## REINFORCEMENT LEARNING Sample Solution 3



## 1 Monte Carlo and $TD(\lambda)$

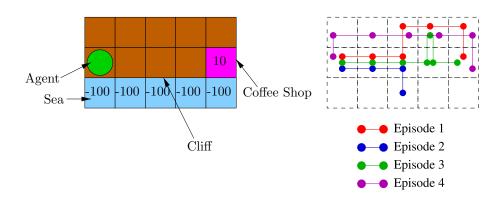


Figure 1: Cliff MDP

Consider the MDP in Figure 1, where all actions (an action moves the agent in a desired direction: up, down, left or right) succeed with a probability of 0.8. With a probability of 0.2 the agent moves randomly in another direction. All transitions result in a reward of -1, except when the coffee shop is reached (terminal state  $s_{2,5}$ : reward of 10) or if the agent falls of the cliff (terminal states  $s_{3,1} 
ldots s_{3,5}$ : reward of -100). The agent always starts in state  $s_{2,1}$  as indicated in Figure 1.

(a) Using Monte-Carlo policy evaluation, calculate  $V_3(i)$  for all states i based on the illustrated episodes 1 to 3 (right part of Figure 1). Use the first-visit-method, i.e. every state is updated only once – on the first-visit – per episode, even if the state is visited again during the episode. In this task, we estimate the value by a running mean with  $\alpha_t = \frac{1}{t}$  for episode t and  $V_0(i) = 0$  for all i. We do not discount, i.e.  $\gamma = 1$ .

**Solution.** We have to iteratively calculate the different returns for the states of a trajectory and then update our estimation. Let  $G_s^t$  denote the return in episode t starting from state s.

For trajectory 1:

- $G_0^1 = -1 1 1 1 1 + 10 = 5$
- $G_1^1 = -1 1 1 1 + 10 = 6$

• 
$$G_2^1 = -1 - 1 - 1 + 10 = 7$$

• 
$$G_3^1 = -1 - 1 + 10 = 8$$

• 
$$G_4^1 = -1 + 10 = 9$$

• 
$$G_5^1 = 10$$

Following MC-policy evaluation, we update by  $V_{t+1}(s) = V_t(s) + \alpha_t(G_s^{t+1} - V_t(s))$  and  $\alpha_1 = \frac{1}{1} = 1$ , we get for  $V_1$ :

•  $V_1(s) = V_0(s)$  for all states s that are not visited on this trajectory, i.e. for  $s \in \{s_{1,1}, s_{1,2}, s_{2,4}, s_{3,k}\}$  with  $1 \le k \le 5$ 

• 
$$V_1(s_{2,1}) = 0 + 1(5-0) = 5$$

• 
$$V_1(s_{2,2}) = 0 + 1(6-0) = 6$$

• 
$$V_1(s_{2,3}) = 0 + 1(7-0) = 7$$

• 
$$V_1(s_{1,3}) = 0 + 1(8 - 0) = 8$$

• 
$$V_1(s_{1.4}) = 0 + 1(9 - 0) = 9$$

• 
$$V_1(s_{1.5}) = 0 + 1(10 - 0) = 10$$

For trajectory 2:

• 
$$G_0^2 = -1 - 1 - 100 = -102$$

• 
$$G_1^2 = -1 - 100 = -101$$

• 
$$G_2^2 = -100$$

With  $\alpha_2 = \frac{1}{2}$ , we get for  $V_2$ :

•  $V_2(s) = V_1(s)$  for all states that are not visited on this trajectory, i.e. for  $s \in \{s_{1,1}, s_{1,2}, s_{1,3}, s_{1,4}, s_{1,5}, s_{2,4}, s_{2,5}, s_{3,1}, s_{3,2}, s_{3,4}, s_{3,5}\}$ 

• 
$$V_2(s_{2,1}) = 5 + \frac{1}{2}(-102 - 5) = 5 - 53\frac{1}{2} = -48\frac{1}{2}$$

• 
$$V_2(s_{2,2}) = 6 + \frac{1}{2}(-101 - 6) = 6 - 53\frac{1}{2} = -47\frac{1}{2}$$

• 
$$V_2(s_{2,3}) = 7 + \frac{1}{2}(-100 - 7) = 7 - 53\frac{1}{2} = -46\frac{1}{2}$$

For trajectory 3:

• 
$$G_0^3 = -1 - 1 - 1 - 1 - 1 + 10 = 5$$

• 
$$G_1^3 = -1 - 1 - 1 - 1 + 10 = 6$$

• 
$$G_2^3 = -1 - 1 - 1 + 10 = 7$$

• 
$$G_3^3 = -1 - 1 + 10 = 8$$

- $G_4^3 = -1 + 10 = 9$
- $G_5^3 = G_3^3$  calculated on first-visit (see above)

With  $\alpha_3 = \frac{1}{3}$ , we get for  $V_3$ :

• 
$$V_3(s_{2,1}) = -48\frac{1}{2} + \frac{1}{3}(5 - (-48\frac{1}{2})) = -48\frac{1}{2} + 17\frac{5}{6} = -30\frac{2}{3}$$

• 
$$V_3(s_{2,2}) = -47\frac{1}{2} + \frac{1}{3}(6 - (-47\frac{1}{2})) = -47\frac{1}{2} + 17\frac{5}{6} = -29\frac{2}{3}$$

• 
$$V_3(s_{2,3}) = -46\frac{1}{2} + \frac{1}{3}(7 - (-46\frac{1}{2})) = -46\frac{1}{2} + 17\frac{5}{6} = -28\frac{2}{3}$$

• 
$$V_3(s_{2,4}) = 0 + \frac{1}{3}(8-0) = 0 + 2\frac{2}{3} = 2\frac{2}{3}$$

- $V_3(s_{1,4}) = 9 + \frac{1}{3}(9-9) = 9$
- $V_3(s_{2,4})$  updated on first-visit (see above)
- (b) Consider now Episode 4 (magenta). Specify for all states visited during this episode the TD-error based on the value-function  $V_3(\cdot)$  calculated in (a).

Solution.

$$\bullet \ \ \text{Episode 4:} \ \underbrace{s_{2,1}}_{s_0} \to \underbrace{s_{1,1}}_{s_1} \to \underbrace{s_{1,2}}_{s_2} \to \underbrace{s_{1,3}}_{s_3} \to \underbrace{s_{1,4}}_{s_4} \to \underbrace{s_{1,5}}_{s_5} \to \underbrace{s_{2,5}}_{s_6}$$

• TD-error:

$$\delta_t := R_{t+1} + V(s_{t+1}) - V(s_t)$$

•

$$\delta_0 = R_1 + V_3(s_1) - V_3(s_0)$$

$$= -1 + 0 - (-30\frac{2}{3})$$

$$= 29\frac{2}{3}$$

•

$$\delta_1 = R_2 + V_3(s_2) - V_3(s_1)$$
  
= -1 + 0 - (-0)  
= -1

•

$$\delta_2 = R_3 + V_3(s_3) - V_3(s_2)$$
  
= -1 + 8 - (-0)  
= 7

•

$$\delta_3 = R_4 + V_3(s_4) - V_3(s_3)$$

$$= -1 + 9 - 8$$

$$= 0$$

•

$$\delta_4 = R_5 + V_3(s_5) - V_3(s_4)$$

$$= 1 + (-10) - (-9)$$

$$= 0$$

•

$$\delta_5 = R_6 + V_3(s_6) - V_3(s_5)$$

$$= 10 + 0 - 10$$

$$= 0$$

(c) Using the  $\text{TD}(\lambda)$ -algorithm, determine for  $\lambda = 0$ ,  $\lambda = 0.5$  and  $\lambda = 1.0$  the expected value  $v_{\pi}(s_{2,1})$  based on the first three episodes. Hint: In the lecture slides, the  $TD(\lambda)$ -update is defined as  $V(s_t) \leftarrow V(s_t) + \alpha(G_t^{\lambda} - V(s_t))$ , where  $G_t^{\lambda} = (1 - \lambda) \sum_{n=1}^{\infty} \lambda^{n-1} G_t^{(n)}$  (in the episodic setting, this becomes  $G_t^{\lambda} = (1 - \lambda) \sum_{n=1}^{T-t-1} \lambda^{n-1} G_t^{(n)} + \lambda^{T-t-1} G_t^{(T-t)}$ ). It can be converted to TD-form (so you can also reuse the results from (b)):  $V(s_t) \leftarrow V(s_t) + \alpha \sum_{i=0}^{\infty} \lambda^i \delta_{t+i}$ .

**Solution.** We consider episode 4, thus t=4 and  $\alpha_4=\frac{1}{4}$ . We already calculated the  $\delta_k$  in exercise (b).

• TD(0):

$$V_4(s_0) = V_3(s_0) + \frac{1}{4} \cdot \delta_0$$
  
=  $-30\frac{2}{3} + \frac{1}{4} \cdot 29\frac{2}{3} = -30\frac{8}{12} + 7\frac{5}{12} = -23\frac{1}{4}$ 

• TD(1):

$$V_4(s_0) = V_3(s_0) + \frac{1}{4} \cdot \sum_{m=0}^{\infty} \delta_{0+m}$$

$$= -30\frac{2}{3} + \frac{1}{4} \cdot (29\frac{2}{3} - 1 + 7 + 0 + 0 + 0) = -30\frac{8}{12} + 8\frac{11}{12} = -21\frac{3}{4}$$

• TD(0.5):

$$V_4(s_0) = V_3(s_0) + \frac{1}{4} \cdot \left( \delta_0 + \frac{1}{2} \delta_1 + \frac{1}{4} \delta_2 + \dots + \frac{1}{2}^{\infty} \delta_{\infty} \right)$$
$$= -30 \frac{2}{3} + \frac{1}{4} \cdot (29 \frac{2}{3} - \frac{1}{2} \cdot 1 + \frac{1}{4} \cdot 7 - \frac{1}{8} \cdot 0 - \frac{1}{16} \cdot 0 - \frac{1}{32} \cdot 0) = -22 \frac{15}{16}$$