## Exercise Sheet 2 - Solutions\*

Omar D. Domingues omar (dot) darwiche-domingues (at) inria.fr

Last update: January 28, 2019

# 1 Exercise 1 (Finite-Horizon Problems and Dynamic Programming)

#### 1.1 Notation

A stochastic and non-stationary policy  $\pi = (\pi_1, \pi_2, \dots, \pi_{T-1})$  is such that  $\pi_t(a|s) = P(A_t = a|S_t = s)$  represents the probability of choosing the action a in state s at time t.

If the policy  $\pi_t$  is deterministic, that is,  $\pi_t(\bar{a}_s|s) = 1$  for some action  $\bar{a}_s$ , we write  $\pi_t$  as a function  $\pi_t : \mathcal{S} \to \mathcal{A}$  from the state space  $\mathcal{S}$  to the action space  $\mathcal{A}$  such that  $\pi_t(s) = \bar{a}_s$ .

#### 1.2 Bellman Equation

In this exercise, we consider a finite-horizon problem. The agent must choose actions in order to maximize the sum of the rewards up to a fixed time T. The value function at time t is defined as:

$$V_t^{\pi}(s) = E_{\pi} \left[ \sum_{n=t}^{T-1} r_t(S_n, A_n) + r_T(S_T) \middle| S_t = s \right]$$
 (1)

and represents how much reward is collected by following the policy  $\pi = (\pi_1, \pi_2, \dots, \pi_{T-1})$  starting from time t. Thus, the agent seeks to find a policy  $\pi$  that maximizes  $V_1^{\pi}$ . Note that the reward function at the final time T does not depend on the action: this is because the interactions between the agent and the environment ends at time T, and the agent's action does not matter once the time is up.

Imagine that  $\pi$  is given and we wish to compute  $V_1^{\pi}(s)$ . A very naive computation is to do the following sum:

$$V_1^{\pi}(s) = \sum_{a_1, a_2, \dots, a_{T-1}} \sum_{s_1, s_2, \dots, s_T} \left( \sum_{n=1}^{T-1} r_t(s_n, a_n) + r_T(s_T) \right) P(s_1, a_1, s_2, a_2, s_3, a_3, \dots, s_{T-1}, a_{T-1}, s_T | S_1 = s_1)$$
(2)

Let  $|\mathcal{S}|$  and  $|\mathcal{A}|$  be the number of states and the number of actions, respectively. Each term in the sum above requires  $\mathcal{O}(T)$  multiplications (to compute the joint probability from the conditional ones) and we have a sum over  $\mathcal{O}(T|\mathcal{S}|^T|\mathcal{A}|^T)$  terms. This gives a total of  $\mathcal{O}(T^2|\mathcal{S}|^T|\mathcal{A}|^T)$  operations, which is huge!

We can find a smarter way to compute it by rewriting  $V_t^{\pi}(s)$  as follows:

<sup>\*</sup>Only for the exercises solved during the course.

$$V_{t}^{\pi}(s) = E_{\pi} \left[ \sum_{n=t}^{T-1} r_{t}(S_{n}, A_{n}) + r_{T}(S_{T}) \middle| S_{t} = s \right]$$

$$= E_{\pi} \left[ r_{t}(S_{t}, A_{t}) + \sum_{n=t+1}^{T-1} r_{t}(S_{n}, A_{n}) + r_{T}(S_{T}) \middle| S_{t} = s \right]$$

$$= E_{\pi} \left[ r_{t}(S_{t}, A_{t}) \middle| S_{t} = s \right] + E_{\pi} \left[ E_{\pi} \left[ \sum_{n=t+1}^{T-1} r_{t}(S_{n}, A_{n}) + r_{T}(S_{T}) \middle| S_{t+1}, S_{t} = s \right] \middle| S_{t} = s \right]$$

$$= E_{\pi} \left[ r_{t}(S_{t}, A_{t}) \middle| S_{t} = s \right] + E_{\pi} \left[ V_{t+1}^{\pi}(S_{t+1}) \middle| S_{t} = s \right]$$

$$(3)$$

Finally, we obtain:

$$V_t^{\pi}(s) = \sum_{a} \pi_t(a|s) \left[ r_t(s,a) + \sum_{s'} p(s'|s,a) V_{t+1}^{\pi}(s') \right]$$
(4)

and, by definition, we have:

$$V_T(s) = E_{\pi}[r_T(S_T)|S_T = s] = r_T(s) \text{ for all } s \in \mathcal{S}$$

$$\tag{5}$$

Equation 4 is called *Bellman Equation* for evaluating the policy  $\pi$ , which is a dynamic programming approach.

Now, we can find  $V_1^{\pi}$  by the following procedure:

- 1. Initialization: set t = T,  $V_T(s) = r_T(s)$ ;
- 2. Compute  $V_{t-1}$  using equation 4;
- 3. Set  $t \leftarrow t 1$ ;
- 4. If t = 1 stop, otherwise go to step 2.

At each iteration t, equation 4 requires  $\mathcal{O}(1)$  multiplications and a sum over  $\mathcal{O}(|\mathcal{S}||\mathcal{A}|)$  terms to compute  $V_t$  for one state. This gives  $\mathcal{O}(|\mathcal{S}|^2|\mathcal{A}|)$  operations per iteration. Since we have T iterations, we have a total of  $\mathcal{O}(T|\mathcal{S}|^2|\mathcal{A}|)$  operations, which is much less than the naive approach! This is the interest of using dynamic programming.

#### 1.3 Bellman Optimatily Equation - Intuition

In this exercise we want to prove that the optimal value function  $V_t^*(s) := \max_{\pi} V_t^{\pi}(s)$  satisfies the equations:

$$V_t^*(s) = \max_{a \in \mathcal{A}} \left[ r_t(s, a) + \sum_{s' \in \mathcal{S}} p(s'|s, a) V_{t+1}^*(s') \right] \text{ for } 1 \le t \le T - 1$$

$$V_T^*(s) = r_T(s)$$
(6)

First, remember that our policy is non stationary and is written as  $\pi = (\pi_1, \pi_2, \dots, \pi_{T-1})$ . Note that  $V_t^{\pi}(s)$  depends only on the actions taken starting from time t. Let's define  $\pi_{t:T-1} := (\pi_t, \pi_2, \dots, \pi_{T-1})$ . With a slight abuse of notation, we can write  $V_t^{\pi} = V_t^{\pi_{t:T-1}}$ .

Now, let's see the intuition behind equation 6. We have, by using equation 4:

$$V_{t}^{*}(s) = \max_{\pi} V_{t}^{\pi}(s)$$

$$= \max_{\pi} \sum_{a} \pi_{t}(a|s) \left[ r_{t}(s,a) + \sum_{s'} p(s'|s,a) V_{t+1}^{\pi}(s') \right]$$

$$= \max_{(\pi_{t},\pi_{t+1:T-1})} \sum_{a} \pi_{t}(a|s) \left[ r_{t}(s,a) + \sum_{s'} p(s'|s,a) V_{t+1}^{\pi}(s') \right]$$

$$= \max_{\pi_{t}} \sum_{a} \pi_{t}(a|s) \left[ r_{t}(s,a) + \max_{\pi_{t+1:T-1}} \sum_{s'} p(s'|s,a) V_{t+1}^{\pi}(s') \right]$$

$$= \max_{\pi_{t}} \sum_{a} \pi_{t}(a|s) \left[ r_{t}(s,a) + \max_{\pi_{t+1:T-1}} \sum_{s'} p(s'|s,a) V_{t+1}^{\pi_{t+1:T-1}}(s') \right]$$

$$= \max_{a} \left[ r_{t}(s,a) + \max_{\pi_{t+1:T-1}} \sum_{s'} p(s'|s,a) V_{t+1}^{\pi_{t+1:T-1}}(s') \right]$$

where the second line comes from equation 4 and the last line comes from the fact that  $\sum_a \pi_t(a|s) f(a) \le \sum_a \pi_t(a|s) \max_a f(a) = \max_a f(a)^1$  for any function f and equality can be achieved by choosing  $\pi_t(a|s)$  that puts probability 1 for one action  $\bar{a}$  such that  $\bar{a} \in \operatorname{argmax}_a f(a)$ .

Observe that:

$$V_{t+1}^*(s') = \max_{\pi_{t+1}, \tau_{t-1}} V_{t+1}^{\pi_{t+1}; \tau_{t-1}}(s')$$
(8)

Thus, if we can invert the max and the sum operator in the last line of equation 7, we prove our desired result, which is equation 6. But can we do this formally?

### 1.4 Bellman Optimality Equation - Formal Proof

Let  $\bar{V}_t$  be such that:

$$\bar{V}_t(s) = \max_{a \in \mathcal{A}} \left[ r_t(s, a) + \sum_{s' \in \mathcal{S}} p(s'|s, a) \bar{V}_{t+1}(s') \right] \text{ for } 1 \le t \le T - 1$$

$$\bar{V}_T(s) = r_T(s)$$

$$(9)$$

We will prove that  $\bar{V}_t(s) = V_t^*(s)$  for all  $s \in \mathcal{S}$  and for all t in two steps:

- 1. Step 1: prove that  $V_t^*(s) \leq \bar{V}_t(s)$
- 2. Step 2: prove that  $\bar{V}_t(s) \leq V_t^*(s)$ ;

#### 1.4.1 Step 1

Let's proceed by induction on t:

- For t = T, we have  $\bar{V}_T(s) = V_T^*(s) = r_T(s)$ ;
- Assume that  $\bar{V}_n^*(s) \leq \bar{V}_n(s)$  for all  $n \in \{t+1,\ldots,T\}$  and for all s.

We have, for an arbitrary policy  $\pi$  and all s:

<sup>&</sup>lt;sup>1</sup>Since  $\pi_t(a|s)$  is a probability distribution over actions, we have  $\sum_a \pi_t(a|s) = 1$ .

$$V_{t}^{\pi}(s) = \sum_{a} \pi_{t}(a|s) \left[ r_{t}(s,a) + \sum_{s'} p(s'|s,a) V_{t+1}^{\pi}(s') \right]$$

$$\leq \max_{a} \left[ r_{t}(s,a) + \sum_{s'} p(s'|s,a) V_{t+1}^{\pi}(s') \right]$$

$$\leq \max_{a} \left[ r_{t}(s,a) + \sum_{s'} p(s'|s,a) V_{t+1}^{*}(s') \right]$$

$$\leq \max_{a} \left[ r_{t}(s,a) + \sum_{s'} p(s'|s,a) \bar{V}_{t+1}(s') \right]$$

$$= \bar{V}_{t}(s)$$

$$(10)$$

Since  $\pi$  is arbitrary, we have  $\forall \pi$ ,  $V_t^{\pi}(s) \leq \bar{V}_t(s) \implies \max_{\pi} V_t^{\pi}(s) \leq \bar{V}_t(s)$  which is what we wanted to prove.

#### 1.4.2 Step 2

Define a deterministic policy  $\pi' = (\pi'_1, \pi'_2, \dots, \pi'_{T-1})$  such that:

$$\pi'_{T-1}(s) \in \underset{a}{\operatorname{argmax}} \left[ r_{T-1}(s, a) + \sum_{s'} p(s'|s, a) r_{T}(s') \right]$$

$$\pi'_{t}(s) \in \underset{a}{\operatorname{argmax}} \left[ r_{t}(s, a) + \sum_{s'} p(s'|s, a) V_{t+1}^{\pi'}(s') \right]$$
(11)

It can be proven by induction that  $V_t^{\pi'}(s) = \bar{V}_t(s)$  for all s:

• For t = T - 1, we have for all s:

$$V_{T-1}^{\pi'}(s) = \max_{a} \left[ r_{T-1}(s, a) + \sum_{s'} p(s'|s, a) r_{T}(s') \right]$$

$$= \bar{V}_{T-1}(s)$$
(12)

• Assuming that  $V_n^{\pi'}(s) = \bar{V}_n(s)$  for all s and for all  $n \in \{t+1, \ldots, T-1\}$ , we have:

$$V_{t}^{\pi'}(s) = \max_{a} \left[ r_{t}(s, a) + \sum_{s'} p(s'|s, a) V_{t+1}^{\pi'}(s') \right]$$

$$= \max_{a} \left[ r_{t}(s, a) + \sum_{s'} p(s'|s, a) \bar{V}_{t+1}(s') \right]$$

$$= \bar{V}_{t}(s)$$
(13)

Finally:

$$\bar{V}_t(s) = V_t^{\pi'}(s) \le \max_{t} V_t^{\pi}(s) = V_t^*(s) \text{ for all } s$$
 (14)