Supplements for "Generalized tensor-response model with multi-sided covariates"

1 Proofs

Theorem 1.1. Consider a generalized tensor regression model with multi-sided covariates $\mathcal{X} = \{X_1, \ldots, X_K\}$. Suppose the entries in \mathcal{Y} are independent realizations of an exponential family distribution, and $\mathbb{E}(\mathcal{Y}|\mathcal{X})$ follows the low-rank tensor regression model (5). Under Assumption 1, there exist two absolute constants $C_1, C_2 > 0$, such that, with probability at least $1 - \exp(-C_1 \sum_k p_k)$,

$$Loss(\mathcal{B}_{true}, \ \hat{\mathcal{B}}) \le C_3 \sum_k p_k,$$

where $C_3 = C_3(\mathbf{r}) = \frac{1}{C_2^{2K}U} \frac{\prod_k r_k}{\max_k r_k} > 0$ is a constant that does not depend on the dimensions $\{d_k\}$ and $\{p_k\}$.

Proof of Theorem 1. Let $\ell(\mathcal{B}) = \mathbb{E}(\mathcal{L}_{\mathcal{Y}}(\mathcal{B}))$, where the expectation is take with respect to $\mathcal{Y} \sim \mathcal{B}_{\text{true}}$ under the true parameter. We show that

- C1. The stochastic deviation $\mathcal{L}_{\mathcal{Y}}(\mathcal{B}) \ell(\mathcal{B})$ is uniformly small for all $\mathcal{B} \in \mathcal{P}$,
- C2. There exist two positive constants $c_1, c_2 > 0$ such that

$$c_1 \|\hat{\mathcal{B}} - \mathcal{B}_{\text{true}}\|_F^2 \le \ell(\hat{\mathcal{B}}) - \ell(\mathcal{B}_{\text{true}}) \le c_2 \|\hat{\mathcal{B}} - \mathcal{B}_{\text{true}}\|_F^2.$$

To prove C1, note that

$$\mathcal{L}_{\mathcal{Y}}(\mathcal{B}) - \ell(\mathcal{B}) = \langle \mathcal{Y} - \mathbb{E}(\mathcal{Y}|\mathcal{X}), \ \Theta(\mathcal{B}) \rangle$$

$$= \langle \mathcal{Y} - b'(\Theta_{\text{true}}), \ \Theta \rangle$$

$$= \langle \mathcal{E} \times_1 \mathbf{X}_1^T \times_2 \cdots \times_K \mathbf{X}_K^T, \ \mathcal{B} \rangle,$$

where $\mathcal{E} = \llbracket \varepsilon_{i_1,\dots,i_K} \rrbracket \stackrel{\text{def}}{=} \mathcal{Y} - b'(\Theta_{\text{true}})$. Based on Assumption A1, \mathcal{E} is a sub-Gaussian tensor with parameter bounded by $C_1 = \phi U$. Therefore, $\check{\mathcal{E}} \stackrel{\text{def}}{=} \mathcal{E} \times_1 \boldsymbol{X}_1^T \times_2 \dots \times_K \boldsymbol{X}_K^T$ is a (p_1,\dots,p_K) -dimensional sub-Gaussian with parameter bounded by $C_2 = \phi U c_2^{2K}$. By Cauchy-Schwarz inequality,

$$|\mathcal{L}_{\mathcal{Y}}(\mathcal{B}) - \ell(\mathcal{B})| \le ||\check{\mathcal{E}}||_2 ||\mathcal{B}||_*$$
.

where $\|\cdot\|_2$ denotes the tensor spectral norm and $\|\cdot\|_*$ denotes the tensor nuclear norm.

We have that $\|\mathcal{B}\|_* \leq \frac{\prod_k r_k}{\max_k r_k} \|\mathcal{B}\|_F$ by [1, 2]. Moreover, the Gaussian tensor theory [3] shows that $\|\check{\mathcal{E}}\|_2 \leq C_1 \sum_k p_k$ with probability at least $1 - \exp(-C_2 \sum_k p_k)$

To prove C2, we note that

$$\ell(\mathcal{B}) = \ell(\mathcal{B}_{\text{true}}) - \frac{1}{2} \text{vec}(\mathcal{B} - \mathcal{B}_{\text{true}})^T \mathbb{E}(\mathcal{H}_{\mathcal{Y}}(\check{\mathcal{B}})) \text{vec}(\mathcal{B} - \mathcal{B}_{\text{true}}), \tag{1}$$

where $\mathcal{H}_{\mathcal{Y}}(\check{\mathcal{B}})$ is the Hession of $\frac{\partial \ell^2(\mathcal{B})}{\partial^2 \mathcal{B}}$ evaluated at $\check{\mathcal{B}} = \alpha \text{vec}(\alpha \mathcal{B} + (1 - \alpha) \mathcal{B}_{\text{true}})$ for some $\alpha \in [0, 1]$. Recall that $b''(\theta) = \text{Var}(y|\theta)$ if $y \in \mathbb{R}$ follows the exponential family distribution with function $b(\cdot)$. Therefore, the equation (1) can be written as

$$\ell(\mathcal{B}) - \ell(\mathcal{B}_{\text{true}}) = -\frac{1}{2} \sum_{i_1, \dots, i_K} b''(\check{\theta}_{i_1, \dots, i_K}) (\theta_{i_1, \dots, i_K} - \theta_{\text{true}, i_1, \dots, i_K})^2 \le -\frac{L}{2} \|\Theta - \Theta_{\text{true}}\|_F^2,$$

holds for all $\mathcal{B} \in \mathcal{P}$, provided that $\min_{|\theta| < \alpha} |b''(\theta)| \ge L > 0$.

Now we consider the constrained MLE $\hat{\mathcal{B}}$. By definition, $\mathcal{L}_{\mathcal{Y}}(\hat{\mathcal{B}}) - \mathcal{L}_{\mathcal{Y}}(\mathcal{B}_{\text{true}}) \geq 0$. This implies that

$$\begin{split} &0 \leq \mathcal{L}_{\mathcal{Y}}(\hat{\mathcal{B}}) - \mathcal{L}_{\mathcal{Y}}(\mathcal{B}_{\text{true}}) \\ &\leq \left(\mathcal{L}_{\mathcal{Y}}(\hat{\mathcal{B}}) - \ell(\hat{\mathcal{B}})\right) - \left(\mathcal{L}_{\mathcal{Y}}(\mathcal{B}_{\text{true}}) - \ell(\mathcal{B}_{\text{true}})\right) + \left(\ell(\hat{\mathcal{B}}) - \ell(\mathcal{B}_{\text{true}})\right) \\ &\leq 2 \sup_{\mathcal{B} \in \mathcal{P}} |\mathcal{Y}| - \frac{L}{2} \|\hat{\Theta} - \Theta_{\text{true}}\|_F^2 \\ &\leq 2 \sup_{\mathcal{B}} |\mathcal{L}_{\mathcal{Y}}(\mathcal{B}) - \ell(\mathcal{B})| - \frac{L}{2} \|\hat{\Theta} - \Theta_{\text{true}}\|_F^2 \end{split}$$

Therefore, the statement

$$\|\hat{\Theta} - \Theta_{\text{true}}\|_{F} \leq \frac{2}{L} \langle \mathcal{E}, \frac{\hat{\Theta} - \Theta_{\text{true}}}{\|\hat{\Theta} - \Theta_{\text{true}}\|_{F}} \rangle$$

$$\leq \frac{2}{L} \sup_{\Theta: \|\Theta\|_{F} = 1, \Theta = \mathcal{B} \times_{1} \mathbf{X}_{1} \times_{2} \cdots \times_{K} \mathbf{X}_{K}} \langle \mathcal{E}, \Theta \rangle$$

$$\leq \frac{2}{L} \sup_{\mathcal{B} \in \mathcal{P}: \|\mathcal{B}\|_{F} \leq \prod_{k} \sigma_{\min}^{-1}(\mathbf{X}_{k})} \langle \mathcal{E} \times_{1} \mathbf{X}_{1}^{T} \times_{2} \cdots \times_{K} \mathbf{X}_{K}^{T}, \mathcal{B} \rangle.$$

$$(2)$$

Combining (2) with C1 yields the final conclusion.

2 Real data analysis

- 1. commonbloc0, blockpositionindex
- 2. officialvisits, violentactions, militaryactions, duration, negative behavior, boycottembargo, aidenemy, negative comm, accusation" "protests" "unoffialacts" [13] "nonviolent behavior" "emigrants" "relexports" [16] "times incewar" "common bloc2" "intergovorgs3" "relintergovorgs" "intergovorgs"
- 3. economicaid" "releconomicaid" "conferences" [4] "booktranslations" "relbooktranslations" "severdiplomatic" [7] "expeldiplomats" "attackembassy" "unweightedunvote" [10] "tourism" "reltourism" "tourism3" [13] "relemigrants" "emigrants3" "students" [16] "relstudents" "exports" "exports3" [19] "lostterritory" "dependent" "militaryalliance" "warning"
- 1 "treaties" "reltreaties" "exportbooks" "relexportbooks" [5] "weightedunvote" "ngo" "relngo" "ngoorgs3" "embassy" [13] "reldiplomacy" "timesinceally" "independence" "commonbloc1"

References

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[3] Ryota Tomioka and Taiji Suzuki. Spectral norm of random tensors. $arXiv\ preprint\ arXiv:1407.1870,\ 2014.$