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designing fast Guruswami-Sudan decoders using univariate polynomial matrix algorithms

CAIPI symposium @ Bordeaux
November 9, 2023

outline

computer algebra

Reed-Solomon decoding

polynomial matrices

efficient list decoding

outline

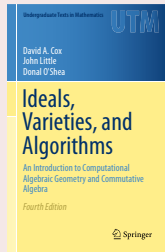
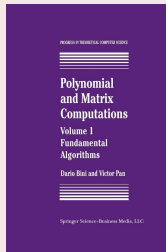
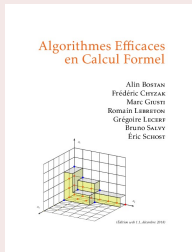
▶ **computer algebra**

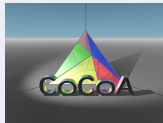
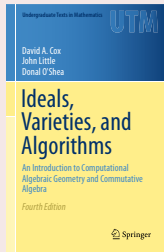
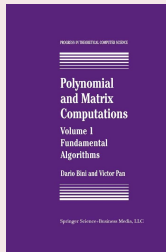
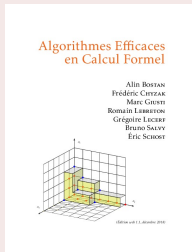
- ▶ efficient algorithms and software
- ▶ for matrices over a field
- ▶ for univariate polynomials

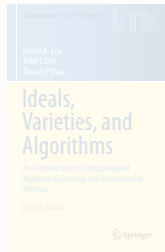
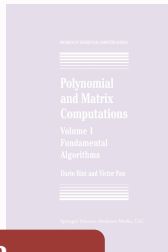
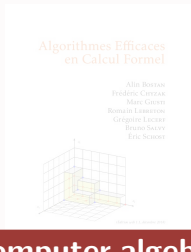
▶ **Reed-Solomon decoding**

▶ **polynomial matrices**

▶ **efficient list decoding**





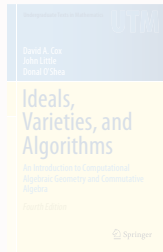
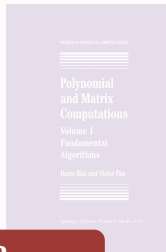
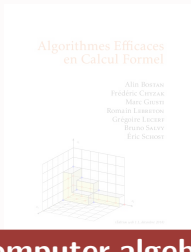


computer algebra

**algorithm design
and software implementations
for exact computations
with mathematical objects**



Euclid's GCD -300



computer algebra

**algorithm design
and software implementations
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with mathematical objects**



Euclid's GCD -300

Gaussian elimination 179

computer algebra

algorithm design
and software implementations
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MAGNUM
COMPUTER • ALGEBRA

RIIP



Euclid's GCD -300

Gaussian elimination 179

Newton's method 1669

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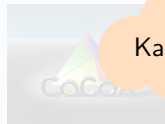
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Karatsuba '62

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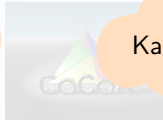


Strassen '69

Karatsuba '62



SymPy



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Buchberger '76

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Maple

WOLFRAM
MATHEMATICA 12

SDGE

LinBox
Linear Algebra

FELAS/FFPAC
Matrix arithmetic

GMP
Arbitrary precision
Integers

BLAS
Linear Algebra
Subroutines

SymPy

GoGo

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LLL '82, NFS '88

FFT 1805, '65

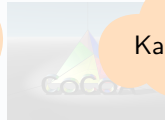
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SymPy



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Newton's method 1669

Principal Discoveries of Efficient Methods of Computing the DFT

| Researcher(s) | Date | Sequence Lengths | Number of DFT Values | Application |
|---------------------------|------|---|----------------------|--|
| C. F. Gauss [10] | 1805 | Any composite integer | All | Interpolation of orbits of celestial bodies |
| F. Carlini [28] | 1828 | 12 | — | Harmonic analysis of barometric pressure |
| A. Smith [25] | 1846 | 4, 8, 16, 32 | 5 or 9 | Correcting deviations in compasses on ships |
| J. D. Everett [23] | 1860 | 12 | 5 | Modeling underground temperature deviations |
| C. Runge [7] | 1903 | 2^k | All | Harmonic analysis of functions |
| K. Stumpff [16] | 1939 | $2^k, 3^k$ | All | Harmonic analysis of functions |
| Danielson and Lanczos [5] | 1942 | 2^n | All | X-ray diffraction in crystals |
| L. H. Thomas [13] | 1948 | Any integer with relatively prime factors | All | Harmonic analysis of functions |
| I. J. Good [3] | 1958 | Any integer with relatively prime factors | All | Harmonic analysis of functions |
| Cooley and Tukey [1] | 1965 | Any composite integer | All | Harmonic analysis of functions |
| S. Winograd [14] | 1976 | Any integer with relatively prime factors | All | Use of complexity theory for harmonic analysis |

FFT 1805, '65

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Gaussian elimination 179

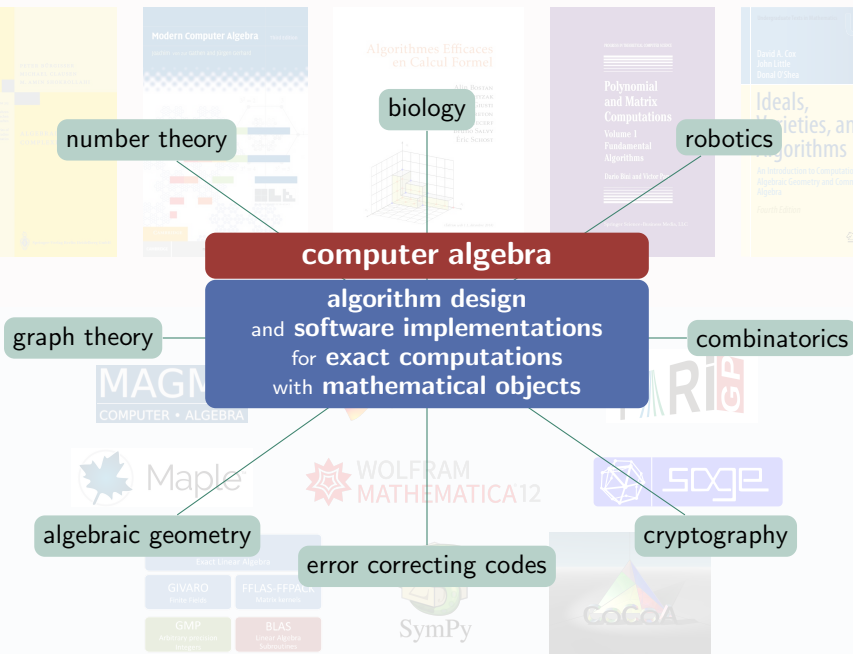
Newton's method 1669

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error correcting codes



cryptographic protocols



XXth-XXIst centuries: digital data & interconnected networks
integrity – confidentiality

discrete structures: **exact** and **intensive** computations

error correcting codes



cryptographic protocols



XXth-XXIst centuries: digital data & interconnected networks
integrity – confidentiality

discrete structures: **exact** and **intensive** computations

- ▶ matrices of large size, with sparsity or structure
- ▶ polynomials and polynomial matrices in one variable
- ▶ polynomials in several variables

goal of computer algebra

fast algorithms: complexity & efficient implementations

reduce to **efficient building blocks**

- ▶ MatMul: matrix multiplication
- ▶ PolMul: polynomial multiplication

measuring efficiency

efficient algorithms for polynomials, matrices, power series, ...
with coefficients in some base field \mathbb{K}

- ▶ low complexity bound
- ▶ low execution time

low memory usage, power consumption, ...

prime field $\mathbb{F}_p = \mathbb{Z}/p\mathbb{Z}$
field extension $\mathbb{F}_p[x]/\langle f(x) \rangle$
rational numbers \mathbb{Q}

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prime field $\mathbb{F}_p = \mathbb{Z}/p\mathbb{Z}$
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rational numbers \mathbb{Q}

algebraic complexity bounds

\rightsquigarrow count number of operations in \mathbb{K}

- 👍 standard complexity model for algebraic computations
- 👍 accurate for finite fields $\mathbb{K} = \mathbb{F}_p$
- 👎 ignores coefficient growth, e.g. over $\mathbb{K} = \mathbb{Q}$

measuring efficiency

efficient algorithms for polynomials, matrices, power series, ...
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- ▶ low complexity bound
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low memory usage, power consumption, ...

prime field $\mathbb{F}_p = \mathbb{Z}/p\mathbb{Z}$
field extension $\mathbb{F}_p[x]/\langle f(x) \rangle$
rational numbers \mathbb{Q}

practical performance

↪ measure software running time

this talk:

- ▶ working over $\mathbb{K} = \mathbb{F}_p$ with word-size prime p
- ▶ Intel Core i7-7600U @ 2.80GHz, no multithreading

matrices: multiplication

$$\mathbf{M} = \begin{bmatrix} 28 & 68 & 75 & 70 \\ 38 & 25 & 75 & 55 \\ 24 & 1 & 56 & 28 \end{bmatrix} \in \mathbb{K}^{3 \times 4} \longrightarrow 3 \times 4 \text{ matrix over } \mathbb{K} \text{ (here } \mathbb{F}_{97}\text{)}$$

fundamental operations on $m \times m$ matrices:

- ▶ **addition** is “quadratic”: $O(m^2)$ operations in \mathbb{K}
- ▶ naive **multiplication** is cubic: $O(m^3)$

[Strassen'69]

breakthrough: **subcubic** matrix multiplication

matrices: multiplication

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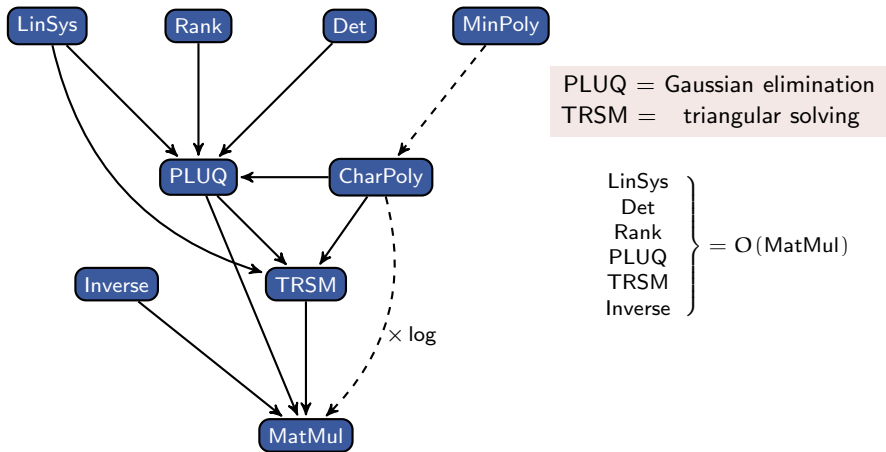
breakthrough: **subcubic** matrix multiplication

- ▶ complexity **exponent** $\omega \approx 2.81$ — i.e. $O(m^\omega)$ complexity
- ▶ **used in practice** for $m \geq$ a few 100s
in NTL, FLINT, fflas-ffpack...

- ▶ best-known exponent $\omega \approx 2.373$
[Le Gall'14] [Alman-Williams'20]
- ▶ “galactic” algorithms: strongly impractical as such

matrices: main computational problems

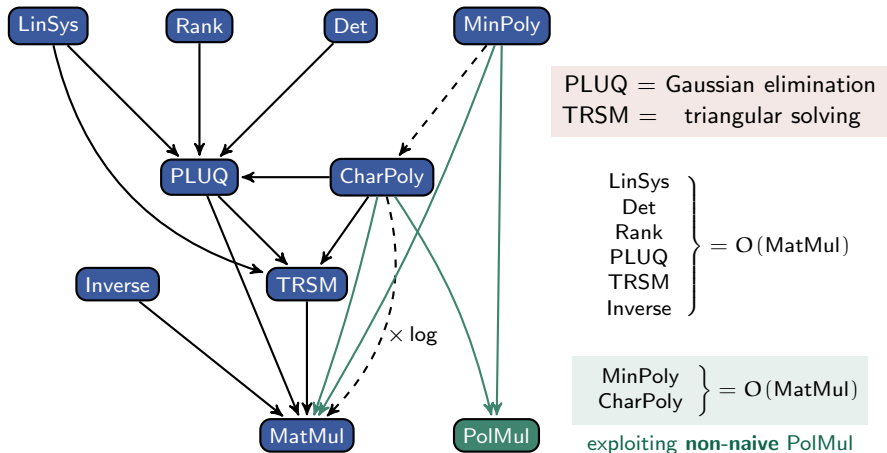
reductions of most problems to matrix multiplication



not closed:
open:

matrices: main computational problems

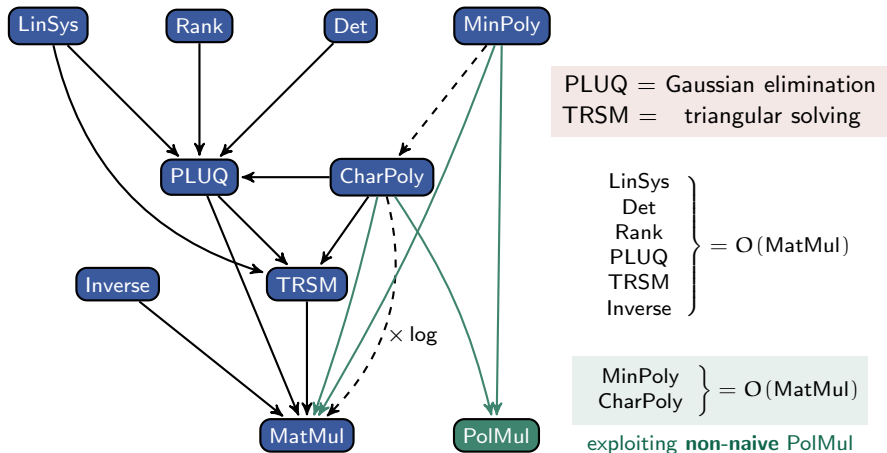
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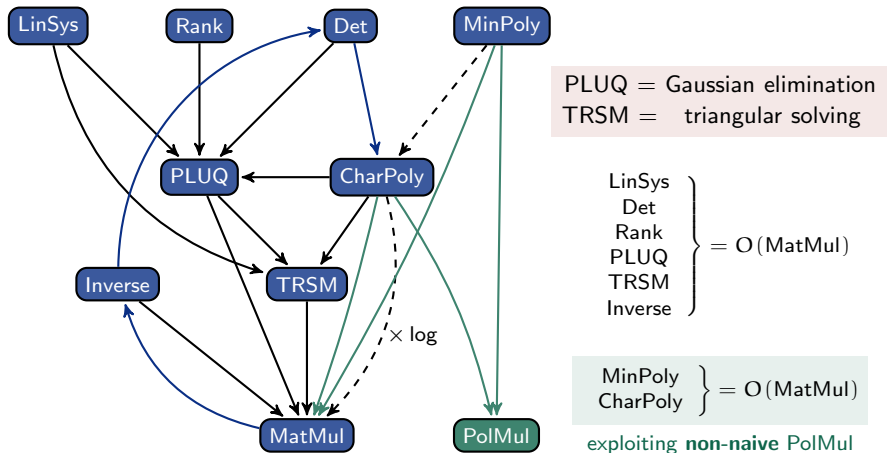
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not closed: is Frobenius normal form in $O(\text{MatMul})$?
open:

matrices: main computational problems

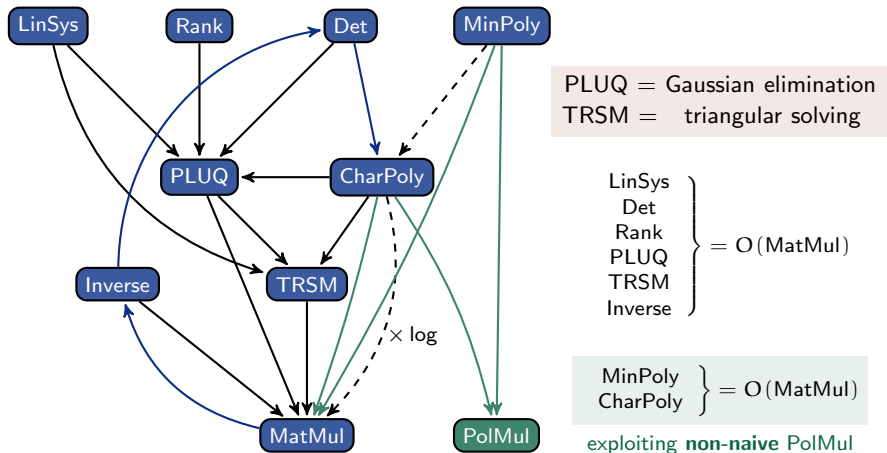
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open:

matrices: main computational problems

reductions of most problems to matrix multiplication



not closed: is Frobenius normal form in $O(\text{MatMul})$?
open: is linear system solving as hard as multiplication?

bonus: some notes

biblio: <https://www.sciencedirect.com/science/article/pii/S0747717113000631>

- ▶ explicit reductions between inversion & MatMul & variants of Gaussian elimination / echelon form computation
- ▶ constants in the $O(\cdot)$ complexities when using classical matrix multiplication ($\omega = 3$) or Strassen's algorithm

“not closed”: it is open, but

- ▶ there is a randomized algorithm for Frobenius form computation which has complexity $O(\text{MatMul})$
↪ <http://www.cs.uwaterloo.ca/~astorjoh/cpoly.pdf>
- ▶ recent developments for the characteristic polynomial gives new insight concerning core operations typically used in Frobenius form algorithms

polynomials: multiplication

$$p = 87x^7 + 74x^6 + 60x^5 + 46x^4 + 16x^3 + 41x^2 + 86x + 69$$

$p \in \mathbb{K}[x]_{<8}$ \longrightarrow univariate polynomial in x of degree < 8 over \mathbb{K}

fundamental operations on polynomials of degree $< d$:

- ▶ **addition** and Horner's **evaluation** are linear: $O(d)$
- ▶ naive **multiplication** is quadratic: $O(d^2)$

[Karatsuba'62] $M(d) \in O(d^{1.58})$

breakthrough: **subquadratic** polynomial multiplication

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breakthrough: **subquadratic** polynomial multiplication

[Schönhage-Strassen'71] [Nussbaumer'80] [Cantor-Kaltofen'91] $M(d) \in O(d \log(d) \log \log(d))$

breakthrough: **quasi-linear** polynomial multiplication

research still active, with recent progress by [Harvey-van der Hoeven-Lecerf]

- ▶ **change of representation** by evaluation-interpolation
- ▶ **used in practice** as soon as $d \approx 100$
- ▶ **FFT techniques** using (virtual) roots of unity

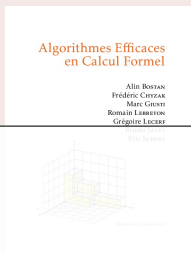
note: $M(d) \in O(d \log(d))$
if **provided** a "good" root of unity

polynomials: main computational problems

most problems have **quasi-linear complexity**

thanks to reductions to `PolMul`

- ▶ addition $f + g$, multiplication $f * g$
- ▶ **division** with remainder $f = qg + r$
- ▶ truncated **inverse** $f^{-1} \bmod x^d$
- ▶ extended **GCD** $fu + gv = \gcd(f, g)$
- ▶ **multipoint eval.** $f \mapsto f(\alpha_1), \dots, f(\alpha_d)$
- ▶ **interpolation** $f(\alpha_1), \dots, f(\alpha_d) \mapsto f$
- ▶ Padé **approximation** $f = \frac{p}{q} \bmod x^d$
- ▶ minpoly of linearly **recurrent sequence**



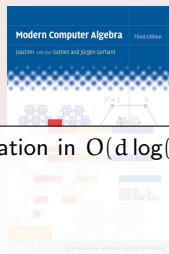
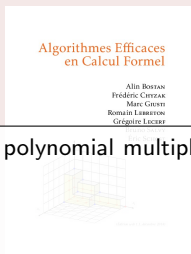
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$O(M(d))$

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not closed: polynomial multiplication in $O(d \log(d))$?
not closed:
open:
open:

polynomials: main computational problems

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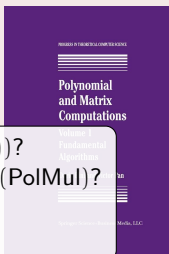
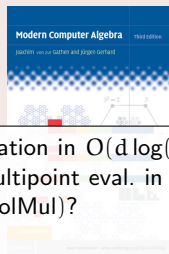
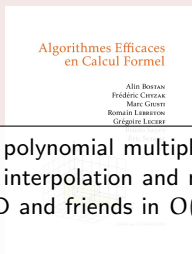
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not closed: polynomial multiplication in $O(d \log(d))$?
not closed: interpolation and multipoint eval. in $O(\text{PolMul})$?
open: XGCD and friends in $O(\text{PolMul})$?
open:

polynomials: main computational problems

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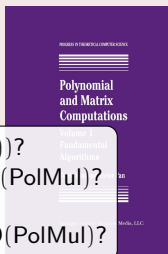
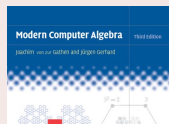
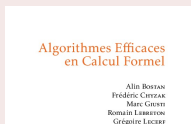
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not closed: polynomial multiplication in $O(d \log(d))$?
not closed: interpolation and multipoint eval. in $O(\text{PolMul})$?
open: XGCD and friends in $O(\text{PolMul})$?
open: modular composition $f(g) \bmod h$ closer to $O(\text{PolMul})$?

bonus: some notes

interpolation and multipoint eval. in $O(\text{PolMul})$ “not closed”:

- ▶ remains open for an arbitrary set of points, with no assumption, but:
- ▶ by design, solved for FFT points (powers of some root of unity)
- ▶ more generally, solved for points forming a geometric sequence
<https://www.sciencedirect.com/science/article/pii/S0885064X05000026>
- ▶ in many applications of interpolation/evaluation, one can choose the points, in which case $O(\text{PolMul})$ is feasible

polynomial multiplication in $O(d \log(d))$ “not closed”:

- ▶ remains open over an arbitrary field, concerning algebraic complexity
- ▶ solved when the field possesses suitable roots of unity for FFT
- ▶ method of choice in practice (using several primes and CRT if needed) when working over prime finite fields $\mathbb{Z}/p\mathbb{Z}$
- ▶ recent progress in the bit complexity model
<https://www.sciencedirect.com/science/article/pii/S0885064X19300378>
<https://dl.acm.org/doi/abs/10.1145/3505584>

```
sage: M.degree_matrix(shifts=[-1,2], row_wise=False)
[ 0 -2 -1]
[ 5 -2 -2]
```

`hermite_form(include_zero_rows=True, transformation=False)`

Return the Hermite form of this matrix.

The Hermite form is also normalized, i.e., the pivot polynomials are monic.

INPUT:

- `include_zero_rows` – boolean (default: True); if False, the zero rows in the output are deleted
- `transformation` – boolean (default: False); if True, return the transformation matrix

OUTPUT:

matrices

software

polynomials

```
sage: M.<<> = GF(7)[]
sage: A = matrix(M, 2, 3, [x, 1, 2*x, x, 1+x, 2])
sage: A.hermite_form()
[ x 1 2*x]
[ 0 x 5*x + 2]
sage: A.hermite_form(transformation=True)
[ x 1 2*x] [1 0]
[ 0 x 5*x + 2] [6 1]
]
sage: A = matrix(M, 2, 3, [x, 1, 2*x, 2*x, 2, 4*x])
sage: A.hermite_form(transformation=True, include_zero_rows=False)
[ x 1 2*x] [0 4]
[ 0 0 0] [5 1]
]
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=True); H, U
[ x 1 2*x] [0 4]
[ 0 0 0] [5 1]
]
sage: U * A == H
True
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=False)
sage: U * A
[ x 1 2*x]
sage: U * A == H
True
```

See also: `is_hermite()`.

`is_hermite(row_wise=True, lower_echelon=False, include_zero_vectors=True)`

Return a boolean indicating whether this matrix is in Hermite form.

```
164 // order that remains to be dealt with
165 VecLong rem_order(order);
166
167 // indices of columns/orders that remain to be dealt with
168 VecLong rem_index(cdn);
169 std::iota(rem_index.begin(), rem_index.end(), 0);
170
171 // all along the algorithm, shift = shifted row degrees of approximant basis
172 // (initially, input shift = shifted row degree of the identity matrix)
173
174 while (not rem_order.empty())
175 {
176     /** Invariant:
177     * - appbas is a shift-ordered weak Popov approximant basis for
178     * (pmat,reached_order) where doneorder is the tuple such that
179     * -->reached_order[j] + rem_order[j] == order[j] for j appearing in
180     * -->reached_order[j] == order[j] for j not appearing in rem_index
181     * - shift == the "input shift"-row degree of appbas
182     * - residual == submatrix of columns (appbas * pmat)[:,:] for all j
183     * in rem_order[j]
```

```
187     j = std::distance(rem_order.begin(), std::max_element(rem_order.begin(),
188 );
189     long deg = order[rem_index[j]] - rem_order[j];
190
191     // record the coefficients of degree deg of the column j of residual
192     // also keep track of which of these are nonzero,
193     // and among the nonzero ones, which is the first with smallest shift
194     Vec<zz_p> const_residual;
195     const_residual.SetLength(rdn);
196     VecLong indices_nonzero;
197     long piv = -1;
198     for (long i = 0; i < rdn; ++i)
199     {
200         const_residual[i] = coeff(residual[i][j],deg);
201         if (const_residual[i] != 0)
202         {
203             indices_nonzero.push_back(i);
204             if (piv<0 || shift[i] < shift[piv])
205                 piv = i;
206         }
207     }
208
209     // if indices_nonzero is empty, const_residual is already zero, there
210     if (not indices_nonzero.empty())
211     {
212         // update all rows of appbas and residual in indices nonzero except
213         src/mat_lzz_pX_approximant.cpp
```

open-source mathematics software system



Python/Cython

high-performance exact linear algebra

INPUT: **LinBox – fflas-ffpack** C/C++

high-performance polynomials (and more)

OUTPUT: **NTL & FLINT** C/C++

matrices

software

polynomials

```
sage: M.<M> = GF(7)[]
sage: A = matrix(M, 2, 3, [x, 1, 2*x, x, 1+x, 2])
sage: A.hermite_form()
[[ x      1      2*x]
 [ 0      x 5*x + 2]]
sage: A.hermite_form(transformation=True)
[[ x      1      2*x] [1 0]
 [ 0      x 5*x + 2], [6 1]]
]
sage: A = matrix(M, 2, 3, [x, 1, 2*x, 2*x, 2, 4*x])
sage: A.hermite_form(transformation=True, include_zero_rows=False)
[[ x  1 2*x], [0 4]]
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=True); H, U
[[ x  1 2*x] [0 4]
 [ 0 0 0], [5 1]]
]
sage: U^T * A == H
True
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=False)
sage: U^T * A
[[ x  1 2*x]
sage: U^T * A == H
True
```

See also: `is_hermite()`.

`is_hermite(row_wise=True, lower Echelon=False, include_zero_vectors=True)`

Return a boolean indicating whether this matrix is in Hermite form.

```
164 // order that remains to be dealt with
165 VecLong rem_order(order);
166
167 // indices of columns/orders that remain to be dealt with
168 VecLong rem_index(cdiIn);
169 std::iota(rem_index.begin(), rem_index.end(), 0);
170
171 // all along the algorithm, shift = shifted row degrees of approxinant basis
172 // (initially, input shift = shifted row degree of the identity matrix)
173
174 while (not rem_order.empty())
175 {
176     /** Invariant:
177     * - appbas is a shift-ordered weak Popov approxinant basis for
178     * (pmat, reached_order) where doneorder is the tuple such that
179     * -->reached_order[j] + rem_order[j] == order[j] for j appearing in
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182     * - residual == submatrix of columns (appbas * pmat)[:,:j] for all j
183     * in rem_order[j]
```

```
187     j = std::distance(rem_order.begin(), std::max_element(rem_order.begin(),
188 );
189     long deg = order[rem_index[j]] - rem_order[j];
190
191     // record the coefficients of degree deg of the column j of residual
192     // also keep track of which of these are nonzero,
193     // and among the nonzero ones, which is the first with smallest shift
194     Vec<zz_p> const_residual;
195     const_residual.SetLength(rdiIn);
196     VecLong indices_nonzero;
197     long piv = -1;
198     for (long i = 0; i < rdiIn; ++i)
199     {
200         const_residual[i] = coeff(residual[i][j], deg);
201         if (const_residual[i] != 0)
202         {
203             indices_nonzero.push_back(i);
204             if (piv < 0 || shift[i] < shift[piv])
205                 piv = i;
206         }
207     }
208
209     // if indices_nonzero is empty, const_residual is already zero, there
210     if (not indices_nonzero.empty())
211     {
212         // update all rows of appbas and residual in indices nonzero exce
213 src/mat lzz_pX approxinant.cpp
```

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[ [ x      1      2*x]
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]
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sage: A.hermite_form(transformation=True, include_zero_rows=False)
([ [ x 1 2*x], [0 4]
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=True); H, U
[ [ x 1 2*x] [0 4]
  [ 0 0 0], [5 1]
]
sage: U^A A == H
True
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=False)
sage: U^A A
[ [ x 1 2*x]
sage: U^A A == H
True
```

See also: `is_hermite()`.

`is_hermite(row_wise=True, lower_echelon=False, include_zero_vectors=True)`

Return a boolean indicating whether this matrix is in Hermite form.

- ▶ choice of algorithms
- ▶ data structures and storage
- ▶ cache efficiency
- ▶ SIMD vectorization instructions
- ▶ multithreading, GPU programming

```
187         j = std::distance(rem_order.begin(), std::max_element(rem_order.begin(),
188 );
189
190     long deg = order[rem_index[j]] - rem_order[j];
191
192     // record the coefficients of degree deg of the column j of residual
193     // also keep track of which of these are nonzero,
194     // and among the nonzero ones, which is the first with smallest shift
195     Vec<zz_p> const_residual;
196     const_residual.SetLength(rdim);
197     VecLong indices_nonzero;
198     long piv = -1;
199     for (long i = 0; i < rdim; ++i)
200     {
201         const_residual[i] = coeff(residual[i][j], deg);
202         if (const_residual[i] != 0)
203         {
204             indices_nonzero.push_back(i);
205             if (piv < 0 || shift[i] < shift[piv])
206                 piv = i;
207         }
208     }
209     // if indices_nonzero is empty, const_residual is already zero, there
210     // if (not indices_nonzero.empty())
211     {
212         // update all rows of appbas and residual in indices nonzero exce
213 src/mat lzz pX approximant.cpp
```


open-source mathematics software system



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matrices

software

polynomials

what you can compute in about 1 second
with fflas-ffpack

with NTL

▶ PLUQ $m = 3800$ 1.00s

▶ LinSys $m = 3800$ 1.00s

▶ MatMul $m = 3000$ 0.97s

▶ Inverse $m = 2800$ 1.01s

▶ CharPoly $m = 2000$ 1.09s

▶ PolMul $d = 7 \times 10^6$ 1.03s

▶ Division $d = 4 \times 10^6$ 0.96s

▶ XGCD $d = 2 \times 10^5$ 0.99s

▶ MinPoly $d = 2 \times 10^5$ 1.10s

▶ MPEval $d = 1 \times 10^4$ 1.01s

outline

▶ **computer algebra**

- ▶ efficient algorithms and software
- ▶ for matrices over a field
- ▶ for univariate polynomials

▶ **Reed-Solomon decoding**

▶ **polynomial matrices**

▶ **efficient list decoding**

outline

computer algebra

- ▶ efficient algorithms and software
- ▶ for matrices over a field
- ▶ for univariate polynomials

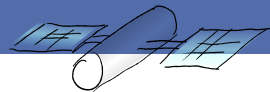
Reed-Solomon decoding

- ▶ context and unique decoding problem
- ▶ key equations and how to solve them
- ▶ correcting more errors?

polynomial matrices

efficient list decoding

error-correcting codes



goal:

reliable data transmission over
unreliable communication channel

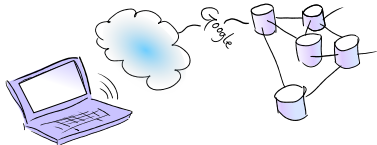
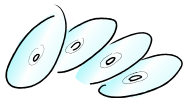
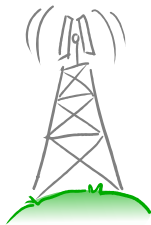
modern development pioneered by
Hamming (1940s), Shannon (1948)

strategy:

add redundancy to the message
add redundancy to the message
add redundancy to the message

intended word (w_0, \dots, w_k) \longrightarrow code word (c_1, \dots, c_n)

$$\text{with } \frac{k+1}{n} \leq 1$$

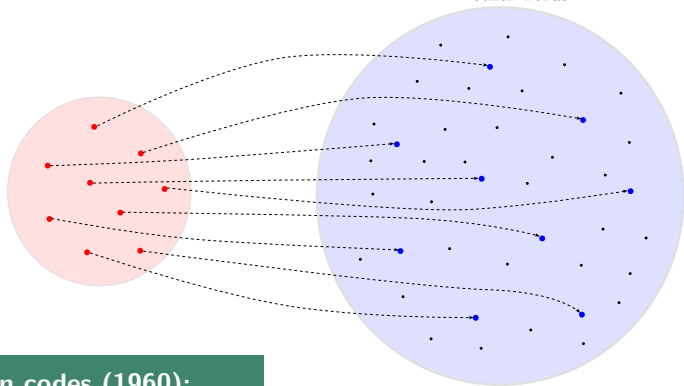


(drawing: courtesy of Johan Nielsen \rightarrow Rosenkilde)

encoding: adding redundancy

all intended words (w_0, \dots, w_k) $\xrightarrow{\text{encoding}}$ all code words (c_1, \dots, c_n)

• = code word
• = other words

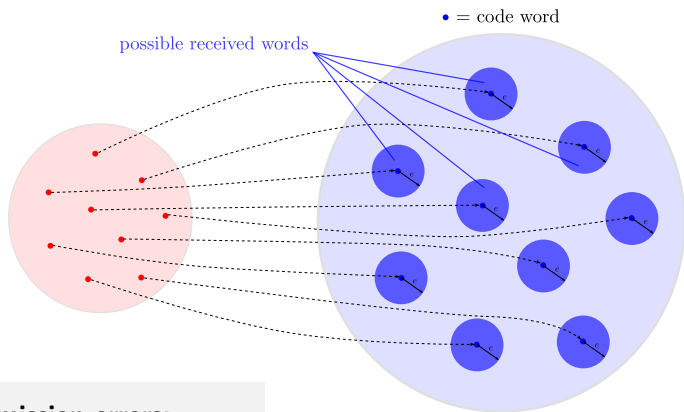


Reed-Solomon codes (1960):

polynomials of degree $\leq k$ $\xrightarrow{\text{encoding}}$ their evaluations at $\alpha_1, \dots, \alpha_n$
 $w(x) = w_0 + w_1x + \dots + w_kx^k$ $\xrightarrow{\text{encoding}}$ $(w(\alpha_1), \dots, w(\alpha_n))$

transmission over unreliable channel

polynomial $w(x)$ of degree $\leq k$ $\xrightarrow{\text{encoding}}$ code word $(w(\alpha_1), \dots, w(\alpha_n))$ $\xrightarrow{\text{noisy channel}}$ received word $(\beta_1, \dots, \beta_n)$



noise \Rightarrow transmission errors:

- ▶ number of errors $\leq e$, meaning $\#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e$ (Hamming distance)
- ▶ possible received words = balls of radius e centered on the code words

unique decoding

decoding:

find the polynomial $w(x)$ of degree $\leq k$
such that $\#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e$

- . $(\alpha_1, \dots, \alpha_n)$ = encoding points
- . $(\beta_1, \dots, \beta_n)$ = received word
- . $n - e$ = agreement

well-defined:

- . existence of w ?
- . uniqueness of w ?

unique decoding

decoding:

find the polynomial $w(x)$ of degree $\leq k$ such that $\#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e$

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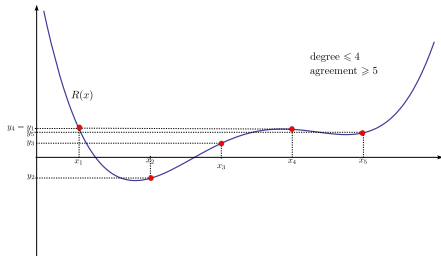
well-defined:

- . existence of w ?
- . uniqueness of w ?

$$n = 5, k = 4$$

$e = 0$: Lagrange interpolation

$e = 1$: no error detection!



unique decoding

decoding:

find the polynomial $w(x)$ of degree $\leq k$
such that $\#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e$

- . $(\alpha_1, \dots, \alpha_n)$ = encoding points
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well-defined:

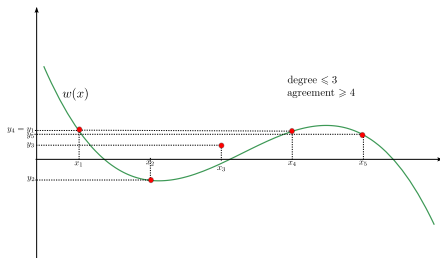
- . existence of w ?
- . uniqueness of w ?

$n = 5, k = 3$

$e = 0$: Lagrange interpolant exists!

$e = 1$: up to 5 possible solutions. . .

→ error is detected, not corrected



unique decoding

decoding:

find the polynomial $w(x)$ of degree $\leq k$
such that $\#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e$

- . $(\alpha_1, \dots, \alpha_n) =$ encoding points
- . $(\beta_1, \dots, \beta_n) =$ received word
- . $n - e =$ agreement

well-defined:

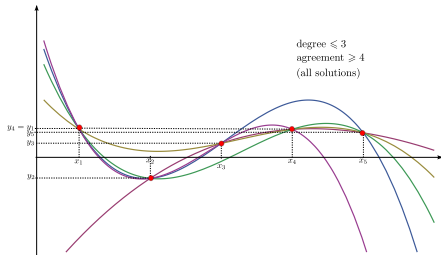
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decoding:

find the polynomial $w(x)$ of **degree** $\leq k$
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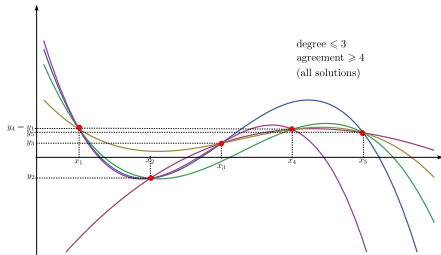
- . **existence of w ?** by construction 👍
- . **uniqueness of w ?** a priori 🚫... yet,
guaranteed **if** no overlap between the
balls of possible received words 👍

$n = 5, k = 3$

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unique decoding

decoding:

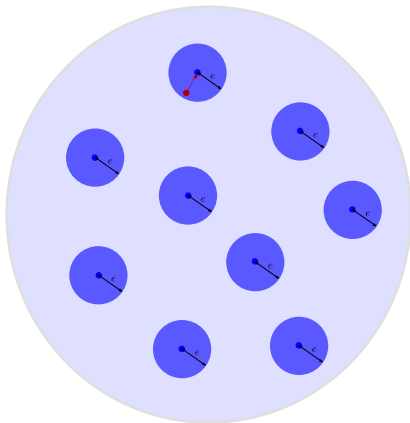
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well-defined:

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- . uniqueness of w ? a priori 🚫... yet, guaranteed **if** no overlap between the balls of possible received words 🍀

- = code word
- = received word



unique decoding

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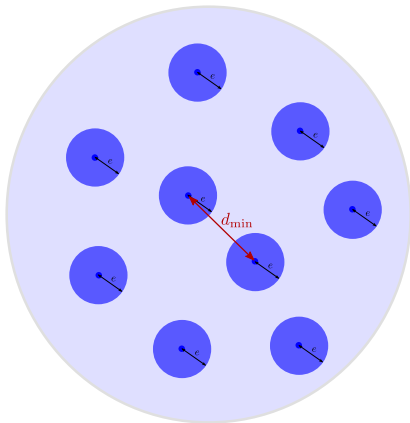
well-defined:

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unique decoding bound:

$$2e < d_{\min}$$

• = code word



Reed-Solomon case:

$$e < \frac{n-k}{2}$$

unique decoding

decoding:

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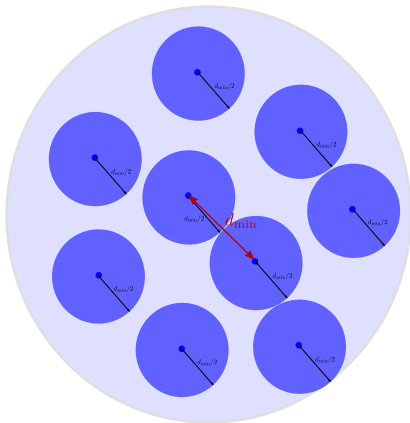
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unique decoding bound:

$$2e < d_{\min}$$

• = code word



Reed-Solomon case:

$$e < \frac{n-k}{2}$$

bonus: minimum distance for Reed-Solomon codes

- ▶ for $v \neq w$ polynomials of degree $\leq k$ over the base field \mathbb{K} ,
 $(v(\alpha_1), \dots, v(\alpha_n))$ and $(w(\alpha_1), \dots, w(\alpha_n))$ agree at $\leq k$ positions
 \Rightarrow distance at least $n - k$ between two code words
- ▶ for $v = 0$ and $w = (x - \alpha_1) \cdots (x - \alpha_k)$, the code words are
 $(0, \dots, 0)$ and $(0, \dots, 0, w(\alpha_{k+1}), \dots, w(\alpha_n))$
 \Rightarrow two code words at distance exactly $n - k$

\implies minimum distance $d_{\min} = n - k$

(for dimension reasons, this is the best one can hope for)

in this case, unique decoding condition: $e < \frac{n - k}{2}$

summary: unique decoding problem

input:

- ▶ $\alpha_1, \dots, \alpha_n$ the n distinct evaluation points in \mathbb{K} ,
- ▶ k the degree bound, e the error-correction radius,
- ▶ $(\beta_1, \dots, \beta_n)$ the received word in \mathbb{K}^n

unique decoding requirement: $e < \frac{n-k}{2}$

output: **the** polynomial $w(x)$ in $\mathbb{K}[x]$ such that

$$\deg(w) \leq k \quad \text{and} \quad \#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e$$

summary: unique decoding problem

input:

- ▶ $\alpha_1, \dots, \alpha_n$ the n distinct evaluation points in \mathbb{K} ,
- ▶ k the degree bound, e the error-correction radius,
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unique decoding requirement: $e < \frac{n-k}{2}$

output: **the** polynomial $w(x)$ in $\mathbb{K}[x]$ such that

$$\deg(w) \leq k \quad \text{and} \quad \#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e$$

multiple viewpoints + fruitful interactions: [coding theory]/[computer algebra]

▶ linear recurrence generator – Toeplitz linear system – Padé approximation

[Berlekamp'68] [Massey'69]

[Brent-Gustavson-Yun'80] [Beckermann-Labahn'94]

▶ modified extended GCD – rational function reconstruction

[Sugiyama-Kasahara-Hirasawa-Namekawa'75] [Welch-Berlekamp'86]

[Knuth'70] [Schönhage'71] [Moenck'73] [Brent-Gustavson-Yun'80]

▶ Vandermonde-like linear system – vector rational interpolation

[Olshevsky-Shokrollahi'99] [Kötter-Vardy 2003]

[Morf'74] [Bitmead-Anderson'80] [Pan'90] [van Barel-Bultheel'92] [Beckermann-Labahn'97]

one target complexity: $O(n^3) \rightarrow O(n^2) \rightarrow O(M(n) \log(n))$

encoding/decoding efficiency: basic remarks

encoding $w(x) \mapsto (w(\alpha_1), \dots, w(\alpha_n))$

▶ **naive**: n times Horner evaluation $O(k)$ $O(nk)$

▶ **fast**: $\frac{n}{k}$ times k -point evaluation $O(\frac{n}{k}M(k) \log(k)) \subseteq O(M(n) \log(n))$

points in geometric sequence \Rightarrow no log factor [Aho-Steiglitz-Ullman'75] [Bostan-Schost 2005]

encoding/decoding efficiency: basic remarks

encoding $w(x) \mapsto (w(\alpha_1), \dots, w(\alpha_n))$

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points in geometric sequence \Rightarrow no log factor [Aho-Steiglitz-Ullman'75] [Bostan-Schost 2005]

naive decoding

▶ **infinitely lucky decoder**: there was no error

\rightsquigarrow Lagrange interpolation in $O(M(n) \log(n))$ 🤖😎

▶ **very lucky decoder**: at most 1 error, unknown position

\rightsquigarrow trial and error, worst case $O(nM(n) \log(n))$ 🤖😞

▶ **lucky decoder**: at most 2 errors, unknown positions

\rightsquigarrow trial and error, worst case $O(n^2M(n) \log(n))$ 🤖😞🤖😞

▶ **ordinary decoder**: at most e errors, unknown positions

\rightsquigarrow life is tough, complexity **exponential in e** 🤖😞🤖😞

next slides = one can be both ordinary and 🤖😎

linear key equations and “rational interpolation” decoding

known interpolant $R(x)$
such that $R(\alpha_i) = \beta_i$

unknown error-locator
 $\Lambda(x) = \prod_{i | \text{error}} (x - \alpha_i)$
 $\Rightarrow \deg(\Lambda) \leq e$

key equations: $\Lambda(\alpha_i)R(\alpha_i) = \Lambda(\alpha_i)w(\alpha_i)$ for $1 \leq i \leq n$

multivariate, non-linear, polynomial system: a priori difficult
(n equations of degree 2 in the $k + 1 + e$ coefficients of w and Λ)

approach: linearization

introducing the new unknown $\mu = \Lambda w$ of degree $\leq k + e$

linear key equations and “rational interpolation” decoding

known **interpolant** $R(x)$
such that $R(\alpha_i) = \beta_i$

unknown **error-locator**
 $\Lambda(x) = \prod_{i | \text{error}} (x - \alpha_i)$
 $\Rightarrow \deg(\Lambda) \leq e$

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multivariate, non-linear, polynomial system: a priori difficult
(n equations of degree 2 in the $k + 1 + e$ coefficients of w and Λ)

approach: linearization

introducing the new unknown $\mu = \Lambda w$ of degree $\leq k + e$

linear system with n equations and $k + 1 + 2e$ unknowns ($k + 1 + 2e \leq n$):

- ▶ Gaussian elimination $O(n^3) \rightarrow O(n^\omega)$ [Bunch-Hopcroft'74] [Ibarra-Moran-Hui'82]
- ▶ $O(n^2) \rightarrow O(M(n) \log(n))$ exploiting the Vandermonde-like structure
[Morf'74] [Bitmead-Anderson'80] [Pan'90] [Olshevsky-Shokrollahi'99]
- ▶ $O(n^2) \rightarrow O(M(n) \log(n))$ via vector rational interpolation
[Beckermann'92] [van Barel-Bultheel'92] [Beckermann-Labahn'94,'97] [Kötter-Vardy 2003]

univariate key equation and “rational reconstruction” decoding

known interpolant $R(x)$
such that $R(\alpha_i) = \beta_i$

unknown error-locator
 $\Lambda(x) = \prod_{i | \text{error}} (x - \alpha_i)$
 $\deg(\Lambda) \leq e$

unknown linearizer
 $\mu(x) = \Lambda(x)w(x)$
 $\deg(\mu) \leq e + k$

$$\Lambda(\alpha_i)R(\alpha_i) = \mu(\alpha_i) \text{ for } 1 \leq i \leq n$$

$$\Updownarrow$$

$$\Lambda(x)R(x) = \mu(x) \bmod (x - \alpha_i) \text{ for } 1 \leq i \leq n$$

$$\Updownarrow$$

$$G(x) = \prod_{1 \leq i \leq n} (x - \alpha_i), \text{ degree } n$$

[Welch-Berlekamp'86]

$$\text{univariate key equation: } \Lambda(x)R(x) = \mu(x) \bmod G(x)$$

approach: rational reconstruction

$$\begin{cases} \Lambda R = \mu \bmod G \\ \deg(\Lambda) \leq e, \deg(\mu) < n - e, \Lambda \text{ monic} \end{cases}$$

note: $e + k < n - e$

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[Welch-Berlekamp'86]

$G(x) = \prod_{1 \leq i \leq n} (x - \alpha_i)$, degree n

univariate key equation: $\Lambda(x)R(x) = \mu(x) \bmod G(x)$

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note: $e + k < n - e$

- ▶ **unique** rational solution $\frac{\mu}{\Lambda}$, which has to be $\frac{\Lambda w}{\Lambda} = w$
- ▶ solved by **XGCD** algorithm stopped at suitable iteration $O(n^2)$
[Sugiyama-Kasahara-Hirasawa-Namekawa'75] [Modern Computer Algebra, v.z.Gathen-Gerhard, 2003]
- ▶ **fast XGCD** algorithms can be adapted $\rightarrow O(M(n) \log(n))$
[Knuth'70] [Schönhage'71] [Moenck'73] [Gustavson-Yun'79][Brent-Gustavson-Yun'80]

classical key equation and “Padé approximation” decoding

$$\begin{cases} \Lambda R = \mu \bmod G = \mu + \nu G & \text{with } \deg(\Lambda) \leq e, \Lambda \text{ monic} \\ \deg(\mu) \leq \deg(\Lambda) + k, \deg(\nu) \leq \deg(\Lambda) - 1 \end{cases}$$

\updownarrow reverse w.r.t. $x^{n-1+\deg(\Lambda)}$

$$\begin{cases} \bar{\Lambda} \bar{R} = \bar{\mu} x^{n-k-1} + \bar{\nu} \bar{G} = \bar{\nu} \bar{G} \bmod x^{n-k-1} & \text{with } \deg(\bar{\Lambda}) \leq e, \bar{\Lambda}(0) = 1 \\ \deg(\bar{\mu}) \leq \deg(\bar{\Lambda}) + k, \deg(\bar{\nu}) \leq \deg(\bar{\Lambda}) - 1 \end{cases}$$

$\downarrow S = \bar{R} / \bar{G} \bmod x^{n-k-1} \quad (\text{Newton iteration})$

approach: linear recurrence

$$\begin{cases} \bar{\Lambda} S = \bar{\nu} \bmod x^{n-k-1} \\ \deg(\bar{\Lambda}) \leq e, \deg(\bar{\nu}) < e, \bar{\Lambda}(0) = 1 \end{cases}$$

classical key equation and “Padé approximation” decoding

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↓ $S = \bar{R}/\bar{G} \bmod x^{n-k-1}$ (Newton iteration)

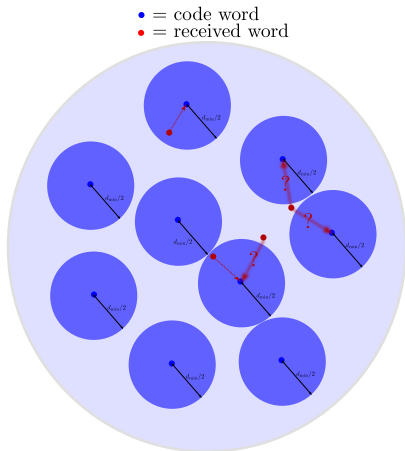
approach: linear recurrence $\begin{cases} \bar{\Lambda} S = \bar{\nu} \bmod x^{n-k-1} \\ \deg(\bar{\Lambda}) \leq e, \deg(\bar{\nu}) < e, \bar{\Lambda}(0) = 1 \end{cases}$

- ▶ **unique** rational solution $\bar{\nu}/\bar{\Lambda}$, which yields Λ
- ▶ coefficients of S : **linearly recurrent sequence** generated by $\bar{\Lambda}$
 - ↪ specific algorithms in $O(n^2)$ [Berlekamp'68] [Massey'69]
 - ↪ in fact equivalent to the **XGCD** approach $O(n^2) \rightarrow O(M(n) \log(n))$
[Sugiyama et al.'75] [Brent-Gustavson-Yun'80] [Dornstetter'84]
- ▶ find $\bar{\Lambda}$ by homogeneous **Toeplitz** linear system $O(n^2) \rightarrow O(M(n) \log(n))$
- ▶ use direct **Padé approximation** $O(n^2) \rightarrow O(M(n) \log(n))$
[Padé 1894] [Sergeyev'86][van Barel-Bultheel'91][Beckermann-Labahn'94]

non-unique decoding

how to decode **more errors**?

- . transmission with $\leq e$ errors
- . where $e \geq d_{\min}/2$



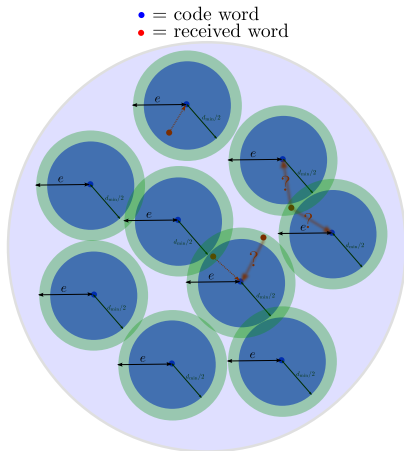
non-unique decoding

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well-defined?

- . **existence of w** : 👍, by construction
- . **uniqueness of w** : 👎, possibly several code words at the same distance
- . closest code word not necessarily the sent code word!



non-unique decoding

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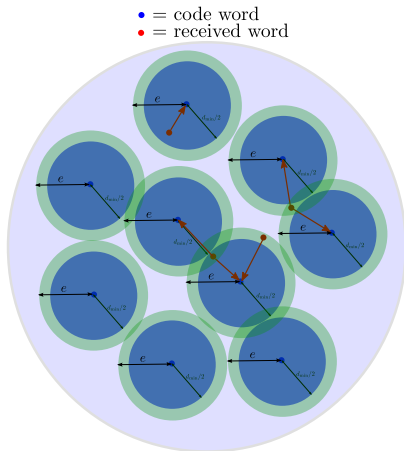
well-defined?

- . **existence of w** : 👍, by construction
- . **uniqueness of w** : 👎, possibly several code words at the same distance
- . closest code word not necessarily the sent code word!

list-decoding:

return a **list** of **all** code words at distance $\leq e$

[Elias'50s]



list decoding problem

for convenience, we use the **agreement parameter** $t = n - e$:
 $\#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e \Leftrightarrow \#\{i \mid w(\alpha_i) = \beta_i\} \geq t$

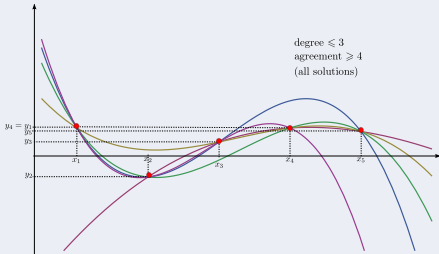
input:

- ▶ $\alpha_1, \dots, \alpha_n$ the n distinct evaluation points in \mathbb{K} ,
- ▶ k the degree bound, $t = n - e$ the agreement,
- ▶ $(\beta_1, \dots, \beta_n)$ the received word in \mathbb{K}^n

list decoding requirement: $t^2 > kn$ [Guruswami-Sudan'99]

output: **all** polynomials $w(x)$ in $\mathbb{K}[x]$ such that

$$\deg(w) \leq k \quad \text{and} \quad \#\{i \mid w(\alpha_i) = \beta_i\} \geq t$$



outline

computer algebra

- ▶ efficient algorithms and software
- ▶ for matrices over a field
- ▶ for univariate polynomials

Reed-Solomon decoding

- ▶ context and unique decoding problem
- ▶ key equations and how to solve them
- ▶ correcting more errors?

polynomial matrices

efficient list decoding

outline

computer algebra

- ▶ efficient algorithms and software
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- ▶ context and unique decoding problem
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polynomial matrices

- ▶ introduction to vector interpolation
- ▶ core algorithms & shifted normal forms
- ▶ fast divide and conquer interpolation

efficient list decoding

introduction to vector interpolation

⇓ earlier in the talk ⇓

$O(M(d))$

- ▶ addition $f + g$, multiplication $f * g$
- ▶ **division** with remainder $f = qg + r$
- ▶ truncated **inverse** $f^{-1} \bmod x^d$
- ▶ extended **GCD** $fu + gv = \gcd(f, g)$

$O(M(d) \log(d))$

- ▶ **multipoint eval.** $f \mapsto f(\alpha_1), \dots, f(\alpha_d)$
- ▶ **interpolation** $f(\alpha_1), \dots, f(\alpha_d) \mapsto f$
- ▶ Padé **approximation** $f = \frac{p}{q} \bmod x^d$
- ▶ minpoly of linearly **recurrent sequence**

⇓ next in the talk ⇓

Padé approximation, sequence minpoly, extended GCD

$O(M(d) \log(d))$ operations in \mathbb{K}

matrix versions of these problems

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

or a tiny bit more for matrix-GCD

introduction to vector interpolation

rational approximation and interpolation

Padé approximation:

given **power series** $f(x)$ at precision d ,

given **degree constraints** $d_1, d_2 > 0$,

→ compute **polynomials** $(p(x), q(x))$ of **degrees** $< (d_1, d_2)$

and such that $f = \frac{p}{q} \bmod x^d$

strong links with linearly recurrent sequences

introduction to vector interpolation

rational approximation and interpolation

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given **power series** $f(x)$ at precision d ,

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and such that $f = \frac{p}{q} \bmod x^d$

strong links with linearly recurrent sequences

Cauchy interpolation:

given $G(x) = (x - \alpha_1) \cdots (x - \alpha_d) \in \mathbb{K}[x]$,

for pairwise distinct $\alpha_1, \dots, \alpha_d \in \mathbb{K}$,

given **degree constraints** $d_1, d_2 > 0$,

→ compute **polynomials** $(p(x), q(x))$ of **degrees** $< (d_1, d_2)$

and such that $f = \frac{p}{q} \bmod G(x)$

introduction to vector interpolation

rational approximation and interpolation

Padé approximation:

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→ compute **polynomials** $(p(x), q(x))$ of **degrees** $< (d_1, d_2)$

and such that $f = \frac{p}{q} \bmod G(x)$

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

introduction to vector interpolation

approximation and structured linear system

$$\mathbb{K} = \mathbb{F}_7$$

$$f = 2x^7 + 2x^6 + 5x^4 + 2x^2 + 4$$

$$d = 8, d_1 = 3, d_2 = 6$$

→ look for (p, q) of degree $< (3, 6)$ such that $f = \frac{p}{q} \bmod x^8$

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

introduction to vector interpolation

approximation and structured linear system

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→ look for (p, q) of degree $< (3, 6)$ such that $f = \frac{p}{q} \pmod{x^8}$

$$[q \quad p] \begin{bmatrix} f \\ -1 \end{bmatrix} = 0 \pmod{x^8}$$

$$[q_0 \quad q_1 \quad q_2 \quad q_3 \quad q_4 \quad 1 \mid p_0 \quad p_1 \quad p_2] \begin{bmatrix} 4 & 0 & 2 & 0 & 5 & 0 & 2 & 2 \\ & 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ & & 4 & 0 & 2 & 0 & 5 & 0 \\ & & & 4 & 0 & 2 & 0 & 5 \\ & & & & 4 & 0 & 2 & 0 \\ & & & & & 4 & 0 & 2 \\ \hline 6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ & 6 & 0 & 0 & 0 & 0 & 0 & 0 \\ & & 6 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} = 0$$

introduction to vector interpolation

approximation and structured linear system

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$$[q_0 \ q_1 \ q_2 \ q_3 \ q_4 \ 1 \mid p_0 \ p_1 \ p_2]$$

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

$$= 0$$

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 (1), occupé de la généralisation des fractions continues algébriques. La question est de déterminer les polynomes X_1, X_2, \dots, X_n , de degrés $\mu_1, \mu_2, \dots, \mu_n$, qui satisfont à l'équation

$$S_1 X_1 + S_2 X_2 + \dots + S_n X_n = S x^{\mu_1 + \mu_2 + \dots + \mu_n + n - 1},$$

S_1, S_2, \dots, 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-

introduction to vector interpolation

approximation and interpolation: the vector case

Hermite-Padé approximation

[Hermite 1893, Padé 1894]

input:

- ▶ polynomials $f_1, \dots, f_m \in \mathbb{K}[x]$
- ▶ precision $d \in \mathbb{Z}_{>0}$
- ▶ degree bounds $d_1, \dots, d_m \in \mathbb{Z}_{>0}$

output:

polynomials $p_1, \dots, p_m \in \mathbb{K}[x]$ such that

- ▶ $p_1 f_1 + \dots + p_m f_m = 0 \pmod{x^d}$
- ▶ $\deg(p_i) < d_i$ for all i

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

introduction to vector interpolation

approximation and interpolation: the vector case

M-Padé approximation / vector rational interpolation

[Cauchy 1821, Mahler 1968]

input:

- ▶ polynomials $f_1, \dots, f_m \in \mathbb{K}[x]$
- ▶ pairwise distinct points $\alpha_1, \dots, \alpha_d \in \mathbb{K}$
- ▶ degree bounds $d_1, \dots, d_m \in \mathbb{Z}_{>0}$

output:

polynomials $p_1, \dots, p_m \in \mathbb{K}[x]$ such that

- ▶ $p_1(\alpha_i)f_1(\alpha_i) + \dots + p_m(\alpha_i)f_m(\alpha_i) = 0$ for all $1 \leq i \leq d$
- ▶ $\deg(p_i) < d_i$ for all i

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

introduction to vector interpolation

approximation and interpolation: the vector case

in this talk: modular equation and fast algebraic algorithms

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

input:

- ▶ polynomials $f_1, \dots, f_m \in \mathbb{K}[x]$
- ▶ field elements $\alpha_1, \dots, \alpha_d \in \mathbb{K}$ \rightsquigarrow not necessarily distinct
- ▶ degree bounds $d_1, \dots, d_m \in \mathbb{Z}_{>0}$ \rightsquigarrow general “shift” $s \in \mathbb{Z}^m$

output:

polynomials $p_1, \dots, p_m \in \mathbb{K}[x]$ such that

- ▶ $p_1 f_1 + \dots + p_m f_m = 0 \pmod{\prod_{1 \leq i \leq d} (x - \alpha_i)}$
- ▶ $\deg(p_i) < d_i$ for all i \rightsquigarrow minimal s -row degree

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

introduction to vector interpolation

interpolation and structured linear system

application of vector rational interpolation:

given pairwise distinct points $\{(\alpha_i, \beta_i), 1 \leq i \leq 8\}$
 $= \{(24, 80), (31, 73), (15, 73), (32, 35), (83, 66), (27, 46), (20, 91), (59, 64)\}$,
compute a **bivariate** polynomial $Q(x, y) \in \mathbb{K}[x, y]$
such that $Q(\alpha_i, \beta_i) = 0$ for $1 \leq i \leq 8$

$$\left. \begin{array}{l} G(x) = (x - 24) \cdots (x - 59) \\ R(x) = \text{Lagrange interpolant} \end{array} \right\} \rightarrow \text{solutions} = \text{ideal } \langle G(x), y - R(x) \rangle$$

solutions of smaller x -degree: $Q(x, y) = Q_0(x) + Q_1(x)y + Q_2(x)y^2$

$$Q(x, R(x)) = [Q_0 \quad Q_1 \quad Q_2] \begin{bmatrix} 1 \\ R \\ R^2 \end{bmatrix} = 0 \text{ mod } G(x)$$

- ▶ instance of **univariate** rational vector interpolation
- ▶ with a **structured** input equation (powers of $R \text{ mod } G$)

introduction to vector interpolation

interpolation and structured linear system

application of vector rational interpolation:

given pairwise distinct points $\{(\alpha_i, \beta_i), 1 \leq i \leq 8\}$

$= \{(24, 80), (31, 73), (15, 73), (32, 35), (83, 66), (27, 46), (20, 91), (59, 64)\}$,

compute a **bivariate** polynomial $Q(x, y) \in \mathbb{K}[x, y]$

such that $Q(\alpha_i, \beta_i) = 0$ for $1 \leq i \leq 8$

add **degree constraints**: seek $Q(x, y)$ of the form

$$q_{00} + q_{01}x + q_{02}x^2 + q_{03}x^3 + q_{04}x^4 + (q_{10} + q_{11}x + q_{12}x^2)y + q_{20}y^2:$$

$$\begin{bmatrix}
 q_{00} & q_{01} & q_{02} & q_{03} & q_{04} & \vdots & q_{10} & q_{11} & q_{12} & \vdots & q_{20}
 \end{bmatrix}
 \begin{bmatrix}
 1 & 1 & \cdots & 1 \\
 \alpha_1 & \alpha_2 & \cdots & \alpha_8 \\
 \alpha_1^2 & \alpha_2^2 & \cdots & \alpha_8^2 \\
 \alpha_1^3 & \alpha_2^3 & \cdots & \alpha_8^3 \\
 \alpha_1^4 & \alpha_2^4 & \cdots & \alpha_8^4 \\
 \hline
 \beta_1 & \beta_2 & \cdots & \beta_8 \\
 \alpha_1\beta_1 & \alpha_2\beta_2 & \cdots & \alpha_8\beta_8 \\
 \alpha_1^2\beta_1 & \alpha_2^2\beta_2 & \cdots & \alpha_8^2\beta_8 \\
 \hline
 \beta_1^2 & \beta_2^2 & \cdots & \beta_8^2
 \end{bmatrix}
 = 0$$

► **\mathbb{K} -linear** system

► **two levels** of structure

$$Q(x, y) = (2x^4 + 56x^3 + 42x^2 + 48x + 15) + (72x^2 + 12x + 30)y + y^2$$

introduction to vector interpolation

polynomial matrices enter the arena

why polynomial matrices here?

introduction to vector interpolation

polynomial matrices enter the arena

why polynomial matrices here?

omitting degree constraints, the set of solutions is

$$\mathcal{M} = \{(p_1, \dots, p_m) \in \mathbb{K}[x]^m \mid p_1 f_1 + \dots + p_m f_m = 0 \text{ mod } G\}$$

recall $G(x) = \prod_{1 \leq i \leq d} (x - \alpha_i)$

introduction to vector interpolation

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\mathcal{M} is a “free $\mathbb{K}[x]$ -module of rank m ”, meaning:

- ▶ stable under $\mathbb{K}[x]$ -linear combinations
- ▶ admits a basis consisting of m elements
- ▶ basis = $\mathbb{K}[x]$ -linear independence + generates all solutions

introduction to vector interpolation

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- ▶ stable under $\mathbb{K}[x]$ -linear combinations
- ▶ admits a basis consisting of m elements
- ▶ basis = $\mathbb{K}[x]$ -linear independence + generates all solutions

$$\text{▶ } \mathcal{M} \subset \mathbb{K}[x]^m \Rightarrow \mathcal{M} \text{ has rank } \leq m$$

$$\text{▶ } G(x)\mathbb{K}[x]^m \subset \mathcal{M} \Rightarrow \mathcal{M} \text{ has rank } \geq m$$

remark: solutions are not considered modulo G

e.g. $(G, 0, \dots, 0)$ is in \mathcal{M} and may appear in a basis

introduction to vector interpolation

polynomial matrices enter the arena

why polynomial matrices here?

omitting degree constraints, the set of solutions is

$$\mathcal{M} = \{(p_1, \dots, p_m) \in \mathbb{K}[\chi]^m \mid p_1 f_1 + \dots + p_m f_m = 0 \text{ mod } G\}$$

$$\text{recall } G(\chi) = \prod_{1 \leq i \leq d} (\chi - \alpha_i)$$

basis of solutions:

- ▶ square nonsingular matrix \mathbf{P} in $\mathbb{K}[\chi]^{m \times m}$
- ▶ each row of \mathbf{P} is a solution
- ▶ any solution is a $\mathbb{K}[\chi]$ -combination \mathbf{uP} , $\mathbf{u} \in \mathbb{K}[\chi]^{1 \times m}$

i.e. \mathcal{M} is the $\mathbb{K}[\chi]$ -row space of \mathbf{P}

introduction to vector interpolation

polynomial matrices enter the arena

why polynomial matrices here?

omitting degree constraints, the set of solutions is

$$\mathcal{M} = \{(p_1, \dots, p_m) \in \mathbb{K}[x]^m \mid p_1 f_1 + \dots + p_m f_m = 0 \pmod{G}\}$$

recall $G(x) = \prod_{1 \leq i \leq d} (x - \alpha_i)$

basis of solutions:

- ▶ square nonsingular matrix \mathbf{P} in $\mathbb{K}[x]^{m \times m}$
- ▶ each row of \mathbf{P} is a solution
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i.e. \mathcal{M} is the $\mathbb{K}[x]$ -row space of \mathbf{P}

fact: $\det(\mathbf{P})$ is a divisor of $G(x)$

introduction to vector interpolation

polynomial matrices enter the arena

why polynomial matrices here?

omitting degree constraints, the set of solutions is

$$\mathcal{M} = \{(p_1, \dots, p_m) \in \mathbb{K}[x]^m \mid p_1 f_1 + \dots + p_m f_m = 0 \text{ mod } G\}$$

$$\text{recall } G(x) = \prod_{1 \leq i \leq d} (x - \alpha_i)$$

basis of solutions:

- ▶ square nonsingular matrix \mathbf{P} in $\mathbb{K}[x]^{m \times m}$
- ▶ each row of \mathbf{P} is a solution
- ▶ any solution is a $\mathbb{K}[x]$ -combination \mathbf{uP} , $\mathbf{u} \in \mathbb{K}[x]^{1 \times m}$

i.e. \mathcal{M} is the $\mathbb{K}[x]$ -row space of \mathbf{P}

fact: $\det(\mathbf{P})$ is a divisor of $G(x)$

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

introduction to vector interpolation

polynomial matrices enter the arena

why polynomial matrices here?

omitting degree constraints, the set of solutions is

$$\mathcal{M} = \{(p_1, \dots, p_m) \in \mathbb{K}[x]^m \mid p_1 f_1 + \dots + p_m f_m = 0 \text{ mod } G\}$$

recall $G(x) = \prod_{1 \leq i \leq d} (x - \alpha_i)$

basis of solutions:

- ▶ square nonsingular matrix \mathbf{P} in $\mathbb{K}[x]^{m \times m}$
- ▶ each row of \mathbf{P} is a solution
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i.e. \mathcal{M} is the $\mathbb{K}[x]$ -row space of \mathbf{P}

computing a **basis** of \mathcal{M} with “**minimal degrees**”

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

polynomial matrices: multiplication

$$\mathbf{A} = \begin{bmatrix} 3x + 4 & x^3 + 4x + 1 & 4x^2 + 3 \\ 5 & 5x^2 + 3x + 1 & 5x + 3 \\ 3x^3 + x^2 + 5x + 3 & 6x + 5 & 2x + 1 \end{bmatrix} \in \mathbb{K}[x]^{3 \times 3}$$

3×3 matrix of degree 3
with entries in $\mathbb{K}[x] = \mathbb{F}_7[x]$

operations on $\mathbb{K}[x]_{<d}^{m \times m}$

- ▶ combination of matrix and polynomial computations
- ▶ **addition** in $O(m^2 d)$, naive **multiplication** in $O(m^3 d^2)$

[Cantor-Kaltofen'91]

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

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

2×2 matrices in XGCD, Padé approximation,
Berlekamp-Massey, Toeplitz linear systems...

\rightsquigarrow $m \times m$ matrix versions of these problems

- ▶ some problems&techniques **shared** with matrices over \mathbb{K}
- ▶ some problems&techniques **specific** to entries in $\mathbb{K}[x]$

polynomial matrices: multiplication

$$\mathbf{A} = \begin{bmatrix} 3x + 4 & x^3 + 4x + 1 & 4x^2 + 3 \\ 5 & 5x^2 + 3x + 1 & 5x + 3 \\ 3x^3 + x^2 + 5x + 3 & 6x + 5 & 2x + 1 \end{bmatrix} \in \mathbb{K}[x]^{3 \times 3}$$

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

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

applying univariate polynomial techniques directly:

- ▶ Newton truncated inversion, matrix-QuoRem $\tilde{O}(m^\omega d)$ 🤖
- ▶ inversion & determinant by evaluation-interpolation $\tilde{O}(m^{\omega+1} d)$ 😞
- ▶ vector rational approximation & interpolation ??? 😞

applying matrix techniques directly: echelonization is exponential time 🗡️

polynomial matrices: main computational problems

reductions of most problems to polynomial matrix multiplication

matrix $m \times m$ of degree d
of "average" degree $\frac{D}{m} \rightarrow O^{\sim}(m^{\omega} d)$
 $\rightarrow O^{\sim}(m^{\omega} \frac{D}{m})$

classical matrix operations

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

univariate specific operations

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

transformation to normal forms

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

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transformation to normal forms

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

Hermite and Popov forms

working over $\mathbb{K} = \mathbb{Z}/7\mathbb{Z}$

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

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

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

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

Hermite and Popov forms

nonsingular $\mathbf{A} \in \mathbb{K}[x]^{m \times m}$

elementary row transformations

Hermite form [Hermite, 1851]

- ▶ triangular
- ▶ column normalized

$$\begin{bmatrix} 16 & & & \\ 15 & 0 & & \\ 15 & & 0 & \\ 15 & & & 0 \end{bmatrix} \quad \begin{bmatrix} 4 & & & \\ 3 & 7 & & \\ 1 & 5 & 3 & \\ 3 & 6 & 1 & 2 \end{bmatrix}$$

Hermite and Popov forms

nonsingular $\mathbf{A} \in \mathbb{K}[x]^{m \times m}$

elementary row transformations

Hermite form [Hermite, 1851]

- ▶ triangular
- ▶ column normalized

Popov form [Popov, 1972]

- ▶ minimal row degrees
- ▶ column normalized

$$\begin{bmatrix} 16 & & & \\ 15 & 0 & & \\ 15 & & 0 & \\ 15 & & & 0 \end{bmatrix} \quad \begin{bmatrix} 4 & & & \\ 3 & 7 & & \\ 1 & 5 & 3 & \\ 3 & 6 & 1 & 2 \end{bmatrix}$$

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

Hermite and Popov forms

nonsingular $\mathbf{A} \in \mathbb{K}[x]^{m \times m}$

elementary row transformations

Hermite form [Hermite, 1851]

- ▶ triangular
- ▶ column normalized

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⋈_{pot}

reduced Gröbner basis

⋈_{top}

$\mathbb{K}[x]$ -module $\mathcal{M} \subset \mathbb{K}[x]^{1 \times m}$ of rank m

Hermite and Popov forms

nonsingular $\mathbf{A} \in \mathbb{K}[x]^{m \times m}$

elementary row transformations

Hermite form [Hermite, 1851]

- ▶ triangular
- ▶ column normalized

Popov form [Popov, 1972]

- ▶ minimal row degrees
- ▶ column normalized

$$\begin{bmatrix} 16 & & & \\ 15 & 0 & & \\ 15 & & 0 & \\ 15 & & & 0 \end{bmatrix} \quad \begin{bmatrix} 4 & & & \\ 3 & 7 & & \\ 1 & 5 & 3 & \\ 3 & 6 & 1 & 2 \end{bmatrix}$$

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

invariant: $D = \deg(\det(\mathbf{A})) = 4 + 7 + 3 + 2 = 7 + 1 + 2 + 6$

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

target cost: $O^{\sim}(m^{\omega} \frac{D}{m})$

Hermite and Popov forms

nonsingular $\mathbf{A} \in \mathbb{K}[x]^{m \times m}$

elementary row transformations

Hermite form [Hermite, 1851]

- ▶ triangular
- ▶ column normalized

Popov form [Popov, 1972]

- ▶ minimal row degrees
- ▶ column normalized

$$\begin{bmatrix} 16 & & & \\ 15 & 0 & & \\ 15 & & 0 & \\ 15 & & & 0 \end{bmatrix}$$

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

$$\begin{bmatrix} 4 & 3 & 3 & 3 \\ 3 & 4 & 3 & 3 \\ 3 & 3 & 4 & 3 \\ 3 & 3 & 3 & 4 \end{bmatrix}$$

$$\begin{bmatrix} 7 & 0 & 1 & 5 \\ 0 & 1 & & 0 \\ & & 2 & \\ 6 & 0 & 1 & 6 \end{bmatrix}$$

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

shifted reduced form:
arbitrary degree constraints + no column normalization

≈ minimal, non-reduced, \leftarrow -Gröbner basis

shifted forms

shift: integer tuple $\mathbf{s} = (s_1, \dots, s_m)$ acting as **column weights**

→ connects Popov and Hermite forms

$$\begin{array}{l} \mathbf{s} = (0, 0, 0, 0) \\ \text{Popov} \end{array} \quad \begin{bmatrix} 4 & 3 & 3 & 3 \\ 3 & 4 & 3 & 3 \\ 3 & 3 & 4 & 3 \\ 3 & 3 & 3 & 4 \end{bmatrix} \quad \begin{bmatrix} 7 & 0 & 1 & 5 \\ 0 & 1 & & 0 \\ & & 2 & \\ 6 & 0 & 1 & 6 \end{bmatrix}$$

$$\begin{array}{l} \mathbf{s} = (0, 2, 4, 6) \\ \text{s-Popov} \end{array} \quad \begin{bmatrix} 7 & 4 & 2 & 0 \\ 6 & 5 & 2 & 0 \\ 6 & 4 & 3 & 0 \\ 6 & 4 & 2 & 1 \end{bmatrix} \quad \begin{bmatrix} 8 & 5 & 1 \\ 7 & 6 & 1 \\ & & 2 \\ 0 & 1 & & 0 \end{bmatrix}$$

$$\begin{array}{l} \mathbf{s} = (0, D, 2D, 3D) \\ \text{Hermite} \end{array} \quad \begin{bmatrix} 16 & & & \\ 15 & 0 & & \\ 15 & & 0 & \\ 15 & & & 0 \end{bmatrix} \quad \begin{bmatrix} 4 & & & \\ 3 & 7 & & \\ 1 & 5 & 3 & \\ 3 & 6 & 1 & 2 \end{bmatrix}$$

- ▶ **normal** form, **average** column degree D/m
- ▶ shifts arise naturally in algorithms (approximants, kernel, ...)
- ▶ they allow one to specify non-uniform degree constraints

from normal forms to relations

$$\begin{cases} p_1 f_{11} + \dots + p_m f_{1m} & = & 0 \bmod g_1 \\ & \vdots & \\ p_1 f_{n1} + \dots + p_m f_{nm} & = & 0 \bmod g_n \end{cases}$$

reconstruction as relations

high-order lifting [Giorgi-Jeannerod-Villard 2003]
[Storjohann, 2003] [Neiger 2016] [Neiger-Vu 2017]

normal form computation

Popov form

shifted
Popov form

Hermite form

```
sage: M.degree_matrix(shifts=[-1,2], row_wise=False)
[ 0 -2 -1]
[ 5 -2 -2]
```

`hermite_form(include_zero_rows=True, transformation=False)`

Return the Hermite form of this matrix.

The Hermite form is also normalized, i.e., the pivot polynomials are monic.

INPUT:

- `include_zero_rows` – boolean (default: True); if False, the zero rows in the output are deleted
- `transformation` – boolean (default: False); if True, return the transformation matrix

OUTPUT:

```
sage: M.<<> = GF(7)[]
sage: A = matrix(M, 2, 3, [x, 1, 2*x, x, 1+x, 2])
sage: A.hermite_form()
[  x      1      2*x]
[  0      x 5*x + 2]
sage: A.hermite_form(transformation=True)
(
 [  x      1      2*x] [1 0]
 [  0      x 5*x + 2] [6 1]
)
sage: A = matrix(M, 2, 3, [x, 1, 2*x, 2*x, 2, 4*x])
sage: A.hermite_form(transformation=True, include_zero_rows=False)
([ x 1 2*x], [0 4])
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=True); H, U
(
 [ x 1 2*x] [0 4]
 [ 0 0 0], [5 1]
)
sage: U^* A == H
True
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=False)
sage: U^* A
[ x 1 2*x]
sage: U^* A == H
True
```

See also: `is_hermite()`.

`is_hermite(row_wise=True, lower_echelon=False, include_zero_vectors=True)`

Return a boolean indicating whether this matrix is in Hermite form.

```
164 // order that remains to be dealt with
165 VecLong rem_order(order);
166
167 // indices of columns/orders that remain to be dealt with
168 VecLong rem_index(cdim);
169 std::iota(rem_index.begin(), rem_index.end(), 0);
170
171 // all along the algorithm, shift = shifted row degrees of approximant basis
172 // (initially, input shift = shifted row degree of the identity matrix)
173
174 while (not rem_order.empty())
175 {
176     /** Invariant:
177     * - appbas is a shift-ordered weak Popov approximant basis for
178     * (pmat,reached_order) where doneorder is the tuple such that
179     * -->reached_order[j] + rem_order[j] == order[j] for j appearing in
180     * -->reached_order[j] == order[j] for j not appearing in rem_index
181     * - shift == the "input shift"-row degree of appbas
182     * - residual == submatrix of columns (appbas * pmat)[:,:] for all j
183     */
184     int j = std::distance(rem_order.begin(), std::max_element(rem_order.begin(), rem_order.end(),
185 );
186     long deg = order[rem_index[j]] - rem_order[j];
187
188     // record the coefficients of degree deg of the column j of residual
189     // also keep track of which of these are nonzero,
190     // and among the nonzero ones, which is the first with smallest shift
191     Vec<zz_p> const_residual;
192     const_residual.SetLength(rdim);
193     VecLong indices_nonzero;
194     long piv = -1;
195     for (long i = 0; i < rdim; ++i)
196     {
197         const_residual[i] = coeff(residual[i][j],deg);
198         if (const_residual[i] != 0)
199         {
200             indices_nonzero.push_back(i);
201             if (piv < 0 || shift[i] < shift[piv])
202                 piv = i;
203         }
204     }
205     // if indices_nonzero is empty, const_residual is already zero, there
206     // is nothing to do
207     if (not indices_nonzero.empty())
208     {
209         // update all rows of appbas and residual in indices_nonzero except
210         // row j
211         for (int i = 0; i < appbas.rows(); ++i)
212             appbas[i][j] = appbas[i][j] + shift[i] * const_residual[i];
213         for (int i = 0; i < residual.rows(); ++i)
214             residual[i][j] = residual[i][j] - shift[i] * const_residual[i];
215     }
216     rem_order.erase(j);
217     rem_index.erase(j);
218 }
```

software development for polynomial matrices

```
187     j = std::distance(rem_order.begin(), std::max_element(rem_order.begin(), rem_order.end(),
188 );
189     long deg = order[rem_index[j]] - rem_order[j];
190
191     // record the coefficients of degree deg of the column j of residual
192     // also keep track of which of these are nonzero,
193     // and among the nonzero ones, which is the first with smallest shift
194     Vec<zz_p> const_residual;
195     const_residual.SetLength(rdim);
196     VecLong indices_nonzero;
197     long piv = -1;
198     for (long i = 0; i < rdim; ++i)
199     {
200         const_residual[i] = coeff(residual[i][j],deg);
201         if (const_residual[i] != 0)
202         {
203             indices_nonzero.push_back(i);
204             if (piv < 0 || shift[i] < shift[piv])
205                 piv = i;
206         }
207     }
208     // if indices_nonzero is empty, const_residual is already zero, there
209     // is nothing to do
210     if (not indices_nonzero.empty())
211     {
212         // update all rows of appbas and residual in indices_nonzero except
213         // row j
214         for (int i = 0; i < appbas.rows(); ++i)
215             appbas[i][j] = appbas[i][j] + shift[i] * const_residual[i];
216         for (int i = 0; i < residual.rows(); ++i)
217             residual[i][j] = residual[i][j] - shift[i] * const_residual[i];
218     }
219     rem_order.erase(j);
220     rem_index.erase(j);
221 }
```

```
sage: M.degree_matrix(shifts=[-1,2], row_wise=False)
[ 0 -2 -1]
[ 5 -2 -2]
```

open-source mathematics software system



Python/Cython

The Hermitian form of a matrix, i.e., the pivot polynomials are monic.

INPUT:

goals: complete, robust, available

(more than 60k downloads per month)

OUTPUT:

```
sage: M.<K> = GF(7)[[
sage: A = matrix(M, 2, 3, [x, 1, 2*x, x, 1+x, 2])
sage: A.hermite_form()
[  x   1   2*x]
[  0   x  5*x + 2]
sage: A.hermite_form(transformation=True)
(
[  x   1   2*x] [1 0]
[  0   x  5*x + 2] [6 1]
)
sage: A = matrix(M, 2, 3, [x, 1, 2*x, 2*x, 2, 4*x])
sage: A.hermite_form(transformation=True, include_zero_rows=False)
([ x  1 2*x], [0 4])
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=True); H, U
(
[ x  1 2*x] [0 4]
[ 0 0 0], [5 1]
)
sage: U^T * A == H
True
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sage: U^T * A
[ x  1 2*x]
sage: U^T * A == H
True
```

See also: `is_hermite()`.

`is_hermite(row_wise=True, lower_echelon=False, include_zero_vectors=True)`

Return a boolean indicating whether this matrix is in Hermite form.

```
164 // order that remains to be dealt with
165 VecLong rem_order(order);
166
167 // indices of columns/orders that remain to be dealt with
168 VecLong rem_index(cdiIn);
169 std::iota(rem_index.begin(), rem_index.end(), 0);
170
171 // all along the algorithm, shift = shifted row degrees of approxinant ba
172 // (initially, input shift = shifted row degree of the identity matrix)
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174 while (not rem_order.empty())
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176     /** Invariant:
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178     * (pmat,reached_order) where doneorder is the tuple such that
179     * -->reached_order[j] + rem_order[j] == order[j] for j appearing in
180     * -->reached_order[j] == order[j] for j not appearing in rem_index
181     * - shift == the "input shift"-row degree of appbas
182     * - residual == submatrix of columns (appbas * pmat)[:,:j] for all j
183     */
184     int j = *rem_order.begin();
185     int deg = order[j];
186     int piv = -1;
187     for (int i = 0; i < rdiIn; ++i)
188     {
189         int dist = std::distance(rem_order.begin(), std::max_element(rem_order.begin(),
190             rem_order.end(), [i, deg]));
191         if (dist < 0)
192             continue;
193         long deg = order[rem_index[j]] - rem_order[j];
194         Vec<zz_p> const_residual;
195         const_residual.SetLength(rdiIn);
196         VecLong indices_nonzero;
197         long piv = -1;
198         for (long i = 0; i < rdiIn; ++i)
199         {
200             const_residual[i] = coeff(residual[i][j],deg);
201             if (const_residual[i] != 0)
202             {
203                 indices_nonzero.push_back(i);
204                 if (piv < 0 || shift[i] < shift[piv])
205                     piv = i;
206             }
207         }
208         // if indices_nonzero is empty, const_residual is already zero, there
209         if (not indices_nonzero.empty())
210         {
211             // update all rows of appbas and residual in indices nonzero exce
212             src/mat_lzz_pX_approxinant.cpp
```

```
sage: M.degree_matrix(shifts=[1,2], row_wise=False)
[ 0 2 -1]
[ 5 -2 -2]
```

open-source mathematics software system



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The Hermitian form of a matrix, i.e., the pivot polynomials are monic.

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goals: complete, robust, available

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OUTPUT:

```
sage: M.<<> - GF(7)[[
sage: A = matrix(M, 2, 3, [x, 1, 2*x, x, 1+x, 2])
sage: A.hermite_form()
[ 0 1 2*x]
[ 0 x 5*x + 2]
sage: A.hermite_form(transformation=True)
[ x 1 2*x] [1 0]
[ 0 x 5*x + 2] [6 1]
]
sage: A = matrix(M, 2, 3, [x, 1, 2*x, 2*x, 2, 4*x])
sage: A.hermite_form(transformation=True, include_zero_rows=False)
[ x 1 2*x] [0 4]
[ 0 0 0] [5 1]
]
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=True); H, U
[ x 1 2*x] [0 4]
[ 0 0 0] [5 1]
]
sage: U^* A == H
True
sage: H, U = A.hermite_form(transformation=True, include_zero_rows=False)
sage: U^* A
[ x 1 2*x]
sage: U^* A == H
True
```

See also: `is_hermite()`.

`is_hermite(row_wise=True, lower_echelon=False, include_zero_vectors=True)`

Return a boolean indicating whether this matrix is in Hermite form.

order that remains to be dealt with

```
VecLong rem_order(order);
```

```
// indices of columns/orders that remain to be dealt with
```

```
VecLong rem_index(cdn);
```

```
int rdn;
```

high-performance exact linear algebra
LinBox – fflas-ffpack C/C++

```
while (not rem_order.empty())
```

```
{
```

goal: optimized basic operations

memory cost, vectorization, multithreading

```
187     j = std::distance(rem_order.begin(), std::max_element(rem_order.begin(),
188 );
189     long deg = order[rem_index[j]] - rem_order[j];
190
191     // record the coefficients of degree deg of the column j of residual
192     // also keep track of which of these are nonzero,
193     // and among the nonzero ones, which is the first with smallest shift
194     Vec<zz_p> const_residual;
195     const_residual.SetLength(rdn);
196     VecLong indices_nonzero;
197     long piv = -1;
198     for (long i = 0; i < rdn; ++i)
199     {
200         const_residual[i] = coeff(residual[i][j], deg);
201         if (const_residual[i] != 0)
202         {
203             indices_nonzero.push_back(i);
204             if (piv < 0 || shift[i] < shift[piv])
205                 piv = i;
206         }
207     }
208
209     // if indices_nonzero is empty, const_residual is already zero, there
210     if (not indices_nonzero.empty())
211     {
212         // update all rows of appbas and residual in indices nonzero exce
src/mat lzz pX approximant.cpp
```

```
M_degree_matrix(shifts=[1,2], row_wise=False)
[[ 8 -2 -1]
 [ 5 -2 -2]]
```

open-source mathematics software system



Python/Cython

INPUT:

goals: **complete, robust, available**

(more than 60k downloads per month)

OUTPUT:

high-performance exact linear algebra
LinBox – fflas-ffpack C/C++

goal: **optimized basic operations**

memory cost, vectorization, multithreading

software development for polynomial matrices

```
M = GF(7)[x]
A = matrix(M, 2, 3, [x, 1, 2*x, x, 1*x, 2])
A.hermite_form()
[[ 8 -2 -1]
 [ 5 -2 -2]]
```

Polynomial Matrix Library C/C++

403 files, 59k lines of code, including 17k lines of comments

<https://github.com/vneiger/pml>

[Hyun-Neiger-Schost '19]

- ▶ current version based on NTL
- ▶ work-in-progress version based on FLINT
- ▶ **welcome** comments, suggestions, contributions
“hey, this doesn't work!”
“yo, plans for implementing this?”
“how to decode RS codes with PML?”

wide range of algorithms
efficiency = state of the art

kernel, high-order lifting,
system solving, reduced form...

polynomial matrices: two open questions

deterministic Smith form

$$\left[\mathbf{A} \right] \longrightarrow \begin{bmatrix} s_1 & & & \\ & s_2 & & \\ & & \ddots & \\ & & & s_m \end{bmatrix}$$

s_{i+1} divides s_i

- ▶ complexity $O^{\sim}(m^{\omega} \frac{D}{m})$ [Storjohann'03]
- ▶ Las Vegas randomized algorithm
- ▶ requires large field \mathbb{K}

deterministic algo in $O^{\sim}(m^{\omega} \frac{D}{m})$?

polynomial matrices: two open questions

deterministic Smith form

$$\begin{bmatrix} \mathbf{A} \end{bmatrix} \longrightarrow \begin{bmatrix} s_1 & & & \\ & s_2 & & \\ & & \ddots & \\ & & & s_m \end{bmatrix}$$

s_{i+1} divides s_i

- ▶ complexity $O^{\sim}(m^{\omega} \frac{D}{m})$ [Storjohann'03]
- ▶ Las Vegas randomized algorithm
- ▶ requires large field \mathbb{K}

deterministic algo in $O^{\sim}(m^{\omega} \frac{D}{m})$?

algebraic interpolants

= main step of Sudan decoding

$$p_1 f_1 + p_2 f_2 + \cdots + p_m f_m = 0 \text{ mod } G$$

structured f_i 's

$$p_1 \mathbf{1} + p_2 \mathbf{R} + \cdots + p_m \mathbf{R}^{m-1} = 0 \text{ mod } G$$

- ▶ most algorithms ignore the structure
- ▶ recent progress [Villard'18]
- ▶ restrictive: genericity, specific m & d

how to leverage this structure?

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 1$ **point:** $24, 31, 15, 32, 83, 27, 20, 59$

shift

$[0 \ 2 \ 4 \ 6]$

basis

$$\begin{bmatrix} 1 & & & & & & 0 & & & & 0 & 0 & 0 \\ & 0 & & & & & 1 & & & & 0 & 0 & 0 \\ & & 0 & & & & 0 & & & & 1 & 0 & 0 \\ & & & 0 & & & 0 & & & & 0 & 1 & 1 \end{bmatrix}$$

values

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 80 & 73 & 73 & 35 & 66 & 46 & 91 & 64 \\ 95 & 91 & 91 & 61 & 88 & 79 & 36 & 22 \\ 34 & 47 & 47 & 1 & 85 & 45 & 75 & 50 \end{bmatrix}$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 1$ **point:** $24, 31, 15, 32, 83, 27, 20, 59$

shift

$[0 \ 2 \ 4 \ 6]$

basis

$$\begin{bmatrix} 1 & & & & 0 & & & 0 & 0 \\ 0 & & & & 1 & & & 0 & 0 \\ 0 & & & & 0 & & & 1 & 0 \\ 0 & & & & 0 & & & 0 & 1 \end{bmatrix}$$

values

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 80 & 73 & 73 & 35 & 66 & 46 & 91 & 64 \\ 95 & 91 & 91 & 61 & 88 & 79 & 36 & 22 \\ 34 & 47 & 47 & 1 & 85 & 45 & 75 & 50 \end{bmatrix}$$

fast divide and conquer interpolation

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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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 1$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[0 2 4 6]

basis

$$\begin{bmatrix} 1 & & & & 0 & & & 0 & 0 & 0 \\ 17 & & & & 1 & & & 0 & 0 & 0 \\ 2 & & & & 0 & & & 1 & 0 & 0 \\ 63 & & & & 0 & & & 0 & 1 & 1 \end{bmatrix}$$

values

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 90 & 90 & 52 & 83 & 63 & 11 & 81 \\ 0 & 93 & 93 & 63 & 90 & 81 & 38 & 24 \\ 0 & 13 & 13 & 64 & 51 & 11 & 41 & 16 \end{bmatrix}$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 1$ **point:** $24, 31, 15, 32, 83, 27, 20, 59$

shift

$[1 \ 2 \ 4 \ 6]$

basis $\left[\begin{array}{cccc|ccc} x + 73 & & & & 0 & & 0 & 0 \\ 17 & & & & 1 & & 0 & 0 \\ 2 & & & & 0 & & 1 & 0 \\ 63 & & & & 0 & & 0 & 1 \end{array} \right]$

values $\left[\begin{array}{cccc|cccc} 0 & 7 & 88 & 8 & 59 & 3 & 93 & 35 \\ 0 & 90 & 90 & 52 & 83 & 63 & 11 & 81 \\ 0 & 93 & 93 & 63 & 90 & 81 & 38 & 24 \\ 0 & 13 & 13 & 64 & 51 & 11 & 41 & 16 \end{array} \right]$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 2$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

$[1 \ 2 \ 4 \ 6]$

basis

$$\left[\begin{array}{cccc} x + 73 & & & \\ 17 & & 0 & 0 \\ 2 & & 1 & 0 \\ 63 & & 0 & 1 \\ & & 0 & 1 \end{array} \right]$$

values

$$\left[\begin{array}{cccccccc} 0 & 7 & 88 & 8 & 59 & 3 & 93 & 35 \\ 0 & 90 & 90 & 52 & 83 & 63 & 11 & 81 \\ 0 & 93 & 93 & 63 & 90 & 81 & 38 & 24 \\ 0 & 13 & 13 & 64 & 51 & 11 & 41 & 16 \end{array} \right]$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 2$ **point:** $24, 31, 15, 32, 83, 27, 20, 59$

shift

$[1 \ 2 \ 4 \ 6]$

basis

$$\begin{bmatrix} x + 73 & 0 & 0 & 0 \\ x + 90 & 1 & 0 & 0 \\ 56x + 16 & 0 & 1 & 0 \\ 12x + 66 & 0 & 0 & 1 \end{bmatrix}$$

values

$$\begin{bmatrix} 0 & 7 & 88 & 8 & 59 & 3 & 93 & 35 \\ 0 & 0 & 81 & 60 & 45 & 66 & 7 & 19 \\ 0 & 0 & 74 & 26 & 96 & 55 & 8 & 44 \\ 0 & 0 & 2 & 63 & 80 & 47 & 90 & 48 \end{bmatrix}$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 2$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[2 2 4 6]

basis $\left[\begin{array}{cccc} x^2 + 42x + 65 & 0 & 0 & 0 \\ x + 90 & 1 & 0 & 0 \\ 56x + 16 & 0 & 1 & 0 \\ 12x + 66 & 0 & 0 & 1 \end{array} \right]$

values $\left[\begin{array}{cccccc} 0 & 0 & 47 & 8 & 61 & 85 & 44 & 10 \\ 0 & 0 & 81 & 60 & 45 & 66 & 7 & 19 \\ 0 & 0 & 74 & 26 & 96 & 55 & 8 & 44 \\ 0 & 0 & 2 & 63 & 80 & 47 & 90 & 48 \end{array} \right]$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 3$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[2 2 4 6]

basis $\left[\begin{array}{cccc} x^2 + 42x + 65 & 0 & 0 & 0 \\ x + 90 & 1 & 0 & 0 \\ 56x + 16 & 0 & 1 & 0 \\ 12x + 66 & 0 & 0 & 1 \end{array} \right]$

values $\left[\begin{array}{cccccc} 0 & 0 & 47 & 8 & 61 & 85 & 44 & 10 \\ 0 & 0 & 81 & 60 & 45 & 66 & 7 & 19 \\ 0 & 0 & 74 & 26 & 96 & 55 & 8 & 44 \\ 0 & 0 & 2 & 63 & 80 & 47 & 90 & 48 \end{array} \right]$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 3$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[3 2 4 6]

basis $\left[\begin{array}{cccc} x^3 + 27x^2 + 17x + 92 & 0 & 0 & 0 \\ 54x^2 + 38x + 11 & 1 & 0 & 0 \\ 17x^2 + 91x + 54 & 0 & 1 & 0 \\ 66x^2 + 68x + 88 & 0 & 0 & 1 \end{array} \right]$

values $\left[\begin{array}{ccccccccc} 0 & 0 & 0 & 39 & 74 & 50 & 26 & 52 \\ 0 & 0 & 0 & 7 & 41 & 0 & 55 & 74 \\ 0 & 0 & 0 & 65 & 66 & 45 & 77 & 20 \\ 0 & 0 & 0 & 9 & 32 & 31 & 84 & 29 \end{array} \right]$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 4$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[3 2 4 6]

basis $\left[\begin{array}{cccc} x^3 + 27x^2 + 17x + 92 & 0 & 0 & 0 \\ 54x^2 + 38x + 11 & 1 & 0 & 0 \\ 17x^2 + 91x + 54 & 0 & 1 & 0 \\ 66x^2 + 68x + 88 & 0 & 0 & 1 \end{array} \right]$

values $\left[\begin{array}{ccccccccc} 0 & 0 & 0 & 39 & 74 & 50 & 26 & 52 \\ 0 & 0 & 0 & 7 & 41 & 0 & 55 & 74 \\ 0 & 0 & 0 & 65 & 66 & 45 & 77 & 20 \\ 0 & 0 & 0 & 9 & 32 & 31 & 84 & 29 \end{array} \right]$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 4$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[3 3 4 6]

basis

$$\left[\begin{array}{l} x^3 + 31x^2 + 27x + 3 \\ 54x^3 + 56x^2 + 56x + 36 \\ 56x^2 + 43x + 35 \\ 52x^2 + 33x + 60 \end{array} \quad \begin{array}{l} 36 \\ x + 65 \\ 60 \\ 68 \end{array} \quad \begin{array}{l} 0 \\ 0 \\ 1 \\ 0 \end{array} \quad \begin{array}{l} 0 \\ 0 \\ 0 \\ 1 \end{array} \right]$$

values

$$\left[\begin{array}{cccccccc} 0 & 0 & 0 & 0 & 95 & 50 & 66 & 0 \\ 0 & 0 & 0 & 0 & 54 & 0 & 19 & 58 \\ 0 & 0 & 0 & 0 & 4 & 45 & 79 & 95 \\ 0 & 0 & 0 & 0 & 7 & 31 & 41 & 17 \end{array} \right]$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 5$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[4 3 4 6]

basis

$$\begin{bmatrix} x^4 + 45x^3 + 73x^2 + 90x + 42 & 36x + 19 & 0 & 0 \\ 81x^3 + 20x^2 + 9x + 20 & x + 67 & 0 & 0 \\ 2x^3 + 21x^2 + 41 & 35 & 1 & 0 \\ 52x^3 + 15x^2 + 79x + 22 & 0 & 0 & 1 \end{bmatrix}$$

values

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 13 & 13 & 0 \\ 0 & 0 & 0 & 0 & 0 & 89 & 55 & 58 \\ 0 & 0 & 0 & 0 & 0 & 48 & 17 & 95 \\ 0 & 0 & 0 & 0 & 0 & 12 & 78 & 17 \end{bmatrix}$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 6$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[4 4 4 6]

basis

$$\begin{bmatrix} x^4 + 19x^3 + 57x^2 + 44x + 26 & 74x + 43 & 0 & 0 \\ 81x^4 + 64x^3 + 51x^2 + 68x + 42 & x^2 + 40x + 34 & 0 & 0 \\ 3x^3 + 44x^2 + 54x + 64 & 6x + 49 & 1 & 0 \\ 28x^3 + 45x^2 + 44x + 52 & 50x + 52 & 0 & 1 \end{bmatrix}$$

values

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 66 & 70 \\ 0 & 0 & 0 & 0 & 0 & 0 & 3 & 13 \\ 0 & 0 & 0 & 0 & 0 & 0 & 56 & 55 \\ 0 & 0 & 0 & 0 & 0 & 0 & 15 & 7 \end{bmatrix}$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 7$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[5 4 4 6]

basis

$$\begin{bmatrix} x^5 + 96x^4 + 65x^3 + 68x^2 + 19x + 62 & 74x^2 + 18x + 13 & 0 & 0 \\ 6x^4 + 94x^3 + 44x^2 + 66x + 32 & x^2 + 19x + 10 & 0 & 0 \\ 55x^4 + 78x^3 + 75x^2 + 49x + 39 & 2x + 86 & 1 & 0 \\ 13x^4 + 81x^3 + 10x^2 + 34x + 2 & 42x + 29 & 0 & 1 \end{bmatrix}$$

values

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 14 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 44 \end{bmatrix}$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 8$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[5 5 4 6]

basis

$$\begin{bmatrix} x^5 + 12x^4 + 10x^3 + 34x^2 + 65x + 2 & 60x^2 + 43x + 67 & 0 & 0 \\ 6x^5 + 31x^4 + 27x^3 + 89x^2 + 18x + 52 & x^3 + 57x^2 + 53x + 89 & 0 & 0 \\ 2x^4 + 56x^3 + 42x^2 + 48x + 15 & 72x^2 + 12x + 30 & 1 & 0 \\ 40x^4 + 19x^3 + 14x^2 + 40x + 49 & 53x^2 + 79x + 74 & 0 & 1 \end{bmatrix}$$

values

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

fast divide and conquer interpolation

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

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 $\mathbf{F} = [1 \ R \ R^2 \ R^3]^T$

iteration: $i = 8$ point: 24, 31, 15, 32, 83, 27, 20, 59

shift

[5 5 4 6]

basis

$$\begin{bmatrix} x^5 + 12x^4 + 10x^3 + 34x^2 + 65x + 2 & 60x^2 + 43x + 67 & 0 & 0 \\ 6x^5 + 31x^4 + 27x^3 + 89x^2 + 18x + 52 & x^3 + 57x^2 + 53x + 89 & 0 & 0 \\ 2x^4 + 56x^3 + 42x^2 + 48x + 15 & 72x^2 + 12x + 30 & 1 & 0 \\ 40x^4 + 19x^3 + 14x^2 + 40x + 49 & 53x^2 + 79x + 74 & 0 & 1 \end{bmatrix}$$

$$Q(x, y) = (2x^4 + 56x^3 + 42x^2 + 48x + 15) + (72x^2 + 12x + 30)y + y^2$$

values

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

fast divide and conquer interpolation

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

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

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

2. for i from 1 to d :

a. choose pivot π with smallest s_π such that $f_\pi(\alpha_i) \neq 0$
update pivot shift $s_\pi = s_\pi + 1$

b. constant elimination: for $j \neq \pi$ do $\mathbf{p}_j \leftarrow \mathbf{p}_j - \frac{f_j(\alpha_i)}{f_\pi(\alpha_i)} \mathbf{p}_\pi$
polynomial elimination: $\mathbf{p}_\pi \leftarrow (x - \alpha_i) \mathbf{p}_\pi$

c. compute residual equation: for $j \neq \pi$ do $f_j \leftarrow f_j - \frac{f_j(\alpha_i)}{f_\pi(\alpha_i)} f_\pi$
 $f_\pi \leftarrow (x - \alpha_i) f_\pi$

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

fast divide and conquer interpolation

iterative algorithm: complexity aspects

at step i , \mathbf{P} and \mathbf{F} are left multiplied by $\mathbf{E}_i = \begin{bmatrix} \mathbf{I}_{\pi-1} & \boldsymbol{\lambda}_1 & \mathbf{0} \\ \mathbf{0} & x-\alpha & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\lambda}_2 & \mathbf{I}_{m-\pi} \end{bmatrix}$
where $\boldsymbol{\lambda}_1 \in \mathbb{K}^{(\pi-1) \times 1}$ and $\boldsymbol{\lambda}_2 \in \mathbb{K}^{(m-\pi) \times 1}$ are constant

fast divide and conquer interpolation

iterative algorithm: complexity aspects

at step i , \mathbf{P} and \mathbf{F} are left multiplied by $\mathbf{E}_i = \begin{bmatrix} \mathbf{I}_{\pi-1} & \lambda_1 & \mathbf{0} \\ \mathbf{0} & x-\alpha & \mathbf{0} \\ \mathbf{0} & \lambda_2 & \mathbf{I}_{m-\pi} \end{bmatrix}$
where $\lambda_1 \in \mathbb{K}^{(\pi-1) \times 1}$ and $\lambda_2 \in \mathbb{K}^{(m-\pi) \times 1}$ are constant

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

- ▶ iteration with d steps
- ▶ each step: evaluation of \mathbf{F} + multiplications $\mathbf{E}_i \mathbf{F}$ and $\mathbf{E}_i \mathbf{P}$
- ▶ at any stage \mathbf{P} has degree $\leq d$ and dimensions $m \times m$
- ▶ at any stage \mathbf{F} has degree $< 2d$ and dimensions $m \times 1$

one gets $O(md^2)$ with either:

- . normalizing at each step + finer analysis
- . “balanced” input shift + finer analysis
(shifts in RS list-decoding are balanced)

fast divide and conquer interpolation

iterative algorithm: complexity aspects

at step i , \mathbf{P} and \mathbf{F} are left multiplied by $\mathbf{E}_i = \begin{bmatrix} \mathbf{I}_{\pi-1} & \lambda_1 & \mathbf{0} \\ \mathbf{0} & x-\alpha & \mathbf{0} \\ \mathbf{0} & \lambda_2 & \mathbf{I}_{m-\pi} \end{bmatrix}$
where $\lambda_1 \in \mathbb{K}^{(\pi-1) \times 1}$ and $\lambda_2 \in \mathbb{K}^{(m-\pi) \times 1}$ are constant

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

- ▶ iteration with d steps
- ▶ each step: evaluation of \mathbf{F} + multiplications $\mathbf{E}_i \mathbf{F}$ and $\mathbf{E}_i \mathbf{P}$
- ▶ at any stage \mathbf{P} has degree $\leq d$ and dimensions $m \times m$
- ▶ at any stage \mathbf{F} has degree $< 2d$ and dimensions $m \times 1$

one gets $O(md^2)$ with either:

- . normalizing at each step + finer analysis
- . “balanced” input shift + finer analysis
(shifts in RS list-decoding are balanced)

correctness:

- ▶ the main task is to prove the base case ($d = 1$, single point)
- ▶ then, correctness follows from the “basis multiplication theorem”

fast divide and conquer interpolation

general multiplication-based approach for relations

algorithms based on polynomial matrix multiplication

[Beckermann-Labahn '94+'97] [Giorgi-Jeannerod-Villard 2003]

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

we want $\mathbf{P}_2\mathbf{P}_1$ shifted reduced

$\mathbf{P}_2\mathbf{P}_1$ reduced not implied by “ \mathbf{P}_1 reduced and \mathbf{P}_2 reduced”

fast divide and conquer interpolation

general multiplication-based approach for relations

algorithms based on polynomial matrix multiplication

[Beckermann-Labahn '94+'97] [Giorgi-Jeannerod-Villard 2003]

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

we want $\mathbf{P}_2\mathbf{P}_1$ shifted reduced

$\mathbf{P}_2\mathbf{P}_1$ reduced not implied by “ \mathbf{P}_1 reduced and \mathbf{P}_2 reduced”

theorem:

(\mathbf{P}_1 is \mathbf{s} -reduced and \mathbf{P}_2 is \mathbf{t} -reduced”) \Rightarrow $\mathbf{P}_2\mathbf{P}_1$ is \mathbf{s} -reduced

where \mathbf{t} is a shift trivially computed from \mathbf{s} and \mathbf{P}_1 ($\mathbf{t} = \text{rdeg}_{\mathbf{s}}(\mathbf{P}_1)$)

fast divide and conquer interpolation

bonus: detailed statement and proof

let $\mathcal{M} \subseteq \mathcal{M}_1$ be two $\mathbb{K}[x]$ -submodules of $\mathbb{K}[x]^m$ of rank m ,

let $\mathbf{P}_1 \in \mathbb{K}[x]^{m \times m}$ be a basis of \mathcal{M}_1 ,

let $\mathbf{s} \in \mathbb{Z}^m$ and $\mathbf{t} = \text{rdeg}_s(\mathbf{P}_1)$,

► the rank of the module $\mathcal{M}_2 = \{\boldsymbol{\lambda} \in \mathbb{K}[x]^{1 \times m} \mid \boldsymbol{\lambda} \mathbf{P}_1 \in \mathcal{M}\}$ is m
and for any basis $\mathbf{P}_2 \in \mathbb{K}[x]^{m \times m}$ of \mathcal{M}_2 ,

the product $\mathbf{P}_2 \mathbf{P}_1$ is a basis of \mathcal{M}

► if \mathbf{P}_1 is \mathbf{s} -reduced and \mathbf{P}_2 is \mathbf{t} -reduced,
then $\mathbf{P}_2 \mathbf{P}_1$ is \mathbf{s} -reduced

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Let $\mathbf{A} \in \mathbb{K}[x]^{m \times m}$ denote the adjugate of \mathbf{P}_1 . Then, we have $\mathbf{A} \mathbf{P}_1 = \det(\mathbf{P}_1) \mathbf{I}_m$. Thus, $\mathbf{p} \mathbf{A} \mathbf{P}_1 = \det(\mathbf{P}_1) \mathbf{p} \in \mathcal{M}$ for all $\mathbf{p} \in \mathcal{M}$, and therefore $\mathcal{M} \mathbf{A} \subseteq \mathcal{M}_2$. Now, the nonsingularity of \mathbf{A} ensures that $\mathcal{M} \mathbf{A}$ 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 $\mathbf{P}_2 \mathbf{P}_1$ is nonsingular since $\det(\mathbf{P}_2 \mathbf{P}_1) \neq 0$. Now let $\mathbf{p} \in \mathcal{M}$; we want to prove that \mathbf{p} is a $\mathbb{K}[x]$ -linear combination of the rows of $\mathbf{P}_2 \mathbf{P}_1$. First, $\mathbf{p} \in \mathcal{M}_1$, so there exists $\lambda \in \mathbb{K}[x]^{1 \times m}$ such that $\mathbf{p} = \lambda \mathbf{P}_1$. But then $\lambda \in \mathcal{M}_2$, and thus there exists $\mu \in \mathbb{K}[x]^{1 \times m}$ such that $\lambda = \mu \mathbf{P}_2$. This yields the combination $\mathbf{p} = \mu \mathbf{P}_2 \mathbf{P}_1$.

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bonus: detailed statement and proof

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Let $\mathbf{d} = \text{rdeg}_t(\mathbf{P}_2)$; we have $\mathbf{d} = \text{rdeg}_s(\mathbf{P}_2 \mathbf{P}_1)$ by the predictable degree property. Using $\mathbf{X}^{-\mathbf{d}} \mathbf{P}_2 \mathbf{P}_1 \mathbf{X}^{\mathbf{s}} = \mathbf{X}^{-\mathbf{d}} \mathbf{P}_2 \mathbf{X}^{\mathbf{t}} \mathbf{X}^{-\mathbf{t}} \mathbf{P}_1 \mathbf{X}^{\mathbf{s}}$, we obtain that $\text{Im}_s(\mathbf{P}_2 \mathbf{P}_1) = \text{Im}_t(\mathbf{P}_2) \text{Im}_s(\mathbf{P}_1)$. By assumption, $\text{Im}_t(\mathbf{P}_2)$ and $\text{Im}_s(\mathbf{P}_1)$ are invertible, and therefore $\text{Im}_s(\mathbf{P}_2 \mathbf{P}_1)$ is invertible as well; thus $\mathbf{P}_2 \mathbf{P}_1$ is \mathbf{s} -reduced.

fast divide and conquer interpolation

divide and conquer algorithm [Beckermann-Labahn '94+'97]

input: $\mathbf{F}, (\alpha_1, \dots, \alpha_d), \mathbf{s}$

output: \mathbf{P}

▶ if $d \leq \text{threshold}$: call iterative algorithm

▶ else:

a. $G_1 \leftarrow (x - \alpha_1) \cdots (x - \alpha_{\lfloor d/2 \rfloor})$; $G_2 \leftarrow (x - \alpha_{\lfloor d/2 \rfloor + 1}) \cdots (x - \alpha_d)$

b. $\mathbf{P}_1 \leftarrow$ recursive call on \mathbf{F} rem $G_1, (\alpha_1, \dots, \alpha_{\lfloor d/2 \rfloor}), \mathbf{s}$

c. updated shift: $\mathbf{t} \leftarrow \text{rdeg}_s(\mathbf{P}_1)$

d. residual equation: $\mathbf{F} \leftarrow \frac{1}{G_1} \mathbf{P}_1 \mathbf{F}$

e. $\mathbf{P}_2 \leftarrow$ recursive call \mathbf{F} rem $G_2, (\alpha_{\lfloor d/2 \rfloor + 1}, \dots, \alpha_d), \mathbf{t}$

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

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correctness:

▶ correctness of base case

▶ then, direct consequence of the “basis multiplication theorem”

▶ residual: $\{\mathbf{p} \mid \mathbf{p} \mathbf{P}_1 \mathbf{F} = 0 \bmod G\} = \{\mathbf{p} \mid \mathbf{p}(\frac{1}{G_1} \mathbf{P}_1 \mathbf{F}) = 0 \bmod G_2\}$

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

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

▶ if $\omega = 2$, quasi-linear in worst-case output size

▶ most expensive step in the recursion is the product $\mathbf{P}_2 \mathbf{P}_1$

▶ equation $\mathcal{C}(m, d) = \mathcal{C}(m, \lfloor d/2 \rfloor) + \mathcal{C}(m, \lceil d/2 \rceil) + O(m^\omega M(d))$

fast divide and conquer interpolation

divide and conquer: complexity aspects

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

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

complexity of each step:

- | | |
|--|--|
| ▶ residual $\mathbf{F} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$ | $O(m^2 M(d))$ |
| ▶ $\mathbf{F} \bmod M_1$ and $\mathbf{F} \bmod M_2$ | $O(m M(d))$ |
| ▶ product $\mathbf{P}_2 \mathbf{P}_1$ | $O(m^\omega M(d))$ |
| ▶ two recursive calls | $2\mathcal{C}(m, \lfloor d/2 \rfloor)$ |

fast divide and conquer interpolation

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

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- ▶ product $\mathbf{P}_2 \mathbf{P}_1$ $O(m^\omega M(d))$
- ▶ two recursive calls $2\mathcal{C}(m, \lfloor d/2 \rfloor)$

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

unrolling: $m^\omega (M(d) + 2M(\frac{d}{2}) + 4M(\frac{d}{4}) + \dots + \frac{d}{2}M(2)) + dm$

fast divide and conquer interpolation

divide and conquer: complexity aspects

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

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

output: $\deg(\mathbf{P}) \approx \lceil \frac{d}{m} \rceil$

complexity of each step:

- ▶ residual $\mathbf{F} \leftarrow \frac{1}{M_1} \mathbf{P}_1 \mathbf{F}$
- ▶ $\mathbf{F} \bmod M_1$ and $\mathbf{F} \bmod M_2$
- ▶ product $\mathbf{P}_2 \mathbf{P}_1$
- ▶ two recursive calls

$O(m^2 M(d))$

$O(m M(d))$

$O(m^\omega M(d))$

$2\mathcal{C}(m, \lfloor d/2 \rfloor)$

$s = 0$ and generic \mathbf{F} :

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

unchanged

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unchanged

- ▶ partial linearization

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

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 $O(m M(d))$
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- ▶ partial linearization
- ▶ base case for $d \approx m$, costs $O(m^\omega)$

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fast divide and conquer interpolation

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 unchanged
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| 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 |

fast divide and conquer interpolation

vector rational interpolation: recent progress

overview of the 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 $n > 1$
- ▶ [Giorgi-Jeannerod-Villard 2003] achieved $O(m^\omega M(d) \log(d))$
for $\mathbf{F} \bmod x^d$, with $n \geq 1$ and $n \in O(m)$
- ▶ for $s = \mathbf{0}$ and **generic** \mathbf{F} : $O^\sim(m^\omega \lceil \frac{nd}{m} \rceil)$ [Lecerf, ca 2001, unpublished]

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[Storjohann 2006] [Zhou-Labahn 2012] [Jeannerod-Neiger-Villard 2020]
 \rightsquigarrow **any** s , **no genericity** assumption, returns the **canonical** s -Popov basis

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 \rightsquigarrow **any** \mathbf{s} , **no genericity** assumption, returns the **canonical** \mathbf{s} -Popov basis
- ▶ $\mathbf{F} \bmod \mathbf{G}$ and **general modular matrix equations** in similar complexity
[Beckermann-Labahn 1997] [Jeannerod-Neiger-Schost-Villard 2017]
[Neiger-Vu 2017] [Rosenkilde-Storjohann 2021]
 \rightsquigarrow **any** \mathbf{s} , **no genericity** assumption, returns the canonical \mathbf{s} -Popov basis

outline

computer algebra

- ▶ efficient algorithms and software
- ▶ for matrices over a field
- ▶ for univariate polynomials

Reed-Solomon decoding

- ▶ context and unique decoding problem
- ▶ key equations and how to solve them
- ▶ correcting more errors?

polynomial matrices

- ▶ introduction to vector interpolation
- ▶ core algorithms & shifted normal forms
- ▶ fast divide and conquer interpolation

efficient list decoding

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efficient list decoding

- ▶ the Guruswami-Sudan algorithm
- ▶ via structured systems or basis reduction
- ▶ a word on extensions

list decoding problem

for convenience, we use the **agreement parameter** $t = n - e$:
 $\#\{i \mid w(\alpha_i) \neq \beta_i\} \leq e \Leftrightarrow \#\{i \mid w(\alpha_i) = \beta_i\} \geq t$

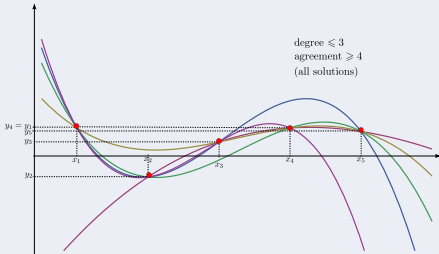
input:

- ▶ $\alpha_1, \dots, \alpha_n$ the n distinct evaluation points in \mathbb{K} ,
- ▶ k the degree bound, $t = n - e$ the agreement,
- ▶ $(\beta_1, \dots, \beta_n)$ the received word in \mathbb{K}^n

list decoding requirement: $t^2 > kn$ [Guruswami-Sudan'99]

output: **all** polynomials $w(x)$ in $\mathbb{K}[x]$ such that

$$\deg(w) \leq k \quad \text{and} \quad \#\{i \mid w(\alpha_i) = \beta_i\} \geq t$$



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Guruswami-Sudan algorithm:

▶ interpolation step

compute $Q(x, y)$ such that: $w(x)$ solution $\Rightarrow Q(x, w(x)) = 0$

▶ root-finding step

compute all y -roots of $Q(x, y)$, keep those that are solutions

introducing the interpolation+root-finding approach

consider **one** solution w_1 :

key equation:

$$\Lambda_1 R = \Lambda_1 w_1 \pmod{G}$$

where $R(\alpha_i) = \beta_i$, $G(x) = \prod_{1 \leq i \leq n} (x - \alpha_i)$ $\Lambda_1(x) = \prod_{i | \text{error}_1} (x - \alpha_i)$



obstacle: no uniqueness of solution $\frac{\mu_1}{\Lambda_1}$ for rational reconstruction

$$\Lambda_1 R = \mu_1 \pmod{G}$$

with $\deg \mu_1 \leq e + k$

since $e \geq \frac{n-k}{2} \Rightarrow$ (unique decoding bound not satisfied),
possibly $\deg(\Lambda_1) + \deg(\Lambda_1 w_1) \geq n = \deg G$
(more unknowns than equations in the linearized problem)

introducing the interpolation+root-finding approach

note $\Lambda_1(\mathbb{R} - w_1) = 0 \pmod{G}$, and consider a **second** solution w_2 :

“extended” key equation:

$$\Lambda(\mathbb{R} - w_1)(\mathbb{R} - w_2) = 0 \pmod{G}$$

where $\Lambda = \prod_{i | \text{error}_{1 \wedge 2}} (x - \alpha_i) = \text{gcd}(\Lambda_1, \Lambda_2)$

w_1 and w_2 are y -roots of the **bivariate polynomial**

$$Q(x, y) = \Lambda(y - w_1)(y - w_2) = \Lambda w_1 w_2 - \Lambda(w_1 + w_2)y + \Lambda y^2$$

↪ similar remark for all ℓ solutions w_1, \dots, w_ℓ

properties of $Q(x, y)$:

- ▶ **degree in y is ℓ** = number of solutions
- ▶ weighted-degree $\text{deg}_x(Q(x, x^k y))$ close to ℓk
- ▶ $Q(\alpha_i, \beta_i) = 0$ for every i (i.e. $Q(x, \mathbb{R}) = 0 \pmod{G}$)

the Guruswami-Sudan algorithm

bivariate interpolation with multiplicities:

Input:

- n points $\{(\alpha_i, \beta_i)\}_{1 \leq i \leq n}$ in \mathbb{K}^2 , with the α_i 's distinct
- k the degree constraint, t the agreement
- ℓ the list-size, s the multiplicity ($s \leq \ell$)

Output:

a nonzero polynomial $Q(x, y)$ in $\mathbb{K}[x, y]$ such that

- (i) $\deg_y(Q) \leq \ell$ (list-size condition)
- (ii) $\deg_x(Q(x, x^k y)) < st$ (weighted-degree condition)
- (iii) $\forall i, Q(\alpha_i, \beta_i) = 0$ with multiplicity s (vanishing condition)

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► find parameters ℓ and s

► **interpolation step**

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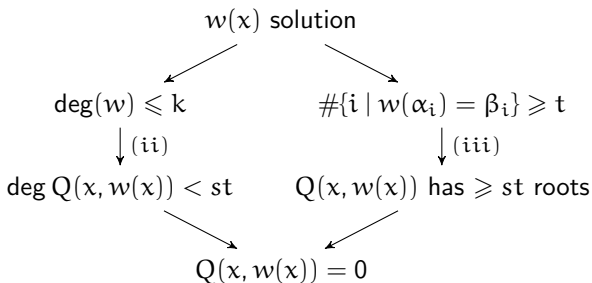
compute $Q(x, y)$ such that: $w(x)$ solution $\Rightarrow Q(x, w(x)) = 0$

► **root-finding step**

compute all y -roots of $Q(x, y)$, keep those that are solutions

the Guruswami-Sudan algorithm

- (i) $\deg_y(Q) \leq \ell$ (list-size condition)
- (ii) $\deg_x(Q(x, x^k y)) < st$ (weighted-degree condition)
- (iii) $\forall i, Q(\alpha_i, \beta_i) = 0$ with multiplicity s (vanishing condition)



► find parameters ℓ and s

► **interpolation step**

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► list-size condition allows to work with **polynomial matrices**

identification $\mathbb{K}[x, y]_{\deg_y \leq \ell} \longleftrightarrow \mathbb{K}[x]^\ell$

$$Q(x, y) = Q_0(x) + Q_1(x)y + \cdots + Q_\ell(x)y^\ell$$

► weighted-degree condition handled via **shifted** forms

degree constraints $\deg(Q_j(x)) < st - jk$ for $j = 0, \dots, \ell$

► find parameters ℓ and s

► **interpolation step**

compute $Q(x, y)$ such that: $w(x)$ solution $\Rightarrow Q(x, w(x)) = 0$

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root-finding step:

quasi-linear complexity

[Alekhovich 2005] [Neiger-Rosenkilde-Schost 2017]

fastest known interpolation step: via univariate relations

$O^{\sim}(\ell^{\omega-1} s^2 n)$

[Jeannerod-Neiger-Schost-Villard 2017]

- ▶ Sudan case ($s = 1$): vector rational interpolation
- ▶ general case: similar problem with s equations, which have respective moduli G^s, G^{s-1}, \dots, G

▶ find parameters ℓ and s

▶ interpolation step

compute $Q(x, y)$ such that: $w(x)$ solution $\Rightarrow Q(x, w(x)) = 0$

▶ root-finding step

compute all y -roots of $Q(x, y)$, keep those that are solutions

alternative approach: structured linear algebra

features common to all algorithms:

- ▶ use (i) + (ii) to fix the linear unknowns:

$$Q = \sum_{0 \leq j \leq \ell} \sum_{0 \leq i < st - jk} q_{i,j} x^i y^j$$

- ▶ same number of **linear unknowns**: $(\ell + 1)st - \frac{\ell(\ell+1)}{2}k$
- ▶ same number of **linear equations**: $\frac{s(s+1)}{2}n$
- ▶ call a **structured linear system solver**

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- ▶ call a **structured linear system solver**

$$\begin{array}{l}
 [Q_0(x) \quad Q_1(x)] \begin{bmatrix} 2x^7 + 2x^6 + 5x^4 + 2x^2 + 4 \\ -1 \end{bmatrix} = 0 \pmod{x^8} \\
 [q_{00} \quad q_{01} \quad q_{02} \quad q_{03} \quad q_{04} \quad q_{05} \mid q_{10} \quad q_{11} \quad q_{12}] \begin{bmatrix} 4 & 0 & 2 & 0 & 5 & 0 & 2 & 2 \\ & 4 & 0 & 2 & 0 & 5 & 0 & 2 \\ & & 4 & 0 & 2 & 0 & 5 & 0 \\ & & & 4 & 0 & 2 & 0 & 5 \\ & & & & 4 & 0 & 2 & 0 \\ & & & & & 4 & 0 & 2 \\ \hline 6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ & 6 & 0 & 0 & 0 & 0 & 0 & 0 \\ & & 6 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} = 0
 \end{array}$$

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$$Q(x, y) = q_{00} + q_{01}x + q_{02}x^2 + q_{03}x^3 + q_{04}x^4 + (q_{10} + q_{11}x + q_{12}x^2)y + q_{20}y^2:$$

$$\begin{bmatrix} q_{00} & q_{01} & q_{02} & q_{03} & q_{04} & \vdots & q_{10} & q_{11} & q_{12} & \vdots & q_{20} \end{bmatrix} \begin{bmatrix} 1 & 1 & \cdots & 1 \\ \alpha_1 & \alpha_2 & \cdots & \alpha_8 \\ \alpha_1^2 & \alpha_2^2 & \cdots & \alpha_8^2 \\ \alpha_1^3 & \alpha_2^3 & \cdots & \alpha_8^3 \\ \alpha_1^4 & \alpha_2^4 & \cdots & \alpha_8^4 \\ \beta_1 & \beta_2 & \cdots & \beta_8 \\ \alpha_1 \beta_1 & \alpha_2 \beta_2 & \cdots & \alpha_8 \beta_8 \\ \alpha_1^2 \beta_1 & \alpha_2^2 \beta_2 & \cdots & \alpha_8^2 \beta_8 \\ \beta_1^2 & \beta_2^2 & \cdots & \beta_8^2 \end{bmatrix} = 0$$

alternative approach: structured linear algebra

Vandermonde-like system

$O(ls^4n^2)$

- ▶ [Olshevsky-Shokrollahi'99]
- ▶ linearize the vanishing condition on each point

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Mosaic-Hankel system

$O(ls^4n^2)$

- ▶ [Roth-Ruckenstein'00] [Zeh-Gentner-Augot 2011]
- ▶ linearize the reversed extended key equation
- ▶ uses an adapted [Feng-Tzeng'91] solver

alternative approach: structured linear algebra

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- ▶ [Roth-Ruckenstein'00] [Zeh-Gentner-Augot 2011]
- ▶ linearize the reversed extended key equation
- ▶ uses an adapted [Feng-Tzeng'91] solver

Toeplitz-like system

$O(\ell^{\omega-1}s^2n)$

- ▶ [Chowdhury-Jeannerod-Neiger-Schost-Villard 2015]
- ▶ linearize the extended key equation
- ▶ uses the solver of [Bostan-Jeannerod-Schost 2007]

Las Vegas randomized

alternative approach: basis reduction

features common to all algorithms:

- ▶ use (i) to fix the **polynomial unknowns**:

$$Q = \sum_{0 \leq j \leq \ell} Q_j(x)y^j \quad \longleftrightarrow \quad [Q_0(x) \cdots Q_\ell(x)]$$

- ▶ consider same **interpolant $\mathbb{K}[x]$ -module**:

$$\{Q \mid (i) + (iii)\} = \{\sum_{0 \leq j \leq \ell} Q_j(x)y^j \mid Q(\alpha_i, \beta_i) = 0 \text{ with mult. } s\}$$

- ▶ use (iii) to derive a **basis** of the module:

$$\{Q \mid (i) + (iii)\} = \langle p_0(x, y), p_1(x, y), \dots, p_\ell(x, y) \rangle$$

- ▶ call a **$\mathbb{K}[x]$ -module basis reduction** algorithm,
using a **shift** to satisfy the weighted-degree condition (ii)

alternative approach: basis reduction

features common to all algorithms:

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$$\begin{array}{l} G \longrightarrow \\ y - R \longrightarrow \\ y(y - R) \longrightarrow \\ y^2(y - R) \longrightarrow \\ \vdots \\ y^{\ell-1}(y - R) \longrightarrow \end{array} \left[\begin{array}{cccccc} G & 0 & 0 & 0 & \cdots & 0 \\ -R & 1 & 0 & 0 & \cdots & 0 \\ 0 & -R & 1 & 0 & \cdots & 0 \\ 0 & 0 & -R & 1 & \cdots & 0 \\ \vdots & & \ddots & \ddots & \ddots & \\ 0 & \cdots & \cdots & 0 & -R & 1 \end{array} \right]$$

alternative approach: basis reduction

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alternative approach: basis reduction

basis reduction \approx [Mulders-Storjohann 2003] quadratic in n

- ▶ [Reinhard 2003] $O(\ell^3 m^2 n^2)$
- ▶ [Lee-O'Sullivan 2008] $O(\ell^4 m n^2)$
- ▶ [Trifonov 2010] $O(m^3 n^2)$ (heuristic)

alternative approach: basis reduction

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$$O(\ell^4 m n^2)$$

▶ [Trifonov 2010]

$$O(m^3 n^2) \text{ (heuristic)}$$

basis reduction = matrix-half-GCD

\sim linear in n

▶ [Alekhovich 2002+2005]

$$O(\ell^4 m^4 n)$$

basis reduction = [Giorgi-Jeannerod-Villard 2003]

\sim linear in n

▶ [Beelen-Brander 2010]

$$O(\ell^4 m n)$$

▶ [Bernstein 2010]

$$O(\ell^{\omega+1} n)$$

▶ [Cohn-Heninger 2011+2015]

$$O(\ell^{\omega} m n)$$

alternative approach: basis reduction

basis reduction \approx [Mulders-Storjohann 2003] quadratic in n

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$$O(\ell^4 m n^2)$$

$$O(m^3 n^2) \text{ (heuristic)}$$

basis reduction = matrix-half-GCD

▶ [Alekhovich 2002+2005]

\tilde{O} linear in n

$$O(\ell^4 m^4 n)$$

basis reduction = [Giorgi-Jeannerod-Villard 2003]

▶ [Beelen-Brander 2010]

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▶ [Cohn-Heninger 2011+2015]

\tilde{O} linear in n

$$O(\ell^4 m n)$$

$$O(\ell^{\omega+1} n)$$

$$O(\ell^{\omega} m n)$$

basis reduction = fastest known

$$O(\ell^{\omega-1} s^2 n)$$

▶ [Neiger 2016] [Neiger-Vu 2017]

▶ do not go this way!

\rightsquigarrow here, better call fast vector interpolation directly

generalizations of the interpolation step

summary for [Sudan '97] [Guruswami-Sudan '99]:

▶ list-decoding of Reed-Solomon codes, **extends** error-correction bound

compute $Q(x, y) = Q_0 + Q_1y + \dots + Q_my^\ell$ such that

- ▶ $[Q_0, \dots, Q_\ell]$ has small shifted degree
- ▶ $Q(\alpha_i, \beta_i) = 0$ with multiplicity μ for all i

generalizations of the interpolation step

[Kötter-Vardy 2003]

soft-decision decoding of Reed-Solomon codes

$\alpha_1, \dots, \alpha_n$ are not pairwise distinct

compute $Q(x, y) = Q_0 + Q_1y + \dots + Q_\ell y^\ell$ such that

- ▶ $[Q_0, \dots, Q_\ell]$ has small shifted degree
- ▶ $Q(\alpha_i, \beta_i) = 0$ with multiplicity μ_i for all i

generalizations of the interpolation step

[Guruswami-Rudra 2006]

list-decoding of **folded** Reed-Solomon codes:

further extends the error-correction bound up to the information-theoretic limit

[Devet-Goldberg-Heninger 2012]

Optimally robust Private Information Retrieval

compute $Q(x, \mathbf{y}_1, \dots, \mathbf{y}_s) = \sum_{(j_1, \dots, j_s) \in \Gamma} Q_{j_1, \dots, j_s} y_1^{j_1} \cdots y_s^{j_s}$ such that

- ▶ $[Q_{j_1, \dots, j_s}]_{(j_1, \dots, j_s) \in \Gamma}$ has small shifted degree
- ▶ $Q(\alpha_i, \beta_{i1}, \dots, \beta_{is}) = 0$ with multiplicity μ for all i

generalizations of the interpolation step

[Beelen-Rosenkilde-Solomatov 2022]

[Beelen-Neiger (preprint) 2023]

Guruswami-Sudan algorithm in the algebraic-geometry code setting

up to more precomputations, very similar context:

... also up to many technical details

$$\mathcal{M}_{s,\ell,\beta} = \left\{ Q = \sum_{t=0}^{\ell} z^t Q_t \in \mathbb{F}[z] \mid Q_t \in \Delta(-tG), \right.$$

Q has a root of multiplicity at least s at (P_j, β_j) for all j $\left. \right\}$.

$$\mathcal{M}_{s,\ell,\beta} = \bigoplus_{t=0}^{s-1} (z - \mathbf{R})^t \Delta(G_t) \oplus \bigoplus_{t=s}^{\ell} f_t(z) (z - \mathbf{R})^s \Delta(G_t).$$

summary

computer algebra

- ▶ efficient algorithms and software
- ▶ for matrices over a field
- ▶ for univariate polynomials

Reed-Solomon decoding

- ▶ context and unique decoding problem
- ▶ key equations and how to solve them
- ▶ correcting more errors?

polynomial matrices

- ▶ introduction to vector interpolation
- ▶ core algorithms & shifted normal forms
- ▶ fast divide and conquer interpolation

efficient list decoding

- ▶ the Guruswami-Sudan algorithm
- ▶ via structured systems or basis reduction
- ▶ a word on extensions