

Fast, deterministic computation of Hermite forms for polynomial matrices

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Joint work with V. Neiger and Wei Zhou

July 16 2016

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- 2 Arne and Erich Story
- 3 Technical Story : Part I
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Background story : Hermite forms

Problem : Find a basis as a module for the set of rows $\begin{bmatrix} \mathbf{A}_1 \\ \vdots \\ \mathbf{A}_n \end{bmatrix}$.

Each \mathbf{A}_i a square matrix of polynomials.

Problem from finding integral basis needed for algebraic Risch

Method: Reduce

$$\begin{bmatrix} \mathbf{A}_1 \\ \vdots \\ \mathbf{A}_n \end{bmatrix}$$

Background story with Hermite forms

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$$\underbrace{\begin{bmatrix} \mathbf{U}_{11} & \cdots & \mathbf{U}_{1n} \\ \vdots & & \vdots \\ \mathbf{U}_{n1} & \cdots & \mathbf{U}_{nn} \end{bmatrix}}_{\text{unimodular}} \cdot \begin{bmatrix} \mathbf{A}_1 \\ \vdots \\ \mathbf{A}_n \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{B}_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}}_{\text{reduced}}$$

Background Story : Matrix Gcds

$$\begin{bmatrix} \mathbf{U}_{11} & \mathbf{U}_{12} \\ \mathbf{U}_{21} & \mathbf{U}_{22} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{B} \\ 0 \end{bmatrix}$$

$$\mathbf{U}_{11} \cdot \mathbf{A}_1 + \mathbf{U}_{12} \cdot \mathbf{A}_2 = \mathbf{B}$$

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$$\mathbf{U} \cdot \mathbf{V} = I_n \quad \implies \quad \mathbf{U}_{11} \cdot \mathbf{V}_{11} + \mathbf{U}_{12} \cdot \mathbf{V}_{21} = \mathbf{I}$$

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Arne's project : see if `gcdheu` could be extended to HNF

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- Seemed like a good idea at the time. **Didn't work**
- Instead Arne discovered probabilistic methods
 - (reading HNF paper of Erich, Krishnamoorthy and Dave)
 - (reading SNF paper of Erich, Krishnamoorthy and Dave)
- Ultimately Arne had nice Las Vegas result with SNF
- However I was not so comfortable with prob. methods

Arne meets Erich

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Erich's point :

Don't tell grad student a result is good. Can always be better

Technical Part I (HNF)

Problem : Given nonsingular $\mathbf{A} \in \mathbb{K}[x]^{n \times n}$. Compute \mathbf{U} and \mathbf{H} :

- (i) \mathbf{U} unimodular,
- (ii) \mathbf{H} in (column) Hermite form
- (iii) $\mathbf{A} \cdot \mathbf{U} = \mathbf{H}$

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Our Results :

- Fast, deterministic algorithms
- Complexity : First Try : $O^\sim(n^\omega d)$ where $d = \deg \mathbf{A}$
- Complexity : Second Try : $O^\sim(n^\omega \lceil s \rceil)$ where s bounded
: by average row and column degrees of \mathbf{A}

References

Report on paper

- G. Labahn, V. Neiger and W. Zhou,
[Fast, deterministic computation of determinants and Hermite normal forms of polynomial matrices](#), Arxiv 2016.

Other relevant papers:

- W. Zhou, G. Labahn and A. Storjohann,
[Computing Minimal Nullspace Bases](#), *ISSAC 2012*,
- W. Zhou and G. Labahn,
[Computing Column Bases for polynomial matrices](#), *ISSAC 2013*
- S. Gupta, S. Sarkar, A. Storjohann, J. Valeriote, [Triangular \$x\$ -basis decompositions ...](#), *ISSAC 2012*
- V. Neiger, [Fast computation of shifted Popov forms](#), *ISSAC 2016*

- Polynomial-time over $\mathbb{Q}[x]$: Kannan 1985.
- $\tilde{O}(n^4 d)$: Hafner-McCurley 1991,
- $\tilde{O}(n^{\omega+1} d)$: Hafner-McCurley (1991),
Storjohann and Labahn (1996), Villard (1996)
- $O(n^3 d^2)$: Mulders and Storjohann (2003)
- $\tilde{O}(n^3 d)$: Gupta and Storjohann (2011)
- $\tilde{O}(n^\omega d)$: Gupta and Storjohann (2011)
- $\tilde{O}(n^\omega s)$: Labahn, Neiger, Zhou (2016)

Algorithm Part I : Finding Diagonal Elements

Partition and reduce \mathbf{A} via

$$\mathbf{A} \cdot \mathbf{U} = \begin{bmatrix} \mathbf{A}_u \\ \mathbf{A}_d \end{bmatrix} \begin{bmatrix} \mathbf{U}_\ell & \mathbf{U}_r \end{bmatrix} = \begin{bmatrix} \mathbf{B}_1 & 0 \\ * & \mathbf{B}_2 \end{bmatrix}.$$

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Here

- (i) \mathbf{B}_1 is nonsingular and a column basis of \mathbf{A}_u .
- (ii) \mathbf{U}_r a right kernel basis of \mathbf{A}_u
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- (iii) $\mathbf{B}_2 = \mathbf{A}_d \cdot \mathbf{U}_r$,

Recurse on \mathbf{B}_1 and \mathbf{B}_2 to get diagonal elements.

Theorem

$\mathbf{A} \in \mathbb{K}[x]^{n \times n}$. *Diagonals of HNF costs* $O^\sim(n^{\omega_s})$. Here $s = \frac{\sum \text{cdeg } \mathbf{A}}{n}$.

Example

$$\mathbf{A} = \begin{bmatrix} x & -x^3 & -2x^4 & 2x & -x^2 \\ 1 & -1 & -2x & 2 & -x \\ -3 & 3x^2 + x & 2x^2 & -x^4 + 1 & 3x \\ 0 & 1 & x^2 + 2x - 2 & x^3 + 2x - 2 & 0 \\ 1 & -x^2 + 2 & -2x^3 - 3x + 3 & 2x + 2 & 0 \end{bmatrix} \in \mathbb{Z}_7[x]^{5 \times 5}.$$

$$\begin{bmatrix} \mathbf{A}_u \\ \mathbf{A}_d \end{bmatrix} \cdot [\mathbf{U}_\ell, \mathbf{U}_r] = \begin{bmatrix} x & -x^3 & -2x^4 & & \\ 1 & -1 & -2x & & \\ -3 & 3x^2 + x & 2x^2 & & \\ * & * & * & x^3 - 1 & 0 \\ * & * & * & -x & x \end{bmatrix}$$

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$$\begin{bmatrix} \mathbf{A}_u \\ \mathbf{A}_d \end{bmatrix} \cdot [\mathbf{U}_\ell^{(2)}, \mathbf{U}_r^{(2)}] = \begin{bmatrix} x & 0 & & & & \\ 1 & x^2 - 1 & & & & \\ * & * & x^3 & & & \\ * & * & * & x^3 - 1 & 0 & \\ * & * & * & -x & x & \end{bmatrix}$$

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Algorithm Part II : Finding Rest of H

Know : $\vec{\delta}$ diagonal degrees of \mathbf{H} . Set $\mu = \max(\vec{\delta})$

$$\mathbf{x}^{\vec{\mu}-\vec{\delta}} \mathbf{A} \xrightarrow{\text{reduce}} \mathbf{x}^{\vec{\mu}-\vec{\delta}} \mathbf{R} \xrightarrow{\text{normalize}} \mathbf{H} = \mathbf{R} \cdot \text{lc}_{-\vec{\delta}}(\mathbf{R})^{-1}$$

where \mathbf{R} is any $-\vec{\delta}$ -column reduced form of \mathbf{A} .

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Use partial linearization of Storjohann (2007): $\mathbf{A} \rightarrow \mathcal{L}(\mathbf{A})$

Smooths shifts, keeps properties of \mathbf{A} while enlarging a bit.

Partial Linearization

Consider \mathbf{H} with diagonal degrees $(2, 37, 7, 18)$.

$$\mathbf{H} = \begin{bmatrix} (2) & & & \\ [36] & (37) & & \\ [6] & [6] & (7) & \\ [17] & [17] & [17] & (18) \end{bmatrix},$$

$[d]$: degree at most d and (d) : monic , degree exactly d .

$\delta = 1 + \lfloor (2 + 37 + 7 + 18)/4 \rfloor = 17$. Construct by “expanding rows”:

$$\tilde{\mathbf{H}} = \begin{bmatrix} (2) & & & & \\ [16] & [16] & & & \\ [16] & [16] & & & \\ [2] & (3) & & & \\ [6] & [6] & (7) & & \\ [16] & [16] & [16] & [16] & \\ [0] & [0] & [0] & (1) & \end{bmatrix}.$$

Main property kept : shifted column reduction.

$$\begin{array}{ccccc}
 \mathbf{x}^{\vec{d}-\vec{\delta}} \mathbf{A} & \xrightarrow{\text{reduce}} & \mathbf{x}^{\vec{d}-\vec{\delta}} \mathbf{R} & \xrightarrow{\text{normalize}} & \mathbf{H} = \mathbf{R} \text{lc}_{-\vec{\delta}}(\mathbf{R})^{-1} \\
 \downarrow & & & & \downarrow \\
 \text{partial linearization} & & & & \text{partial linearization} \\
 \downarrow & & & & \downarrow \\
 \mathbf{x}^{\vec{m}-\vec{d}} \mathcal{L}_{\vec{\delta}}(\mathbf{A}) & \xrightarrow{\text{reduce}} & \mathbf{x}^{\vec{m}-\vec{d}} \hat{\mathbf{R}} & \xrightarrow{\text{normalize}} & \mathcal{L}_{\vec{\delta}}(\mathbf{H}) = \hat{\mathbf{R}} \text{lc}_{-\vec{d}}(\hat{\mathbf{R}})^{-1}
 \end{array}$$

Theorem

$\mathbf{A} \in \mathbb{K}[x]^{n \times n}$ nonsingular. $\vec{\delta}$ degrees of the diag. entries of the Hermite form. Then Hermite form computed using $\tilde{O}(n^\omega d)$ field operations.

Improving the Complexity

Repeat : partial linearization (this time with columns) :

(i) Enlarge : $\mathbf{A} \rightarrow \mathcal{L}^c(\mathbf{A})$

- size of $\mathcal{L}^c(\mathbf{A})$ at most twice size of \mathbf{A}
- degree $\mathcal{L}^c(\mathbf{A})$ at most average of \mathbf{A}

(ii) Compute HNF of $\mathcal{L}^c(\mathbf{A})$

(iii) \mathbf{H} in lower right corner of Hermite form of $\mathcal{L}^c(\mathbf{A})$

Theorem

$\mathbf{A} \in \mathbb{K}[x]^{n \times n}$ nonsingular. Hermite form computed: $\tilde{O}(n^\omega \lceil s \rceil)$.

We want to make progress with:

- Fast but with coefficient control (e.g. matrices over $Z[x]$)
 - Beckermann, Labahn, Villard (2006)

$$\tilde{O}((m+n)(m^2 d \min(m,n))^3 \log \|\mathbf{A}\|)$$

- Fast Popov form; Fast shifted Popov form
- Fast Hermite and Popov for alternate domains (e.g. matrices over $\mathbb{K}(x)[D_x]$)

Algorithm Part II : Finding Rest of \mathbf{H} (First Try)

Use method of Gupta and Storjohann (2012) to get rest of \mathbf{H} .

- (i) Convert HNF to shifted \vec{s} -minimal kernel basis problem

$$\mathbf{AU} = \mathbf{H} \quad \text{same as} \quad [\mathbf{A} \quad -\mathbf{I}] \begin{bmatrix} \mathbf{U} \\ \mathbf{H} \end{bmatrix} = \mathbf{0}.$$

- (ii) Adjust to alternate \vec{s}' -minimal kernel basis problem

$$[\mathbf{A} \quad -\mathbf{E}] \begin{bmatrix} \mathbf{U} \\ \mathbf{H}' \end{bmatrix} = \mathbf{0}.$$

Easily construct \mathbf{E} . Easily get \mathbf{H} from \mathbf{H}'

- (iii) Find \mathbf{Q} and \mathbf{R} such that $\mathbf{E} = \mathbf{AQ} + \mathbf{R}$. Solve via HOL.

Then repeat (ii) but with \mathbf{E} replaced by \mathbf{R} .

- (iv) Complexity is $O^\sim(n^\omega d)$