

1 MEX on infinite hypothesis set

Given an infinity hypothesis set \mathcal{H}_{inf} , how to run MEX algorithm on it? In this case, we can get a regret

$$\text{Reg}(K) \lesssim \sqrt{HK} + K\varepsilon_\psi$$

by running MEX on a random set \mathcal{H} where

$$\varepsilon_\psi \triangleq \min_{\pi \in \mathcal{H}} |V(\psi(\pi), \pi) - V(\psi(\pi^*), \pi^*)|.$$

We also denote

$$\pi_{\text{det}}^* \triangleq \text{argmin}_{\pi \in \mathcal{H}} |V(\psi(\pi), \pi) - V(\psi(\pi^*), \pi^*)|$$

Lemma 1. *If $\pi^* \in \mathcal{H}$, $\text{Reg}(K) \lesssim \sqrt{HK}$.*

2 Proof of the regret bound

Proof. We decompose the regret into two terms,

$$\begin{aligned} \text{Regret}(K) &\triangleq \sum_{k=1}^K V(\psi(\pi^*), \pi^*) - V(\psi(\pi^k), \pi^*) \\ &= \underbrace{\sum_{k=1}^K V(\psi(\pi^*), \pi^*) - V(\psi(\pi^k), \pi^k)}_{\text{Term (i)}} + \underbrace{\sum_{k=1}^K V(\psi(\pi^k), \pi^k) - V(\psi(\pi^k), \pi^*)}_{\text{Term (ii)}}. \end{aligned}$$

Term (i). By the choice of π^k , we have

$$V(\psi(\pi_{\text{det}}^*), \pi_{\text{det}}^*) - \eta \sum_{h=1}^H L_h^{k-1}(\pi_{\text{det}}^*) \leq V(\mu^k, \pi^k) - \eta \sum_{h=1}^H L_h^{k-1}(\pi^k)$$

for all $k \in [K]$. By definition

$$V(\psi(\pi_{\text{det}}^*), \pi_{\text{det}}^*) \geq V(\psi(\pi^*), \pi^*) - \varepsilon_\psi.$$

Thus,

$$V(\psi(\pi^*), \pi^*) - V(\mu^k, \pi^k) \leq \eta \sum_{h=1}^H L_h^{k-1}(\pi_{\text{det}}^*) - \eta \sum_{h=1}^H L_h^{k-1}(\pi^k) + \varepsilon_\psi. \quad (1)$$

for any $\pi^k \stackrel{\psi}{\sim} \pi^{k'}$, we have

$$V(\psi(\pi^k), \pi^k) = V(\psi(\pi^{k'}), \pi^{k'}).$$

Thus, an upper bound for $V(\psi(\pi^*), \pi^*) - V(\mu^k, \pi^k)$ is also an upper bound for $V(\psi(\pi^*), \pi^*) - V(\mu^{k'}, \pi^{k'})$. Applying Lemma 2, we have that with probability at least $1 - \delta$, for any $(h, k) \in [H] \times [K]$, $\mu^s = \psi(\pi^s)$ and $\pi^k \in \mathcal{H}$,

$$L_h^{k-1}(\pi_{\text{det}}^*) - L_h^{k-1}(\pi^k) \leq -2 \sum_{s=1}^{k-1} \mathbb{E}_{\xi_h \sim \mu^s} [\ell_{\pi^s}(\pi; \xi_h)] + 2 \log(H n_{\text{type}}^\psi(\mathcal{H}) / \delta).$$

Substituting the above equation into (1) gives us that with probability at least $1 - \delta$, for any $k \in [K]$, $\mu^s = \psi(\pi^s)$ and $\pi^k \in \mathcal{H}$

$$V(\psi(\pi^*), \pi^*) - V(\mu^k, \pi^k) \leq -2\eta \sum_{h=1}^H \sum_{s=1}^{k-1} \mathbb{E}_{\xi_h \sim \mu^s} [\ell_{\pi^s}(\pi; \xi_h)] + 2H\eta \log(Hn_{\text{type}}^\psi(\mathcal{H})/\delta) + \varepsilon_\psi.$$

Summing over $[K]$ gives us

$$\text{Term (i)} \leq -2\eta \sum_{k=1}^K \sum_{h=1}^H \sum_{s=1}^{k-1} \mathbb{E}_{\xi_h \sim \mu^s} [\ell_{\pi^s}(\pi; \xi_h)] + 2\eta KH \log(Hn_{\text{type}}^\psi(\mathcal{H})/\delta) + K\varepsilon_\psi.$$

Term (ii). Follow the proof of Theorem 4.4 in [1], we have that for all $\mu^s = \psi(\pi^s)$

$$\text{Term (ii)} \leq 2\eta \sum_{k=1}^K \sum_{h=1}^H \sum_{s=1}^{k-1} \mathbb{E}_{\xi_h \sim \mu^s} [\ell_{\pi^s}(\pi; \xi_h)] + \frac{d_{\text{GEC}}(\varepsilon_{\text{conf}})}{8\eta} + \sqrt{d_{\text{GEC}}(\varepsilon_{\text{conf}})HK} + \varepsilon_{\text{conf}}HK.$$

Combining Term (i) and Term (ii).

$$\begin{aligned} \text{Regret}(K) &= \text{Term (i)} + \text{Term (ii)} \\ &\leq 2\eta KH \log(Hn_{\text{type}}^\psi(\mathcal{H})/\delta) + \frac{d_{\text{GEC}}(\varepsilon_{\text{conf}})}{8\eta} + \sqrt{d_{\text{GEC}}(\varepsilon_{\text{conf}})HK} + \varepsilon_{\text{conf}}HK + K\varepsilon_\psi. \end{aligned}$$

Set $\varepsilon_{\text{conf}} = \frac{1}{\sqrt{HK}} - \frac{\varepsilon_\psi}{H}$. For $\varepsilon_{\text{conf}} > 0$, we need

$$\varepsilon_\psi \leq \sqrt{\frac{H}{K}}$$

□

3 Appendix

Lemma 2. With probability at least $1 - \delta$, for any $(h, k) \in [H] \times [K]$, $\mu^s \in \text{BR}(\pi^s)$, and $\pi \in \Pi$

$$L_h^{k-1}(\pi^*) - L_h^{k-1}(\pi) \leq -2 \sum_{s=1}^{k-1} \mathbb{E}_{\xi_h \sim \mu^s} [\ell_{\pi^s}(\pi; \xi_h)] + 2\log(H|\Pi|/\delta).$$

Proof. Given $\pi \in \mathcal{H}$, we denote the random variable $X_{h,\pi}^k$ as

$$X_{h,\pi}^k = \log \left(\frac{\mathbb{P}_{h,\pi^*}(s_{h+1}^k | s_h^k, a_h^k)}{\mathbb{P}_{h,\pi}(s_{h+1}^k | s_h^k, a_h^k)} \right).$$

Now we define a filtration $\{\mathcal{F}_{h,k}\}_{k=1}^K$ as (B.25) in [1]. Thus we have $X_{h,\pi}^k \in \mathcal{F}_{h,k}$. Therefore, by applying Lemma D.1 in [1], we have that with probability at least $1 - \delta$, for any $(h, k) \in [H] \times [K]$, and $\pi \in \Pi$, we have

$$-\frac{1}{2} \sum_{s=1}^{k-1} X_{h,\pi}^s \leq \sum_{s=1}^{k-1} \log \mathbb{E} \left[\exp \left\{ -\frac{1}{2} X_{h,\pi}^s \right\} \middle| \mathcal{F}_{h,s-1} \right] + \log(H|\Pi|/\delta). \quad (2)$$

Meanwhile, by (B.27) in [1], for any $\mu^s \in \text{BR}(\pi^s)$, the conditional expectation equals to

$$\mathbb{E} \left[\exp \left\{ -\frac{1}{2} X_{h,\pi}^s \right\} \middle| \mathcal{F}_{h,s-1} \right] = 1 - \mathbb{E}_{(s_h^s, a_h^s) \sim \mu^s} [D_H(\mathbb{P}_{h,\pi^*}(\cdot | s_h^s, a_h^s) || \mathbb{P}_{h,\pi}(\cdot | s_h^s, a_h^s))]. \quad (3)$$

Denote $\mathbb{E}_{(s_h^s, a_h^s) \sim \mu^s} [D_H(\mathbb{P}_{h, \pi^*}(\cdot | s_h^s, a_h^s) || \mathbb{P}_{h, \pi^s}(\cdot | s_h^s, a_h^s))]$ as $\mathbb{E}_{\xi_h \sim \mu^s} [\ell_{\pi^s}(\pi; \xi_h)]$. Using the fact $\log(x) \leq x - 1$ and substituting (3) into (2) finishes the proof. \square

Bibliography

- [1] Zhihan Liu, Miao Lu, Wei Xiong, Han Zhong, Hao Hu, Shenao Zhang, Sirui Zheng, Zhuoran Yang, and Zhaoran Wang. One Objective to Rule Them All: A Maximization Objective Fusing Estimation and Planning for Exploration. may 2023.