Markov Decision Processes: Discrete Stochastic Dynamic Programming

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4 Chapter4: Finite-Horizon Markov Decision Processes

4.1 OPTIMALITY CRITERIA

4.1.1 Some Preliminaries

About MDP:

1. $\pi = (d_1, d_2, \ldots, d_{N-1}, \ldots) \in \Pi^{HR}$;
2. $h_N = (s_1, a_1, s_2, \ldots, s_N)$
3. Rewards sequence: $\{r_1(s_1, a_1), r_2(s_2, a_2), \ldots, r_{N-1}(s_{N-1}, a_{N-1}), r_N(s_N)\}$
   - $\pi \in \Pi^{HD}$, $\{r_1(X_1, d_1(h_1)), \ldots, r_{N-1}(X_{N-1}, d_{N-1}(h_{N-1})), r_N(X_N)\}$
   - $\pi \in \Pi^{MD}$, $\{r_1(X_1, d_1(X_1)), \ldots, r_{N-1}(X_{N-1}, d_{N-1}(X_{N-1})), r_N(X_N)\}$
4. $R = (R_1, R_2, \ldots, R_N)$, where $R_t = r_t(X_t, Y_t)$, and $|R_t| \leq M < \infty$.
5. $\mathbb{P}_R^\pi(\rho_1, \rho_2, \ldots, \rho_N) = \mathbb{P}^\pi\left[\{(s_1, a_1, \ldots, s_N) : (r(s_1, a_1), \ldots, r_N(s_N)) = (\rho_1, \ldots, \rho_N)\}\right]$

Definition:

1. The random vairable U is stochastically greater than V:
$$\forall t \in \mathbb{R}, \quad P(V > t) \leq P(U > t).$$
2. Probability distribution P_2 is stochastically greater than P_1 if:
$$\forall t \in \mathbb{R}, \quad \int_t^\infty p_1(t)dt \leq \int_t^\infty p_2(t)dt.$$
3. The random vector $\vec{U} = (U_1, \ldots, U_n)$ is stochastically greater than the random vector $\vec{V} = (V_1, \ldots, V_n)$:
$$\forall f \in \{f : \mathbb{R}^n \to \mathbb{R} | \vec{v} \preceq \vec{u} \Rightarrow f(\vec{v}) \leq f(\vec{u})\}, \quad \mathbb{E}[f(\vec{V})] \leq \mathbb{E}[f(\vec{U})]$$

4.1.2 The Expected Total Reward Criterion

The expected total reward criterion:

1. $\pi \in \Pi^{HR}$: $v_N^\pi(s) = \mathbb{E}_S^\pi \left\{ \sum_{t=1}^{N-1} r_t(X_t, Y_t) + r_N(X_N) \right\}$.
2. $\pi \in \Pi^{HD}$: $v_N^\pi(s) = \mathbb{E}_S^\pi \left\{ \sum_{t=1}^{N-1} r_t(X_t, d_t(h_t)) + r_N(X_N) \right\}$.
3. Discounted reward:$\pi \in \Pi^{HR}$,
   $v_{N,\lambda}^\pi(s) = \mathbb{E}_S^\pi \left\{ \sum_{t=1}^{N-1} \lambda^{t-1} r_t(X_t, d_t(h_t)) + \lambda^{N-1} r_N(X_N) \right\}$.
   Taking the discount factor into account does not effect any theoretical results or algorithms in the finite-horizon case but might effect the decision maker's preference for policies.

4.1.3 Optimal Policies

Definition:

1. Optimal policy $\pi^* : \forall \pi \in \Pi^{HR}, v_N^{\pi^*} \succeq v_N^{\pi}$.
2. $\epsilon-$optimal policy, $\pi^* : \forall \pi \in \Pi^{HR}, v_N^{\pi_\epsilon^*} + \epsilon \succeq v_N^{\pi}$.
3. Optimal value: $v_N^* = \sup_{\pi \in \Pi^{HR}} v_N^{\pi}$.
4. We can get $v_N^{\pi^*} = v_N^*$ and $v_N^{\pi_\epsilon^*} + \epsilon > v_N^*$.
5. Considering initial state distribution P_1: $v_N^{\pi, P_1} = \sum_{s \in S} v_N^{\pi}(s) P_1\{X_1 = s\}$.

Markov decision problem = Markov decision process + Optimality criteria

4.2 FINITE-HORIZON POLICY EVALUATION

1. $\pi = (d_1, d_2, \ldots, d_{N-1}) \in \Pi^{HR}$
2. Define: $u_t^{\pi}(h_t) = \mathbb{E}_{h_t}^{\pi} \left\{ \sum_{n=t}^{N-1} r_n(X_n, Y_n) + r_N(X_N) \right\}$, $(u_t^{\pi} : H_t \to \mathbb{R})$. And we define $u_N^{\pi}(h_N) = r_N(s_N)$.
3. Finite horizon-policy evaluation algorithm ($\pi \in \Pi^{HD}$):

$$\begin{aligned}
\hat{u}_t^{\pi}(h_t) =& r_t(s_t, d_t(h_t)) + \sum_{s' \in S} p_t(s'|s_t, d_t(h_t)) \hat{u}_{t+1}^{\pi}(h_t, d_t(h_t), s'). \quad ((h_t, d_t(h_t), s') \in H_{t+1}) \\
=& r_t(s_t, d_t(h_t)) + \mathbb{E}_{h_t}^{\pi} \left\{ \hat{u}_{t+1}^{\pi}(h_t, d_t(h_t), X_{t+1}) \right\}
\end{aligned}$$

Proof. Part proof with backward induction hypothesis ($u_{h_{t+1}}^{\pi} = \hat{u}_{h_{t+1}}^{\pi}$):

$$\begin{aligned}
\hat{u}_t^{\pi}(h_t) =& r_t(s_t, d_t(h_t)) + \mathbb{E}_{h_t}^{\pi} \left\{ u_{t+1}^{\pi}(h_t, d_t(h_t), X_{t+1}) \right\} \\
=& r_t(s_t, d_t(h_t)) + \mathbb{E}_{h_t}^{\pi} \left\{ \mathbb{E}_{h_{t+1}}^{\pi} \left\{ \sum_{n=t+1}^{N-1} r_n(X_n, Y_n) + r_N(X_N) \right\} \right\} \\
=& r_t(s_t, d_t(h_t)) + \mathbb{E}_{h_t}^{\pi} \left\{ \sum_{n=t+1}^{N-1} r_n(X_n, Y_n) + r_N(X_N) \right\} \\
=& \mathbb{E}_{h_t}^{\pi} \left\{ r_t(s_t, d_t(h_t)) + \sum_{n=t+1}^{N-1} r_n(X_n, Y_n) + r_N(X_N) \right\} = u_t^{\pi}(h_t)
\end{aligned}$$

□

4. Finite horizon-policy evaluation algorithm ($\pi \in \Pi^{HR}$):

$$\hat{u}_t^{\pi}(h_t) = \sum_{a \in A_{s_t}} q_{d_t(h_t)}(a) \left\{ r_t(s_t, a) + \sum_{s' \in S} p_t(s'|s_t, a) \hat{u}_{t+1}^{\pi}(h_t, a, s'). \right\}$$

5. Finite horizon-policy evaluation algorithm ($\pi \in \Pi^{MD}$):

$$\hat{u}_t^{\pi}(s_t) = r_t(s_t, d_t(s_t)) + \sum_{s' \in S} p_t(s'|s_t, d_t(s_t)) \hat{u}_{t+1}^{\pi}(s').$$

6. The computation complexity. There are K states and L actions, then:
    - If $\pi \in \Pi^{HD}$, then requiring $K\sum_{i=0}^{N-1}(KL)^i$ multiplications.
    - If $\pi \in \Pi^{MD}$, then requiring $(N-1)K^2L$ multiplications.

4.3 OPTIMALITY EQUATIONS AND THE PRINCIPLE OF OPTIMALITY

Optimality equations (Bellman equations or functional equations).

We start study this equation:

$$u_t^*(h_t) = \sup_{\pi \in \Pi^{HR}} u_t^\pi(h_t)$$

When minimizing costs instead of maximizing rewards, we sometimes refer to u_t^* as a **cost-to-go** funciton.

Definition 1. ***(Optimality equations).***

$$\hat{u}_t(h_t) = \sup_{a \in A_{s_t}} \left\{ r_t(s_t, a) + \sum_{s' \in S} p_t(s'|s_t, a)\hat{u}_{t+1}(h_t, a, s') \right\}, \quad s.t.\ \hat{u}_N(h_N) = r_N(s_N). \tag{1}$$

If A_{s_t} is finite, it can be replaced by max*. Then, $\forall h_t, \hat{u}_t(h_t) = u_t^*(h_t)$.*

Proof. The proof is in two parts.
Let arbitrary $\pi' = (d_1', d_2', \dots, d_{N-1}') \in \Pi^{HR}$.
Step1:
First, we have $u_N^{\pi'}(h_N) = \hat{u}_N(h_N) = u_N^*(h_N)$.
Then, because we take the operation sup, we reasonably have $\hat{u}_{N-1}(h_{N-1}) \geq u_{N-1}^*(h_{N-1})$.
Assuming that $\forall h_t \in H_t$, and $t = n+1, \dots, N$, we have $\hat{u}_t(h_t) \geq u_t^*(h_t)$.

$$\begin{aligned}
\hat{u}_n(h_n) &= \sup_{a \in A_{s_n}} \left\{ r_n(s_n, a) + \sum_{s' \in S} p_n(s'|s_n, a)\hat{u}_{n+1}(h_n, a, s') \right\} \\
&\geq \sup_{a \in A_{s_n}} \left\{ r_n(s_n, a) + \sum_{s' \in S} p_n(s'|s_n, a)u_{n+1}^*(s_n, a, s') \right\} \\
&\geq \sum_{a \in A_{s_n}} q_{d_n'(h_n)}(a) \left\{ r_n(s_n, a) + \sum_{s' \in S} p_n(s'|s_n, a)u_{n+1}^{\pi'}(s_n, a, s') \right\} \\
&\geq u_n^{\pi'}(h_n)
\end{aligned}$$

Which means that, $\forall \pi \in \Pi^{HR}, \hat{u}_n(h_n) \geq u_n^\pi(h_n)$.
Step2:
$\forall \epsilon$, we can construct $\pi' \in \Pi^{HR}$ for which: $u_n^{\pi'}(h_n) + (N-n)\epsilon \geq \hat{u}_n(h_n)$.
To do this, construct a policy $\pi' = (d_1', d_2', \dots, d_{N-1}') \in \Pi^{HR}$ by choosing $d_n(h_n)$ to satisfy

$$\sum_{a \in A_{S_t}} q_{d_n'(h_n)}(a) \left\{ r_n(s_n, a) + \sum_{s' \in S} p_n(s'|s_n, a)\hat{u}_{n+1}(s_n, a, s') \right\} + \epsilon \geq \hat{u}_n(h_n).$$

First, we have $u_N^{\pi'}(h_N) = u_N(h_N)$.
Then, we assume that $u_t^{\pi'}(h_t) + (N-t)\epsilon \geq u_t(h_t)$ for $t = n+1, \ldots, N$.

$$
\begin{aligned}
u_n^{\pi'}(h_n) =& \sum_a q_{d'_n(h_n)}(a) \left\{ r_n(s_n, a) + \sum_{s' \in S} p_n(s'|s_n, a) u_{n+1}^{\pi'}(s_n, a, s') \right\} \\
\geq& \sum_a q_{d'_n(h_n)}(a) \left\{ r_n(s_n, a) + \sum_{s' \in S} p_n(s'|s_n, a) \hat{u}_{n+1}(s_n, a, s') \right\} - (N-n-1)\epsilon \\
\geq& \hat{u}_n(h_n) - (N-n)\epsilon
\end{aligned}
$$

Step3: $u_n^*(h_n) + (N-n)\epsilon \geq u_n^{\pi'}(h_n) + (N-n)\epsilon \geq u_n(h_n) \geq u_n^*(h_n)$.
The lefting question is

$$
\int_{a \in A_{s_n}} q_{d'_n(h_n)}(a) \left\{ r_n(s_n, a) + \sum_{s' \in S} p_n(s'|s_n, a) u_{n+1}^{\pi'}(s_n, a, s') \right\} da
$$

□

Theorem 1. *Suppose $u_t^*, t = 1, \ldots, N$ are solutions of the optimality equation (*max *version). Then we can construct a corresponding policy $\pi^* = (d_1^*, d_2^*, \ldots, d_{N-1}^*) \in \Pi^{HD}$ satisfies*

$$
d_t^*(h_t) \in \arg\max_{a \in A_{s_t}} \left\{ r_t(s_t, a) + \sum_{s' \in S} p_t(s'|s_t, a) u_{t+1}^*(h_t, a, s') \right\}
$$

for $t = 1, \ldots, N-1$. Then

1. $u_t^{\pi^*}(h_t) = u_t^*(h_t), \quad h_t \in H_t$.
2. $v_N^{\pi^*}(s) = v_N^*(s), \quad s \in S$.

Proof. Clearly, $u_N^{\pi^*}(h_n) = u_N^*(h_n), h_n \in H_n$.
We assume that $u_{n+1}^{\pi^*}(h_{n+1}) = u_{n+1}^*(h_{n+1})$,

$$
\begin{aligned}
u_n^*(h_n) =& \max_{a \in A_{s_n}} \left\{ r_n(s_n, a) + \sum_{s' \in S} p_n(s'|s_n, a) u_{n+1}^*(h_n, a, s') \right\} \\
=& r_n(s_n, d_n^*(h_n)) + \sum_{s' \in S} p_n(s'|s_n, d_n^*(h_n)) u_{n+1}^*(h_n, d_n^*(h_n), s') \\
=& r_n(s_n, d_n^*(h_n)) + \sum_{s' \in S} p_n(s'|s_n, d_n^*(h_n)) u_{n+1}^{\pi^*}(h_n, d_n^*(h_n), s') \\
=& u_n^{\pi^*}(h_n)
\end{aligned}
$$

□

Theorem 2. *Let $\epsilon > 0$ be arbitrary and suppose $u_t^*, t = 1, \ldots, N$ are solutions of the optimality equation (*sup *version, a is continuous). Then we can construct a corresponding policy $\pi^\epsilon = (d_1^\epsilon, d_2^\epsilon, \ldots, d_{N-1}^\epsilon) \in \Pi^{HD}$ satisfies*

$$
\left\{ r_t(s_t, d_t^\epsilon) + \sum_{s' \in S} p_t(s'|s_t, d_t^\epsilon) u_{t+1}^*(h_t, d_t^\epsilon, s') \right\} + \frac{\epsilon}{N-1}
$$

$$\geq \sup_{a \in A_{s_t}} \left\{ r_t(s_t, a) + \sum_{s' \in S} p_t(s'|s_t, a) u^*_{t+1}(h_t, a, s') \right\}$$

for $t = 1, \ldots, N-1$. Then

1. $u_t^{\pi^\epsilon}(h_t) + (N-t)\frac{\epsilon}{N-1} \geq u_t^*(h_t), \quad h_t \in H_t.$

2. $v_N^{\pi^\epsilon}(s) + \epsilon = v_N^*(s), \quad s \in S.$

The proof is analogous.

4.4 OPTIMALITY OF DETERMINISTIC MARKOV POLICIES

Theorem 3. *Let $u_t^*(h_t)$ is the solution of the optimality equations, then:*

1. *$\forall t = 1, \ldots, N$, $u_t^*(h_t)$ depends on h_t only through s_t.*

2. *$\forall \epsilon > 0$, there exists an $\epsilon-$ optimal policy which is deterministic and Markov.*

3. *if a is reachable, then there exists an optimal policy which is deterministic Markov.*

Proof. First, we have $\forall h_{N-1} \in H_{N-1}, a_{N-1} \in A_{S_{N-1}}, u_N^*(h_N) = u_N^*(s_N) = r_N(s_N)$. Then, we assume that $\forall n = t+1, \ldots, N, u_n^*(h_n) = u_n^*(s_n)$.

$$\begin{aligned}
u_t^*(h_t) &= \sup_{a \in A_{s_t}} \left\{ r_t(s_t, a) + \sum_{s'=S} p_t(s'|s_t, a) u^*_{t+1}(h_t, a, s') \right\} \\
&= \sup_{a \in A_{s_t}} \left\{ r_t(s_t, a) + \sum_{s'=S} p_t(s'|s_t, a) u^*_{t+1}(s') \right\} \\
&= u_t^*(s_t)
\end{aligned}$$

□

We have established that

$$v_N^*(s) = \sup_{\pi \in \Pi^{HR}} v_N^\pi(s) = \sup_{\pi \in \Pi^{MD}} v_N^\pi(s), \quad s \in S$$

Proposition 1. *Assume S is finite or countable, and that*

1. *A_s is finite for each $s \in S$, or*

2. *A_s is compact; $p_t(s'|s, a), r_t(s, a)$ is continuous in a, and $|r_t(s, a)| \leq M < \infty$*

3. *A_s is compact; $r_t(s, a)$ is upper semicontinuous in a; and $|r_t(s, a)| \leq M < \infty$; $p_t(s'|s, a)$ is lower semi-continuous in a.*

Then there exists a deterministic Markovian policy which is optimal. (Which means that sup *is reachable.)*

4.5 BACKWARD INDUCTION

The terms "backward induction" and "dynamic programming" are synonymous. Key assumption: optimal action is obtainable.

Definition 2. ***(The backward induction algorithm).***

1. *$\forall s \in S$, let $\hat{u}_N(s) = r_N(s)$.*
2. *$t = N - 1 : 1$, we calculate that*

$$\forall s \in S, \hat{u}_t(s) = \max_{a \in A_s} \left\{ r_t(s,a) + \sum_{s' \in S} p_t(s'|s,a)\hat{u}_{t+1}(s') \right\}$$

4.6 OPTIMALITY OF MONOTONE POLICIES

4.6.1 Structured Policies

4.6.2 Superadditive Functions

Definition 3. *Let X and Y be partially ordered sets and $g : X \times Y \to \mathbb{R}$. We say g is **superadditive** if for $x^+ \geq x^-$ and $y^+ \geq y^-$, we have*

$$g(x^+, y^+) + g(x^-, y^-) \geq g(x^+, y^-) + g(x^-, y^+)$$

If the reverse inequality above holds, $g(x,y)$ is said to be **subadditive**. If superadditive function g is twice differetiable, we have $\frac{\partial^2 g(x,y)}{\partial x \partial y} \geq 0$.

Lemma 1. *Let*

$$f(x) = \max_y \left\{ y \in \arg\max_{y' \in Y} g(x, y') \right\}$$

If g is a superadditive function, then $f(x)$ is monotone nondecreasing in x.

Proof. Let corresponding numbers: (x^+, y^+) and (x^-, y^-), where $y^+ = f(x^+)$ and $y^- = f(x^-)$. We assume that $x^+ > x^-$, but $y^+ \leq y^-$,then:

1. By the definition of $f(x)$, we have $g(x^-, y^-) \geq g(x^-, y^+)$.
2. By the definition of supperadditive, we have $g(x^+, y^-) + g(x^-, y^+) \geq g(x^-, y^-) + g(x^+, y^+)$.
3. Then we have $g(x^+, y^-) \geq g(x^+, y^+)$, which contradicts with the definition of f.

□

4.7 Optimality of Monotone Policies

Leaving...

5 Infinite-Horizon Models: Foundations

- S is finite or countable.
- stationary policy: $d^\infty = (d, d, \ldots)$

5.1 THE VALUE OF A POLICY

1. **Expected total reward** of policy $\pi \in \Pi^{HR}$:

$$v^\pi(s) = \lim_{n\to\infty} \mathbb{E}_S^\pi \left\{ \sum_{t=1}^{N} r(X_t, Y_t) \right\} = \lim_{n\to\infty} v_{n+1}^\pi(s) \tag{2}$$

   If the limit exists and when interchanging the limits and expectation is valid, we have

$$v^\pi(s) = \mathbb{E}_S^\pi \left\{ \sum_{t=1}^{\infty} r(X_t, Y_t) \right\} \tag{3}$$

2. **Expected total discounted reward** of policy $\pi \in \Pi^{HR}$:

$$v_\lambda^\pi(s) = \lim_{n\to\infty} \mathbb{E}_S^\pi \left\{ \sum_{t=1}^{n} \lambda^{t-1} r(X_t, Y_t) \right\} \tag{4}$$

   For $0 \le \lambda \le 1$, the limits exists when $\sup_{s\in S} \sup_{a\in A_s} |r(s,a)| = M < \infty$. When the limit exists and interchainging the limit and expectation are valid, we have

$$v_\lambda^\pi(s) = \mathbb{E}_S^\pi \left\{ \sum_{t=1}^{\infty} \lambda^{t-1} r(X_t, Y_t) \right\} \tag{5}$$

3. **Average reward or gain** of policy $\pi \in \Pi^{HR}$:

$$g^\pi(s) = \lim_{n\to\infty} \frac{1}{n} \mathbb{E}_S^\pi \left\{ \sum_{t=1}^{n} r(X_t, Y_t) \right\} = \lim_{n\to\infty} \frac{1}{n} v_{n+1}^\pi(s) \tag{6}$$

   If the limit doesn't exist, we define:

$$g_-^\pi(s) = \liminf_{n\to\infty} \frac{1}{n} v_{n+1}^\pi(s), \quad g_+^\pi(s) = \limsup_{n\to\infty} \frac{1}{n} v_{n+1}^\pi(s).$$

5.2 MARKOV POLICIES

Theorem 4. *$\forall \pi = (d_1, d_2, \ldots) \in \Pi^{HR}$. Then, for each $s_1 \in S_1$, $\exists \pi' = (d_1', d_2', \ldots) \in \Pi^{MR}$, satisfying*

$$\forall t, \quad P^{\pi'}\{X_t = s', Y_t = a | X_1 = s_1\} = P^\pi\{X_t = s', Y_t = a | X_1 = s_1\} \tag{7}$$

Proof. We construct the randomized Markov decision rule $d_t' \in \pi'$ by

$$q_{d_t'(s')}(a) = P^\pi\{Y_t = a | X_t = s', X_1 = s_1\}$$

Then,

$$P^{\pi'}\{Y_t = a|X_t = s'\} = P^{\pi'}\{Y_t = a|X_t = s', X_1 = s_1\} = P^{\pi}\{Y_t = a|X_t = s', X_1 = s_1\}$$

We use indunction method. Clearly the theorem holds with $t = 1$. We assume that the theorem holds for $t = 1, 2, \ldots, n-1$. Then,

$$\begin{aligned}
P^{\pi}\{X_n = s'|X_1 = s_1\} =& \sum_{s\in S}\sum_{a\in A_s} P^{\pi}\{X_{n-1} = s, Y_{n-1} = a|X_1 = s_1\}\, p(s'|s,a) \\
=& \sum_{s\in S}\sum_{a\in A_s} P^{\pi'}\{X_{n-1} = s, Y_{n-1} = a|X_1 = s_1\}\, p(s'|s,a) \\
=& P^{\pi'}\{X_n = s'|X_1 = s_1\} \\
P^{\pi'}\{X_n = s', Y_n = a|X_1 = s_1\} =& P^{\pi'}\{Y_n = a|X_n = s'\}\, P^{\pi'}\{X_n = s'|X_1 = s_1\} \\
=& P^{\pi}\{Y_n = a|X_n = s', X_1 = s_1\}\, P^{\pi}\{X_n = s'|X_1 = s_1\} \\
=& P^{\pi}\{X_n = s', Y_n = a|X_1 = s_1\}
\end{aligned}$$

□

Note that, in the above theorem, π' depends on the initial state X_1. When the state at decision epoch 1 is chosen according to a probability distribution, then π' is depended on the distribution intead of $X_1 = s_1$.

Corollary 1. $\forall \mathcal{D}_1 \sim X_1, \pi \in \Pi^{HR}, \exists \pi' \in \Pi^{MR}$ *for which*

$$P^{\pi'}\{X_t = s', Y_t = a\} = P^{\pi}\{X_t = s', Y_t = a\}$$

Noting that

$$\begin{aligned}
v_N^{\pi}(s) =& \sum_{t=1}^{N-1}\sum_{s'\in S}\sum_{a\in A_{s'}} r(s',a)P^{\pi}\{X_t = s', Y_t = a|X_1 = s_1\} \\
&+ \sum_{s'\in S}\sum_{a\in A_{s'}} r_N(s')P^{\pi}\{X_N = s', Y_N = a|X_1 = s_1\} \qquad (8) \\
v_{\lambda}^{\pi}(s) =& \sum_{t=1}^{\infty}\sum_{s'\in S}\sum_{a\in A_{s'}} \lambda^{t-1} r(s',a)P^{\pi}\{X_t = s', Y_t = a|X_1 = s_1\}
\end{aligned}$$

6 Discounted Markov Decision Problems

Assumptions in this chapter:

1. Stationary rewards and transition probabilities; $r(s,a)$ and $p(s'|s,a)$ do not vary from decision epoch to decision epoch.
2. Bounded rewards; $|r(s,a)| \leq M < \infty$.
3. Discount factor λ.
4. Discrete state spaces.

6.1 POLECY EVALUATION

$$v_\lambda^*(s) = \sup_{\pi \in \Pi^{HR}} v_\lambda^\pi(s) = \sup_{\pi \in \Pi^{MR}} v_\lambda^\pi(s)$$

Let $\pi = (d_1, d_2, \dots) \in \Pi^{MR}$,then

$$v_\lambda^\pi(s_1) = \mathbb{E}_{s_1}^\pi \left\{ \sum_{t=1}^\infty \lambda^{t-1} r(X_t, Y_t) \right\} = r_{d_1} + \lambda P_{d_1} v_\lambda^{\pi' = \{d_2, d_3, \dots\}}$$

Let $d^\infty = (d, d, \dots)$, then $v_\lambda^{d^\infty}(s_1) = r_d(s_1) + \lambda P_d v_\lambda^{d^\infty}$.
Let $\forall v \in V, L_d v = r_d + \lambda P_d v$, then $v_\lambda^{d^\infty} = L_d v_\lambda^{d^\infty}$, which means $v_\lambda^{d^\infty}$ is a fixed point of L_d in V.

Theorem 5. *Suppose $0 \leq \lambda < 1$. Then $\forall d^\infty$ with $d \in D^{MR}$, $\vec{v}_\lambda^{d^\infty}$ is the unique solution in V of $\vec{v} = r_d + \lambda P_d \vec{v}$, and $\vec{v}_\lambda^{d^\infty} = (I - \lambda P_d)^{-1} r_d$.*

Proof. Key theorem: $\|P_d\| = 1$ and $\sigma(\lambda P_d) \leq \|\lambda P_d\| = \lambda \leq 1$, then $(I - \lambda P_d)^{-1}$ exists.

$$\vec{v} = (I - \lambda P_d)^{-1} r_d = \sum_{t=1}^\infty \lambda^{t-1} P_d^{t-1} r_d = \vec{v}_\lambda^{d^\infty}$$

□

Lemma 2. *1.* $\vec{u} \succeq \vec{0} \Rightarrow (I - \lambda P_d)^{-1} \vec{u} \succeq \vec{u} \succeq \vec{0}$

2. $\vec{u} \succeq \vec{v} \Rightarrow (I - \lambda P_d)^{-1} \vec{u} \succeq (I - \lambda P_d)^{-1} \vec{v}$

3. $\vec{u} \succeq \vec{0} \Rightarrow \vec{u}^T (I - \lambda P_d)^{-1} \succeq \vec{u}^T$

6.2 OPTIMALITY EQUATIONS

Optimality equations or Bellamn equations:

$$v(s) = \sup_{a \in A_s} \left\{ r(s,a) + \sum_{s' \in S} \lambda p(s'|s,a) v(s') \right\}$$

Lemma 3. $\forall v \in V, 0 \leq \lambda < 1, \sup_{d \in D^{MD}} \{r_d + \lambda P_d v\} = \sup_{d \in D^{MR}} \{r_d + \lambda P_d v\}$

Proof. First, $D^{MD} \subset D^{MR}$, so $\sup_{d \in D^{MD}} \{r_d + \lambda P_d v\} \preceq \sup_{d \in D^{MR}} \{r_d + \lambda P_d v\}$.
Second, $\forall d^{MR} \in D^{MR}$,

$$\sum_{a \in A_s} q_{d^{MR}}(a) \left[r(s,a) + \sum_{s' \in S} \lambda p(s'|s,a) v(s') \right] \leq \sup_{a \in A_s} \left\{ r(s,a) + \sum_{s' \in S} \lambda p(s'|s,a) v(s') \right\}$$

which means,

$$r_{d^{MR}} + \lambda P_{d^{MR}} v \preceq \sup_{d \in D^{MD}} \{r_d + \lambda P_d v\} \Rightarrow \sup_{d \in D^{MR}} \{r_d + \lambda P_d v\} \preceq \sup_{d \in D^{MD}} \{r_d + \lambda P_d v\}$$

□

Definition 4. *(Bellman operator).*

$$\forall v \in V, \mathcal{L}v = \sup_{d \in D^{MD}} \{r_d + \lambda P_d v\} \tag{9}$$

If the supremum is attained for all $v \in V$, we define L by

$$\forall v \in V, Lv = \max_{d \in D^{MD}} \{r_d + \lambda P_d v\} \tag{10}$$

Theorem 6. *Suppose there exists a $v \in V$ for which*

1. $v \succeq \mathcal{L}v \Rightarrow v \succeq v_\lambda^*$;
2. $v \preceq \mathcal{L}v \Rightarrow v \preceq v_\lambda^*$;
3. $v = \mathcal{L}v \Rightarrow v$ *is unique and* $v = v_\lambda^*$.

Proof. First, we proof 1.
$\forall \pi = (d_1, d_2, \ldots) \in \Pi^{MR}$,

$$\begin{aligned} v \succeq & \sup_{d \in D^{MD}} \{r_d + \lambda P_d v\} = \sup_{d \in D^{MR}} \{r_d + \lambda P_d v\} \\ \succeq & r_{d_1} + \lambda P_{d_1} v = \sum_{t=1}^{n} (\lambda P^\pi)^{k-1} r_{d_t} + (\lambda P^\pi)^n v \\ v - v_\lambda^\pi \succeq & (\lambda P^\pi)^n v - \sum_{t=n+1}^{\infty} (\lambda P^\pi)^{t-1} r_{d_t} \\ \succeq & -\lambda^n \|v\|_\infty \cdot \vec{e} - \lambda^n \cdot \frac{M}{1-\lambda} \cdot \vec{e} \end{aligned}$$

Because r is bounded, so $\forall \epsilon, \exists N$, when $n \geq N$, we have

$$v \succeq v_\lambda^\pi - \epsilon \cdot \vec{e}$$

$$v \succeq \sup_{\pi \in \Pi^{MR}} v_\lambda^\pi = \sup_{\pi \in \Pi^{HR}} v_\lambda^\pi = v_\lambda^*$$

Second, we proof 2.
If $v \preceq \mathcal{L}v$, by definition of sup, we have

$$\forall \epsilon, \exists d \in D^{MD}, v \preceq r_d + \lambda P_d v + \epsilon \cdot \vec{e}$$

$$\Rightarrow v \preceq (I - \lambda P_d)^{-1} (r_d + \epsilon \cdot \vec{e}) = v_\lambda^{d^\infty} + (1-\lambda)^{-1} \epsilon \cdot \vec{e} \preceq \sup_{\pi \in \Pi^{HR}} v_\lambda^\pi + (1-\lambda)^{-1} \epsilon \cdot \vec{e}$$

□