

6.3 LinUCB Analysis

There are two main propositions that the upper bounds follow.

[Proposition 6.6] (Confidence)

Let $\delta > 0$. We have that $\Pr(\forall t, \mu^* \in \text{BALL}_t) \geq 1 - \delta$

[Proposition 6.7] (Sum of Squared Regret bounds)

Suppose that $\|x\| \leq B$ for $x \in D$. Suppose that β_t is \uparrow and $\beta_t \geq 1$. For LinUCB, if $\mu^* \in \text{BALL}_t$ for all t , then

$$\sum_{t=0}^{T-1} \text{reget}_t^2 \leq 8\beta_T d \log\left(1 + \frac{TB^2}{d\lambda}\right)$$

where $\text{reget}_t = \mu^* \cdot x^* - \mu^* \cdot x_t$ (the instantaneous regret)

We will prove the two propositions later. First we use the two props. to prove Th. 6.3.

[Th 6.3] Suppose $|\mu^* \cdot x| \leq 1$ for all $x \in D$, $\|\mu^*\| \leq W$ and $\|x\| \leq B$ for all $x \in D$, and that η_t is σ^2 sub-Gaussian. Set $\lambda = \sigma^2/W^2$, $\beta_t := \sigma^2 \left(2 + 4d \log\left(1 + \frac{TB^2W^2}{d}\right) + 8 \log(4/\delta)\right)$, we have that with prob. $\geq 1 - \delta$, for all $T \geq 0$,

$$R_T \leq c\sigma\sqrt{T} \left(d \log\left(1 + \frac{TB^2W^2}{d\sigma^2}\right) + \log(4/\delta)\right)$$

where c is an absolute constant.

Pf: By prop 6.6 and prop 6.7, with Cauchy-Schwartz ineq., we have:

$$\begin{aligned} R_T &= \sum_{t=0}^{T-1} \text{reget}_t \leq \sqrt{T \sum_{t=0}^{T-1} \text{reget}_t^2} \leq \sqrt{8T\beta_T d \log\left(1 + \frac{TB^2}{d\lambda}\right)} \\ &\leq \left[8Td \log\left(1 + \frac{TB^2W^2}{d\sigma^2}\right) \sigma^2 \left(2 + 4d \log\left(1 + \frac{TB^2W^2}{d}\right) + 8 \log(4/\delta)\right)\right]^{\frac{1}{2}} \\ &= 2\sigma\sqrt{Td} \left(4 \log\left(1 + \frac{TB^2W^2}{d\sigma^2}\right)\right)^{\frac{1}{2}} \left(1 + 2d \log\left(1 + \frac{TB^2W^2}{d}\right) + 4 \log(4/\delta)\right)^{\frac{1}{2}} \\ &\leq c\sqrt{Td} \left[4 \log\left(1 + \frac{TB^2W^2}{d\sigma^2}\right) + 1 + 2d \log\left(1 + \frac{TB^2W^2}{d}\right) + 4 \log(4/\delta)\right]^{\frac{1}{2}} \end{aligned}$$

$$\leq \sigma \sqrt{Td} (4 + 1 + dm) [\log(1 + \frac{TB^2W^2}{d\sigma^2}) + \log(4/s)]$$

Let $c = (5 + dm)\sqrt{d}$, we complete the proof.

Addition: Since $4/s \geq 4$, we have $1 \leq \log(1 + \frac{TB^2W^2}{d\sigma^2}) + \log(4/s)$

Since $2d\log(1 + \frac{TB^2W^2}{d\sigma^2}) = d\log((1 + \frac{TB^2W^2}{d\sigma^2})^2) \leq d\log(1 + \frac{TB^2W^2}{d\sigma^2}) + d\log(1 + \sigma^2)$

and $\log(1 + \sigma^2) = \frac{\log(1 + \sigma^2)}{\log(4/s)} \log(4/s)$, let $m = \max\{1, \frac{\log(1 + \sigma^2)}{\log(4/s)}\}$

then we have $2d\log(1 + \frac{TB^2W^2}{d\sigma^2}) \leq dm(\log(1 + \frac{TB^2W^2}{d\sigma^2}) + \log(4/s))$

which implies c, m are constant independently with T . \square

Now we turn back to the proofs of these two props.

6.3.1 Regret Analysis.

Goal: prove Prop. 6.7

Recap: $BALL_t = \{\mu \mid (\hat{\mu}_t - \mu)' \Sigma_t (\hat{\mu}_t - \mu) \leq \beta_t\}$

where $\Sigma_t = \lambda I + \sum_{\tau=0}^{t-1} x_\tau x_\tau'$ with $\Sigma_0 = \lambda I$.

[Lemma 6.8] Let $x \in D$. If $\mu \in BALL_t$, then

$$|(\mu - \hat{\mu}_t)' x| \leq \sqrt{\beta_t x' \Sigma_t^{-1} x}$$

$$\begin{aligned} \text{pf: } |(\mu - \hat{\mu}_t)' x| &= |(\mu - \hat{\mu}_t)' \Sigma_t^{-1/2} \Sigma_t^{1/2} x| \\ &= |(\Sigma_t^{1/2} (\mu - \hat{\mu}_t))' \Sigma_t^{-1/2} x| \\ &\leq \|\Sigma_t^{1/2} (\mu - \hat{\mu}_t)\| \|\Sigma_t^{-1/2} x\| \\ &= \|\Sigma_t^{1/2} (\mu - \hat{\mu}_t)\| \sqrt{x' \Sigma_t^{-1} x} \\ &\leq \sqrt{\beta_t x' \Sigma_t^{-1} x} \quad \text{since } \mu \in BALL_t \quad \square \end{aligned}$$

To show the upper bound for the instantaneous regret, we define

$$w_t := \sqrt{x_t' \Sigma_t^{-1} x_t}$$

which we interpret as the "normalized width" at time t .

[Lemma 6.9] Fix $t \leq T$. If $\mu^* \in \text{BALL}_t$ and $\beta_t \geq 1$, then

$$\text{regret}_t \leq 2 \min(\sqrt{\beta_t W_t}, 1) \leq 2\sqrt{\beta_t} \min(W_t, 1)$$

Pf: Let $\hat{\mu} \in \text{BALL}_t$ s.t. $\hat{\mu}$ maximises $\hat{\mu}' x_t$.

$$\hat{\mu}' x_t = \max_{\mu \in \text{BALL}_t} \mu' x_t = \max_{x \in D} \max_{\mu \in \text{BALL}_t} \mu' x \geq \mu^* \cdot x^*$$

where $x^* \in \arg \max_{x \in D} \mu^* \cdot x$.

with the hypothesis $\mu^* \in \text{BALL}_t$.

Hence,

$$\begin{aligned} \text{regret}_t &= \mu^* \cdot x^* - \mu^* \cdot x_t \\ &\leq (\hat{\mu} - \mu^*)' x_t \\ &= (\hat{\mu} - \hat{\mu}_t)' x_t + (\hat{\mu}_t - \mu^*)' x_t \\ &\leq 2\sqrt{\beta_t} W_t \quad (\text{by Lemma 6.8}) \end{aligned}$$

Since $r_t \in [-1, 1]$, regret_t is always at most 2.

$$\begin{aligned} \Rightarrow \text{regret}_t &\leq 2 \min\{\sqrt{\beta_t} W_t, 1\} \\ &\leq 2 \min\{\sqrt{\beta_t} W_t, \sqrt{\beta_t}\} \quad (\text{since } \beta_t \geq 1) \\ &= 2\sqrt{\beta_t} \min\{W_t, 1\} \quad \square \end{aligned}$$

The following two lemmas provide useful tools to view the log determinant as a potential function, where can bound the sum of the width.

[Lemma 6.10]. We have

$$\det \Sigma_T = \det \Sigma_0 \prod_{t=0}^{T-1} (1 + W_t^2).$$

Pf: By the definition of Σ_{t+1} , we have that

$$\begin{aligned}
\det \Sigma_{t+1} &= \det(\Sigma_t + x_t x_t') \\
&= \det(\Sigma_t^{\frac{1}{2}} (I + \Sigma_t^{-\frac{1}{2}} x_t x_t' \Sigma_t^{-\frac{1}{2}}) \Sigma_t^{\frac{1}{2}}) \\
&= \det(\Sigma_t) \det(I + (\Sigma_t^{-\frac{1}{2}} x_t)(\Sigma_t^{-\frac{1}{2}} x_t)') \\
&=: \det(\Sigma_t) \det(V_t V_t')
\end{aligned}$$

Now observe that $V_t' V_t = W_t^2$

$$(I + V_t V_t') V_t = V_t + V_t (V_t' V_t) = (1 + W_t^2) V_t$$

Hence, $(1 + W_t^2)$ is an eigenvalue of $I + V_t V_t'$. Since $V_t V_t'$ is a rank one matrix, all other eigenvalues of $I + V_t V_t'$ are 1. (which can be seen by $|\lambda I - V_t V_t'| = (\lambda - W_t^2) \lambda^{n-1}$)

$$\Rightarrow \det(I + V_t V_t') = 1 + W_t^2.$$

$$\Rightarrow \det(\Sigma_{t+1}) = \prod_{k=0}^t (1 + W_k^2) \quad \square$$

[Lemma 6.11] ("Potential Function" Bound)

For any sequence x_0, \dots, x_{T-1} s.t. for $t \leq T$, $\|x_t\|_2 \leq B$, we have

$$\log(\det \Sigma_{T-1} / \det \Sigma_0) = \log \det(I + \frac{1}{\lambda} \sum_{t=0}^{T-1} x_t x_t') \leq d \log(1 + \frac{TB^2}{d\lambda})$$

Pf: Denote the eigenvalues of $\sum_{t=0}^{T-1} x_t x_t'$ as $\sigma_1, \dots, \sigma_d$.

$$\sum_{i=1}^d \sigma_i = \text{Trace} \left(\sum_{t=0}^{T-1} x_t x_t' \right) = \sum_{t=0}^{T-1} \|x_t\|^2 \leq TB^2$$

$$\begin{aligned}
\Rightarrow \log \det(I + \frac{1}{\lambda} \sum_{t=0}^{T-1} x_t x_t') &= \log \left(\prod_{i=1}^d (1 + \sigma_i / \lambda) \right) \\
&= d \log \left(\left[\prod_{i=1}^d (1 + \sigma_i / \lambda) \right]^{\frac{1}{d}} \right) \\
&\leq d \log \left(\frac{1}{d} \sum_{i=1}^d (1 + \sigma_i / \lambda) \right) \\
&\leq d \log \left(1 + \frac{TB^2}{d\lambda} \right) \quad \square
\end{aligned}$$

Finally we prove that if μ^* always stays in $BALL_t$, then our regret is under control, which is prop. 6.7.

[Proposition 6.7] Suppose $\|x_t\| \leq B \quad \forall x \in D$ Suppose B_t is increasing

Proposition 6.1: Suppose $\mu^* \in \mathbb{R}^d$ and $\beta_t \geq 1$. Suppose β_t is increasing and $\beta_t \geq 1$. For LinUCB, if $\mu^* \in \text{BALL}_t \forall t$, then

$$\sum_{t=0}^{T-1} \text{regret}_t^2 \leq 8\beta_T d \log\left(1 + \frac{TB^2}{d\lambda}\right).$$

Pf: with the conditions, we have

$$\begin{aligned} \sum_{t=0}^{T-1} \text{regret}_t^2 &\leq \sum_{t=0}^{T-1} 4\beta_t \min(W_t^2, 1) \leq 4\beta_T \sum_{t=0}^{T-1} \min(W_t^2, 1) \\ &\leq 8\beta_T \sum_{t=0}^{T-1} \ln(1 + W_t^2) \quad (\text{for } 0 \leq y \leq 1, y \leq 2\ln(1+y)) \\ &= 8\beta_T \log(\det \Sigma_{T-1} / \det \Sigma_0) \quad (\text{by Lemma 6.10}) \\ &\leq 8\beta_T d \log\left(1 + \frac{TB^2}{d\lambda}\right) \quad (\text{by Lemma 6.11}) \quad \square \end{aligned}$$

We now prove Prop. 6.6.

[Proposition 6.6] Let $\delta > 0$. We have that

$$\Pr(\forall t, \mu^* \in \text{BALL}_t) \geq 1 - \delta$$

Pf: Since $r_T = x_T \cdot \mu^* + \eta_T$, we have

$$\begin{aligned} \hat{\mu}_t - \mu^* &= \Sigma_t^{-1} \sum_{T=0}^{t-1} r_T x_T - \mu^* \quad (\text{by def of } \hat{\mu}_t) \\ &= \Sigma_t^{-1} \sum_{T=0}^{t-1} x_T (x_T \cdot \mu^* + \eta_T) - \mu^* \\ &= \Sigma_t^{-1} \left(\sum_{T=0}^{t-1} x_T x_T' \right) \mu^* - \mu^* + \Sigma_t^{-1} \sum_{T=0}^{t-1} \eta_T x_T \\ &= \Sigma_t^{-1} (\Sigma_t - \lambda I) \mu^* - \mu^* + \Sigma_t^{-1} \sum_{T=0}^{t-1} \eta_T x_T \\ &= -\lambda \Sigma_t^{-1} \mu^* + \Sigma_t^{-1} \sum_{T=0}^{t-1} \eta_T x_T \end{aligned}$$

For any $0 < \delta_t < 1$,

$$\begin{aligned} \sqrt{(\hat{\mu}_t - \mu^*)' \Sigma_t (\hat{\mu}_t - \mu^*)} &= \|\Sigma_t^{1/2} (\hat{\mu}_t - \mu^*)\| \\ &\leq \|\lambda \Sigma_t^{-1/2} \mu^*\| + \|\Sigma_t^{-1/2} \sum_{T=0}^{t-1} \eta_T x_T\| \end{aligned}$$

With prob. $\geq 1 - \delta_t$, the RHS satisfies

$$\leq \sqrt{\lambda} \|\mu^*\| + \sqrt{2\sigma^2 \log(\det(\Sigma_t) \det(\Sigma_0)^{-1} / \delta_t)} \quad \dots (*)$$

(by lemma 6.10)

where we used $\|\Sigma_t^{-1}\| \leq 1/\lambda$ and the following lemma:

[Lemma A.9] for $t \geq 1$, with $\text{prob} > 1 - \delta$

$$\left\| \sum_{i=1}^t \mathbf{X}_i \varepsilon_i \right\|_{\Sigma_t^{-1}}^2 \leq \sigma^2 \log \left(\frac{\det(\Sigma_t) \det(\Sigma_0)^{-1}}{\delta^2} \right)$$

where $\{\varepsilon_i\}$: martingale difference sequence and conditionally
 σ sub-Gaussian

$\{\mathbf{X}_i\}$: stochastic process.

$$\Sigma_t = \Sigma_0 + \sum_{i=1}^t \mathbf{X}_i \mathbf{X}_i'$$

Note that at $t=0$, by our choice of λ , we have BALL_0 contains

μ^* , $\Pr(\mu^* \in \text{BALL}_0) = 1$. For $t \geq 1$, let us assign failure prob.

$$\delta_t = \frac{3\delta}{\pi^2 t^2} \quad \text{for } t\text{-th event.}$$

$$\begin{aligned} 1 - \Pr(\forall t, \mu^* \in \text{BALL}_t) &= \Pr(\exists t, \mu^* \notin \text{BALL}_t) \\ &\leq \sum_{t=1}^{\infty} \Pr(\mu^* \notin \text{BALL}_t) \\ &< \delta \cdot \frac{3}{\pi^2} \cdot \sum_{t=1}^{\infty} \frac{1}{t^2} \\ &= \frac{\delta}{2} \end{aligned}$$

By (*) and Lemma 6.11. with $\text{prob.} > 1 - \delta$

$$\begin{aligned} \sqrt{(\hat{\mu}_t - \mu^*)' \Sigma_t (\hat{\mu}_t - \mu^*)} &\leq \sqrt{\lambda} \|\mu^*\| + \sqrt{2\sigma^2 \log((\det \Sigma_t / \det \Sigma_0) / \delta_t)} \\ &\leq \sqrt{\lambda} \|\mu^*\| + \sqrt{2\sigma^2 (d \log(1 + \frac{tB^2}{d\lambda}) + \log(1/\delta_t))} \\ &\leq \sigma^2 + \sqrt{2\sigma^2 (d \log(1 + \frac{tB^2 W^2}{d\sigma^2}) + \log(1/\delta_t))} \\ &\leq \sqrt{\beta_t} \quad (\text{Remain confusion about } 1/\delta_t) \quad \square \end{aligned}$$