## A Regret Bounds

The following lemma bounds the expected per-round regret of any randomized algorithm that chooses the perturbed solution in round $t, \tilde{\theta}_{t}$, as a function of the history.
Lemma 2. Let $p_{2} \geq \mathbb{P}_{t}\left(\bar{E}_{2, t}\right), p_{3} \leq \mathbb{P}_{t}\left(E_{3, t}\right)$, and $p_{3}>p_{2}$. Then on event $E_{1, t}$,

$$
\begin{gathered}
\mathbb{E}_{t}\left[\Delta_{I_{t}}\right] \leq \dot{\mu}_{\max }\left(c_{1}+c_{2}\right)\left(1+\frac{2}{p_{3}-p_{2}}\right) \times \\
\mathbb{E}_{t}\left[\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}\right]+\Delta_{\max } p_{2}
\end{gathered}
$$

Proof. Let $\tilde{\Delta}_{i}=x_{1}^{\top} \theta_{*}-x_{i}^{\top} \theta_{*}$ and $c=c_{1}+c_{2}$. Let

$$
\bar{S}_{t}=\left\{i \in[K]: c\left\|x_{i}\right\|_{G_{t}^{-1}} \geq \tilde{\Delta}_{i}\right\}
$$

be the set of undersampled arms in round $t$. Note that $1 \in \bar{S}_{t}$ by definition. We define the set of sufficiently sampled arms as $S_{t}=[K] \backslash \bar{S}_{t}$. Let $J_{t}=\arg \min _{i \in \bar{S}_{t}}\left\|x_{i}\right\|_{G_{t}^{-1}}$ be the least uncertain undersampled arm in round $t$.
In all steps below, we assume that event $E_{1, t}$ occurs. In round $t$ on event $E_{2, t}$,

$$
\begin{aligned}
\Delta_{I_{t}} & \leq \dot{\mu}_{\max } \tilde{\Delta}_{I_{t}}=\dot{\mu}_{\max }\left(\tilde{\Delta}_{J_{t}}+x_{J_{t}}^{\top} \theta_{*}-x_{I_{t}}^{\top} \theta_{*}\right) \leq \dot{\mu}_{\max }\left(\tilde{\Delta}_{J_{t}}+x_{J_{t}}^{\top} \tilde{\theta}_{t}-x_{I_{t}}^{\top} \tilde{\theta}_{t}+c\left(\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}+\left\|x_{J_{t}}\right\|_{G_{t}^{-1}}\right)\right) \\
& \leq \dot{\mu}_{\max } c\left(\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}+2\left\|x_{J_{t}}\right\|_{G_{t}^{-1}}\right),
\end{aligned}
$$

where the first inequality holds because $\dot{\mu}_{\max }$ is the maximum derivative of $\mu$, the second is by the definitions of events $E_{1, t}$ and $E_{2, t}$, and the last follows from the definitions of $I_{t}$ and $J_{t}$. Now we take the expectation of both sides and get

$$
\mathbb{E}_{t}\left[\Delta_{I_{t}}\right]=\mathbb{E}_{t}\left[\Delta_{I_{t}} \mathbb{1}\left\{E_{2, t}\right\}\right]+\mathbb{E}_{t}\left[\Delta_{I_{t}} \mathbb{\mathbb { 1 }}\left\{\bar{E}_{2, t}\right\}\right] \leq \dot{\mu}_{\max } c \mathbb{E}_{t}\left[\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}+2\left\|x_{J_{t}}\right\|_{G_{t}^{-1}}\right]+\Delta_{\max } \mathbb{P}_{t}\left(\bar{E}_{2, t}\right) .
$$

The last step is to replace $\mathbb{E}_{t}\left[\left\|x_{J_{t}}\right\|_{G_{t}^{-1}}\right]$ with $\mathbb{E}_{t}\left[\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}\right]$. To do so, observe that

$$
\mathbb{E}_{t}\left[\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}\right] \geq \mathbb{E}_{t}\left[\left\|x_{I_{t}}\right\|_{G_{t}^{-1}} \mid I_{t} \in \bar{S}_{t}\right] \mathbb{P}_{t}\left(I_{t} \in \bar{S}_{t}\right) \geq\left\|x_{J_{t}}\right\|_{G_{t}^{-1}} \mathbb{P}_{t}\left(I_{t} \in \bar{S}_{t}\right),
$$

where the last inequality follows from the definition of $J_{t}$ and that $\bar{S}_{t}$ is $\mathcal{F}_{t-1}$-measurable. We rearrange the inequality as $\left\|x_{J_{t}}\right\|_{G_{t}^{-1}} \leq \mathbb{E}_{t}\left[\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}\right] / \mathbb{P}_{t}\left(I_{t} \in \bar{S}_{t}\right)$ and bound $\mathbb{P}_{t}\left(I_{t} \in \bar{S}_{t}\right)$ from below next.
In particular, on event $E_{1, t}$,

$$
\begin{aligned}
\mathbb{P}_{t}\left(I_{t} \in \bar{S}_{t}\right) & \geq \mathbb{P}_{t}\left(\exists i \in \bar{S}_{t}: x_{i}^{\top} \tilde{\theta}_{t}>\max _{j \in S_{t}} x_{j}^{\top} \tilde{\theta}_{t}\right) \geq \mathbb{P}_{t}\left(x_{1}^{\top} \tilde{\theta}_{t}>\max _{j \in S_{t}} x_{j}^{\top} \tilde{\theta}_{t}\right) \\
& \geq \mathbb{P}_{t}\left(x_{1}^{\top} \tilde{\theta}_{t}>\max _{j \in S_{t}} x_{j}^{\top} \tilde{\theta}_{t}, E_{2, t} \text { occurs }\right) \geq \mathbb{P}_{t}\left(x_{1}^{\top} \tilde{\theta}_{t}>x_{1}^{\top} \theta_{*}, E_{2, t} \text { occurs }\right) \\
& \geq \mathbb{P}_{t}\left(x_{1}^{\top} \tilde{\theta}_{t}>x_{1}^{\top} \theta_{*}\right)-\mathbb{P}_{t}\left(\bar{E}_{2, t}\right) \geq \mathbb{P}_{t}\left(x_{1}^{\top} \tilde{\theta}_{t}-x_{1}^{\top} \bar{\theta}_{t}>c_{1}\left\|x_{1}\right\|_{G_{t}^{-1}}\right)-\mathbb{P}_{t}\left(\bar{E}_{2, t}\right) .
\end{aligned}
$$

Note that we require a sharp inequality because $I_{t} \in \bar{S}_{t}$ is not guaranteed on event $\left\{\exists i \in \bar{S}_{t}: x_{i}^{\top} \tilde{\theta}_{t} \geq \max _{j \in S_{t}} x_{j}^{\top} \tilde{\theta}_{t}\right\}$. The fourth inequality holds because on event $E_{1, t} \cap E_{2, t}$,

$$
x_{j}^{\top} \tilde{\theta}_{t} \leq x_{j}^{\top} \theta_{*}+c\left\|x_{j}\right\|_{G_{t}^{-1}}<x_{j}^{\top} \theta_{*}+\tilde{\Delta}_{j}=x_{1}^{\top} \theta_{*}
$$

holds for any $j \in S_{t}$. The last inequality holds because $x_{1}^{\top} \theta_{*} \leq x_{1}^{\top} \bar{\theta}_{t}+c_{1}\left\|x_{1}\right\|_{G_{t}^{-1}}$ holds on event $E_{1, t}$. Finally, we use the definitions of $p_{2}$ and $p_{3}$ to complete the proof.

The regret bound of GLM-TSL is proved below.

Theorem 3. The n-round regret of GLM-TSL is bounded as

$$
\begin{array}{r}
R(n) \leq \dot{\mu}_{\max }\left(c_{1}+c_{2}\right)\left(1+\frac{2}{0.15-1 / n}\right) \times \\
\sqrt{2 d n \log (2 n / d)}+(\tau+3) \Delta_{\max }
\end{array}
$$

where

$$
\begin{aligned}
a & =c_{1} \sqrt{\dot{\mu}_{\max }} \\
c_{1} & =\sigma \dot{\mu}_{\min }^{-1} \sqrt{d \log (n / d)+2 \log n} \\
c_{2} & =c_{1} \sqrt{2 \dot{\mu}_{\min }^{-1} \dot{\mu}_{\max } \log (K n)}
\end{aligned}
$$

and the number of exploration rounds $\tau$ satisfies

$$
\lambda_{\min }\left(G_{\tau}\right) \geq \max \left\{\sigma^{2} \dot{\mu}_{\min }^{-2}(d \log (n / d)+2 \log n), 1\right\}
$$

Proof. Fix $\tau \in[n]$. Let

$$
E_{4, t}=\left\{\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1\right\}
$$

and $p_{4} \geq \mathbb{P}\left(\bar{E}_{4, t}\right)$ for $t \geq \tau$. Let $p_{1} \geq \mathbb{P}\left(\bar{E}_{1, t}, E_{4, t}\right), p_{2} \geq \mathbb{P}_{t}\left(\bar{E}_{2, t}\right)$ on event $E_{4, t}$, and $p_{3} \leq \mathbb{P}_{t}\left(E_{3, t}\right)$. By elementary algebra, we get

$$
\begin{aligned}
R(n) & \leq \sum_{t=\tau}^{n} \mathbb{E}\left[\Delta_{I_{t}}\right]+\tau \Delta_{\max } \\
& \leq \sum_{t=\tau}^{n} \mathbb{E}\left[\Delta_{I_{t}} \mathbb{1}\left\{E_{4, t}\right\}\right]+\left(\tau+p_{4} n\right) \Delta_{\max } \\
& \leq \sum_{t=\tau}^{n} \mathbb{E}\left[\Delta_{I_{t}} \mathbb{1}\left\{E_{1, t}, E_{4, t}\right\}\right]+\left(\tau+\left(p_{1}+p_{4}\right) n\right) \Delta_{\max } \\
& =\sum_{t=\tau}^{n} \mathbb{E}\left[\mathbb{E}_{t}\left[\Delta_{I_{t}}\right] \mathbb{1}\left\{E_{1, t}, E_{4, t}\right\}\right]+\left(\tau+\left(p_{1}+p_{4}\right) n\right) \Delta_{\max }
\end{aligned}
$$

To get $p_{1} \leq 1 / n$, we set $c_{1}$ as in Lemma 8 . Now we apply Lemma 2 to $\mathbb{E}_{t}\left[\Delta_{I_{t}}\right] \mathbb{1}\left\{E_{1, t}, E_{4, t}\right\}$ and get

$$
R(n) \leq \dot{\mu}_{\max }\left(c_{1}+c_{2}\right)\left(1+\frac{2}{p_{3}-p_{2}}\right) \mathbb{E}\left[\sum_{t=\tau}^{n}\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}\right]+\left(\tau+\left(p_{1}+p_{2}+p_{4}\right) n\right) \Delta_{\max }
$$

where $a$ and $c_{2}$ are set as in Lemma 4. For these settings, $p_{2} \leq 1 / n$ and $p_{3} \geq 0.15$. To bound $\sum_{t=\tau}^{n}\left\|x_{I_{t}}\right\|_{G_{t}^{-1}}$, we use Lemma 2 in Li et al. [2017]. Finally, to get $p_{4} \leq 1 / n$, we choose $\tau$ as in Lemma 9.

The regret bound of GLM-FPL is proved below.
Theorem 5. The n-round regret of GLM-FPL is bounded as

$$
\begin{aligned}
& R(n) \leq \dot{\mu}_{\max }\left(c_{1}+c_{2}\right)\left(1+\frac{2}{0.15-2 / n}\right) \times \\
& \sqrt{2 d n \log (2 n / d)}+(\tau+4) \Delta_{\max }
\end{aligned}
$$

where

$$
\begin{aligned}
a & =c_{1} \dot{\mu}_{\max } \\
c_{1} & =\sigma \dot{\mu}_{\min }^{-1} \sqrt{d \log (n / d)+2 \log n} \\
c_{2} & =c_{1} \dot{\mu}_{\min }^{-1} \dot{\mu}_{\max } \sqrt{2 \log (K n)}
\end{aligned}
$$

and the number of exploration rounds $\tau$ satisfies

$$
\begin{gathered}
\lambda_{\min }\left(G_{\tau}\right) \geq \max \left\{4 \sigma^{2} \dot{\mu}_{\min }^{-2}(d \log (n / d)+2 \log n)\right. \\
\left.8 a^{2} \dot{\mu}_{\min }^{-2} \log n, 1\right\}
\end{gathered}
$$

Proof. The proof is almost identical to that of Theorem 3. There are two main differences. First, $a$ and $c_{2}$ are set as in Lemma 6. For these settings, $p_{2} \leq 2 / n$ and $p_{3} \geq 0.15$. Second, $\tau$ is set as in Lemma 10.

## B Technical Lemmas

We need an extension of Theorem 1 in Abbasi-Yadkori et al. [2011], which is concerned with concentration of a certain vector-valued martingale. The setup of the claim is as follows. Let $\left(\mathcal{F}_{t}\right)_{t \geq 0}$ be a filtration, $\left(\eta_{t}\right)_{t \geq 1}$ be a stochastic process such that $\eta_{t}$ is real-valued and $\mathcal{F}_{t}$-measurable, and $\left(X_{t}\right)_{t \geq 1}$ be another stochastic process such that $X_{t}$ is $\mathbb{R}^{d}$-valued and $\mathcal{F}_{t-1}$-measurable. We also assume that $\left(\eta_{t}\right)_{t}$ is conditionally $R^{2}$-sub-Gaussian, that is

$$
\begin{equation*}
\forall \lambda \in \mathbb{R}: \quad \mathbb{E}\left[\exp \left[\lambda \eta_{t}\right] \mid \mathcal{F}_{t-1}\right] \leq \exp \left[\frac{\lambda^{2} R^{2}}{2}\right] \tag{10}
\end{equation*}
$$

We call the triplet $\left(\left(X_{t}\right)_{t},\left(\eta_{t}\right)_{t}, \mathbb{F}\right)$ "nice" when these conditions hold. The modified claim is stated and proved below.
Lemma 7. Let $\left(\left(X_{t}\right)_{t},\left(\eta_{t}\right)_{t}, \mathbb{F}\right)$ be a "nice" triplet, $S_{t}=\sum_{s=1}^{t} \eta_{s} X_{s}, V_{t}=\sum_{s=1}^{t} X_{s} X_{s}^{\top}$; and for $V \succ 0$, let $\tau_{0}=$ $\min \left\{t \geq 1: V_{t} \succeq V\right\}$. Then for any $\delta \in(0,1)$ and $\mathbb{F}$-stopping time $\tau \geq 1$ such that $\tau \geq \tau_{0}$ holds almost surely, with probability at least $1-\delta$,

$$
\left\|S_{\tau}\right\|_{V_{\tau}^{-1}}^{2} \leq 2 R^{2} \log \left(\frac{\operatorname{det}\left(V_{\tau}\right)^{\frac{1}{2}} \operatorname{det}\left(V_{\tau_{0}}\right)^{-\frac{1}{2}}}{\delta}\right)
$$

Proof. The proof in Abbasi-Yadkori et al. [2011] can easily adjusted as follows. If $\left(\left(X_{t}\right)_{t},\left(\eta_{t}\right)_{t}, \mathbb{F}\right)$ is a "nice" triplet, then for any $\delta \in(0,1), \mathcal{F}_{0}$-measurable matrix $V \succ 0$, and stopping time $\tau \geq 1$,

$$
\begin{equation*}
\mathbb{P}\left(\left.\left\|S_{\tau}\right\|_{V_{\tau}^{-1}}^{2} \leq 2 R^{2} \log \left(\frac{\operatorname{det}\left(V_{\tau}\right)^{\frac{1}{2}} \operatorname{det}\left(V_{\tau_{0}}\right)^{-\frac{1}{2}}}{\delta}\right) \right\rvert\, \mathcal{F}_{0}\right) \geq 1-\delta \tag{11}
\end{equation*}
$$

Now, for $t \geq 0$, let $X_{t}^{\prime}=X_{\tau_{0}+t}, \eta_{t}^{\prime}=\eta_{\tau_{0}+t}$, and $\mathcal{F}_{t}^{\prime}=\mathcal{F}_{\tau_{0}+t}$. Then $\left(\left(X_{t}^{\prime}\right)_{t \geq 1},\left(\eta_{t}^{\prime}\right)_{t \geq 1},\left(\mathcal{F}_{t}^{\prime}\right)_{t \geq 0}\right)$ is a nice triplet and the result follows from (11).

We use the last lemma to prove the following result.
Lemma 8. Let $c_{1}=\sigma \dot{\mu}_{\min }^{-1} \sqrt{d \log (n / d)+2 \log n}$ and $\tau$ be any round such that $\lambda_{\min }\left(G_{\tau}\right) \geq 1$. Then for any $t \geq \tau$,

$$
\mathbb{P}\left(\bar{E}_{1, t} \text { occurs, }\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1\right) \leq 1 / n
$$

Proof. Let $S_{t}=\sum_{\ell=1}^{t-1}\left(Y_{\ell}-\mu\left(X_{\ell}^{\top} \theta_{*}\right)\right) X_{\ell}$. By Lemma 1, where $\mathcal{D}_{1}=\left\{\left(X_{\ell}, \mu\left(X_{\ell}^{\top} \theta_{*}\right)\right)\right\}_{\ell=1}^{t-1}$ and $\mathcal{D}_{2}=\left\{\left(X_{\ell}, Y_{\ell}\right)\right\}_{\ell=1}^{t-1}$, we have that

$$
S_{t}=\underbrace{\nabla^{2} L\left(\mathcal{D}_{1} ; \theta^{\prime}\right)}_{V}\left(\bar{\theta}_{t}-\theta_{*}\right)
$$

where $\theta^{\prime}=\alpha \theta_{*}+(1-\alpha) \bar{\theta}_{t}$ for $\alpha \in[0,1]$. We rearrange the equality as $V^{-1} S_{t}=\bar{\theta}_{t}-\theta_{*}$ and note that $\dot{\mu}_{\min } G_{t} \preceq V$ on $\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1$. Now fix arm $i$. By the Cauchy-Schwarz inequality and from the above discussion,

$$
\begin{aligned}
\left|x_{i}^{\top} \bar{\theta}_{t}-x_{i}^{\top} \theta_{*}\right| & \leq\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{G_{t}}\left\|x_{i}\right\|_{G_{t}^{-1}}=\left(\bar{\theta}_{t}-\theta_{*}\right)^{\top} G_{t}\left(\bar{\theta}_{t}-\theta_{*}\right)\left\|x_{i}\right\|_{G_{t}^{-1}} \\
& =S_{t}^{\top} V^{-1} G_{t} V^{-1} S_{t}\left\|x_{i}\right\|_{G_{t}^{-1}} \leq \dot{\mu}_{\min }^{-2}\left\|S_{t}\right\|_{G_{t}^{-1}}\left\|x_{i}\right\|_{G_{t}^{-1}}
\end{aligned}
$$

By (13) in Lemma 9, which is derived using Lemma 7, $\left\|S_{t}\right\|_{G_{t}^{-1}} \leq \sigma \sqrt{d \log (n / d)+2 \log n}$ holds with probability at least $1-1 / n$ in any round $t \geq \tau$. In this case, event $E_{1, t}$ is guaranteed to occur when $c_{1}$ is set as in the claim. It follows that $\bar{E}_{1, t}$ occurs on $\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1$ with probability of at most $1 / n$.

The number of initial exploration rounds in GLM-TSL is set below.
Lemma 9. Let $\tau$ be any round such that

$$
\lambda_{\min }\left(G_{\tau}\right) \geq \max \left\{\sigma^{2} \dot{\mu}_{\min }^{-2}(d \log (n / d)+2 \log n), 1\right\}
$$

Then for any $t \geq \tau, \mathbb{P}\left(\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2}>1\right) \leq 1 / n$.
Proof. Fix round $t$ and let $S_{t}=\sum_{\ell=1}^{t-1}\left(Y_{\ell}-\mu\left(X_{\ell}^{\top} \theta_{*}\right)\right) X_{\ell}$. By the same argument as in the proof of Theorem 1 in Li et al. [2017], who use Lemma A of Chen et al. [1999], we have that

$$
\left\|S_{t}\right\|_{G_{t}^{-1}} \leq \dot{\mu}_{\min } \sqrt{\lambda_{\min }\left(G_{t}\right)} \Longrightarrow\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1
$$

Now fix $\tau$ such that $\lambda_{\min }\left(G_{\tau}\right) \geq 1$. For any $t \geq \tau, G_{t} \succeq G_{\tau}$ and thus

$$
\begin{equation*}
\left\|S_{t}\right\|_{G_{t}^{-1}} \leq \dot{\mu}_{\min } \sqrt{\lambda_{\min }\left(G_{\tau}\right)} \Longrightarrow\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1 \tag{12}
\end{equation*}
$$

In the next step, we bound $\left\|S_{t}\right\|_{G_{t}^{-1}}$ from above. By Lemma 7,

$$
\left\|S_{t}\right\|_{G_{t}^{-1}}^{2} \leq 2 \sigma^{2} \log \left(\operatorname{det}\left(G_{t}\right)^{\frac{1}{2}} \operatorname{det}\left(G_{\tau}\right)^{-\frac{1}{2}} n\right)
$$

holds jointly in all rounds $t \geq \tau$ with probability at least $1-1 / n$. By Lemma 11 in Abbasi-Yadkori et al. [2011] and from $\left\|X_{t}\right\|_{2} \leq 1$, we get $\log \operatorname{det}\left(G_{t}\right) \leq d \log (n / d)$. By the choice of $\tau, \operatorname{det}\left(G_{\tau}\right)^{-1} \leq 1$. It follows that

$$
\begin{equation*}
\left\|S_{t}\right\|_{G_{t}^{-1}}^{2} \leq \sigma^{2}(d \log (n / d)+2 \log n) \tag{13}
\end{equation*}
$$

for any $t \geq \tau$ with probability at least $1-1 / n$. Now we combine this claim with (12) and have that $\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1$ holds with probability at least $1-1 / n$ when

$$
\lambda_{\min }\left(G_{\tau}\right) \geq \sigma^{2} \dot{\mu}_{\min }^{-2}(d \log (n / d)+2 \log n)
$$

This concludes the proof.
The number of initial exploration rounds in GLM-FPL is set below.
Lemma 10. Let $\tau$ be any round such that

$$
\lambda_{\min }\left(G_{\tau}\right) \geq \max \left\{4 \sigma^{2} \dot{\mu}_{\min }^{-2}(d \log (n / d)+2 \log n), 8 a^{2} \dot{\mu}_{\min }^{-2} \log n, 1\right\}
$$

Then for any $t \geq \tau, \mathbb{P}\left(\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2}>1 / 2\right) \leq 1 / n$ and $\mathbb{P}_{t}\left(\left\|\tilde{\theta}_{t}-\theta_{*}\right\|_{2}>1\right) \leq 1 / n$ on event $\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1 / 2$.
Proof. Fix round $t$. Let $S_{t}$ be defined as in Lemma 9 and $\tau_{1}$ be any round such that

$$
\lambda_{\min }\left(G_{\tau_{1}}\right) \geq \min \left\{4 \sigma^{2} \dot{\mu}_{\min }^{-2}(d \log (n / d)+2 \log n), 1\right\}
$$

Then by the same argument as in Lemma 9, $\mathbb{P}\left(\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2}>1 / 2\right) \leq 1 / n$ holds for any $t \geq \tau_{1}$.
Now fix round $t$, history $\mathcal{F}_{t-1}$, and assume that $\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1 / 2$ holds. Let

$$
\bar{S}_{t}=\sum_{\ell=1}^{t-1}\left(Y_{\ell}+Z_{\ell}-\mu\left(X_{\ell}^{\top} \bar{\theta}_{t}\right)\right) X_{\ell}=\sum_{\ell=1}^{t-1} Z_{\ell} X_{\ell}
$$

where the last equality holds because $\sum_{\ell=1}^{t-1}\left(Y_{\ell}-\mu\left(X_{\ell}^{\top} \bar{\theta}_{t}\right)\right) X_{\ell}=\mathbf{0}$. Since $\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1 / 2$, the 0.5 -ball centered at $\bar{\theta}_{t}$ is within the unit ball centered at $\theta_{*}$. So, the minimum derivative of $\mu$ in the 0.5 -ball is not larger than that in the unit ball, and we have by a similar argument to Lemma 9 that

$$
\begin{equation*}
\left\|\bar{S}_{t}\right\|_{G_{t}^{-1}} \leq \frac{1}{2} \dot{\mu}_{\min } \sqrt{\lambda_{\min }\left(G_{t}\right)} \Longrightarrow\left\|\tilde{\theta}_{t}-\bar{\theta}_{t}\right\|_{2} \leq \frac{1}{2} \tag{14}
\end{equation*}
$$

By definition, $\left\|\bar{S}_{t}\right\|_{G_{t}^{-1}}=\|U\|_{2}$ for $U=G_{t}^{-\frac{1}{2}} \sum_{\ell=1}^{t-1} Z_{\ell} X_{\ell}$. Since $Z_{\ell}$ are i.i.d. random variables that are resampled in each round, we have $U \sim \mathcal{N}\left(\mathbf{0}, a^{2} I_{d}\right)$ given $\mathcal{F}_{t-1}$, and that $\|U\|_{2} \leq a \sqrt{2 \log n}$ holds with probability at least $1-1 / n$ given $\mathcal{F}_{t-1}$. Now we combine this claim with (14) and have that $\left\|\tilde{\theta}_{t}-\bar{\theta}_{t}\right\|_{2} \leq 1 / 2$ holds with probability at least $1-1 / n$ for any round $t$ such that

$$
\lambda_{\min }\left(G_{t}\right) \geq 8 a^{2} \dot{\mu}_{\min }^{-2} \log n
$$

For any such round, when $\left\|\bar{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1 / 2$ holds, $\mathbb{P}_{t}\left(\left\|\tilde{\theta}_{t}-\theta_{*}\right\|_{2} \leq 1\right) \geq 1-1 / n$. This concludes our proof.

