

TENSOR METHODS FOR DATA SCIENCE AND SCIENTIFIC COMPUTING

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1 Assignment 5

1.1 Truncated TT-MPS

Given an MPS-TT factorization U_1, \dots, U_d of $A \in \mathbb{R}^{n_1 \times \dots \times n_d}$, with ranks $p_1, \dots, p_{d-1} \in \mathbb{N}$, we will produce a MPS-TT approximation of ranks not exceeding r_1, \dots, r_{d-1} with factors V_1, \dots, V_d of quasioptimal accuracy in the Forbenius norm.

Algorithm 1 rank truncation MPS-TT

```
 $\tilde{U}_1 \leftarrow U_1$ 
for  $k = 1, \dots, d-1$  do
   $\tilde{U}_k \leftarrow \text{reshape}(\tilde{U}_k, (p_{k-1} \cdot n_k, r_k))$ 
   $\tilde{U}_k \leftarrow \hat{P}_k \hat{\Sigma}_k \hat{W}_k^*$   $\triangleright$  rank-  $r_k$  T-SVD of  $\tilde{U}_k$ 
   $\hat{Q}_k \leftarrow \text{reshape}(\hat{P}_k, (p_{k-1}, n_k, r_k))$ 
   $\hat{Z}_k \leftarrow \text{reshape}(\hat{\Sigma}_k \hat{W}_k^*, (r_k, 1, p_k))$ 
   $(\tilde{U}_{k+1})_{\beta_k, i_{k+1}, \alpha_{k+1}} \leftarrow \sum_{\alpha_k=1}^{r_k} (\hat{Z}_k)_{\beta_k, 1, \alpha_k} (U_{k+1})_{\alpha_k, i_{k+1}, \alpha_{k+1}}$ 
   $\text{save}(\hat{Q}_k)$ 
end for
 $\text{save}(\tilde{U}_d)$ 
```

1.2 TT-MPS arithmetic

1.2.1 Addition

Consider two tensors U and V of size $n_1 \times \dots \times n_d \in \mathbb{N}$ for $d \in \mathbb{N}$, with TT-MPS factorization U_k with rank p_k and V_k with rank q_k respectively (for $k \in \{1, \dots, d-1\}$). Then TT-MPS factorization of $W = U + V$ can

be calculated without evaluating U or V , just by using U_1, \dots, U_d and V_1, \dots, V_d by the following

$$\begin{aligned}
 W &= U_1 \bowtie \dots \bowtie U_d + V_1 \bowtie \dots \bowtie V_d = \\
 &= [U_1 \quad V_1] \bowtie \begin{bmatrix} U_2 \bowtie \dots \bowtie U_d \\ V_2 \bowtie \dots \bowtie V_d \end{bmatrix} = \\
 &= \dots = \\
 &= [U_1 \quad V_1] \bowtie \begin{bmatrix} U_2 & 0 \\ 0 & V_2 \end{bmatrix} \bowtie \dots \bowtie \begin{bmatrix} U_{d-1} & 0 \\ 0 & V_{d-1} \end{bmatrix} \bowtie \begin{bmatrix} U_d \\ V_d \end{bmatrix} = \\
 &= W_1 \bowtie \dots \bowtie W_d,
 \end{aligned} \tag{1}$$

where W has a decomposition of ranks $(p_1 + q_1), \dots, (p_{d-1} + q_{d-1})$. The construction of these matrices and vectors can be done by initializing the W_k and then slicing for U_k and V_k in the second dimension, meaning n_k . Thereby for the k -th ($2 \leq k \leq d-2$) step we would have

$$(W_k)_{:,i_k,:} = \begin{bmatrix} (U_k)_{:,i_k,:} & 0 \\ 0 & (V_k)_{:,i_k,:} \end{bmatrix} \quad \forall i_k \in \{1, \dots, n_k\}. \tag{2}$$

For the first step we have $p_0 = q_0 = 1$ and thereby

$$(W_1)_{:,i_1,:} = [(U_1)_{1,i_1,:} \quad (V_1)_{1,i_1,:}] \quad \forall i_1 \in \{1, \dots, n_1\}. \tag{3}$$

And for the $k = d$ -th step we have $p_d = q_d = 1$ and thereby

$$(W_d)_{:,i_d,:} = \begin{bmatrix} (U_d)_{:,i_d,1} \\ (V_d)_{:,i_d,1} \end{bmatrix} \quad \forall i_d \in \{1, \dots, n_d\}. \tag{4}$$

This concludes the construction of the algorithm for addition

1.2.2 Hadamard Product

Now consider again two tensors U and V of size $n_1 \times \dots \times n_d \in \mathbb{N}$ for $d \in \mathbb{N}$, with TT-MPS factorization U_k with rank p_k and V_k with rank q_k respectively (for $k \in \{1, \dots, d-1\}$). Then TT-MPS factorization of $W = U \otimes V$ can be calculated without evaluating U or V , just by using U_1, \dots, U_d and V_1, \dots, V_d by the following

$$\begin{aligned}
 W_{i_1, \dots, i_d} &= \sum_{\alpha_1=1}^{q_1} \dots \sum_{\alpha_{d-1}=1}^{q_{d-1}} \prod_{k=1}^d U_k(\alpha_{k-1}, i_k, \alpha_k) \cdot \sum_{\beta_1=1}^{q_1} \dots \sum_{\beta_{d-1}=1}^{q_{d-1}} \prod_{k=1}^d V_k(\beta_{k-1}, i_k, \beta_k) = \\
 &= \sum_{\gamma_1=1}^{r_1} \dots \sum_{\gamma_{d-1}=1}^{r_{d-1}} \prod_{k=1}^d W_k(\gamma_{k-1}, i_k, \gamma_k).
 \end{aligned} \tag{5}$$

Thereby the factors W_k can be calculated with the factor wise product

$$W_k(\alpha_{k-1} \beta_{k-1}, i_k, \alpha_k \beta_k) = U_k(\alpha_{k-1}, i_k, \alpha_k) \cdot V_k(\beta_{k-1}, i_k, \beta_k), \tag{6}$$

for all $\alpha_k \in \{1, \dots, p_k\}$ and $\beta_k \in \{1, \dots, q_k\}$ and $p_0 = p_d = q_0 = q_d = 1$. Where the TT-MPS calculated by the algorithm is of ranks $(p_1 q_1), \dots, (p_{d-1} q_{d-1})$.

The computer reads in slices and Kronecker products

$$(W_k)_{:,i_k,:} = (U_k)_{:,i_k,:} \otimes (V_k)_{:,i_k,:} \quad \forall i_k \in \{1, \dots, n_k\}. \tag{7}$$

1.2.3 Matrix Vector product

Now consider $A \in \mathbb{R}^{n_1 \times \dots \times n_d \times m_1 \times \dots \times m_d}$ and $u \in \mathbb{R}^{m_1 \times \dots \times m_d}$. The TT-MPS factorization of A is $A_k \in \mathbb{R}^{p_{k-1} \times n_k \times m_k \times q_k}$ and the TT-MPS factorization of U is $U_k \in \mathbb{R}^{q_{k-1} \times m_k \times q_k}$. The TT-MPS factors W_k of $w = A \cdots u$ can be

explicitly calculated with

$$\begin{aligned}
W_{i_1, \dots, i_d} &= \sum_{j_1, \dots, j_d} A_{i_1 \dots i_d, j_1 \dots j_d} U_{j_1 \dots j_d} \\
&= \sum_{j_1, \dots, j_d} \sum_{\alpha_1=1}^{p_1} \cdots \sum_{\alpha_{d-1}=1}^{p_{d-1}} \prod_{k=1}^d A_k(\alpha_{k-1}, i_k, j_k, \alpha_k) \cdot \sum_{\beta_1=1}^{q_1} \cdots \sum_{\beta_{d-1}=1}^{q_{d-1}} \prod_{k=1}^d U_k(\beta_{k-1}, j_k, \beta_k) \\
&= \sum_{\alpha_1 \beta_1} \cdots \sum_{\alpha_{d-1} \beta_{d-1}} \prod_{k=1}^d \left(\sum_{j_k}^{n_k} A_k(\alpha_{k-1}, i_k, j_k, \alpha_k) U_k(\beta_{k-1}, j_k, \beta_k) \right) \\
&= \sum_{\gamma_1}^{r_1} \cdots \sum_{\gamma_{d-1}}^{r_{d-1}} \prod_{k=1}^d W_k(\gamma_{k-1}, i_k, \gamma_k),
\end{aligned} \tag{8}$$

for $r_k = q_k \cdot p_k$. The computer reads

$$(W_k)_{:, i_k, :} = \sum_{j_k=1}^{n_k} (A_k)_{:, i_k, j_k, :} \otimes (U_k)_{:, j_k, :} \quad \forall i_k \in \{1, \dots, n_k\} \tag{9}$$

for all $k = 1, \dots, d$

1.3 Testing

Consider the grid for $n = 51$

$$t_i = 2 \frac{i-1}{n-1} - 1 \quad i = 1, \dots, n \tag{10}$$

for the tensors $X, Y \in \mathbb{R}^{n \times n \times n \times n}$ given by

$$x_{i_1, \dots, i_4} = T_p \left(\sum_{k=1}^4 \frac{t_{i_k}}{4} \right) \tag{11}$$

$$y_{i_1, \dots, i_4} = T_q \left(\sum_{k=1}^4 \frac{t_{i_k}}{4} \right) \tag{12}$$

$$\tag{13}$$

for $p, q \in \mathbb{N}_0$ and T_r is the Chebyshev polynomial for a $k \in \mathbb{N}_0$. The Chebyshev polynomials are defined by

$$T_r(x) = \begin{cases} \cos(r \cdot \arccos(x)) & |x| \leq 1 \\ \cosh(r \cdot \operatorname{arccosh}(x)) & x \geq 1 \\ (-1)^r \cosh(r \cdot \operatorname{arccosh}(x)) & x \leq -1 \end{cases} \tag{14}$$

Additionally we define

$$S := X + Y \tag{15}$$

$$Z := X \otimes Y. \tag{16}$$

The following figures show for $(p, q) = 3, 4$ and $(p, q) = 5, 7$ the TT-MPS unfolding singular values of tensors X, Y, S, Z .

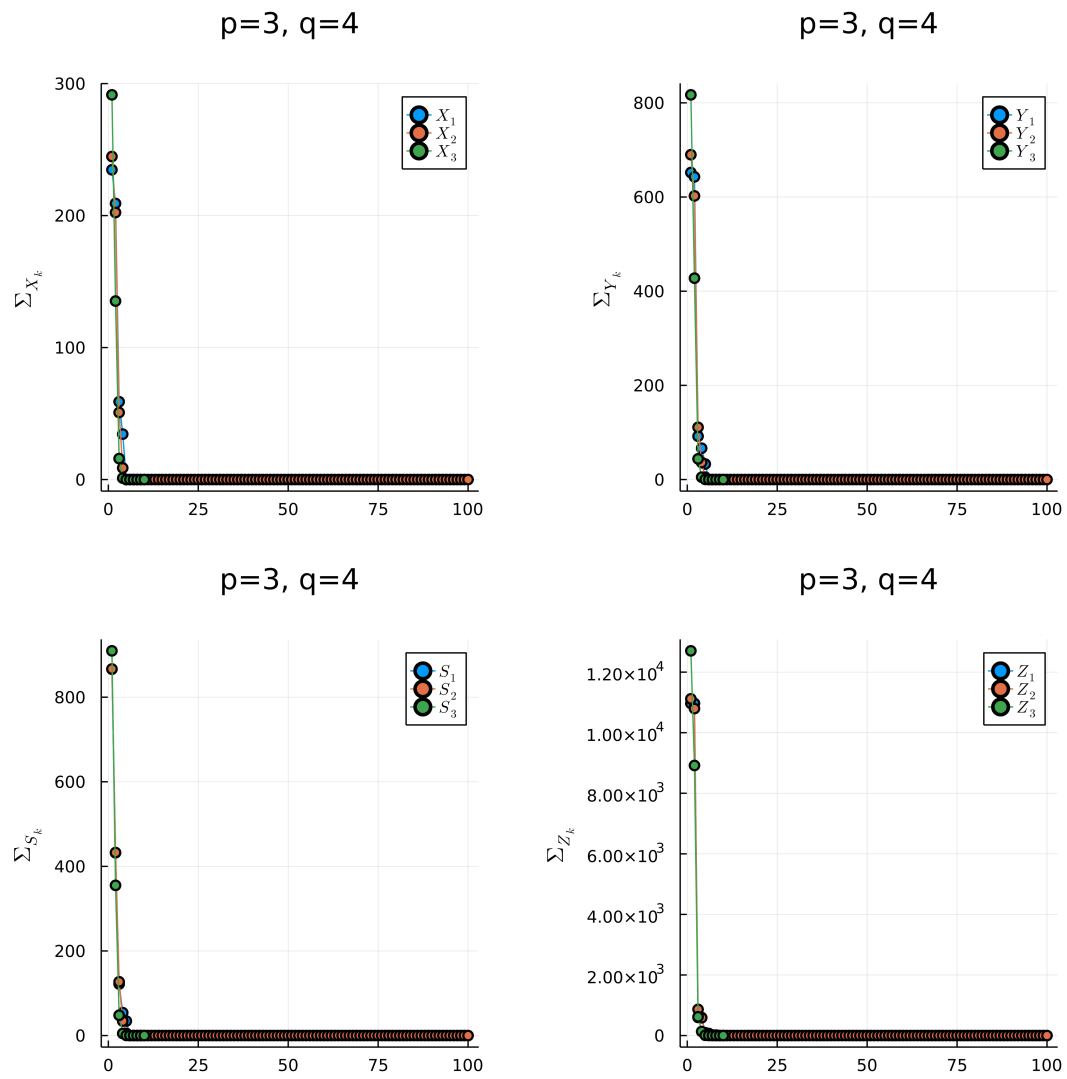


Figure 1: Some text

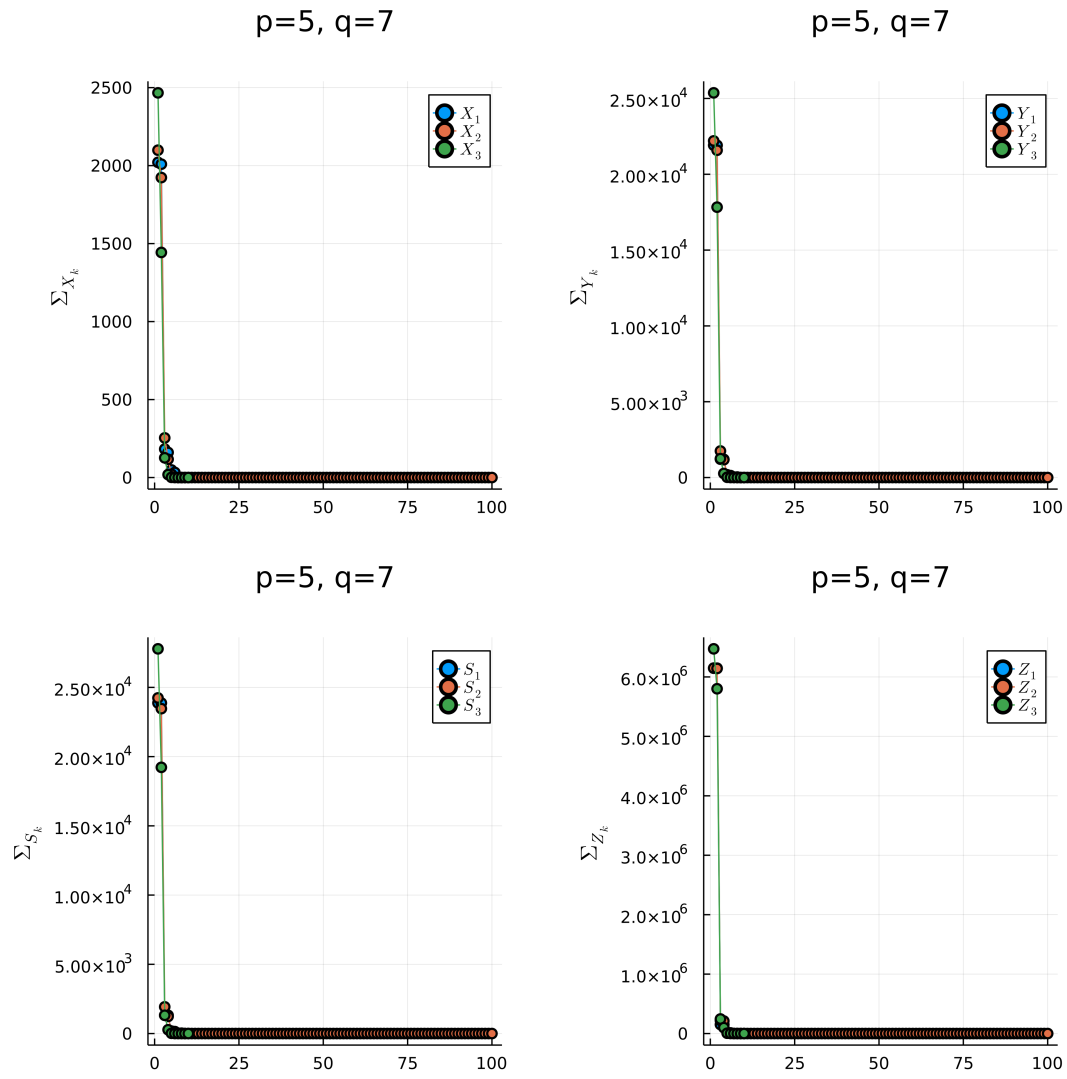


Figure 2: Some text

The following figures show the ranks MPS-TT unfolding matrices of X, Y, S, Z for $(p, q) = 3, 4$ and $(p, q) = 5, 7$ respectively

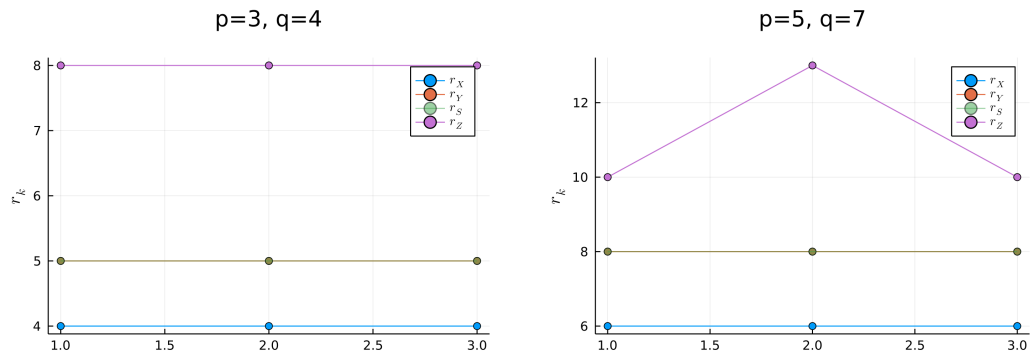


Figure 3: Some text

References

- [1] Popovic Milutin. *Git Instance, Tensor Methods for Data Science and Scientific Computing*. URL: [git://popovic.xyz/tensor_methods.git](https://popovic.xyz/tensor_methods.git).