

Supplementary Appendix for High-dimensional Subgroup Regression Analysis

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In this appendix, we first present a number of supporting lemmas. We then present the proofs of Theorems 1 and 2 of the paper.

S.1 Supporting lemmas

Lemma S1. *Let U be the uniformity of vector \mathbf{x} defined as the ratio between the smallest nonzero entry and the largest one. Then*

$$\sqrt{\|\mathbf{x}\|_0} \leq \frac{1 + U \|\mathbf{x}\|_1}{2\sqrt{U} \|\mathbf{x}\|_2}$$

Proof: The lemma follows Lemma III.3 in Yin et al. (2014).

Lemma S2. *Let $\mathbf{A} = \mathbf{W}^\top \mathbf{W} / n$, and \mathcal{M} and \mathcal{N} denote the non-overlapping indices in $(1, \dots, pq)$. Then,*

$$\|\mathbf{A}_{\mathcal{M}, \mathcal{N}}\|_2 \leq \sqrt{\{\rho_+(\mathcal{M}) - \rho_-(\mathcal{M} \cup \mathcal{N})\} \{\rho_+(\mathcal{N}) - \rho_-(\mathcal{M} \cup \mathcal{N})\}}.$$

PROOF: A direct application of Lemma D.1 of Huang and Zhang (2010) completes the proof of Lemma S2. \square

Lemma S3. *Denote $\Delta = \widehat{\Theta} - \Theta_0$, and let Q_r and Q_c denote the sets of indices of the nonzero rows and columns of $\widehat{\Theta} - \Theta_0$. Let $R_j = \{(k-1)p + j, k = 1, \dots, q\}$ be the ordered set of indices of $\text{vec}(\Theta_0)$ corresponding to the elements in the j th row of Θ_0 , and $C_k = \{(k-1)p + j, j = 1, \dots, p\}$ be the set of indices of $\text{vec}(\Theta_0)$ corresponding to the elements in k th column of Θ_0 . Furthermore, we define $R_j(Q)$ and $C_k(Q)$ to be the subset of R_j and C_k with elements in a index set Q . For a given $m \geq 1$, let S_{r0}, S_{r1}, \dots and S_{c0}, S_{c1}, \dots be the consecutive blocks containing indices $j > g_r, k > g_c$, such that $2b_1 \leq |R_{S_{ru}}(Q_c)| \leq 2b_1 + m$, and $2b_1 \leq |C_{S_{cv}}(Q_r)| \leq 2b_1 + m$, where $R_{S_{ru}}(Q_c) = \{R_j(Q_c), j \in S_{ru}\}$, and $R_{S_{cv}}(Q_r) = \{R_j(Q_r), j \in S_{cv}\}$, $u, v = 0, 1, 2, \dots$, respectively. Let $\bar{G}_r = \cup_{j \in S_r \cup S_{r0}} R_j(Q_c)$, $\bar{G}_c = \cup_{k \in S_c \cup S_{c0}} C_k(Q_r)$, and $G = \bar{G}_r \cup \bar{G}_c$. Define $\tilde{\rho}_+(a, b) = ([\{\rho_+(a) - \rho_-(a+b)\}][\{\rho_+(b) - \rho_-(a+b)\}])^{1/2}$. Then,*

$$\sum_{j \notin S_r \cup S_{r0}, k \notin S_c \cup S_{c0}} \|\Delta_{R_j \cap C_k}\|_2^2 \leq \min_{u,v} (4|S_{ru}|, 4|S_{cv}|)^{-1} \left(\sum_{j \notin S_r} \|\Delta_{R_j}\|_2 + \sum_{k \notin S_c} \|\Delta_{C_k}\|_2 \right)^2,$$

$$\begin{aligned}
& \frac{1}{n} \left| \sum_{j \notin S_r \cup S_{r0}, k \notin S_c \cup S_{c0}} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_{R_j \cap C_k} \Delta_{R_j \cap C_k} \right| \\
& \leq \tilde{\rho}_+(|G|, 2b_1 + m) \|\Delta_G\|_2 \left\{ \min_{u,v} (|S_{ru}|, |S_{cv}|) \right\}^{-1/2} \left\{ \sum_{j \notin S_r} \|\Delta_{R_j}\|_2 + \sum_{k \notin S_c} \|\Delta_{C_k}\|_2 \right\} / 2.
\end{aligned}$$

PROOF: We have that,

$$\begin{aligned}
& \sum_{j \notin S_r \cup S_{r0}, k \notin S_c \cup S_{c0}} \|\Delta_{R_j \cap C_k}\|_2^2 \\
& \leq \sum_{j \notin S_r \cup S_{r0}} \|\Delta_{R_j}\|_2^2 / 2 + \sum_{k \notin S_c \cup S_{c0}} \|\Delta_{C_k}\|_2^2 / 2 \\
& \leq \sum_{j \notin S_r \cup S_{r0}} \|\Delta_{R_j}\|_2 \max_{j \notin S_r \cup S_{r0}} \|\Delta_{R_j}\|_2 / 2 + \sum_{k \notin S_c \cup S_{c0}} \|\Delta_{C_k}\|_2 \max_{k \notin S_c \cup S_{c0}} \|\Delta_{C_k}\|_2 / 2 \\
& \leq \sum_{j \notin S_r \cup S_{r0}} \|\Delta_{R_j}\|_2 \min_{j \in S_{r0}} \|\Delta_{R_j}\|_2 / 2 + \sum_{k \notin S_c \cup S_{c0}} \|\Delta_{C_k}\|_2 \min_{k \in S_{c0}} \|\Delta_{C_k}\|_2 / 2 \\
& \leq \sum_{j \notin S_r \cup S_{r0}} \|\Delta_{R_j}\|_2 \sum_{j \in S_{r0}} \|\Delta_{R_j}\|_2 / (2|S_{r0}|) \\
& \quad + \sum_{k \notin S_c \cup S_{c0}} \|\Delta_{C_k}\|_2 \sum_{k \in S_{c0}} \|\Delta_{C_k}\|_2 / (2|S_{c0}|) \\
& \leq \min_{u,v} (4|S_{ru}|, 4|S_{cv}|)^{-1} \left(\sum_{j \notin S_r} \|\Delta_{R_j}\|_2 + \sum_{k \notin S_c} \|\Delta_{C_k}\|_2 \right)^2.
\end{aligned}$$

The last inequality holds by the fact that $ab \leq (a+b)^2/2$ for any positive a, b .

Furthermore, we have that,

$$\begin{aligned}
& \sum_{u \geq 1, v \geq 1} \|\Delta_{R_{S_{ru}} \cap C_{S_{cv}}}\|_2 = \sum_{u \geq 1, v \geq 1} \sqrt{\sum_{j \in S_{ru}, k \in S_{cv}} \|\Delta_{R_j \cap C_k}\|_2^2} \\
& \leq \sum_{u \geq 1, v \geq 1} \sqrt{\sum_{j \in S_{ru}, k \in S_{cv}} \|\Delta_{R_j \cap C_k}\|_2^2} \\
& \leq \sum_{u \geq 1, v \geq 1} \sqrt{\sum_{j \in S_{ru}} \|\Delta_{R_j}\|_2 \max_{j \in S_{ru}} \|\Delta_{R_j}\|_2 + \sum_{k \in S_{cv}} \|\Delta_{C_k}\|_2 \max_{k \in S_{cv}} \|\Delta_{C_k}\|_2} \\
& \leq \sum_{u \geq 1, v \geq 1} \sqrt{\sum_{j \in S_{ru}} \|\Delta_{R_j}\|_2 \min_{j \in S_{ru-1}} \|\Delta_{R_j}\|_2 + \sum_{k \in S_{cv}} \|\Delta_{C_k}\|_2 \min_{k \in S_{cv-1}} \|\Delta_{C_k}\|_2} \\
& \leq \sum_{u \geq 1, v \geq 1} \left\{ \sum_{j \in S_{ru}} \|\Delta_{R_j}\|_2 \sum_{j \in S_{ru-1}} \|\Delta_{R_j}\|_2 / |S_{ru-1}| + \sum_{k \in S_{cv}} \|\Delta_{C_k}\|_2 \sum_{j \in S_{cv-1}} \|\Delta_{C_k}\|_2 / |S_{cv-1}| \right\}^{1/2}
\end{aligned}$$

$$\begin{aligned}
&\leq \left\{ \min_{u,v}(|S_{ru}|, |S_{cv}|) \right\}^{-1/2} 1/2 \sum_{u \geq 1, v \geq 1} \left\{ \left(\sum_{j \in S_{ru}} \|\Delta_{R_j}\|_2 + \sum_{j \in S_{ru-1}} \|\Delta_{R_j}\|_2 \right)^2 \right. \\
&\quad \left. + \left(\sum_{j \in S_{cv}} \|\Delta_{C_k}\|_2 + \sum_{k \in S_{cv-1}} \|\Delta_{C_k}\|_2 \right)^2 \right\}^{1/2} \\
&\leq \left\{ \min_{u,v}(|S_{ru}|, |S_{cv}|) \right\}^{-1/2} 1/2 \sum_{u \geq 1, v \geq 1} \left(\sum_{j \in S_{ru}} \|\Delta_{R_j}\|_2 + \sum_{j \in S_{ru-1}} \|\Delta_{R_j}\|_2 \right. \\
&\quad \left. + \sum_{j \in S_{cv}} \|\Delta_{C_k}\|_2 + \sum_{k \in S_{cv-1}} \|\Delta_{C_k}\|_2 \right) \\
&\leq \left\{ \min_{u,v}(|S_{ru}|, |S_{cv}|) \right\}^{-1/2} 1/2 \left(\sum_{u \geq 0} \sum_{j \in S_{ru}} \|\Delta_{R_j}\|_2 + \sum_{v \geq 0} \sum_{k \in S_{cv}} \|\Delta_{C_k}\|_2 \right) \\
&= \left\{ \min_{u,v}(4|S_{ru}|, 4|S_{cv}|) \right\}^{-1/2} \left(\sum_{j \notin S_r} \|\Delta_{R_j}\|_2 + \sum_{k \notin S_c} \|\Delta_{C_k}\|_2 \right).
\end{aligned}$$

Therefore, we have that,

$$\begin{aligned}
&\frac{1}{n} \left| \sum_{j \notin S_r \cup S_{r0}, k \notin S_c \cup S_{c0}} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_{R_j \cap C_k} \Delta_{R_j \cap C_k} \right| \\
&\leq \frac{1}{n} \sum_{u \geq 1, v \geq 1} \left| \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_{R_{S_{ru}} \cap C_{S_{cv}}} \Delta_{R_{S_{ru}} \cap C_{S_{cv}}} \right| \\
&\leq \frac{1}{n} \sum_{u \geq 1, v \geq 1} \|\mathbf{W}_G^\top \mathbf{W}_{R_{S_{ru}}(Q_c) \cap R_{S_{cv}}(Q_r)}\|_2 \|\Delta_G\|_2 \|\Delta_{R_{S_{ru}}(Q_c) \cap C_{S_{cv}}(Q_r)}\|_2 \\
&\leq \tilde{\rho}_+ (|G|, 2b_1 + m) \|\Delta_G\|_2 \sum_{u \geq 1, v \geq 1} \|\Delta_{G_{S_{ru}} \cap G_{S_{cv}}}\|_2 \\
&\leq \tilde{\rho}_+ (|G|, 2b_1 + m) \|\Delta_G\|_2 \left\{ \min_{u,v}(|S_{ru}|, |S_{cv}|) \right\}^{-1/2} \left\{ \sum_{j \notin S_r} \|\Delta_{R_j}\|_2 + \sum_{k \notin S_c} \|\Delta_{C_k}\|_2 \right\} / 2.
\end{aligned}$$

The third inequality holds due to Lemma S2. This completes the proof of Lemma S3. \square

Lemma S4. Suppose that $\lambda_r \sqrt{q} \geq 2n^{-1} \max_{j=1, \dots, p, j \in Q_r} \|\mathbf{W}_{R_j(Q_c)}^\top \boldsymbol{\epsilon}\|_2$, and $\lambda_c \sqrt{p} \geq 2n^{-1} \max_{k=1, \dots, q, k \in Q_c} \|\mathbf{W}_{C_k(Q_r)}^\top \boldsymbol{\epsilon}\|_2$. Then, the solution for (2) satisfies that,

$$\lambda_c \sqrt{p} \sum_{k=2, k \notin S_c}^q \|\{\text{vec}(\hat{\Theta})\}_{C_k}\|_2 + \lambda_r \sqrt{q} \sum_{j=1, j \notin S_r}^p \|\{\text{vec}(\hat{\Theta})\}_{R_j}\|_2$$

$$\leq 3\lambda_c\sqrt{p} \sum_{k=2, k \in S_c}^q \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{C_k}\|_2 + 3\lambda_r\sqrt{q} \sum_{j=1, j \in S_r}^p \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{R_j}\|_2.$$

PROOF: From (2), we obtain the subgradient condition for the minimizer that

$$\mathbf{W}^\top \mathbf{W} \text{vec}(\widehat{\Theta} - \Theta_0) - \mathbf{W}^\top \boldsymbol{\epsilon} + n\lambda_c\sqrt{p} \sum_{k=2}^q \boldsymbol{\nu}_k + n\lambda_r\sqrt{q} \sum_{j=1}^p \boldsymbol{\mu}_j = \mathbf{0}, \quad (\text{S.1})$$

where $\boldsymbol{\mu}$ is the subgradient of $\|\Theta_{j\cdot}\|_2$ with respect to $\text{vec}(\Theta)$ evaluated at $\widehat{\Theta}$; i.e.,

$$\begin{aligned} \boldsymbol{\mu}_{jR_j^c} &= \mathbf{0}, \\ \boldsymbol{\mu}_{jR_j} &= \begin{cases} \frac{\widehat{\Theta}_{j\cdot}}{\|\widehat{\Theta}_{j\cdot}\|_2}, & \text{if } \widehat{\Theta}_{j\cdot} \neq \mathbf{0}, \\ \forall \boldsymbol{\mu}, \|\boldsymbol{\mu}\|_2 \leq 1, & \text{if } \widehat{\Theta}_{j\cdot} = \mathbf{0}. \end{cases} \end{aligned}$$

and $\boldsymbol{\nu}$ is the subgradient of $\|\Theta_{\cdot k}\|_2$ with respect to $\text{vec}(\Theta)$ evaluated at $\widehat{\Theta}$; i.e.,

$$\begin{aligned} \boldsymbol{\nu}_{kC_k^c} &= \mathbf{0}, \\ \boldsymbol{\nu}_{kC_k} &= \begin{cases} \frac{\widehat{\Theta}_{\cdot k}}{\|\widehat{\Theta}_{\cdot k}\|_2}, & \text{if } \widehat{\Theta}_{\cdot k} \neq \mathbf{0}, \\ \forall \boldsymbol{\nu} : \|\boldsymbol{\nu}\|_2 \leq 1, & \text{if } \widehat{\Theta}_{\cdot k} = \mathbf{0}. \end{cases} \end{aligned}$$

By definition, we then have

$$\begin{aligned} \text{vec}(\widehat{\Theta})^\top \boldsymbol{\mu}_j &= \|\text{vec}(\widehat{\Theta})_{R_j}\|_2, \quad \text{vec}(\widehat{\Theta})^\top \boldsymbol{\nu}_k = \|\text{vec}(\widehat{\Theta})_{C_k}\|_2, \\ |\text{vec}(\widehat{\Theta} - \Theta_0)^\top \boldsymbol{\mu}_j| &\leq \|\text{vec}(\widehat{\Theta} - \Theta_0)_{R_j}\|_2, \quad \text{and } |\text{vec}(\widehat{\Theta} - \Theta_0)^\top \boldsymbol{\nu}_k| \leq \|\text{vec}(\widehat{\Theta} - \Theta_0)_{C_k}\|_2. \end{aligned}$$

Multiplying both sides of (S.1) by $\text{vec}(\widehat{\Theta} - \Theta_0)$, we obtain that

$$\begin{aligned} 0 &\geq -\text{vec}(\widehat{\Theta} - \Theta_0)^\top \mathbf{W}^\top \mathbf{W} \text{vec}(\widehat{\Theta} - \Theta_0) = -\text{vec}(\widehat{\Theta} - \Theta_0)^\top \mathbf{W}^\top \boldsymbol{\epsilon} \\ &\quad + n\lambda_c\sqrt{p} \sum_{k=2}^q \text{vec}(\widehat{\Theta} - \Theta_0)^\top \boldsymbol{\nu}_k + n\lambda_r\sqrt{q} \sum_{j=1}^p \text{vec}(\widehat{\Theta} - \Theta_0)^\top \boldsymbol{\mu}_j \\ &= -\text{vec}(\widehat{\Theta} - \Theta_0)^\top \mathbf{W}^\top \boldsymbol{\epsilon} \\ &\quad + n\lambda_c\sqrt{p} \sum_{k=2, k \in S_c}^q \text{vec}(\widehat{\Theta} - \Theta_0)^\top \boldsymbol{\nu}_k + n\lambda_r\sqrt{q} \sum_{j=1, j \in S_r}^p \text{vec}(\widehat{\Theta} - \Theta_0)^\top \boldsymbol{\mu}_j \\ &\quad + n\lambda_c\sqrt{p} \sum_{k=2, k \notin S_c}^q \text{vec}(\widehat{\Theta} - \Theta_0)^\top \boldsymbol{\nu}_k + n\lambda_r\sqrt{q} \sum_{j=1, j \notin S_r}^p \text{vec}(\widehat{\Theta} - \Theta_0)^\top \boldsymbol{\mu}_j \\ &\geq -\text{vec}(\widehat{\Theta} - \Theta_0)^\top \mathbf{W}^\top \boldsymbol{\epsilon} \\ &\quad - n\lambda_c\sqrt{p} \sum_{k=2, k \in S_c}^q \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{C_k}\|_2 - n\lambda_r\sqrt{q} \sum_{j=1, j \in S_r}^p \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{R_j}\|_2 \end{aligned}$$

$$+n\lambda_c\sqrt{p} \sum_{k=2, k \notin S_c}^q \|\{\text{vec}(\widehat{\Theta})\}_{C_k}\|_2 + n\lambda_r\sqrt{q} \sum_{j=1, j \notin S_r}^p \|\{\text{vec}(\widehat{\Theta})\}_{R_j}\|_2,$$

which implies that

$$\begin{aligned} & \lambda_c\sqrt{p} \sum_{k=2, k \notin S_c}^q \|\{\text{vec}(\widehat{\Theta})\}_{C_k}\|_2 + \lambda_r\sqrt{q} \sum_{j=1, j \notin S_r}^p \|\{\text{vec}(\widehat{\Theta})\}_{R_j}\|_2 \\ \leq & \lambda_c\sqrt{p} \sum_{k=2, k \in S_c}^q \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{C_k}\|_2 + \lambda_r\sqrt{q} \sum_{j=1, j \in S_r}^p \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{R_j}\|_2 \\ & + n^{-1} \text{vec}(\widehat{\Theta} - \Theta_0)^\top \mathbf{W}^\top \boldsymbol{\epsilon} \\ \leq & \lambda_c\sqrt{p} \sum_{k=2, k \in S_c}^q \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{C_k}\|_2 + \lambda_r\sqrt{q} \sum_{j=1, j \in S_r}^p \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{R_j}\|_2 \\ & + n^{-1} \sum_{j=1, j \in Q_r}^p \|\text{vec}(\widehat{\Theta} - \Theta_0)_{R_j}\|_2 \|\mathbf{W}_{R_j(Q_c)}^\top \boldsymbol{\epsilon}\|_2 \\ & + n^{-1} \sum_{k=2, k \in Q_c}^q \|\text{vec}(\widehat{\Theta} - \Theta_0)_{C_k}\|_2 \|\mathbf{W}_{C_k(Q_r)}^\top \boldsymbol{\epsilon}\|_2 \\ \leq & \lambda_c\sqrt{p} \sum_{k=2, k \in S_c}^q \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{C_k}\|_2 + \lambda_r\sqrt{q} \sum_{j=1, j \in S_r}^p \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{R_j}\|_2 \\ & + 0.5\lambda_r\sqrt{q} \sum_{j=1}^p \|\text{vec}(\widehat{\Theta} - \Theta_0)_{R_j}\|_2 + 0.5\lambda_c\sqrt{p} \sum_{k=2}^q \|\text{vec}(\widehat{\Theta} - \Theta_0)_{C_k}\|_2. \end{aligned}$$

Therefore, we have obtained that

$$\begin{aligned} & \lambda_c\sqrt{p} \sum_{k=2, k \notin S_c}^q \|\{\text{vec}(\widehat{\Theta})\}_{C_k}\|_2 + \lambda_r\sqrt{q} \sum_{j=1, j \notin S_r}^p \|\{\text{vec}(\widehat{\Theta})\}_{R_j}\|_2 \\ \leq & 3\lambda_c\sqrt{p} \sum_{k=2, k \in S_c}^q \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{C_k}\|_2 + 3\lambda_r\sqrt{q} \sum_{j=1, j \in S_r}^p \|\{\text{vec}(\widehat{\Theta} - \Theta_0)\}_{R_j}\|_2, \end{aligned}$$

which completes the proof of Lemma S4. \square

Lemma S5. Suppose $\mathbf{X} \in \mathbb{R}^{m \times p}$ is zero-mean sub-Gaussian with the parameters (Σ, σ^2) . Let $\mathbb{K}(s) \equiv (\mathbf{v} \in \mathbb{R}^p \mid \|\mathbf{v}\|_2 \leq 1, \|\mathbf{v}\|_0 \leq s)$. Then, there exists a constant $c > 0$, such that

$$\Pr \left[\sup_{\mathbf{v} \in \mathbb{K}(2s)} \left| \frac{\|\mathbf{X}\mathbf{v}\|_2^2}{n} - E \left(\frac{\|\mathbf{X}\mathbf{v}\|_2^2}{n} \right) \right| \geq t \right] \leq 2 \exp \left\{ -cn \min \left(\frac{t^2}{\sigma^4}, \frac{t}{\sigma^2} \right) + 2s \log(p) \right\}.$$

PROOF: A direct application of Lemma 15 of Loh and Wainwright (2012) completes the proof of Lemma S5. \square

Lemma S6. *Suppose $n > \log(p)$. There is a constant $c > 0$, such that*

$$\begin{aligned} \Pr \left\{ \max_{j=1, \dots, p, j \in Q_r} n^{-1} \|\mathbf{W}_{R_j(Q_c)}^\top \boldsymbol{\epsilon}\|_2 > \sqrt{4b_1 \log(p)/(cn)} \right\} &\leq 12 \exp \{-b_1 \log(p)\}, \\ \Pr \left\{ \max_{k=1, \dots, q, k \in Q_c} n^{-1} \|\mathbf{W}_{C_k(Q_r)}^\top \boldsymbol{\epsilon}\|_2 > \sqrt{4b_1 \log(q)/(cn)} \right\} &\leq 12 \exp \{-b_1 \log(q)\}. \end{aligned}$$

PROOF: First, we note that

$$\|\mathbf{W}_{C_k(Q_r)}^\top \boldsymbol{\epsilon}\|_2 \leq \sup_{\mathbf{v} \in \mathbb{K}(2b_1)} |\boldsymbol{\epsilon}^\top \mathbf{W} \mathbf{v}|.$$

Letting $\phi(\mathbf{v}) = \|\mathbf{v}\|_2^2/n - E(\|\mathbf{v}\|_2^2/n)$, we have

$$\boldsymbol{\epsilon}^\top \mathbf{W} \mathbf{v}/n = \frac{1}{2} \{\phi(\mathbf{W} \mathbf{v} + \boldsymbol{\epsilon}) - \phi(\mathbf{W} \mathbf{v}) - \phi(\boldsymbol{\epsilon})\}.$$

Therefore, by Lemma S5, for some universal constant c , we have

$$\begin{aligned} \Pr(n^{-1} \|\mathbf{W}_{C_k(Q_r)}^\top \boldsymbol{\epsilon}\|_2 > t) &\leq \Pr \left\{ \sup_{\mathbf{v} \in \mathbb{K}(2b_1)} |\boldsymbol{\epsilon}^\top \mathbf{W} \mathbf{v}/n| > t \right\} \\ &\leq 6 \exp \{-cn \min(t^2, t) + 2b_1 \log(q)\}. \end{aligned}$$

Letting $t = \sqrt{4b_1 \log(q)/(cn)}$, we have

$$\begin{aligned} \Pr \left(\max_{k=1, \dots, q, k \in Q_c} n^{-1} \|\mathbf{W}_{C_k(Q_r)}^\top \boldsymbol{\epsilon}\|_2 > t \right) &\leq \Pr \left\{ \max_{k=1, \dots, q, k \in Q_c} \sup_{\mathbf{v} \in \mathbb{K}(2b_1)} |\boldsymbol{\epsilon}^\top \mathbf{W} \mathbf{v}/n| > t \right\} \\ &\leq 12b_1 \exp \{-cn \min(t^2, t) + 2b_1 \log(q)\} \\ &\leq 12 \exp \{-cn \min(t^2, t) + 3b_1 \log(q)\} \\ &= 12 \exp \{-b_1 \log(q)\}. \end{aligned}$$

Using the same argument, we can show that

$$\Pr \left\{ \max_{j=1, \dots, p, j \in Q_r} n^{-1} \|\mathbf{W}_{R_j(Q_c)}^\top \boldsymbol{\epsilon}\|_2 > \sqrt{4b_1 \log(p)/(cn)} \right\} \leq 12 \exp \{-b_1 \log(p)\}.$$

This completes the proof of Lemma S6. \square

Lemma S7. Suppose $\mathbf{a} = (\mathbf{a}_g, g = 1, \dots, \tilde{G})^\top$ be an arbitrary group center, such that $\|\mathbf{a}_g\|_0 \leq b_1$ and the group size $\tilde{G} < \infty$. Let $P_{\hat{\Theta}}$ denote the probability measure induced by $\hat{\Theta}\mathbf{Z}_i$. Suppose the conditions in Theorem 1 hold. Then,

$$\left| \int \min_{1 \leq g \leq \tilde{G}} \|\mathbf{v} - \mathbf{a}_g\|_2^2 dP_{\hat{\Theta}}(\mathbf{v}) - \int \min_{1 \leq g \leq \tilde{G}} \|\mathbf{v} - \mathbf{a}_g\|_2^2 dP_{\Theta_0}(\mathbf{v}) \right| = O_p \left\{ b_1 \sqrt{\log(pq)/n} \right\}.$$

PROOF: Let k_r, k_c denote the number of nonzero rows and columns of $\hat{\Theta} - \Theta_0$. By Lemma S1 and Condition ((A2)), we have that $k_r + k_c \leq 2b_1$. Let $\mathbf{E}_R \in \mathbb{R}^{k_r \times p}$ and $\mathbf{E}_C \in \mathbb{R}^{q \times k_c}$ be the selection matrix, so that $\mathbf{E}_R \hat{\Theta}$ corresponds to the nonzero rows, and $\hat{\Theta} \mathbf{E}_C$ the nonzero columns of $\hat{\Theta} - \Theta_0$. Also the dimensions of $\hat{\Theta}\mathbf{Z}_i$ and $\Theta_0\mathbf{Z}_i$ are both smaller than b_1 . Then, for any given center \mathbf{a} ,

$$\begin{aligned} & \left| \int \|\mathbf{v} - \mathbf{a}\|_2^2 dP_{\hat{\Theta}}(\mathbf{v}) - \int \|\mathbf{v} - \mathbf{a}\|_2^2 dP_{\Theta_0}(\mathbf{v}) \right| \\ &= \left| \frac{\partial \int \|\mathbf{v} - \mathbf{a}\|_2^2 dP_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} \text{vec} \left\{ \mathbf{E}_R (\hat{\Theta} - \Theta_0) \mathbf{E}_C \right\} \right| \\ &\leq \left\| \frac{\partial \int \|\mathbf{v} - \mathbf{a}\|_2^2 dP_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} \right\|_2 \|\hat{\Theta} - \Theta_0\|_F \\ &= \left\| \int \|\mathbf{v} - \mathbf{a}\|_2^2 \frac{\partial f_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} d\mathbf{v} \right\|_2 \|\hat{\Theta} - \Theta_0\|_F \\ &= \left\| \int \|\mathbf{v}\|_2^2 \frac{\partial f_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} d\mathbf{v} \right\|_2 \|\hat{\Theta} - \Theta_0\|_F \\ &\quad + \left\| 2\mathbf{a}^\top \int \mathbf{v} \frac{\partial f_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} d\mathbf{v} \right\|_2 \|\hat{\Theta} - \Theta_0\|_F \\ &\quad + \left\| \int \|\mathbf{a}\|_2^2 \frac{\partial f_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} d\mathbf{v} \right\|_2 \|\hat{\Theta} - \Theta_0\|_F \\ &\leq \|\mathbf{a}\|_2^2 \left\| \int \frac{\partial f_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} d\mathbf{v} \right\|_2 \|\hat{\Theta} - \Theta_0\|_F \\ &\quad + 2\|\mathbf{a}\|_2 \left\| \int \mathbf{v} \frac{\partial f_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} d\mathbf{v} \right\|_{op} \|\hat{\Theta} - \Theta_0\|_F \\ &\quad + \|\mathbf{v}\|_2^2 \left\| \int \frac{\partial f_{\Theta^*}(\mathbf{v})}{\partial \text{vec}(\mathbf{E}_R \hat{\Theta} \mathbf{E}_C)^\top} d\mathbf{v} \right\|_2 \|\hat{\Theta} - \Theta_0\|_F \\ &= O_p \{ b_1 \sqrt{\log(pq)/n} \}, \end{aligned}$$

where $\|\cdot\|_{op}$ is the matrix operator norm, Θ^* is a point between $\hat{\Theta}$ and Θ_0 . The last equality holds by Theorem 1, and Condition (B3) that $|\int \|\mathbf{v}\|_2^2 \partial f_{\Theta^*}(\mathbf{v}) / \partial \text{vec}(\Theta)^\top \mathbf{e}_j d\mathbf{v}|$, $|\partial f_{\Theta^*}(\mathbf{v}) / \partial \text{vec}(\Theta)^\top \mathbf{e}_j|$, and $\|\int \mathbf{v} \partial f_{\Theta^*}(\mathbf{v}) / \partial \text{vec}(\Theta)^\top \mathbf{e}_j d\mathbf{v}\|_2$ are finite. This lead to $\int \|\mathbf{v}\|_2^2 \partial f_{\Theta^*}(\mathbf{v}) / \partial \text{vec}(\Theta)^\top \mathbf{e}_j d\mathbf{v} = O(1)$, $\int \partial f_{\Theta^*}(\mathbf{v}) / \partial \text{vec}(\Theta)^\top \mathbf{e}_j d\mathbf{v} = O(1)$, $\|\int \mathbf{v} \partial f_{\Theta^*}(\mathbf{v}) / \partial \text{vec}(\Theta)^\top \mathbf{e}_j d\mathbf{v}\|_2 = O(1)$, and that $\hat{\Theta} - \Theta_0$ has at most $2b_1$ nonzero entries by Condition (A2) and Lemma S1.

This completes the proof of Lemma S7. \square

S.2 Proof of Theorem 1

We first present a more general theorem, which establishes the relationship between the convergence order of $\widehat{\Theta}$, the choice of the penalty parameters, and $\rho_-(s)$. Then the result of Theorem 1 follows immediately from Theorem S1 and Lemma S6 for some specific choices of the penalty parameters and $\rho_-(s)$.

Theorem S1. *Suppose Conditions (A1), (A2) and (A3) hold. Furthermore, suppose that*

$$\lambda_r \sqrt{q} \geq \frac{2}{n} \max_{j \in Q_r} \|\mathbf{W}_{R_j(Q_c)}^\top \boldsymbol{\epsilon}\|_2, \quad \lambda_c \sqrt{p} \geq \frac{2}{n} \max_{k \in Q_c} \|\mathbf{W}_{C_k(Q_r)}^\top \boldsymbol{\epsilon}\|_2, \quad (\text{S.2})$$

almost surely. Then,

$$\|\text{vec}(\widehat{\Theta} - \Theta_0)\|_2 \leq 3 \left\{ 2.25 \frac{(\lambda_r \sqrt{q} g_r + \lambda_c \sqrt{p} g_c)^2}{\min\{\lambda_r \sqrt{q}, \lambda_c \sqrt{p}\}^2} + 1 \right\}^{1/2} \times \frac{\lambda_r \sqrt{q} g_r + \lambda_c \sqrt{p} g_c}{\rho_-(s)}.$$

PROOF: Recall that $\Delta = \text{vec}(\widehat{\Theta} - \Theta_0)$. Multiplying both sides of (S.1) by a vector $\mathbf{v} \in \mathbb{R}^{pq}$, such that $\mathbf{v}_G = \Delta_G$ and $\mathbf{v}_{G^c} = \mathbf{0}$, where G is defined in Lemma (S3), we obtain that,

$$\frac{1}{n} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_G \Delta - \Delta_G^\top \mathbf{W}_G^\top \boldsymbol{\epsilon} + \lambda_r \sqrt{q} \sum_{j \in S_r \cup S_{r0}} \Delta_{R_j}^\top \boldsymbol{\mu}_{jR_j} + \lambda_c \sqrt{p} \sum_{k \geq 2, k \in S_c \cup S_{c0}} \Delta_{C_k}^\top \boldsymbol{\nu}_{kC_k} = 0.$$

By the definition of G , we have that $|G| \leq d_0 + 2b_1 + m$. Using the same argument as those leading to (S.1), we obtain that,

$$\begin{aligned} & 2 \frac{1}{n} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_G \Delta + \lambda_r \sqrt{q} \sum_{j \in S_{r0}} \|\text{vec}(\widehat{\Theta})_{R_j}\|_2 + \lambda_c \sqrt{p} \sum_{k \geq 2, k \in S_{c0}} \|\text{vec}(\widehat{\Theta})_{C_k}\|_2 \\ & \leq 3 \lambda_r \sqrt{q} \sum_{j \in S_r} \|\Delta_{R_j}\|_2 + 3 \lambda_c \sqrt{p} \sum_{k \geq 2, k \in S_c} \|\Delta_{C_k}\|_2. \end{aligned} \quad (\text{S.3})$$

Furthermore, denote $s = d_0 + 2b_1 + m$. Then $|G| \leq s$ and

$$\begin{aligned} & n^{-1} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_G \Delta = n^{-1} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_G \Delta_G + n^{-1} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_{G^c} \Delta_{G^c} \\ & = n^{-1} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_G \Delta_G + n^{-1} \sum_{j \notin S_r \cup S_{r0}, k \notin S_c \cup S_{c0}} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_{R_j \cap C_k} \Delta_{R_j \cap C_k} \\ & \geq n^{-1} \Delta_G^\top \mathbf{W}_G^\top \mathbf{W}_G \Delta_G \\ & \quad - \tilde{\rho}_+(|G|, 2b_1 + m) \|\Delta_G\|_2 \left\{ \min_{u,v}(|S_{ru}|, |S_{cv}|) \right\}^{-1/2} \left\{ \sum_{j \notin S_r} \|\Delta_{R_j}\|_2 + \sum_{k \notin S_c} \|\Delta_{C_k}\|_2 \right\} / 2 \end{aligned}$$

$$\begin{aligned}
&\geq n^{-1} \mathbf{\Delta}_G^\top \mathbf{W}_G^\top \mathbf{W}_G \mathbf{\Delta}_G - \tilde{\rho}_+(|G|, 2b_1 + m) \|\mathbf{\Delta}_G\|_2 \left\{ \min_{u,v}(|S_{ru}|, |S_{cv}|) \right\}^{-1/2} / 2 \\
&\quad \times \min(\lambda_r \sqrt{q}, \lambda_c \sqrt{p})^{-1} \left\{ \lambda_r \sqrt{q} \sum_{j \notin S_r} \|\mathbf{\Delta}_{R_j}\|_2 + \lambda_c \sqrt{p} \sum_{k \notin S_c} \|\mathbf{\Delta}_{C_k}\|_2 \right\} \\
&\geq \rho_-(s) \|\mathbf{\Delta}_G\|_2^2 - 3\tilde{\rho}_+(s, s - d_0) \left\{ \min_{u,v}(|S_{ru}|, |S_{cv}|) \right\}^{-1/2} / 2 \\
&\quad \times \min(\lambda_r \sqrt{q}, \lambda_c \sqrt{p})^{-1} \{ \lambda_r \sqrt{q} |S_r| + \lambda_c \sqrt{p} |S_c| \} \|\mathbf{\Delta}_G\|_2^2 \\
&\geq \rho_-(s) \|\mathbf{\Delta}_G\|_2^2 - 3\{\rho_+(s) - \rho_-(2s - d_0)\}^{1/2} \{\rho_+(s - d) - \rho_-(2s - d_0)\}^{1/2} / 2 \\
&\quad \times \min(\lambda_r \sqrt{q}, \lambda_c \sqrt{p})^{-1} \{ \lambda_r \sqrt{q} |S_r| + \lambda_c \sqrt{p} |S_c| \} \|\mathbf{\Delta}_G\|_2^2 \\
&\geq 0.5\rho_-(s) \|\mathbf{\Delta}_G\|_2^2.
\end{aligned}$$

The third line holds due to Lemma S3. The fifth line holds due to Lemma S4, the equality in (S.1), and the fact that each $\|\mathbf{\Delta}_{R_j}\|_2$ and $\|\mathbf{\Delta}_{C_k}\|_2$ is smaller than $\|\mathbf{\Delta}_G\|_2$. The sixth line holds by the definition of $\tilde{\rho}_+(a, b)$, and the fact that $|G| \leq s$, $\rho_-(s) \leq \rho_-(G)$. Besides, because $R_{S_{ru}}(Q_c)$ or $R_{S_{cv}}(Q_r)$ must include at least $2b_1$ elements, therefore, $\{\min_{u,v}(|S_{ru}|, |S_{cv}|)\}$ is lower bounded by 1. The last inequality holds because of the fact that m can be any positive constant and by Condition (A3).

Therefore, combined with (S.3), we obtain that,

$$\begin{aligned}
\|\mathbf{\Delta}_G\|_2^2 &\leq 3\rho_-(s)^{-1} \lambda_r \sqrt{q} \sum_{j \in S_r} \|\mathbf{\Delta}_{R_j}\|_2 + 3\rho_-(s)^{-1} \lambda_c \sqrt{p} \sum_{k \geq 2, k \in S_c} \|\mathbf{\Delta}_{C_k}\|_2 \\
&\leq 3\rho_-(s)^{-1} (\lambda_r \sqrt{q} |S_r| + \lambda_c \sqrt{p} |S_c|) \|\mathbf{\Delta}_G\|_2,
\end{aligned}$$

In turn, we have

$$\|\mathbf{\Delta}_G\|_2^2 \leq 9\rho_-(s)^{-2} (\lambda_r \sqrt{q} |S_r| + \lambda_c \sqrt{p} |S_c|)^2. \quad (\text{S.4})$$

Now we have that,

$$\begin{aligned}
\|\mathbf{\Delta}\|_2^2 - \|\mathbf{\Delta}_G\|_2^2 &\leq \|\mathbf{\Delta}_{G^c}\|_2^2 \leq \sum_{j \notin S_r \cup S_{r0}, k \notin S_c \cup S_{c0}} \|\mathbf{\Delta}_{R_j \cap C_k}\|_2^2 \\
&\leq \min_{u,v} (4|S_{ru}|, 4|S_{cv}|)^{-1} \left(\sum_{j \notin S_r} \|\mathbf{\Delta}_{R_j}\|_2 + \sum_{k \notin S_c} \|\mathbf{\Delta}_{C_k}\|_2 \right)^2 \\
&\leq 2.25 \min_{u,v} (|S_{ru}|, |S_{cv}|)^{-1} \min\{\lambda_r \sqrt{q}, \lambda_c \sqrt{p}\}^{-2} \left(\lambda_r \sqrt{q} \sum_{j \in S_r} \|\mathbf{\Delta}_{R_j}\|_2 + \lambda_c \sqrt{p} \sum_{k \in S_c} \|\mathbf{\Delta}_{C_k}\|_2 \right)^2 \\
&\leq 2.25 \min_{u,v} (|S_{ru}|, |S_{cv}|)^{-1} \min\{\lambda_r \sqrt{q}, \lambda_c \sqrt{p}\}^{-2} (\lambda_r \sqrt{q} |S_r| + \lambda_c \sqrt{p} |S_c|)^2 \|\mathbf{\Delta}_G\|_2^2.
\end{aligned}$$

The third inequality holds due to Lemma S3, and the fourth inequality holds due to Lemma S4. Combine with (S.4), we obtain that,

$$\|\mathbf{\Delta}\|_2^2 \leq 9\{2.25 \min_{u,v} (|S_{ru}|, |S_{cv}|)^{-1} \min\{\lambda_r \sqrt{q}, \lambda_c \sqrt{p}\}^{-2} (\lambda_r \sqrt{q} |S_r| + \lambda_c \sqrt{p} |S_c|)^2 + 1\}$$

$$\begin{aligned}
& \times \rho_-(s)^{-2} (\lambda_r \sqrt{q} |S_r| + \lambda_c \sqrt{p} |S_c|)^2 \\
\leq & 9 \{2.25 \min\{\lambda_r \sqrt{q}, \lambda_c \sqrt{p}\}^{-2} (\lambda_r \sqrt{q} |S_r| + \lambda_c \sqrt{p} |S_c|)^2 + 1\} \\
& \times \rho_-(s)^{-2} (\lambda_r \sqrt{q} g_r + \lambda_c \sqrt{p} g_c)^2.
\end{aligned}$$

This completes the proof of Theorem S1. \square

S.3 Proof of Theorem 2

PROOF: Let $\mathbf{a} = (\mathbf{a}_1^\top, \dots, \mathbf{a}_G^\top)^\top$ be a vector of G group centers with fewer than Gb_1 number of nonzero entries in probability. Define

$$W(\mathbf{a}, P_\Theta) = \int \min_{1 \leq g \leq G} \|\mathbf{v} - \mathbf{a}_g\|_2^2 dP_\Theta,$$

Then, by Lemma A of Pollard et al. (1982), we have that $W(\mathbf{a}, P_{\hat{\Theta}})$ and $W(\mathbf{a}, P_{\Theta_0})$ are both differentiable functions with respect to \mathbf{a} . Furthermore, $W_n(\mathbf{a}, \Theta) = \sum_{i=1}^n \{\min_{1 \leq g \leq G} \|\Theta \mathbf{Z}_i - \mathbf{a}_g\|_2^2\} / n$. Let $\tilde{\mathbf{a}}$ and \mathbf{a}_0 be the minimizer for $W(\mathbf{a}, P_{\hat{\Theta}})$, and $W(\mathbf{a}, P_{\Theta_0})$, respectively. By Lemma S7, we have that $\|\tilde{\mathbf{a}} - \mathbf{a}_0\|_2 = o_p(1)$. By the consistency of the K -means algorithm as shown in Pollard (1981), we have $\|\hat{\mathbf{a}} - \tilde{\mathbf{a}}\|_2 = o_p(1)$. Henceforth, $\|\hat{\mathbf{a}} - \mathbf{a}_0\|_2 = o_p(1)$.

Next, because $\hat{\mathbf{a}}$ is the minimizer for $W(\hat{\mathbf{a}}, P_{\hat{\Theta}, n})$, we have that,

$$\begin{aligned}
0 & \geq W_n(\hat{\mathbf{a}}, \hat{\Theta}) - W_n(\mathbf{a}_0, \hat{\Theta}) \\
& = W_n(\hat{\mathbf{a}}, \Theta_0) - W_n(\mathbf{a}_0, \Theta_0) + W_n(\hat{\mathbf{a}}, \hat{\Theta}) - W_n(\hat{\mathbf{a}}, \Theta_0) + W_n(\mathbf{a}_0, \hat{\Theta}) - W_n(\mathbf{a}_0, \Theta_0) \\
& = W_n(\hat{\mathbf{a}}, \Theta_0) - W_n(\mathbf{a}_0, \Theta_0) + W(\hat{\mathbf{a}}, P_{\hat{\Theta}}) - W(\hat{\mathbf{a}}, P_{\Theta_0}) + W(\mathbf{a}_0, P_{\hat{\Theta}}) - W(\mathbf{a}_0, P_{\Theta_0}) \\
& \quad + o_p(n^{-1/2}) \\
& = -n^{-1/2} \mathbf{Z}_n^\top (\hat{\mathbf{a}} - \mathbf{a}_0) + 1/2 (\hat{\mathbf{a}} - \mathbf{a}_0)^\top \frac{\partial^2 W(\mathbf{a}_0, P_{\Theta_0})}{\partial \mathbf{a} \mathbf{a}^\top} (\hat{\mathbf{a}} - \mathbf{a}_0) + O_p \left\{ b_1 \sqrt{\log(pq)/n} \right\} \\
& \quad + o_p(n^{-1/2}) \\
& \geq \|\hat{\mathbf{a}} - \mathbf{a}_0\|_2^2 D_{\min} - n^{-1/2} \mathbf{Z}_n^\top (\hat{\mathbf{a}} - \mathbf{a}_0) + O_p \left\{ b_1 \sqrt{\log(pq)/n} \right\},
\end{aligned}$$

where \mathbf{Z}_n is a random vector with at most $2Gb_1$ nonzero elements, and is asymptotically normally distributed (Gänssler and Stute, 1979), and $2D_{\min}$ is the smallest eigenvalue of the matrix $\partial^2 W(\mathbf{a}, P_\Theta) / \partial \mathbf{a} \mathbf{a}^\top |_{(\mathbf{a}, \Theta) = (\mathbf{a}_0, \Theta_0)}$. By Condition (B1) that $W(\mathbf{a}, P_{\Theta_0})$ is convex with a unique minimizer, i.e., $D_{\min} > 0$. The third line holds by the central limit theorem. The fourth line holds by Lemma S7 that both $W(\hat{\mathbf{a}}, P_{\hat{\Theta}} - P_{\Theta_0})$ and $W(\mathbf{a}_0, P_{\hat{\Theta}} - P_{\Theta_0})$ are of order $O_p \left\{ b_1 \sqrt{\log(pq)/n} \right\}$, and by Lemma D and Theorem of Pollard (1981).

Therefore, we obtain that,

$$\|\hat{\mathbf{a}} - \mathbf{a}_0\|_2^2 D_{\min} \leq n^{-1/2} \mathbf{Z}_n^\top (\hat{\mathbf{a}} - \mathbf{a}_0) + O_p \left\{ b_1 \sqrt{\log(pq)/n} \right\} \leq D_1 n^{-1/2} (Gb_1)^{1/2} \|\hat{\mathbf{a}} - \mathbf{a}_0\|_2$$

$$+O_p \left\{ b_1 \sqrt{\log(pq)/n} \right\},$$

for some constant D_1 , which implies that,

$$\{ \|\hat{\mathbf{a}} - \mathbf{a}_0\|_2 - D_1(4n)^{-1/2}(Gb_1)^{1/2} \}^2 \leq O_p \left\{ b_1 \sqrt{\log(pq)/n} \right\} + D_1^2(4n)^{-1}Gb_1.$$

Therefore,

$$\|\hat{\mathbf{a}} - \mathbf{a}_0\|_2 = O_p \left[\{b_1^2 \log(pq)/n\}^{1/4} + n^{-1/2}(Gb_1)^{1/2} \right].$$

This completes the proof of Theorem 2. □

References

- Gänssler, P. and Stute, W. (1979). Empirical processes: a survey of results for independent and identically distributed random variables. *The Annals of Probability*, pages 193–243.
- Huang, J. and Zhang, T. (2010). The benefit of group sparsity. *The Annals of Statistics*, 38(4):1978–2004.
- Loh, P.-L. and Wainwright, M. J. (2012). High-dimensional regression with noisy and missing data: provable guarantees with nonconvexity. *The Annals of Statistics*, 40(3):1637–1664.
- Pollard, D. (1981). Strong consistency of k-means clustering. *The Annals of Statistics*, pages 135–140.
- Pollard, D. et al. (1982). A central limit theorem for k -means clustering. *The Annals of Probability*, 10(4):919–926.
- Yin, P., Esser, E., and Xin, J. (2014). Ratio and difference of l_1 and l_2 norms and sparse representation with coherent dictionaries. *Communications in Information and Systems*, 14(2):87–109.