

Sparse representations from moments

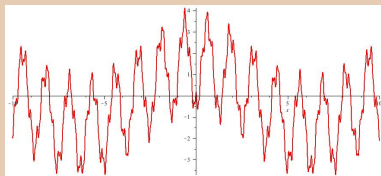
Bernard Mourrain

Inria Méditerranée, Sophia Antipolis
Bernard.Mourrain@inria.fr

AMF18, Lille, 1st June 2018

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

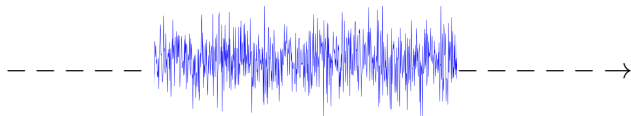
- ▶ Evaluate f at $2r$ regularly spaced points: $\sigma_0 := f(0), \sigma_1 := f(1), \dots$
- ▶ Compute a non-zero element $\mathbf{p} = [\mathbf{p}_0, \dots, \mathbf{p}_r]$ in the kernel:

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

- ▶ 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

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

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:

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

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 $\sigma_k = c(x^k) \cdot r = c(x^k) \cdot e = \sum_{j=1}^r \omega_j \xi_j^k$.
- ▶ 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 $p(x) = \sum_{i=0}^r p_i x^i = p_r \prod_{j=1}^r (x - \xi_j)$.
- ▶ Deduce the errors ω_j .

1 Sequences of moments, series, duality

2 Algebraic structure

3 Decomposition

4 Optimization

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

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

$$\begin{aligned} x \star \sigma &= \sum_{k=1}^{\infty} \sigma_k \frac{y^{k-1}}{(k-1)!} = \partial(\sigma(y)) \\ p(x) \star \sigma &= p(\partial)(\sigma(y)). \end{aligned}$$

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 $\alpha! = \prod \alpha_j!$ for $\alpha = (\alpha_1, \dots, \alpha_n) \in \mathbb{N}$.

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 σ .

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 operators

Hankel operator: For $\sigma \in \mathbb{K}[[\mathbf{y}]]$ (**symbol** of the Hankel operator),

$$H_\sigma : \mathbb{K}[\mathbf{x}] \rightarrow \mathbb{K}[[\mathbf{y}]]$$

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

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: $I_\sigma = \ker H_\sigma = \{p \in \mathbb{K}[\mathbf{x}] \mid p \star \sigma = 0\}$,

$$= \left\{ p = \sum_{\alpha} p_{\alpha} \mathbf{x}^{\alpha} \mid \forall \beta \in \mathbb{N}^n \sum_{\alpha} p_{\alpha} \sigma_{\alpha+\beta} = 0 \right\}$$

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: $\dim \mathcal{A}_\sigma < \infty$ i.e. \mathcal{A}_σ **Artinian**.

① Sequences of moments, series, duality

② **Algebraic structure**

③ Decomposition

④ Optimization

Structure of an Artinian algebra \mathcal{A}

Definition: $\mathcal{A} = \mathbb{K}[\mathbf{x}]/I$ is **Artinian** if $\dim_{\mathbb{K}} \mathcal{A} < \infty$.

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

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

Structure of the dual \mathcal{A}^*

Sparse series:

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

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,

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

- ▶ $\mathcal{V}_{\overline{\mathbb{K}}}(I) = \{\xi_1, \dots, \xi_r\}$
- ▶ $\mathcal{D}_i = \mathcal{D}(\omega_{i,1}, \dots, \omega_{i,l_i}) = Q_i^\perp$ 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 ξ_i .

The roots by eigencomputation

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

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

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

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

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

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

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

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

Solution of partial differential equations (with constant coeff.)

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

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

Hankel operators and Gorenstein 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: $\mathcal{A}_\sigma = \mathbb{K}[\mathbf{x}]/I_\sigma$ where $I_\sigma = \ker H_\sigma$.

Definition: \mathcal{A} **Gorenstein** iff $\exists \sigma \in \mathcal{A}^*$ such that $\mathcal{A}^* = \mathcal{A} \star \sigma$ is a free \mathcal{A} .

☞ **Isomorphism between $\mathcal{A}_\sigma = \mathbb{K}[\mathbf{x}]/I_\sigma$ and its dual space \mathcal{A}_σ^* :**

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

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

① Sequences of moments, series, duality

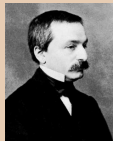
② Algebraic structure

③ **Decomposition**

④ Optimization

Univariate series:

Kronecker (1881)



The Hankel operator $H_\sigma : (p_m) \in \mathbb{C}^{\mathbb{N}, \text{finite}} \mapsto (\sum_m \sigma_{m+n} p_m)_{n \in \mathbb{N}} \in \mathbb{C}^{\mathbb{N}}$ 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_σ 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}_σ -module of rank 1).
- ▶ $(a, b) \mapsto \langle \sigma | ab \rangle$ is non-degenerate in \mathcal{A}_σ .

Decomposition from the structure of \mathcal{A}_σ

For $\sigma = \sum_{i=1}^r \omega_i \mathbf{e}_{\xi_i}$, 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 ξ_1, \dots, ξ_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}_σ is such that

$$\mathbf{H}_\sigma^{B', x_i B} = \mathbf{H}_{x_i * \sigma}^{B', B} = \mathbf{H}_\sigma^{B', B} \mathbf{M}_i$$

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

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

- ▶ 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 $\mathbf{l} = l_1 x_1 + \dots + l_n x_n$;
- 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

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

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

$$H_0 := H_\sigma^{B,B} = \begin{bmatrix} h(0,0) & h(1,0) & h(0,1) \\ h(1,0) & h(2,0) & h(1,1) \\ h(0,1) & h(1,1) & h(0,2) \end{bmatrix} = \begin{bmatrix} 4 & 5 & 7 \\ 5 & 5 & 11 \\ 7 & 11 & 13 \end{bmatrix},$$

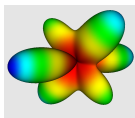
$$H_1 := H_\sigma^{B, x_1 B} = \begin{bmatrix} 5 & 5 & 7 \\ 5 & -1 & 17 \\ 811 & 178 & 23 \end{bmatrix}, \quad H_2 := H_\sigma^{B, x_2 B} = \begin{bmatrix} 7 & 11 & 13 \\ 11 & 17 & 23 \\ 13 & 23 & 25 \end{bmatrix}.$$

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

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

- This yields the weights $\mathbf{2}, \mathbf{3}, \mathbf{-1}$ and the roots $(\mathbf{1}, \mathbf{1}), (\mathbf{2}, \mathbf{2}), (\mathbf{3}, \mathbf{1})$.

Symmetric tensor decomposition



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

$$\psi^* \equiv \mathbf{e}_{(-1,3)}(\mathbf{y}) + \mathbf{e}_{(1,1)}(\mathbf{y}) - 3\mathbf{e}_{(2,2)}(\mathbf{y}) \quad (\text{by apolarity for } \psi^* : p \mapsto \langle \psi, p \rangle_d)$$

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

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

$$H_{\psi^*}^{B,B} = \begin{bmatrix} -1 & -2 & -6 \\ -2 & -2 & -14 \\ -6 & -14 & -10 \end{bmatrix}$$

$$H_{\psi^*}^{B,x_2B} = \begin{bmatrix} -6 & -14 & -10 \\ -14 & -32 & -20 \\ -10 & -20 & -24 \end{bmatrix}$$

$$H_{\psi^*}^{B,x_1B} = \begin{bmatrix} -2 & -2 & -14 \\ -2 & 4 & -32 \\ -14 & -32 & -20 \end{bmatrix}$$

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

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

- ▶ 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

$$U(x) = \left[\frac{1}{2} x_2 - \frac{1}{2} x_1 \quad -2 + \frac{3}{4} x_2 + \frac{1}{4} x_1 \quad -1 + \frac{1}{2} x_2 + \frac{1}{2} x_1 \right].$$

- ▶ We deduce the weights and the frequencies:

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

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

Decomposition: $\psi^*(\mathbf{y}) = \mathbf{e}_{(-1,3)}(\mathbf{y}) + \mathbf{e}_{(1,1)}(\mathbf{y}) - 3\mathbf{e}_{(2,2)}(\mathbf{y}) + (\mathbf{y})^4$

Sparse interpolation

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

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

- ▶ 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 $H_{\sigma}^{1,2}$:

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

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

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

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

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

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.

Extends [Peter, Plonka 2013] to the multivariate case.

Sparse interpolation of PolyLog functions

- ▶ $\mathcal{F} = \text{POLYLOG}(\mathbf{x}) = \{\sum_{(\beta,\gamma) \in A} h_{\beta,\gamma} \log^\beta(\mathbf{x}) \mathbf{x}^\gamma, A \text{ finite}\},$
- ▶ $S_j : h(x_1, \dots, x_n) \mapsto h(\dots, x_{j-1}, \varphi_j x_j, x_{j+1}, \dots)$ for $\varphi_j \in \mathbb{C} - \{1\},$
- ▶ $\Delta : h(x_1, \dots, x_n) \mapsto \Delta[h] = h(1, \dots, 1).$

Generating series of h : $\sigma_h(\mathbf{y}) = \sum_{\alpha \in \mathbb{N}^n} h(\varphi_1^{\alpha_1}, \dots, \varphi_n^{\alpha_n}) \frac{\mathbf{y}^\alpha}{\alpha!}.$

Eigenfunctions: \mathbf{x}^γ ; **Generalized eigenfunctions**: $\log^\beta(\mathbf{x}) \mathbf{x}^\gamma.$

$h = \sum_{i=1}^{r'} \sum_{\beta \in B_i} \omega_{i,\beta} \log^\beta(\mathbf{x}) \mathbf{x}^{\gamma_i}$ iff the generating series σ_h is of the form

$$\sigma_h(\mathbf{y}) = \sum_{i=1}^{r'} \omega_i(\mathbf{y}) \mathbf{e}_{\xi_i}(\mathbf{y})$$

with $\xi_i = (\varphi_1^{\gamma_{i,1}}, \dots, \varphi_n^{\gamma_{i,n}}) \in \mathbb{C}^n$ and $\omega_i(\mathbf{y}) = \sum_{\beta \in B_i} \omega_{i,\beta} \mathbf{y}^\beta \in \mathbb{C}[\mathbf{y}].$

👉 Decomposition from the moments $\sigma_\alpha = h(\varphi_1^{\alpha_1}, \dots, \varphi_n^{\alpha_n}).$

Sparse Fourier analysis

- ▶ $\mathcal{F} = L^2(\Omega)$,
- ▶ $S_j : h(\mathbf{x}) \mapsto e^{\frac{2\pi x_j}{T_j}} h(\mathbf{x}) \in L^2(\Omega)$,
- ▶ $\Delta : h(\mathbf{x}) \mapsto \int h(\mathbf{x}) d\mathbf{x}$.

Generating series of h : $\sigma(h) = \frac{1}{\prod_{j=1}^n T_j} \mathcal{F}(h) \left(2\pi \frac{\gamma_1}{T_1}, \dots, 2\pi \frac{\gamma_n}{T_n} \right)$

Eigenfunctions: δ_ξ ; **Generalized eigenfunctions**: $\delta_\xi^{(\beta)}$.

Let $h \in L^2(\Omega)$ and let $\sigma(h) = (\sigma_\gamma)_{\gamma \in \mathbb{Z}^n}$ its Fourier coefficients.

$$\Gamma_{\sigma(h)} : (\rho_\beta)_{\beta \in \mathbb{Z}^n} \in \ell^2(\mathbb{Z}^n) \mapsto \left(\sum_{\beta} \sigma_{\alpha+\beta} \rho_\beta \right)_{\alpha \in \mathbb{Z}^n} \in \ell^2(\mathbb{Z}^n).$$

$\Gamma_{\sigma(h)}$ is of finite rank r iff

$$\sigma(h) = \sum_{i=1}^{r'} \sum_{\alpha \in A_i} \omega_{i,\alpha} \mathbf{y}^\alpha \mathbf{e}_{\xi_i}(\mathbf{y}) \Leftrightarrow h = \sum_{i=1}^{r'} \sum_{\alpha \in A_i; \mathbb{C}\mathbb{N}^n} \omega_{i,\alpha} \mathbf{i}^{|\alpha|} \delta_{\xi_i}^{(\alpha)}$$

with $\xi_i = (\xi_{i,1}, \dots, \xi_{i,n}) \in \Omega$, $\omega_{i,\alpha} \in \mathbb{C}$ and $r = \sum_{i=1}^{r'} \mu(\sum_{\alpha \in A_i} \omega_{i,\alpha} \mathbf{y}^\alpha)$

- 1 Sequences of moments, series, duality
- 2 Algebraic structure
- 3 Decomposition
- 4 Optimization**

(joint work with C. Jozs, J.B. Lasserre)

For noisy data, transform the decomposition problem into an optimization problem which gives the **closest sparse decomposition**.

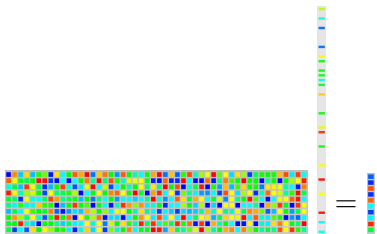
Compress sensing

Problem: For $f(\mathbf{x}) = \sum_{\alpha \in A} \omega_{\alpha} \mathbf{x}^{\alpha}$, find A and $(\omega_{\alpha})_{\alpha \in A}$ from values $f(\zeta_k)$ for $\zeta_k \in \mathbb{R}^n$, $k = 1, \dots, s$.

Find a solution of

$$V \Omega = F$$

where $V = (\zeta_k^{\alpha})_{k,\alpha}$, $\Omega = [\omega_{\alpha}]_{\alpha}$
and $F = [f(\zeta_k)]_{k=1,\dots,m}$, with
 $\|\Omega\|_0 = \#\{\omega_{\alpha} \neq 0\}$ minimal.



Linear Programming

$$\inf \sum_{\alpha \in A} \omega_{\alpha}^{+} + \omega_{\alpha}^{-}$$

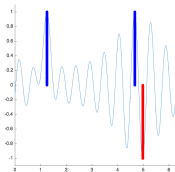
$$\text{s.t. } \omega_{\alpha}^{+} \geq 0, \omega_{\alpha}^{-} \geq 0, \sum_{\alpha} (\omega_{\alpha}^{+} - \omega_{\alpha}^{-}) \zeta_k^{\alpha} - f(\zeta_k) = 0, k = 1, \dots, s$$

- 👉 Sparse solution with r terms when $s = r$.
- 👉 Exact recovery for enough points well-separated.

Super-resolution

For $f(\mathbf{x}) = \sum_{\alpha \in A} \omega_{\alpha} \mathbf{x}^{\alpha}$, $\zeta \in \mathbb{C}^n$

$$f(\zeta^{\beta}) = \sum_{\alpha \in A} \omega_{\alpha} \zeta^{\alpha \cdot \beta} = \int \mathbf{x}^{\beta} d\mu$$



where $\mu = \sum_{\alpha \in A} \omega_{\alpha} \delta_{\zeta^{\alpha}}$ is a weighted sum of Dirac measures at ζ^{α} .

Find a measure $\mu = \sum_{\alpha \in A} \omega_{\alpha} \delta_{\xi}$, which is a minimizer of

$$(*) \quad \inf \quad \|\mu\|_{TV} \\ \text{s.t.} \quad \int \mathbf{x}^{\beta} d\mu = f(\zeta^{\beta}), \beta \in B$$

($\|\mu\|_{TV} = \sup_{\pi} \sum_{A \in \pi} |\mu(A)|$; for $\mu = \sum_{\alpha \in A} \omega_{\alpha} \delta_{\xi}$ $\|\mu\|_{TV} = \sum_{\alpha \in A} |\omega_{\alpha}|$.)

Theorem (Candès, Fernandez-Granda'14)

Let $\zeta \in \mathbb{T}^n$, $\delta = \min\{|\zeta^{\alpha} - \zeta^{\alpha'}| \mid \alpha \neq \alpha' \in A\}$ with $A \subset [-a, a]^n$.

If $\delta > C_n/a$, then $(*)$ has a unique optimal solution, which is a weighted sum of Dirac measures at ζ^{α} for $\alpha \in A$.



Semi-Definite Programming

Relaxation in convex optimization problems on moment matrices.

$$\begin{aligned} \mu \text{ positive measure} &\Rightarrow \forall p \in \mathbb{R}[\mathbf{x}], \int p^2 d\mu \geq 0 \\ &\Rightarrow H_\mu \succcurlyeq 0 \text{ where } \langle p | H_\mu p \rangle = \int p^2 d\mu \end{aligned}$$

If $\zeta \in \mathbb{R}^n$, $\mu = \sum_{\alpha \in A} \omega_\alpha \delta_{\zeta^\alpha} = \mu^+ - \mu^-$ with μ^+, μ^- positive measures.

Find moment matrices H^+, H^- indexed by $\alpha, \beta \in \mathbb{N}^n$ with $|\alpha| \leq d, |\beta| \leq d$, which is a minimizer of

$$\begin{aligned} (\star) \quad \inf \quad & h_{0,0}^+ + h_{0,0}^- \\ \text{s.t.} \quad & H^+ = (h_{\alpha,\beta}^+) \succcurlyeq 0, H^- = (h_{\alpha,\beta}^-) \succcurlyeq 0, \\ & H^+, H^- \text{ Hankel : } h_{\alpha,\beta} = h_{\alpha',\beta'} \text{ if } \alpha + \beta = \alpha' + \beta' \\ & h_{\beta,0}^+ - h_{\beta,0}^- = f(\zeta^\beta) \text{ for } \beta \in B \end{aligned}$$

If a **flat extension** property holds, decompose the series of moments $h_{\alpha,0}$ as a weighted sum of exponentials to get the support and weights of the optimal measure.

Some numerical results

Blackbox Polynomial	Rigorous LP	Super Resolution	Hankel Prony
$-1.2x^4 + 6.7x^5$	2.32%	1.66%	0.97%
$2.3x^6 + 5.6x^3 - 1.5x^2$	1.71%	2.31%	3.33%
$-2.1x^3 + 5.4x^2 - 2.0x + 6.2x^5 - 5.2$	0.80%	1.64%	2.89%
$0.8x_1x_2 - x_1x_2^2$	14.91%	11.03%	52.14%
$-5.8x_1^2x_2^2 - 8.2x_1^2x_2^3 + 5.5x_1^3x_2 + 1.1$	0.73%	1.01%	2.13%
$-7.2x_1x_2^2 + 1.8x_1^3x_2^2 + 2.6x_1^4x_2^5 + 6.2x_1x_2^5 + 2.5x_1$	1.19%	12.30%	2.67%
$-3.5 + 8.1x_1^3x_2x_3$	0.82%	1.32%	0.93%
$-1.2x_1^2x_2^2x_3^3 + 7.3x_1^2x_2 - 2.4x_2$	3.29%	2.13%	16.99%
$-6.1x_1^2x_5 + 2.5x_2x_4 + 4.8x_3$	2.90%	1.64%	6.74%
$2.9x_2x_3x_5^4x_{10} - 5.6x_1x_4^2x_7 - 4.1x_3x_5x_6^3x_8$	107.87% (1)	161.36% (1)	134.87% (1)
	N.A. (2)	2.12% (2)	134.69% (2)
	N.A. (3)	N.A. (3)	0.57% (3)

Relative error with uniform noise between -0.1 and 0.1 for the real and imaginary parts on the measurements; evaluations in the points $(e^{i\alpha_1}, \dots, e^{i\alpha_n})$ with $\alpha_i \in \mathbb{N}$, $\sum_i \alpha_i \leq d = \deg(f)$.

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

References

A package (Julia): <https://gitlab.inria.fr/AlgebraicGeometricModeling/TensorDec.jl>



Gaspard Riche Baron de Prony.

Essai expérimental et analytique: Sur les lois de la dilatabilité de fluides élastiques et sur celles de la force expansive de la vapeur de l'alcool, à différentes températures.

J. Ecole Polyt., 1:24–76, 1795.



Elwyn R. Berlekamp.

Nonbinary BCH decoding.

IEEE Transactions on Information Theory, 14(2):242–242, 1968.



Alessandra Bernardi, Jérôme Brachat, Pierre Comon, and Bernard Mourrain.

General tensor decomposition, moment matrices and applications.

Journal of Symbolic Computation, 52:51–71, 2013.



Jérôme Brachat, Pierre Comon, Bernard Mourrain, and Elias P. Tsigaridas.

Symmetric tensor decomposition.

Linear Algebra and Applications, 433(11-12):1851–1872, 2010.



Emmanuel J. Candès and Carlos Fernandez-Granda.

Towards a Mathematical Theory of Super-resolution.

Communications on Pure and Applied Mathematics, 67(6):906–956, 2014.



Cédric Jozz, Jean Bernard Lasserre, and Bernard Mourrain.

Sparse polynomial interpolation: Compressed sensing, super resolution, or Prony?

hal-01575325, ArXiv:1708.06187, 2017.



Monique Laurent and Bernard Mourrain.

A generalized flat extension theorem for moment matrices.

Archiv der Mathematik, 93(1):87–98, 2009.



James Massey.

Shift-register synthesis and BCH decoding.

IEEE transactions on Information Theory, 15(1):122–127, 1969.



Bernard Mourrain.

Polynomial-Exponential Decomposition from Moments.

Foundations of Computational Mathematics, 2017.
doi:10.1007/s10208-017-9372-x.



James Joseph Sylvester.

Essay on Canonical Form.

The collected mathematical papers of J. J. Sylvester, Vol. I, Paper 34, Cambridge University Press. 1909 (XV und 688). G. Bell, London, 1851.