

Dynamic Programming

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Prediction

Bellman operator

$$\begin{aligned}\mathcal{T}_\pi v &\doteq r_\pi + \gamma P_\pi v, \\ v_{k+1} &\doteq \mathcal{T}_\pi v_k\end{aligned}$$

Sample complexity of applying Bellman operator

$$\left\| \mathcal{T}_\pi^{(n)} v_k - v_\pi \right\|_\infty \leq \gamma^n \|v_0 - v_\pi\|_\infty$$

Control: Value Iteration

Bellman optimality operator

$$\mathcal{T}_* v \doteq \max_a \left\{ r(s, a) + \sum_{s'} p(s'|s, a) v(s') \right\},$$
$$v_{k+1} \doteq \mathcal{T}_* v_k$$

Sample complexity of value iteration

$$\left\| \mathcal{T}_*^{(n)} v_k - v_* \right\|_{\infty} \leq \gamma^n \|v_0 - v_*\|_{\infty}$$

Control: Async Value Iteration

$$v_{k+1}(s) \doteq \begin{cases} (\mathcal{T}_* v_k)(s), & \text{if } s = s_k \\ v_k(s), & \text{otherwise} \end{cases}$$

Convergence of Async Value Iteration

When $\mathcal{T}_* v_0 \geq v_0$:

$$\begin{aligned} & \mathcal{T}_* v_k \geq v_0, v_k \geq v_0 \\ \implies & \mathcal{T}_* v_{k+1} \geq v_0, v_{k+1} \geq v_0 \end{aligned}$$

$$v_{k+1}(s) = \begin{cases} v_k(s) \geq v_0(s) \\ (\mathcal{T}_* v_k)(s) \geq (\mathcal{T}_* v_0)(s) \geq v_0(s) \end{cases}$$

$$\mathcal{T}_* v_{k+1} \geq \mathcal{T}_* v_0 \geq v_0$$

Convergence of Async Value Iteration

Let $k_0 = 0$ and k_m be the first time that each state has been updated at least once after k_{m-1} .

$\forall k \geq k_1, \exists k' < k$ such that

$$v_k(s) = (\mathcal{T}_* v_{k'})(s) \geq (\mathcal{T}_* v_0)(s)$$

$$v_k \geq \mathcal{T}_* v_0$$

$\forall k \geq k_2, \exists k' \in [k_1, k_2)$ such that

$$v_k(s) = (\mathcal{T}_* v_{k'})(s) \geq (\mathcal{T}_* \mathcal{T}_* v_0)(s)$$

$$v_k \geq \mathcal{T}_*^{(2)} v_0$$

...

$$\forall k > k_m, v_* \geq v_k \geq \mathcal{T}_*^{(m)} v_0$$

$$v_k \rightarrow v_*$$

Convergence of Async Value Iteration

When $\mathcal{T}_* v_0 \leq v_0$:

$$v_k \geq \mathcal{T}_*^{k+1} v_0$$

$$v_{k+1}(s) = \begin{cases} v_k(s) \geq (\mathcal{T}_*^{k+1} v_0)(s) \geq (\mathcal{T}_*^{k+2} v_0)(s) \\ (\mathcal{T}_* v_k)(s) \geq (\mathcal{T}_*^{k+2} v_0)(s) \end{cases}$$

$$v_k \rightarrow v_*$$

Convergence of Async Value Iteration

$$\begin{aligned}v_0^+ &\doteq v_0 + c1 \\ \mathcal{T}_* v_0^+ &= \mathcal{T}_* v_0 + c\gamma 1 \\ v_0^- &\doteq v_0 - c1 \\ \mathcal{T}_* v_0^- &= \mathcal{T}_* v_0 - c\gamma 1\end{aligned}$$

For sufficiently large c ,

$$\begin{aligned}v_0^+ &\geq \mathcal{T}_* v_0^+ \\ v_0^- &\leq \mathcal{T}_* v_0^- \\ v_k^+ &\rightarrow v_*, \quad v_k^- \rightarrow v_*\end{aligned}$$

Convergence of Async Value Iteration

$$v_k \leq v_k^+ \implies v_{k+1} \leq v_{k+1}^+$$

$$v_k \geq v_k^- \implies v_{k+1} \geq v_{k+1}^-$$

$$v_k^- \leq v_k \leq v_k^+$$

Policy Improvement Theorem

$$\forall s, \sum_a \pi'(a|s) q_\pi(s, a) \geq v_\pi(s) \implies \forall s, v_{\pi'}(s) \geq v_\pi(s)$$

$$\begin{aligned} & v_\pi(s) \\ & \leq \mathbb{E}[R_{t+1} + \gamma v_\pi(S_{t+1}) | S_t = s, A_t \sim \pi'(\cdot | S_t)] \\ & \leq \mathbb{E}[R_{t+1} + \gamma \mathbb{E}[R_{t+2} + v_\pi(S_{t+2}) | S_{t+1}, A_{t+1} \sim \pi'] | S_t = s, A_t \sim \pi'(\cdot | S_t)] \\ & \leq v_{\pi'}(s) \end{aligned}$$

Control: Policy Iteration

For $k = 0, 1, \dots$

- Policy evaluation $\pi_k \rightarrow v_{\pi_k}$
- Policy Improvement $v_{\pi_k} \rightarrow \pi_{k+1}$

$$\lim_{k \rightarrow \infty} v_{\pi_k} = v_*$$

Control: Policy Iteration

Finite MDP $\implies v_{\pi_{k+1}} = v_{\pi_k}$

$$v_{\pi_{k+1}}(s) = \sum_a \pi_{k+1}(a|s) \left(r(s, a) + \gamma \sum_{s'} p(s'|s, a) v_{\pi_{k+1}}(s') \right)$$

$$v_{\pi_k}(s) = \sum_a \pi_{k+1}(a|s) \left(r(s, a) + \gamma \sum_{s'} p(s'|s, a) v_{\pi_k}(s') \right)$$

$$v_{\pi_k}(s) = \max_a \left(r(s, a) + \gamma \sum_{s'} p(s'|s, a) v_{\pi_k}(s') \right)$$

Control: Async Policy Iteration

At $(k + 1)$ -the iteration, either

$$v_{k+1}(s) = \begin{cases} (\mathcal{T}_{\pi_k} v_k)(s) & \text{if } s \in \mathcal{S}_k \\ v_k(s) & \text{otherwise} \end{cases}$$

or

$$\pi_{k+1}(s) = \begin{cases} \text{greedy}(v_k)(s) & \text{if } s \in \mathcal{S}_k \\ \pi_k(s) & \text{otherwise} \end{cases}$$

If $\mathcal{T}_{\pi_0} v_0 \geq v_0$, then

$$\lim_{k \rightarrow \infty} v_k = v_*.$$

If $\mathcal{T}_{\pi_0} v_0 \geq v_0$ does not hold, no convergence guarantee.

Convergence of Async Policy Iteration

$$\mathcal{T}_{\pi_k} v_k \geq v_k \implies \mathcal{T}_{\pi_{k+1}} v_{k+1} \geq v_{k+1} \geq v_k$$

In case of value update

$$v_{k+1}(s) = \begin{cases} (\mathcal{T}_{v_k} v_k)(s) \geq v_k(s) & \text{if } s \in \mathcal{S}_k \\ v_k(s) & \text{otherwise} \end{cases}$$

$$(\mathcal{T}_{\pi_{k+1}} v_{k+1})(s) = (\mathcal{T}_{\pi_k} v_{k+1})(s) \geq (\mathcal{T}_{\pi_k} v_k)(s) \begin{cases} = v_{k+1}(s) \\ \geq v_k(s) = v_{k+1}(s) \end{cases}$$

Convergence of Async Policy Iteration

$$\mathcal{T}_{\pi_k} v_k \geq v_k \implies \mathcal{T}_{\pi_{k+1}} v_{k+1} \geq v_{k+1} \geq v_k$$

In case of policy update, for $s \in \mathcal{S}_k$,

$$\begin{aligned} (\mathcal{T}_{\pi_{k+1}} v_{k+1})(s) &= (\mathcal{T}_{\pi_{k+1}} v_k)(s) = (\mathcal{T}_* v_k)(s) \geq (\mathcal{T}_{\pi_k} v_k)(s) \\ &\geq v_k(s) = v_{k+1}(s) \end{aligned}$$

For $s \notin \mathcal{S}_k$,

$$(\mathcal{T}_{\pi_{k+1}} v_{k+1})(s) = (\mathcal{T}_{\pi_{k+1}} v_k)(s) = (\mathcal{T}_{\pi_k} v_k)(s) \geq v_k(s) = v_{k+1}(s)$$

Convergence of Async Policy Iteration

$$v_k \leq v_{k+1} \leq v_*, \mathcal{T}_* v_k \geq \mathcal{T}_{\pi_k} v_k \geq v_k$$

$$\lim_{k \rightarrow \infty} v_k = \bar{v},$$

$$v_k \leq \bar{v},$$

$$\mathcal{T}_* \bar{v} \geq \bar{v}$$

Convergence of Async Policy Iteration

If $\exists s, (\mathcal{T}_* \bar{v})(s) > \bar{v}(s)$, then $\exists \bar{k}$ such that $\forall k \geq \bar{k}$,

$$(\mathcal{T}_* v_k)(s) > \bar{v}(s)$$

Let $k > \bar{k}$ be an iteration where policy update is done for s ; let k' be an iteration of the first value update for s after k .

$$\begin{aligned} v_{k'+1}(s) &= (\mathcal{T}_{\pi_{k'}} v_{k'})(s) \\ &\geq (\mathcal{T}_{\pi_k} v_k)(s) \\ &\geq (\mathcal{T}_{\pi_k} v_{k-1})(s) \\ &= (\mathcal{T}_* v_{k-1})(s) \\ &> \bar{v}(s) \end{aligned}$$

Contradiction!

Span Seminorm for Average Reward

$$\text{sp}(v) = \max_s v(s) - \min_s v(s)$$

Contraction under Span Seminorm

$$\mathrm{sp}(P_{\pi}v) \leq \gamma_d \mathrm{sp}(v)$$

where

$$\gamma_d \doteq 1 - \min_{s,s'} \sum_j \min \{P_{\pi}(s,j), P_{\pi}(s',j)\}$$

Prediction

$$\mathcal{T}_\pi v \doteq r_\pi + P_\pi v$$

$$\lim_{k \rightarrow \infty} \text{sp} \left(\mathcal{T}_\pi^{(k)} v - \bar{v}_\pi \right) = 0$$

Control

$$\mathcal{T}_* v \doteq \max_{\pi} \{r_{\pi} + P_{\pi} v\}$$

If there exists an n such that $\forall \pi_1, \pi_2$,

$$\eta(\pi_1, \pi_2) \doteq \min_{s, s'} \sum_j \min \{P_{\pi_1}^n(s, j), P_{\pi_2}^n(s', j)\} > 0,$$

then

$$\text{sp}(\mathcal{T}_*^n v - \mathcal{T}_*^n v') \leq \gamma' \text{sp}(v - v'),$$

where

$$\gamma' \doteq 1 - \min_{\pi_1, \pi_2} \{\eta(\pi_1, \pi_2)\}$$

References

- Markov Decision Processes: Discrete Stochastic Dynamic Programming by Martin Puterman
- Neuro-Dynamic Programming by Dimitri Bertsekas and John Tsitsiklis