

A new random polynomial time algorithm for factoring
sparse multivariate polynomials.

Michael Monagan

Department of Mathematics
Simon Fraser University
British Columbia

This is joint work with Baris Tuncer.

Problem: Let $a \in \mathbb{Z}[x_1, x_2, \dots, x_n]$.

Factor a into irreducible factors over \mathbb{Z} .

Example:

$$x_1^6 - 27 x_2^3 = (x_1^2 - 3 x_2) (x_1^4 + 3 x_1^2 x_2 + 9 x_2^2)$$

For the talk assume

(i) a has two factors f and g and (ii) a is monic in x_1 .

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Talk Outline:

- Wang's multivariate Hensel lifting.
- Wang's solution to the MDP $f_k g_0 + g_k f_0 = c_k$ in $\mathbb{Z}_p[x_1, \dots, x_{j-1}]$.
- Our random polynomial time solution.
- A probabilistic analysis.
- Two benchmarks.
- Can we parallelize it?

Factoring polynomials using Wang's Hensel lifting

```
> e1 := (a = f*g);
```

$$\begin{aligned}e1 &:= x^5 + 20x^2y^6z + 5x^4y^3z + 30xy^4z^3 + 12xy^4z^2 + 4x^3y^3 \\ &\quad + 3x^3yz^2 + 18y^2z^4 + 6x^2yz^2 \\ &= (x^2 + 5xy^3z + 3yz^2)(x^3 + 4xy^3 + 6yz^2)\end{aligned}$$

```
> e2 := eval(e1,z=3);
```

$$\begin{aligned}e2 &:= x^5 + 60x^2y^6 + 15x^4y^3 + 4x^3y^3 + 918xy^4 + 27x^3y + 54x^2y + 1458y^2 \\ &= (x^2 + 15xy^3 + 27y)(x^3 + 4xy^3 + 54y)\end{aligned}$$

```
> e3 := eval(e2,y=-5);
```

$$\begin{aligned}e3 &:= x^5 - 1875x^4 - 635x^3 + 937230x^2 + 573750x + 36450 \\ &= (x^2 - 1875x - 135)(x^3 - 500x - 270)\end{aligned}$$

Notes: Let h be any factor of a and let $B > \max(\|h\|_\infty, \|a\|_\infty)$.
Multivariate Hensel Lifting (MHL) is done modulo a prime $p > 2B$.

Not all evaluation points can be used

$$f = (x^2 + 5xy^3z + 3yz^2)(x^3 + 4xy^3 + 6yz^2) + (y - z)$$

The polynomial f in $\mathbb{Z}[x, y, z]$ is irreducible over \mathbb{Q} but

> eval(f, [z=3, y=3]);

$$(x^2 + 405x + 81)(x^3 + 108x + 162)$$

Theorem (Hilbert irreducibility)

If f is irreducible over \mathbb{Q} and α, β are chosen from a sufficiently large set $S \subset \mathbb{Z}$ then $f(x, z = \alpha, y = \beta)$ is irreducible in \mathbb{Q} with high probability.

Wang's Multivariate Hensel Lifting (MHL) : j 'th step

Input $a \in \mathbb{Z}_p[x_1, \dots, x_j]$, $\alpha = (\alpha_2, \dots, \alpha_j)$, $f_0, g_0 \in \mathbb{Z}_p[x_1, \dots, x_{j-1}]$ s.t.

- (i) $a(x_1, \dots, x_{j-1}, \alpha_j) = f_0 g_0$ and
- (ii) $\gcd(f_0(x_1, \alpha), g_0(x_1, \alpha)) = 1$ in $\mathbb{Z}_p[x_1]$.

Idea: $f(x_j) = f_0 + f_1(x_j - \alpha_j) + f_2(x_j - \alpha_j)^2 + \dots$ where $f_k = f^{(k)}(\alpha_j)/k!$

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Initialize: $f \leftarrow f_0$; $g \leftarrow g_0$ and $error := a - fg$

For $k = 1, 2, \dots$, while $\deg(f, x_j) + \deg(g, x_j) < \deg(a, x_j)$ do

$c_k := \text{coeff}(error, (x_j - \alpha_j)^k)$

If $c_k \neq 0$ then

Solve the MDP $f_k g_0 + g_k f_0 = c_k$ for $f_k, g_k \in \mathbb{Z}_p[x_1, \dots, x_{j-1}]$.

Set $f \leftarrow f + f_k(x_j - \alpha_j)^k$ and $g \leftarrow g + g_k(x_j - \alpha_j)^k$.

Set $error := a - fg$

If $error = 0$ output (f, g) else output FAIL.

Implemented in Magma, Maple, Macsyma, Mathematica and Singular \implies Sage.

Ref: Ch. 6 of [Algorithms for Computer Algebra](#), Geddes, Czapora, and Labahn, 1992.

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- (i) $a(x_1, \dots, x_{j-1}, \alpha_j) = f_0 g_0$ and
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I noticed that often over 90% of the time was solving MDPs.

Wang's Multivariate Diophantine Solver

Input $A, B, C \in \mathbb{Z}_p[x_1, \dots, x_n]$ and $\alpha = (\alpha_2, \dots, \alpha_n)$

Output $\sigma, \tau \in \mathbb{Z}_p[x_1, \dots, x_n]$ satisfying

$$\sigma A + \tau B = C \text{ with } \deg(\sigma, x_1) < \deg(B, x_1)$$

- 1 If $n = 1$ solve $\sigma A + \tau B = C$ using the Euclidean algorithm in $\mathbb{Z}_p[x_1]$.
- 2 $(\sigma_0, \tau_0) := \text{MultiDioLift}(A(x_n = \alpha_n), B(x_n = \alpha_n), C(x_n = \alpha_n), \alpha)$

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- 3 Initialize: $(\sigma, \tau) := (\sigma_0, \tau_0)$ $error := C - \sigma A - \tau B$
- 4 For $k = 1, 2, \dots$ while $error \neq 0$ do
 - $c_k := \text{coeff}(error, (x_n - \alpha_n)^k)$
 - If $c_k \neq 0$ then
 - Solve the MDP $\sigma_k \tau_0 + \tau_k \sigma_0 = c_k$ in $\mathbb{Z}_p[x_1, \dots, x_{n-1}]$.
 - $\sigma_k, \tau_k := \text{MultiDioLift}(\sigma_0, \tau_0, c_k, \alpha)$
 - $\sigma := \sigma + \sigma_k(x_n - \alpha_n)^k$; $\tau := \tau + \tau_k(x_n - \alpha_n)^k$
 - $error := error - \sigma_k(x_n - \alpha_n)^k A - \tau_k(x_n - \alpha_n)^k B$
- 5 output (σ, τ) .

Wang's Multivariate Diophantine Solver

Input $A, B, C \in \mathbb{Z}_p[x_1, \dots, x_n]$ and $\alpha = (\alpha_2, \dots, \alpha_n)$

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4 For $k = 1, 2, \dots$ while $error \neq 0$ do

$$c_k := \text{coeff}(error, (x_n - \alpha_n)^k)$$

if $c_k \neq 0$ then

$$\text{Solve the MDP } \sigma_k \tau_0 + \tau_k \sigma_0 = c_k \text{ in } \mathbb{Z}_p[x_1, \dots, x_{n-1}].$$

$$\sigma_k, \tau_k := \text{MultiDioLift}(\sigma_0, \tau_0, c_k, \alpha)$$

$$\sigma := \sigma + \sigma_k (x_n - \alpha_n)^k; \tau := \tau + \tau_k (x_n - \alpha_n)^k$$

$$error := error - \sigma_k (x_n - \alpha_n)^k A - \tau_k (x_n - \alpha_n)^k B$$

5 output (σ, τ) .

Let $M(n)$ count calls to the Euclidean algorithm and $d > \deg(C's, x_i)$.

$$\text{Then } M(1) = 1, M(n) \leq M(n-1) + (d-1)M(n-1) \implies M(n) \leq d^{n-1}.$$

The Taylor Coefficients

$$f = x^3 - xyz^2 + y^3z^2 + z^4 - 2$$

$$\text{Consider } f = f_0 + f_1(z - \alpha_3) + f_2(z - \alpha_3)^2 + f_3(z - \alpha_3)^3 + f_4(z - \alpha_3)^4.$$

$$\text{If } \alpha_3 = 0 \text{ then } f(z) = \underbrace{(x^3 - 2)}_{f_0} + \underbrace{(y^3 - xy)}_{f_2} z^2 + \underbrace{1}_{f_4} z^4.$$

If $\alpha_3 = 2$ then

$$\begin{aligned} f(z) = & \underbrace{(x^3 + 4y^3 - 4xy + 14)}_{f_0} + \underbrace{(4y^3 - 4xy + 32)}_{f_1}(z - 2) + \\ & \underbrace{(y^3 - xy + 24)}_{f_2}(z - 2)^2 + \underbrace{8}_{f_3}(z - 2)^3 + \underbrace{1}_{f_4}(z - 2)^4 \end{aligned}$$

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Lemma (MT 2016)

If α_j is chosen at random from a sufficiently large set then

$\text{Prob}[\text{supp}(f_0) \supseteq \text{supp}(f_1) \supseteq \cdots \supseteq \text{supp}(f_k)]$ is high

MTSHL : Our Multivariate Diophantine Solver

Solve the MDP $f_k g_0 + g_k f_0 = c_k$ for $f_k, g_k \in \mathbb{Z}_p[x_1, \dots, x_l]$.

1: Let $f_{k-1} = \sum_{i=0}^{df} a_i(x_2, \dots, x_l)x_1^i$. Let $t_i = |\text{supp}(a_i)|$.
Set $f_k = \sum_{i=0}^{df} \left(\sum_{M \in \text{supp}(a_i)} a_{iM} M \right) x_1^i$. Assumes $\text{supp}(f_k) \subseteq \text{supp}(f_{k-1})$.

2: Set $t = \max(t_i)$. Pick $\beta = (\beta_2, \dots, \beta_l) \in \mathbb{Z}_p$, all non-zero, at random.

3: For $1 \leq j \leq t$ solve $\sigma_j g_0(\beta^j) + \tau_j f_0(\beta^j) = c_k(\beta^j)$ for $\sigma_j, \tau_j \in \mathbb{Z}_p[x_1]$.

Needs $\gcd(g_0(\beta^j), f_0(\beta^j)) = 1$ for all $1 \leq j \leq t$.

4: For $1 \leq j < df$ solve the $t_i \times t_i$ shifted Vandermonde linear system
 $\{ \text{coeff}(f_k(\beta^j), x_1^i) = \text{coeff}(\sigma_j, x_1^i) \text{ for } 1 \leq j \leq t_i \}$.

Needs $X(\beta) \neq Y(\beta)$ for each pair (X, Y) in $\text{supp}(a_i)$ for $0 \leq i < df$.

5: Do this also for g_k .

Shifted Transposed Vandermonde Systems

Let $f_k = \sum_{i=0}^{df} \left(\sum_{j=1}^{t_i} a_{ij} M_{ij}(x_2, \dots, x_l) \right) x_1^i$, M_{ij} known, a_{ij} unknown.

Compute $m_{ij} = M_{ij}(\beta)$ for $1 \leq j \leq t_i$ and solve the t_i by t_i linear system $V_i a = b$

$$\begin{bmatrix} m_{i1} & m_{i2} & \cdots & m_{it_i} \\ m_{i1}^2 & m_{i2}^2 & \cdots & m_{it_i}^2 \\ \vdots & \vdots & \vdots & \vdots \\ m_{i1}^{t_i} & m_{i2}^{t_i} & \cdots & m_{it_i}^{t_i} \end{bmatrix} \begin{bmatrix} a_{i1} \\ a_{i2} \\ \vdots \\ a_{it_i} \end{bmatrix} = \begin{bmatrix} b_{i1} \\ b_{i2} \\ \vdots \\ b_{it_i} \end{bmatrix}$$

using [Zip90] in $O(t_i^2)$ time and $O(t_i)$ space and using the factorization

$$V_i = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ m_{i1} & m_{i2} & \cdots & m_{it_i} \\ \vdots & \vdots & \vdots & \vdots \\ m_{i1}^{t_i-1} & m_{i2}^{t_i-1} & \cdots & m_{it_i}^{t_i-1} \end{bmatrix} \begin{bmatrix} m_{i1} & 0 & \cdots & 0 \\ 0 & m_{i2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & m_{it_i} \end{bmatrix}$$

The matrix V_i is invertible iff $m_{ij} \neq m_{ik}$ and $m_{ij} \neq 0$.

The Schwartz-Zippel Lemma

$$\text{Let } L = \begin{bmatrix} 1 & k & k & k \\ s & 1 & 0 & 0 \\ 0 & s & 1 & 0 \\ 0 & 0 & s & sk \end{bmatrix} \text{ and } f = \det(L) = sk(s-1)(ks-s-1)$$

If we pick α, β from a finite set S e.g. \mathbb{F}_9 , what is $\text{Prob}[f(\alpha, \beta) = 0]$?

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Lemma (Schwartz-Zippel, 1979)

See wikipedia for a proof.

Let f be a non-zero polynomial in $F[x_1, \dots, x_n]$ where F is a field e.g. \mathbb{Q} or \mathbb{F}_q .

If $\alpha_1, \dots, \alpha_n$ are chosen at random from $S \subset F$ then

$$\text{Prob}[f(\alpha_1, \dots, \alpha_n) = 0] \leq \frac{\deg f}{|S|}.$$

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$$\text{Prob}[f(\alpha_1, \dots, \alpha_n) = 0] \leq \frac{\deg f}{|S|}.$$

Note: $\deg(\det L) \leq 1 + 1 + 1 + 2 = 5$ so the SZ bound is **$5/9 = 45/81$** .

Monomial evaluations

Let $f_k = \sum_{i=0}^{df} \left(\sum_{j=1}^{t_i} a_{ij} M_{ij}(x_2, \dots, x_l) \right) x_1^i$.

2: Pick $\beta = (\beta_2, \dots, \beta_l) \in \mathbb{Z}_p$, **all non-zero**, at random.

Compute $S_i = \{m_{ij} = M_{ij}(\beta) : 1 \leq j \leq t_i\}$ for $1 \leq i \leq df$.

We need distinct monomial evaluations m_{ij} for each S_i , equivalently, $|S_i| = t_i$.

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Let $R_i(x_2, \dots, x_l) = \prod_{1 \leq j < k \leq t_i} (M_{ij} - M_{ik})$ for $1 \leq i \leq df$.

$$\text{Prob}[|S_i| < t_i] = \text{Prob}[R_i(\beta) = 0]$$

Monomial evaluations

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Let $R_i(x_2, \dots, x_l) = \prod_{1 \leq j < k \leq t_i} (M_{ij} - M_{ik})$ for $1 \leq i \leq df$.

$$\begin{aligned} \text{Prob}[|S_i| < t_i] &= \text{Prob}[R_i(\beta) = 0] \\ &\leq \frac{\deg R_i}{p-1} \quad \text{by Schwartz - Zippel} \\ &\leq \frac{\binom{t_i}{2} \deg f_k}{p-1}. \end{aligned}$$

Benchmark 1

$n/d/T$	Wang (MDP)	Kaltofen (MDP)	MTSHL (MDP)
4/35/100	13.07 (11.95)	1.75 (1.18)	1.51 (0.24)
5/35/100	88.10 (86.28)	3.75 (2.57)	1.16 (0.36)
7/35/100	800.0 (797.0)	5.04 (4.08)	1.58 (0.59)
9/35/100	4451.6 (4449.4)	8.13 (6.22)	2.94 (0.56)
4/35/500	33.96 (26.48)	642.2 (635.1)	11.29 (0.82)
5/35/500	472.1 (402.5)	1916.2 (1899.6)	26.0 (4.86)
7/35/500	3870.5 (3842.2)	2329.4 (2305.5)	43.1 (6.84)
9/35/500	> 60000	3866.3 (3805.9)	79.6 (9.71)

- > $M := \text{product}(x_i, i = 2..n);$
- > $f := x_1^d + M \text{randpoly}([x_1, \dots, x_n], \text{terms} = T - 1, \text{degree} = d);$
- > $g := x_1^d + \text{randpoly}([x_1, \dots, x_n], \text{terms} = T - 1, \text{degree} = d);$

M forces the evaluation points $x_2 \neq 0, \dots, x_n \neq 0$.

Kaltofen, E., Sparse Hensel lifting. Proceedings of EUROCAL '85, LNCS 204, pp. 4–17, 1985.

Factoring the determinants of Cyclic matrices.

Let C_n denote the $n \times n$ cyclic matrix below.

$$C_n = \begin{bmatrix} x_1 & x_2 & \dots & x_{n-1} & x_n \\ x_n & x_1 & \dots & x_{n-2} & x_{n-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_3 & x_4 & \dots & x_1 & x_2 \\ x_2 & x_3 & \dots & x_n & x_1 \end{bmatrix}$$

The determinant of C_n is a homogeneous polynomial in n variables. It has dense factors – not suited to MTSHL.

Example

$$\det C_4 = (x_4 + x_3 + x_1 + x_2)(x_4 - x_3 - x_1 + x_2) \\ (x_1^2 - 2x_1x_3 + x_2^2 - 2x_2x_4 + x_3^2 + x_4^2)$$

Benchmark 2

n	$\#d_n$	$\#f_{\max}$	Maple	(MDP)	MTSHL	Magma	Singular
7	246	924	0.045	90%	0.026	0.01	0.02
8	810	86	0.059	46%	0.063	0.07	0.06
9	2704	1005	0.225	74%	0.120	0.74	0.24
10	7492	715	0.853	62%	0.500	8.44	2.02
11	32066	184756	7.160	91%	0.945	104.3	11.39
12	86500	621	19.76	76%	5.121	7575.1	30.27
13	400024	2704156	263.4	92%	27.69	30871.9	??
14	1366500	27132	1664.4	77%	523.07	$> 10^6$	288463.2
15	4614524	303645	18432.	82%	7496.9	–	–

Table: Factorization timings (seconds) for $\det C_n$ evaluated at $x_n = 1$

Notes: ?? = I cannot compute $\det(C_n)$ nor read in $\det(C_n)$ nor it's factors.

$a_j(x_1, x_2, \dots, x_j)$
 $f_{j-1}(x_1, x_2, \dots, x_{j-1})$
 evaluate x_3, \dots, x_{j-1} for $1 \leq k \leq s$

\downarrow
 $a_j(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

$f_{j-1}(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k)$
 evaluate x_2 for $1 \leq l \leq \deg(a_j, x_2)$

\downarrow
 $a_j(x_1, \gamma_m, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

$f_{j-1}(x_1, \gamma_m, \beta_3^k, \dots, \beta_{j-1}^k)$

Hensel
 lift x_j

\longrightarrow

$f_j(x_1, x_2, x_3, \dots, x_j)$
 $g_j(x_1, x_2, x_3, \dots, x_j)$

\uparrow

interpolate x_3, \dots, x_{j-1}
 $f_j(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

$g_j(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

\uparrow

dense interpolate x_2

$f_j(x_1, \gamma_m, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

Hensel
 lift x_j

\longrightarrow

$g_j(x_1, \gamma_m, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

$a_j(x_1, x_2, \dots, x_j)$
 $f_{j-1}(x_1, x_2, \dots, x_{j-1})$
 evaluate x_3, \dots, x_{j-1} for $1 \leq k \leq s$

\downarrow
 $a_j(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

$f_{j-1}(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k)$
 evaluate x_2 for $1 \leq l \leq \deg(a_j, x_2)$

\downarrow
 $a_j(x_1, \gamma_m, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

$f_{j-1}(x_1, \gamma_m, \beta_3^k, \dots, \beta_{j-1}^k)$

Hensel
 lift x_j

\longrightarrow

$f_j(x_1, x_2, x_3, \dots, x_j)$
 $g_j(x_1, x_2, x_3, \dots, x_j)$

\uparrow

interpolate x_3, \dots, x_{j-1}
 $f_j(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

$g_j(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

\uparrow

dense interpolate x_2

$f_j(x_1, \gamma_m, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

Hensel
 lift x_j

\longrightarrow

$g_j(x_1, \gamma_m, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$

Parallelized evaluations $a(x_1, x_2, \beta_3^k, \dots, \beta_{j-1}^k, x_j)$ using Cilk C
 Do evaluations $x_2 = \gamma_m$ and **bivariate Hensel lifts** in parallel.
 Optimize the bivariate Hensel lifts in $\mathbb{Z}_p[x_1, x_j] \bmod (x_j - \alpha_j)^k$.

Parallel Benchmark 1

On a server with 2 Intel Xeon E2660 8 core CPUs – 2.2 GHz(base) – 3.0 GHz(turbo)

n	d	t	Maple 2018		New times (1 core)			New times (16 cores)		
			best	worst	total	(hensel)	(eval)	total	(hensel)	(eval)
6	7	500	0.411	28.84	0.098	(0.015)	(0.042)	0.074	(0.019)	(0.008 – 5.2x)
6	7	1000	1.140	58.46	0.414	(0.025)	(0.247)	0.180	(0.027)	(0.030 – 8.2x)
6	7	2000	3.066	99.88	1.593	(0.041)	(1.132)	0.285	(0.042)	(0.121 – 9.4x)
6	7	4000	7.173	162.49	5.072	(0.069)	(4.070)	0.814	(0.074)	(0.380 – 10.7x)
9	7	500	1.171	7564.9	0.105	(0.013)	(0.040)	0.101	(0.024)	(0.010 – 4.0x)
9	7	1000	3.704	10010.4	0.524	(0.025)	(0.297)	0.233	(0.026)	(0.030 – 11.4x)
9	7	2000	13.43	NA	2.838	(0.042)	(1.973)	0.483	(0.045)	(0.193 – 10.2x)
9	7	4000	51.77	NA	18.35	(0.078)	(14.84)	2.325	(0.083)	(1.350 – 11.0x)

Table 1: Timings (real time in seconds) for Hensel lift of x_n .

Legend: $n = \#$ variables, $d = \deg(f, x_j) = \deg(g, x_j)$, $t = \#f = \#g$.

Parallel Benchmark 2

n	d	t	Maple 2018		New time (1 core)			New time (16 cores)		
			best	worst	total	(hensel)	(eval)	total	(hensel)	(eval)
6	15	500	0.751	7956.5	0.134	(0.070)	(0.016)	0.093	(0.034 – 2.1x)	(0.006)
6	20	500	0.919	48610.1	0.238	(0.168)	(0.017)	0.130	(0.065 – 2.6x)	(0.005)
6	40	500	1.615	NA	1.207	(1.128)	(0.015)	0.282	(0.203 – 5.6x)	
6	80	500	4.485	NA	13.76	(13.65)	(0.016)	1.674	(1.554 – 8.8x)	(0.012)
6	15	2000	7.166	23128.5	1.616	(0.221)	(0.706)	0.413	(0.107 – 2.1x)	(0.061)
6	20	2000	9.195	NA	1.635	(0.451)	(0.480)	0.431	(0.150 – 3.0x)	(0.040)
6	40	2000	15.98	NA	4.008	(2.993)	(0.260)	0.854	(0.505 – 5.9x)	(0.038)
6	80	2000	57.33	NA	26.34	(25.25)	(0.217)	3.340	(2.839 – 8.9x)	(0.050)

Table 2: Timings (real time in seconds) for increasing degree d .

Legend: $n = \#$ variables, $d = \deg(f, x_j) = \deg(g, x_j)$, $t = \#f = \#g$.

Concluding Remarks

Baris has installed the new MTSHL code into Maple for Maple 2019. This was done under a MITACS internship with Maplesoft.



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