

# Early Termination in Ben-Or/Tiwari Sparse Interpolation and a Hybrid of Zippel's Algorithm

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Joint work with

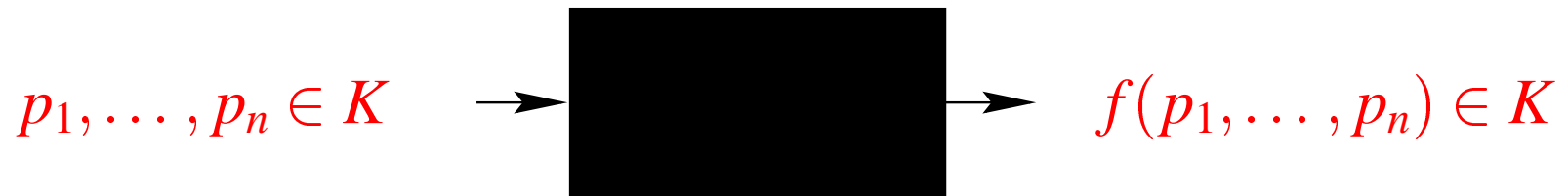
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## Objective

## Black box polynomial interpolation

Black box polynomial  $f$



Interpolation

$$f(x_1, \dots, x_n) \in K[x_1, \dots, x_n]$$

## Question

What if  $f(x_1, \dots, x_n)$  is sparse?

## Previous Research 1 An algorithm sensitive to the sparsity of the target polynomial

Zippel's probabilistic interpolation (1979).

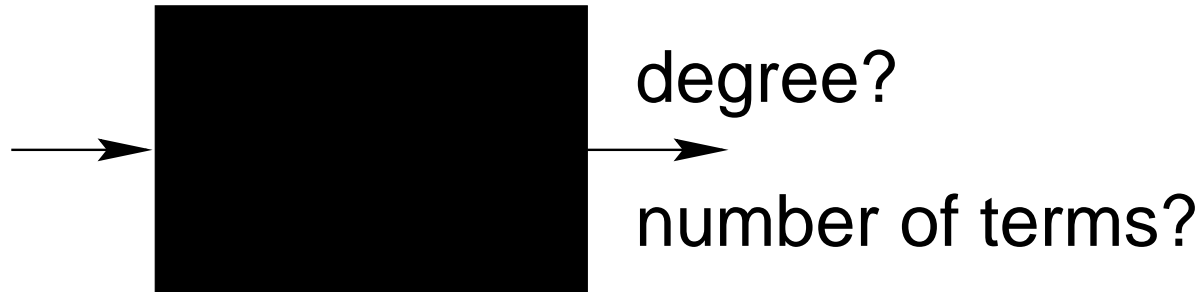
- ☹ Interpolate variable by variable.
- 😊 Sensitive to the sparsity after each variable is interpolated.
- 😊 Sensitive to the degree bound in every variable.
- ☹ Still interpolates each variable densely.
- ☹ Might falsely drop non-zero coefficients.
- ☹ Needs an upper bound of the degree in each variable.
- 😊 Does not need a large modulus for the recovery of polynomial terms.  $O(\max_i \deg(f(x_i)))$

## Previous Research 2 | Another algorithm sensitive to the sparsity of the target polynomial

Ben-Or's/Tiwari's deterministic algorithm.

- ☹ Interpolate all the variables at once.
- 😊 Sensitive to the sparsity of the terms in the target polynomial.
- 😊 A deterministic algorithm that always interpolates correctly.
- ☹ Needs an upper bound of the number of terms.
- ☹ Might need a very large modulus for the recovery of polynomial terms.  $O(\max_{\mathbf{e}} p_1^{e_1} \cdots p_n^{e_n})$ ,  $p_i$  the  $i$ -th prime,  $e_i = \deg(f(x_i))$ .

## Idea # 1 Early termination



What if *an upper bound of degree* and *an upper bound of the number of terms* of the target polynomial are *not known*?

- Guess and check.

And double the guess if fails.

- ***Early termination.***

Interpolate the polynomial at a random point, when the polynomial stops changing, it is done with high probability.

## Why early termination?

- Save time and space.
- A useful tool for controlling intermediate expression swell in computer algebra.
- Sensitive to the sparsity of the target polynomial without knowing any bounds on degree or number of terms.

## Early termination in Newton interpolation

*For  $i \leftarrow 1, 2, \dots$  Do*

*Pick random  $p_i$  and from  $f(p_i)$*

*compute*

$$\begin{aligned} f^{[i]}(x) &\leftarrow c_0 + c_1(x - p_1) + c_2(x - p_1)(x - p_2) + \dots \\ &\equiv f(x) \pmod{(x - p_1) \cdots (x - p_i)} \end{aligned}$$

*If  $c_i = 0$  stop.*

*End For*

### Threshold $\eta$

In order to obtain a better probability, we require  $c_i = 0$  more than once before terminating.

## Analysis with thresholds

Let  $p_0, p_1, p_2, \dots$  be chosen randomly and uniformly from a subset  $S$  of the domain of values, and  $f^{[i]}$  denote the interpolation polynomial that interpolates  $f(p_0), \dots, f(p_i)$ .

If  $f^{[d]} = f^{[d+1]} = \dots = f^{[d+\eta]}$ , then  $f^{[d]}$  correctly interpolates  $f$  with probability at least

$$1 - (d + 1) \left( \frac{\deg(f)}{\#(S)} \right)^\eta.$$



## Early termination of Ben-Or/Tiwari

If  $p_1, \dots, p_n$  are chosen randomly and uniformly from a subset  $S$  of the domain of values, then for the sequence

$$a_i = f(p_1^i, \dots, p_n^i), i = 1, 2, \dots$$

the Berlekamp/Massey algorithm encounters  $\Delta = 0$  and  $2L < r$  the first time for  $r = 2t + 1$  with probability no less than

$$1 - \frac{t(t+1)(2t+1) \deg(f)}{6 \cdot \#(S)},$$

where  $t$  is the number of terms of  $f$ .

## Threshold $\zeta$

In order to obtain a better probability, we require  $\Delta = 0$  ( when  $2L < r$  ) more than once before terminating.

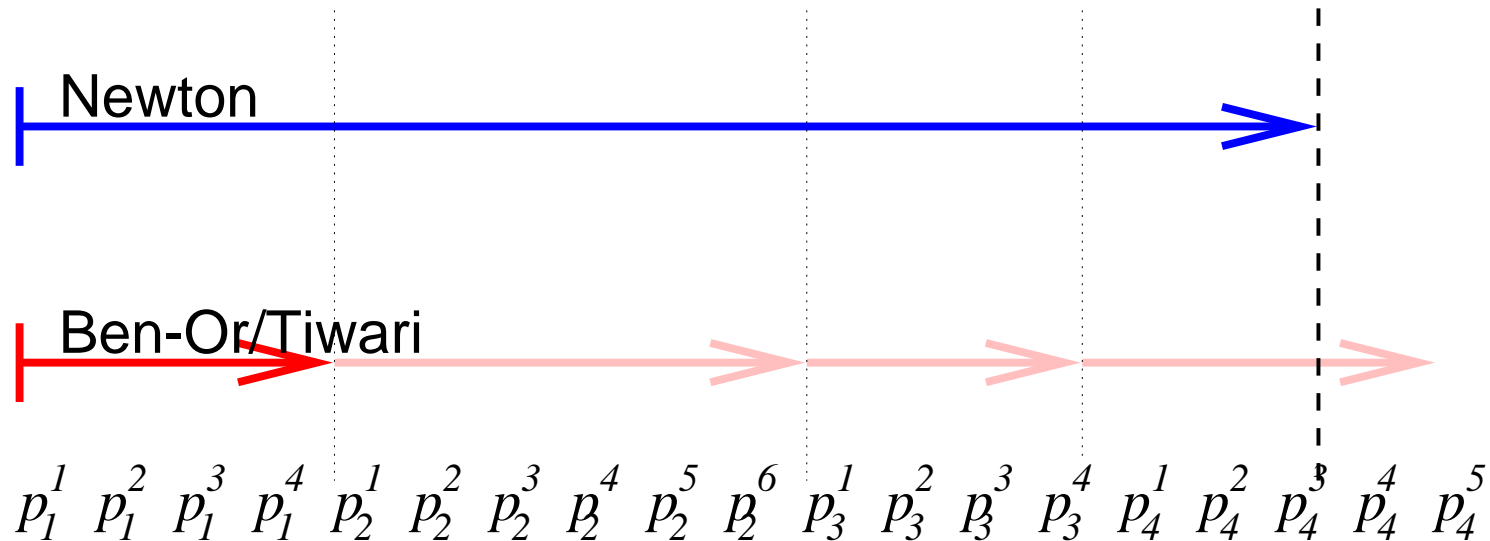
## Idea # 2 Zippel with univariate Ben-Or/Tiwari

Implement Ben-Or/Tiwari on a single variable, and embed it as the univariate interpolation algorithm into Zippel's algorithm.

- ☺ Univariate interpolations within Zippel are now also sparse.
- ☺ Reduce the magnitude of the modulus needed for the recovery of all the terms.  $O(\max_{\mathbf{e}} p_1^{e_1} \cdots p_n^{e_n}) \longrightarrow O(\max_{e_i} 2^{e_i})$

## Idea # 3 Racing Newton against Ben-Or/Tiwari

A likely racing scenario in univariate interpolations.



We embed this “racing” algorithm into Zippel’s algorithm.

## Why Racing?

- Terminate earlier when there are few terms.  
( Ben-Or/Tiwari )
- Newton outraces Ben-Or/Tiwari, e.g., in the dense case.  
( Newton )
- Algorithms can cross check their results.  
( Ben-Or/Tiwari + Newton )

## Implementation | *protobox* package

The *protobox* package is our Maple V.5.1 implementation of this new hybrid algorithm.

# Minimum black box probes needed under different embedded univariate interpolations in *protobox*

	mod	Newton	Ben-Or/Tiwari	“Racing”
$f_1$	100003	147	137	126
$f_2$	100003	146	143	124
$f_3$	100003	209	143	133
$f_4$	100003	188	149	133
$f_5$	100000007 <sup>†</sup>	2652	251	251
$f_6$	100000007 <sup>†</sup>	965	1256	881
$f_7$	100003	94	46	41

<sup>†</sup> This is tested in Maple 6

# Throughputs under different modulus and thresholds

$$f_1 = x_1^2 x_3^3 x_4 x_6 x_8 x_9^2 + x_1 x_2 x_3 x_4^2 x_5^2 x_8 x_9 + x_2 x_3 x_4 x_5^2 x_8 x_9 + x_1 x_3^3 x_4^2 x_5^2 x_6^2 x_7 x_8^2 + x_2 x_3 x_4 x_5^2 x_6 x_7 x_8^2$$

$$f_2 = x_1 x_2^2 x_4^2 x_8 x_9^2 x_{10}^2 + x_2^2 x_4 x_5^2 x_6 x_7 x_9 x_{10}^2 + x_1^2 x_2 x_3 x_5^2 x_7^2 x_9^2 + x_1 x_3^2 x_4^2 x_7^2 x_9^2 + x_1^2 x_3 x_4 x_7^2 x_8^2$$

$$f_3 = 9x_2^3 x_3^3 x_5^2 x_6^2 x_8^3 x_9^3 + 9x_1^3 x_2^2 x_3^3 x_5^2 x_7^2 x_8^2 x_9^3 + x_1^4 x_3^4 x_4^2 x_5^4 x_6^4 x_7 x_8^5 x_9 + 10x_1^4 x_2 x_3^4 x_4^4 x_5^4 x_7 x_8^3 x_9 + 12x_2^3 x_4^3 x_6^3 x_7^2 x_8^3$$

$$f_4 = 9x_1^2 x_3 x_4 x_6^3 x_7^2 x_8 x_{10}^4 + 17x_1^3 x_2 x_5^2 x_6^2 x_7 x_8^3 x_9^4 x_{10}^3 + 17x_2^2 x_3^4 x_4^2 x_7^3 x_8^3 x_9 x_{10}^3 + 3x_1^3 x_2^2 x_6^3 x_{10}^2 + 10x_1 x_3 x_5^2 x_6^2 x_7^4 x_8^4$$

	Thresholds			mod 31			mod 37			mod 41			mod 43			mod 47			mod 53		
	$\eta, \zeta$	$\tau$	$\kappa, \gamma$	=	$\neq$	!	=	$\neq$	!	=	$\neq$	!	=	$\neq$	!	=	$\neq$	!	=	$\neq$	!
$f_1$	1	0	0	8	2	90	7	1	92	15	3	82	11	5	84	25	3	72	20	2	78
	2	1	2	30	0	70	38	1	61	44	0	56	55	0	45	71	0	29	52	0	48
	3	2	4	38	0	62	36	0	64	50	0	50	60	0	40	79	0	21	70	0	30
$f_2$	1	0	0	4	3	93	4	3	93	5	3	92	7	5	88	22	4	74	23	1	76
	2	1	2	22	0	78	36	0	64	38	0	62	48	1	51	61	0	39	66	0	34
	3	2	4	41	0	59	45	0	55	51	0	49	57	0	43	83	0	17	81	0	19
$f_3$	1	0	0	0	2	98	0	6	94	3	3	94	4	0	96	6	5	89	9	1	90
	2	1	2	3	1	96	8	0	92	16	0	84	10	0	90	37	0	63	27	0	73
	3	2	4	9	0	91	8	0	92	26	0	74	15	0	85	52	0	48	54	0	46
$f_4$	1	0	0	1	4	95	0	2	98	4	2	94	8	3	89	18	2	80	5	3	92
	2	1	2	8	0	92	5	0	95	20	0	80	22	0	78	63	0	37	44	0	56
	3	2	4	10	0	90	10	0	90	33	0	67	32	0	68	80	0	20	47	0	53

# Performance on small moduli

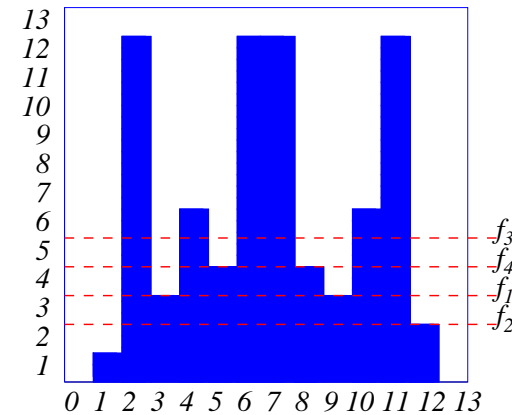
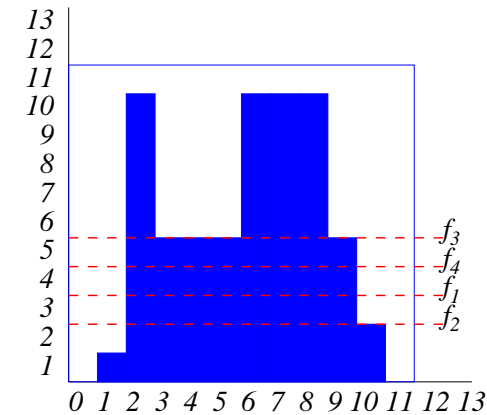
$$f_1 = x_1^2 x_3^3 x_4 x_6 x_8 x_9^2 + x_1 x_2 x_3 x_4^2 x_5^2 x_8 x_9 + x_2 x_3 x_4 x_5^2 x_8 x_9 + x_1 x_3^3 x_4^2 x_5^2 x_6^2 x_7 x_8^2 + x_2 x_3 x_4 x_5^2 x_6 x_7 x_8^2$$

$$f_2 = x_1 x_2^2 x_4^2 x_8 x_9^2 x_{10}^2 + x_2^2 x_4 x_5^2 x_6 x_7 x_9 x_{10}^2 + x_1^2 x_2 x_3 x_5^2 x_7^2 x_9^2 + x_1 x_3^2 x_4^2 x_7^2 x_9^2 + x_1^2 x_3 x_4 x_7^2 x_8^2$$

$$f_3 = 9x_2^3 x_3^3 x_5^2 x_6^2 x_8^3 x_9^3 + 9x_1^3 x_2^2 x_3^3 x_5^2 x_7^2 x_8^2 x_9^3 + x_1^4 x_3^4 x_4^2 x_5^4 x_6^4 x_7 x_8^5 x_9 + 10x_1^4 x_2 x_3^4 x_4^4 x_5^4 x_7 x_8^3 x_9 + 12x_2^3 x_4^3 x_6^3 x_7^2 x_8^3$$

$$f_4 = 9x_1^2 x_3 x_4 x_6^3 x_7^2 x_8 x_{10}^4 + 17x_1^3 x_2 x_5^2 x_6^2 x_7 x_8^3 x_9^4 x_{10}^3 + 17x_2^2 x_3^4 x_4^2 x_7^3 x_8^3 x_9 x_{10}^3 + 3x_1^3 x_2^2 x_6^3 x_{10}^2 + 10x_1 x_3 x_5^2 x_6^2 x_7^4 x_8^4$$

	Thresholds			mod 11			mod 13		
	$\eta, \zeta$	$\tau$	$\kappa, \gamma$	=	$\neq$	!	=	$\neq$	!
$f_1$	2	2	6	28	2	70	28	0	72
Average black box probes: =				151.3928571			196.2142857		
Average black box probes: =, $\neq$				151.1666667			196.2142857		
$f_2$	2	2	6	8	1	91	26	0	74
Average black box probes: =				162.			164.3076923		
Average black box probes: =, $\neq$				161.6666667			164.3076923		
$f_3$	2	2	6	7	1	92	2	0	98
Average black box probes: =				167.2857143			167.		
Average black box probes: =, $\neq$				167.1250000			167.		
$f_4$	2	2	6	5	0	95	0	1	99
Average black box probes: =				170.					
Average black box probes: =, $\neq$				170.			180.		



The order of elements in mod 11

The order of elements in mod 13



For further developments  
see  
[www.wen-shin.com](http://www.wen-shin.com)

## Thresholds

$\eta$ : (default **1**) Newton interpolation threshold.

$\zeta$ : (default **1**) Ben-Or/Tiwari interpolation threshold.

$\tau$ : (default **0**) number of points used for post test.

$\kappa$ : (default **0**) number of random numbers retried before abort the interpolation if two terms map to a same value and cause the interpolation failure.

$\gamma$ : (default **0**) extends the upper bound of each univariate interpolation loop. This regards the delay in updating Newton interpolants.

## Polynomials tested

$$f_1(x_1, \dots, x_{10}) = x_1^2 x_3^3 x_4 x_6 x_8 x_9^2 + x_1 x_2 x_3 x_4^2 x_5^2 x_8 x_9 + x_2 x_3 x_4 x_5^2 x_8 x_9 \\ + x_1 x_3^3 x_4^2 x_5^2 x_6^2 x_7 x_8^2 + x_2 x_3 x_4 x_5^2 x_6 x_7 x_8^2$$

$$f_2(x_1, \dots, x_{10}) = x_1 x_2^2 x_4 x_8 x_9^2 x_{10}^2 + x_2^2 x_4 x_5^2 x_6 x_7 x_9 x_{10}^2 + x_1^2 x_2 x_3 x_5^2 x_7 x_9^2 \\ + x_1 x_3^2 x_4^2 x_7^2 x_9^2 + x_1^2 x_3 x_4 x_7^2 x_8^2$$

$$f_3(x_1, \dots, x_{10}) = 9x_2^3 x_3^3 x_5^2 x_6^2 x_8^3 x_9^3 + 9x_1^3 x_2^2 x_3^3 x_5^2 x_7^2 x_8^2 x_9^3 + x_1^4 x_3^4 x_4^2 x_5^4 x_6^4 x_7 x_8^5 x_9 \\ + 10x_1^4 x_2 x_3^4 x_4^4 x_5^4 x_7 x_8^3 x_9 + 12x_2^3 x_4^3 x_6^3 x_7^2 x_8^3$$

$$f_4(x_1, \dots, x_{10}) = 9x_1^2 x_3 x_4 x_6^3 x_7^2 x_8 x_{10}^4 + 17x_1^3 x_2 x_5^2 x_6^2 x_7 x_8^3 x_9^4 x_{10}^3 \\ + 17x_2^2 x_3^4 x_4^2 x_7^4 x_8^3 x_9 x_{10}^3 + 3x_1^3 x_2^2 x_6^3 x_{10}^2 + 10x_1 x_3 x_5^2 x_6^2 x_7^4 x_8^4$$

$$f_5(x_1, \dots, x_{50}) = \sum_{i=1}^{50} x_i^{50}$$

$$f_6(x_1, \dots, x_5) = \sum_{i=1}^5 (x_1 + x_2 + x_3 + x_4 + x_5)^i$$

$$f_7(x_1, x_2, x_3) = x_1^{20} + 2x_2 + 2x_2^2 + 2x_2^3 + 2x_2^4 + 3x_3^{20}$$