# Preliminaries needed to understand Proximal Policy Optimization Algorithms

Notes on discussion and derivations from Sutton’s book and John Schulman’s articles

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## A bit of theory on Policy Gradient Reinforcement Learning Methods

Assumptions:

The environment can be represented by a finite MDP

This is equivalent of saying that its state , action and reward sets are finite, and its dynamics is given by a set of probabilities , for all and ( is plus a terminal state if the problem is episodic).

We would like to compute value functions to organize and search for good policies.

The optimal value functions satisfying the Bellman’s optimality equations were derived and discussed in (Gueorguiev, 2023) (see Eq. (22) and (23)).

(1)

(2)

### Policy evaluation (Prediction)

**Definition**: *policy evaluation* - computation of the state-value function for a given policy . This is also known as the *prediction problem*.

Question: How to compute the state-value function for an arbitrary policy .

From (11) and (12) in (Gueorguiev, 2023) we can write:

(3)

(4)

(5)

where is the probability of taking action in state under policy , and the expectations are subscribed by to indicate that they are conditional on being followed.

The existence and uniqueness of are guaranteed as long as either or eventual termination is guaranteed from all states under the policy .

If the environment’s dynamics are completely known, then (5) is a system of simultaneous linear equations in unknowns (the ).

Clearly, is fixed point for (5) because the Bellman equation for assures equality in this case. We are going to be looking into iterative solution of (5). Indeed, the sequence can be shown to converge to under the same conditions which guarantee the existence of . This algorithm is known as *iterative policy evaluation*.

To produce each successive approximation , the iterative policy evaluation applies the same operation to each state : it replaces the old value of with a new value obtained from the old values of the successor states of , along all the one-step transitions possible under the policy being evaluated. We call this kind of operation an *expected update*. Each iteration of the iterative policy evaluation updates the value of every state once to produce the new approximate value function .

Note: There are several different kinds of expected updates, depending on whether a **state** (as in (5)) or a **state-action pair** is being updated, and, depending on the precise way the estimated values of the successor states are combined.

Note2: All the updates done in the algorithms based on Bellman equations are ***expected updates*** because they are based on the expectation over ***all possible next states*** rather than on a sample next state.

Note3: the nature of the update can be expressed by using backup diagram (backup diagrams were discussed in (Gueorguiev, 2023) and in Chapter 3 of (Richard D. Sutton, 2020)).

In-place Algorithm for iterative policy evaluation:

Input: Policy to be evaluated, the environment dynamics

Output:

## Appendix

### Solution of the Bellman system of equations for

We notice that the Bellman system of equations with respect to (5) can be rewritten as:

(A1)

hence

(A2)

The left-hand side of (A2) can be rewritten as:

(A3)

The right-hand side of (A2) are rearranged as :

(A4)

we denote with and the following expressions:

(A5)

(A6)

(A7)

Using (A3)-(A7) in (A2) leads to :

(A8)

(A8) represents a linear system of equations with respect to the unknowns .

(A8) in matrix form:

(A9)

For convenience we abbreviate:

, , (A10)

Thus,

, (A11)

//TODO: derive degeneracy conditions on the function of the environment dynamics

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