

Relaxed algorithms, p -adic lifting and polynomial system solving*

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BIPOP-CASYS Seminar

Laboratoire Jean Kuntzmann, Grenoble
March 7, 2013

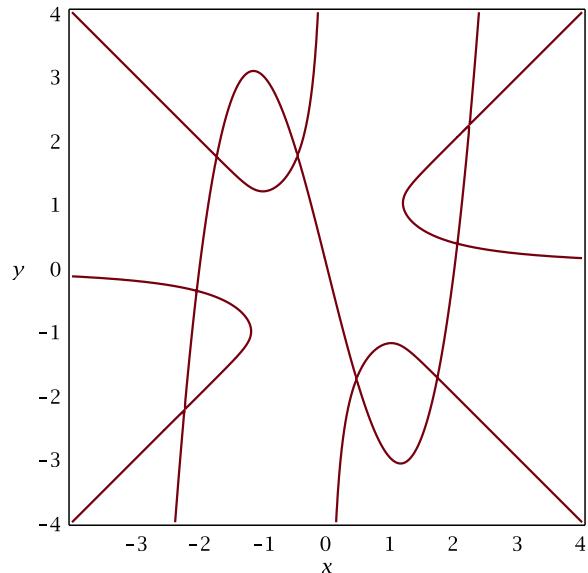
*. This document has been written using the GNU $\text{\TeX}_{\text{MACS}}$ text editor (see www.texmacs.org).

1. Why is p -adic lifting interesting?
2. Relaxed p -adic lifting
 - a. On-line algorithms
 - b. Recursive p -adic
 - c. Application to:
 - i. Linear systems
 - ii. Linear q -differential systems
 - iii. Polynomial root lifting
 - iv. Univariate representation lifting
3. Conclusion

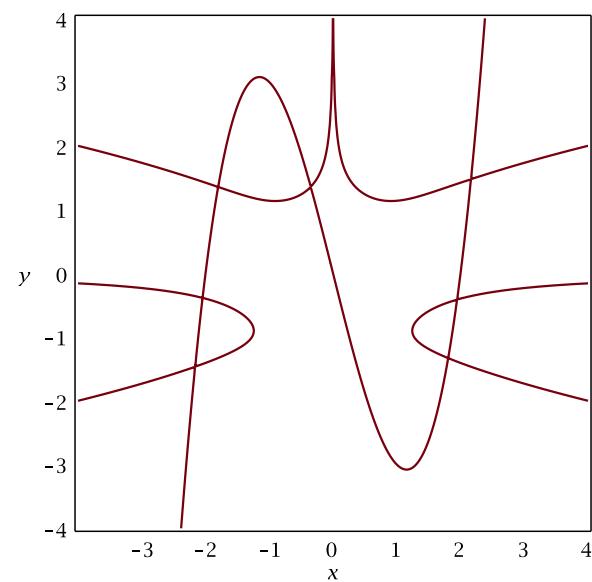
Why modular computation?

$$\begin{aligned}P_1 = & \ x^5 y^8 + (-x^8 + 4x^6)y^7 - x^7 y^6 \\& +(x^{10} - 4x^8)y^5 + y - x^3 + 4x\end{aligned}$$

$$\begin{aligned}P_2 = & \ -x^2 y^8 + (x^5 - 4x^3)y^7 + x^4 y^4 \\& +(-x^7 + 4x^5)y^3 + y - x^3 + 4x\end{aligned}$$



Solutions of $P_1 = 0$



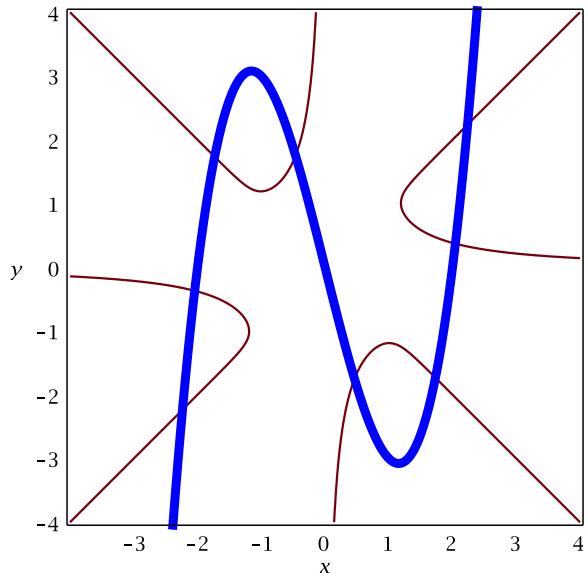
Solutions of $P_2 = 0$

Do they have a curve in common?

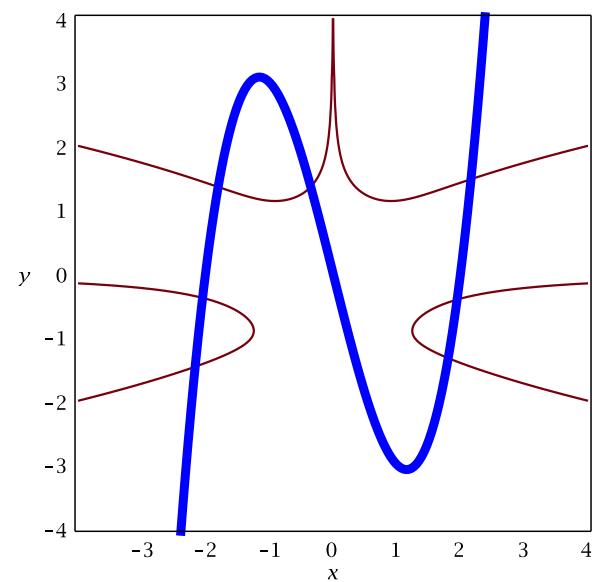
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Solutions of $P_1 = 0$



Solutions of $P_2 = 0$

Do they have a curve in common?

YES !

Why modular computation?

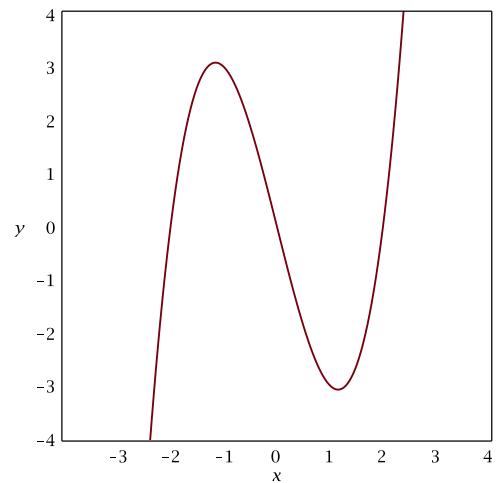
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↓
Euclid's algorithm
(in $\mathbb{Q}(x)[y]$)
↓

$$R = y - x^3 + x$$

Solutions of $R = 0$



Why modular computation?

$$\begin{aligned} P_1 = & \quad x^5 y^8 + (-x^8 + 4x^6)y^7 - x^7 y^6 \\ & +(x^{10} - 4x^8)y^5 + y - x^3 + 4x \end{aligned}$$

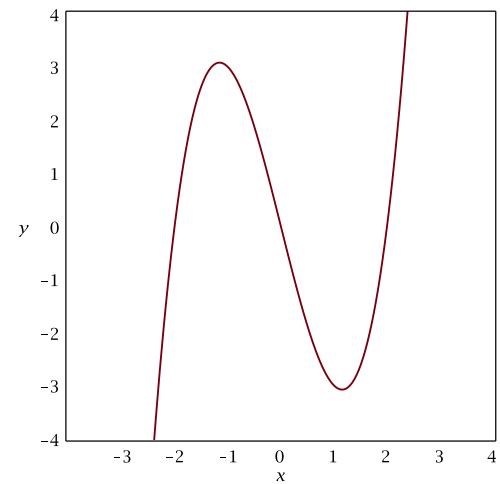
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 Euclid's algorithm
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$$R_1 = y^2 + (-x^{34} + x^{33} + 5x^{32} - 5x^{31} - 5x^{30} + 5x^{29} + x^{28} - x^{27} \\ - 4x^{23} + 4x^{22} + 4x^{21} - 13x^{20} + 10x^{19} + 12x^{18} - 18x^{17} + 2x^{16} \\ + 15x^{15} - 13x^{14} - 11x^{13} + 11x^{12} - 5x^{11} - 11x^{10} + 8x^9 + 2x^8 \\ - 6x^7 + 6x^6 + 4x^5 - 4x^4 + 4x^3 + x^2 - x + 1) / (x^{31} - x^{30} - x^{29} \\ + x^{28} - x^{22} + x^{21} + x^{20} - 3x^{19} + 2x^{18} + 3x^{17} - 4x^{16} + 3x^{14} \\ - 3x^{13} - 3x^{12} + 2x^{11} - 2x^{10} - 2x^9 + x^8 - x^7) y + (x^{32} - x^{31} \\ - 5x^{30} + 5x^{29} + 4x^{28} - 3x^{27} - x^{26} - 5x^{25} + 7x^{24} + 2x^{23} \\ - 14x^{22} + 10x^{21} + 8x^{20} - 9x^{19} + x^{18} + 4x^{17} - 5x^{16} + x^{15} + 3x^{14} \\ - 8x^{13} + 8x^{12} + 12x^{11} - 22x^{10} + 22x^9 + 18x^8 - 28x^7 + \dots)$$

$$R = y - x^3 + x$$

Solutions of $R = 0$

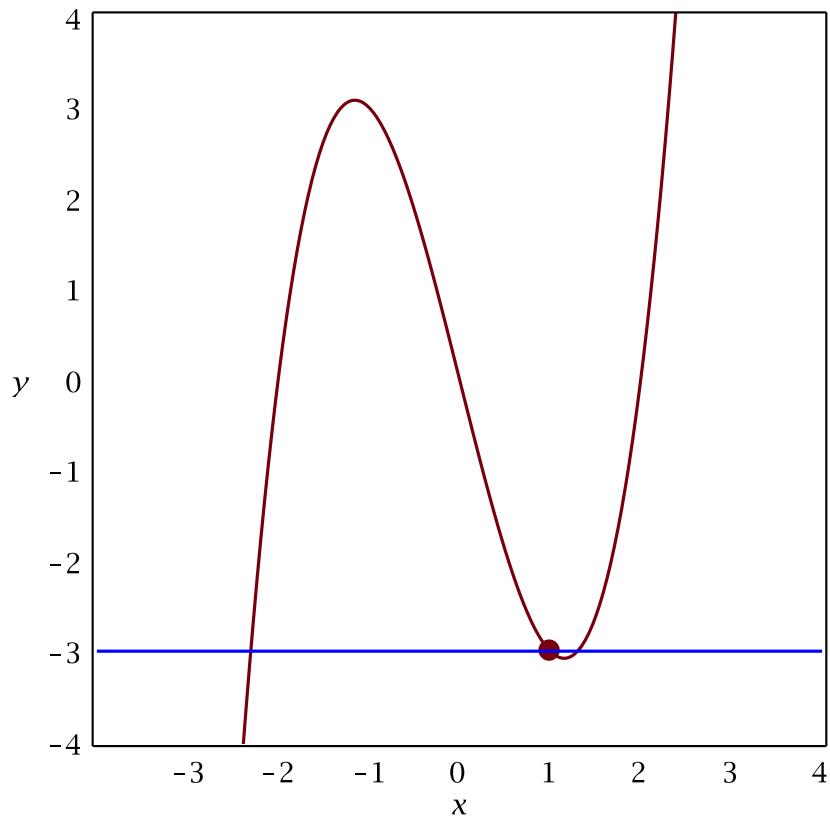


High precision modular computation

Two different approaches:

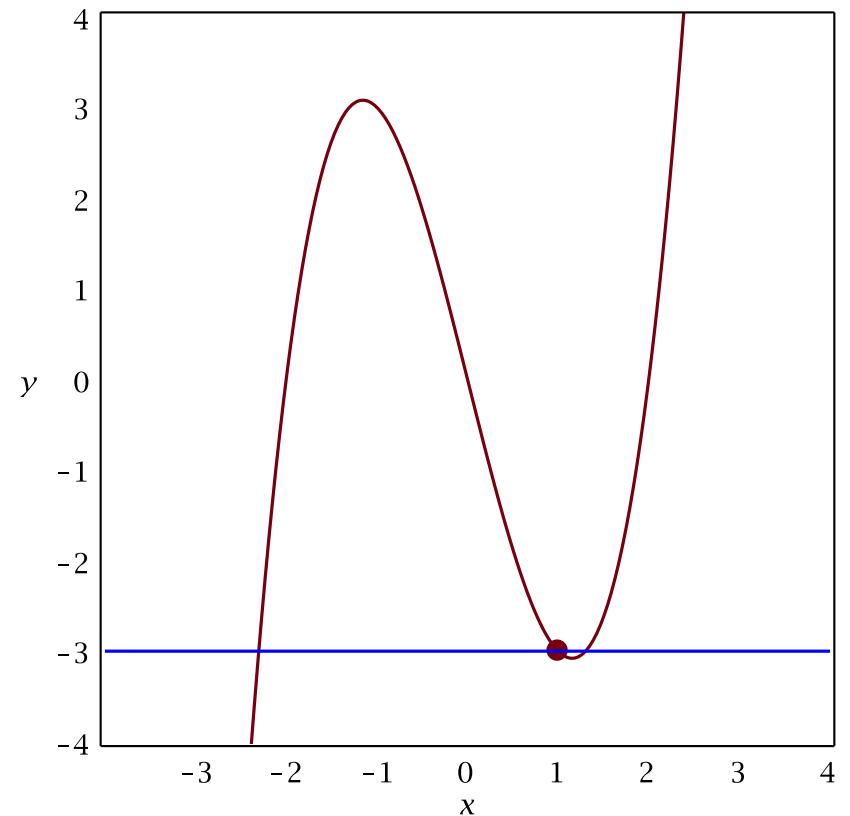
multi-modular lifting

Precision 1



Hensel lifting

Precision 1

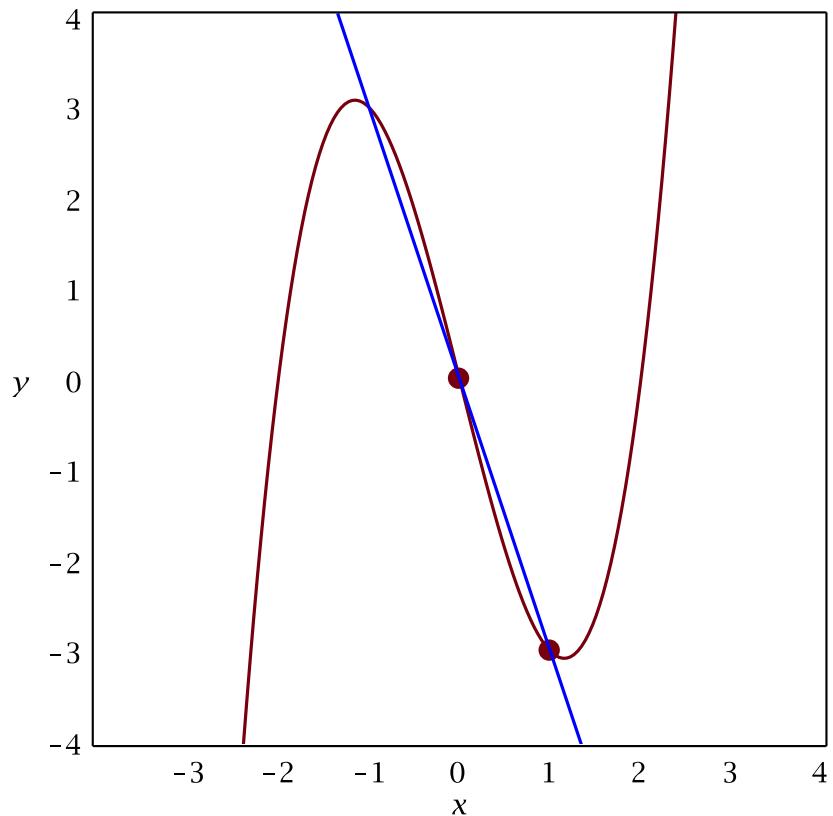


High precision modular computation

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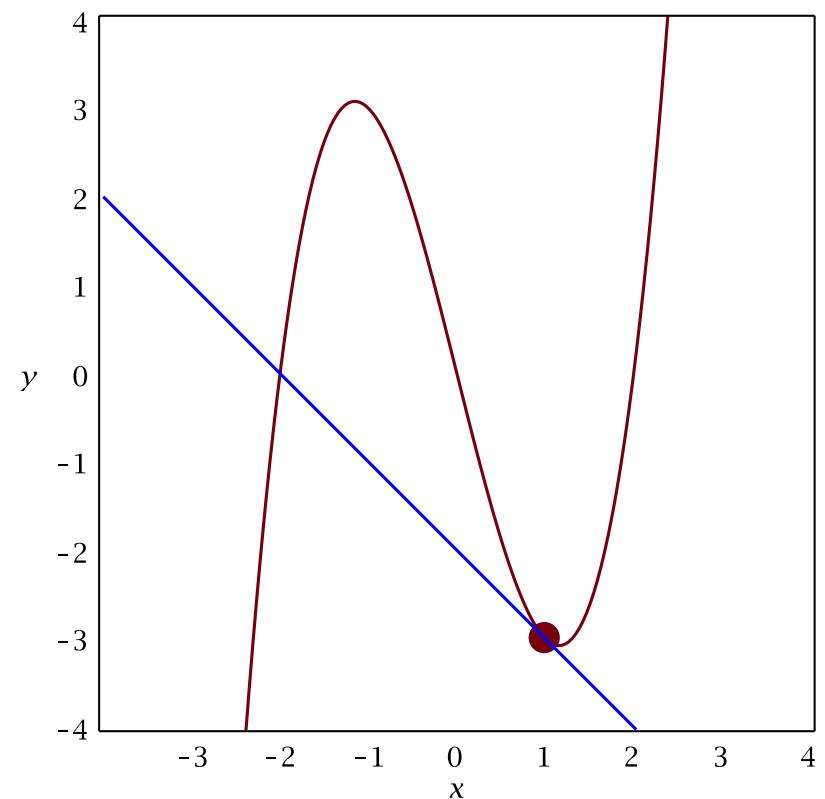
multi-modular lifting

Precision 2



Hensel lifting

Precision 2

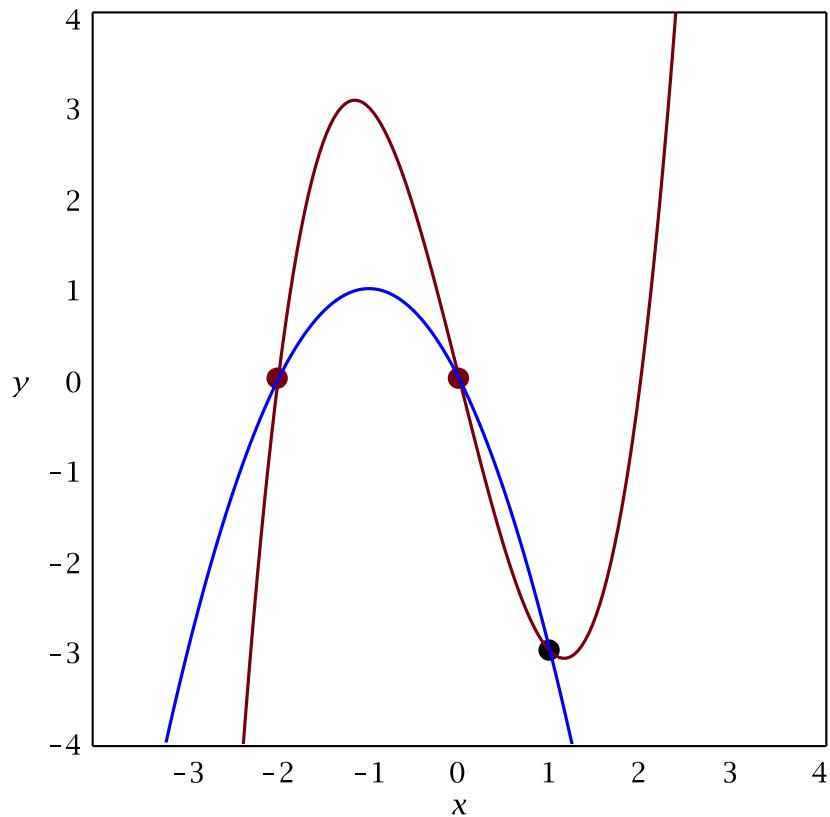


High precision modular computation

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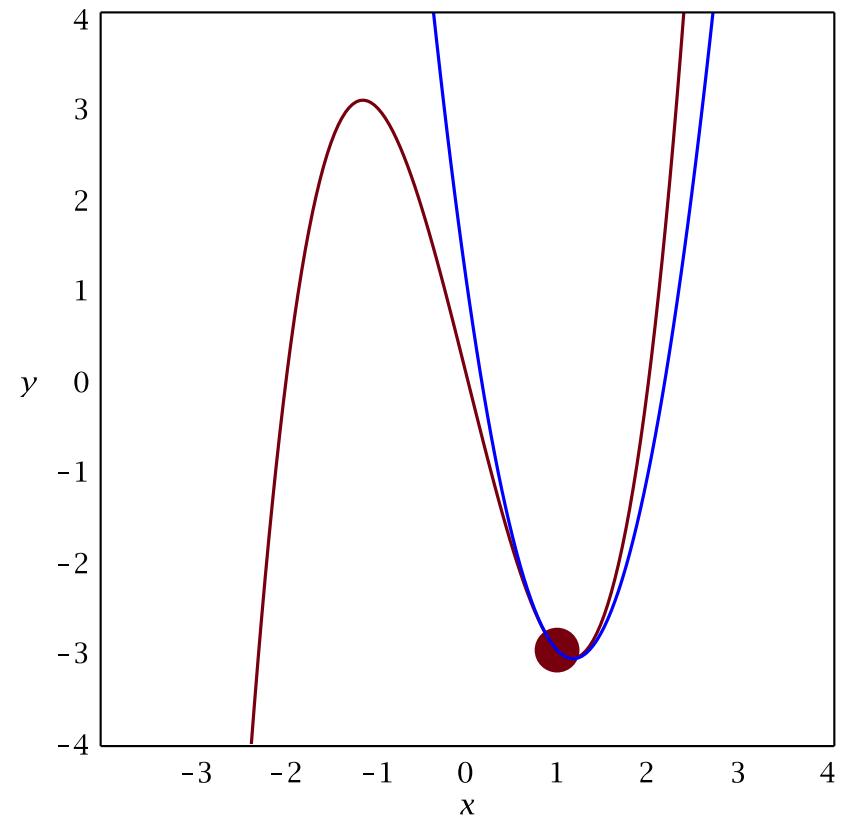
multi-modular lifting

Precision 3



Hensel lifting

Precision 3

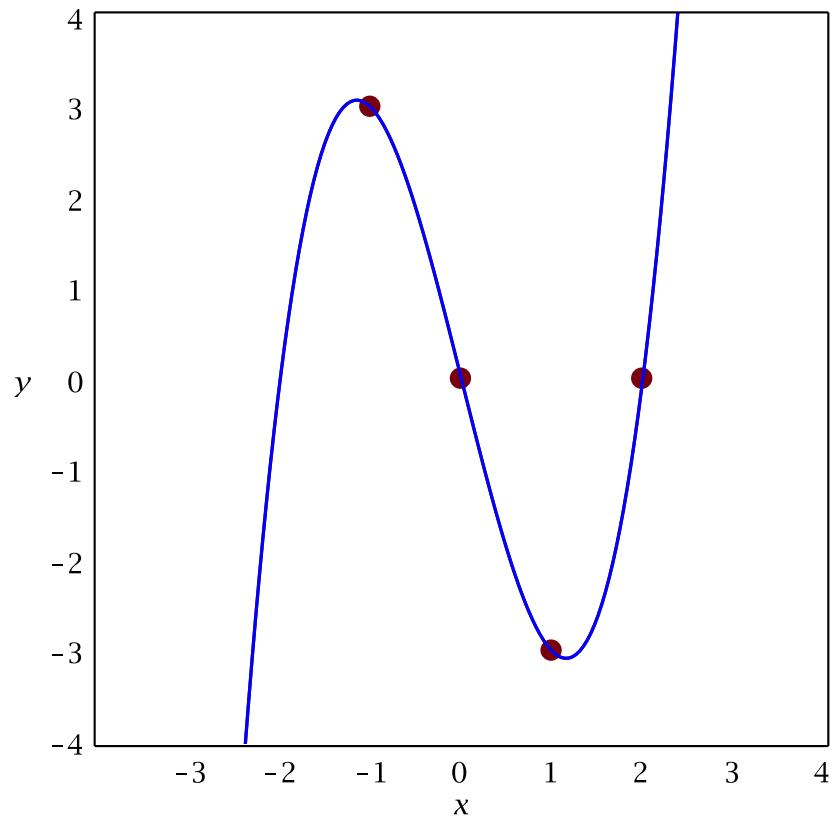


High precision modular computation

Two different approaches:

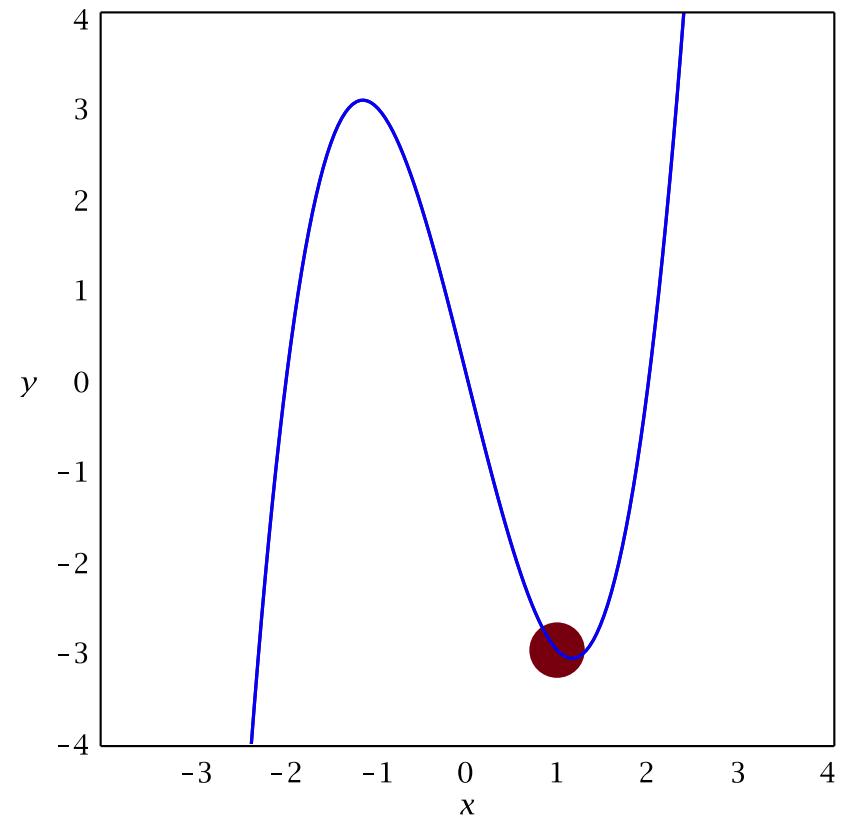
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Precision 4



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Relaxed algorithms

Definition. (*on-line* or *relaxed* algorithm) [HENNIE '66]

$$a = \sum_{i \geq 0} a_i x^i$$

a_0	a_1	a_2	\dots
-------	-------	-------	---------

$$b = \sum_{i \geq 0} b_i x^i$$

b_0	b_1	b_2	\dots
-------	-------	-------	---------

$\downarrow f$

$$c = f(a, b) = \sum_{i \geq 0} c_i x^i$$

c_0			\dots
-------	--	--	---------

 : reading allowed

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Half-line or semi-relaxed algorithm : condition on one input.

Off-line or zealous algorithm : condition not met.

Relaxed algorithms

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a_0	a_1	$\textcolor{blue}{a}_2$	\dots
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b_0	b_1	b_2	\dots
-------	-------	-------	---------

 : reading allowed

$\downarrow f$

$$c = f(a, b) = \sum_{i \geq 0} c_i x^i \quad \boxed{c_0 \mid c_1 \mid \textcolor{red}{c}_2 \mid \dots}$$

Half-line or semi-relaxed algorithm : condition on one input.

Off-line or zealous algorithm : condition not met.

Example.

- The naive addition algorithm is on-line:

`for i from 0 to N do $c_i := a_i + b_i$`

- The naive multiplication algorithm is on-line:

`for i from 0 to N do $c_i := a_i b_0 + a_{i-1} b_1 + \dots + a_0 b_i$`

Challenge. Find a *quasi-optimal on-line* multiplication algorithm

Relaxed multiplication $c = a \times b$ - step 0

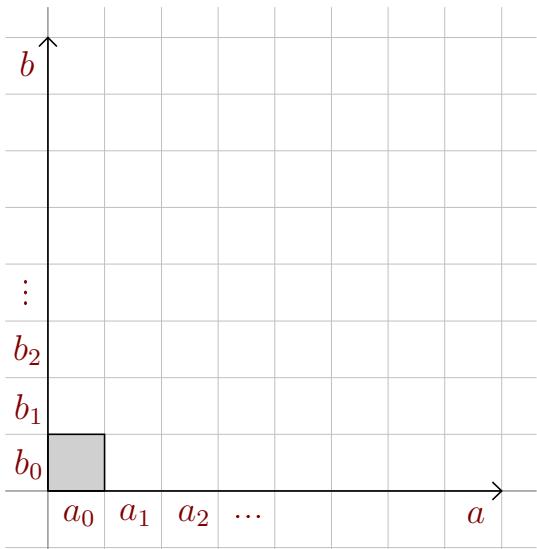


Figure. What we must compute

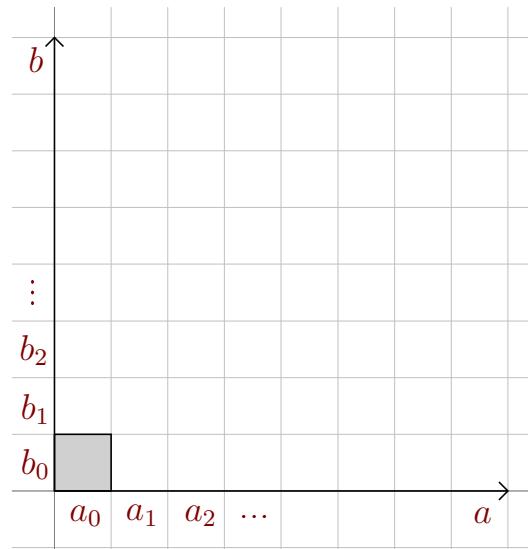


Figure. Minimum knowledge on the input



Figure. What we compute

$$\text{step 0: } c = a_0 b_0$$

Relaxed multiplication $c = a \times b$ - step 1

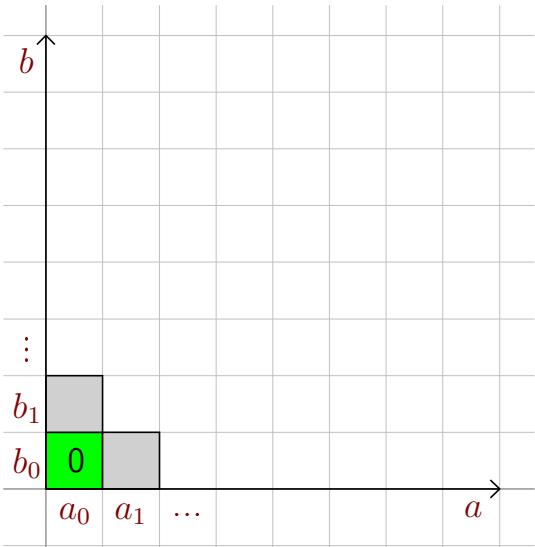


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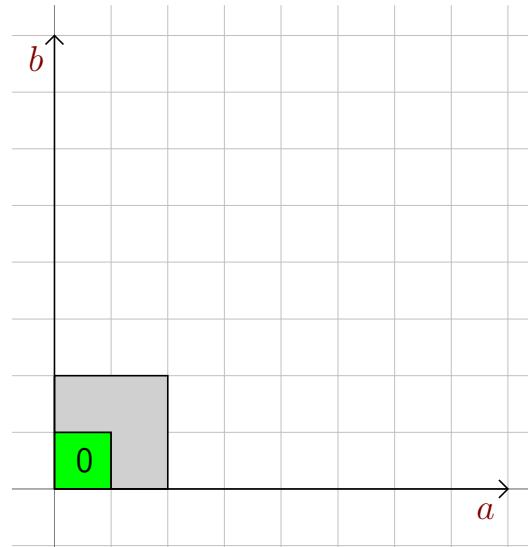


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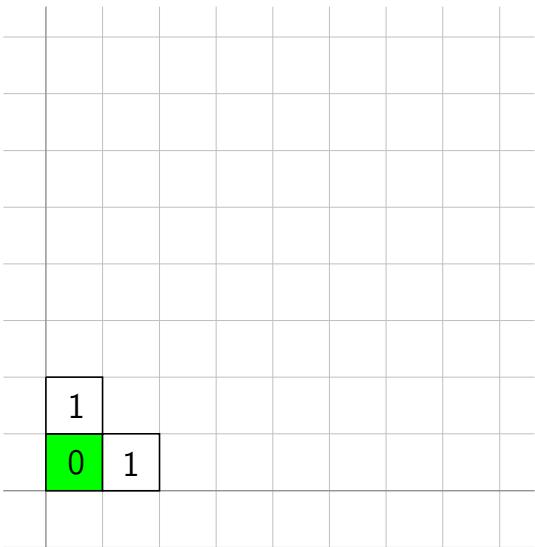


Figure. What we compute

step 0: $c = a_0 b_0$
step 1: $c += z (a_0 b_1 + a_1 b_0)$

Relaxed multiplication $c = a \times b$ - step 2

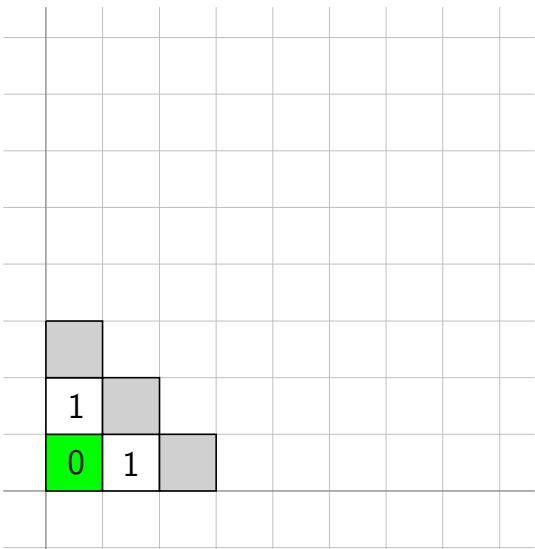


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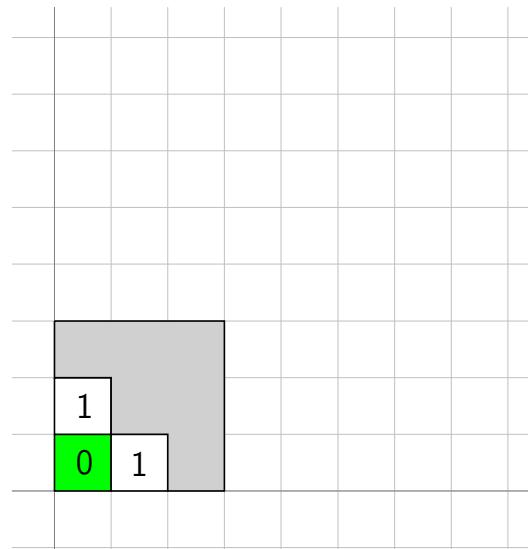


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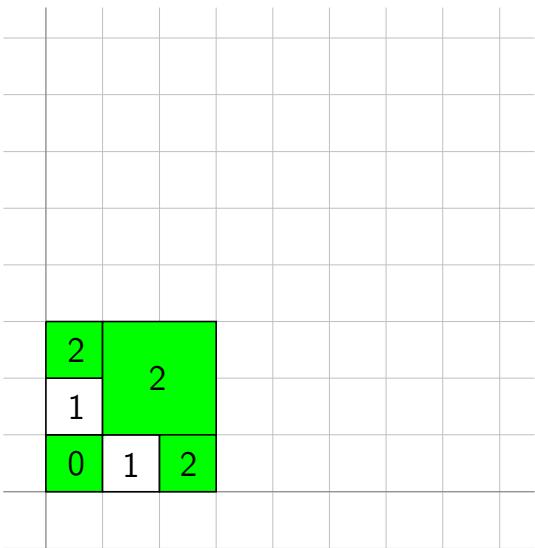


Figure. What we compute

step 0: $c = a_0 b_0$
step 1: $c += z (a_0 b_1 + a_1 b_0)$
step 2: $c += z^2 (a_0 b_2 + a_2 b_0 + (a_1 + a_2) z) (b_1 + b_2 z)$

Relaxed multiplication $c = a \times b$ - step 3

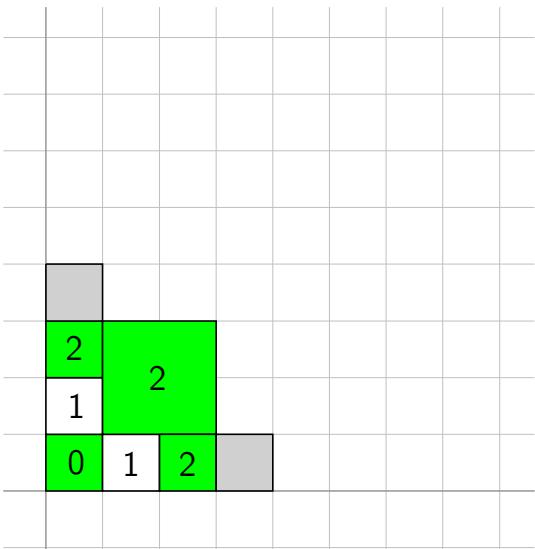


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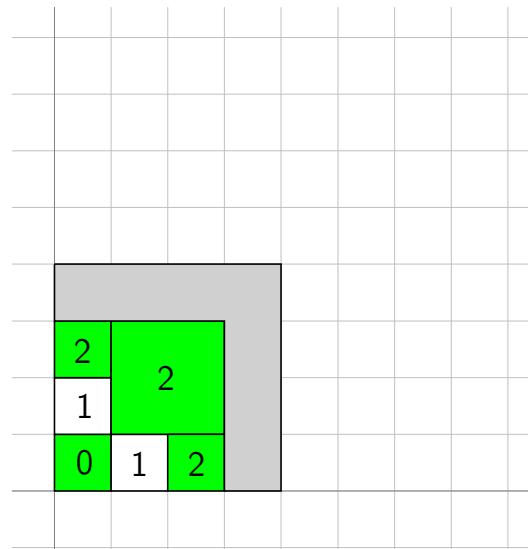


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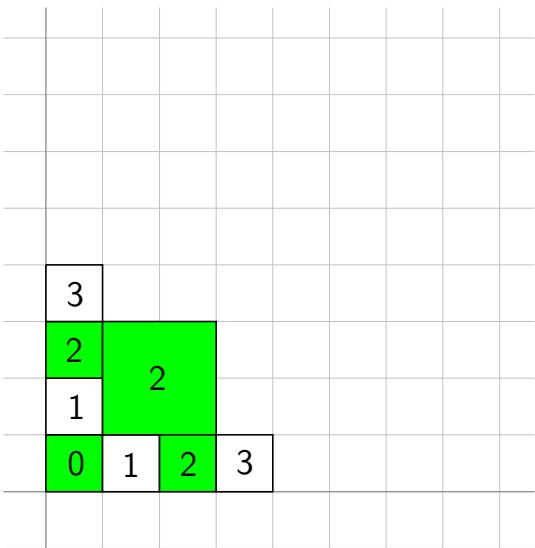


Figure. What we compute

- step 0: $c = a_0 b_0$
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- step 3: $c += z^3 (a_0 b_3 + a_3 b_0)$

Relaxed multiplication $c = a \times b$ - step 4

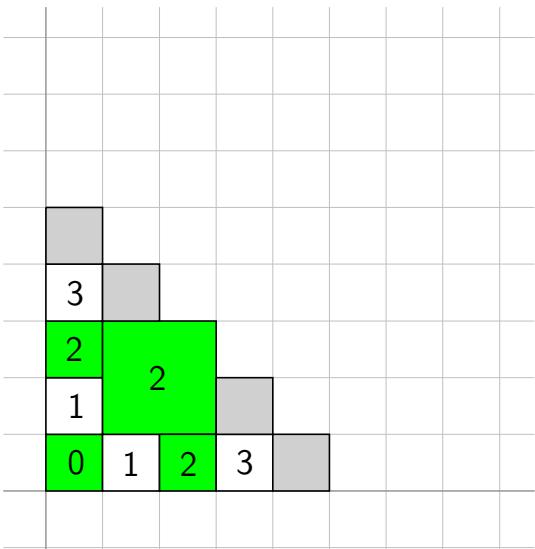


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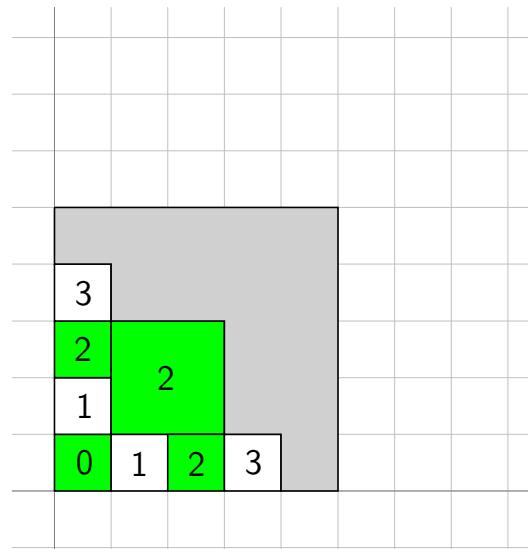


Figure. Minimum knowledge on the input

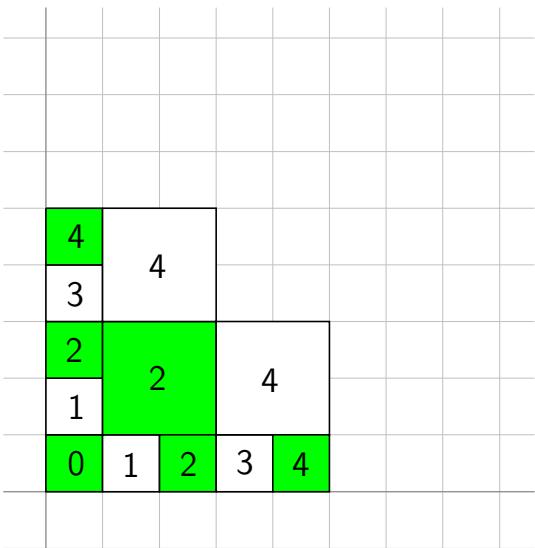


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- step 0: $c = a_0 b_0$
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- step 4: $c += z^4 (a_0 b_4 + a_4 b_0 + (a_1 + a_2 z) (b_3 + b_4 z) + (a_3 + a_4 z) (b_1 + b_2 z))$

Relaxed multiplication $c = a \times b$ - step 5

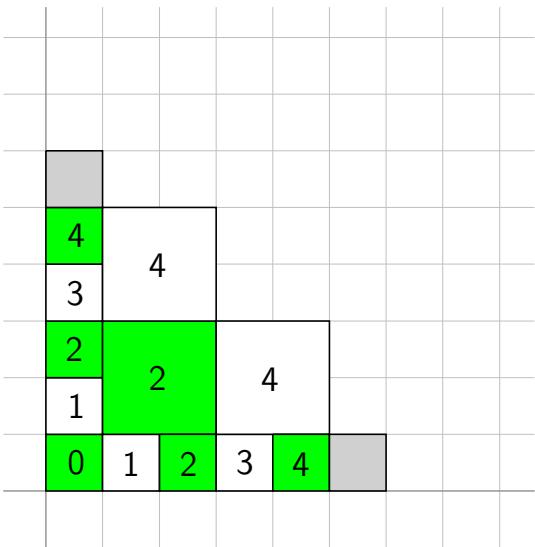


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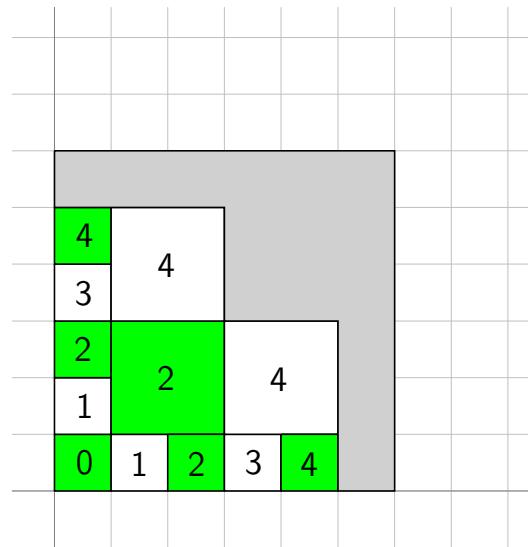


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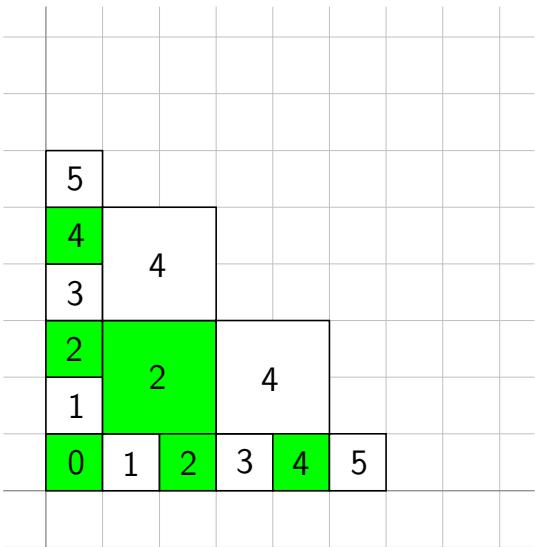


Figure. What we compute

- step 0: $c = a_0 b_0$
- step 1: $c += z (a_0 b_1 + a_1 b_0)$
- step 2: $c += z^2 (a_0 b_2 + a_2 b_0 + (a_1 + a_2 z) (b_1 + b_2 z))$
- step 3: $c += z^3 (a_0 b_3 + a_3 b_0)$
- step 4: $c += z^4 (a_0 b_4 + a_4 b_0 + (a_1 + a_2 z) (b_3 + b_4 z) + (a_3 + a_4 z) (b_1 + b_2 z))$
- step 5: $c += z^5 (a_0 b_5 + a_5 b_0)$

Relaxed multiplication $c = a \times b$ - step 6

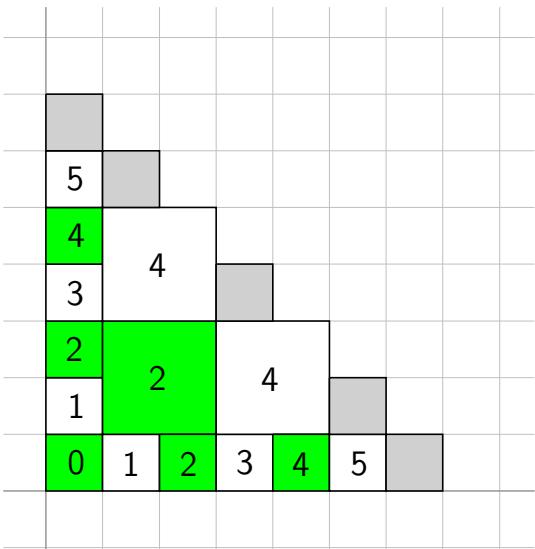


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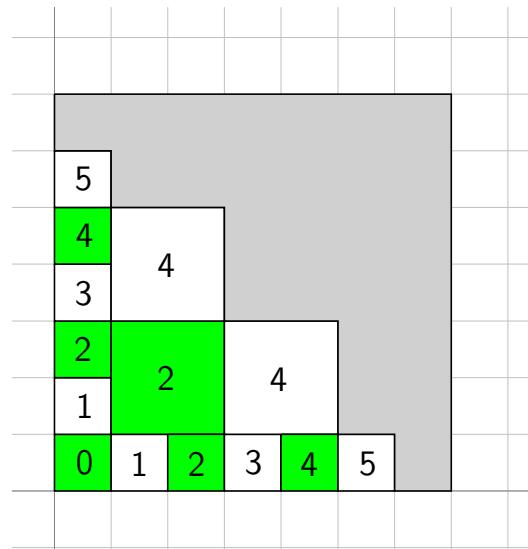


Figure. Minimum knowledge on the input

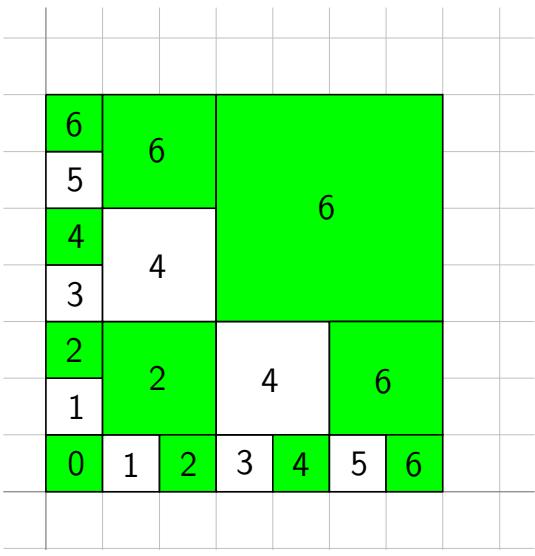


Figure. What we compute

$$\text{step 0: } c = a_0 b_0$$

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$$\text{step 2: } c += z^2 (a_0 b_2 + a_2 b_0 + (a_1 + a_2 z) (b_1 + b_2 z))$$

$$\text{step 3: } c += z^3 (a_0 b_3 + a_3 b_0)$$

$$\begin{aligned} \text{step 4: } c &+= z^4 (a_0 b_4 + a_4 b_0 + (a_1 + a_2 z) (b_3 + b_4 z) \\ &\quad + (a_3 + a_4 z) (b_1 + b_2 z)) \end{aligned}$$

$$\text{step 5: } c += z^5 (a_0 b_5 + a_5 b_0)$$

$$\begin{aligned} \text{step 6: } c &+= z^6 (a_0 b_6 + a_6 b_0 + (a_1 + a_2 z) (b_5 + b_6 z) \\ &\quad + (a_5 + a_6 z) (b_1 + b_2 z) \\ &\quad + (a_3 + \dots + a_6 z^3) (b_3 + \dots + b_6 z^3)) \end{aligned}$$

Relaxed multiplications

Theorem. [FISCHER, STOCKMEYER '74], [SCHRÖDER '97], [VAN DER HOEVEN '97], [BERTHOMIEU, VAN DER HOEVEN, LECERF '11], [L., SCHOST '12]

$M(N)$: cost of $a \times b$ in $k[[x]]$ at precision N by an off-line algorithm.

$R(N)$: cost of $a \times b$ in $k[[x]]$ at precision N by an on-line algorithm. Then

$$R(N) = \mathcal{O}(M(N) \log N) = \tilde{\mathcal{O}}(N).$$

Relaxed multiplications

Theorem. [FISCHER, STOCKMEYER '74], [SCHRÖDER '97], [VAN DER HOEVEN '97], [BERTHOMIEU, VAN DER HOEVEN, LECERF '11], [L., SCHOST '12]

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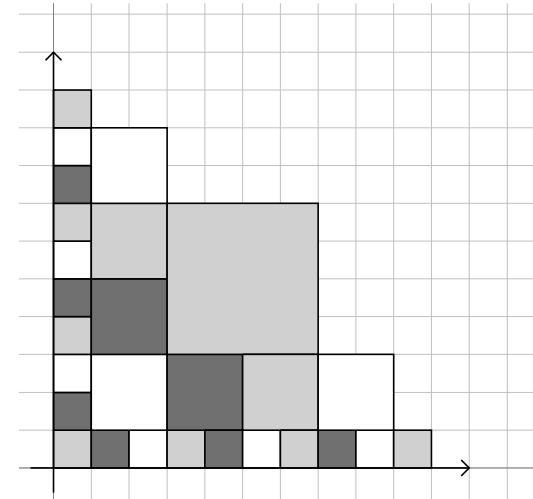
$$R(N) = \mathcal{O}(M(N) \log N) = \tilde{\mathcal{O}}(N).$$

Theorem. [VAN DER HOEVEN '07, '12]

$$R(N) = M(N) \log(N)^{o(1)}.$$

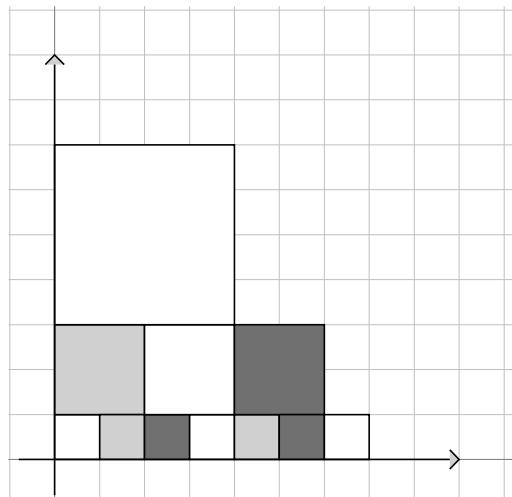
Seems not to be used yet in practice.

Relaxed multiplications

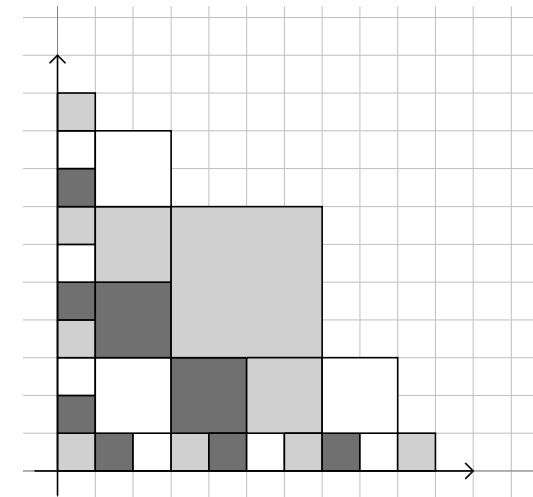


Relaxed multiplication [FISCHER, STOCKMEYER '74]

Relaxed multiplications

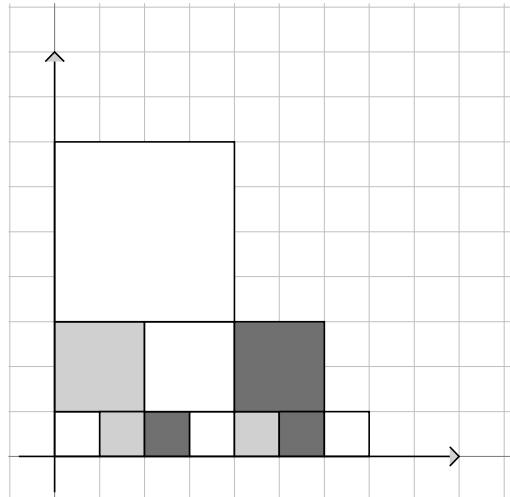


Semi-relaxed multiplication [FISCHER, STOCKMEYER '74]

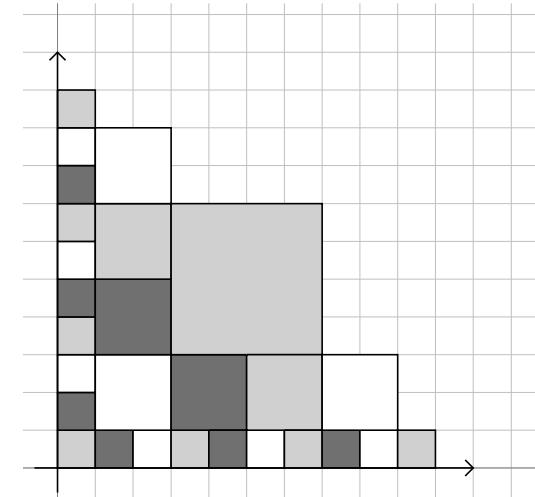


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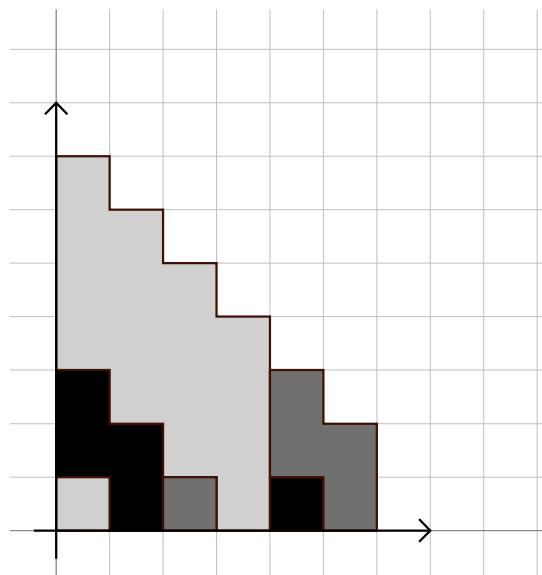
Relaxed multiplications



Semi-relaxed multiplication [FISCHER, STOCKMEYER '74]



Relaxed multiplication [FISCHER, STOCKMEYER '74]

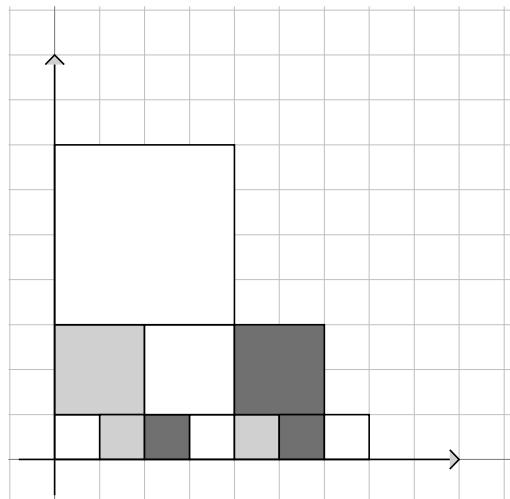


Semi-relaxed multiplication [VAN DER HOEVEN '03]

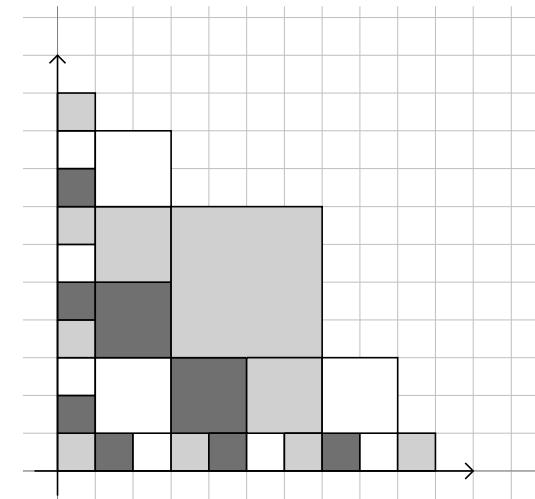


?

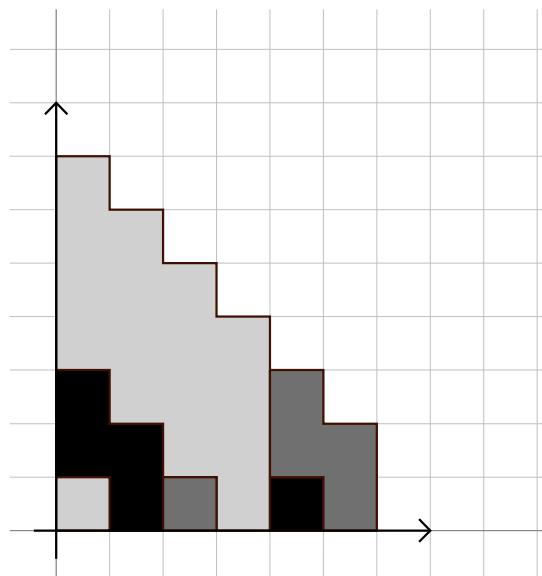
Relaxed multiplications



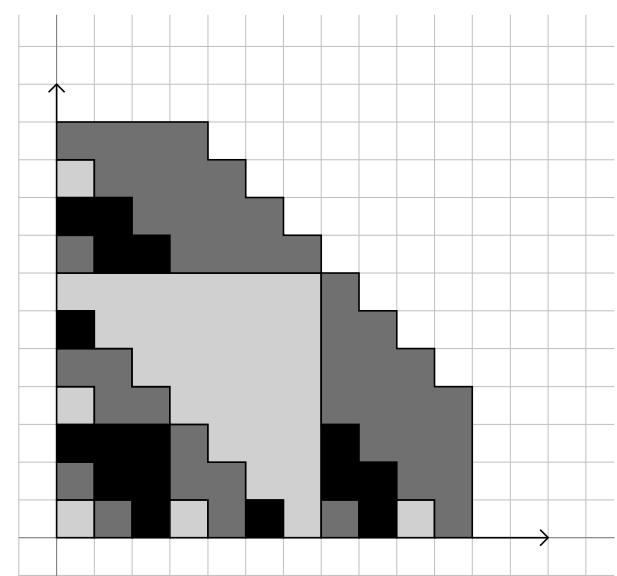
Semi-relaxed multiplication [FISCHER, STOCKMEYER '74]



Relaxed multiplication [FISCHER, STOCKMEYER '74]



Semi-relaxed multiplication [VAN DER HOEVEN '03]



Relaxed multiplication [L., SCHOST '12]

Timings of relaxed multiplications

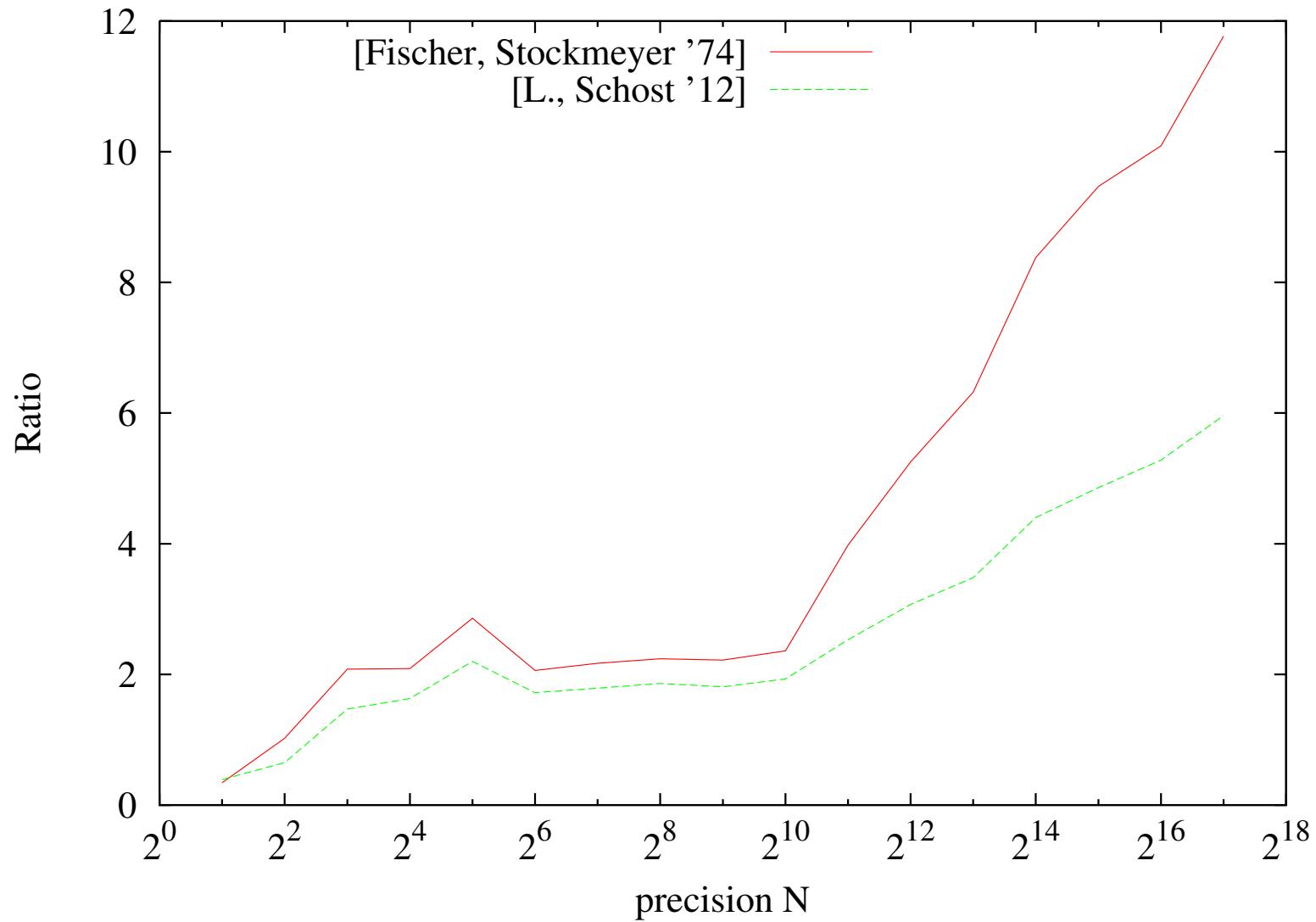


Figure. Ratio $R(N)/M(N)$ for different relaxed multiplication algorithms over $\mathbb{F}_{268435459}[[x]]$.

1. Why is p -adic lifting interesting?

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a. On-line algorithms

b. Recursive p -adic

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3. Conclusion

Relaxed recursive power series

Definition. A power series $y \in k[[x]]$ is recursive if there exists Φ such that

- $y = \Phi(y)$
- $\Phi(y)_n$ only depends on y_0, \dots, y_{n-1}

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Definition. (*Shifted algorithm*)

$$a = \sum_{i \geq 0} a_i x^i \quad \begin{array}{|c|c|c|c|c|} \hline a_0 & a_1 & a_2 & \cdots & \\ \hline \end{array} \quad \begin{array}{|c|} \hline \text{blue} \\ \hline \end{array} : \text{reading allowed}$$
$$\downarrow f$$
$$c = f(a) = \sum_{i \geq 0} c_i x^i \quad \begin{array}{|c|c|c|c|c|} \hline c_0 & & & \cdots & \\ \hline \end{array}$$

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Theorem. [WATT '88], [VAN DER HOEVEN '02]

Let $y \in k[[x]]$ such that $y = \Phi(y)$. Given y_0 and Φ , we can compute y at precision N in the time necessary to evaluate $\Phi(y)$.

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Let $y \in k[[x]]$ such that $y = \Phi(y)$. Given y_0 and Φ , we can compute y at precision N in the time necessary to evaluate $\Phi(y)$ by a *shifted algorithm*.

Proof. $y = \Phi(y)$

$$y = \sum_{i \geq 0} y_i x^i \quad \begin{array}{|c|c|c|c|c|} \hline y_0 & ? & ? & \dots & \end{array} \quad \begin{array}{|c|} \hline \end{array} : \text{reading allowed}$$
$$\downarrow \Phi$$
$$\Phi(y) = \sum_{i \geq 0} \varphi_i x^i \quad \begin{array}{|c|c|c|c|c|} \hline \varphi_0 & \color{red}{\varphi_1} & \color{white}{\varphi_2} & \dots & \end{array}$$

□

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Let $y \in k[[x]]$ such that $y = \Phi(y)$. Given y_0 and Φ , we can compute y at precision N in the time necessary to evaluate $\Phi(y)$ by a *shifted algorithm*.

Proof. $y = \Phi(y) \Rightarrow \varphi_1 = y_1$

$$y = \sum_{i \geq 0} y_i x^i$$

$$\downarrow \Phi$$

$$\Phi(y) = \sum_{i \geq 0} \varphi_i x^i$$

y_0	y_1	?	\dots
-------	-------	---	---------

: reading allowed



φ_0	φ_1		\dots
-------------	-------------	--	---------

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$$\begin{array}{l} y = \sum_{i \geq 0} y_i x^i \\ \downarrow \Phi \\ \Phi(y) = \sum_{i \geq 0} \varphi_i x^i \end{array} \quad \begin{array}{c|c|c|c|c} y_0 & y_1 & ? & \dots & \end{array} \quad \begin{array}{c} \text{---} \\ \text{---} \end{array} : \text{reading allowed}$$

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Let $y \in k[[x]]$ such that $y = \Phi(y)$. Given y_0 and Φ , we can compute y at precision N in the time necessary to evaluate $\Phi(y)$ by a *shifted algorithm*.

Proof. $y = \Phi(y) \Rightarrow \varphi_2 = y_2$

$$y = \sum_{i \geq 0} y_i x^i$$

$$\boxed{y_0} \boxed{y_1} \boxed{\color{red}{y_2}} \cdots \quad \boxed{} : \text{reading allowed}$$

$$\downarrow \Phi$$

$$\Phi(y) = \sum_{i \geq 0} \varphi_i x^i$$

$$\boxed{\varphi_0} \boxed{\varphi_1} \boxed{\color{red}{\varphi_2}} \cdots$$



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Plan

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Two paradigms

Lifting solutions methods:

Zealous algorithms	Relaxed algorithms
Newton operator	Fundamental theorem
implicit equations $\mathbf{P}(\mathbf{Y}) = 0$	recursive equations $\mathbf{Y} = \Phi(\mathbf{Y})$

To do:

- Transform an implicit equations into recursive equations (+ shifted algorithm)

$$\mathbf{P}(\mathbf{Y}) = \mathbf{0} \longrightarrow \mathbf{Y} = \Psi(\mathbf{Y})$$

Linear systems

		Zealous algorithms	Relaxed algorithms
Linear systems	dense	$\tilde{\mathcal{O}}(r^\omega d + r^{\omega-1} N)$	
	structured	$\tilde{\mathcal{O}}(\alpha^2 r d + \alpha r N)$	

Example. Find $a(x), b(x), c(x) \in k[[x]]$ such that

$$\begin{cases} (1+x)a(x) + (3-x^2)b(x) + 2c(x) = 1 \\ (x-x^3)a(x) + (1+x)b(x) + (3-x^2)c(x) = x \\ (4-2x)a(x) + (x-x^3)b(x) + (1+x)c(x) = x^2 \end{cases}$$

r number of unknowns

d degree of polynomials in input

N precision of the output

α parameter associated to structured matrices $\alpha \ll r$

ω exponent of matrix multiplication $2 \leq \omega \leq 3$

Example of system

$$A \cdot Y = B \Leftrightarrow \begin{pmatrix} (1+x) & (3-x^2) & 2 \\ (x-x^3) & (1+x) & (3-x^2) \\ (4-2x) & (x-x^3) & (1+x) \end{pmatrix} \cdot \begin{pmatrix} a(x) \\ b(x) \\ c(x) \end{pmatrix} = \begin{pmatrix} 1 \\ x \\ x^2 \end{pmatrix}$$

Transformation of equation

Implicit equation	$0 = f(Y) := A \cdot Y - B$
Recursive equation	$Y = \Phi(Y) := A_0^{-1} \cdot (B - (A - A_0) \cdot Y)$
Shifted algorithm	$\Psi(Y) := A_0^{-1} \cdot \left(B - x \times \left[\left(\frac{A - A_0}{x} \right) \cdot_{\text{online}} Y \right] \right)$

Linear systems

		Zealous algorithms	Relaxed algorithms
Linear systems	dense	$\tilde{\mathcal{O}}(r^\omega d + r^{\omega-1} N)$	$\tilde{\mathcal{O}}(r^\omega + r^2 N)$
	structured	$\tilde{\mathcal{O}}(\alpha^2 r d + \alpha r N)$	$\tilde{\mathcal{O}}(\alpha^2 r + \alpha r N)$
[BERTHOMIEU, L., ISSAC '12], [L., SCHOST '12]			

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Linear systems:

[MOENCK, CARTER '79], [STORJOHANN '03]

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Differential systems

	Zealous algorithms	Relaxed algorithms
Regular differential systems	$\mathcal{O}(r^\omega) \mathsf{M}(N) + \mathcal{O}_{N \rightarrow \infty}(N)$	$\mathcal{O}(r^2) \mathsf{R}(N) + \mathcal{O}_{N \rightarrow \infty}(N)$
(q) -differential singular systems		

Example. Find $a(x) \in k[[x]]$ such that

$$(1+x) a(x) + (3-x^2) (a(2x) - a(x)) = x$$

Applications:

- List-decoding of folded Reed-Solomon codes: solve $Q(x, f(x), f(qx)) = 0$
- Composition of power series $f(g)$ with $g(0) = 0$ when f solution of a singular differential equation.

Differential systems

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(q) -differential singular systems	$\mathcal{O}(r^\omega) \mathsf{M}(N) + \mathcal{O}_{N \rightarrow \infty}(N)$	$\mathcal{O}(r^2) \mathsf{R}(N) + \mathcal{O}_{N \rightarrow \infty}(N)$

[BOSTAN, CHOWDHURY, L., SALVY, SCHOST, *ISSAC '12*]

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Differential systems:

[BRENT, KUNG '78], [VAN DER HOEVEN '02 '11], [BOSTAN, CHYZAK *et al.* '07]

Polynomial systems

	Zealous algorithms	Relaxed algorithms
Polynomial systems	$\mathcal{O}(r L + r^\omega) \mathbf{M}(N) + \mathcal{O}_{N \rightarrow \infty}(N)$	
Univariate representations	$\mathcal{O}(r L + r^\omega) \mathbf{M}(N) \mathbf{M}(d) + \mathcal{O}_{N \rightarrow \infty}(N)$	

Example. Find $a(x), b(x), c(x) \in k[[x]]$ such that

$$\left\{ \begin{array}{l} (1+x) + (4-2x) a(x)^2 c(x)^4 + 2 b(x) = 0 \\ (x-x^3) + (3-x^2) a(x) b(x)^2 + (1+x+x^2) c(x) = 0 \\ 1 + b(x)^4 c(x)^5 + x a(x)^3 = 0 \end{array} \right.$$

r number of unknowns, N precision of the output, L complexity of evaluation

Polynomial systems:

[NEWTON 1736], [HENSEL 1918], [LIPSON '76]

[BERTHOMIEU, VAN DER HOEVEN, LECERF '11], [VAN DER HOEVEN '11]

Univariate representations:

[GIUSTI, LECERF, SALVY '01], [HEINTZ, MATERA, WAISSBEIN '01]

Polynomial systems

	Zealous algorithms	Relaxed algorithms
Polynomial systems	$\mathcal{O}(rL + r^\omega) \mathsf{M}(N) + \mathcal{O}_{N \rightarrow \infty}(N)$	$\mathcal{O}(L) \mathsf{R}(N) + \mathcal{O}_{N \rightarrow \infty}(N)$
Univariate representations	$\mathcal{O}(rL + r^\omega) \mathsf{M}(N) \mathsf{M}(d) + \mathcal{O}_{N \rightarrow \infty}(N)$	$\mathcal{O}(L) \mathsf{R}(N) \mathsf{M}(d) + \mathcal{O}_{N \rightarrow \infty}(N)$

[BERTHOMIEU, L., *ISSAC '12*], [L. '12]

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Timings

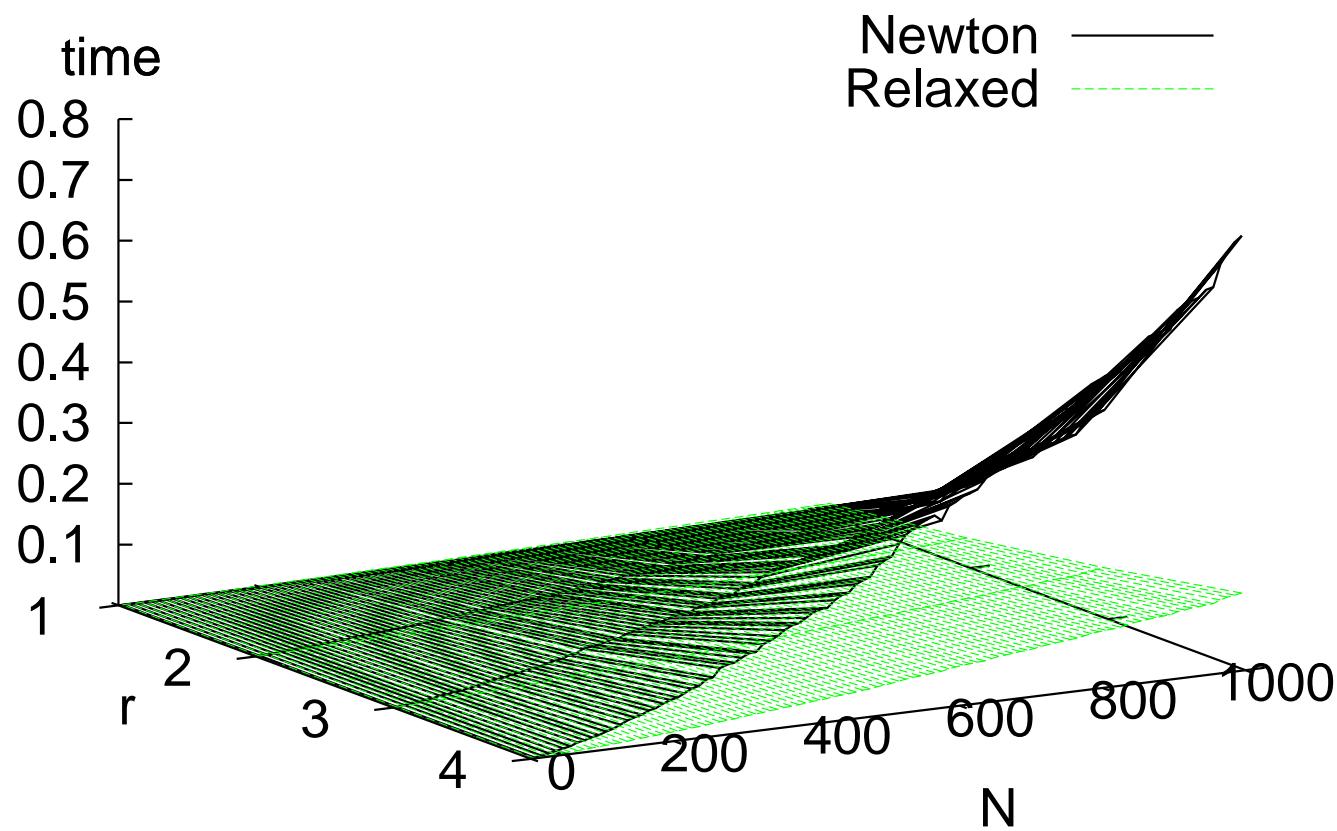


Figure. Timings with systems of singular (q)-differential equations

Timings

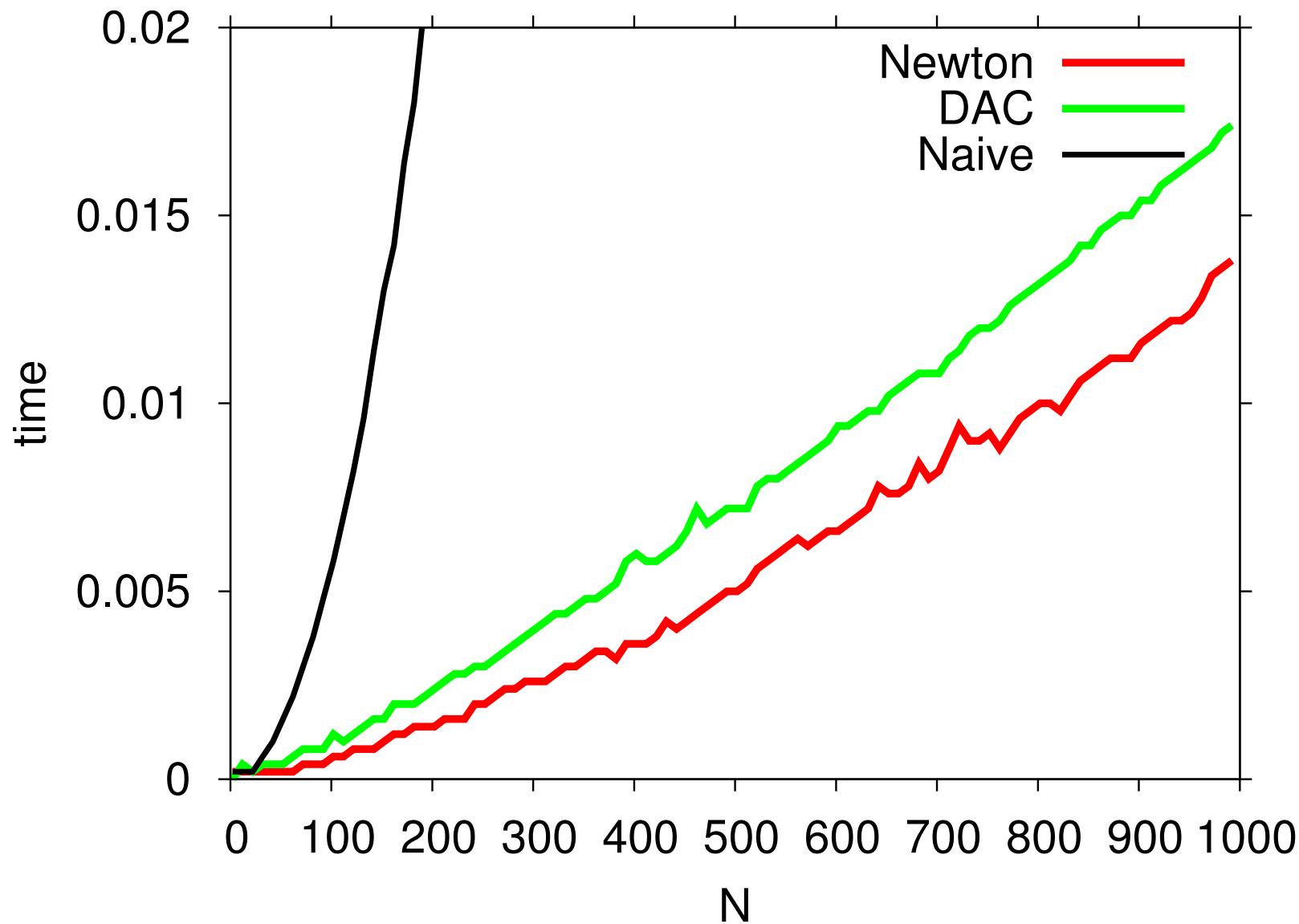


Figure. Timings with a singular (q)-differential equation

Timings

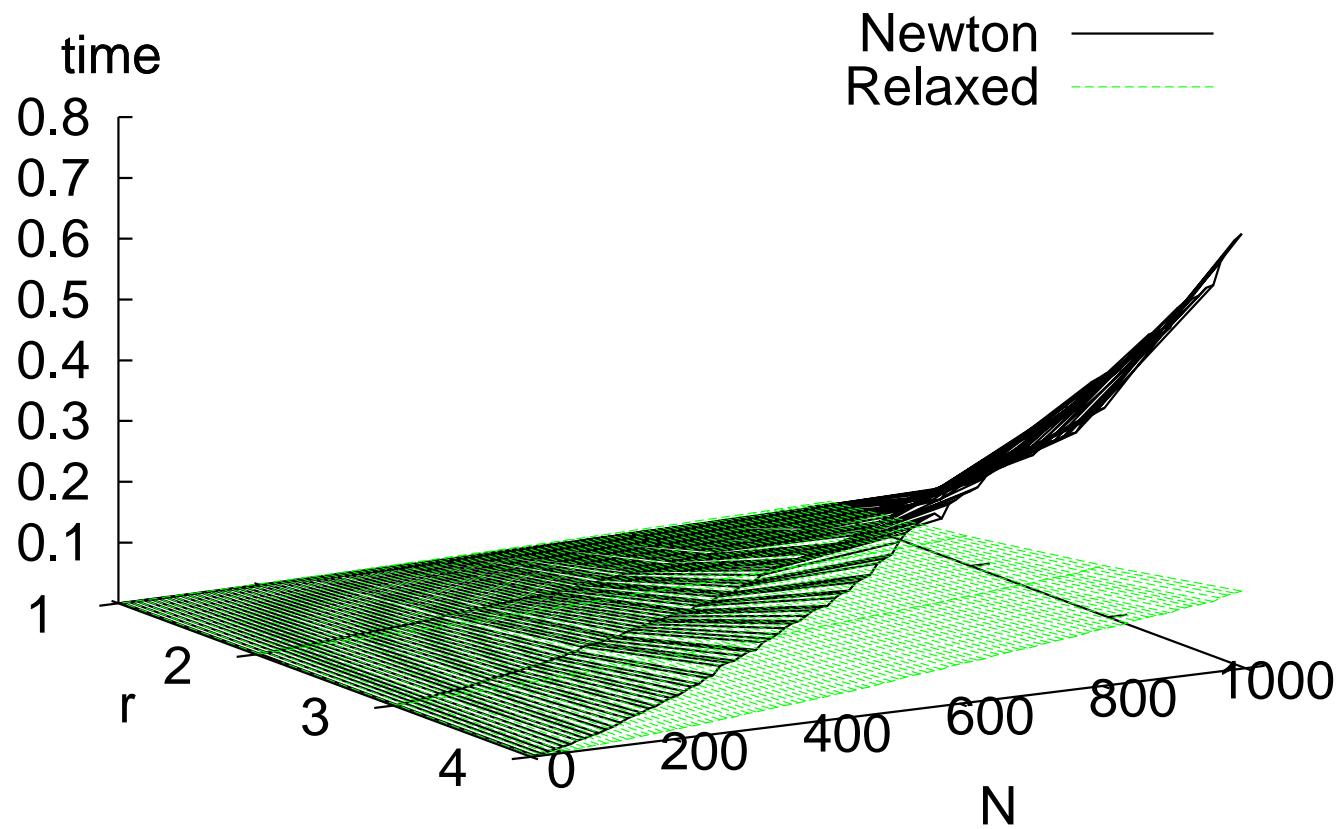


Figure. Timings with systems of singular (q)-differential equations

Timings

N	KATSURA-3		KATSURA-4		KATSURA-5		KATSURA-6	
	zealous	relaxed	zealous	relaxed	zealous	relaxed	zealous	relaxed
2	0.02	0.007	0.08	0.02	0.25	0.06	0.8	0.17
4	0.03	0.01	0.10	0.03	0.35	0.08	1.1	0.22
8	0.05	0.02	0.17	0.05	0.55	0.13	1.7	0.36
16	0.08	0.04	0.29	0.09	0.9	0.24	1.9	0.70
32	0.14	0.07	0.51	0.20	1.7	0.53	5.2	1.5
64	0.26	0.16	1.0	0.44	3.3	1.2	10	3.6
128	0.51	0.36	1.9	1	6.6	2.8	21	8.6

Table. Timings in seconds of lifting of univariate representations over $\mathbb{F}_{16411}[[x]]$ for KATSURA- n .

Conclusion

Two general paradigms:

Newton operator

Relaxed algorithms

Solve implicit equations $P(y) = 0$

Solve recursive equations $y = \Phi(y)$

Faster for higher precision

Less on-line multiplications

Implementations:

Contributions to ALGEBRAMIX and GEOMSOLVEX packages of MATHEMAGIX;

Perspectives:

- Lift a polynomial root under more general hypotheses (multiplicities);
- Link between relaxed and divide-and-conquer algorithms
- New horizons : Relaxed Gröbner bases?

Thank you for your attention ;-)