

CS 234 Winter 2018
Assignment 1
Due: January 23 at 11:59 pm

For submission instructions please refer to [website](#)

1 Optimal Policy for Simple MDP [20 pts]

Consider the simple n -state MDP shown in Figure 1. Starting from state s_1 , the agent can move to the right (a_0) or left (a_1) from any state s_i . Actions are **deterministic** and always succeed (e.g. going left from state s_2 goes to state s_1 , and going left from state s_1 transitions to itself). Rewards are given upon taking an action from the state. Taking any action from the goal state G earns a reward of $r = +1$ and the agent stays in state G . Otherwise, each move has zero reward ($r = 0$). Assume a discount factor $\gamma < 1$.

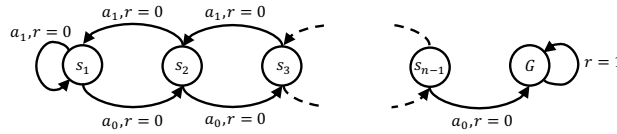


Figure 1: n -state MDP

- The optimal action from any state s_i is taking a_0 (right) until the agent reaches the goal state G . Find the optimal value function for all states s_i and the goal state G . [5 pts]
- Does the optimal policy depend on the value of the discount factor γ ? Explain your answer. [5 pts]
- Consider adding a constant c to all rewards (i.e. taking any action from states s_i has reward c and any action from the goal state G has reward $1 + c$). Find the new optimal value function for all states s_i and the goal state G . Does adding a constant reward c change the optimal policy? Explain your answer. [5 pts]
- After adding a constant c to all rewards now consider scaling all the rewards by a constant a (i.e. $r_{new} = a(c + r_{old})$). Find the new optimal value function for all states s_i and the goal state G . Does that change the optimal policy? Explain your answer, If yes, give an example of a and c that changes the optimal policy. [5 pts]

2 Running Time of Value Iteration [20 pts]

In this problem we construct an example to bound the number of steps it will take to find the optimal policy using value iteration. Consider the infinite MDP with discount factor $\gamma < 1$ illustrated in Figure 2. It consists of 3 states, and rewards are given upon taking an action from the state. From state s_0 , action a_1 has zero immediate reward and causes a deterministic transition to state s_1 where there is reward $+1$ for every time step afterwards (regardless of action). From state s_0 , action a_2 causes a deterministic transition to state s_2 with immediate reward of $\gamma^2/(1-\gamma)$ but state s_2 has zero reward for every time step afterwards (regardless of action).

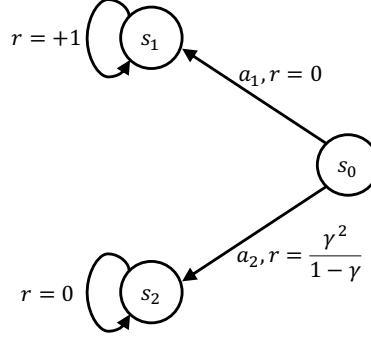


Figure 2: infinite 3-state MDP

- What is the total discounted return $(\sum_{t=0}^{\infty} \gamma^t r_t)$ of taking action a_1 from state s_0 at time step $t = 0$? [5 pts]
- What is the total discounted return $(\sum_{t=0}^{\infty} \gamma^t r_t)$ of taking action a_2 from state s_0 at time step $t = 0$? What is the optimal action? [5 pts]
- Assume we initialize value of each state to zero, (i.e. at iteration $n = 0$, $\forall s : V_{n=0}(s) = 0$). Show that value iteration continues to choose the sub-optimal action until iteration n^* where,

$$n^* \geq \frac{\log(1-\gamma)}{\log \gamma} \geq \frac{1}{2} \log\left(\frac{1}{1-\gamma}\right) \frac{1}{1-\gamma}$$

Thus, value iteration has a running time that grows faster than $1/(1-\gamma)$. (You just need to show the first inequality) [10 pts]

3 Approximating the Optimal Value Function [35 pts]

Consider a finite MDP $M = \langle S, A, T, R, \gamma \rangle$, where S is the state space, A action space, T transition probabilities, R reward function and γ the discount factor. Define Q^* to be the optimal state-action value $Q^*(s, a) = Q_{\pi^*}(s, a)$ where π^* is the optimal policy. Assume we have an estimate \tilde{Q} of Q^* , and \tilde{Q} is bounded by l_{∞} norm as follows:

$$\|\tilde{Q} - Q^*\|_{\infty} \leq \varepsilon$$

Where $\|x\|_\infty = \max_{s,a} |x(s,a)|$.

Assume that we are following the greedy policy with respect to \tilde{Q} , $\pi(s) = \operatorname{argmax}_{a \in \mathcal{A}} \tilde{Q}(s,a)$. We want to show that the following holds:

$$V_\pi(s) \geq V^*(s) - \frac{2\varepsilon}{1-\gamma}$$

Where $V_\pi(s)$ is the value function of the greedy policy π and $V^*(s) = \max_{a \in \mathcal{A}} Q^*(s,a)$ is the optimal value function. This shows that if we compute an approximately optimal state-action value function and then extract the greedy policy for that approximate state-action value function, the resulting policy still does well in the real MDP.

- (a) Let π^* be the optimal policy, V^* the optimal value function and as defined above $\pi(s) = \operatorname{argmax}_{a \in \mathcal{A}} \tilde{Q}(s,a)$. Show the following bound holds for all states $s \in S$. [10 pts]

$$V^*(s) - Q^*(s, \pi(s)) \leq 2\varepsilon$$

- (b) Using the results of part 1, prove that $V_\pi(s) \geq V^*(s) - \frac{2\varepsilon}{1-\gamma}$. [10 pts]

Now we show that this bound is tight. Consider the 2-state MDP illustrated in figure 3. State s_1 has two actions, "stay" self transition with reward 0 and "go" that goes to state s_2 with reward 2ε . State s_2 transitions to itself with reward 2ε for every time step afterwards.

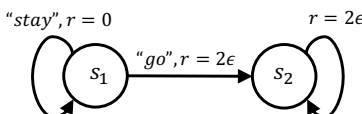


Figure 3: 2-state MDP

- (c) Compute the optimal value function $V^*(s)$ for each state and the optimal state-action value function $Q^*(s,a)$ for state s_1 and each action. [5 pts]
- (d) Show that there exists an approximate state-action value function \tilde{Q} with ε error (measured with l_∞ norm), such that $V_\pi(s_1) - V^*(s_1) = -\frac{2\varepsilon}{1-\gamma}$, where $\pi(s) = \operatorname{argmax}_{a \in \mathcal{A}} \tilde{Q}(s,a)$. (You may need to define a consistent tie break rule) [10 pts]

4 Frozen Lake MDP [25 pts]

Now you will implement value iteration and policy iteration for the Frozen Lake environment from [OpenAI Gym](#). We have provided custom versions of this environment in the starter code.

- (a) **(coding)** Read through `vi_and_pi.py` and implement `policy_evaluation`, `policy_improvement` and `policy_iteration`. The stopping tolerance (defined as $\max_s |V_{old}(s) - V_{new}(s)|$) is $\text{tol} = 10^{-3}$. Use $\gamma = 0.9$. Return the optimal value function and the optimal policy. [10pts]

- (b) **(coding)** Implement `value_iteration` in `vi_and_pi.py`. The stopping tolerance is $\text{tol} = 10^{-3}$. Use $\gamma = 0.9$. Return the optimal value function and the optimal policy. [10 pts]
- (c) **(written)** Run both methods on the Deterministic-4x4-FrozenLake-v0 and Stochastic-4x4-FrozenLake-v0 environments. In the second environment, the dynamics of the world are stochastic. How does stochasticity affect the number of iterations required, and the resulting policy? [5 pts]