CMPT 419/983: Theoretical Foundations of Reinforcement Learning

Lecture 6

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Recap

- We have studied algorithms (VI/PI/LP) that use knowledge of the transition probabilities $\mathcal{P}$ and rewards r to compute the optimal policy.
- These quantities are difficult to obtain in practical scenarios, and hence we need methods that can compute the optimal policy without explicitly relying on this information.
- Today, we will consider evaluating a fixed policy π without explicit knowledge of $\mathcal{P}$ and r.

Policy Evaluation

For a fixed policy π and starting state s_0, $v^{\pi}(s_0) = \mathbb{E}\left[X|S_0 = s_0\right]$ where $X := \sum_{t=0}^{\infty} \gamma^t R_t$.

$$\mathbb{E}\left[X|S_0 = s_0\right] = \mathbb{E}_{A_0|S_0}\left[\mathbb{E}\left[X|S_0 = s_0, A_0\right]\right] = \mathbb{E}_{A_0|S_0}\left[\mathbb{E}_{S_1|\{S_0,A_0\}}\left[\mathbb{E}\left[X|S_0 = s_0, A_0, S_1\right]\right]\right]$$

(Using that $\mathbb{E}[X] = \mathbb{E}_Y[\mathbb{E}[X|Y]]$)

$$= \mathbb{E}_{A_0|S_0}\mathbb{E}_{S_1|\{S_0,A_0\}}\mathbb{E}_{A_1|\{S_0,A_0,S_1\}}\ldots\mathbb{E}_{S_t|\{S_0,A_0,\ldots S_{t-1},A_{t-1}\}}\mathbb{E}\left[X|\{S_0, A_0, \ldots, S_{t-1}, A_{t-1}\}\right]$$

(Unrolling recursively)

$$= \mathbb{E}_{A_0|S_0}\mathbb{E}_{S_1|\{S_0,A_0\}}\mathbb{E}_{A_1|\{S_0,A_0,S_1\}}\ldots\mathbb{E}_{S_t|\{S_{t-1},A_{t-1}\}}\mathbb{E}\left[X|\{S_0, A_0, \ldots, S_{t-1}, A_{t-1}\}\right]$$

(Markov assumption)

$$= \mathbb{E}_{A_0|S_0}\mathbb{E}_{S_1|\{S_0,A_0\}}\mathbb{E}_{A_1|S_1}\ldots\mathbb{E}_{S_t|\{S_{t-1},A_{t-1}\}}\mathbb{E}\left[X|\{S_0, A_0, \ldots, S_{t-1}\}\right]$$

(Restricting to Markov policies)

$$= \mathbb{E}_{A_0|S_0}\left[R_0 + \mathbb{E}_{S_1|\{S_0,A_0\}}\mathbb{E}_{A_1|S_1}\left[\gamma R_1 + \ldots\mathbb{E}_{S_t|\{S_{t-1},A_{t-1}\}}\left[\gamma^t R_t + \ldots\right]\right]\right]$$

(Distributing the sum)

Policy Evaluation

The unrolling on the previous slide suggests a Monte-Carlo sampling scheme:

- Starting from s_0, for $t \geq 0$, sample $a_t \sim \pi(\cdot|s_t)$, the environment transitions to s_{t+1} (equivalent to sampling $s_{t+1} \sim \mathcal{P}(\cdot|s_t, a_t)$). This generates a trajectory $\tau = (s_0, a_0, s_1, \ldots)$.
- Collect rewards $r_t = r(s_t, a_t)$, calculate $R(\tau) = \sum_{t=0}^{\infty} \gamma^t r_t$. Note that $\mathbb{E}[R(\tau)] = v^\pi(s_0)$.
- In order to reduce the variance, generate m trajectories $\{\tau_i\}_{i=1}^m$, calculate $R(\tau_i)$ and output the empirical average: $\hat{v} := \frac{\sum_{i=1}^m R(\tau_i)}{m}$ as an approximation to $v^\pi(s_0)$.

Q: What is the problem with this approach? Ans: Need to generate infinitely long trajectories.

Solution 1: Truncate the trajectory to H steps, i.e. calculate $R(\tau) = \sum_{t=0}^{H-1} \gamma^t r_t$.

$$R(\tau) = \sum_{t=0}^{\infty} \gamma^t r_t - \sum_{t=H}^{\infty} \gamma^t r_t \implies \mathbb{E}[R(\tau)] = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t\right] - \mathbb{E}\left[\sum_{t=H}^{\infty} \gamma^t r_t\right] = v^\pi(s_0) - \sum_{t=H}^{\infty} \gamma^t r_t$$

$$\implies |v^\pi(s_0) - \mathbb{E}[R(\tau)]| \leq \frac{\gamma^H}{1-\gamma} \qquad (r_t \leq 1, \text{ Sum of geometric series.})$$

Policy Evaluation

Claim: Using $m = \frac{\ln(2/\delta)}{2\epsilon^2 (1-\gamma)^2}$ trajectories with $H \geq \frac{\ln(1/\epsilon\,(1-\gamma))}{\ln(1/\gamma)}$ guarantees that $|\hat{v} - v^\pi(s_0)| \leq \epsilon$ with probability $1 - \delta$.

Proof: Recall that $\hat{v} = \frac{\sum_{i=1}^m R(\tau_i)}{m}$.

$$|v^\pi(s_0) - \mathbb{E}[\hat{v}]| = \left| v^\pi(s_0) - \frac{\sum_{i=1}^m \mathbb{E}[R(\tau_i)]}{m} \right| = \left| \frac{\sum_{i=1}^m [v^\pi(s_0) - \mathbb{E}[R(\tau_i)]]}{m} \right|$$

$$\leq \frac{\sum_{i=1}^m |[v^\pi(s_0) - \mathbb{E}[R(\tau_i)]]|}{m} \leq \frac{\gamma^H}{1-\gamma}$$

$$|\hat{v} - v^\pi(s_0)| = |\hat{v} - \mathbb{E}[\hat{v}] + \mathbb{E}[\hat{v}] - v^\pi(s_0)| \leq |\hat{v} - \mathbb{E}[\hat{v}]| + |\mathbb{E}[\hat{v}] - v^\pi(s_0)|$$

$$\leq |\hat{v} - \mathbb{E}[\hat{v}]| + \frac{\gamma^H}{1-\gamma} \leq |\hat{v} - \mathbb{E}[\hat{v}]| + \frac{\epsilon}{2} \qquad \left(\text{Using } H \geq \frac{\ln(1/\epsilon\,(1-\gamma))}{\ln(1/\gamma)}\right)$$

$$|\hat{v} - \mathbb{E}[\hat{v}]| = \left| \frac{X_m - \mathbb{E}[X_m]}{m} \right| \qquad \left(X_m := \sum_{i=1}^m R(\tau_i)\right)$$

Since the $R(\tau_i)$ r.v's are i.i.d, we can use Hoeffding's inequality.

Policy Evaluation

Recall that $|\hat{v} - v^\pi(s_0)| \leq |\hat{v} - \mathbb{E}[\hat{v}]| + \frac{\epsilon}{2}$. Here, $|\hat{v} - \mathbb{E}[\hat{v}]| = \left|\frac{X_m - \mathbb{E}[X_m]}{m}\right|$ where $X_m := \sum_{i=1}^m R(\tau_i)$.

Hoeffding's Inequality: For m i.i.d. r.v's such that $X_i \in [a_i, b_i]$. For $t > 0$,

$$\Pr[|X_m - \mathbb{E}[X_m]| \geq t] \leq 2\exp\left(\frac{-2t^2}{\sum_{i=1}^m (b_i - a_i)^2}\right)$$

$R(\tau_i) \in [0, {}^1\!/\!{}_{1-\gamma}]$. Setting $t = m\,\epsilon$,

$$\Pr\left[\left|\frac{X_m - \mathbb{E}[X_m]}{m}\right| \geq \epsilon\right] \leq 2\exp\left(-2m\,\epsilon^2\,(1-\gamma)^2\right)$$

$$\implies \Pr\left[\left|\frac{X_m - \mathbb{E}[X_m]}{m}\right| \geq \epsilon\right] \leq \delta \qquad (\text{Setting } m = \tfrac{\ln(2/\delta)}{2\epsilon^2\,(1-\gamma)^2})$$

Putting everything together, with probability $1 - \delta$, $|\hat{v} - v^\pi(s_0)| \leq \epsilon$. □

Solution 2: Randomly truncate the trajectory i.e. sample H from a geometric distribution with parameter $1 - \gamma$, return $R(\tau) = \sum_{t=0}^{H-1} r_t$. Eliminates the bias from using a fixed truncation.

Claim: $\mathbb{E}_H\,\mathbb{E}_\tau[R(\tau)] = v^\pi(s_0)$. Prove in Assignment 2!

Policy Evaluation

- **Problem 1**: To estimate $v^\pi \in \mathbb{R}^S$, we need fresh trajectories for estimating $v^\pi(s)$ for each $s \in \mathcal{S}$. We need to restart the sampling each time, which may not always be possible.
- *Sol*: Sample a single trajectory, estimate $v^\pi(s)$ as the cumulative discounted sum of rewards following the first time state s is visited. This is referred to as "first visit" Monte-Carlo. Can also average the returns following "every visit" to state s. Both strategies can be shown to produce unbiased estimates of v^π. For more details, see [SB18, Chapter 5].
- If $\hat{v}_k$ is the empirical average after sampling $k \in [1, m]$ trajectories, we can update it in an online fashion: $\hat{v}_k = \hat{v}_{k-1} + \frac{R(\tau_k) - \hat{v}_{k-1}}{k-1}$.
- **Problem 2**: Hence, $\hat{v}_k$ is updated only after observing the rewards from the entire trajectory. This could be slow when the trajectories are long. Moreover, Monte-Carlo estimation does not exploit the MDP structure effectively.
- *Sol*: Temporal Difference Learning

Temporal Difference Learning

Idea: Exploit the Bellman equation and combine it with Monte-Carlo estimation.

Recall that, for starting state s, for a fixed policy π,

$$v^\pi(s) = \mathbf{r}_\pi(s) + \gamma \sum_{s'} \mathbf{P}_\pi[s, s']\, v^\pi(s') = \sum_{a \in \mathcal{A}} r(s,a)\, \pi[a|s] + \gamma \sum_{s' \in \mathcal{S}} \sum_{a \in \mathcal{A}} \mathcal{P}[s'|s,a]\, \pi[a|s]\, v^\pi(s')$$

$$= \sum_{a \in \mathcal{A}} \pi[a|s] \left[r(s,a) + \gamma \sum_{s' \in \mathcal{S}} \mathcal{P}[s'|s,a] v^\pi(s') \right] = \mathbb{E}_{a \sim \pi(\cdot|s)} \left[r(s,a) + \gamma\, \mathbb{E}_{s' \sim \mathcal{P}(\cdot|s,a)}[v^\pi(s')] \right]$$

$$\implies v^\pi(s) = \mathbb{E}_{a \sim \pi(\cdot|s)}\, \mathbb{E}_{s' \sim \mathcal{P}(\cdot|s,a)} \left[r(s,a) + \gamma v^\pi(s') \right]$$

Sampling a from $\pi(\cdot|s)$ and the environment samples $s' \sim \mathcal{P}(\cdot|s,a)$, $\hat{v}^\pi(s) = r(s,a) + \gamma\, v^\pi(s')$.

Since we do not know $v^\pi(s')$ either, we can use the estimate instead, implying that, $\hat{v}^\pi(s) = r(s,a) + \gamma\, \hat{v}^\pi(s')$. This is known as *bootstrapping* since we are using an estimate at s' to estimate the value function at state s.

Using this idea, we can design an iterative algorithm – TD(0).

Temporal Difference Learning

Algorithm Temporal Difference Learning. [TD(0)]

```
Input: MDP $M = (\mathcal{S}, \mathcal{A}, \rho)$, $v_0 = 0$, Policy $\pi$. Step-sizes $\{\alpha_t\}_{t=0}^{T-1}$.
Sample state $s_0 \sim \rho$.
for $t = 0 \to T - 1$ do
    Take action $a_t \sim \pi(\cdot|s_t)$, observe reward $r(s_t, a_t)$ and transition to state $s_{t+1}$.
    Update $v_{t+1}(s_t) = (1 - \alpha_t)\, v_t(s_t) + \alpha_t\, [r(s_t, a_t) + \gamma\, v_t(s_{t+1})]$.
    $\forall s \neq s_t$, $v_{t+1}(s) = v_t(s)$
end for
```

- Unlike Monte-Carlo estimation, TD(0) does not require waiting until the end of trajectories to start updating the value function estimates.
- Unlike using $\mathcal{T}_\pi$, TD(0) does not require knowledge of $\mathcal{P}$ and r.
- Under some technical assumptions, TD(0) will converge, i.e. $\lim_{t\to\infty} v_t = v^\pi$.
- TD(0) can handle linear function approximation and has non-asymptotic theoretical convergence guarantees. We will prove this next.

Linear Temporal Difference Learning

Linear TD(0)

Assumption: Have access to features $\Phi \in \mathbb{R}^{S \times d}$ such that for every policy π, there exists a $\theta \in \mathbb{R}^d$ such that $v^\pi = \Phi\theta$. For the specific policy π being evaluated, there exists a unique θ^* such that $v^\pi = \Phi\theta^* = v_{\theta^*}$ where $v_\theta := \Phi\theta$.

Define $\phi(s)$ as the feature vector corresponding to state s. Hence, $v_\theta(s) = \langle \phi(s), \theta \rangle$. For convenience, we will assume that $\forall s, \|\phi(s)\| \leq 1$.

Algorithm TD(0) with linear function approximation

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Input: MDP $M = (\mathcal{S}, \mathcal{A}, \rho)$, Features $\Phi \in \mathbb{R}^{S \times d}$, Policy $\pi$. $\theta_0 \in R^d$, Step-sizes $\{\alpha_t\}_{t=0}^{T-1}$.
Sample state $s_0 \sim \rho$
for $t = 0 \to T - 1$ do
    Take action $a_t \sim \pi(\cdot|s_t)$, observe reward $r(s_t, a_t)$ and transition to state $s_{t+1}$.
    Define $g_t(\theta) = [r_t + \gamma\langle \theta, \phi(s_{t+1})\rangle - \langle \theta, \phi(s_t)\rangle]\, \phi(s_t)$
    Update $\theta_{t+1} = \theta_t + \alpha_t\, g_t(\theta_t)$
end for
```

If $d = S$ and $\phi(s)$ correspond to one-hot vectors, then we recover TD(0) from the previous slide.

Linear TD(0) Analysis

The TD(0) update is $\theta_{t+1} = \theta_t + \alpha_t \, g_t(\theta)$ where $g_t(\theta) = [r_t + \gamma \langle \theta, \phi(s_{t+1}) \rangle - \langle \theta, \phi(s_t) \rangle] \, \phi(s_t)$.

Q: Could we use a Gradient Descent type analysis? Ans: Note that $g_t(\theta)$ does not correspond to the gradient of a specific loss function (Prove in Assignment 3!). Hence, TD(0) is a "semi-gradient" method. But we can use a GD type analysis!

We will analyze Linear TD(0) in 4 steps:

(1) Warmup: Analyze a hypothetical algorithm that performs GD on $f(\theta) := \frac{1}{2} \left\| v_{\theta^*} - v_\theta \right\|_D^2$.

(2) Mean-path: Make an analogy between Linear TD(0) and GD, and analyze Linear TD(0) assuming access to the stationary distribution.

(3) IID: Analyze Linear TD(0) assuming access to (s_t, s_{t+1}) sampled i.i.d from the stationary distribution.

(4) Markovian: Analyze *Projected* Linear TD(0) assuming access to (s_t, s_{t+1}) that are gathered from a "fast-mixing" Markov chain (will not cover this in detail).

Linear TD(0) Analysis

Define $P(s'|s)$ to be the probability of transitioning from s to s' when acting according to π.

Assumption: The Markov chain induced by policy π is ergodic (can visit every state) with a unique stationary distribution $\omega \in \Delta_S$. For $s \in \mathcal{S}$, $\omega(s) = \lim_{t \to \infty} \Pr[s_t = s]$. Hence, $\omega \, \mathbf{P}^{\pi} = \omega$ meaning that if $s \sim \omega$ and $s' \sim P(\cdot|s)$, then the marginal distribution of s' is ω.

Define a diagonal matrix $D \in \mathbb{R}^{S \times S}$ such that $D_{i,i} = \omega(i)$. For any $u, w \in \mathbb{R}^S$, define $\|u - w\|_D^2 = \sum_s \omega(s) \, [u(s) - w(s)]^2$.
For v_θ and $v_{\theta'}$, define $\Sigma := \sum_s \omega(s) \, \phi(s)\phi(s)^T \in \mathbb{R}^{d \times d}$ and $\lambda := \lambda_{\min}[\Sigma]$.

$$\|v_\theta - v_{\theta'}\|_D^2 = \sum_s \omega(s) \, [v_\theta(s) - v_{\theta'}(s)]^2 = \sum_s \omega(s) \, [\langle \phi(s), \theta - \theta' \rangle]^2$$

$$= (\theta - \theta')^T \sum_s \omega(s) \, \phi(s)\phi(s)^T (\theta - \theta') = \|\theta - \theta'\|_\Sigma^2$$

Q: Prove that $\lambda_{\max}[\Sigma] \leq 1$

Ans: $\lambda_{\max}[\Sigma] \leq \mathrm{Tr}[\Sigma] = \sum_s \omega(s) \, \mathrm{Tr}[\phi(s)\phi(s)^T] = \sum_s \omega(s) \, \|\phi(s)\|^2 \leq 1$ Hence, for any θ, $\sqrt{\lambda} \, \|\theta\| \leq \|v_\theta\|_D \leq \|\theta\|$ (by setting $\theta' = 0$ above).

Linear TD(0) Analysis – Warmup

Define $f(\theta) := \frac{1}{2}\|v_{\theta^*} - v_\theta\|_D^2 = \frac{1}{2}\|\theta^* - \theta\|_\Sigma^2$. Consider a hypothetical algorithm that performs GD on $f(\theta)$ i.e. at iteration t, $\theta_{t+1} = \theta_t - \alpha \nabla f(\theta_t)$. Note that $\nabla f(\theta) = \Sigma(\theta - \theta^*)$.

$$\|\theta_{t+1} - \theta^*\|^2 = \|\theta_t - \alpha\,\nabla f(\theta_t) - \theta^*\|^2 = \|\theta_t - \theta^*\|^2 + 2\alpha\,\langle \nabla f(\theta_t), \theta^* - \theta_t\rangle + \alpha^2\,\|\nabla f(\theta_t)\|^2$$

$$\langle \nabla f(\theta_t), \theta^* - \theta_t\rangle = \langle \Sigma(\theta_t - \theta^*), \theta^* - \theta_t\rangle = -\|\theta_t - \theta^*\|_\Sigma^2 = -\|v_{\theta_t} - v_{\theta^*}\|_D^2$$

For any vector u s.t. $\|u\| \leq 1$,

$$\langle u, \nabla f(\theta)\rangle = \langle u, \Sigma(\theta - \theta^*)\rangle \leq \left\|\Sigma^{1/2}\,u\right\|\,\left\|\Sigma^{1/2}\,(\theta - \theta^*)\right\| \qquad \text{(Cauchy Schwarz)}$$

$$= \|u\|_\Sigma\,\|\theta - \theta^*\|_\Sigma \leq \lambda_{\max}[\Sigma]\,\|u\|\,\|\theta - \theta^*\|_\Sigma \leq \|v_\theta - v_{\theta^*}\|_D \qquad (\lambda_{\max}[\Sigma] \leq 1,\ \|u\| \leq 1)$$

$$\implies \|\nabla f(\theta)\|^2 \leq \|v_\theta - v_{\theta^*}\|_D^2 \qquad (\text{Setting } u = {}^{\nabla f(\theta)}/_{\|\nabla f(\theta)\|})$$

$$\implies \|\theta_{t+1} - \theta^*\|^2 \leq \|\theta_t - \theta^*\|^2 - 2\alpha\,\|v_{\theta_t} - v_{\theta^*}\|_D^2 + \alpha^2\,\|v_{\theta_t} - v_{\theta^*}\|_D^2$$

$$\|\theta_{t+1} - \theta^*\|^2 \leq \|\theta_t - \theta^*\|^2 - \|v_{\theta_t} - v_{\theta^*}\|_D^2 \leq (1 - \lambda)\,\|\theta_t - \theta^*\|^2 \qquad (\text{Set } \alpha = 1,\ \lambda = \lambda_{\min}[\Sigma])$$

$$\implies \|\theta_T - \theta^*\|^2 \leq (1 - \lambda)^T\,\|\theta_0 - \theta^*\|^2 \qquad (\text{Recursing from } t = 0 \text{ to } T - 1)$$

Linear TD(0) Analysis – Mean-path

The previous analysis relied on bounding two key quantities: (i) $\langle \nabla f(\theta_t), \theta^* - \theta_t \rangle$ and (ii) $\|\nabla f(\theta)\|^2$. We now consider analyzing Mean-path TD. For this, define $\bar{g}(\theta)$ and the corresponding update as:

$$\bar{g}(\theta) := \mathbb{E}_{s \sim \omega} \mathbb{E}_{s' \sim P(\cdot|s)} \left[r(s, \pi(s)) + \gamma \langle \theta, \phi(s') \rangle - \langle \theta, \phi(s) \rangle \right] \phi(s)$$
$$\theta_{t+1} = \theta_t + \alpha \, \bar{g}(\theta)$$

- Intuitively, $\bar{g}(\theta)$ is the Linear TD update in expectation if s was sampled from the stationary distribution, and the Markov chain transitioned to s'.
- Importantly, recall that the marginal distribution of s' is the stationary distribution ω.
- If $\mathcal{T}_\pi$ is the policy evaluation operator for π, then, $\bar{g}(\theta) = \Phi^T D \left[\mathcal{T}_\pi \Phi \theta - \Phi \theta \right]$ (Prove in Assignment 3!).

Similar to the warm-up, we will show two important properties for $\bar{g}(\theta)$. For all θ,

(1) $\langle \bar{g}(\theta), \theta^* - \theta \rangle \geq (1 - \gamma) \, \|v_\theta - v_{\theta^*}\|_D^2$
(2) $\|\bar{g}(\theta)\| \leq 2\sqrt{2} \, \|v_\theta - v_{\theta^*}\|_D$

Linear TD(0) Analysis – Mean-path

Claim: $\langle \bar{g}(\theta), \theta^* - \theta \rangle \geq (1-\gamma) \left\| v_\theta - v_{\theta^*} \right\|_D^2$.

Proof: Since $\bar{g}(\theta) = \Phi^T D \left[\mathcal{T}_\pi \Phi\theta - \Phi\theta \right]$, using the definition of θ^*, $\bar{g}(\theta^*) = \Phi^T D \left[\mathcal{T}_\pi \Phi\theta^* - \Phi\theta^* \right] = \Phi^T D \left[\mathcal{T}_\pi v^\pi - v^\pi \right] = 0$. Hence,

$$\begin{aligned} \bar{g}(\theta) &= \bar{g}(\theta) - \bar{g}(\theta^*) \\ &= \mathbb{E}_{s,s'} \left[\left[(r(s,\pi(s)) + \gamma\langle \theta, \phi(s')\rangle - \langle \theta, \phi(s)\rangle) - (r(s,\pi(s)) + \gamma\langle \theta^*, \phi(s')\rangle - \langle \theta^*, \phi(s)\rangle) \right] \phi(s) \right] \\ &= \mathbb{E}_{s,s'} \left[\left(\langle \phi(s), \theta^* - \theta \rangle - \gamma \langle \phi(s'), \theta^* - \theta \rangle \right) \phi(s) \right] \end{aligned}$$

Define $\zeta_s := \langle \theta^* - \theta, \phi(s) \rangle$ and $\zeta_{s'} := \langle \theta^* - \theta, \phi(s') \rangle$

$$\implies \bar{g}(\theta) = \mathbb{E}_{s,s'} \left[(\zeta_s - \gamma \zeta_{s'}) \, \phi(s) \right]$$

$$\begin{aligned} \langle \bar{g}(\theta), \theta^* - \theta \rangle &= \langle \mathbb{E}_{s,s'} \left[(\zeta_s - \gamma\zeta_{s'}) \, \phi(s) \right], \theta^* - \theta \rangle = \mathbb{E}_{s,s'} \left[(\zeta_s - \gamma\zeta_{s'}) \, \langle \phi(s), \theta^* - \theta \rangle \right] \\ &= \mathbb{E}_{s,s'} \left[(\zeta_s - \gamma\zeta_{s'}) \; \zeta_s \right] = \mathbb{E}_{s,s'} \left[\zeta_s^2 - \gamma \zeta_{s'} \, \zeta_s \right] \end{aligned}$$

$$\implies \langle \bar{g}(\theta), \theta^* - \theta \rangle = \mathbb{E}_{s\sim\omega}[\zeta_s^2] - \gamma \, \mathbb{E}_{s\sim\omega, s'\sim P(\cdot|s)} \left[\zeta_{s'} \, \zeta_s \right]$$

Linear TD(0) Analysis – Mean-path

Recall that $\langle \bar{g}(\theta), \theta^* - \theta \rangle = \mathbb{E}_{s\sim\omega}\mathbb{E}[\zeta_s^2] - \gamma\, \mathbb{E}_{s\sim\omega, s'\sim P(\cdot|s)}\left[\zeta_{s'}\, \zeta_s\right]$ where $\zeta_s := \langle \theta^* - \theta, \phi(s) \rangle$.

$$\begin{aligned}
\langle \bar{g}(\theta), \theta^* - \theta \rangle &= \mathbb{E}_{s\sim\omega}[\zeta_s^2] - \gamma\, \mathbb{E}_{s\sim\omega, s'\sim P(\cdot|s)}\left[\zeta_{s'}\, \zeta_s\right] \\
&\geq \mathbb{E}_{s\sim\omega}\mathbb{E}[\zeta_s^2] - \gamma \sqrt{\mathbb{E}_{s\sim\omega, s'\sim P(\cdot|s)}[\zeta_s^2]}\, \sqrt{\mathbb{E}_{s\sim\omega, s'\sim P(\cdot|s)}[\zeta_{s'}^2]} && \text{(Cauchy Schwarz)} \\
&= \mathbb{E}_{s\sim\omega}[\zeta_s^2] - \gamma \sqrt{\mathbb{E}_{s\sim\omega}[\zeta_s^2]}\, \sqrt{\mathbb{E}_{s'\sim\omega}[\zeta_{s'}^2]} && \text{(ω is the stationary distribution)} \\
&= (1-\gamma)\, \mathbb{E}_{s\sim\omega}[\zeta_s^2] = (1-\gamma) \sum_s \omega(s)\, \zeta^2(s) \\
&= (1-\gamma) \sum_s \omega(s)\, (\theta^* - \theta)^T \phi(s)\phi(s)^T\, (\theta^* - \theta) && \text{(By def. of ζ_s)} \\
&= (1-\gamma)\, \|\theta - \theta^*\|_\Sigma^2 && \text{(By def. of Σ)} \\
\implies \langle \bar{g}(\theta), \theta^* - \theta \rangle &\geq (1-\gamma)\, \|v_\theta - v_{\theta^*}\|_D^2 \quad \square && \text{(Since $\|\theta - \theta^*\|_\Sigma = \|v_\theta - v_{\theta^*}\|_D$)}
\end{aligned}$$

Linear TD(0) Analysis – Mean-path

Claim: $\|\bar{g}(\theta)\| \leq 2\sqrt{2}\, \|v_\theta - v_{\theta^*}\|_D$.

Proof: Since $\bar{g}(\theta) = \mathbb{E}_{s,s'}\left[(\zeta_s - \gamma\zeta_{s'})\,\phi(s)\right]$,

$$\|\bar{g}(\theta)\| = \|\mathbb{E}_{s,s'}\left[(\zeta_s - \gamma\zeta_{s'})\,\phi(s)\right]\| \leq \mathbb{E}_{s,s'}\,\|[(\zeta_s - \gamma\zeta_{s'})\,\phi(s)]\| \qquad \text{(Jensen's inequality)}$$

$$= \mathbb{E}_{s,s'}\left[|\zeta_s - \gamma\zeta_{s'}|\;\|\phi(s)\|\right] \leq \sqrt{\mathbb{E}\left[(\zeta_s - \gamma\zeta_{s'})^2\right]}\sqrt{\mathbb{E}[\|\phi(s)\|^2]} \quad \text{(Cauchy Schwarz)}$$

$$\leq \sqrt{\mathbb{E}\left[(\zeta_s - \gamma\zeta_{s'})^2\right]} \qquad \text{(Since } \|\phi(s)\| \leq 1\text{)}$$

$$\leq \sqrt{2}\sqrt{\mathbb{E}\left[\zeta_s^2 + \gamma^2\zeta_{s'}^2\right]} \leq \sqrt{2}\sqrt{\mathbb{E}_{s\sim\omega}[\zeta_s^2]} + \sqrt{2}\sqrt{\gamma^2\mathbb{E}_{s\sim\omega,s'\sim P(\cdot|s)}[\zeta_{s'}^2]}$$

(Since $(a+b)^2 \leq 2(a^2+b^2)$ and $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$ for all $a \geq 0, b \geq 0$)

$$= \sqrt{2}\sqrt{\mathbb{E}_{s\sim\omega}[\zeta_s^2]} + \sqrt{2}\,\gamma\sqrt{\mathbb{E}_{s'\sim\omega}[\zeta_{s'}^2]} = \sqrt{2}\,(1+\gamma)\,\sqrt{\mathbb{E}[\zeta_s^2]}$$

(Since ω is the stationary distribution)

$$\leq 2\sqrt{2}\,\sqrt{\mathbb{E}[\zeta_s^2]} \qquad \text{(Since } 1+\gamma < 2\text{)}$$

$$\implies \|\bar{g}(\theta)\| \leq 2\sqrt{2}\,\|v_\theta - v_{\theta^*}\|_D \quad \square \qquad \text{(Using the bound on } \mathbb{E}[\zeta_s^2]\text{)}$$

Linear TD(0) Analysis – Mean-path

Claim: $\left\|\theta_T - \theta^*\right\|^2 \leq \left(1 - \frac{(1-\gamma)^2\,\lambda}{8}\right)^T \left\|\theta_0 - \theta^*\right\|^2$.

Proof: We have proven (1) $\langle \bar{g}(\theta), \theta^* - \theta \rangle \geq (1-\gamma)\left\|v_\theta - v_{\theta^*}\right\|_D^2$ and (2) $\left\|\bar{g}(\theta)\right\| \leq 2\sqrt{2}\left\|v_\theta - v_{\theta^*}\right\|_D$.

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\begin{aligned}
\left\|\theta_{t+1} - \theta^*\right\|^2 &= \left\|\theta_t + \alpha \bar{g}(\theta) - \theta^*\right\|^2 = \left\|\theta_t - \theta^*\right\|^2 + 2\alpha\langle \bar{g}(\theta_t), \theta_t - \theta^* \rangle + \alpha^2 \left\|\bar{g}(\theta_t)\right\|^2 \\
&\leq \left\|\theta_t - \theta^*\right\|^2 - 2\alpha\,(1-\gamma)\left\|v_{\theta_t} - v_{\theta^*}\right\|_D^2 + 8\,\alpha^2 \left\|v_{\theta_t} - v_{\theta^*}\right\|_D^2 \\
&\leq \left\|\theta_t - \theta^*\right\|^2 - \frac{(1-\gamma)^2}{8}\left\|v_{\theta_t} - v_{\theta^*}\right\|_D^2 && \left(\text{Setting } \alpha = \tfrac{1-\gamma}{8}\right) \\
&= \left\|\theta_t - \theta^*\right\|^2 - \frac{(1-\gamma)^2}{8}\left\|\theta_t - \theta^*\right\|_\Sigma^2 && \left(\text{Since } \left\|v_\theta - v_{\theta^*}\right\|_D^2 = \left\|\theta - \theta^*\right\|_\Sigma^2\right) \\
&\leq \left\|\theta_t - \theta^*\right\|^2 - \lambda_{\min}[\Sigma]\,\frac{(1-\gamma)^2}{8}\left\|\theta_t - \theta^*\right\|^2 \\
\left\|\theta_{t+1} - \theta^*\right\|^2 &\leq \left(1 - \frac{(1-\gamma)^2\,\lambda}{8}\right)\left\|\theta_t - \theta^*\right\|^2 && (\text{Since } \lambda = \lambda_{\min}[\Sigma]) \\
\implies \left\|\theta_T - \theta^*\right\|^2 &\leq \left(1 - \frac{(1-\gamma)^2\,\lambda}{8}\right)^T \left\|\theta_0 - \theta^*\right\|^2 \quad \square && (\text{Recursing from } t = 0 \text{ to } T-1)
\end{aligned}
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References i

Richard S Sutton and Andrew G Barto, *Reinforcement learning: An introduction*, MIT press, 2018.