

Algebra for the analysis of tensors and moment sequences

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Examples of problems

Guessing sequences

Given a sequence of values

$$\sigma_0, \sigma_1, \dots, \sigma_s \in \mathbb{C},$$

find/guess the values of σ_n for all $n \in \mathbb{N}$.

👉 Find $r \in \mathbb{N}, \omega_i, \xi_i \in \mathbb{C}$ such that $\sigma_n = \sum_1^r \omega_i \xi_i^n$, for all $n \in \mathbb{N}$.

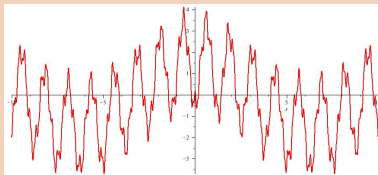
Example: 0, 1, 1, 2, 3, 5, 8, 13,

Solution:

- ▶ Find a recurrence relation valid for the first terms: $\sigma_{k+2} - \sigma_{k+1} - \sigma_k = 0$.
- ▶ Find the roots $\xi_1 = \frac{1+\sqrt{5}}{2}$, $\xi_2 = \frac{1-\sqrt{5}}{2}$ (golden numbers) of the characteristic polynomial: $x^2 - x - 1 = 0$.
- ▶ Deduce $\sigma_n = \frac{1}{\sqrt{5}} \left(\frac{1+\sqrt{5}}{2} \right)^n - \frac{1}{\sqrt{5}} \left(\frac{1-\sqrt{5}}{2} \right)^n$.

Reconstruction of signals

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



decompose it as

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

Blind identification



Observing $\mathbf{y}(t)$ with

$$\mathbf{y}(t) = H \mathbf{s}(t)$$

🔍 **find H and $\mathbf{s}(t)$**

- ▶ If the sources are statistically independent, using the high order statistics $\mathbb{E}(y_i y_j y_k \cdots)$ of the signal $\mathbf{y}(t)$, **decompose the symmetric tensor**

$$T = \sum_{i,j,k,\dots} \mathbb{E}(y_i y_j y_k \cdots) x_i x_j x_k \cdots = \sum_{|\alpha|=d} \binom{d}{\alpha} \mathbb{E}(\mathbf{y}^\alpha) \mathbf{x}^\alpha \text{ as}$$

$$T(\mathbf{x}) = \sum_{i=1}^r (H_i, \mathbf{x})^d$$

- ▶ Deduce the geometry of the sources $H = [H_1, \dots, H_r]$ and $\mathbf{s}(t)$.

Tensor of matrix multiplication

Given two matrices $X = \begin{pmatrix} x_1 & x_2 \\ x_3 & x_4 \end{pmatrix}$, $Y = \begin{pmatrix} y_1 & y_2 \\ y_3 & y_4 \end{pmatrix} \in \mathbb{R}^{2 \times 2} = \mathbb{R}^4$ the product $X Y$ is $Z = \begin{pmatrix} z'_1 & z'_2 \\ z'_3 & z'_4 \end{pmatrix}$ with

$$z'_1 = x_1 y_1 + x_2 y_3$$

$$z'_2 = x_1 y_2 + x_2 y_4$$

$$z'_3 = x_3 y_1 + x_4 y_3$$

$$z'_4 = x_3 y_2 + x_4 y_4$$

It defines the following tensor in $\mathbb{R}^4 \otimes \mathbb{R}^4 \otimes \mathbb{R}^4 = \mathbb{R}^{4 \times 4 \times 4}$:

$$T_{2,2} = (x_1 y_1 + x_2 y_3) z_1 + (x_1 y_2 + x_2 y_4) z_2 + (x_3 y_2 + x_4 y_4) z_3 + (x_3 y_1 + x_4 y_3) z_4$$

Decomposing minimally as

$$T_{2,2} = \sum_{i=1}^r l_i(x_1, \dots, x_4) m_i(y_1, \dots, y_4) n_i(z_1, \dots, z_4)$$

where l_i, m_i, n_i are linear in x, y, z , allows to compute the matrix product **more efficiently**.

- ▶ Such a decomposition exists with $r = 7$ (< 8) for 2×2 matrices.
- ▶ For 3×3 matrices, $r = 22$ (< 27).
- ▶ These decompositions are useful to bound the **exponent of linear algebra**:

$$\text{Multiplication of } n \times n \text{ matrices} \in \mathcal{O}(n^\omega)$$

where $\omega < 2.38 \dots$ (Conjecture: $\omega = 2$!).

Multilinear, symmetric tensors and moment sequences over

$$\mathbb{K} = \mathbb{R}, \mathbb{C}, \dots$$

Multilinear tensors

- ▶ A multilinear tensor is of the form

$$T = [t_{i_1, \dots, i_l}] \in \mathbb{K}^{n_1 \times \dots \times n_l}$$

as a **multi-dimensional array**

$$T(\mathbf{x}) = \sum_{i_1, \dots, i_l} t_{i_1, \dots, i_l} x_{1, i_1} \cdots x_{l, i_l}$$

as a **multilinear polynomial** in variables $x_{j,i}$

- ▶ Vector space denoted $\mathbb{K}^{n_1} \otimes \dots \otimes \mathbb{K}^{n_l}$, dimension = $n_1 \times \dots \times n_l$.

Symmetric tensors of order d

$T \in \mathbb{K}^{\overbrace{n \times \cdots \times n}^d}$ is **symmetric** iff $t_{i_{\tau(1)}, \dots, i_{\tau(d)}} = t_{i_1, \dots, i_d}$ for any permutation τ of $[1, \dots, d]$.

► For any $i_1, \dots, i_d \in 1 : n$ with $\#\{i_k = j\} = \alpha_j$, we have

$$t_{i_1, \dots, i_d} = t_{\overbrace{1, \dots, 1}^{\alpha_1}, \overbrace{2, \dots, 2}^{\alpha_2}, \dots, \overbrace{n, \dots, n}^{\alpha_n}} =: t_{\alpha_1, \dots, \alpha_n}$$

with $|\alpha| := \alpha_1 + \dots + \alpha_n = d$.

► If T is symmetric and $x_1 = \dots = x_d = x = (x_1, \dots, x_n)$,

$$T(x) = \sum_{i_1, \dots, i_d} t_{i_1, \dots, i_d} x_{i_1} \cdots x_{i_d} = \sum_{|\alpha|=d} t_{\alpha} \binom{d}{\alpha} x^{\alpha}$$

where $x^{\alpha} = x_1^{\alpha_1} \cdots x_n^{\alpha_n}$, $\binom{d}{\alpha} = \frac{d!}{\alpha_1! \cdots \alpha_n!}$.

= **homogeneous polynomial** of degree d in n variables $x = (x_1, \dots, x_n)$

► Space denoted $\mathcal{S}_{n,d}$, of dimension $s_{n,d} := \binom{n-1+d}{d}$

Multilinear tensor

```
In [1]: T = [i+j+k for i in 0:2, j in 0:2, k in 0:2 ]
```

```
Out[1]: 3×3×3 Array{Int64,3}:
```

```
[:, :, 1] =
```

```
0 1 2
1 2 3
2 3 4
```

```
[:, :, 2] =
```

```
1 2 3
2 3 4
3 4 5
```

```
[:, :, 3] =
```

```
2 3 4
3 4 5
4 5 6
```

```
In [2]: using DynamicPolynomials;
```

```
X = @polyvar x0 x1 x2; Y = @polyvar y0 y1 y2; Z = @polyvar z0 z1 z2;
```

```
In [3]: Txyz = sum( T[i,j,k]*X[i+1]*Y[j+1]*Z[k+1] for i in 0:2, j in 0:2, k in 0:2 )
```

```
Out[3]: x0y0z1 + 2x0y0z2 + x0y1z0 + 2x0y1z1 + 3x0y1z2 + 2x0y2z0 + 3x0y2z1 + 4x0y2z2
        + x1y0z0 + 2x1y0z1 + 3x1y0z2 + 2x1y1z0 + 3x1y1z1 + 4x1y1z2
        + 3x1y2z0 + 4x1y2z1 + 5x1y2z2 + 2x2y0z0 + 3x2y0z1 + 4x2y0z2
        + 3x2y1z0 + 4x2y1z1 + 5x2y1z2 + 4x2y2z0 + 5x2y2z1 + 6x2y2z2
```

Symmetric tensor

```
In [4]: F = sum( T[i,j,k]*X[i+1]*X[j+1]*X[k+1] for i in 0:2, j in 0:2, k in 0:2 )
```

```
Out[4]:
```

$$3x_0^2x_1 + 6x_0^2x_2 + 6x_0x_1^2 + 18x_0x_1x_2 + 12x_0x_2^2 + 3x_1^3 + 12x_1^2x_2 + 15x_1x_2^2 + 6x_2^3$$

Apolar product

Apolar product: For $F = \sum_{|\alpha|=d} f_\alpha x^\alpha$, $F' = \sum_{|\alpha|=d} f'_\alpha x^\alpha \in \mathcal{S}_{n,d}$,

$$\langle F, F' \rangle_d = \sum_{|\alpha|=d} \binom{d}{\alpha}^{-1} f_\alpha f'_\alpha.$$

Properties:

- $\langle F, (\mathbf{u} \cdot \mathbf{x})^d \rangle_d = F(\mathbf{u})$
- $\langle F, (\mathbf{v} \cdot \mathbf{x})(\mathbf{u} \cdot \mathbf{x})^{d-1} \rangle_d = \frac{1}{d} D_{\mathbf{v}} F(\mathbf{u})$
- $\langle F, (\mathbf{v}_1 \cdot \mathbf{x}) \cdots (\mathbf{v}_k \cdot \mathbf{x})(\mathbf{u} \cdot \mathbf{x})^{d-k} \rangle_d = \frac{(d-k)!}{d!} D_{\mathbf{v}_1} \cdots D_{\mathbf{v}_k} F(\mathbf{u})$

Taylor expansion: For an **orthonormal** basis $\mathbf{u}_1, \dots, \mathbf{u}_n$ of \mathbb{K}^n :

$$\begin{aligned} F &= \sum_{|\alpha|=d} \frac{1}{\alpha_1! \cdots \alpha_n!} (\mathbf{u}_1 \cdot \mathbf{x})^{\alpha_1} \cdots (\mathbf{u}_n \cdot \mathbf{x})^{\alpha_n} D_{\mathbf{u}_1}^{\alpha_1} \cdots D_{\mathbf{u}_n}^{\alpha_n} F(\mathbf{u}_1) \\ &= \sum_{|\alpha|=d} \binom{d}{\alpha} (\mathbf{u}_1 \cdot \mathbf{x})^{\alpha_1} \cdots (\mathbf{u}_n \cdot \mathbf{x})^{\alpha_n} \langle F, (\mathbf{u}_1 \cdot \mathbf{x})^{\alpha_1} \cdots (\mathbf{u}_n \cdot \mathbf{x})^{\alpha_n} \rangle_d \end{aligned}$$

✎ $(\sqrt{\binom{d}{\alpha}} \prod_{i=1}^n (\mathbf{u}_i \cdot \mathbf{x})^{\alpha_i})_{|\alpha|=d}$ **orthonormal basis** of $\mathcal{S}_{n,d}$.

Definition

For $F \in \mathcal{S}_{n,d}$ and $h \in \mathcal{S}_{n,k}$,

- $F^* : p \in \mathcal{S}_{n,d} \mapsto \langle F, p \rangle \in \mathbb{K}$ is a linear functional $\in \mathcal{S}_{n,d}^*$
- $q \star F^* : p \in \mathcal{S}_{n,d-k} \mapsto \langle F, h p \rangle$

Theorem: Weighted Sum of Evaluations (WSE)

$$F(\mathbf{x}) = \sum_{i=1}^r \omega_i (\xi_i, \mathbf{x})^d \Leftrightarrow F^* = \left(\sum_{i=1}^r \omega_i e_{\xi_i} \right)^{[d]}.$$

where $e_{\xi_i} : p \in S^d(\mathbb{K}^n) \mapsto p(\xi_i)$ is the **evaluation** (= **Dirac** measure δ_{ξ_i}) at ξ_i , and $\Lambda^{[d]}$ is the restriction in degree d .

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:

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

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

$$\Lambda : p = \sum_{i=0}^d p_i x^i \in \mathbb{K}[x] \mapsto \langle \Lambda | p \rangle = \sum_{i \in \mathbb{N}} \Lambda_i p_i$$

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

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

Examples:

- $p \mapsto$ coefficient of x^i in $p = \frac{1}{i!} \partial^i(p)(0)$ represented as

$$y^i \quad \text{or} \quad \frac{1}{i!} z^i$$

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

$$x \star y^i = y^{i-1}, \quad x \star z^i = iz^{i-1} \text{ for } i > 0 \quad (= 0 \text{ for } i = 0)$$

- $e_\zeta : p \mapsto p(\zeta)$ **evaluation** at ζ represented as

$$e_\zeta(y) = \sum_{k=0}^{\infty} \zeta^k y^k = \frac{1}{1 - \zeta y} \in \mathbb{K}[[y]] \text{ or } e_\zeta(z) = \sum_{k=0}^{\infty} \zeta^k \frac{z^k}{k!} = e^{\zeta z} \in \mathbb{K}[[z]]$$

$$x \star e_\zeta = \zeta e_\zeta$$

Sequences, series, duality (nD)

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

► **Formal power series:**

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

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

► **Linear functionals:** $\Lambda \in R^* = \{\Lambda : R \rightarrow \mathbb{K}, \text{ linear}\}$ where $R = \mathbb{K}[x_1, \dots, x_n]$

$$\Lambda : p = \sum_{\alpha} p_{\alpha} x^{\alpha} \mapsto \langle \Lambda | p \rangle = \sum_{\alpha} \Lambda_{\alpha} p_{\alpha}$$

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

$(y^\alpha)_{\alpha \in \mathbb{N}^n}$ (resp. $(\frac{1}{\alpha!} z^\alpha)_{\alpha \in \mathbb{N}^n}$) dual basis in R^* of the monomial basis $(x^\alpha)_{\alpha \in \mathbb{N}^n}$

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

$$p \star \sigma = \pi_+(p(y_1^{-1}, \dots, y_n^{-1})\sigma(y)) \quad p \star \sigma = p(\partial_1, \dots, \partial_n)(\sigma)(z)$$

Truncated moment sequences

For $\mathbf{x} = (x_1, \dots, x_n)$, $\mathcal{R}_n := \mathbb{K}[\mathbf{x}]$, $\mathcal{R}_{n,d} := \mathbb{K}[\mathbf{x}]_{\leq d}$ spanned by $\mathbf{x}^\alpha = x_1^{\alpha_1} \cdots x_n^{\alpha_n}$ with $|\alpha| = \alpha_1 + \cdots + \alpha_n \leq d$.

- **Truncated moment sequences:** $(\sigma_\alpha)_{|\alpha| \leq d}$
- **Truncated linear functionals:** $\mathcal{R}_{n,d}^* = \{\Lambda : \mathcal{R}_{n,d} \rightarrow \mathbb{K}, \text{ linear}\}$.
- **Truncated series:** For $\sigma(\mathbf{y}) = \sum_{\alpha \in \mathbb{N}^n} \sigma_\alpha \mathbf{y}^\alpha \in \mathbb{K}[[\mathbf{y}]]$,

or $\sigma(\mathbf{z}) = \sum_{\alpha \in \mathbb{N}^n} \sigma_\alpha \frac{\mathbf{z}^\alpha}{\alpha!} \in \mathbb{K}[[\mathbf{z}]]_{\leq d}$,

$$\sigma(\mathbf{y})^{[d]} = \sum_{|\alpha| \leq d} \sigma_\alpha \mathbf{y}^\alpha \in \mathbb{K}[\mathbf{y}]_{\leq d} \text{ or } \sigma(\mathbf{z})^{[d]} = \sum_{|\alpha| \leq d} \sigma_\alpha \frac{\mathbf{z}^\alpha}{\alpha!} \in \mathbb{K}[\mathbf{z}]_{\leq d}$$

- **Coproduct:** For $p \in \mathcal{R}_{n,k}$, $\Lambda \in \mathcal{R}_{n,d}^*$, $p \star \Lambda \in \mathcal{R}_{n,d-k}^*$

- **From tensors to moment sequences:**

$$F = \sum_{|\alpha|=d} F_\alpha x_0^{\alpha_0} x_1^{\alpha_1} \cdots x_n^{\alpha_n} \in \mathcal{S}_{n+1,d} \Rightarrow \check{F} = \sum_{|\alpha|=d} F_\alpha \binom{d}{\alpha}^{-1} y_1^{\alpha_1} \cdots y_n^{\alpha_n} \in \mathcal{R}_{n,d}^* \text{ s.t.}$$

$$F^* = \check{F} \circ \iota_0, \quad \check{F} = F^* \circ h_{d,x_0}$$

where $\iota_0 : p(x_0, \dots, x_n) \in \mathcal{S}_{n+1,d} \mapsto p(1, x_1, \dots, x_n) \in \mathcal{R}_{n,d}$, $h_{d,x_0} : p \in \mathcal{R}_{n,d} \mapsto x_0^d p(\frac{\mathbf{x}}{x_0}) \in \mathcal{S}_{n+1,d}$.

Duality

We describe the relations between tensors, linear functionals, moment sequences and duality in action on effective examples.

See also <https://github.com/tensors-network/TENORS-L1-Inria/blob/main/courses/Algebra-for-Analysis-of-Tensors/Duality.ipynb>

```
[1]: using DynamicPolynomials, MultivariateSeries
X = @polyvar x0 x1 x2
d = 3
F = x0^d + 2.0* (x0+x1-x2)^d
```

[1]:

$$-2.0x_2^3 + 6.0x_1x_2^2 - 6.0x_1^2x_2 + 2.0x_1^3 + 6.0x_0x_2^2 - 12.0x_0x_1x_2 + 6.0x_0x_1^2 - 6.0x_0^2x_2 + 6.0x_0^2x_1 + 3.0x_0^3$$

We compute the linear functional $F^* \in (\mathcal{S}_{3,d})^*$ by apolarity:

```
[2]: Fstar = dual(F,d)
```

```
[2]: -2.0dx2^3 + 2.0dx1*dx2^2 - 2.0dx1^2dx2 + 2.0dx1^3 + 2.0dx0*dx2^2 -
2.0dx0*dx1*dx2 + 2.0dx0*dx1^2 - 2.0dx0^2dx2 + 2.0dx0^2dx1 + 3.0dx0^3
```

The variables of the dual basis of the monomials basis are denoted dx_i .

We compute now the **affine** polynomial obtained by the substitution $x_0 \Rightarrow 1$:

```
[3]: f = subs(F,x0=>1)
```

[3]:

$$3.0 - 6.0x_2 + 6.0x_1 + 6.0x_2^2 - 12.0x_1x_2 + 6.0x_1^2 - 2.0x_2^3 + 6.0x_1x_2^2 - 6.0x_1^2x_2 + 2.0x_1^3$$

Its dual $s = \check{f} \in (\mathcal{R}_{n,d})^*$ is:

```
[4]: s = dual(f,d)
```

```
[4]: 3.0 - 2.0dx2 + 2.0dx1 + 2.0dx2^2 - 2.0dx1*dx2 + 2.0dx1^2 - 2.0dx2^3 +  
2.0dx1*dx2^2 - 2.0dx1^2dx2 + 2.0dx1^3
```

We apply the linear functional s on x_1 :

```
[5]: dot(s,x1)
```

```
[5]: 2.0
```

We can notice that it coincides with $\langle \mathbf{e}_{0,0} + 2\mathbf{e}_{1,-1} | x_1 \rangle$ where $\mathbf{e}_{a,b}$ is the evaluation at the point (a,b) .

We compute $x_2 \star s$, which coincides with $(-2\mathbf{e}_{1,-1})^{[2]}$ (i.e. $-2\mathbf{e}_{1,-1}$ truncated in degree ≤ 2)

```
[6]: s2 = x2*s
```

```
[6]: -2.0 + 2.0dx2 - 2.0dx1 - 2.0dx2^2 + 2.0dx1*dx2 - 2.0dx1^2
```

as we can check, when applying the linear functional $x_2 \star s$ on $x_1^2 + x_2^2$:

```
[7]: dot(s2, x1^2+x2^2)
```

```
[7]: -4.0
```

Decomposition of tensors and moment sequences

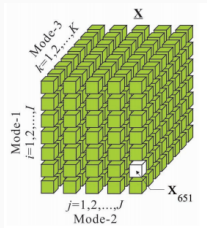
$M \in \mathbb{K}^{n_1 \times n_2} = \mathbb{K}^{n_1} \otimes \mathbb{K}^{n_2}$ is of **rank** r iff there exist $U \in \mathbb{K}^{n_1 \times n_1}$, $V \in \mathbb{K}^{n_2 \times n_2}$ invertible and Σ_r diagonal invertible s.t.

$$M = U \begin{pmatrix} \Sigma_r & 0 \\ 0 & 0 \end{pmatrix} V^t$$

- Σ_r not unique
- $\Sigma_r = I_r$ for some U, V .
- U, V unitary \Rightarrow Singular Value Decomposition
- U, V are **eigenvectors** of $M M^t$ (resp. $M^t M$)
- Best low rank approximation from truncated SVD

Multilinear tensors of $\mathbb{K} = \mathbb{R}, \mathbb{C}, \dots$

A tri-linear tensor $T \in \mathbb{K}^{n_1 \times n_2 \times n_3} = \mathbb{K}^{n_1} \otimes \mathbb{K}^{n_2} \otimes \mathbb{K}^{n_3}$



Decomposition of a trilinear tensor

$$T = \sum_{j=1}^r U_j \otimes V_j \otimes W_j \text{ with } U_j \in \mathbb{K}^{n_1}, V_j \in \mathbb{K}^{n_2}, W_j \in \mathbb{K}^{n_3}$$

with r minimal.

$$\text{Coefficient-wise: } T_{i_1, i_2, i_3} = \sum_{j=1}^r U_{i_1, j} V_{i_2, j} W_{i_3, j}$$

Decomposition of a multilinear tensor

$$T = \sum_{j=1}^r U_j^1 \otimes \cdots \otimes U_j^l \text{ with } U_j^i \in \mathbb{K}^{n_i},$$

with r minimal.

Decomposition as polynomial:

$$T(x) = \sum_{j=1}^r (U_j^1 \cdot x_1) \cdots (U_j^l \cdot x_l)$$

with $x_k = (x_{k,1}, \dots, x_{k,n_k})$ and $(U_j^k \cdot x_k) = U_{1,j}^k x_{k,1} + \cdots + U_{n_k,j}^k x_{k,n_k}$.

Coefficient-wise: $T_{i_1, \dots, i_l} = \sum_{j=1}^r U_{i_1,j}^1 \cdots U_{i_l,j}^l$

Symmetric tensor decomposition and Waring problem (1770)



Symmetric tensor decomposition problem:

Given a homogeneous polynomial F of degree d in the variables $\bar{x} = (x_0, x_1, \dots, x_n)$ with coefficients $\in \mathbb{K}$:

$$F(\bar{x}) = \sum_{|\alpha|=d} t_\alpha \bar{x}^\alpha,$$

find a minimal decomposition of F of the form

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

with $\xi_i = (\xi_{i,0}, \xi_{i,1}, \dots, \xi_{i,n}) \in \overline{\mathbb{K}}^{n+1}$ spanning distinct lines, $\omega_i \in \overline{\mathbb{K}}$.

The minimal r in such a decomposition is called the **rank** of T .

Moment sequence decomposition

Moment sequence decomposition

Given $\sigma = (\sigma_\alpha)_{|\alpha| \leq d} \in \mathbb{N}^{s_n, d}$, find r minimal, $\omega_i \in \mathbb{K}$, $\xi_i \in \mathbb{K}^n$ for $i = 1, \dots, r$ s.t.

$$\sigma(\mathbf{z}) := \sum_{|\alpha| \leq d} \sigma_\alpha \frac{\mathbf{z}^\alpha}{\alpha!} = \left(\sum_{i=1}^r \omega_i e_{\xi_i}(\mathbf{z}) \right)^{[d]}$$

where $e_\xi(\mathbf{z}) = \sum_{\alpha \in \mathbb{N}^n} \xi^\alpha \frac{\mathbf{z}^\alpha}{\alpha!} = \exp(\mathbf{z}, \xi)$.

 r is called the **rank** of σ .

Polynomial-exponential sequence decomposition

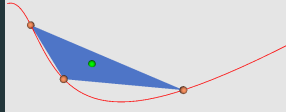
Given $\sigma = (\sigma_\alpha)_{|\alpha| \leq d} \in \mathbb{N}^{s_n, d}$, find $r' \in \mathbb{N}$, $\omega_i(\mathbf{z}) \in \mathbb{K}[\mathbf{z}]$, $\xi_i \in \mathbb{K}^n$ s.t.

$$\sigma(\mathbf{z}) = \left(\sum_{i=1}^{r'} \omega_i(\mathbf{z}) e_{\xi_i}(\mathbf{z}) \right)^{[d]}$$

and $r = \sum_{i=1}^{r'} \dim \langle \omega_i \rangle$ is minimal.

 r is called the **polynomial-exponential rank** of σ .

Geometric point of view



- $\mathcal{V}_{n+1,d} = \{\omega(\xi, \mathbf{x})^d, \omega \in \mathbb{K}, \xi \in \mathbb{K}^{n+1}\}$ **Veronese** variety (smooth except at 0)

$$F = \sum_{i=1}^r \omega_i(\xi_i, \mathbf{x})^d \text{ iff } F \in \overbrace{\mathcal{V}_{n+1,d} + \cdots + \mathcal{V}_{n+1,d}}^r$$

- $\text{Sec}_{n+1,d}^r = \overline{\sum_{i=1}^r \mathcal{V}_{n+1,d}}$ **r^{th} -secant** variety of $\mathcal{V}_{n+1,d}$.
- For $S \subset \mathbb{R}^n$ (compact),

$\mathcal{M}_+(S) =$ **positive measures** supported on S

$= \text{Conv}(\delta_\xi \mid \xi \in S)$ where $\delta_\xi =$ **Dirac** at $\xi = \mathbf{e}_\xi$

$\mathcal{M}_+(S)^{[d]} =$ **truncated moment sequences** of $\mu \in \mathcal{M}_+(S)$

$= \text{Conv}((1 + (\xi, \mathbf{x}))^d \mid \xi \in S)$

- 👉 How to **decompose** a tensor or a moment sequence?
- 👉 Are there matrices **revealing the rank**?
- 👉 How can we **deduce** the decomposition?

Flattening, matricisation

Multilinear tensors

For a multilinear tensor $T = [t_{i_1, \dots, i_l}] \in \mathbb{K}^{n_1 \times \dots \times n_l}$, **flattening** or **matricisation** in mode $(n_1 \times \dots \times n_k, n_{k+1} \times \dots \times n_l)$:

$$[t_{I,J}]_{I \in [n_1] \times \dots \times [n_k], J \in [n_{k+1}] \times \dots \times [n_l]}$$

\Rightarrow matrix of size $M \times N$ with $M = n_1 \times \dots \times n_k$, $N = n_{k+1} \times \dots \times n_l$.

$$\begin{aligned} & \mathbb{K}^{n_1} \otimes \dots \otimes \mathbb{K}^{n_k} \otimes \mathbb{K}^{n_{k+1}} \otimes \dots \otimes \mathbb{K}^{n_l} \\ & \sim \overbrace{(\mathbb{K}^{n_1} \otimes \dots \otimes \mathbb{K}^{n_k})}^E \otimes \overbrace{(\mathbb{K}^{n_{k+1}} \otimes \dots \otimes \mathbb{K}^{n_l})}^F \\ & \sim E \otimes F \end{aligned}$$

Symmetric tensors

For $F = \sum_{|\gamma|=d} F_\gamma x^\gamma \in S^d(\mathbb{K}^n)$, **matricisation** in degree $(k, d - k)$:

$$\blacktriangleright H_F^{k,d-k} = [\langle F, x^{\alpha+\beta} \rangle_d]_{|\alpha|=k, |\beta|=d-k} = \left[\binom{d}{\alpha+\beta}^{-1} F_{\alpha+\beta} \right]_{|\alpha|=k, |\beta|=d-k}$$

also known as **flattening** or **Catalecticant** or **Hankel** matrix of F in degree $(k, d - k)$.

$H_\mu^{k,d-k} = (\int x^{\alpha+\beta} d\mu)_{|\alpha|=k, |\beta|=d-k}$ is a.k.a the **moment** matrix of $\mu \equiv \check{F}$.

For $A \subset \mathcal{S}_{n,k}, B \subset \mathcal{S}_{n,d-k}$,

$$H_F^{A,B} = [\langle F, a b \rangle_d]_{a \in A, b \in B}$$

Catalecticant, Hankel operator:

$$\begin{aligned} H_F^{k,d-k} : \mathcal{S}_{n,d-k} &\rightarrow \mathcal{S}_{n,k}^* \\ b &\mapsto b \star F^* \end{aligned}$$

Hankel matrix factorisation

Definition

For $\Xi = \{\xi_1, \dots, \xi_r\}$ and $A = \{a_1, \dots, a_s\} \subset S^k$

$$V_{A,\Xi} = \begin{bmatrix} a_1(\xi_1) & \cdots & a_1(\xi_r) \\ \vdots & & \vdots \\ a_s(\xi_1) & \cdots & a_s(\xi_r) \end{bmatrix}$$

is the **Vandermonde** matrix of A, Ξ .

Vandermonde factorization

If $F = \sum_{i=1}^r \omega_i (\xi \cdot \mathbf{x})^d$ and $\mathbf{m}_k = \{\mathbf{x}^\alpha\}_{|\alpha|=k}$, then

$$H_F^{k,d-k} = V_{\mathbf{m}_k, \Xi} \text{diag}(\omega_1, \dots, \omega_r) V_{\mathbf{m}_{d-k}, \Xi}^t$$

Example with Fibonacci sequence $\sigma = (0, 1, 1, 2, 3, 5, 8, 13, \dots)$, $d = 4$

$$\blacktriangleright F = \sum_{i=0}^4 \sigma_i \binom{d}{i} x_0^{d-i} x_1^i = 4x_0^3 x_1 + 6x_0^2 x_1^2 + 8x_0 x_1^3 + 3x_1^4$$

$$\blacktriangleright k = 2, d - k = 2$$

$$H_F^{2,2} = (\langle F, x_0^{d-i-j} x_1^{i+j} \rangle_d)_{0 \leq i,j \leq 3} = (\sigma_{i+j})_{0 \leq i,j \leq 3} = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 1 & 2 \\ 1 & 2 & 3 \end{pmatrix}$$

$$\blacktriangleright \text{rank } H_F^{2,2} = 2$$

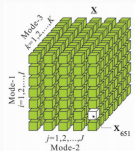
$$\blacktriangleright H_T^{2,2} = \begin{bmatrix} 1 & 1 \\ \xi_1 & \xi_2 \\ \xi_1^2 & \xi_2^2 \end{bmatrix} \text{diag}(\omega_1, \omega_2) \begin{bmatrix} 1 & \xi_1 & \xi_1^2 \\ 1 & \xi_2 & \xi_2^2 \end{bmatrix}$$

with ξ_i roots of $X^2 - X - 1 = 0$ for $X = \frac{x_1}{x_0}$.

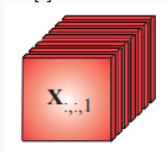
Decomposition via linear algebra

Multilinear tensors

$$T \in \mathbb{K}^{n_1} \otimes \mathbb{K}^{n_2} \otimes \mathbb{K}^{n_3} \equiv [T_{[i]}]_{i=1}^{n_3} \text{ pencil of } n_3 \text{ matrices of size } n_1 \times n_2.$$



\equiv



For $T \in \mathbb{K}^r \otimes \mathbb{K}^r \otimes \mathbb{K}^{n_3}$,

$$T = \sum_{j=1}^r U_j \otimes V_j \otimes W_j \text{ with } U, V \in \mathbb{K}^{r \times r}, W \in \mathbb{K}^{n_3 \times r}$$

$$\text{iff } T_{[i]} = U \text{diag}(W_{i,1}, \dots, W_{i,r}) V^t \quad i \in 1:n_3$$

If $T_{[1]}$ inv., U = matrix of **common eigenvectors** of $M_i = T_{[i]} T_{[1]}^{-1}$
 V^{-t} = matrix of **common eigenvectors** of $M'_i = T_{[1]}^{-1} T_{[i]}$.

Sylvester approach (1851)



Theorem:

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

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

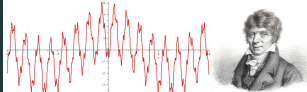
iff there exists a polynomial $p(x_0, x_1) := p_0 x_0^r + p_1 x_0^{r-1} x_1 + \cdots + p_r x_1^r$ s.t.

$$\begin{bmatrix} t_0 & t_1 & \cdots & t_r \\ t_1 & & & t_{r+1} \\ \vdots & & & \vdots \\ t_{d-r} & \cdots & t_{d-1} & t_d \end{bmatrix} \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_r \end{bmatrix} = 0$$

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

If $\alpha_k \neq 0$, $\xi_k = \frac{\beta_k}{\alpha_k}$ root of $p(x) = \sum_{i=0}^r p_i x^i$ (or generalized eigenvalues of (H_0, H_1)). 26

Prony's method (1795)



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

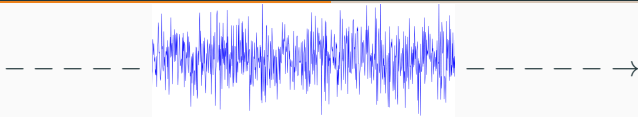
- Evaluate f at $2r$ regularly spaced points: $\sigma_0 := f(0), \sigma_1 := f(1), \dots$
- Find $p = [p_0, \dots, p_r]$ with $p_r = 1$ s.t. $\sigma_{k+r} + \sigma_{k+r-1}p_{r-1} + \dots + \sigma_k p_0 = 0$ by solving:

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

- Compute the roots $\xi_1 = e^{\zeta_1}, \dots, \xi_r = e^{\zeta_r}$ of $p(x) := \sum_{i=0}^r p_i x^i$ (or generalized eigenvalues of (H_0, H_1))
- 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:

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

Encoding messages using the dual code:

$$C = V^\perp = \{c \mid c \cdot [f(\xi_1), \dots, f(\xi_m)] = 0 \text{ for } f = x^k, 0 \leq k \leq d\}$$

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 $\sigma_k = v(x^k) \cdot r = c(x^k) \cdot e = \sum_{j=1}^r \omega_{ij} \xi_{ij}^k$.
- 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 ω_{ij} by solving a Vandermonde linear system.

Solving polynomial equations

How to solve $f = 0$ for $f = \sum_{i=0}^d f_i x^i \in \mathbb{K}[x]$?

The matrix of the **multiplication** by x modulo f , assuming $f_d = 1$:

$$\mathcal{M}_x : \mathbb{K}[x]/(f) \rightarrow \mathbb{K}[x]/(f)$$

$$\bar{p} \mapsto \overline{x p}$$

In the mon. basis $1, x, \dots, x^{d-1}$:

$$\begin{bmatrix} 0 & \dots & 0 & -f_0 \\ 1 & \ddots & \vdots & \vdots \\ & \ddots & 0 & \vdots \\ 0 & & 1 & -f_{d-1} \end{bmatrix}$$

$$\mathcal{M}_x(x^i) = x^{i+1} \text{ for } i \in 0:d-2$$

$$\mathcal{M}_x(x^{d-1}) = -\sum_{i=0}^{d-1} f_i x^i$$

In the Lagrange basis (for simple roots):

$$\begin{bmatrix} \xi_1 & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \xi_r \end{bmatrix}$$

$$\mathcal{M}_x(\sum_{i=1}^d \lambda_i \mathbf{u}_i) = \sum_{i=1}^d \xi_i \lambda_i \mathbf{u}_i$$

Theorem:

- ▶ The **eigenvalues** of \mathcal{M}_x are the roots ξ_i of $f(x) = 0$.
- ▶ The **eigenvectors** of \mathcal{M}_x are the Lagrange interpolation polynomials \mathbf{u}_i (when the roots are simple).

- The dual space \mathcal{A}^* of \mathcal{A} is the set $\text{Hom}_{\mathbb{K}}(\mathcal{A}, \mathbb{K})$ of linear forms $\Lambda : \mathcal{A} \rightarrow \mathbb{K}$

$$\mathcal{A}^* = (f)^\perp = \{\Lambda \in \mathbb{K}[x]^* \mid \forall p \in (f), \langle \Lambda | p \rangle = 0\}.$$

- The multiplication by x in \mathcal{A}^* is the transposed of \mathcal{M}_x :

$$\begin{aligned} \mathcal{M}_x^t : \mathcal{A}^* &\rightarrow \mathcal{A}^* \\ \Lambda &\mapsto x \star \Lambda \end{aligned}$$

where $x \star \Lambda : f \mapsto \langle \Lambda | x f \rangle = \langle \Lambda | \mathcal{M}_x(f) \rangle$.

- If the roots are simple, a basis of \mathcal{A}^* is the set of **evaluations** $e_{\xi_i} : f \mapsto f(\xi_i)$.

It is dual to the basis of **interpolation polynomials** $(u_i)_{i=1:d}$.

Proposition

The evaluations e_{ξ_i} for $i \in 1:d$ are **eigenvectors** of \mathcal{M}_x^t .

Proof: $\mathcal{M}_x(e_{\xi_i}) = x \star e_{\xi_i} = (p \mapsto \xi_i p(\xi_i)) = \xi_i e_{\xi_i}$.

The matrix of $(e_{\xi_1}, \dots, e_{\xi_d})$ in the dual basis of $(1, x, \dots, x^{d-1})$ is the **Vandermonde** matrix of ξ_1, \dots, ξ_d :

$$V = \begin{pmatrix} 1 & 1 & \dots & 1 \\ \xi_1 & \xi_2 & \dots & \xi_d \\ \vdots & \vdots & & \vdots \\ \xi_1^{d-1} & \xi_2^{d-1} & \dots & \xi_d^{d-1} \end{pmatrix}$$

If U is the coefficient matrix of Lagrange basis $\mathbf{u}_1, \dots, \mathbf{u}_d$ in the basis $(1, x, \dots, x^{d-1})$ of $\mathcal{A} = \mathbb{K}[x]/(f)$, we have

$$V^t U = \text{Id}$$

since $(1, \xi_i, \dots, \xi_i^{d-1})U_j = \mathbf{u}_j(\xi_i) = \delta_{i,j}$

The roots by eigencomputation

Hypothesis: $\mathcal{V}_{\mathbb{K}}(I) = \{\xi_1, \dots, \xi_r\} \Leftrightarrow \mathcal{A} = \mathcal{R}/I$ Artinian (i.e. $\dim_{\mathbb{K}} \mathcal{A} = r < \infty$).

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

Theorem:

- The eigenvalues of \mathcal{M}_g are $\{g(\xi_1), \dots, g(\xi_r)\}$.
- The common eigenvectors of all $(\mathcal{M}_g^t)_{g \in \mathcal{A}}$ are $e_{\xi_i} : p \mapsto p(\xi_i)$ (up to a sc.).

Proposition

If the roots are **simple**,

- the operators \mathcal{M}_g are diagonalizable,
- their common eigenvectors are the **interpolation polynomials** u_i at the roots (up to a sc.), which form a basis of idempotents of \mathcal{A} .

Structure of \mathcal{A}

Theorem:

If $I = Q_1 \cap \cdots \cap Q_{r'}$ with Q_i \mathbf{m}_{ξ_i} -primary, then

- $\mathcal{V}_{\overline{\mathbb{K}}}(I) = \{\xi_1, \dots, \xi_{r'}\}$
- $\mathcal{A} = \mathcal{A}_1 \oplus \cdots \oplus \mathcal{A}_{r'}$ with $\mathcal{A}_i = \mathcal{R}/Q_i$
- $1 = \mathbf{u}_1 \oplus \cdots \oplus \mathbf{u}_{r'}$ with $\mathcal{A}_i = \mathbf{u}_i \mathcal{A}$, $\mathbf{u}_i^2 = \mathbf{u}_i$, $\mathbf{u}_i \mathbf{u}_j = 0$ if $i \neq j$.
(\mathbf{u}_i idempotents).

Theorem:

In a basis of \mathcal{A} , all the matrices M_g ($g \in \mathcal{A}$) are of the form

$$M_g = \begin{bmatrix} M_g^1 & & 0 \\ & \ddots & \\ 0 & & M_g^{r'} \end{bmatrix} \quad \text{with } M_g^i = \begin{bmatrix} g(\xi_i) & \star & \star \\ & \ddots & \\ 0 & & g(\xi_i) \end{bmatrix}$$

Corollary (Chow form)

$\Delta(\mathbf{u}) = \det(v_0 + v_1 M_{x_1} + \cdots + v_n M_{x_n}) = \prod_{i=1}^r (v_0 + v_1 \xi_{i,1} + \cdots + v_n \xi_{i,n})^{\mu_{\xi_i}}$ where $\mu_{\xi_i} = \dim \mathcal{A}_i$ is the multiplicity of ξ .

Structure of the dual \mathcal{A}^*

Definition (Polynomial-Exponential series)

$$\mathcal{PolExp} = \left\{ \sigma(\mathbf{z}) = \sum_{i=1}^r \omega_i(\mathbf{z}) e_{\xi_i}(\mathbf{z}) \mid \omega_i(\mathbf{z}) \in \mathbb{K}[\mathbf{z}], \xi_i \in \mathbb{K}^n \right\}$$

where $e_{\xi_i}(\mathbf{z}) = e^{\mathbf{z}_1 \xi_{i,1} + \dots + \mathbf{z}_n \xi_{i,n}} = \sum_{\alpha} \xi_i^{\alpha} \frac{\mathbf{z}^{\alpha}}{\alpha!}$ is the evaluation $e_{\xi} : p \in \mathcal{R} \mapsto p(\xi)$.

Inverse system generated by $\omega_1(\mathbf{z}), \dots, \omega_r(\mathbf{z}) \in \mathbb{K}[\mathbf{z}]$

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

Theorem:

For $\mathbb{K} = \overline{\mathbb{K}}$ algebraically closed and $\mathcal{A} = \mathcal{R}/I$ artinian with $I = Q_1 \cap \dots \cap Q_{r'}$, Q_i \mathbf{m}_{ξ_i} -primary,

$$\mathcal{A}^* = I^{\perp} = \bigoplus_{i=1}^{r'} \mathcal{D}_i e_{\xi_i}(\mathbf{z}) \subset \mathcal{PolExp}$$

- $\mathcal{D}_i = Q_i^{\perp} = \langle \langle \omega_{i,1}(\mathbf{z}), \dots, \omega_{i,l_i}(\mathbf{z}) \rangle \rangle$ with $\omega_{i,j}(\mathbf{z}) \in \mathbb{K}[\mathbf{z}]$.
- $\dim_{\mathbb{K}}(\mathcal{D}_i) = \mu_i$ multiplicity of ξ_i .

Example

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

$$\mathcal{A} = \mathcal{R}/I \sim B = \langle 1, x_1, x_2 \rangle, \quad I = (x_1^2 - x_2, x_1 x_2 - x_2, x_2^2 - x_2)$$

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

$$I = Q_1 \cap Q_2 \quad \text{with primary comp.} \quad Q_1 = (x_1^2, x_2), \quad Q_2 = (x_1 - 1, x_2 - 1)$$

$$\mathcal{A} = \mathcal{A}_1 \oplus \mathcal{A}_2 \quad \text{with} \quad \mathcal{A}_1 = \langle \mathbf{u}_1, x_1 \mathbf{u}_1 \rangle \equiv \mathcal{R}/Q_1 \quad \mathcal{A}_2 = \langle \mathbf{u}_2 \rangle \equiv \mathcal{R}/Q_2$$

$$\mathcal{A}^* = I^\perp = Q_1^\perp \oplus Q_2^\perp = \langle \mathbf{e}_{(0,0)}, z_1 \mathbf{e}_{(0,0)} \rangle \oplus \langle \mathbf{e}_{(1,1)} \rangle$$

$$\text{where } \mathbf{e}_{(a,b)} : p \mapsto p(a, b), \quad z_1 \mathbf{e}_{(0,0)} : p \mapsto \partial_{x_1}(p)(0, 0).$$

The algebraic structure from Hankel operators

Kronecker theorems



Univariate series:

Kronecker (1881)

The Hankel operator

$$\begin{aligned}\mathcal{H}_\sigma : \mathbb{C}^{\mathbb{N}, \text{finite}} &\rightarrow \mathbb{C}^{\mathbb{N}} \\ (p_m) &\mapsto (\sum_m \sigma_{m+n} p_m)_{n \in \mathbb{N}}\end{aligned}$$

is of **finite rank** r iff $\exists \omega_1, \dots, \omega_{r'} \in \mathbb{C}[z]$ and $\xi_1, \dots, \xi_{r'} \in \mathbb{C}$ distincts s.t.

$$\sigma(z) = \sum_{n \in \mathbb{N}} \sigma_n \frac{z^n}{n!} = \sum_{i=1}^{r'} \omega_i(z) e_{\xi_i}(z)$$

with $\sum_{i=1}^{r'} (\deg(\omega_i) + 1) = r$.

Multivariate series:

Theorem: Generalized Kronecker Theorem ^[M'2018]

For $\sigma \in \mathcal{R}^*$, the Hankel operator

$$\begin{aligned}\mathcal{H}_\sigma : \mathcal{R} &\rightarrow \mathcal{R}^* \\ p &\mapsto p \star \sigma\end{aligned}$$

is of rank r iff

$$\sigma(\mathbf{z}) = \sum_{i=1}^{r'} \omega_i(\mathbf{z}) \mathbf{e}_{\xi_i}(\mathbf{z}) \quad \text{with } \omega_i(\mathbf{z}) \in \mathbb{K}[\mathbf{z}],$$

with $r = \sum_{i=1}^{r'} \dim \langle \omega_i(\mathbf{z}) \rangle = \sum_{i=1}^{r'} \dim \langle \partial_{\mathbf{z}}^\gamma \omega_i(\mathbf{z}) \rangle$. In this case, we have

- $I_\sigma = \ker H_\sigma$ with $\mathcal{V}_{\mathbb{C}}(I_\sigma) = \{\xi_1, \dots, \xi_{r'}\}$.
- $I_\sigma = Q_1 \cap \dots \cap Q_{r'}$ with $Q_i^\perp = \langle \omega_i \rangle \mathbf{e}_{\xi_i}(\mathbf{z})$.

👉 \mathcal{A}_σ is **Gorenstein**^a; $(a, b) \mapsto \langle \sigma | ab \rangle$ is non-degenerate in \mathcal{A}_σ .

👉 Can be generalized to $\sigma = (\sigma_1, \dots, \sigma_m) \in (\mathcal{R}^*)^m$.

^a $\mathcal{A}_\sigma^* = \mathcal{A}_\sigma \star \sigma$ is a free \mathcal{A}_σ -module of rank 1

For $F = \sum_{i=1}^r \omega_i (\xi_i, \mathbf{x})^d$ or $F^* = (\sum_{i=1}^r \omega_i e_{\xi_i})^{[d]}$ with $\xi_{i,0} = 1$, let

- $I_{\Xi} := \{p \in \mathcal{R} \text{ s.t. } p(\xi_i) = 0\}$ be the defining ideal of $\Xi = \{\xi_1, \dots, \xi_r\}$
- $\mathcal{A}_{\Xi} := \mathcal{R}/I_{\Xi}$ the quotient algebra by I_{Ξ} , of dimension r .

Theorem:

Let $A = \{a_1, \dots, a_s\}$, $A' = \{a'_1, \dots, a'_t\}$, and $H = H_F^{A,A'}$ be a **flattening** of F . Then

$$H_F^{A,A'} = V_{A,\Xi} \Delta_{\omega} V_{A',\Xi}^t$$

where $V_{A,\Xi} = \begin{bmatrix} a_1(\xi_1) & \cdots & a_1(\xi_r) \\ \vdots & & \vdots \\ a_s(\xi_1) & \cdots & a_s(\xi_r) \end{bmatrix}$ is the **Vandermonde** matrix A, Ξ .

If A and A' contain a basis of \mathcal{A}_{Ξ} , then

- $\ker H = I_{\Xi} \cap \langle A' \rangle$
- $\text{im } H = (I_{\Xi}^{\perp})|_{\langle A \rangle} = \text{im } V_{A,\Xi}$ where

$$I_{\Xi}^{\perp} = \{\Lambda \in \mathbb{K}[\mathbf{x}]^* \mid \forall p \in I_{\Xi}, \langle \Lambda, p \rangle = 0\} = \mathcal{A}_{\Xi}^* = \langle e_{\xi_1}, \dots, e_{\xi_r} \rangle.$$

Proof: A contains a basis of $\mathcal{A}_{\Xi} \Rightarrow V_{A,\Xi}$ of rank r .

Proposition

For $g \in \mathcal{R}$, $\mathcal{M}_g : a \in \mathcal{A}_\Xi \mapsto ga \in \mathcal{A}_\Xi$, $\Lambda \in \mathcal{R}^*$,
 $\mathcal{H}_{g \star \Lambda} = \mathcal{H}_\Lambda \circ \mathcal{M}_g = \mathcal{M}_g^t \circ \mathcal{H}_\Lambda$

Proposition

The sets $B \subset A$, $B' \subset A'$ of size $r := \dim(\mathcal{A})$ are bases of \mathcal{A} iff
 $H_0 = H_F^{B', B}$ is invertible.

Proposition

Assume that $x_i \cdot B \subset A$, let $H_i = H_F^{B', x_i B}$. Then
 $M_i = H_0^{-1} H_i$ is the multiplication by x_i in B modulo I_Ξ

Proposition

$\exists E, F$ invertible such that

$H_i = E \operatorname{diag}(\xi_{1,i}, \dots, \xi_{r,i}) F \Rightarrow$ **joint diagonalisation** of $H_0^{-1} H_i$.

Example with Fibonacci sequence

$$\sigma = (0, 1, 1, 2, 3, 5, 8, 13, \dots), \quad d = 6, \quad \psi = \sum_{i=0}^d \sigma_i \binom{d}{i} x_0^{d-i} x_1^i.$$

$$\blacktriangleright H_\psi = \begin{pmatrix} 0 & 1 & 1 & 2 \\ 1 & 1 & 2 & 3 \\ 1 & 2 & 3 & 5 \\ 2 & 3 & 5 & 8 \end{pmatrix} \quad H_0 = \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix}, \quad H_1 = \begin{pmatrix} 1 & 1 \\ 1 & 2 \end{pmatrix}$$

$$\blacktriangleright M_x = H_0^{-1} H_1 = \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix}.$$

$$\blacktriangleright \text{Eigenvalues: } \xi_i = \frac{1 \pm \sqrt{5}}{2}; \text{ Eigenvectors: } u_i = \pm \frac{1}{\sqrt{5}}(x - \xi_i), \quad i = 1, 2.$$

$$\blacktriangleright \text{Weights: } U^t H_0 U = \begin{pmatrix} \frac{1}{\sqrt{5}} & 0 \\ 0 & -\frac{1}{\sqrt{5}} \end{pmatrix}.$$

 **Decomposition:**

$$\psi = \frac{1}{\sqrt{5}} \left(x_0 + \frac{1 + \sqrt{5}}{2} x_1 \right)^d - \frac{1}{\sqrt{5}} \left(x_0 + \frac{1 - \sqrt{5}}{2} x_1 \right)^d$$

Symmetric tensor decomposition



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

$$\langle \psi, p \rangle_4 = \langle \psi^* | p \rangle \text{ where } \psi^* = e_{(3,-1)} + e_{(1,1)} - 3e_{(2,2)} \text{ (by apolarity)}$$

$$H_{\psi^*}^{2,2} :=$$

-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

$$\text{For } B' = \{x_0, x_1, x_2\}, B = x_0 B'$$

$$H_{\psi}^{B, x_0 B'} = \begin{bmatrix} -1 & -2 & -6 \\ -2 & -2 & -14 \\ -6 & -14 & -10 \end{bmatrix}$$

$$H_{\psi}^{B, x_1 B'} = \begin{bmatrix} -2 & -2 & -14 \\ -2 & 4 & -32 \\ -14 & -32 & -20 \end{bmatrix}$$

$$H_{\psi}^{B, x_2 B'} = \begin{bmatrix} -6 & -14 & -10 \\ -14 & -32 & -20 \\ -10 & -20 & -24 \end{bmatrix}$$

- The matrix of multiplication by x_2 in $B' = \{x_0, x_1, x_2\}$ is

$$M_2 = (H_{\psi}^{B, x_0 B'})^{-1} H_{\psi}^{B, x_2 B'} = \begin{bmatrix} 0 & -2 & -2 \\ 0 & \frac{1}{2} & \frac{3}{2} \\ 1 & \frac{5}{2} & \frac{3}{2} \end{bmatrix}.$$

- 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

$$U(x) = \begin{bmatrix} \frac{1}{2} x_1 - \frac{1}{2} x_2 & -2 + \frac{3}{4} x_1 + \frac{1}{4} x_2 & -1 + \frac{1}{2} x_1 + \frac{1}{2} x_2 \end{bmatrix}.$$

- We deduce the weights and the frequencies:

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

Weights: $1, 1, -3$;

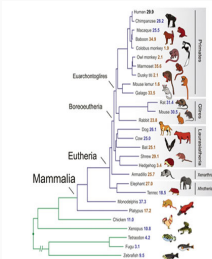
Frequencies: $(3, -1), (1, 1), (2, 2)$.

Decomposition:

$$\psi^* = e_{(3,-1)} + e_{(1,1)} - 3e_{(2,2)}$$

$$\psi(x) = (x_0 + 3x_1 - x_2)^4 + (x_0 + x_1 + x_2)^4 - 3(x_0 + 2x_1 + 2x_2)^4$$

Phylogenetic tree multilinear tensors



Problem: study probability vectors for genes $[A, C, G, T]$ and the transitions described by Markov matrices M^i .

Example:

Ancestor : A
 Transitions : $M^1 \quad M^2 \quad M^3$
 Species : $S_1 \quad S_2 \quad S_3$

For $i_1, i_2, i_3 \in \{A, C, G, T\}$, the probability to observe i_1, i_2, i_3 is

$$p_{i_1, i_2, i_3} = \sum_{k=1}^4 \omega_k M_{k, i_1}^1 M_{k, i_2}^2 M_{k, i_3}^3 \Leftrightarrow \mathbf{p} = \sum_{k=1}^4 \omega_k \mathbf{u}_k \otimes \mathbf{v}_k \otimes \mathbf{w}_k$$

where $\mathbf{u}_k = (M_{k,1}^1, \dots, M_{k,4}^1)$, $\mathbf{v}_k = (M_{k,1}^2, \dots, M_{k,4}^2)$, $\mathbf{w}_k = (M_{k,1}^3, \dots, M_{k,4}^3)$.

👉 \mathbf{p} is a tensor $\in \mathbb{K}^4 \otimes \mathbb{K}^4 \otimes \mathbb{K}^4$ of rank ≤ 4 .

👉 Its decomposition yields the M^i and the ancestor probability (ω_j) .

1 Phylogenetic trees

We describe how the decomposition method works on a trilinear tensor of $\mathbb{R}^4 \otimes \mathbb{R}^4 \otimes \mathbb{R}^4$ of rank 4.

See also <https://github.com/tensor-network/TENORS-L1-Inria/blob/main/courses/Algebra-for-Analysis-of-Tensors/Phylogenetic.ipynb>

1.1 Problem

We are given a tensor T of the form

$$T = \sum_{i=1}^4 \omega_i A[:, i] \otimes B[:, i] \otimes C[:, i]$$

where $A, B, C \in \mathbb{R}^{4 \times 4}$ are Markov matrices and $\omega = (\omega_1, \dots, \omega_4) \in (\mathbb{R}_+)^4$ are positive weights.

How to recover the weights ω and the factors A, B, C from the coefficients of T ?

```
[1]: using TensorDec, DynamicPolynomials, LinearAlgebra
```

```
# scale the columns of A, B, C and the weights w so that the sum of the columns is 1
normalize_markov! = function(w,A,B,C)
    for i in 1:size(A,2)
        l = sum(A[j,i] for j in 1:size(A,1) )
        A[:,i] /= l
        w[i] *= l
    end
    for i in 1:size(B,2)
        l = sum(B[j,i] for j in 1:size(B,1) )
        B[:,i] /=l
    end
end
```



```

        w[i] *= 1
    end
    for i in 1:size(C,2)
        l = sum(C[j,i] for j in 1:size(B,1) )
        C[:,i] ./=l
        w[i] *= 1
    end
    w, A,B,C
end;
# scale the columns of A so that the first row is [1, ..., 1]
normalize_affine = function(A0::AbstractMatrix) A = Matrix(A0); for i in 1:size(A,2)
    A[:,i] /= A[1,i] end; A end;

```

```

[2]: A = rand(4,4); B = rand(4,4); C = rand(4,4); w = rand(4);
    normalize_markov!(w,A,B,C);

```

We verify that the columns sum to 1.:

```

[3]: fill(1.,4)'*A, fill(1.,4)'*B, fill(1.,4)'*C

```

```

[3]: ([1.0 0.9999999999999999 1.0 0.9999999999999999], [1.0 1.0 1.0
0.9999999999999999], [1.0 1.0 0.9999999999999998 1.0])

```

```

[4]: #w = fill(1.,4); A=[1 1 1 1; 0 1. 0 0; 0 0 2. 0; 0 0 0 3.]; B= A; C=A

```

```

[5]: T = tensor(w,A,B,C)

```

[5]: 4x4x4 Array{Float64, 3}:

```
[:, :, 1] =  
 0.63856  0.498562  0.609002  0.492611  
 0.659005  0.576221  0.588409  0.480191  
 0.331819  0.218192  0.31365  0.291366  
 0.217415  0.142356  0.211895  0.192002
```

```
[:, :, 2] =  
 0.459046  0.304443  0.516376  0.307711  
 0.31125  0.259229  0.270975  0.217506  
 0.323017  0.194411  0.324703  0.241424  
 0.20303  0.116249  0.226682  0.158003
```

```
[:, :, 3] =  
 0.147284  0.102441  0.122958  0.0951209  
 0.0896452  0.0735928  0.0659168  0.0550932  
 0.129666  0.0858343  0.0949834  0.0865085  
 0.0728417  0.04477  0.0620078  0.0559637
```

```
[:, :, 4] =  
 0.320664  0.218559  0.39174  0.197574  
 0.240617  0.205661  0.21549  0.166941  
 0.191538  0.117397  0.215483  0.130113  
 0.124318  0.0727524  0.155088  0.0859419
```

The corresponding polynomial is:

```
[6]: X = @polyvar x0 x1 x2 x3; Y = @polyvar y0 y1 y2 y3; Z = @polyvar z0 z1 z2 z3;
F= sum(T[i,j,k]*X[i]*Y[j]*Z[k] for i in 1:4 for j=1:4 for k=1:4)
```

```
[6]:
0.0859418985158878x3y3z3+0.05596366474953316x3y3z2+0.1580025087257289x3y3z1+0.19200166860542914x3y3z0+
```

```
[7]: H = [T[:, :, i] for i in 1:4];
```

1.2 Matrices from the tensor

The flattening or Hankel matrix of the tensor indexed by monomials $A = (x_i)_{0 \leq i \leq 3}$, $A' = (y_j z_k)_{0 \leq j, k \leq 3}$ is:

```
[8]: hcat(H...)
```

```
[8]: 4×16 Matrix{Float64}:
 0.63856  0.498562  0.609002  0.492611  ...  0.218559  0.39174  0.197574
 0.659005  0.576221  0.588409  0.480191      0.205661  0.21549  0.166941
 0.331819  0.218192  0.31365  0.291366      0.117397  0.215483  0.130113
 0.217415  0.142356  0.211895  0.192002      0.0727524  0.155088  0.0859419
```

By scaling the factors and the weights of the decomposition, we assume that the factors U, V, W have their first coordinates equal to 1. We set $x_0 = 1$, $y_0 = 1$, $z_0 = 1$ and work on an affine chart of $\mathbb{P}^3 \times \mathbb{P}^3 \times \mathbb{P}^3$.

A basis of \mathcal{A} is $B = \{1, y_1, y_2, y_3\}$. The operators M_i of multiplication by z_i in the basis B of \mathcal{A} are:

```
[9]: M = [inv(H[1])*H[i] for i in 2:4];
```

1.3 Joint diagonalisation

We take a random combination M_{rnd} of M_i and compute its eigenvectors:

```
[10]: Mrnd = sum(M[i]*rand() for i in 1:3);
```

```
[11]: E = eigen(Mrnd).vectors
```

```
[11]: 4×4 Matrix{Float64}:  
 -0.677549  0.671611 -0.399447  0.818269  
  0.69611  -0.69861  0.510161 -0.373124  
  0.161483 -0.178923 -0.515211 -0.256734  
  0.174016  0.169907  0.561013 -0.353981
```

We verify that the operators of multiplication M_i are diagonal (up to numerical error) in the basis of eigenvectors of M_{rnd} :

```
[12]: D = [inv(E)*M[i]*E for i in 1:3];
```

```
[13]: D[1]
```

```
[13]: 4×4 Matrix{Float64}:  
  0.384224      1.22402e-14 -4.45199e-14 -1.49325e-14  
 -7.77156e-16  1.00375      -3.35287e-14 -1.22125e-14  
 -6.73073e-15  3.69843e-15  3.18572      7.68829e-15  
  9.4022e-15   -8.44463e-15  1.27676e-15  3.56338
```

```
[14]: D[2]
```

```
[14]: 4×4 Matrix{Float64}:
  0.0804996  7.34135e-15 -3.58047e-15  9.50628e-15
 -6.43929e-15  0.389043  2.88658e-15  5.21805e-15
  3.08781e-16  9.09862e-16  0.434225  2.05391e-15
 -6.7793e-15  5.46785e-15 -1.44051e-14  2.95996
```

```
[15]: D[3]
```

```
[15]: 4×4 Matrix{Float64}:
  0.330232  1.78468e-14 -1.29896e-14  6.10623e-15
 -8.60423e-15  0.472936 -1.9762e-14  4.21885e-15
  4.4964e-15 -6.50868e-15  2.82149 -6.18949e-15
  6.83481e-15 -3.38271e-15  3.11001e-14  1.79256
```

1.4 The factors from the eigenvectors

The corresponding terms on the diagonal give the factor W (with the first coordinate equal to 1):

```
[16]: W = fill(1.,4,4); for i in 1:3 for j in 1:4 W[i+1,j] = D[i][j,j] end end; W
```

```
[16]: 4×4 Matrix{Float64}:
  1.0  1.0  1.0  1.0
  0.384224  1.00375  3.18572  3.56338
  0.0804996  0.389043  0.434225  2.95996
  0.330232  0.472936  2.82149  1.79256
```

The eigenvectors E are (up to a scalar) the interpolation polynomials at the points in the basis B . Therefore, $\text{inv}(E)'$ is (up to a scaling of the columns) the **Vandermonde** matrix of the points in $B = \{1, y_1, y_2, y_3\}$:

$$V = \begin{pmatrix} 1 & 1 & 1 & 1 \\ v_{1,1} & v_{2,1} & v_{3,1} & v_{4,1} \\ v_{1,2} & v_{2,2} & v_{3,2} & v_{4,2} \\ v_{1,3} & v_{2,3} & v_{3,3} & v_{4,3} \end{pmatrix}$$

This gives the factor V

```
[17]: V = inv(E)'
```

```
[17]: 4x4 adjoint(::Matrix{Float64}) with eltype Float64:
```

```
 4.54037  2.71845  -0.717092  2.40036
 4.10939  1.28546  -0.264018  2.21873
 4.05693  2.53245  -1.75912   0.421948
 3.2216   3.09232  -0.103501  0.0789611
```

We remove the scaling factors, by normalizing the columns so that the first coordinate of the points is 1:

```
[18]: V = normalize_affine(V)
```

```
[18]: 4x4 Matrix{Float64}:
```

```
 1.0      1.0      1.0      1.0
 0.905077 0.472864 0.368179 0.924333
 0.893524 0.93158  2.45313  0.175785
 0.709546 1.13753  0.144335 0.0328955
```

Since $T = \sum_i \omega_i U[:, i] \otimes V[:, i] \otimes W[:, i]$ and $W[1, i] = 1$, we have $H_1 = T[:, :, 1] = \sum_i \omega_i U[:, i] \otimes V[:, i]$ and the columns of U coincides up to a scaling with the columns $H_1(V')^{-1} = H_1 E$:

```
[19]: U = normalize_affine(H[1]*E)
```

```
[19]: 4×4 Matrix{Float64}:  
  1.0      1.0      1.0      1.0  
  1.35261  0.29567  0.0795717 0.555197  
  0.288573 1.15391  0.507942  1.11787  
  0.197175 0.746456 0.411169  0.420357
```

1.5 The weights from the factors

We solve a Vandermonde system

$$\begin{pmatrix} \vdots & \vdots \\ u_{1,i}v_{1,j}w_{1,k} & u_{4,i}v_{4,j}w_{4,k} \\ \vdots & \vdots \end{pmatrix} \begin{pmatrix} \omega_1 \\ \vdots \\ \omega_4 \end{pmatrix} = \begin{pmatrix} \vdots \\ T[i,j,k] \\ \vdots \end{pmatrix}$$

selecting only the rows where $k = 1$, s.t. $w_{l,1} = 1$ just to simplify the matrix constructions.

```
[20]: Vdm = hcat([U[i,k]*V[j,k] for i in 1:4 for j in 1:4] for k in 1:4)...  
theta = [H[i][i,j] for i in 1:4 for j in 1:4];  
  
w1 = Vdm\theta
```

```
[20]: 4-element Vector{Float64}:  
 0.4470649786874177  
 0.15032225861369847  
 0.027340579174909594  
 0.0138317894444849434
```

```
[21]: normalize_markov!(w1,U,V,W); T1 = tensor(w1,U,V,W); norm(T-T1)
```

```
[21]: 5.750349421984536e-14
```

```
[ ]:
```


Sparse interpolation

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

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 $H_{\sigma}^{1,2}$:

$$\begin{bmatrix} 97.00000 & 97.01771 + 3.93695i & 95.50360 - 1.47099i & 98.46280 + 4.88062i & 97.42748 + 1.82098i \\ 97.01771 + 3.93695i & 98.46280 + 4.88062i & 97.42748 + 1.82098i & 102.35770 + 3.77300i & 99.50853 + 5.29465i \\ 95.50360 - 1.47099i & 97.42748 + 1.82098i & 95.73130 - .33862i & 99.50853 + 5.29465i & 95.42134 + 1.47298i \end{bmatrix}$$

- Deduce the decomposition of $\sigma = \sum_{i=1}^3 \omega_i e_{\xi_i}$:

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

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

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

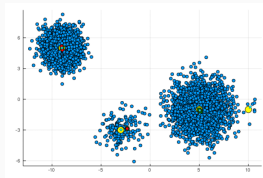
Machine Learning and clustering

A mixture of (spherical) Gaussian distributions

$$g(\mathbf{y}) = \sum_{k=1}^r \omega_k f(\mathbf{y}, \mu_k, \sigma_k)$$

where

- $f(\mathbf{y}, \mu_k, \sigma_k)$ is the normal distribution of mean $\mu_k \in \mathbb{R}^n$ and covariance $\Sigma_k = \text{diag}(\sigma_k^2) \in \mathbb{R}^{n \times n}$,
- ω_k is the proportion of mixture of the k^{th} normal distribution $f(\mathbf{y}, \mu_k, \sigma_k)$.



Theorem:

For $\bar{\sigma}$ the smallest eigenvalue of $\mathbb{E}[\mathbf{y} \otimes \mathbf{y}] - \mathbb{E}[\mathbf{y}] \otimes \mathbb{E}[\mathbf{y}]$ and \mathbf{v} its unit eigenvector,

- $M_1(\mathbf{x}) := \mathbb{E}[\langle \mathbf{v}, \mathbf{y} - \mathbb{E}[\mathbf{y}] \rangle^2 (\mathbf{y} \cdot \mathbf{x})] = \sum_k \omega_k \sigma_k^2 (\mu_k \cdot \mathbf{x})$
- $M_2(\mathbf{x}) := \mathbb{E}[(\mathbf{y} \cdot \mathbf{x})^2] - \bar{\sigma} \|\mathbf{x}\|^2 = \sum_k \omega_k (\mu_k \cdot \mathbf{x})^2$
- $M_3(\mathbf{x}) := \mathbb{E}[(\mathbf{y} \cdot \mathbf{x})^3] - 3M_1(\mathbf{x}) \|\mathbf{x}\|^2 = \sum_k \omega_k (\mu_k \cdot \mathbf{x})^3$

Gaussian Mixtures

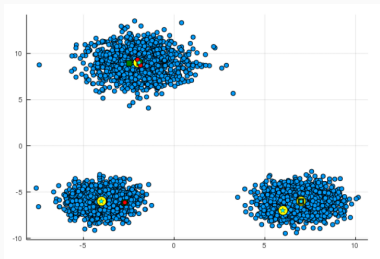
$g(\mathbf{x}) = \sum_{k=1}^r \omega_k f(\mathbf{x}, \mu_k, \sigma_k)$ where $f(\mathbf{x}, \mu_k, \sigma_k)$ of means μ_k , covariance $\sigma_k^2 Id$.

Expectation Maximisation (EM):

$$\max \sum_{i=1}^P \log(\sum_{k=1}^r \omega_k f(\mathbf{x}_i, \mu_k, \sigma_k))$$

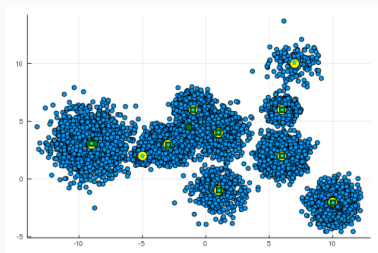
by alternate iterative optimization from an initial start.

Comparison with k-means, split and tensor decomposition:



Examples with $n = 6, r = 4$;

See [Khouja-Mattei-M'22]



$n = 30, r = 10$

How the tensor rank differs from the matrix rank?

- ▶ $\text{rank}(F) \geq \text{rank}$ of any matricization of F .
- ▶ $\text{rank}(F)$ can be **strictly bigger** than the rank of its matricization.
- ▶ The rank for a random/generic multilinear (resp. symmetric) tensor is $\lceil \frac{\prod n_i}{\sum n_i} \rceil$ (resp. $r_g = \lceil \frac{\binom{d+n-1}{d}}{n} \rceil$) except in few exceptional cases (symmetric tensor exceptions: $d = 2$ and $(d, n) \in \{(3, 5), (4, 3), (4, 4), (4, 5)\}$, Alexander-Hirschowitz'95).
- ▶ The rank of a tensor can be **strictly bigger** than r_g (not for matrices).
- ▶ The rank decomposition of a tensor F is generically **unique** if $\text{rank}(F) < r_g$ (not for matrices).
There are **infinitely** many rank decompositions if $\text{rank}(F) > r_g$ (not possible for matrices).

Low rank Hankel matrices and Generalized Additive Decomposition

Low rank decomposition of Hankel matrices

Rank 1 Hankel matrices: $H_\xi = [\xi^{\alpha+\beta}]_{\alpha \in A, \beta \in B}$ for some $\xi \in \mathbb{K}^n$ or \mathbb{P}^n .

Rank r Hankel matrices are not necessarily the sum of r rank one matrices:

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \neq \lambda_1 \begin{bmatrix} 1 & \xi_1 & \xi_1^2 \\ \xi_1 & \xi_1^2 & \xi_1^3 \\ \xi_1^2 & \xi_1^3 & \xi_1^4 \end{bmatrix} + \lambda_2 \begin{bmatrix} 1 & \xi_2 & \xi_2^2 \\ \xi_2 & \xi_2^2 & \xi_2^3 \\ \xi_2^2 & \xi_2^3 & \xi_2^4 \end{bmatrix}$$

but

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} = \lim_{\epsilon \rightarrow 0} \frac{1}{2\epsilon} \begin{bmatrix} 1 & \epsilon & \epsilon^2 \\ \epsilon & \epsilon^2 & \epsilon^3 \\ \epsilon^2 & \epsilon^3 & \epsilon^4 \end{bmatrix} - \frac{1}{2\epsilon} \begin{bmatrix} 1 & -\epsilon & \epsilon^2 \\ -\epsilon & \epsilon^2 & -\epsilon^3 \\ \epsilon^2 & -\epsilon^3 & \epsilon^4 \end{bmatrix}$$

Generalized Additive Decomposition

Recall: For an orthogonal basis $\mathbf{u} = (\mathbf{u}_1, \dots, \mathbf{u}_n)$ of \mathbb{K}^n and $P \in \mathcal{S}_{n,d}$,

$$\langle (\mathbf{u}_1, \mathbf{x})^{d-k} (\mathbf{u}_2, \mathbf{x})^{\beta_2} \dots (\mathbf{u}_n, \mathbf{x})^{\beta_n}, P \rangle_d = \frac{1}{d \dots (d - k + \beta_1 + 1)} D_{\mathbf{u}_2}^{\beta_2} \dots D_{\mathbf{u}_n}^{\beta_n} (P) (\mathbf{u}_1)$$

Theorem: Weighted Sum of Dirac Differentials (WSD)

$$F(\mathbf{x}) = \sum_{i=1}^{r'} w_i(\mathbf{x}) (\xi_i, \mathbf{x})^{d-k_i}$$

with $w_i(\mathbf{x}) = \sum_{|\beta|=k_i} \omega_{i,\beta} (\xi_i \cdot \mathbf{x})^{\beta_1} \prod_{j=2}^n (\zeta_{i,j} \cdot \mathbf{x})^{\beta_j}$, $(\xi_i, \zeta_{i,2}, \dots, \zeta_{i,n})$ ortho. b.

$$\Leftrightarrow$$

$$F^* = \left(\sum_{i=1}^{r'} \sum_{|\beta|=k_i} \omega_{i,\beta} \frac{(d - k_i + \beta_1)!}{d!} \mathbf{e}_\xi \circ \prod_{j=2}^n D_{\zeta_{i,j}}^{\beta_j} \right)^{[d]}$$

If $\xi_{i,1} = 1$, then

$$\begin{aligned} \check{F} &= \left(\sum_{i=1}^r \sum_{|\beta|=k_i} \omega_{i,\beta} \frac{(d - k_i + \beta_1)!}{d!} (\zeta_{i,2}, \mathbf{z})^{\beta_2} \dots (\zeta_{i,n}, \mathbf{z})^{\beta_n} \mathbf{e}_\xi(\mathbf{z}) \right)^{[d]} \\ &= \left(\sum_{i=1}^{r'} \check{\omega}_i(\mathbf{z}) \mathbf{e}_{\xi_i}(\mathbf{z}) \right)^{[d]} \in \mathcal{R}_{n-1,d}^* \end{aligned}$$

Definition (Generalized Additive Decomposition)

find r' , $w_i(\mathbf{x}) \in \mathcal{S}_{n,k_i}$ and $\Xi = [\xi_1, \dots, \xi_r] \in \mathbb{K}^{n \times r'}$ such that

$$F = \sum_{i=1}^{r'} w_i(\mathbf{x}) (\xi_i, \mathbf{x})^{d-k_i}$$

with $\sum_{i=1}^{r'} \dim \langle \check{\omega}_i \rangle$ **minimal**.

Example: For $d > 5$, $F = x_0^{d-1}x_1 + (x_0 + x_1 + 2x_2)^{d-2}(x_0 - x_1)^2$ is a GAD of

$$\begin{aligned} \text{rank}_{\text{gad}}(F) &= \dim \langle \langle z_1 \rangle \rangle + \dim \langle \langle (z_1 - 1)^2 \rangle \rangle \\ &= \dim \langle 1, z_1 \rangle + \dim \langle 1, z_1 - 1, (z_1 - 1)^2 \rangle = 5 \end{aligned}$$

with $\xi_1 = [1, 0, 0]$, $\xi_2 = [1, 1, 2]$.

Geometric point of view

- $\mathcal{V}_{n,d} = \{\omega(\xi, \mathbf{x})^d, \omega \in \mathbb{K}, \xi \in \mathbb{K}^n, \xi \neq 0\}$ **Veronese** variety
- $\mathcal{T}_{n,d} = \{\omega(\mathbf{x})(\xi, \mathbf{x})^{d-1}, \omega(\mathbf{x}) \in \mathcal{S}_{n,1}, \xi \in \mathbb{K}^n, \xi \neq 0\}$ **tangential** variety
(= points on tangents to $\mathcal{V}_{n,d}$).
- $\mathcal{O}_{n,d}^k = \{\omega(\mathbf{x})(\xi, \mathbf{x})^{d-k}, \omega(\mathbf{x}) \in \mathcal{S}_{n,k}, \xi \in \mathbb{K}^n, \xi \neq 0\}$ **osculating**
variety (= points on osculating linear spaces to $\mathcal{V}_{n,d}$).

Proposition

The singular locus of $\mathcal{O}_{n,d}^k$ is $\mathcal{O}_{n,d}^{k-1}$.

$$F = \sum_{i=1}^{r'} \omega_i(\mathbf{x})(\xi_i, \mathbf{x})^{d-k_i} \quad \text{iff} \quad F \in \sum_{i=1}^{r'} \mathcal{O}_{d,n}^{k_i}$$

For $F = \sum_{i=1}^{r'} \omega_i(\mathbf{x})(1 + (\xi_i, \mathbf{x}))^{d-k_i}$, let $A, A' \subset \mathcal{R}_n$ and

- $I_F := (\ker H_{\check{F}}^{A', A}) \subset \mathcal{R}_n (= \mathcal{R})$.
- $\mathcal{A}_F := \mathcal{R}/I_F$ the quotient algebra by I_F .

Theorem:

Let $B \subset A, B' \subset A'$ s.t. $B^+ = B \cup x_1 B \cup \dots \cup x_n B \subset A, B'^+ \subset A'$ and $|B| = |B'| = r$. Assume that $\text{rank}_{\check{F}}^{B', B} = \text{rank} H_{\check{F}}^{A', A} = r$.

- $\text{rank}_{\text{gad}}(F) = r$
- $\mathcal{A}_F = \mathcal{A}_1 \oplus \dots \oplus \mathcal{A}_{r'}$ with $\mathcal{A}_i^* = \langle \langle \check{\omega}_i(\mathbf{z}) \rangle \rangle e_{\xi_i}(\mathbf{z})$
- $\text{rank}_{\text{gad}}(F) = \text{rank}(H_{\check{F}}^{A', A}) = r = \mu_1 + \dots + \mu_{r'}$ where $\mu_i = \dim \langle \langle \check{\omega}_i(\mathbf{z}) \rangle \rangle$
- $H_0 = H_{\check{F}}^{B', B}$ is **invertible**.
- For $H_i = H_{\check{F}}^{B', x_i B}$, $M_i = H_0^{-1} H_i$ is **multiplication** by x_i in the basis B of \mathcal{A}_F .

👉 GAD via joint triangularization (e.g. joint Schur factorization) of the M_i .

Different notions of rank of a tensor $F \in \mathcal{S}_{n,d}$:

- **rank(F)** = minimal r such that $F = \sum_{i=1}^r \omega_i (\xi_i, \mathbf{x})^d$ or $F^* = (\sum_{i=1}^r \omega_i e_{\xi_i})^{[d]}$ or $F^* \in I_{\Xi}^{\perp}$
- **rank_{gad}(F)** = minimal r such that $F = \sum_{i=1}^{r'} \omega_i(\mathbf{x}) (\xi_i, \mathbf{x})^d$ or $\check{F} = (\sum_{i=1}^{r'} \check{\omega}_i(\mathbf{z}) e_{\xi_i}(\mathbf{z}))^{[d]}$ with $\sum_i \dim \langle \langle \check{\omega}_i(\mathbf{z}) \rangle \rangle = r$
- **rank_{border}(F)** = minimal r s.t. $F = \lim_{n \rightarrow \infty} F_n$ with $\text{rank}(F_n) = r$
- **rank_{cactus}(F)** = minimal r s.t. $F^* \in I^{\perp}$ and $\dim(\mathcal{S}/I)_{[l]} = r$ for $l \gg 0$.

Many open questions

- How to compute the rank of specific tensors (e.g. matrix multiplication tensors) ?
- How to compute $\text{rank}(F)$, $\text{rank}_{gad}(T)$... when it is high but not too high (less than the generic rank)?
- How to characterize algebraically varieties of tensors of given rank_{border} , (resp. rank_{gad}), (resp. rank_{cactus})?
- How to find close low rank tensors ? the best low rank tensor approximation ?
- ...



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