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polynomial matrices: fast approximation and applications

Algorithmes Efficaces en Calcul Formel Master Parisien de Recherche en Informatique 9 December 2024

outline

introduction

shifted reduced forms

fast algorithms

applications

outline

introduction

- rational approximation and interpolation
- ► the vector case
- ► pol. matrices: reminders and motivation

shifted reduced forms

fast algorithms

applications

 \Downarrow earlier in the course \Downarrow

 \Downarrow in this lecture \Downarrow

\Downarrow earlier in the course \Downarrow

- addition f + g, multiplication f * g
- \blacktriangleright division with remainder f=qg+r
- truncated inverse $f^{-1} \mod X^d$
- extended GCD uf + vg = gcd(f, g)

- multipoint eval. $f \mapsto f(\alpha_1), \ldots, f(\alpha_d)$
- interpolation $f(\alpha_1), \ldots, f(\alpha_d) \mapsto f$
- Padé approximation $f = \frac{p}{a} \mod X^d$
- minpoly of linearly recurrent sequence

 \Downarrow in this lecture \Downarrow

\Downarrow earlier in the course \Downarrow

O(M(d))

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$O(\mathsf{M}(d) \mathsf{log}(d))$

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\Downarrow in this lecture \Downarrow

Padé approximation, sequence minpoly, extended GCD $O(\mathsf{M}(d) \mathsf{log}(d)) \text{ operations in } \mathbb{K}$

matrix versions of these problems

 $O(\mathfrak{m}^{\omega}\mathsf{M}(d)\log(d))$ operations in \mathbb{K}

or a tiny bit more for matrix-GCD

rational approximation and interpolation

 $\begin{array}{ll} \mbox{given power series } p(X) \mbox{ and } q(X) \mbox{ over } \mathbb{K} \mbox{ at precision } d, \\ \mbox{with } q(X) \mbox{ invertible,} \\ \rightarrow \mbox{ compute } \frac{p(X)}{q(X)} \mbox{ mod } X^d \mbox{ algo} \ref{eq: compute } O(\ref{eq: compute } d) \end{array}$

rational approximation and interpolation

given power series p(X) and q(X) over $\mathbb K$ at precision d, with q(X) invertible, $\rightarrow \text{ compute } \frac{p(X)}{q(X)} \text{ mod } X^d \qquad \qquad \text{algo?? O(??)} \\ \text{ inv+mul: O(M(d))}$

rational approximation and interpolation

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 $\begin{array}{ll} \mbox{given } M(X) \in \mathbb{K}[X] \mbox{ of degree } d > 0, \\ \mbox{given polynomials } p(X) \mbox{ and } q(X) \mbox{ over } \mathbb{K} \mbox{ of degree } < d, \\ \mbox{with } q(X) \mbox{ invertible modulo } M(X), \\ \mbox{ or mpute } \frac{p(X)}{q(X)} \mbox{ mod } M(X) \mbox{ algo} \ref{eq:model} O(\ref{eq:model}) \label{eq:model} \end{array}$

rational approximation and interpolation

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given power series p(X) and q(X) over \mathbb{K} at precision d, with q(X) invertible, $\rightarrow \text{ compute } \frac{p(X)}{q(X)} \mod X^d$ algo?? O(??) inv+mul: O(M(d))

given
$$M(X) = (X - \alpha_1) \cdots (X - \alpha_d) \in \mathbb{K}[X]$$
,
for pairwise distinct $\alpha_1, \ldots, \alpha_d \in \mathbb{K}$,
given polynomials $p(X)$ and $q(X)$ over \mathbb{K} of degree $< d$,
with $q(X)$ invertible modulo $M(X)$, what does that mean?
 $\rightarrow \text{ compute } \frac{p(X)}{q(X)} \mod M(X)$ algo?? $O(??)$

rational approximation and interpolation

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 $\rightarrow \text{ compute } \frac{p(X)}{q(X)} \mod M(X)$ algo?? $O(??)$
eval+div+interp $O(M(d) \log(d))$

rational approximation and interpolation

rational fractions ↔ linearly recurrent sequences reminders from lectures 3+6

rational approximation and interpolation

 $\begin{array}{c} \textbf{rational fractions} \longleftrightarrow \textbf{linearly recurrent sequences} \\ \textbf{reminders from lectures 3+6} \end{array}$



rational approximation and interpolation

rational fractions \longleftrightarrow linearly recurrent sequences reminders from lectures 3+6



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rational approximation and interpolation

Padé approximation:

given power series f(X) at precision d, \rightarrow compute p(X), q(X) such that $f = \frac{p}{q} \mod X^d$

rational approximation and interpolation

Padé approximation:

given power series f(X) at precision d, \rightarrow compute p(X), q(X) such that $f = \frac{p}{q} \text{ mod } X^d$

opinions on this algorithmic problem?

rational approximation and interpolation

Padé approximation:

given power series f(X) at precision d, given degree constraints $d_1, d_2 > 0, \\ \rightarrow \text{ compute polynomials } (p(X), q(X)) \text{ of degrees} < (d_1, d_2) \\ \text{and such that } f = \frac{p}{q} \mod X^d$

rational approximation and interpolation

Padé approximation:

given power series f(X) at precision d, given degree constraints $d_1, d_2 > 0, \\ \rightarrow \text{ compute polynomials } (p(X), q(X)) \text{ of degrees} < (d_1, d_2) \\ \text{ and such that } f = \frac{p}{q} \mod X^d$

Cauchy interpolation:

given $M(X) = (X - \alpha_1) \cdots (X - \alpha_d) \in \mathbb{K}[X]$, for pairwise distinct $\alpha_1, \ldots, \alpha_d \in \mathbb{K}$, given degree constraints $d_1, d_2 > 0$, \rightarrow compute polynomials (p(X), q(X)) of degrees $< (d_1, d_2)$ and such that $f = \frac{p}{a} \mod M(X)$

rational approximation and interpolation

Padé approximation:

given power series f(X) at precision d, given degree constraints $d_1, d_2 > 0,$ \rightarrow compute polynomials (p(X), q(X)) of degrees $< (d_1, d_2)$ and such that $f = \frac{p}{q} \mod X^d$

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- degree constraints specified by the context
- ${\scriptstyle \bullet}$ usual choices have $d_1+d_2\approx d$ and existence of a solution

Sur la généralisation des fractions continues algébriques; PAR M. H. PADÉ.

Docteur ès Sciences mathématiques, Professeur au lycée de Lille.

[1894, Journal de mathématiques pures et appliquées] INTRODUCTION.

M. Hermite s'est, dans un travail récemment paru ('), occupé de la généralisation des fractions continues algébriques. La question est de déterminer les polynomes $X_1, X_2, ..., X_n$, de degrés $\mu_1, \mu_2, ..., \mu_n$, qui satisfont à l'équation

$$S_1X_1 + S_2X_2 + \ldots + S_nX_n = S x^{\mu_1 + \mu_2 + \ldots + \mu_n + n-1},$$

 S_1, S_2, \ldots, S_n étant des séries entières données, et S une série également entière. Ou plutôt, il s'agit d'obtenir un algorithme qui permette le calcul de proche en proche de ces systèmes de *n* polynomes, et qui soit analogue à l'algorithme par lequel le numérateur et le dénominateur d'une réduite d'une fraction continue se déduisent des numérateurs et dénominateurs des réduites précédentes. D'élégantes considé-

approximation and interpolation: the vector case

Hermite-Padé approximation

[Hermite 1893, Padé 1894]

input:

- ${\scriptstyle \blacktriangleright}$ polynomials $f_1,\ldots,f_m\in \mathbb{K}[X]$
- ${\scriptstyle \bullet} \mbox{ precision } d \in \mathbb{Z}_{>0}$
- ${\scriptstyle \bullet} \mbox{ degree bounds } d_1, \ldots, d_m \in \mathbb{Z}_{>0}$

output:

polynomials $p_1,\ldots,p_{\mathfrak{m}}\in\mathbb{K}[X]$ such that

$$\bullet p_1 f_1 + \dots + p_m f_m = 0 \mod X^d$$

(Padé approximation: particular case m=2 and $f_2=-1$)

approximation and interpolation: the vector case

M-Padé approximation / vector rational interpolation

[Cauchy 1821, Mahler 1968]

input:

- ${\scriptstyle \blacktriangleright}$ polynomials $f_1,\ldots,f_m\in \mathbb{K}[X]$
- ${\scriptstyle \blacktriangleright}$ pairwise distinct points $\alpha_1,\ldots,\alpha_d\in\mathbb{K}$
- ${\scriptstyle \bullet} \mbox{ degree bounds } d_1, \ldots, d_m \in \mathbb{Z}_{>0}$

output:

polynomials $p_1,\ldots,p_m\in\mathbb{K}[X]$ such that

- $\centerdot \, p_1(\alpha_i)f_1(\alpha_i) + \dots + p_m(\alpha_i)f_m(\alpha_i) = 0 \text{ for all } 1 \leqslant i \leqslant d$

(rational interpolation: particular case m=2 and $f_2=-1$)

approximation and interpolation: the vector case

in this lecture: modular equation and fast algebraic algorithms

[van Barel-Bultheel 1992; Beckermann-Labahn 1994, 1997, 2000; Giorgi-Jeannerod-Villard 2003; Storjohann 2006; Zhou-Labahn 2012; Jeannerod-Neiger-Schost-Villard 2017, 2020]

input:

- ${\scriptstyle \bullet}$ polynomials $f_1,\ldots,f_m\in \mathbb{K}[X]$
- ${\scriptstyle \bullet}\xspace$ field elements $\alpha_1,\ldots,\,\alpha_d\in\mathbb{K}$
- ${\scriptstyle \bullet} \mbox{ degree bounds } d_1, \ldots, d_m \in \mathbb{Z}_{>0}$

 $\stackrel{\scriptstyle \sim \rightarrow}{\quad} \text{not necessarily distinct} \\ \stackrel{\scriptstyle \sim \rightarrow}{\quad} \text{general "shift" } s \in \mathbb{Z}^m$

output:

polynomials $p_1,\ldots,p_{\mathfrak{m}}\in\mathbb{K}[X]$ such that

•
$$p_1 f_1 + \dots + p_m f_m = 0 \mod \prod_{1 \leqslant i \leqslant d} (X - \alpha_i)$$

(Hermite-Padé: $\alpha_1 = \cdots = \alpha_d = 0$; interpolation: pairwise distinct points)

approximation and interpolation: the vector case

applications:

► univariate polynomials and linearly recurrent sequences XGCD, rational reconstruction, "fast Berlekamp-Massey", ...

► sparse K-linear systems Coppersmith's block-Wiedemann approach

▶ structured K-matrices

Hankel/Toeplitz/Vandermonde, block structures, displacement rank, ...

 \blacktriangleright computations with $\mathbb K\text{-matrices}$ Krylov iterates, minimal/characteristic polynomial, Frobenius form, \ldots

 \blacktriangleright computations with $\mathbb{K}[X]\text{-matrices}$ determinant, nullspace/kernel, inversion, Hermite normal form, \ldots

► computations with multivariate polynomials multivariate interpolation, syzygy modules, Gröbner bases, ...

approximation and structured linear system

$$\begin{split} \mathbb{K} &= \mathbb{F}_7 \\ f &= 2X^7 + 2X^6 + 5X^4 + 2X^2 + 4 \\ d &= 8, \, d_1 = 3, \, d_2 = 6 \\ &\to \text{look for } (p,q) \text{ of degree} < (3,6) \text{ such that } f = \frac{p}{q} \text{ mod } X^8 \end{split}$$

$$\begin{bmatrix} q & p \end{bmatrix} \begin{bmatrix} f \\ -1 \end{bmatrix} = 0 \mod X^8$$

approximation and structured linear system

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г <u>л</u>

$$\begin{bmatrix} q & p \end{bmatrix} \begin{bmatrix} f \\ -1 \end{bmatrix} = 0 \mod X^{8}$$

$$\begin{bmatrix} q & q \end{bmatrix} \begin{bmatrix} 4 & 0 & 2 & 0 & 5 & 0 & 2 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ 6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 6 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} = 0$$

approximation and structured linear system

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interpolation and structured linear system

application of vector rational interpolation: given pairwise distinct points $\{(\alpha_i, \beta_i), 1 \leqslant i \leqslant 8\} = \{(24, 80), (31, 73), (15, 73), (32, 35), (83, 66), (27, 46), (20, 91), (59, 64)\},$ compute a bivariate polynomial $p(X, Y) \in \mathbb{K}[X, Y]$ such that $p(\alpha_i, \beta_i) = 0$ for $1 \leqslant i \leqslant 8$

 $\left. \begin{array}{l} M(X) = (X-24) \cdots (X-59) \\ L(X) = \text{Lagrange interpolant} \end{array} \right\} \longrightarrow \text{solutions} = \text{ideal } \langle M(X), Y - L(X) \rangle \\ \end{array} \right.$

solutions of smaller X-degree: $p(X, Y) = p_0(X) + p_1(X)Y + p_2(X)Y^2$

$$p(X, L(X)) = \begin{bmatrix} p_0 & p_1 & p_2 \end{bmatrix} \begin{bmatrix} 1 \\ L \\ L^2 \end{bmatrix} = 0 \mod M(X)$$

- ▶ instance of univariate rational vector interpolation
- with a structured input equation (powers of $L \mod M$)

interpolation and structured linear system

application of vector rational interpolation: given pairwise distinct points $\{(\alpha_i, \beta_i), 1 \leqslant i \leqslant 8\} = \{(24, 80), (31, 73), (15, 73), (32, 35), (83, 66), (27, 46), (20, 91), (59, 64)\},$ compute a bivariate polynomial $p(X, Y) \in \mathbb{K}[X, Y]$ such that $p(\alpha_i, \beta_i) = 0$ for $1 \leqslant i \leqslant 8$



polynomial matrices: reminder and motivation

why polynomial matrices here?

polynomial matrices: reminder and motivation

why polynomial matrices here?

omitting degree constraints, the set of solutions is
$$\begin{split} & \mathcal{S} = \{(p_1, \ldots, p_m) \in \mathbb{K}[X]^m \mid p_1 f_1 + \cdots + p_m f_m = 0 \text{ mod } M\} \\ & \text{ recall } \mathcal{M}(X) = \prod_{1 \leq i \leq d} (X - \alpha_i) \end{split}$$

polynomial matrices: reminder and motivation

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 $\mathbb S$ is a "free $\mathbb K[X]\text{-module}$ of rank $\mathfrak m$ ", meaning:

- \blacktriangleright stable under $\mathbb{K}[X]\text{-linear combinations}$
- $\scriptstyle \bullet$ admits a basis consisting of m elements
- basis = $\mathbb{K}[X]$ -linear independence + generates all solutions
polynomial matrices: reminder and motivation

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- basis = $\mathbb{K}[X]$ -linear independence + generates all solutions

 $\begin{array}{ll} \bullet \ & S \subset \mathbb{K}[X]^m \ \Rightarrow \ & S \text{ has rank} \leqslant m \\ \bullet \ & M(X)\mathbb{K}[X]^m \subset \ & S \ \Rightarrow \ & S \text{ has rank} \geqslant m \end{array}$

remark: solutions are not considered modulo M e.g. $(M,0,\ldots,0)$ is in ${\cal S}$ and may appear in a basis

polynomial matrices: reminder and motivation

why polynomial matrices here?

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basis of solutions:

- square nonsingular matrix \mathbf{P} in $\mathbb{K}[X]^{m \times m}$
- \blacktriangleright each row of **P** is a solution
- lacksimany solution is a $\mathbb{K}[X]$ -combination \mathbf{uP} , $\mathbf{u} \in \mathbb{K}[X]^{1 imes m}$

i.e. ${\mathbb S}$ is the ${\mathbb K}[X]\text{-row}$ space of P

polynomial matrices: reminder and motivation

why polynomial matrices here?

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i.e. ${\mathbb S}$ is the ${\mathbb K}[X]\text{-row}$ space of P

prove: det(P) is a divisor of $M(X)^m$

polynomial matrices: reminder and motivation

why polynomial matrices here?

omitting degree constraints, the set of solutions is
$$\begin{split} & \mathcal{S} = \{(p_1, \ldots, p_m) \in \mathbb{K}[X]^m \mid p_1 f_1 + \cdots + p_m f_m = 0 \text{ mod } M\} \\ & \text{ recall } \mathcal{M}(X) = \prod_{1 \leq i \leq d} (X - \alpha_i) \end{split}$$

basis of solutions: • square nonsingular matrix P in $\mathbb{K}[X]^{m \times m}$ • each row of P is a solution • any solution is a $\mathbb{K}[X]$ -combination $\mathbf{u}\mathbf{P}, \mathbf{u} \in \mathbb{K}[X]^{1 \times m}$ i.e. S is the $\mathbb{K}[X]$ -row space of P

prove: $det(\mathbf{P})$ is a divisor of $M(X)^m$

prove: any other basis is UP for $U\in\mathbb{K}[X]^{m\times m}$ with $\mathsf{det}(U)\in\mathbb{K}\setminus\{0\}$

polynomial matrices: reminder and motivation

why polynomial matrices here?

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$$\begin{split} & \mathcal{S} = \{(p_1, \ldots, p_m) \in \mathbb{K}[X]^m \mid p_1 f_1 + \cdots + p_m f_m = 0 \text{ mod } M\} \\ & \text{ recall } \mathcal{M}(X) = \prod_{1 \leq i \leq d} (X - \alpha_i) \end{split}$$

basis of solutions:

- square nonsingular matrix \mathbf{P} in $\mathbb{K}[X]^{m \times m}$
- ${\scriptstyle \blacktriangleright}$ each row of P is a solution
- ${\scriptstyle \bullet}$ any solution is a $\mathbb{K}[X]{\rm -combination}~{\bf uP}, {\bf u} \in \mathbb{K}[X]^{1 \times m}$

i.e. ${\mathbb S}$ is the ${\mathbb K}[X]\text{-row}$ space of P

computing a basis of S with "minimal degrees"

- ▶ has many more applications than a single small-degree solution
- ▶ is in most cases the fastest known strategy anyway(!)
- \rightsquigarrow degree minimality ensured via shifted reduced forms

polynomial matrices: reminder and motivation

 $\mathbf{A} = \begin{bmatrix} 3X+4 & X^3+4X+1 & 4X^2+3 \\ 5 & 5X^2+3X+1 & 5X+3 \\ 3X^3+X^2+5X+3 & 6X+5 & 2X+1 \end{bmatrix} \in \mathbb{K}[X]^{3\times 3} \qquad \begin{array}{c} 3\times 3 \text{ matrix of degree 3} \\ \text{with entries in } \mathbb{K}[X] = \mathbb{F}_7[X] \end{array}$

operations in $\mathbb{K}[X]_{\leq d}^{m \times m}$:

- combination of matrix and polynomial computations
- $\scriptstyle \bullet$ addition in $O(m^2d),$ naive multiplication in $O(m^3d^2)$
- \blacktriangleright some tools shared with $\mathbb K\text{-matrices},$ others specific to $\mathbb K[X]\text{-matrices}$

[Cantor-Kaltofen'91]

multiplication in $O(m^{\omega} d \log(d) + m^2 d \log(d) \log \log(d))$

 $\in O(\mathfrak{m}^{\omega}\mathsf{M}(d))\subset O\tilde{}(\mathfrak{m}^{\omega}d)$

polynomial matrices: reminder and motivation

 $\mathbf{A} = \begin{bmatrix} 3X+4 & X^3+4X+1 & 4X^2+3 \\ 5 & 5X^2+3X+1 & 5X+3 \\ 3X^3+X^2+5X+3 & 6X+5 & 2X+1 \end{bmatrix} \in \mathbb{K}[X]^{3\times 3} \qquad \begin{array}{c} 3\times 3 \text{ matrix of degree } 3 \\ \text{with entries in } \mathbb{K}[X] = \mathbb{F}_7[X] \end{array}$

operations in $\mathbb{K}[X]_{\leq d}^{m \times m}$:

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[Cantor-Kaltofen'91]

multiplication in $O(m^{\omega} d \log(d) + m^2 d \log(d) \log \log(d))$

 $\in O(\mathfrak{m}^{\omega}\mathsf{M}(d))\subset \mathsf{O}\tilde{}(\mathfrak{m}^{\omega}d)$

- ► Newton truncated inversion, matrix-QuoRem
- ▶ inversion and determinant via evaluation-interpolation
- ▶ vector rational approximation & interpolation

- \rightarrow fast $O^{\sim}(m^{\omega}d)$
- \rightarrow medium O[~](m^{ω +1}d)

 \rightarrow ???

polynomial matrices: reminder and motivation

 $\begin{array}{rcl} \mbox{reductions of most problems to polynomial matrix multiplication} \\ \mbox{matrix } m \times m \mbox{ of degree } d & \rightarrow & O^{\sim}(m^{\omega} d) \\ & & of "average" \mbox{ degree } \frac{D}{m} & \rightarrow & O^{\sim}(m^{\omega} \frac{D}{m}) \end{array}$

classical matrix operations

- multiplication
- kernel, system solving
- ▶ rank, determinant
- inversion $O^{(m^3d)}$

univariate specific operations

- truncated inverse, QuoRem
- Hermite-Padé approximation
- vector rational interpolation
- syzygies / modular equations

transformation to normal forms

- ▶ triangularization: Hermite form
- ▶ row reduction: Popov form
- diagonalization: Smith form

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- row reduction: Popov form
- diagonalization: Smith form

outline

introduction

- rational approximation and interpolation
- ► the vector case
- ► pol. matrices: reminders and motivation

shifted reduced forms

fast algorithms

applications

outline

introduction

shifted reduced forms

- rational approximation and interpolation
- ► the vector case
- ▶ pol. matrices: reminders and motivation
- ▶ reducedness: examples and properties
- ▶ shifted forms and degree constraints
- stability under multiplication

fast algorithms

applications

reducedness: examples and properties

notation:

let
$$\mathbf{A} \in \mathbb{K}[X]^{m \times n}$$
 with no zero row,
define $\mathbf{d} = (d_1, \dots, d_m) = \mathsf{rdeg}(\mathbf{A})$
and $\mathbf{X}^{\mathbf{d}} = \begin{bmatrix} X^{d_1} & & \\ & \ddots & \\ & & X^{d_m} \end{bmatrix} \in \mathbb{K}[X]^{m \times m}$

definition: (row-wise) leading matrix

the leading matrix of A is the unique matrix ${\sf Im}(A) \in \mathbb{K}^{m \times n}$ such that $A = X^d {\sf Im}(A) + R$ with ${\sf rdeg}(R) < d$ entry-wise

equivalently, $X^{-d}A = \mathsf{Im}\left(A\right) + \mathsf{terms}$ of strictly negative degree

reducedness: examples and properties

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definition: (row-wise) reduced matrix

 $\mathbf{A} \in \mathbb{K}[X]^{m \times n}$ is said to be reduced if $\mathsf{Im}(\mathbf{A})$ has full row rank

reducedness: examples and properties

consider the following matrices, with $\mathbb{K}=\mathbb{F}_7:$

$$\mathbf{A}_{1} = \begin{bmatrix} 3X+4 & X^{3}+4X+1 & 4X^{2}+3\\ 5 & 5X^{2}+3X+1 & 5X+3 \end{bmatrix}$$
$$\mathbf{A}_{2} = \begin{bmatrix} 3X+1 & 4X+3 & 5X+5\\ 0 & 4X^{2}+6X & 5\\ 4X^{2}+5X+2 & 5 & 6X^{2}+1 \end{bmatrix}$$

 $A_3 = transpose of A_1$

 $\mathbf{A}_4 = \text{transpose of } \mathbf{A}_2$

answer the following, for $i \in \{1, 2, 3, 4\}$:

- 1. what is $\mathsf{rdeg}(\mathbf{A}_i)$?
- 2. what is $Im(\mathbf{A}_i)$?
- 3. is \mathbf{A}_i reduced?

reducedness: examples and properties

let $\mathbf{A} \in \mathbb{K}[X]^{m \times n}$ with $m \leqslant n$, the following are equivalent:

(i) A is reduced (i.e. Im(A) has full rank)

reducedness: examples and properties

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(ii) for any vector $\mathbf{u} = [\mathbf{u}_1 \ 1 \ \mathbf{u}_2] \in \mathbb{K}[X]^{1 \times m}$ with 1 at index i, $\mathsf{rdeg}(\mathbf{u} \mathbf{A}) \geqslant \mathsf{rdeg}(\mathbf{A}_{i,*})$

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(iii) predictable degree: for any vector $\mathbf{u} = [u_1 \cdots u_m] \in \mathbb{K}[X]^{1 \times m}$, rdeg $(\mathbf{u}\mathbf{A}) = \max_{1 \leqslant i \leqslant m} (deg(u_i) + rdeg(\mathbf{A}_{i,*}))$

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reducedness: examples and properties

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(v) predictable determinantal degree: deg det(A) = $|\mathsf{rdeg}(A)|$ (only when $\mathfrak{m}=\mathfrak{n})$

reducedness: examples and properties

recall the matrix, with
$$\mathbb{K} = \mathbb{F}_7$$
,
 $\mathbf{A} = \begin{bmatrix} 3X+1 & 4X+3 & 5X+5\\ 0 & 4X^2+6X & 5\\ 4X^2+5X+2 & 5 & 6X^2+1 \end{bmatrix}$
1. what is deg det(\mathbf{A})?
2. what is rdeg($[4X^2+1 & 2X & 4X+5]\mathbf{A}$)?
3. is it possible to find a matrix
 $\mathbf{P} = \begin{bmatrix} p_{00} & p_{01} & p_{02}\\ p_{10} & p_{11} & p_{12} \end{bmatrix}$
whose rank is 2, whose degree is 1, and which is a left-multiple of \mathbf{A} ?

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find a row vector \mathbf{u} of degree 1 such that \mathbf{uA} has degree 2, where $\mathbf{A} = \begin{bmatrix} 3X+4 & X^3+4X+1 & 4X^2+3\\ 5 & 5X^2+3X+1 & 5X+3 \end{bmatrix}$

shifted forms and degree constraints

keeping our problem in mind:

- \bullet input: $f_i{\,}'s$ and $\alpha_i{\,}'s$ and degree constraints $d_1,\ldots,d_m\in\mathbb{Z}_{>0}$
- ${\scriptstyle \bullet}$ output: a solution p satisfying the constraints $\mathsf{cdeg}(p) < (d_1, \ldots, d_m)$

obstacle: computing a reduced basis of solutions ignores the constraints

exercise: suppose we have a reduced basis $P \in \mathbb{K}[X]^{m \times m}$ of solutions

- ${\scriptstyle \bullet}$ think of particular constraints (d_1,\ldots,d_m) that can be handled via ${\bf P}$
- ${\scriptstyle \bullet}$ give constraints (d_1,\ldots,d_m) for which P is "typically" not satisfactory

shifted forms and degree constraints

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solution: compute P in shifted reduced form

shifted forms and degree constraints

$$\mathbf{A} = \begin{bmatrix} 3X+4 & X^3+4X+1 & 4X^2+3 \\ 5 & 5X^2+3X+1 & 5X+3 \\ 3X^3+X^2+5X+3 & 6X+5 & 2X+1 \end{bmatrix}$$

using elementary row operations, transform ${\bf A}$ into...

Hermite form
$$\mathbf{H} = \begin{bmatrix} X^6 + 6X^4 + X^3 + X + 4 & 0 & 0\\ 5X^5 + 5X^4 + 6X^3 + 2X^2 + 6X + 3 & X & 0\\ 3X^4 + 5X^3 + 4X^2 + 6X + 1 & 5 & 1 \end{bmatrix}$$

Popov form
$$\mathbf{P} = \begin{bmatrix} X^3 + 5X^2 + 4X + 1 & 2X + 4 & 3X + 5 \\ 1 & X^2 + 2X + 3 & X + 2 \\ 3X + 2 & 4X & X^2 \end{bmatrix}$$

shifted forms and degree constraints



$$\begin{bmatrix} 10 \\ 15 & 0 \\ 15 & 0 \\ 15 & 0 \\ 15 & 0 \end{bmatrix} \begin{bmatrix} 4 \\ 3 & 7 \\ 1 & 5 & 3 \\ 3 & 6 & 1 & 2 \end{bmatrix}$$

shifted forms and degree constraints



shifted forms and degree constraints



shifted forms and degree constraints



invariant: D = deg(det(A)) = 4 + 7 + 3 + 2 = 7 + 1 + 2 + 6

► average column degree is $\frac{D}{m}$ ► size of object is $mD + m^2 = m^2(\frac{D}{m} + 1)$

shifted forms and degree constraints



[Beckermann-Labahn-Villard, 1999; Mulders-Storjohann, 2003]

shifted reduced form: **arbitrary** degree constraints + **no** column normalization

pprox minimal, non-reduced, \prec -Gröbner basis

shift: integer tuple $s = (s_1, \dots, s_m)$ acting as column weights \rightarrow connects Popov and Hermite forms

$\mathbf{s} = (0, 0, 0, 0)$ Popov	4 3 3 3	3 4 3 3	3 3 4 3	3 3 3 4	[7 0 6	0 1 0	1 2 1	5 0 6
s = (0, 2, 4, 6) s-Popov	7 6 6 6	4 5 4 4	2 2 3 2	0 0 0 1	8 7 0	5 6 1	1 1 2	0
$\mathbf{s} = (0, D, 2D, 3D)$ Hermite	16 15 15 15	0	0	0	4 3 1 3	7 5 6	3 1	2

- \blacktriangleright normal form, average column degree D/m
- ▶ shifted reduced form: same without normalization
- \blacktriangleright shifts arise naturally in algorithms (approximants, kernel, ...)

shifted forms and degree constraints

shifted row degree of a polynomial matrix = the list of the maximum shifted degree in each of its rows

$$\begin{split} &\text{for } \mathbf{A} = (\mathfrak{a}_{i,j}) \in \mathbb{K}[X]^{m \times n} \text{, and } \mathbf{s} = (s_1, \dots, s_n) \in \mathbb{Z}^n \text{,} \\ &\text{rdeg}_{\mathbf{s}}(\mathbf{A}) = (\text{rdeg}_{\mathbf{s}}(\mathbf{A}_{1,*}), \dots, \text{rdeg}_{\mathbf{s}}(\mathbf{A}_{m,*})) \\ &= \left(\max_{1 \leqslant j \leqslant n} (\text{deg}(\mathbf{A}_{1,j}) + s_j), \ \dots, \ \max_{1 \leqslant j \leqslant n} (\text{deg}(\mathbf{A}_{m,j}) + s_j) \right) \in \mathbb{Z}^m \end{split}$$

example: for the matrix $\mathbf{A} = \begin{bmatrix} 3X + 4 & X^3 + 4X + 1 & 4X^2 + 3 \\ 5 & 5X^2 + 3X + 1 & 5X + 3 \end{bmatrix}$, describe $\mathsf{rdeg}_{(0,0,0)}(\mathbf{A})$, $\mathsf{rdeg}_{(0,1,2)}(\mathbf{A})$, and $\mathsf{rdeg}_{(-1,-3,-2)}(\mathbf{A})$

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- ${\scriptstyle \blacktriangleright } \operatorname{rdeg}_{s}(\mathbf{A}) = \operatorname{rdeg}(\mathbf{A}\mathbf{X}^{s})$
- ${\scriptstyle \sf \bullet} \, {\sf rdeg}_s(A)$ only depends on s and the degrees in A

shifted forms and degree constraints

notation:

let
$$\mathbf{A} \in \mathbb{K}[X]^{m \times n}$$
 with no zero row, and $\mathbf{s} \in \mathbb{Z}^n$, define $\mathbf{d} = (d_1, \dots, d_m) = \mathsf{rdeg}_{\mathbf{s}}(\mathbf{A})$ and $\mathbf{X}^{\mathbf{d}} = \begin{bmatrix} X^{d_1} & & \\ & \ddots & \\ & & X^{d_m} \end{bmatrix} \in \mathbb{K}[X, X^{-1}]^{m \times m}$

definition: s-leading matrix / s-reduced matrix

assuming $s \ge 0$,

- ullet the s-leading matrix of A is $\mathsf{Im}_{s}(A) = \mathsf{Im}(AX^{s}) \in \mathbb{K}^{m imes n}$
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- the s-leading matrix of A is $\mathsf{Im}_{s}(A) = \mathsf{Im}(AX^{s}) \in \mathbb{K}^{m \times n}$
- ${\scriptstyle \blacktriangleright}\, {\bf A} \in \mathbb{K}[X]^{m \times n}$ is s-reduced if ${\sf Im}_{{\boldsymbol s}}({\bf A})$ has full row rank
- ${\scriptstyle \bullet}$ these notions are invariant under $s \rightarrow s + (c, \ldots, c)$
- ${\scriptstyle \bullet}$ they coincide with the non-shifted case when $s=({\tt 0},\ldots,{\tt 0})$
- ${\scriptstyle\blacktriangleright}\, X^{-d}AX^s = {\sf Im}_s(A) + {\sf terms}$ of strictly negative degree
shifted forms and degree constraints

exercise: for each of the matrices below, and each shift s, 1. give the s-leading matrix 2. deduce whether the matrix is s-reduced

$$\mathbf{A} = \begin{bmatrix} 3X+4 & X^3+4X+1 & 4X^2+3\\ 5 & 5X^2+3X+1 & 5X+3\\ 3X^3+X^2+5X+3 & 6X+5 & 2X+1 \end{bmatrix}$$

$$\mathbf{H} = \begin{bmatrix} X^6 + 6X^4 + X^3 + X + 4 & 0 & 0\\ 5X^5 + 5X^4 + 6X^3 + 2X^2 + 6X + 3 & X & 0\\ 3X^4 + 5X^3 + 4X^2 + 6X + 1 & 5 & 1 \end{bmatrix}$$

$$\mathbf{P} = \begin{bmatrix} X^3 + 5X^2 + 4X + 1 & 2X + 4 & 3X + 5 \\ 1 & X^2 + 2X + 3 & X + 2 \\ 3X + 2 & 4X & X^2 \end{bmatrix}$$

$$\mathbf{s} = (0, 0, 0), \ \mathbf{s} = (0, 5, 6), \ \mathbf{s} = (-3, -2, -2)$$

shifted forms and degree constraints

the characterizations generalize to the s-shifted case, using s-row degrees and s-leading matrices where appropriate (proofs: direct, with: A is s-reduced $\Leftrightarrow AX^s$ is reduced)

for example recall the predictable degree property:

 $\begin{array}{l} \mathbf{A} \text{ is reduced if and only if for any } \mathbf{u} = [u_1 \cdots u_m] \in \mathbb{K}[X]^{1 \times m},\\ \mathsf{rdeg}(\mathbf{u} \mathbf{A}) = \mathsf{max}_{1 \leqslant i \leqslant m}(\mathsf{deg}(u_i) + \mathsf{rdeg}(\mathbf{A}_{i,*})) \end{array}$

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 ${\scriptstyle \bullet}$ this means $\mathsf{rdeg}(\mathbf{u}A) = \mathsf{rdeg}_t(\mathbf{u})$ where $t = \mathsf{rdeg}(A)$

 $\textbf{`i.e. rdeg}(\mathbf{uA}) = \mathsf{rdeg}(\mathbf{uX}^{\mathsf{rdeg}(\mathbf{A})}) \textbf{, ``no surprising cancellation''}$

- proof: let $\delta = \mathsf{rdeg}_t(\mathbf{u})$, our goal is to show $\mathsf{rdeg}(\mathbf{u}\mathbf{A}) = \delta$ terms of $X^{-\delta}\mathbf{u}\mathbf{A}$ have degree $\leqslant 0$, and $X^{-\delta}\mathbf{u}\mathbf{A} = (X^{-\delta}\mathbf{u}X^t)(\mathbf{X}^{-t}\mathbf{A})$; the term of degree 0 is $\mathsf{Im}_t(\mathbf{u})\mathsf{Im}(\mathbf{A})$, it is nonzero since $\mathsf{Im}(\mathbf{A})$ has full rank and $\mathsf{Im}_t(\mathbf{u}) \neq 0$ (the case $\mathbf{u} = \mathbf{0}$ is trivial)

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- \blacktriangleright s-reduced forms provide vectors of minimal s-degree in the module
- \blacktriangleright satisfying degree constraints (d_1,\ldots,d_m) \Rightarrow taking $s=(-d_1,\ldots,-d_m)$
- $\bullet \text{ indeed } \mathsf{cdeg}([p_1 \ \cdots \ p_{\mathfrak{m}}]) < (d_1, \ldots, d_{\mathfrak{m}})$
- if and only if $\mathsf{rdeg}_{(-d_1,\ldots,-d_\mathfrak{m})}([p_1 \ \cdots \ p_\mathfrak{m}]) < 0$

stability under multiplication

algorithms based on polynomial matrix multiplication

[iterative: van Barel-Bultheel 1991, Beckermann-Labahn 2000] [divide and conquer: Beckermann-Labahn 1994, Giorgi-Jeannerod-Villard 2003]

- \blacktriangleright compute a first basis P_1 for a subproblem
- update the input instance to get the second subproblem
- ${\scriptstyle \bullet}$ compute a second basis P_2 for this second subproblem
- \blacktriangleright the output basis of solutions is $\mathbf{P}_2\mathbf{P}_1$

we want P_2P_1 to be reduced: 1. is it implied by " P_1 reduced and P_2 reduced"? 2. any idea of how to fix this?

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```
we want P_2P_1 to be reduced
theorem: implied by "P_1 is reduced and P_2 is t-reduced"
where t = rdeg(P_1)
```

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[iterative: van Barel-Bultheel 1991, Beckermann-Labahn 2000] [divide and conquer: Beckermann-Labahn 1994, Giorgi-Jeannerod-Villard 2003]

- \blacktriangleright compute a first basis P_1 for a subproblem
- update the input instance to get the second subproblem
- \blacktriangleright compute a second basis \mathbf{P}_2 for this second subproblem
- \blacktriangleright the output basis of solutions is $\mathbf{P}_2\mathbf{P}_1$

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we want P_2P_1 to be reduced:
1. is it implied by "P_1 reduced and P_2 reduced"?
2. any idea of how to fix this?
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we want P_2P_1 to be s-reduced
theorem: implied by "P_1 is s-reduced and P_2 is t-reduced"
where t = \mathsf{rdeg}_s(P_1)
```

stability under multiplication

let $\mathcal{M}\subseteq \mathcal{M}_1$ be two $\mathbb{K}[X]$ -submodules of $\mathbb{K}[X]^m$ of rank m, let $P_1\in \mathbb{K}[X]^{m\times m}$ be a basis of \mathcal{M}_1 , let $s\in \mathbb{Z}^m$ and $t=\mathsf{rdeg}_s(P_1)$, • the rank of the module $\mathcal{M}_2=\{\lambda\in \mathbb{K}[X]^{1\times m}\mid \lambda P_1\in \mathcal{M}\}$ is m and for any basis $P_2\in \mathbb{K}[X]^{m\times m}$ of \mathcal{M}_2 , the product P_2P_1 is a basis of \mathcal{M} • if P_1 is s-reduced and P_2 is t-reduced, then P_2P_1 is s-reduced

stability under multiplication

let $\mathcal{M}\subseteq \mathcal{M}_1$ be two $\mathbb{K}[X]$ -submodules of $\mathbb{K}[X]^m$ of rank m, let $P_1\in \mathbb{K}[X]^{m\times m}$ be a basis of \mathcal{M}_1 , let $s\in \mathbb{Z}^m$ and $t=\mathsf{rdeg}_s(P_1)$, • the rank of the module $\mathcal{M}_2=\{\lambda\in \mathbb{K}[X]^{1\times m}\mid \lambda P_1\in \mathcal{M}\}$ is m and for any basis $P_2\in \mathbb{K}[X]^{m\times m}$ of \mathcal{M}_2 , the product P_2P_1 is a basis of \mathcal{M} • if P_1 is s-reduced and P_2 is t-reduced, then P_2P_1 is s-reduced

Let $A \in \mathbb{K}[X]^{m \times m}$ denote the adjugate of P_1 . Then, we have $AP_1 = det(P_1)I_m$. Thus, $pAP_1 = det(P_1)p \in \mathcal{M}$ for all $p \in \mathcal{M}$, and therefore $\mathcal{M}A \subseteq \mathcal{M}_2$. Now, the nonsingularity of A ensures that $\mathcal{M}A$ has rank m; this implies that \mathcal{M}_2 has rank m as well (see e.g. [Dummit-Foote 2004, Sec. 12.1, Thm. 4]). The matrix P_2P_1 is nonsingular since $det(P_2P_1) \neq 0$. Now let $p \in \mathcal{M}$; we want to prove that p is a $\mathbb{K}[X]$ -linear combination of the rows of P_2P_1 . First, $p \in \mathcal{M}_1$, so there exists $\lambda \in \mathbb{K}[X]^{1 \times m}$ such that $p = \lambda P_1$. But then $\lambda \in \mathcal{M}_2$, and thus there exists $\mu \in \mathbb{K}[X]^{1 \times m}$ such that $\lambda = \mu P_2$. This yields the combination $p = \mu P_2P_1$.

stability under multiplication

$$\begin{split} &\text{let }\mathcal{M}\subseteq\mathcal{M}_1\text{ be two }\mathbb{K}[X]\text{-submodules of }\mathbb{K}[X]^m\text{ of rank }m,\\ &\text{let }P_1\in\mathbb{K}[X]^{m\times m}\text{ be a basis of }\mathcal{M}_1,\\ &\text{let }s\in\mathbb{Z}^m\text{ and }t=\text{rdeg}_s(P_1),\\ &\text{ the rank of the module }\mathcal{M}_2=\{\lambda\in\mathbb{K}[X]^{1\times m}\mid\lambda P_1\in\mathcal{M}\}\text{ is }m\\ &\text{ and for any basis }P_2\in\mathbb{K}[X]^{m\times m}\text{ of }\mathcal{M}_2,\\ &\text{ the product }P_2P_1\text{ is a basis of }\mathcal{M}\\ &\text{ if }P_1\text{ is }s\text{-reduced and }P_2\text{ is }t\text{-reduced},\\ &\text{ then }P_2P_1\text{ is }s\text{-reduced} \end{split}$$

Let $d=\mathsf{rdeg}_t(P_2);$ we have $d=\mathsf{rdeg}_s(P_2P_1)$ by the predictable degree property. Using $X^{-d}P_2P_1X^s=X^{-d}P_2X^tX^{-t}P_1X^s$, we obtain that $\mathsf{Im}_s(P_2P_1)=\mathsf{Im}_t(P_2)\mathsf{Im}_s(P_1)$. By assumption, $\mathsf{Im}_t(P_2)$ and $\mathsf{Im}_s(P_1)$ are invertible, and therefore $\mathsf{Im}_s(P_2P_1)$ is invertible as well; thus P_2P_1 is s-reduced.

outline

introduction

shifted reduced forms

- rational approximation and interpolation
- ► the vector case
- ► pol. matrices: reminders and motivation
- ▶ reducedness: examples and properties
- ▶ shifted forms and degree constraints
- stability under multiplication

fast algorithms

applications

outline

introduction

shifted reduced forms

fast algorithms

$\scriptstyle \bullet$ rational approximation and interpolation

- the vector case
- ► pol. matrices: reminders and motivation
- ▶ reducedness: examples and properties
- shifted forms and degree constraints
- stability under multiplication
- iterative algorithm and output size
- ▶ base case: modulus of degree 1
- ▶ recursion: residual and basis multiplication

applications

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

$$\label{eq:rescaled} \text{input: vector } \mathbf{F} = \begin{bmatrix} f_1 \\ \vdots \\ f_m \end{bmatrix} \text{, points } \alpha_1, \dots, \alpha_d \in \mathbb{K} \text{, shift } \mathbf{s} = (s_1, \dots, s_m) \in \mathbb{Z}^m$$

1.
$$\mathbf{P} = \begin{bmatrix} -\mathbf{p}_1 - \\ \vdots \\ -\mathbf{p}_m - \end{bmatrix} = \text{identity matrix in } \mathbb{K}[X]^{m \times m}$$

2. for i from 1 to d:

а

. evaluate updated vector
$$\begin{bmatrix} (\mathbf{p}_1 \cdot \mathbf{F})(\alpha_i) \\ \vdots \\ (\mathbf{p}_m \cdot \mathbf{F})(\alpha_i) \end{bmatrix} = (\mathbf{P} \cdot \mathbf{F})(\alpha_i)$$

- b. choose pivot π with smallest s_{π} such that $(\mathbf{p}_{\pi} \cdot \mathbf{F})(\alpha_i) \neq 0$ update pivot shift $s_{\pi} = s_{\pi} + 1$
- $\begin{array}{ll} \text{c. eliminate:} & /* \text{ after this, } \forall j \neq \pi, \ (p_j \cdot F)(\alpha_i) = 0 \ */ \\ \text{for } j \neq \pi \text{ do } p_j \leftarrow p_j \frac{(p_j \cdot F)(\alpha_i)}{(p_\pi \cdot F)(\alpha_i)} p_\pi; & p_\pi \leftarrow (X \alpha_i) p_\pi \end{array}$

after i iterations: P is an s-reduced basis of solutions for $(\alpha_1,\ldots,\alpha_i)$

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift			[02	4 6]				
basis		1 0 0 0					0 1 0 0		0 0 1 0	0 0 0 1
values	「1 80 95 34	1 73 91 47	1 73 91 47	1 35 61 1	1 66 88 85	1 46 79 45	1 91 36 75	1 64 22 50		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

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shift			[(02	4 6]				
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shift			[02	4 6]				
basis	:	1 17 2 63					0 1 0 0		0 0 1 0	0 0 0 1
values	$\left[\begin{array}{c}1\\0\\0\\0\end{array}\right]$	1 90 93 13	1 90 93 13	1 52 63 64	1 83 90 51	1 63 81 11	1 11 38 41	1 81 24 16		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift			[12	4 6]				
basis	X	+ 73 17 2 63					0 1 0 0		0 0 1 0	0 0 0 1
values	0 0 0 0	7 90 93 13	88 90 93 13	8 52 63 64	59 83 90 51	3 63 81 11	93 11 38 41	35 81 24 16		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift			[12	4 6]				
basis	X - 1 6	+ 73 17 2 53					0 1 0 0		0 0 1 0	0 0 0 1
values	0 0 0 0	7 90 93 13	88 90 93 13	8 52 63 64	59 83 90 51	3 63 81 11	93 11 38 41	35 81 24 16		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

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shift			[1 2	4 6]				
basis	X - X - 56X 12X	+ 73 + 90 + 16 + 66					0 1 0 0		0 0 1 0	0 0 0 1
values	0 0 0 0	7 0 0 0	88 81 74 2	8 60 26 63	59 45 96 80	3 66 55 47	93 7 8 90	35 19 44 48		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift			[2	2	4 6]					
basis	$X^{2} + 42$ X + 56X - 12X -	X + 65 90 ⊢ 16 ⊢ 66	i				0 1 0 0		0 0 1 0	0 0 0 1
values	0 0 0 0	0 0 0 0	47 81 74 2	8 60 26 63	61 45 96 80	85 66 55 47	44 7 8 90	10 19 44 48		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

shift			[2	2	4 6]					
basis	$X^{2} + 42$ X + 56X - 12X -	X + 65 90 ⊢ 16 ⊢ 66	5				0 1 0 0		0 0 1 0	0 0 0 1
values	0 0 0 0	0 0 0 0	47 81 74 2	8 60 26 63	61 45 96 80	85 66 55 47	44 7 8 90	10 19 44 48		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift				[<mark>3</mark> 2	4 6]				
basis	[,	$ \begin{array}{r} X^3 + 27X^2 \\ 54X^2 + 3 \\ 17X^2 + 3 \\ 66X^2 + 3 \end{array} $	+ 17X 38X + 91X + 58X +	1 + 92 11 54 88				0 1 0 0		0 0 1 0	0 - 0 0 1 _
values		0 0 0 0	0 0 0 0	0 0 0 0	39 7 65 9	74 41 66 32	50 0 45 31	26 55 77 84	52 74 20 29		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift			[3 2	4 6]				
basis	$+ 27X^{2}$ $54X^{2} + 32$ $17X^{2} + 92$ $56X^{2} + 92$	+ 17X 38X + 91X + 68X +	1 + 92 11 54 88				0 1 0 0		0 0 1 0	0 0 0 1
values	0 0 0 0	0 0 0 0	0 0 0 0	39 7 65 9	74 41 66 32	50 0 45 31	26 55 77 84	52 74 20 29		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift				[3	3 3	4 6	5]				
basis	$\begin{array}{c} X^3 + 31X^2 + 27X + 3\\ 54X^3 + 56X^2 + 56X + 3\\ 56X^2 + 43X + 35\\ 52X^2 + 33X + 60 \end{array}$						>	36 (+ 65 60 68		0 0 1 0	0 0 0 1
values		0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	95 54 4 7	50 0 45 31	66 19 79 41	0 58 95 17		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift				[43	4 6	5]					
basis	$X^4 + 452$ $81X^3$ 2 $52X^3$	42		36 X	X + 19 X + 67 35 0)	())) [)	0 0 0 1			
values		0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	13 89 48 12	13 55 17 78	0 58 95 17			

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift				[•	4 <mark>4</mark>	4 6	5]				
basis	$\begin{array}{c} X^4 + 19X^3 + 57X^2 + 44X + 26 \\ 81X^4 + 64X^3 + 51X^2 + 68X + 42 \\ 3X^3 + 44X^2 + 54X + 64 \\ 28X^3 + 45X^2 + 44X + 52 \end{array}$						$74X + 43 \\ X^2 + 40X + 34 \\ 6X + 49 \\ 50X + 52$				0 0 0 1
values		0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	66 3 56 15	70 13 55 7		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift				[54	4	6]				
basis	$\begin{bmatrix} X^5 + 96X^4 - 6X^4 + 94\\ 55X^4 + 94\\ 13X^4 + 8 \end{bmatrix}$	$+65X^{3} + 68X^{2} + 19X + 62$ $+X^{3} + 44X^{2} + 66X + 32$ $+8X^{3} + 75X^{2} + 49X + 39$ $+81X^{3} + 10X^{2} + 34X + 2$					$74X^{2} + 18X + 13 X^{2} + 19X + 10 2X + 86 42X + 29$				0 0 0 1
values		0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	14 1 25 44		

iterative algorithm [van Barel-Bultheel / Beckermann-Labahn]

parameters: d = 8 m = 4 s = (0, 2, 4, 6), base field \mathbb{F}_{97} input: (24, 31, 15, 32, 83, 27, 20, 59) and $\mathbf{F} = [1 \ L \ L^2 \ L^3]^T$

shift				[!	5 <mark>5</mark>	4 6]				
basis	$\begin{bmatrix} X^5 + 12X^4 \\ 6X^5 + 31X^4 \\ 2X^4 + 56 \\ 40X^4 + 19 \end{bmatrix}$	$\begin{array}{c} + 10X^3 + 34X^2 + 65X + 2 \\ + 27X^3 + 89X^2 + 18X + 52 \\ X^3 + 42X^2 + 48X + 15 \\ 9X^3 + 14X^2 + 40X + 49 \end{array}$				$\begin{array}{c} 60X^2 + 43X + 67\\ X^3 + 57X^2 + 53X + 89\\ 72X^2 + 12X + 30\\ 53X^2 + 79X + 74 \end{array}$				0 0 1 0	0 - 0 0 1 _
values		0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0		

base case: modulus of degree 1

modular vector equation

input:

- ${\scriptstyle \bullet} \text{ vector } \mathbf{F} = [f_1 \ \cdots \ f_m]^{\sf T} \in \mathbb{K}[X]^{m \times 1} \text{ of degree} < d$
- ${\scriptstyle \bullet}$ field elements $(\alpha_1,\ldots,\alpha_d)\in \mathbb{K}^d$
- $\bullet \mathsf{ shift } s = (s_1, \ldots, s_m) \in \mathbb{Z}^m$

output:

matrix $P \in \mathbb{K}[X]^{m \times m}$ such that

- $\mathbf{PF}=0 \mbox{ mod } \prod_{1\leqslant i\leqslant d} (X-\alpha_i)$
- ${\scriptstyle \bullet}\, P$ generates all vectors p such that $pF=0 \mbox{ mod } \prod_{1\leqslant i\leqslant d} (X-\alpha_i)$
- $\bullet \mathbf{P}$ is s-reduced

notation: $\mathbb{I}(\pmb{\alpha},\mathbf{F})=\{\mathbf{p}\in\mathbb{K}[X]^{1\times\mathfrak{m}}\mid\mathbf{pF}=0\text{ mod }\prod_{1\leqslant i\leqslant d}(X-\alpha_i)\}$

base case: modulus of degree 1

modular vector reconstruction: base case

input:

- ${\scriptstyle \bullet} \text{ vector } \mathbf{F} = [f_1 \ \cdots \ f_m]^{\sf T} \in \mathbb{K}[X]^{m \times 1} \text{ of degree} < 1$
- $\bullet \ \text{field element} \ \alpha \in \mathbb{K}$
- $\bullet \mathsf{ shift } s = (s_1, \ldots, s_m) \in \mathbb{Z}^m$

output:

matrix $P \in \mathbb{K}[X]^{\mathfrak{m} \times \mathfrak{m}}$ such that

- ${\scriptstyle \bullet} \, {\bf PF} = 0 \ \text{mod} \ (X-\alpha)$
- ${\scriptstyle \bullet} \, {\bf P}$ generates all vectors ${\bf p}$ such that ${\bf pF}=0 \mbox{ mod } (X-\alpha)$
- $\bullet \mathbf{P}$ is s-reduced

base case: modulus of degree 1

modular vector reconstruction: base case

input:

- $\textbf{ vector } \mathbf{F} = [f_1 \ \cdots \ f_m]^\mathsf{T} \in \mathbb{K}[X]^{m \times 1} \text{ of degree} < 1 \qquad \qquad \mathbf{F} \in \mathbb{K}^{m \times 1}$
- ${\scriptstyle \bullet} \, {\sf field} \, \, {\sf element} \, \, \alpha \in \mathbb{K}$
- $\bullet \mathsf{ shift } s = (s_1, \ldots, s_m) \in \mathbb{Z}^m$

output:

matrix $P \in \mathbb{K}[X]^{m \times m}$ such that

• $\mathbf{PF} = 0 \mod (X - \alpha)$

- $(\mathbf{PF})(\alpha) = \mathbf{P}(\alpha)\mathbf{F} = \mathbf{0}$
- ${\scriptstyle \bullet}\, {\bf P}$ generates all vectors ${\bf p}$ such that ${\bf pF}=0 \mbox{ mod } (X-\alpha)$
- $\bullet \mathbf{P}$ is s-reduced

base case: modulus of degree 1

modular vector reconstruction: base case

$$\label{eq:relative} \mbox{iterative algorithm:} \qquad P = \begin{bmatrix} I_{\pi-1} & \lambda_1 & 0 \\ 0 & X-\alpha & 0 \\ 0 & \lambda_2 & I_{m-\pi} \end{bmatrix}$$

where

- π minimizes s_{π} among indices such that $(\mathbf{p}_{\pi}\mathbf{F})(\alpha_{i}) \neq 0$
- \blacktriangleright the vectors $\lambda_1\in\mathbb{K}^{(\pi-1)\times 1}$ and $\lambda_2\in\mathbb{K}^{(m-\pi)\times 1}$ are constant

base case: modulus of degree 1

modular vector reconstruction: base case

$$\label{eq:relative} \mbox{iterative algorithm:} \qquad P = \begin{bmatrix} I_{\pi-1} & \lambda_1 & 0 \\ 0 & X-\alpha & 0 \\ 0 & \lambda_2 & I_{m-\pi} \end{bmatrix}$$

where

• π minimizes s_{π} among indices such that $(\mathbf{p}_{\pi}\mathbf{F})(\alpha_i) \neq 0$

 \blacktriangleright the vectors $\lambda_1\in\mathbb{K}^{(\pi-1)\times 1}$ and $\lambda_2\in\mathbb{K}^{(m-\pi)\times 1}$ are constant

iterative algorithm:

- $\mathbf{P} = \text{identity matrix in } \mathbb{K}[X]^{m \times m}$
- ▶ for i from 1 to d:
 - a. from the evaluation $F(\alpha_i),$ find P_i as above
 - **b.** update shift $s_{\pi} \leftarrow s_{\pi} + 1$
 - **c.** update $\mathbf{P} \leftarrow \mathbf{P}_i \mathbf{P}$ as well as $\mathbf{F} \leftarrow \frac{\mathbf{P}_i \mathbf{F}}{X \alpha_i} \mod \prod_{i+1 \leq j \leq d} (X \alpha_j)$

called residual vector

base case: modulus of degree 1

modular vector reconstruction: base case

$$\label{eq:product} \text{iterative algorithm:} \qquad P = \begin{bmatrix} I_{\pi-1} & \lambda_1 & 0 \\ 0 & X-\alpha & 0 \\ 0 & \lambda_2 & I_{m-\pi} \end{bmatrix}$$

where

- π minimizes s_{π} among indices such that $(\mathbf{p}_{\pi}\mathbf{F})(\alpha_i) \neq 0$
- \blacktriangleright the vectors $\lambda_1\in\mathbb{K}^{(\pi-1)\times 1}$ and $\lambda_2\in\mathbb{K}^{(m-\pi)\times 1}$ are constant

complexity $O(m^2d^2)$:

- iteration with d steps
- $\scriptstyle \bullet$ each step: evaluation of F + multiplications $P_{\rm i}F$ and $P_{\rm i}P$
- ${\scriptstyle \bullet}$ at any stage ${\bf F}$ has degree < d and size $m \times 1$
- $\scriptstyle \bullet$ at any stage ${\bf P}$ has degree $\leqslant d$ and size $m\times m$

normalizing at each step + refined analysis yields $O(md^2)$

base case: modulus of degree 1

modular vector reconstruction: base case

$$\label{eq:relative} \mbox{iterative algorithm:} \qquad P = \begin{bmatrix} I_{\pi-1} & \lambda_1 & 0 \\ 0 & X-\alpha & 0 \\ 0 & \lambda_2 & I_{m-\pi} \end{bmatrix}$$

where

- π minimizes s_{π} among indices such that $(\mathbf{p}_{\pi}\mathbf{F})(\alpha_i) \neq 0$
- \blacktriangleright the vectors $\lambda_1\in\mathbb{K}^{(\pi-1)\times 1}$ and $\lambda_2\in\mathbb{K}^{(m-\pi)\times 1}$ are constant

correctness:

- ${\scriptstyle \bullet}$ the main task is to prove the base case with ${\bf P}_{i}$
- ▶ then, direct consequence of the "basis multiplication theorem"
iterative algorithm – complexity aspects

- ${\scriptstyle \bullet} \text{ input size: } md+d \text{ elements from } \mathbb{K}$
 - . md coefficients of ${\bf F}\xspace{-1mu}$, assumed reduced modulo M(X)
 - . d points α_1,\ldots,α_d
- ${\scriptstyle \bullet} \, \text{output size:} \leqslant m^2(d+1)$ elements from $\mathbb K$
 - . $m\times m$ matrix P of degree at most i at step i

is this output size bound tight?

iterative algorithm – complexity aspects

- ${\scriptstyle \bullet} \text{ input size: } md+d \text{ elements from } \mathbb{K}$

 - . d points α_1,\ldots,α_d
- ${\scriptstyle \bullet} \, \text{output size:} \leqslant m^2(d+1)$ elements from $\mathbb K$

. $m \times m$ matrix $I\!\!P$ of degree at most i at step i

is this output size bound tight?

- ${\scriptstyle \blacktriangleright}$ one can prove ${\sf deg}({\sf det}(P)) \leqslant d$
 - . P is a basis of $\mathbb{J}(\alpha,F)$, which is the kernel of $\mathbb{K}[X]^m \to \mathbb{K}[X]/\langle M(X)\rangle, p \mapsto pF$
 - . $\mathbb{K}[X]^m/\mathbb{I}(\pmb{\alpha},F)$ has $\mathbb{K}\text{-dimension}$ at most $\text{dim}_\mathbb{K}(\mathbb{K}[X]/\langle M(X)\rangle)=d$
- ${\scriptstyle \bullet}$ normalized bases have average column degree $\leqslant d,$ and size $\leqslant m(d+1)$
- $\scriptstyle \bullet$ yet the bound $\Theta(m^2(d+1))$ is tight for this algorithm
 - . normalizing at each step is feasible for the iterative version
 - . but is much harder to incorporate in fast divide and conquer versions

iterative algorithm – complexity aspects

example instance of Hermite-Padé approximation where the output size is in $\Omega(m^2d)$

parameters: $\mathbb{K} = \mathbf{F}_{97}$, $\mathfrak{m} = 4$, $\boldsymbol{\alpha} = \mathbf{0}$, $\mathfrak{d} = 128$, $\mathbf{s} = (0, \dots, 0)$

choose random polynomial R(X) of degree $<128\,$

$$\mathbf{F} = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \end{bmatrix} = \begin{bmatrix} R \\ R + XR \\ XR + X^2R \\ X^2R + X^3R \end{bmatrix}$$

- approximants are ${f p}$ such that ${f p}{f F}=0$ mod X^{128}
- $ightarrow {f F}$ has small vectors in its left kernel
- \Rightarrow reduced approximant basis has unbalanced row degrees (1, 1, 1, 125)
- will help to build an example with output size $\Omega(m^2d)$

iterative algorithm – complexity aspects

running the iterative algorithm:

i	1
s	(0, 0, 0, 0)
f_1	R
f_2	R + XR
f ₃	$XR + X^2R$
f_4	$X^2R + X^3R$

Р

iterative algorithm - complexity aspects

i	1	2
S	(<mark>0</mark> , 0, 0, 0)	(1, 0, 0, 0)
f_1	R	XR
f_2	$\mathbf{R} + \mathbf{XR}$	XR
f ₃	$XR + X^2R$	$XR + X^2R$
f_4	$X^2R + X^3R$	$X^2R + X^3R$
Р	$\begin{bmatrix} 1 & & \\ 0 & 0 & \\ & & 0 \\ & & & 0 \end{bmatrix}$	

iterative algorithm – complexity aspects

. •

. ...

•

.. ..

running the iterative algorithm:			
i	1	2	3
S	(<mark>0</mark> , 0, 0, 0)	(1, <mark>0</mark> , 0, 0)	(1, 1, 0, 0)
f ₁	R	XR	0
f_2	R + XR	XR	X ² R
f ₃	$XR + X^2R$	$XR + X^2R$	X ² R
f_4	$X^2R + X^3R$	$X^2R + X^3R$	$X^2R + X^3R$
Р		$\begin{bmatrix} 1 & 0 & & \\ 1 & 1 & & \\ 0 & 0 & 0 & \\ & & & 0 \end{bmatrix}$	

iterative algorithm - complexity aspects

i	1	2	3	4
s	(<mark>0</mark> , 0, 0, 0)	(1, <mark>0</mark> , 0, 0)	(1, 1, <mark>0</mark> , 0)	(1, 1, 1, <mark>0</mark>)
f_1	R	XR	0	0
f_2	R + XR	XR	X^2R	0
f_3	$XR + X^2R$	$XR + X^2R$	X^2R	X ³ R
f_4	$X^2R + X^3R$	$X^2R + X^3R$	$X^2R + X^3R$	X ³ R
Р	$\begin{bmatrix} 1 & & \\ 0 & 0 & \\ & & 0 \\ & & & 0 \end{bmatrix}$	$\begin{bmatrix} 1 & 0 & & \\ 1 & 1 & & \\ 0 & 0 & 0 & \\ & & & 0 \end{bmatrix}$	$\begin{bmatrix} 1 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	

iterative algorithm - complexity aspects

i	1	2	3	4	•••
S	(<mark>0</mark> , 0, 0, 0)	(1, <mark>0</mark> , 0, 0)	(1, 1, <mark>0</mark> , 0)	(1, 1, 1, <mark>0</mark>)	•••
f_1	R	XR	0	0	0
f_2	$\mathbf{R} + \mathbf{XR}$	XR	X^2R	0	0
f_3	$XR + X^2R$	$XR + X^2R$	X^2R	X ³ R	0
f_4	$X^2R + X^3R$	$X^2R + X^3R$	$X^2R + X^3R$	X ³ R	X^4R
Р		$\begin{bmatrix} 1 & 0 & & \\ 1 & 1 & & \\ 0 & 0 & 0 & \\ & & & 0 \end{bmatrix}$	$\begin{bmatrix} 1 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 1 & 0 & & \\ 1 & 1 & 0 & \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}$	

iterative algorithm - complexity aspects



iterative algorithm - complexity aspects

parameters: m = 8, d = 128, s = (0, 0, 0, 0, d, d, d, d)

input \mathbf{F} : same f₁, f₂, f₃, f₄ / random f₅, f₆, f₇, f₈



iterative algorithm - complexity aspects

parameters: m = 8, d = 128, s = (0, 0, 0, 0, d, d, d, d)

input \mathbf{F} : same f₁, f₂, f₃, f₄ / random f₅, f₆, f₇, f₈



iterative algorithm - complexity aspects

parameters: m = 8, d = 128, s = (0, 0, 0, 0, d, d, d, d)

input \mathbf{F} : same f₁, f₂, f₃, f₄ / random f₅, f₆, f₇, f₈



- $\blacktriangleright 1/4$ of the entries have degree $\approx d$: size $\Theta(m^2d)$
- ▶ remark: complexity of iterative algorithm is $O(m^2d^2)$ → improved to $O(md^2)$ via normalization
- ▶ opinions on a "reasonable" target cost for fast algorithms?

recursion: residual and basis multiplication

divide and conquer algorithm:

input: \mathbf{F} , $(\alpha_1, \ldots, \alpha_d)$, $\mathbf{s} \mid \text{output: } \mathbf{P}$

 \blacktriangleright if d=1, use the base case algorithm to find P and return \blacktriangleright otherwise:

a.
$$M_1 \leftarrow (X - \alpha_1) \cdots (X - \alpha_{\lfloor d/2 \rfloor}); M_2 \leftarrow (X - \alpha_{\lfloor d/2 \rfloor + 1}) \cdots (X - \alpha_d)$$

b. $P_1 \leftarrow \mathsf{call}$ the algorithm on \mathbf{F} rem $M_1, (\alpha_1, \dots, \alpha_{\lfloor d/2 \rfloor}), s$

- $\textbf{c. updated shift: } t \gets \mathsf{rdeg}_s(P_1)$
- **d.** residual: $\mathbf{G} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$
- e. $P_2 \leftarrow \mathsf{call}$ the algorithm on G rem $M_2, (\alpha_{\lfloor d/2 \rfloor + 1}, \ldots, \alpha_d), t$
- **f.** return the product P_2P_1

recursion: residual and basis multiplication

divide and conquer algorithm:

input: \mathbf{F} , $(\alpha_1, \ldots, \alpha_d)$, $\mathbf{s} \mid \text{output: } \mathbf{P}$

• if d = 1, use the base case algorithm to find P and return • otherwise:

a.
$$M_1 \leftarrow (X - \alpha_1) \cdots (X - \alpha_{\lfloor d/2 \rfloor}); M_2 \leftarrow (X - \alpha_{\lfloor d/2 \rfloor + 1}) \cdots (X - \alpha_d)$$

b. $P_1 \leftarrow call the algorithm on F rem M_1, (\alpha_1, \dots, \alpha_{\lfloor d/2 \rfloor}), s$

- $\textbf{c. updated shift: } t \gets \mathsf{rdeg}_s(P_1)$
- **d.** residual: $\mathbf{G} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$
- e. $P_2 \leftarrow \mathsf{call}$ the algorithm on G rem $M_2, (\alpha_{|d/2|+1}, \dots, \alpha_d), t$
- **f.** return the product $\mathbf{P}_2\mathbf{P}_1$

correctness:

- correctness of base case
- ▶ then, direct consequence of the "basis multiplication theorem"
- \blacktriangleright about the residual: $\{\mathbf{p} \mid \mathbf{pP}_1\mathbf{F} = 0 \text{ mod } \mathcal{M}\} = \{\mathbf{p} \mid \mathbf{pG} = 0 \text{ mod } \mathcal{M}_2\}$

recursion: residual and basis multiplication

divide and conquer algorithm:

input: \mathbf{F} , $(\alpha_1, \ldots, \alpha_d)$, $\mathbf{s} \mid \text{output: } \mathbf{P}$

 \blacktriangleright if d=1, use the base case algorithm to find P and return \blacktriangleright otherwise:

a.
$$M_1 \leftarrow (X - \alpha_1) \cdots (X - \alpha_{\lfloor d/2 \rfloor}); M_2 \leftarrow (X - \alpha_{\lfloor d/2 \rfloor + 1}) \cdots (X - \alpha_d)$$

b. $\mathbf{P}_1 \leftarrow \text{call the algorithm on } \mathbf{F} \text{ rem } M_1, (\alpha_1, \dots, \alpha_{\lfloor d/2 \rfloor}), \mathbf{s}$

- $\textbf{c. updated shift: } t \gets \mathsf{rdeg}_s(P_1)$
- **d.** residual: $\mathbf{G} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$
- e. $P_2 \leftarrow \mathsf{call}$ the algorithm on G rem $M_2, (\alpha_{\lfloor d/2 \rfloor + 1}, \ldots, \alpha_d), t$

f. return the product $\mathbf{P}_2\mathbf{P}_1$

complexity $O(m^{\omega}M(d)\log(d))$:

- $\scriptstyle \bullet$ if ω = 2, quasi-linear in worst-case output size
- ${\scriptstyle \blacktriangleright}$ most expensive step in the recursion is the product P_2P_1
- $\textbf{\tiny equation } \mathcal{C}(\mathfrak{m}, d) = \mathcal{C}(\mathfrak{m}, \lfloor d/2 \rfloor) + \mathcal{C}(\mathfrak{m}, \lceil d/2 \rceil) + O(\mathfrak{m}^{\omega} \mathsf{M}(d))$

recursion: residual and basis multiplication

 $\mathsf{input:} \, \mathsf{deg}(\mathbf{F}) < d$

 $\texttt{output:} \; \mathsf{deg}(P) \leqslant d$

complexity of each step:

- ullet residual $\mathbf{G} \leftarrow rac{1}{M_1} \mathbf{P}_1 \mathbf{F}$
- $\blacktriangleright {\bf F}$ rem M_1 and ${\bf G}$ rem M_2
- product P_2P_1
- ► two recursive calls

 $\begin{array}{c} O(\mathfrak{m}^2 \mathsf{M}(d))\\ O(\mathfrak{m}\mathsf{M}(d))\\ O(\mathfrak{m}^{\omega}\mathsf{M}(d))\\ 2\mathfrak{C}(\mathfrak{m}, \lfloor d/2 \rceil) \end{array}$

recursion: residual and basis multiplication

 $\mathsf{input:} \, \mathsf{deg}(\mathbf{F}) < d$

output: $deg(\mathbf{P}) \leqslant d$

complexity of each step:

- residual $\mathbf{G} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$ • \mathbf{F} rem M_1 and \mathbf{G} rem M_2
- product P_2P_1
- ► two recursive calls

 $\begin{array}{c} O(\mathfrak{m}^2 \mathsf{M}(d))\\ O(\mathfrak{m} \mathsf{M}(d))\\ O(\mathfrak{m}^{\omega} \mathsf{M}(d))\\ 2 \mathbb{C}(\mathfrak{m}, \lfloor d/2 \rfloor) \end{array}$

$$\begin{split} & \mathbb{C}(\mathfrak{m},d) = \mathbb{C}(\mathfrak{m},\lfloor d/2 \rfloor) + \mathbb{C}(\mathfrak{m},\lceil d/2 \rceil) + O(\mathfrak{m}^{\varpi}\mathsf{M}(d)) \\ & \text{d base cases, each one costs } \ldots \ref{eq:model} \end{split}$$

recursion: residual and basis multiplication

 $\begin{array}{lll} \mathsf{input:} \deg(F) < d & \mathsf{output:} \deg(P) \leqslant d \\ \hline \mathbf{complexity of each step:} \\ \mathsf{\cdot} \mathsf{residual} \ \mathbf{G} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F} & O(\mathfrak{m}^2 \mathsf{M}(d)) \\ \mathsf{\cdot} \ \mathbf{F} \mathsf{rem} \ M_1 \ \mathsf{and} \ \mathbf{G} \mathsf{rem} \ M_2 & O(\mathfrak{m} \mathsf{M}(d)) \\ \mathsf{\cdot} \mathsf{product} \ \mathbf{P}_2 \mathbf{P}_1 & O(\mathfrak{m}^\omega \mathsf{M}(d)) \\ \mathsf{\cdot} \mathsf{two} \ \mathsf{recursive} \ \mathsf{calls} & 2 \mathcal{C}(\mathfrak{m}, \lfloor d/2 \rfloor) \end{array}$

$$\begin{split} & \mathfrak{C}(\mathfrak{m},d) = \mathfrak{C}(\mathfrak{m},\lfloor d/2 \rfloor) + \mathfrak{C}(\mathfrak{m},\lceil d/2 \rceil) + O(\mathfrak{m}^{\omega}\mathsf{M}(d)) \\ & d \text{ base cases, each one costs } O(\mathfrak{m}) \end{split}$$

 $\Rightarrow O(m^{\omega}M(d)\log(d))$

unrolling: $\mathfrak{m}^{\omega}\left(\mathsf{M}(d) + 2\mathsf{M}(\frac{d}{2}) + 4\mathsf{M}(\frac{d}{4}) + \dots + \frac{d}{2}\mathsf{M}(2)\right) + d\mathfrak{m}$

recursion: residual and basis multiplication

output: deg(**P**) $\approx \left\lceil \frac{d}{m} \right\rceil$ input: $deg(\mathbf{F}) < d$ output: $deg(\mathbf{P}) \leq d$ complexity of each step: s = 0 and generic F: • residual $\mathbf{G} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$ $O(m^2M(d))$ $O(\mathfrak{m}^{\omega} M(\lceil \frac{d}{m} \rceil))$ • **F** rem M_1 and **G** rem M_2 O(mM(d))unchanged $O(\mathfrak{m}^{\omega} M(\lceil \frac{d}{\mathfrak{m}} \rceil))$ • product $\mathbf{P}_2\mathbf{P}_1$ $O(m^{\omega}M(d))$ two recursive calls 2C(m, |d/2])unchanged

partial linearization

$$\begin{split} & \mathcal{C}(\mathfrak{m},d) = \mathcal{C}(\mathfrak{m},\lfloor d/2 \rfloor) + \mathcal{C}(\mathfrak{m},\lceil d/2 \rceil) + O(\mathfrak{m}^{\omega}\mathsf{M}(d)) \\ & d \text{ base cases, each one costs } O(\mathfrak{m}) \end{split}$$

 $\Rightarrow \quad O(m^{\omega}\mathsf{M}(d) \mathsf{log}(d))$

recursion: residual and basis multiplication

output: deg(**P**) $\approx \left\lceil \frac{d}{m} \right\rceil$ input: $deg(\mathbf{F}) < d$ output: $deg(\mathbf{P}) \leq d$ complexity of each step: s = 0 and generic F: • residual $\mathbf{G} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$ $O(m^2M(d))$ $O(\mathfrak{m}^{\omega} \mathsf{M}(\lceil \frac{d}{\mathfrak{m}} \rceil))$ **•** \mathbf{F} rem M_1 and \mathbf{G} rem M_2 O(mM(d))unchanged $O(\mathfrak{m}^{\omega} M(\lceil \frac{d}{\mathfrak{m}} \rceil))$ • product $\mathbf{P}_2\mathbf{P}_1$ $O(m^{\omega}M(d))$ two recursive calls 2C(m, |d/2])unchanged partial linearization • base case for $d \approx m$, costs $O(m^{\omega})$
$$\begin{split} & \mathbb{C}(\mathfrak{m},d) = \mathbb{C}(\mathfrak{m},\lfloor d/2 \rfloor) + \mathbb{C}(\mathfrak{m},\lceil d/2 \rceil) + O(\mathfrak{m}^{\omega}\mathsf{M}(d)) \\ & d \text{ base cases, each one costs } O(\mathfrak{m}) \end{split}$$

 $\Rightarrow O(\mathfrak{m}^{\omega} \mathsf{M}(d) \log(d)) O(\mathfrak{m}^{\omega} \mathsf{M}(\lceil \frac{d}{\mathfrak{m}} \rceil) \log(\lceil \frac{d}{\mathfrak{m}} \rceil))$

recursion: residual and basis multiplication

output: deg(**P**) $\approx \left\lceil \frac{d}{m} \right\rceil$ input: $deg(\mathbf{F}) < d$ output: $deg(\mathbf{P}) \leq d$ complexity of each step: s = 0 and generic F: • residual $\mathbf{G} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$ $O(m^2M(d))$ $O(\mathfrak{m}^{\omega} \mathsf{M}(\lceil \frac{d}{\mathfrak{m}} \rceil))$ **•** \mathbf{F} rem M_1 and \mathbf{G} rem M_2 O(mM(d))unchanged $O(\mathfrak{m}^{\omega} M(\lceil \frac{d}{\mathfrak{m}} \rceil))$ • product $\mathbf{P}_2\mathbf{P}_1$ $O(m^{\omega}M(d))$ two recursive calls 2C(m, |d/2])unchanged partial linearization • base case for $d \approx m$, costs $O(m^{\omega})$
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 $\Rightarrow O(m^{\omega}M(d)\log(d))$

 $O(\mathfrak{m}^{\omega} M(\lceil \frac{d}{m} \rceil) \log(\lceil \frac{d}{m} \rceil))$

m	n	d	PM-BASIS	PM-BASIS with linearization
4	1	65536	1.6693	1.26891
16	1	16384	1.8535	0.89652
64	1	2048	2.2865	0.14362
256	1	1024	36.620	0.20660

recursion: residual and basis multiplication

state of the art:

- recursive algorithm: from [Beckermann-Labahn 1994] (for Hermite-Padé) it also works for $\mathbf{F} \in \mathbb{K}[X]^{m \times n}$ with n > 1
- $\label{eq:constraint} \begin{array}{l} \mbox{-} [Giorgi-Jeannerod-Villard 2003] \text{ achieved } O(\mathfrak{m}^{\omega}\mathsf{M}(d) \log(d)) \\ \text{for } \mathbf{F} \mbox{ mod } X^d, \mbox{ with } \mathfrak{n} \geqslant 1 \mbox{ and } \mathfrak{n} \in O(\mathfrak{m}) \end{array}$
- for s = 0 and generic \mathbf{F} : O[~](m^{ω}[$\frac{nd}{m}$]) [Lecerf, ca 2001, unpublished]

recursion: residual and basis multiplication

state of the art:

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- for s = 0 and generic \mathbf{F} : O[~](m^{ω} $\lceil \frac{nd}{m} \rceil$) [Lecerf, ca 2001, unpublished]

► more recently: O[~](m^{ω-1}nd) for F mod X^d
 [Storjohann 2006] [Zhou-Labahn 2012] [Jeannerod-Neiger-Villard 2020]
 ~ any s, no genericity assumption, returns the canonical basis "s-Popov"

recursion: residual and basis multiplication

state of the art:

- ▶ recursive algorithm: from [Beckermann-Labahn 1994] (for Hermite-Padé) it also works for $\mathbf{F} \in \mathbb{K}[X]^{m \times n}$ with n > 1
- $\label{eq:constraint} \begin{array}{l} \mbox{-} [Giorgi-Jeannerod-Villard 2003] \text{ achieved } O(\mathfrak{m}^{\omega}\mathsf{M}(d) \log(d)) \\ \text{for } \mathbf{F} \mbox{ mod } X^d, \mbox{ with } \mathfrak{n} \geqslant 1 \mbox{ and } \mathfrak{n} \in O(\mathfrak{m}) \end{array}$
- for s = 0 and generic \mathbf{F} : O[~](m^{ω} $\lceil \frac{nd}{m} \rceil$) [Lecerf, ca 2001, unpublished]

► more recently: $O^{\sim}(m^{\omega-1}nd)$ for $\mathbf{F} \mod X^d$ [Storjohann 2006] [Zhou-Labahn 2012] [Jeannerod-Neiger-Villard 2020] \rightsquigarrow any \mathbf{s} , no genericity assumption, returns the canonical basis "s-Popov"

 ▶ F mod M and general modular matrix equations in similar complexity [Beckermann-Labahn 1997] [Jeannerod-Neiger-Schost-Villard 2017] [Neiger-Vu 2017] [Rosenkilde-Storjohann 2021]
 → any s, no genericity assumption, returns the canonical "s-Popov" basis

outline

introduction

shifted reduced forms

fast algorithms

rational approximation and interpolation

- the vector case
- ► pol. matrices: reminders and motivation
- ▶ reducedness: examples and properties
- shifted forms and degree constraints
- stability under multiplication
- iterative algorithm and output size
- ▶ base case: modulus of degree 1
- ▶ recursion: residual and basis multiplication

applications

outline

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- ▶ recursion: residual and basis multiplication
- minimal kernel bases and linear systems
- $\scriptstyle \bullet \ensuremath{\mathsf{fast}}$ gcd and extended gcd
- ► perspectives

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

 ${\scriptstyle \blacktriangleright}\, \mathfrak{K}(\mathbf{F})$ is a $\mathbb{K}[X]\text{-module}$

 ${\scriptstyle \bullet}$ it has rank m-r, where r is the rank of ${\bf F}$

 $\Rightarrow \mathsf{basis}\ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r)\times\mathfrak{m}}$

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{ \mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0} \}$$

 ${\scriptstyle \blacktriangleright}\, \mathfrak{K}(\mathbf{F})$ is a $\mathbb{K}[X]\text{-module}$

• it has rank m - r, where r is the rank of F

$$\Rightarrow \mathsf{basis} \ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r) imes \mathfrak{m}}$$

kernel basis for a constant matrix?

input matrix ${\bf F}$

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

• $\mathcal{K}(\mathbf{F})$ is a $\mathbb{K}[X]$ -module

• it has rank m - r, where r is the rank of ${f F}$

$$\Rightarrow \mathsf{basis} \ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r) imes \mathfrak{m}}$$

kernel basis	, for a constant matrix? $ ightarrow$	usual nullspace
		input matrix ${f F}$
kernel basis	K	_[5 6
5610	o]	6 1
0 5 0 1	0	2 6
0 0 3 2	1	5 2
L	2	5 6

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

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$$\Rightarrow \mathsf{basis} \ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r) imes \mathfrak{m}}$$

kernel basis of the following matrix over \mathbb{F}_2 ?

input matrix \mathbf{F}

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ X^2 & X^2 + X + 1 & X^2 + X \\ X^2 + 1 & X^2 & X^2 + X + 1 \\ X^2 & X^2 + X & X^2 \end{bmatrix}$$

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

• $\mathcal{K}(\mathbf{F})$ is a $\mathbb{K}[X]$ -module

• it has rank m - r, where r is the rank of \mathbf{F}

$$\Rightarrow \mathsf{basis} \ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r) imes \mathfrak{m}}$$

kernel basis of the following matrix over \mathbb{F}_2 ?

 $\begin{bmatrix} X^2 & X^2 + X + 1 & X^2 + X & 1 & 0 & 0 \\ X^2 + 1 & X^2 & X^2 + X + 1 & 0 & 1 & 0 \\ X^2 & X^2 + X & X^2 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ X^2 & X^2 + X + 1 & X^2 + X \\ X^2 + 1 & X^2 & X^2 + X + 1 \\ X^2 & X^2 + X & X^2 \end{bmatrix}$

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

• $\mathcal{K}(\mathbf{F})$ is a $\mathbb{K}[X]$ -module

• it has rank m - r, where r is the rank of F

$$\Rightarrow \mathsf{basis} \ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r) imes \mathfrak{m}}$$

kernel basis of the following block matrix with G nonsingular?

input matrix
$$\mathbf{F}$$

 $\begin{bmatrix} \mathbf{G} \\ \mathbf{H} \end{bmatrix} \in \mathbb{K}[X]^{(n+m) \times n}$

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

• $\mathcal{K}(\mathbf{F})$ is a $\mathbb{K}[X]$ -module

• it has rank m - r, where r is the rank of \mathbf{F}

$$\Rightarrow \mathsf{basis} \ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r) imes \mathfrak{m}}$$

kernel basis of the following block matrix with G nonsingular?

$$\begin{array}{ll} \mbox{kernel basis } K & \mbox{input matrix } F \\ \mbox{... is left multiple of } \begin{bmatrix} -HG^{-1} & I_m \end{bmatrix} & \begin{bmatrix} G \\ H \end{bmatrix} \in \ensuremath{\mathbb{K}}[X]^{(n+m)\times n} \\ \mbox{... det}(G) \begin{bmatrix} -HG^{-1} & I_m \end{bmatrix} \mbox{ is left multiple of it } \end{array}$$

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

• $\mathcal{K}(\mathbf{F})$ is a $\mathbb{K}[X]$ -module

• it has rank m - r, where r is the rank of F

$$\Rightarrow \mathsf{basis} \ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r) imes \mathfrak{m}}$$

kernel basis of the following 4 \times 1 vector with R $\,\in\, \mathbb{K}[X]\,\setminus\,\{0\}?$

input matrix \mathbf{F} $\begin{bmatrix} \mathbf{R} \\ \mathbf{R} + X\mathbf{R} \\ X\mathbf{R} + X^{2}\mathbf{R} \\ X^{2}\mathbf{R} + X^{3}\mathbf{R} \end{bmatrix}$

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

• $\mathcal{K}(\mathbf{F})$ is a $\mathbb{K}[X]$ -module

 \bullet it has rank m - r, where r is the rank of ${f F}$

$$\Rightarrow \mathsf{basis} \ \mathbf{K} \in \mathbb{K}[X]^{(\mathfrak{m}-r) imes \mathfrak{m}}$$

kernel basis of the following 4 \times 1 vector with R $\in \mathbb{K}[X] \setminus \{0\}$?

$$\begin{bmatrix} \text{kernel basis } \mathbf{K} \\ 1 + X & -1 \\ 0 & X & -1 \\ 0 & 0 & X & -1 \end{bmatrix}$$

input matrix \mathbf{F} $\begin{bmatrix} \mathbf{R} \\ \mathbf{R} + X\mathbf{R} \\ X\mathbf{R} + X^{2}\mathbf{R} \\ X^{2}\mathbf{R} + X^{3}\mathbf{R} \end{bmatrix}$

minimal kernel bases and linear systems

for $\mathbf{F} \in \mathbb{K}[X]^{m \times n},$ its left kernel is

$$\mathcal{K}(\mathbf{F}) = \{\mathbf{p} \in \mathbb{K}[X]^{1 \times m} \mid \mathbf{pF} = \mathbf{0}\}$$

• $\mathcal{K}(\mathbf{F})$ is a $\mathbb{K}[X]$ -module • it has rank m - r, where r is the rank of \mathbf{F} \Rightarrow basis $\mathbf{K} \in \mathbb{K}[X]^{(m-r) \times m}$

 $\begin{array}{l} \text{inclusion } \mathcal{K}(\mathbf{F}) \ \subset \ \mathfrak{I}(M,\mathbf{F}) \ = \ \{\mathbf{p} \in \ \mathbb{K}[X]^{1 \times \mathfrak{m}} \ | \ \mathbf{pF} \ = \ \mathbf{0} \ \text{mod} \ M \} \\ \Rightarrow \ \text{recover kernel via interpolation with suitable choices of } M \end{array}$
minimal kernel bases and linear systems

input:

- ${\scriptstyle \bullet} \mbox{ matrix } {\bf F} \in \mathbb{K}[X]^{m \times n}$
- ${\scriptstyle\blacktriangleright}\,\delta\in\mathbb{Z}_{>0}$ such that there exists a basis of $\mathcal{K}(\mathbf{F})$ of degree $\leqslant\delta$

algorithm via interpolation at sufficiently many points

$$\begin{array}{l} \bullet \ d \leftarrow \delta + deg(\mathbf{F}) + 1 \\ \bullet \ \boldsymbol{\alpha} \leftarrow \text{choose some } (\alpha_1, \ldots, \alpha_d) \text{ in } \mathbb{K}^d \quad (\text{not necessarily distinct}) \\ \bullet \ \mathbf{P} \in \mathbb{K}[X]^{m \times m} \leftarrow \text{reduced basis of } \mathcal{I}(\boldsymbol{\alpha}, \mathbf{F}) \\ \bullet \ \mathbf{K} \in \mathbb{K}[X]^{k \times m} \leftarrow \text{rows of } \mathbf{P} \text{ which have degree} \leqslant \delta \end{array}$$

minimal kernel bases and linear systems

input:

- ${\scriptstyle \bullet} \mbox{ matrix } {\bf F} \in \mathbb{K}[X]^{m \times n}$
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 $\begin{array}{l} \Rightarrow \mathbf{K} \text{ is a reduced basis of } \mathcal{K}(\mathbf{F}) \\ \Rightarrow \text{ complexity } O(\mathfrak{m}^{\omega}\mathsf{M}(\lceil \frac{\mathtt{nd}}{\mathfrak{m}}\rceil) \log(\lceil \frac{\mathtt{nd}}{\mathfrak{m}}\rceil)) \end{array}$

minimal kernel bases and linear systems

input:

- ${\scriptstyle \bullet} \mbox{ matrix } {\bf F} \in \mathbb{K}[X]^{m \times n}$
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$$\begin{array}{l} \bullet \ d \leftarrow \delta + deg(\mathbf{F}) + 1 \\ \bullet \ \pmb{\alpha} \leftarrow \text{choose some } (\alpha_1, \ldots, \alpha_d) \text{ in } \mathbb{K}^d \quad (\text{not necessarily distinct}) \\ \bullet \ \mathbf{P} \in \mathbb{K}[X]^{m \times m} \leftarrow \text{reduced basis of } \mathcal{I}(\pmb{\alpha}, \mathbf{F}) \\ \bullet \ \mathbf{K} \in \mathbb{K}[X]^{k \times m} \leftarrow \text{rows of } \mathbf{P} \text{ which have degree} \leqslant \delta \end{array}$$

 $\Rightarrow \mathbf{K} \text{ is a reduced basis of } \mathcal{K}(\mathbf{F}) \\ \Rightarrow \text{ complexity } O(\mathfrak{m}^{\omega}\mathsf{M}(\lceil \frac{nd}{\mathfrak{m}} \rceil) \log(\lceil \frac{nd}{\mathfrak{m}} \rceil))$

how to find the degree bound δ ?

minimal kernel bases and linear systems

knowing $\delta\in\mathbb{Z}_{>0}$ such that there exists a basis of $\mathcal{K}(F)$ of degree $\leqslant\delta$

- $\textbf{ take } d \leftarrow \delta + \mathsf{deg}(\mathbf{F}) + 1 \text{ and some } \pmb{\alpha} \leftarrow (\alpha_1, \ldots, \alpha_d) \text{ in } \mathbb{K}^d$
- $\mathbf{P} \in \mathbb{K}[X]^{m imes m}$ reduced basis of $\mathfrak{I}(\boldsymbol{\alpha}, \mathbf{F})$
- ${\scriptstyle \blacktriangleright} K \in \mathbb{K}[X]^{k \times m}$ rows of P which have degree $\leqslant \delta$

 \Rightarrow **K** is a reduced basis of $\mathcal{K}(\mathbf{F})$

minimal kernel bases and linear systems

knowing $\delta\in\mathbb{Z}_{>0}$ such that there exists a basis of $\mathcal{K}(F)$ of degree $\leqslant\delta$

- $\textbf{ take } d \leftarrow \delta + \mathsf{deg}(\mathbf{F}) + 1 \text{ and some } \pmb{\alpha} \leftarrow (\alpha_1, \ldots, \alpha_d) \text{ in } \mathbb{K}^d$
- $\mathbf{P} \in \mathbb{K}[X]^{m \times m}$ reduced basis of $\mathfrak{I}(\boldsymbol{\alpha}, \mathbf{F})$
- ${\scriptstyle \blacktriangleright}\, K \in \mathbb{K}[X]^{k \times \mathfrak{m}}$ rows of P which have degree $\leqslant \delta$

\Rightarrow K is a reduced basis of $\mathcal{K}(F)$

proof:

 \Rightarrow K is reduced by construction

. K satisfies
$$KF=0 \mbox{ mod } (X-\alpha_1) \cdots (X-\alpha_d)$$

- . and $\mathsf{deg}(K) \leqslant \delta,$ hence $\mathsf{deg}(KF) \leqslant \delta + \mathsf{deg}(F) < d$
- $\Rightarrow KF=0,$ i.e. the rows of K are in $\mathcal{K}(F)$

. let
$$\mathbf{B} \in \mathbb{K}[X]^{(m-r) \times m}$$
 be a basis of $\mathcal{K}(\mathbf{F})$ of degree $\leqslant \delta$

- . then $\mathbf{B}=\mathbf{U}\mathbf{P}$ for some \mathbf{U}
- . by the predictable degree property, in fact $\mathbf{B}=\mathbf{V}\mathbf{K}$
- \Rightarrow any vector in $\mathcal{K}(F)$ is generated by K

minimal kernel bases and linear systems

knowing $\delta\in\mathbb{Z}_{>0}$ such that there exists a basis of $\mathcal{K}(F)$ of degree $\leqslant\delta$

how to find the degree bound δ ?

a specific bound may be known from the context e.g. gcd, "row bases"

→ a general bound is $\delta = n \operatorname{deg}(\mathbf{F})$ → yields complexity O[~](m^ω [$\frac{n^2 \operatorname{deg}(\mathbf{F})}{m}$]) how far from "optimal"?

minimal kernel bases and linear systems

knowing $\delta\in\mathbb{Z}_{>0}$ such that there exists a basis of $\mathcal{K}(F)$ of degree $\leqslant\delta$

how to find the degree bound δ ?

a specific bound may be known from the context e.g. gcd, "row bases"

• a general bound is $\delta = n \operatorname{deg}(\mathbf{F})$ • yields complexity $O^{\sim}(m^{\omega} \lceil \frac{n^2 \operatorname{deg}(\mathbf{F})}{m} \rceil)$ how far from "optimal"?

proof:

complexity $O^{\text{-}}(\mathfrak{m}^{\omega}\lceil \frac{n\,d}{\mathfrak{m}}\rceil)$ with $d=\delta+\text{deg}(\mathbf{F})+1=(n+1)\,\text{deg}(\mathbf{F})+1$

minimal kernel bases and linear systems

knowing $\delta\in\mathbb{Z}_{>0}$ such that there exists a basis of $\mathcal{K}(F)$ of degree $\leqslant\delta$

how to find the degree bound δ ?

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→ a general bound is $\delta = n \operatorname{deg}(\mathbf{F})$ → yields complexity O[~](m^ω [$\frac{n^2 \operatorname{deg}(\mathbf{F})}{m}$]) → how far from "optimal"?

proof:

up to row and column permutation, $\mathbf{F} = [\begin{smallmatrix} \mathbf{G} & * \\ \mathbf{H} & * \end{smallmatrix}]$ with $\mathbf{G} \in \mathbb{K}[X]^{r \times r}$ nonsingular then, $\mathcal{K}(\mathbf{F}) = \mathcal{K}([\begin{smallmatrix} \mathbf{G} \\ \mathbf{H} \end{smallmatrix}])$

 $\begin{array}{ll} \text{the matrix } [-H(\text{det}(G)G^{-1}) & \text{det}(G)I_{m-r}] \text{ has polynomial entries,} \\ \text{it has rank } m-r \text{ and its rows are in } \mathcal{K}(F), \\ \text{it has degree} \leqslant \max(\text{deg det}(G), \text{deg}(H) + (r-1) \text{deg}(G)) \leqslant r \text{deg}(F) \\ \end{array}$

by degree minimality of reduced matrices, any reduced basis of $\mathcal{K}(F)$ must have degree $\leqslant r\,\text{deg}(F)$

minimal kernel bases and linear systems

knowing $\delta\in\mathbb{Z}_{>0}$ such that there exists a basis of $\mathcal{K}(F)$ of degree $\leqslant\delta$

how to find the degree bound δ ?

a specific bound may be known from the context e.g. gcd, "row bases"

→ a general bound is $\delta = n \operatorname{deg}(\mathbf{F})$ → yields complexity O[~](m^ω [$\frac{n^2 \operatorname{deg}(\mathbf{F})}{m}$]) how far from "optimal"?

rules of thumb, generically:
 "quantity of information is preserved"

 +
 "degrees in reduced basis are uniform"

 $\begin{array}{l} \rightsquigarrow \quad (\mathfrak{m}-r)\mathfrak{m}\operatorname{\mathsf{deg}}(\mathbf{K})\approx \mathfrak{m}\mathfrak{n}\operatorname{\mathsf{deg}}(\mathbf{F}) \\ \Leftrightarrow \operatorname{\mathsf{deg}}(\mathbf{K})\approx \frac{\mathfrak{n}}{\mathfrak{m}-r}\operatorname{\mathsf{deg}}(\mathbf{F}), \text{ which is } \leqslant \frac{\mathfrak{n}}{\mathfrak{m}-\mathfrak{n}}\operatorname{\mathsf{deg}}(\mathbf{F}) \end{array}$

example: if **F** is $m \times \frac{m}{2}$, generically deg(**K**) = deg(**F**) $\Rightarrow d = 2 \text{deg}(\mathbf{F}) + 1$ and complexity $O^{\sim}(m^{\omega} \text{deg}(\mathbf{F}))$ how far from optimal?

minimal kernel bases and linear systems

breakthrough [Zhou-Labahn-Storjohann 2012]

• complexity $O^{\sim}(m^{\omega} \lceil \frac{n \deg(F)}{m} \rceil)$ without assumption

-computes s-reduced basis of $\mathcal{K}(\mathbf{F})$ for $s=\mathsf{rdeg}(\mathbf{F})$

n large: divide and conquer on n, via residual + basis multiplication
 partial linearization for multiplying matrices with weakly unbalanced degrees
 n small: use fast approximation/interpolation algorithms
 well-chosen d yields at least half the kernel efficiently

minimal kernel bases and linear systems

breakthrough [Zhou-Labahn-Storjohann 2012]

- complexity $O^{\sim}(m^{\omega} \lceil \frac{n \deg(F)}{m} \rceil)$ without assumption
- -computes s-reduced basis of $\mathcal{K}(\mathbf{F})$ for $s=\mathsf{rdeg}(\mathbf{F})$

n large: divide and conquer on n, via residual + basis multiplication
 partial linearization for multiplying matrices with weakly unbalanced degrees
 n small: use fast approximation/interpolation algorithms
 well-chosen d yields at least half the kernel efficiently

$$\begin{array}{l} \text{if } n > \frac{m}{2} \text{:} \\ \mathbf{K}_1 \leftarrow \text{ recursive call on first } \frac{n}{2} \text{ columns of } \mathbf{F} \text{, and shift } \mathbf{s} \\ \mathbf{G} \leftarrow \text{ multiply } \mathbf{K}_1 \cdot \mathbf{F}_{*, \frac{n}{2} \dots n} \qquad (\text{last } \frac{n}{2} \text{ columns of } \mathbf{F}) \\ \mathbf{K}_2 \leftarrow \text{ recursive call on } \mathbf{G} \text{, and shift } \mathbf{t} = \text{rdeg}_s(\mathbf{K}_1) \\ \text{ return } \mathbf{K}_2 \mathbf{K}_1 \end{array}$$

minimal kernel bases and linear systems

breakthrough [Zhou-Labahn-Storjohann 2012]

• complexity $O^{\sim}(m^{\omega} \lfloor \frac{n \deg(F)}{m} \rfloor)$ without assumption

-computes s-reduced basis of $\mathcal{K}(\mathbf{F})$ for $s=\mathsf{rdeg}(\mathbf{F})$

n large: divide and conquer on n, via residual + basis multiplication
 partial linearization for multiplying matrices with weakly unbalanced degrees
 n small: use fast approximation/interpolation algorithms
 well-chosen d yields at least half the kernel efficiently

$$\begin{split} & \text{if } n \leqslant \frac{m}{2} \text{:} \\ & \delta \leftarrow \text{ degree of kernel basis expected generically} \\ & d \leftarrow \delta + \text{deg}(\mathbf{F}) + 1 \text{ and take some } \boldsymbol{\alpha} \leftarrow (\alpha_1, \ldots, \alpha_d) \text{ in } \mathbb{K}^d \\ & \mathbf{P} \in \mathbb{K}[X]^{m \times m} \leftarrow \text{s-reduced basis of } \mathfrak{I}(\boldsymbol{\alpha}, \mathbf{F}) \\ & \mathbf{K}_1, \mathbf{Q} \leftarrow \text{rows of } \mathbf{P} \text{ which are in } \mathcal{K}(\mathbf{F}) \ / \text{ which are not in } \mathcal{K}(\mathbf{F}) \\ & \mathbf{K}_2 \leftarrow \text{recursive call on } \frac{1}{(X - \alpha_1) \cdots (X - \alpha_d)} \mathbf{Q} \mathbf{F}, \text{ return } [\frac{K_1}{K_2}] \end{split}$$

minimal kernel bases and linear systems

linear system solving: given $\mathbf{A} \in \mathbb{K}[X]^{m \times m}$ nonsingular and $\mathbf{v} \in \mathbb{K}[X]^{1 \times m}$ find $\mathbf{u} \in \mathbb{K}[X]^{1 \times m}$ and $g \in \mathbb{K}[X]$ such that $\mathbf{u}\mathbf{A} = g\mathbf{v}$ and g has minimal degree.

- . the equation has a solution: $\mathbf{u} = g \mathbf{v} \mathbf{A}^{-1}$ with $g = \mathsf{det}(\mathbf{A})$
- . but there is often no polynomial solution with $g = \mathbf{1}$
- . target complexity? (recall that $\mathsf{det}(A)A^{-1}$ can have degree $\approx m\,\mathsf{deg}(A))$
- . propose an algorithm based on a kernel computation

minimal kernel bases and linear systems

linear system solving: given $\mathbf{A} \in \mathbb{K}[X]^{m \times m}$ nonsingular and $\mathbf{v} \in \mathbb{K}[X]^{1 \times m}$ find $\mathbf{u} \in \mathbb{K}[X]^{1 \times m}$ and $q \in \mathbb{K}[X]$ such that $\mathbf{u}\mathbf{A} = \mathbf{q}\mathbf{v}$ and \mathbf{q} has minimal degree.

- . the equation has a solution: $\mathbf{u} = q\mathbf{v}\mathbf{A}^{-1}$ with $q = det(\mathbf{A})$
- . but there is often no polynomial solution with q = 1
- . target complexity? (recall that $\mathsf{det}(A)A^{-1}$ can have degree $\approx \mathsf{m}\,\mathsf{deg}(A))$
- . propose an algorithm based on a kernel computation

 $\text{compute } [\mathbf{u} \quad g] \in \mathbb{K}[X]^{1 \times (m+1)} \text{ kernel basis of } \mathbf{F} = \begin{bmatrix} \mathbf{A} \\ -\mathbf{v} \end{bmatrix} \in \mathbb{K}[X]^{(m+1) \times m}$

- using the shift $\mathbf{s} = (\mathsf{rdeg}(\mathbf{A}), \mathsf{deg}(\mathbf{v}))$
- ► complexity $O^{\sim}(m^{\omega} \max(\deg(\mathbf{A}), \deg(\mathbf{v})))$ in fact: $\max(\deg(\mathbf{A}), \frac{\deg(\mathbf{v})}{m})$
- minimality of deg(q) follows from *basis* of $\mathcal{K}(\mathbf{F})$

fast gcd and extended gcd



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: h=gcd(f,g)



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: (u, v, h) where h = gcd(f, g) = uf + vg

fast gcd and extended gcd



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: h=gcd(f,g)



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: (u, v, h) where h = gcd(f, g) = uf + vg

some notation:

earlier in the course: **claim:** gcd and xgcd are solved in $O(M(d) \log(d))$

where d = max(m, n)

fast gcd and extended gcd



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: h=gcd(f,g)

some notation:

. polynomials $\bar{f}=f/h$ and $\bar{g}=g/h$, m=deg(f) and n=deg(g) , we assume m,n>0

 $\textbf{result: gcd is solved in } O(\mathsf{M}(\mathsf{max}(m,n)) \mathsf{log}(\mathsf{max}(m,n)))$

fast gcd and extended gcd



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: h=gcd(f,g)

some notation:

. polynomials
$$\overline{f} = f/h$$
 and $\overline{g} = g/h$ \overline{f} and \overline{g} are coprime
. $m = \text{deg}(f)$ and $n = \text{deg}(g)$ we assume $m, n > 0$

result: gcd is solved in $O(M(max(m, n)) \log(max(m, n)))$

lemma: $[-\overline{g} \ \overline{f}]$ is a basis of the left kernel of $\begin{bmatrix} f \\ g \end{bmatrix}$

proof:

this kernel has rank 1 (f and g are nonzero) let $[a\ b]$ be a basis of it; all other bases are $[ca\ cb]$ for some $c\in\mathbb{K}\setminus\{0\}$ since $[-\bar{g}\ \bar{f}][\frac{f}{g}]=-\frac{g}{h}f+\frac{f}{h}g=0$, we get $[-\bar{g}\ \bar{f}]=[\lambda a\ \lambda b]$ for some $\lambda\in\mathbb{K}[X]\setminus\{0\}$ then λ divides \bar{f} and \bar{g} , so λ is a nonzero constant

fast gcd and extended gcd



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: h=gcd(f,g)

some notation:

. polynomials $\bar{f}=f/h$ and $\bar{g}=g/h$ $\bar{f} \text{ and } \bar{g} \text{ are coprime}$. m=deg(f) and n=deg(g) we assume m,n>0

result: gcd is solved in $O(M(max(m, n)) \log(max(m, n)))$

lemma: $[-\overline{g} \ \overline{f}]$ is a basis of the left kernel of $\begin{bmatrix} f \\ g \end{bmatrix}$

algorithm: kernel basis via interpolation at sufficiently many points

$$\label{eq:product} \begin{array}{l} \mbox{ the input matrix } \mathbf{F} = \left[\begin{smallmatrix} t \\ g \end{smallmatrix}\right] \mbox{ has degree max}(m,n) \\ \mbox{ the sought kernel basis has degree at most } \delta = \max(m,n) \\ \mbox{ the sought kernel basis has degree at most } \delta = \max(m,n) \\ \mbox{ l. pick } \delta + \deg(\mathbf{F}) + 1 = 2\delta + 1 \mbox{ points } \pmb{\alpha} \in \mathbb{K}^{2\delta+1} \quad O(1) \\ \mbox{ 2. find } [-\bar{g}\ \bar{f}] \mbox{ via a reduced basis of } \mathbb{J}(\pmb{\alpha}, [\begin{smallmatrix} f \\ g \end{smallmatrix}]) \quad O(\mathsf{M}(\delta)\log(\delta)) \\ \mbox{ 3. deduce } h = g/\bar{g} \quad O(\mathsf{M}(\delta)) \end{array}$$

fast gcd and extended gcd



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: (u,ν,h) where $h=\text{gcd}(f,g)=uf+\nu g$

fast gcd and extended gcd



```
input: f and g univariate polynomials in \mathbb{K}[X] output: (u, \nu, h) where h = \mathsf{gcd}(f, g) = uf + \nu g
```

some notation:

$\begin{array}{l} \mbox{lemma:}\\ .\mbox{ there exists a unique }(u,\nu)\mbox{ in }\mathbb{K}[X]^2\mbox{ such that}\\ \left\{ \begin{array}{l} uf+\nu g=h,\\ deg(u)< n-\ell \mbox{ and } deg(\nu)< m-\ell. \end{array} \right.\\ .\mbox{ for this }(u,\nu)\in\mathbb{K}[X]^2\mbox{ one has } \left[\begin{matrix} u & \nu\\ -\bar{g} & \bar{f} \end{matrix} \right] \left[\begin{matrix} f\\ g \end{matrix} \right] = \left[\begin{matrix} h\\ 0 \end{matrix} \right],\\ \mbox{ and the leftmost matrix in this identity is unimodular} \end{array}$

fast gcd and extended gcd



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: (u, v, h) where h = gcd(f, g) = uf + vg

$$\begin{array}{l} \mbox{theorem:} \\ \mbox{. defining } R = \begin{bmatrix} \mathsf{rev}(\mathfrak{u}, \mathfrak{n} - \ell - 1) & \mathsf{rev}(\mathfrak{v}, \mathfrak{m} - \ell - 1) \\ -\,\mathsf{rev}(\bar{\mathfrak{g}}, \mathfrak{n} - \ell) & \mathsf{rev}(\bar{\mathfrak{f}}, \mathfrak{m} - \ell) \end{bmatrix} \in \mathbb{K}[X]^{2 \times 2}, \\ \mbox{one has:} & R \begin{bmatrix} \mathsf{rev}(\mathfrak{f}, \mathfrak{m}) \\ \mathsf{rev}(\mathfrak{g}, \mathfrak{n}) \end{bmatrix} = \begin{bmatrix} x^{\mathfrak{m} + \mathfrak{n} - 2\ell - 1} \, \mathsf{rev}(\mathfrak{h}, \ell) \\ 0 \end{bmatrix} \\ \mbox{. the matrix } R \mbox{ is a } (-\mathfrak{n}, -\mathfrak{m}) \mbox{-reduced basis of } \mathfrak{I}(\mathbf{0}, [\frac{\mathsf{rev}(\mathfrak{f}, \mathfrak{m})}{\mathsf{rev}(\mathfrak{g}, \mathfrak{n})}]) \\ & = \left\{ [\mathfrak{p} \ \mathfrak{q}] \in \mathbb{K}[X]^{1 \times 2} \ \Big| \ [\mathfrak{p} \ \mathfrak{q}] \begin{bmatrix} \mathsf{rev}(\mathfrak{f}, \mathfrak{m}) \\ \mathsf{rev}(\mathfrak{g}, \mathfrak{n}) \end{bmatrix} = 0 \ \mathsf{mod} \ x^{\mathfrak{m} + \mathfrak{n} - 2\ell - 1} \right\} \end{array}$$

fast gcd and extended gcd



```
input: f and g univariate polynomials in \mathbb{K}[X] output: (u, v, h) where h = gcd(f, g) = uf + vg
```

$$\begin{array}{ll} \mbox{. polynomials $\bar{f}=f/h$ and $\bar{g}=g/h$} & \bar{f} and \bar{g} are coprime} \\ \mbox{. } m=deg(f), $n=deg(g)$, $\ell=deg(h)$} & $m,n>0$, $\ell\leqslant\min(m,n)$} \\ \rightsquigarrow deg(\bar{f})=m-\ell$ and $deg(\bar{g})=n-\ell$} \end{array}$$

$$\begin{array}{l} \textbf{theorem:}\\ . \text{ defining } R = \begin{bmatrix} \mathsf{rev}(\mathfrak{u}, \mathfrak{n} - \ell - 1) & \mathsf{rev}(\mathfrak{v}, \mathfrak{m} - \ell - 1) \\ -\mathsf{rev}(\bar{\mathfrak{g}}, \mathfrak{n} - \ell) & \mathsf{rev}(\bar{\mathfrak{f}}, \mathfrak{m} - \ell) \end{bmatrix} \in \mathbb{K}[X]^{2 \times 2},\\ \text{one has:} \qquad R \begin{bmatrix} \mathsf{rev}(f, \mathfrak{m}) \\ \mathsf{rev}(g, \mathfrak{n}) \end{bmatrix} = \begin{bmatrix} x^{\mathfrak{m} + \mathfrak{n} - 2\ell - 1} \mathsf{rev}(\mathfrak{h}, \ell) \\ 0 \end{bmatrix} \\ . \text{ the matrix } R \text{ is a } (-\mathfrak{n}, -\mathfrak{m})\text{-reduced basis of } \mathfrak{I}(\mathbf{0}, [\overset{\mathsf{rev}(f, \mathfrak{m})}{\mathsf{rev}(g, \mathfrak{n})}]) \\ = \left\{ [\mathfrak{p} \ q] \in \mathbb{K}[X]^{1 \times 2} \ \left| [\mathfrak{p} \ q] \begin{bmatrix} \mathsf{rev}(f, \mathfrak{m}) \\ \mathsf{rev}(g, \mathfrak{n}) \end{bmatrix} = 0 \mod x^{\mathfrak{m} + \mathfrak{n} - 2\ell - 1} \right\} \end{array} \right\}$$

fast gcd and extended gcd



input: f and g univariate polynomials in $\mathbb{K}[X]$ output: (u, v, h) where h = gcd(f, g) = uf + vg

$$\begin{array}{ll} \mbox{. polynomials $\bar{f}=f/h$ and $\bar{g}=g/h$} & \bar{f} and \bar{g} are coprime} \\ \mbox{. } m=deg(f), $n=deg(g)$, $\ell=deg(h)$} & $m,n>0$, $\ell\leqslant\min(m,n)$} \\ \rightsquigarrow deg(\bar{f})=m-\ell$ and $deg(\bar{g})=n-\ell$} \end{array}$$

$$\begin{array}{l} \mbox{corollary: xgcd in } O(\mathsf{M}(d) \mbox{log}(d)) \\ \mbox{for any } d \geqslant n+m-2\ell-1 & e.g. \ d=n+m+1 \\ \mbox{let } e=d-(n+m-2\ell-1) & hence \ e=2\ell \\ \mbox{then } \begin{bmatrix} x^e & 0 \\ 0 & 1 \end{bmatrix} R = \begin{bmatrix} x^e \ rev(u,n-\ell-1) & x^e \ rev(v,m-\ell-1) \\ -rev(\bar{g},n-\ell) & rev(\bar{f},m-\ell) \end{bmatrix} \\ \mbox{is } a \ (-n,-m) \mbox{-reduced basis of} \\ = \left\{ \begin{bmatrix} p & q \end{bmatrix} \in \mathbb{K}[X]^{1\times 2} \ \left| \begin{bmatrix} p & q \end{bmatrix} \begin{bmatrix} rev(f,m) \\ rev(g,n) \end{bmatrix} = 0 \ \text{mod } x^d \right\} \end{array} \right\}$$

perspectives — row bases

a row basis of a matrix $\mathbf{F} \in \mathbb{K}[X]^{m \times n}$ is a basis of its $\mathbb{K}[X]$ -row space $\{\mathbf{pF} \mid \mathbf{p} \in \mathbb{K}[X]^{1 \times m}\}$

 \rightsquigarrow represented as $\mathbf{R} \in \mathbb{K}[X]^{r \times n}$, where r is the rank of \mathbf{F} \rightsquigarrow $\mathbf{F} = \mathbf{U}\mathbf{R}$ for some $\mathbf{U} \in \mathbb{K}[X]^{m \times r}$

perspectives — row bases

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examples:

row basis for F ∈ K[X]^{m×m} nonsingular?
row basis of [f]
for f, g coprime polynomials?
K ∈ K[X]^{(m-r)×m} a left kernel basis of F ∈ K[X]^{m×n} row basis of K? column basis of K?

perspectives — row bases

a row basis of a matrix $\mathbf{F} \in \mathbb{K}[X]^{m \times n}$ is a basis of its $\mathbb{K}[X]$ -row space $\{\mathbf{pF} \mid \mathbf{p} \in \mathbb{K}[X]^{1 \times m}\}$

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examples:

$$\begin{array}{ll} \bullet \text{ row basis for } \mathbf{F} \in \mathbb{K}[X]^{m \times m} \text{ nonsingular}? & \mathbf{R} = \mathbf{F} \\ \bullet \text{ row basis of } \begin{bmatrix} f \\ g \end{bmatrix} \text{ for } f,g \text{ coprime polynomials}? \\ \bullet \mathbf{K} \in \mathbb{K}[X]^{(m-r) \times m} \text{ a left kernel basis of } \mathbf{F} \in \mathbb{K}[X]^{m \times n} \\ \text{ row basis of } \mathbf{K}? \text{ column basis of } \mathbf{K}? \end{array}$$

perspectives — row bases

a row basis of a matrix $\mathbf{F} \in \mathbb{K}[X]^{m \times n}$ is a basis of its $\mathbb{K}[X]$ -row space $\{\mathbf{pF} \mid \mathbf{p} \in \mathbb{K}[X]^{1 \times m}\}$

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K has full rank so C is $(m-r)\times(m-r)$ nonsingular and by definition $K=C\bar{K}$ for some \bar{K} so $KF=0\Rightarrow\bar{K}F=0$, hence $\bar{K}=VK$ from K=CVK, with K having full row rank, we deduce $CV=I_{m-r}$

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applications:

- \blacktriangleright compute an s-reduced basis of the row space
- verify that a matrix is a kernel basis
- triangularization: Hermite normal form and determinant

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applications:

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algorithm:

- ${\scriptstyle \blacktriangleright } K \leftarrow$ left kernel basis for F
- ${\scriptstyle \blacktriangleright }\, {\bf R} \leftarrow$ matrix such that ${\bf F} = {\bf G} {\bf R}$

complexity $O(mn^{\omega-1} \operatorname{deg}(\mathbf{F}))$, assuming $m \ge n$ [Zhou-Labahn, 2013]

perspectives — triangularization

perspectives — triangularization



Hermite normal form and determinant in $O^{\sim}(m^{\omega} \operatorname{deg}(\mathbf{A}))$

[Zhou, 2012] [Labahn-Neiger-Zhou, 2017]

perspectives — block Wiedemann techniques

given a sparse matrix $\mathbf{A} \in \mathbb{K}^{n \times n}$:

- ${\scriptstyle \blacktriangleright}$ solve a linear system $\mathbf{A}\mathbf{u}=\mathbf{v}$
- compute the minimal polynomial of A
- . sparse means that ${\bf A}$ has a large proportion of zero entries
- . goal: exploit sparsity to do better than exponent $\boldsymbol{\omega}$

[Wiedemann 1986, Coppersmith 1994, Kaltofen 1995, Villard 1997] block Wiedemann approach, for block dimension m: 1. choose random blocking matrices $\mathbf{U}, \mathbf{V} \in \mathbb{K}^{n \times m}$ 2. compute linearly recurrent sequence of matrices in $\mathbb{K}^{m \times m}$ $\mathbf{U}^{\mathsf{T}}\mathbf{V}, \mathbf{U}^{\mathsf{T}}\mathbf{A}\mathbf{V}, \dots, \mathbf{U}^{\mathsf{T}}\mathbf{A}^{\mathsf{k}}\mathbf{V}, \dots$

3. find polynomial matrix generator $\textbf{P} \in \mathbb{K}[X]^{m \times m}$ of this sequence

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- ${\scriptstyle \bullet}$ generically, $d=2\frac{n}{m}-1$ terms of the sequence are sufficient
- ▶ step 3 is matrix-Padé approx., in $O^{\sim}(\mathfrak{m}^{\omega} d) = O^{\sim}(\mathfrak{m}^{\omega-1}\mathfrak{n})$
- \blacktriangleright often, m is taken as the number of threads available for parallel computation of the matrix sequence

summary

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shifted reduced forms

fast algorithms

applications

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- stability under multiplication
- iterative algorithm and output size
- ▶ base case: modulus of degree 1
- ▶ recursion: residual and basis multiplication
- minimal kernel bases and linear systems
- ▶ fast gcd and extended gcd
- ► perspectives