

# Sparse representations from moments

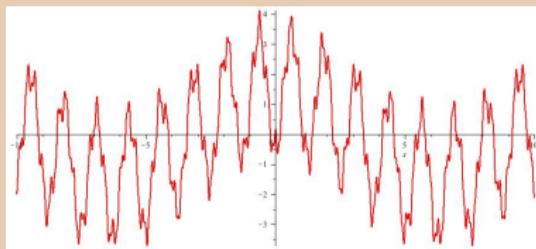
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# Sparse representation of signals

Given a function or signal  $f(t)$ :



decompose it as

$$f(t) = \sum_{i=1}^{r'} (a_i \cos(\mu_i t) + b_i \sin(\mu_i t)) e^{\nu_i t} = \sum_{i=1}^r \omega_i e^{\zeta_i t}$$

# Prony's method (1795)



For the signal  $f(t) = \sum_{i=1}^r \omega_i e^{\zeta_i t}$ , ( $\omega_i, \zeta_i \in \mathbb{C}$ ),

- ▶ Evaluate  $f$  at  $2r$  regularly spaced points:  $\sigma_0 := f(0), \sigma_1 := f(1), \dots$
- ▶ Compute a non-zero element  $\mathbf{p} = [\mathbf{p}_0, \dots, \mathbf{p}_r]$  in the kernel:

$$\begin{bmatrix} \sigma_0 & \sigma_1 & \dots & \sigma_r \\ \sigma_1 & & & \sigma_{r+1} \\ \vdots & & & \vdots \\ \sigma_{r-1} & \dots & \sigma_{2r-1} & \sigma_{2r-1} \end{bmatrix} \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_r \end{bmatrix} = 0$$

- ▶ Compute the roots  $\xi_1 = e^{\zeta_1}, \dots, \xi_r = e^{\zeta_r}$  of  $p(x) := \sum_{i=0}^r p_i x^i$ .
- ▶ Solve the system

$$\begin{bmatrix} 1 & \dots & \dots & 1 \\ \xi_1 & & & \xi_r \\ \vdots & & & \vdots \\ \xi_1^{r-1} & \dots & \dots & \xi_r^{r-1} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_r \end{bmatrix} = \begin{bmatrix} \sigma_0 \\ \sigma_1 \\ \vdots \\ \sigma_{r-1} \end{bmatrix}.$$



# Symmetric tensor decomposition and Waring problem (1770)

**Tensor decomposition problem:** given a homogeneous polynomial  $\Psi$  of degree  $d$  in the variables  $\bar{\mathbf{x}} = (x_0, x_1, \dots, x_n)$ :

$$\Psi(\bar{\mathbf{x}}) = \sum_{|\alpha|=d} \sigma_\alpha \binom{d}{\alpha} \bar{\mathbf{x}}^\alpha,$$

**find a minimal decomposition of  $\Psi$  of the form**

$$\Psi(\bar{\mathbf{x}}) = \sum_{i=1}^r \omega_i (\xi_{i,0}x_0 + \xi_{i,1}x_1 + \cdots + \xi_{i,n}x_n)^d$$

**for**  $\xi_i = (\xi_{i,0}, \xi_{i,1}, \dots, \xi_{i,n}) \in \mathbb{C}^{n+1}$ ,  $\omega_i \in \mathbb{C}$ .

The minimal  $r$  in such a decomposition is called the **rank** of  $\tau$ .



# Sylvester approach (1851)

## Theorem

The binary form  $\Psi(x_0, x_1) = \sum_{i=0}^d \sigma_i \binom{d}{i} x_0^{d-i} x_1^i$  can be decomposed as a sum of  $r$  distinct powers of linear forms

$$\Psi = \sum_{k=1}^r \omega_k (\alpha_k x_0 + \beta_k x_1)^d$$

iff there exists a polynomial  $p(x_0, x_1) := p_0 x_0^r + p_1 x_0^{r-1} x_1 + \cdots + p_r x_1^r$  s.t.

$$\begin{bmatrix} \sigma_0 & \sigma_1 & \dots & \sigma_r \\ \sigma_1 & & & \sigma_{r+1} \\ \vdots & & & \vdots \\ \sigma_{d-r} & \dots & \sigma_{d-1} & \sigma_d \end{bmatrix} \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_r \end{bmatrix} = 0$$

and of the form  $p = c \prod_{k=1}^r (\beta_k x_0 - \alpha_k x_1)$ .

# Sparse interpolation

Given a black-box polynomial function  $f(x)$



find what are the terms inside from output values.

☞ Find  $r \in \mathbb{N}, \omega_i \in \mathbb{C}, \alpha_i \in \mathbb{N}$  such that  $f(x) = \sum_{i=1}^r \omega_i x^{\alpha_i}$ .

- ▶ Choose  $\varphi \in \mathbb{C}$
- ▶ Compute the sequence of terms  $\sigma_0 = f(1), \dots, \sigma_{2r-1} = f(\varphi^{2r-1})$ ;
- ▶ Construct the matrix  $H = [\sigma_{i+j}]$  and its kernel  $p = [p_0, \dots, p_r]$  s.t.

$$\begin{bmatrix} \sigma_0 & \sigma_1 & \dots & \sigma_r \\ \sigma_1 & & & \sigma_{r+1} \\ \vdots & & & \vdots \\ \sigma_{r-1} & \dots & \sigma_{2r-1} & \sigma_{2r-1} \end{bmatrix} \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_r \end{bmatrix} = 0$$

- ▶ Compute the roots  $\xi_1 = \varphi^{\alpha_1}, \dots, \xi_r = \varphi^{\alpha_r}$  of  $p(x) := \sum_{i=0}^r p_i x^i$  and deduce the exponents  $\alpha_i = \log_\varphi(\xi_i)$ .
- ▶ Deduce the weights  $W = [\omega_i]$  by solving  $V_{\Xi} W = [\sigma_0, \dots, \sigma_{r-1}]$  where  $V_{\Xi}$  is the Vandermonde system of the roots  $\xi_1, \dots, \xi_r$ .

# Decoding



An algebraic code:

$$E = \{c(f) = [f(\xi_1), \dots, f(\xi_m)] \mid f \in \mathbb{K}[x]; \deg(f) \leq d\}.$$

Encoding messages using the dual code:

$$C = E^\perp = \{\mathbf{c} \mid \mathbf{c} \cdot [f(\xi_1), \dots, f(\xi_l)] = 0 \ \forall f \in V = \langle \mathbf{x}^{\mathbf{a}} \rangle \subset \mathbb{F}[\mathbf{x}]\}$$

**Message received:**  $r = m + e$  for  $m \in C$  where  $e = [\omega_1, \dots, \omega_m]$  is an error with  $\omega_j \neq 0$  for  $j = i_1, \dots, i_r$  and  $\omega_j = 0$  otherwise.

☞ Find the error  $e$ .

## Berlekamp-Massey method (1969)

- ▶ Compute the syndrome  $\sigma_k = c(x^k) \cdot r = c(x^k) \cdot e = \sum_{j=1}^r \omega_{ij} \xi_{ij}^k$ .
- ▶ Compute the matrix

$$\begin{bmatrix} \sigma_0 & \sigma_1 & \dots & \sigma_r \\ \sigma_1 & & & \sigma_{r+1} \\ \vdots & & & \vdots \\ \sigma_{r-1} & \dots & \sigma_{2r-1} & \sigma_{2r-1} \end{bmatrix} \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_r \end{bmatrix} = 0$$

and its kernel  $p = [p_0, \dots, p_r]$ .

- ▶ Compute the roots of the error locator polynomial  $p(x) = \sum_{i=0}^r p_i x^i = p_r \prod_{j=1}^r (x - \xi_{ij})$ .
- ▶ Deduce the errors  $\omega_{ij}$ .

# Sequences, series, duality (1D)

**Sequences:**  $\sigma = (\sigma_k)_{k \in \mathbb{N}} \in \mathbb{K}^{\mathbb{N}}$  indexed by  $k \in \mathbb{N}$ .

**Formal power series:**

$$\sigma = \sum_{k=0}^{\infty} \sigma_k \frac{y^k}{k!} \in \mathbb{K}[[y]] \quad (\text{or } \sum_{k=0}^{\infty} \sigma_k z^k \in \mathbb{K}[[z]])$$

**Linear functionals:**  $\mathbb{K}[x]^* = \{\Lambda : \mathbb{K}[x] \rightarrow \mathbb{K} \text{ linear}\}$ .

**Example:**

- ▶  $p \mapsto$  coefficient of  $x^i$  in  $p = \frac{1}{i!} \partial^i(p)(0)$
- ▶  $\mathbf{e}_\zeta : p \mapsto p(\zeta)$ .

**Series as linear functionals:** For  $\sigma = \sum_{k=0}^{\infty} \sigma_k \frac{y^k}{k!} \in \mathbb{K}[[y]]$ ,

$$\sigma : p = \sum_k p_k x^k \mapsto \langle \sigma | p \rangle = \sum_k \sigma_k p_k$$

$(\frac{y^k}{k!})$  is the dual basis of the monomial basis  $(x^k)_{k \in \mathbb{N}}$ .

**Example:**  $\mathbf{e}_\zeta = \sum_{k=0}^{\infty} \zeta^k \frac{y^k}{k!} = e^{\zeta y} \in \mathbb{K}[[y]]$ .

**Structure of  $\mathbb{K}[x]$ -module:**  $p(x) \star \Lambda : q \mapsto \Lambda(p q)$ .

$$x \star \sigma = \sum_{k=1}^{\infty} \sigma_k \frac{y^{k-1}}{(k-1)!} = \partial(\sigma(y))$$

$$p(x) \star \sigma = p(\partial)(\sigma(y)).$$

## Sequences, series, duality (nD)

**Multi-index sequences:**  $\sigma = (\sigma_\alpha)_{\alpha \in \mathbb{N}^n} \in \mathbb{K}^{\mathbb{N}^n}$  indexed by  $\alpha = (\alpha_1, \dots, \alpha_n) \in \mathbb{N}^n$ .

**Taylor series:**

$$\sigma(\mathbf{y}) = \sum_{\alpha \in \mathbb{N}^n} \sigma_\alpha \frac{\mathbf{y}^\alpha}{\alpha!} \in \mathbb{K}[[y_1, \dots, y_n]] \quad (\text{or } \sum_{\alpha \in \mathbb{N}^n} \sigma_\alpha \mathbf{z}^\alpha \in \mathbb{K}[[z_1, \dots, z_n]])$$

where  $\alpha! = \prod \alpha_i!$  for  $\alpha = (\alpha_1, \dots, \alpha_n) \in \mathbb{N}^n$ .

**Linear functionals:**  $\sigma \in R^* = \{\sigma : R \rightarrow \mathbb{K}, \text{ linear}\}$

$$\sigma : p = \sum_{\alpha} p_{\alpha} \mathbf{x}^{\alpha} \mapsto \langle \sigma | p \rangle = \sum_{\alpha} \sigma_{\alpha} p_{\alpha}$$

The coefficients  $\langle \sigma | \mathbf{x}^{\alpha} \rangle = \sigma_{\alpha} \in \mathbb{K}$ ,  $\alpha \in \mathbb{N}^n$  are called the **moments** of  $\sigma$ .

**Structure of  $R$ -module:**  $\forall p \in R, \sigma \in R^*, p \star \sigma : q \mapsto \langle \sigma | p q \rangle$ .



$$p \star \sigma = p(\partial_1, \dots, \partial_n)(\sigma)(\mathbf{y})$$

**Hankel operator:** For  $\sigma \in \mathbb{K}[[\mathbf{y}]]$ ,

$$\begin{aligned} H_\sigma : \mathbb{K}[\mathbf{x}] &\rightarrow \mathbb{K}[[\mathbf{y}]] \\ p &\mapsto p \star \sigma = p(\partial_1, \dots, \partial_n)(\sigma)(\mathbf{y}) \end{aligned}$$

$\sigma$  is the **symbol** of  $H_\sigma$ .

**Truncated Hankel operator:**  $V, V' \subset \mathbb{K}[\mathbf{x}]$ ,

$$H_\sigma^{V', V} : p \in V \rightarrow p \star \sigma|_{V'} \in V'^*$$

**Example:**  $V = \langle \mathbf{x}^A \rangle, V' = \langle \mathbf{x}^B \rangle \subset \mathbb{K}[\mathbf{x}]$

$$H_\sigma^{A, B} = [\sigma_{\alpha+\beta}]_{\alpha \in A, \beta \in B}.$$

**Ideal:**

$$\begin{aligned} I_\sigma &= \ker H_\sigma = \{p \in \mathbb{K}[\mathbf{x}] \mid p \star \sigma = 0\}, \\ &= \{p = \sum_{\alpha} p_{\alpha} \mathbf{x}^{\alpha} \mid \forall \beta \in \mathbb{N}^n \sum_{\alpha} p_{\alpha} \sigma_{\alpha+\beta} = 0\} \end{aligned}$$

Linear recurrence relations on the sequence  $\sigma = (\sigma_\alpha)_{\alpha \in \mathbb{N}^n}$ .

**Quotient algebra:**  $\mathcal{A}_\sigma = \mathbb{K}[x_1, \dots, x_n]/I_\sigma$

☞ **Studied case:**  $\dim \mathcal{A}_\sigma < \infty$

## Structure of an Artinian algebra $\mathcal{A}$

**Hypothesis:**  $\mathcal{A} = \mathbb{K}[\mathbf{x}]/I$  is Artinian , i.e.  $\dim_{\mathbb{K}} \mathcal{A} < \infty$ .

**Hilbert nullstellensatz:**  $\mathcal{A} = \mathbb{K}[\mathbf{x}]/I$  Artinian  $\Leftrightarrow \mathcal{V}_{\overline{\mathbb{K}}}(I) = \{\xi_1, \dots, \xi_r\}$  is finite.

Assuming  $\mathbb{K} = \overline{\mathbb{K}}$  is algebraically closed, we have

- ▶  $I = Q_1 \cap \cdots \cap Q_r$  where  $Q_i$  is  $m_{\xi_i}$ -primary where  $\mathcal{V}_{\overline{\mathbb{K}}}(I) = \{\xi_1, \dots, \xi_r\}$ .
- ▶  $\mathcal{A} = \mathbb{K}[\mathbf{x}]/I = \mathcal{A}_1 \oplus \cdots \oplus \mathcal{A}_r$ , with
  - ▶  $\mathcal{A}_i = \mathbf{u}_i \mathcal{A} \sim \mathbb{K}[x_1, \dots, x_n]/Q_i$ ,
  - ▶  $\mathbf{u}_i^2 = \mathbf{u}_i$ ,  $\mathbf{u}_i \cdot \mathbf{u}_j = 0$  if  $i \neq j$ ,  $\mathbf{u}_1 + \cdots + \mathbf{u}_r = 1$ .
- ▶  $\dim R/Q_i = \mu_i$  is the multiplicity of  $\xi_i$ .

# Structure of the dual $\mathcal{A}^*$

Sparse series:

$$\mathcal{P}olExp = \left\{ \sigma(\mathbf{y}) = \sum_{i=1}^r \omega_i(\mathbf{y}) \mathbf{e}_{\xi_i}(\mathbf{y}) \mid \omega_i(\mathbf{y}) \in \mathbb{K}[\mathbf{y}], \right\}$$

where  $\mathbf{e}_{\xi_i}(\mathbf{y}) = e^{\mathbf{y} \cdot \xi_i} = e^{y_1 \xi_{1,i} + \dots + y_n \xi_{n,i}}$  with  $\xi_{i,j} \in \mathbb{K}$ .

**Inverse system** generated by  $\omega_1, \dots, \omega_r \in \mathbb{K}[\mathbf{y}]$

$$\mathcal{D}(\omega_1, \dots, \omega_r) = \langle \partial_{\mathbf{y}}^{\alpha}(\omega_i), \alpha \in \mathbb{N}^n \rangle$$

## Theorem

For  $\mathbb{K} = \overline{\mathbb{K}}$  algebraically closed,

$$\mathcal{A}^* = \bigoplus_{i=1}^r \mathcal{D}_i \mathbf{e}_{\xi_i}(\mathbf{y}) \subset \mathcal{P}olExp$$

- ▶  $\mathcal{V}_{\overline{\mathbb{K}}}(I) = \{\xi_1, \dots, \xi_r\}$
- ▶  $\mathcal{D}_i = \mathcal{D}(\omega_{i,1}, \dots, \omega_{i,l_i}) = Q_i^\perp$  with  $\omega_{i,j} \in \mathbb{K}[\mathbf{y}]$  and  $I = Q_1 \cap \dots \cap Q_r$
- ▶  $\mu(\omega_{i,1}, \dots, \omega_{i,l_i}) := \dim_{\mathbb{K}}(\mathcal{D}_i) = \mu_i$  multiplicity of  $\xi_i$ .

# The roots by eigencomputation

**Hypothesis:**  $\mathcal{V}_{\overline{\mathbb{K}}}(I) = \{\xi_1, \dots, \xi_r\} \Leftrightarrow \mathcal{A} = \mathbb{K}[\mathbf{x}]/I$  Artinian.

$$\begin{array}{rcl} \mathcal{M}_a : \mathcal{A} & \rightarrow & \mathcal{A} \\ u & \mapsto & au \end{array} \qquad \begin{array}{rcl} \mathcal{M}_a^t : \mathcal{A}^* & \rightarrow & \mathcal{A}^* \\ \Lambda & \mapsto & a \star \Lambda = \Lambda \circ \mathcal{M}_a \end{array}$$

## Theorem

- ▶ The eigenvalues of  $\mathcal{M}_a$  are  $\{a(\xi_1), \dots, a(\xi_r)\}$ .
- ▶ The eigenvectors of all  $(\mathcal{M}_a^t)_{a \in \mathcal{A}}$  are (up to a scalar)  $\mathbf{e}_{\xi_i} : p \mapsto p(\xi_i)$ .

## Proposition

If the roots are simple, the operators  $\mathcal{M}_a$  are diagonalizable. Their common eigenvectors are, up to a scalar, interpolation polynomials  $\mathbf{u}_i$  at the roots and idempotent in  $\mathcal{A}$ .

## Example

### Roots of polynomial systems

$$\begin{cases} f_1 = x_1^2 x_2 - x_1^2 \\ f_2 = x_1 x_2 - x_2 \end{cases} \quad I = (f_1, f_2) \subset \mathbb{C}[\mathbf{x}]$$

$$\mathcal{A} = \mathbb{C}[\mathbf{x}]/I \equiv \langle 1, x_1, x_2 \rangle \quad I = (x_1^2 - x_2, x_1 x_2 - x_2, x_2^2 - x_2)$$

$$M_1 = \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix}, \quad M_2 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix} \quad \begin{matrix} \text{common} \\ \text{eigvecs of} \\ M_1^t, M_2^t \end{matrix} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

$$I = Q_1 \cap Q_2 \quad \text{where} \quad Q_1 = (x_1^2, x_2), \quad Q_2 = \mathbf{m}_{(1,1)} = (x_1 - 1, x_2 - 1)$$

$$I = Q_1^\perp \oplus Q_2^\perp \quad Q_1^\perp = \langle 1, y_1 \rangle = \langle 1, y_1 \rangle \mathbf{e}_{(0,0)}(\mathbf{y}) \quad Q_2^\perp = \langle 1 \rangle \mathbf{e}_{(1,1)}(\mathbf{y}) = \langle e^{y_1+y_2} \rangle$$

### Solution of partial differential equations (with constant coeff.)

$$\begin{cases} \partial_{y_1}^2 \partial_{y_2} \sigma - \partial_{y_1}^2 \sigma = 0 & f_1 \star \sigma = 0 \\ \partial_{y_1} \partial_{y_2} \sigma - \partial_{y_2} \sigma = 0 & f_2 \star \sigma = 0 \end{cases} \Rightarrow \sigma \in I^\perp = Q_1^\perp \oplus Q_2^\perp$$

$$\sigma = a + b y_1 + c e^{y_1+y_2} \quad a, b, c \in \mathbb{C}$$

# Hankel operators and quotient algebra

**Hankel operator:** For  $\sigma \in \mathbb{K}[[\mathbf{y}]]$ ,

$$\begin{aligned} H_\sigma : \mathbb{K}[\mathbf{x}] &\rightarrow \mathbb{K}[[\mathbf{y}]] \\ p &\mapsto p \star \sigma = p(\partial_1, \dots, \partial_n)(\sigma)(\mathbf{y}) \end{aligned}$$

**Quotient algebra:**  $\mathcal{A}_\sigma = \mathbb{K}[x_1, \dots, x_n]/I_\sigma$

- ▶  $\mathcal{A} = \mathbb{K}[x_1, \dots, x_n]/I$  **Artinian** iff  $\dim_{\mathbb{K}} \mathcal{A} < \infty$ .
- ▶  $\mathcal{A}$  **Gorenstein** iff  $\exists \sigma \in \mathcal{A}^*$  such that  $\mathcal{A}^* = \mathcal{A} \star \sigma$  is a free  $\mathcal{A}$ .
- ☞ **Isomorphism with the dual space  $\mathcal{A}_\sigma^*$ :**

$$\begin{aligned} 0 \rightarrow I_\sigma \rightarrow \mathbb{K}[\mathbf{x}] &\xrightarrow{H_\sigma} \mathcal{A}_\sigma^* \rightarrow 0 \\ p &\mapsto p \star \sigma \end{aligned}$$

Correspondence between **sequences**  $\sigma \in \mathbb{K}^{\mathbb{N}^n}$  with  $\text{rank } H_\sigma < \infty$  and **Artinian Gorenstein algebras**  $\mathcal{A}_\sigma := \mathbb{K}[\mathbf{x}]/I_\sigma$ .

## Univariate series:

### Kronecker (1881)



The Hankel operator  $H_\sigma : (p_m) \in \mathbb{C}^{\mathbb{N}, finite} \mapsto (\sum_m \sigma_{m+n} p_m)_{n \in \mathbb{N}} \in \mathbb{C}^{\mathbb{N}}$  is of **finite rank**  $r$  iff  $\exists \omega_1, \dots, \omega_{r'} \in \mathbb{C}[y]$  and  $\xi_1, \dots, \xi_{r'} \in \mathbb{C}$  distincts s.t.

$$\sigma(y) = \sum_{n \in \mathbb{N}} \sigma_n \frac{y^n}{n!} = \sum_{i=1}^{r'} \omega_i(y) \mathbf{e}_{\xi_i}(y) \text{ with } \sum_{i=1}^{r'} (\deg(\omega_i) + 1) = r.$$

## Multivariate series:

### Theorem (Generalized Kronecker Theorem)

$H_\sigma$  is of rank  $r$  iff  $\sigma = \sum_{i=1}^{r'} \omega_i(\mathbf{y}) \mathbf{e}_{\xi_i}(\mathbf{y}) \in \mathcal{PolExp}$  with  $r = \sum_{i=1}^{r'} \mu(\omega_i)$ .  
In this case, we have

- ▶  $\mathcal{V}_{\mathbb{C}}(I_\sigma) = \{\xi_1, \dots, \xi_{r'}\}$ .
- ▶  $I_\sigma = Q_1 \cap \dots \cap Q_{r'}$  with  $Q_i^\perp = \mathcal{D}(\omega_i) \mathbf{e}_{\xi_i}(\mathbf{y})$ .
- ▶  $\mathcal{A}_\sigma^* = \mathcal{A}_\sigma \star \sigma$  (free  $\mathcal{A}_\sigma$ -module of rank 1).
- ▶  $(a, b) \mapsto \langle \sigma | ab \rangle$  is non-degenerate in  $\mathcal{A}_\sigma$ .

## The structure of $\mathcal{A}_\sigma$

For  $\sigma = \sum_{i=1}^r \omega_i e_{\xi_i}$ , with  $\omega_i \in \mathbb{C} \setminus \{0\}$  and  $\xi_i \in \mathbb{C}^n$  distinct.

- ▶ rank  $H_\sigma = r$  and the multiplicity of the points  $\xi_1, \dots, \xi_r$  in  $\mathcal{V}(I_\sigma)$  is 1.
- ▶ For  $B, B'$  be of size  $r$ ,  $H_\sigma^{B', B}$  invertible iff  $B$  and  $B'$  are bases of  $\mathcal{A}_\sigma = \mathbb{K}[\mathbf{x}]/I_\sigma$ .
- ▶ The matrix  $M_i$  of multiplication by  $x_i$  in the basis  $B$  of  $\mathcal{A}_\sigma$  is such that

$$H_\sigma^{B', x_i B} = H_{x_i * \sigma}^{B', B} = H_\sigma^{B', B} M_i$$

- ▶ The common **eigenvectors** of  $M_i$  are (up to a scalar) the Lagrange **interpolation polynomials**  $u_{\xi_i}$  at the points  $\xi_i$ ,  $i = 1, \dots, r$ .

$$u_{\xi_i}(\xi_j) = \begin{cases} 1 & \text{if } i = j, \\ 0 & \text{otherwise} \end{cases} \quad u_{\xi_i}^2 \equiv u_{\xi_i}, \quad \sum_{i=1}^r u_{\xi_i} \equiv 1.$$

- ▶ The common **eigenvectors** of  $M_i^t$  are (up to a scalar) the vectors  $[B(\xi_i)]$ ,  $i = 1, \dots, r$ .

## Decomposition algorithm

**Input:** The first coefficients  $(\sigma_\alpha)_{\alpha \in A}$  of the series

$$\sigma = \sum_{\alpha \in \mathbb{N}^n} \sigma_\alpha \frac{\mathbf{y}^\alpha}{\alpha!} = \sum_{i=1}^r \omega_i \mathbf{e}_{\xi_i}(\mathbf{y})$$

- ① Compute bases  $B, B' \subset \langle \mathbf{x}^A \rangle$  s.t. that  $H^{B', B}$  invertible and  $|B| = |B'| = r = \dim \mathcal{A}_\sigma$ ;
- ② Deduce the tables of multiplications  $M_i := (H_\sigma^{B', B})^{-1} H_\sigma^{B', x_i B}$
- ③ Compute the eigenvectors  $\mathbf{v}_1, \dots, \mathbf{v}_r$  of  $\sum_i l_i M_i$  for a generic  $\mathbf{l} = l_1 \mathbf{x}_1 + \dots + l_n \mathbf{x}_n$ ;
- ④ Deduce the points  $\xi_i = (\xi_{i,1}, \dots, \xi_{i,n})$  s.t.  $M_j \mathbf{v}_i - \xi_{i,j} \mathbf{v}_i = 0$  and the weights  $\omega_i = \frac{1}{\mathbf{v}_i(\xi_i)} \langle \sigma | \mathbf{v}_i \rangle$ .

**Output:** The decomposition  $\sigma = \sum_{i=1}^r \frac{1}{\mathbf{v}_i(\xi_i)} \langle \sigma | \mathbf{v}_i \rangle \mathbf{e}_{\xi_i}(\mathbf{y})$ .

## Multivariate Prony method (1)

Let  $h(t_1, t_2) = 2 + 3 \cdot 2^{t_1} \cdot 2^{t_2} - 3^{t_1}$ ,  $\sigma = \sum_{\alpha \in \mathbb{N}^2} h(\alpha) \frac{y^\alpha}{\alpha!} = 2e_{(1,1)}(y) + 3e_{(2,2)}(y) - e_{(3,1)}(y)$ .

- Take  $B = \{1, x_1, x_2\}$  and compute

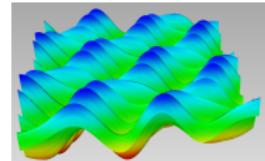
$$H_0 := H_\sigma^{B,B} = \begin{bmatrix} h(0,0) & h(1,0) & h(0,1) \\ h(1,0) & h(2,0) & h(1,1) \\ h(0,1) & h(1,1) & h(0,2) \end{bmatrix} = \begin{bmatrix} 4 & 5 & 7 \\ 5 & 5 & 11 \\ 7 & 11 & 13 \end{bmatrix},$$
$$H_1 := H_\sigma^{B,x_1 B} = \begin{bmatrix} 5 & 5 & 7 \\ 5 & -1 & 17 \\ 811 & 178 & 23 \end{bmatrix}, \quad H_2 := H_\sigma^{B,x_2 B} = \begin{bmatrix} 7 & 11 & 13 \\ 11 & 17 & 23 \\ 13 & 23 & 25 \end{bmatrix}.$$

- Compute the generalized eigenvectors of  $(aH_1 + bH_2, H_0)$ :

$$U = \begin{bmatrix} 2 & -1 & 0 \\ -1/2 & 0 & 1/2 \\ -1/2 & 1 & -1/2 \end{bmatrix} \text{ and } H_0 U = \begin{bmatrix} 2 & 3 & -1 \\ 2 \times 1 & 3 \times 2 & -1 \times 3 \\ 2 \times 1 & 3 \times 2 & -1 \times 1 \end{bmatrix}.$$

- This yields the weights  $2, 3, -1$  and the roots  $(1, 1), (2, 2), (3, 1)$ .

## Multivariate Prony method (2)



$$h(t_1, t_2) := \sum_{i=1}^r \omega_i e^{f_1 t_1 + f_2 t_2} \text{ with}$$

$$\mathbf{f} := \begin{bmatrix} -0.5 & 1.0 + 3.141592654 i \\ 0.1 + 21.36283005 i & 1.5 + 32.67256360 i \\ 0.1 + 21.36283005 i & -0.5 + 79.16813488 i \\ -2.5 + 145.7698991 i & -10.0 + 517.1061508 i \end{bmatrix} \quad \omega := \begin{bmatrix} 1.375328890 + 0.9992349291 i \\ 1.046162168 + 0.3399186938 i \\ 0.9 \\ -9.2 \end{bmatrix}$$

For the sampling  $[\frac{1}{50}, \frac{1}{170}]$ ,  $B = \{1, x_1, x_2, x_1 x_2\}$ , the SVD of  $H_\sigma^{B, B}$  is

$$[33.1196344300301391, 14.3767453860219057, 0.244096952193142480, 0.0230734326225932214]$$

and the computed decomposition is

$$\mathbf{f}^* = \begin{bmatrix} -2.4999999703636711 + 145.769899153890435 i & -9.999999913514852 + 517.106150711515852 i \\ 0.0999940670173818935 + 21.3628392917863437 i & -0.500045063743692286 + 79.1681566575291527 i \\ 0.100028305341504586 + 21.3628527756206275 i & 1.50002358381760881 + 32.6725933609709571 i \\ -0.499926454593063452 + 0.0000142466247443506387 i & 1.00008814016387371 + 3.14161379568963772 i \end{bmatrix}$$

$$\omega^* = \begin{bmatrix} -9.1999999613861696 - 0.00000000772422142913953280 i \\ 0.899999936743709261 - 0.00000156202814849404348 i \\ 1.04615643213670850 + 0.339923495269889020 i \\ 1.37533468654902213 + 0.999231697828891208 i \end{bmatrix}$$

# Sparse interpolation

$$f(\mathbf{x}) = \sum_{i=1}^r \omega_i \mathbf{x}^{\alpha_i} \Rightarrow \sigma = \sum_{\gamma} f(\varphi^{\gamma}) \frac{\mathbf{y}^{\gamma}}{\gamma!} = \sum_{i=1}^r \omega_i \mathbf{e}_{\varphi^{\alpha_i}}(\mathbf{y})$$

**Example:**  $f(x_1, x_2) = x_1^{33}x_2^{12} - 5x_1x_2^{45} + 101.$

- ▶ Compute  $\sigma_{\alpha} = f(\varphi_1^{\alpha_1}, \varphi_2^{\alpha_2})$  for  $\alpha_1 + \alpha_2 \leq 3$  and  $\varphi_1 = \varphi_2 = e^{\frac{2i\pi}{50}}$ .
- ▶ Compute the Hankel matrix  $H_{\sigma}^{1,2}$ :

$$\begin{bmatrix} 97.00000 & 97.01771 + 3.93695i & 95.50360 - 1.47099i & 98.46280 + 4.88062i & 97.42748 + 1.82098i \\ 97.01771 + 3.93695i & 98.46280 + 4.88062i & 97.42748 + 1.82098i & 102.35770 + 3.77300i & 99.50853 + 5.29465i \\ 95.50360 - 1.47099i & 97.42748 + 1.82098i & 95.73130 - .33862i & 99.50853 + 5.29465i & 95.42134 + 1.47250i \end{bmatrix}$$

- ▶ Deduce the decomposition of  $\sigma = \sum_{i=1}^3 \omega_i \mathbf{e}_{\xi_i}$ :

$$\Xi = \begin{bmatrix} 0.99211 + 0.12533i & 0.80902 - 0.58779i \\ 1.00000 + 4.86234e^{-11}i & 1.00000 - 6.91726e^{-10}i \\ -0.53583 - 0.84433i & 0.06279 + 0.99803i \end{bmatrix} \omega = \begin{bmatrix} -5.00000 - 4.43772e^{-7}i \\ 101.00000 + 4.65640e^{-7}i \\ 1.00000 - 1.92279e^{-8}i \end{bmatrix}$$

- ▶ and the exponents  $\frac{50\Xi}{2\pi i} \bmod 50$  of the terms of  $f$ :

$$\begin{bmatrix} 1.00000 - 0.414119e^{-7}i & -5.00000 + 0.270858e^{-6}i, \\ 0.386933e^{-9} + 0.137963e^{-8}i & -0.550458e^{-8} - 0.38761e^{-8}i \\ -17.00000 - 0.100085e^{-6}i & 12.00000 + 0.700984e^{-6}i \end{bmatrix}$$

## Symmetric tensor and apolarity

**Apolar product:** For  $f = \sum_{|\alpha|=d} f_\alpha \binom{d}{\alpha} \bar{\mathbf{x}}^\alpha$ ,  $g = \sum_{|\alpha|=d} g_\alpha \binom{d}{\alpha} \bar{\mathbf{x}}^\alpha \in \mathbb{K}[\bar{\mathbf{x}}]_d$ ,

$$\langle f, g \rangle_d = \sum_{|\alpha| \leq d} f_\alpha g_\alpha \binom{d}{\alpha}.$$

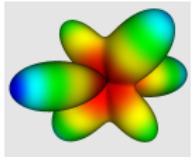
**Property:**  $\langle f, (\xi_0 x_0 + \cdots + \xi_n x_n)^d \rangle = f(\xi_0, \dots, \xi_n)$

**Duality:**

$$\tau = \sum_{\alpha \in \mathbb{N}^{n+1}, |\alpha|=d} \tau_\alpha \binom{d}{\alpha} \mathbf{x}^\alpha \quad \Rightarrow \quad \tau^* = \sum_{\alpha' \in \mathbb{N}^n, |\alpha'| \leq d} \tau_{\overline{\alpha'}} \frac{\mathbf{y}^{\alpha'}}{\alpha'!}$$

where  $\overline{(\alpha_1, \dots, \alpha_n)} = (d - \sum_i \alpha_i, \alpha_1, \dots, \alpha_n) \in \mathbb{N}^{n+1}$

$$\tau(\mathbf{x}) = \sum_{i=1}^r \omega_i (1 + \xi_{i,1} x_1 + \cdots + \xi_{i,n} x_n)^d \Leftrightarrow \tau^*(\mathbf{y}) = \sum_{i=1}^r \omega_i \mathbf{e}_{\xi_i}(\mathbf{y}) + (\mathbf{y})^{d+1}$$



# Symmetric tensor decomposition

$$\begin{aligned}\tau &= (\mathbf{x}_0 - \mathbf{x}_1 + 3\mathbf{x}_2)^4 + (\mathbf{x}_0 + \mathbf{x}_1 + \mathbf{x}_2)^4 - 3(\mathbf{x}_0 + 2\mathbf{x}_1 + 2\mathbf{x}_2)^4 \\ &= -x_0^4 - 24x_0^3x_1 - 8x_0^3x_2 - 60x_0^2x_1^2 - 168x_0^2x_1x_2 - 12x_0^2x_2^2 \\ &\quad - 96x_0x_1^3 - 240x_0x_1^2x_2 - 384x_0x_1x_2^2 + 16x_0x_2^3 - 46x_1^4 - 200x_1^3x_2 \\ &\quad - 228x_1^2x_2^2 - 296x_1x_2^3 + 34x_2^4 \\ \tau^* &= \mathbf{e}_{(-1,3)}(\mathbf{y}) + \mathbf{e}_{(1,1)}(\mathbf{y}) - 3\mathbf{e}_{(2,2)}(\mathbf{y}) \quad (\text{by apolarity})\end{aligned}$$

$$H_{\tau^*}^{2,2} := \begin{bmatrix} -1 & -2 & -6 & -2 & -14 & -10 \\ -2 & -2 & -14 & 4 & -32 & -20 \\ -6 & -14 & -10 & -32 & -20 & -24 \\ -2 & 4 & -32 & 34 & -74 & -38 \\ -14 & -32 & -20 & -74 & -38 & -50 \\ -10 & -20 & -24 & -38 & -50 & -46 \end{bmatrix}$$

For  $B = \{1, x_2, x_1\}$ ,

$$H_{\tau^*}^{B,B} = \begin{bmatrix} -1 & -2 & -6 \\ -2 & -2 & -14 \\ -6 & -14 & -10 \end{bmatrix}, H_{\tau^*}^{B,x_1B} = \begin{bmatrix} -6 & -14 & -10 \\ -14 & -32 & -20 \\ -10 & -20 & -24 \end{bmatrix}, H_{\tau^*}^{B,x_2B} = \begin{bmatrix} -2 & -2 & -14 \\ -2 & 4 & -32 \\ -14 & -32 & -20 \end{bmatrix}$$

- The matrix of multiplication by  $x_1$  in  $B = \{1, x_2, x_1\}$  is

$$M_1 = (H_{\tau^*}^{B,B})^{-1} H_{\tau^*}^{B,x_1 B} = \begin{bmatrix} 0 & -2 & -2 \\ 0 & \frac{1}{2} & \frac{3}{2} \\ 1 & \frac{5}{2} & \frac{3}{2} \end{bmatrix}.$$

- Its eigenvalues are  $[-1, 1, 2]$  and the eigenvectors:

$$U := \begin{bmatrix} 0 & -2 & -1 \\ \frac{1}{2} & \frac{3}{4} & \frac{1}{2} \\ -\frac{1}{2} & \frac{1}{4} & \frac{1}{2} \end{bmatrix}.$$

that is the polynomials

$$U(x) = \left[ \begin{array}{ccc} \frac{1}{2}x_2 - \frac{1}{2}x_1 & -2 + \frac{3}{4}x_2 + \frac{1}{4}x_1 & -1 + \frac{1}{2}x_2 + \frac{1}{2}x_1 \end{array} \right].$$

- We deduce the weights and the frequencies:

$$H_{\tau^*}^{[1,x_1,x_2],U} = \begin{bmatrix} 1 & 1 & -3 \\ 1 \times -1 & 1 \times 1 & -3 \times 2 \\ 1 \times 3 & 1 \times 1 & -3 \times 2 \end{bmatrix}.$$

Weights:  $1, 1, -3$ ; frequencies:  $(-1, 3), (1, 1), (2, 2)$ .

Decomposition:  $\tau^*(y) = e_{(-1,3)}(y) + e_{(1,1)}(y) - 3e_{(2,2)}(y) + (y)^4$

# A general framework

- ▶  $\mathfrak{F}$  the functional space, in which the “signal” lives.
- ▶  $S_1, \dots, S_n : \mathfrak{F} \rightarrow \mathfrak{F}$  commuting linear operators:  $S_i \circ S_j = S_j \circ S_i$ .
- ▶  $\Delta : h \in \mathfrak{F} \mapsto \Delta[h] \in \mathbb{C}$  a linear functional on  $\mathfrak{F}$ .

Generating series associated to  $h \in \mathfrak{F}$ :

$$\sigma_h(\mathbf{y}) = \sum_{\alpha \in \mathbb{N}^n} \Delta[S^\alpha(h)] \frac{\mathbf{y}^\alpha}{\alpha!} = \sum_{\alpha \in \mathbb{N}^n} \sigma_\alpha \frac{\mathbf{y}^\alpha}{\alpha!}.$$

- ▶ Eigenfunctions:

$$S_j(E) = \xi_j E, j = 1, \dots, n \Rightarrow \sigma_E = \mathbf{e}_\xi(\mathbf{y}).$$

- ▶ Generalized eigenfunctions:

$$S_j(E_k) = \xi_j E_k + \sum_{k' < k} m_{j,k'} E_{k'} \Rightarrow \sigma_{E_k} = \omega_i(\mathbf{y}) \mathbf{e}_\xi(\mathbf{y}).$$

☞ If  $h \mapsto \sigma_h$  is injective  $\Rightarrow$  unique decomposition of  $f$  as a linear combination of generalized eigenfunctions.

## Other applications

- ▶ Decomposition of measures as sums of spikes from moments (images, spectroscopy, radar, astronomy, ...)
- ▶ Decomposition of convolution operators of finite rank
- ▶ Sparse interpolation of PolyLog functions
- ▶ Polynomial optimisation and convex relaxations
- ▶ Vanishing ideal of points:  $\sigma = \sum_{i=1}^r \mathbf{e}_{\xi_i}(\mathbf{y})$
- ▶ Change of ordering for Grobner basis or basis representation for zero-dimensional (Gorenstein) ideals:  $\sigma_\alpha = \langle u, N(\mathbf{x}^\alpha) \rangle$ ,
- ▶ ...

## Challenges, open questions

- ▶ Numerical stability, correction of errors,
- ▶ Efficient construction of basis, complexity,
- ▶ Super-resolution, collision of points,
- ▶ Super-extrapolation,
- ▶ Best low rank approximation,
- ▶ ...

Thanks for your attention