

pc-10

* Policy Improvement theorem:

For all deterministic policies, π & π' , if $\forall s \in S$

$$q^\pi(s, \pi'(s)) \geq v^\pi(s)$$

Then $\pi' \geq \pi$

$$\forall s \in S, v^{\pi'}(s) \geq v^\pi(s)$$

Proof:

$$v^\pi(s) \leq q^\pi(s, \pi'(s))$$

$$= \mathbb{E}[R_t + \gamma R_{t+1} \dots | s_t = s, \pi']$$

$$= \mathbb{E}[R_t + \gamma v^\pi(s_{t+1}) | s_t = s, \pi']$$

$$\leq \mathbb{E}[R_t + \gamma q^\pi(s_{t+1}, \pi'(s_{t+1})) | s_t = s, \pi']$$

$$= \mathbb{E}[R_t + \gamma \mathbb{E}[R_{t+1} + \gamma v^\pi(s_{t+2}) | s_t = s, \pi'] | s_t = s, \pi']$$

$$= \mathbb{E}[R_t + \gamma R_{t+1} + \gamma^2 v^\pi(s_{t+2}) | s_t = s, \pi']$$

Refer page 35, Sutton Barto

$$\begin{aligned} &\leq \mathbb{E} \left[R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \gamma^3 V^\pi(s_{t+3}) \mid s_t = s, \pi \right] \\ &\leq \mathbb{E} \left[R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \dots \mid s_t = s, \pi \right] \\ &\leq V^\pi(s) \end{aligned}$$

Policy improvement

- For all states select an action 'a' that maximizes $q^\pi(s, a)$. This is 'Greedy' policy, greedy w.r.t q^π .

$$V^{\pi'}(s) \Leftarrow \arg \max_a \sum_{s'} P(s, a, s') (R(s, a, s') + \gamma V^{\pi'}(s'))$$

- what if $\pi' = \pi$?

so,

$$V^{\pi'}(s) = \max_a \sum_{s'} P(s, a, s') (R(s, a, s') + \gamma V^{\pi'}(s'))$$

Policy Iteration $\Rightarrow \pi_0 \xrightarrow{\text{evaluate}} V^{\pi_0} \xrightarrow{\text{improve}} \pi_1 \rightarrow \dots$

- This will terminate after finite iteration
- Exists an optimal policy that is deterministic (there could be multiple optimal solutions)

* Value Iteration

- One full backup during policy evaluation in policy iteration

V_0 : arbitrary, π_0 = arbitrary

$$V_1 : \forall s \quad V_1(s) = \sum_{s'} P(s, \pi_0(s), s') \left[R(s, \pi_0(s), s') + \gamma \cdot V_0(s') \right]$$

$$\pi_1 : \forall s \quad \pi_1(s) \in \arg \max_a \sum_{s'} P(s, a, s') \left[R(s, a, s') + \gamma \cdot V_1(s') \right]$$

⋮

$$V_{k+1}(s) = \max_a \sum_{s'} P(s, a, s') \left[R(s, a, s') + \gamma \cdot V_k(s') \right]$$

V_k converges to optimal
 $V_k \rightarrow V^*$

Proof:

Bellman operator:

View state value function as vectors
in $\mathbb{R}^{|S|}$

$$V_k = \begin{bmatrix} V_k(s_1) \\ V_k(s_2) \\ \vdots \\ V_k(s_{|S|}) \end{bmatrix}$$

Operator:

$$T: \mathbb{R}^{|S|} \Rightarrow \mathbb{R}^{|S|}$$

$$T(V_k) \triangleq V_{k+1}$$

$$T(V_k)(s) = V_{k+1}(s)$$

$$= \max_a \sum_{s'} P(s, a, s') (R(s, a, s') + \gamma V_k(s'))$$

Contraction mapping

$$F: X \rightarrow X$$

is a contraction mapping

if there exists a $\gamma \in [0, 1]$ such that
 $\forall a \in X \quad \forall b \in X$

$d(f(x), f(y)) \leq \lambda d(x, y)$ where
 d is a distance function

Banach fixed point theorem

if f is a contraction mapping
on a non-empty complete normed
vector space, then f has a unique
fixed point & the sequence defined
by ~~x_{k+1}~~ $x_{k+1} = f(x_k)$ with

Bellman operator is a contraction mapping

$$f \leftarrow T, \quad x \leftarrow R^{1 \times 1} \text{ (matrix)}$$

$$d(v, v') \triangleq \max_s |v(s) - v'(s)| \\ = \|v - v'\|$$

$$\|T_v - T_{v'}\| \leq \lambda \|v - v'\|$$

$$= \max_s |T_v(s) - T_{v'}(s)|$$

$$= \max_s \left| \max_a \sum_{s'} P(s, a, s') (R(s, a, s') + \gamma \cdot V(s')) - \max_a \sum_{s'} P(s, a, s') (R(s, a, s') + \gamma \cdot V'(s')) \right|$$

$$= \max_s \left| \max_a \sum_{s'} P(s, a, s') (R(s, a, s') + \gamma \cdot V(s')) - \max_a \sum_{s'} P(s, a, s') (R(s, a, s') + \gamma \cdot V'(s')) \right|$$

claim $\Rightarrow \left| \max_x f(x) - \max_x g(x) \right| \leq \max_x |f(x) - g(x)|$

$$\forall x \quad f(x) - g(x) \leq |f(x) - g(x)|$$

$$f(x) \leq |f(x) - g(x)| + g(x)$$

$$\max_x f(x) \leq \max_x |f(x) - g(x)| + g(x)$$

$$\leq \max_x |f(x) - g(x)| + \max_x g(x)$$

$$\therefore \max_x f(x) - \max_x g(x) \leq \max_x |f(x) - g(x)|$$