Value-based Approach Learning a Critic

Critic

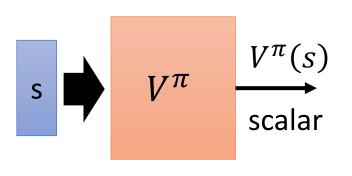
- A critic does not determine the action.
- Given an actor, it evaluates the how good the actor is

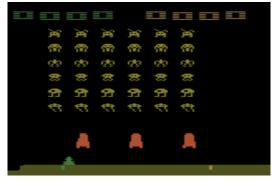


http://combiboilersleeds.com/picaso/critics/critics-4.html

Three kinds of Critics

- A critic is a function depending on the actor π it is evaluated
 - The function is represented by a neural network
- State value function $V^{\pi}(s)$
 - When using actor π , the *cumulated* reward expects to be obtained after seeing observation (state) s





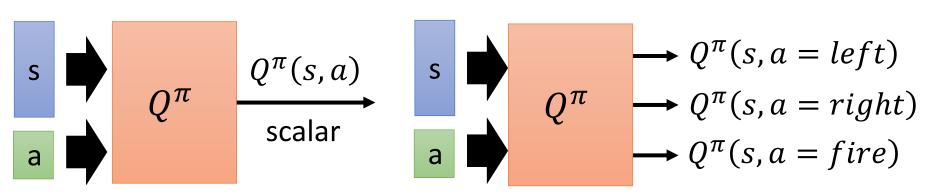


 $V^{\pi}(s)$ is large

 $V^{\pi}(s)$ is smaller

Three kinds of Critics

- State-action value function $Q^{\pi}(s, a)$
 - When using actor π , the *cumulated* reward expects to be obtained after seeing observation s and taking a



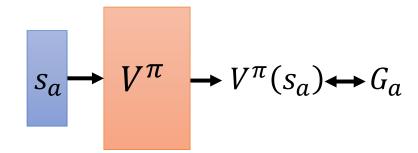
for discrete action only

How to estimate $V^{\pi}(s)$

- Monte-Carlo based approach
 - The critic watches π playing the game

After seeing s_a ,

Until the end of the episode, the cumulated reward is G_a



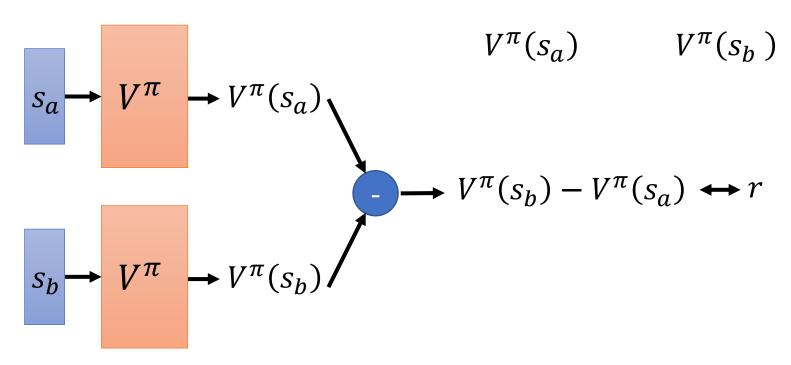
After seeing s_b ,

Until the end of the episode, the cumulated reward is G_h

$$S_b \longrightarrow V^{\pi} \longrightarrow V^{\pi}(s_b) \longrightarrow G_b$$

How to estimate $V^{\pi}(s)$

• Temporal-difference approach $\cdots s_a, a, r, s_b \cdots$



Some applications have very long episodes, so that delaying all learning until an episode's end is too slow.

How to estimate $V^{\pi}(s)$

[Sutton, v2, Example 6.4]

The critic has the following 8 episodes

•
$$s_a, r = 0, s_b, r = 0$$
, END

•
$$s_h, r = 1$$
, END

•
$$s_h, r = 1$$
, END

•
$$s_b, r = 1$$
, END

•
$$s_h, r = 1$$
, END

•
$$s_h, r = 1$$
, END

•
$$s_b, r = 1$$
, END

•
$$s_b, r = 0$$
, END

$$V^{\pi}(s_b) = 3/4$$

$$V^{\pi}(s_a) = ? 0? 3/4?$$

Monte-Carlo:
$$V^{\pi}(s_{\alpha}) = 0$$

Temporal-difference:

$$V^{\pi}(s_a) + r = V^{\pi}(s_b)$$

3/4 0 3/4

(The actions are ignored here.)