

A Higher-order Generalization of the Matrix SVD as a Product of Higher-order Tensors

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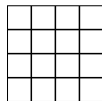
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Joint Meetings, Washington D.C.

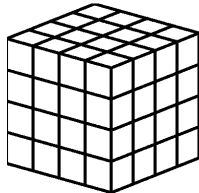
January 7, 2009

What are Tensors?

- Second-order tensor $A = (a_{ij}) \in \mathbb{R}^{n_1 \times n_2}$



- Third-order tensor $\mathcal{A} = (a_{ijk}) \in \mathbb{R}^{n_1 \times n_2 \times n_3}$



- p^{th} -order tensor $\mathcal{A} = (a_{i_1 i_2 \dots i_p}) \in \mathbb{R}^{n_1 \times \dots \times n_p}$

Motivation: A two-way decomposition

Suppose $U \in \mathbb{R}^{M \times M}$, $V \in \mathbb{R}^{N \times N}$ are orthogonal, and $\Sigma = U^T A V$, then

$$\begin{aligned} A = U \Sigma V^T &= \sum_{i=1}^M \sum_{j=1}^N \sigma_{ij} u_i v_j^T \\ &= \sum_{i=1}^M \sum_{j=1}^N \sigma_{ij} (u_i \circ v_j) \end{aligned}$$

where $u_i = U(:, i)$, $v_j = V(:, j)$

Tensor Decompositions

Let $\mathcal{A} \in \mathbb{R}^{M \times N \times P}$

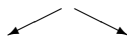
Goal: To find $U \in \mathbb{R}^{M \times M}$, $V \in \mathbb{R}^{N \times N}$, $W \in \mathbb{R}^{P \times P}$, and $\Sigma = (\sigma_{ijk}) \in \mathbb{R}^{M \times N \times P}$ such that

$$\mathcal{A} = \sum_{i=1}^M \sum_{j=1}^N \sum_{k=1}^P \sigma_{ijk} (u_i \circ v_j \circ w_k)$$

where $u_i = U(:, i)$, $v_j = V(:, j)$, $w_k = W(:, k)$

Orthogonal or Diagonal for Tensors

$$\begin{array}{cccc}
 m \times n & & m \times r & & r \times r & & r \times n \\
 \boxed{A} & = & \boxed{U} & & \boxed{\Sigma} & & \boxed{V^T}
 \end{array}$$



Case 1:
Diagonal Σ

$$\begin{array}{ccccccc}
 m \times n \times p & & m \times r & & p \times r & & \\
 \boxed{A} & = & \boxed{U} & & \boxed{W^T} & & \\
 & & & & & & \\
 & & & & \text{3D cube} & & \boxed{V^T} \\
 & & & & r \times r \times r & & n \times r
 \end{array}$$

Case 2:
Orthogonal U, V, W

$$\begin{array}{ccccccc}
 m \times n \times p & & m \times r_1 & & p \times r_2 & & \\
 \boxed{A} & = & \boxed{U} & & \boxed{W^T} & & \\
 & & & & & & \\
 & & & & \text{3D cube} & & \boxed{V^T} \\
 & & & & r_1 \times r_2 \times r_3 & & n \times r_2
 \end{array}$$

Previous Work

Tensor-tensor Multiplication using contracted product...

- Set of all third-order tensors is not closed
- No notion of inverse possible

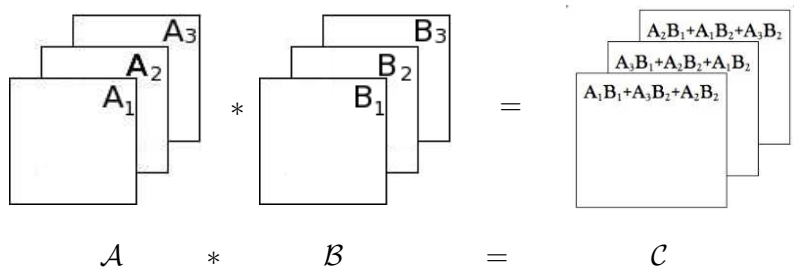
New multiplication operation defined that is closed, inverse exists, that gives way to a new way of thinking about the SVD

New tensor-tensor multiplication

$$\begin{array}{l} \mathcal{A} \in \mathbb{R}^{L \times M \times N} \\ \mathcal{B} \in \mathbb{R}^{M \times P \times N} \end{array} \Rightarrow \mathcal{A} * \mathcal{B} \in \mathbb{R}^{L \times P \times N}$$

- Multiplication defined in terms of the tensor “slices”
- Circulant matrices play a role
- Operation is associative
- Can define an inverse
- Set of $N \times N \times N$ invertible tensors form a group under this multiplication

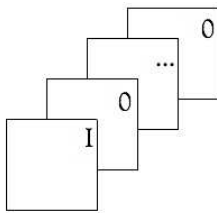
New tensor-tensor multiplication



$$\begin{bmatrix} A_1 & A_3 & A_2 \\ A_2 & A_1 & A_3 \\ A_3 & A_2 & A_1 \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \\ B_3 \end{bmatrix} = \begin{bmatrix} A_1 B_1 + A_3 B_2 + A_2 B_3 \\ A_2 B_1 + A_1 B_2 + A_3 B_3 \\ A_3 B_1 + A_2 B_2 + A_1 B_3 \end{bmatrix} = \begin{bmatrix} C(:, :, 1) \\ C(:, :, 2) \\ C(:, :, 3) \end{bmatrix}$$

Identity

The $N \times N \times P$ **identity tensor**, \mathcal{I} , is the tensor whose frontal face is the $N \times N$ identity matrix and whose other faces are zeros.



In general, $\mathcal{A} * \mathcal{I} = \mathcal{I} * \mathcal{A} = \mathcal{A}$

Inverse

Let $\mathcal{A} \in \mathbb{R}^{N \times N \times N}$. Then the **tensor inverse** of \mathcal{A} is any tensor $\mathcal{B} \in \mathbb{R}^{N \times N \times N}$ such that

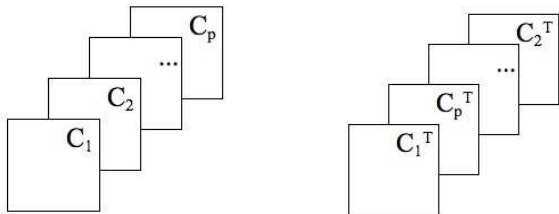
$$\mathcal{A} * \mathcal{B} = \mathcal{B} * \mathcal{A} = \mathcal{I}$$

We denote the inverse of \mathcal{A} as \mathcal{A}^{-1} .

It follows that $(\mathcal{A} * \mathcal{B})^{-1} = \mathcal{B}^{-1} * \mathcal{A}^{-1}$

Transpose

Let $\mathcal{C} \in \mathbb{R}^{L \times M \times P}$ with faces $C_1, \dots, C_P \in \mathbb{R}^{L \times M}$. Then



It follows that $(\mathcal{B} * \mathcal{C})^T = \mathcal{C}^T * \mathcal{B}^T$

Frobenius Norm and Orthogonality

Let $\mathcal{A} = (a_{ijk}) \in \mathbb{R}^{L \times M \times N}$. Then the **Frobenius norm** of \mathcal{A} is

$$\|\mathcal{A}\|_F = \sqrt{\sum_{i=1}^L \sum_{j=1}^M \sum_{k=1}^N a_{ijk}^2}$$

Let $Q \in \mathbb{R}^{N \times N \times P}$. Q is **orthogonal** if

$$Q^T * Q = Q * Q^T = \mathcal{I}$$

If \mathcal{A} is a tensor, then it follows that

$$\|Q * \mathcal{A}\|_F = \|\mathcal{A}\|_F$$

Tensor SVD

Let $\mathcal{A} \in \mathbb{R}^{L \times M \times N}$. Then \mathcal{A} can be factored as

$$\mathcal{A} = \mathcal{U} * \mathcal{S} * \mathcal{V}^T$$

where $\mathcal{U} \in \mathbb{R}^{L \times L \times N}$ and $\mathcal{V} \in \mathbb{R}^{M \times M \times N}$ are orthogonal tensors and $\mathcal{S} \in \mathbb{R}^{L \times M \times N}$ has diagonal matrix faces.

If $\mathcal{A} \in \mathbb{R}^{N \times N \times N}$,

$$\mathcal{A} = \sum_{i=1}^N \mathcal{U}(:, i, :) * \mathcal{S}(i, i, :) * \mathcal{V}(:, i, :)^T$$

Tensor SVD: computation

- Computation of the tensor SVD involves SVDs of block diagonal elements obtained from block diagonalizing the circulant matrix generated by \mathcal{A}
- Using the SVDs of the blocks leads to algorithms for compression
- Operation extends recursively to order- p tensors when $p > 3$

One Compression Strategy

Suppose $\mathcal{A} \in \mathbb{R}^{N \times N \times N}$

Can prove that if $\mathcal{A} = \mathcal{U} * \mathcal{S} * \mathcal{V}^T$ then

$$\sum_{i=1}^N \mathcal{U}(:, :, i) \quad \text{is orthogonal.}$$

Therefore

$$\sum_{i=1}^N \mathcal{A}(:, :, i) = \left(\sum_{i=1}^N \mathcal{U}(:, :, i) \right) \left(\sum_{i=1}^N \mathcal{S}(:, :, i) \right) \left(\sum_{i=1}^N \mathcal{V}(:, :, i) \right)^T$$

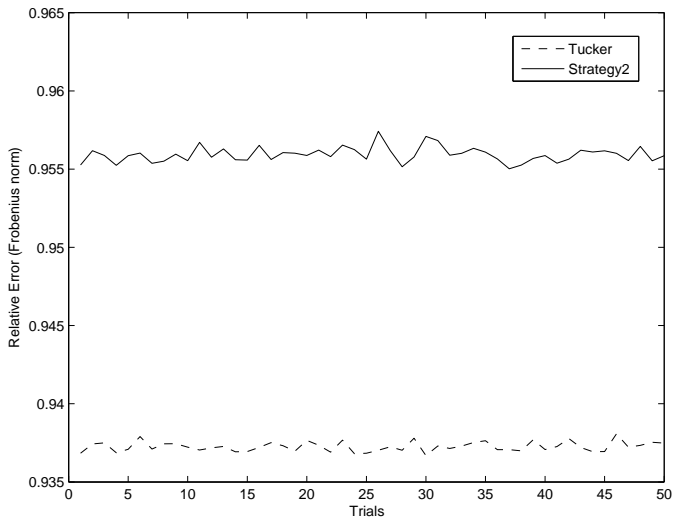
One Compression Strategy

$$\sum_{i=1}^N \mathcal{A}(:, :, i) = \left(\sum_{i=1}^N \mathcal{U}(:, :, i) \right) \left(\sum_{i=1}^N \mathcal{S}(:, :, i) \right) \left(\sum_{i=1}^N \mathcal{V}(:, :, i) \right)^T$$

- Take rank- k approximation and “build” back approximation to the tensor \mathcal{A}
- Can rewrite “compressed” tensor \mathcal{A}_c as sum of outer products:

$$\mathcal{A} \approx \mathcal{A}_c = \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} \tilde{\mathcal{U}}(:, i) \circ \tilde{\mathcal{V}}(:, j) \circ \mathcal{M}(i, j, :)$$

Numerical Results



Summary

- New definitions allow for greater flexibility in design of compression algorithms for tensors
- Can be extended to other matrix factorizations (e.g., QR)
- Computationally efficient
- Allows for weighting of tensor faces

Thank you!