The Loewner framework... in the eye of the tensor

The Kolmogorov superposition theorem, the curse of dimensionality & benchmark

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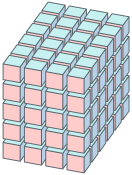
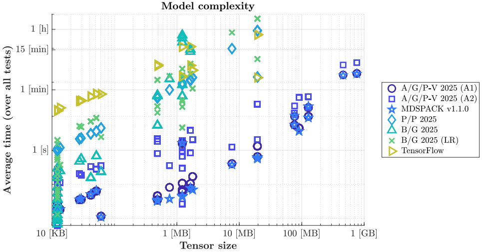
Presentation at ONERA UDSG

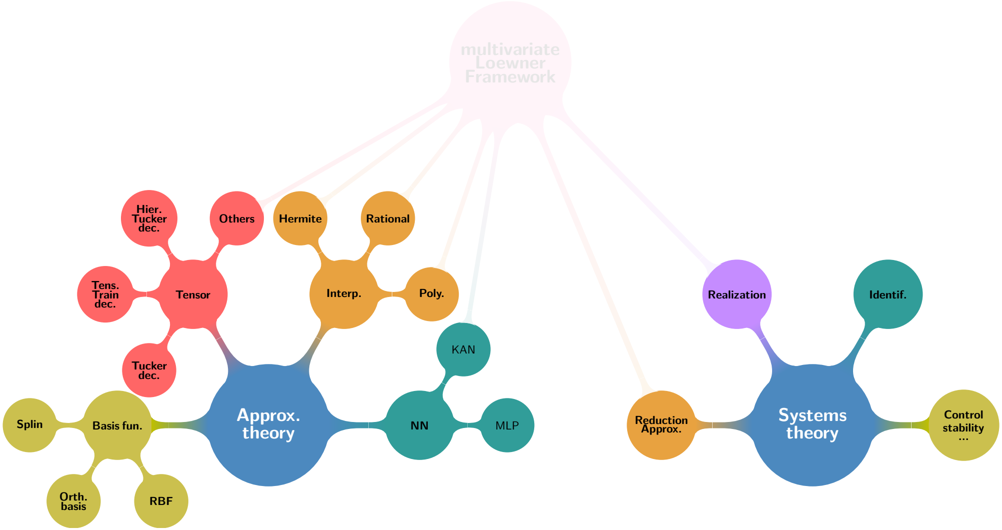
https://arxiv.org/abs/2405.00495 [in SIAM Review - Research Spotlight]
https://arxiv.org/abs/2506.04791 [extensive benchmark]
https://github.com/cpoussot/mLF [research code]





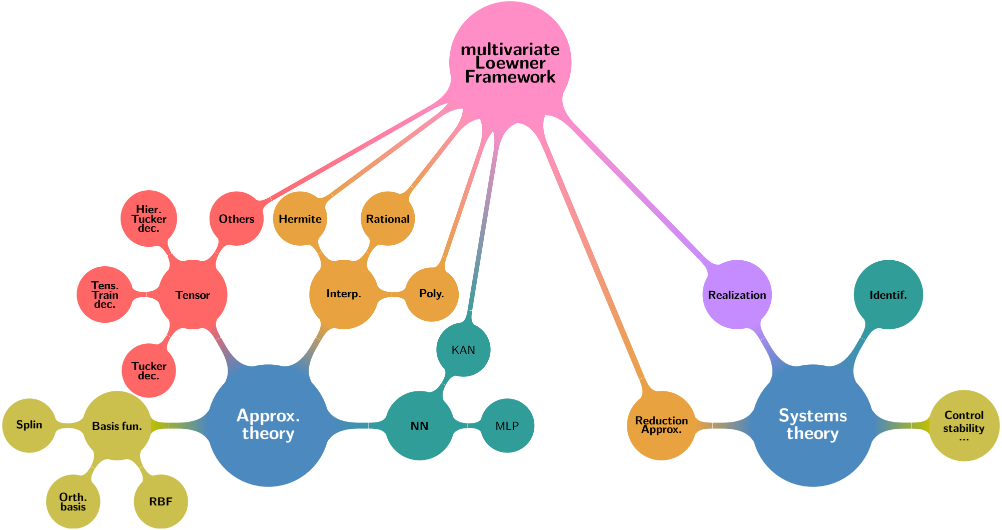
Forewords

Approximation & systems theory... where we stand



Forewords

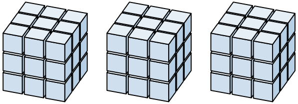
Approximation & systems theory... where we stand



Forewords

Starting (motivating) examples - Borehole function

$$\mathbf{H}({}^1x,\cdots,{}^8x) = \mathbf{H}(r_w, r, T_u, H_u, T_l, H_l, L, K_w) = \frac{2\pi T_u(H_u - H_l)}{\ln\left(\frac{r}{r_w}\right)\left(1 + \frac{2LT_u}{\ln(r/r_w) r_w^2 K_w}\right) + \frac{T_u}{T_l}}$$



$$\begin{array}{ccccc} {}^1x & \times & \cdots & \times & {}^8x \\ [\underline{r_w}, \overline{r_w}] & \times & \cdots & \times & [\underline{K_w}, \overline{K_w}] \end{array}$$

$\mathbf{tab}_8 \in \mathbb{C}^{8\times 8\times\cdots\times 8}$

≈130 `Mo ('real')`

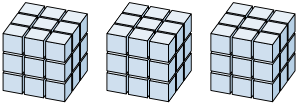
$r_w \in [0.05, 0.15]$	radius of borehole (m)
$r \in [100, 50\,000]$	radius of influence (m)
$T_u \in [63\,070, 115\,600]$	transmissivity of upper aquifer (m^2/yr)
$H_u \in [990, 1110]$	potentiometric head of upper aquifer (m)
$T_l \in [63.1, 116]$	transmissivity of lower aquifer (m^2/yr)
$H_l \in [700, 820]$	potentiometric head of lower aquifer (m)
$L \in [1120, 1680]$	length of borehole (m)
$K_w \in [9855, 12\,045]$	hydraulic conductivity of borehole (m/yr)

S. Surjanovic, *"Borehole function"*, `https://www.sfu.ca/~ssurjano/borehole.html`.

Forewords

Starting (motivating) examples - Borehole function

$$\mathbf{H}({}^1x,\cdots,{}^8x) = \mathbf{H}(r_w,r,T_u,H_u,T_l,H_l,L,K_w) = \frac{2\pi T_u(H_u-H_l)}{\ln\left(\frac{r}{r_w}\right)\left(1+\frac{2LT_u}{\ln(r/r_w)r_w^2K_w}\right)+\frac{T_u}{T_l}}$$



$$\begin{array}{ccccc} {}^1x & \times & \cdots & \times & {}^8x \\ [\underline{r_w},\overline{r_w}] & \times & \cdots & \times & [\underline{K_w},\overline{K_w}] \end{array}$$

$\textbf{tab}_8 \in \mathbb{C}^{8\times 8\times\cdots\times 8}$

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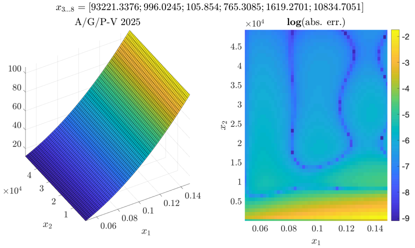
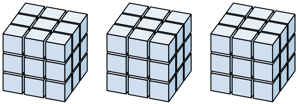


S. Surjanovic, *"Borehole function"*, `https://www.sfu.ca/~ssurjano/borehole.html`.

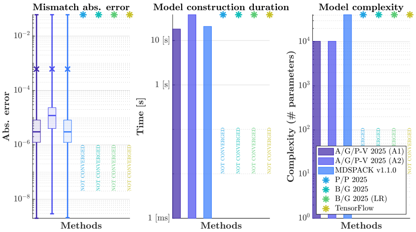
$$\mathbf{H}({}^1x,\cdots,{}^8x) = \mathbf{H}(r_w, r, T_u, H_u, T_l, H_l, L, K_w) = \frac{2\pi T_u(H_u - H_l)}{\ln\left(\frac{r}{r_w}\right)\left(1 + \frac{2LT_u}{\ln(r/r_w)r_w^2K_w}\right) + \frac{T_u}{T_l}}$$



$$\begin{array}{ccccc} {}^1x & \times & \cdots & \times & {}^8x \\ [\underline{r_w}, \overline{r_w}] & \times & \cdots & \times & [\underline{K_w}, \overline{K_w}] \end{array}$$

$\textbf{tab}_8 \in \mathbb{C}^{8\times 8\times\cdots\times 8}$

≈130 Mo (’real’)



S. Surjanovic, *"Borehole function"*, `https://www.sfu.ca/~ssurjano/borehole.html`.

Forewords

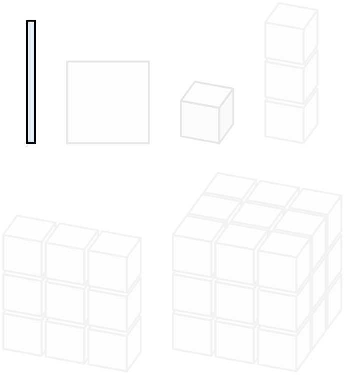
Data (and tensors)

Column / Row data

$$^1\mathbf{x} = \left.{}^1\lambda_{j_1}, {}^1\mu_{i_1}\right\} \xrightarrow{\mathbf{H}(^1x)} \left\{ \mathbf{w}_{j_1}, \mathbf{v}_{i_1}\right.$$

^1x	
$^1\lambda_{1,\cdots,k_1}$	$\mathbf{W}_{k_1}$
$^1\mu_{1,\cdots,q_1}$	$\mathbf{V}_{q_1}$

Tensors (1-D) tab_1



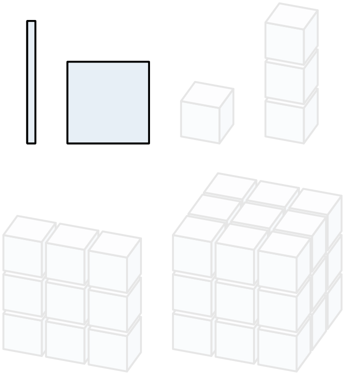
Forewords
Data (and tensors)

Column / Row data

$$\left.\begin{array}{l} {}^1\mathbf{x} = {}^1\lambda_{j_1}, {}^1\mu_{i_1} \\ {}^2\mathbf{x} = {}^2\lambda_{j_2}, {}^2\mu_{i_2} \end{array}\right\} \xrightarrow{\mathbf{H}({}^1x,{}^2x)} \left\{ \mathbf{w}_{j_1,j_2}, \mathbf{v}_{i_1,i_2} \right.$$

${}^1x$ \ ${}^2x$	${}^2\lambda_{1,\cdots,k_2}$	${}^2\mu_{1,\cdots,q_2}$
${}^1\lambda_{1,\cdots,k_1}$	$\mathbf{W}_{k_1,k_2}$	ϕ_{cr}
${}^1\mu_{1,\cdots,q_1}$	ϕ_{rc}	$\mathbf{V}_{q_1,q_2}$

Tensors (2-D) tab_2



Forewords

Data (and tensors)

Column / Row data

$$\left.\begin{array}{l} {}^1\mathbf{x} = {}^1\lambda_{j_1}, {}^1\mu_{i_1} \\ {}^2\mathbf{x} = {}^2\lambda_{j_2}, {}^2\mu_{i_2} \\ {}^3\mathbf{x} = {}^3\lambda_{j_3}, {}^3\mu_{i_3} \end{array}\right\} \xrightarrow{\mathbf{H}({}^1x,{}^2x,{}^3x)} \left\{ \mathbf{w}_{j_1,j_2,j_3}, \mathbf{v}_{i_1,i_2,i_3} \right.$$

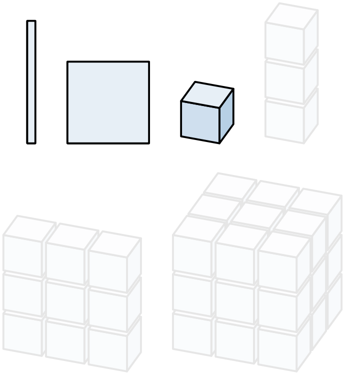
$${}^3x = {}^3\lambda_{1,\cdots,k_3}$$

${}^1x$ \ ${}^2x$	${}^2\lambda_{1,\cdots,k_2}$	${}^2\mu_{1,\cdots,q_2}$
${}^1\lambda_{1,\cdots,k_1}$	$\mathbf{W}_{k_1,k_2,k_3}$	ϕ_{crc}
${}^1\mu_{1,\cdots,q_1}$	ϕ_{rcc}	ϕ_{rrc}

$${}^3x = {}^3\mu_{1,\cdots,q_3}$$

${}^1x$ \ ${}^2x$	${}^2\lambda_{1,\cdots,k_2}$	${}^2\mu_{1,\cdots,q_2}$
${}^1\lambda_{1,\cdots,k_1}$	ϕ_{crr}	ϕ_{crr}
${}^1\mu_{1,\cdots,q_1}$	ϕ_{rcr}	$\mathbf{V}_{q_1,q_2,q_3}$

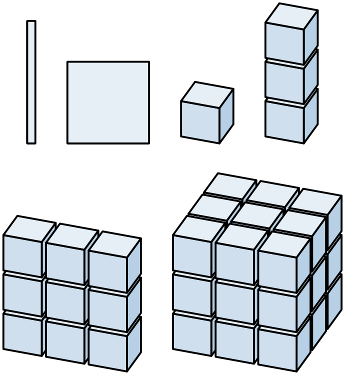
Tensors (3-D) tab_3



Column / Row data

$$\left.\begin{array}{l} {}^1\mathbf{x} = {}^1\lambda_{j_1}, {}^1\mu_{i_1} \\ {}^2\mathbf{x} = {}^2\lambda_{j_2}, {}^2\mu_{i_2} \\ {}^3\mathbf{x} = {}^3\lambda_{j_3}, {}^3\mu_{i_3} \\ \vdots \\ {}^n\mathbf{x} = {}^n\lambda_{j_n}, {}^n\mu_{i_n} \end{array}\right\} \xrightarrow{\mathbf{H}({}^1x, \cdots, {}^nx)} \left\{ \mathbf{w}_{j_1,\cdots,j_n}, \mathbf{v}_{i_1,\cdots} \right.$$

Tensors (n-D) tab$_n$



List of contributions

- n-D tensor data to n-D Loewner matrix $\mathbb{L}_n$
- n-variable transfer functions
- Taming the curse of dimensionality
  - » in computation effort (`flop`)
  - » in storage needs (`Bytes`)
  - » in accuracy
- n-variable **decoupling**
  - » **KST** formulation for rational functions
  - » connection with **KAN**
- Comparison with **MLP, KAN, AAA**

A.C. Antoulas, I-V. Gosea and C. P-V., *"On the Loewner framework, the Kolmogorov superposition theorem, and the curse of dimensionality"*, SIAM Review, November, 2025 (`https://arxiv.org/abs/2405.00495`).

A.C. Antoulas, I-V. Gosea, C. P-V. and P. Vuillemin, *"Tensor-based multivariate function approximation: methods benchmarking and comparison"*, June, 2025 `https://arxiv.org/abs/2506.04791`.

A.C. Antoulas, I-V. Gosea, C. P-V. and P. Vuillemin, *"mLF package"*, `https://github.com/cpoussot/mLF`.

Multi-variate data, function & Loewner matrix

1-D case

$$\begin{cases} P_c^{(1)} & := & \left\{ \left({}^1\lambda_{j_1} ; \mathbf{w}_{j_1} \right),\ j_1 = 1, \dots, k_1 \right\} \\ P_r^{(1)} & := & \left\{ \left({}^1\mu_{i_1} ; \mathbf{v}_{i_1} \right),\ i_1 = 1, \dots, q_1 \right\} \end{cases}$$

Loewner matrix

$$\mathbb{L}_1 \in \mathbb{C}^{q_1 \times k_1}$$

$$(\mathbb{L}_1)_{i_1, j_1} = \frac{\mathbf{v}_{i_1} - \mathbf{w}_{j_1}}{{}^1\mu_{i_1} - {}^1\lambda_{j_1}}$$

Lagrangian form

$$\mathbf{g}({}^1x) = \frac{\sum_{j_1=1}^{k_1} \frac{c_{j_1} \mathbf{w}_{j_1}}{{}^1x - {}^1\lambda_{j_1}}}{\sum_{j_1=1}^{k_1} \frac{c_{j_1}}{{}^1x - {}^1\lambda_{j_1}}}$$

Null space

$$\mathbf{span}\ (\mathbf{c}_1) = \mathcal{N}(\mathbb{L}_1)$$

$$\mathbf{c}_1 = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_{k_1} \end{bmatrix} \in \mathbb{C}^{k_1}$$

Multi-variate data, function & Loewner matrix

1-D case (example)

Data generated from $\mathbf{H}({}^1x) = \mathbf{H}(s) = (s^2+4)/(s+1)$ of complexity (2)

$$\left.\begin{array}{rcl} {}^1\lambda_{j_1} & = & [1,3,5] \\ {}^1\mu_{i_1} & = & [2,4,6,8] \end{array}\right\} \xrightarrow{\mathbf{H}} \left\{\begin{array}{rcl} \mathbf{w}_{j_1} & = & [5/2, 13/4, 29/6] \\ \mathbf{v}_{i_1} & = & [8/3, 4, 40/7, 68/9] \end{array}\right.$$

Loewner matrix

$$\mathbb{L}_1 = \begin{bmatrix} \frac{1}{6} & \frac{7}{12} & \frac{13}{18} \\ \frac{1}{2} & \frac{3}{4} & \frac{5}{6} \\ \frac{9}{14} & \frac{23}{28} & \frac{37}{42} \\ \frac{13}{18} & \frac{31}{36} & \frac{49}{54} \end{bmatrix}$$

Null space

$$\mathbf{c}_1 = \begin{bmatrix} \frac{1}{3} \\ -\frac{4}{3} \\ 1 \end{bmatrix}$$

Lagrangian form

$$\mathbf{g}(s) = \frac{\frac{5}{6\,(s-1)} - \frac{13}{3\,(s-3)} + \frac{29}{6\,(s-5)}}{\frac{1}{3\,(s-1)} - \frac{4}{3\,(s-3)} + \frac{1}{s-5}} = \mathbf{H}(s)$$

Multi-variate data, function & Loewner matrix

2-D case

$$\begin{cases} P_c^{(2)} & := & \left\{ ({}^1\lambda_{j_1}, {}^2\lambda_{j_2}; \mathbf{w}_{j_1,j_2}),\ j_1 = 1,\dots,k_1 \quad j_2 = 1,\dots,k_2 \right\} \\ P_r^{(2)} & := & \left\{ ({}^1\mu_{i_1}, {}^2\mu_{i_2}; \mathbf{v}_{i_1,i_2}),\ i_1 = 1,\dots,q_1 \quad i_2 = 1,\dots,q_2 \right\} \end{cases}$$

Loewner matrix

$$\mathbb{L}_2 \in \mathbb{C}^{q_1 q_2 \times k_1 k_2}$$

$$\ell_{j_1,j_2}^{i_1,i_2} = \frac{\mathbf{v}_{i_1,i_2} - \mathbf{w}_{j_1,j_2}}{({}^1\mu_{i_1} - {}^1\lambda_{j_1})({}^2\mu_{i_2} - {}^2\lambda_{j_2})}$$

Lagrangian form

$$\mathbf{g}({}^1x, {}^2x) = \frac{\sum_{j_1=1}^{k_1} \sum_{j_2=1}^{k_2} \frac{c_{j_1,j_2} \mathbf{w}_{j_1,j_2}}{({}^1x - {}^1\lambda_{j_1})({}^2x - {}^2\lambda_{j_2})}}{\sum_{j_1=1}^{k_1} \sum_{j_2=1}^{k_2} \frac{c_{j_1,j_2}}{({}^1x - {}^1\lambda_{j_1})({}^2x - {}^2\lambda_{j_2})}}$$

Null space

$$\textbf{span}\ (\mathbf{c}_2) = \mathcal{N}(\mathbb{L}_2)$$

$$\mathbf{c}_2 = \left[\begin{array}{c} c_{1,1} \\ \vdots \\ c_{1,k_2} \\ \hline \vdots \\ \hline c_{k_1,1} \\ \vdots \\ c_{k_1,k_2} \end{array} \right] \in \mathbb{C}^{k_1 k_2}$$

Multi-variate data, function & Loewner matrix

2-D case (example)

Data generated from $\mathbf{H}({}^1x, {}^2x) = \mathbf{H}(s,t) = (s^2t)/(s-t+1)$ of complexity $(2,1)$

$$\left.\begin{array}{rcl} {}^1\lambda_{j_1} & = & [1,3,5] \\ {}^1\mu_{i_1} & = & [0,2,4] \\ {}^2\lambda_{j_2} & = & [-1,-3] \\ {}^2\mu_{i_2} & = & [-2,-4] \end{array}\right\} \xrightarrow{\mathbf{H}} \left[\begin{array}{cc|cc} -\frac{1}{3} & -\frac{3}{5} & -\frac{1}{2} & -\frac{2}{3} \\ -\frac{9}{5} & -\frac{27}{7} & -3 & -\frac{9}{2} \\ -\frac{25}{7} & -\frac{25}{3} & -\frac{25}{4} & -10 \\ \hline 0 & 0 & 0 & 0 \\ -1 & -2 & -\frac{8}{5} & -\frac{16}{7} \\ -\frac{8}{3} & -6 & -\frac{32}{7} & -\frac{64}{9} \end{array}\right]$$

Loewner matrix

$$\mathbb{L}_2 = \left[\begin{array}{cc|cc|cc} \frac{1}{3} & -\frac{3}{5} & \frac{3}{5} & -\frac{9}{7} & \frac{5}{7} & -\frac{5}{3} \\ \frac{1}{9} & \frac{3}{5} & \frac{1}{5} & \frac{9}{7} & \frac{5}{21} & \frac{5}{3} \\ \frac{19}{15} & -1 & \frac{1}{5} & -\frac{79}{35} & \frac{23}{35} & -\frac{101}{45} \\ \hline \frac{41}{63} & \frac{59}{35} & -\frac{17}{105} & \frac{11}{7} & \frac{1}{7} & \frac{127}{63} \\ \frac{89}{63} & -\frac{139}{105} & \frac{97}{35} & -\frac{5}{7} & -1 & -\frac{79}{21} \\ \frac{61}{81} & \frac{293}{135} & \frac{239}{135} & \frac{205}{63} & -\frac{223}{189} & \frac{11}{9} \end{array}\right]$$

Null space

$$\mathbf{c}_2 = \left[\begin{array}{c} -\frac{1}{3} \\ \frac{5}{9} \\ \hline \frac{10}{9} \\ -\frac{14}{9} \\ \hline -\frac{7}{9} \\ 1 \end{array}\right]$$

Multi-variate data, function & Loewner matrix

2-D case (example)

Data generated from $\mathbf{H}({}^1x, {}^2x) = \mathbf{H}(s,t) = (s^2t)/(s-t+1)$ of complexity $(2,1)$

$$\left.\begin{array}{rcl} {}^1\lambda_{j_1} & = & [1,3,5] \\ {}^1\mu_{i_1} & = & [0,2,4] \\ {}^2\lambda_{j_2} & = & [-1,-3] \\ {}^2\mu_{i_2} & = & [-2,-4] \end{array}\right\} \xrightarrow{\mathbf{H}} \left[\begin{array}{cc|cc} -\frac{1}{3} & -\frac{3}{5} & -\frac{1}{2} & -\frac{2}{3} \\ -\frac{9}{5} & -\frac{27}{7} & -3 & -\frac{9}{2} \\ -\frac{25}{7} & -\frac{25}{3} & -\frac{25}{4} & -10 \\ \hline 0 & 0 & 0 & 0 \\ -1 & -2 & -\frac{8}{5} & -\frac{16}{7} \\ -\frac{8}{3} & -6 & -\frac{32}{7} & -\frac{64}{9} \end{array}\right]$$

Lagrangian form

$$\mathbf{g}(s,t) = -\frac{\frac{1}{9(s-1)(t+1)} - \frac{1}{3(s-1)(t+3)} - \frac{2}{(s-3)(t+1)} + \frac{6}{(s-3)(t+3)} + \frac{25}{9(s-5)(t+1)} - \frac{25}{3(s-5)(t+3)}}{\frac{1}{3(s-1)(t+1)} - \frac{5}{9(s-1)(t+3)} - \frac{10}{9(s-3)(t+1)} + \frac{14}{9(s-3)(t+3)} + \frac{7}{9(s-5)(t+1)} - \frac{1}{(s-5)(t+3)}} = \mathbf{H}(s,t)$$

Multi-variate data, function & Loewner matrix

n-D case

$$\begin{cases} P_c^{(n)} := \left\{ ({}^1\lambda_{j_1}, {}^2\lambda_{j_2}, \cdots, {}^n\lambda_{j_n}; \mathbf{w}_{j_1,j_2,\cdots,j_n}),\ j_l = 1,\ldots,k_l, \quad l = 1,\cdots,n \right\} \\ P_r^{(n)} := \left\{ ({}^1\mu_{i_1}, {}^2\mu_{i_2}, \cdots, {}^n\mu_{i_n}; \mathbf{v}_{i_1,i_2,\cdots,i_n}),\ i_l = 1,\ldots,q_l, \quad l = 1,\cdots,n \right\} \end{cases}$$

Loewner matrix

$$\mathbb{L}_n \in \mathbb{C}^{q_1 q_2 \cdots q_n \times k_1 k_2 \cdots k_n}$$

$$\ell_{j_1,j_2,\cdots,j_n}^{i_1,i_2,\cdots,i_n} = \frac{\mathbf{v}_{i_1,i_2,\cdots,i_n} - \mathbf{w}_{j_1,j_2,\cdots,j_n}}{({}^1\mu_{i_1} - {}^1\lambda_{j_1}) \cdots ({}^n\mu_{i_n} - {}^n\lambda_{j_n})}$$

Lagrangian form

$$\mathbf{g}({}^1x, \cdots, {}^nx) = \frac{\sum_{j_1=1}^{k_1} \cdots \sum_{j_n=1}^{k_n} \frac{c_{j_1,\cdots,j_n} \mathbf{w}_{j_1,\cdots,j_n}}{({}^1x - {}^1\lambda_{j_1}) \cdots ({}^nx - {}^n\lambda_{j_n})}}{\sum_{j_1=1}^{k_1} \cdots \sum_{j_n=1}^{k_n} \frac{c_{j_1,\cdots,j_n}}{({}^1x - {}^1\lambda_{j_1}) \cdots ({}^nx - {}^n\lambda_{j_n})}}$$

Null space

$$\textbf{span}\ (\mathbf{c}_n) = \mathcal{N}(\mathbb{L}_n)$$

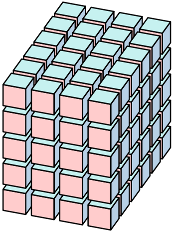
$$\mathbf{c}_n = \left[\begin{array}{c} c_{1,\cdots,1} \\ \vdots \\ c_{1,\cdots,k_n} \\ \hline \vdots \\ \hline c_{k_1,\cdots,1} \\ \vdots \\ c_{k_1,\cdots,k_n} \end{array} \right] \in \mathbb{C}^{k_1 \cdots k_n}$$

Taming the curse of dimensionality

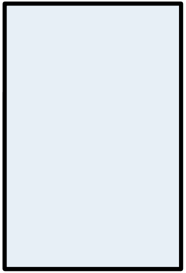
n-variable Loewner matrix operator

$$
\begin{array}{rcl}
\mathbb{C}^{k_1} \times \mathbb{C}^{q_1} \times \ldots \times \mathbb{C}^{k_n} \times \mathbb{C}^{q_n} \times \mathbb{C}^{(k_1+q_1)\times\cdots\times(k_n+q_n)} & \longrightarrow & \mathbb{C}^{Q\times K} \\
\left({}^1\lambda_{j_1}, {}^1\mu_{i_1}, \ldots, {}^n\lambda_{j_n}, {}^n\mu_{i_n}, \mathbf{tab}_n\right) & \longmapsto & \mathbb{L}_n
\end{array}
$$

n-D tensor $\mathbf{tab}_n$

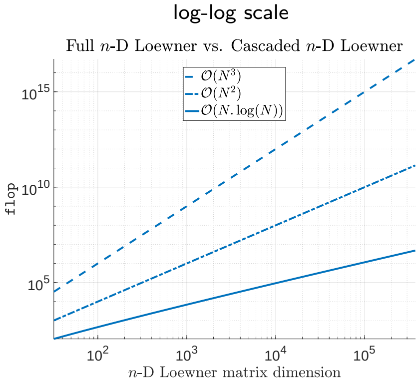


matrix $\mathbb{L}_n$



Taming the curse of dimensionality

Null space `flop` and memory issues



(rows) $Q = q_1 q_2 \dots q_n$ and
(columns) $K = k_1 k_2 \dots k_n$

$$\mathbb{L}_n \in \mathbb{C}^{Q \times K}$$

Computational issue

Note that $Q \times K$ matrix SVD `flop` estimation is

- QK^2 (if $Q > K$)
- N^3 (if $Q = K = N$)

Storage issue

Note that $Q \times K$ matrix storage estimation is

- in real double $QK\frac{8}{2^{20}}$ `MB`
- in complex double $2QK\frac{8}{2^{20}}$ `MB`

Taming the curse of dimensionality

2-D case (example cont'd, to get the idea)

Data generated from $\mathbf{H}({}^1x, {}^2x) = \mathbf{H}(s,t) = (s^2t)/(s-t+1)$ of complexity $(2,1)$

${}^1x$ \ ${}^2x$	${}^2\lambda_1 = -1$	${}^2\lambda_2 = -3$	${}^2\mu_1 = -2$	${}^2\mu_2 = -4$
${}^1\lambda_1 = 1$	$h_{1,1} = -\frac{1}{3}$	$h_{1,2} = -\frac{3}{5}$	$h_{1,3} = -\frac{1}{2}$	$h_{1,4} = -\frac{2}{3}$
${}^1\lambda_2 = 3$	$h_{2,1} = -\frac{9}{5}$	$h_{2,2} = -\frac{27}{7}$	$h_{2,3} = -3$	$h_{2,4} = -\frac{9}{2}$
${}^1\lambda_3 = 5$	$h_{3,1} = -\frac{25}{7}$	$h_{3,2} = -\frac{25}{3}$	$h_{3,3} = -\frac{25}{4}$	$h_{3,4} = -10$
${}^1\mu_1 = 0$	$h_{4,1} = 0$	$h_{4,2} = 0$	$h_{4,3} = 0$	$h_{4,4} = 0$
${}^1\mu_2 = 2$	$h_{5,1} = -1$	$h_{5,2} = -2$	$h_{5,3} = -\frac{8}{5}$	$h_{5,4} = -\frac{16}{7}$
${}^1\mu_3 = 4$	$h_{6,1} = -\frac{8}{3}$	$h_{6,2} = -6$	$h_{6,3} = -\frac{32}{7}$	$h_{6,4} = -\frac{64}{9}$

$$\xrightarrow{\mathcal{N}(\mathbb{L}_2)} \mathbf{c}_2 = \left[\begin{array}{c} -\frac{1}{3} \\ \frac{5}{9} \\ \hline \frac{10}{9} \\ -\frac{14}{9} \\ \hline -\frac{7}{9} \\ 1 \end{array}\right]$$

- 1 $\mathbb{L}_1$ along ${}^1x$, for ${}^2x = {}^2\lambda_2 = -3$
- 3 $\mathbb{L}_1$ along ${}^2x$ for ${}^1x = \{{}^1\lambda_1, {}^1\lambda_2, {}^1\lambda_3\}$
- Scaled null space $\mathbf{c}_2^\top =$

$$\left[\begin{array}{ccc} \mathbf{c}_1^{{}^1\lambda_1} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_1 & \mathbf{c}_1^{{}^1\lambda_2} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_2 & \mathbf{c}_1^{{}^1\lambda_3} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_3 \end{array}\right]^\top$$

Taming the curse of dimensionality

2-D case (example cont'd, to get the idea)

Data generated from $\mathbf{H}({}^1x, {}^2x) = \mathbf{H}(s,t) = (s^2 t)/(s-t+1)$ of complexity $(2,1)$

${}^1x \backslash {}^2x$	${}^2\lambda_1 = -1$	${}^2\lambda_2 = -3$	${}^2\mu_1 = -2$	${}^2\mu_2 = -4$
${}^1\lambda_1 = 1$	$h_{1,1} = -\frac{1}{3}$	$h_{1,2} = -\frac{3}{5}$	$h_{1,3} = -\frac{1}{2}$	$h_{1,4} = -\frac{2}{3}$
${}^1\lambda_2 = 3$	$h_{2,1} = -\frac{9}{5}$	$h_{2,2} = -\frac{27}{7}$	$h_{2,3} = -3$	$h_{2,4} = -\frac{9}{2}$
${}^1\lambda_3 = 5$	$h_{3,1} = -\frac{25}{7}$	$h_{3,2} = -\frac{25}{3}$	$h_{3,3} = -\frac{25}{4}$	$h_{3,4} = -10$
${}^1\mu_1 = 0$	$h_{4,1} = 0$	$h_{4,2} = 0$	$h_{4,3} = 0$	$h_{4,4} = 0$
${}^1\mu_2 = 2$	$h_{5,1} = -1$	$h_{5,2} = -2$	$h_{5,3} = -\frac{8}{5}$	$h_{5,4} = -\frac{16}{7}$
${}^1\mu_3 = 4$	$h_{6,1} = -\frac{8}{3}$	$h_{6,2} = -6$	$h_{6,3} = -\frac{32}{7}$	$h_{6,4} = -\frac{64}{9}$

$$\xrightarrow{\mathcal{N}(\mathbb{L}_2)} \mathbf{c}_2 = \begin{bmatrix} -\frac{1}{3} \\ \frac{5}{9} \\ \hline \frac{10}{9} \\ -\frac{14}{9} \\ \hline -\frac{7}{9} \\ 1 \end{bmatrix}$$

- 1 $\mathbb{L}_1$ along ${}^1x$, for ${}^2x = {}^2\lambda_2 = -3$
- 3 $\mathbb{L}_1$ along ${}^2x$ for ${}^1x = \{{}^1\lambda_1, {}^1\lambda_2, {}^1\lambda_3\}$
- Scaled null space $\mathbf{c}_2^\top = \left[\begin{array}{ccc} \mathbf{c}_1^{{}^1\lambda_1} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_1 & \mathbf{c}_1^{{}^1\lambda_2} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_2 & \mathbf{c}_1^{{}^1\lambda_3} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_3 \end{array}\right]^\top$

$$\mathbf{c}_1^{{}^2\lambda_2} = \begin{bmatrix} \frac{5}{9} \\ -\frac{14}{9} \\ 1 \end{bmatrix}$$

Taming the curse of dimensionality

2-D case (example cont'd, to get the idea)

Data generated from $\mathbf{H}({}^1x, {}^2x) = \mathbf{H}(s,t) = (s^2t)/(s-t+1)$ of complexity $(2,1)$

${}^1x \backslash {}^2x$	${}^2\lambda_1 = -1$	${}^2\lambda_2 = -3$	${}^2\mu_1 = -2$	${}^2\mu_2 = -4$
${}^1\lambda_1 = 1$	$h_{1,1} = -\frac{1}{3}$	$h_{1,2} = -\frac{3}{5}$	$h_{1,3} = -\frac{1}{2}$	$h_{1,4} = -\frac{2}{3}$
${}^1\lambda_2 = 3$	$h_{2,1} = -\frac{9}{5}$	$h_{2,2} = -\frac{27}{7}$	$h_{2,3} = -3$	$h_{2,4} = -\frac{9}{2}$
${}^1\lambda_3 = 5$	$h_{3,1} = -\frac{25}{7}$	$h_{3,2} = -\frac{25}{3}$	$h_{3,3} = -\frac{25}{4}$	$h_{3,4} = -10$
${}^1\mu_1 = 0$	$h_{4,1} = 0$	$h_{4,2} = 0$	$h_{4,3} = 0$	$h_{4,4} = 0$
${}^1\mu_2 = 2$	$h_{5,1} = -1$	$h_{5,2} = -2$	$h_{5,3} = -\frac{8}{5}$	$h_{5,4} = -\frac{16}{7}$
${}^1\mu_3 = 4$	$h_{6,1} = -\frac{8}{3}$	$h_{6,2} = -6$	$h_{6,3} = -\frac{32}{7}$	$h_{6,4} = -\frac{64}{9}$

$$\xrightarrow{\mathcal{N}(\mathbb{L}_2)} \mathbf{c}_2 = \begin{bmatrix} -\frac{1}{3} \\ \frac{5}{9} \\ \hline \frac{10}{9} \\ -\frac{14}{9} \\ \hline -\frac{7}{9} \\ 1 \end{bmatrix}$$

- 1 $\mathbb{L}_1$ along ${}^1x$, for ${}^2x = {}^2\lambda_2 = -3$
- 3 $\mathbb{L}_1$ along ${}^2x$ for ${}^1x = \{{}^1\lambda_1, {}^1\lambda_2, {}^1\lambda_3\}$
- Scaled null space $\mathbf{c}_2^\top = \left[\begin{array}{ccc} \mathbf{c}_1^{{}^1\lambda_1} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_1 & \mathbf{c}_1^{{}^1\lambda_2} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_2 & \mathbf{c}_1^{{}^1\lambda_3} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_3 \end{array}\right]^\top$

$$\mathbf{c}_1^{{}^2\lambda_2} = \begin{bmatrix} \frac{5}{9} \\ -\frac{14}{9} \\ 1 \end{bmatrix} \text{ and } \mathbf{c}_1^{{}^1\lambda_1} = \begin{bmatrix} -\frac{3}{5} \\ 1 \end{bmatrix}, \mathbf{c}_1^{{}^1\lambda_2} = \begin{bmatrix} -\frac{5}{7} \\ 1 \end{bmatrix}, \mathbf{c}_1^{{}^1\lambda_3} = \begin{bmatrix} -\frac{7}{9} \\ 1 \end{bmatrix}$$

Data generated from $\mathbf{H}({}^1x, {}^2x) = \mathbf{H}(s,t) = (s^2t)/(s-t+1)$ of complexity $(2,1)$

${}^1x$ \ ${}^2x$	${}^2\lambda_1 = -1$	${}^2\lambda_2 = -3$	${}^2\mu_1 = -2$	${}^2\mu_2 = -4$
${}^1\lambda_1 = 1$	$h_{1,1} = -\frac{1}{3}$	$h_{1,2} = -\frac{3}{5}$	$h_{1,3} = -\frac{1}{2}$	$h_{1,4} = -\frac{2}{3}$
${}^1\lambda_2 = 3$	$h_{2,1} = -\frac{9}{5}$	$h_{2,2} = -\frac{27}{7}$	$h_{2,3} = -3$	$h_{2,4} = -\frac{9}{2}$
${}^1\lambda_3 = 5$	$h_{3,1} = -\frac{25}{7}$	$h_{3,2} = -\frac{25}{3}$	$h_{3,3} = -\frac{25}{4}$	$h_{3,4} = -10$
${}^1\mu_1 = 0$	$h_{4,1} = 0$	$h_{4,2} = 0$	$h_{4,3} = 0$	$h_{4,4} = 0$
${}^1\mu_2 = 2$	$h_{5,1} = -1$	$h_{5,2} = -2$	$h_{5,3} = -\frac{8}{5}$	$h_{5,4} = -\frac{16}{7}$
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$$\xrightarrow{\mathcal{N}(\mathbb{L}_2)} \mathbf{c}_2 = \begin{bmatrix} -\frac{1}{3} \\ \frac{5}{9} \\ \hline \frac{10}{9} \\ -\frac{14}{9} \\ \hline -\frac{7}{9} \\ 1 \end{bmatrix}$$

- 1 $\mathbb{L}_1$ along ${}^1x$, for ${}^2x = {}^2\lambda_2 = -3$
- 3 $\mathbb{L}_1$ along ${}^2x$ for ${}^1x = \{{}^1\lambda_1, {}^1\lambda_2, {}^1\lambda_3\}$
- Scaled null space $\mathbf{c}_2^\top =$

$$\left[\ \mathbf{c}_1^{{}^1\lambda_1} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_1 \quad \mathbf{c}_1^{{}^1\lambda_2} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_2 \quad \mathbf{c}_1^{{}^1\lambda_3} \cdot [\mathbf{c}_1^{{}^2\lambda_2}]_3\ \right]^\top$$

$$\mathbf{c}_1^{{}^2\lambda_2} = \begin{bmatrix} \frac{5}{9} \\ -\frac{14}{9} \\ 1 \end{bmatrix} \text{ and } \mathbf{c}_1^{{}^1\lambda_1} = \begin{bmatrix} -\frac{3}{5} \\ 1 \end{bmatrix}, \mathbf{c}_1^{{}^1\lambda_2} = \begin{bmatrix} -\frac{5}{7} \\ 1 \end{bmatrix}, \mathbf{c}_1^{{}^1\lambda_3} = \begin{bmatrix} -\frac{7}{9} \\ 1 \end{bmatrix}$$

Theorem: 2-D to 1-D

Being given the tableau $\mathbf{tab}_2$ tensor in response of the 2-variables $\mathbf{H}({}^1x, {}^2x)$ function, the null space of the corresponding 2-D Loenwer matrix $\mathbb{L}_2$, is spanned by

$$\mathcal{N}(\mathbb{L}_2) = \mathbf{c}_2 = \mathbf{vec}\left[\mathbf{c}_1^{{}^2\lambda_1} \cdot \left[\mathbf{c}_1^{{}^1\lambda_{k_1}}\right]_1, \cdots, \mathbf{c}_1^{{}^2\lambda_{k_2}} \cdot \left[\mathbf{c}_1^{{}^1\lambda_{k_1}}\right]_{k_2}\right],$$

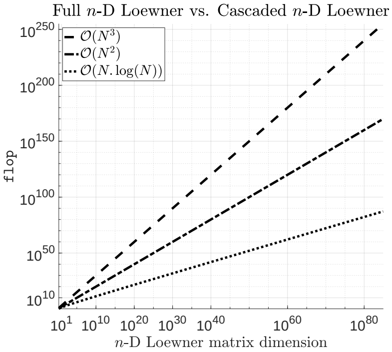
where

- $\mathbf{c}_1^{{}^1\lambda_{k_1}} = \mathcal{N}(\mathbb{L}_1^{{}^1\lambda_{k_1}})$,
  i.e. the null space of the **1-D Loewner matrix** for frozen ${}^1x = {}^1\lambda_{k_1}$, and
- $\mathbf{c}_1^{{}^2\lambda_{j_2}} = \mathcal{N}(\mathbb{L}_1^{{}^2\lambda_{j_2}})$,
  i.e. the j_1-th null space of the **1-D Loewner matrices** for frozen ${}^2x = \{{}^2\lambda_1, \cdots, {}^2\lambda_{k_2}\}$.

Taming the curse of dimensionality

Null space - `flop` complexity

log-log scale



(rows) $Q = q_1 q_2 \dots q_n$ and
(columns) $K = k_1 k_2 \dots k_n$

$$\mathbb{L}_n \in \mathbb{C}^{Q \times K}$$

Computational issue

Note that $Q \times K$ matrix SVD `flop` estimation is

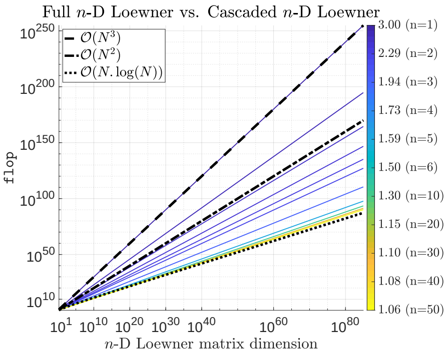
- QK^2 (if $Q > K$)
- N^3 (if $Q = K = N$)

$\Rightarrow$ **The CURSE of dimensionality**

Taming the curse of dimensionality

Null space - `flop` complexity

log-log scale



Theorem: Worst case complexity

k interpolation points per variables.

$$\overline{\texttt{flop}_1} = k^3 \frac{1-k^n}{1-k} = k^3 \frac{1-N}{1-k},$$

which is a (n finite) geometric series of ratio k.

$\Rightarrow$ **The CURSE of dimensionality is TAMED**

$$\begin{array}{llll} \mathcal{O}(N^3) & \rightarrow & \mathcal{O}(N^{2.29}) & \text{for } n=2 \\ & \rightarrow & \mathcal{O}(N^{1.94}) & \text{for } n=3 \\ & \vdots & & \\ & \rightarrow & \mathcal{O}(N^{1.06}) & \text{for } n=50 \end{array}$$

Taming the curse of dimensionality

Null space - memory and storage

The data (tableau) storage is (in complex and double precision)

$$\frac{8}{2^{20}} \prod_{l}^{n} q_l + k_l \ \texttt{MB} \text{ (example tableau } 2 \cdot [20, 6, 4, 6, 8, 2] = 2 \cdot [k_1, k_2, k_3, k_4, k_5, k_6] \text{ needs } 45\ \texttt{MB})$$

Full n-D Loewner

Construction of

$$\mathbb{L}_n \in \mathbb{C}^{N \times N}$$

where $N = k_1 k_2 \cdots k_n$, needs

$$\frac{8}{2^{20}} N^2 \ \texttt{MB}$$

Example: $N = 46,080$
Memory: 31.64 `GB`
`flop`: $9.78 \cdot 10^{13}$

Taming the curse of dimensionality

Null space - memory and storage

The data (tableau) storage is (in complex and double precision)

$$\frac{8}{2^{20}} \prod_{l}^{n} q_l + k_l \;\; \texttt{MB} \text{ (example tableau } 2 \cdot [20,6,4,6,8,2] = 2 \cdot [k_1,k_2,k_3,k_4,k_5,k_6] \text{ needs } 45 \; \texttt{MB}\text{)}$$

Full n-D Loewner

Construction of

$$\mathbb{L}_n \in \mathbb{C}^{N \times N}$$

where $N = k_1 k_2 \cdots k_n$, needs

$$\frac{8}{2^{20}} N^2 \;\; \texttt{MB}$$

Example: $N = 46,080$
Memory: 31.64 GB
flop: $9.78 \cdot 10^{13}$

Cascaded n-D Loewner

Construction of

$$\mathbb{L}_1 \in \mathbb{C}^{\overline{k} \times \overline{k}}$$

where $\overline{k} = \max_j k_j$, needs

$$\frac{8}{2^{20}} \overline{k}^2 \;\; \texttt{MB}$$

Example: $\overline{k} = 20$
Memory: 6.25 KB
flop: $8.13 \cdot 10^5$

Kolmogorov, Arnold, Kahane, Lorentz and Sprecher

For any $n \in \mathbb{N}$, $n \geq 2$, there exist

- real numbers $\lambda_1, \ldots, \lambda_n$;
- continuous functions $\Phi_k : \mathbb{I} \mapsto \mathbb{R}$, $k = 1, \ldots, 2n+1$, with the property that for every continuous function $\mathbf{f} : \mathbb{I}^n \mapsto \mathbb{R}$;
- a continuous function $\mathbf{g} : \mathbb{R} \mapsto \mathbb{R}$;

such that:

$$\forall ({}^1x, \cdots, {}^nx) \in \mathbb{I}^n, \quad \mathbf{f}({}^1x, \cdots, {}^nx) = \sum_{k=1}^{2n+1} \mathbf{g}(\lambda_1 \Phi_k({}^1x) + \cdots + \lambda_n \Phi_k({}^nx))$$

"Kolmogorov proved that every continuous function of several variables can be represented as a superposition of continuous functions of one variable and the operation of addition (1957). Thus, it is as if there are no functions of several variables at all. Seriously speaking, Kolmogorov's theorem is a brilliant example of his mastery. In particular, the theorem shows that Hilbert's conjecture (to it's 13th problem) is wrong."

A.G. Vitushkin, *"On Hilbert's thirteenth problem and related questions"*, Russian Math. Surveys 59:1, pp. 11-25.

Remember that (in 2-D)

$$\mathcal{N}(\mathbb{L}_2) = \mathbf{c}_2 = \mathbf{vec}\left[\mathbf{c}_1^{2\lambda_1} \cdot \left[\mathbf{c}_1^{1\lambda_{k_1}}\right]_1, \cdots, \mathbf{c}_1^{2\lambda_{k_2}} \cdot \left[\mathbf{c}_1^{1\lambda_{k_1}}\right]_{k_2} \right],$$

Variable decoupling

Given data $\mathbf{tab}_n$, the latter achieves variables decoupling, and the null space can be equivalently written as:

$$\mathbf{c}_n = \underbrace{\mathbf{c}^{{}^n x}}_{\mathbf{Bary}({}^n x)} \odot \underbrace{(\mathbf{c}^{{}^{n-1} x} \otimes \mathbf{1}_{k_n})}_{\mathbf{Bary}({}^{n-1} x)} \odot \underbrace{(\mathbf{c}^{{}^{n-2} x} \otimes \mathbf{1}_{k_n k_{n-1}})}_{\mathbf{Bary}({}^{n-2} x)} \odot \cdots \odot \underbrace{(\mathbf{c}^{{}^1 x} \otimes \mathbf{1}_{k_n \dots k_2})}_{\mathbf{Bary}({}^1 x)}.$$

where $\mathbf{c}^{{}^l x}$ denotes the vectorized barycentric coefficients related to the l-th variable.

This is decoupling !

A.G. Vitushkin, *"On Hilbert's thirteenth problem and related questions"*, Russian Math. Surveys 59:1, pp. 11-25.

Remember that (in 2-D)

$$\mathcal{N}(\mathbb{L}_2) = \mathbf{c}_2 = \mathbf{vec}\left[\mathbf{c}_1^{2\lambda_1} \cdot \left[\mathbf{c}_1^{1\lambda_{k_1}} \right]_1, \cdots, \mathbf{c}_1^{2\lambda_{k_2}} \cdot \left[\mathbf{c}_1^{1\lambda_{k_1}} \right]_{k_2} \right],$$

Variable decoupling

Given data $\textbf{tab}_n$, the latter achieves variables decoupling, and the null space can be equivalently written as:

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where $\mathbf{c}^{l_x}$ denotes the vectorized barycentric coefficients related to the l-th variable.

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Variables decoupling, KST and KANs

Decoupling, KST and KANs via Loewner with rational activation functions ($\mathbf{H} = {}^1x \cdot {}^2x$)

$$
\begin{aligned}
{}^1\lambda_{j_1} &= \begin{pmatrix} -1 & 1 \end{pmatrix} \\
{}^2\lambda_{j_2} &= \begin{pmatrix} -1 & 1 \end{pmatrix}
\end{aligned}
$$

$$
\begin{pmatrix}
\mathbf{c} & \mathbf{w} & \mathbf{c}\cdot\mathbf{w} & \mathbf{Lag} \\
1.0 & 1.0 & 1.0 & \frac{1}{({}^1x+1.0)({}^2x+1.0)} \\
-1.0 & -1.0 & 1.0 & \frac{1}{({}^1x+1.0)({}^2x-1.0)} \\
-1.0 & -1.0 & 1.0 & \frac{1}{({}^1x-1.0)({}^2x+1.0)} \\
1.0 & 1.0 & 1.0 & \frac{1}{({}^1x-1.0)({}^2x-1.0)}
\end{pmatrix}
$$

$$
\begin{aligned}
\mathbf{c}^{{}^2x} &= \mathbf{vec}\begin{pmatrix} -1.0 & -1.0 \\ 1.0 & 1.0 \end{pmatrix} \\
\mathbf{c}^{{}^1x} &= \begin{pmatrix} -1.0 \\ 1.0 \end{pmatrix}
\end{aligned}
$$

$$\mathbf{c}_2 = \mathbf{c}^{{}^2x} \odot (\mathbf{c}^{{}^1x} \otimes \mathbf{1}_{k_2})$$

Variables decoupling, KST and KANs

Decoupling, KST and KANs via Loewner with rational activation functions ($\mathbf{H} = {}^1x \cdot {}^2x$)

$$
\begin{array}{rcl}
{}^1\lambda_{j_1} & = & \begin{pmatrix} -1 & 1 \end{pmatrix} \\
{}^2\lambda_{j_2} & = & \begin{pmatrix} -1 & 1 \end{pmatrix}
\end{array}
$$

$$
\begin{pmatrix}
\mathbf{c} & \mathbf{w} & \mathbf{c}\cdot\mathbf{w} & \mathbf{Lag} \\
1.0 & 1.0 & 1.0 & \frac{1}{({}^1x+1.0)({}^2x+1.0)} \\
-1.0 & -1.0 & 1.0 & \frac{1}{({}^1x+1.0)({}^2x-1.0)} \\
-1.0 & -1.0 & 1.0 & \frac{1}{({}^1x-1.0)({}^2x+1.0)} \\
1.0 & 1.0 & 1.0 & \frac{1}{({}^1x-1.0)({}^2x-1.0)}
\end{pmatrix}
$$

$$
\begin{array}{rcl}
\mathbf{c}^{{}^2x} & = & \textbf{vec}\begin{pmatrix} -1.0 & -1.0 \\ 1.0 & 1.0 \end{pmatrix} \\
\mathbf{c}^{{}^1x} & = & \begin{pmatrix} -1.0 \\ 1.0 \end{pmatrix}
\end{array}
$$

$$
\mathbf{c}_2 = \mathbf{c}^{{}^2x} \odot (\mathbf{c}^{{}^1x} \otimes \mathbf{1}_{k_2})
$$

$$
\mathbf{D} = \begin{pmatrix}
\overbrace{\mathbf{c}^{{}^1x} \cdot \mathbf{Lag}({}^1x)}^{\textsf{Bary}({}^1x)} & \overbrace{\mathbf{c}^{{}^2x} \cdot \mathbf{Lag}({}^2x)}^{\textsf{Bary}({}^2x)} \\
-\frac{1.0}{{}^1x+1.0} & -\frac{1.0}{{}^2x+1.0} \\
-\frac{1.0}{{}^1x+1.0} & \frac{1}{{}^2x-1.0} \\
\frac{1}{{}^1x-1.0} & -\frac{1.0}{{}^2x+1.0} \\
\frac{1}{{}^1x-1.0} & \frac{1}{{}^2x-1.0}
\end{pmatrix}
$$

Equivalent denominator and numerator read:

$$
\sum_{i\text{-th row}} \prod_{j\text{-th col}} [\mathbf{D}]_{i,j} \text{ and } \sum_{i\text{-th row}} \mathbf{w} \cdot \prod_{j\text{-th col}} [\mathbf{D}]_{i,j}
$$

Variables decoupling, KST and KANs

Decoupling, KST and KANs via Loewner with rational activation functions ($\mathbf{H} = {}^1x \cdot {}^2x$)

$$
\begin{aligned}
{}^1\lambda_{j_1} &= \begin{pmatrix} -1 & 1 \end{pmatrix} \\
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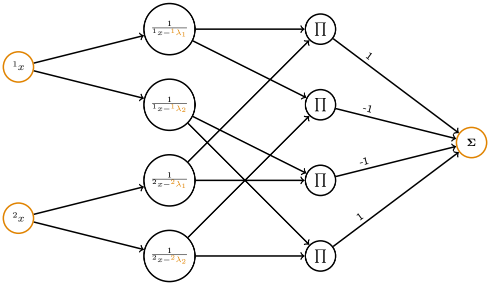
\end{aligned}
$$

$$
\begin{array}{c}
\begin{array}{cccc} \mathbf{c} & \mathbf{w} & \mathbf{c}\cdot\mathbf{w} & \mathbf{Lag} \end{array} \\
\begin{pmatrix}
1.0 & 1.0 & 1.0 & \frac{1}{\left({}^1x+1.0\right)\left({}^2x+1.0\right)} \\
-1.0 & -1.0 & 1.0 & \frac{1}{\left({}^1x+1.0\right)\left({}^2x-1.0\right)} \\
-1.0 & -1.0 & 1.0 & \frac{1}{\left({}^1x-1.0\right)\left({}^2x+1.0\right)} \\
1.0 & 1.0 & 1.0 & \frac{1}{\left({}^1x-1.0\right)\left({}^2x-1.0\right)}
\end{pmatrix}
\end{array}
$$

$$
\begin{aligned}
\mathbf{c}^{{}^2x} &= \textbf{vec}\begin{pmatrix} -1.0 & -1.0 \\ 1.0 & 1.0 \end{pmatrix} \\
\mathbf{c}^{{}^1x} &= \begin{pmatrix} -1.0 \\ 1.0 \end{pmatrix}
\end{aligned}
$$

$$
\mathbf{c}_2 = \mathbf{c}^{{}^2x} \odot \left(\mathbf{c}^{{}^1x} \otimes \mathbf{1}_{k_2}\right)
$$

Denominator Network view



Variables decoupling, KST and KANs

Decoupling, KST and KANs via Loewner with rational activation functions ($\mathbf{H} = {}^1x \cdot {}^2x$)

KST via Loewner

$$
= \frac{\sum_{j_1=1}^{k_1} \sum_{j_2=1}^{k_2} \frac{c_{j_1,j_2} \mathbf{w}_{j_1,j_2}}{\left({}^1x - {}^1\lambda_{j_1}\right)\left({}^2x - {}^2\lambda_{j_2}\right)}}{\sum_{j_1=1}^{k_1} \sum_{j_2=1}^{k_2} \frac{c_{j_1,j_2}}{\left({}^1x - {}^1\lambda_{j_1}\right)\left({}^2x - {}^2\lambda_{j_2}\right)}}
$$

$$
= \frac{\sum_{j_1=1}^{k_1} \sum_{j_2=1}^{k_2} \exp\left(\log \mathbf{w}_{j_1,j_2} + \log \frac{\text{Bary}_{j_1}^{{}^1x}}{\left({}^1x - {}^1\lambda_{j_1}\right)} + \log \frac{\text{Bary}_{j_2}^{{}^2x}}{\left({}^2x - {}^2\lambda_{j_2}\right)} \right)}{\sum_{j_1=1}^{k_1} \sum_{j_2=1}^{k_2} \exp\left(\log \frac{\text{Bary}_{j_1}^{{}^1x}}{\left({}^1x - {}^1\lambda_{j_1}\right)} + \log \frac{\text{Bary}_{j_2}^{{}^2x}}{\left({}^2x - {}^2\lambda_{j_2}\right)} \right)}
$$

Decoupled barycentric weights

$$
\overbrace{\mathbf{c}^{{}^1x} \cdot \mathbf{Lag}({}^1x)}^{\text{Bary}({}^1x)} \qquad \overbrace{\mathbf{c}^{{}^2x} \cdot \mathbf{Lag}({}^2x)}^{\text{Bary}({}^2x)}
$$

$$
\begin{array}{cc}
-\frac{1.0}{{}^1x+1.0} & -\frac{1.0}{{}^2x+1.0} \\
-\frac{1.0}{{}^1x+1.0} & \frac{1}{{}^2x-1.0} \\
\frac{1}{{}^1x-1.0} & -\frac{1.0}{{}^2x+1.0} \\
\frac{1}{{}^1x-1.0} & \frac{1}{{}^2x-1.0}
\end{array}
$$

This solution of KST for rational forms !

Comparisons
Some competitors

Rat. app [B/G 2025]

- Lagrangian interpolation theorem
- p-AAA

KAN [P/P 2025]

- Kolmogorov Arnold theorem
- Kolmogorov Arnold Network

MLP [TensorFlow by Google - Keras 2025]

- Universal approximation theorem
- Multi Layer Perceptron
- Dense connected / ReLU / ADAM / 1000 it. / rand. init.

TensorFlow interface
(Python code)

```python
import numpy as np
import math
import matplotlib.pyplot as plt
import tensorflow as tf
from keras.models import Sequential
from matplotlib import cm

# Data
def H(x):
    #y = pow(x[:,0],2)*x[:,1]
    #y = 1/2*(x[:,0] + np.abs(x[:,0])) + 1/10*x[:,1] #1
    #y = x[:,0]*x[:,1] #3
    #y = np.exp(x[:,0]*x[:,1])/( (pow(x[:,0],2)-1.44)*(pow(x[:,1],2)-1.44) ) #6
    #y = np.tanh(4*(x[:,0]-x[:,1])) #8
    #y = pow(np.abs((x[:,0]-x[:,1])),3) #10
    y = (pow(x[:,0],2) + pow(x[:,1],2) + x[:,0] - x[:,1] + 1) / (pow(x[:,0],3)  + pow(x[:,1],2) + 4) #15
    return np.transpose(np.array([y]))

n   = 2
N1  = 40
N2  = 40
x1  = np.linspace(-1, 1, N1)
x2  = np.linspace(-1, 1, N2)

# IP
N   = N1*N2
tab = np.zeros((N,1))
```

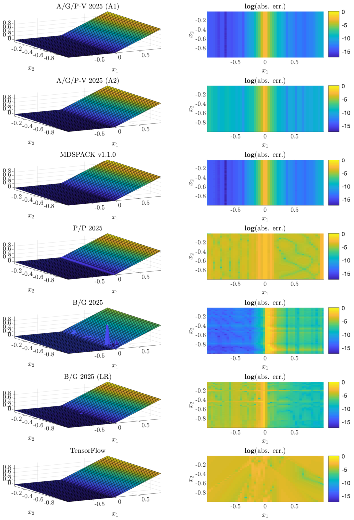

L. Balicki and S. Gugercin, *"Multivariate Rational Approximation via Low-Rank Tensors and the p-AAA Algorithm"*, SISC, 2025.

M. Poluektov and A. Polar, *"Construction of the Kolmogorov-Arnold representation using the Newton-Kaczmarz method"*, https://arxiv.org/abs/2305.08194.

M. Abadi et al., *"TensorFlow: Large-scale machine learning on heterogeneous systems, 2015"*, Software available from tensorflow.org.

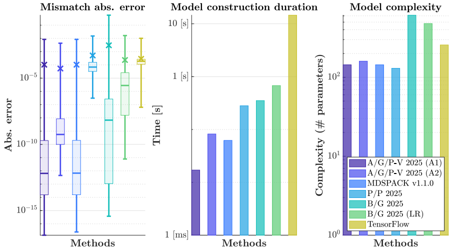
Comparisons

Irrational functions (example #1)



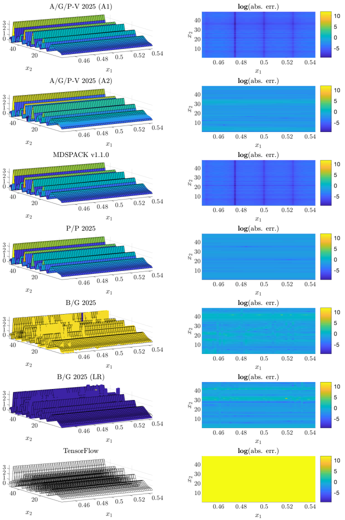
$$\mathrm{ReLU}({}^{1}x) + \frac{1}{100}\,{}^{2}x$$

- Reference: Personal communication, [none]
- Domain: $\mathbb{R}$
- Tensor size: 12.5 **KB** (40^2 points)
- Bounds: $\begin{pmatrix} -1 & 1 \end{pmatrix} \times \begin{pmatrix} -1 & -10^{-10} \end{pmatrix}$



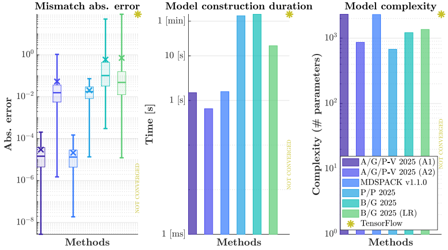
Comparisons

Irrational functions (example #34)



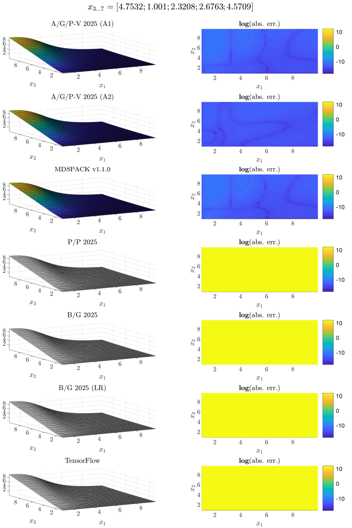
$$\mathsf{Re}(\zeta({}^1x + \imath\,{}^2x))$$

- Riemann ζ function (real part), [none]
- Domain: $\mathbb{R}$
- Tensor size: 1.22 **MB** (400^2 points)
- Bounds: $\begin{pmatrix} \frac{9}{20} & \frac{11}{20} \end{pmatrix} \times \begin{pmatrix} 1 & 50 \end{pmatrix}$



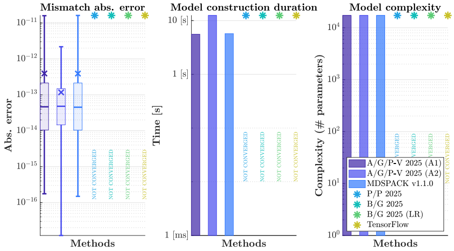
Comparisons

Irrational functions (example #43)



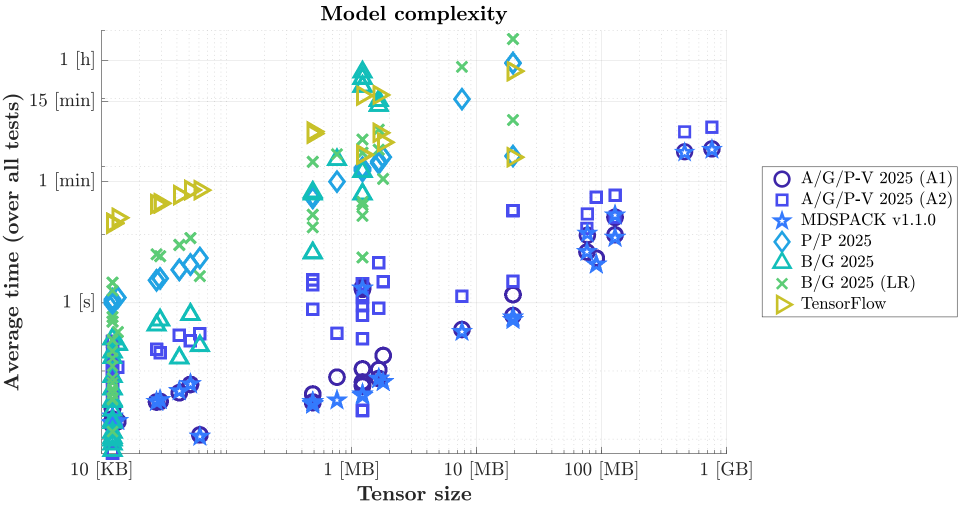
$$\frac{{}^3x\;{}^2x^3+1}{{}^1x^4+{}^2x^2\;{}^3x+{}^4x^2+{}^5x+{}^6x^3+{}^7x}$$

- Reference: Personal communication, [Riemann]
- Domain: $\mathbb{R}$
- Tensor size: 76.3 **MB** (10^7 points)
- Bounds: $\begin{pmatrix} 1 & 10 \end{pmatrix}^7$



Comparisons

Irrational functions (time, scalability)



Conclusion

Take home message

Main contributions

From any n-th order multi-variate transfer function / data tensor

- Construct a transfer function in barycentric form
- **Construct a realization with controlled complexity**
- **Tame the computational complexity**
- Two algorithms (direct & iterative)
- Connection with Kolmogorov theorem
- Connection with Kolmogorov networks

Side effects

[Sci. con.] Tensor rank approximation

[Sci. con.] Achieve multi-linearization of NEVP

[Sci. con.] Exact (Loewner) matrix null space computation

[Dyn. sys.] Multi-variate / parametric realization

Collaboration with
A.C. Antoulas [Rice Univ.]
I.V. Goșea [MPI]
P. Vuillemin [ONERA]

`https://arxiv.org/abs/2405.00495`
`https://arxiv.org/abs/2506.04791`
`https://github.com/cpoussot/mLF`
`https://cpoussot.github.io`

In parting... if enough time

Numerical examples, 20-D example

$$\mathbf{H}({}^1x, {}^2x, \dots, {}^{20}x) =$$

$$\frac{3 \cdot {}^1x^3 + 4 \cdot {}^8x + {}^{12}x + {}^{13}x \cdot {}^{14}x + {}^{15}x}{{}^1x + {}^2x^2 \cdot {}^3x + {}^4x + {}^5x + {}^6x + {}^7x \cdot {}^8x + {}^9x \cdot {}^{10}x \cdot {}^{11}x + {}^{13}x + {}^{13}x^3 \cdot \pi + {}^{17}x + {}^{18}x \cdot {}^{19}x - {}^{20}x}$$

Statistics

- 20-D tensor of dimension (≥ 48 TB in real double precision)
- Complexity: $(3, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 3, 1, 1, 1, 1)$
- n-D Loewner matrix
  $6, 291, 456^2 \rightarrow 288$ TB of storage in real double precision
- Full SVD: $2.49 \cdot 10^{20}$ `flop` and 288 TB
  Recursive SVD: $5.43 \cdot 10^7$ `flop` and 0.12 KB
- error $\approx 10^{-11}$

$$\mathbf{H}({}^1x, {}^2x, \ldots, {}^{20}x) = \frac{3 \cdot {}^1x^3 + 4 \cdot {}^8x + {}^{12}x + {}^{13}x \cdot {}^{14}x + {}^{15}x}{{}^1x + {}^2x^2 \cdot {}^3x + {}^4x + {}^5x + {}^6x + {}^7x \cdot {}^8x + {}^9x \cdot {}^{10}x \cdot {}^{11}x + {}^{13}x + {}^{13}x^3 \cdot \pi + {}^{17}x + {}^{18}x \cdot {}^{19}x - {}^{20}x}$$

Statistics

- 20-D tensor of dimension (≥ 48 TB in real double precision)
- Complexity: $(3, 3, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)$
- n-D Loewner matrix
  $6,291,456^2 \rightarrow 288$ TB of storage in real double precision
- Full SVD: $2.49 \cdot 10^{20}$ `flop` and 288 TB
  Recursive SVD: $5.03 \cdot 10^7$ `flop` and 0.12 KB
- error $\approx 10^{-11}$