

# Supplementary Material for “Estimation of Functional Sparsity in Nonparametric Varying Coefficient Models for Longitudinal Data Analysis”

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This supplementary material includes technical assumptions and proofs of the theoretical properties of our proposed method. The technical assumptions are given in Section [A](#). The proofs of Theorems [1](#) and [2](#) are given in Section [B](#) and Section [C](#) respectively.

## Appendix: Technical assumptions and proofs

### A Technical assumptions

The following assumptions are made for Theorems [1](#) and [2](#) in Section [3](#). These are standard assumptions used to establish asymptotic properties of nonparametric estimation procedures for varying coefficient models; see Huang et al. [[2](#)] and Wang et al. [[4](#)] for more details.

**(A1)** The response and covariate processes  $\{y_k(t), \mathbf{x}_k(t), k = 1, \dots, n\}$  are iid as  $\{y(t), \mathbf{x}(t)\}$ .

And the observation time points,  $t_{kl}, l = 1, \dots, n_k, k = 1, \dots, n$ , are iid from an unknown

density,  $f(t)$ , on  $[0, M]$ , where  $f(t)$  is uniformly bounded away from zero and infinity. That is,  $0 < h_1 \leq f(t) \leq h_2 < \infty$  for some positive constants  $h_1$  and  $h_2$ . Moreover, the observation time points are independent of the response and covariate processes  $\{y_k(t), \mathbf{x}_k(t), k = 1, \dots, n\}$ .

**(A2)** The eigenvalues of the matrix  $E[\mathbf{x}(t)\mathbf{x}^T(t)]$  are uniformly bounded away from zero and infinity for  $t \in [0, M]$ , that is, there exist positive constants  $M_1$  and  $M_2$  to be the lower and upper bound of the eigenvalues for all  $t \in [0, M]$ .

**(A3)** There exists a positive constant  $M_3$  such that  $|x_i(t)| \leq M_3$  for  $t \in [0, M]$  and  $i = 1, \dots, p$ .

**(A4)** There exists a positive constant  $M_4$  such that  $E\{\epsilon^2(t)\} \leq M_4$  for all  $t \in [0, M]$

**(A5)**  $\limsup_n(\max_i K_i / \min_i K_i) < \infty$ .

**(A6)** The process  $\epsilon(t)$  can be decomposed as the sum of two independent stochastic processes,  $\epsilon^{(1)}$  and  $\epsilon^{(2)}$ , where  $\epsilon^{(1)}$  is an arbitrary mean zero process, and  $\epsilon^{(2)}$  is a process of measurement errors that are independent at different time points and have mean zero and finite constant variance  $\sigma^2$ .

## B Proof of Theorem 1

The following lemma from Lemma A.3 of Huang et al. [2] will be used in the proof.

**Lemma 1.** *Suppose that  $\lim_{n \rightarrow \infty} K_n \log K_n / n = 0$ . There are positive constants  $C_1$  and  $C_2$  such that, except on an event whose probability tends to zero, all eigenvalues of  $n^{-1}K_n \mathbf{U}^T \mathbf{U}$  fall between  $C_1$  and  $C_2$ , and consequently  $\mathbf{U}^T \mathbf{U}$  is invertible.*

*Proof of Theorem 1.* Note that

$$\|\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}\|_2 \leq \|\widetilde{\boldsymbol{\beta}}^0 - \boldsymbol{\beta}\|_2 + \|\widehat{\boldsymbol{\beta}} - \widetilde{\boldsymbol{\beta}}^0\|_2.$$

By B-spline property,  $\|\beta_i - \widetilde{\beta}_i\|_2 = O_p(K_n^{-2})$  where  $\widetilde{\beta}_i$  is an approximation in B-spline space as defined in (2.3). It can be shown that the same rate holds true if  $\widetilde{\beta}_i$  is replaced by its sparse approximation of  $\widetilde{\beta}_i^0$  (see Lemma 1 in Wang and Kai [3]). Thus,  $\|\widetilde{\boldsymbol{\beta}}^0 - \boldsymbol{\beta}\|_2 = O_p(K_n^{-2})$ .

For the second term, by (A5) and B-spline property, we have  $\|\widetilde{\beta}_i\|_2^2 \leq D_i \|\boldsymbol{\alpha}_i\|_2^2 / K_n$  for some positive constant  $D_i$ ,  $i = 1, \dots, p$  [1, 2]. Denote  $D_* = \max_i D_i$ , and we have

$$\|\widetilde{\boldsymbol{\beta}}^0 - \widehat{\boldsymbol{\beta}}\|_2^2 = \sum_{i=1}^p \|\widetilde{\beta}_i^0 - \widehat{\beta}_i\|_2^2 \leq \sum_{i=1}^p \frac{D_i}{K_n} \|\widetilde{\boldsymbol{\alpha}}_i^0 - \widehat{\boldsymbol{\alpha}}_i\|_2^2 \leq D_* \frac{\|\widehat{\boldsymbol{\alpha}} - \widetilde{\boldsymbol{\alpha}}^0\|_2^2}{K_n}$$

Therefore,

$$\|\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}\|_2^2 = O_p\left(K_n^{-4} + \frac{\|\widehat{\boldsymbol{\alpha}} - \widetilde{\boldsymbol{\alpha}}^0\|_2^2}{K_n}\right).$$

Below we concentrate on the term  $\|\widehat{\boldsymbol{\alpha}} - \widetilde{\boldsymbol{\alpha}}^0\|_2$  and in particular we show that  $\|\widehat{\boldsymbol{\alpha}} - \widetilde{\boldsymbol{\alpha}}^0\|_2 = O_p(n^{-1}K_n^2)$ .

By the minimality of  $\widehat{\boldsymbol{\alpha}}$ , we have  $\text{pl}(\widehat{\boldsymbol{\alpha}}) \leq \text{pl}(\widetilde{\boldsymbol{\alpha}}^0)$ ; that is,

$$\|\mathbf{y} - \mathbf{U}\widehat{\boldsymbol{\alpha}}\|_2^2 - \|\mathbf{y} - \mathbf{U}\widetilde{\boldsymbol{\alpha}}^0\|_2^2 \leq \lambda_n \sum_{i=1}^p \sum_{g=1}^{G_i} \|\widetilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^\gamma - \lambda_n \sum_{i=1}^p \sum_{g=1}^{G_i} \|\widehat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma. \quad (1)$$

Note that, the right hand side of (1) can be decomposed into two terms,  $\lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\widetilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^\gamma - \lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\widehat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma$  and  $\lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\widetilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^\gamma - \lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\widehat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma$ . For the first term, applying the inequality  $|b^\gamma - a^\gamma| \leq 2|b - a|b^{\gamma-1}$ , for  $a, b \geq 0$ , and Cauchy-Schwarz inequality yields that

$$\begin{aligned}
& \left| \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^\gamma - \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \right| \\
& \leq 2 \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \left| \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1 - \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1 \right| \cdot \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^{\gamma-1} \\
& \leq 2 \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0 - \hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1 \cdot \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^{\gamma-1} \\
& \leq 2(d+1)^{1/2} \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^{\gamma-1} \cdot \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0 - \hat{\boldsymbol{\alpha}}_{A_{ig}}\|_2 \\
& \leq 2(d+1)^{1/2} \left( \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^{2(\gamma-1)} \right)^{1/2} \left( \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0 - \hat{\boldsymbol{\alpha}}_{A_{ig}}\|_2^2 \right)^{1/2}.
\end{aligned}$$

For the second term, note that  $\|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1 = 0$  for  $g \in \mathcal{A}_{i2}$ . Thus, the second term is less than or equal to zero. Combining above results and (1), we have

$$\begin{aligned}
& \|\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}}\|_2^2 - \|\mathbf{y} - \mathbf{U}\tilde{\boldsymbol{\alpha}}^0\|_2^2 \\
& \leq \lambda_n \left| \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^\gamma - \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \right| + \lambda_n \left( \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^\gamma - \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_2^\gamma \right) \\
& \leq \lambda_n \left| \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^\gamma - \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \right| \\
& \leq 2\lambda_n \phi_n \left( \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0 - \hat{\boldsymbol{\alpha}}_{A_{ig}}\|_2^2 \right)^{1/2}
\end{aligned}$$

It follows that

$$\|\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}}\|_2^2 - \|\mathbf{y} - \mathbf{U}\tilde{\boldsymbol{\alpha}}^0\|_2^2 \leq 2\lambda_n \phi_n (d+1)^{1/2} \|\tilde{\boldsymbol{\alpha}}^0 - \hat{\boldsymbol{\alpha}}\|_2, \quad (2)$$

where  $\phi_n = (d+1)^{1/2} \left( \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0\|_1^{2(\gamma-1)} \right)^{1/2}$ .

On the other hand, straightforward calculation gives that

$$\begin{aligned}
\|\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}}\|_2^2 - \|\mathbf{y} - \mathbf{U}\tilde{\boldsymbol{\alpha}}^0\|_2^2 &= (\mathbf{U}\hat{\boldsymbol{\alpha}})^T \mathbf{U}\hat{\boldsymbol{\alpha}} - (\mathbf{U}\tilde{\boldsymbol{\alpha}}^0)^T \mathbf{U}\tilde{\boldsymbol{\alpha}}^0 - 2\mathbf{y}^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0) \\
&= (\mathbf{U}\hat{\boldsymbol{\alpha}} + \mathbf{U}\tilde{\boldsymbol{\alpha}}^0 - 2\mathbf{U}\tilde{\boldsymbol{\alpha}}^0 - 2\boldsymbol{\epsilon}_*)^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0) \\
&= \|\mathbf{U}(\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0)\|_2^2 - 2\boldsymbol{\epsilon}_*^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0) \\
&\geq \|\mathbf{U}(\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0)\|_2^2 - 2|\boldsymbol{\epsilon}_*^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0)|,
\end{aligned}$$

where  $\boldsymbol{\epsilon}_* = \boldsymbol{\epsilon} - \mathbf{e}$ ,  $\mathbf{e} = (\mathbf{e}_1^T, \dots, \mathbf{e}_n^T)^T$  with

$$\mathbf{e}_k = (\mathcal{U}_k(t_{k1})\tilde{\boldsymbol{\alpha}}^0 - \mathbf{x}_k(t_{k1})^T \boldsymbol{\beta}(t_{k1}), \dots, \mathcal{U}_k(t_{kn_k})\tilde{\boldsymbol{\alpha}}^0 - \mathbf{x}_k(t_{kn_k})^T \boldsymbol{\beta}(t_{kn_k}))^T.$$

Let  $\delta_n = \|\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0\|_2$ , then by Lemma 1,  $\|\mathbf{U}(\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0)\|_2^2 \geq C_1 n K_n^{-1} \delta_n^2$  with probability approaching 1. In addition, applying Cauchy-Schwarz inequality yields that  $(\boldsymbol{\epsilon}_*^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0))^2 \leq \delta_n^2 (\boldsymbol{\epsilon}_*^T \mathbf{U} \mathbf{U}^T \boldsymbol{\epsilon}_*)$ . Further,  $E(\boldsymbol{\epsilon}_*^T \mathbf{U} \mathbf{U}^T \boldsymbol{\epsilon}_*) = E(\boldsymbol{\epsilon}^T \mathbf{U} \mathbf{U}^T \boldsymbol{\epsilon}) + E(\mathbf{e}^T \mathbf{U} \mathbf{U}^T \mathbf{e})$ . As a consequence of Lemma A.3 of [4], we have  $E(\boldsymbol{\epsilon}^T \mathbf{U} \mathbf{U}^T \boldsymbol{\epsilon}) = O(n)$  with  $n_k$  uniformly bounded. Similarly, we have  $E(\mathbf{e}^T \mathbf{U} \mathbf{U}^T \mathbf{e}) = O(n)$  since  $E(e(t_{kl})e(t_{kl}')) \leq C \|\boldsymbol{\beta} - \tilde{\boldsymbol{\beta}}^0\|_\infty^2$  for some constant  $C$  and  $\|\boldsymbol{\beta} - \tilde{\boldsymbol{\beta}}^0\|_\infty$  is bounded by  $O(K_n^{-2})$ . Therefore,  $E(\boldsymbol{\epsilon}_*^T \mathbf{U} \mathbf{U}^T \boldsymbol{\epsilon}_*) = O(n)$ . Thus, we have

$$\|\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}}\|_2^2 - \|\mathbf{y} - \mathbf{U}\tilde{\boldsymbol{\alpha}}^0\|_2^2 \geq C_1 n K_n^{-1} \delta_n^2 - \delta_n O_p(n^{1/2}). \quad (3)$$

Combining (2) and (3), we have

$$\frac{nC_1}{K_n} \delta_n^2 - \delta_n O_p(n^{1/2}) \leq 2\lambda_n \phi_n (d+1)^{1/2} \delta_n,$$

and by (S1) we have  $\|\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0\|_2^2 = O_p(n^{-1} K_n^2)$ .

□

## C Proof of Theorem 2

*Proof.* First, for any  $i$ , define  $\hat{\alpha}_{ij}^*$  in the following way. Let  $\hat{\alpha}_{ij}^* = 0$  if  $\{j-d, \dots, j\} \cap \mathcal{A}_{i2} \neq \emptyset$ , otherwise,  $\hat{\alpha}_{ij}^* = \hat{\alpha}_{ij}$ . Note that  $\hat{\alpha}_{A_{ig}}^* = \mathbf{0}$  for  $g \in \mathcal{A}_{i2}$ .

By Karush-Kuhn-Tucker conditions, for  $\hat{\alpha}_{ij} \neq 0$  we have

$$2(\mathbf{y} - \mathbf{U}\hat{\alpha})^T U_{(ij)} = \sum_{g=j-d}^j \gamma \lambda_n \|\hat{\alpha}_{A_{ig}}\|_1^{\gamma-1} \text{sgn}(\hat{\alpha}_{ij}),$$

where  $U_{(ij)}$  is the column of  $\mathbf{U}$  corresponding to  $\hat{\alpha}_{ij}$ . Multiplying both sides by  $(\hat{\alpha}_{ij} - \hat{\alpha}_{ij}^*)$  yields

$$\begin{aligned} 2(\mathbf{y} - \mathbf{U}\hat{\alpha})^T \mathbf{U}(\hat{\alpha} - \hat{\alpha}^*) &= \sum_{i,j} \sum_{g=j-d}^j \gamma \lambda_n \|\hat{\alpha}_{A_{ig}}\|_1^{\gamma-1} \text{sgn}(\hat{\alpha}_{ij})(\hat{\alpha}_{ij} - \hat{\alpha}_{ij}^*) \\ &= \gamma \lambda_n \sum_{i,j} \sum_{g \in \mathcal{A}_{i2} \cap \{j-d, \dots, j\}} \|\hat{\alpha}_{A_{ig}}\|_1^{\gamma-1} |\hat{\alpha}_{ij}| \cdot \\ &= \gamma \lambda_n \sum_{i=1}^p \sum_{g=1}^{G_i} \|\hat{\alpha}_{A_{ig}}\|_1^{\gamma-1} (\|\hat{\alpha}_{A_{ig}}\|_1 - \|\hat{\alpha}_{A_{ig}}^*\|_1). \end{aligned}$$

Note that,  $(\hat{\alpha}_{ij} - \hat{\alpha}_{ij}^*) \text{sgn}(\hat{\alpha}_{ij}) = |\hat{\alpha}_{ij}|$  if  $\{j-d, \dots, j\} \cap \mathcal{A}_{i2} \neq \emptyset$ .

Since  $\gamma b^{\gamma-1}(b-a) \leq b^\gamma - a^\gamma$  for  $0 \leq a \leq b$ , we have, for  $g \in \mathcal{A}_{i1}$ ,

$$\gamma \|\hat{\alpha}_{A_{ig}}\|_1^{\gamma-1} (\|\hat{\alpha}_{A_{ig}}\|_1 - \|\hat{\alpha}_{A_{ig}}^*\|_1) \leq \|\hat{\alpha}_{A_{ig}}\|_1^\gamma - \|\hat{\alpha}_{A_{ig}}^*\|_1^\gamma.$$

Consequently, we have

$$2 |(\mathbf{y} - \mathbf{U}\hat{\alpha})^T \mathbf{U}(\hat{\alpha} - \hat{\alpha}^*)| \leq \lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} (\|\hat{\alpha}_{A_{ig}}\|_1^\gamma - \|\hat{\alpha}_{A_{ig}}^*\|_1^\gamma) + \gamma \lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\alpha}_{A_{ig}}\|_1^\gamma. \quad (4)$$

By the minimality of  $\hat{\alpha}$ , we have

$$\lambda_n \sum_{i=1}^p \sum_{g=1}^{G_i} \|\hat{\alpha}_{A_{ig}}\|_1^\gamma - \lambda_n \sum_{i=1}^p \sum_{g=1}^{G_i} \|\hat{\alpha}_{A_{ig}}^*\|_1^\gamma \leq \|\mathbf{y} - \mathbf{U}\hat{\alpha}^*\|_2^2 - \|\mathbf{y} - \mathbf{U}\hat{\alpha}\|_2^2.$$

Note that  $\|\hat{\alpha}_{A_{ig}}^*\|_1 = 0$  for  $g \in \mathcal{A}_{i2}$ . Thus, we have  $\sum_{i=1}^p \sum_{g=1}^{G_i} \|\hat{\alpha}_{A_{ig}}^*\|_1^\gamma = \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\hat{\alpha}_{A_{ig}}^*\|_1^\gamma$ ,

and

$$\begin{aligned}
& 2|(\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}})^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \hat{\boldsymbol{\alpha}}^*)| + (1 - \gamma)\lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \\
& \leq \lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} (\|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma - \|\hat{\boldsymbol{\alpha}}_{A_{ig}}^*\|_1^\gamma) + \lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \\
& = \lambda_n \sum_{i=1}^p \sum_{g=1}^{G_i} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma - \lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i1}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}^*\|_1^\gamma \\
& \leq \|\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}}^*\|_2^2 - \|\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}}\|_2^2 \\
& = \|\mathbf{U}(\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}})\|_2^2 + 2(\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}})^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \hat{\boldsymbol{\alpha}}^*).
\end{aligned}$$

By Lemma 1 we have

$$\begin{aligned}
& (1 - \gamma)\lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \\
& \leq \|\mathbf{U}(\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}})\|_2^2 + 2(\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}})^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \hat{\boldsymbol{\alpha}}^*) - 2|(\mathbf{y} - \mathbf{U}\hat{\boldsymbol{\alpha}})^T \mathbf{U}(\hat{\boldsymbol{\alpha}} - \hat{\boldsymbol{\alpha}}^*)| \\
& \leq \|\mathbf{U}(\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}})\|_2^2 \\
& \leq \frac{nC_2}{K_n} \|\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}}\|_2^2
\end{aligned}$$

Note that  $\tilde{\boldsymbol{\alpha}}_{A_{ig}}^0 = \mathbf{0}$  for  $g \in \mathcal{A}_{i2}$ . Thus, we have  $\|\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}}\|_2^2 \leq \|\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0\|_2^2$ , and

$$(1 - \gamma)\lambda_n \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \leq \frac{nC_2}{K_n} \|\hat{\boldsymbol{\alpha}} - \tilde{\boldsymbol{\alpha}}^0\|_2^2 = O_p(K_n)$$

Since

$$\sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \geq \left( \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1 \right)^\gamma \geq \|\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}}\|_2^\gamma,$$

then if  $\|\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}}\|_2 > 0$ , we have

$$\begin{aligned}
(1 - \gamma)\lambda_n & \leq \frac{nC_2}{K_n} \|\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}}\|_2^2 \left\{ \sum_{i=1}^p \sum_{g \in \mathcal{A}_{i2}} \|\hat{\boldsymbol{\alpha}}_{A_{ig}}\|_1^\gamma \right\}^{-1} \\
& \leq \frac{nC_2}{K_n} \|\hat{\boldsymbol{\alpha}}^* - \hat{\boldsymbol{\alpha}}\|_2^{2-\gamma} \\
& \leq O_p(n^{\gamma/2} K_n^{1-\gamma}),
\end{aligned}$$

and thus

$$\Pr \{ \|\widehat{\boldsymbol{\alpha}}^* - \widehat{\boldsymbol{\alpha}}\|_2^2 > 0 \} \leq \Pr \left\{ \frac{\lambda_n}{n^{\gamma/2} K_n^{1-\gamma}} \leq O_p(1) \right\}.$$

By assumption (S2), the right hand side converges to zero as  $n$  goes to infinity, which implies that  $(\widehat{\boldsymbol{\alpha}}_{A_{ig}} : g \in \mathcal{A}_{i2}) = \mathbf{0}$  with probability approaching to one.  $\square$

## References

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