Reinforcement Learning

value-based

policy-based

一般方法

目标函数

$$J(\theta) = E_S[V_\pi(S)]$$

策略梯度定理

$$\frac{\partial J(\theta)}{\partial \theta} = \nabla_\theta J(\theta) = \mathbb{E}_S[\mathbb{E}_{A\backsim\pi(\cdot|S;\theta)}[\frac{\partial \ln \pi(A|S;\theta)}{\partial \theta} \cdot Q_\pi(S,A)]]$$

随机梯度——策略梯度的无偏估计

$$g(s,a;\theta) \triangleq Q_\pi(s,a) \cdot \nabla_\theta \ln \pi(a|s;\theta)$$

策略网络提升

$$\theta \leftarrow \theta + \beta \cdot g(s,a;\theta)$$

带基线的策略梯度方法

带基线的策略梯度定理——b是不依赖于A的任意函数

$$\nabla_\theta J(\theta) = \mathbb{E}_S[\mathbb{E}_{A\backsim\pi(\cdot|S;\theta)}[(Q_\pi(S,A)] - b) \cdot \nabla_\theta \ln \pi(A|S;\theta)]$$

随机梯度

$$g_b(s,a;\theta) = [Q_\pi(S,A) - b] \cdot \nabla_\theta \ln \pi(A|S;\theta)$$

$g_b(s,a;\theta)$ 是 $\nabla_\theta J(\theta)$ 的无偏估计

$$Bias = \mathbb{E}_{S,A}[g_b(s,a;\theta)] - \nabla_\theta J(\theta) = 0$$

b 的取值对 $g_b(s,a;\theta)$ 是有影响的

$$Var = \mathbb{E}_{S,A}[\|g_b(s,a;\theta) - \nabla_\theta J(\theta)\|^2]$$

b 接近 $Q_\pi(s,a)$ 关于 a 的均值，方差会比较小

$\Rightarrow b = V_\pi(s)$ 是很好的基线

REINFORCE

折扣回报

$$U_t = \sum_{k-t}^{n} \gamma^{k-t} \cdot R_k$$

动作价值是折扣回报的期望

$$Q_\pi(s_t,a_t) = \mathbb{E}[U_t|S_t = s_t, A_t = a_t]$$

用折扣回报的观测值蒙特卡洛近似动作价值

$$\tilde{g}(s_T,a_t;\theta) = u_t \cdot \nabla_\theta \ln \pi(a_t|s_t;\theta)$$

策略网络提升

$$\theta_{new} \leftarrow \theta_{now} + \beta \cdot \sum_{t=1}^{n} \gamma^{t-1} \cdot \tilde{g}(s_t.a_t;\theta_{now})$$

带基线的REINFORCE

折扣回报

$$u_t = \sum_{k-t}^{n} \gamma^{k-t} \cdot r_k$$

策略网络

基线——价值网络做出的预测

$$\hat{v_t} = v(s_t;\omega)$$

带基线的策略梯度

$$\tilde{g}(s_t,a_t;\theta) = (u_t - \hat{v_t}) \cdot \nabla_\theta \ln \pi(a_t|s_t;\theta)$$

梯度上升

$$\theta \leftarrow \theta + \beta \cdot \tilde{g}(s_t,a_t;\theta)$$

价值网络

损失函数

$$L(\omega) = \frac{1}{2n} \sum_{t=1}^{n} [v(s_t;\omega) - u_t]^2$$

损失函数的梯度

$$\nabla_\omega L(\omega) = \frac{1}{n} \sum_{t=1}^{n} [v(s_t;\omega) - u_t] \cdot \nabla_\omega v(s_t;\omega)$$

梯度下降

$$\omega \leftarrow \omega - \alpha \cdot \nabla_\omega L(\omega)$$

价值网络只起到基线的作用

Actor-Critic

策略网络

用价值网络近似动作价值

$$\hat{g}(s,a;\theta) \triangleq q(s,a;\omega) \cdot \nabla_\theta \ln \pi(a|s;\theta)$$

策略网络提升

$$\theta \leftarrow \theta + \beta \cdot \hat{g}(s,a;\theta)$$

价值网络

TD目标

$$\hat{y_t} \triangleq r_t + \gamma \cdot q(s_{t+1},a_{t+1};\omega)$$

损失函数

$$L(\omega) \triangleq \frac{1}{2}[q(s_t,a_t;\omega) - \hat{y_t}]^2$$

损失函数梯度

$$\nabla_\omega L(\omega) = [q(s_t,a_t;\omega) - \hat{y_t}] \cdot \nabla_\omega q(s_t,a_t;\omega)$$

梯度下降

$$\omega \leftarrow \omega - \alpha \cdot \nabla_\omega L(\omega)$$

价值网络直接参与策略提升

Advantage Actor-Critic (A2C)

策略网络

贝尔曼公式

$$Q_\pi(s_t,a_t) = \mathbb{E}_{S_{t+1}\backsim p(\cdot|s_t,a_t)}[R_t + \gamma \cdot V_\pi(S_{t+1})]$$

优势函数(Advantage function)

$$Q_\pi(s,a) - V_\pi(s)$$

近似策略梯度

$$\begin{aligned} g(s_t,a_t;\theta) &= [Q_\pi(s_t,a_t) - V_\pi(s_t)] \cdot \nabla_\theta \ln \pi(a_t|s_t;\theta) \\ &= [\mathbb{E}_{S_{t+1}}[R_t + \gamma \cdot V_\pi(S_{t+1})] - V_\pi(s_t)] \cdot \nabla_\theta \ln \pi(a_t|s_t;\theta) \end{aligned}$$

蒙特卡洛近似

$$\approx [r_t + \gamma \cdot V_\pi(s_{t+1})] - V_\pi(s_t)] \cdot \nabla_\theta \ln \pi(a_t|s_t;\theta)$$

用价值网络 $v(s;\omega)$ 替换状态价值函数 $V_\pi(s)$

$$\tilde{g}(s_t.a_t;\theta) \triangleq [r_t + \gamma \cdot v_\pi(s_{t+1};\omega)] - v_\pi(s_t;\omega)] \cdot \nabla_\theta \ln \pi(a_t|s_t;\theta)$$

策略网络提升

$$\theta \leftarrow \theta + \beta \cdot \tilde{g}(s,a;\theta)$$

价值网络

贝尔曼公式

$$V_\pi(s_t) = \mathbb{E}_{A_t\backsim\pi(\cdot|s_t;\theta)}[\mathbb{E}_{S_{t+1}\backsim p(\cdot|s_t,A_t)}[R_t + \gamma \cdot V_\pi(S_{t+1})]]$$

TD目标

$$\hat{y_t} \triangleq r_t + \gamma \cdot v(s_{t+1};\omega)$$

损失函数

$$L(\omega) \triangleq \frac{1}{2}[v(s_t;\omega) - \hat{y_t}]^2$$

损失函数的梯度

$$\nabla_\omega L(\omega) = [v(s_t;\omega) - \hat{y_t}] \cdot \nabla_\omega v(s_t;\omega)$$

梯度下降

$$\omega \leftarrow \omega - \alpha \cdot \nabla_\omega L(\omega)$$

Multi-agent

Subtopic 1