
Generalized tensor response regression with multi-sided covariates

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Abstract

We consider the problem of learning higher-order tensors with side information on a set of modes. Such data problems arise frequently in applications such as neuroimaging, network analysis, and ... We propose a new family of tensor response regression models that incorporate covariate information, and obtain the theoretical accuracy guarantees. An efficient alternating updating algorithm is further developed. Our proposal handles a broad range of applications, including modeling brain connection in populations, link prediction in networks, and spatial-temporal growth model. The efficacy of our method is demonstrated through both simulations and analyses of two real-world datasets.

1 Introduction

Many contemporary scientific and engineering studies collect multi-way array data, a.k.a. tensor, accompanied by additional covariates. For example, in neuro-imaging analysis, researchers measure brain connections from a sample of individuals with the goal to identify the brain edges affected by age and gender. In social network analysis, how to explain the connection (e.g. community, transitive, etc.) by attributable of both nodes. ... see demonstration plot.

In this article, we provide a general treatment to these seemingly different problems.

Comparison with other models

Our model is related to, but fundamentally different from, several lines of existing work.

Unsupervised tensor. supervised learning.

Tensor-predictor regression multilinear in coefficients.

Tensor-response regression multilinear in coefficient vs. multilinear in covariates.

Generalized linear model. In the high-dimensions both p and n increase while $p \leq d$. This is the case we consider. Classical GLM fixes p . Compared to Gaussian model, the log-likelihood is not strictly convex in the linear predictor. We allow various types of dependent variable.

2 Preliminaries

We begin by reviewing a few basic factors about tensors [?]. We use $\mathcal{Y} = \llbracket y_{i_1, \dots, i_K} \rrbracket \in \mathbb{R}^{d_1 \times \dots \times d_K}$ to denote an order- K (d_1, \dots, d_K)-dimensional tensor. The multilinear multiplication of a tensor $\mathcal{Y} \in \mathbb{R}^{d_1 \times \dots \times d_K}$ by matrices $\mathbf{M}_k = \llbracket m_{i_k, j_k}^{(k)} \rrbracket \in \mathbb{R}^{s_k \times d_k}$ is defined as

$$\mathcal{Y} \times_1 \mathbf{M}_1 \dots \times_K \mathbf{M}_K = \llbracket \sum_{i_1, \dots, i_K} y_{i_1, \dots, i_K} m_{i_1, j_1}^{(1)} \dots m_{i_K, j_K}^{(K)} \rrbracket,$$

which results in an order- K tensor (s_1, \dots, s_K)-dimensional tensor. For ease of notation, we also write the above Tucker product $\mathcal{Y} \times \{\mathbf{M}_1, \dots, \mathbf{M}_K\}$ for short. For any two tensors $\mathcal{Y} = \llbracket y_{i_1, \dots, i_K} \rrbracket$, $\mathcal{Y}' = \llbracket y'_{i_1, \dots, i_K} \rrbracket$ of identical order and dimensions, their inner product is defined as $\langle \mathcal{Y}, \mathcal{Y}' \rangle = \sum_{i_1, \dots, i_K} y_{i_1, \dots, i_K} y'_{i_1, \dots, i_K}$. The Frobenius norm of tensor \mathcal{Y} is defined as $\|\mathcal{Y}\|_F = \langle \mathcal{Y}, \mathcal{Y} \rangle^{1/2}$; it is the Euclidean norm of \mathcal{Y} regarded as an $\prod_k d_k$ -dimensional vector. We use lower-case letters (a, b, c, \dots) for scalars and vectors, upper-case bold-face letters ($\mathbf{A}, \mathbf{B}, \mathbf{C}, \dots$) for matrices, and calligraphy letter ($\mathcal{A}, \mathcal{B}, \mathcal{C}, \dots$) for tensors of order 3 or greater.

3 Motivation and model

Let $\mathcal{Y} = \llbracket y_{i_1, \dots, i_K} \rrbracket \in \mathbb{R}^{d_1 \times \dots \times d_K}$ denote an order- K data tensor of interest. In addition, suppose we observe covariates on a subset of modes. Let $\mathbf{X}_k \in \mathbb{R}^{d_k \times p_k}$ be the available covariates on the mode- k , where $p_k \leq d_k$. We propose the following multilinear structure in the mean of the tensor. Specifically,

$$\begin{aligned} \mathbb{E}(\mathcal{Y} | \mathbf{X}_1, \dots, \mathbf{X}_K) &= f(\Theta), \text{ where} \\ \Theta &= \mathcal{B} \times \{\mathbf{X}_1, \dots, \mathbf{X}_K\}, \end{aligned} \quad (1)$$

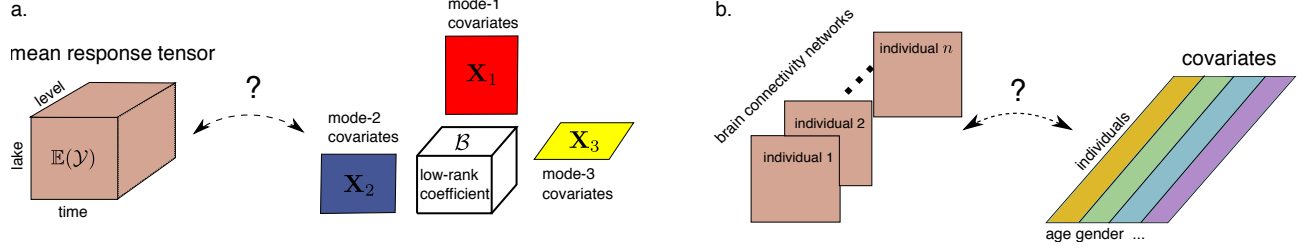


Figure 1: Examples of tensor regression with multi-sided covariates. (a) Spatio-temporal growth model. (b) Network population model.

where $f(\cdot)$ is a known link function, $\Theta \in \mathbb{R}^{d_1 \times \dots \times d_K}$ is called the linear predictor tensor, $\mathcal{B} \in \mathbb{R}^{p_1 \times \dots \times p_K}$ is the parameter tensor of interest, and \times denotes the tensor Tucker product. The link function depends on the distribution family of the response. Some common choices are identity link for Gaussian tensor, logistic link for binary tensor, and log link for Poisson tensor. We give three examples of multi-covariates tensor regression model that arises in practice.

Example 1 (Spatio-temporal growth model). Let $\mathcal{Y} = \llbracket y_{ijk} \rrbracket \in \mathbb{R}^{d \times m \times n}$ denote the pH measurements of d lakes at m levels of depth and for n time points. Suppose the sampled lakes belong to q types, with p lakes in each type. Let $\{\ell_j\}_{j \in [m]}$ denote the sampled depth levels and $\{t_k\}_{k \in [n]}$ the time points. Assume the expected pH trend in depth is a polynomial of order r and that the expected trend in time is a polynomial of order s . Then, a classical spatio-temporal growth model can be represented as

$$\mathbb{E}(\mathcal{Y}|\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3) = \mathcal{B} \times \{\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3\},$$

where $\mathcal{B} \in \mathbb{R}^{p \times (r+1) \times (s+1)}$ is the coefficient tensor of interest, $\mathbf{X}_1 = \text{blockdiag}\{\mathbf{1}_p, \dots, \mathbf{1}_p\} \in \{0, 1\}^{d \times p}$ is the design matrix for lake types,

$$\mathbf{X}_2 = \begin{pmatrix} 1 & \ell_1 & \dots & \ell_1^r \\ 1 & \ell_2 & \dots & \ell_2^r \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \ell_m & \dots & \ell_m^r \end{pmatrix}, \quad \mathbf{X}_3 = \begin{pmatrix} 1 & t_1 & \dots & t_1^s \\ 1 & t_2 & \dots & t_2^s \\ \vdots & \vdots & \ddots & \vdots \\ 1 & t_n & \dots & t_n^s \end{pmatrix}$$

are the design matrices for spatial and temporal effects, respectively.

Example 2 (Network population model). Network response model is recently developed in the context of neuroimaging analysis. The goal is to study the relationship between the network-valued response with the individual covariates. Suppose we observe n i.i.d. observations $\{(\mathbf{Y}_i, \mathbf{x}_i) : i = 1, \dots, n\}$, where $\mathbf{Y}_i \in \{0, 1\}^{d \times n}$ is the brain connectivity network on the i -th individual and $\mathbf{x}_i \in \mathbb{R}^p$ is the subject covariate such as age, gender. The network-response model has the form

$$\text{logit}(\mathbb{E}(\mathbf{Y}_i|\mathbf{x}_i)) = \mathcal{B} \times_3 \mathbf{x}_i, \quad \text{for } i = 1, \dots, n \quad (2)$$

where $\mathcal{B} \in \mathbb{R}^{d \times d \times p}$ is the coefficient tensor of interest. In fact, the model (2) is a special case of our multilinear tensor-response model. To see this, let $\mathcal{Y} \in \{0, 1\}^{d \times d \times n}$ denote the response tensor by stacking $\{\mathbf{Y}_i\}$ together along the 3rd mode and $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_n] \in \mathbb{R}^{p \times n}$, then model (2) can be expressed as

$$\text{logit}(\mathbb{E}(\mathcal{Y}|\mathbf{X})) = \mathcal{B} \times_3 \mathbf{X} = \mathcal{B} \times \{\mathbf{I}_d, \mathbf{I}_d, \mathbf{X}\},$$

where \mathbf{I}_d denotes the identity matrix of dimension d .

Example 3 (Link model with node attributes). Let $V = [n]$ be a set of vertices and explanatory variable $\mathbf{x}_i \in \mathbb{R}^p$ associated to each $i \in V$. The network $G = (V, E)$ is described by the following matrix model. The edge connects the two vertices i and j independently of the others. The probability of connection is modeled as

$$\text{logit}(\mathbb{P}((i, j) \in E)) = \mathbf{x}_i^T \mathcal{B} \mathbf{x}_j = \langle \mathcal{B}, \mathbf{x}_i^T \mathbf{x}_j \rangle.$$

Again, we show that this model is a special case of our tensor regression model. Let $\mathcal{Y} = \llbracket y_{ij} \rrbracket$ where $y_{ij} = \mathbb{1}_{(i, j) \in E}$. Define $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_n] \in \mathbb{R}^{p \times n}$. Then the above model can be expressed as

$$\text{logit}(\mathbb{E}(\mathcal{Y}|\mathbf{X})) = \mathcal{B} \times \{\mathbf{X}, \mathbf{X}\}.$$

In the above three example and many other studies, researchers are interested in uncovering the variation in the data tensor that are explained by the covariates.

Without any structure on the coefficient tensor \mathcal{B} : A naive approach is to regress the tensor entry, one at a time, on the covariates, and this model is repeatedly fitted for each tensor element. Though this approach is scalable, it suffers from two drawbacks: (1) ignore the multilinear structure in the tensor (?) and (2) suffers from the multiplicity issue. To allow the structure among ..we further impose a multilinear low-rank structure on the coefficient tensor \mathcal{B}

$$\mathcal{P} = \{\mathcal{B} \in \mathbb{R}^{p_1 \times \dots \times p_K} : r_k(\mathcal{B}) \leq r_k \text{ for } k \in [K]\}, \quad (3)$$

where $r_k(\mathcal{B})$ is the Tucker rank of the tensor at mode k . We assume that r_k is known and $r_k \leq p_k$. Other

low-rankness such as CP rank is also possible. We choose the Tucker decomposition due to the following observation.

The low-rank structure in (3) implies that the coefficient tensor can be expressed as $\mathcal{B} = \mathcal{C} \times_1 \mathbf{M}_1 \times \dots \times \mathbf{M}_K$. Then, our tensor regression model (4) is equivalent to

$$f(\mathbb{E}(\mathcal{Y}|\mathbf{X}_1, \dots, \mathbf{X}_K)) = \mathcal{C} \times \{\mathbf{X}_1 \mathbf{M}_1, \dots, \mathbf{X}_K \mathbf{M}_K\}.$$

The goal is to find a joint dimension reduction of \mathcal{Y} and \mathbf{X}_K such that the unexplained variation in the mean tensor. The factorization is restricted to the space spanned by \mathbf{X}_k . Here $\mathbf{X}_1 \mathbf{M}_1$ can be interpreted as the latent covariates that explains the variation in the response tensor. The core tensor \mathcal{C} collects the interaction effects of latent covariates across the K modes.

(Question: the columns of \mathbf{X} should be normalized??)

Question: any connection to tensor completion?? If \mathbf{X}_K is a random design matrix?

4 Rank-constrained likelihood-based estimation

Note that our tensor regression model is able to incorporate covariates on some or all modes, whenever available. Without loss of generality, we denote by $\mathcal{X} = \{\mathbf{X}_1, \dots, \mathbf{X}_K\}$ the covariates in all modes and treat $\mathbf{X}_k = \mathbf{I}_{d_k}$ when the mode- k has no (informative) covariate. Our general tensor regression model can be written as

$$\mathbb{E}(\mathcal{Y}|\mathcal{X}) = f(\Theta), \quad \Theta = \mathcal{B} \times \{\mathbf{X}_1, \dots, \mathbf{X}_K\}, \quad (4)$$

where $\text{rank}(\mathcal{B}) = (r_1, \dots, r_K)$,

where $\mathcal{B} \in \mathbb{R}^{p_1 \times \dots \times p_K}$ is a low-rank coefficient tensor of interest. In the following theoretical analysis, we assume the Tucker rank $\mathbf{r} = (r_1, \dots, r_K)$ is known. The adaptation of unknown \mathbf{r} will be addressed in Section 5.2.

We develop a likelihood-based procedure to estimate \mathcal{B} . The exponential family is a flexible framework for different data types. In a classical glm with a scalar response y and covariate \mathbf{x} , the density is

$$p(y|\mathbf{x}, \boldsymbol{\beta}) = c(y) \exp\left(\frac{y\theta - b(\theta)}{\phi}\right) \text{ with } \theta = \boldsymbol{\beta}^T \mathbf{x},$$

where $c(\cdot)$ and $b(\cdot)$ are known functions and θ is the linear predictor. Note that the canonical link function f is chosen to be $f(\cdot) = b'(\cdot)$. Table 1 summarizes the canonical link function for common distributions.

In our context, the log-likelihood of (4) is the (?) divergence between the conditional distribution of $\mathcal{Y}|\Theta$

and the exponential family

$$\mathcal{L}_{\mathcal{Y}}(\mathcal{B}) = \langle \mathcal{Y}, \Theta \rangle - \sum_{i_1, \dots, i_K} b(\theta_{i_1, \dots, i_K}),$$

$$\text{where } \Theta = \mathcal{B} \times \{\mathbf{X}_1, \dots, \mathbf{X}_K\}.$$

Assume that we have an additional information on an upper bound $a > 0$ such that $\|\Theta\|_{\infty} \leq \alpha$. (more comments? ill-condition in the bernoulli model?) We propose the following constrained maximum likelihood estimation for the tensor coefficient

$$\hat{\mathcal{B}} = \arg \max_{\text{rank}(\mathcal{B})=\mathbf{r}, \|\Theta(\mathcal{B})\|_{\infty} \leq \alpha} \mathcal{L}_{\mathcal{Y}}(\mathcal{B}).$$

4.1 Statistical properties

We assess the estimation accuracy using the deviation in the Frobenius norm. For the true coefficient tensor $\mathcal{B}_{\text{true}}$ and its estimator $\hat{\mathcal{B}}$, define

$$\text{Loss}(\mathcal{B}_{\text{true}}, \hat{\mathcal{B}}) = \frac{1}{\prod_k p_k} \|\mathcal{B}_{\text{true}} - \hat{\mathcal{B}}\|_F^2.$$

We focus on the high-dimensional region in which both $d_k \rightarrow \infty$ and $p_k \rightarrow \infty$ while $\frac{p_k}{d_k} \rightarrow \gamma_k \in [0, 1]$.

Assumption 1. We make the following assumptions:

1. There exists two positive constants $c_1, c_2 > 0$ such that $c_1 \leq \sigma_{\min}(\mathbf{X}_k) \leq \sigma_{\max}(\mathbf{X}_k) \leq c_2$ for all $k \in [K]$.
2. There exist two positive constants $L, U > 0$ such that $L \leq \text{Var}(y_{i_1, \dots, i_K}|\mathcal{X}) \leq U$ uniformly over the parameter space \mathcal{P} .
- 2'. Equivalently, $L \leq b''(x) \leq U$ for all $x \leq \alpha$, where $b(\cdot)$ is the known function in the exponential family distribution and α is the upper bound of the linear predictor.

Theorem 4.1 (Convergence). Consider a generalized tensor regression model with multi-sided covariates. Let $\mathcal{Y} \in \mathbb{R}^{d_1 \times \dots \times d_K}$ be the tensor response and $\mathcal{X} = \{\mathbf{X}_1, \dots, \mathbf{X}_K\}$ the covariates, where $\mathbf{X}_k \in \mathbb{R}^{p_k \times d_k}$ is the covariate matrix on mode- 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 (4). Under Assumption 1, there exist two constants $C_1, C_2 > 0$ such that, with probability at least $1 - \exp(-C_1 \sum_k p_k)$,

$$\text{Loss}(\mathcal{B}_{\text{true}}, \hat{\mathcal{B}}) \leq \frac{2}{c_1^{2K}} \min \left\{ \frac{C(\mathbf{r}, \alpha) \sum_k p_k}{\prod_k p_k}, 2\alpha^2 \right\},$$

where $C(\alpha, \mathbf{r}) = \frac{1}{b''(\alpha)} \frac{\sum_k r_k}{r_{\max}} > 0$ is a constant that does not depend on dimension $\{d_k\}$ and $\{p_k\}$.

Algorithm 1 Generalized tensor response regression with multi-sided covariates

Input: Response tensor $\mathcal{Y} \in \mathbb{R}^{d_1 \times \dots \times d_K}$, covariate matrices $\mathbf{X}_k \in \mathbb{R}^{d_k \times p_k}$ for $k = 1, \dots, K$, target Tucker rank (r_1, \dots, r_K) , link function f , entrywise bound α

Output: Estimated low-rank coefficient tensor $\mathcal{B} \in \mathbb{R}^{p_1 \times \dots \times p_K}$.

- 1: Calculate $\check{\mathcal{B}} = \mathcal{Y} \times_1 [(\mathbf{X}_1^T \mathbf{X}_1)^{-1} \mathbf{X}_1^T] \times_2 \dots \times_K [(\mathbf{X}_K^T \mathbf{X}_K)^{-1} \mathbf{X}_K^T]$.
- 2: Initialize the iteration index $t = 0$.
- 3: Initialize the core tensor $\mathcal{C}^{(0)}$ and factor matrices $\mathbf{M}_k^{(0)} \in \mathbb{R}^{p_k \times r_k}$ via rank- (r_1, \dots, r_K) Tucker approximation of $\check{\mathcal{B}}$, in the least-square sense.
- 4: **while** the relative increase in objective function $\mathcal{L}_{\mathcal{Y}}(\mathcal{B})$ is less than the tolerance **do**
- 5: Update iteration index $t \leftarrow t + 1$.
- 6: **for** $k = 1$ to K **do**
- 7: Obtain the factor matrix $\mathbf{M}_k^{(t+1)} \in \mathbb{R}^{p_k \times r_k}$ by solving d_k separate GLMs with link function f .
- 8: Update the columns of $\mathbf{M}_k^{(t+1)}$ by Gram-Schmidt orthogonalization.
- 9: **end for**
- 10: Obtain the core tensor $\mathcal{C}^{(t+1)} \in \mathbb{R}^{r_1 \times \dots \times r_K}$ by solving a GLM with $\text{vec}(\mathcal{Y})$ as response, $\odot_{k=1}^K [\mathbf{X}_k \mathbf{M}_k^{(t)}]$ as covariates, and f as link function.
- 11: Rescale the core tensor subject to the entrywise bound constraint.
- 12: Update $\mathcal{B}^{(t+1)} \leftarrow \mathcal{C}^{(t+1)} \times_1 \mathbf{M}_1^{(t+1)} \times_2 \dots \times_K \mathbf{M}_K^{(t+1)}$.
- 13: **end while**

To gain further insight on the bound we consider the special case when dimensions are equal at each of the modes. 1. binary case; 2. large dimension region. $\mathcal{O}(\frac{p}{d^k}) \leq \mathcal{O}(d^{-(k-1)})$.

Corollary 1 (Spatio-temporal growth model). Our method yields the convergence rate $\mathcal{O}(\frac{p+r+s}{dmn})$. Note that $p \leq d$, $r \leq m$ and $s \leq m$, so consistent estimator.

Corollary 2 (Network population model). Our method yields the convergence rate $\mathcal{O}(\frac{2d+p}{d^2n})$. Note that $p \leq m$, so this is a consistent estimator. In contrast, a naive repeated glm will give $\mathcal{O}(\frac{p}{n})$.

Corollary 3 (Link model with node attributes). Our method yields the convergence rate is $\mathcal{O}(\frac{p}{d^2})$. Note that $p \leq m$, so again a consistent estimator. In contrast, a naive repeated glm will give $\mathcal{O}(\frac{p}{n})$.

We provide the prediction accuracy for the response tensor.

Theorem 4.2 (Prediction error). *Assume the same set-up as in Theorem (4.1). Let $\mathbb{P}_{\mathcal{Y}_{true}}$ the distribution of \mathcal{Y} given the true \mathcal{B}_{true} and $\mathbb{E}(\mathcal{Y}|\mathcal{X})$ the true mean. Let $\mathbb{P}_{\hat{\mathcal{Y}}}$ denote the distribution given the estimated $\hat{\mathcal{B}}$ and $\mathbb{E}(\widehat{\mathcal{Y}}|\mathcal{X})$ the predicted mean. We have, with probability at least $1 - \exp(-C_1 \sum_k d_k)$,*

$$KL(\mathbb{P}_{\mathcal{Y}_{true}}, \mathbb{P}_{\hat{\mathcal{Y}}}) \leq C(\dots) \sum_k p_k,$$

$$Loss(\mathbb{E}(\mathcal{Y}|\mathcal{X}), \mathbb{E}(\widehat{\mathcal{Y}}|\mathcal{X})) \leq b''(\alpha) C(\dots) \frac{\sum_k p_k}{\prod_k p_k}.$$

4.1.1 Comparison between Gaussian and non-Gaussian models

Our earlier result gives the general bound with a constant factor C . The factor depends on the tensor order, rank, the distribution family, and the infinity norm bound. We now discuss its specific form for various distribution types of the response. We consider the special case when $d_1 = \dots = d_K = d$, $p_1 = \dots = p_K = p$, $r_1 = \dots = r_K = r$. The constant $C = \frac{2}{b''(\alpha)} \prod_k \sigma_{\min}^{-1}(\mathbf{X}_k)$. For Bernoulli model with logistic link $b''(\alpha) = \frac{e^\alpha}{(1+e^\alpha)^2}$. The bound

$$Loss(\mathcal{B}_{true}, \hat{\mathcal{B}}) \leq \frac{2}{c_1^2 K} \min \left\{ \frac{r^{K-1} e^\alpha}{(1+e^\alpha)^2} \frac{p}{d^K}, 2\alpha^2 \right\}.$$

The α can be interpreted as the signal level. As $p \rightarrow \infty, d \rightarrow \infty, \frac{p}{d} \rightarrow \gamma \in [0, 1]$. For consistent estimation, we require $\mathcal{O}(d^{-(K-1)}) \ll \alpha \ll \mathcal{O}((K-1) \log d)$.

Type	$\alpha \lesssim d^{-(K-1)/2}$	$d^{-(K-1)/2} \ll \alpha \ll \mathcal{O}((K-1) \log d)$	$\alpha \gg (K-1) \log d$
Bernoulli	$\frac{1}{2\alpha^2}$		$\frac{1}{e^{\alpha - (K-1) \log d}}$

5 Numerical implementation

5.1 Alternating optimization

5.2 Tuning parameter selection

We propose to use Bayesian information criterion (BIC) and choose the rank that minimizes BIC; i.e.

$$\begin{aligned}\hat{\mathbf{r}} &= \arg \min_{\mathbf{r}=(r_1, \dots, r_K)} \text{BIC}(\mathbf{r}) \\ &= \arg \min_{\mathbf{r}=(r_1, \dots, r_K)} \left[-2\mathcal{L}_{\mathcal{Y}}(\hat{\mathcal{B}}) + p_e(\mathbf{r}) \log \left(\prod_k d_k \right) \right],\end{aligned}$$

where $p_e(\mathbf{r}) \stackrel{\text{def}}{=} \sum_k (d_k - 1)r_k + \prod_k r_k$ is the effective number of parameters in the model. We choose $\hat{\mathbf{r}}$ that minimizes $\text{BIC}(\mathbf{r})$ via grid search. Our choice of BIC aims to balance between the goodness-of-fit for the data and the degree of freedom in the population model. We test its empirical performance in Section 6.

6 Simulation

We evaluate the empirical performance of our generalized tensor regression through simulations. We focus on order-3 tensors of common distribution types, namely, Gaussian, Bernoulli and Poisson. The response tensors are generated from model (4) with canonical links, and covariates are set available on a subset of the modes. We simulate the entries in the covariates \mathbf{X}_k , whenever available, from i.i.d. Gaussian $(0, \sigma^2)$, where $\sigma = 1/\sqrt{d_3}$. The choice of σ is to guarantee the singular values of \mathbf{X}_k are bounded as d_k increases. In each simulation study, we report the mean squared error for the coefficient tensor averaged across $n_{\text{sim}} = 30$ replications.

The first experiment considers covariates on all modes. We set $d_i = d$, $p_i = 0.2p$ and $r_i = r$ for $i = 1, 2, 3$. We vary $d \in \{20, 40, 60, 80, 100\}$ and $r \in \{3, 5, 10\}$. The signal level for the linear predictor $\mathcal{U} = \mathcal{B} \times \{\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3\}$ is set to be $\alpha = \|\mathcal{U}\|_{\infty} = 1$. Recall that our theoretical analysis suggests $\hat{\mathcal{B}}$ has a convergence rate $\mathcal{O}\left(\frac{0.6d}{0.2^3 d^3}\right)$ in this setting. Figure 2 plots the recovery error versus the effective sample size $N = d^2$ under three different distribution models. We found that the RMSE decreases roughly at the rate of $1/N$. This is consistent with our theoretical ascertainment. We observed that the coefficient with a higher rank tend to yield higher recovery errors, as reflected by the upward shift of the curves as r increases. Indeed, a higher r implies a higher complexity of the model, thus increasing the difficulty of the estimation. Similar behaviors can be observed in the non-Gaussian data from Figure 2b-c.

The second experiment mimics the scenario of network population model. In this case, only the 3rd mode has

available covariates. We set $d_1 = d_2 = 20$, $p_3 = 0.2d_3$ and vary $d_3 \in \{20, 40, 60, 80, 100\}$.

In the third experiment, we mimic the scenario for temporal growth model.

7 Data analysis

8 SUPPLEMENTARY MATERIAL

If you need to include additional appendices during submission, you can include them in the supplementary material file.

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\usepackage[accepted]{aistats2020}
```

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