

$$\min \left\{ L_\alpha(\Sigma) + \lambda \|\Sigma\|_{1,\text{off}} \right\} \quad (1)$$

Given zero-mean samples \mathbf{x}_i , $i = 1, \dots, n$ from a heavy-tailed distribution, we define

$$L_\alpha(\Sigma) := \sum_{k,\ell} \frac{1}{n} \sum_{i=1}^n \rho_\alpha(\Sigma_{k\ell} - x_{ik}x_{i\ell})$$

with $\rho_\alpha : \mathbb{R} \rightarrow \mathbb{R}_+$ a Huber loss function defined as

$$\rho_\alpha(x) = \begin{cases} x^2/2 & \text{if } |x| \leq \alpha, \\ \alpha|x| - \alpha^2/2 & \text{if } |x| > \alpha. \end{cases}$$

I. THEORETICAL RESULTS

We denote the underlying true covariance matrix by Σ^* . Let $\mathcal{S} = \{(i, j) \mid \Sigma_{ij}^* \neq 0\}$ be the support set of Σ^* and s be its cardinality, i.e., $s = |\mathcal{S}|$. In the following, we impose some mild conditions on the true covariance matrix Σ^* and the distribution of the i.i.d. samples \mathbf{x}_i , $i = 1, \dots, n$.

Assumption 1. $\mathbf{x}_i \in \mathbb{R}^d$ is a heavy-tailed random variable with zero mean, i.e. $\mathbb{E}[x_{ij}] = 0$ and $\mathbb{E}[|x_{ij}|^4] \leq \sigma^2$ for all $1 \leq j \leq d$ with some positive σ .

Remark 2. Assumption 1 immediately implies that there exists constant $K > 0$, such that $\mathbb{E}[(\Sigma_{kl}^* - x_{ik}x_{il})^2] \leq K$ for all $k, l \in [d]$.

Lemma 3. Let $\hat{\Sigma} \in \mathbb{R}^{d \times d}$ be any estimator to the true covariance matrix Σ^* . Assume $\|\nabla L_\alpha(\hat{\Sigma})\|_\infty < \beta$ always hold, with some $\beta = O(1)$. Take $\alpha = \sqrt{Kn/\log d}$. If the sample size satisfies $n \gtrsim \log d$, then

$$\|\hat{\Sigma} - \Sigma^*\|_\infty \lesssim \sqrt{\log d/n} + \beta \quad (2)$$

holds with high probability.

Proof: For fixed k, l , let $\hat{\theta} := (\hat{\Sigma})_{kl}$ and define

$$\Psi(\theta) := \frac{1}{n} \sum_{i=1}^n \rho'_\alpha(\theta - x_{ik}x_{il}), \quad \theta \in \mathbb{R}.$$

Note that $|\Psi(\hat{\theta})| = \left| \left(\nabla L_\alpha(\hat{\Sigma}) \right)_{kl} \right| < \beta$ always hold. In addition, it is easy to verify the inequality that

$$-\log(1 - x + x^2) \leq \rho'_1(x) \leq \log(1 + x + x^2) \quad (3)$$

By (3) and the fact that $\alpha^{-1}\rho'_\alpha(t) = \rho'_1(t/\alpha)$,

$$\begin{aligned} \mathbb{E}e^{(n/\alpha) \cdot \Psi(\theta)} &= \prod_{i=1}^n \mathbb{E}e^{\rho'_1((\theta - x_{ik}x_{il})/\alpha)} \\ &\leq \prod_{i=1}^n \mathbb{E} \left\{ 1 + \alpha^{-1}(\theta - x_{ik}x_{il}) + \alpha^{-2}(\theta - x_{ik}x_{il})^2 \right\} \\ &\leq \prod_{i=1}^n \left[1 + \alpha^{-1}(\theta - \Sigma_{kl}^*) + \alpha^{-2} \left\{ (\theta - \Sigma_{kl}^*)^2 + K \right\} \right] \\ &\leq \exp \left[n\alpha^{-1}(\theta - \Sigma_{kl}^*) + n\alpha^{-2} \left\{ (\theta - \Sigma_{kl}^*)^2 + K \right\} \right]. \end{aligned} \quad (4)$$

Similarly, it can be shown that

$$\begin{aligned} &\mathbb{E}e^{-(n/\alpha) \cdot \Psi(\theta)} \\ &\leq \exp \left[-n\alpha^{-1}(\theta - \Sigma_{kl}^*) + n\alpha^{-2} \left\{ (\theta - \Sigma_{kl}^*)^2 + K \right\} \right]. \end{aligned} \quad (5)$$

For $\eta \in (0, 1)$, define

$$B_-(\theta) = (\theta - \Sigma_{kl}^*) + \left\{ (\theta - \Sigma_{kl}^*)^2 + K \right\} / \alpha - (\alpha/n) \log \eta$$

$$B_+(\theta) = -(\theta - \Sigma_{kl}^*) + \left\{ (\theta - \Sigma_{kl}^*)^2 + K \right\} / \alpha + (\alpha/n) \log \eta$$

Together, (4), (5) and Markov's inequality imply

$$\begin{aligned} \Pr(\Psi(\theta) > B_-(\theta)) &\leq e^{-nB_-(\theta)/\alpha} \cdot \mathbb{E}e^{(n/\alpha) \cdot \Psi(\theta)} \leq \eta, \\ \text{and } \Pr(\Psi(\theta) < B_+(\theta)) &\leq e^{-nB_+(\theta)/\alpha} \cdot \mathbb{E}e^{-(n/\alpha) \cdot \Psi(\theta)} \leq \eta. \end{aligned}$$

Let θ_+ be the smallest solution of the quadratic equation $B_+(\theta_+) = \beta$, and θ_- be the largest solution of the quadratic equation $B_-(\theta_-) = -\beta$. We need to check that θ_- and θ_+ are well-defined. Let Δ_- and Δ_+ denote the discriminant of $B_-(\theta) = -\beta$ and $B_+(\theta) = \beta$, respectively. Since $\alpha = \sqrt{Kn/\log d}$, $\beta = O(1)$ and by taking $n \gtrsim \log d$, $\eta = 1/d^3$, we have

$$\Delta_- = 1 - (4/\alpha) \cdot (K/\alpha - (\alpha/n) \cdot \log \eta + \beta) > 0,$$

which implies that θ_- is well-defined as a solution to $B_-(\theta) = -\beta$ on $(\Sigma_{kl}^* - \alpha/2, \Sigma_{kl}^*)$. Similarly, θ_+ is also well-defined. Then, with at least $1 - 2\eta$ probability,

$$\Psi(\theta_+) \geq B_+(\theta_+) = \beta \quad \text{and} \quad \Psi(\theta_-) \leq B_-(\theta_-) = -\beta.$$

Recall that $|\Psi(\hat{\theta})| < \beta$ always hold, and given that $\Psi(\theta)$ is nondecreasing, $\Psi(\theta_-) < \Psi(\hat{\theta}) < \Psi(\theta_+)$ immediately implies $\theta_- \leq \hat{\theta} \leq \theta_+$.

Now we estimate θ_- and θ_+ . Notice that by convexity, the following holds for all $\theta \in (\Sigma_{kl}^* - \alpha/2, \Sigma_{kl}^*)$:

$$B_-(\theta) \leq (1/2) \cdot (\theta - \Sigma_{kl}^*) + B_-(\Sigma_{kl}^*),$$

which immediately implies that

$$\theta_- - \Sigma_{kl}^* \geq -2(K/\alpha - (\alpha/n) \log \eta + \beta).$$

It can be seen that assuming $B_+(\theta_+) - \beta = K/\alpha + (\alpha/n) \log \eta - \beta > 0$, we have $\theta_+ \in (\Sigma_{kl}^*, \Sigma_{kl}^* + \alpha/2)$, and similarly

$$\theta_+ - \Sigma_{kl}^* \leq 2(K/\alpha + (\alpha/n) \log \eta - \beta). \quad (6)$$

Otherwise if $B_+(\theta_+) - \beta \leq 0$, then $\theta_+ \leq 0$. Combining this with (6), we have

$$\theta_+ - \Sigma_{kl}^* \leq \max \{ 2(K/\alpha + (\alpha/n) \log \eta - \beta), 0 \}.$$

Therefore, with $\theta_- \leq \hat{\theta} \leq \theta_+$,

$$|\hat{\theta} - \Sigma_{kl}^*| \leq 2(K/\alpha - (\alpha/n) \log \eta + \beta).$$

With $\eta = 1/d^3$ and the union bound, we have that with at least $1 - 2/d$ probability, $\|\hat{\Sigma} - \Sigma^*\|_\infty \lesssim \sqrt{\log d/n} + \beta$. ■

Proposition 4. Let $\tilde{\Sigma}$ denote an ϵ -optimal solution to (1). Then, $\tilde{\Sigma} \in \Sigma + \mathbb{C}(l)$, where $l = 4s^{1/2}$. Further, assume

$$\left\| \tilde{\Sigma} - \Sigma^* \right\| \leq \alpha/2. \text{ Conditioned on the event } \mathcal{E}_1(\alpha/2, 1/2) \cap \{ \|\nabla L_\alpha(\Sigma^*)\|_\infty + \epsilon \leq 0.5\lambda \},$$

$$\left\| \tilde{\Sigma} - \Sigma^* \right\|_F \leq 3\lambda s^{1/2} \quad \text{and} \quad \left\| \tilde{\Sigma} - \Sigma^* \right\|_1 \leq 12\lambda s.$$

Proposition 4 gives the deterministic interpretation of Theorem 7. In the following propositions we will analyze the probability of the conditioned event $\mathcal{E}_1(\alpha/2, 1/2) \cap \{ \|\nabla L_\alpha(\Sigma^*)\|_\infty + \epsilon \leq 0.5\lambda \}$ mentioned in Proposition 4.

Proposition 5. Suppose that Assumption 1 holds. Recall that K is the constant defined in Remark 2. Assume $n \gtrsim \log d$. Then, for any $\kappa \in (0, 1)$ and $C > 0$,

$$\langle \nabla L_\alpha(\Sigma) - \nabla L_\alpha(\Sigma^*), \Sigma - \Sigma^* \rangle \geq \min\{\kappa, \kappa/2C\} \|\Sigma - \Sigma^*\|_F^2$$

holds uniformly for all $\Sigma \in \Sigma^* + \mathbb{B}^\infty(C\alpha)$ with high probability.

Proof: Let $D_{kl} = (1/n) \sum_{i=1}^n 1(|\Sigma_{kl}^* - x_{ik}x_{il}| \leq \alpha/2)$. By Chebyshev's inequality,

$$\mathbb{E}[D_{kl}] = \Pr(|\Sigma_{kl}^* - x_{ik}x_{il}| \leq \alpha/2) \geq 1 - 4K/\alpha^2 > (1+\kappa)/2.$$

The last inequality holds because $4K/\alpha^2 < (1-\kappa)/2$, which follows from $n \gtrsim \log d$.

For each fixed $k, l \in [d]$, let $X_i = 1(|\Sigma_{kl}^* - x_{ik}x_{il}| \leq \alpha/2)$. To invoke Bernstein's inequality, compute

$$\begin{aligned} \text{Var}[X_i] &= \Pr(|\Sigma_{kl}^* - x_{ik}x_{il}| \leq \alpha/2) \\ &\quad \cdot (1 - \Pr(|\Sigma_{kl}^* - x_{ik}x_{il}| \leq \alpha/2)) \\ &\leq 1/4 \end{aligned}$$

and with $|X_i - \mathbb{E}[X_i]| \leq 1$,

$$\mathbb{E}|X_i - \mathbb{E}[X_i]|^l \leq \mathbb{E}|X_i - \mathbb{E}[X_i]|^2 \cdot 1 \leq 1/4.$$

Therefore, with Bernstein's inequality

$$\begin{aligned} &\Pr\left(\left|\sum_{i=1}^n \{X_i - \mathbb{E}[X_i]\}\right| \geq (1-\kappa)n/2\right) \\ &\leq 2 \cdot \exp\left(-\frac{(1-\kappa)^2 n^2 / 8}{n/4 + (1-\kappa)n/2}\right) = 2 \cdot \exp\left(-\frac{(1-\kappa)^2 n}{6-4\kappa}\right) \end{aligned}$$

and

$$\begin{aligned} &\Pr\{D_{kl} < \kappa\} \\ &\leq \Pr\{|D_{kl} - \mathbb{E}[D_{kl}]| \geq (1-\kappa)/2\} \\ &= \Pr\left\{\left|(1/n) \sum_{i=1}^n \{X_i - \mathbb{E}[X_i]\}\right| \geq (1-\kappa)/2\right\} \\ &\leq 2 \cdot \exp\left(-\frac{(1-\kappa)^2 n}{6-4\kappa}\right). \end{aligned}$$

With union bound we have

$$\Pr\left[\min_{k,l} D_{kl} < \kappa\right] \leq 2d^2 \cdot \exp\left(-\frac{(1-\kappa)^2 n}{6-4\kappa}\right) < 1/d,$$

where the last inequality follows from $n \gtrsim \log d$. Let $\mathcal{G}_{kl} := \{i \in [n] : |\Sigma_{kl}^* - x_{ik}x_{il}| \leq \alpha/2\}$. Under the event that $\min_{k,l} D_{kl} \geq \kappa$,

$$\begin{aligned} &\frac{1}{n} \sum_{i=1}^n \{\rho'_\alpha(\Sigma_{kl} - x_{ik}x_{il}) - \rho'_\alpha(\Sigma_{kl}^* - x_{ik}x_{il})\} \cdot (\Sigma_{kl} - \Sigma_{kl}^*) \\ &\geq \frac{1}{n} \sum_{i \in \mathcal{G}_{kl}} \{\rho'_\alpha(\Sigma_{kl} - x_{ik}x_{il}) - \rho'_\alpha(\Sigma_{kl}^* - x_{ik}x_{il})\} \cdot (\Sigma_{kl} - \Sigma_{kl}^*) \\ &\geq \frac{1}{n} \sum_{i \in \mathcal{G}_{kl}} \min\{|\Sigma_{kl} - \Sigma_{kl}^*|, \alpha/2\} \cdot |\Sigma_{kl} - \Sigma_{kl}^*| \\ &\geq \frac{1}{n} \sum_{i \in \mathcal{G}_{kl}} \min\{1, 1/2C\} (\Sigma_{kl} - \Sigma_{kl}^*)^2 \\ &\geq \kappa \min\{1, 1/2C\} (\Sigma_{kl} - \Sigma_{kl}^*)^2 \end{aligned}$$

The second last inequality holds since $\Sigma \in \Sigma^* + \mathbb{B}^\infty(C\alpha)$ implies $\alpha/2 \geq |\Sigma_{kl} - \Sigma_{kl}^*|/2C$, and the last inequality follows from $|\mathcal{G}_{kl}|/n = D_{kl}$. Therefore

$$\begin{aligned} &\langle \nabla L_\alpha(\Sigma) - \nabla L_\alpha(\Sigma^*), \Sigma - \Sigma^* \rangle \\ &= \sum_{k,l} \frac{1}{n} \sum_{i=1}^n \{\rho'_\alpha(\Sigma_{kl} - x_{ik}x_{il}) - \rho'_\alpha(\Sigma_{kl}^* - x_{ik}x_{il})\} \cdot (\Sigma_{kl} - \Sigma_{kl}^*) \\ &\geq \kappa \cdot \min\{1, 1/2C\} \cdot \|\Sigma - \Sigma^*\|_F^2 \end{aligned}$$

with at least $1 - 1/d$ probability. \blacksquare

Proposition 5 implies that for any $\kappa \in (0, 1)$ and $C > 0$, with $n \gtrsim \log d$, event $\mathcal{E}_1(C, \min\{\kappa, \kappa/2C\})$ happens with high probability.

Proposition 6. Suppose that Assumption 1 holds. Let K be the constant defined in Remark 2. Assume $\alpha = \sqrt{Kn/\log d}$, then

$$\|\nabla L_\alpha(\Sigma^*)\|_\infty \leq 8\sqrt{\frac{K \log d}{n}} \quad (7)$$

with at least $1 - 2/d$ probability.

In Proposition 6, (7) indicates that $\{\|\nabla L_\alpha(\Sigma^*)\|_\infty + \epsilon \leq 0.5\lambda\}$ happens with high probability if we take $\lambda \asymp \sqrt{\log d/n}$ and $\epsilon \lesssim \sqrt{\log d/n}$.

Theorem 7. Suppose that Assumption 1 holds. Take $\lambda \asymp \sqrt{\log d/n}$ and let $\alpha = \sqrt{Kn/\log d}$, $\epsilon \lesssim \sqrt{\log d/n}$. If the sample size satisfies $n \gtrsim \log d$, then

$$\left\| \tilde{\Sigma} - \Sigma^* \right\|_F \lesssim \sqrt{\frac{s \log d}{n}} \quad \text{and} \quad \left\| \tilde{\Sigma} - \Sigma^* \right\|_1 \lesssim s \sqrt{\frac{\log d}{n}}$$

hold simultaneously with high probability (w.h.p.).

Proof: The proof combines Proposition 4 with Lemma 3, Proposition 5 and Proposition 6. To invoke Proposition 4, we first notice that given $\left\| \nabla L_\alpha(\tilde{\Sigma}) + \lambda \Xi \right\|_\infty \leq \epsilon$ for some $\Xi \in \partial \left\| \tilde{\Sigma} \right\|_{1, \text{off}}$, we must have $\left\| \nabla L_\alpha(\tilde{\Sigma}) \right\|_\infty < 2\lambda + \epsilon$ always hold. Lemma 3 indicates that

$$\left\| \tilde{\Sigma} - \Sigma^* \right\|_\infty \lesssim \sqrt{\log d/n} + 2\lambda + \epsilon \lesssim \sqrt{\log d/n} \leq \alpha/2$$

where the last inequality hold with $n \gtrsim \log d$.

By Proposition 6, $\|\nabla L_\alpha(\Sigma^*)\|_\infty \leq 8\sqrt{K \log d/n}$. With $\epsilon \lesssim \sqrt{\log d/n}$ and $\lambda \asymp \sqrt{\log d/n}$, event

$\{\|\nabla L_\alpha(\Sigma^*)\|_\infty + \epsilon \leq 0.5\lambda\}$ happens with at least $1 - 2/d$ probability. Still, with $n \geq \log d$, Proposition 5 indicates that $\mathcal{E}_1(\alpha/2, 1/2)$ happens with high probability. With union bound, event $\mathcal{E}_1(\alpha/2, 1/2) \cap \{\|\nabla L_\alpha(\Sigma^*)\|_\infty + \epsilon \leq 0.5\lambda\}$ holds with high probability. Under this event and by Proposition 4,

$$\|\tilde{\Sigma} - \Sigma^*\|_F \leq 3\lambda s^{1/2} \quad \text{and} \quad \|\tilde{\Sigma} - \Sigma^*\|_1 \leq 12\lambda s. \quad \blacksquare$$

APPENDIX

Lemma 8. For any $\Sigma \in \mathbb{R}^{d \times d}$ satisfying $\Sigma_{\bar{S}} = \mathbf{0}$ and $\epsilon > 0$, provided $\lambda > \|\nabla L_\alpha(\Sigma)_{\bar{S}}\|_\infty + \epsilon$, any ϵ -optimal solution $\tilde{\Sigma}$ to (1) satisfies

$$\begin{aligned} & \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 \\ & \leq (\lambda - \|\nabla L_\alpha(\Sigma)_{\bar{S}}\|_\infty - \epsilon)^{-1} \\ & \quad \cdot (\lambda + \|\nabla L_\alpha(\Sigma)_S\|_\infty + \epsilon) \cdot \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1 \end{aligned}$$

Proof: For any $\Xi \in \partial \left\| \tilde{\Sigma} \right\|_{1, \text{off}}$, define $U(\Xi) = \nabla L_\alpha(\tilde{\Sigma}) + \lambda \Xi \in \mathbb{R}^{d \times d}$. By convexity of $L_\alpha(\Sigma)$ and $-\log \det \Sigma$:

$$\langle \nabla L_\alpha(\tilde{\Sigma}) - \nabla L_\alpha(\Sigma), \tilde{\Sigma} - \Sigma \rangle \geq 0.$$

Therefore,

$$\begin{aligned} & \|U(\Xi)\|_\infty \left\| \tilde{\Sigma} - \Sigma \right\|_1 \geq \langle U(\Xi), \tilde{\Sigma} - \Sigma \rangle \\ & = \langle \nabla L_\alpha(\tilde{\Sigma}) - \nabla L_\alpha(\Sigma), \tilde{\Sigma} - \Sigma \rangle + \langle \nabla L_\alpha(\Sigma), \tilde{\Sigma} - \Sigma \rangle \\ & \quad + \langle \lambda \Xi, \tilde{\Sigma} - \Sigma \rangle \\ & \geq 0 - \|\nabla L_\alpha(\Sigma)_S\|_\infty \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1 \\ & \quad - \|\nabla L_\alpha(\Sigma)_{\bar{S}}\|_\infty \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 + \langle \lambda \Xi, \tilde{\Sigma} - \Sigma \rangle \end{aligned}$$

Moreover, we have

$$\begin{aligned} & \langle \lambda \Xi, \tilde{\Sigma} - \Sigma \rangle \\ & = \lambda \langle \Xi_{\bar{S}}, (\tilde{\Sigma} - \Sigma)_{\bar{S}} \rangle + \lambda \langle \Xi_S, (\tilde{\Sigma} - \Sigma)_S \rangle \\ & \geq \lambda \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 - \lambda \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1 \end{aligned}$$

Together, the last two displays imply

$$\begin{aligned} & \|U(\Xi)\|_\infty \left\| \tilde{\Sigma} - \Sigma \right\|_1 \\ & \geq -\|\nabla L_\alpha(\Sigma)_S\|_\infty \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1 - \|\nabla L_\alpha(\Sigma)_{\bar{S}}\|_\infty \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 \\ & \quad + \lambda \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 - \lambda \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1 \end{aligned}$$

Since the right-hand side of this inequality does not depend on Ξ , taking the infimum with respect to $\Xi \in \partial \left\| \tilde{\Sigma} \right\|_{1, \text{off}}$ on both sides to reach

$$\begin{aligned} & \epsilon \left\| \tilde{\Sigma} - \Sigma \right\|_1 \\ & \geq -\|\nabla L_\alpha(\Sigma)_S\|_\infty \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1 - \|\nabla L_\alpha(\Sigma)_{\bar{S}}\|_\infty \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 \\ & \quad + \lambda \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 - \lambda \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1 \end{aligned}$$

Decompose $\left\| \tilde{\Sigma} - \Sigma \right\|_1$ as $\left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1 + \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1$, the stated result follows immediately. \blacksquare

Lemma 9. Conditioned on event $\{\|\nabla L_\alpha(\Sigma)\|_\infty + \epsilon \leq 0.5\lambda\}$, any ϵ -optimal solution $\tilde{\Sigma}$ to (1) satisfies $\tilde{\Sigma} \in \Sigma + \mathbb{C}(l)$, where $l = 4s^{1/2}$. Moreover, assume $\Sigma \in \Sigma + \mathbb{B}^\infty(C\alpha)$. Then, conditioned on the event $\mathcal{E}_1(C\alpha, \kappa) \cap \{\|\nabla L_\alpha(\Sigma)\|_\infty + \epsilon \leq 0.5\lambda\}$,

$$\begin{aligned} \left\| \tilde{\Sigma} - \Sigma \right\|_F & \leq \kappa^{-1} \left\{ \lambda s^{1/2} + \|\nabla L_\alpha(\Sigma)_S\|_F + s^{1/2} \epsilon \right\} \\ & \leq 1.5\kappa^{-1} \lambda s^{1/2}. \end{aligned}$$

Proof: Conditioned on the stated event, Lemma 8 indicates

$$\left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 \leq 3 \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_1.$$

Therefore,

$$\left\| \tilde{\Sigma} - \Sigma \right\|_1 \leq 4s^{1/2} \left\| \tilde{\Sigma} - \Sigma \right\|_F,$$

which implies that $\tilde{\Sigma} \in \Sigma + \mathbb{C}(l)$.

Now we prove the second statement. Since $\tilde{\Sigma} - \Sigma \in \mathbb{B}^\infty(C\alpha)$, conditioned on event $\mathcal{E}_1(C\alpha, \kappa)$, we have

$$\langle \nabla L_\alpha(\tilde{\Sigma}) - \nabla L_\alpha(\Sigma), \tilde{\Sigma} - \Sigma \rangle \geq \kappa \left\| \tilde{\Sigma} - \Sigma \right\|_F^2 \quad (8)$$

Now we upper bound the right-hand side of (8). For any $\Xi \in \partial \left\| \tilde{\Sigma} \right\|_{1, \text{off}}$, write

$$\begin{aligned} & \langle \nabla L_\alpha(\tilde{\Sigma}) - \nabla L_\alpha(\Sigma), \tilde{\Sigma} - \Sigma \rangle \\ & = \underbrace{\langle U(\Xi), \tilde{\Sigma} - \Sigma \rangle}_{:=\Pi_1} - \underbrace{\langle \nabla L_\alpha(\Sigma), \tilde{\Sigma} - \Sigma \rangle}_{:=\Pi_2} - \underbrace{\langle \lambda \Xi, \tilde{\Sigma} - \Sigma \rangle}_{:=\Pi_3} \end{aligned} \quad (9)$$

where $U(\Xi) := \nabla L_\alpha(\tilde{\Sigma}) + \lambda \Xi \in \mathbb{R}^{d \times d}$. We have

$$\begin{aligned} |\Pi_1| & \leq \|U(\Xi)\|_\infty \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 + \|(U(\Xi))_S\|_F \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_F \\ |\Pi_2| & \leq \|\nabla L_\alpha(\Sigma)_S\|_F \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_F \\ & \quad + \|\nabla L_\alpha(\Sigma)_{\bar{S}}\|_\infty \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 \end{aligned}$$

Turning to Π_3 , decompose $\lambda \Xi$ and $\tilde{\Sigma} - \Sigma$ according to $S \cup \bar{S}$ to reach

$$\Pi_3 = \langle (\lambda \Xi)_S, (\tilde{\Sigma} - \Sigma)_S \rangle + \langle (\lambda \Xi)_{\bar{S}}, (\tilde{\Sigma} - \Sigma)_{\bar{S}} \rangle$$

Since $\Sigma_{\bar{S}} = \mathbf{0}$ and $\Xi \in \partial \left\| \tilde{\Sigma} \right\|_{1, \text{off}}$, we have $\langle (\lambda \Xi)_{\bar{S}}, (\tilde{\Sigma} - \Sigma)_{\bar{S}} \rangle = \langle (\lambda \Xi)_{\bar{S}}, \tilde{\Sigma}_{\bar{S}} \rangle = \lambda \left\| \tilde{\Sigma}_{\bar{S}} \right\|_1 = \lambda \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1$.

Therefore,

$$\Pi_3 \geq \lambda \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 - \lambda s^{1/2} \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_F$$

Combining (9) with our estimation for Π_1, Π_2 and Π_3 , we have

$$\begin{aligned} & \langle \nabla L_\alpha(\tilde{\Sigma}) - \nabla L_\alpha(\Sigma), \tilde{\Sigma} - \Sigma \rangle \\ & \leq -\{\lambda - \|\nabla L_\alpha(\Sigma)\|_\infty - \|U(\Xi)\|_\infty\} \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 \\ & \quad + \|\nabla L_\alpha(\Sigma)_S\|_F \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_F + \|(U(\Xi))_S\|_F \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_F \\ & \quad + \lambda s^{1/2} \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_F \end{aligned}$$

Taking the infimum with respect to $\Xi \in \partial \left\| \tilde{\Sigma} \right\|_{1,\text{off}}$ on both sides, it follows that

$$\begin{aligned} & \langle \nabla L_\alpha(\tilde{\Sigma}) - \nabla L_\alpha(\Sigma), \tilde{\Sigma} - \Sigma \rangle \\ & \leq -\{\lambda - \|\nabla L_\alpha(\Sigma)\|_\infty - \epsilon\} \left\| (\tilde{\Sigma} - \Sigma)_{\bar{S}} \right\|_1 \\ & \quad + \{\|\nabla L_\alpha(\Sigma)_S\|_F + s^{1/2}\epsilon\} \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_F \\ & \quad + \lambda s^{1/2} \left\| (\tilde{\Sigma} - \Sigma)_S \right\|_F \end{aligned} \quad (10)$$

It follows from $\tilde{\Sigma} \in \Sigma + \mathbb{B}^\infty(C\alpha)$, (8) and (10) that conditioned on $\mathcal{E}_1(C\alpha, \kappa) \cap \{\|\nabla L_\alpha(\Sigma)\|_\infty + \epsilon \leq 0.5\lambda\}$,

$$\begin{aligned} \kappa \left\| \tilde{\Sigma} - \Sigma \right\|_F^2 & \leq \\ & \left\{ \lambda s^{1/2} + \|\nabla L_\alpha(\Sigma)_S\|_F + s^{1/2}\epsilon \right\} \left\| \tilde{\Sigma} - \Sigma \right\|_F \end{aligned}$$

Therefore,

$$\begin{aligned} & \left\| \tilde{\Sigma} - \Sigma \right\|_F \\ & \leq \kappa^{-1} \left\{ \lambda s^{1/2} + \|\nabla L_\alpha(\Sigma)_S\|_F + s^{1/2}\epsilon \right\} \\ & \leq \kappa^{-1} \{ \lambda s^{1/2} + 0.5\lambda s^{1/2} \} = 1.5\kappa^{-1} \lambda s^{1/2} \end{aligned} \quad (11)$$

A. Proof of Proposition 4

Proof: $\left\| \tilde{\Sigma} - \Sigma^* \right\|_F \leq 3\lambda s^{1/2}$ follows immediately from Lemma 9 with $\Sigma = \Sigma^*$ and $C = \kappa = 1/2$. Combining this with $\tilde{\Sigma} \in \Sigma^* + \mathbb{C}(l)$, where $l = 4s^{1/2}$, yields $\left\| \tilde{\Sigma} - \Sigma^* \right\|_1 \leq 12\lambda s$. ■

B. Proof of Proposition 5

We adopt the following notations for the next stage of proof. Recall that $L_\alpha(\Sigma) = \sum_{k,\ell} \frac{1}{n} \sum_{i=1}^n \rho_\alpha(\Sigma_{k\ell} - x_{ik}x_{i\ell})$. Define $\mathbf{B}^* := \mathbb{E}[\nabla L_\alpha(\Sigma^*)]$, and $\mathbf{W}^* := \nabla L_\alpha(\Sigma^*) - \mathbb{E}[\nabla L_\alpha(\Sigma^*)]$.

Lemma 10. Recall that K is the constant defined in Remark 2. We have $|(\mathbf{B}^*)_{kl}| = |\mathbb{E}[\rho'_\alpha(\epsilon_{kl})]| < \frac{K}{\alpha}$ for all $k, l \in [d]$.

Proof: For fixed $k, l \in [d]$, let $\epsilon_{kl} := \Sigma_{k\ell}^* - x_{ik}x_{i\ell}$, then

$$\begin{aligned} |\mathbb{E}[\rho'_\alpha(\epsilon_{kl})]| & = |\mathbb{E}[\epsilon_{kl}I(|\epsilon_{kl}| \leq \alpha) + \alpha \text{sgn}(\epsilon_{kl})I(|\epsilon_{kl}| > \alpha)]| \\ & = |\mathbb{E}[\epsilon_{kl} + (\alpha \text{sgn}(\epsilon_{kl}) - \epsilon_{kl})I(|\epsilon_{kl}| > \alpha)]| \\ & = |\mathbb{E}\{[\epsilon_{kl} - \alpha \text{sgn}(\epsilon_{kl})]I(|\epsilon_{kl}| > \alpha)\}| \\ & \leq |\mathbb{E}[(|\epsilon_{kl}| - \alpha \text{sgn}(\epsilon_{kl}))I(|\epsilon_{kl}| > \alpha)]| \\ & \leq \frac{|\mathbb{E}[(\epsilon_{kl}^2 - \alpha^2)I(|\epsilon_{kl}| > \alpha)]|}{\alpha} \\ & < \frac{K}{\alpha}. \end{aligned}$$

Therefore, for all k, l

$$|(\mathbf{B}^*)_{kl}| = \frac{1}{n} \left| \sum_{i=1}^n \mathbb{E}[\rho'_\alpha(\Sigma_{k\ell}^* - x_{ik}x_{i\ell})] \right| < \frac{K}{\alpha}.$$

C. Proof of Proposition 6

Proof: $W_{kl}^* = \frac{1}{n} \sum_{i=1}^n \{\rho'_\alpha(\Sigma_{k\ell}^* - x_{ik}x_{i\ell}) - \mathbb{E}[\rho'_\alpha(\Sigma_{k\ell}^* - x_{ik}x_{i\ell})]\}$. Given that $|\rho'_\alpha(\Sigma_{k\ell}^* - x_{ik}x_{i\ell})| \leq \alpha$, for all $m \geq 2$:

$$\begin{aligned} & \mathbb{E}[\rho'_\alpha(\Sigma_{k\ell}^* - x_{ik}x_{i\ell})]^m \\ & \leq \alpha^{m-2} \cdot \text{Var}[\rho'_\alpha(\Sigma_{k\ell}^* - x_{ik}x_{i\ell})] \\ & \leq \alpha^{m-2} \cdot \text{Var}[\Sigma_{k\ell}^* - x_{ik}x_{i\ell}] \\ & \leq \alpha^{m-2} K \leq \alpha^{m-2} K \cdot m!/2 \end{aligned}$$

The second inequality follows given $\rho'_\alpha(\cdot)$ is 1-Lipschitz. With Bernstein's inequality,

$$\Pr \left(\left| \sum_{i=1}^n \{\rho'_\alpha(\Sigma_{k\ell}^* - x_{ik}x_{i\ell}) - \mathbb{E}[\rho'_\alpha(\Sigma_{k\ell}^* - x_{ik}x_{i\ell})]\} \right| \geq 7\sqrt{Kn \log d} \right)$$

$$\begin{aligned} & \leq 2 \cdot \exp \left(-\frac{(7\sqrt{Kn \log d})^2/2}{Kn + \alpha \cdot 7\sqrt{Kn \log d}} \right) \\ & = 2 \cdot \exp \left(-\frac{49 \log d}{16} \right) < \frac{2}{d^3} \end{aligned}$$

Recall that $\nabla L_\alpha(\Sigma^*) = \mathbf{B}^* + \mathbf{W}^*$. With Lemma 10, we have $\|\mathbf{B}^*\|_\infty < \frac{K}{\alpha} \leq \sqrt{K \log d/n}$. Combing the two parts together and with the union bound, we have

$$\|\nabla L_\alpha(\Sigma^*)\|_\infty \leq 8\sqrt{\frac{K \log d}{n}}$$

with at least $1 - 2/d$ probability. ■