

**ECEN 689: RL: Reinforcement Learning**  
**Exam 1**

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1. (2 point) Consider an MDP  $M_1 = (\mathcal{X}, \mathcal{A}, P, R_1, \gamma)$  and let  $\pi_1^*$  be the optimal policy of  $M_1$ . Let  $M_2$  be another MDP, exactly the same as  $M_1$  except in its reward function  $R_2$ , which is given as  $R_2(x, a) = cR_1(x, a), \forall (x, a) \in \mathcal{X} \times \mathcal{A}, c > 0$ . Show that the optimal policy of  $M_2$  is also  $\pi_1^*$ .

**Solution:**

$$\mathbb{E}_{\pi_1^*} \left[ \sum_{t=0}^{\infty} \gamma^t R_1(x_t, a_t) \right] \geq \max_{\pi} \mathbb{E}_{\pi} \left[ \sum_{t=0}^{\infty} \gamma^t R_1(x_t, a_t) \right]$$

where  $E_{\pi}[\cdot]$  indicates the expectation with respect to the transition probability function  $P$  when policy  $\pi$  is used. Multiply both sides by  $c$  and we get

$$\mathbb{E}_{\pi_1^*} \left[ \sum_{t=0}^{\infty} \gamma^t R_2(x_t, a_t) \right] \geq \max_{\pi} \mathbb{E}_{\pi} \left[ \sum_{t=0}^{\infty} \gamma^t R_2(x_t, a_t) \right].$$

So,  $\pi_1^*$  is the optimal policy for the MDP  $M_2$ .

2. (2 points) Define the mapping  $F : \mathbb{R}^{|\mathcal{X}||\mathcal{A}|} \rightarrow \mathbb{R}^{|\mathcal{X}||\mathcal{A}|}$  as

$$(FQ)(x, a) = R(x, a) + \gamma \sum_y P(y|x, a) \max_b Q(y, b)$$

Show that  $F$  is contraction w.r.t.  $\|\cdot\|_{\infty}$

**Solution:** For any arbitrary  $(x, a)$ ,

$$\begin{aligned} |(FQ_1)(x, a) - (FQ_2)(x, a)| &= \left| \gamma \sum_y P(y|x, a) (\max_b Q_1(y, b) - \max_b Q_2(y, b)) \right| \\ &\leq \gamma \sum_y P(y|x, a) |(\max_b Q_1(y, b) - \max_b Q_2(y, b))| \\ &\leq \gamma \sum_y P(y|x, a) \max_b |Q_1(y, b) - Q_2(y, b)| \\ &\leq \gamma \sum_y P(y|x, a) \|Q_1 - Q_2\|_{\infty} = \gamma \|Q_1 - Q_2\|_{\infty}. \end{aligned}$$

Since  $(x, a)$  is arbitrary, we have

$$\max_{(x, a)} |(FQ_1)(x, a) - (FQ_2)(x, a)| \leq \gamma \|Q_1 - Q_2\|_{\infty}.$$

This, by definition, is the desired result.

3. (4 points) Consider the value iteration algorithm,  $V_{k+1} = TV_k$ , with  $V_0 = 0$ . Let  $k_0$  be a given integer. Show that, for any  $\epsilon > 0$ , we can find an integer  $n_0$  (that will depend on  $\epsilon$ ) such that  $\|V_{n_0+k_0} - V_{n_0}\|_\infty < \epsilon$ . Give a sufficient condition for selecting such an  $n_0$ .

**Solution:** Denote  $V_k = TV_{k-1} = TTV_{k-2} = \dots = T^{(k)}V_0$ , where  $T^{(k)}$  indicates  $k$  repeated application of  $T$ .

We can show that  $T^{(k)}$  is a contraction with contraction coefficient  $\gamma^k$ . To see this, for any  $U_1, U_2$

$$\|T^{(k)}U_1 - T^{(k)}U_2\|_\infty = \|TT^{(k-1)}U_1 - TT^{(k-1)}U_2\|_\infty \leq \gamma\|T^{(k-1)}U_1 - T^{(k-1)}U_2\|_\infty.$$

Repeating this, we get,  $\|T^{(k)}U_1 - T^{(k)}U_2\|_\infty \leq \gamma^k\|U_1 - U_2\|_\infty$ .

Now, for any  $n \geq 1$ ,

$$\begin{aligned} \|V_{n+k_0} - V_n\|_\infty &\leq \sum_{i=0}^{k_0-1} \|V_{n_0+i+1} - V_{n_0+i}\|_\infty = \sum_{i=0}^{k_0-1} \|T^{(n+i+1)}V_0 - T^{(n+i)}V_0\|_\infty \\ &\leq \sum_{i=0}^{k_0-1} \gamma^{n+i}\|TV_0 - V_0\|_\infty \leq R_{\max}\gamma^n \frac{1}{(1-\gamma)}. \end{aligned}$$

So, for any  $n \geq n_0 = \frac{1}{\log(1/\gamma)} \log \frac{R_{\max}}{\epsilon(1-\gamma)}$ , we get  $\|V_{n+k_0} - V_n\|_\infty \leq \epsilon$ .

4. (8 points) Prof. K has an umbrella that he takes from his home to office and back. If it rains, and if the umbrella is in the place where he is, Prof. K takes the umbrella and goes to the other place, and this involves no cost. However, if he doesn't have the umbrella and it rains, there is a cost  $C_w$  for getting wet. If he takes the umbrella with him when it is not raining, he suffers an inconvenience cost  $C_i$ . If he does not take the umbrella with him when it is not raining, that incurs no additional cost. Assume that the probability of rain is  $p$  and costs are discounted at a factor  $\gamma$ . What is the optimal policy that will minimize the expected cumulative discounted cost?

- (a) (1 point) Formulate this as an MDP with three states.

**Solution:** Define three states:

(i)  $(s, r)$  for the case when the umbrella is in the same location as the person and it is raining, (ii)  $(s, n)$  for the case when the umbrella is in the same location as the person and it is not raining, (iii)  $o$  for the case when the umbrella is in the other location.

- (b) (1 point) How many control policies should we consider?

**Solution:** In state  $(s, n)$ , the person makes the decision whether or not to take the umbrella. In state  $(s, r)$ , the person has no choice and takes the umbrella. In state  $o$ , the person also has no choice and does not take the umbrella.

- (c) (3 points) Write down the Bellman optimality equation for all states.

**Solution:**

$$V(o) = pC_w + \gamma pV(s, r) + \gamma(1 - p)V(s, n) \quad (1)$$

$$V(s, r) = \gamma pV(s, r) + \gamma(1 - p)V(s, n) \quad (2)$$

$$V(s, n) = \min\{C_i + \gamma pV(s, r) + \gamma(1 - p)V(s, n), \gamma V(o)\} \quad (3)$$

- (d) (3 points) What is the optimal policy? Note that this will depend on the value of  $p$  (similar to the Homework problem)

**Solution:** From Eq. (2)

$$V(s, n) = \frac{(1 - \gamma p)}{\gamma(1 - p)} V(s, r) \quad (4)$$

using this in Eq. (1),

$$V(o) = pC_w + V(s, r), \quad (5)$$

and using this in Eq. (3),

$$V(s, n) = \min\{C_i + V(s, r), \gamma pC_w + \gamma V(s, r)\} \quad (6)$$

Now, with Eq. (4),

$$\frac{(1 - \gamma p)}{\gamma(1 - p)} V(s, r) = \min\{C_i + V(s, r), \gamma pC_w + \gamma V(s, r)\} \quad (7)$$

The optimal action at  $(s, n)$  is “take umbrella” if

$$C_i + V(s, r) < \gamma pC_w + \gamma V(s, r), \text{ or equivalently, } p > \frac{C_i + (1 - \gamma)V(s, r)}{\gamma C_w}.$$

For this scenario, from Eq. (7),  $V(s, r) = \frac{C_i \gamma (1 - p)}{(1 - \gamma)}$ . Substituting, this in the above condition for  $p$ , we get

$$p > \frac{C_i(1 + \gamma)}{\gamma(C_i + C_w)}. \quad (8)$$

5. (4 points) Let  $(V_k^i)_{k \geq 1}$  be the sequence of value functions generated by value iteration. Also, let  $(V_k^p)_{k \geq 1}$  be the sequence of value functions generated by policy iteration, where  $V_k^p = V_{\pi_k}$ , and  $\pi_k$  is the policy at iterate  $k$ . Assume that  $V_0^p = V_0^i$ . Then, show that  $V_k^i \leq V_k^p \leq V^*$ , for all  $k \geq 0$ , where  $V^*$  is the optimal value function.

**Solution:** We will prove this by induction. For  $k = 0$ , the hypothesis is true.

Assume that  $V_m^i \leq V_m^p \leq V^*$ . By the monotonicity of  $T$ , we get

$$TV_m^i = V_{m+1}^i \leq TV_m^p \leq V^* \quad (9)$$

Now, by definition,  $TV_m^p = TV_{\pi_m} = T_{\pi_{m+1}} V_{\pi_m}$ . Also, the monotone property of  $T_{\pi_{m+1}}$ ,

$$V_{\pi_m} \leq T_{\pi_{m+1}} V_{\pi_m} \leq T_{\pi_{m+1}}^{(2)} V_{\pi_m} \leq \dots \leq T_{\pi_{m+1}}^{(m)} V_{\pi_m} \leq \dots \leq \lim_{n \rightarrow \infty} T_{\pi_{m+1}}^{(n)} V_{\pi_m} = V_{\pi_{m+1}}.$$

So, we get  $T_{\pi_{m+1}} V_{\pi_m} \leq V_{\pi_{m+1}}$ . Also, by definition,  $V_{\pi_{m+1}} \leq V^*$