Proximal Policy Optimization with Dynamic Clipping

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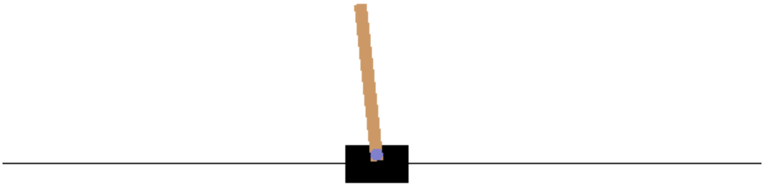
Background

Reinforcement Learning

- A set of algorithms that seek to replicate behavioral learning.
- Basic vocabulary:
  - **Environment**: a general setting with changeable parameters in which actions can be performed that affect these parameters
  - **State** (denoted s): a specific configuration (i.e. “snapshot”) of an environment
  - **Agent**: an entity that learns to accomplish a task in a specific evironment
  - **Action** (denoted a): a decision made by the agent that is intended to affect subsequent states
  - **Episode**: a sequence of states and actions in an environment
  - **Reward** (denoted r): a number associated with a state-action pair
- Overall goal: train an agent that picks actions such that the sum of the rewards over an episode is maximimized.

Background (contd.)

- Example: cart-pole demo



Background (contd.)

Policy Gradient Methods

- An agent can be provided with a **policy**, usually denoted π, that completely specifies the probabilty distribution of the action that should be taken at any particular state.
- π is parameterized by some vector θ and can be any function of a state s_t.
- The task of the agent is to learn θ.

Background (contd.)

Generic Policy Gradient Algorithm

Algorithm Generic Policy Gradient

Initialize θ arbitrarily

while True **do** ▷ loop forever

  $\theta_{old} \leftarrow \theta$

  $rollout \leftarrow (s, a, r)$ from multiple π_θ episodes

  Set θ to maximize the loss function $L(rollout, \theta, \theta_{old})$

Background (contd.)

Trust Region Policy Optimization (TRPO)

- The theory behind TRPO suggests using the loss function:

$$L_{\theta_{old}}(\theta) - CD_{KL}^{max}(\theta, \theta_{old})$$

where C is a constant and

$$L_{\theta_{old}}(\theta) = \mathbb{E}_t \left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} A_t \right]$$

.

- Using this loss function guarantees monotonic improvement.
- Using the penalty term $CD_{KL}^{max}(\theta, \theta_{old})$ leads to small step sizes in practice, so TRPO uses a hard constraint on the KL divergence.

Background (contd.)

Proximal Policy Optimization (PPO)

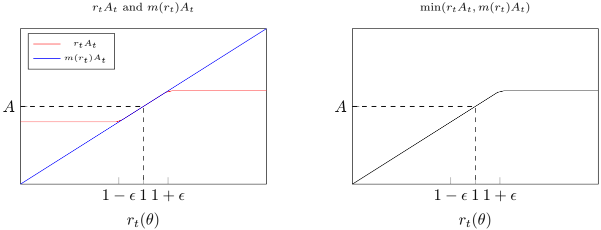
- PPO uses a loss function that is an approximation to the TRPO loss:

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

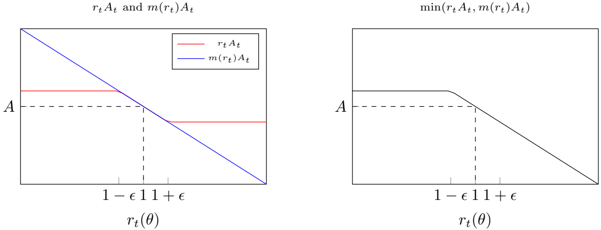
where $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$.

Background (contd.)

– Resultant clipping behavior:



Case $A > 0$



Case $A > 0$

Background (contd.)

- Research question: how can we more precisely control penalties introduced through the clipping objective?

Potential Shortcoming of PPO

- We can separate the loss into its positive and negative components:

$$\begin{aligned} L^{CLIP}(\theta) &= \mathbb{E}_t \left[\min\left(r_t A_t, \mathrm{clip}(r_t, 1-\epsilon, 1+\epsilon) A_t \right) \right] \\ &= \mathbb{E}_t \left[\begin{cases} \min\left(r_t, \mathrm{clip}(r_t, 1+\epsilon) \right) A_t & A_t > 0 \\ \max\left(r_t, \mathrm{clip}(r_t, 1-\epsilon) \right) A_t & A_t < 0 \end{cases} \right] \end{aligned}$$

- Let:

$$\begin{aligned} r^+_{t,CLIP} &= \min\left(r_t, \mathrm{clip}(r_t, 1+\epsilon) \right) \\ r^-_{t,CLIP} &= \max\left(r_t, \mathrm{clip}(r_t, 1-\epsilon) \right) \end{aligned}$$

- We know that:

$$\begin{aligned} \mathbb{E}_t[r^+_{t,CLIP}] < 1 \\ \mathbb{E}_t[r^-_{t,CLIP}] > 1 \end{aligned}$$

Potential Shortcoming of PPO (contd.)

- Now, we can define the "expected penalty contributions" of positive and negative advantages:

$$1 - \mathbb{E}_t[r_{t,CLIP}^{+}]$$

and

$$\mathbb{E}_t[r_{t,CLIP}^{-}] - 1$$

- Because r_t and A_t are not independent, these expected penalty contributions do not suggest actual penalty contributions.
- However, they can indicate inherent imbalances in the system.

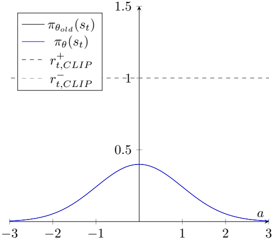
Potential Shortcoming of PPO (contd.)

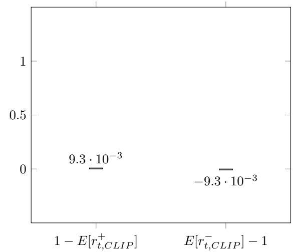
Conceptual Example

- Consider a typical example in reinforcement learning where:
  - We have an agent using a continuous action space (continuous control).
  - The policy is encoded by a gaussian with state-dependent means but constant standard deviation.

Potential Shortcoming of PPO (contd.)

What happens as we learn?





Idea

Results

Future Directions