

Smooth tensor estimation and completion

Miaoyan Wang, April 26, 2020

1 Model

Let $\mathcal{Y} = \llbracket y_{i_1, \dots, i_K} \rrbracket \in \{0, 1\}^{d \times \dots \times d}$ be an order- K , (d, \dots, d) -dimensional binary tensor. Let $\boldsymbol{\xi}^{(k)} = (\xi_1^{(k)}, \dots, \xi_d^{(k)}) \in [0, 1]^d$ be random vectors following (unknown) distributions $\mathbb{P}^{(k)}$ for all $k \in [K]$, and $\boldsymbol{\xi}^{(k)}$ and $\boldsymbol{\xi}^{(k')}$ are mutually independent for $k \neq k' \in [K]$. Assume that the entries of \mathcal{Y} are independent sub-Gaussian random variables conditional on $\{\boldsymbol{\xi}^{(k)}\}$.

$$\mathbb{E} \left(y_{i_1, \dots, i_K} | \{\boldsymbol{\xi}^{(k)}\} \right) = f \left(\xi_{i_1}^{(1)}, \dots, \xi_{i_K}^{(K)} \right), \quad \text{for all } (i_1, \dots, i_K) \in [d] \times \dots \times [d],$$

where $f: [0, 1]^K \mapsto [0, 1]$ is an unknown multivariate function belonging to a function class $f \in \mathcal{F}_\alpha(M)$. Specifically, the function class is defined as

$$\mathcal{F}_\alpha(R) = \{f: \text{Im}(f) \in [0, 1] \text{ and } \|f\|_{\mathcal{H}_\alpha} \leq R\},$$

where $\alpha > 0$ is the smoothness parameter and $R > 0$ is the Hölder norm bound for the functions in the class.

Recall that the function Hölder norm $\|f\|_{\mathcal{H}_\alpha}$ is defined as

$$\|f\|_{\mathcal{H}_\alpha} \stackrel{\text{def}}{=} \max_{|\mathbf{i}| \leq \lfloor \alpha \rfloor} \sup_{\mathbf{x} \in \mathcal{D}} |\nabla_{\mathbf{i}} f(\mathbf{x})| + \max_{|\mathbf{i}| = \lfloor \alpha \rfloor} \sup_{\mathbf{x} \neq \mathbf{x}' \in \mathcal{D}} \frac{|\nabla_{\mathbf{i}} f(\mathbf{x}) - \nabla_{\mathbf{i}} f(\mathbf{x}')|}{\|\mathbf{x} - \mathbf{x}'\|_1^{\alpha - \lfloor \alpha \rfloor}},$$

where we have used the short-hand notation

$$\nabla_{\mathbf{i}} f(\mathbf{x}) = \frac{\partial^{i_1 + \dots + i_K}}{\partial x_1^{i_1} \dots \partial x_K^{i_K}} f(x_1, \dots, x_K),$$

for multi-indices $\mathbf{i} = (i_1, \dots, i_K)$ with $|\mathbf{i}| = i_1 + \dots + i_K$, and $\mathbf{x} = (x_1, \dots, x_K)$ in the function domain.

2 Estimation

Define the objective function

$$L(\mathcal{C}, \{\mathbf{M}_k\}) = \|\mathcal{Y} - \mathcal{C} \times_1 \mathbf{M}_1 \times \dots \times_K \mathbf{M}_K\|_F^2.$$

Denote $\Theta = \mathcal{C} \times_1 \mathbf{M}_1 \times \cdots \times_K \mathbf{M}_K$ and $\mathbf{r} = (r_1, \dots, r_K)$. Then the feasible domain is

$$\mathcal{P}(\mathbf{r}) = \left\{ \Theta \in \mathbb{R}^{d_1 \times \cdots \times d_K} : \Theta = \mathcal{C} \times_1 \mathbf{M}_1 \times \cdots \times_K \mathbf{M}_K, \text{ where } \mathcal{C} \in \mathbb{R}^{r_1 \times \cdots \times r_K} \text{ and } \mathbf{M}_k \in \{0, 1\}^{d_k \times r_k} \text{ are membership matrices for all } k \in [K] \right\}.$$

We propose an adaptive smooth (?) estimation,

$$\begin{aligned} \hat{\Theta} &= \arg \min_{\Theta \in \mathcal{P}(\mathbf{r}^*)} L(\Theta), \quad \text{with } \mathbf{r}^* = (r_1^*, \dots, r_K^*), \\ \text{and } r_k^* &= \lceil d_k^{1/(\alpha \wedge 1 + 1)} \rceil \text{ for all } k \in [K]. \end{aligned}$$

Theorem 2.1. *Consider a function class $\mathcal{F}_\alpha(R)$ with $\alpha > 0$ and $M > 0$. We have*

$$\sup_{f \in \mathcal{F}_\alpha(R)} \sup_{\boldsymbol{\xi}^{(k)} \sim \mathbb{P}^{(k)}, k \in [K]} \frac{1}{d^K} \mathbb{E} \left(\|\hat{\Theta} - f(\xi_{i_1}^{(1)}, \dots, \xi_{i_K}^{(K)})\|_F^2 \right) \leq C \left(d^{-K\alpha/(\alpha+1)} + \frac{\log d}{d^{K-1}} \right),$$

where the constant $C > 0$ depends only on R , and the expectation is taken jointly over \mathcal{Y} , $\{\boldsymbol{\xi}^{(k)}\}$ for all $k \in [K]$.

Phase transition at $\alpha = 1$ only for $K \geq 3$??