

# Numerical Linear Algebra Algorithms to Solve (Multivariate) Polynomial Systems

Minisymposium SIAM LA24

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# Numerical linear algebra meets algebraic geometry



# Numerical linear algebra meets algebraic geometry



`svd()`

`qr()` `eig()`

homotopy continuation  
& symbolic approaches

$$\begin{cases} p_1(x) = 0 \\ \vdots \\ p_s(x) = 0 \end{cases}$$

# Multivariate polynomials

A **multivariate polynomial**  $p(\mathbf{x})$ , or  $p(x_1, \dots, x_n)$ , in  $n$  variables is a finite linear combination of monomials  $\mathbf{x}^\alpha$  from  $K^n$  with coefficients  $c_\alpha$  from  $K$ :

$$p(\mathbf{x}) = \sum_{\mathcal{A}} c_\alpha \mathbf{x}^\alpha,$$

where the summation runs over all the exponents in the set  $\mathcal{A}$ .

- $K$  can be any field: complex numbers  $\mathbb{C}$ , real numbers  $\mathbb{R}$ , or finite numbers  $\mathbb{F}_q$
- $\alpha = (\alpha_1, \dots, \alpha_n)$  indexes the monomials  $\mathbf{x}^\alpha$  and coefficients  $c_\alpha$
- example:  $p(\mathbf{x}) = 3 + \sqrt{5}x_1 + (1 + i)x_2 + \frac{3}{2}x_1^2x_2^8$

# Multivariate polynomial systems

- Typically, multivariate polynomials appear in systems of equations:

$$\begin{cases} p_1(\mathbf{x}) = \sum_{\mathcal{A}^{(1)}} c_{\alpha}^{(1)} \mathbf{x}^{\alpha} = 0, \\ \vdots \\ p_s(\mathbf{x}) = \sum_{\mathcal{A}^{(s)}} c_{\alpha}^{(s)} \mathbf{x}^{\alpha} = 0. \end{cases}$$

- Every polynomial has a total degree:  $d_i = \max(|\alpha|)$ .

# Two limit cases

univariate polynomial

$$(n = 1)$$

$$p(x) = \sum_{i=0}^d c_i x^i$$

↓

$$C_p = \begin{bmatrix} 0 & 0 & \cdots & 0 & -c_0/c_n \\ 1 & 0 & \cdots & 0 & -c_1/c_n \\ 0 & 1 & \cdots & 0 & -c_2/c_n \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & -c_{n-1}/c_n \end{bmatrix}$$

$$C_p \mathbf{x} = \lambda \mathbf{x}$$

linear systems

$$(d_i = 1)$$

$$\begin{cases} p_1(\mathbf{x}) = b_1 + \sum_{j=1}^n a_{1j} x_j \\ \vdots \\ p_s(\mathbf{x}) = b_s + \sum_{j=1}^n a_{sj} x_j \end{cases}$$

↓

$$\mathbf{Ax} = \mathbf{b}$$

These are well-known problems from linear algebra!

## What does solving mean?

Find all the values for  $\mathbf{x} \in \bar{K}^n$  such that  $p_1(\mathbf{x}) = \cdots = p_s(\mathbf{x}) = 0$ , i.e., the variety of the polynomial system

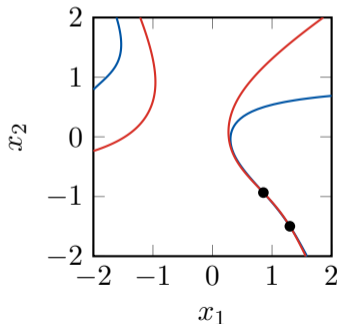
$$\mathcal{V}(p_1, \dots, p_s) = \{\mathbf{a} \in \bar{K}^n : p_i(\mathbf{a}) = 0, \forall i = 1, \dots, s\}$$

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- Typically, we consider polynomial systems which are well-determined! This can be for both square and rectangular systems.



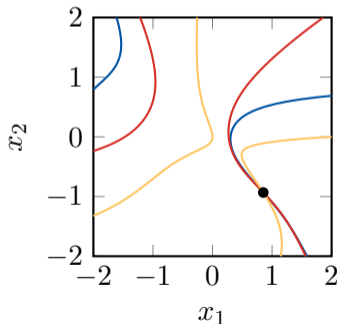


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- Some solution approaches can deal with over-determined and rectangular polynomial systems.

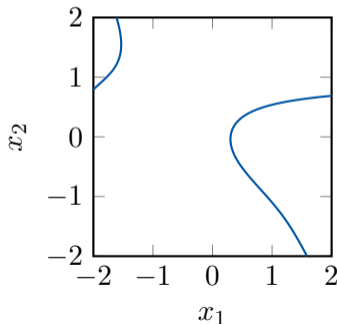


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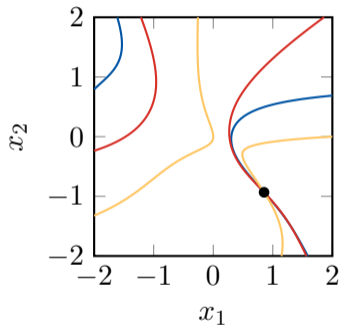
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- Typically, we consider polynomial systems which are well-determined! This can be for both square and rectangular systems.
- Some solution approaches can deal with over-determined and rectangular polynomial systems.
- Under-determined polynomial systems could be solved in a certain sense, but what does it mean?



# What does solving mean?

Everything depends on the ground field that you consider!



This polynomial system has 9 solutions in  $\mathbb{C}^2$ , 1 solution in  $\mathbb{R}^2$ , and 0 solutions in  $\mathbb{Q}^2$

Some examples:

- $\mathbb{C}$ : homotopy continuation, particle physics
- $\mathbb{R}$ : optimization, chemical reaction networks, robotics
- $\mathbb{Q}$ : discriminants/resultants, Grassmannians, number theory
- $\mathbb{F}_q$ : cryptography
- $\mathbb{C}\{\{t\}\}, \mathbb{Q}_p$ : tropical geometry

# Number of solutions?

- For univariate polynomials (i.e.,  $n = 1$ ), the **fundamental theorem of algebra** states that a degree  $d$  polynomial has  $d$  roots.
- The **theorem of Bézout** is the multivariate extension of that theorem.

For any square system (i.e.,  $s = n$ ) of multivariate polynomial equations  $p_1(\mathbf{x}), \dots, p_n(\mathbf{x})$ , the number of isolated solutions in the projective space  $\mathbb{P}^n$  when the solution set is zero-dimensional, i.e., the number of isolated points in the zero-dimensional variety  $\mathcal{V}(p_1(\mathbf{x}), \dots, p_n(\mathbf{x})) \subset \mathbb{P}^n$ , is exactly equal to

$$m_b = d_1 \cdots d_n = \prod_{i=1}^n d_i,$$

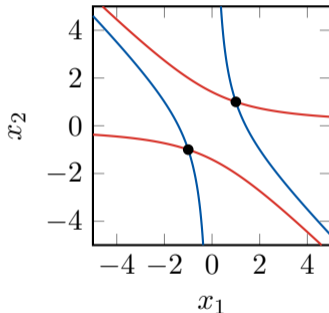
where  $d_i$  is the total degree of the polynomial  $p_i(\mathbf{x})$ .

# Number of solutions?

- The theorem of Bézout counts the number of isolated solutions in the projective space:

$$m_b = m_a + m_\infty$$

- For generic systems,  $m_b = m_a$ , but in practice this is not the case
- There exist more refined bounds on the number of affine solutions (e.g., Kushnirenko, BKK, etc.)



# Different solution approaches

When we consider an algebraically closed field, there are two main methods to solve systems of multivariate polynomial equations:

## normal form methods

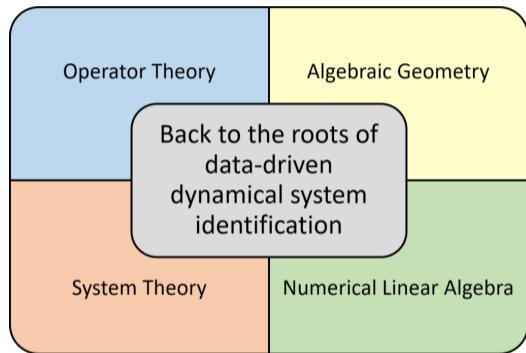
- reduce problem to a univariate problem
- (numerical) linear algebra
- any field  $K^n$
- rectangular systems:  $s \geq n$
- $m_b < \pm 10\,000$  solutions

## homotopy continuation methods

- continuously deform a system with known solutions
- ordinary differential equations
- field of complex numbers  $\mathbb{C}^n$
- square systems:  $s = n$
- $m_b < \pm 1\,000\,000$  solutions

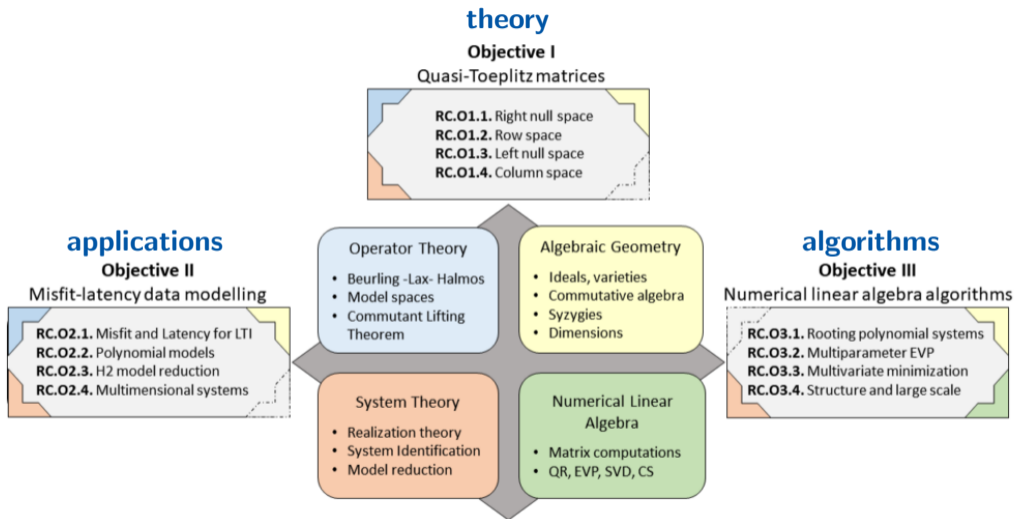
# “Back to the Roots” project

- **What:** Advanced ERC grant of prof. Bart De Moor
- **Goal:** find globally optimal models for LTI systems
- **Difficulty:** large, non-convex optimization problems
- **Approach:** go “back to the roots” of mathematical modeling!



<https://homes.esat.kuleuven.be/~sista/www/bdm/backtotheroots/>

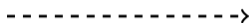
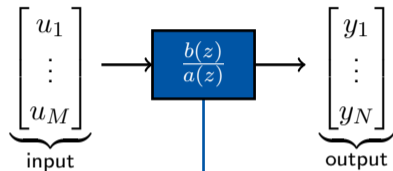
# “Back to the Roots” project





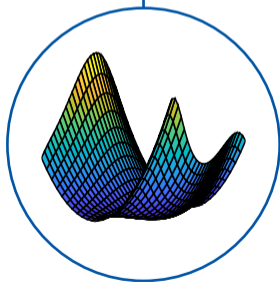
# A taste of this approach

identification problem



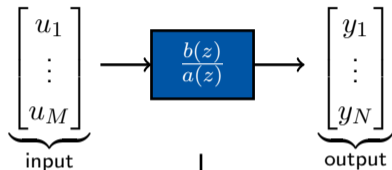
globally optimal model

$$\frac{\hat{b}_n z^n + \dots + \hat{b}_1 z + \hat{b}_0}{\hat{a}_n z^n + \dots + \hat{a}_1 z + \hat{a}_0}$$



# A taste of this approach

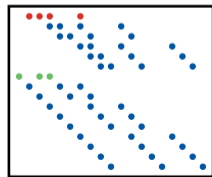
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$$\frac{\hat{b}_n z^n + \dots + \hat{b}_1 z + \hat{b}_0}{\hat{a}_n z^n + \dots + \hat{a}_1 z + \hat{a}_0}$$

$$\begin{cases} p_1(\mathbf{a}, \mathbf{b}) = 0 \\ \vdots \\ p_s(\mathbf{a}, \mathbf{b}) = 0 \end{cases}$$



$$\begin{cases} Q\Lambda_{a_1}Q^{-1} = A_{a_1} \\ \vdots \\ Q\Lambda_{b_n}Q^{-1} = A_{b_n} \end{cases}$$

multivariate polynomial system

quasi-Toeplitz matrix

eigenvalue problems

- Solving Equations Using Khovanskii Bases  
by **Barbara Betti**, Marta Panizzut, and Simon Telen  
15h45 - 16h05
- Block Krylov Methods from the Perspective of Orthogonal Matrix Polynomials  
by **Michele Rinelli**, Marc Van Barel, and Raf Vandebril  
16h10 - 16h30
- Solving Polynomial Systems Using Determinantal Formulas  
by **Matías Bender**  
16h35 - 16h55

- Direct Numerical Computation of Polynomial Multiplication Maps  
by **Lukas Vanpoucke** and Bart De Moor  
17h10 - 16h30
- Tensor Decomposition Using Numerical (Non)Linear Algebra  
by Fulvio Gesmundo, **Leonie Kayser**, and Simon Telen  
17h35 - 17h55
- Solving Applications from Systems Theory via Efficient Numerical Linear Algebra  
Root-Finding Algorithms  
by **Sibren Lagauw**, Christof Vermeersch, and Bart De Moor  
18h00 - 18h20

# A minisymposium filled with fascinating topics!

## theory

### Objective I

Quasi-Toeplitz matrices

- RC.O1.1. Right null space
- RC.O1.2. Row space
- RC.O1.3. Left null space
- RC.O1.4. Column space

Solving Equations Using  
Khovanskii Bases

Solving Polynomial  
Systems Using  
Determinantal Formulas

## applications

### Objective II

Misfit-latency data modelling

- RC.O2.1. Misfit and Latency for LTI
- RC.O2.2. Polynomial models
- RC.O2.3. H2 model reduction
- RC.O2.4. Multidimensional systems

Tensor Decomposition  
Using Numerical  
(Non)Linear Algebra

Solving Applications from  
Systems Theory via  
Efficient Numerical Linear  
Algebra Root-Finding  
Algorithms

## algorithms

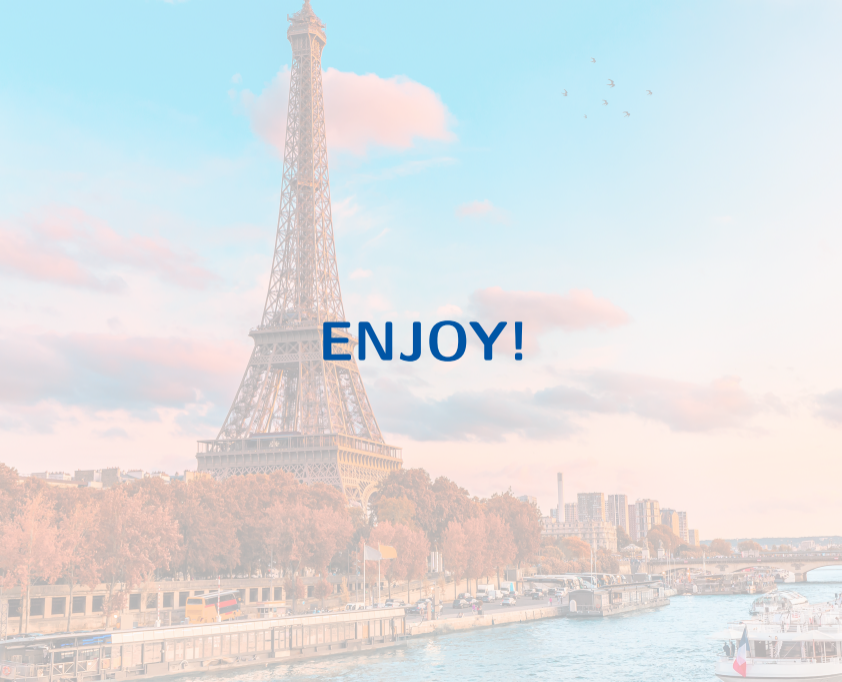
### Objective III

Numerical linear algebra algorithms

- RC.O3.1. Rooting polynomial systems
- RC.O3.2. Multiparameter EVP
- RC.O3.3. Multivariate minimization
- RC.O3.4. Structure and large scale

Block Krylov Methods  
from the Perspective of  
Orthogonal Matrix  
Polynomials

Direct Numerical  
Computation of  
Polynomial Multiplication  
Maps



**ENJOY!**



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