

Gaussian width and Statistical convergence

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1 Gaussian width for tucker tensor

In this section, we show **Gaussian width for a rank (R_1, \dots, R_K) tucker tensor is the Gaussian width for this tensor's tucker core.**

Consider a orthonormal tucker decomposition

$$\mathcal{Y} = \mathcal{C} \times_1 A^1 \dots \times_K A^K$$

where $\mathcal{Y} \in R^{d_1 \times \dots \times d_K}$, $\mathcal{C} \in R^{R_1 \times \dots \times R_K}$.

Consider \mathcal{E} as a random sub-Gaussian tensor that \forall entries $\varepsilon \in \mathcal{E}$, $\varepsilon \in \text{sG}(\sigma^2)$. We have:

$$\begin{aligned} \langle \mathcal{Y}, \mathcal{E} \rangle &= \langle \mathcal{C} \times_1 A^1 \dots \times_K A^K, \mathcal{E} \rangle \\ &= \langle \mathcal{C}, \mathcal{E} \times_1 (A^1)^T \dots \times_K (A^K)^T \rangle \\ &= \langle \mathcal{C}, \mathcal{B} \rangle \end{aligned}$$

where

$$\begin{aligned} \mathcal{B} &= \mathcal{E} \times_1 (A^1)^T \dots \times_K (A^K)^T \\ \mathcal{B}_{i_1 \dots i_K} &= \sum_{j_1=1}^{d_1} \dots \sum_{j_K=1}^{d_K} \mathcal{E}_{i_1 \dots i_K} A_{j_1 i_1}^1 A_{j_2 i_2}^2 \dots A_{j_K i_K}^K \end{aligned}$$

Since

$$E \left[e^{t \mathcal{E}_{i_1 \dots i_K}} \right] \leq e^{\sigma^2 t^2 / 2}$$

then we have:

$$E \left[\exp\{t \mathcal{E}_{i_1 \dots i_K} A_{j_1 i_1}^1 A_{j_2 i_2}^2 \dots A_{j_K i_K}^K\} \right] \leq \exp\{\sigma^2 (A_{j_1 i_1}^1)^2 (A_{j_2 i_2}^2)^2 \dots (A_{j_K i_K}^K)^2 t^2 / 2\}$$

Thus, we have:

$$\begin{aligned} E[\exp\{t\mathcal{B}_{i_1 \dots i_K}\}] &\leq \exp\left\{\frac{\sigma^2 t^2}{2} \sum_{j_1=1}^{d_1} (A_{j_1 i_1}^1)^2 \dots \sum_{j_K=1}^{d_K} (A_{j_K i_K}^K)^2\right\} \\ &= e^{\sigma^2 t^2 / 2} \end{aligned}$$

Therefore, \mathcal{B} is also a random sub-Gaussian tensor that \forall entries $\beta \in \mathcal{B}$, $\beta \in \text{sG}(\sigma^2)$.

Recall

$$\langle \mathcal{Y}, \mathcal{E} \rangle = \langle \mathcal{C}, \mathcal{B} \rangle$$

We conclude the Gaussian width for a tucker tensor is the same as the gaussian width for its tucker core.

2 Statistical convergence rate

Recall the note in *Evidence Theory about statistical convergence* in 7/30/2019, consider a K-way tensor, we obtain the convergence rate as

$$\frac{1}{\sqrt{\prod_k d_k}} \left\| \hat{\Theta} - \Theta_{\text{true}} \right\|_F = 2C_2 \frac{L_\alpha}{\gamma_\alpha} \sqrt{\frac{\prod_{k=1}^{K-1} R_k \sum_{k=1}^K d_k}{\prod_k d_k}}$$

We simplify the condition that $R_1 = \dots = R_K = R$ and $d_1 = \dots = d_K = d$, we obtain the rate as R^{K-1}/d^{K-1} . We called it the *initial rate* in our last meeting.

With the property above, we can improve the sharpness of this rate.

Following the main step in *Evidence Theory about statistical convergence* in 7/30/2019, consider the linear term in second-order Taylor's series. We have:

$$|\langle S_{\mathcal{Y}}(\Theta_{\text{true}}), \Theta - \Theta_{\text{true}} \rangle| \leq \max |\langle S, \mathcal{C} \rangle| \leq \|S\|_\sigma \|\mathcal{C}\|_*$$

where $\mathcal{S} \in R^{R_1 \times \dots \times R_K}$ is a random tensor whose entries are independently distributed and satisfy

$$E(s_{i_1, \dots, i_K}) = 0, E\left(e^{tL_\alpha^{-1}s_{i_1, \dots, i_K}}\right) \leq e^{t^2/2}$$

Thus, with probability at least $1 - \exp(-C_1 \log K \sum_k R_k)$:

$$\|S\|_\sigma \leq C_2 L_\alpha \log K \sqrt{\sum_k R_k} \quad (1)$$

Consider \mathcal{C} is the tucker core tensor of $\Theta - \Theta_{\text{true}}$.
We still have:

$$\|\mathcal{C}\|_* \leq \sqrt{\prod_{k=1}^{K-1} 2R_k} \|\Theta - \Theta_{\text{true}}\|_F \quad (2)$$

Combining the results above, we have, with probability at least $1 - \exp(-C_1 \log K \sum_k R_k)$:

$$|\langle S_Y(\Theta_{\text{true}}), \Theta - \Theta_{\text{true}} \rangle| \leq C_2 L_\alpha \sqrt{\prod_{k=1}^{K-1} R_k \sum_{k=1}^K R_k} \|\Theta - \Theta_{\text{true}}\|_F$$

Henceforth,

$$\frac{1}{\sqrt{\prod_k d_k}} \|\hat{\Theta} - \Theta_{\text{true}}\|_F \leq \frac{2C_2 L_\alpha \sqrt{\prod_{k=1}^{K-1} R_k \sum_{k=1}^K R_k}}{\gamma_\alpha \sqrt{\prod_k d_k}} = 2C_2 \frac{L_\alpha}{\gamma_\alpha} \sqrt{\frac{\prod_{k=1}^{K-1} R_k \sum_{k=1}^K R_k}{\prod_k d_k}}$$

When simplifying the condition, we obtain the rate as R^K/d^K . This rate surpassed all the rate we've got so far, and also attained the rate in the professor's conjecture.