$

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Proximal Policy Optimization Algorithms

Now We've Learned GAE

$\nabla \log \text{prob. of actions}$  GAE



Let's improve the right part

Efficiently Use Data

- We should **drop all trajectory data** after update the agent. Because the distribution of the agent's action **shifts** after update.
- Can't we use old data to update the agent more times?

PPO is a method that we could leverage old data by simply multiplying a correction item when update the agent

Importance Sampling

- Importance sampling is a statistic technique to **estimate one distribution by sampling from another distribution**

$$\begin{aligned} E_{x \sim p}[f(x)] &= \int f(x)p(x)dx \\ &= \int f(x) \frac{p(x)}{q(x)} q(x)dx \\ &= E_{x \sim q}\left[f(x) \frac{p(x)}{q(x)}\right] \\ &\approx \frac{1}{N} \sum_{i=1, x^i \in q}^N f(x^i) \frac{p(x^i)}{q(x^i)} \end{aligned}$$

Estimate p from q

No Free Lunch

Problem? No free lunch!

Two expectations are same, but we are using sampling method to estimate them

→ variance is also important

$$E_{x \sim p}[f(x)] = E_{x \sim q}\left[f(x) \frac{p(x)}{q(x)}\right]$$

$$VAR[X] = E[X^2] - (E[X])^2$$

$$\begin{aligned} & Var_{x \sim p}[f(x)] \\ &= E_{x \sim p}[f(x)^2] - (E_{x \sim p}[f(x)])^2 \end{aligned}$$

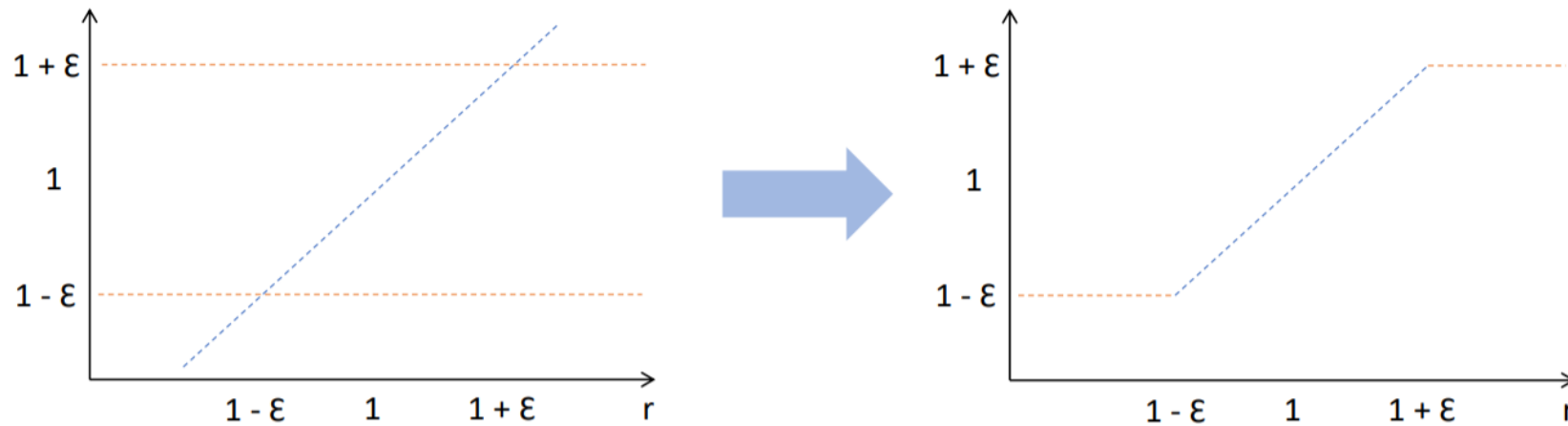
$$\begin{aligned} & Var_{x \sim q}\left[f(x) \frac{p(x)}{q(x)}\right] \\ &= E_{x \sim q}\left[\left(f(x) \frac{p(x)}{q(x)}\right)^2\right] - \left(E_{x \sim q}\left[f(x) \frac{p(x)}{q(x)}\right]\right)^2 \\ &= E_{x \sim p}\left[f(x)^2 \frac{p(x)}{q(x)}\right] - (E_{x \sim p}[f(x)])^2 \end{aligned}$$

Price (Tradeoff): we may need to sample more data, if $\frac{p(x)}{q(x)}$ is far away from 1

PPO with Clipped Objective

$$\underset{\theta}{\text{maximize}} \quad \hat{\mathbb{E}}_t \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t \right] \quad r_t(\theta) = \frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)}$$


Fluctuation happens when r changes too quickly \rightarrow limit r within a range?




$$L^{CLIP}(\theta) = \hat{\mathbb{E}}_t \left[\min(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t) \right]$$

PPO in Practice

$$L_t^{CLIP+VF+S}(\theta) = \hat{\mathbb{E}}_t [L_t^{CLIP}(\theta) - c_1 L_t^{VF}(\theta) + c_2 S[\pi_\theta](s_t)]$$




Surrogate objective function



a squared-error loss
for "critic"

$$(V_\theta(s_t) - V_t^{\text{targ}})^2$$



entropy bonus to ensure
sufficient exploration

encourage "diversity"

* c1, c2: empirical values, in the paper, c1=1, c2=0.01

Eventually

$$\frac{\nabla \log \text{prob. of actions}}{\nabla \log \text{prob. of actions - old}} \times \text{GAE}$$

Assignment

Running the code of PPO X GAE.

Writing a report about what you observe.

Deadline:

2021/12/30 11:59 p.m.