

Back to the Roots: Solving Polynomial Systems with Numerical Linear Algebra Tools

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Outline

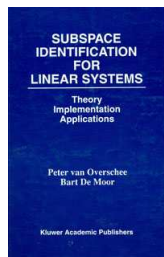
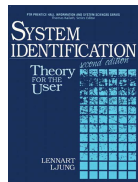
- 1 Introduction
- 2 History
- 3 Linear Algebra
- 4 Multivariate Polynomials
- 5 Applications
- 6 Conclusions

System Identification: PEM

- LTI models
- Non-convex optimization
- Considered 'solved' early nineties

Linear Algebra approach

⇒ **Subspace methods**



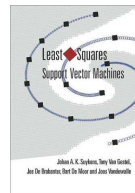
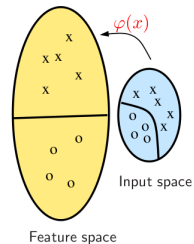
Nonlinear regression, modelling and clustering

- Most regression, modelling and clustering problems are nonlinear when formulated in the input data space
- This requires nonlinear nonconvex optimization algorithms

Linear Algebra approach

⇒ Least Squares Support Vector Machines

- 'Kernel trick' = projection of input data to a high-dimensional feature space
- Regression, modelling, clustering problem becomes a large scale linear algebra problem (set of linear equations, eigenvalue problem)



Nonlinear Polynomial Optimization

- Polynomial object function + polynomial constraints
- Non-convex
- Computer Algebra, Homotopy methods, Numerical Optimization
- Considered 'solved' by mathematics community

Linear Algebra Approach

⇒ **Linear Polynomial Algebra**

Conceptual/Geometric Level

- Polynomial system solving is an eigenvalue problem!
- Row and Column Spaces: Ideal/Variety \leftrightarrow Row space/Kernel of M , ranks and dimensions, nullspaces and orthogonality
- Geometrical: intersection of subspaces, angles between subspaces, Grassmann's theorem,...

Numerical Linear Algebra Level

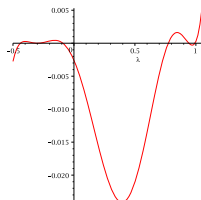
- Eigenvalue decompositions, SVDs,...
- Solving systems of equations (consistency, nb sols)
- QR decomposition and Gram-Schmidt algorithm

Numerical Algorithms Level

- Modified Gram-Schmidt (numerical stability), GS 'from back to front'
- Exploiting sparsity and Toeplitz structure (computational complexity $O(n^2)$ vs $O(n^3)$), FFT-like computations and convolutions,...
- Power method to find smallest eigenvalue (= minimizer of polynomial optimization problem)

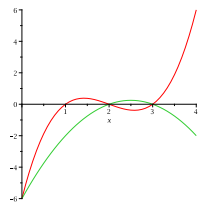
Four instances of polynomial rooting problems

$$p(\lambda) = \det(A - \lambda I) = 0$$



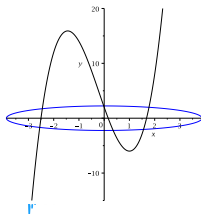
$$(x - 1)(x - 3)(x - 2) = 0$$

$$-(x - 2)(x - 3) = 0$$



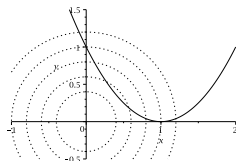
$$x^2 + 3y^2 - 15 = 0$$

$$y - 3x^3 - 2x^2 + 13x - 2 = 0$$



$$\min_{x,y} x^2 + y^2$$

$$\text{s. t. } y - x^2 + 2x - 1 = 0$$



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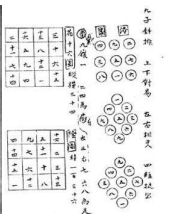
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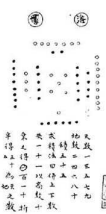
Diophantus
(c200-c284)
Arithmetica



Al-Khwarizmi
(c780-c850)



Zhu Shijie (c1260-c1320) *Jade Mirror of the Four Unknowns*



Pierre de Fermat
(c1601-1665)



René Descartes
(1596-1650)



Isaac Newton
(1643-1727)



Gottfried Wilhelm Leibniz
(1646-1716)

...leading to "Algebraic Geometry"



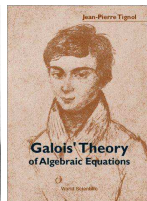
Etienne Bézout
(1730-1783)



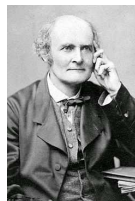
Jean-Victor Poncelet
(1788-1867)



August Ferdinand Möbius (1790-1868)



Evariste Galois
(1811-1832)



Arthur Cayley
(1821-1895)



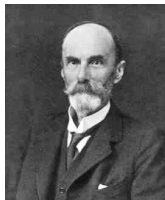
Leopold Kronecker
(1823-1891)



Edmond Laguerre
(1834-1886)



James Joseph Sylvester
(1814-1897)



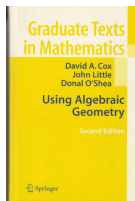
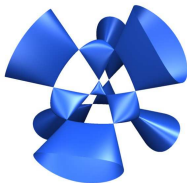
Francis Sowerby Macaulay
(1862-1937)



David Hilbert
(1862-1943)

Computational Algebraic Geometry

- Emphasis on symbolic manipulations
- Computer algebra
- Huge body of literature in Algebraic Geometry
- Computational tools: Gröbner Bases (next slide)



Wolfgang Gröbner
(1899-1980)



Bruno Buchberger

Example: Gröbner basis

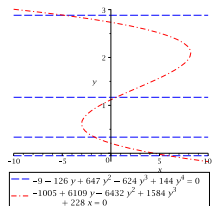
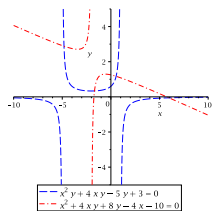
Input system:

$$\begin{aligned}x^2 y + 4xy - 5y + 3 &= 0 \\x^2 + 4xy + 8y - 4x - 10 &= 0\end{aligned}$$

- Generates simpler but equivalent system (same roots)
- Symbolic eliminations and reductions
- Monomial ordering (e.g., lexicographic)
- Exponential complexity
- Numerical issues! Coefficients become very large

Gröbner Basis:

$$\begin{aligned}-9 - 126y + 647y^2 - 624y^3 + 144y^4 &= 0 \\-1005 + 6109y - 6432y^2 + 1584y^3 + 228x &= 0\end{aligned}$$



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$$\begin{array}{ccc}
 A & X & = & 0 \\
 p \times q & q \times (q-r) & & p \times (q-r)
 \end{array}$$

- $C(A^T) \perp C(X)$
- $\text{rank}(A) = r$
- $\dim N(A) = q - r = \text{rank}(X)$



James Joseph Sylvester

$$A = [U_1 \quad U_2] \begin{bmatrix} S_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix}$$

$$\Downarrow$$

$$X = V_2$$

$$\begin{array}{ccc} A & X & = & 0 \\ p \times q & q \times (q-r) & & p \times (q-r) \end{array}$$

Reorder columns of A and partition

$$\begin{array}{ccc} p \times q & p \times (q-r) & p \times r \\ \bar{A} & = & [\bar{A}_1 \quad \bar{A}_2] \quad \text{rank}(\bar{A}_2) = r \quad (\bar{A}_2 \text{ full column rank}) \end{array}$$

Reorder rows of X and partition accordingly

$$[\bar{A}_1 \quad \bar{A}_2] \begin{array}{c} \begin{array}{c} q-r \\ \bar{X}_1 \\ r \\ \bar{X}_2 \end{array} \end{array} = 0$$

$$\begin{array}{l} \text{rank}(\bar{A}_2) = r \\ \updownarrow \\ \text{rank}(\bar{X}_1) = q - r \end{array}$$

$$\begin{bmatrix} \overline{A_1} & \overline{A_2} \end{bmatrix} \begin{bmatrix} \overline{X_1} \\ \overline{X_2} \end{bmatrix} \begin{matrix} q-r \\ r \end{matrix} = 0$$

- $\overline{X_1}$: independent variables
- $\overline{X_2}$: dependent variables

$$\begin{aligned} \overline{X_2} &= -\overline{A_2}^\dagger \overline{A_1} \overline{X_1} \\ \overline{A_1} &= -\overline{A_2} \overline{X_2} \overline{X_1}^{-1} \end{aligned}$$

- Number of different ways of choosing r linearly independent columns out of q columns (upper bound):

$$\binom{q}{q-r} = \frac{q!}{(q-r)! r!}$$

$$\begin{array}{c} A \\ p \times q \end{array} \quad \begin{array}{c} X \\ q \times (q - r_A) \end{array} = \begin{array}{c} 0 \\ p \times (q - r_A) \end{array} \quad \text{and} \quad \begin{array}{c} B \\ p \times t \end{array} \quad \begin{array}{c} Y \\ t \times (t - r_B) \end{array} = \begin{array}{c} 0 \\ p \times (t - r_B) \end{array}$$

What is the nullspace of $[A \ B]$?

$$[A \ B] \begin{array}{c} q - r_A \quad t - r_B \quad ? \\ \left[\begin{array}{ccc} X & 0 & ? \\ 0 & Y & ? \end{array} \right] = 0$$

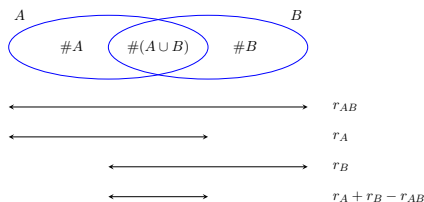
Let $\text{rank}([A \ B]) = r_{AB}$

$$(q - r_A) + (t - r_B) + ? = (p + t) - r_{AB} \Rightarrow ? = r_A + r_B - r_{AB}$$

$$[A \quad B] \begin{bmatrix} q-r_A & t-r_B & r_A+r_B-r_{AB} \\ X & 0 & Z_1 \\ 0 & Y & Z_2 \end{bmatrix} = 0$$

Intersection between column space of A and B :

$$AZ_1 = -BZ_2$$



Hermann Grassmann

$$\#(A \cup B) = \#A + \#B - \#(A \cap B)$$

- **Characteristic Polynomial**

The eigenvalues of A are the roots of

$$p(\lambda) = \det(A - \lambda I) = 0$$

- **Companion Matrix**

Solving

$$q(x) = 7x^3 - 2x^2 - 5x + 1 = 0$$

leads to

$$\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -1/7 & 5/7 & 2/7 \end{bmatrix} \begin{bmatrix} 1 \\ x \\ x^2 \end{bmatrix} = x \begin{bmatrix} 1 \\ x \\ x^2 \end{bmatrix}$$

Consider the univariate equation

$$x^3 + a_1x^2 + a_2x + a_3 = 0,$$

having three distinct roots x_1 , x_2 and x_3

$$\begin{bmatrix} a_3 & a_2 & a_1 & 1 & 0 & 0 \\ 0 & a_3 & a_2 & a_1 & 1 & 0 \\ 0 & 0 & a_3 & a_2 & a_1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ x_1 & x_2 & x_3 \\ x_1^2 & x_2^2 & x_3^2 \\ x_1^3 & x_2^3 & x_3^3 \\ x_1^4 & x_2^4 & x_3^4 \\ x_1^5 & x_2^5 & x_3^5 \end{bmatrix} = 0$$

- Homogeneous linear system
- Rectangular Vandermonde
- corank = 3
- Observability matrix-like
- Realization theory!

Consider

$$x^3 + a_1x^2 + a_2x + a_3 = 0$$

$$x^2 + b_1x + b_2 = 0$$

Build the Sylvester Matrix:

$$\begin{bmatrix} 1 & a_1 & a_2 & a_3 & 0 \\ 0 & 1 & a_1 & a_2 & a_3 \\ 1 & b_1 & b_2 & 0 & 0 \\ 0 & 1 & b_1 & b_2 & 0 \\ 0 & 0 & 1 & b_1 & b_2 \end{bmatrix} \begin{bmatrix} 1 \\ x \\ x^2 \\ x^3 \\ x^4 \end{bmatrix} = 0$$

Row Space	Null Space
Ideal = union of ideals = multiply rows with powers of x	Variety = intersection of null spaces

- Corank of Sylvester matrix = number of common zeros
- null space = intersection of null spaces of two Sylvester matrices
- common roots follow from realization theory in null space
- notice 'double' Toeplitz-structure of Sylvester matrix

● Sylvester Resultant

Consider two polynomials $f(x)$ and $g(x)$:

$$f(x) = x^3 - 6x^2 + 11x - 6 = (x - 1)(x - 2)(x - 3)$$

$$g(x) = -x^2 + 5x - 6 = -(x - 2)(x - 3)$$

Common roots iff $S(f, g) = 0$

$$S(f, g) = \det \begin{bmatrix} -6 & 11 & -6 & 1 & 0 \\ 0 & -6 & 11 & -6 & 1 \\ -6 & 5 & -1 & 0 & 0 \\ 0 & -6 & 5 & -1 & 0 \\ 0 & 0 & -6 & 5 & -1 \end{bmatrix}$$



James Joseph Sylvester

The corank of the Sylvester matrix is 2!

Sylvester's construction can be understood from

$$\begin{array}{l}
 f(x) = 0 \\
 x \cdot f(x) = 0 \\
 g(x) = 0 \\
 x \cdot g(x) = 0 \\
 x^2 \cdot g(x) = 0
 \end{array}
 \begin{array}{c}
 1 \quad x \quad x^2 \quad x^3 \quad x^4 \\
 \left[\begin{array}{ccccc}
 -6 & 11 & -6 & 1 & 0 \\
 & -6 & 11 & -6 & 1 \\
 -6 & 5 & -1 & & \\
 & -6 & 5 & -1 & \\
 & & -6 & 5 & -1
 \end{array} \right]
 \end{array}
 \begin{array}{c}
 \left[\begin{array}{cc}
 1 & 1 \\
 x_1 & x_2 \\
 x_1^2 & x_2^2 \\
 x_1^3 & x_2^3 \\
 x_1^4 & x_2^4
 \end{array} \right] = 0
 \end{array}$$

where $x_1 = 2$ and $x_2 = 3$ are the common roots of f and g

The vectors in the canonical kernel K obey a 'shift structure':

$$\begin{bmatrix} 1 \\ x \\ x^2 \\ x^3 \end{bmatrix} x = \begin{bmatrix} x \\ x^2 \\ x^3 \\ x^4 \end{bmatrix}$$

The canonical kernel K is not available directly, instead we compute Z , for which $ZV = K$. We now have

$$\begin{aligned} S_1KD &= S_2K \\ S_1ZVD &= S_2ZV \end{aligned}$$

leading to the generalized eigenvalue problem

$$(S_2Z)V = (S_1Z)VD$$

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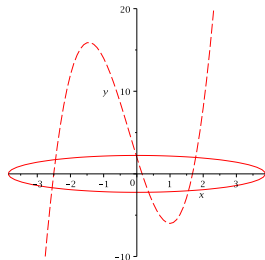
- Consider

$$\begin{cases} p(x, y) = x^2 + 3y^2 - 15 = 0 \\ q(x, y) = y - 3x^3 - 2x^2 + 13x - 2 = 0 \end{cases}$$

- Fix a monomial order, e.g., $1 < x < y < x^2 < xy < y^2 < x^3 < x^2y < \dots$

- Construct M : write the system in matrix-vector notation:

$$\begin{array}{l} p(x, y) \\ q(x, y) \\ x \cdot p(x, y) \\ y \cdot p(x, y) \end{array} \begin{bmatrix} 1 & x & y & x^2 & xy & y^2 & x^3 & x^2y & xy^2 & y^3 \\ -15 & & & 1 & & 3 & & & & \\ -2 & 13 & 1 & -2 & & & -3 & & & \\ -15 & & & & & & 1 & & 3 & \\ -15 & & & & & & & 1 & & 3 \end{bmatrix}$$



$$\begin{cases} p(x, y) = x^2 + 3y^2 - 15 = 0 \\ q(x, y) = y - 3x^3 - 2x^2 + 13x - 2 = 0 \end{cases}$$

Continue to enlarge M :

it #	form	1	x	y	x ²	xy	y ²	x ³	x ² y	xy ²	y ³	x ⁴	x ³ y	yx ²	y ² x	xy ³	y ⁴	x ⁵	x ⁴ y	yx ³	y ² x ²	y ³ xy	x ⁴ y ²	y ⁵	
d = 3	p xp yp q	-15	-15	-15	1	3		1	3																
d = 4	x ² p xy ² p y ² p xq yq		-2		-15	-15		-2				-3	1	3											
d = 5	x ³ p x ² y ² p xy ² p y ³ p x ² q xyq y ² q			-2				-15	-15	-15									1	3					

- # rows grows faster than # cols \Rightarrow overdetermined system
- rank deficient by construction!

- Coefficient matrix M :

$$M = \begin{bmatrix} \times & \times & \times & \times & 0 & 0 & 0 \\ 0 & \times & \times & \times & \times & 0 & 0 \\ 0 & 0 & \times & \times & \times & \times & 0 \\ 0 & 0 & 0 & \times & \times & \times & \times \end{bmatrix}$$

- Solutions generate vectors in kernel of M :

$$Mk = 0$$

- Number of solutions s follows from corank

Canonical nullspace K built from s solutions (x_i, y_i) :

1	1	...	1
x_1	x_2	...	x_s
y_1	y_2	...	y_s
x_1^2	x_2^2	...	x_s^2
$x_1 y_1$	$x_2 y_2$...	$x_s y_s$
y_1^2	y_2^2	...	y_s^2
x_1^3	x_2^3	...	x_s^3
$x_1^2 y_1$	$x_2^2 y_2$...	$x_s^2 y_s$
$x_1 y_1^2$	$x_2 y_2^2$...	$x_s y_s^2$
y_1^3	y_2^3	...	y_s^3
x_1^4	x_2^4	...	x_s^4
$x_1^3 y_1$	$x_2^3 y_2$...	$x_s^3 y_s$
$x_1^2 y_1^2$	$x_2^2 y_2^2$...	$x_s^2 y_s^2$
$x_1 y_1^3$	$x_2 y_2^3$...	$x_s y_s^3$
y_1^4	y_2^4	...	y_s^4
⋮	⋮	⋮	⋮

- Choose s linear independent rows in K

$$S_1 K$$

- This corresponds to finding linear dependent columns in M

1	1	...	1
x_1	x_2	...	x_s
y_1	y_2	...	y_s
x_1^2	x_2^2	...	x_s^2
$x_1 y_1$	$x_2 y_2$...	$x_s y_s$
y_1^2	y_2^2	...	y_s^2
x_1^3	x_2^3	...	x_s^3
$x_1^2 y_1$	$x_2^2 y_2$...	$x_s^2 y_s$
$x_1 y_1^2$	$x_2 y_2^2$...	$x_s y_s^2$
y_1^3	y_2^3	...	y_s^3
x_1^4	x_2^4	...	x_s^4
$x_1^3 y_1$	$x_2^3 y_2$...	$x_s^3 y_s$
$x_1^2 y_1^2$	$x_2^2 y_2^2$...	$x_s^2 y_s^2$
$x_1 y_1^3$	$x_2 y_2^3$...	$x_s y_s^3$
y_1^4	y_2^4	...	y_s^4
⋮	⋮	⋮	⋮

Shift property in monomial basis

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ x \\ y \\ x^2 \\ xy \\ y^2 \end{bmatrix} x = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ x \\ y \\ x^2 \\ xy \\ y^2 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ x \\ y \\ x^2 \\ xy \\ y^2 \end{bmatrix} y = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ x \\ y \\ x^2 \\ xy \\ y^2 \end{bmatrix}$$

- Finding the x -roots: let $D = \text{diag}(x_1, x_2, \dots, x_s)$, then

$$S_1 K D = S_2 K,$$

where S_1 and S_2 select rows from K wrt. shift property

- Reminiscent of **Realization Theory**

Nullspace of M

Find a basis for the nullspace of M using an SVD:

$$M = \begin{bmatrix} \times & \times & \times & \times & 0 & 0 & 0 \\ 0 & \times & \times & \times & \times & 0 & 0 \\ 0 & 0 & \times & \times & \times & \times & 0 \\ 0 & 0 & 0 & \times & \times & \times & \times \end{bmatrix} = [X \quad Y] \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} W^T \\ Z^T \end{bmatrix}$$

Hence,

$$MZ = 0$$

We have

$$S_1 K D = S_2 K$$

However, K is not known, instead a basis Z is computed as

$$ZV = K$$

Which leads to

$$(S_2 Z)V = (S_1 Z)VD$$

Algorithm

- 1 Fix a monomial ordering scheme
- 2 Construct coefficient matrix M
- 3 Compute basis for nullspace of M , Z
- 4 Find s linear independent rows in Z
- 5 Choose shift function, e.g., x
- 6 Write down shift relation in monomial basis k for the chosen shift function using row selection matrices S_1 and S_2
- 7 The construction of above gives rise to a generalized eigenvalue problem

$$(S_2 Z)V = (S_1 Z)VD$$

of which the eigenvalues correspond to the, e.g., x -solutions of the system of polynomial equations.

- 8 Reconstruct canonical kernel $K = ZV$

Data-Driven root-finding

- Dual version of Kernel-based root-finding
- All operations are done on coefficient matrix M
 - Find linear dependent columns of M instead of linear independent rows of K (corank)
 - Write down eigenvalue problem in terms of partitioning of M
 - Allows sparse representation of M
 - Rank-revealing QR instead of SVD

$$\begin{cases} p(x, y) = x^2 + 3y^2 - 15 = 0 \\ q(x, y) = y - 3x^3 - 2x^2 + 13x - 2 = 0 \end{cases}$$

Finding linear dependent columns of M

	1	x	y	x^2	xy	y^2	x^3	x^2y	xy^2	y^3	...
p	-15			1			3				
xp		-15					1		3		
yp			-15					1		3	
q	-2	13	1	-2			-3				
x^2p				-15							
xy^2p					-15						
y^2p						-15					
xq		-2		13	1		-2				
yq			-2		13	1		-2			
x^3p							-15				
x^2yp								-15			
xy^3p									-15		
y^3p										-15	
x^2q				-2			13	1			
xyq					-2			13	1		
y^2q						-2			13	1	
⋮											⋮

$$\begin{cases} p(x, y) = x^2 + 3y^2 - 15 = 0 \\ q(x, y) = y - 3x^3 - 2x^2 + 13x - 2 = 0 \end{cases}$$

- Writing down the eigenvalue problem in terms of a **re-ordered** partitioning of M
- all linear dependent columns of M corresponding with monomials of the lowest possible degree are grouped in M_1

$$M = \begin{bmatrix} \times & \times & \times & \times & 0 & 0 & 0 \\ 0 & \times & \times & \times & \times & 0 & 0 \\ 0 & 0 & \times & \times & \times & \times & 0 \\ 0 & 0 & 0 & \times & \times & \times & \times \end{bmatrix} = [M_1 \ M_2]$$

$$[M_1 \ M_2] \begin{bmatrix} K_1 \\ K_2 \end{bmatrix} = 0$$

$$K_2 = -M_2^\dagger M_1 K_1$$

(\dagger : Moore-Penrose pseudoinverse)

$$\begin{cases} p(x, y) = x^2 + 3y^2 - 15 = 0 \\ q(x, y) = y - 3x^3 - 2x^2 + 13x - 2 = 0 \end{cases}$$

Writing down the eigenvalue problem in terms of a partitioning of M

$$K_1 \begin{bmatrix} x_1 & & 0 \\ & \ddots & \\ 0 & & x_s \end{bmatrix} = S_x \begin{bmatrix} K_1 \\ K_2 \end{bmatrix}$$

$$K_1 \begin{bmatrix} x_1 & & 0 \\ & \ddots & \\ 0 & & x_s \end{bmatrix} = S_x \begin{bmatrix} I_{tcr} \\ -M_2^\dagger M_1 \end{bmatrix} K_1$$

There are 3 kinds of roots:

- ① Roots in zero
- ② Finite nonzero roots
- ③ Roots at infinity

Applying Grassmann's Dimension theorem on the Kernel allows to write the following partitioning

$$[M_1 \ M_2] \begin{bmatrix} X_1 & 0 & X_2 \\ 0 & Y_1 & Y_2 \end{bmatrix} = 0$$

- X_1 corresponds with the roots in zero (multiplicities included!)
- Y_1 corresponds with the roots at infinity (multiplicities included!)
- $[X_2; Y_2]$ corresponds with the finite nonzero roots (multiplicities included!)

Roots at infinity: univariate case

$$0x^2 + x - 2 = 0$$

transform $x \rightarrow \frac{1}{X}$

$$\Rightarrow X(1 - 2X) = 0$$

- 1 affine root $x = 2$ ($X = \frac{1}{2}$)
- 1 root at infinity $x = \infty$ ($X = 0$)

Roots at infinity: multivariate case

$$\begin{cases} (x-2)y = 0 \\ y-3 = 0 \end{cases}$$

transform $x \rightarrow \frac{X}{T}$, $y \rightarrow \frac{Y}{T}$

$$\Rightarrow \begin{cases} XY - 2YT = 0 \\ Y - 3T = 0 \end{cases}$$

- 1 affine root (2,3,1) ($T = 1$)
- 1 root at infinity (1,0,0) ($T = 0$)

General Canonical null space K

- Multiplicities of roots \rightarrow multiplicity structure of kernel K
- Partial derivatives

$$\partial_{j_1 j_2 \dots j_s} \equiv \partial_{x_1^{j_1} x_2^{j_2} \dots x_s^{j_s}} \equiv \frac{1}{j_1! j_2! \dots j_s!} \frac{\partial^{j_1 + j_2 + \dots + j_s}}{\partial x_1^{j_1} \partial x_2^{j_2} \dots \partial x_s^{j_s}}$$

needed to describe extra columns of K

- Currently investigating technicalities
- Possibility of trading in multiplicities for extra equations (Radical Ideal)

Univariate case

$$f(x) = (x - 1)^3 = 0$$

triple root in $x = 1$: $f'(1) = 0$ and $f''(1) = 0$

$$f \begin{bmatrix} 1 & 3 & -3 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ x & 1 & 0 \\ x^2 & 2x & 1 \\ x^3 & 3x^2 & 3x \end{bmatrix} = 0$$

or

$$\begin{bmatrix} \partial_0 f \\ \partial_1 f \\ \partial_2 f \end{bmatrix} \begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -6 & 3 & 0 \\ -3 & 3 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ x \\ x^2 \\ x^3 \end{bmatrix} = 0$$

Multivariate case

- Polynomial system in 2 unknowns (x, y) with
 - 1 affine root $z_1 = (x_1, y_1)$ with multiplicity 3:
 $[\partial_{00}|_{z_1} \quad \partial_{10}|_{z_1} \quad \partial_{01}|_{z_1}]$
 - 1 root $z_2 = (x_2, y_2)$ at infinity: $\partial_{00}|_{z_2}$
 - M matrix of degree 4

Canonical Kernel K

$$K = \begin{matrix} & \partial_{00}|_{z_1} & \partial_{10}|_{z_1} & \partial_{01}|_{z_1} & \partial_{00}|_{z_2} \\ \left(\begin{array}{cccc} 1 & 0 & 0 & 0 \\ x_1 & 1 & 0 & 0 \\ y_1 & 0 & 1 & 0 \\ x_1^2 & 2x_1 & 0 & 0 \\ x_1y_1 & y_1 & x_1 & 0 \\ y_1^2 & 0 & 2y_1 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^4 & 4x_1 & 0 & 0 \\ x_1^3y_1 & 3x_1^2y_1 & x_1^3 & 1 \\ x_1^2y_1^2 & 2x_1y_1^2 & 2x_1^2y_1 & 0 \\ x_1y_1^3 & y_1^3 & 3x_1y_1^2 & 0 \\ y_1^4 & 0 & 4y_1^3 & 0 \end{array} \right) \end{matrix}$$

Polynomial Optimization Problems

If

$$A_1 b = x b$$

and

$$A_2 b = y b$$

then

$$(A_1^2 + A_2^2) b = (x^2 + y^2) b.$$

(choose any polynomial objective function as an eigenvalue!)

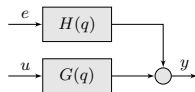
Polynomial optimization problems with a polynomial objective function and polynomial constraints can always be written as eigenvalue problems where we search for the minimal eigenvalue!

→ 'Convexification' of polynomial optimization problems

Outline

- 1 Introduction
- 2 History
- 3 Linear Algebra
- 4 Multivariate Polynomials
- 5 Applications**
- 6 Conclusions

- PEM System identification
- Measured data $\{u_k, y_k\}_{k=1}^N$
- Model structure



$$y_k = G(q)u_k + H(q)e_k$$

- Output prediction

$$\hat{y}_k = H^{-1}(q)G(q)u_k + (1 - H^{-1})y_k$$

- Model classes: ARX, ARMAX, OE, BJ

$$A(q)y_k = B(q)/F(q)u_k + C(q)/D(q)e_k$$

Class	Polynomials
ARX	$A(q), B(q)$
ARMAX	$A(q), B(q), C(q)$
OE	$B(q), F(q)$
BJ	$B(q), C(q), D(q), F(q)$

- Minimize the prediction errors $y - \hat{y}$, where

$$\hat{y}_k = H^{-1}(q)G(q)u_k + (1 - H^{-1})y_k,$$

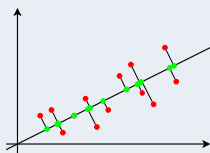
subject to the model equations

- Example

ARMAX identification: $G(q) = B(q)/A(q)$ and $H(q) = C(q)/A(q)$, where
 $A(q) = 1 + aq^{-1}$, $B(q) = bq^{-1}$, $C(q) = 1 + cq^{-1}$, $N = 5$

$$\begin{aligned} \min_{\hat{y}, a, b, c} \quad & (y_1 - \hat{y}_1)^2 + \dots + (y_5 - \hat{y}_5)^2 \\ \text{s. t.} \quad & \hat{y}_5 - c\hat{y}_4 - bu_4 - (c - a)y_4 = 0, \\ & \hat{y}_4 - c\hat{y}_3 - bu_3 - (c - a)y_3 = 0, \\ & \hat{y}_3 - c\hat{y}_2 - bu_2 - (c - a)y_2 = 0, \\ & \hat{y}_2 - c\hat{y}_1 - bu_1 - (c - a)y_1 = 0, \end{aligned}$$

Static Linear Modeling



- Rank deficiency
- minimization problem:

$$\begin{aligned} \min \quad & \| [\Delta A \quad \Delta b] \|_F^2, \\ \text{s. t.} \quad & (A + \Delta A)v = b + \Delta b, \\ & v^T v = 1 \end{aligned}$$

- Singular Value Decomposition:
find (u, σ, v) which minimizes σ^2
Let $M = [A \quad b]$

$$\begin{cases} Mv = u\sigma \\ M^T u = v\sigma \\ v^T v = 1 \\ u^T u = 1 \end{cases}$$

Dynamical Linear Modeling



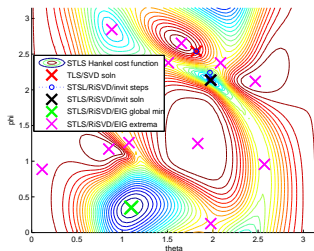
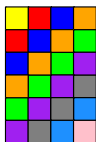
- Rank deficiency
- minimization problem:

$$\begin{aligned} \min \quad & \| [\Delta A \quad \Delta b] \|_F^2, \\ \text{s. t.} \quad & (A + \Delta A)v = b + \Delta b, \\ & v^T v = 1 \\ & [\Delta A \quad \Delta b] \text{ structured} \end{aligned}$$

- Riemannian SVD:
find (u, τ, v) which minimizes τ^2

$$\begin{cases} Mv = D_v u \tau \\ M^T u = D_u v \tau \\ v^T v = 1 \\ u^T D_v u = 1 (= v^T D_u v) \end{cases}$$

$$\begin{aligned} \min_v \quad & \tau^2 = v^T M^T D_v^{-1} M v \\ \text{s. t.} \quad & v^T v = 1. \end{aligned}$$



method	TLS/SVD	STLS inv. it.	STLS eig
v_1	.8003	.4922	.8372
v_2	-.5479	-.7757	.3053
v_3	.2434	.3948	.4535
τ^2	4.8438	3.0518	2.3822
global solution?	no	no	yes

CpG Islands

- genomic regions that contain a high frequency of sites where a cytosine (C) base is followed by a guanine (G)
- rare because of methylation of the C base
- hence CpG islands indicate functionality

Given observed sequence of DNA:

CTCACGTGATGAGAGCATTCTCAGA
CCGTGACGCGTGTAGCAGCGGCTCA

Problem

Decide whether the observed sequence came from a CpG island

The model

- 4-dimensional state space $[m] = \{A, C, G, T\}$
- Mixture model of 3 distributions on $[m]$
 - ① : CG rich DNA
 - ② : CG poor DNA
 - ③ : CG neutral DNA
- Each distribution is characterised by probabilities of observing base A,C,G or T

Table: Probabilities for each of the distributions (Durbin; Pachter & Sturmfels)

DNA Type	A	C	G	T
CG rich	0.15	0.33	0.36	0.16
CG poor	0.27	0.24	0.23	0.26
CG neutral	0.25	0.25	0.25	0.25

- The probabilities of observing each of the bases A to T are given by

$$p(A) = -0.10 \theta_1 + 0.02 \theta_2 + 0.25$$

$$p(C) = +0.08 \theta_1 - 0.01 \theta_2 + 0.25$$

$$p(G) = +0.11 \theta_1 - 0.02 \theta_2 + 0.25$$

$$p(T) = -0.09 \theta_1 + 0.01 \theta_2 + 0.25$$

- θ_i is probability to sample from distribution i ($\theta_1 + \theta_2 + \theta_3 = 1$)
- Maximum Likelihood Estimate:

$$(\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3) = \arg \max_{\theta} l(\theta)$$

where the log-likelihood $l(\theta)$ is given by

$$l(\theta) = 11 \log p(A) + 14 \log p(C) + 15 \log p(G) + 10 \log p(T)$$

- Need to solve the following polynomial system

$$\begin{cases} \frac{\partial l(\theta)}{\partial \theta_1} = \sum_{i=1}^4 \frac{u_i}{p(i)} \frac{\partial p(i)}{\partial \theta_1} = 0 \\ \frac{\partial l(\theta)}{\partial \theta_2} = \sum_{i=1}^4 \frac{u_i}{p(i)} \frac{\partial p(i)}{\partial \theta_2} = 0 \end{cases}$$

Solving the Polynomial System

- $\text{corank}(M) = 9$
- Reconstructed Kernel

$$K = \begin{bmatrix} 1 & 1 & 1 & 1 & \dots \\ 0.52 & 3.12 & -5.00 & 10.72 & \dots \\ 0.22 & 3.12 & -15.01 & 71.51 & \dots \\ 0.27 & 9.76 & 25.02 & 115.03 & \dots \\ 0.11 & 9.76 & 75.08 & 766.98 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \begin{matrix} 1 \\ \theta_1 \\ \theta_2 \\ \theta_1^2 \\ \theta_1\theta_2 \\ \vdots \end{matrix}.$$

- θ_i 's are probabilities: $0 \leq \theta_i \leq 1$
- Could have introduced slack variables to impose this constraint!
- Only solution that satisfies this constraint is $\hat{\theta} = (0.52, 0.22, 0.26)$

Applications are found in

- Polynomial Optimization Problems
- Structured Total Least Squares
- Model order reduction
- Analyzing identifiability nonlinear model structures
- Robotics: kinematic problems
- Computational Biology: conformation of molecules
- Algebraic Statistics
- Signal Processing
- ...

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- Finding roots of multivariate polynomials is linear algebra and realization theory!
- Finding minimizing zero of a polynomial optimization problem is extremal eigenvalue problem
- (Numerical) linear algebra/systems theory version of results in algebraic geometry/symbolic algebra (Gröbner bases, resultants, rings, ideals, varieties, ...)
- These relations in principle 'convexify'/linearize many problems
 - Algebraic geometry
 - System identification (PEM)
 - Numerical linear algebra (STLS, affine EVP $Ax = x\lambda + a$, etc.)
 - Multilinear algebra (tensor least squares approximation problems)
 - Algebraic statistics (HMM, Bayesian networks, discrete probabilities)
 - Differential algebra (Glad/Ljung)
- Convexification occurs by projecting up to higher dimensional vector space (difficult in low number of dimensions; 'easy' in high number of dimensions: an eigenvalue problem)
- Many challenges remain:
 - Efficient construction of the eigenvalue problem - exploiting sparseness and structure
 - Algorithms to find the minimizing solution directly (inverse power method)
 - ...

Questions?



Bart De Moor
(1960-...)



Kim Batselier
(1981-...)



Philippe Dreesen
(1982-...)

“At the end of the day,
the only thing we really understand,
is linear algebra”.