

# UC Berkeley CS285

## homework 1: Imitation Learning

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November 7, 2025

### 1 Analysis

1. given

$$\begin{aligned} \frac{1}{T} \sum_{t=1}^T E_{p_{\pi^*}(s_t)} \pi_\theta(a_t \pi^*(s_t) | s_t) &\leq \varepsilon \\ \sum_{t=1}^T E_{p_{\pi^*}(s_t)} \pi_\theta(a_t \pi^*(s_t) | s_t) &\leq \varepsilon T \end{aligned}$$

we introduce the event  $M_t : \{\pi_\theta(a_t \neq \pi^*(s_t))\}$   
and by the union bound

$$\Pr\left(\bigcup_{k=1}^t M_k\right) \leq \sum_{k=1}^t \Pr(M_k) \leq \sum_{k=1}^T \Pr(M_k) \leq \varepsilon T$$

$$|p_{\pi\theta}(s_t) - p_{\theta^*}(s_t)| = \Pr\left(\bigcup_t M_t\right) |p_{\text{mistake}}(s_t) - p_{\pi^*}(s_t)|$$

$$\sum_{s_t} |p_{\pi\theta}(s_t) - p_{\theta^*}(s_t)| = \Pr\left(\bigcup_t M_t\right) \sum_{s_t} |p_{\text{mistake}}(s_t) - p_{\theta^*}(s_t)|$$

therefore

$$\sum_{s_t} |p_{\pi\theta}(s_t) - p_{\theta^*}(s_t)| \leq 2\varepsilon T$$

2. (a) Given a state-dependent reward  $r(s_t)$ , where  $|r(s_t)| \leq \mathcal{R}_{max}$ , we consider the total expected reward:

$$\mathcal{J}(\pi) = \sum_{t=1}^T E_{p_{\pi^*}(s_t)} r(s_t)$$

$$\mathcal{J}(\pi^*) - \mathcal{J}(\pi_\theta) = \sum_{t=1}^T \left( E_{p_{\pi^*}(s_t)} r(s_t) - E_{p_{\pi_\theta}(s_t)} r(s_t) \right) = \sum_{t=1}^T E_{s_t} (p_{\pi^*}(s_t) - p_{\pi_\theta}(s_t)) r(s_t)$$

since  $r(s_t) = 0$  for all  $t < T$ , we have:

$$\mathcal{J}(\pi^*) - \mathcal{J}(\pi_\theta) = \sum_{s_T} (p_{\pi^*}(s_T) - p_{\pi_\theta}(s_T)) \nabla(s_T).$$

thus,

$$\sum_{s_t} |p_{\pi^*}(s_t) - p_{\pi_\theta}(s_t)| \mathcal{R}_{\max} = \mathcal{O}(2\varepsilon T \mathcal{R}_{\max}) = \mathcal{O}(\varepsilon T).$$

(b) Given that

$$\mathcal{J}(\pi^*) - \mathcal{J}(\pi_\theta) = \sum_{t=1}^T \left( E_{p_{\pi^*}(s_t)} r(s_t) - E_{p_{\pi_\theta}(s_t)} r(s_t) \right),$$

where each term is  $\mathcal{O}(2\varepsilon T \mathcal{R}_{\max})$ , we get:

$$\mathcal{J}(\pi^*) - \mathcal{J}(\pi_\theta) = \mathcal{O}(2\varepsilon T^2 \mathcal{R}_{\max}) = \mathcal{O}(\varepsilon T^2).$$