

A KNOWN RESULTS

Our proofs depend on the following result.

Lemma 9 (Lemma 11 of Abbasi-Yadkori et al. (2011)). Let $\{x_t\}_{t \in [T]}$ be any sequence such that $x_t \in \mathbb{R}^d$ and $\|x_t\|_2 \leq L$ for all $t \in [T]$. Let V be a positive definite matrix and $V_t = V + \sum_{s \in [t]} x_s x_s^\top$. Then, we have

$$\sum_{t \in [T]} \min \left(1, \|x_t\|_{V_{t-1}^{-1}}^2 \right) \leq 2(d \log((\text{trace}(V) + L^2 T)/d) - \log \det(V)).$$

B MISSING PROOFS

B.1 Proof of Lemma 1

Proof of Lemma 1. We fix $t \in [T]$ and $s \geq 1$ arbitrarily. For all $t' \in \Psi_{t,s}$ we have $\|x_{t'}(i_{t'})\|_{V_{t'-1,s}^{-1}} > c^{-s}$ by definition of $i_{t'}$. Thus, from $c > 1$ and Lemma 9, we obtain

$$\begin{aligned} |\Psi_{t,s}|c^{-2s} &\leq \sum_{t' \in \Psi_{t,s}} \min \left(1, \|x_{t'}(i_{t'})\|_{V_{t'-1,s}^{-1}}^2 \right) \\ &\leq 2d \log(1 + L^2 |\Psi_{t,s}| / (d\lambda)). \end{aligned}$$

□

B.2 Proof of Lemma 3

To prove Lemma 3, we use the following concentration inequality.

Lemma 10. Let $\{\mathcal{F}_t\}_{t=1}^\infty$ be a filtration. Let $\{\eta_t\}_{t=1}^\infty$ be a real-valued stochastic process such that η_t is \mathcal{F}_t -measurable. Assume that η_t is conditionally R_t -sub-Gaussian for all t . Then, for any $t > 0$ and $a > 0$,

$$\mathbb{P} \left(\sum_{s \in [t]} \eta_s > a \right) \leq \exp \left(-\frac{a^2}{2 \sum_{s \in [t]} R_s^2} \right).$$

Proof. Using Markov's inequality, for any $\lambda > 0$, we have

$$\begin{aligned} \mathbb{P} \left(\sum_{s \in [t]} \eta_s > a \right) &= \mathbb{P} \left(\exp \left(\lambda \sum_{s \in [t]} \eta_s \right) > \exp(\lambda a) \right) \\ &\leq \exp(-\lambda a) \mathbb{E} \left(\exp \left(\lambda \sum_{s \in [t]} \eta_s \right) \right). \end{aligned}$$

For the second term on the right-hand side, we have

$$\begin{aligned} \mathbb{E} \left[\exp \left(\lambda \sum_{s \in [t]} \eta_s \right) \right] &= \mathbb{E} \left[\mathbb{E} \left[\exp \left(\lambda \sum_{s \in [t]} \eta_s \right) \mid \mathcal{F}_{t-1} \right] \right] \\ &= \mathbb{E} \left[\mathbb{E} \left[\prod_{s \in [t]} \exp(\lambda \eta_s) \mid \mathcal{F}_{t-1} \right] \right]. \end{aligned}$$

Since η_s is measurable with respect to \mathcal{F}_{t-1} for all $t > 0$ and $s \in [t-1]$, we have

$$\begin{aligned} \mathbb{E} \left[\mathbb{E} \left[\prod_{s \in [t]} \exp(\lambda \eta_s) \mid \mathcal{F}_{t-1} \right] \right] &= \mathbb{E} \left[\mathbb{E} [\exp(\lambda \eta_t) \mid \mathcal{F}_{t-1}] \prod_{s \in [t-1]} \exp(\lambda \eta_s) \right] \\ &\leq \exp(\lambda^2 R_t^2 / 2) \mathbb{E} \left[\prod_{s \in [t-1]} \exp(\lambda \eta_s) \right] \\ &\leq \exp \left(\lambda^2 \sum_{s \in [t]} R_s^2 / 2 \right). \end{aligned}$$

Thus, we obtain

$$\mathbb{P} \left(\sum_{s \in [t]} \eta_s > a \right) \leq \exp(-\lambda a) \exp \left(\lambda^2 \sum_{s \in [t]} R_s^2 / 2 \right).$$

Choosing $\lambda = a / \sum_{s \in [t]} R_s^2$, we have the desired result. \square

Proof of Lemma 3. Recall that $\tilde{\theta}_{t,s} = V_{t-1,s}^{-1} \sum_{\tau \in \Psi_{t,s}} (\theta^\top x_\tau(i_\tau) + \eta_\tau) x_\tau(i_\tau)$. We arbitrarily fix $s \in [S]$, $t \in [T]$, and $i \in I_{t,s}$. From the definition of $\tilde{\theta}_{t,s}$, we have

$$\begin{aligned} (\tilde{\theta}_{t,s} - \theta)^\top x_t(i) &= \left(V_{t-1,s}^{-1} \sum_{\tau \in \Psi_{t,s}} (\theta^\top x_\tau(i_\tau) + \eta_\tau) x_\tau(i_\tau) - \theta \right)^\top x_t(i) \\ &= x_t(i)^\top V_{t-1,s}^{-1} \sum_{\tau \in \Psi_{t,s}} \eta_\tau x_\tau(i_\tau) + x_t(i)^\top V_{t-1,s}^{-1} \left(\sum_{\tau \in \Psi_{t,s}} x_\tau(i_\tau) x_\tau(i_\tau)^\top - V_{t-1,s}^{-1} \right) \theta \\ &= x_t(i)^\top V_{t-1,s}^{-1} \sum_{\tau \in \Psi_{t,s}} \eta_\tau x_\tau(i_\tau) - \lambda x_t(i)^\top V_{t-1,s}^{-1} \theta. \end{aligned} \tag{10}$$

Let $\alpha = R \sqrt{2 \log(2/\delta)}$. For the first term on the right-hand side of (10), from Lemma 14 of Auer (2002) and Lemma 10, we have

$$\begin{aligned} &\mathbb{P} \left(\left| x_t(i)^\top V_{t-1,s}^{-1} \sum_{\tau \in \Psi_{t,s}} \eta_\tau x_\tau(i_\tau) \right| > \alpha \|x_t(i)\|_{V_{t-1,s}^{-1}} \right) \\ &= \mathbb{P} \left(\left| \sum_{\tau \in \Psi_{t,s}} x_t(i)^\top V_{t-1,s}^{-1} x_\tau(i_\tau) \eta_\tau \right| > \alpha \|x_t(i)\|_{V_{t-1,s}^{-1}} \right) \\ &\leq 2 \exp \left(- \frac{\alpha^2 \|x_t(i)\|_{V_{t-1,s}^{-1}}^2}{2R^2 \sum_{\tau \in \Psi_{t,s}} (x_t(i)^\top V_{t-1,s}^{-1} x_\tau(i_\tau))^2} \right) \\ &= 2 \exp \left(- \frac{\alpha^2 \|x_t(i)\|_{V_{t-1,s}^{-1}}^2}{2R^2 x_t(i)^\top V_{t-1,s}^{-1} (\sum_{\tau \in \Psi_{t,s}} x_\tau(i_\tau) x_\tau(i_\tau)^\top) V_{t-1,s}^{-1} x_t(i)^\top} \right) \\ &\leq 2 \exp \left(- \frac{\alpha^2}{2R^2} \right) \\ &= \delta. \end{aligned}$$

Thus, replacing δ with $\delta/(KST)$, we have

$$\left| x_t(i)^\top V_{t-1,s}^{-1} \sum_{\tau \in \Psi_{t,s}} \eta_\tau x_\tau(i_\tau) \right| < R \sqrt{2 \log(2KST/\delta)} \|x_t(i)\|_{V_{t-1,s}^{-1}}$$

with probability at least $1 - \delta/(KST)$. For the second term on the right-hand side of (3), we have

$$\begin{aligned}\lambda x_t(i)^\top V_{t-1,s}^{-1} \theta &\leq \lambda \|\theta\|_{V_{t-1,s}^{-1}} \|x_t(i)\|_{V_{t-1,s}^{-1}} \\ &\leq \sqrt{\lambda} \|\theta\|_2 \|x_t(i)\|_{V_{t-1,s}^{-1}} \\ &\leq \sqrt{\lambda} M \|x_t(i)\|_{V_{t-1,s}^{-1}}.\end{aligned}$$

□

B.3 Proof of Lemma 7

Proof of Lemma 7. We arbitrarily fix $t \in \Psi_0$ and $i \in I_{t,s_t}$. By the same line of calculation in the proof for Lemma 2, we obtain

$$\begin{aligned}|(\hat{\theta}_{t,s} - \theta)^\top x_t(i)| &\leq \left| \left(V_{t-1,s_t}^{-1} \sum_{\tau \in \Psi_0} r_\tau(i_\tau) x_\tau(i_\tau) - \theta \right)^\top x_t(i) \right| \\ &\leq \left| \left(V_{t-1,s_t}^{-1} \sum_{\tau \in \Psi_0} (\theta^\top x_\tau(i_\tau) + \eta_\tau) x_\tau(i_\tau) - \theta \right)^\top x_t(i) \right| \quad (11)\end{aligned}$$

$$+ \left| \left(V_{t-1,s_t}^{-1} \sum_{\tau \in \Psi_0} \varepsilon_\tau(i_\tau) x_\tau(i_\tau) \right)^\top x_t(i) \right|. \quad (12)$$

Applying Lemma 3 to the term (11), we have

$$\left| \left(V_{t-1,s_t}^{-1} \sum_{\tau \in \Psi_0} (\theta^\top x_\tau(i_\tau) + \eta_\tau) x_\tau(i_\tau) - \theta \right)^\top x_t(i) \right| \leq \beta_t(\delta) \|x_t(i)\|_{V_{t-1,s_t}^{-1}}$$

with probability at least $1 - \delta/(KST)$. Taking the union bound over the rounds and arms, the above inequality holds with probability at least $1 - \delta/S$ for all $t \in \Psi_0$ and $i \in I_{t,s_t}$. For the term (12), from the same line of calculation in the proof for Lemma 2, we have

$$\left| \left(V_{t-1,s_t}^{-1} \sum_{\tau \in \Psi_0} \varepsilon_\tau(i_\tau) x_\tau(i_\tau) \right)^\top x_t(i) \right| \leq \varepsilon \sqrt{|\Psi_0| x_t(i)^\top V_{t-1,s_t}^{-1} x_t(i)}.$$

From the definition of Ψ_0 , we have $\|x_t(i)\|_{V_{t-1,s_t}^{-1}} \leq \sqrt{d/T}$. Since $|\Psi_0| \leq T$, we have

$$\varepsilon \sqrt{|\Psi_0| x_t(i)^\top V_{t-1,s_t}^{-1} x_t(i)} \leq \varepsilon \sqrt{d}.$$

□

B.4 Proof of Lemma 8

Proof of Lemma 8. We arbitrarily fix $t \in \Psi_0$. From Assumption 2, we have

$$\mu_t(i_{t,s_t}^*) - \mu_t(i_t) \leq \theta^\top (x_t(i_{t,s_t}^*) - x_t(i_t)) + 2\varepsilon.$$

Using Lemma 7, we have

$$\theta^\top (x_t(i_{t,s_t}^*) - x_t(i_t)) + 2\varepsilon \leq \hat{\theta}_{t,s_t}^\top x_t(i_{t,s_t}^*) + \beta(\delta) \|x_t(i_{t,s_t}^*)\|_{V_{t-1,s_t}^{-1}} + \varepsilon \sqrt{d} - \theta^\top x_t(i_t) + 2\varepsilon.$$

From the fact that $i_t \in \text{argmax}_{i \in I_{t,s_t}} (\hat{r}_{t,s}(i) + w_{t,s}(i))$, we obtain

$$\hat{\theta}_{t,s_t}^\top x_t(i_{t,s_t}^*) + \beta(\delta) \|x_t(i_{t,s_t}^*)\|_{V_{t-1,s_t}^{-1}} \leq \hat{\theta}_{t,s_t}^\top x_t(i_t) + \beta(\delta) \|x_t(i_t)\|_{V_{t-1,s_t}^{-1}}.$$

Since $\|x_t(i_t)\|_{V_{t-1,s_t}^{-1}} \leq \sqrt{d/T}$, we have

$$\hat{\theta}_{t,s_t}^\top x_t(i_t) + \beta(\delta) \|x_t(i_t)\|_{V_{t-1,s_t}^{-1}} \leq \hat{\theta}_{t,s_t}^\top x_t(i_t) + \beta(\delta) \sqrt{d/T}.$$

Therefore, we obtain

$$\begin{aligned} & \hat{\theta}_{t,s_t}^\top x_t(i_{t,s_t}^*) + \beta(\delta) \|x_t(i_{t,s_t}^*)\|_{V_{t-1,s_t}^{-1}} + \varepsilon \sqrt{d} - \theta^\top x_t(i_t) + 2\varepsilon \\ & \leq (\hat{\theta}_{t,s_t} - \theta)^\top x_t(i_t) + \beta(\delta) \sqrt{d/T} + \varepsilon(2 + \sqrt{d}). \end{aligned}$$

Using Lemma 7 again, we have

$$(\hat{\theta}_{t,s_t} - \theta)^\top x_t(i_t) + \beta(\delta) \sqrt{d/T} + \varepsilon(2 + \sqrt{d}) \leq 2\beta(\delta) \sqrt{d/T} + 2\varepsilon(1 + \sqrt{d}).$$

□