

Parallel Algorithms for Factoring Multivariate Polynomials Represented by Black Boxes

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Goal + Outline

Our goal is to develop **faster parallelizable** algorithms to factor multivariate polynomials with coefficients in the ring of integers.

- ① The Sparse and the Black Box Representation of a Polynomial
- ② The Algorithm CMSHL and Modification for the Black Box
- ③ Complexity Analysis
- ④ A hybrid Maple + C implementation
- ⑤ Future Work

The sparse and the black box representation of a polynomial

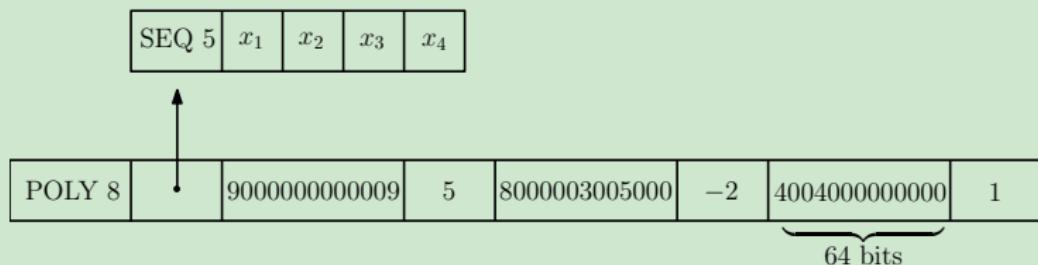
The **sparse representation** of $f \in \mathbb{Z}[x_1, \dots, x_n]$ consists of a list of coefficients a_k and exponents $(e_{k_1}, \dots, e_{k_n})$ such that

$$f = \sum_{k=1}^t a_k \cdot x_1^{e_{k_1}} \cdots x_n^{e_{k_n}}, a_k \neq 0, a_k \in \mathbb{Z}.$$

It is a natural, readable and **explicit** representation.

Example

Maple's packed monomial representation for $f = 5x_4^9 - 2x_2^3x_3^5 + x_1^4$.



The sparse and the black box representation of a polynomial

The **black box representation** of $f \in \mathbb{Z}[x_1, \dots, x_n]$ is a [program](#) that accepts inputs a prime p and $\alpha \in \mathbb{Z}_p^n$ and outputs $f(\alpha) \bmod p$.

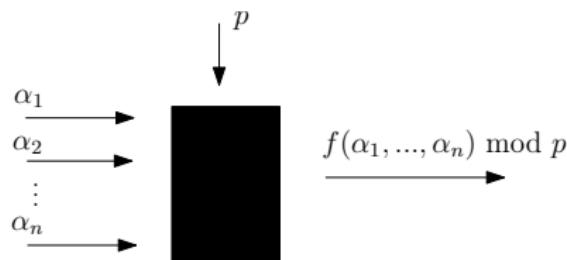


Figure: The black box representation of $f \in \mathbb{Z}[x_1, \dots, x_n]$.

It is one of the most [space efficient implicit](#) representations (Kaltofen and Trager (1990)).

Given the black box representation of $f \in \mathbb{Z}[x_1, \dots, x_n]$, its sparse representation can be computed in random polynomial time via [sparse interpolation](#).

Background/Motivation

Sparse Hensel lifting

- Wang (1975), (1978): Multivariate Hensel lifting (MHL). Recovers the factors one variable at a time. Solves MDP $\sigma_i g_{j-1} + \tau_i f_{j-1} = c_i$ for $\sigma_i, \tau_i \in \mathbb{Z}_p[x_1, \dots, x_{j-1}]$ one variable at a time. (**exponential**)
- Zippel (1981), Kaltofen (1985): Sparse Hensel lifting (SHL).
- Monagan and Tuncer (2016): Solves MDP via sparse interpolation (MTSHL).
- Monagan and Tuncer (2018): Bivariate Hensel lifts to get σ_i, τ_i .
- Chen and Monagan (2020): No multivariate polynomial arithmetic. No expression swell. **Highly parallelizable.** (CMSHL)
Dominating cost is in polynomial evaluations → Consider black box

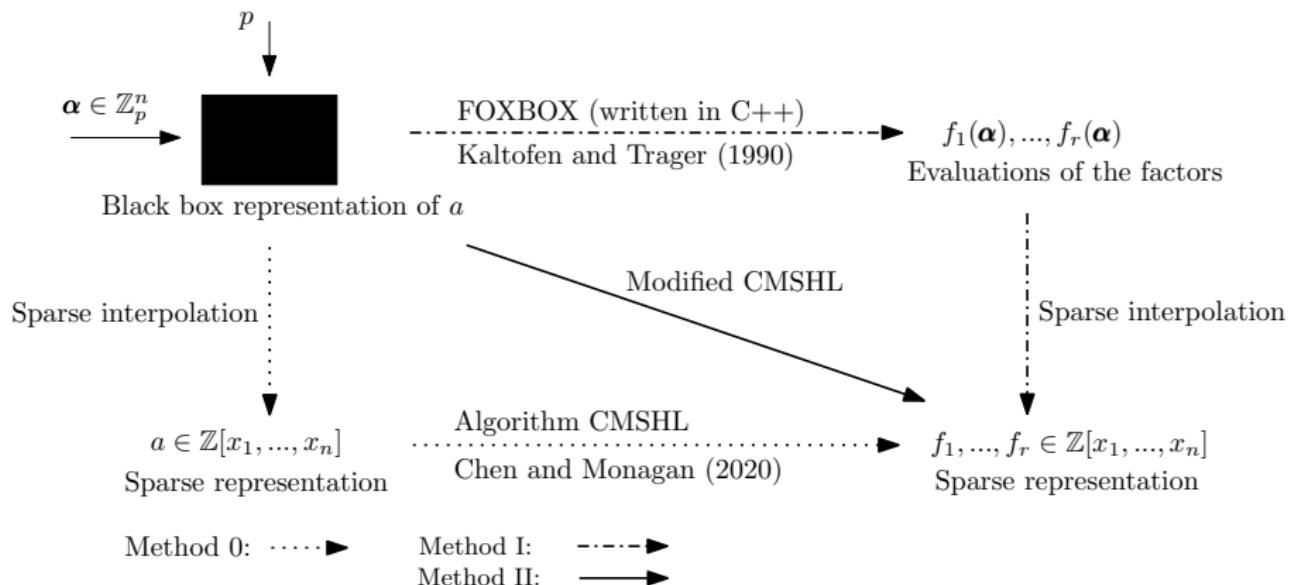
Black box factorization

- Kaltofen and Trager (1990): Black box factorization that outputs the evaluation of the factors.
- Diaz and Kaltofen (1998): FOXBOX. Implemented in C++.

There has not been any black box factorization algorithm developed since Kaltofen and Trager (1990).

Factoring $a \in \mathbb{Z}[x_1, \dots, x_n]$ represented by a black box

Develop new black box factorization algorithms that **output** the factors in **sparse representation directly** via algorithm CMSHL (**highly parallelizable**).



Example: Computing the determinant of a Toeplitz matrix

Let T_n denote an $n \times n$ symmetric Toeplitz matrix

$$T_n = \begin{pmatrix} x_1 & x_2 & x_3 & \cdots & x_n \\ x_2 & x_1 & x_2 & & \\ x_3 & x_2 & x_1 & & \\ \vdots & & \ddots & \ddots & \\ x_n & & \cdots & & x_1 \end{pmatrix}.$$

For example, $\det(T_4) =$

$$(x_1^2 - x_1x_2 - x_1x_4 - x_2^2 + 2x_2x_3 + x_2x_4 - x_3^2)(x_1^2 + x_1x_2 + x_1x_4 - x_2^2 - 2x_2x_3 + x_2x_4 - x_3^2).$$

n	$\#\det(T_n)$	$\#f_i$	s
7	427	30, 56	8
8	1628	167, 167	38
9	6090	294, 153	50
10	23797	931, 931	229
11	90296	1730, 849	337
12	350726	5579, 5579	1465
13	1338076	10611, 4983	2297
14	5165957	34937, 34937	9705

Table: Number of terms of $\det(T_n)$ and its factors.

Method II:

- Since $\#f_i \ll \#\det(T_n)$, Method II saves space by not storing $a = \det(T_n)$.
- Method II is potentially more efficient than Method I since $s \ll \#f_{\max}$ (see analysis).

Computing the factors of $a = \det(T_n) \in \mathbb{Z}[x_1, \dots, x_n]$.

Method 0: Get sparse representation of a , then use SHL.

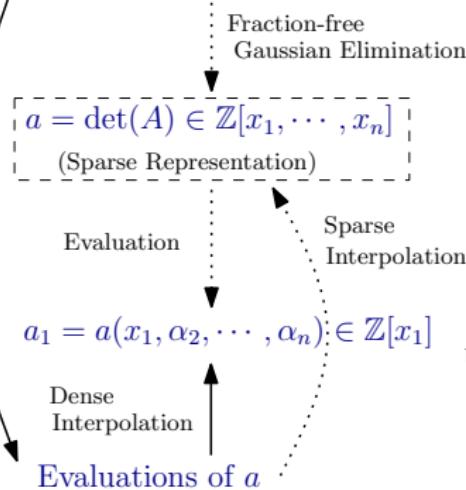
Method I: Kaltofen and Trager (1990) (modified).

Method II: Modified CMSHL (Chen and Monagan (2020)).

$$\text{Matrix } A, \text{ e.g. } A = \begin{pmatrix} x_1 & x_2 & \cdots & x_n \\ x_2 & x_1 & \cdots & x_{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ x_n & x_{n-1} & \cdots & x_1 \end{pmatrix}.$$

Method I:

Probes to \mathbf{B}



Computing the factors of $a = \det(T_n) \in \mathbb{Z}[x_1, \dots, x_n]$.

Example (Method II: Modified CMSHL ($n = 4$))

- Choose $\alpha = (3, 5, 4)$.

Computing the factors of $a = \det(T_n) \in \mathbb{Z}[x_1, \dots, x_n]$.

Example (Method II: Modified CMSHL ($n = 4$))

- Choose $\alpha = (3, 5, 4)$.
- $a(x_1, \alpha) = x_1^4 - 93x_1^2 + 420x_1 - 416 = (x_1^2 - 7x_1 + 8)(x_1^2 + 7x_1 - 52) \in \mathbb{Z}[x_1]$.

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- Choose $p = 101$. After the first step of Hensel lifting, we get

$$f_2 = x_1^2 - x_1x_2 - x_2^2 - 4x_1 + 14x_2 - 25,$$

$$g_2 = x_1^2 + x_1x_2 - x_2^2 + 4x_1 - 6x_2 - 25.$$

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- After the second step, we get

$$f_3 = x_1^2 - x_1x_2 - x_2^2 + 2x_2x_3 - x_3^2 - 4x_1 + 4x_2,$$

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- At the final step, we obtain the true factors

$$f = x_1^2 - x_1x_2 - x_1x_4 - x_2^2 + 2x_2x_3 + x_2x_4 - x_3^2,$$

$$g = x_1^2 + x_1x_2 + x_1x_4 - x_2^2 - 2x_2x_3 + x_2x_4 - x_3^2.$$

Algorithm CMSHL: distributed: two factors (CASC 2020)

Input: $p, \alpha_j \in \mathbb{Z}_p, a_j \in \mathbb{Z}_p[x_1, \dots, x_j], f_{j-1}, g_{j-1} \in \mathbb{Z}_p[x_1, \dots, x_{j-1}]$.

Output: f_j, g_j s.t. $a_j = f_j g_j$ and $f_j(x_j = \alpha_j) = f_{j-1}, g_j(x_j = \alpha_j) = g_{j-1}$ or FAIL.

- 1: Let $f_{j-1} = x_1^{\text{df}} + \sum_{i=0}^{\text{df}-1} \sigma_i(x_2, \dots, x_{j-1}) x_1^i$ with $\sigma_i = \sum_{k=1}^{s_i} c_{ik} M_{ik}$
 $g_{j-1} = x_1^{\text{dg}} + \sum_{i=0}^{\text{dg}-1} \tau_i(x_2, \dots, x_{j-1}) x_1^i$ with $\tau_i = \sum_{k=1}^{t_i} d_{ik} N_{ik}$,
- 2: Pick $\beta = (\beta_2, \dots, \beta_{j-1}) \in \mathbb{Z}_p^{j-2}$ at random and evaluate monomials at β :
 $\{S_i = \{m_{ik} = M_{ik}(\beta), 1 \leq k \leq s_i\}, 0 \leq i < \text{df}\}; \{T_i = \{n_{ik} = N_{ik}(\beta), 1 \leq k \leq t_i\}, 0 \leq i < \text{dg}\}$.
- 3: Check if monomial evaluations are distinct. If not, **return** FAIL.
- 4: Let s be the maximum of s_i and t_i .
- 5: **for** k from 1 to s **in parallel do**
- 6: Let $Y_k = (x_2 = \beta_2^k, \dots, x_{j-1} = \beta_{j-1}^k)$.
- 7: $A_k, F_k, G_k \leftarrow a_j(x_1, Y_k, x_j), f_{j-1}(x_1, Y_k), g_{j-1}(x_1, Y_k)$ **Eval:** $\mathcal{O}(s(\#f + \#g + \#a))$
- 8: **if** $\text{gcd}(F_k, G_k) \neq 1$ **then return** FAIL **end if** // unlucky evaluation
- 9: $f_k, g_k \leftarrow \text{BivariateHenselLift}(A_k, F_k, G_k, \alpha_j, p)$ **BHL:** $\mathcal{O}(s(d_1^2 d_j + d_1 d_j^2))$
- 10: **end for**
- 11: Let $f_k = x_1^{\text{df}} + \sum_{l=1}^{\mu} \alpha_{kl} \tilde{M}_l(x_1, x_j)$ for $1 \leq k \leq s$, where $\mu \leq d_1 d_j$.
- 12: **for** l from 1 to μ **in parallel do**
- 13: $i \leftarrow \deg(\tilde{M}_l, x_1)$.
- 14: Solve the $s_i \times s_i$ linear system for c_{lk} : $\{\sum_{k=1}^{s_i} m_{ik}^n c_{lk} = \alpha_{nl} \text{ for } 1 \leq n \leq s_i\}$
- 15: **end for**
- 16: Construct $f_j \leftarrow x_1^{\text{df}} + \sum_{l=1}^{\mu} (\sum_{k=1}^{s_i} c_{lk} M_{ik}(x_2, \dots, x_{j-1})) \tilde{M}_l(x_1, x_j)$.
- 17: Similarly, construct g_j **VSSolve:** $\mathcal{O}(sd_j(\#f + \#g))$
- 18: **if** $a_j = f_j g_j$ **then return** (f_j, g_j) **else return** FAIL **end if**

Algorithm CMSHL: distributed: two factors (CASC 2020)

Theorem (Chen and Monagan (2020))

Let p be a large prime, $d = \deg(a)$, $d_1 = \deg(a, x_1)$, $d_j = \deg(a, x_j)$ and s_j be the number s defined in line 4 of Algorithm CMSHL and $T_{fg_{j-1}} = \max(\#f_{j-1}, \#g_{j-1})$. With a failure probability less than

$$\frac{d s_j (T_{fg_{j-1}} + d s_j) + 2d^2 T_{fg_{j-1}}}{p - d + 1},$$

the number of arithmetic operations in \mathbb{Z}_p for the j^{th} Hensel lifting step via Algorithm CMSHL in the worst case is

$$O(d_j s_j (\underbrace{\#f_{j-1} + \#g_{j-1}}_{\text{VSolve}} + \underbrace{d_1^2 + d_1 d_j}_{\text{BHL}}) + \underbrace{s_j \# a_j}_{\text{Eval}}).$$

Usually $\#f_j \ll \#a_j$, $\#g_j \ll \#a_j$ and Eval dominates the cost of CMSHL.

Algorithm CMSHL: black box: multi-factors

```

1: Let  $f_{\rho,j-1} = x_1^{\text{df}_\rho} + \sum_{i=0}^{\text{df}_\rho-1} \sigma_{\rho,i}(x_2, \dots, x_{j-1})x_1^i$  for  $1 \leq \rho \leq r$ , where  $\sigma_{\rho,i} = \sum_{k=1}^{s_{\rho,i}} c_{\rho,ik} M_{\rho,ik}$  and  $M_{\rho,ik}$  are the monomials in  $\sigma_{\rho,i}$ .
2: Pick  $\beta = (\beta_2, \dots, \beta_{j-1}) \in \mathbb{Z}_p^{j-2}$  at random.
3:  $\{S_\rho = \{S_{\rho,i} = \{m_{\rho,ik} = M_{\rho,ik}(\beta), 1 \leq k \leq s_{\rho,i}\}, 0 \leq i \leq \text{df}_\rho - 1\}, 1 \leq \rho \leq r\}$ .
4: if any  $|S_{\rho,i}| \neq s_{\rho,i}$  then return FAIL end if
5: Let  $s$  be the maximum of  $s_{\rho,i}$ .
6: for  $k$  from 1 to  $s$  do
7:   Let  $Y_k = (x_2 = \beta_2^k, \dots, x_{j-1} = \beta_{j-1}^k)$ .
8:    $A_k \leftarrow a_j(x_1, Y_k, x_j)$ . // via probes to  $B$  and dense interpolation ...  $\mathcal{O}(sd_1d_j \cdot C(\text{probe } B))$ 
9:    $F_{1,k}, \dots, F_{r,k} \leftarrow f_{1,j-1}(x_1, Y_k), \dots, f_{r,j-1}(x_1, Y_k)$ . ....  $\mathcal{O}(s(\#f_1 + \dots + \#f_r))$ 
10:  if  $\text{gcd}(F_{\rho,k}, F_{\phi,k}) \neq 1$  for any  $\rho \neq \phi$  ( $1 \leq \rho, \phi \leq r$ ) then return FAIL end if
11:   $f_{1,k}, \dots, f_{r,k} \leftarrow \text{BivariateHenselLift}(A_k, F_{1,k}, \dots, F_{r,k}, \alpha_j, p)$ . ....  $\mathcal{O}(d_1d_j^2 + d_1^2d_j)$ 
12: end for
13: Let  $f_{\rho,k} = x_1^{\text{df}_\rho} + \sum_{l=1}^{\mu_\rho} \alpha_{\rho,kl} \tilde{M}_{\rho,l}(x_1, x_j)$  for  $1 \leq k \leq s$  where  $\mu_\rho \leq d_1d_j$ , for  $1 \leq \rho \leq r$ .
14: for  $\rho$  from 1 to  $r$  do
15:   for  $l$  from 1 to  $\mu_\rho$  do
16:      $i \leftarrow \deg(\tilde{M}_{\rho,l}, x_1)$ . Solve the  $s_{\rho,i} \times s_{\rho,i}$  linear system for  $c_{\rho,ik}$ :  

         $\left\{ \sum_{k=1}^{s_{\rho,i}} m_{\rho,ik}^n c_{\rho,ik} = \alpha_{\rho,nl} \text{ for } 1 \leq n \leq s_{\rho,i} \right\}$ .
17:   end for .....  $\mathcal{O}(sd_j(\#f_1 + \dots + \#f_r))$ 
18:   Construct  $f_{\rho,j} \leftarrow x_1^{\text{df}_\rho} + \sum_{l=1}^{\mu_\rho} \left( \sum_{k=1}^{s_{\rho,i}} c_{\rho,ik} M_{\rho,ik}(x_2, \dots, x_{j-1}) \right) \tilde{M}_{\rho,l}(x_1, x_j)$ .
19: end for
20: if  $a_j = \prod_{\rho=1}^r f_{\rho,j}$  then return  $f_{1,j} \dots, f_{r,j}$  else return FAIL end if

```

Complexity Analysis

- Interested in the number of probes to the black box \mathbf{B} .
- Preliminary estimates show that Method II requires a lot fewer probes to the black box than Method I since $s \ll \#f_{\max}$ (Chen and Monagan (2020)).
(s is the number of bivariate images needed in algorithm CMSHL and $\#f_{\max}$ is the maximum number of terms among the factors of a .)

n	6	7	8	9	10	11	12	13	14
$\#f_{\max}$	32	56	167	294	931	1730	5579	10611	34937
s	6	8	38	50	229	337	1465	2297	9705

Table: $\#f_{\max}$ and s for $\det(T_n)$.

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- Method I:
 $O(nd_1 d_{\max} \#f_{\max})$ probes \mathbf{B} using sparse interpolation (Zippel (1990)), plus $O(nd_{\max} \#f_{\max})$ times the cost of univariate polynomial factorization.
- Method II:
 $O(nd_1 d_{\max} s)$ probes to the black box \mathbf{B} .
Total cost:
 $O((n - 2) (sd_{\max} (\sum_{i=1}^r \#f_i + d_1^2 + d_1 d_{\max}) + sd_1 d_{\max} C(\text{probe } \mathbf{B})))$.

A Hybrid Maple + C Implementation of Method II

n	10	11	12	13	14
total time	9.817	23.268	111.592	321.486	2836.336
total probes	109139	267465	894358	2180399	6981462
Maple Det	0.566	5.095	359.249	3127.827	N/A
Maple factor	1.687	3.836	50.143	364.842	N/A
Maple total	2.253	8.931	409.392	3492.669	–
Hensel Lift x_n total	2.069	3.446	26.936	61.186	867.773
s (Hensel lift x_n)	522	814	3174	5223	19960
BB (C)	0.475	0.843	4.403	8.381	43.931
BB+Interp	1.103	1.671	8.542	16.214	83.621
Eval f, g (Maple)	0.109	0.327	7.229	19.165	416.548
BHL (Maple)	0.4331	0.750	3.107	5.522	27.707
table (Maple)	0.163	0.459	4.556	13.772	224.573
VSolve (C)	0.239	0.170	3.209	5.973	112.495

Table: Timings for computing $\det(T_n)$ using CMSHL black box algorithm.

Future Work

- Next Goal: Compute $\det(T_n)$ for $n = 15$
- Possible speed ups for Method II:
 - Eval f, g in C
 - BB + Interp
 - Integrate BHL in C
- Implement Method I in Maple
- A detailed complexity analysis with failure probabilities
- Non-monic factors

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Thank you for attending!

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