
Lecture Note 2

1 Summary: Markov Decision Processes

Markov decision processes can be characterized by $(\mathcal{S}, \mathcal{A}, g(\cdot), \mathbb{P}(\cdot, \cdot))$, where

\mathcal{S} denotes a finite set of states

\mathcal{A}_x denotes a finite set of actions for state $x \in \mathcal{S}$

$g_a(x)$ denotes the finite time-stage cost for action $a \in \mathcal{A}_x$ and state $x \in \mathcal{S}$

$\mathbb{P}_a(x, y)$ denotes the transmission probability when the taken action is $a \in \mathcal{A}_x$, current state is x , and the next state is y

Let $u(x, t)$ denote the *policy* for state x at time t and, similarly, let $u(x)$ denote the *stationary policy* for state x . Taking the stationary policy $u(x)$ into consideration, we introduce the following notation

$$\begin{aligned} g_u(x) &\equiv g_{u(x)}(x) \\ \mathbb{P}_u(x, y) &\equiv \mathbb{P}_{u(x)}(x, y) \end{aligned}$$

to represent the cost function and transition probabilities under policy $u(x)$.

2 Cost-to-go Function and Bellman's Equation

In the previous lecture, we defined the discounted-cost, infinite horizon cost-to-go function as

$$J^*(x) = \min_u \mathbb{E} \left[\sum_{t=0}^{\infty} \alpha^t g_u(x_t) \mid x_0 = x \right].$$

We also conjectured that J^* should satisfy the *Bellman's equation*

$$J^*(x) = \min_a \left\{ g_a(x) + \alpha \sum_{y \in \mathcal{S}} P_a(x, y) J^*(y) \right\},$$

or, using the operator notation introduced in the previous lecture,

$$J^* = TJ^*.$$

Finally, we conjectured that an optimal policy u^* could be obtained by taking a *greedy policy* with respect to J^* .

In this and the following lecture, we will present and analyze algorithms for finding J^* , and prove optimality of policies that are greedy with respect to it.

3 Value Iteration

The value iteration algorithm goes as follows:

1. $J_0, k = 0$
2. $J_{k+1} = TJ_k, k = k + 1$
3. Go back to 2

Theorem 1

$$\lim_{k \rightarrow \infty} J_k = J^*$$

Proof Since $J_0(\cdot)$ and $g(\cdot)$ are finite, there exists a real number M satisfying $|J_0(x)| \leq M$ and $|g_a(x)| \leq M$ for all $a \in \mathcal{A}_x$ and $x \in \mathcal{S}$. Then we have, for every integer $K \geq 1$ and real number $\alpha \in (0, 1)$,

$$\begin{aligned} J_K(x) &= T^K J_0(x) \\ &= \min_u \mathbb{E} \left[\sum_{t=0}^{K-1} \alpha^t g_u(x_t) + \alpha^K J_0(x_K) \middle| x_0 = x \right] \\ &\leq \min_u \mathbb{E} \left[\sum_{t=0}^{K-1} \alpha^t g_u(x_t) \middle| x_0 = x \right] + \alpha^K M \end{aligned}$$

From

$$J^*(x) = \min_u \left\{ \sum_{t=0}^{K-1} \alpha^t g_u(x_t) + \sum_{t=K}^{\infty} \alpha^t g_u(x_t) \right\},$$

we have

$$\begin{aligned} &(T^K J_0)(x) - J^*(x) \\ &= \min_u \mathbb{E} \left[\sum_{t=0}^{K-1} \alpha^t g_u(x_t) + \alpha^K J_0(x_K) \middle| x_0 = x \right] - \min_u \mathbb{E} \left[\sum_{t=0}^{K-1} \alpha^t g_u(x_t) + \sum_{t=K}^{\infty} \alpha^t g_u(x_t) \middle| x_0 = x \right] \\ &\leq \mathbb{E} \left[\sum_{t=0}^{K-1} \alpha^t g_{\bar{u}}(x_t) + \alpha^K J_0(x_K) \middle| x_0 = x \right] - \mathbb{E} \left[\sum_{t=0}^{K-1} \alpha^t g_{\bar{u}}(x_t) + \sum_{t=K}^{\infty} \alpha^t g_{\bar{u}}(x_t) \middle| x_0 = x \right] \\ &\leq \mathbb{E} \left[\alpha^K |J_0(x_K)| + \sum_{t=K}^{\infty} \alpha^t g_{\bar{u}}(x_t) \middle| x_0 = x \right] \\ &\leq \max_u \mathbb{E} \left[\alpha^K |J_0(x_K)| + \sum_{t=K}^{\infty} \alpha^t |g_0(x_t)| \middle| x_0 = x \right] \\ &\leq \alpha^K M \left(1 + \frac{1}{1 - \alpha} \right), \end{aligned}$$

where \bar{u} is the policy minimizing the second term in the first line. We can bound $J^*(x) - (T^K J_0)(x) \leq \alpha^K M(1 + 1/(1 - \alpha))$ by using the same reasoning. It follows that $T^K J_0$ converges to J^* as K goes to infinity.

□

Theorem 2 J^* is the unique solution of the Bellman's equation.

Proof We first show that $J^* = TJ^*$. By contraction principle,

$$\begin{aligned} \|T(T^k J_0) - T^k J_0\|_\infty &= \|T^{k+1} J_0 - T^k J_0\|_\infty \\ &\leq \alpha \|T^k J_0 - T^{k-1} J_0\|_\infty \\ &\leq \alpha^k \|T J_0 - J_0\|_\infty \rightarrow 0 \quad \text{as } k \rightarrow \infty \end{aligned}$$

Since for all k we have $\|J^* - TJ^*\|_\infty \leq \|TJ^* - T^{k+1} J_0\|_\infty + \|J^* - T^k J_0\|_\infty + \|T^{k+1} J_0 - T^k J_0\|_\infty$, we conclude that $J^* = TJ^*$. We next show that J^* is the unique solution to $J = TJ$. Suppose that $J_1^* \neq J_2^*$. Then

$$0 < \|J_1^* - J_2^*\|_\infty = \|TJ_1^* - TJ_2^*\|_\infty \leq \alpha \|J_1^* - J_2^*\|_\infty$$

which is a contradiction. \square

Alternative Proof We prove the statement by showing that $T^k J$ is a Cauchy sequence in \mathbb{R}^n .¹ Observe

$$\begin{aligned} \|T^{k+m} J - T^k J\|_\infty &= \left\| \sum_{n=0}^{m-1} (T^{k+n+1} J - T^{k+n} J) \right\|_\infty \\ &\leq \sum_{n=0}^{m-1} \|T^{k+n+1} J - T^{k+n} J\|_\infty \\ &\leq \sum_{n=0}^{m-1} \alpha^{k+n} \|TJ - J\|_\infty \rightarrow 0 \quad \text{as } k, m \rightarrow \infty \end{aligned}$$

\square

From above, we know that $\|T^k J - J^*\|_\infty \leq \alpha^k \|J - J^*\|_\infty$. Therefore, the value iteration algorithm converges to J^* . Furthermore, we notice that J^* is the fixed point w.r.t. the operator T , i.e., $J^* = TJ^*$. We next introduce another value iteration algorithm.

3.1 Gauss-Seidel Value Iteration

The Gauss-Seidel value iteration goes as follows:

$$\begin{aligned} J_{K+1}(x) &= (T\tilde{J}_K)(x) \quad \text{where} \\ \tilde{J}_K(y) &= \begin{cases} J_K(x), & \text{if } x \leq y, \text{ (not being updated yet)} \\ J_{K+1}(y), & \text{if } x > y. \end{cases} \end{aligned}$$

We hence define the operator F as follows

$$(FJ)(x) = \min_a \left\{ g_a(x) + \underbrace{\alpha \sum_{y < x} \mathbb{P}_a(x, y) (FJ)(y)}_{\text{updated already}} + \underbrace{\alpha \sum_{y \geq x} \mathbb{P}_a(x, y) J(y)}_{\text{not being updated yet}} \right\} \quad (1)$$

Does the operator F satisfy the maximum contraction? We answer this question by the following lemma.

¹A sequence x_n in a metric space X is said to be a Cauchy sequence if for every $\epsilon > 0$ there exists an integer N such that $\|x_n - x_m\| \leq \epsilon$ if $m, n \geq N$. Furthermore, in \mathbb{R}^n , every Cauchy sequence converges.

Lemma 1

$$\|FJ - F\bar{J}\|_\infty \leq \alpha \|J - \bar{J}\|_\infty$$

Proof By the definition of F , we consider the case $x = 1$,

$$|(FJ)(1) - (F\bar{J})(1)| = |(TJ)(1) - (T\bar{J})(1)| \leq \alpha \|J - \bar{J}\|_\infty$$

For the case $x = 2$, by the definition of F , we have

$$\begin{aligned} |(FJ)(2) - (F\bar{J})(2)| &\leq \alpha \max \{ |(FJ)(1) - (F\bar{J})(1)|, |J(2) - \bar{J}(2)|, \dots, |J(|\mathcal{S}|) - \bar{J}(|\mathcal{S}|)| \} \\ &\leq \alpha \|J - \bar{J}\|_\infty \end{aligned}$$

Repeating the same reasoning for $x = 3, \dots$, we can show by induction that $|(FJ)(x) - (F\bar{J})(x)| \leq \alpha \|J - \bar{J}\|_\infty, \forall x \in \mathcal{S}$. Hence, we conclude $\|FJ - F\bar{J}\|_\infty \leq \alpha \|J - \bar{J}\|_\infty$. \square

Theorem 3 F has the unique fixed point J^* .

Proof By the definition of operator F and the Bellman's equation $J^* = TJ^*$, we have $J^* = FJ^*$. The convergence result follows from the previous lemma. Therefore, $FJ^* = J^*$. By maximum contraction property, the uniqueness of J^* holds. \square