

# Factoring multivariate sparse polynomials

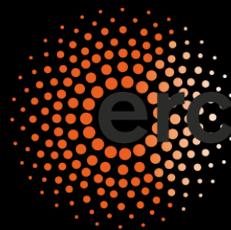
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Joint work with Alexander DEMIN and Grégoire LECERF

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**Funded by  
the European Union**



**European Research Council**  
Established by the European Commission

**ODELIX thematic program, Palaiseau**

**November 14, 2025**

Symbolic expressions  $\rightarrow$  sparse polynomials or rational functions

# Sparse polynomials — example 1

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Symbolic expressions  $\rightarrow$  sparse polynomials or rational functions

```
Caas] derive (x^x^x, x, x, x, x)
```

```
Caas]
```

# Sparse polynomials — example 1

2/21

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```

$$\begin{aligned} & \left( 6 \frac{(\log(x) + 1)^2 x^x \log(x)}{x} - 4 \frac{(\log(x) + 1) x^x \log(x)}{x^2} - 6 \frac{(\log(x) + 1)^2 x^x}{x^2} + (\log(x) + \right. \\ & 1)^4 x^x \log(x) + 4 \frac{(\log(x) + 1)^3 x^x}{x} + 8 \frac{(\log(x) + 1) x^x}{x^3} + 12 \frac{(\log(x) + 1) x^x}{x^2} + 2 \frac{x^x \log(x)}{x^3} + \\ & 3 \frac{x^x \log(x)}{x^2} - 6 \frac{x^x}{x^4} - 10 \frac{x^x}{x^3} \Big) x^{x^x} + 4 \left( (\log(x) + 1)^3 x^x \log(x) + 3 \frac{(\log(x) + 1) x^x \log(x)}{x} + \right. \\ & 3 \frac{(\log(x) + 1)^2 x^x}{x} - 3 \frac{(\log(x) + 1) x^x}{x^2} - \frac{x^x \log(x)}{x^2} + 2 \frac{x^x}{x^3} + 3 \frac{x^x}{x^2} \Big) \left( (\log(x) + 1) x^x \log(x) + \right. \\ & \left. \frac{x^x}{x} \right) x^{x^x} + 6 \left( (\log(x) + 1)^2 x^x \log(x) + 2 \frac{(\log(x) + 1) x^x}{x} + \frac{x^x \log(x)}{x} - \frac{x^x}{x^2} \right) \left( (\log(x) + \right. \\ & 1) x^x \log(x) + \frac{x^x}{x} \Big)^2 x^{x^x} + 3 \left( (\log(x) + 1)^2 x^x \log(x) + 2 \frac{(\log(x) + 1) x^x}{x} + \frac{x^x \log(x)}{x} - \frac{x^x}{x^2} \right)^2 x^{x^x} + \\ & \left( (\log(x) + 1) x^x \log(x) + \frac{x^x}{x} \right)^4 x^{x^x} \end{aligned}$$



# Sparse polynomials — example 1

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Symbolic expressions  $\rightarrow$  sparse polynomials or rational functions

**Caas**] derive  $(x^{x^x}, x, x, x)$

$$\begin{aligned} & \left( (\log(x) + 1)^3 x^x \log(x) + 3 \frac{(\log(x) + 1) x^x \log(x)}{x} + 3 \frac{(\log(x) + 1)^2 x^x}{x} - 3 \frac{(\log(x) + 1) x^x}{x^2} - \right. \\ & \left. \frac{x^x \log(x)}{x^2} + 2 \frac{x^x}{x^3} + 3 \frac{x^x}{x^2} \right) x^{x^x} + 3 \left( (\log(x) + 1)^2 x^x \log(x) + 2 \frac{(\log(x) + 1) x^x}{x} + \frac{x^x \log(x)}{x} - \right. \\ & \left. \frac{x^x}{x^2} \right) \left( (\log(x) + 1) x^x \log(x) + \frac{x^x}{x} \right) x^{x^x} + \left( (\log(x) + 1) x^x \log(x) + \frac{x^x}{x} \right)^3 x^{x^x} \end{aligned}$$

Symbolic expressions  $\rightarrow$  sparse polynomials or rational functions

**Caas**] derive  $(x^{x^x}, x, x, x)$

$$\begin{aligned} & \left( (\log(x) + 1)^3 x^x \log(x) + 3 \frac{(\log(x) + 1) x^x \log(x)}{x} + 3 \frac{(\log(x) + 1)^2 x^x}{x} - 3 \frac{(\log(x) + 1) x^x}{x^2} - \right. \\ & \left. \frac{x^x \log(x)}{x^2} + 2 \frac{x^x}{x^3} + 3 \frac{x^x}{x^2} \right) x^{x^x} + 3 \left( (\log(x) + 1)^2 x^x \log(x) + 2 \frac{(\log(x) + 1) x^x}{x} + \frac{x^x \log(x)}{x} - \right. \\ & \left. \frac{x^x}{x^2} \right) \left( (\log(x) + 1) x^x \log(x) + \frac{x^x}{x} \right) x^{x^x} + \left( (\log(x) + 1) x^x \log(x) + \frac{x^x}{x} \right)^3 x^{x^x} \end{aligned}$$

$$f = x^{x^x}$$

$$f', f'', f''', \dots \in \mathbb{Q}\left[\log x, \frac{1}{x}, x^x, x^{x^x}\right]$$

Symbolic expressions  $\rightarrow$  sparse polynomials or rational functions

`Caas`] derive (x<sup>x</sup>, x, x, x)

$$\begin{aligned} & \left( (\log(x) + 1)^3 x^x \log(x) + 3 \frac{(\log(x) + 1) x^x \log(x)}{x} + 3 \frac{(\log(x) + 1)^2 x^x}{x} - 3 \frac{(\log(x) + 1) x^x}{x^2} - \right. \\ & \left. \frac{x^x \log(x)}{x^2} + 2 \frac{x^x}{x^3} + 3 \frac{x^x}{x^2} \right) x^{x^x} + 3 \left( (\log(x) + 1)^2 x^x \log(x) + 2 \frac{(\log(x) + 1) x^x}{x} + \frac{x^x \log(x)}{x} - \right. \\ & \left. \frac{x^x}{x^2} \right) \left( (\log(x) + 1) x^x \log(x) + \frac{x^x}{x} \right) x^{x^x} + \left( (\log(x) + 1) x^x \log(x) + \frac{x^x}{x} \right)^3 x^{x^x} \end{aligned}$$

$$f = x^{x^x}$$

$$f', f'', f''', \dots \in \mathbb{Q}\left[\log x, \frac{1}{x}, x^x, x^{x^x}\right]$$

$$\subseteq \mathbb{Q}(\log x, x, x^x, x^{x^x})$$

# Sparse polynomials — example 2

3/21

```
Caas] M == [ a, b, c; d, e, f; g, h, i ]
```

```
Caas] det M
```

```
Caas] simplify invert M
```

```
Caas] simplify transpose invert transpose invert M
```

```
Caas]
```

# Sparse polynomials — example 2

3/21

```
Caas] M == [ a, b, c; d, e, f; g, h, i ]
```

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

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$(cg + fh)(-a - e) + (ac + bf)g + (cd + ef)h + (ae - bd)i$

```
Caas] simplify invert M
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Caas] simplify transpose invert transpose invert M
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$$\left[ \begin{array}{c} \frac{ei - fh}{(dh - eg)c + (ei - fh)a + (fg - di)b} \\ \frac{fg - di}{(dh - eg)c + (ei - fh)a + (fg - di)b} \\ \frac{dh - eg}{(dh - eg)c + (ei - fh)a + (fg - di)b} \end{array} \quad \begin{array}{c} \frac{ch - bi}{(dh - eg)c + (ei - fh)a + (fg - di)b} \\ \frac{ai - cg}{(dh - eg)c + (ei - fh)a + (fg - di)b} \\ \frac{bg - ah}{(dh - eg)c + (ei - fh)a + (fg - di)b} \end{array} \quad \begin{array}{c} \frac{bf - c}{(dh - eg)c + (ei - fh)a + (fg - di)b} \\ \frac{cd - a}{(dh - eg)c + (ei - fh)a + (fg - di)b} \\ \frac{ae - b}{(dh - eg)c + (ei - fh)a + (fg - di)b} \end{array} \right]$$

```
Caas] simplify transpose invert transpose invert M
```

```
Caas]
```

# Sparse polynomials — example 2

3/21

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3/21

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$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

```
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# Sparse polynomials — example 2

3/21

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Computations with parameters  $\rightarrow$  expression swell

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3/21

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Computations with parameters  $\rightarrow$  expression swell

**How to make running times depend only on the input & output size ?**

## Input



## Output

$$f(x_1, \dots, x_n) = c_1 x_1^{e_{1,1}} \cdots x_n^{e_{1,n}} + \cdots + c_t x_1^{e_{t,1}} \cdots x_n^{e_{t,n}}$$

**Complexity of sparse interpolation (see previous talk by Grégoire)**

## Complexity of sparse interpolation (see previous talk by Grégoire)

INPUT: an SLP  $f$  of size  $L$

OUTPUT: sparse interpolation  $f = c_1 x^{e_1} + \dots + c_t x^{e_t}$

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$$T(t) = O(Lt) + S(t), \quad S(t) = \tilde{O}(t)$$

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CONSTRAINT: evaluation points  $\rightarrow$  roots of unity or geometric progression

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**Other operations ?**

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## Other operations ?

- Greatest common divisors

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Long history  $\rightarrow$  paper with Alexander Demin

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## Other operations ?

- Greatest common divisors
- Sparse interpolation of rational functions
- Factorization

Long history  $\rightarrow$  paper with Alexander Demin

We will focus on the case where the total degree  $d$  is “modest”

$$G(x_1, \dots, x_n) = \gcd(A(x_1, \dots, x_n), B(x_1, \dots, x_n))$$

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$$A(x_1, \dots, x_n) = U(x_1, \dots, x_n) G(x_1, \dots, x_n)$$

$$B(x_1, \dots, x_n) = V(x_1, \dots, x_n) G(x_1, \dots, x_n)$$

$U, V$  coprime

$$G(x_1, \dots, x_n) = \gcd(A(x_1, \dots, x_n), B(x_1, \dots, x_n))$$

$$\begin{aligned} A(x_1, \dots, x_n) &= U(x_1, \dots, x_n) G(x_1, \dots, x_n) \\ B(x_1, \dots, x_n) &= V(x_1, \dots, x_n) G(x_1, \dots, x_n) \end{aligned} \quad U, V \text{ coprime}$$

$$A(\alpha_1 t, \dots, \alpha_n t) = U(\alpha_1 t, \dots, \alpha_n t) G(\alpha_1 t, \dots, \alpha_n t)$$

$$B(\alpha_1 t, \dots, \alpha_n t) = V(\alpha_1 t, \dots, \alpha_n t) G(\alpha_1 t, \dots, \alpha_n t)$$

$$G(x_1, \dots, x_n) = \gcd(A(x_1, \dots, x_n), B(x_1, \dots, x_n))$$

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$$A_\alpha(t) = A(\alpha_1 t, \dots, \alpha_n t) = U(\alpha_1 t, \dots, \alpha_n t) G(\alpha_1 t, \dots, \alpha_n t) = U_\alpha(t) G_\alpha(t)$$

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**With high probability**

$$G_\alpha(t) \stackrel{\text{HP}}{=} \gcd(A_\alpha(t), B_\alpha(t))$$

$$G(x_1, \dots, x_n) = \gcd(A(x_1, \dots, x_n), B(x_1, \dots, x_n))$$

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**With high probability**

$$G_\alpha(t) \stackrel{\text{HP}}{=} \gcd(A_\alpha(t), B_\alpha(t))$$

**Why?**

$$G(x_1, \dots, x_n) = \gcd(A(x_1, \dots, x_n), B(x_1, \dots, x_n))$$

$$\begin{aligned} A(x_1, \dots, x_n) &= U(x_1, \dots, x_n) G(x_1, \dots, x_n) \\ B(x_1, \dots, x_n) &= V(x_1, \dots, x_n) G(x_1, \dots, x_n) \end{aligned} \quad U, V \text{ coprime}$$

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**With high probability** (over Laurent polynomials)

$$G_\alpha(t) \stackrel{\text{HP}}{=} \gcd(A_\alpha(t), B_\alpha(t))$$

Indeed,

$$U_\alpha, V_\alpha \text{ not coprime} \iff \text{Res}_t(U_\alpha(t), V_\alpha(t)) = 0$$

$$G(x_1, \dots, x_n) = \gcd(A(x_1, \dots, x_n), B(x_1, \dots, x_n))$$

$$\begin{aligned} A(x_1, \dots, x_n) &= U(x_1, \dots, x_n) G(x_1, \dots, x_n) \\ B(x_1, \dots, x_n) &= V(x_1, \dots, x_n) G(x_1, \dots, x_n) \end{aligned} \quad U, V \text{ coprime}$$

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**With high probability**

$$G_\alpha(t) \stackrel{\text{HP}}{=} \gcd(A_\alpha(t), B_\alpha(t))$$

**Normalization problem**

$G_\alpha(t)$  defined up to a “constant”  $c_\alpha$

$$G(x_1, \dots, x_n) = \gcd(A(x_1, \dots, x_n), B(x_1, \dots, x_n))$$

$$\begin{aligned} A(x_1, \dots, x_n) &= U(x_1, \dots, x_n) G(x_1, \dots, x_n) \\ B(x_1, \dots, x_n) &= V(x_1, \dots, x_n) G(x_1, \dots, x_n) \end{aligned} \quad U, V \text{ coprime}$$

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**With high probability**

$$G_\alpha(t) \stackrel{\text{HP}}{=} \gcd(A_\alpha(t), B_\alpha(t))$$

**Normalization problem**

$G_\alpha(t)$  defined up to a “constant”  $c_\alpha$

→ no completely specified SLP to compute the coefficients of  $G_\alpha(t)$

# A lucky example when normalization is easy

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$$A = -2025xyz - 14x^4y - 11xy^3 - xy + 14x^3 + 11y^2 + 2025z + 1$$

$$B = 14x^3z + 11y^2z + 14x^3 + 11y^2 + 2025z^2 + 2026z + 1$$

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## Standard projection

$$A(x_1, \dots, x_n) \longrightarrow A(\alpha_1 t, \dots, \alpha_n t)$$

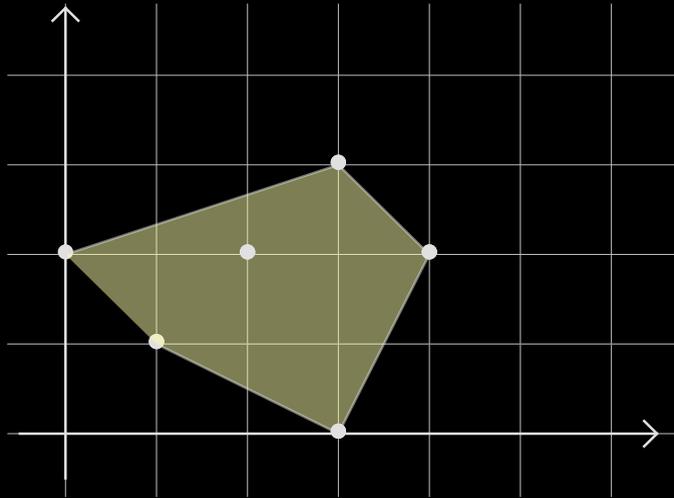
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## Newton polytopes



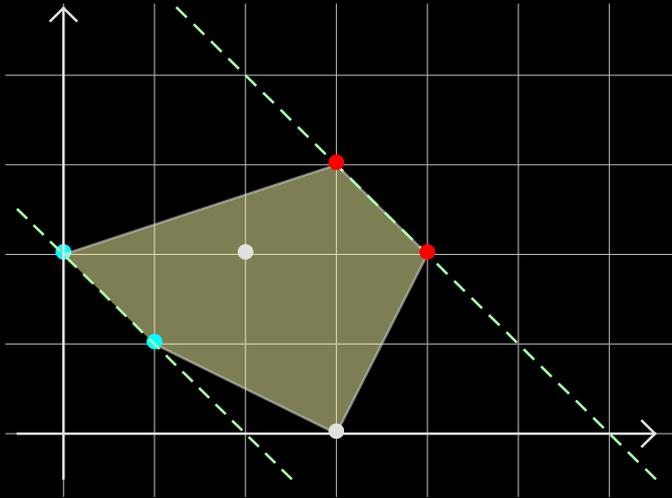
$$A(x, y) = x^4 y^2 + x^3 y^3 - x^2 y^2 - x^3 + x y - 2 y^2$$

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## Newton polytopes



$$A(x, y) = x^4 y^2 + x^3 y^3 - x^2 y^2 - x^3 + xy - 2y^2$$

$$A_\alpha(t) = \square t^6 + \square t^4 + \square t^3 + \square t^2$$

## Weighted projection with integer weights

$$A(x_1, \dots, x_n) \longrightarrow A(\alpha_1 t^{w_1}, \dots, \alpha_n t^{w_n})$$

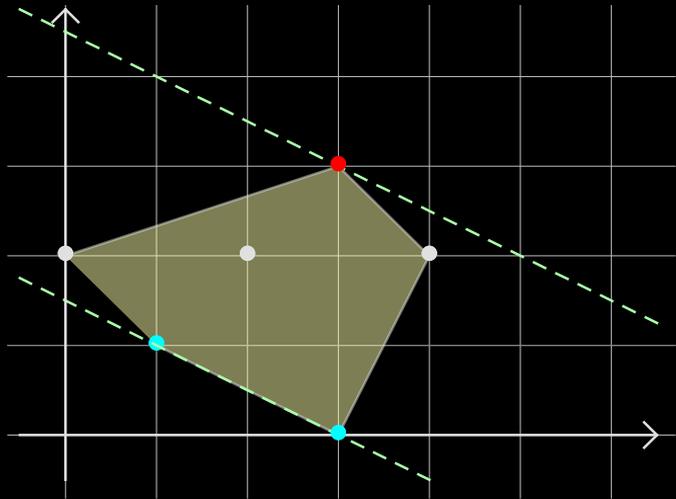
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## Newton polytopes



Head regularizing weight  $w = (1, 2)$

$$A(x, y) = x^4 y^2 + x^3 y^3 - x^2 y^2 - x^3 + xy - 2y^2$$

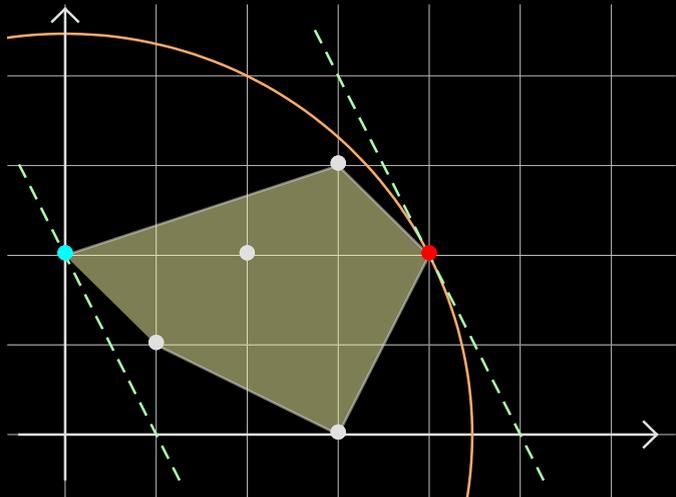
$$A_\alpha(t) = \square t^9 + \square t^8 + \square t^6 + \square t^4 + \square t^3$$

## Weighted projection with integer weights

$$A(x_1, \dots, x_n) \rightarrow A(\alpha_1 t^{w_1}, \dots, \alpha_n t^{w_n})$$

$$B(x_1, \dots, x_n) \rightarrow B(\alpha_1 t^{w_1}, \dots, \alpha_n t^{w_n})$$

## Existence of regularizing weight of small norm $|w| \leq d$



Regularizing weight  $w = (4, 2)$

$$A(x, y) = x^4 y^2 + x^3 y^3 - x^2 y^2 - x^3 + x y - 2 y^2$$

$$A_\alpha(t) = \square t^{20} + \square t^{18} + \square t^{12} + \square t^6 + \square t^4$$

## Notation

$s_P$ : number of terms of  $P \in \mathbb{K}[x_1, \dots, x_n]$

$d_P$ : total degree of  $P$

$ec_w P = \deg_w P - \text{val}_w P$ : weighted écart of  $P$

$S(s)$  complexity of sparse interpolation (for  $s$  terms)

$M(d)$  complexity of dense polynomial multiplication (for degree  $d$ )

## Theorem

*Let  $A, B \in \mathbb{K}[x_1, \dots, x_n]$ ,  $G = \gcd(A, B)$ , and  $w$  regularizing for  $A$  or  $B$ .*

*Let  $s := s_G$ ,  $\bar{s} := s_A + s_B + s_G$ ,  $d := \max(d_A, d_B)$ , and  $e := \max(ec_w A, ec_w B) \leq d^2$ .*

*Then there is an algorithm to compute  $G$  with high probability, in time*

$$O((\bar{s}/s + e) S(s) + s M(e) \log e).$$

## Goal

$$G(x_1, \dots, x_{n-1}, x_n) = \gcd(A(x_1, \dots, x_{n-1}, x_n), B(x_1, \dots, x_{n-1}, x_n))$$

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## Fibers for sparse interpolation

$$\underbrace{G(\alpha_1, \dots, \alpha_{n-1}, t)}_{G_\alpha(t)} = \gcd \left( \underbrace{A(\alpha_1, \dots, \alpha_{n-1}, t)}_{A_\alpha(t)}, \underbrace{B(\alpha_1, \dots, \alpha_{n-1}, t)}_{B_\alpha(t)} \right)$$

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## Recursively compute

$$G_c(x_1, \dots, x_{n-1}) = \gcd(A(x_1, \dots, x_{n-1}, c), B(x_1, \dots, x_{n-1}, c))$$

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## Iterative normalization

$$G_\alpha(t) = \gcd(A_\alpha(t), B_\alpha(t))$$

$$G_\alpha(c) = G_c(x_1, \dots, x_{n-1})$$

## Notation

$\delta_P = \max (\deg_{x_1} P, \dots, \deg_{x_n} P)$ : maximum of partial degrees of  $P$

## Theorem

*Let  $A, B \in \mathbb{K} [x_1, \dots, x_n]$  and  $G = \gcd (A, B)$ .*

*Let  $s := s_G$ ,  $\bar{s} := s_P + s_Q + s_G$ ,  $d := \max (d_P, d_Q)$ , and  $\delta := \max (\delta_P, \delta_Q)$ .*

*Then there is an algorithm to compute  $G$  with high probability, in time*

$$O(n ((\bar{s}/s + \delta) S(s) + s M(\delta) \log \delta)).$$

## Content factorization

$$\begin{aligned}\text{cont}_z(xz - yz + x^2 - y^2 + x - y) &= \gcd(x - y, x^2 - y^2 + x - y) = x - y \\ xz - yz + x^2 - y^2 + x - y &= (x - y)(1 + x + y + z)\end{aligned}$$

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$$F = A_1 A_2^2 \cdots A_k^k, \quad A_1, \dots, A_k \text{ pairwise coprime}$$

E.g. repeat  $\gcd(F, F')$  and root extraction.

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## Sparse interpolation of rational function $f = \frac{A}{B}$

- Guess regularizing weight for  $A$  and  $B$  (fast to check), next as for gcd.
- Iterative approach (straightforward to adapt).

$$G(\mathbf{x}, t) = \gcd(A(\mathbf{x}, t), B(\mathbf{x}, t))$$

$$\Downarrow_{\text{HP}}$$

$$G(\boldsymbol{\alpha}, t) = \gcd(A(\boldsymbol{\alpha}, t), B(\boldsymbol{\alpha}, t))$$

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**Example.** Over  $\mathbb{K} = \mathbb{F}_p$  with  $p$  odd consider

$$F(x, y, z) = \Phi(x, y)^2 - z$$

$$\Phi(x, y) = x + y$$

(or  $\Phi$  irreducible)

A random  $\alpha \in \mathbb{F}_p^*$  is square  $\alpha = \beta^2$  with probability  $\frac{1}{2}$ .

In that case  $F(x, y, \alpha) = (\Phi + \beta)(\Phi - \beta)$ .

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**Problem:** how to recombine projected factors when lifting back?

## Hilbert-Bertini irreducibility Theorem

Assume  $F \in \mathbb{K}[x_1, \dots, x_n] \setminus \mathbb{K}$  irreducible. Let  $U$  be the set of points  $(\alpha_1, \dots, \alpha_n, \beta_1, \dots, \beta_n, \gamma_1, \dots, \gamma_n) \in \mathbb{K}^{3n}$  for which

$$F(\alpha_1 t + \beta_1 u + \gamma_1, \dots, \alpha_n t + \beta_n u + \gamma_n)$$

is irreducible in  $\mathbb{K}[t, u]$ . Then  $U$  is a Zariski open subset of  $\mathbb{K}^{3n}$ , which is dense over the algebraic closure of  $\mathbb{K}$ .

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→ modulo random shifts, bivariate instead of univariate projections suffice

→ in practice a shift is often not necessary

## Notation

$2 \leq \omega \leq 3$ : two  $n \times n$  matrices can be multiplied in time  $n^\omega$

$F_{\mathbb{K}}(d)$ : cost to completely factor a polynomial of degree  $d$  in  $\mathbb{K}[x]$

## Theorem (Lecerf 2010)

*Let  $F \in \mathbb{K}[x, y]$  of bidegree  $(d_x, d_y)$  be square-free and content-free in both  $x$  and  $y$ . Assume that  $\text{char } \mathbb{K} = 0$  or  $\text{char } \mathbb{K} > d_y(2d_x - 1)$ . Then, with high probability, we can compute the irreducible factorization of  $F$  in time*

$$\tilde{O}(d_x^2 d_y + d_x^\omega) + F_{\mathbb{K}}(d_x).$$

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$$\alpha \rightarrow \text{cube} \rightarrow F_\alpha(t, u) = A_\alpha(t, u) B_\alpha(t, u), \quad \begin{aligned} A_\alpha(t, c) &= A_c(\alpha_1 t, \dots, \alpha_{n-1} t) \\ B_\alpha(t, c) &= B_c(\alpha_1 t, \dots, \alpha_{n-1} t) \end{aligned}$$

## Theorem

Let  $s := \min(s_A, s_B)$ ,  $s' := \max(s_A, s_B)$ ,  $\bar{s} := \max(s', s_F)$ ,  $d := \deg F$ , and  $\delta := \max(\deg_{x_1} F, \dots, \deg_{x_n} F)$ . Then Hensel lifting can be done with HP in time

$$O(n((\bar{s}/s)S(s') + \delta d S(s) + sM(\delta d) + sM(d) \log d))$$

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In favorable cases, this leads to a HP algorithm to completely factor

$$F = A_1 \cdots A_\ell$$

in time

$$O(n((\bar{s}/s + \delta d)S(s) + sM(\delta d) \log \ell + sM(d) \log d)) + \tilde{O}(\delta^3) + F_{\mathbb{K}}(\delta)$$

$\alpha_1, \dots, \alpha_n, \beta_1, \dots, \beta_n, \gamma_1, \dots, \gamma_n$  random

$$\hat{F}(x_1, \dots, x_n, t, u, \lambda) := F((1 - \lambda + \alpha_1 \lambda) (t + \beta_1 u + \gamma_1) x_1, \dots, (1 - \lambda + \alpha_n \lambda) (t + \beta_n u + \gamma_n) x_n).$$

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We use  $\alpha^k = (\alpha_1^k, \dots, \alpha_n^k)$  as our interpolation points

$$F^{(i)}(t, u, \lambda) := \hat{F}(\alpha_1^i, \dots, \alpha_n^i, t, u, \lambda)$$

$\alpha_1, \dots, \alpha_n, \beta_1, \dots, \beta_n, \gamma_1, \dots, \gamma_n$  random

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We use  $\alpha^k = (\alpha_1^k, \dots, \alpha_n^k)$  as our interpolation points

$$F^{\langle i \rangle}(t, u, \lambda) := \hat{F}(\alpha_1^i, \dots, \alpha_n^i, t, u, \lambda)$$

By construction

$$F^{\langle i+1 \rangle}(t, u, 0) = F^{\langle i \rangle}(t, u, 1)$$

By Hilbert-Bertini, with high probability,  
we have the following “propagation” of irreducible factorizations:

$$\begin{array}{rcccl}
 F^{(i)}(t, u, 0) & = & A_1^{(i)}(t, u, 0) & \cdots & A_\ell^{(i)}(t, u, 0) & & \text{Hensel} \\
 \downarrow & & \downarrow & & \downarrow & & \\
 F^{(i)}(t, u, \lambda) & = & A_1^{(i)}(t, u, \lambda) & \cdots & A_\ell^{(i)}(t, u, \lambda) & & \text{evaluate} \\
 \downarrow & & \downarrow & & \downarrow & & \\
 F^{(i)}(t, u, 1) & = & A_1^{(i)}(t, u, 1) & \cdots & A_\ell^{(i)}(t, u, 1) & & \text{identify} \\
 \parallel & & \parallel & & \parallel & & \\
 F^{(i+1)}(t, u, 0) & = & A_1^{(i+1)}(t, u, 0) & \cdots & A_\ell^{(i+1)}(t, u, 0) & & \\
 \downarrow & & \downarrow & & \downarrow & & \\
 \vdots & & \vdots & & \vdots & & 
 \end{array}$$

By Hilbert-Bertini, with high probability,  
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 F^{\langle i \rangle}(t, u, 0) & = & A_1^{\langle i \rangle}(t, u, 0) & \cdots & A_\ell^{\langle i \rangle}(t, u, 0) & & \text{Hensel} \\
 \downarrow & & \downarrow & & \downarrow & & \\
 F^{\langle i \rangle}(t, u, \lambda) & = & A_1^{\langle i \rangle}(t, u, \lambda) & \cdots & A_\ell^{\langle i \rangle}(t, u, \lambda) & & \text{evaluate} \\
 \downarrow & & \downarrow & & \downarrow & & \\
 F^{\langle i \rangle}(t, u, 1) & = & A_1^{\langle i \rangle}(t, u, 1) & \cdots & A_\ell^{\langle i \rangle}(t, u, 1) & & \text{identify} \\
 \parallel & & \parallel & & \parallel & & \\
 F^{\langle i+1 \rangle}(t, u, 0) & = & A_1^{\langle i+1 \rangle}(t, u, 0) & \cdots & A_\ell^{\langle i+1 \rangle}(t, u, 0) & & \\
 \downarrow & & \downarrow & & \downarrow & & \\
 \vdots & & \vdots & & \vdots & & 
 \end{array}$$

After one further tweak for normalization  $\rightarrow$  SLP for computing  $A_1^{\langle i \rangle}, \dots, A_\ell^{\langle i \rangle}$

## Theorem

Let  $s := \max(s_{P_1}, \dots, s_{P_\ell})$ ,  $\bar{s} := \max(s, s_F)$ ,  $d := \deg F$ , and  $e := ec_w F \leq d^2$  (for a suitable regularizing weight  $w$ ). Assume  $\text{char } \mathbb{K} = 0$  or  $\text{char } \mathbb{K} > 2d^2$ . Then, with high probability, we can compute the irreducible factorization of  $F$  in time

$$O(S(d^3 \bar{s}) + M(d^3) s \log d) + \tilde{O}(e^5) + F_{\mathbb{K}}(e + 3d)$$

**Thank you !**



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