

4. INFINITE TIME HORIZON


[REALLY INDEFINATE TIME LENGTH.]

INFINITE TIME

INFINITE $\downarrow$ ∞ DISCOUNT FACTOR $\beta \in (0,1]$ $\downarrow$

$$V(x) = \underbrace{\underbrace{\underbrace{\max_{\pi}}_{\max_{\pi_0}} \underbrace{\mathbb{E}_x}_{\mathbb{E}_{x_1}}}_{\max_{\pi_1, \pi_2, \dots}} \left[\underbrace{\sum_{t=0}^{\infty} \beta^t r(X_t)}_{r(x) + \beta \sum_{t=1}^{\infty} \beta^{t-1} r(X_t)} \right]$$

$$= \max_{\pi_0} \mathbb{E}_{x_{\pi_0}} \left[r(x) + \beta \underbrace{\mathbb{E}_{x_1} \left[\max_{\pi_1, \pi_2, \dots} \sum_{t=1}^{\infty} \beta^{t-1} r(X_t) \right]}_{\mathbb{E}_{x_1} V(x_1)} \right]$$

$$= \max_{\pi_0} r(x) + \beta \mathbb{E}_{x, \pi_0} [V(x_1)] \quad \text{— BELLMAN EQUATION}$$

BEFORE SOLVING THIS GAVE THE OPTIMAL
[POLICY, BUT WHAT ABOUT NOW?

DISCOUNTED, POSITIVE, NEGATIVE & AVERAGE PROGRAMMING

$$V(x) = \max_{\pi} \lim_{T \rightarrow \infty} \mathbb{E}_x \left[\sum_{t=0}^T \beta^t r(X_t, \pi_t) \right]$$

LIMIT & MAX INTERACT. SO DIFFERENT CASES

- DISCOUNTED PROGRAMMING: $\beta \in (0, 1)$, $\max_{x, a} |r(x, a)| < \infty$
- POSITIVE PROGRAMMING: $\beta \in (0, 1]$, $r(x, a) \geq 0$
- NEGATIVE PROGRAMMING: $\beta \in (0, 1]$, $r(x, a) \leq 0$
[OR MINIMIZE $c(x, a) \geq 0$]
- AVERAGE PROGRAMMING:

$$\lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E}_x \left[\sum_{t=0}^T r(X_t, \pi_t) \right]$$

DISCOUNTED PROGRAMMING RESULT.

Thrm 43. For a discounted program, the optimal policy $V(x)$ satisfies

$$V(x) = \max_{a \in \mathcal{A}} \left\{ r(x, a) + \beta \mathbb{E}_{x,a} [V(\hat{X})] \right\}.$$

Moreover, if we find a function $R(x)$ such that

$$R(x) = \max_{a \in \mathcal{A}} \left\{ r(x, a) + \beta \mathbb{E}_{x,a} [R(\hat{X})] \right\}$$

then $R(x) = V(x)$, i.e. the solution to the Bellman equation is unique, and we find a function $\pi(x)$ such that

$$\pi(x) \in \operatorname{argmax}_{a \in \mathcal{A}} \left\{ r(x, a) + \beta \mathbb{E}_{x,a} [R(\hat{X})] \right\}$$

Then π is optimal and $R(x, \pi) = R(x) = V(x)$ the optimal value function.

PROOF: FIRST LETS SHOW THE BELLMAN EQUATION HOLDS:

$$R_t(x, \pi) = r(x, \pi_0) + \beta \mathbb{E}[R_{t+1}(\hat{x}, \hat{\pi})]$$

TAKE LIMITS
 $t \rightarrow \infty$

$$\begin{aligned} R(x, \pi) &= r(x, \pi_0) + \beta \mathbb{E}_{x, \pi} [R(\hat{x}, \hat{\pi})] \\ &\leq r(x, \pi_0) + \beta \mathbb{E}_{x, \pi_0} [V(\hat{x})] \end{aligned}$$

NOW MAXIMIZE

OVER π_0 & π ,

$$V(x) = \max_{\pi} R(x, \pi)$$

$$\leq \max_a \{ r(x, a) + \beta \mathbb{E}_{x, a} [V(\hat{x})] \}$$

SO WE HAVE

$$V(x) \leq \max_a \{ r(x, a) + \beta \mathbb{E}_{x, a} [V(\hat{x})] \}.$$

LET $\hat{\pi}$ BE SUCH THAT $R(\hat{x}, \hat{\pi}) \geq V(\hat{x}) - \epsilon$

THEN FOR POLICY π THAT DOES a THEN $\hat{\pi}$

$$V(x) \geq R(x, \pi)$$

$$= r(x, a) + \beta \mathbb{E}_{x, a}[R(\hat{x}, \hat{\pi})]$$

$$\geq r(x, a) + \beta \mathbb{E}_{x, a}[V(\hat{x})] - \beta \epsilon$$

LET $\epsilon \rightarrow 0$ & THEN MAXIMIZE OVER a :

$$V(x) \geq \max_a \{ r(x, a) + \beta \mathbb{E}_{x, a}[V(\hat{x})] \}$$

$\therefore$ BELLMAN HOLDS

$$V(x) = \max_a \{ r(x, a) + \beta \mathbb{E}_{x, a}[V(\hat{x})] \} \checkmark$$

PROOF (CONTINUED):

WANT: TO SHOW UNIQUENESS OF SOLN

FIRST A DEFINITION

↗ [SIMILAR TO UNIQUENESS FOR MARKOV CHAINS].

Def 9 (Q-Factor). The Q-factor of reward function $R(\cdot)$ is the value for taking action a in state x and then at the next step receiving reward $R(\hat{X})$:

$$Q_R(x, a) = \mathbb{E}_{x,a}[r(x, a) + \beta R(\hat{X})].$$

Similarly the Q-factor for a policy π , denoted by $Q_\pi(x, a)$, is given by the above expression with $R(x) = R(x, \pi)$. The Q-factor of the optimal policy is given by

$$Q^*(x, a) = \max_{\pi} Q_\pi(x, a).$$

SUPPOSE $R(x)$ IS ANOTHER SOL^N. SO $R(x) = \max_a Q_R(x, a)$
THEN

$$\begin{aligned} Q_V(x, a) - Q_R(x, a) &= \beta \mathbb{E}_{x, a} [V(\hat{x}) - R(\hat{x})] \\ &= \beta \mathbb{E}_x \left[\max_a Q(\hat{x}, a) - \max_{a'} Q(\hat{x}, a') \right] \end{aligned}$$

SO

$$\begin{aligned} \|Q_V - Q_R\|_\infty &\leq \beta \max_x \left| \max_a Q_V(\hat{x}, a) - \max_{a'} Q_R(\hat{x}, a') \right| \\ &\leq \beta \max_{x, a} |Q_V(\hat{x}, a) - Q_R(\hat{x}, a)| \\ &= \beta \|Q_V - Q_R\|_\infty \end{aligned}$$

$\therefore$ ONLY SOLUTION $\hookrightarrow Q_V = Q_R$

$$\therefore R(x) = \max_a Q_R(x, a) = \max_a Q_V(x, a) = V(x) \quad \checkmark$$

SOLUTION IS
UNIQUE

PROOF (CONTINUED):

WANT: IF $\pi(x) \in \underset{a}{\text{ARG-MAX}} \left\{ r(x,a) + \beta \mathbb{E}_{x,a} [R(\hat{x})] \right\}$
THEN $R(x,\pi) \stackrel{a}{=} R(x)$. (+).

TO SHOW THIS NOTE $R(x)$ SOLVES

$$R(x) = r(x, \pi(x)) + \beta \mathbb{E}_{x,\pi} [R(\hat{x})] \quad (\#)$$

WHERE UNDER π X_t IS NOW A MARKOV CHAIN.

BY OUR PROPOSITION ON MARKOV CHAINS

SOLUTION TO (#) IS UNIQUE & GIVEN BY $R(x,\pi)$

SO $R(x) = R(x,\pi) \therefore \pi$ IS OPTIMAL. $\square$

SOME FACTS ON Q-FACTORS:

Prop 49. a) Stationary Q-factors satisfy the recursion

$$Q_{\pi}(x, a) = \mathbb{E}_{x,a}[r(x, a) + \beta Q_{\pi}(\hat{X}, \pi(\hat{X}))].$$

b) Bellman's Equation can be re-expressed in terms of Q-factors as follows

$$Q^*(x, a) = \mathbb{E}_{x,a}[r(x, a) + \beta \max_{\hat{a}} Q^*(\hat{X}, \hat{a}))].$$

The optimal value function satisfies

$$V(x) = \max_{a \in \mathcal{A}} Q^*(x, a).$$

c) The operation

$$F_{x,a}(Q) = \mathbb{E}_{x,a}[r(x, a) + \beta Q_{\pi}(\hat{X}, \pi(\hat{X}))]$$

is a contraction with respect to the supremum norm, that is,

$$\|F(Q_1) - F(Q_2)\|_{\infty} \leq \|Q_1 - Q_2\|_{\infty}.$$

POSITIVE PROGRAMMING.

Thrm 50. Consider a positive program the optimal value function $V(x)$ is the minimal non-negative solution to the Bellman equation

$$R(x) = \max_{a \in \mathcal{A}} \left\{ r(x, a) + \beta \mathbb{E}_{x, a} [R(\hat{X})] \right\}.$$

Thus if we find a policy π whose reward function $R(x, \pi)$ satisfies the Bellman equation. Then it is optimal.

PROOF: SOLUTION OVER $T+1$ STEPS IS

$$V_{T+1}(x) = \max_a r(x, a) + \beta \mathbb{E}_{x, a} [V_T(\hat{x})]$$

WITH $V_0(x) = 0$. $V_T(x)$ IS INCREASING IN T

LET

$$V_{\infty}(x) = \sup_T V_T(x) = \lim_{T \rightarrow \infty} V_T(x)$$

$$\begin{aligned}
 V_{\infty}(x) &= \sup_T \max_{a \in A} r(x, a) + \beta \mathbb{E}_{x, a} [V_T(\hat{x})] \\
 &= \max_a r(x, a) + \beta \mathbb{E}_{x, a} \left[\sup_T V_T(\hat{x}) \right] \\
 &= \max_a r(x, a) + \beta \mathbb{E}_{x, a} [V_{\infty}(\hat{x})]
 \end{aligned}$$

MONOTONE
CONVEX

CLEARLY $V(x) \geq V_T(x) \therefore V(x) \geq V_{\infty}(x)$

BUT

$$V_T(x) \geq R_T(x, \pi) \quad \forall \pi \quad \therefore V_{\infty}(x) \geq R(x, \pi) \quad \forall \pi$$

$$\therefore V_{\infty}(x) \geq V(x)$$

So $V_{\infty}(x) = V(x)$. $\square$ [THIS GIVES VALUE
ITERATION ARGUMENT].

NEGATIVE PROGRAMMING:

NEEDS STRONGER CONDITIONS TO WORK

$$L_T(x) = \min_{\pi} C_T(x, \pi) \leq L(x)$$

i.e. $\max_T \min_{\pi} C_T(x, \pi) \leq \min_{\pi} \max_T C_T(x, \pi)$

[NOT OBVIOUS HOW TO SWAP MIN & MAX]

Thrm 52. Consider a negative program, minimizing positive costs.
For the minimal non-negative solution to the Bellman equation

$$L(x) = \min_{a \in \mathcal{A}} \{l(x, a) + \beta \mathbb{E}_{x,a} [L(\hat{X})]\}, \quad (1.8)$$

any stationary policy Π that solves the Bellman equation:

$$\pi(x) \in \operatorname{argmin}_{a \in \mathcal{A}} \{c(x, a) + \beta \mathbb{E}_{x,a} [L(\hat{X})]\}$$

is optimal.

PROOF: USE ROLL OUT.

$$\begin{aligned} L(x) &= \min_{a \in \mathcal{A}} \{c(x, a) + \beta \mathbb{E}_{x,a}[L(X_1)]\} \\ &= c(x, \pi(x)) + \beta \mathbb{E}_{x, \pi(x)} [L(X_1)] \\ &= c(X_0, \pi(X_0)) + \beta \mathbb{E}_{X_0, \pi(X_0)} \left[c(X_1, \pi(X_1)) + \beta \mathbb{E}_{X_1, \pi(X_1)} [L(X_2)] \right] \\ &= C_1(x, \pi) + \beta^2 \mathbb{E}_{x, \pi} [L(X_2)] \\ &\vdots \\ &= C_T(x, \pi) + \beta^T \mathbb{E}_{x, \pi} [L(X_{T+1})]. \end{aligned}$$

Thus

$$L(x) = C_T(x, \pi) + \beta^T \mathbb{E}_{x, \pi} [L(x_{T+1})] \geq C_T(x, \pi) \xrightarrow[T \rightarrow \infty]{\text{M.C.T.}} C(x, \pi).$$

So the policy has lower cost, and thus is optimal.

AVERAGE PROGRAMMING:

CONSIDER

$$\bar{R}(\pi) = \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E}_x \left[\sum_{t=0}^T r(x_t, \pi_t) \right]$$

WANT

$$\bar{V} = \max_{\pi} \bar{R}(\pi)$$

[NOTICE $\bar{V}$ NO LONGER DEPENDS ON x
BECAUSE x_t SHOULD BE CONVERGING TO AN EQUILIBRIUM.]

A BELLMAN EQUATION STILL HOLDS

THINK:

$$R_T(x, \pi) = T \cdot V_{\pi} + \rho(x) + \varepsilon(x, T)$$

LONG RUN
VALUE OF π

SHORT TERM
EFFECT FOR BEING
IN x .

OTHER
VANISHING
TERM

AVERAGE PROGRAMMING:

FOR $V_T(x) = T \cdot V^* + p(x)$

THE BELLMAN EQUATION BECOMES:

$$\begin{array}{ccc} V_{T+1}(x) & = \max_a \{ r(x,a) + \mathbb{E}_{x,a} [V_T(\hat{x})] \} \\ \parallel & & \parallel \\ \cancel{(T+1)}V^* + p(x) & & \cancel{T}V^* + p(\hat{x}) \end{array}$$


$$\therefore V^* = \max_a \{ r(x,a) + \mathbb{E}_{x,a} [p(\hat{x})] - p(x) \}$$

AVERAGE PROGRAMMING:

✓ THE SAME
RESULT HOLDS
FOR MINIMIZING

THEOREM: IF WE CAN FIND A CONSTANT $\bar{V}$
& A BOUNDED FUNCTION $p(x)$ SUCH THAT $\forall x$

$$V^* = \max_a r(x, a) + \mathbb{E}_{x, a} [p(\hat{x})] - p(x)$$

& IF GIVEN THIS V^* & $p(x)$ WE CAN CHOOSE A POLICY SUCH THAT

$$\pi^*(x) \in \operatorname{ARGMAX}_a r(x, a) + \mathbb{E}_{x, a} [p(\hat{x})] - p(x)$$

THEN

V^* IS THE MAXIMUM AVERAGE REWARD

& $\pi^*(x)$ IS THE OPTIMAL POLICY

PROOF: WE PROVE THE RESULT BY PROVING INEQUALITIES IN BOTH DIRECTIONS.

IF V, p IS SUCH THAT $V \geq \max_x \max_a r(x, a) + \mathbb{E}_{x, a} [p(\hat{x})] - p(x)$ (†)

THEN, WE CLAIM THAT, $V \geq \limsup_{T \rightarrow \infty} \bar{R}_T(x, \pi)$ $\forall$ POLICIES π

PROOF OF CLAIM: $M_0 = 0$

DEFINE $M_t - M_{t-1} = r(X_t, \pi_t) - V + \mathbb{E}_{X_t, \pi_t} [p(\hat{x})] - p(X_t)$

CLEARLY $\mathbb{E}[M_t - M_{t-1} | \mathcal{F}_{t-1}] \leq 0 \quad \therefore M_t$ IS A SUPER-M_g BY (†)

$$0 \geq \mathbb{E}_x \left[\frac{M_T}{T} \right] = \bar{R}_T(x, \pi) - V + \mathbb{E}_x \left[\frac{p(X_{T+1})}{T} \right] - \frac{p(x)}{T}$$

LETTING $T \rightarrow \infty \quad V \geq \bar{R}(x, \pi) \quad \forall \pi$

FROM THIS CLAIM WE SEE THAT $V^* \geq \bar{R}(x, \pi)$

PROOF (CONT) SUPPOSE THAT $\pi^*(x)$, IS THE POLICY AS DESCRIBED IN THE THEOREM

$$M_t^* - M_{t-1}^* = r(X_t, \pi_t) - V^* + \mathbb{E}_{X_t, \pi_t} [\rho(\hat{x})] - \rho(X_t)$$

$\therefore M_t^*$ IS A MARTINGALE &

$$0 = \underbrace{\mathbb{E}_x[M_T^*]}_T = \bar{R}_T(x, \pi^*) - V^* + \underbrace{\mathbb{E}_x[\rho(\frac{X_{T+1}}{T})]}_T - \rho(\frac{x}{T})$$

$$\therefore \lim_{T \rightarrow \infty} \bar{R}_T(x, \pi^*) = V^* \underset{\substack{\uparrow \\ \text{BY FIRST PM}}}{\geq} \limsup_{T \rightarrow \infty} \bar{R}_T(x, \pi)$$

$\therefore \pi^*$ IS OPTIMAL & ITS VALUE IS V^*

□.

MARTINGALE PRINCIPLE OF OPTIMALITY.

Prop 54 (A Martingale Principle of Optimal Control.). Consider discounted program. Suppose for a bounded function $R : \mathcal{X} \rightarrow \mathbb{R}$ we define a process $(M_t : t \in \mathbb{Z}_+)$ whose increments, $\Delta M(X_t) := M_{t+1} - M_t$, are given by

$$\Delta M(x) = R(x) - \beta R(\hat{x}) - r(x, \pi(x))$$

If M_t is a supermartingale for all policies π' and, for some π , M_t is a martingale, then π is the optimal policy and $R(x) = R(x, \pi)$.

Proof. M_t is a martingale [resp. supermartingale] iff

$$M_t^\beta := \sum_{s=0}^{\infty} \beta^s \Delta M(X_s)$$

is a martingale [resp. supermartingale]. Taking expectations,

$$0 \leq \mathbb{E}_x[M_t^\beta] = \mathbb{E}_x\left[R(x) - \beta^{t+1}R(X_{t+1}) - \sum_{s=0}^t \beta^s r(X_s, \pi(X_s))\right]$$

Rearranging and letting $t \rightarrow \infty$ gives, for π' ,

$$R(x) \geq \mathbb{E}\left[\sum_{s=0}^{\infty} \beta^s r(X_s, \pi'(X_s))\right],$$

where the inequality above holds with equality if M_t^β is a martingale for some π . Thus we see that $R(x) \geq V(x)$, where $V(x)$ is the value function for the MDP and $R(x) = V(x) = R(x, \pi)$. $\square$

SUMMARY: INFINITE TIME MDPs

- BELLMAN'S EQN STILL HOLDS

$$V(x) = \underset{a}{\text{MAX}} \left\{ r(x, a) + \beta \mathbb{E}_{x, a} [V(\hat{x})] \right\}$$

OR

$$Q(x, a) = r(x, a) + \beta \mathbb{E}_{x, a} \left[\underset{a'}{\text{MAX}} Q(\hat{x}, a') \right]$$

- DISCOUNTED PROGRAMMING $\beta \in (0, 1)$, $\|r\|_{\infty} < \infty$
 - ANY SOLUTION TO BELLMAN WILL DO
 - PROOF USES CONTRACTION PROPERTY OF $Q(x, a)$

- POSITIVE PROGRAMMING $r \geq 0, \beta = 1$

- MINIMAL SOLUTION TO BELLMAN OR A POLICY WILL DO
- PROOF REPEATEDLY SOLVE FINITE TIME BELLMAN EQN.

- NEGATIVE PROGRAM $c \geq 0$ OR $r \leq 0, \beta = 1$

- MINIMAL SOLUTION TO BELLMAN & A STATIONARY POLICY!
- PROOF ROLL OUT BELLMAN EQN.

- AVERAGE PROGRAM $\frac{1}{T} \mathbb{E} \left[\sum_{t=1}^T r(x_t, a_t) \right]$

- FIND k, λ s.t. $k(x) = \min_a \{ c(x, a) - \lambda + \mathbb{E}_{x, a} [k(\hat{x})] \}$
- PROOF MARTINGALE ARGUMENT.

