

Back to the Roots

Polynomial System Solving Using Linear Algebra

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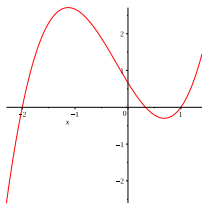
Stadius Center for Dynamical Systems, Signal Processing and Data Analytics

Outline

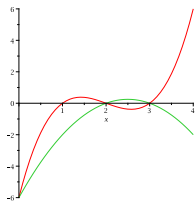
- 1 Motivation and History
- 2 Univariate Polynomials
- 3 Multivariate Polynomials
- 4 Algebraic Optimization
- 5 Conclusions

Four instances of polynomial root-finding problems

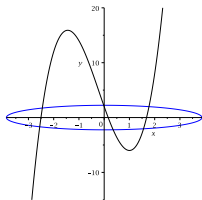
$$(x - 1)(x + 2) \left(x - \frac{1}{3}\right) = 0$$



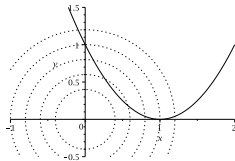
$$\begin{aligned}(x - 1)(x - 3)(x - 2) &= 0 \\ -(x - 2)(x - 3) &= 0\end{aligned}$$



$$\begin{aligned}x^2 + 3y^2 - 15 &= 0 \\ y - 3x^3 - 2x^2 + 13x - 2 &= 0\end{aligned}$$



$$\begin{aligned}\min_{x,y} \quad & x^2 + y^2 \\ \text{s. t.} \quad & y - x^2 + 2x - 1 = 0\end{aligned}$$



Why Study Polynomial Equations?

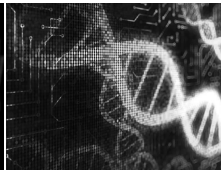
- fundamental mathematical objects
- powerful modelling tools
- ubiquitous in Science and Engineering (often *hidden*)



Systems and Control



Signal Processing



Computational Biology



Kinematics/Robotics

A long and rich history...



Egypt
(3000BCE-300BCE)



Babylon
(3000BCE-539BCE)



Euclid
(fl. 300BCE)

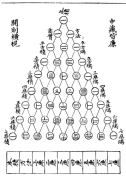


Diophantus
(c200-c284)



Al-Khwarizmi
(c780-c850)

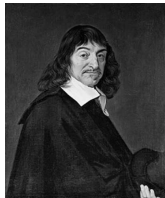
古法七乘方圖



Zhu Shijie
(c1260-c1320)



Pierre de Fermat
(c1601-1665)



René Descartes
(1596-1650)



Isaac Newton
(1643-1727)



Gottfried Leibniz
(1646-1716)

...leading to "Algebraic Geometry"



Etienne Bézout
(1730-1783)



Carl Friedrich Gauss
(1777-1755)



Jean-Victor Poncelet
(1788-1867)



Evariste Galois
(1811-1832)



Arthur Cayley
(1821-1895)



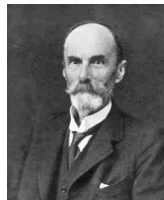
Leopold Kronecker
(1823-1891)



Edmond Laguerre
(1834-1886)



James J. Sylvester
(1814-1897)



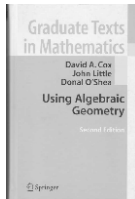
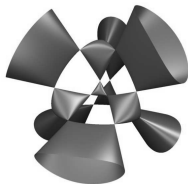
Francis S. Macaulay
(1862-1937)



David Hilbert
(1862-1943)

Algebraic Geometry and Computer Algebra

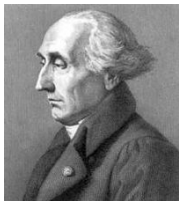
- large body of literature
- emphasis not (anymore) on *solving* equations
- computer algebra: symbolic manipulations (e.g., Gröbner Bases)
- numerical issues!



Wolfgang Gröbner
(1899-1980)



Bruno Buchberger



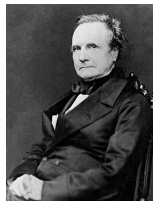
Joseph-Louis Lagrange
(1736-1813)



Augustin-Louis Cauchy
(1789-1857)



Hermann Grassmann
(1809-1877)



Charles Babbage
(1791-1871)



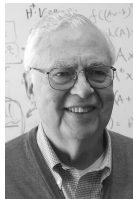
Ada Lovelace
(1815-1852)



Alan Turing
(1912-1954)



John von Neumann
(1903-1957)



Gene Golub
(1932-2007)



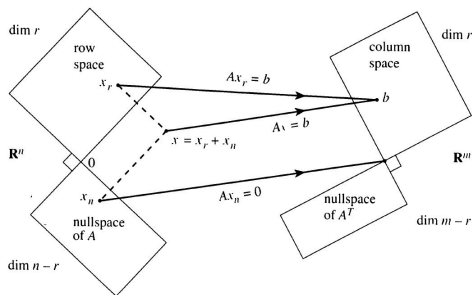
Daniel Lazard



Hans J. Stetter

Why Linear Algebra?

- comprehensible and accessible language
- intuitive geometric interpretation
- computationally powerful framework
- well-established methods and stable numerics



Eigenvalue Problems

Eigenvalue equation

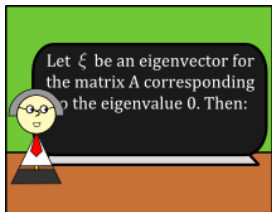
$$Av = \lambda v$$

and eigenvalue decomposition

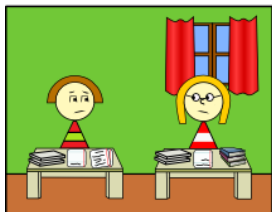
$$A = V\Lambda V^{-1}$$

Enormous importance in (numerical) linear algebra and apps

- ‘understand’ the action of matrix A
- at the heart of a multitude of applications: oscillations, vibrations, quantum mechanics, data analytics, graph theory, and **many** more



Let ξ be a
the matrix



Let ~~xi~~ be

spikedmath.com
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- 2 Univariate Polynomials**
- 3 Multivariate Polynomials
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Univariate Polynomials and Linear Algebra: Known Facts

Characteristic Polynomial

The eigenvalues of A are the roots of

$$p(\lambda) = |A - \lambda I|$$

Companion Matrix

Solving

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

leads to

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

Sylvester Matrix

Consider two polynomial equations

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

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

Common roots if $|S(f, g)| = 0$

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



James Joseph Sylvester

Sylvester's construction can be understood from

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

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

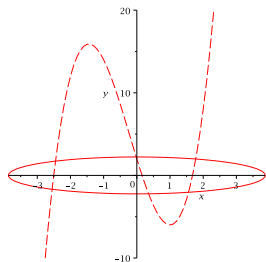
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Consider the system

$$p(x, y) = x^2 + 3y^2 - 15 = 0$$

$$q(x, y) = y - 3x^3 - 2x^2 + 13x - 2 = 0$$



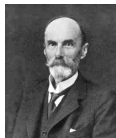
Matrix representation of the system: Macaulay matrix M

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

Null space based Root-finding

$$p(x, y) = x^2 + 3y^2 - 15 = 0$$

$$q(x, y) = y - 3x^3 - 2x^2 + 13x - 2 = 0$$



Continue to enlarge the Macaulay matrix M :

	1	x	y	x ²	xy	y ²	x ³	x ² y	xy ²	y ³	x ⁴	x ³ y	x ² y ²	xy ³	y ⁴	x ⁵	x ⁴ y	x ³ y ²	x ² y ³	xy ⁴	y ⁵	→	
$d = 3$	p	-15		1		3																	
	xp		-15				1		3														
	yp			-15				1		3													
	q	-2	13	1	-2		-3																
$d = 4$	x^2p				-15						1		3										
	xy^2p					-15						1		3									
	y^2p						-15						1		3								
	xq		-2		13	1	-2				-3												
	yq			-2		13	1					-3											
$d = 5$	x^3p						-15									1		3					
	x^2y^2p							-15									1		3				
	xy^3p								-15									1		3			
	y^3p									-15									1		3		
	x^2q			-2			13	1				-2				-3							
	xy^2q				-2			13	1				-2				-3						
	xyq					-2			13	1				-2				-3					
	y^2q						-2			13	1				-2				-3				

- Macaulay 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 null space

$$MK = 0$$

- number of solutions $m = \text{nullity}$

Multivariate Vandermonde basis for the null space:

1	1	...	1
x_1	x_2	...	x_m
y_1	y_2	...	y_m
x_1^2	x_2^2	...	x_m^2
$x_1 y_1$	$x_2 y_2$...	$x_m y_m$
y_1^2	y_2^2	...	y_m^2
x_1^3	x_2^3	...	x_m^3
$x_1^2 y_1$	$x_2^2 y_2$...	$x_m^2 y_m$
$x_1 y_1^2$	$x_2 y_2^2$...	$x_m y_m^2$
y_1^3	y_2^3	...	y_m^3
x_1^4	x_2^4	...	x_m^4
$x_1^3 y_1$	$x_2^3 y_2$...	$x_m^3 y_m$
$x_1^2 y_1^2$	$x_2^2 y_2^2$...	$x_m^2 y_m^2$
$x_1 y_1^3$	$x_2 y_2^3$...	$x_m y_m^3$
y_1^4	y_2^4	...	y_m^4
⋮	⋮	⋮	⋮

Select the 'top' m linear independent rows of K

$$S_1 K$$

1	1	...	1
x_1	x_2	...	x_m
y_1	y_2	...	y_m
x_1^2	x_2^2	...	x_m^2
$x_1 y_1$	$x_2 y_2$...	$x_m y_m$
y_1^2	y_2^2	...	y_m^2
x_1^3	x_2^3	...	x_m^3
$x_1^2 y_1$	$x_2^2 y_2$...	$x_m^2 y_m$
$x_1 y_1^2$	$x_2 y_2^2$...	$x_m y_m^2$
y_1^3	y_2^3	...	y_m^3
x_1^4	x_2^4	...	x_m^4
$x_1^3 y_1$	$x_2^3 y_2$...	$x_m^3 y_m$
$x_1^2 y_1^2$	$x_2^2 y_2^2$...	$x_m^2 y_m^2$
$x_1 y_1^3$	$x_2 y_2^3$...	$x_m y_m^3$
y_1^4	y_2^4	...	y_m^4
⋮	⋮	⋮	⋮

Shifting the selected rows gives (shown for 3 columns)

$$\begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline x_1 & x_2 & x_3 \\ y_1 & y_2 & y_3 \\ \hline x_1^2 & x_2^2 & x_3^2 \\ x_1 y_1 & x_2 y_2 & x_3 y_3 \\ y_1^2 & y_2^2 & y_3^2 \\ \hline x_1^3 & x_2^3 & x_3^3 \\ x_1^2 y_1 & x_2^2 y_2 & x_3^2 y_3 \\ x_1 y_1^2 & x_2 y_2^2 & x_3 y_3^2 \\ y_1^3 & y_2^3 & y_3^3 \\ \hline x_1^4 & x_2^4 & x_3^4 \\ x_1^3 y_1 & x_2^3 y_2 & x_3^3 y_3 \\ x_1^2 y_1^2 & x_2^2 y_2^2 & x_3^2 y_3^2 \\ x_1 y_1^3 & x_2 y_2^3 & x_3 y_3^3 \\ x_1 y_1^2 & x_2 y_2^2 & x_3 y_3^2 \\ y_1^4 & y_2^4 & y_3^4 \\ \hline \vdots & \vdots & \vdots \\ \hline \end{array} \rightarrow \text{"shift with } x" \rightarrow \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline x_1 & x_2 & x_3 \\ y_1 & y_2 & y_3 \\ \hline x_1^2 & x_2^2 & x_3^2 \\ x_1 y_1 & x_2 y_2 & x_3 y_3 \\ y_1^2 & y_2^2 & y_3^2 \\ \hline x_1^3 & x_2^3 & x_3^3 \\ x_1^2 y_1 & x_2^2 y_2 & x_3^2 y_3 \\ x_1 y_1^2 & x_2 y_2^2 & x_3 y_3^2 \\ y_1^3 & y_2^3 & y_3^3 \\ \hline x_1^4 & x_2^4 & x_3^4 \\ x_1^3 y_1 & x_2^3 y_2 & x_3^3 y_3 \\ x_1^2 y_1^2 & x_2^2 y_2^2 & x_3^2 y_3^2 \\ x_1 y_1^3 & x_2 y_2^3 & x_3 y_3^3 \\ x_1 y_1^2 & x_2 y_2^2 & x_3 y_3^2 \\ y_1^4 & y_2^4 & y_3^4 \\ \hline \vdots & \vdots & \vdots \\ \hline \end{array}$$

simplified:

$$\begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline x_1 & x_2 & x_3 \\ y_1 & y_2 & y_3 \\ \hline x_1 y_1 & x_2 y_2 & x_3 y_3 \\ x_1^2 & x_2^2 & x_3^2 \\ x_1 y_1 & x_2 y_2 & x_3 y_3 \\ \hline \end{array} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{array}{|c|c|c|} \hline x_1 & x_2 & x_3 \\ x_1^2 & x_2^2 & x_3^2 \\ x_1 y_1 & x_2 y_2 & x_3 y_3 \\ x_1^2 y_1 & x_2^2 y_2 & x_3^2 y_3 \\ x_1^4 & x_2^4 & x_3^4 \\ x_1 & x_2 & x_3 \\ x_1 y_1 & x_2 y_2 & x_3 y_3 \\ \hline \end{array}$$

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

$$S_1 K D_x = S_x K,$$

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

- reminiscent of **Realization Theory**

We have

$$S_1 K D_x = S_x K$$

However, K is not known, instead a basis Z is computed that satisfies

$$ZV = K$$

Which leads to

$$(S_x Z)V = (S_1 Z)V D_x$$

It is possible to shift with y as well. . .

We find

$$S_1 K D_y = S_y K$$

with D_y diagonal matrix of y -components of roots, leading to

$$(S_y Z) V = (S_1 Z) V D_y$$

Some interesting results:

- same eigenvectors V !
- $(S_3 Z)^{-1}(S_1 Z)$ and $(S_2 Z)^{-1}(S_1 Z)$ commute

The null space of the Macaulay matrix is the interface between polynomial system and n D state space description

- Attasi model (for $n = 2$)

$$v(k+1, l) = A_x v(k, l)$$

$$v(k, l+1) = A_y v(k, l)$$

- null space of Macaulay matrix: n D state sequence

$$\left(\begin{array}{c|c|c|c|c|c|c|c|c|c|c} | & | & | & | & | & | & | & | & | & | & | \\ v_{00} & v_{10} & v_{01} & v_{20} & v_{11} & v_{02} & v_{30} & v_{21} & v_{12} & v_{03} & \\ | & | & | & | & | & | & | & | & | & | & | \end{array} \right)^T =$$

$$\left(\begin{array}{c|c|c|c|c|c|c|c} | & | & | & \cdots & | & | & | & | \\ v_{00} & A_x v_{00} & A_y v_{00} & \cdots & A_x^3 v_{00} & A_x^2 A_y v_{00} & A_x A_y^2 v_{00} & A_y^3 v_{00} \\ | & | & | & | & | & | & | & | \end{array} \right)^T$$

- shift-invariance property, e.g., for y :

$$\begin{pmatrix} -v_{00} - \\ -v_{10} - \\ -v_{01} - \\ -v_{20} - \\ -v_{11} - \\ -v_{02} - \end{pmatrix} A_y^T = \begin{pmatrix} -v_{01} - \\ -v_{11} - \\ -v_{02} - \\ -v_{21} - \\ -v_{12} - \\ -v_{03} - \end{pmatrix},$$

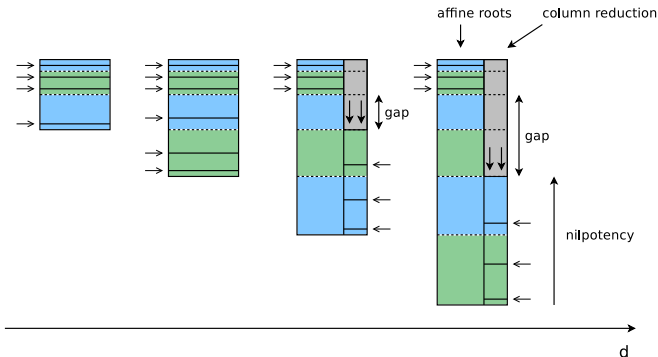
- corresponding n D system realization

$$\begin{aligned} v(k+1, l) &= A_x v(k, l) \\ v(k, l+1) &= A_y v(k, l) \\ v(0, 0) &= v_{00} \end{aligned}$$

- choice of basis null space leads to different system realizations
- eigenvalues of A_x and A_y invariant: x and y components of roots

Mind the Gap!

- dynamics in the null space of $M(d)$ for increasing degree d
- nilpotency gives rise to a ‘gap’
- mechanism to count and separate affine from infinity



Roots at Infinity: nD Descriptor Systems

Weierstrass Canonical Form decouples affine/infinity

$$\begin{bmatrix} \frac{v(k+1)}{w(k-1)} \end{bmatrix} = \begin{bmatrix} A & 0 \\ 0 & E \end{bmatrix} \begin{bmatrix} \frac{v(k)}{w(k)} \end{bmatrix}$$

Singular nD Attasi model (for $n = 2$)

$$v(k+1, l) = A_x v(k, l)$$

$$v(k, l+1) = A_y v(k, l)$$

$$w(k-1, l) = E_x w(k, l)$$

$$w(k, l-1) = E_y w(k, l)$$

with E_x and E_y nilpotent matrices.

Two extensions of the root-finding method:

Column-space based root-finding method

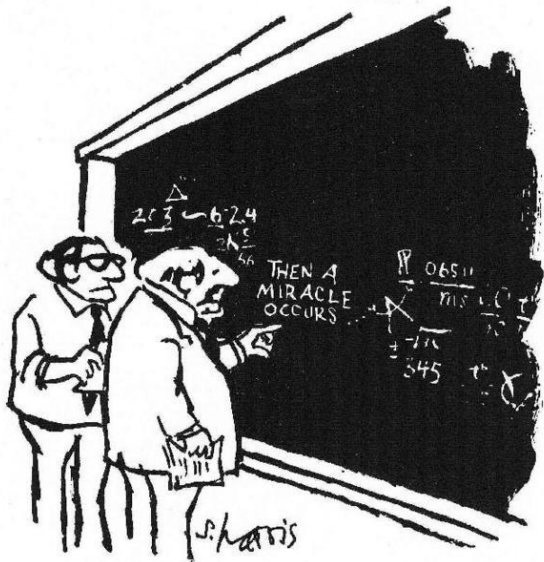
- dual method operating on column space instead of null space
- leads again to eigenvalue problems
- employs (Q)R-decomposition

Finding approximate solutions of over-constrained systems

- generalization to over-constrained (noisy) systems
- approximate solutions detectable by computing SVD of M
- example from computer vision: camera pose determination

Summary

- solving multivariate polynomials
 - question in linear algebra
 - realization theory in null space of Macaulay matrix
 - nD autonomous (descriptor) Attasi model
- decisions made based upon (numerical) rank
 - # roots (nullity)
 - # affine roots (column reduction)
- mind the gap phenomenon: affine vs. infinity roots
- not discussed
 - multiplicity of roots
 - column-space based method
 - over-constrained systems



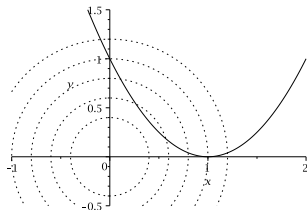
"I think you should be more explicit here in step two."

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Polynomial Optimization Problems

$$\begin{array}{ll} \min_{x,y} & x^2 + y^2 \\ \text{s. t.} & y - x^2 + 2x - 1 = 0 \end{array}$$



Lagrange multipliers give conditions for optimality:

$$L(x, y, z) = x^2 + y^2 + z(y - x^2 + 2x - 1)$$

we find

$$\partial L / \partial x = 0 \rightarrow 2x - 2xz + 2z = 0$$

$$\partial L / \partial y = 0 \rightarrow 2y + z = 0$$

$$\partial L / \partial z = 0 \rightarrow y - x^2 + 2x - 1 = 0$$

Observations:

- everything remains polynomial
- system of polynomial equations
- shift with objective function to find minimum/maximum

Let

$$A_x V = xV$$

and

$$A_y V = yV$$

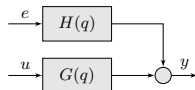
then find min/max eigenvalue of

$$(A_x^2 + A_y^2)V = (x^2 + y^2)V$$

Polynomial Optimization Problems: Applications

- PEM System identification = EVP !!
- 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

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

<i>Class</i>	<i>Polynomials</i>
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

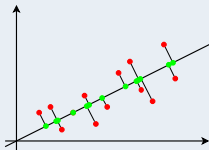
$$\hat{y}_k = H^{-1}(q)G(q)u_k + (1 - H^{-1})y_k,$$

subject to the model equations

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

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

Static Linear Modeling



- Rank deficiency
- minimization problem:

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

- 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



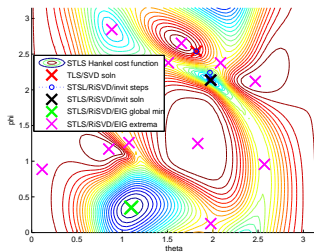
- Rank deficiency
- minimization problem:

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

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

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

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



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

Outline

- 1 Motivation and History
- 2 Univariate Polynomials
- 3 Multivariate Polynomials
- 4 Algebraic Optimization
- 5 Conclusions**

Conclusions

- bridging the gap between algebraic geometry and engineering
- finding roots: linear algebra and realization theory!
- extension to over-constrained systems
- polynomial optimization: extremal eigenvalue problems

Open Problems

Many challenges remain

- exploiting sparsity and structure of M
- efficient (more direct) construction of the eigenvalue problem
- algorithms to find the minimizing solution efficiently (inverse power method?)
- nD version of Cayley-Hamilton theorem
- analyzing the conditioning of the root-finding problem

Thank you for listening!