The Loewner framework, the Kolmogorov superposition theorem, and the curse of dimensionality

... from tensor to multivariate rational approximation and more

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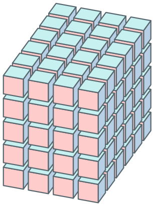
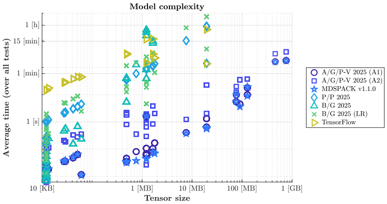
Workshop on data-driven control and analysis of dynamical systems

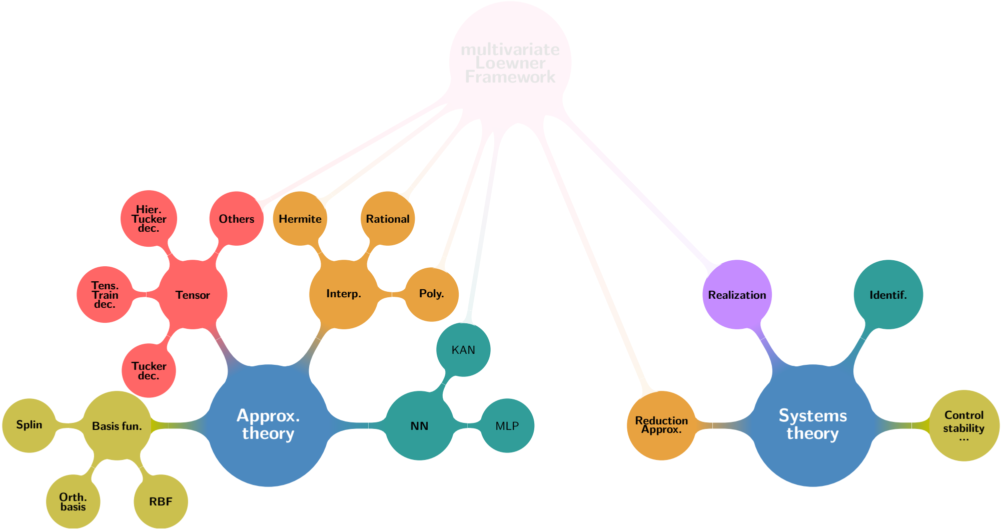
`https://arxiv.org/abs/2405.00495` [in SIAM Review - Research Spotlight]
`https://arxiv.org/abs/2506.04791` [extensive benchmark]
`https://github.com/cpoussot/mLF` [research code package]





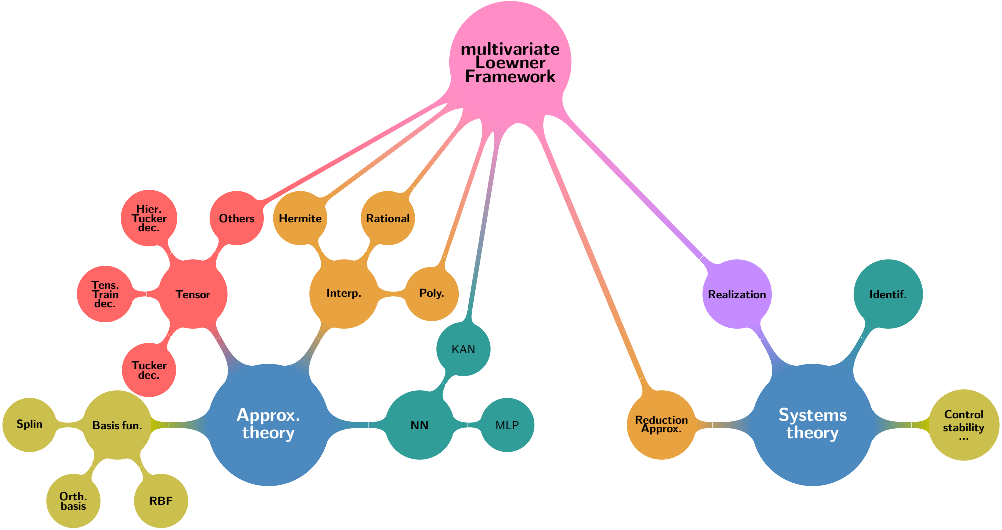
Forewords

Approximation & systems theory... where we stand



Forewords

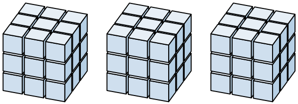
Approximation & systems theory... where we stand



Forewords

Starting (motivating) examples - Borehole function

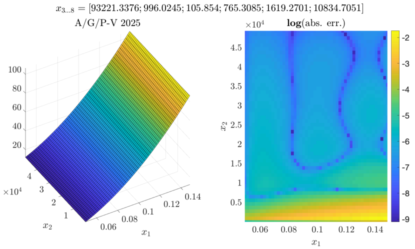
$$\mathbf{H}({}^1x,\cdots,{}^8x) = \mathbf{H}(r_w, r, T_u, H_u, T_l, H_l, L, K_w) = \frac{2\pi T_u (H_u - H_l)}{\ln\left(\frac{r}{r_w}\right)\left(1 + \frac{2LT_u}{\ln(r/r_w) r_w^2 K_w}\right) + \frac{T_u}{T_l}}$$



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

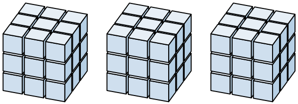
tab$_8 \in \mathbb{C}^{8\times 8 \times \cdots \times 8}$

$\approx$130 `Mo ('real')`



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

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



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

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

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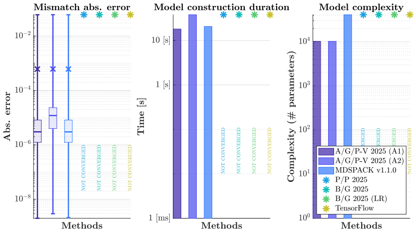


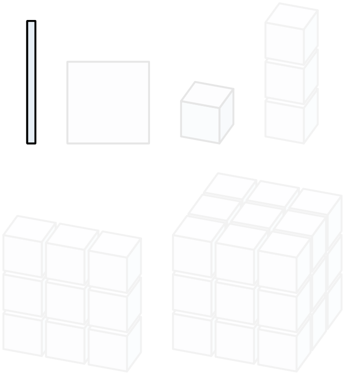
S. Surjanovic, *"Borehole function"*, `https://www.sfu.ca/~ssurjano/borehole.html`.

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

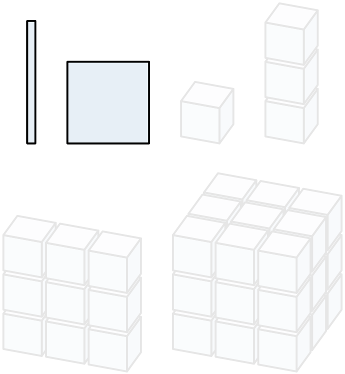
Data (and tensors)

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

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

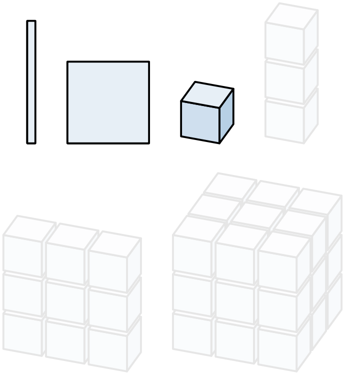
$^3x = {}^3\lambda_{1,\cdots,k_3}$

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

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

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

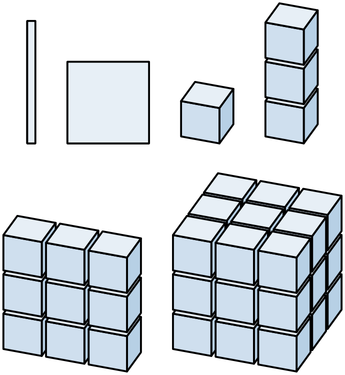
Tensors (3-D) tab$_3$



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$_n$



Forewords

Contributions claim & trajectory of the presentation

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

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

Loewner matrix

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

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

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

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

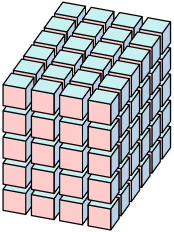
$$\mathbf{c}_n = \left[\begin{array}{c} c_{1,\cdots,1} \\ \vdots \\ c_{1,\cdots,k_n} \\ \hline \vdots \\ \hline c_{k_1,\cdots,1} \\ \vdots \\ c_{k_1,\cdots,k_n} \end{array} \right] \in \mathbb{C}^{k_1 \cdots k_n}$$

Taming the curse of dimensionality

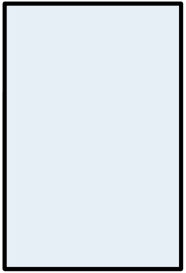
n-variable Loewner matrix operator

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

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



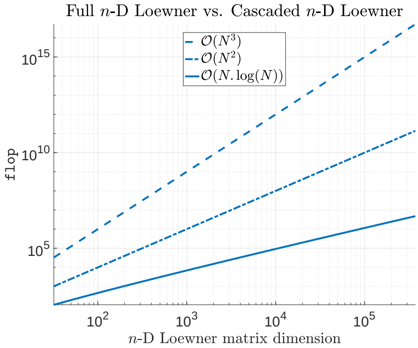
matrix $\mathbb{L}_n$



Taming the curse of dimensionality

Null space `flop` and memory issues

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 $Q = K = N$)

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 $(2,1)$

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

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

- 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 ${}^2x = {}^2\lambda_2 = -3$

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

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

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

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 $(2,1)$

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

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

- 1 $\mathbb{L}_1$ along ${}^1x$, for ${}^2x = {}^2\lambda_2 = -3$
- 3 $\mathbb{L}_1$ along ${}^2x$ for ${}^1x = \{{}^1\lambda_1, {}^1\lambda_2, {}^1\lambda_3\}$

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

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

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

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

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

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

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

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

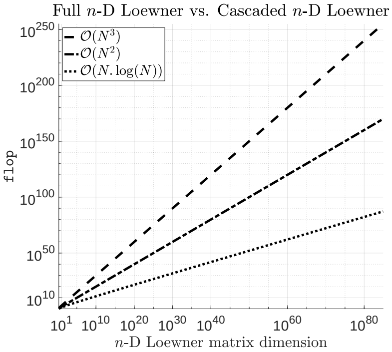
where

- $\mathbf{c}_1^{{}^1\lambda_{k_1}} = \mathcal{N}(\mathbb{L}_1^{{}^1\lambda_{k_1}})$,
  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_2-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

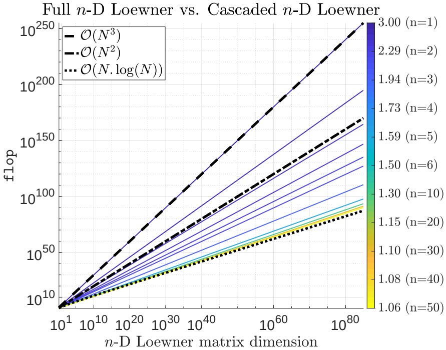
- QK^2 (if $Q > K$)
- N^3 (if $Q = K = N$)

$\Rightarrow$ **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

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

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: $9.78 \cdot 10^{13}$

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 every continuous function $\mathbf{f} : \mathbb{I}^n \mapsto \mathbb{R}$ and any $n \in \mathbb{N}$, $n \geq 2$, there exist

- real numbers $\lambda_1, \ldots, \lambda_n$;
- continuous functions $\Phi_k : \mathbb{I} \mapsto \mathbb{R}$, $k = 1, \ldots, 2n+1$;
- 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)

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

Variable decoupling

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

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

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

This is decoupling !

Remember that (in 2-D)

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

Variable decoupling

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

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

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

This is decoupling !

Variables decoupling, KST and KANs

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

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

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

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

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

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:

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

Variables decoupling, KST and KANs

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

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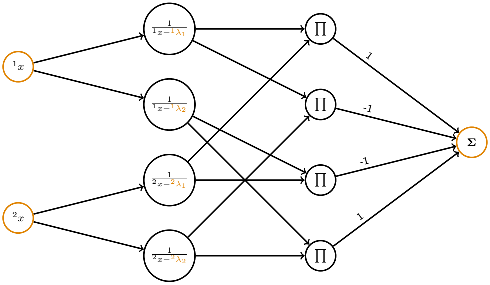
{}^2\lambda_{j_2} &= \begin{pmatrix} -1 & 1 \end{pmatrix}
\end{aligned}
$$

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

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

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

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

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

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

Decoupled barycentric weights

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

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

This is the 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))
```

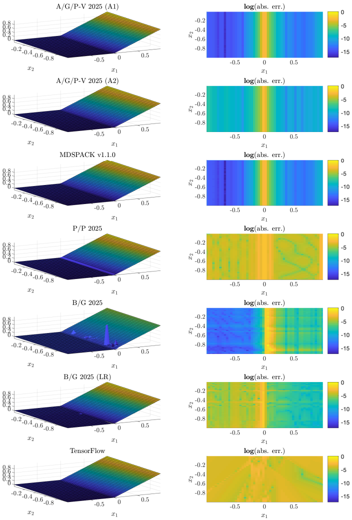

L. Balicki and S. Gugercin, *"Multivariate Rational Approximation via Low-Rank Tensors and the p-AAA Algorithm"*, SISC, 2025.

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.

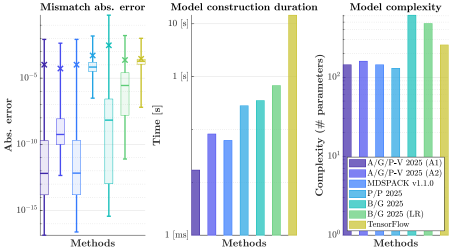
Comparisons

Irrational functions (example #1)



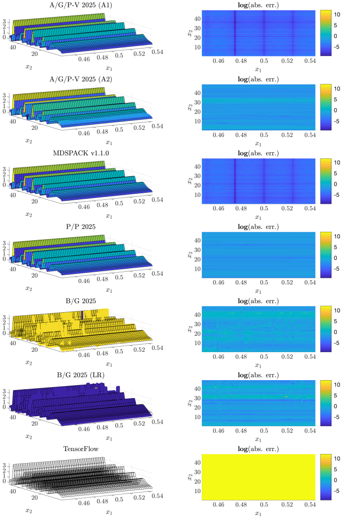
$$\mathrm{ReLU}({}^1x) + \frac{1}{100}\,{}^2x$$

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



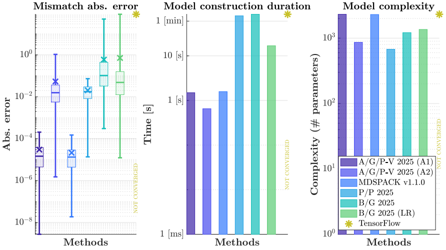
Comparisons

Irrational functions (example #34)



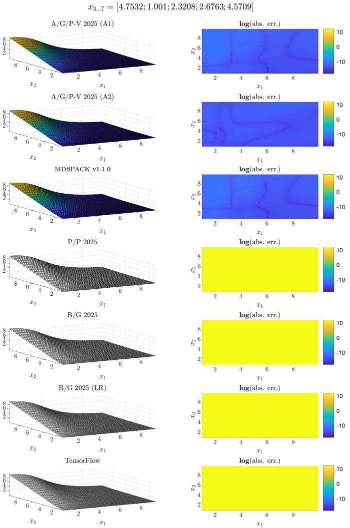
$$\mathrm{Re}(\zeta({}^1x + \imath\, {}^2x))$$

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



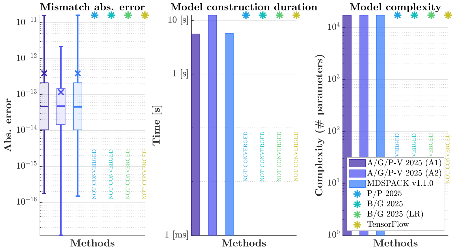
Comparisons

Irrational functions (example #43)



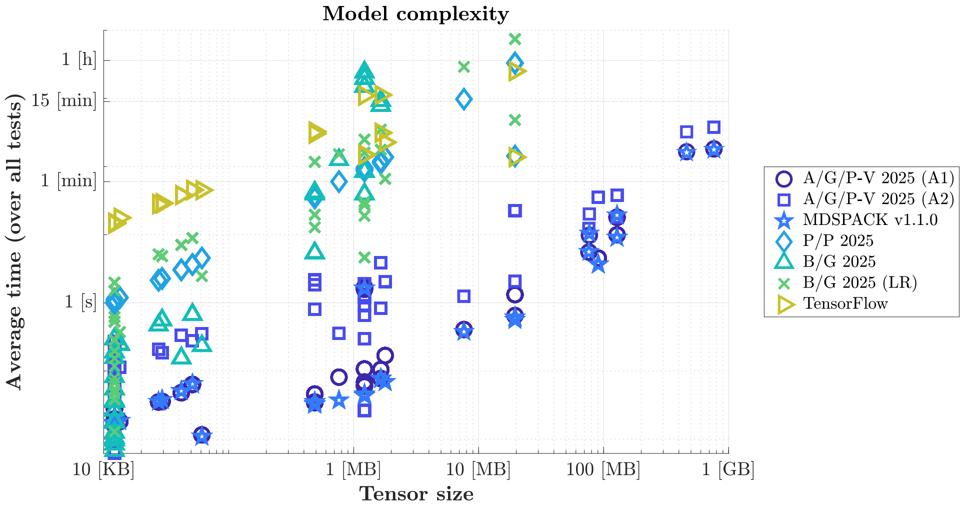
$$\frac{{}^{3}x\ {}^{2}x^{3}+1}{{}^{1}x^{4}+{}^{2}x^{2}\ {}^{3}x+{}^{4}x^{2}+{}^{5}x+{}^{6}x^{3}+{}^{7}x}$$

- 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

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

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`
  Recursive SVD: $5.43 \cdot 10^{7}$ `flop`
- error $\approx 10^{-11}$

In parting... if enough time

Numerical examples, 20-D example

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

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

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`
  Recursive SVD: $5.43 \cdot 10^7$ `flop` $\rightarrow 5.03 \cdot 10^7$ `flop`
- error $\approx 10^{-11}$

In parting... if enough time

Numerical examples (from 2 to 20 variables)

#4 Rational function

$$s_4{}^3 + \frac{s_1\, s_3}{s_3{}^2 + s_1 + s_2 + 1}$$

#5 Rational function

$$\frac{s_3{}^2 + s_1\, s_3\, s_5{}^3}{s_1{}^3 + s_4 + s_2\, s_3}$$

#6 Rational function

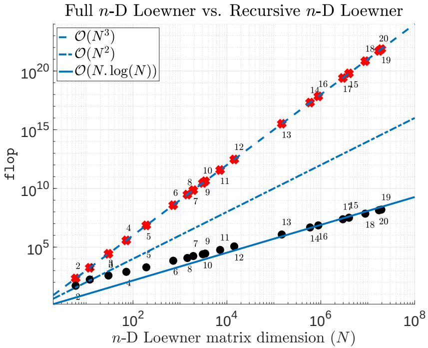
$$\frac{-\sqrt{2}\, s_6{}^2 + s_1 + s_3}{s_1{}^2 + s_4{}^3 + s_5{}^2 + s_6 + s_2\, s_3}$$

#7 Rational function

$$\frac{s_3\, s_2{}^3 + 1}{s_3\, s_2{}^2 + s_4{}^2 + s_6{}^3 + s_1 + s_5 + s_7}$$

#19 Rational function

$$\frac{3\, s_1{}^3 + s_{18}{}^2 + 4\, s_8 + s_{12} + s_{15} + s_{13}\, s_{14}}{s_3\, s_2{}^2 + \pi\, s_{16}{}^3 + s_{17}{}^2 + s_1 + s_4 + s_5 + s_6 + s_{13} + s_{19} + s_7\, s_8 + s_9\, s_{10}\, s_{11}}$$



In parting... if enough time

Numerical examples (rational and irrational)

#16 Arc-tangent function

$$\frac{\operatorname{atan}(x_1)+\operatorname{atan}(x_2)+\operatorname{atan}(x_3)+\operatorname{atan}(x_4)}{{x_1}^2\,{x_2}^2-{x_1}^2-{x_2}^2+1}$$

#17 Exponential function

$$\frac{e^{x_1\,x_2\,x_3\,x_4}}{{x_1}^2+{x_2}^2-x_3\,x_4+3}$$

#18 Sinc function

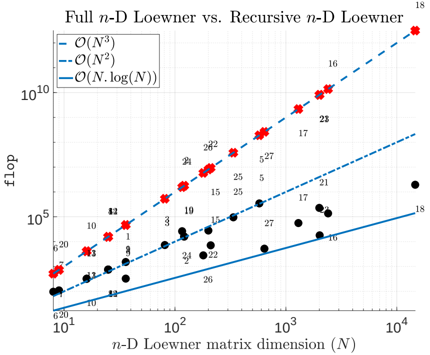
$$\frac{10\,\sin(x_1)\,\sin(x_2)\,\sin(x_3)\,\sin(x_4)}{x_1\,x_2\,x_3\,x_4}$$

#19 Sinc function

$$\frac{10\,\sin(x_1)\,\sin(x_2)}{x_1\,x_2}$$

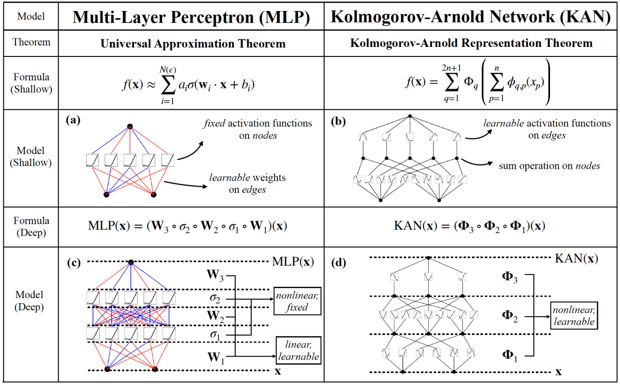
#20 Polynomial function

$${x_1}^2+x_1\,x_2+{x_2}^2-x_2+1$$



KANs features

- **Inspired by the Kolmogorov-Arnold representation theorem**
- The model output is a composition of **sums** and **learnable activation functions** (e.g. splines)
- Alternate to Multi-Layer Perceptrons (MLP), having fixed activation functions (e.g. ReLU), **inspired by the universal approximation theorem**



Comparison between MLP and KAN (figure from *Z. Liu et al.*)

Z. Liu et al., *"KAN: Kolmogorov–Arnold Networks"*, `https://arxiv.org/abs/2404.19756`.

In parting... if enough time

KANs with splines

Building the Kolmogorov-Arnold model as follows

$$F({}^1x, {}^2x, \cdots, {}^nx) = \sum_{k=1}^{2m+1} \Phi_k \left(\sum_{j=1}^{m} f_{kj}({}^jx) \right)$$

$f_{kj} : [0,1] \mapsto \mathbb{R}$ and $\Phi_k : \mathbb{R} \mapsto \mathbb{R}$ are continuous functions.

The relation is approximated by $k = 1, \cdots, d = 2m+1$ as

$$\hat{F}({}^1x, {}^2x, \cdots, {}^nx) = \sum_{k=1}^{d} \Phi_k \underbrace{\left(\sum_{j=1}^{m} f_{kj}({}^jx_i) \right)}_{\theta_{ik}}$$

where θ_{ik} denotes the k-th component of θ_i vector (interpreted as a hidden variable between two layers), which describes **splines**

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

In parting... if enough time

KANs with splines

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