

# X-rank and identifiability for a polynomial decomposition model

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# Overview

Matrix and tensor rank

A polynomial decomposition

Waring decomposition

X-rank and identifiability

Results

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# Matrix rank

Rank of  $M \in \mathbb{K}^{I \times J}$  ( $\mathbb{K} = \mathbb{R}, \mathbb{C}$ )

Two definitions:

1.  $\text{rank}(M) \stackrel{\text{def}}{=} \dim \text{colspan } M = \dim \text{rowspan } M$
2.  $\text{rank}(M) \stackrel{\text{def}}{=} \text{minimal } r \text{ such that}$

$$M = \mathbf{a}_1 \mathbf{b}_1^\top + \cdots + \mathbf{a}_r \mathbf{b}_r^\top, \quad \mathbf{a}_k \in \mathbb{K}^I, \mathbf{b}_k \in \mathbb{K}^J$$

sum of  $r$  **rank-one** matrices

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- Rank does not exceed dimensions ( $r \leq \min(I, J)$ ),  
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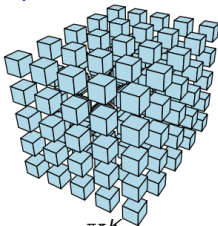
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we can take  $\mathbf{a}_k$  and/or  $\mathbf{b}_k$  orthogonal (SVD, QR)
- $\text{rank}_{\mathbb{C}}(M) = \text{rank}_{\mathbb{R}}(M)$ ,

# Tensor CP (canonical polyadic) rank

Tensor:  $d$ -dimensional array  $\mathcal{T} = [\mathcal{T}_{i,j,\dots,k}]_{i,j,\dots,k=1}^{l,j,\dots,k}$



Rank-one tensor:  $\mathcal{T}_{i,j,\dots,k} = a_i b_j \cdots c_k$

Notation:  $\mathcal{T} = \mathbf{a} \otimes \mathbf{b} \otimes \cdots \otimes \mathbf{c}$ ,  $\mathbf{a} \in \mathbb{K}^l, \mathbf{b} \in \mathbb{K}^j, \dots, \mathbf{c} \in \mathbb{K}^k$

## Definition (Hitchcock, 1927)

$\text{rank}(\mathcal{T}) \stackrel{\text{def}}{=} \text{minimal } r \text{ such that}$

$$\mathcal{T} = \sum_{\ell=1}^r \mathbf{a}_\ell \otimes \mathbf{b}_\ell \otimes \cdots \otimes \mathbf{c}_\ell \quad (\text{CP decomposition})$$

A picture:  $\mathcal{T} = \mathbf{a}_1 \left| \begin{array}{c} \mathbf{c}_1 \\ \mathbf{b}_1 \end{array} \right. + \cdots + \mathbf{a}_r \left| \begin{array}{c} \mathbf{c}_r \\ \mathbf{b}_r \end{array} \right.$



## Usefulness of tensor CPD

$$\boxed{\mathcal{T}} = \begin{array}{|c} \diagup \\ \hline \\ \hline \end{array} + \dots + \begin{array}{|c} \diagup \\ \hline \\ \hline \end{array}$$

- Data mining (**identification** problems)

Tensor = data/signal, CP rank = # of components in a signal

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- **Complexity of matrix multiplication**

# of operations:  $O(N^3)$

$$\boxed{C} = N \begin{array}{c} N \\ \boxed{A} \end{array} \cdot \begin{array}{c} N \\ \boxed{B} \end{array}$$

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- Complexity of matrix multiplication**

(Strassen, 1969):

# of operations:  $O(N^3)$   $\rightarrow O(N^{2.8})$

$$\boxed{C} = N \begin{array}{|} N \\ \hline \\ N \end{array} \boxed{A} \cdot \begin{array}{|} N \\ \hline \\ N \end{array} \boxed{B} \leftrightarrow \text{vec} C = \begin{array}{|} \text{multiplication} \\ \hline \\ \text{tensor} \end{array} \bullet_2 \text{vec} A \bullet_3 \text{vec} B$$

## Symmetric tensor CPD

$$\mathcal{T} = [\mathcal{T}_{(i_1, \dots, i_d)}]_{i_1, \dots, i_d=1}^{m, \dots, m} \in \mathbb{K}^{m \times \dots \times m} \quad \underbrace{\mathcal{T}_{(i_1, \dots, i_d)} = \mathcal{T}_{\pi(i_1, \dots, i_d)}, \forall \pi}_{\text{symmetric}}$$

Symmetric rank of the tensor: minimal  $r$ , such that

$$\mathcal{T} = \sum_{k=1}^r c_k \mathbf{a}_k \otimes \dots \otimes \mathbf{a}_k \quad (*)$$

## Symmetric tensor CPD

$$\mathcal{T} = [\mathcal{T}_{(i_1, \dots, i_d)}]_{i_1, \dots, i_d=1}^{m, \dots, m} \in \mathbb{K}^{m \times \dots \times m} \quad \underbrace{\mathcal{T}_{(i_1, \dots, i_d)} = \mathcal{T}_{\pi(i_1, \dots, i_d)}, \forall \pi}_{\text{symmetric}}$$

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Useful for **blind source separation** (Comon, Jutten, 2010):

Mixing model:  $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} = \underbrace{\begin{bmatrix} \boxed{A} \end{bmatrix}}_{\text{unknown}} \underbrace{\begin{bmatrix} s_1 \\ \vdots \\ s_r \end{bmatrix}}_{\text{unknown}}.$

If  $s_k$  are independent (real) random variables, then the cumulant of  $\mathbf{x}$  has the form (\*).

## Tensors ( $d \geq 3$ ): bad news

- Set  $\{\mathcal{T} \mid \text{rank}(\mathcal{T}) \leq r\}$  is not closed.

$$\mathcal{T} = \mathbf{a} \otimes \mathbf{b} \otimes \mathbf{b} + \mathbf{b} \otimes \mathbf{a} \otimes \mathbf{b} + \mathbf{b} \otimes \mathbf{b} \otimes \mathbf{a}$$

$\text{rank}(\mathcal{T}) = 3$ , but

$$\mathcal{T} = \frac{1}{\varepsilon} ((\mathbf{a} + \varepsilon \mathbf{b})^{\otimes 3} - \mathbf{a}^{\otimes 3}) + O(\varepsilon)$$

- No polynomial time algorithm to determine rank (Hastad, 1990).
- $\text{rank}_{\mathbb{C}}(\mathcal{T}) \leq \text{rank}_{\mathbb{R}}(\mathcal{T})$ , may be strict
- For **symmetric** tensors: symmetric rank  $\stackrel{?}{=} \text{rank}$  (Comon conjecture)

## Tensors ( $d \geq 3$ ): good (or interesting) news

- Rank can exceed dimensions

Example:  $\mathcal{T} = \left[ \begin{array}{cc|cc} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 \end{array} \right], \text{rank}(\mathcal{T}) = 3$

- CP decomposition is often unique, doesn't need to be orthogonal
- Unusual rank properties (take  $2 \times 2 \times 2$  tensor):
  - maximal rank is 3
  - random (Gaussian i.i.d.) real tensor:  
 $P(\text{rank}(\mathcal{T}) = 2) = \pi/4, P(\text{rank}(\mathcal{T}) = 3) = 1 - \pi/4.$
  - random complex tensor: rank 2



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**A polynomial decomposition**

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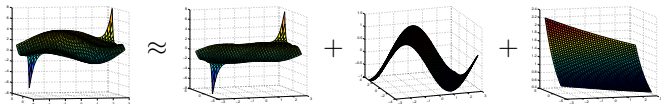
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## A polynomial decomposition

Given a **multivariate polynomial**  $f(u_1, \dots, u_m) = \sum_{i_1, \dots, i_m=0}^{|i_1+\dots+i_m| \leq d} f_{i_1, \dots, i_m} u_1^{i_1} \cdots u_m^{i_m}$ ,  
find its shortest representation

$$f(\mathbf{u}) = g_1(\mathbf{v}_1^\top \mathbf{u}) + \cdots + g_r(\mathbf{v}_r^\top \mathbf{u}),$$

where  $\mathbf{v}_k \in \mathbb{K}^m$ ,  $g_k(t) = c_{1,k}t + c_{2,k}t^2 + \cdots + c_{d,k}t^d$ ,  $\deg g_k \leq d$



Appears in

- approximation theory (ridge approximation, (Lin, Pinkus, 1993))
- machine learning (polynomial neural networks, (Shin, Ghosh, 1995))
- blind source separation

## Decomposition of polynomial maps

Given a **polynomial map**  $\mathbf{f} : \mathbb{K}^m \rightarrow \mathbb{K}^n$ , degree  $d$ ,  $\mathbf{f}(\mathbf{u}) = [f_1(\mathbf{u}) \cdots f_n(\mathbf{u})]^\top$   
find its shortest representation

$$\mathbf{f}(\mathbf{u}) = \mathbf{w}_1 g_1(\mathbf{v}_1^\top \mathbf{u}) + \cdots + \mathbf{w}_r g_r(\mathbf{v}_r^\top \mathbf{u}),$$

where  $\mathbf{v}_k \in \mathbb{K}^m$ ,  $\mathbf{w}_k \in \mathbb{K}^n$ ,  $g_k(t) = c_{1,k}t + c_{2,k}t^2 + \cdots + c_{d,k}t^d$

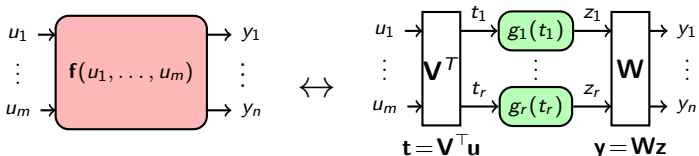
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Block-structured nonlinear system identification (Schoukens et al., 2014):



where  $\mathbf{V} = [\mathbf{v}_1 \cdots \mathbf{v}_r]^\top$  and  $\mathbf{W} = [\mathbf{w}_1 \cdots \mathbf{w}_r]^\top$ .

Remarks:

- Degree 1 — matrix factorization
- Can be also interpreted as polynomial neural network.

## A tensor-based algorithm\*

Given a polynomial map  $\mathbf{f}$  (of degree  $d$ ), find  $r$ ,  $\mathbf{w}_k$ ,  $\mathbf{v}_k$ ,  $g_k$  such that

$$\mathbf{f}(\mathbf{u}) = \mathbf{w}_1 g_1(\mathbf{v}_1^\top \mathbf{u}) + \cdots + \mathbf{w}_r g_r(\mathbf{v}_r^\top \mathbf{u}),$$

(Dreesen et al, 2015), (Van Mulders et al, 2014): transform to a [tensor CPD](#)

### Algorithm.

1. Evaluate  $\mathbf{J}_f(\mathbf{u})$  at  $N$  points  $\mathbf{u}_1, \dots, \mathbf{u}_N \in \mathbb{K}^m$
2. Stack it into a tensor:

The diagram shows a 3D tensor  $\mathcal{T}$  with dimensions  $n$ ,  $m$ , and  $N$ . This tensor is equal to the stack of Jacobian matrices  $\mathbf{J}_f(\mathbf{u}_1), \dots, \mathbf{J}_f(\mathbf{u}_N)$ . This stack is then decomposed into a sum of rank-1 terms:  $\mathbf{w}_1 \frac{d_1}{\mathbf{v}_1} + \cdots + \mathbf{w}_r \frac{d_r}{\mathbf{v}_r}$ . Below this decomposition, a bracket indicates the next step: "3. Retrieve  $\mathbf{v}_k, \mathbf{w}_k, g_k$ ".

### Our questions:

- When is the decomposition unique? (identifiability of the model)
- What is the maximal/typical number of terms?

## Existing results

For  $f$  of degree  $d$ :

$$f(u_1, \dots, u_m) = g_1(\mathbf{v}_1^\top \mathbf{u}) + \dots + g_r(\mathbf{v}_r^\top \mathbf{u}),$$

- (Schinzel, 2002),  $m = 2$ :  
a general (“random”) polynomial in  $\mathbb{C}$  has  $r = \lceil \frac{2d+5-\sqrt{8d+17}}{2} \rceil$  terms
- (Białynicki-Birula, Schinzel, 2008):  
any  $f$  can be represented with  $r \leq \binom{m+d-2}{d-1}$  terms
- nothing about identifiability

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## Special case: homogeneous polynomials

Given a **homogeneous polynomial**

$$f(u_1, \dots, u_m) = \sum_{|i_1 + \dots + i_m| = d} f_{i_1, \dots, i_m} u_1^{i_1} \cdots u_m^{i_m}$$

find its shortest representation of the form

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Waring decomposition

$$\iff f(\mathbf{u}) = \mathcal{F} \circ_1 \mathbf{u} \cdots \circ_d \mathbf{u}$$

symmetric tensor CP decomposition

$$\begin{array}{|c|} \hline \mathcal{F} \\ \hline \end{array} = c_1 \begin{array}{|c|} \hline \mathbf{v}_1 \\ \hline \end{array} \begin{array}{|c|} \hline \mathbf{v}_1 \\ \hline \end{array} + \cdots + c_r \begin{array}{|c|} \hline \mathbf{v}_r \\ \hline \end{array} \begin{array}{|c|} \hline \mathbf{v}_r \\ \hline \end{array}$$

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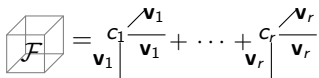
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Waring decomposition

$$\Updownarrow \quad f(\mathbf{u}) = \mathcal{F} \circ_1 \mathbf{u} \cdots \circ_d \mathbf{u}$$

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$$\mathcal{F} = c_1 \begin{array}{c} \mathbf{v}_1 \\ | \\ \mathbf{v}_1 \end{array} + \cdots + c_r \begin{array}{c} \mathbf{v}_r \\ | \\ \mathbf{v}_r \end{array}$$

**Example.** ( $d = 2$ ):

$$\mathbf{u}^\top T \mathbf{u} = c_1 \cdot (..)^2 + \cdots + c_r \cdot (..)^2$$

diagonalize a **quadratic form**

$\Updownarrow$

diagonalize a **symmetric matrix**

$$T = A \begin{pmatrix} c_1 & & \\ & \ddots & \\ & & c_r \end{pmatrix} A^\top$$

## Waring problem for $n = 2$ (binary forms)

### Theorem (J.J. Sylvester)

A polynomial  $f(x, y) = \sum_{j=0}^d \binom{d}{j} f_j x^{d-j} y^j$  has the Waring decomposition

$$f(x, y) = \sum_{k=1}^r c_k \cdot (x + \lambda_k y)^d,$$

if and only if there exist  $q_j, j = 0, \dots, r$  such that

$$\begin{bmatrix} q_0 & \cdots & q_r \end{bmatrix} \begin{bmatrix} f_0 & f_1 & \cdots & f_{d-r} \\ f_1 & f_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ f_r & \cdots & \cdots & f_d \end{bmatrix} = 0,$$

and  $q(t) = \sum_{k=0}^r q_k t^k$  has  $r$  distinct roots  $\lambda_k \in \mathbb{K} \cup \{\infty\}$ .

**Proof.** follows from  $(x + \lambda y)^d = \sum_{j=0}^d \binom{d}{j} \lambda^j x^{d-j} y^j$

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## X-rank: definitions

Let  $\mathbb{K} = \mathbb{R}, \mathbb{C}$ ,  $A$  —  $N$ -dim vector space over  $\mathbb{K}$ .

$\text{rank}_X(\mathbf{v}) \stackrel{\text{def}}{=} \text{the minimal } r \text{ such that}$

$$\mathbf{v} = \mathbf{p}_1 + \cdots + \mathbf{p}_r \text{ for some } \mathbf{p}_i \in \widehat{X},$$

where  $\widehat{X}$  is the set of **rank-one elements** ( $\text{rank}_X(\mathbf{0}) = 0$ )

Similar to atomic/sparse decomposition.

Convenient conditions:

- $\widehat{X}$  is scale-invariant ( $\alpha\widehat{X} = \widehat{X}$  for  $\alpha \in \mathbb{K}$ )
- $\widehat{X}$  nondegenerate, i.e.,  $\widehat{X}$  does not lie in a linear subspace of  $A$ ;
- $\widehat{X}$  (irreducible) **algebraic variety**.

Introduced by (Zak, 2004) (“rank w.r.t. a projective variety”)

## Some definitions

- $Z \subseteq A$  is an affine **algebraic variety**, if

$$Z = \{\mathbf{v} \in A \mid h_1(\mathbf{v}) = \cdots = h_M(\mathbf{v}) = 0\},$$

for some polynomials  $h_k$ .

- **Zariski closure** of  $Y \subseteq A$ :  
 $\stackrel{\text{def}}{=} \text{the smallest algebraic variety } Z \text{ containing } Y.$
- A nonempty  $Z$  is **irreducible**, if it cannot be decomposed as a union  $Z = Z_1 \cup Z_2$  of distinct (i.e.  $Z_1 \not\subseteq Z_2$ ) varieties.
- Dimension of  $Z$  — dimension of the tangent space at smooth points,  
 Tangent space  $\stackrel{\text{def}}{=} \text{kernel of } J_{\mathbf{h}}(\mathbf{v}) = \left[ \frac{\partial h_i}{\partial v_j}(\mathbf{v}) \right]_{i,j=1}^{M,N}.$

## X-rank: examples

$$\text{rank}_X(v) \stackrel{\text{def}}{=} \min r : \mathbf{v} = \mathbf{p}_1 + \cdots + \mathbf{p}_r, \quad \mathbf{p}_k \in \widehat{X}.$$

object ( $v \in A$ )	$\dim(A)$	variety $\widehat{X}$	$\dim(\widehat{X})$
$\mathcal{T} \in \mathbb{K}^{l_1 \times \cdots \times l_d}$ tensor	$l_1 \cdots l_d$	$\{\mathbf{a}_1 \otimes \cdots \otimes \mathbf{a}_d\}$ Segre	$\sum_{k=1}^d l_k - d + 1$
$f \in \mathbb{K}_{=d}[x, y]$ binary form	$d + 1$	$\{c \cdot (ax + by)^d\}$ rational normal curve	2
$f \in \mathbb{K}_{=d}[\mathbf{u}]$ $m$ -ary form	$\binom{m+d-1}{d}$	$\{c \cdot (\mathbf{a}^\top \mathbf{u})^d\}$ Veronese	$m$
$f \in \mathbb{K}_{\leq d}[x, y]$ polynomial	$\binom{2+d}{d} - 1$	$\{g(ax + by)\}$ rational normal scroll	$d + 1$
$f \in \mathbb{K}_{\leq d}[\mathbf{u}]$ polynomial	$\binom{m+d}{d} - 1$	$\{g(\mathbf{a}^\top \mathbf{u})\}$ Veronese scroll	$m + d - 1$



## Maximum and typical ranks: definitions

- Maximal rank

$$r_{max} \stackrel{\text{def}}{=} \max_{\mathbf{v} \in \mathbb{K}^N} \{\text{rank}_{\mathcal{X}}(\mathbf{v}) = k\}.$$

- $r$  is called a **typical rank** if the set  $\{\mathbf{v} \in A : \text{rank}_{\mathcal{X}}(\mathbf{v}) = r\}$  contains an open ball

### Properties:

- If  $\mathbb{K} = \mathbb{C}$  there exists only one typical rank, called generic rank  $r_{gen}$
- (Bernardi et al, 2015): If  $\mathbb{K} = \mathbb{R}$ , typical ranks form a contiguous set  $\{r_{typ}^{min}, \dots, r_{typ}^{max}\}$
- (Blekherman, Teitler, 2014):  
If  $\widehat{X}_{\mathbb{C}} \subset \mathbb{C}^N$  is a complexification of  $\widehat{X}_{\mathbb{R}} \subset \mathbb{R}^N$  and  $\widehat{X}_{\mathbb{C}}$  has a smooth real point, then  $r_{gen}(\widehat{X}_{\mathbb{C}}) = r_{typ}^{min}(\widehat{X}_{\mathbb{R}})$

## Example: binary forms

Example: (binary forms of degree  $d$ ,  $\widehat{X}$  — rational normal curve)

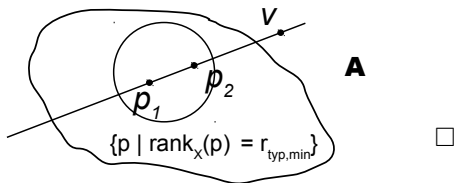
- $r_{max} = d$
- $r_{gen} = \lceil \frac{d+1}{2} \rceil$  (Sylvester)
- (Blekherman, 2014): all ranks  $\{r_{gen}, \dots, r_{max}\}$  are real typical

# Relations between maximal, typical and generic rank

## Theorem ((Blekherman, Teitler, 2014))

- $r_{max}(\widehat{X}_{\mathbb{R}}) \leq 2r_{typ}^{min}(\widehat{X}_{\mathbb{R}})$
- $r_{max}(\widehat{X}_{\mathbb{C}}) \leq 2r_{gen}(\widehat{X}_{\mathbb{C}})$

### Proof.



- Sharp for binary forms  $d \leq 2\lceil \frac{d+1}{2} \rceil$
- Improved upper bounds on  $r_{max}$  for:
  - Waring decomposition for  $m$ -ary forms
  - rank of  $2 \times \dots \times 2$  non-symmetric tensors

## Secant varieties and generic rank ( $\mathbb{K} = \mathbb{C}$ )

$r$ -th secant variety = closure of set of elements of rank  $\leq r$

$$\sigma_r(\widehat{X}) \stackrel{\text{def}}{=} \overline{\{\mathbf{p}_1 + \cdots + \mathbf{p}_r \mid \mathbf{p}_i \in \widehat{X}\}}$$

Properties:

- $\widehat{X} = \sigma_1(\widehat{X}) \subset \sigma_2(\widehat{X}) \subset \cdots \subset \sigma_{r_{gen}}(\widehat{X}) = \sigma_{r_{gen}+1}(\widehat{X}) = \cdots = A$ .  
 $\Rightarrow r_{gen}$  — the smallest  $r$  such that  $\dim \sigma_r(\widehat{X}) = \dim(A)$

**Expected dimension:**  $\exp \dim \sigma_r(\widehat{X}) \stackrel{\text{def}}{=} \min(r \dim \widehat{X}, \dim A)$

- In general,  $\exp \dim \sigma_r(\widehat{X}) \geq \dim \sigma_r(\widehat{X})$ .
- If “ $>$ ”,  $\widehat{X}$  is called  **$r$ -defective**.
- If  $\widehat{X}$  is not  $r$ -defective for all  $r$ , then  $r_{gen} = \lceil \frac{\dim(A)}{\dim \widehat{X}} \rceil$

## Generic rank: examples

$\dim(A)$	variety $\widehat{X}$	$\dim(\widehat{X})$	$r_{gen} \stackrel{?}{=} \lceil \frac{\dim(A)}{\dim \widehat{X}} \rceil$
$l_1 \cdots l_d$	$\{\mathbf{a}_1 \otimes \cdots \otimes \mathbf{a}_d\}$ Segre	$\sum_{k=1}^d l_k - d + 1$	conjecture* (Chiantini et al., 2014)
$d + 1$	$\{c \cdot (ax + by)^d\}$ rat. norm. curve	2	yes (Sylvester)
$\binom{m+d-1}{d}$	$\{c \cdot (\mathbf{a}^\top \mathbf{u})^d\}$ Veronese	$m$	yes* (Alexander, Hirschowitz, 1995)
$\binom{2+d}{d} - 1$	$\{g(ax + by)\}$ rat. norm scroll	$d + 1$	no, but $\exists$ formula (Schinzel, 2002)
$\binom{m+d}{d} - 1$	$\{g(\mathbf{a}^\top \mathbf{u})\}$ Veronese scroll	$m + d - 1$	no

\* = except finite exceptions and degenerate cases

## Identifiability (definition)

$$\mathbf{v} = \mathbf{p}_1 + \cdots + \mathbf{p}_r, \quad \mathbf{p}_k \in \widehat{X} \quad (*)$$

- Uniqueness of (\*) — up to permutation
- A general point in  $\sigma_r(\widehat{X})$  is of the form (\*)

### Definition (Global identifiability)

$\widehat{X}$  is  $r$ -identifiable if a general  $\mathbf{v} \in \sigma_r(\widehat{X})$  has unique decomposition (\*).

### Theorem (Strassen, 1983)

- If  $\dim \sigma_r(\widehat{X}) < \text{expdim } \sigma_r(\widehat{X})$ , a general point in  $\sigma_r(\widehat{X})$  has infinite number of decompositions.
- If  $\dim \sigma_r(\widehat{X}) = \text{expdim } \sigma_r(\widehat{X})$ , a general point in  $\sigma_r(\widehat{X})$  has a finite number of decompositions.

Non-defectivity can be checked numerically:

- For  $r$  random points  $\mathbf{p}_1, \dots, \mathbf{p}_r \in \widehat{X}$ , check if  $\dim \text{Span}\langle T_{\mathbf{p}_1} \widehat{X}, \dots, T_{\mathbf{p}_r} \widehat{X} \rangle = \text{expdim } \sigma_r(\widehat{X})$ ;

## Hierarchy of properties

$X$  not  $r$ -weakly-defective  $\Rightarrow X$  not  $r$ -tangentially weakly defective  $\Rightarrow X$   
is  $r$ -identifiable  $\Rightarrow X$  is non-defective

### Definition (Chiantini-Ottaviani)

$\widehat{X}$  is called not  $r$ -tangentially weakly defective if there exists a set of  $r$  points  $\mathbf{p}_1, \dots, \mathbf{p}_r \in \widehat{X}$ , such that the span  $\text{Span}\langle T_{\mathbf{p}_1}\widehat{X}, \dots, T_{\mathbf{p}_r}\widehat{X} \rangle$  does not contain  $T_{\mathbf{p}}\widehat{X}$  for  $\mathbf{p} \notin \{\mathbf{p}_1, \dots, \mathbf{p}_r\}$ .

We can construct a [certificate](#) to check [global identifiability](#)  
(Chiantini et. al, 2014)

# Overview

Matrix and tensor rank

A polynomial decomposition

Waring decomposition

X-rank and identifiability

**Results**



## $(s, r)$ -partial identifiability

= generic uniqueness of rank- $r$  decomposition (except  $\{c_{j,k}\}_{j < s}$ )

$$\mathbf{f}(\mathbf{u}) = \mathbf{w}_1 g_1(\mathbf{v}_1^\top \mathbf{u}) + \cdots + \mathbf{w}_r g_r(\mathbf{v}_r^\top \mathbf{u}),$$

where  $\mathbf{v}_k \in \mathbb{K}^m$ ,  $\mathbf{w}_k \in \mathbb{K}^n$ ,  $g_k(t) = c_{1,k}t + c_{2,k}t^2 + \cdots + c_{d,k}t^d$

### Proposition ((Comon, Q., U., 2016), simplified)

Let  $d, m, n$  be such that  $d > 3$ ,  $m \geq 2$ , and  $s$  be a number  $1 \leq s < d$

If  $r \leq \min \left( \binom{m+s-1}{s}, \left\lceil \frac{\binom{m+d-1}{d}}{m+n-1} - 1 \right\rceil \right)$

then the decomposition  $(\star)$  is  $(s, r)$ -partially identifiable.

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then the decomposition  $(\star)$  is  $(s, r)$ -partially identifiable.

Sketch of the proof:

- Prove identifiability of  $d$ -th homogeneous part of general  $\mathbf{f}(\mathbf{u})$ .
- Determine  $c_{j,k}$ ,  $j \geq s$  from the linear system:

$$\mathbf{f}^{(j)}(\mathbf{u}) = c_{j,1} \cdot \mathbf{w}_1 (\mathbf{v}_1^\top \mathbf{u})^j + \cdots + c_{j,r} \cdot \mathbf{w}_r (\mathbf{v}_r^\top \mathbf{u})^j$$

# Identifiability: examples

## Corollary

1. The decomposition **cannot be  $r$ -identifiable for  $r > mn$ .**
2. Given  $m, n$ : the decomposition is  **$mn$ -identifiable for large  $d$**

**Table:** Our bound for maximal identifiable ranks, for  $d = 3$ .

$m \setminus n$	1	2	3	4	5	6	7	8	9	10	11	12
2	1	2	0	0	0	0	0	0	0	0	0	0
3	<b>3</b>	4	3	4	5	6	7	0	0	0	0	0
4	<b>4</b>	6	9	8	10	12	7	8	9	10	11	12
5	<b>5</b>	<b>10</b>	12	16	15	18	21	16	18	20	22	24
6	<b>6</b>	<b>12</b>	<b>18</b>	<b>24</b>	25	30	28	32	27	30	33	36
7	<b>7</b>	<b>14</b>	<b>21</b>	<b>28</b>	<b>35</b>	36	42	40	45	50	44	48
8	<b>8</b>	<b>16</b>	<b>24</b>	<b>32</b>	<b>40</b>	<b>48</b>	<b>56</b>	56	63	70	66	72
9	<b>9</b>	<b>18</b>	<b>27</b>	<b>36</b>	<b>45</b>	<b>54</b>	<b>63</b>	<b>72</b>	<b>81</b>	<b>90</b>	88	96
10	<b>10</b>	<b>20</b>	<b>30</b>	<b>40</b>	<b>50</b>	<b>60</b>	<b>70</b>	<b>80</b>	<b>90</b>	<b>100</b>	<b>110</b>	<b>120</b>
11	<b>11</b>	<b>22</b>	<b>33</b>	<b>44</b>	<b>55</b>	<b>66</b>	<b>77</b>	<b>88</b>	<b>99</b>	<b>110</b>	<b>121</b>	<b>132</b>
12	<b>12</b>	<b>24</b>	<b>36</b>	<b>48</b>	<b>60</b>	<b>72</b>	<b>84</b>	<b>96</b>	<b>108</b>	<b>120</b>	<b>132</b>	<b>144</b>

# Identifiability: examples

## Corollary

1. The decomposition **cannot be  $r$ -identifiable for  $r > mn$ .**
2. Given  $m, n$ : the decomposition is  **$mn$ -identifiable for large  $d$**

Table: Our bound for maximal identifiable ranks, for  $d = 4$ .

$m \setminus n$	1	2	3	4	5	6	7	8	9	10	11	12
2	<b>2</b>	2	3	0	0	0	0	0	0	0	0	0
3	<b>3</b>	<b>6</b>	6	8	10	6	7	8	9	10	11	12
4	<b>4</b>	<b>8</b>	<b>12</b>	<b>16</b>	<b>20</b>	18	21	24	18	20	22	24
5	<b>5</b>	<b>10</b>	<b>15</b>	<b>20</b>	<b>25</b>	<b>30</b>	<b>35</b>	<b>40</b>	<b>45</b>	40	44	48
6	<b>6</b>	<b>12</b>	<b>18</b>	<b>24</b>	<b>30</b>	<b>36</b>	<b>42</b>	<b>48</b>	<b>54</b>	<b>60</b>	<b>66</b>	<b>72</b>
7	<b>7</b>	<b>14</b>	<b>21</b>	<b>28</b>	<b>35</b>	<b>42</b>	<b>49</b>	<b>56</b>	<b>63</b>	<b>70</b>	<b>77</b>	<b>84</b>
8	<b>8</b>	<b>16</b>	<b>24</b>	<b>32</b>	<b>40</b>	<b>48</b>	<b>56</b>	<b>64</b>	<b>72</b>	<b>80</b>	<b>88</b>	<b>96</b>
9	<b>9</b>	<b>18</b>	<b>27</b>	<b>36</b>	<b>45</b>	<b>54</b>	<b>63</b>	<b>72</b>	<b>81</b>	<b>90</b>	<b>99</b>	<b>108</b>
10	<b>10</b>	<b>20</b>	<b>30</b>	<b>40</b>	<b>50</b>	<b>60</b>	<b>70</b>	<b>80</b>	<b>90</b>	<b>100</b>	<b>110</b>	<b>120</b>
11	<b>11</b>	<b>22</b>	<b>33</b>	<b>44</b>	<b>55</b>	<b>66</b>	<b>77</b>	<b>88</b>	<b>99</b>	<b>110</b>	<b>121</b>	<b>132</b>
12	<b>12</b>	<b>24</b>	<b>36</b>	<b>48</b>	<b>60</b>	<b>72</b>	<b>84</b>	<b>96</b>	<b>108</b>	<b>120</b>	<b>132</b>	<b>144</b>

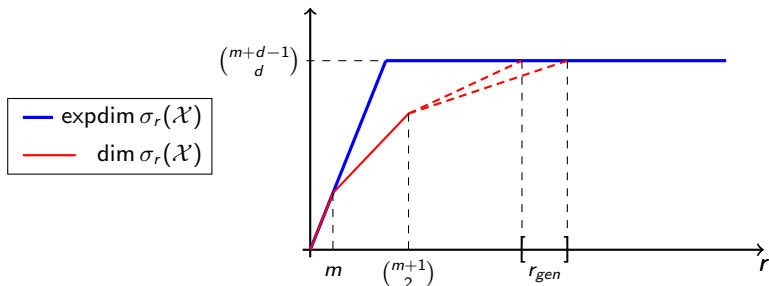
# Generic and maximal ranks (univariate poly)

## Proposition ((Comon, Qi, U., 2016), simplified)

Let  $d \geq 4$ ,  $n = 1$ , and  $m > (d - 2)(d - 1)$ . Then

$$\left\lceil \frac{\binom{m+d-2}{d-1} + \binom{m+d-1}{d}}{m+1} \right\rceil \leq r_{gen} \leq \left\lceil \frac{\binom{m+d-2}{d-1} + (m-1) \lceil \frac{\binom{m+d-1}{d} \rceil}{m} \right\rceil$$

Proof (sketch). from the result on partial identifiability, we have that:



## Maximal ranks

Recall that  $r_{max} \leq 2r_{gen}$  (Blekherman, Teitler, 2014)

### Corollary

$$r_{max} \leq 2 \left\lceil \frac{\binom{m+d-2}{d-1} + (m-1) \left\lceil \frac{\binom{m+d-1}{d}}{m} \right\rceil}{m} \right\rceil$$

Best known previous bound (Białynicki-Birula, Schinzel, 2008):

$$r_{max} \leq \binom{m+d-2}{d-1}$$

Our bound is better, the ratio  $\sim \frac{2}{d}$  (as  $m \rightarrow \infty$ )

# Summary

arXiv:1603.01566

- X-rank is very useful (or at least interesting).
- Can be extended to semialgebraic  $X$ , e.g. nonnegative tensors (Qi et al, 2016).
- Hopefully, useful for other sparse decompositions.

# Summary

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- X-rank is very useful (or at least interesting).
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Thank you for your attention!