

lec 1

State / state space: $\{s_1, s_2, \dots\} = S$

Action / Action space: $\{a_1, a_2, \dots\} = A(s)$

State Transition: $p(s'|s, a) = P(S_{t+1}=s' | S_t=s, A_t=a)$
 $\sum_{s'} p(s'|s, a) = 1$

Policy: $\pi(a|s) = P(A_t=a | S_t=s)$

Return: 沿着 trajectory 的 Reward 之和

Discounted Return: $G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \dots$

lec 2 Bellman Equation:

State value: $V(\pi, s) = V_{\pi}(s) = E[G_t | S_t=s]$

$\therefore G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \dots = G_t = r_{t+1} + \gamma G_{t+1}$

$\therefore V(s) = E[r_{t+1} + \gamma V(s') | S_t=s] = E[r_{t+1} | S_t=s] + \gamma E[V(s') | S_t=s]$

$= E[r_{t+1} | S_t=s] + \gamma \sum_{s'} \pi(s'|s) E[r_{t+1} | S_t=s, A_t=a]$

$= \sum_{a \in A} \pi(a|s) \cdot \sum_{s'} p(s'|s, a) \cdot r$

$E[G_{t+1} | S_t=s] = \sum_{s'} p(s'|s) \cdot E[G_{t+1} | S_{t+1}=s', S_t=s] = \sum_{s'} p(s'|s) \cdot \frac{E[G_{t+1} | S_{t+1}=s']}{V_{\pi}(s')}$

$= \sum_{s'} \frac{1}{|A|} \pi(a|s) \cdot p(s'|s, a) \cdot V_{\pi}(s') = \sum_{s'} \pi(s'|s) \cdot \sum_{a \in A} p(s'|s, a) \cdot V_{\pi}(s')$

$\therefore V_{\pi}(s) = \sum_{a \in A} \pi(a|s) \left[\sum_{s'} p(s'|s, a) \cdot r + \gamma \sum_{s'} p(s'|s, a) \cdot V_{\pi}(s') \right]$ (Bellman's Element-wise form)

矩阵形式 (Matrix-Vector form):

$V_{\pi} = \begin{bmatrix} V_{\pi}(s_1) \\ V_{\pi}(s_2) \\ \vdots \\ V_{\pi}(s_n) \end{bmatrix}$ $R_{\pi} = \begin{bmatrix} R_{\pi}(s_1) \\ R_{\pi}(s_2) \\ \vdots \\ R_{\pi}(s_n) \end{bmatrix} = \begin{bmatrix} \sum_{a \in A} \pi(a|s_1) \cdot \sum_{s'} p(s'|s_1, a) \cdot r \\ \vdots \\ \sum_{a \in A} \pi(a|s_n) \cdot \sum_{s'} p(s'|s_n, a) \cdot r \end{bmatrix}$

$P_{\pi} \in R^{n \times n}$: $[P_{\pi}]_{ij} = P(s_j | s_i) = \sum_{a \in A} \pi(a | s_i) \cdot P(s_j | s_i, a)$

$\Rightarrow V_{\pi} = R_{\pi} + \gamma P_{\pi} V_{\pi}$

\therefore 解析解: $V_{\pi} = (I - \gamma P_{\pi})^{-1} R_{\pi}$

迭代解: $V_{k+1} = R_{\pi} + \gamma P_{\pi} V_k$

收敛性证明: $\begin{cases} \textcircled{1} V_{k+1} = R_{\pi} + \gamma P_{\pi} V_k \\ \textcircled{2} V_k = R_{\pi} + \gamma P_{\pi} V_k \end{cases}$

$\textcircled{1} - \textcircled{2}$: $V_{k+1} - V_k = \gamma P_{\pi} (V_k - V_{k-1})$ $\delta_{k+1} = \gamma P_{\pi} \delta_k$

$\therefore \delta_{k+1} = \gamma^{k+1} P_{\pi}^{k+1} \delta_0$ $\therefore P_{\pi}$ 为随机矩阵 $V[P_{\pi}]_j \in [0, 1]$

又有 $\gamma < 1$

$\therefore \delta_{k+1} \rightarrow 0$

Action Value (动作价值): $Q_{\pi}(s, a) = E[G_t | S_t=s, A_t=a]$

$V_{\pi}(s) = \sum_{a \in A} \pi(a|s) \cdot Q_{\pi}(s, a)$

如果知道所有 Action Value \rightarrow 求平均得到这个状态的 State Value

如果知道所有状态的 State Value \rightarrow 能求出所有 Action Value

lec 3. Bellman Optimal Equation

Optimal Policy: $V_{\pi^*}(s) \geq V_{\pi}(s) \quad \forall s \in S, \forall \pi$

BE: $V_{\pi}(s) = \sum_{a \in A} \pi(a|s) \left[\underbrace{\sum_{s'} p(s'|s, a) \cdot r + \gamma \sum_{s'} p(s'|s, a) V_{\pi}(s')}_{Q_{\pi}(s, a)} \right]$

BE: $V(s) = \max_a \sum_{s'} \pi(s'|s) Q_{\pi}(s, a)$ 找一个使这个式子最大

\Rightarrow 把所有权重各编最大 $Q_{\pi}(s, a)$

$\Rightarrow \max_{\pi} \sum_{a \in A} \pi(a|s) Q_{\pi}(s, a) = \max_a Q_{\pi}(s, a)$

$\Rightarrow V(s) = \max_a \left[\sum_{s'} p(s'|s, a) \cdot r + \gamma \sum_{s'} p(s'|s, a) \cdot V(s') \right]$

Matrix-Vector Form: $V = \max_{\pi} (R_{\pi} + \gamma P_{\pi} V)$

$f(V) = \max_{\pi} (R_{\pi} + \gamma P_{\pi} V)$ $V = f(V)$

由压缩映射定理: 可证条件 $\|f(w) - f(u)\|_{\infty} \leq \gamma \|w - u\|_{\infty}$ $\gamma \in [0, 1]$

\therefore 存在唯一不动点 $V^* = f(V^*)$ \therefore 算法收敛

值迭代求解 BE: $\textcircled{1}: Q_k(s, a) = \sum_{s'} p(s'|s, a) \cdot r + \gamma \sum_{s'} p(s'|s, a) \cdot V_k(s')$

$\textcircled{2} V_{k+1} = \max_a Q_k(s, a)$

迭代结束:

$\pi^*(a|s) = \begin{cases} 1 & \text{argmax}_a Q^*(s, a) \\ 0 & \text{else} \end{cases}$

奖励函数仿射不变性: 对奖励进行仿射变换 $r' = ar + b$ (a>0)

最优策略不变

lec 4. 值迭代 / 策略迭代

值迭代: $V_{k+1} = f(V_k) = \max_{\pi} (R_{\pi} + \gamma P_{\pi} V_k)$

Step 1: $\pi_{k+1} = \text{argmax}_{\pi} (R_{\pi} + \gamma P_{\pi} V_k)$ (PI)

Step 2: $V_{k+1} = R_{\pi_{k+1}} + \gamma P_{\pi_{k+1}} V_k$ (PE)

策略迭代: $\pi_0 \xrightarrow{\text{PE}} V_{\pi_0} \xrightarrow{\text{PI}} \pi_1 \xrightarrow{\text{PE}} V_{\pi_1} \xrightarrow{\text{PI}} \pi_2 \rightarrow \dots$

Step 1. (PI): 计算当前 π_k 对应真实 V_{π_k}

Bellman Equation: $V_{\pi_k} = R_{\pi_k} + \gamma P_{\pi_k} V_{\pi_k}$

Step 2 (PE): 根据 V_{π_k} 寻找更好策略 π_{k+1}

$\pi_{k+1} = \text{argmax}_{\pi} (R_{\pi} + \gamma P_{\pi} V_{\pi_k})$

PE 利用迭代解 (固定策略下的值迭代)

$V_{\pi_k}^{(j+1)} = R_{\pi_k} + \gamma P_{\pi_k} V_{\pi_k}^{(j)}$

$j \rightarrow \infty \quad V_{\pi_k}^{(j)} \rightarrow V_{\pi_k}$

可证明: $V_{k+1} \geq V_{\pi_k}$

$\pi_{k+1} = \text{argmax}_{\pi} (R_{\pi} + \gamma P_{\pi} V_{\pi_k}) \Rightarrow V_{\pi_{k+1}} + \gamma P_{\pi_{k+1}} V_{\pi_k} \geq R_{\pi_k} + \gamma P_{\pi_k} V_{\pi_k} = V_{\pi_k}$

$\Delta = V_{\pi_{k+1}} - V_{\pi_k} \Rightarrow \Delta = (R_{\pi_{k+1}} + \gamma P_{\pi_{k+1}} V_{\pi_k}) - V_{\pi_k}$

$= V_{\pi_{k+1}} + \gamma P_{\pi_{k+1}} V_{\pi_k} - \gamma P_{\pi_{k+1}} V_{\pi_k} - \gamma P_{\pi_k} V_{\pi_k} - V_{\pi_k}$

$= \gamma P_{\pi_{k+1}} (V_{\pi_{k+1}} - V_{\pi_k}) + (V_{\pi_{k+1}} + \gamma P_{\pi_{k+1}} V_{\pi_k} - V_{\pi_k})$

$\delta = V_{\pi_{k+1}} + \gamma P_{\pi_{k+1}} V_{\pi_k} - V_{\pi_k}$, 由 $\textcircled{1} \quad \delta \geq 0$

$\therefore \Delta = \gamma P_{\pi_{k+1}} \delta + \delta = \gamma (P_{\pi_{k+1}} \delta + \delta) = \delta + \gamma P_{\pi_{k+1}} \delta + \gamma P_{\pi_k} \delta + \dots$

$\therefore \delta \geq 0 \quad P \geq 0 \quad \gamma \geq 0 \quad \therefore \Delta \geq 0 \quad \therefore V_{k+1} \geq V_{\pi_k}$

截断策略迭代:

PE 阶段迭代固定次, 不继续迭代 - 截断策略迭代 - 次

也不继续策略迭代 - 截断策略迭代 - 次