The result follows by letting $\kappa = \sigma/\sqrt{c_{\min}}(\sqrt{2\log(t_S)/T}+\delta)$ and simplifying terms in the exponential term. $\square$

***Lemma* 13.** *Let $\mathbf{p} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$, where $\mathbf{\Sigma} \in \mathbb{R}^{l\times l}$ is a positive definite matrix. Then, $\mathbb{P}[\|\mathbf{p}\|_2 \geq t] \leq 5^l \exp(-t^2/(8\|\mathbf{\Sigma}\|_2))$. Furthermore, $\|\mathbf{p}\|_2 \leq 4\sqrt{\|\mathbf{\Sigma}\|_2 l} + 2\sqrt{\|\mathbf{\Sigma}\|_2 \log(1/\delta)}$ with probability at least $1-\delta$ for $\delta \in (0,1)$.*

Proof. Follows from Lemma 8.2 and Theorem 8.3 in [38]. $\square$

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