

# Condition numbers of tensor decompositions

and their invariance properties

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## 0 Motivating example

Suppose we want to decompose the  $3 \times 3 \times 3$  tensor

$$\mathcal{A} = \left[ \begin{array}{c} \begin{bmatrix} 1 & 1 \\ 1 & \end{bmatrix} \\ \begin{bmatrix} 1 & \varepsilon \\ \varepsilon & \varepsilon^2 \end{bmatrix} \\ \begin{bmatrix} \varepsilon \\ \end{bmatrix} \end{array} \right]$$

where  $\varepsilon = 10^{-6}$ . In practice, we only measure an approximation:

$$\tilde{\mathcal{A}} = \left[ \begin{array}{c} \begin{bmatrix} 1 & 1 \\ 1 & \varepsilon \end{bmatrix} \\ \begin{bmatrix} 1 & \varepsilon \\ \varepsilon & \varepsilon^2 \end{bmatrix} \\ \begin{bmatrix} \varepsilon \\ \end{bmatrix} \end{array} \right].$$

Since  $\|\mathcal{A} - \tilde{\mathcal{A}}\|_F \approx \sqrt{7}\varepsilon$ , this is pretty accurate.

↪ Surely, we can recover the model accurately ...right?

## 0 Motivating example

$\mathcal{A}$  splits uniquely into 3 tensors of rank 1:

$$\mathcal{A} = \underbrace{e_1 \otimes e_1 \otimes e_2}_{\mathbf{E}_{112}} + \underbrace{(e_1 + \varepsilon e_3) \otimes e_2 \otimes e_1}_{\approx \mathbf{E}_{121}} + \underbrace{e_2 \otimes (e_1 + \varepsilon e_3) \otimes (e_1 + \varepsilon e_3)}_{\approx \mathbf{E}_{211}}.$$

(where  $\mathbf{E}_{ijk} \in \mathbb{R}^{3 \times 3 \times 3}$  has entry 1 at index  $ijk$  and 0 otherwise).

But  $\tilde{\mathcal{A}}$  decomposes uniquely as

$$\tilde{\mathcal{A}} = \underbrace{\varepsilon^{-1}(e_1 + \varepsilon e_2)^{\otimes 3}}_{\approx \varepsilon^{-1} \mathbf{E}_{111}} - \underbrace{\varepsilon^{-1} e_1^{\otimes 3}}_{\varepsilon^{-1} \mathbf{E}_{111}} + \underbrace{\varepsilon e_3^{\otimes 3}}_{\varepsilon \mathbf{E}_{333}}.$$

The rank-1 terms are entirely different! The model is *uninterpretable!*

## 0 Motivating example

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(where  $\mathbf{E}_{ijk} \in \mathbb{R}^{3 \times 3 \times 3}$  has entry 1 at index  $ijk$  and 0 otherwise).

For another small perturbation of  $\mathcal{A}$ , there isn't even a unique decomposition anymore:

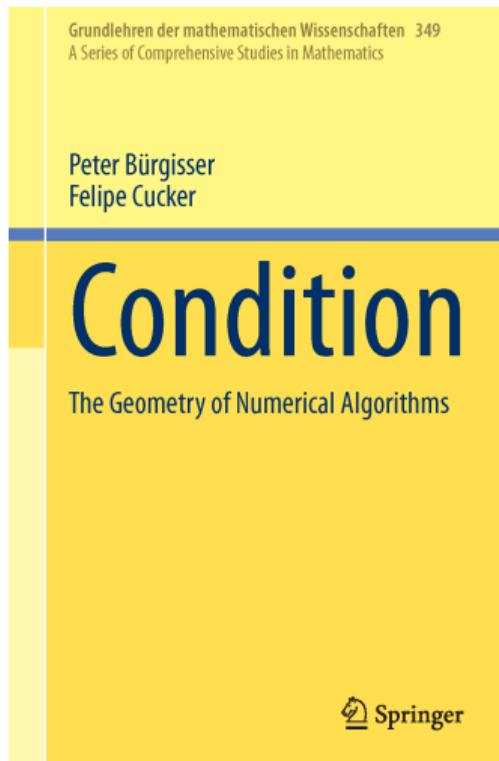
$$\begin{aligned} \tilde{\mathcal{A}} &:= e_1 \otimes e_1 \otimes e_2 + e_1 \otimes e_2 \otimes e_1 + e_2 \otimes e_1 \otimes e_1 \\ &= e_1 \otimes \underbrace{(e_1 \otimes e_2 + e_2 \otimes e_1)}_{\infty \text{ many rank-2 decompositions}} + e_2 \otimes e_1 \otimes e_1. \end{aligned}$$

There's some numerical shenanigans here. We should measure the precise amount of it.

# 1 Outline

- ① Condition: the main concept
- ② Tensor manifolds and join sets
- ③ Condition of additive decompositions
- ④ Compression and invariance of the condition number

# 1 Condition numbers



*Condition number* = estimate of *numerical difficulty*.

I.e., how difficult it is to compute something precisely when working with inexact data or inexact arithmetic?

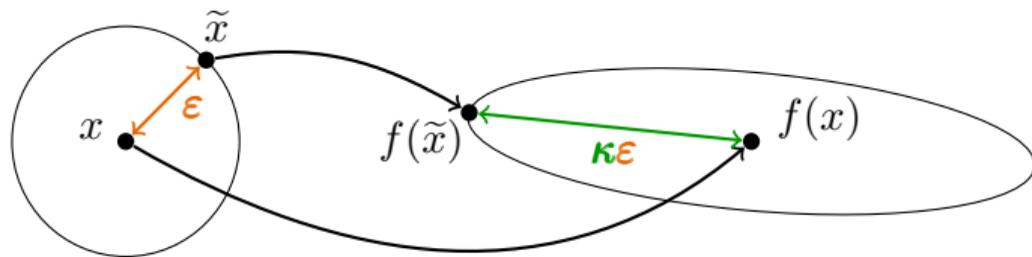
A staple in numerical analysis, it is used in

- ▶ perturbation theory
- ▶ analysis of (iterative) algorithms
- ▶ regression analysis
- ▶ ...

## 1 Definition of the condition number

Let  $f : \mathcal{X} \rightarrow \mathcal{Y}$  be a map between metric spaces. The condition number of  $f$  is

$$\kappa[f](x) := \lim_{\epsilon \rightarrow 0} \sup_{d(x, \tilde{x}) \leq \epsilon} \frac{d(f(x), f(\tilde{x}))}{d(x, \tilde{x})}.$$



If  $\mathcal{X}$  and  $\mathcal{Y}$  are Riemannian manifolds, then  $\kappa[f](x)$  is the spectral norm of  $Df(x)$  [Rice 1966].

## 1 Some celebrated theorems involving condition numbers

Theorem (distance to ill-posedness, Eckart & Young 1936; Schmidt 1907)

Let  $A \in GL(n)$  and let  $\Sigma := \mathbb{R}^{n \times n} \setminus GL(n)$ . Then

$$d(A, \Sigma) := \inf_{X \in \Sigma} \frac{\|A - X\|_F}{\|A\|_F} = \frac{1}{\kappa(\mathbf{A})}$$

where  $\kappa(\mathbf{A})$  is the condition number of  $A \mapsto A^{-1}$ .

Similar theorems exist for polynomial systems, eigenvalues, ...

## 1 Some celebrated theorems involving condition numbers

Theorem (condition numbers and convergence rate, see e.g. Nocedal & Wright 2006)

Let  $h : \mathbb{R}^n \rightarrow \mathbb{R}, x \mapsto \frac{1}{2}x^T Ax - b^T x$  be convex. If  $x_\star = \arg \min_x h(x)$  is computed with the conjugate gradient algorithm, yielding iterates  $x_0, x_1, \dots$ , then

$$\|x_\star - x_k\|_A \leq 2 \left( \frac{\sqrt{\kappa(\mathbf{A})} - 1}{\sqrt{\kappa(\mathbf{A})} + 1} \right)^k \|x_\star - x_0\|_A.$$

## 1 Some celebrated theorems involving condition numbers

Theorem (Region of attraction, Blum et al. 1998)

Let  $F(z) = 0$  be a homogeneous polynomial system of degree  $D$  with simple roots  $\zeta_1, \dots, \zeta_K \in \mathbb{C}\mathbb{P}^n$ . For  $k = 1, \dots, K$ , there exists a local solution map  $G_k : F \mapsto \zeta_k$ . Let  $z_0, z_1, z_2, \dots$  be the iterates from Newton's method applied to  $F(z) = 0$ . If

$$d(z_0, \zeta_k) \leq \frac{3 - \sqrt{7}}{D^2 \kappa[\mathbf{G}_k](\mathbf{F})}$$

then the iterates converge quadratically to  $\zeta_k$ .

# 1 Ongoing research project

- 1 Characterise the condition number of any tensor decomposition
- 2 Compute it efficiently
- 3 Connect it to the previous theorems.

Today's talk: answer 1-2 for general additive decompositions.

## 2 Outline

- ① Condition: the main concept
- ② Tensor manifolds and join sets
- ③ Condition of additive decompositions
- ④ Compression and invariance of the condition number

## 2 Basic concepts

Tensors:  $\mathcal{A} \in \mathbb{R}^{n_1 \times \dots \times n_D}$ . Rank 1 tensors:  $\mathbf{a}_1 \otimes \dots \otimes \mathbf{a}_D$ .

Multilinear multiplication / Tucker product:

$$\mathcal{A} = (U_1 \otimes \dots \otimes U_D) \mathcal{G} \quad (1)$$

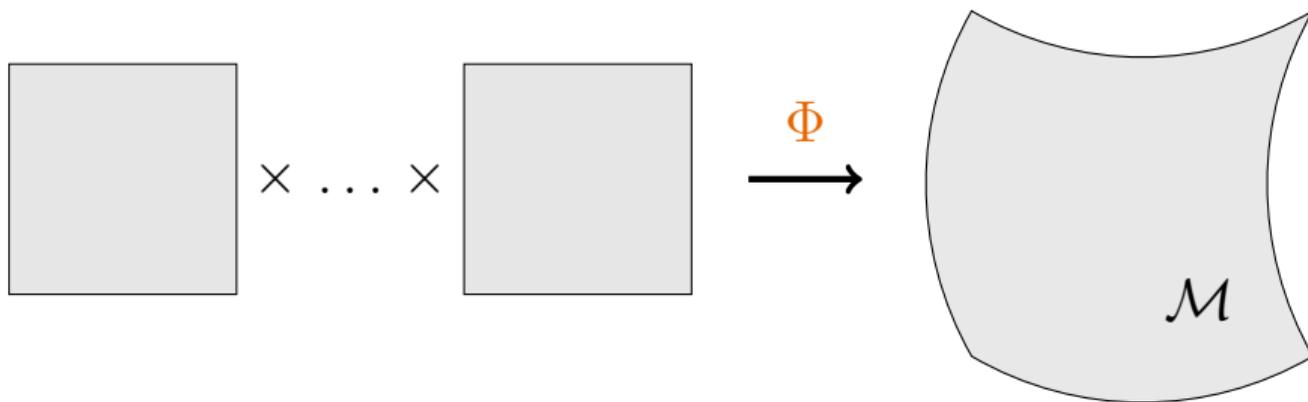
with  $\mathcal{G} \in \mathbb{R}^{m_1 \times m_2 \times m_3}$

- ▶ Coordinate definition:  $\mathcal{A}_{ijk} = \sum_{l,m,n} (U_1)_{il} (U_2)_{jm} (U_3)_{kn} \mathcal{G}_{lmn}$
- ▶ Linear extension of  $(U_1 \otimes \dots \otimes U_D)(\mathbf{g}_1 \otimes \mathbf{g}_2 \otimes \mathbf{g}_3) = (U_1 \mathbf{g}_1 \otimes U_2 \mathbf{g}_2 \otimes U_3 \mathbf{g}_3)$ .

Multilinear rank of  $\mathcal{A}$  = dimensions of the smallest  $\mathcal{G}$  so that (1) holds. A dense subset  $\mathbb{R}_{\star}^{n_1 \times \dots \times n_D}$  has the maximal ML rank.

## 2 Tensor manifolds

Maps defined with multilinear products often have smooth manifolds as their image.



## 2 Examples of tensor manifolds

Segre manifold:

$$(\mathbb{R}^{n_1} \setminus \{0\}) \times (\mathbb{R}^{n_2} \setminus \{0\}) \times (\mathbb{R}^{n_3} \setminus \{0\}) \rightarrow \mathbb{R}^{n_1 \times n_2 \times n_3}$$
$$\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3 \mapsto \mathbf{a}_1 \otimes \mathbf{a}_2 \otimes \mathbf{v}_3$$

Tucker manifold:

$$\mathbb{R}_*^{n_1 \times m_1} \times \mathbb{R}_*^{n_2 \times m_2} \times \mathbb{R}_*^{n_3 \times m_2} \times \mathbb{R}_*^{m_1 \times m_2 \times m_3} \rightarrow \mathbb{R}^{n_1 \times n_2 \times n_3}$$
$$U_1, U_2, U_3, \mathcal{G} \mapsto (U_1 \otimes U_2 \otimes U_3) \mathcal{G}$$

Tensor train manifold:

$$A, \mathcal{B}, C, D \mapsto \mathcal{X} \quad \text{where} \quad x_{ijkl} = \sum_{\alpha, \beta, \gamma} A_{i,\alpha} \mathcal{B}_{\alpha,j,\beta} C_{\beta,k,\gamma} D_{\gamma,k}$$

## 2 The structured Tucker manifold

### Definition

A smooth manifold  $\mathcal{N} \subseteq \mathbb{R}_{\star}^{m_1 \times \dots \times m_D}$  is a *core structure* if it is invariant under arbitrary changes of basis.

### Definition (D, Breiding & Vannieuwenhoven 2021)

A *structured Tucker manifold* is the image of

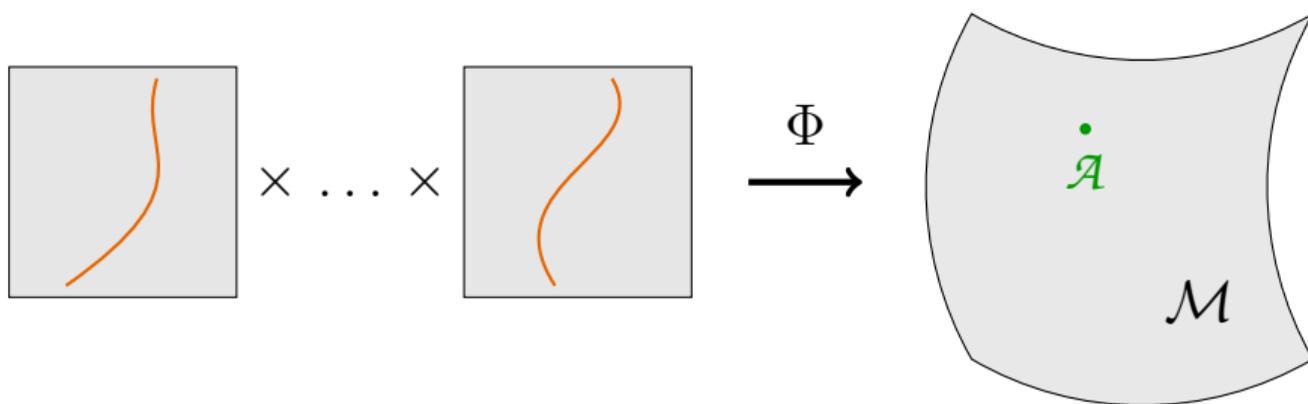
$$\begin{aligned} \Phi : \mathbb{R}_{\star}^{n_1 \times m_1} \times \dots \times \mathbb{R}_{\star}^{n_D \times m_D} \times \mathcal{N} &\rightarrow \mathbb{R}^{n_1 \times \dots \times n_D} \\ U_1, \dots, U_D, \mathcal{G} &\mapsto (U_1 \otimes \dots \otimes U_D) \mathcal{G} \end{aligned}$$

where  $\mathcal{N}$  is a core structure.

This is also a smooth manifold.

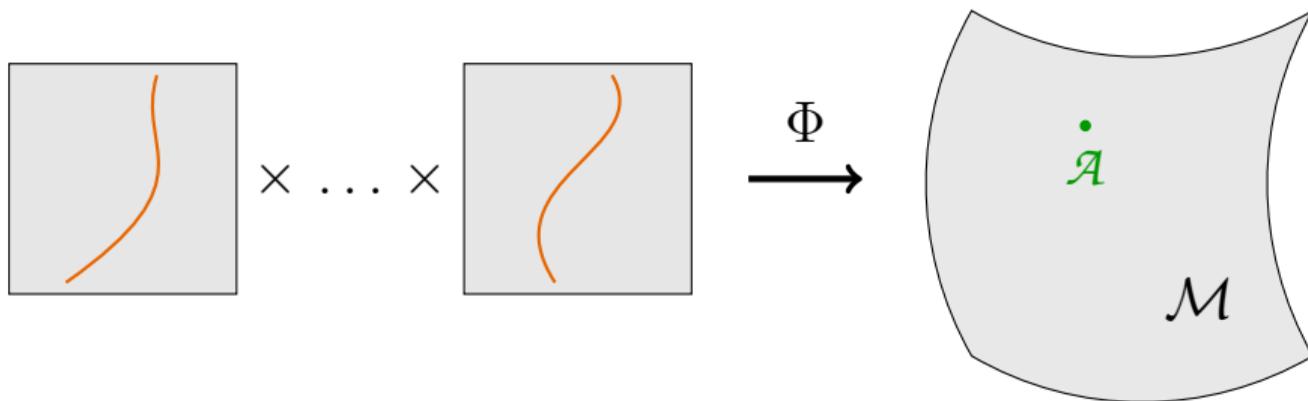
## 2 Intuition behind the manifold

Structured Tucker manifold  $\approx$  smoothly factorisable tensors.



Given  $\mathcal{A} \in \mathcal{M}$ , the fibre  $\Phi^{-1}(\mathcal{A})$  is a smooth submanifold of the domain. If you glue each fibre to one point, the above is a diffeomorphism.

## 2 Sidenote: condition of multiplicative decompositions



Because  $\Phi^{-1}(\mathcal{A})$  is not single valued, it is not so easy to define how it changes under small perturbations of  $\mathcal{A}$ .

Ongoing work: we can compute a condition number that measures local changes to the fibres.

## 2 Additive decompositions

Given manifolds  $\mathcal{M}_1, \dots, \mathcal{M}_R$ , the *join set* is the image of

$$\begin{aligned}\Sigma : \mathcal{M}_1 \times \dots \times \mathcal{M}_R &\mapsto \mathbb{R}^{n_1 \times \dots \times n_D} \\ \mathcal{A}_1, \dots, \mathcal{A}_R &\mapsto \mathcal{A}_1 + \dots + \mathcal{A}_R.\end{aligned}$$

Decomposition problem: given  $\mathcal{A}$  in the join set, solve  $\Sigma(\mathcal{A}_1, \dots, \mathcal{A}_R) = \mathcal{A}$ .

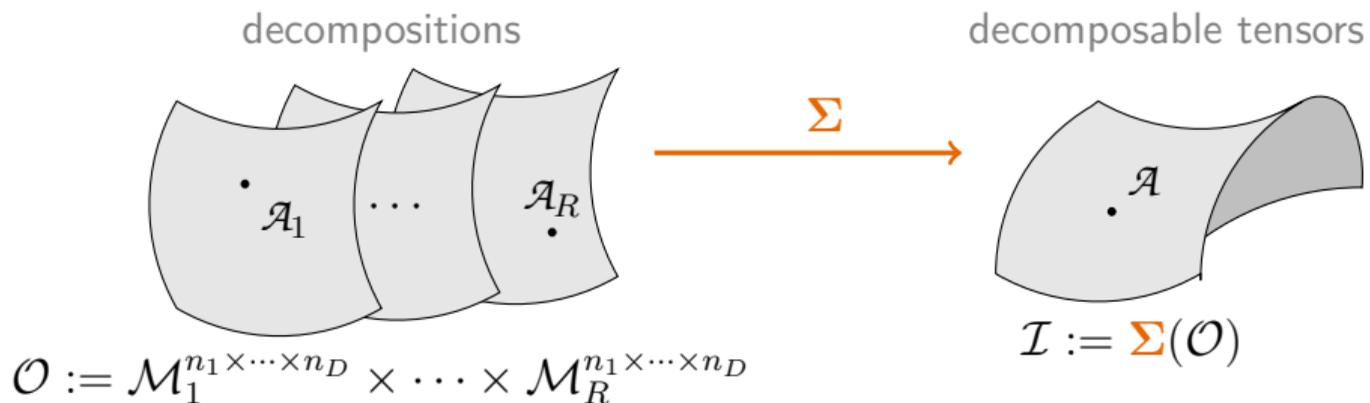
$\mathcal{M}_1, \dots, \mathcal{M}_R$	decomposition
Segre manifold	polyadic decomposition
Tucker manifold	block term decomposition
TT manifold	SoTT decomposition
structured Tucker manifold	<i>structured block term decomposition (SBTD)</i>

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- ④ Compression and invariance of the condition number

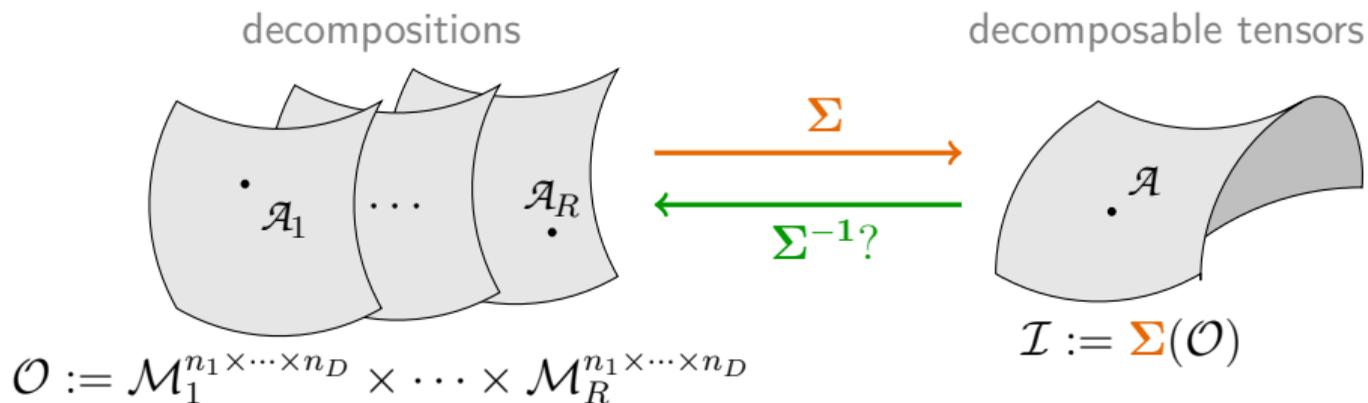
### 3 Finding the decomposition map geometrically

The easy version of the problem is *evaluating* the decomposition:  $\mathcal{A} = \sum_{r=1}^R \mathcal{A}_r$ .



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But what about *decomposing*  $\mathcal{A}$ ?

By the inverse function theorem,  $\exists$  smooth local map  $\Sigma^{-1}$  with closed-form derivative [Breiding & Vannieuwenhoven 2018], similar to [Bürgisser & Cucker 2013].

### 3 Algorithm to compute the condition number

**Given:**  $\mathcal{A}_1 \in \mathcal{M}_1^{n_1, \dots, n_D}, \dots, \mathcal{A}_R \in \mathcal{M}_R^{n_1, \dots, n_D}$  so that  $\mathcal{A} = \sum_{r=1}^R \mathcal{A}_r$ .

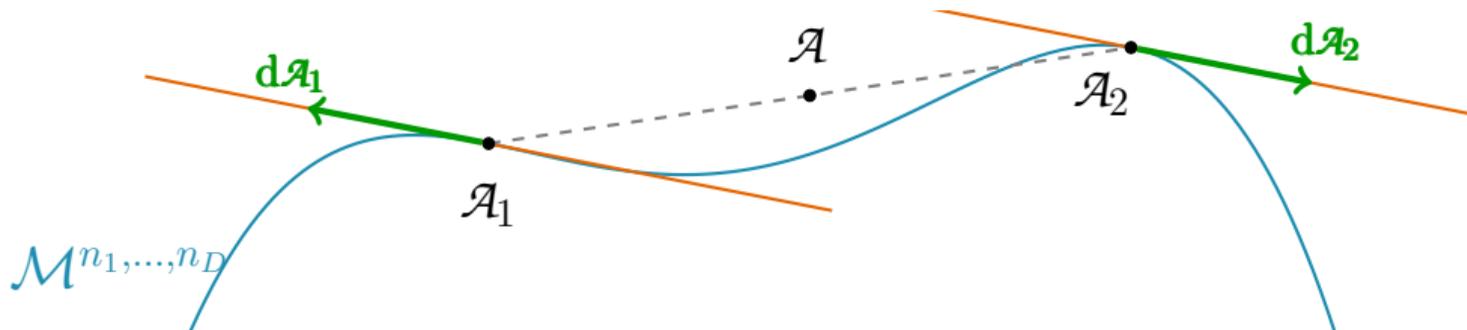
By [Breiding & Vannieuwenhoven 2018], the following computes the condition number of the decomposition map  $\Sigma^{-1}: \mathcal{A} \mapsto (\mathcal{A}_1, \dots, \mathcal{A}_R)$  at  $\mathcal{A}$ .

- 1 For  $r = 1, \dots, R$ , construct a matrix  $T_r$  containing an orthonormal basis of  $T_{\mathcal{A}_r} \mathcal{M}_r^{n_1, \dots, n_D}$ .
- 2  $\kappa = \sigma_{\min} ([T_1 \ \cdots \ T_R])^{-1}$ .

An expression for step 1 was provided by [D, Breiding & Vannieuwenhoven 2021].

### 3 Geometric intuition behind the condition number

$\kappa$  measures the collinearity between the **tangent spaces**. E.g., let  $\mathcal{A} = \frac{1}{2}\mathcal{A}_1 + \frac{1}{2}\mathcal{A}_2$ :



Suppose there are almost parallel tangent vectors  $d\mathcal{A}_1 \approx -d\mathcal{A}_2$ . Then

- 1 A tiny nudge to  $\mathcal{A}$  can push  $\mathcal{A}_1$  and  $\mathcal{A}_2$  far away in opposite directions.
- 2 The derivative of  $(\mathcal{A}_1, \mathcal{A}_2) \mapsto \frac{1}{2}\mathcal{A}_1 + \frac{1}{2}\mathcal{A}_2 - \mathcal{A}$  is singular at the solution.

### 3 Revisiting the bad tensor

Take our example from the beginning:

$$\mathcal{A} = \left[ \begin{bmatrix} & 1 \\ 1 & \end{bmatrix} \begin{bmatrix} 1 & \varepsilon \\ \varepsilon & \varepsilon^2 \end{bmatrix} \begin{bmatrix} \varepsilon \\ \end{bmatrix} \right].$$

For  $\varepsilon = 10^{-6}$  the unique tensor rank decomposition  $\mathcal{A} = \mathcal{A}_1 + \mathcal{A}_2 + \mathcal{A}_3$  has  $\kappa \approx 10^{12}$ .

Suppose  $\tilde{\mathcal{A}} = \tilde{\mathcal{A}}_1 + \tilde{\mathcal{A}}_2 + \tilde{\mathcal{A}}_3$  is an approximation of  $\mathcal{A}$ .

To get  $\left\| (\tilde{\mathcal{A}}_1, \tilde{\mathcal{A}}_2, \tilde{\mathcal{A}}_3) - (\mathcal{A}_1, \mathcal{A}_2, \mathcal{A}_3) \right\| \leq 10^{-p}$ , we may need  $\left\| \tilde{\mathcal{A}} - \mathcal{A} \right\| \lesssim 10^{-12-p}$ .

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## 4 Compression

Many tensors in applications live in the tensor product of low-dimensional subspaces  $\mathbf{V}_1, \dots, \mathbf{V}_D$  with  $\dim(\mathbf{V}_i) = m_i$ . In coordinates,  $\exists \mathcal{G} \in \mathbb{R}^{m_1 \times \dots \times m_D}$  so that

$$\mathcal{A} = (\mathbf{Q}_1 \otimes \dots \otimes \mathbf{Q}_D) \mathcal{G} \quad \text{where} \quad \text{span}(\mathbf{Q}_i) = \mathbf{V}_i.$$

The SBTD is defined precisely so that the decompositions of  $\mathcal{A}$  and  $\mathcal{G}$  can be converted into each other:

$$\mathcal{G} = \sum_{r=1}^R (U_1 \otimes \dots \otimes U_D) C_r \quad \Rightarrow \quad \mathcal{A} = \sum_{r=1}^R (\mathbf{Q}_1 U_1 \otimes \dots \otimes \mathbf{Q}_D U_D) C_r.$$

Conversely, if  $\mathcal{A}$  has an SBTD, so does  $\mathcal{G}$ .

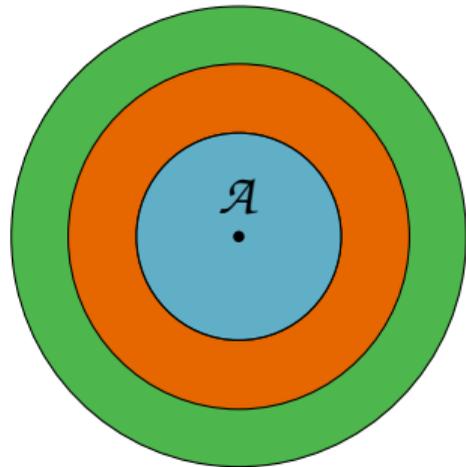
## 4 Algorithm to decompose tensors by compression

- 1 (*Compress*) Identify the lowest dimensional subspaces  $\mathbf{V}_1, \dots, \mathbf{V}_D$  so that  $\mathcal{A} \in \mathbf{V}_1 \otimes \dots \otimes \mathbf{V}_D$ . In coordinates:  $\mathcal{A} = (\mathbf{Q}_1 \otimes \dots \otimes \mathbf{Q}_D) \mathcal{G}$
- 2 (*Decompose*) Decompose  $\mathcal{G} = \sum_{r=1}^R (U_1 \otimes \dots \otimes U_D) C_r$ .
- 3 (*Expand*) Convert step 2 to  $\mathcal{A} = \sum_{r=1}^R (\mathbf{Q}_1 U_1 \otimes \dots \otimes \mathbf{Q}_D U_D) C_r$ .

We often use orthonormal bases  $Q_1, \dots, Q_D$ .

## 4 The importance of the domain

Tensors  $\mathcal{A}$  for which this algorithm works are special in several ways:



- ▶  $\mathcal{I}_1$  : decomposable
- ▶  $\mathcal{I}_2$  : decomposition in an  $(m_1, \dots, m_D)$ -dimensional tensor subspace
- ▶  $\mathcal{I}_3$  : decomposition in  $\mathbb{V}_1 \otimes \dots \otimes \mathbb{V}_D$

$$\mathcal{I}_3 \subseteq \mathcal{I}_2 \subseteq \mathcal{I}_1$$

Recall the definition of the condition number of a map  $f : \mathcal{I} \rightarrow \mathcal{O}$ :

$$\kappa[f](\mathcal{A}) := \limsup_{\mathcal{I} \ni \tilde{\mathcal{A}} \rightarrow \mathcal{A}} \frac{d(f(\mathcal{A}), f(\tilde{\mathcal{A}}))}{d(\mathcal{A}, \tilde{\mathcal{A}})}.$$

## 4 The importance of the domain

- ▶  $\mathcal{I}_1$  : decomposable
- ▶  $\mathcal{I}_2$  : decomposition in an  $(m_1, \dots, m_D)$ -dimensional tensor subspace
- ▶  $\mathcal{I}_3$  : decomposition in  $\mathbb{V}_1 \otimes \dots \otimes \mathbb{V}_D$

Let  $f$  be the SBTB decomposition map:

$$\kappa[f](\mathcal{A}) := \limsup_{\mathcal{I} \ni \tilde{\mathcal{A}} \rightarrow \mathcal{A}} \frac{d(f(\mathcal{A}), f(\tilde{\mathcal{A}}))}{d(\mathcal{A}, \tilde{\mathcal{A}})}.$$

If  $\mathcal{A} = (Q_1 \otimes \dots \otimes Q_D)\mathcal{G}$  and  $\mathcal{G}$  has an SBTB, then  $\kappa[f](\mathcal{G})$  corresponds to the case  $\mathcal{I} = \mathcal{I}_3$ .

However,  $\kappa[f](\mathcal{A})$  corresponds to  $\mathcal{I} = \mathcal{I}_1 \supseteq \mathcal{I}_3$ .

## 4 Invariance of the condition number

Theorem (D, Breiding & Vannieuwenhoven 2021)

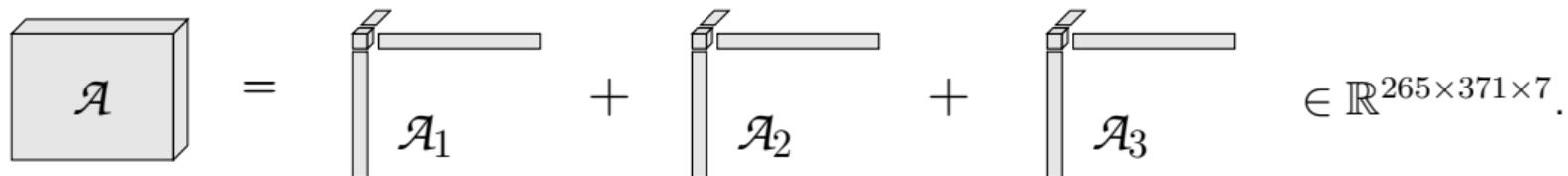
*Suppose  $\mathcal{A} = \sum_{r=1}^R \mathcal{A}_r$  and  $\mathcal{G} = \sum_{r=1}^R \mathcal{G}_r$  are two SBTDs related by  $\mathcal{A}_r = (Q_1, \dots, Q_D) \cdot \mathcal{G}_r$  for some matrices  $Q_1, \dots, Q_D$  with orthonormal columns. Then these two SBTDs have the same condition number.*

**Bad news:** making the problem smaller does not make it numerically easier.

**Good news:** properties of a large SBTD can be revealed through small-scale calculations.

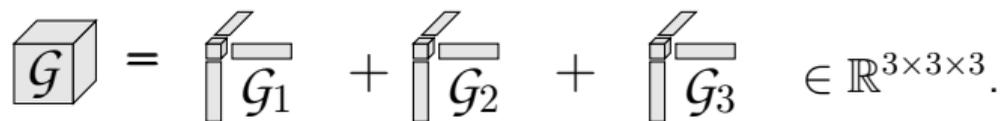
## 4 Fast computation of the condition number: example

Let's take a tensor rank decomposition from chemometrics [Bro & Andersson 1998]:



The diagram shows a 3D tensor  $\mathcal{A}$  represented as a rectangular box. It is equated to the sum of three rank-1 tensors,  $\mathcal{A}_1$ ,  $\mathcal{A}_2$ , and  $\mathcal{A}_3$ . Each rank-1 tensor is depicted as a vertical bar connected to a horizontal bar at a corner. To the right of the sum, the dimensions of the tensor are given as  $\in \mathbb{R}^{265 \times 371 \times 7}$ .

Computing the condition number takes **110 seconds**. However, since  $\mathcal{A}$  has rank 3, it can be compressed to

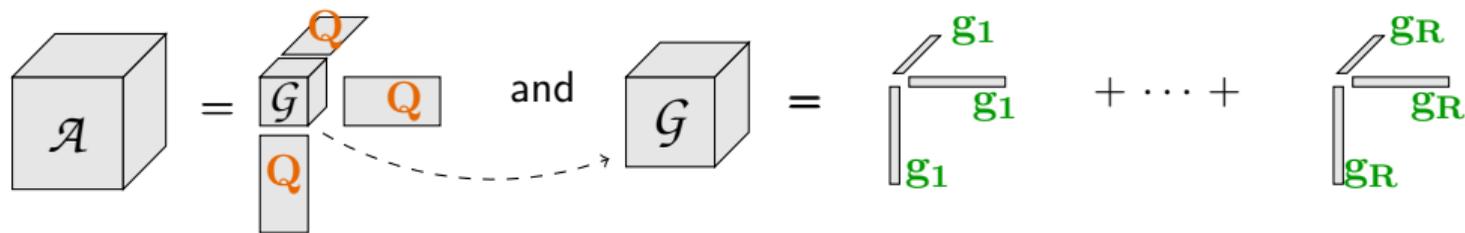


The diagram shows a 3D tensor  $\mathcal{G}$  represented as a small cube. It is equated to the sum of three rank-1 tensors,  $\mathcal{G}_1$ ,  $\mathcal{G}_2$ , and  $\mathcal{G}_3$ . Each rank-1 tensor is depicted as a small vertical bar connected to a small horizontal bar at a corner. To the right of the sum, the dimensions of the tensor are given as  $\in \mathbb{R}^{3 \times 3 \times 3}$ .

Compressing and computing the condition number of  $(\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3)$  takes **6.9 milliseconds** (combined)!

## 4 Compressed symmetric decompositions

The symmetric decomposition expresses  $\mathcal{A} = \mathbf{a}_1^{\otimes D} + \dots + \mathbf{a}_R^{\otimes D}$  where  $\mathbf{a}^{\otimes D} = \mathbf{a} \otimes \dots \otimes \mathbf{a}$ . Similar compression methods exist in which



$$\mathcal{A} = \mathbf{Q}^{\otimes D} \sum_{r=1}^R \mathbf{g}_r^{\otimes D} = \sum_{r=1}^R (\mathbf{Q} \mathbf{g}_r)^{\otimes D}$$

so that  $\mathcal{A}$  and  $\mathcal{G}$  have equivalent decompositions.

## 4 Several ways to quantify the condition number

Let  $\mathcal{A} = Q^{\otimes D} \mathcal{G}$  for some orthonormal basis  $Q$ .

There are 4 condition numbers, each of which accounts for some perturbation  $\tilde{\mathcal{A}}$  or  $\tilde{\mathcal{G}}$ .

$$\begin{array}{c|c} \kappa_{\tilde{\mathcal{A}}}^{\text{sym}}: & \tilde{\mathcal{A}} = \sum_{r=1}^R \tilde{\mathbf{a}}_r^{\otimes D} \\ \kappa_{\tilde{\mathcal{A}}}^{\text{cpd}}: & \tilde{\mathcal{A}} = \sum_{r=1}^R \tilde{\mathbf{a}}_r^1 \otimes \dots \otimes \tilde{\mathbf{a}}_r^D \end{array} \quad \left| \quad \begin{array}{c|c} \kappa_{\tilde{\mathcal{G}}}^{\text{sym}}: & \tilde{\mathcal{G}} = \sum_{r=1}^R \tilde{\mathbf{g}}_r^{\otimes D} \\ \kappa_{\tilde{\mathcal{G}}}^{\text{cpd}}: & \tilde{\mathcal{G}} = \sum_{r=1}^R \tilde{\mathbf{g}}_r^1 \otimes \dots \otimes \tilde{\mathbf{g}}_r^D \end{array} \right.$$

**Theorem 1:**  $\kappa_{\tilde{\mathcal{G}}}^{\text{sym}} = \kappa_{\tilde{\mathcal{A}}}^{\text{sym}}$  if  $\mathcal{G}$  is not minimal.

**Theorem 2:**  $\kappa_{\tilde{\mathcal{G}}}^{\text{sym}} \leq \kappa_{\tilde{\mathcal{A}}}^{\text{sym}} \leq \sqrt{D} \kappa_{\tilde{\mathcal{G}}}^{\text{sym}}$ .

**Theorem 3:**  $\kappa_{\tilde{\mathcal{A}}}^{\text{sym}} = \kappa_{\tilde{\mathcal{A}}}^{\text{cpd}}$  if  $R \leq 2$ .

**Conjecture:** all equal!

## 5 References I



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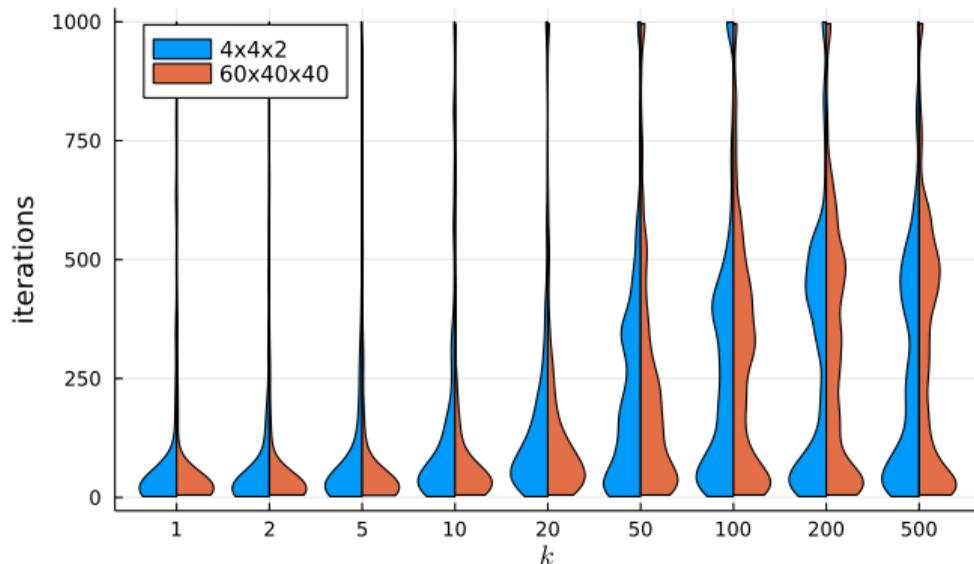
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## 5 Iterative methods

The invariance of the condition number indicates that the convergence rate of iterative algorithms is unaffected by compression, even though the search space is reduced.



*Performance of Tensorlab's `ll1_nls` algorithm [Vervliet, Debals & De Lathauwer 2017] to compute the two-term (2,2,1) block term decomposition.*

*As  $k$  increases from 1 to 500, the condition number increases from  $\sim 10$  to  $\sim 10^8$  on average*