

About the Fundamental Subspaces of the Macaulay Matrix

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Introduction

A presentation about linear algebra in algebraic geometry

	map	→	matrix
	ideal	→	row space
normal set/standard monomials		→	linearly (in)dependent rows/columns
	Gröbner basis	→	set of rows
	Buchberger's algorithm	→	singular value decomposition
	roots	→	eigenvalues

Polynomials and Macaulay Matrix

We consider **polynomials** $p_i(\mathbf{x}) \in \mathcal{P}^n = \mathbb{C}[x_1, \dots, x_n]$, $\forall i = 1, \dots, s$,

$$p_i(\mathbf{x}) = \sum_{\{\alpha\}} c_{\alpha} \mathbf{x}^{\alpha}.$$

The **ideal** $\mathcal{I} \subset \mathcal{P}^n$ generated by these polynomials is defined by

$$\mathcal{I} = \langle p_1(\mathbf{x}), \dots, p_s(\mathbf{x}) \rangle = \left\{ \sum_{i=1}^s h_i(\mathbf{x}) p_i(\mathbf{x}) : h_i(\mathbf{x}) \in \mathbb{C}[x_1, \dots, x_n] \right\}.$$

Of course, an other important object is the **variety** of that ideal, i.e.,

$$\mathcal{V}(\mathcal{I}) = \{\mathbf{a} \in \mathbb{C}^n : p_i(\mathbf{a}) = 0, \forall i = 1, \dots, s\}.$$

Polynomials and Macaulay matrix

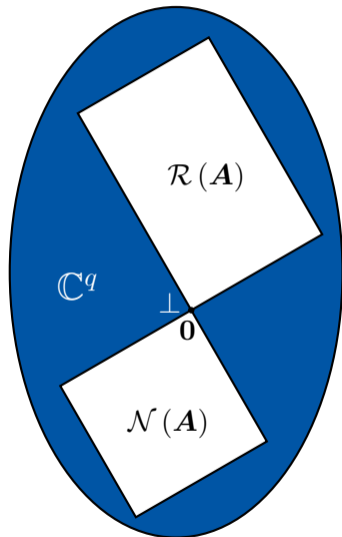
$$\begin{cases} p_1(\mathbf{x}) = -3x_2 + 6x_1x_2 + (-1)x_2^2 + 1x_1^2x_2 + (-3)x_1x_2^2 + 1x_2^3 = 0 \\ p_2(\mathbf{x}) = 1 + 2x_1 + (-2)x_2 + 1x_1^2 + (-2)x_1x_2 + 1x_2^2 = 0 \\ p_3(\mathbf{x}) = (-4)x_2 + 1x_2^2 = 0 \end{cases}$$

⇓

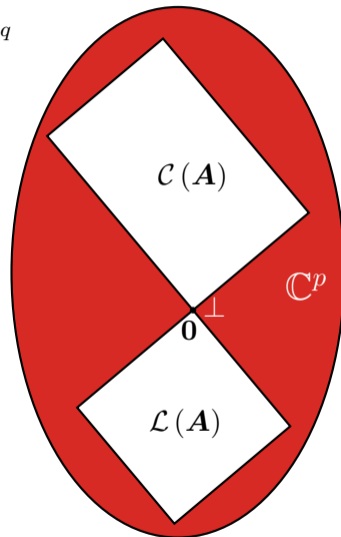
$$\begin{array}{l} p_1(\mathbf{x}) \\ p_2(\mathbf{x}) \\ x_1p_2(\mathbf{x}) \\ x_2p_2(\mathbf{x}) \\ p_3(\mathbf{x}) \\ x_1p_3(\mathbf{x}) \\ x_2p_3(\mathbf{x}) \end{array} \begin{bmatrix} 1 & x_1 & x_2 & x_1^2 & x_1x_2 & x_2^2 & x_1^3 & x_1^2x_2 & x_1x_2^2 & x_2^3 \\ 0 & 0 & -3 & 0 & 6 & -1 & 0 & 1 & -3 & 1 \\ 1 & 2 & -2 & 1 & -2 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 2 & -2 & 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & 0 & 2 & -2 & 0 & 1 & -2 & 1 \\ 0 & 0 & -4 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -4 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -4 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ x_1 \\ x_2 \\ x_1^2 \\ x_1x_2 \\ x_2^2 \\ x_1^3 \\ x_1^2x_2 \\ x_1x_2^2 \\ x_2^3 \end{bmatrix} = \mathbf{0}$$

Macaulay matrix M_3

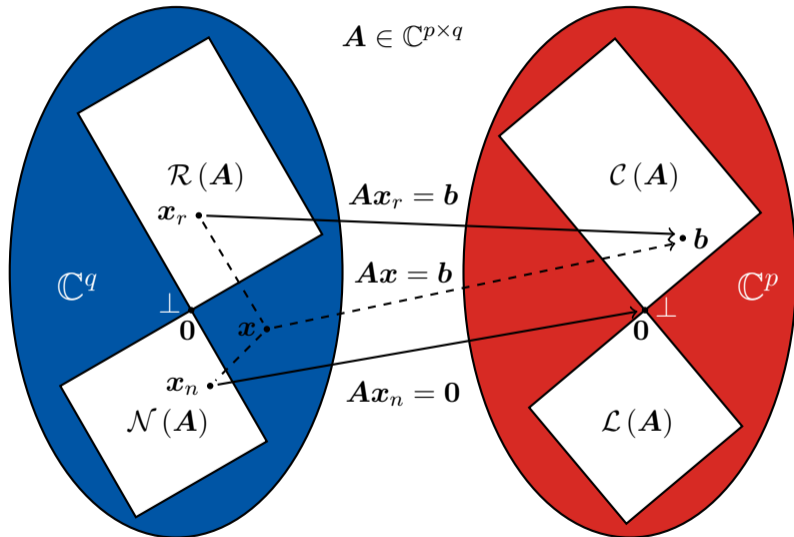
Fundamental subspaces of a matrix



$$A \in \mathbb{C}^{p \times q}$$



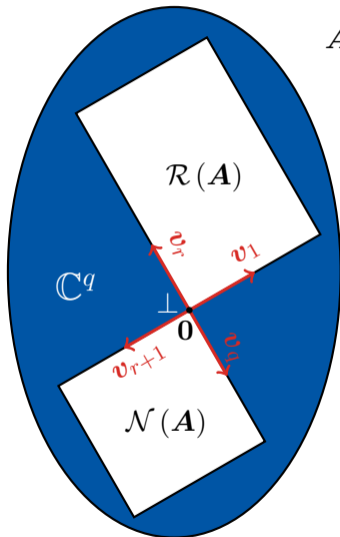
Fundamental subspaces of a matrix



Fundamental subspaces of a matrix

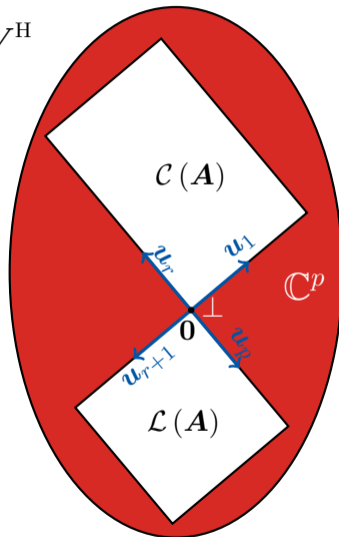
$$A = U\Sigma V^H$$

dim = r



dim = n

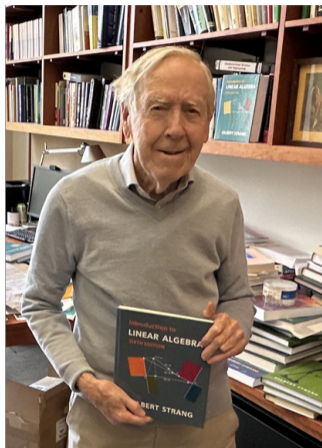
dim = c



dim = l

singular value decomposition as our “work horse”!

Two important theorems



Gilbert Strang poses with his “Introduction to Linear Algebra”.

The photo of Gilbert Strang was taken by Miller (2023).

Rank-nullity theorem

$$c = \dim(\mathcal{C}(\mathbf{A})) = \dim(\mathcal{R}(\mathbf{A})) = r$$

Fundamental theorem of linear algebra

$$\text{rank}(\mathbf{A}) + \text{nullity}(\mathbf{A}) = r + n = q$$

Outline

- 1 | Introduction
- 2 | Row Space
- 3 | Left Null Space
- 4 | Right Null Space
- 5 | Column space
- 6 | Conclusion

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Row space of the Macaulay matrix

What can we find in the row space?

$$\begin{array}{l} p_1(\mathbf{x}) \\ p_2(\mathbf{x}) \\ x_1 p_2(\mathbf{x}) \\ x_2 p_2(\mathbf{x}) \\ p_3(\mathbf{x}) \\ x_1 p_3(\mathbf{x}) \\ x_2 p_3(\mathbf{x}) \end{array} \begin{bmatrix} 1 & x_1 & x_2 & x_1^2 & x_1 x_2 & x_2^2 & x_1^3 & x_1^2 x_2 & x_1 x_2^2 & x_2^3 \\ 0 & 0 & -3 & 0 & 6 & -1 & 0 & 1 & -3 & 1 \\ 1 & 2 & -2 & 1 & -2 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 2 & -2 & 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & 0 & 2 & -2 & 0 & 1 & -2 & 1 \\ 0 & 0 & -4 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -4 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -4 & 0 & 0 & 0 & 1 \end{bmatrix}$$

\Downarrow

$$\left\{ \sum_{i=0}^s h_i(\mathbf{x}) p_i(\mathbf{x}) : h_i(\mathbf{x}) \in \mathcal{P}_{d-d_i}^n \right\}$$

Ideal?

So, it is now very tempting to say that

$$\mathcal{R}(\mathbf{M}_d) \stackrel{?}{=} \langle p_1(\mathbf{x}), \dots, p_s(\mathbf{x}) \rangle \cap \mathcal{P}_d^n \stackrel{\Delta}{=} \langle p_1(\mathbf{x}), \dots, p_s(\mathbf{x}) \rangle_d.$$

Ideal?

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$$\mathcal{R}(\mathbf{M}_d) \stackrel{?}{=} \langle p_1(\mathbf{x}), \dots, p_s(\mathbf{x}) \rangle \cap \mathcal{P}_d^n \triangleq \langle p_1(\mathbf{x}), \dots, p_s(\mathbf{x}) \rangle_d.$$

However, this is not true!

Counter example

$$\begin{cases} p_1(\mathbf{x}) = x_1^2 + 2x_1 + 1 = 0 \\ p_2(\mathbf{x}) = x_1^2 + x_1 + 1 = 0 \end{cases} \quad \mathbf{M}_2 = \begin{bmatrix} 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$1 \in \langle p_1(\mathbf{x}), p_2(\mathbf{x}) \rangle$, because

$$(-1 - x_1)p_1(\mathbf{x}) + (2 + x_1)p_2(\mathbf{x}) = 1,$$

but $1 \notin \mathcal{R}(\mathbf{M}_2)$. In fact, the polynomial combination implies that $1 \in \mathcal{R}(\mathbf{M}_3)$.

Ideal?

So, it is now very tempting to say that

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Counter example

$$\begin{cases} p_1(\mathbf{x}) = x_1^2 + 2x_1 + 1 = 0 \\ p_2(\mathbf{x}) = x_1^2 + x_1 + 1 = 0 \end{cases} \quad \mathbf{M}_3 = \begin{bmatrix} 1 & 2 & 1 & 0 \\ 0 & 1 & 2 & 1 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \end{bmatrix}$$

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but $1 \notin \mathcal{R}(\mathbf{M}_2)$. In fact, the polynomial combination implies that $1 \in \mathcal{R}(\mathbf{M}_3)$.

Interpretation of the row space of the Macaulay matrix

We consider the homogeneous ideal instead:

$$\left\langle p_1^h(\tilde{\mathbf{x}}), \dots, p_s^h(\tilde{\mathbf{x}}) \right\rangle = \left\{ \sum_{i=0}^s h_i(\tilde{\mathbf{x}}) p_i^h(\tilde{\mathbf{x}}) : h_i(\tilde{\mathbf{x}}) \in \mathcal{P}_{d-d_i}^n \right\}.$$

The homogeneity guarantees that all homogeneous polynomials of degree d are contained in the $\mathcal{R}(\mathbf{M}_d)$, which corresponds to

$$\mathcal{R}(\mathbf{M}_d) = \left\langle p_1^h(\mathbf{x}), \dots, p_s^h(\mathbf{x}) \right\rangle_d.$$

An important consequence is that

$$\dim \left(\left\langle p_1^h(\tilde{\mathbf{x}}), \dots, p_s^h(\tilde{\mathbf{x}}) \right\rangle_d \right) = r_d.$$

But, what makes $r_d \leq p_d$?

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But, what makes $r_d \leq p_d$? **Linearly dependent rows or syzygies!**

Linearly dependent rows and syzygies

A linearly dependent row can be written as a linear combination of the previous rows:

$$\begin{array}{l} p_1(\mathbf{x}) \\ p_2(\mathbf{x}) \\ x_1 p_2(\mathbf{x}) \\ x_2 p_2(\mathbf{x}) \\ p_3(\mathbf{x}) \\ x_1 p_3(\mathbf{x}) \\ x_2 p_3(\mathbf{x}) \end{array} \begin{bmatrix} 1 & x_1 & x_2 & x_1^2 & x_1 x_2 & x_2^2 & x_1^3 & x_1^2 x_2 & x_1 x_2^2 & x_2^3 \\ 0 & 0 & -3 & 0 & 6 & -1 & 0 & 1 & -3 & 1 \\ 1 & 2 & -2 & 1 & -2 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 2 & -2 & 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & 0 & 2 & -2 & 0 & 1 & -2 & 1 \\ 0 & 0 & -4 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -4 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -4 & 0 & 0 & 0 & 1 \end{bmatrix} \quad r_6 = r_5 + r_4 - r_1$$

In terms of the polynomials, this means that there are **syzygies!**

- basis syzygy: $\sum_{i=1}^s h_i(\mathbf{x}) p_i(\mathbf{x}) = 0$
- derived syzygy: $\mathbf{x}^\beta \sum_{i=1}^s h_i(\mathbf{x}) p_i(\mathbf{x}) = 0$

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- basis syzygy: $\sum_{i=1}^s h_i(\mathbf{x}) p_i(\mathbf{x}) = 0 \quad (1 - x_1) p_3(\mathbf{x}) + x_2 p_2(\mathbf{x}) - p_1(\mathbf{x}) = 0$
- derived syzygy: $\mathbf{x}^\beta \sum_{i=1}^s h_i(\mathbf{x}) p_i(\mathbf{x}) = 0$

Linearly dependent rows and syzygies

A linearly dependent row can be written as a linear combination of the previous rows:

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In terms of the polynomials, this means that there are **syzygies!**

- basis syzygy: $\sum_{i=1}^s h_i(\mathbf{x}) p_i(\mathbf{x}) = 0 \quad (1 - x_1) p_3(\mathbf{x}) + x_2 p_2(\mathbf{x}) - p_1(\mathbf{x}) = 0$
- derived syzygy: $\mathbf{x}^\beta \sum_{i=1}^s h_i(\mathbf{x}) p_i(\mathbf{x}) = 0 \quad x_1^2 ((1 - x_1) p_3(\mathbf{x}) + x_2 p_2(\mathbf{x}) - p_1(\mathbf{x})) = 0$

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Dimension of the left null space

The left null space contains the “coefficients” of the syzygies:

$$\mathcal{L}(M_d) = \{\mathbf{h} \in \mathbb{C}^{1 \times p} : \mathbf{h}M_d = \mathbf{0}\}.$$

↓

$$\sum_{i=1}^s h_i(\mathbf{x}) p_i(\mathbf{x}) = 0.$$

The dimension l_d of the left null space counts the total number of syzygies in $\mathcal{R}(M_d)$:

$$\binom{d - d_l + n}{n}$$

is added to l_d for every degree d_l basis syzygy.

Degree of regularity

An important consequence is the degree of regularity:

Definition

The minimal degree d^* for which the dimension l_d can be computed via the obtained syzygies at that degree is called the **degree of regularity**.

Once l_d is known, then the rank r_d and nullity n_d of the Macaulay matrix are also fully determined!

- We need higher degrees to check whether we found d^*
- There are upper bounds, but sometimes d^* is much lower (Lazard, 1983)
- Recursive algorithms are essential (Batselier et al., 2014a,b)

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Multiplication maps

Consider an ideal $\mathcal{I} = \langle p_1(\mathbf{x}), \dots, p_s(\mathbf{x}) \rangle \subset \mathcal{P}^n$ and zero-dimensional variety $\mathcal{V}(\mathcal{I})$

\Downarrow

The **quotient ring** $\mathcal{R} \triangleq \mathcal{P}^n / \langle p_1(\mathbf{x}), \dots, p_s(\mathbf{x}) \rangle$ is a finite-dimensional vector space. We can define the **multiplication maps**:

$$M_g : \mathcal{R} \rightarrow \mathcal{R} : p(\mathbf{x}) + \mathcal{I} \mapsto g(\mathbf{x})p(\mathbf{x}) + \mathcal{I}$$

with properties

- Eigenvalues of M_g are $g(\mathbf{x})|_{(j)}$
- The multiplication maps commute, i.e., $M_{g_1}M_{g_2} = M_{g_2}M_{g_1}$

How do we construct these maps?

Stetter's eigenvalue problem

Stetter's approach

1. Compute a Gröbner basis G for \mathcal{I}
2. Derive a monomial basis for \mathcal{R} from G
3. Solve the eigenvalue problems that expresses the monomial multiplication within the \mathcal{R} (simultaneous)
4. Read the affine solutions from the eigenvalues/eigenvectors

Our approach

1. Compute a numerical basis matrix Z_d for the null space of M_d , with $d \geq d^*$.
2. Determine the linearly independent rows of Z_d
3. Solve the eigenvalue problems that expresses the monomial multiplication within the \mathcal{R} (simultaneous)
4. Read the affine solutions from the eigenvalues/eigenvectors

Dual vector space

Basis matrix of the right null space can be written in terms of the solutions ($d \geq d^*$)

- solutions can be described by the dual vector space of the quotient space \mathcal{R}
- from the rank-nullity theorem

$$\begin{aligned} n_d &= q_d - r_d \\ &= \dim \mathcal{P}_d^n / \left\langle p_1^h(\tilde{\mathbf{x}}), \dots, p_s^h(\tilde{\mathbf{x}}) \right\rangle_d \end{aligned}$$

- requires dual vector space $\mathcal{C}_d^{n'}$ of \mathcal{C}_d^n and differential functionals

$$\partial_{\mathbf{i}}(\cdot)|_{(j)} \triangleq \frac{1}{i_1! \dots i_n!} \frac{\partial^{|\mathbf{i}|}(\cdot)}{\partial x_1^{i_1} \dots \partial x_n^{i_n}} \Big|_{(j)}$$

confluent multivariate Vandermonde basis matrix

$$\mathbf{V}_d = \begin{bmatrix} x_0^2|_{(1)} & 0 & x_0^2|_{(2)} \\ x_0x_1|_{(1)} & x_0|_{(1)} & x_0x_1|_{(2)} \\ x_0x_2|_{(1)} & 0 & x_0x_2|_{(2)} \\ x_1^2|_{(1)} & 2x_1|_{(1)} & x_1^2|_{(2)} \\ x_1x_2|_{(1)} & x_2|_{(1)} & x_1x_2|_{(2)} \\ x_2^2|_{(1)} & 0 & x_2^2|_{(2)} \end{bmatrix}$$

$\downarrow \qquad \qquad \downarrow \qquad \qquad \downarrow$
 $\partial_{00}(\mathbf{v})|_{(1)} \quad \partial_{10}(\mathbf{v})|_{(1)} \quad \partial_{00}(\mathbf{v})|_{(2)}$

Monomial multiplication property

one projective solution

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}}_{\mathcal{S}_{x_1, x_0}} \underbrace{\begin{bmatrix} x_0^2|_{(1)} \\ x_0x_1|_{(1)} \\ x_0x_2|_{(1)} \\ \hline x_1^2|_{(1)} \\ x_1x_2|_{(1)} \\ x_2^2|_{(1)} \end{bmatrix}}_{\partial_{00}(\mathbf{v})|_{(1)}} x_1|_{(1)} = \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{\mathcal{S}_{x_0, x_1}} \underbrace{\begin{bmatrix} x_0^2|_{(1)} \\ x_0x_1|_{(1)} \\ x_0x_2|_{(1)} \\ \hline x_1^2|_{(1)} \\ x_1x_2|_{(1)} \\ x_2^2|_{(1)} \end{bmatrix}}_{\partial_{00}(\mathbf{v})|_{(1)}} x_0|_{(1)}$$

Note that we consider differential functionals in $\mathcal{C}_2^{2'}$ in this exposition

Monomial multiplication property

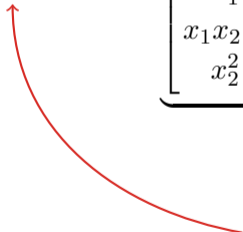
one projective solution

$$\mathbf{S}_{x_1, x_0} \underbrace{\begin{bmatrix} x_0^2 |_{(1)} \\ x_0 x_1 |_{(1)} \\ x_0 x_2 |_{(1)} \\ x_1^2 |_{(1)} \\ x_1 x_2 |_{(1)} \\ x_2^2 |_{(1)} \end{bmatrix}}_{\partial_{00}(\mathbf{v})|_{(1)}} x_1 |_{(1)} = \mathbf{S}_{x_0, x_1} \underbrace{\begin{bmatrix} x_0^2 |_{(1)} \\ x_0 x_1 |_{(1)} \\ x_0 x_2 |_{(1)} \\ x_1^2 |_{(1)} \\ x_1 x_2 |_{(1)} \\ x_2^2 |_{(1)} \end{bmatrix}}_{\partial_{00}(\mathbf{v})|_{(1)}} x_0 |_{(1)}$$

Monomial multiplication property

multiple simple projective solutions

$$\mathbf{S}_{x_1, x_0} \underbrace{\begin{bmatrix} x_0^2 |_{(1)} & x_0^2 |_{(2)} \\ x_0 x_1 |_{(1)} & x_0 x_1 |_{(2)} \\ x_0 x_2 |_{(1)} & x_0 x_2 |_{(2)} \\ x_1^2 |_{(1)} & x_1^2 |_{(2)} \\ x_1 x_2 |_{(1)} & x_1 x_2 |_{(2)} \\ x_2^2 |_{(1)} & x_2^2 |_{(2)} \end{bmatrix}}_{\mathbf{V}_d} \mathbf{D}_{x_1} = \mathbf{S}_{x_0, x_1} \underbrace{\begin{bmatrix} x_0^2 |_{(1)} & x_0^2 |_{(2)} \\ x_0 x_1 |_{(1)} & x_0 x_1 |_{(2)} \\ x_0 x_2 |_{(1)} & x_0 x_2 |_{(2)} \\ x_1^2 |_{(1)} & x_1^2 |_{(2)} \\ x_1 x_2 |_{(1)} & x_1 x_2 |_{(2)} \\ x_2^2 |_{(1)} & x_2^2 |_{(2)} \end{bmatrix}}_{\mathbf{V}_d} \mathbf{D}_{x_0}$$


$$\begin{bmatrix} x_1 |_{(1)} & 0 \\ 0 & x_1 |_{(2)} \end{bmatrix}$$

Note that we consider differential functionals in $\mathcal{C}_2^{2'}$ in this exposition

Monomial multiplication property

multiple projective solutions with multiplicity larger than one

$$\mathbf{S}_{x_1, x_0} \underbrace{\begin{bmatrix} x_0^2|_{(1)} & 0 & x_0^2|_{(2)} \\ x_0x_1|_{(1)} & x_0|_{(1)} & x_0x_1|_{(2)} \\ x_0x_2|_{(1)} & 0 & x_0x_2|_{(2)} \\ x_1^2|_{(1)} & 2x_1|_{(1)} & x_1^2|_{(2)} \\ x_1x_2|_{(1)} & x_2|_{(1)} & x_1x_2|_{(2)} \\ x_2^2|_{(1)} & 0 & x_2^2|_{(2)} \end{bmatrix}}_{\mathbf{V}_d} \mathbf{D}_{x_1} = \mathbf{S}_{x_0, x_1} \underbrace{\begin{bmatrix} x_0^2|_{(1)} & 0 & x_0^2|_{(2)} \\ x_0x_1|_{(1)} & x_0|_{(1)} & x_0x_1|_{(2)} \\ x_0x_2|_{(1)} & 0 & x_0x_2|_{(2)} \\ x_1^2|_{(1)} & 2x_1|_{(1)} & x_1^2|_{(2)} \\ x_1x_2|_{(1)} & x_2|_{(1)} & x_1x_2|_{(2)} \\ x_2^2|_{(1)} & 0 & x_2^2|_{(2)} \end{bmatrix}}_{\mathbf{V}_d} \mathbf{D}_{x_0}$$

$$\begin{bmatrix} x_1|_{(1)} & \times & \times \\ 0 & x_1|_{(1)} & \times \\ 0 & 0 & x_1|_{(2)} \end{bmatrix}$$

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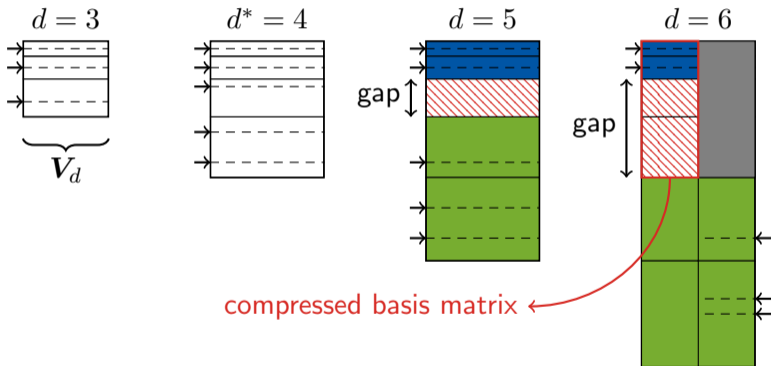
Monomial multiplication property

multiple affine solutions with multiplicity larger than one

$$\begin{array}{c}
 \mathbf{S}_1 \\
 \curvearrowright \\
 \underbrace{\begin{bmatrix} 1 & 0 & 1 \\ x_1|_{(1)} & 1 & x_1|_{(2)} \\ x_2|_{(1)} & 0 & x_2|_{(2)} \\ x_1^2|_{(1)} & 2x_1|_{(1)} & x_1^2|_{(2)} \\ x_1x_2|_{(1)} & x_2|_{(1)} & x_1x_2|_{(2)} \\ x_2^2|_{(1)} & 0 & x_2^2|_{(2)} \end{bmatrix}}_{\mathbf{V}_d}
 \end{array}
 \mathbf{D}_{x_1} = \mathbf{S}_{x_1}
 \underbrace{\begin{bmatrix} 1 & 0 & 1 \\ x_1|_{(1)} & 1 & x_1|_{(2)} \\ x_2|_{(1)} & 0 & x_2|_{(2)} \\ x_1^2|_{(1)} & 2x_1|_{(1)} & x_1^2|_{(2)} \\ x_1x_2|_{(1)} & x_2|_{(1)} & x_1x_2|_{(2)} \\ x_2^2|_{(1)} & 0 & x_2^2|_{(2)} \end{bmatrix}}_{\mathbf{V}_d}
 \mathbf{I}$$

select the linearly independent rows of \mathbf{V}_d

Removing solutions at infinity



Two difficulties

$$\mathbf{S}_1 \mathbf{V}_d \mathbf{D}_{x_1} = \mathbf{S}_{x_1} \mathbf{V}_d$$

- Solutions/confluent Vandermonde basis vectors are not known in advanced:

numerical basis matrix \mathbf{Z}_d of the null space

$$\Downarrow \mathbf{V}_d = \mathbf{Z}_d \mathbf{T}$$

$$(\mathbf{S}_1 \mathbf{Z}_d) \mathbf{T} \mathbf{D}_{x_1} = (\mathbf{S}_{x_1} \mathbf{Z}_d) \mathbf{T}$$

$$\mathbf{T} \mathbf{D}_{x_1} \mathbf{T}^{-1} = (\mathbf{S}_1 \mathbf{Z}_d)^{-1} (\mathbf{S}_{x_1} \mathbf{Z}_d)$$

- Not possible to numerically stable compute Jordan normal form:

numerically stable **Schur decomposition**

$$\Downarrow$$

$$\mathbf{Q} \mathbf{U}_{x_1} \mathbf{Q}^{-1} = (\mathbf{S}_1 \mathbf{Z}_d)^{-1} (\mathbf{S}_{x_1} \mathbf{Z}_d)$$

Multidimensional realization theory

- It is **possible to shift with any polynomial** in the eigenvalues – for example, x_2

$$QU_{x_2}Q^{-1} = (S_1Z_d)^{-1} (S_{x_2}Z_d)$$

- This leads to the same Q

- Solved via simultaneous triangularization
- Different shift polynomials can be useful
- Entire degree block rows instead of single rows can be considered

Realization theory for any shift polynomial $g(x)$:

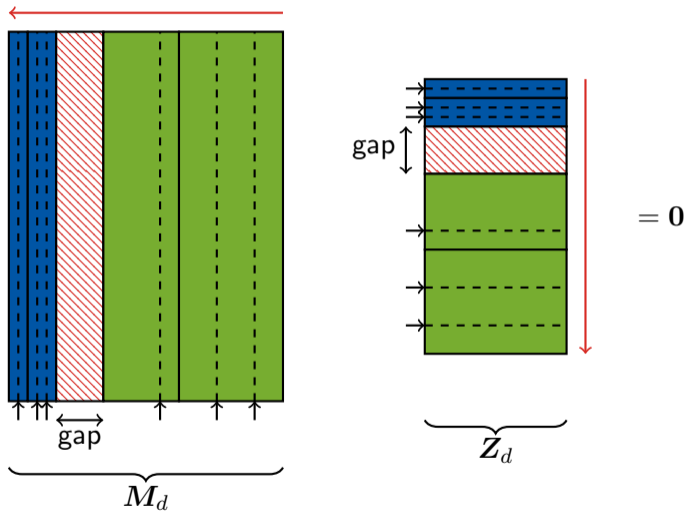
$$QU_gQ^{-1} = (S_1Z_d)^\dagger (S_gZ_d),$$

where S_1 and S_g select rows from Z_d

Outline

- 1 | Introduction
- 2 | Row Space
- 3 | Left Null Space
- 4 | Right Null Space
- 5 | Column space**
- 6 | Conclusion

Complementarity between right null space and column space



Reordered Macaulay matrix

$$\underbrace{\begin{bmatrix} M_1 & M_2 & M_3 & M_4 \end{bmatrix}}_N \begin{bmatrix} A & 0 \\ B & 0 \\ C & 0 \\ W_{21} & W_{22} \end{bmatrix} = 0$$

A : affine standard monomials

B : other affine shifted monomials

C : other affine monomials and gap

$W_{2 \times}$: remaining rows of the basis matrix

The multiplication property

$$AD_g = S_g \begin{bmatrix} A \\ B \end{bmatrix}$$

yields again an eigenvalue problem

$$AD_g A^{-1} = S_g \begin{bmatrix} I \\ BA^{-1} \end{bmatrix}$$

Backward QR decomposition

The backward QR decomposition **eliminates** the dependency on **the right null space**

$$\begin{bmatrix} R_{14} & R_{13} & R_{12} & R_{11} \\ R_{24} & R_{23} & R_{22} & 0 \\ R_{34} & R_{33} & 0 & 0 \\ R_{44} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} A & 0 \\ B & 0 \\ C & 0 \\ W_{21} & W_{22} \end{bmatrix} = 0$$

Backward QR decomposition

The backward QR decomposition **eliminates** the dependency on **the right null space**

$$\begin{bmatrix} R_{14} & R_{13} & R_{12} & R_{11} \\ R_{24} & R_{23} & R_{22} & 0 \\ R_{34} & R_{33} & 0 & 0 \\ R_{44} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} A & 0 \\ B & 0 \\ C & 0 \\ W_{21} & W_{22} \end{bmatrix} = 0$$

$$BA^{-1} = -R_{33}^{-1}R_{34}$$

Realization theory for any shift polynomial $g(x)$:

$$AD_g A^{-1} = S_g \begin{bmatrix} I \\ -R_{33}^{-1} R_{34} \end{bmatrix},$$

where S_g selects rows from I and $-R_{33}^{-1} R_{34}$

- a standard eigenvalue problem, with A the matrix of eigenvectors
- backward QR decomposition removes influence of solutions at infinity implicitly
- same adaptation to multiple Schur decompositions is possible

Outline

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Conclusions and future work

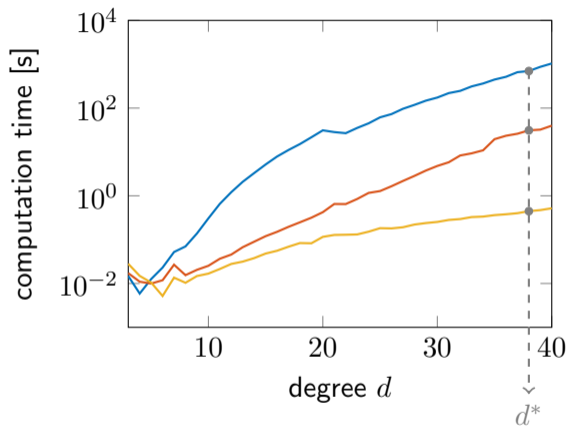
Each of the fundamental subspaces of the Macaulay matrix has a purpose:

- Many properties/questions from algebraic geometry hide in one of the fundamental subspaces of the Macaulay matrix
- A full treatment of the column space is not yet available
- Some algorithmic issues make the column space currently less useful to solve polynomial systems

Some current research efforts are:

- Investigating the properties of the column space
- Translating the interpretations to the block Macaulay matrix

A final note on the computational complexity



Comparison of the computation time to construct a numerical basis matrix of the right null space of a Macaulay matrix via the standard (—), recursive (—), and sparse (—) approach.

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Any questions?



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A system theoretic intermezzo!

discrete-time overdetermined autonomous multidimensional systems

state space representation

$$\mathbf{x} [k_1 + 1, k_2, \dots, k_n] = \mathbf{A}_1 \mathbf{x} [\mathbf{k}],$$

\vdots

$$\mathbf{x} [k_1, \dots, k_{n-1}, k_n + 1] = \mathbf{A}_n \mathbf{x} [\mathbf{k}],$$

$$\mathbf{y} [\mathbf{k}] = \mathbf{c}^T \mathbf{x} [\mathbf{k}],$$

where $\mathbf{x} \in \mathbb{R}^m$ is the state vector, $\mathbf{A}_i \in \mathbb{R}^{m \times m}$ define the autonomous state transitions, and $\mathbf{c} \in \mathbb{R}^m$ defines how the one-dimensional output y is composed from the state vector

trajectories representation

$$\mathbf{r} (\mathbf{z}) w [k_1, \dots, k_n] = \mathbf{0},$$

where $\mathbf{r} \in \mathbb{R}^{n \times 1}$ and $\mathbf{z} = (z_1, \dots, z_n)$ denotes the multidimensional shift operator, for which holds that

$$z_i : (z_i w) [\mathbf{k}] = w [k_1, \dots, k_i + 1, \dots, k_n].$$

Via this shift operator, a difference equation can be associated with a multivariate polynomial in $\mathbf{x} = \mathbf{z}$.

A system theoretic intermezzo!

Consider the following set of difference equations

$$\begin{cases} \text{trajectory 1: } w[k_1, k_2 + 1] + 2w[k_1 + 1, k_2 + 1] + 3w[k_1, k_2 + 2] = 0, \\ \text{trajectory 2: } 4w[k_1, k_2] + 5w[k_1 + 1, k_2] + 6w[k_1, k_2 + 1] = 0. \end{cases}$$

By shifting these equations up to order/degree two, we find

$$\begin{bmatrix} 0 & 0 & 1 & 0 & 2 & 3 \\ 4 & 5 & 6 & 0 & 0 & 0 \\ 0 & 4 & 0 & 5 & 6 & 0 \\ 0 & 0 & 4 & 0 & 5 & 6 \end{bmatrix} \begin{bmatrix} w[k_1, k_2] \\ w[k_1 + 1, k_2] \\ w[k_1, k_2 + 1] \\ w[k_1 + 2, k_2] \\ w[k_1 + 1, k_2 + 1] \\ w[k_1, k_2 + 2] \end{bmatrix} = \mathbf{0}.$$

A system theoretic intermezzo!

Consider the following system of multivariate polynomial equations

$$\begin{cases} p_1(\mathbf{z}) = z_2 + 2z_1z_2 + 3z_2^2 = 0, \\ p_2(\mathbf{z}) = 4 + 5z_1 + 6z_2 = 0. \end{cases}$$

By shifting these equations up to order/degree two, we find

$$\begin{bmatrix} 0 & 0 & 1 & 0 & 2 & 3 \\ 4 & 5 & 6 & 0 & 0 & 0 \\ 0 & 4 & 0 & 5 & 6 & 0 \\ 0 & 0 & 4 & 0 & 5 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ z_1 \\ z_2 \\ z_1^2 \\ z_1z_2 \\ z_2^2 \end{bmatrix} = \mathbf{0}.$$

A system theoretic intermezzo!

A special basis matrix of the null space of the Macaulay matrix is the column echelon basis matrix

$$\mathbf{H}_d = \mathbf{Z}_d \mathbf{T}_Z = \mathbf{V}_d \mathbf{T}_V.$$

The multiplication property in \mathbf{H} leads to eigenvalue problems

$$\mathbf{S}_0 \mathbf{H}_d \mathbf{A}_i = \mathbf{S}_i \mathbf{H}_d,$$

or

$$\mathbf{A}_i = (\mathbf{S}_0 \mathbf{H}_d)^\dagger (\mathbf{S}_i \mathbf{H}_d).$$

This gives us the system matrices \mathbf{A}_i via Ho–Kalman’s shift trick; a **multidimensional realization problem!**

multidimensional extended observability matrix

$$\mathbf{\Gamma} = \begin{bmatrix} \mathbf{c}^T \\ \hline \mathbf{c}^T \mathbf{A}_1 \\ \mathbf{c}^T \mathbf{A}_2 \\ \hline \mathbf{c}^T \mathbf{A}_1^2 \\ \mathbf{c}^T \mathbf{A}_1 \mathbf{A}_2 \\ \mathbf{c}^T \mathbf{A}_2^2 \\ \hline \vdots \\ \hline \mathbf{c}^T \mathbf{A}_1^d \\ \vdots \\ \mathbf{c}^T \mathbf{A}_2^d \end{bmatrix}$$