# Reinforcement Learnig: Homework 1

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## 1 Dynamic Programming

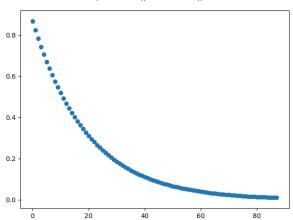
#### 1.1 Question 1

The optimal policy  $\pi^*$  is easy to find because their is only 3 (state, action) that have a reward. And their is only three steps.

$$\pi^*=[1,1,2]$$

#### 1.2 Question 2

Figure 1:  $\|v^k - v^*\|_{\infty}$ 



The value iteration find the same policy  $\pi^*$  and:

$$v^* = [15.204, 16.361, 17.819]$$

#### 1.3 Question 3

The exact policy iteration returned the same policy.

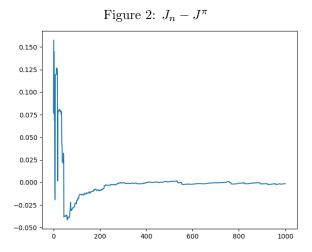
To compare both algorithm we used the *timeit* module of python.

	Mean of 100 runs
VI	0.00208620
PI	0.00179925

- Value Iteration
  - Pros: each iteration is very computationally efficient.
  - Cons: convergence is only asymptotic.
- Policy Iteration
  - Pros: converge in a finite number of iterations (often small in practice).
  - Cons: each iteration requires a full policy evaluation and it might be expensive.

## 2 Reinforcement Learning

#### 2.1 Question 4



#### 2.2 Question 5

The parameters choosed for the Q learning algorithm are the following.

- $\gamma = 0.95$
- $\alpha_n(x,a) = \frac{1}{n}$  because it is easier to make it independent of (x,a) and we know that it satisfies the usual stochastic approximation requirements.
- $\epsilon$  represent the tradeoff between exploration and exploitation. We decided to try with  $\epsilon = 0.95, 0.7, 0.6$

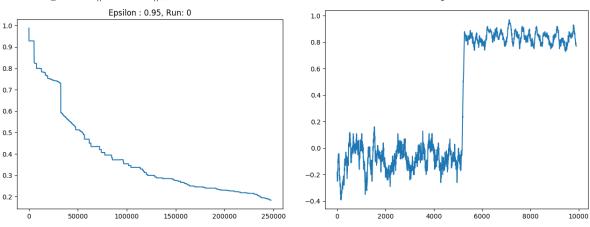


Figure 3:  $||v^k - v^*||_{\infty}$  and mean of cummulated reward over a 100 episodes for  $\epsilon = 0.95$ 

Figure 4:  $||v^k - v^*||_{\infty}$  and mean of cumulated reward over a 100 episodes for  $\epsilon = 0.7$ 

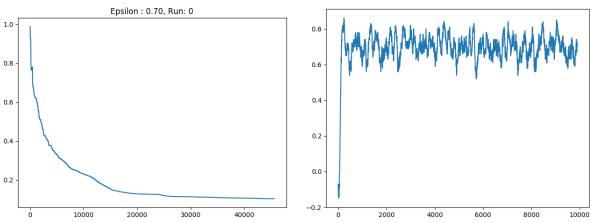
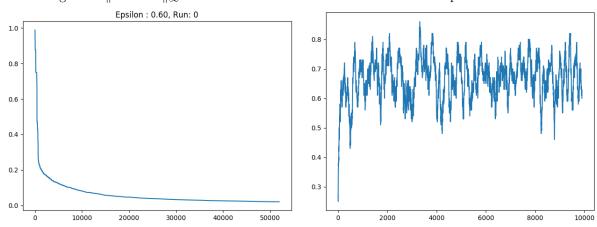


Figure 5:  $||v^k - v^*||_{\infty}$  and mean of cumulated reward over a 100 episodes for  $\epsilon = 0.6$ 



We clearly see that  $\epsilon$  has an important effect on the convergence. A higher  $\epsilon$  makes the convergence slower but gives a better reward.

#### 2.3 Question 6

The optimal policy of a MDP is not affected by the the change of the initial distribution if all the states are still visited an infinit number of time.