

$$\pi(a|s, \boldsymbol{\theta}) \doteq \Pr\{A_t = a \mid S_t = s\}$$

$$r(\pi) \doteq \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{t=1}^n \mathbb{E}_\pi[R_t] = \sum_s d_\pi(s) \sum_a \pi(a|s) \sum_{s', r} p(s', r|s, a) r$$

$$d_\pi \doteq \lim_{t \rightarrow \infty} \Pr\{S_t = s\} \quad \sum_s d_\pi(s) \sum_a \pi(a|s, \boldsymbol{\theta}) p(s'|s, a) = d_\pi(s')$$

$$\tilde{v}_\pi(s) \doteq \sum_{k=1}^{\infty} \mathbb{E}_\pi[R_{t+k} - r(\pi) \mid S_t = s]$$

$$\tilde{q}_\pi(s, a) \doteq \sum_{k=1}^{\infty} \mathbb{E}_\pi[R_{t+k} - r(\pi) \mid S_t = s, A_t = a]$$

$$\Delta \boldsymbol{\theta}_t \doteq \alpha \frac{\partial \widehat{r}(\pi)}{\partial \boldsymbol{\theta}} \doteq \alpha \widehat{\nabla r(\pi)}$$

$$\begin{aligned} \nabla r(\pi) &= \sum_s d_\pi(s) \sum_a \tilde{q}_\pi(s, a) \nabla \pi(a|s, \boldsymbol{\theta}) \quad (\text{the policy-gradient theorem}) \\ &= \sum_s d_\pi(s) \sum_a \left(\tilde{q}_\pi(s, a) - v(s) \right) \nabla \pi(a|s, \boldsymbol{\theta}) \quad (\text{for any } v : \mathcal{S} \rightarrow \mathbb{R}) \\ &= \sum_s d_\pi(s) \sum_a \pi(a|s, \boldsymbol{\theta}) \left(\tilde{q}_\pi(s, a) - v(s) \right) \frac{\nabla \pi(a|s, \boldsymbol{\theta})}{\pi(a|s, \boldsymbol{\theta})} \\ &= \mathbb{E} \left[\left(\tilde{q}_\pi(S_t, A_t) - v(S_t) \right) \frac{\nabla \pi(A_t|S_t, \boldsymbol{\theta})}{\pi(A_t|S_t, \boldsymbol{\theta})} \mid S_t \sim d_\pi, A_t \sim \pi(\cdot|S_t, \boldsymbol{\theta}) \right] \end{aligned}$$

Forward view:

$$\begin{aligned} \boldsymbol{\theta}_{t+1} &\doteq \boldsymbol{\theta}_t + \alpha \widehat{\nabla r(\pi)} \\ &\doteq \boldsymbol{\theta}_t + \alpha \left(\tilde{G}_t^\lambda - \hat{v}(S_t, \mathbf{w}) \right) \frac{\nabla \pi(A_t|S_t, \boldsymbol{\theta})}{\pi(A_t|S_t, \boldsymbol{\theta})} \end{aligned}$$

e.g., in the one-step linear case:

$$\begin{aligned} &= \boldsymbol{\theta}_t + \alpha \left(R_{t+1} - \bar{R}_t + \mathbf{w}_t^\top \boldsymbol{\phi}_{t+1} - \mathbf{w}_t^\top \boldsymbol{\phi}_t \right) \frac{\nabla \pi(A_t|S_t, \boldsymbol{\theta})}{\pi(A_t|S_t, \boldsymbol{\theta})} \\ &\doteq \boldsymbol{\theta}_t + \alpha \delta_t \mathbf{e}(S_t, A_t) \end{aligned}$$

Deriving the policy-gradient theorem: $\nabla r(\pi) = \sum_s d_\pi(s) \sum_a \tilde{q}_\pi(s, a) \nabla \pi(a|s, \boldsymbol{\theta})$:

$$\begin{aligned}
\nabla \tilde{v}_\pi(s) &= \nabla \sum_a \pi(a|s, \boldsymbol{\theta}) \tilde{q}_\pi(s, a) \\
&= \sum_a \left[\nabla \pi(a|s, \boldsymbol{\theta}) \tilde{q}_\pi(s, a) + \pi(a|s, \boldsymbol{\theta}) \nabla \tilde{q}_\pi(s, a) \right] \\
&= \sum_a \left[\nabla \pi(a|s, \boldsymbol{\theta}) \tilde{q}_\pi(s, a) + \pi(a|s, \boldsymbol{\theta}) \nabla \sum_{s', r} p(s', r|s, a) [r - r(\pi) + \tilde{v}_\pi(s')] \right] \\
&= \sum_a \left[\nabla \pi(a|s, \boldsymbol{\theta}) \tilde{q}_\pi(s, a) + \pi(a|s, \boldsymbol{\theta}) \left[-\nabla r(\pi) + \sum_{s'} p(s'|s, a) \nabla \tilde{v}_\pi(s') \right] \right]
\end{aligned}$$

Re-arranging terms:

$$\nabla r(\pi) = \sum_a \left[\nabla \pi(a|s, \boldsymbol{\theta}) \tilde{q}_\pi(s, a) + \pi(a|s, \boldsymbol{\theta}) \sum_{s'} p(s'|s, a) \nabla \tilde{v}_\pi(s') \right] - \nabla \tilde{v}_\pi(s)$$

Summing both sides over s , weighted by $d_\pi(s)$:

$$\begin{aligned}
\sum_s d_\pi(s) \nabla r(\pi) &= \sum_s d_\pi(s) \sum_a \nabla \pi(a|s, \boldsymbol{\theta}) \tilde{q}_\pi(s, a) \\
&\quad + \sum_s d_\pi(s) \sum_a \pi(a|s, \boldsymbol{\theta}) \sum_{s'} p(s'|s, a) \nabla \tilde{v}_\pi(s') - \sum_s d_\pi(s) \nabla \tilde{v}_\pi(s) \\
\nabla r(\pi) &= \sum_s d_\pi(s) \sum_a \nabla \pi(a|s, \boldsymbol{\theta}) \tilde{q}_\pi(s, a) \\
&\quad + \underbrace{\sum_{s'} \sum_s d_\pi(s) \sum_a \pi(a|s, \boldsymbol{\theta}) p(s'|s, a)}_{d_\pi(s')} \nabla \tilde{v}_\pi(s') - \sum_s d_\pi(s) \nabla \tilde{v}_\pi(s) \\
&= \sum_s d_\pi(s) \sum_a \nabla \pi(a|s, \boldsymbol{\theta}) \tilde{q}_\pi(s, a) \\
&\quad + \sum_{s'} d_\pi(s') \nabla \tilde{v}_\pi(s') - \sum_s d_\pi(s) \nabla \tilde{v}_\pi(s) \\
&= \sum_s d_\pi(s) \sum_a \tilde{q}_\pi(s, a) \nabla \pi(a|s, \boldsymbol{\theta}) \quad \text{Q.E.D.}
\end{aligned}$$

Final, complete policy-gradient algorithm:

Initialize parameters of policy $\boldsymbol{\theta} \in \mathbb{R}^n$, and state-value function $\mathbf{w} \in \mathbb{R}^m$

Initialize eligibility traces $\mathbf{z}^\theta \in \mathbb{R}^n$ and $\mathbf{z}^w \in \mathbb{R}^m$ to $\mathbf{0}$

Initialize $\bar{R} = 0$

On each step, in state S :

Choose A according to $\pi(\cdot|S, \boldsymbol{\theta})$

Take action A , observe S', R

$\delta \leftarrow R - \bar{R} + \hat{v}(S', \mathbf{w}) - \hat{v}(S, \mathbf{w})$

$\bar{R} \leftarrow \bar{R} + \alpha_1 \delta$

$\mathbf{z}^w \leftarrow \lambda \mathbf{z}^w + \nabla_{\mathbf{w}} \hat{v}(S, \mathbf{w})$

$\mathbf{w} \leftarrow \mathbf{w} + \alpha_2 \delta \mathbf{z}^w$

$\mathbf{z}^\theta \leftarrow \lambda \mathbf{z}^\theta + \frac{\nabla \pi(A|S, \boldsymbol{\theta})}{\pi(A|S, \boldsymbol{\theta})}$

$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha_3 \delta \mathbf{z}^\theta$

$$\pi(a|s, \boldsymbol{\theta}) \doteq \frac{\exp(\boldsymbol{\theta}^\top \boldsymbol{\phi}(s, a))}{\sum_b \exp(\boldsymbol{\theta}^\top \boldsymbol{\phi}(s, b))}$$

$$\mathbf{e}(s, a) \doteq \frac{\nabla \pi(a|s, \boldsymbol{\theta})}{\pi(a|s, \boldsymbol{\theta})} = \boldsymbol{\phi}(s, a) - \sum_b \pi(b|s, \boldsymbol{\theta}) \boldsymbol{\phi}(s, b)$$

$$\boldsymbol{\mu}(s) \doteq \boldsymbol{\theta}_\mu^\top \boldsymbol{\phi}(s)$$

$$\boldsymbol{\sigma}(s) \doteq \exp(\boldsymbol{\theta}_\sigma^\top \boldsymbol{\phi}(s))$$

$$\pi(a|s, \boldsymbol{\theta}) \doteq \frac{1}{\boldsymbol{\sigma}(s) \sqrt{2\pi}} \exp\left(-\frac{(a - \boldsymbol{\mu}(s))^2}{2\boldsymbol{\sigma}(s)^2}\right)$$

$$\boldsymbol{\theta} \doteq (\boldsymbol{\theta}_\mu^\top; \boldsymbol{\theta}_\sigma^\top)^\top$$

$$\frac{\nabla_{\boldsymbol{\theta}_\mu} \pi(a|s, \boldsymbol{\theta})}{\pi(a|s, \boldsymbol{\theta})} = \frac{1}{\boldsymbol{\sigma}(s)^2} (a - \boldsymbol{\mu}(s)) \boldsymbol{\phi}_\mu(s)$$

$$\frac{\nabla_{\boldsymbol{\theta}_\sigma} \pi(a|s, \boldsymbol{\theta})}{\pi(a|s, \boldsymbol{\theta})} = \left(\frac{(a - \boldsymbol{\mu}(s))^2}{\boldsymbol{\sigma}(s)^2} - 1 \right) \boldsymbol{\phi}_\sigma(s)$$