

Precision clustering

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1 Preliminary

1.1 Model and Notations

Suppose we have K categories in R groups. Let $z(k) \in [R]^K$ denote the group assignment, and $X_{z(k)} \sim \mathcal{N}_p(0, \Sigma_{z(k)})$, where

$$\Sigma_{z(k)}^{-1} = \Omega_{z(k)} = \Theta_0 + u_k \Theta_{z(k)},$$

where Σ_r, Ω_r are the true covariance and precision matrices, respectively, Θ_0 is denoted as intercept matrix and Θ_r for $r \in [R]$ are denoted as factor matrices.

1. Let $z^*, u^*, \Theta_0^*, \Theta_r^*, I_r^*, \Omega_k^*$ denote the true parameters.
2. Let S_k denote the sample covariance matrix for k -th category with n independent sample $X_{z(k),1}, \dots, X_{z(k),n}$.
3. Let $I_r = \{k \in [K] : z(k) = r\}$.

1.2 Parameter Space

Suppose the true parameters $(u^*, \Theta_0^*, \Theta_r^*)$ belongs to the space \mathcal{P}^* with given assignment z^* , where

$$\mathcal{P}^*(z^*, \tau_1, \tau_2, \delta, \beta, m, M) = \left\{ (u, \Theta_0, \Theta_r) : \begin{aligned} &\Theta_0, \Theta_r \text{ are positive definite for all } r \in [R]; \\ &0 < \tau_1 < \min_{r \in \{0\} \cup [R]} \varphi_{\min}(\Theta_r) \leq \max_{r \in \{0\} \cup [R]} \varphi_{\max}(\Theta_r) < \tau_2; \\ &\max_{r, r' \in [R]} \cos(\Theta_r, \Theta_{r'}) < \delta < 1; \\ &\frac{K}{\beta R} \leq |I_r| \leq \frac{K\beta}{R}, r \in [R]; \quad \min_{k \in [K]} |u_k| > m > 0; \\ &\sum_{k \in I_r} u_k^2 = M^2 K, \quad \sum_{k \in I_r} u_k = 0, \text{ for all } r \in [R] \end{aligned} \right\}.$$

Suppose we find the estimate in a larger space \mathcal{P} with given assignment z , where

$$\mathcal{P}(z, \delta, \beta, m, M) = \left\{ (u, \Theta_0, \Theta_r) : \begin{aligned} &\Theta_0, \Theta_r \text{ are positive definite for all } r \in [R]; \\ &\max_{r, r' \in [R]} \cos(\Theta_r, \Theta_{r'}) < \delta < 1; \\ &\frac{K}{\beta R} \leq |I_r| \leq \frac{K\beta}{R}, r \in [R]; \quad \min_{k \in [K]} |u_k| > m > 0; \\ &\sum_{k \in I_r} u_k^2 = M^2 K, \quad \sum_{k \in I_r} u_k = 0, \text{ for all } r \in [R] \end{aligned} \right\}.$$

1.3 Oracle Estimation error

Suppose we already know the true assignment z^* . Consider the MLE $(\hat{u}(z^*), \hat{\Theta}_0(z^*), \hat{\Theta}_r(z^*))$ with given z^* , where

$$(\hat{u}(z^*), \hat{\Theta}_0(z^*), \hat{\Theta}_r(z^*)) = \arg \min_{(u, \Theta_0, \Theta_r) \in \mathcal{P}(z^*, \delta, \beta, m, M)} \mathcal{Q}(z^*, u, \Theta_0, \Theta_r),$$

and

$$\mathcal{Q}(z, u, \Theta_0, \Theta_r) = \sum_{k \in [K]} \mathcal{Q}_k(z(k), u_k, \Theta) = \sum_{k \in [K]} \langle S_k, \Theta_0 + u_k \Theta_{z(k)} \rangle - \log \det(\Theta_0 + u_k \Theta_{z(k)}).$$

The following Lemma shows the estimation error of the oracle estimator. Let

$$\Delta_0 = \hat{\Theta}_0(z^*) - \Theta_0^*, \quad \Delta_r = \hat{\Theta}_r(z^*) - \Theta_r^*.$$

Lemma 1 (Oracle estimation error). *The optimizer $(\hat{u}(z^*), \hat{\Theta}_0(z^*), \hat{\Theta}_r(z^*))$ satisfies the following inequalities simultaneously with probability at least $1 - \exp(-\sqrt{n})$,*

$$\|\Delta_0\|_F \leq M_0 \sqrt{\frac{p^2 \log p}{\sqrt{n} K}}, \quad \|\Delta_r\|_F \leq M_r \sqrt{\frac{p^2 \log p}{\sqrt{n} |I_r^*|}}, \quad |\hat{u}_k(z^*) - u_k^*| \leq M_k \sqrt{\frac{p^2 \log p}{\sqrt{n}}},$$

for some large positive constants M_0, M_r, M_k .

Remark 1. Note that the estimation in Lemma 1 is not optimal, and this version is a compromise for the exponential rate. If we require a slower rate, e.g., $1 - \mathcal{O}(1/n)$, then the \sqrt{n} can be replaced by n in the denominator. Also, the p^2 can be reduced to sparsity s if we add more constraints.

Proof. Very similar to the proof in Note 0626. The set \mathcal{A} is convex now since we know the true assignment. \square

2 Misclassification rate

For simplicity, we define the function

$$\Omega_k(u, \Theta, z(k)) = \Theta_0 + u_k \Theta_{z(k)}.$$

Define the misclassification loss

$$\begin{aligned}\ell(z, z^*) &= \sum_{k \in [K]} \|\Omega_k(u^*, \Theta^*, z^*(k)) - \Omega_k(u^*, \Theta^*, z(k))\|_F^2 \\ &= \sum_{k \in [K]} \sum_{b \in [R]/z^*(k)} \|\Omega_k(u^*, \Theta^*, z^*(k)) - \Omega_k(u^*, \Theta^*, b)\|_F^2 \mathbf{1}\{z(k) = b\}\end{aligned}$$

Also define the minimal gap between different groups

$$\begin{aligned}\Delta_{\min}^2(p, m, \tau_1, \tau_2, \delta) &= \min_{k \in [K]} \min_{a \neq b \in [R]} \|\Omega_k(u^*, \Theta^*, a) - \Omega_k(u^*, \Theta^*, b)\|_F^2 \\ &\geq m^2 \min_{a \neq b \in [R]} \|\Theta_a^* - \Theta_b^*\|_F^2 \\ &\geq 2m^2 [p\tau_1^2 - \tau_2^2\delta],\end{aligned}$$

where the last inequality follow by the fact that

$$\|A - B\|_F^2 \geq \|A\|_F^2 + \|B\|_F^2 - 2\langle A, B \rangle \geq p[\varphi_{\min}^2(A) + \varphi_{\min}^2(B)] - 2\|A\|_2\|B\|_2 \cos(A, B),$$

for $A, B \in \mathbb{R}^{p \times p}$. For simplicity, we use Δ_{\min}^2 to denote the minimal gap. Consider the Hamming loss $h(z, z^*) = \sum_{k \in [K]} \mathbf{1}\{z(k) \neq z^*(k)\}$. Then, we have

$$\ell(z, z^*) \geq \Delta_{\min}^2 h(z, z^*).$$

Our goal is to bound the misclassification error $\ell(z, z^*)$ for the MLE $(\hat{z}, \hat{u}(\hat{z}), \hat{\Theta}(\hat{z}))$. First, we mimic Theorem 3 in (Gao and Zhang, 2019) to decompose the loss, then mimic Lemma 4.1 in (Gao and Zhang, 2019) to find the oracle misclassification rate.

2.1 Error decomposition

Suppose $z^*(k) = a$. We need to analyze the following event to study the misclassification of MLE \hat{z} which implies $\hat{z}(k) = b$.

$$\mathcal{Q}_k(b, \hat{u}(\hat{z}), \hat{\Theta}(\hat{z})) \leq \mathcal{Q}_k(a, \hat{u}(\hat{z}), \hat{\Theta}(\hat{z})). \quad (1)$$

Let

$$\begin{aligned}\Delta(b, a) &= \Omega_k(\hat{u}(\hat{z}), \hat{\Theta}(\hat{z}), b) - \Omega_k(u^*, \Theta^*, a) \\ \Delta^*(b, a) &= \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(u^*, \Theta^*, a) \\ \hat{\Delta}(b, a) &= \Omega_k(\hat{u}(\hat{z}), \hat{\Theta}(\hat{z}), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), a),\end{aligned}$$

and $\tilde{\Delta} = \text{vec}(\Delta)$. Note that by Taylor Expansion we have

$$\mathcal{Q}_k(b, \hat{u}(z), \hat{\Theta}(z)) - \mathcal{Q}_k(a, u^*, \Theta^*) = \langle S_k - \Sigma_k, \Delta(b, a) \rangle + T_2(b, a), \quad (2)$$

where

$$\begin{aligned}T_2(b, a) &= (\tilde{\Delta}(b, a))^T \int_0^1 (1-v)(\Omega_k^* + \Delta(b, a))^{-1} \otimes (\Omega_k^* + \Delta(b, a))^{-1} dv \tilde{\Delta}(b, a) \\ &= c \|\Delta(b, a)\|_F^2,\end{aligned}$$

with a constant c related to the τ_1, τ_2 and the second equation follows by the fact that $\Delta(b, a)$ has bounded Frobenius norm due the property of MLE. (Trivial estimation error for the MLE implies that $\Delta(b, a) \rightarrow 0$ as $n \rightarrow \infty$. Will add the corresponding Lemma later.)

Plugging the Taylor Expansion (2) into the event (1), the event is upper bounded by the event

$$\langle S_k - \Sigma_k, \Delta(b, a) - \Delta(a, a) \rangle \leq C \left[\|\Delta(a, a)\|_F^2 - \|\Delta(b, a)\|_F^2 \right].$$

Rearranging the inequality, we have

$$\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), a) \rangle \leq -C\bar{\Delta}_k(a, b)^2 + CG_k(a, b, \hat{z}) + CH_k(a, b, \hat{z}) + F_k(a, b, \hat{z})$$

where

$$\begin{aligned} \bar{\Delta}_k(a, b)^2 &= \|\Omega_k(u^*, \Theta^*, a) - \Omega_k(u^*, \Theta^*, b)\|_F^2 \geq \Delta_{\min}^2. \\ F_k(a, b, \hat{z}) &= \langle S_k - \Sigma_k, \hat{\Delta}(a, a) - \hat{\Delta}(b, b) \rangle. \\ G_k(a, b, \hat{z}) &= \left(\|\Delta(a, a)\|_F^2 - \|\Delta^*(a, a)\|_F^2 \right) - \left(\|\Delta(b, a)\|_F^2 - \|\Delta^*(b, a)\|_F^2 \right). \\ H_k(a, b) &= \|\Delta^*(a, a)\|_F^2 - \left(\|\Delta^*(b, a)\|_F^2 - \|\Omega_k(u^*, \Theta^*, a) - \Omega_k(u^*, \Theta^*, b)\|_F^2 \right). \end{aligned}$$

Note that F_k, G_k can be controlled the difference between $(\hat{u}(\hat{z}), \Theta(\hat{z}))$ between $(\hat{u}(z^*), \Theta(z^*))$, which further depends on $\ell(z, z^*)$, and H_k can be controlled by the difference between $(\hat{u}(z^*), \Theta(z^*))$ and (u^*, Θ^*) , which can be bounded by the conclusion of oracle estimation error. Therefore, we impose three reasonable conditions:

Condition 2.1. Assume that

$$\max_{\{z: \ell(z, z^*) \leq \tau\}} \sum_{k \in [K]} \max_{b \in [K]/z^*(k)} \frac{F_k(z^*(k), b, z)^2 \|\Omega_k(u^*, \Theta^*, z^*(k)) - \Omega_k(u^*, \Theta^*, b)\|_F^2}{\bar{\Delta}_k(z^*(k), b)^4 \ell(z, z^*)} \leq C_1 \delta^2,$$

holds with probability at least $1 - \eta_1$ for some $\tau, \delta, \eta_1 > 0$.

Condition 2.2. Assume that

$$\max_{\{z: \ell(z, z^*) \leq \tau\}} \max_{T \subset [K]} \frac{\tau}{4\Delta_{\min}^2 |T| + \tau} \sum_{k \in [K]} \max_{b \in [K]/z^*(k)} \frac{G_k(z^*(k), b, z)^2 \|\Omega_k(u^*, \Theta^*, z^*(k)) - \Omega_k(u^*, \Theta^*, b)\|_F^2}{\bar{\Delta}_k(z^*(k), b)^4 \ell(z, z^*)} \leq C_2 \delta^2,$$

holds with probability at least $1 - \eta_2$ for some $\tau, \delta, \eta_2 > 0$.

Condition 2.3. Assume that

$$\max_{k \in [K]} \max_{b \in [K]/z^*(k)} \frac{|H_k(z^*(k), b)|}{\bar{\Delta}_k(z^*(k), b)^2} \leq C_3 \delta,$$

holds with probability at least $1 - \eta_3$ for some $\tau, \delta, \eta_3 > 0$.

Lemma 2 (Condition check). The MLE \hat{z} satisfies the Conditions 2.1, 2.2, 2.3.

Proof Sketch for Lemma 2. For Conditions 2.1, 2.2, we need to consider the term

$$\left\| \Omega_k(\hat{u}(\hat{z}), \hat{\Theta}(\hat{z}), a) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), a) \right\|_F^2.$$

To bound this term with the misclassification loss, we consider the following facts

$$(\hat{u}(\hat{z}), \Theta(\hat{z})_a, \Theta(\hat{z})_a) = \arg \min_{(u, \Theta_0, \Theta_a)} \sum_{k \in \hat{I}_a} \mathcal{Q}_k(a, \hat{u}(\hat{z}), \hat{\Theta}(\hat{z})),$$

and

$$\begin{aligned} 0 &\geq \sum_{k \in \hat{I}_a} \mathcal{Q}_k(a, \hat{u}(\hat{z}), \hat{\Theta}(\hat{z})) - \mathcal{Q}_k(a, \hat{u}(z^*), \hat{\Theta}(z^*)) \\ &= \sum_{k \in I_{aa}} \mathcal{Q}_k(a, \hat{u}(\hat{z}), \hat{\Theta}(\hat{z})) - \mathcal{Q}_k(a, \hat{u}(z^*), \hat{\Theta}(z^*)) + \sum_{b \neq a} \sum_{k \in I_{ab}} \mathcal{Q}_k(a, \hat{u}(\hat{z}), \hat{\Theta}(\hat{z})) - \mathcal{Q}_k(b, \hat{u}(z^*), \hat{\Theta}(z^*)), \end{aligned}$$

where $I_{ab} = \{k \in [K] : \hat{z}(k) = a, z^*(k) = b\}$. The second term is related to the misclassification loss $\ell(\hat{z}, z^*)$, and the objective function \mathcal{Q} is related to the desired Frobenius norm. Therefore, we may proof the model satisfies the first two conditions.

For Conditions 2.3, we may use the results in Lemma 1 directly to find the upper bound for H_k . \square

Noticed that F_k, G_k, H_k are bounded, we only need to consider the oracle misclassification rate. Hence, we define the oracle misclassification loss as

$$\begin{aligned} \xi_{\text{ideal}}(\varepsilon) &= \sum_{k \in [K]} \sum_{b \in [R]/z^*(k)} \left\| \Omega_k(u^*, \Theta^*, z^*(k)) - \Omega_k(u^*, \Theta^*, b) \right\|_F^2. \\ &\quad \mathbf{1} \left\{ \langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), z^*(k)) \rangle \leq -C(1 - \varepsilon) \bar{\Delta}_k(z^*(k), b)^2 \right\}. \end{aligned}$$

Lemma 3 (Error Decomposition). *The MLE \hat{z} satisfies following inequality*

$$\ell(\hat{z}, z^*) \leq C' \xi_{\text{ideal}}(\varepsilon),$$

with probability at least $1 - \eta_1 - \eta_2 - \eta_3$ for some constant C' .

Proof Sketch of Lemma 3. To bound $\ell(\hat{z}, z^*)$, we need to consider the event

$$\begin{aligned}
\mathbf{1}\{\hat{z}(k) = b\} &\leq \mathbf{1}\left\{\mathcal{Q}_k(b, \hat{u}(\hat{z}), \hat{\Theta}(\hat{z})) \leq \mathcal{Q}_k(z^*(k), \hat{u}(\hat{z}), \hat{\Theta}(\hat{z}))\right\} \\
&\leq \mathbf{1}\left\{\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), z^*(k)) \rangle \leq -C(1 - \varepsilon)\bar{\Delta}_k(z^*(k), b)^2\right\} \\
&\quad + \mathbf{1}\left\{C\varepsilon\bar{\Delta}_k(z^*(k), b)^2 \leq CG_k(z^*(k), b, \hat{z}) + CH_k(z^*(k), b, \hat{z}) + F_k(z^*(k), b, \hat{z})\right\} \\
&\leq \mathbf{1}\left\{\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), z^*(k)) \rangle \leq -C(1 - \varepsilon)\bar{\Delta}_k(z^*(k), b)^2\right\} \\
&\quad + \mathbf{1}\left\{C\varepsilon\bar{\Delta}_k(z^*(k), b)^2/2 \leq CG_k(z^*(k), b, \hat{z}) + F_k(z^*(k), b, \hat{z})\right\} \\
&\leq \mathbf{1}\left\{\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), z^*(k)) \rangle \leq -C(1 - \varepsilon)\bar{\Delta}_k(z^*(k), b)^2\right\} \\
&\quad + C' \frac{G_k(z^*(k), b, \hat{z})^2}{\varepsilon^2 \bar{\Delta}_k(z^*(k), b)^4} + C'' \frac{F_k(z^*(k), b, \hat{z})^2}{\varepsilon^2 \bar{\Delta}_k(z^*(k), b)^4},
\end{aligned}$$

where the second inequality follows by the error decomposition, the third inequality follows by Condition (2.3), and the last inequality follows by the fact that if $C' \frac{G_k(z^*(k), b, \hat{z})^2}{\varepsilon^2 \bar{\Delta}_k(z^*(k), b)^4} + C'' \frac{F_k(z^*(k), b, \hat{z})^2}{\varepsilon^2 \bar{\Delta}_k(z^*(k), b)^4} < 1$ then the indicator $\mathbf{1}\{C\varepsilon\bar{\Delta}_k(z^*(k), b)^2/2 \leq CG_k(z^*(k), b, \hat{z}) + F_k(z^*(k), b, \hat{z})\} = 0$.

Therefore, by the definition of $\ell(\hat{z}, z^*)$, the loss is upper bounded by

$$\begin{aligned}
&\sum_{k \in [K]} \sum_{b \in [R]/z^*(k)} \|\Omega_k(u^*, \Theta^*, z^*(k)) - \Omega_k(u^*, \Theta^*, z(k))\|_F^2 \cdot \\
&\quad \mathbf{1}\left\{\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), z^*(k)) \rangle \leq -C(1 - \varepsilon)\bar{\Delta}_k(z^*(k), b)^2\right\} \\
&\quad + \sum_{k \in [K]} \sum_{b \in [R]/z^*(k)} \|\Omega_k(u^*, \Theta^*, z^*(k)) - \Omega_k(u^*, \Theta^*, z(k))\|_F^2 \cdot \left[C' \frac{G_k(z^*(k), b, \hat{z})^2}{\varepsilon^2 \bar{\Delta}_k(z^*(k), b)^4} + C'' \frac{F_k(z^*(k), b, \hat{z})^2}{\varepsilon^2 \bar{\Delta}_k(z^*(k), b)^4}\right] \\
&\leq \xi_{\text{ideal}}(\varepsilon) + C_0 \ell(\hat{z}, z^*),
\end{aligned}$$

where the inequality follows by the Condition 2.1 and 2.2 and the definition of $\xi_{\text{ideal}}(\varepsilon)$. Hence, with proper constants, we have

$$\ell(\hat{z}, z^*) \leq C' \xi_{\text{ideal}}(\varepsilon).$$

□

2.2 Oracle Misclassification rate

The only part we left is to find the upper bound of the oracle misclassification rate, $\xi_{\text{ideal}}(\varepsilon)$.

Lemma 4 (Oracle Misclassification rate). *Assume $\Delta_{\min} = \mathcal{O}(K^\gamma)$ for some $\gamma > 0$. For any sequence $\varepsilon_K = o(1)$, we have*

$$\xi_{\text{ideal}}(\varepsilon_p) \leq K \exp\left(-(1 + o(1))C\Delta_{\min}^2\right),$$

with probability $1 - \exp(-\Delta_{\min})$ as $K \rightarrow \infty$.

Proof Sketch of Lemma 4. Note that

$$\begin{aligned}
& \mathbb{P} \left(\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), a) \rangle \leq -C(1 - \varepsilon) \bar{\Delta}_k(a, b)^2 \right) \\
& \leq \mathbb{P} \left(\langle S_k - \Sigma_k, \Omega_k(u^*, \Theta^*, b) - \Omega_k(u^*, \Theta^*, a) \rangle \leq -C(1 - \varepsilon - \varepsilon') \bar{\Delta}_k(a, b)^2 \right) \\
& \quad + \mathbb{P} \left(\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(u^*, \Theta^*, b) \rangle \leq -C \frac{\varepsilon'}{2} \bar{\Delta}_k(a, b)^2 \right) \\
& \quad + \mathbb{P} \left(-\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), a) - \Omega_k(u^*, \Theta^*, a) \rangle \leq -C \frac{\varepsilon'}{2} \bar{\Delta}_k(a, b)^2 \right).
\end{aligned}$$

For the first term, we have

$$\begin{aligned}
& \mathbb{P} \left(\langle S_k - \Sigma_k, \Omega_k(u^*, \Theta^*, b) - \Omega_k(u^*, \Theta^*, a) \rangle \leq -C(1 - \varepsilon - \varepsilon') \bar{\Delta}_k(a, b)^2 \right) \\
& \leq \mathbb{P} \left(\|S_k - \Sigma_k\|_{\max} \geq C(1 - \varepsilon - \varepsilon') \bar{\Delta}_k(a, b)/p \right) \\
& \leq C_1 \exp \left(-C_2 n(1 - \varepsilon - \varepsilon')^2 \bar{\Delta}_k(a, b)^2/p^2 \right).
\end{aligned}$$

For the second term, note that

$$\begin{aligned}
\left\| \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(u^*, \Theta^*, b) \right\|_F & \leq \|\Delta_0\|_F + M\sqrt{K} \|\Delta_a\|_F + |\hat{u}(\hat{z})_k - u_k^*| p\tau_2 \\
& \leq M_0 \sqrt{\frac{p^2 \log p}{\sqrt{n}K}} + M_r M \sqrt{\frac{p^2 \alpha R \log p}{\sqrt{n}}} + M_k \sqrt{\frac{p^2 \log p}{\sqrt{n}}} p\tau_2,
\end{aligned}$$

with probability $1 - \exp(-\sqrt{n})$. Then, we have

$$\begin{aligned}
& \mathbb{P} \left(\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(u^*, \Theta^*, b) \rangle \leq -C \frac{\varepsilon'}{2} \bar{\Delta}_k(a, b)^2 \right) \\
& \leq \mathbb{P} \left(\|S_k - \Sigma_k\|_{\max} \left\| \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(u^*, \Theta^*, b) \right\|_F \geq C \frac{\varepsilon'}{2} \bar{\Delta}_k(a, b)^2/p \right) \\
& \leq \mathbb{P} \left(\|S_k - \Sigma_k\|_{\max} \left[M_0 \sqrt{\frac{p^2 \log p}{\sqrt{n}K}} + M_r M \sqrt{\frac{p^2 \alpha \log p}{\sqrt{n}}} + M_k \sqrt{\frac{p^2 \log p}{\sqrt{n}}} p\tau_2 \right] \geq C \frac{\varepsilon'}{2} \bar{\Delta}_k(a, b)^2/p \right) + \\
& \quad + \mathbb{P} \left(\left\| \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(u^*, \Theta^*, b) \right\|_F \geq M_0 \sqrt{\frac{p^2 \log p}{\sqrt{n}K}} + M_r M \sqrt{\frac{p^2 \alpha R \log p}{\sqrt{n}}} + M_k \sqrt{\frac{p^2 \log p}{\sqrt{n}}} p\tau_2 \right) \\
& \leq C_3 \exp \left(-C_4 \frac{n^{3/2} K(\varepsilon')^2 \bar{\Delta}_k(a, b)^4}{p^4 \log p} \right) + C_5 \exp \left(-C_6 \frac{n^{3/2} (\varepsilon')^2 \bar{\Delta}_k(a, b)^4}{p^4 \alpha^2 R^2 \log p} \right) \\
& \quad + C_7 \exp \left(-C_8 \frac{n^{3/2} (\varepsilon')^2 \bar{\Delta}_k(a, b)^4}{p^6 \tau_2^2 \log p} \right) + C_9 \exp(-C_{10} \sqrt{n}).
\end{aligned}$$

Similar bound for $\mathbb{P} \left(-\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), a) - \Omega_k(u^*, \Theta^*, a) \rangle \leq -C \frac{\varepsilon'}{2} \bar{\Delta}_k(a, b)^2 \right)$. Take $n = C_{11} \bar{\Delta}_k(a, b)^4$. Then, we finally have

$$\begin{aligned}
& \mathbb{P} \left(\langle S_k - \Sigma_k, \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), b) - \Omega_k(\hat{u}(z^*), \hat{\Theta}(z^*), a) \rangle \leq -C(1 - \varepsilon) \bar{\Delta}_k(a, b)^2 \right) \\
& \leq C_{12} \exp \left(-C_{13} (1 - \varepsilon - \varepsilon')^2 \bar{\Delta}_k(a, b)^2 \right).
\end{aligned}$$

Therefore, for $\varepsilon = \varepsilon_p = o(1)$ we have

$$\mathbb{E}\xi_{\text{ideal}}(\varepsilon_p) \leq K \exp\left(-(1 + o(1))C\Delta_{\min}^2\right).$$

By Markov's inequality, we have

$$\xi_{\text{ideal}}(\varepsilon_p) \leq K \exp\left(-(1 + o(1))C\Delta_{\min}^2\right),$$

with probability $1 - \exp(-\Delta_{\min})$ as $\Delta_{\min} \rightarrow \infty$.

□

References

Gao, C. and Zhang, A. Y. (2019). Iterative algorithm for discrete structure recovery. [arXiv preprint arXiv:1911.01018](#).