למידה במערכות דינמיות אביב תש"פ

תרגיל בית 3

מגישים:

יאיר נחום 034462796

דר ערבה 205874951

* 1. It is easy to see that the optimal policy must be to reach state n as fast as we can since the reward is 0 on every other state. Thus, the policy is to go right on every stage. In stage n we have no other option than to go back to 0.
  2. For the fixed policy we can apply policy evaluation by solving |S| equations (the same as calculating inverse matrix ). Also, we notice that in this case the MDP is deterministic once we know the action by the policy:

We can solve these equations by noticing the connection between the first stage and the last stage:

* 1. According to total probability on the actions, we can calculate the transitions matrix as follows:  
     for each state other than n, the policy is stochastic with 0.5 chance for every action.  
     In order to calculate the stationary distribution of the states, one needs to solve the vector equation:

Or per state probability:  
According to the formula above for the transition probabilities we have n equations and also the demand:

We note that the dynamics are deterministic once the action is selected, thus, the transition probability is actually the policy probability.

Again, by applying the recursion of the equations and using the normalization to a probability vector we get:

* 1. FPVI specifies

In matrix description   
In our case, since we started with then we get:   
The transition matrix can be calculated using:

On state 1 we have only one action possible, so we can only move to state 2.  
On other states other than n, we select an action randomly with probability 0.5 for each action and then continue the dynamics deterministically.  
Thus:  
The same for going from i state to 1.  
On the n state we have no option than going back to 1 state.  
When:  
Therefore, If = 0, then:

From FPVI convergence Proposition 5.2, we get that   
BTW, can be calculated directly from as we proved in Lemma 5.2 in the lecture.

* 1. We can apply recursive expectation calculation. First, let’s observe what happens in simple cases like n=2,3,4:  
     Let’s denote in the time (expectation of it) to reach state n from state k.  
     We want to find   
       
     In case of n=2:

As there is only one possible transition to state 2.

In case of n=3:  
Another way to calculate it is by explicit total expectation:

When in our case, the p denotes the probability to move from state i to state i+1.

In case of n=4:

In the general case:  
   
for

* 1. In order to go through all state actions pairs, we will define a policy such that at the first time we encounter some state i we get back to 1 from it. Otherwise, we continue to next state i+1.  
     We note that going over state 1 +action right, we do it already for reaching state 2.  
     Thus, the number of steps needed to go over all state action pairs can be calculated as follows:  
     and we can check it’s correct for all n using induction (base: n=2 => N=2).
  2. Since we want to maximize the rewards which are exponentially reduced as times goes by due to discount factor, the optimal policy is to select the path that gives us as much as possible consecutive rewards in the near future.   
     Meaning, we will go from stage 1 to n and back to 1 in order to collect these consecutive rewards (that are reduced constantly by discount factor) and then collect rewards as we did on the previous section (1->2->1->2->3->1…).  
     If we look at the summary of steps, we get the same amount as in previous section (just in a different order of execution in order to collect the maximum reward)
  3. As we saw in section d. in case n=3 the rewards vector and transition matrix (under the stochastic policy is as follows):

Applying the closed solution of the 3 equations:  
 we get:

**2.**

**3.**

**4.**

**5.**