

A Appendix: Supplementary Material

A.1 Proof of Lemma 2

Proof: Let k be fixed and $n_k = n$. Let $(X_t)_{t=1}^n$ denote the sequence of rewards associated with arm k , where we recall that $X_t \sim \mathcal{N}(\boldsymbol{\mu}, \sigma_k^2 \mathbf{I}_2/2)$. Then $\bar{\mathbf{x}}_{k,n} = \frac{1}{n} \sum_{t=1}^n X_t \sim \mathcal{N}(\boldsymbol{\mu}, \sigma_k^2 \mathbf{I}_2/(2n))$, implying that $\text{cov}\{(X_t - \bar{\mathbf{x}}_{k,n}), \bar{\mathbf{x}}_{k,n}\} = \frac{1}{n^2}(n\sigma^2 \mathbf{I} - n\sigma^2 \mathbf{I}) = 0$. It follows that, conditioned on σ_k^2 and $\boldsymbol{\mu}_k$, $\bar{\mathbf{x}}_{k,n}$ and $(X_t - \bar{\mathbf{x}}_{k,n})$ are statistically independent for every $t \in \{1, \dots, n\}$, so $\bar{\mathbf{x}}_{k,n}$ and $S_{k,n}$ are also independent.

On the other hand, because $\text{Re } X_t$ and $\text{Im } X_t$ have equal variances, $S_{k,n}$ satisfies

$$\begin{aligned} S_{k,n} &= \sum_{t=1}^n \left\| X_t - \frac{1}{n} \sum_{i=1}^n X_i \right\|^2 \\ &= \sum_{t=1}^n X_t^\top X_t - \frac{1}{n} \sum_{i,j=1}^n X_i^\top X_j, \end{aligned} \quad (18)$$

hence, defining

$$\mathbf{A} := \begin{bmatrix} \left(\frac{\lambda}{n} + \frac{1}{\sigma_k^2} - \lambda\right) \mathbf{I}_2 & -\frac{\lambda}{\sigma_k^2} \mathbf{I}_2 & \cdots & \frac{\lambda}{\sigma_k^2} \mathbf{I}_2 \\ \frac{\lambda}{n} \mathbf{I}_2 & \left(\frac{\lambda}{n} + \frac{1}{\sigma_k^2} - \lambda\right) \mathbf{I}_2 & \cdots & \frac{\lambda}{\sigma_k^2} \mathbf{I}_2 \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\lambda}{n} \mathbf{I}_2 & \frac{\lambda}{\sigma_k^2} \mathbf{I}_2 & \cdots & \left(\frac{\lambda}{n} + \frac{1}{\sigma_k^2} - \lambda\right) \mathbf{I}_2 \end{bmatrix} \in \mathbb{R}^{2n \times 2n}, \quad (19)$$

it follows that

$$\begin{aligned} \mathbb{E}\{e^{\lambda S_{k,n}}\} &= \frac{1}{(\pi\sigma_k^2)^n} \int_{\mathbb{R}^{2n}} e^{\lambda(\sum_{t=1}^n X_t^\top X_t - \frac{1}{n} \sum_{t=1}^n X_t^\top X_i) - \frac{1}{\sigma_k^2} \sum_{t=1}^n X_t^\top X_t} dX_1 \cdots dX_n \\ &= \frac{1}{(\pi\sigma_k^2)^n} \int_{\mathbb{R}^{2n}} e^{[X_1^\top \cdots X_n^\top] \mathbf{A} \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix}} dX_1 \cdots dX_n \\ &= \frac{\sqrt{\det \mathbf{A}^{-1}}}{\sigma_k^{2n}} \\ &= \frac{\det^{-1/2} \left\{ \left[\frac{1}{\sigma_k^2} - \lambda \right] \mathbf{I}_{2n} + \frac{\lambda}{n} \mathbf{1}_n \mathbf{1}_n^\top \otimes \mathbf{I}_2 \right\}}{\sigma_k^{2n}} \\ &= \frac{1}{\sigma_k^{2n}} \left(\frac{1}{\sigma_k^2} - \lambda \right)^{-(2n)/2} \left(\left(1 + \frac{\lambda n}{n(\frac{1}{\sigma_k^2} - \lambda)} \right)^2 \right)^{-1/2} \\ &= \frac{1}{(1 - \sigma_k^2 \lambda)^{n-1}}, \quad \lambda < 1/\sigma_k^2, \end{aligned} \quad (20)$$

where \otimes denotes Kronecker's product. Thus, $S_{k,n}/(\sigma_k^2/2) \sim \chi_{2(n-1)}^2$ because of uniqueness of the moment-generating function, so its pdf is given by

$$f_{S_{k,n}|\boldsymbol{\mu},\sigma_k^2}(s) = \frac{s^{n-2}}{\Gamma(n-1)} \frac{e^{-s/\sigma_k^2}}{\sigma_k^{2(n-1)}}, \quad (21)$$

and the likelihood of $(\bar{\mathbf{x}}_{k,n}, S_{k,n})$ is given by

$$\begin{aligned} f_{S_{k,n}, \bar{\mathbf{x}}_{k,n}|\boldsymbol{\mu}_k, \sigma_k^2}(s, \mathbf{x}) &= f_{S_{k,n}|\boldsymbol{\mu}_k, \sigma_k^2}(s) f_{\bar{\mathbf{x}}_{k,n}|\boldsymbol{\mu}_k, \sigma_k^2}(\mathbf{x}) \\ &= \frac{n}{\pi\sigma_k^2} e^{-\frac{n}{\sigma_k^2} \|\mathbf{x} - \boldsymbol{\mu}\|^2} \frac{s^{n-2}}{\Gamma(n-1)} \frac{e^{-s/\sigma_k^2}}{\sigma_k^{2(n-1)}} \\ &= \frac{ns^{n-2}}{\pi\Gamma(n-1)} \frac{e^{-\frac{1}{\sigma_k^2}(s+n\|\mathbf{x} - \boldsymbol{\mu}\|^2)}}{\sigma_k^{2n}}. \end{aligned} \quad (22)$$

It now follows that, for a uniform (improper) prior over $(\boldsymbol{\mu}_k, \sigma_k^2)$, for every arm $k \in \{1, \dots, K\}$,

$$\begin{aligned}
 f_{\boldsymbol{\mu}_k, \sigma_k^2 | \bar{\mathbf{x}}_{k,n} = \mathbf{x}, S_{k,n} = s}(\boldsymbol{\mu}_k, \sigma_k^2) &= \frac{f_{S_{k,n}, \bar{\mathbf{x}}_{k,n} | \boldsymbol{\mu}_k, \sigma_k^2}(s, \mathbf{x}) \cdot 1}{\int_0^\infty \int_{\mathbb{R}^2} f_{S_{k,n}, \bar{\mathbf{x}}_{k,n} | \boldsymbol{\mu}_k, \sigma_k^2}(s, \mathbf{x}) \cdot 1 d\boldsymbol{\mu}_k d(\sigma_k^2)} \\
 &= \frac{\frac{ns^{n-2}}{\pi\Gamma(n-1)\sigma_k^{2n}} e^{-\frac{1}{\sigma_k^2}(s+n\|\mathbf{x}-\boldsymbol{\mu}_k\|^2)}}{\int_0^\infty \left(\frac{ns^{n-2}}{\pi\Gamma(n-1)\sigma_k^{2n}} e^{-s/\sigma_k^2} \int_{\mathbb{R}^2} e^{\frac{-n}{\sigma_k^2}\|\mathbf{x}-\boldsymbol{\mu}_k\|^2} d\boldsymbol{\mu}_k \right) d(\sigma_k^2)} \\
 &= \frac{\frac{ns^{n-2}}{\pi\Gamma(n-1)\sigma_k^n} e^{-\frac{1}{\sigma_k^2}(s+n\|\mathbf{x}-\boldsymbol{\mu}_k\|^2)}}{\int_0^\infty \frac{ns^{n-2}}{\pi\Gamma(n-1)\sigma_k^{2n}} e^{-\frac{s}{\sigma_k^2}} \frac{\sigma_k^2 \pi}{n} d(\sigma_k^2)} \\
 &\stackrel{(a)}{=} \frac{\frac{ns^{n-2}}{\pi\sigma_k^{2n}} e^{-\frac{1}{\sigma_k^2}(s+n\|\mathbf{x}-\boldsymbol{\mu}_k\|^2)}}{\int_0^\infty u^{n-3} e^{-u} du} \\
 &= \frac{ns^{n-2}}{\pi\Gamma(n-2)\sigma_k^{2n}} e^{-\frac{1}{\sigma_k^2}(s+n\|\mathbf{x}-\boldsymbol{\mu}_k\|^2)},
 \end{aligned} \tag{23}$$

where (a) follows from $u = s/\sigma_k^2$. Therefore, the posterior distribution for the mean $\boldsymbol{\mu}_k$ is

$$\begin{aligned}
 f_{\boldsymbol{\mu}_k | \bar{\mathbf{x}}_{k,n} = \mathbf{x}, S_{k,n} = s}(\boldsymbol{\mu}_k) &= \int f_{\boldsymbol{\mu}_k, \sigma^2 | \bar{\mathbf{x}}_{k,n} = \mathbf{x}, S_{k,n} = s}(\boldsymbol{\mu}_k, \sigma_k^2) d(\sigma_k^2) \\
 &= \frac{ns^{n-2}}{\pi\Gamma(n-2)} \int_0^\infty \frac{e^{-\frac{1}{\sigma_k^2}(s+n\|\mathbf{x}-\boldsymbol{\mu}_k\|^2)}}{\sigma_k^{2n}} d(\sigma_k^2) \\
 &= \frac{ns^{n-2}}{\pi\Gamma(n-2)} \left(s + n\|\mathbf{x} - \boldsymbol{\mu}_k\|^2 \right)^{-n+1} \int_0^\infty e^{-u} u^{n-2} du \\
 &= \frac{n(n-2)}{\pi s} \left(1 + \frac{n\|\mathbf{x} - \boldsymbol{\mu}_k\|^2}{s} \right)^{-n+1},
 \end{aligned} \tag{24}$$

where (b) follows from $u = (s + n\|\mathbf{x} - \boldsymbol{\mu}_k\|^2)/\sigma_k^2$. ■

A.2 Lemma 5

Lemma 5 Under the conditions of Theorem 1,

$$\mathbb{E} \left\{ \sum_{t=\bar{T}+1}^T \mathbb{1} \{ k^{\text{TS}}(t) = k, \mathcal{A}(t), \mathcal{B}_k(t) \} \right\} \leq \frac{\log T}{\log \left(1 + \frac{(\|\boldsymbol{\mu}_1\| - \|\boldsymbol{\mu}_k\| - 2\epsilon)^2}{\sigma_k^2 + \epsilon} \right)} + 3. \tag{25}$$

Proof: Firstly, the fact that $\mathbb{1} \{ k^{\text{TS}}(t) = k, \mathcal{A}(t), \mathcal{B}_k(t) \} = 1$ implies that $\|\tilde{\boldsymbol{\mu}}^*(t)\| = \|\tilde{\boldsymbol{\mu}}_k(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon$ under $\mathcal{B}_k(t)$. Recall also the fact that $k^{\text{TS}}(t) = k \implies N_k(t+1) \geq N_k(t) + 1$. Then, for every $n > 0$ it holds that

$$\begin{aligned}
 \sum_{t=\bar{T}+1}^T \mathbb{1} \{ k^{\text{TS}}(t) = k, \mathcal{A}(t), \mathcal{B}_k(t) \} &= \sum_{t=\bar{T}+1}^T \mathbb{1} \{ k^{\text{TS}}(t) = k, \|\tilde{\boldsymbol{\mu}}_k(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon, \mathcal{B}_k(t) \} \\
 &\leq \mathbb{1} \{ k^{\text{TS}}(t) = k, \|\tilde{\boldsymbol{\mu}}_k(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon, \mathcal{B}_k(t), N_k(t) \geq n \} \\
 &\quad + \sum_{t=\bar{T}+1}^T \mathbb{1} \{ k^{\text{TS}}(t) = k, N_k(t) \leq n \} \\
 &\leq n + \sum_{t=\bar{T}+1}^T \mathbb{1} \{ \|\tilde{\boldsymbol{\mu}}_k(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon, \mathcal{B}_k(t), N_k(t) \geq n \}.
 \end{aligned} \tag{26}$$

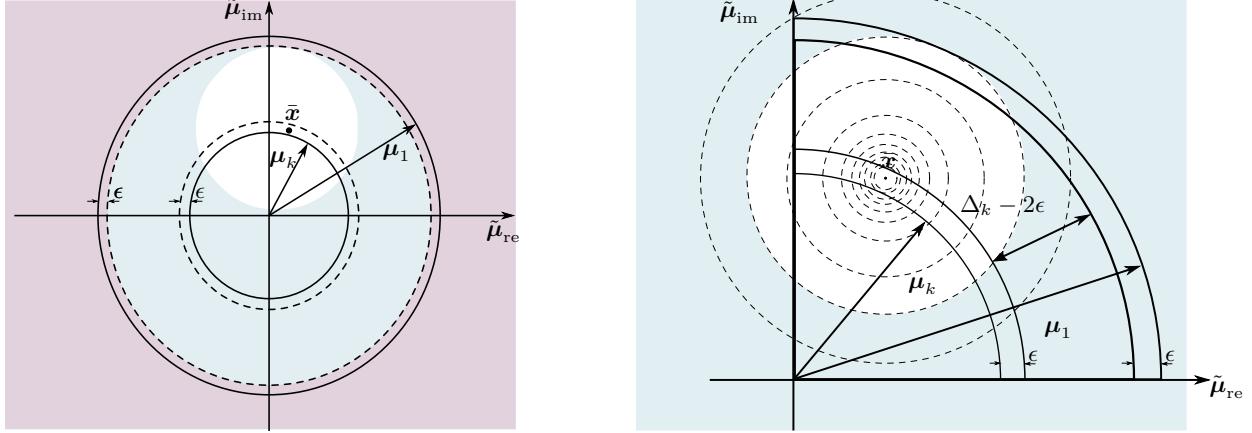


Figure 6: Upper-bounding the probability of $\|\tilde{\mu}_k(t)\| \leq \|\mu_1(t)\| - \epsilon$, given $\hat{\theta}_{k,n}$. On the left side, the red area is upper bounded by the points outside the white circle centered at \bar{x} . The right figure shows that the symmetric distribution around \bar{x} and an upper bound for the area outside the circle of radius $\|\mu_1\| - \epsilon$ is upper bounded by any circle of radius $\Delta_k - 2\epsilon$ centered at \bar{x} , whenever $\|\bar{x}_k\| \leq \|\mu_k\| - \epsilon$.

Secondly, we can upper bound $P\{\|\tilde{\mu}_k(t)\| \geq \|\mu_1\| - \epsilon \mid \mathcal{B}_k(t), N_k(t) = n\}$ as depicted in Fig. 6. From Lemma 4, it follows that

$$\begin{aligned} P\{\|\tilde{\mu}_k(t)\| \geq \|\mu_1\| - \epsilon \mid \mathcal{B}_k(t), N_k(t) = n\} \\ \leq P\{\|\tilde{\mu}_k(t) - \bar{x}_{k,n}\| \geq \|\mu_1\| - \|\mu_k\| - 2\epsilon \mid \mathcal{B}_k(t), N_k(t) = n\} \\ \leq \left(1 + \frac{(\|\mu_1\| - \|\mu_k\| - 2\epsilon)^2}{\sigma_k^2 + \epsilon}\right)^{-n+2}. \end{aligned} \quad (27)$$

Now notice that (27) is decreasing in n , which means that $P\{\|\tilde{\mu}_k(t)\| \geq \|\mu_1\| - \epsilon \mid \mathcal{B}_k(t), N_k(t) \geq n\} \leq P\{\|\tilde{\mu}_k(t)\| \geq \|\mu_1\| - \epsilon \mid \mathcal{B}_k(t), N_k(t) = n\}$, for every $n > 0$. Then, the expected value of (26) yields

$$\begin{aligned} \mathbb{E} \left\{ \sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) = k, \mathcal{A}(t), \mathcal{B}_k(t)\} \right\} &\leq n + \sum_{t=\bar{T}+1}^T P\{k^{\text{TS}}(t) = k, \mathcal{A}(t), \mathcal{B}_k(t), N_k(t) \geq n\} \\ &\leq n + \sum_{t=\bar{T}+1}^T P\{k^{\text{TS}}(t) = k, \mathcal{A}(t), \mathcal{B}_k(t), N_k(t) = n\} \\ &\leq n + T \left(1 + \frac{(\|\mu_1\| - \|\mu_k\| - 2\epsilon)^2}{\sigma_k^2 + \epsilon}\right)^{-n+2}. \end{aligned}$$

In particular, for $n = 2 + \frac{\log T}{\log(1 + (\|\mu_1\| - \|\mu_k\| - 2\epsilon)^2 / (\sigma_k^2 + \epsilon))} > 0$ we have that

$$\mathbb{E} \left\{ \sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) = k, \mathcal{A}(t), \mathcal{B}_k(t)\} \right\} \leq \frac{\log T}{\log \left(1 + \frac{(\|\mu_1\| - \|\mu_k\| - 2\epsilon)^2}{\sigma_k^2 + \epsilon}\right)} + 3, \quad (28)$$

which concludes the proof. ■

A.3 Lemma 6

Lemma 6 Under the conditions of Theorem 1, and for every $k \in \{2, \dots, K\}$:

$$\mathbb{E} \left\{ \sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) = k, \mathcal{B}_k(t)^c\} \right\} \leq O(\epsilon^{-2}). \quad (29)$$

Proof: We start by noting that the event $B_k^c(t)$ is independent of t whenever $N_k(t)$ is known. Then,

$$\begin{aligned} \sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) = k, B_k^c(t)\} &= \sum_{n=\bar{T}/K}^T \mathbb{1}\left\{\bigcup_{t=\bar{T}+1}^T \{k^{\text{TS}}(t) = k, B_k^c(t), N_k(t) = n\}\right\} \\ &\leq \sum_{n=\bar{T}/K}^T \mathbb{1}\{\|\bar{x}_{n,k}\| \geq \|\mu_k\| + \epsilon \quad \text{or} \quad S_{n,k} \geq n(\sigma_k^2 + \epsilon)\}. \end{aligned} \quad (30)$$

Then, by means of Lemma 3, the expected value of (30) yields

$$\begin{aligned} \mathbb{E}\left\{\sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) = k, B_k^c(t)\}\right\} &\leq \sum_{n=\bar{T}/K}^T \mathbb{P}\{\|\bar{x}_{n,k}\| \geq \|\mu_k\| + \epsilon\} + \mathbb{P}\{S_{n,k} \geq n(\sigma_k^2 + \epsilon)\} \\ &\leq \sum_{n=\bar{T}/K}^T \left(e^{-ne^2/\sigma^2} + \left(1 + \frac{\epsilon}{\sigma_k^2}\right)^{-1} e^{-nh(\epsilon/\sigma_k^2)}\right) \\ &\leq \frac{1}{1 - e^{-\epsilon^2/\sigma^2}} + \left(1 + \frac{\epsilon}{\sigma_k^2}\right)^{-1} \frac{1}{1 + e^{-h(\epsilon/\sigma^2)}}. \\ &= O(\epsilon^{-2}) + O(\epsilon^{-2}). \end{aligned} \quad (31)$$

■

A.4 Lemma 7

Lemma 7 Under the conditions of Theorem 1,

$$\mathbb{E}\left\{\Delta_{\max} \sum_{t=\bar{T}+1}^T \mathbb{E}\{\mathbb{1}\{k^{\text{TS}}(t) \neq 1, \mathcal{A}^c(t)\}\}\right\} \leq O(\epsilon^{-6}). \quad (32)$$

Proof: Note that

$$\begin{aligned} \sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) \neq 1, \mathcal{A}^c(t)\} &= \sum_{t=\bar{T}+1}^T \sum_{n=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) \neq 1, \mathcal{A}^c(t), N_1(t) = n\} \\ &= \sum_{n=\bar{T}+1}^T \sum_{m=1}^T \mathbb{1}\left\{m \leq \sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) \neq 1, \mathcal{A}^c(t), N_1(t) = n\}\right\}, \end{aligned} \quad (33)$$

since, for a fixed t , $\mathbb{1}\{k^{\text{TS}}(t) \neq 1, \mathcal{A}^c(t), N_1(t) = n\} = 1$ only for that value of n being exactly $N_1(t)$. Observe that $k^{\text{TS}}(t) \neq 1$ means that $\|\tilde{\mu}_1(t)\| \leq \|\tilde{\mu}^*(t)\|$, and $\mathcal{A}^c(t)$ means $\|\tilde{\mu}^*(t)\| \leq \|\mu_1\| - \epsilon$. Then, (33) implies that, for a fixed n , the event $\|\tilde{\mu}_1(t)\| \leq \|\mu_1\| - \epsilon$ has taken place, at least, m times. Let $\nu_n := \mathbb{P}\{\|\tilde{\mu}_1(t)\| \geq \|\mu_1\| - \epsilon \mid \hat{\theta}_{1,n}\}$. This implies that

$$\begin{aligned} \mathbb{E}\left\{\sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) \neq 1, \mathcal{A}^c(t)\}\right\} &= \sum_{n=\bar{T}+1}^T \sum_{m=1}^T \mathbb{P}\left\{m \leq \sum_{t=\bar{T}+1}^T \mathbb{1}\{k^{\text{TS}}(t) \neq 1, \mathcal{A}^c(t), N_1(t) = n\}\right\} \\ &\leq \mathbb{E}\left\{\sum_{n=\bar{T}+1}^T \sum_{m=1}^T \left(1 - \mathbb{P}\{\|\tilde{\mu}_1(t)\| \geq \|\mu_1\| - \epsilon \mid \hat{\theta}_{1,n}\}\right)^m\right\} \\ &\leq \sum_{n=\bar{T}+1}^T \mathbb{E}\left\{\frac{1 - \mathbb{P}\{\|\tilde{\mu}_1(t)\| \geq \|\mu_1\| - \epsilon \mid \hat{\theta}_{1,n}\}}{\mathbb{P}\{\|\tilde{\mu}_1(t)\| \geq \|\mu_1\| - \epsilon \mid \hat{\theta}_{1,n}\}}\right\}. \end{aligned} \quad (34)$$

Now, when $\|\bar{\mathbf{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \epsilon$ the symmetry of $p_{k,n}(\tilde{\boldsymbol{\mu}}_1)$ (defined in (10)) around $\bar{\mathbf{x}}_{1,n}$ guarantees that $P\{\|\tilde{\boldsymbol{\mu}}_1\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\} \geq 1/2$, and then it follows that

$$\begin{aligned} 1 - P\{\|\tilde{\boldsymbol{\mu}}_1\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\} &\leq \frac{1}{2} \\ \frac{1}{P\{\|\tilde{\boldsymbol{\mu}}_1\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}} &\leq 2. \end{aligned} \quad (35)$$

This argument allows us to split (34) as

$$\begin{aligned} &\mathbb{E} \left\{ \frac{1 - P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}}{P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}} \right\} \\ &= \mathbb{E}\{\mathbb{1}\{\|\bar{\mathbf{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \epsilon\}\} + \mathbb{E} \left\{ \frac{\mathbb{1}\{\|\bar{\mathbf{x}}_{1,n}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon\}}{P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}} \right\} \\ &= \mathbb{E}\left\{\mathbb{1}\left\{\|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2} \geq \|\bar{\mathbf{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \epsilon\right\}\right\} + \mathbb{E} \left\{ \frac{\mathbb{1}\{\|\bar{\mathbf{x}}_{1,n}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon\}}{P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}} \right\} \\ &\quad + \mathbb{E}\left\{\mathbb{1}\left\{\|\bar{\mathbf{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}, S_{k,n} \geq 2\sigma_1^2 n\right\}\right\} \\ &\quad + 2\mathbb{E}\left\{\mathbb{1}\left\{\|\bar{\mathbf{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}, S_{k,n} \leq 2\sigma_1^2 n\right\}\left(1 - P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}\right)\right\}. \end{aligned} \quad (36)$$

We now proceed to upper bound each term in (36). For the first term, we have that

$$\begin{aligned} \mathbb{E}\left\{\mathbb{1}\left\{\|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2} \geq \|\bar{\mathbf{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \epsilon\right\}\right\} &\leq P\left\{\|\bar{\mathbf{x}}_{1,n}\| \leq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}\right\} \\ &= \int_{\|\mathbf{z}\| \leq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}} \frac{n}{\pi\sigma_1^2} e^{\frac{-n}{\sigma_1^2} \|\mathbf{z} - \boldsymbol{\mu}_1\|^2} d\mathbf{z} \\ &\leq \int_{\|\mathbf{z}\| \leq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}} \frac{n}{\pi\sigma_1^2} e^{\frac{-n}{\sigma_1^2} (\|\boldsymbol{\mu}_1\| - \|\mathbf{z}\|)^2} d\mathbf{z} \\ &\leq \int_{\|\mathbf{z}\| \leq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}} \frac{n}{\pi\sigma_1^2} e^{\frac{-n}{4\sigma_1^2} \epsilon^2} d\mathbf{z} \\ &= \left(\|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}\right)^2 \frac{n}{\sigma_1^2} e^{\frac{-n\epsilon^2}{4\sigma_1^2}} \\ &\leq \|\boldsymbol{\mu}_1\|^2 \frac{n}{\sigma_1^2} e^{\frac{-n\epsilon^2}{4\sigma_1^2}}. \end{aligned} \quad (37)$$

For the second term, observe that, given $\|\bar{\mathbf{x}}_{1,n}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon$ and $S_{1,n} = s$:

$$\begin{aligned} P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\} &\geq \int_{-\alpha}^{\alpha} \int_{\substack{\|\boldsymbol{\mu}_1\| - \|\bar{\mathbf{x}}_{1,n}\| - \epsilon \\ \cos \alpha}}^{\infty} \frac{n(n-2)}{\pi s} \left(1 + \frac{nr^2}{s}\right)^{-n+1} r dr d\phi \\ &= \frac{\alpha}{\pi} \left(1 + \frac{n(\|\boldsymbol{\mu}_1\| - \|\bar{\mathbf{x}}_{1,n}\| - \epsilon)^2}{s \cos^2 \alpha}\right)^{-n+2}, \end{aligned} \quad (38)$$

for every $\alpha \in (0, \pi/2)$. It then follows that

$$\mathbb{E} \left\{ \frac{\mathbb{1}\{\|\bar{\mathbf{x}}_{1,n}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon\}}{P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}} \right\}$$

$$\begin{aligned}
 &= \int_0^\infty \int_{\|\boldsymbol{x}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon} \frac{ns^{n-2}}{\pi \Gamma(n-1)} \frac{e^{-\frac{1}{\sigma^2}(s+n\|\boldsymbol{x}-\boldsymbol{\mu}\|^2)}}{\sigma_k^{2n}} \frac{\pi}{\alpha} \left(1 + \frac{n(\|\boldsymbol{\mu}_1\| - \|\boldsymbol{x}\| - \epsilon)^2}{s \cos^2 \alpha} \right)^{n-2} d\boldsymbol{x} ds \\
 &\stackrel{(a)}{\leq} \frac{n e^{-n\epsilon^2/\sigma_1^2}}{\alpha \Gamma(n-1) \sigma_1^{2n}} \int_0^\infty s^{n-2} e^{-s/\sigma_1^2} \int_{\|\boldsymbol{x}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon} e^{\frac{-n(\|\boldsymbol{\mu}_1\| - \|\boldsymbol{x}\| - \epsilon)^2}{\sigma_1^2}} \left(1 + \frac{n(\|\boldsymbol{\mu}_1\| - \|\boldsymbol{x}\| - \epsilon)^2}{s \cos^2 \alpha} \right)^{n-2} d\boldsymbol{x} ds \\
 &\stackrel{(b)}{=} \frac{2\pi n e^{-n\epsilon^2/\sigma_1^2}}{\alpha \Gamma(n-1) \sigma_1^{2n}} \int_0^\infty s^{n-2} e^{-s/\sigma_1^2} \int_0^{\|\boldsymbol{\mu}_1\| - \epsilon} e^{\frac{-n(\|\boldsymbol{\mu}_1\| - v - \epsilon)^2}{\sigma_1^2}} \left(1 + \frac{n(\|\boldsymbol{\mu}_1\| - v - \epsilon)^2}{s \cos^2 \alpha} \right)^{n-2} v dv ds \\
 &\stackrel{(c)}{=} \frac{2\pi n e^{-n\epsilon^2/\sigma_1^2}}{\alpha 2^{n-1} \Gamma(n-1) \sigma_1^{2n}} \int_0^\infty s^{n-2} e^{-s/\sigma_1^2} \int_\epsilon^{\|\boldsymbol{\mu}_1\|} e^{\frac{-n(r-\epsilon)^2}{\sigma_1^2}} \left(1 + \frac{n(r-\epsilon)^2}{s \cos^2 \alpha} \right)^{n-2} (\|\boldsymbol{\mu}_1\| - r) dr ds \\
 &\leq \frac{2\pi \|\boldsymbol{\mu}_1\| n e^{-n\epsilon^2/\sigma_1^2}}{\alpha \Gamma(n-1) \sigma_1^{2n}} \int_0^\infty s^{n-2} e^{-s/\sigma_1^2} \int_\epsilon^\infty e^{\frac{-n(r-\epsilon)^2}{\sigma_1^2}} \left(1 + \frac{n(r-\epsilon)^2}{s \cos^2 \alpha} \right)^{n-2} dr ds,
 \end{aligned} \tag{39}$$

where inequality (a) follows from $\|\boldsymbol{\mu}_1 - \boldsymbol{x}\|^2 \geq (\|\boldsymbol{\mu}_1 - \boldsymbol{x}\| - \epsilon)^2 + \epsilon^2 \geq (\|\boldsymbol{\mu}_1\| - \|\boldsymbol{x}\| - \epsilon)^2$ whenever $\|\boldsymbol{x}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon$. Equality in (b) follows from a change of variables \boldsymbol{x} to polar coordinates (v, θ) , while (c) is consequence of changing v via $r = \|\boldsymbol{\mu}_1\| - v$. We now introduce a new change of variables in (39):

$$\left. \begin{array}{l} r = \epsilon - \cos \alpha \sqrt{\frac{zw}{n}} \\ s = z(1-w) \end{array} \right\} \implies dr ds = \left| \det \begin{bmatrix} \frac{\cos \alpha}{2} \sqrt{\frac{w}{nz}} & (1-w) \\ \frac{\cos \alpha}{2} \sqrt{\frac{z}{nw}} & -z \end{bmatrix} \right| dw dz = \frac{\cos \alpha}{2} \sqrt{\frac{z}{nw}} dw dz,$$

allowing us to rewrite the double integral in (39) as

$$\begin{aligned}
 &\int_0^\infty z^{n-2} \sqrt{z} e^{\frac{-z}{\sigma^2}} \int_0^1 e^{-z/\sigma_1^2} w^{\frac{-1}{2}} \frac{\cos \alpha}{2\sqrt{n}} dw dz \\
 &= \frac{\cos \alpha}{2\sqrt{n}} \int_0^\infty z^{n-2} \sqrt{z} e^{-z/\sigma_1^2} \frac{\sigma_1}{\sqrt{z} \sin \alpha} e^{\frac{z \sin^2 \alpha}{\sigma_1^2}} D \left(\sqrt{z} \frac{\sin \alpha}{\sigma_1^2} \right) dz \\
 &\stackrel{(d)}{\leq} \frac{\sigma_1}{2\sqrt{n} \tan \alpha} \int_0^\infty z^{n-2} e^{-z \cos^2 \alpha / \sigma_1^2} dz \\
 &= \frac{\sigma_1}{2\sqrt{n} \tan(\alpha)} \frac{\sigma_1^{2(n-1)}}{\cos^{2(n-1)}(\alpha)} \Gamma(n-1),
 \end{aligned} \tag{40}$$

where (d) follows from Dawson's function D [27] being upper bounded by 1. Finally, using this upper bound in (39) yields

$$\mathbb{E} \left\{ \frac{\mathbb{1}\{\|\bar{\boldsymbol{x}}_{1,n}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon\}}{\mathbb{P}\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon | \hat{\theta}_{1,n}\}} \right\} \leq \frac{\pi \|\boldsymbol{\mu}_1\| \cos^3 \alpha}{\sigma_1 \sin \alpha} \sqrt{n} \left(\frac{e^{-\epsilon^2/\sigma_1^2}}{\cos^2 \alpha} \right)^n, \tag{41}$$

for every $\alpha \in (0, 2\pi)$. In particular, when α is small, the sequence in n defined by the right-hand side of (41) converges to zero for α satisfying $\cos^2 \alpha \approx 1 - \alpha^2/2 = e^{-\epsilon^2/(2\sigma_1^2)}$, i.e., for $\alpha = \sqrt{2(1 - e^{\epsilon^2/(2\sigma_1^2)})} = O(\epsilon)$. With this particular choice, and for small ϵ , the bound in (41) becomes

$$\mathbb{E} \left\{ \frac{\mathbb{1}\{\|\bar{\boldsymbol{x}}_{1,n}\| \leq \|\boldsymbol{\mu}_1\| - \epsilon\}}{\mathbb{P}\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon | \hat{\theta}_{1,n}\}} \right\} \leq \frac{\pi \|\boldsymbol{\mu}_1\|}{\alpha^2 \sigma_1} \sqrt{n} \left(e^{-\epsilon^2/(2\sigma_1^2)} \right)^n. \tag{42}$$

From Lemma 3, the third term in (36) is upper bounded as

$$\mathbb{E} \left\{ \mathbb{1}\left\{\|\bar{\boldsymbol{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}, S_{1,n} \geq n2\sigma_1^2\right\} \right\} \leq \mathbb{P}\{S_{1,n} \geq n2\sigma_1^2\} \leq 2 \left(1 + \frac{\epsilon}{\sigma_k^2} \right)^{-1} e^{-nh(1)}. \tag{43}$$

To upper bound the fourth term in (36), denote $\mathcal{C}_{1,n} := \{\|\bar{\mathbf{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}, S_{1,n} \leq 2\sigma_1^2 n\}$. Then by introducing a polar-coordinates change of variable:

$$\begin{aligned} 1 - P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \mathcal{C}_{1,n}\} &= P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \leq \|\boldsymbol{\mu}_1\| - \epsilon \mid \mathcal{C}_{1,n}\} \\ &\leq \int_{-\pi}^{\pi} \int_{\frac{\epsilon}{2}}^{\infty} \frac{n(n-2)}{\pi s} \left(1 + \frac{nr^2}{s}\right)^{-n+1} r dr d\phi, \quad (\cdot, s) \in \mathcal{C}_{1,n}, \\ &\leq \left(1 + \frac{\epsilon^2}{8\sigma_1^2}\right)^{-n+2}, \end{aligned} \quad (44)$$

and therefore

$$\begin{aligned} \mathbb{E} \left\{ \mathbb{1} \left\{ \|\bar{\mathbf{x}}_{1,n}\| \geq \|\boldsymbol{\mu}_1\| - \frac{\epsilon}{2}, S_{k,n} \leq n2\sigma_1^2 \right\} \left(1 - P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}\right) \right\} \\ \leq \left(1 + \frac{\epsilon^2}{8\sigma_1^2}\right)^{-n+2}. \end{aligned} \quad (45)$$

Putting together (37),(42),(43) and (45) together with (34) lead us to

$$\begin{aligned} &\sum_{n=\bar{T}+1}^T \mathbb{E} \left\{ \frac{1 - P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}}{P\{\|\tilde{\boldsymbol{\mu}}_1(t)\| \geq \|\boldsymbol{\mu}_1\| - \epsilon \mid \hat{\theta}_{1,n}\}} \right\} \\ &\leq \sum_{n=\bar{T}+1}^T \|\boldsymbol{\mu}_1\|^2 \frac{n}{\sigma_1^2} e^{-\frac{n\epsilon^2}{4\sigma_1^2}} + \frac{\pi\|\boldsymbol{\mu}_1\|}{\alpha^2\sigma_1} \sqrt{n} \left(e^{-\epsilon^2/(2\sigma_1^2)}\right)^n + 2 \left(1 + \frac{\epsilon}{\sigma_k^2}\right)^{-1} e^{-nh(1)} + \left(1 + \frac{\epsilon^2}{8\sigma_1^2}\right)^{-n+2} \\ &\leq \frac{\|\boldsymbol{\mu}_1\|^2}{\sigma_1^2} \frac{e^{-\epsilon^2/(4\sigma_1^2)}}{1 - e^{-\epsilon^2/(4\sigma_1^2)}} + \frac{\pi\|\boldsymbol{\mu}_1\|}{\alpha^2\sigma_1} \frac{e^{-\epsilon^2/(2\sigma_1^2)}}{\left(1 - e^{-\epsilon^2/(2\sigma_1^2)}\right)^2} + \frac{2 \left(1 + \frac{\epsilon}{\sigma_k^2}\right)^{-1}}{1 - e^{-h(1)}} + \frac{8\sigma_1^2}{\epsilon^2} \\ &= O(\epsilon^{-2}) + O(\epsilon^{-6}) + O(1) + O(\epsilon^{-2}) = O(\epsilon^{-6}). \end{aligned} \quad (46)$$

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