

Qs ① Limiting ODE of the TD(0) algorithm with linear function approximation:

$$\dot{\omega}(t) = b - A\omega(t)$$

where,

$$b = \phi^T D R$$

$$A = \phi^T D [I - \gamma P] \phi$$

Global Lyapunov function for the limiting ODE

$$V(x) = \|\omega - \omega_*\|_p$$

Here, $\omega_* = A^{-1} b$

Verification:

① To show: $V(x) \geq 0 \quad \forall x$ with equality iff $x = x_*$

Here, $V(\omega) = \|\omega - \omega_*\|_p$

$$= \left(\sum_{i=1}^d \|\omega_i - \omega_{*i}\|^p \right)^{1/p}$$

w.k.t $\omega_i \geq \omega_{*i}$

$$\therefore V(\omega) \geq 0$$

with $V(\omega) = 0$ iff $\omega_i = \omega_{*i} \quad \forall i$

$$\Rightarrow \omega = \omega_*$$

② To show: $\lim_{\|w\| \rightarrow \infty} V(w) = +\infty$

$$\lim_{\|w\| \rightarrow \infty} \|w - w_*\|_p = \lim_{\|w\| \rightarrow \infty} \left(\sum_{i=1}^d |w_i - w_{*,i}|^p \right)^{1/p}$$

$$\leq \lim_{\|w\| \rightarrow \infty} \left(\sum_{i=1}^d \|w_i\|^p \|w_*\|^p \right)^{1/p} \quad \text{[Using Cauchy-Swartz Inequality]}$$

$$\leq \lim_{\|w\| \rightarrow \infty} (\|w\|_p - \|w_*\|_p)$$

$$\leq +\infty$$

$$\Rightarrow \lim_{\|w\| \rightarrow \infty} \|w - w_*\|_p \leq +\infty$$

$$\Rightarrow \lim_{\|w\| \rightarrow \infty} \|w - w_*\|_p = +\infty$$

Qs (2) Given: $\phi(1)=1$ $\phi(2)=2$

$$\Rightarrow \phi = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

Target policy μ and Behavior policy η

$$* \eta(\text{right} | 1) = 0.5$$

$$\therefore \eta(\text{left} | 1) = 1 - \eta(\text{right} | 1) = 1 - 0.5 = 0.5$$

$$* \eta(\text{right} | 2) = 0.5$$

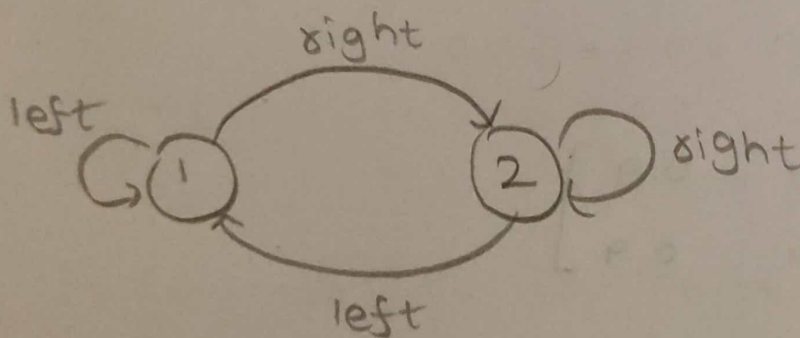
$$\Rightarrow \eta(\text{left} | 2) = 1 - \eta(\text{right} | 2) = 1 - 0.5 = 0.5$$

$$* \mu(\text{right} | 1) = 0.9$$

$$\Rightarrow \mu(\text{left} | 1) = 1 - \mu(\text{right} | 1) = 1 - 0.9 = 0.1$$

$$* \mu(\text{right} | 2) = 0.9$$

$$\Rightarrow \mu(\text{left} | 2) = 1 - \mu(\text{right} | 2) = 1 - 0.9 = 0.1$$



Q8 (2) (a) To find: PM

$$\begin{aligned} PM(s_{t+1}=1 | s_t=1) &= \mu(\text{right} | s_t=1) PM(s_{t+1}=1 | s_t=1, a_t=\text{right}) \\ &\quad + \mu(\text{left} | s_t=1) PM(s_{t+1}=1 | s_t=1, a_t=\text{left}) \\ &= 0.9 * 0 + 0.1 * 1 = 0.1 \end{aligned}$$

$$\begin{aligned} PM(s_{t+1}=2 | s_t=1) &= \mu(\text{right} | 1) PM(2 | 1, \text{right}) + \\ &\quad \mu(\text{left} | 1) PM(2 | 1, \text{left}) \\ &= 0.9 * 1 + 0.1 * 0 = 0.9 \end{aligned}$$

$$\begin{aligned} PM(s_{t+1}=1 | s_t=2) &= \mu(\text{right} | 2) PM(1 | 2, \text{right}) + \\ &\quad \mu(\text{left} | 2) PM(1 | 2, \text{left}) \\ &= 0.9 * 0 + 0.1 * 1 = 0.1 \end{aligned}$$

$$\begin{aligned} PM(s_{t+1}=2 | s_t=2) &= \mu(\text{right} | 2) PM(2 | 2, \text{right}) + \\ &\quad \mu(\text{left} | 2) PM(2 | 2, \text{left}) \\ &= 0.9 * 1 + 0.1 * 0 = 0.9 \end{aligned}$$

$$\therefore PM = \begin{bmatrix} 0.1 & 0.9 \\ 0.1 & 0.9 \end{bmatrix}$$

To find: d^M

we know that $d^{MT} PM = d^{MT}$

$$\Rightarrow [d^M(1) \ d^M(2)] \begin{bmatrix} 0.1 & 0.9 \\ 0.1 & 0.9 \end{bmatrix} = [d^M(1) \ d^M(2)]$$

$$\Rightarrow 0.1 d^M(1) + 0.1 d^M(2) = d^M(1)$$

$$\Rightarrow 0.1 d^H(2) = 0.9 d^H(1)$$

$$\Rightarrow d^H(2) = 9 d^H(1) \rightarrow \textcircled{1}$$

We also
know that

$$d^H(1) + d^H(2) = 1$$

Subs Eq $\textcircled{1}$

$$\Rightarrow d^H(1) + 9 d^H(1) = 1$$

$$\Rightarrow 10 d^H(1) = 1$$

$$\Rightarrow d^H(1) = 0.1$$

From $\textcircled{1}$ $d^H(2) = 9 \times 0.1 = 0.9$

$$\therefore d^H = \begin{bmatrix} 0.1 \\ 0.9 \end{bmatrix}$$

To find : A

w.k.t $A = \Phi^T D (\mathbf{I} - \gamma \mathbf{P}^H) \Phi$

$$= \begin{bmatrix} 1 & 2 \end{bmatrix} \begin{bmatrix} 0.1 & 0 \\ 0 & 0.9 \end{bmatrix} \left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \gamma \begin{bmatrix} 0.1 & 0.9 \\ 0.1 & 0.9 \end{bmatrix} \right) \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= \begin{bmatrix} 0.1 & 1.8 \end{bmatrix} \left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} 0.09 & 0.81 \\ 0.09 & 0.81 \end{bmatrix} \right) \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= \begin{bmatrix} 0.1 & 1.8 \end{bmatrix} \begin{bmatrix} 0.91 & -0.81 \\ -0.09 & 0.19 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= \begin{bmatrix} -0.071 & 0.261 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= \begin{bmatrix} -0.071 + 0.522 \end{bmatrix}$$

$$= \begin{bmatrix} 0.451 \end{bmatrix}$$

As the entry in A is positive, here, A is a positive definite matrix.

\therefore The limiting ODE associated with the on-policy TD(0) has a globally asymptotically stable equilibrium.

Qs (2) (b) To find: P^π

$$P^\pi = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix}$$

To find: d^π

w.k.t $d^\pi{}^T P^\pi = d^\pi{}^T$

$$\Rightarrow [d^\pi(1) \ d^\pi(2)] \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix} = [d^\pi(1) \ d^\pi(2)]$$

$$\Rightarrow 0.5d^\pi(1) + 0.5d^\pi(2) = d^\pi(1)$$

$$\Rightarrow d^\pi(1) = d^\pi(2) \rightarrow (2)$$

Also, $d^\pi(1) + d^\pi(2) = 1$

Subs Eq (2)

$$\Rightarrow d^\pi(1) + d^\pi(1) = 1$$

$$\Rightarrow d^\pi(1) = d^\pi(2) = 0.5$$

$$\therefore d^\pi = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$$

To find: A'

$$\text{w.k.t } A' = \Phi^T D^T (\mathbf{I} - \gamma P^H) \Phi$$

$$= \begin{bmatrix} 1 & 2 \end{bmatrix} \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \left[\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - 0.9 \begin{bmatrix} 0.1 & 0.9 \\ 0.1 & 0.9 \end{bmatrix} \right] \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= \begin{bmatrix} 0.5 & 1 \end{bmatrix} \begin{bmatrix} 0.91 & -0.81 \\ -0.09 & 0.19 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= \begin{bmatrix} 0.365 & -0.215 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= \begin{bmatrix} 0.365 & -0.43 \end{bmatrix}$$

$$= \begin{bmatrix} -0.065 \end{bmatrix}$$

The entry in A' is negative.

\therefore Here, A' is not a positive definite matrix

\therefore The limiting ODE associated with the naive off-policy algorithm ~~has~~ does not have a globally asymptotically stable equilibrium.

Qs ② (c) Given:

$$f(s) = d_{\eta}(s) \lim_{t \rightarrow \infty} \mathbb{E}_{\eta}[F_t | s_t = s]$$

$$\text{Here, } F_t = p_{t-1} \gamma K_{t-1} + 1$$

$$\Rightarrow f(s) = d_{\eta}(s) + \gamma \sum_{s'} d_{\eta}(s') P_{s',s}^{\mu} \quad [\text{Derived in Lecture 9}]$$

$$\Rightarrow f(s) = d_{\eta}(s) + \gamma f^T P_{\cdot,s}$$

$$\Rightarrow f^T (I - \gamma P^{\mu}) = d_{\eta}^T$$

$$\Rightarrow [f(1) \ f(2)] \left[\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - 0.9 \begin{bmatrix} 0.1 & 0.9 \\ 0.1 & 0.9 \end{bmatrix} \right] = [0.5 \ 0.5]$$

$$\Rightarrow [f(1) \ f(2)] \begin{bmatrix} 0.91 & -0.81 \\ -0.09 & 0.19 \end{bmatrix} = [0.5 \ 0.5]$$

$$\Rightarrow 0.91 f(1) - 0.09 f(2) = 0.5 \rightarrow \textcircled{3}$$

$$-0.81 f(1) + 0.19 f(2) = 0.5 \rightarrow \textcircled{4}$$

Multiplying $\textcircled{3}$ by 0.19 and $\textcircled{4}$ by 0.09

$$\Rightarrow 0.1729 f(1) - 0.0171 f(2) = 0.095$$

$$\Rightarrow -0.0729 f(1) + 0.0171 f(2) = 0.045$$

Adding the two equations

$$\Rightarrow 0.1 f(1) = 0.14$$

$$\Rightarrow f(1) = 1.4$$

Subs in (3)

$$0.91 + 1.4 - 0.09 f(2) = 0.5$$

$$\Rightarrow 1.274 - 0.09 f(2) = 0.5$$

$$\Rightarrow -0.09 f(2) = -0.774$$

$$\Rightarrow f(2) = 8.6$$

$$\therefore f(1) = 1.4 \quad f(2) = 8.6$$

To find: A''

$$\text{w.k.t } A'' = \Phi^T D^e (\mathbb{I} - \gamma P^H) \Phi$$

$$= [1 \ 2] \begin{bmatrix} 1.4 & 0 \\ 0 & 8.6 \end{bmatrix} \left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - 0.9 \begin{bmatrix} 0.1 & 0.9 \\ 0.1 & 0.9 \end{bmatrix} \right) \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= [1.4 \ 17.2] \begin{bmatrix} 0.91 & -0.81 \\ -0.09 & 0.19 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= [0.274 \ 2.134] \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= [-0.274 + 4.268]$$

$$A'' = [3.994]$$

As the entry in A'' is positive. Here, A'' is a positive definite matrix.

\therefore The limiting ODE associated with emphatic TD(0) has a globally asymptotically stable equilibrium.

Qs (3) To find: $\sum_s f(s)$

w.k.t $f(s) = d_\eta(s) + \gamma f^T P_{\cdot, s}$

$$\therefore \sum_s f(s) = \sum_s d_\eta(s) + \gamma f^T P_{\cdot, s}$$

$$= \sum_s d_\eta(s) + \gamma \sum_s f^T P_{\cdot, s}$$

$$= 1 + \gamma \sum_s f^T P_{\cdot, s} \quad [\because \sum_s d_\eta(s) = 1]$$

$$= 1 + \gamma \sum_s \sum_{s'} f(s') P_{s', s}$$

$$= 1 + \gamma \sum_s f(s) \sum_{s'} P_{s, s'}$$

$$= 1 + \gamma \sum_s f(s) \cdot 1$$

[\because sum of row vector of P^H is 1]

$$\Rightarrow \sum_s f(s) - \gamma \sum_s f(s) = 1$$

$$\Rightarrow \sum_s f(s) [1 - \gamma] = 1$$

$$\Rightarrow \sum_s f(s) = \frac{1}{1 - \gamma}$$

Yes, we can identify $\sum_s f(s)$, which is

$$\sum_s f(s) = \frac{1}{1 - \gamma}$$

Qs (4) Optimization Problem : $\min \mathcal{E}(\omega)$

$$\mathcal{E}(\omega) = \frac{1}{2} \|Q^H(s,a) - Q^*(s,a)\|_D^2$$

Intuition: The optimization problem tries to reduce the difference between the true (or target) Q value and the current estimate of the Q -value, which is what we want. We want our estimate of Q -value to be as close as to value of true Q -value.

* But, the problem (or difficulty) in doing this is, we don't know the $Q^*(s,a)$ value.

\therefore we try to approximate the $Q^*(s,a)$ value by

$$Q^*(s,a) \approx \phi^T(s,a) \cdot \omega$$

where,

ϕ - approxi known feature matrix

ω - parameter.

$$\therefore \min \mathcal{E}(\omega) = \min \frac{1}{2} \|Q^H(s,a) - \phi^T(s,a)\omega\|_D^2$$

Convex Optimization:

\therefore Differentiate $\mathcal{E}(\omega)$ w.r.t ω

$$\text{Here, } \mathcal{E}(\omega) = \frac{1}{2} \sum_{a,s} d_\mu(s) \mu(a) (Q^H(s,a) - \phi^T(s,a)\omega)^2$$

$$\therefore \nabla \mathcal{E}(\omega) = -\mathbb{E}[(Q^H(s_t, a_t) - \phi^T(s_t, a_t)\omega)\phi(s_t, a_t)]$$

where, $s_t \sim d_\mu$ \hookrightarrow ①
 $a_t \sim \mu$

From Bellman Equation, we know that

$$Q^H(s, a) = \mathbb{E}[r(s_t, a_t, s_{t+1}) + \gamma Q^H(s_{t+1}, a_{t+1}) | s_t = s, a_t = a]$$

$$= \sum_{a', s'} \mathbb{P}\{a_{t+1} = a', s_{t+1} = s' | s_t = s, a_t = a\} [r(s, a, s') + \gamma Q^H(s', a')]$$

Subs value of $Q^H(s, a)$ in ①

$$\nabla \mathcal{E}(\omega) = - \sum_{a, s} \mathbb{P}\{s_t = s\} \mu(a_t = a) [Q^H(s, a) - \phi^T(s, a)\omega] \phi(s, a)$$

$$= - \sum_{a, s} \mathbb{P}\{s\} \mu(a) \sum_{a', s'} \mathbb{P}\{s', a' | s, a\} (r(s, a, s') + \gamma Q^H(s', a') - \phi^T(s, a)\omega) \phi(s, a)$$

$$= - \sum_{a, s, s', a'} \mathbb{P}\{s_t = s, a_t = a, s_{t+1} = s', a_{t+1} = a'\} (r(s, a, s') + \gamma Q^H(s', a') - \phi^T(s, a)\omega) \phi(s, a)$$

$$= -\mathbb{E}[(r(s, a, s') + \gamma Q^H(s', a') - \phi^T(s, a)\omega)\phi(s, a)]$$

where, $s_t \sim d_\mu$ $s_{t+1} \sim \mathbb{P}(\cdot | s_t, a_t)$
 $a_t \sim \mu(\cdot | s_t)$ $a_{t+1} \sim \mu(\cdot | s_{t+1})$

Hence, the SGD algorithm would be:

$$w_{t+1} = w_t + \alpha_t [\gamma (r(s, a, s') + \gamma Q^{\pi}(s', a') - \phi^T(s, a) w)] \phi(s, a)$$

where, $\alpha_t \rightarrow$ step size