

Existence of best low rank tensor approximations

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Decompose signal into canonical components.

A **tensor** \mathcal{T} is a multiindexed array.

$$\mathcal{T} = \text{[cube icon]} \in \mathbb{R}^{N_1 \times N_2 \times N_3}$$

Canonical **P**olyadic **D**ecomposition (CPD) expresses \mathcal{T} as minimal sum of rank 1 terms.

$$\mathcal{T} = \sum_{r=1}^R \mathbf{a}_r \otimes \mathbf{b}_r \otimes \mathbf{c}_r = \text{[L-shaped icon]} + \dots + \text{[L-shaped icon]} = \text{[cube icon]}$$

R is the **rank** of \mathcal{T} .

Notation: $\mathbf{a}_r, \mathbf{b}_r, \mathbf{c}_r$ are vectors of length N_1, N_2, N_3 , respectively.

In practice measured signal tensors are corrupted by noise. Must compute a low rank approximation

A common problem in applications: Given $\mathcal{M} = \mathcal{T} + \mathcal{N}$ of size $l_1 \times l_2 \times l_3$ where \mathcal{T} is a rank R signal tensor, compute a best rank (less than or equal to) R approximation of \mathcal{M} .

Intuition: Computing rank R approximation allows (approximate) recovery of \mathcal{T} from \mathcal{M} .

Low rank tensor approximation is ill-posed: A best rank $\leq R$ approximation may not exist.

This leads to considering the set of border rank $\leq R$ tensors. This is the closure of the set of rank R tensors.

What is border rank and why?

Why care:

1. Optimization always has solution over border rank R tensors.
2. Decomposition is uninterpretable if solution has rank $>$ border rank.

Tensor phenomena: Limit of rank 2 tensors could have rank 3.

E.g.

$$\lim_{n \rightarrow \infty} n(\mathbf{e}_1)^{\otimes 3} - n \left(\mathbf{e}_1 + \frac{\mathbf{e}_2}{n} \right)^{\otimes 3}$$

In general: \mathcal{T} has **border rank** R means:

1. \mathcal{T} is a limit of rank R tensors.
2. \mathcal{T} is not a limit of tensors having rank $< R$.

Commonly proposed “solutions” if best approximation has rank $>$ border rank have issues.

Common suggestions are:

1. Take close to optimal approximation: Suffers from diverging components
2. Increase rank: Can lose uniqueness of decomposition.
3. Impose constraints: Solution will always be on boundary of constraint.

Recap

Tensor approximation always has best approximation over border rank R solutions

Rank $>$ border rank leads to big problems for interpretation

1. Diverging components
2. Loss of uniqueness
3. Artificially chosen solution.

Need good, meaningful solutions!

Need guarantee solution has rank = border rank.

Start by understanding $R \times R \times 2$ examples. A good case: Distinct generalized eigenvalues

Write $\mathbf{T}_1 = \mathcal{T}(:, :, 1)$ and $\mathbf{T}_2 = \mathcal{T}(:, :, 2)$.

Let \mathcal{T} be defined by

$$\mathbf{T}_1 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad \mathbf{T}_2 = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \quad \text{has} \quad \mathbf{T}_2^{-1} \mathbf{T}_1 = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

$\mathbf{T}_2^{-1} \mathbf{T}_1$ eigenvalues 1 and -1 and eigenvectors \mathbf{e}_1 and \mathbf{e}_2 .

The tensor has real rank 2.

A bad case: Repeated generalized eigenvalues

Let \mathcal{T} be defined by

$$\mathbf{T}_1 = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \quad \mathbf{T}_2 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad \text{has} \quad \mathbf{T}_2^{-1}\mathbf{T}_1 = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}$$

$\mathbf{T}_2^{-1}\mathbf{T}_1$ eigenvalue 0 (with algebraic multiplicity 2) and eigenvector \mathbf{e}_1 .

The tensor has rank > 2 and border rank 2.

This tensor is the limit of the first example I showed.

Story for $R \times R \times 2$ tensors is completely told by generalized eigenvalues.

The **generalized eigenvalues** and **generalized eigenvectors** of \mathcal{T} are (essentially) equal to the classical eigenvalues and eigenvectors of the matrix

$$\mathbf{T}_2^{-1}\mathbf{T}_1$$

Theorem: $\mathcal{T} \in \mathbb{R}^{R \times R \times 2}$ has rank R IFF \mathcal{T} has a basis of generalized eigenvectors.

Idea: To guarantee rank = border rank, use perturbation theory for generalized eigenvalues to guarantee perturbation has distinct generalized eigenvalues.

An existence bound for $R \times R \times 2$ tensors

Theorem

Let \mathcal{T} and $\hat{\mathcal{T}}$ be tensors of size $R \times R \times 2$. Assume that \mathcal{T} has \mathbb{R} -rank R with CPD $[[\mathbf{A}, \mathbf{B}, \mathbf{C}]]$. If

$$\|\mathcal{T} - \hat{\mathcal{T}}\|_{sp} < \frac{\sigma_{\min}(\mathbf{A})\sigma_{\min}(\mathbf{B}) \min_{i \neq j} \chi(\mathbf{C}_i, \mathbf{C}_j)}{2},$$

then $\hat{\mathcal{T}}$ has \mathbb{R} -rank R and

$$md[\mathcal{T}, \hat{\mathcal{T}}] < \frac{\|\mathcal{T} - \hat{\mathcal{T}}\|_{sp}}{\sigma_{\min}(\mathbf{A})\sigma_{\min}(\mathbf{B})}. \quad (1)$$

A perturbation bound for $R \times R \times K$ tensors. The tensor Bauer-Fike theorem.

Theorem

Let $\mathcal{T}, \hat{\mathcal{T}} \in \mathbb{R}^{R \times R \times K}$ be rank R tensors and let $\mathcal{T} = \llbracket \mathbf{A}, \mathbf{B}, \mathbf{C} \rrbracket$. Then

$$sv[\mathcal{T}, \hat{\mathcal{T}}] \leq \sqrt{R} \|(\mathcal{T} - \tilde{\mathcal{T}}) \cdot_1 \mathbf{A}^{-1} \cdot_2 \mathbf{B}^{-1}\|_{sp} \leq \frac{\sqrt{R} \|\mathcal{T} - \hat{\mathcal{T}}\|_{sp}}{\sigma_{\min}(\mathbf{A}) \sigma_{\min}(\mathbf{B})}.$$

Getting an existence bound in the $R \times R \times K$ setting

Key ideas:

1. Show best border rank R approximation \hat{T} has rank R .
2. If \hat{T} has border rank $< \text{rank}$, then every subpencil of \hat{T} must have a repeated generalized eigenvalue.
3. If \hat{T} has border rank $< \text{rank}$, then so does $\hat{T} \cdot_3 \mathbf{U}$ for any invertible matrix \mathbf{U} .

A multiple pencil based bound for existence

Theorem

Let $\mathcal{M} \in \mathbb{R}^{R \times R \times K}$ be any tensor. For each $i = 1, \dots, \lfloor K/2 \rfloor$, let $\epsilon_i \geq 0$ the bound computed using the $K = 2$ theorem for the pencil

$$(\mathbf{M}_{2i-1}, \mathbf{M}_{2i})$$

and set $\epsilon = \|(\epsilon_1, \dots, \epsilon_{\lfloor K/2 \rfloor})\|_2$. If there exists some \mathbb{R} -rank R tensor \mathcal{T}' such that

$$\|\mathcal{M} - \mathcal{T}'\|_F < \epsilon,$$

then \mathcal{M} has a best \mathbb{R} -rank R approximation and any best \mathbb{R} -rank R approximation of \mathcal{M} has a unique CPD.

Explanation of the Theorem

1. A best border rank R approximation $\hat{\mathcal{T}}$ of \mathcal{M} is guaranteed to exist.
2. Have $\|\hat{\mathcal{T}} - \mathcal{M}\|_F \leq \|\mathcal{T}' - \mathcal{M}\|_F < \epsilon$
3. This implies there is an index i so that

$$\|(\hat{\mathbf{T}}_{2i-1}, \hat{\mathbf{T}}_{2i}) - (\mathbf{M}_{2i-1}, \mathbf{M}_{2i})\| < \epsilon_i$$

4. The subpencil $(\hat{\mathbf{T}}_{2i-1}, \hat{\mathbf{T}}_{2i})$ cannot have a repeated generalized eigenvalue.
5. The tensor $\hat{\mathcal{T}}$ must have rank = border rank = R .

A multiple pencil based bound for existence (improved version)

Theorem

Let $\mathcal{M} \in \mathbb{R}^{R \times R \times K}$ be any tensor. Let $\mathbf{U} \in \mathbb{K}^{K \times K}$ be a unitary matrix and set $\mathcal{S} = \mathcal{M} \cdot_3 \mathbf{U}$. For each $i = 1, \dots, \lfloor K/2 \rfloor$, let $\epsilon_i \geq 0$ the bound computed using the $K = 2$ theorem for the pencil

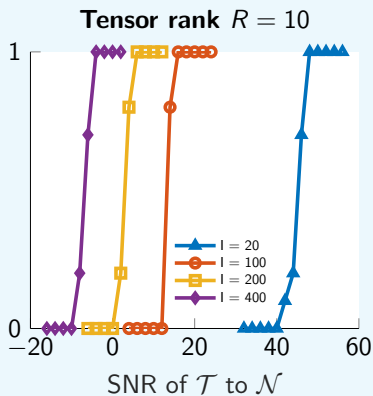
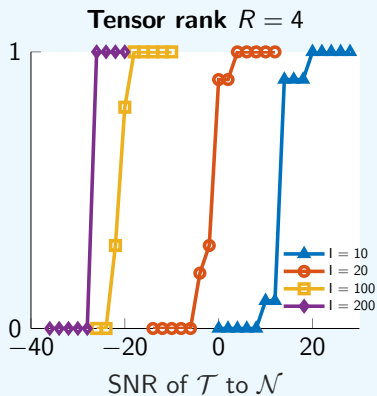
$$(\mathbf{S}_{2i-1}, \mathbf{S}_{2i})$$

and set $\epsilon = \|(\epsilon_1, \dots, \epsilon_{\lfloor K/2 \rfloor})\|_2$. If there exists some \mathbb{R} -rank R tensor \mathcal{T}' such that

$$\|\mathcal{M} - \mathcal{T}'\|_F < \epsilon,$$

then \mathcal{M} has a best \mathbb{R} -rank R approximation and any best \mathbb{R} -rank R approximation of \mathcal{M} has a unique CPD.

SNR at which tensors of various sizes are guaranteed
(in experiments) to have a best rank R approximation



Proportion of $l \times l \times l$ tensors $\mathcal{T} + \mathcal{N}$ with truncated MLSVD
guaranteed to have a best rank R approximation

Bonus: The tensor Procrustes problem

This talk: $R \times R \times K$ tensors. In general $l_1 \times l_2 \times l_3$ is okay.

Key ingredient: The tensor Procrustes problem.

Theorem

Let $\mathcal{T}, \hat{\mathcal{T}} \in \mathbb{R}^{l_1 \times \dots \times l_\ell}$ be tensors having the same multilinear rank. Then there exist orthogonal compressions $\mathcal{T}^c, \hat{\mathcal{T}}^c$ of \mathcal{T} and $\hat{\mathcal{T}}$, respectively, such that

$$\|\mathcal{T}^c - \hat{\mathcal{T}}^c\|_F \leq \|\mathcal{T} - \hat{\mathcal{T}}\|_F.$$

Contributions

Deterministic method for showing that a tensor has a best rank R approximation.

Tensor decomposition is stable and well-posed in a computable neighborhood around a given rank R tensor.

Guarantees that a decomposition will not suffer from the dreaded diverging components or loss of uniqueness.