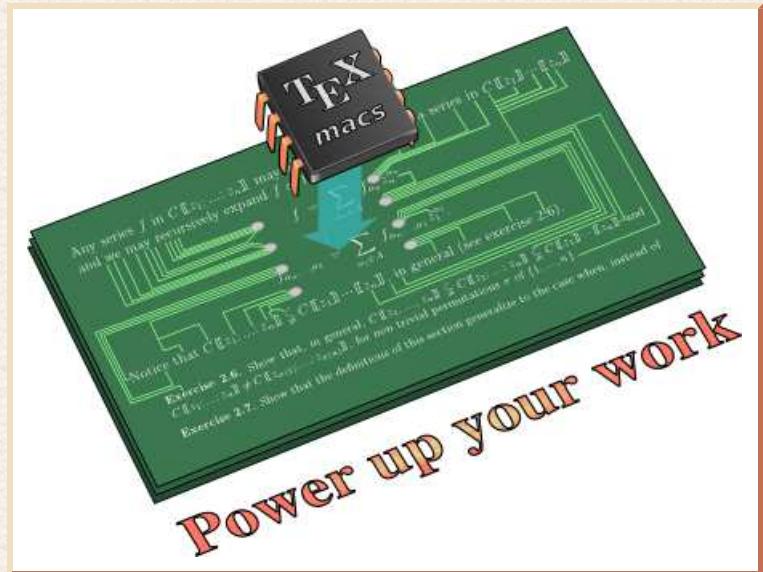


On the practical complexity of computations with real numbers

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<http://www.TEXMACS.org>



Computer algebra *and* analysis system



Computer algebra

Exact computations with algebraic, arithmetic or combinatorial objects



Computer algebra

Exact computations with algebraic, arithmetic or combinatorial objects

Numerical analysis

Approximate numerical computations with (generally) manual error estimates



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Exact computations with algebraic, arithmetic or combinatorial objects

Numerical analysis

Approximate numerical computations with (generally) manual error estimates

Computer analysis

Mathematically exact computations with analytic objects.



Example 1: certified integration



Pendulum

$$\ddot{y} = -\alpha \sin y,$$

For $\alpha = 1$, $y(0) = 0$, $\dot{y}(0) = 1$, compute $\tilde{y} \in \mathbb{Q}$ (where $\tilde{y} \in \mathbb{D} = \mathbb{Z} 2^{\mathbb{Z}}$) with

$$|\tilde{y} - y(2013)| < 2^{-2013}.$$



Example 1: certified integration



Dynamical systems

Let $P = (P_1, \dots, P_d) \in \mathbb{Q}[Y]^d = \mathbb{Q}[Y_1, \dots, Y_d]^d$ and consider

$$\dot{Y} = P(Y).$$

For $Y(0) \in \mathbb{Q}^d$, $t \in \mathbb{Q}^>$ and $\varepsilon \in \mathbb{Q}^>$, compute (when possible) $\tilde{Y} \in \mathbb{Q}^d$ with

$$\|\tilde{Y} - Y(t)\| < \varepsilon.$$



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Special functions

- Elementary functions $\exp, \log, \cos, \sin, \tan$, etc.
- Holonomic functions: $L(f) = L_r f^{(r)} + \dots + L_0 f = 0$, $L \in \mathbb{Q}[z][\partial]$.
- Other : \wp , Γ , ζ , theta functions, Mathieu functions, etc.



Example 2: polynomial system solving



Given a zero dimensional system

$$\begin{cases} P_1(z_1, \dots, z_n) = 0 \\ \vdots \\ P_n(z_1, \dots, z_n) = 0 \end{cases}$$

with $P_1, \dots, P_n \in \mathbb{Q}[z_1, \dots, z_n]$, find the zeros “in \mathbb{C}^n ”.



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with $P_1, \dots, P_n \in \mathbb{E}[z_1, \dots, z_n]$, find the zeros “in \mathbb{C}^n ”.

\mathbb{E} = “field of exp-log constants”, constructed from \mathbb{Q} using $+, -, \times, \exp, \log$.



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with $P_1, \dots, P_n \in \mathbb{E}[z_1, \dots, z_n]$, find the zeros “in \mathbb{R}^n ”.

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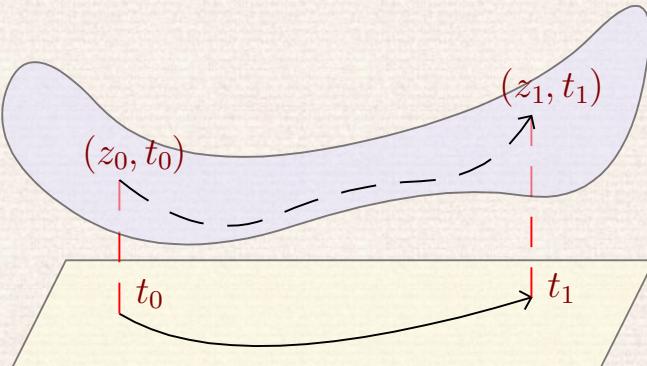
Example 3: path following



$$H(z, t) = 0 \quad \left\{ \begin{array}{l} H_1(z_1, \dots, z_n, t) = 0 \\ \vdots \\ H_n(z_1, \dots, z_n, t) = 0 \end{array} \right.,$$

with $H(z, t) \in \mathbb{Q}[z, t]^n$ zero-dimensional in z for $t \in \mathbb{C} \setminus \Sigma$ and finite Σ .

Given (z_0, t_0) avec $H(z_0, t_0) = 0$ and a path $t_0 \rightsquigarrow t_1$ which avoids Σ , compute the path $z_0 \rightsquigarrow z_1$ with $H(z_\lambda, t_\lambda) = 0$ for all $\lambda \in [0, 1]$.





Example 3: path following, application



Polynomial system solving using numerical homotopies

$$P(x, y) \quad \begin{cases} x^2 + 2xy - y^2 - 3x + 5y + 8 = 0 \\ 3x^2 - xy + y^2 + 8x - 2y + 7 = 0 \end{cases}$$

$$\text{Easy}(x, y) \quad \begin{cases} x^2 - 1 = 0 \\ y^2 - 1 = 0 \end{cases}$$

$$H(x, y, t) \quad \begin{cases} (x^2 - 1)t + (x^2 + 2xy - y^2 - 3x + 5y + 8)(1-t) = 0 \\ (y^2 - 1)t + (3x^2 - xy + y^2 + 8x - 2y + 7)(1-t) = 0 \end{cases}$$



Example 4: Bell numbers



$$B(z) = \sum_{n=0}^{\infty} \frac{B_n}{n!} z^n = e^{e^z - 1}.$$

Problem 1: compute B_{10000} with a relative error 10^{-10}

Problem 2: automatically find/guess asymptotic expansion

$$\log\left(\frac{B_n}{n!}\right) = n\left(-\log\log n + \frac{1}{\log n} + \frac{\log\log n}{\log n} + \mathcal{O}\left(\frac{1}{\log^2 n}\right)\right)$$

Problem 3: for $n \geq 10^{10}$, find an explicit constant for the $\mathcal{O}\left(\frac{1}{\log^2 n}\right)$ term



Challenges



- Which problems can be solved, at least theoretically?
- Automatic computation of error bounds for numerical computations
- Redevelop numerical analysis for multiple precision computations



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Computable analysis, BSS computability, ...
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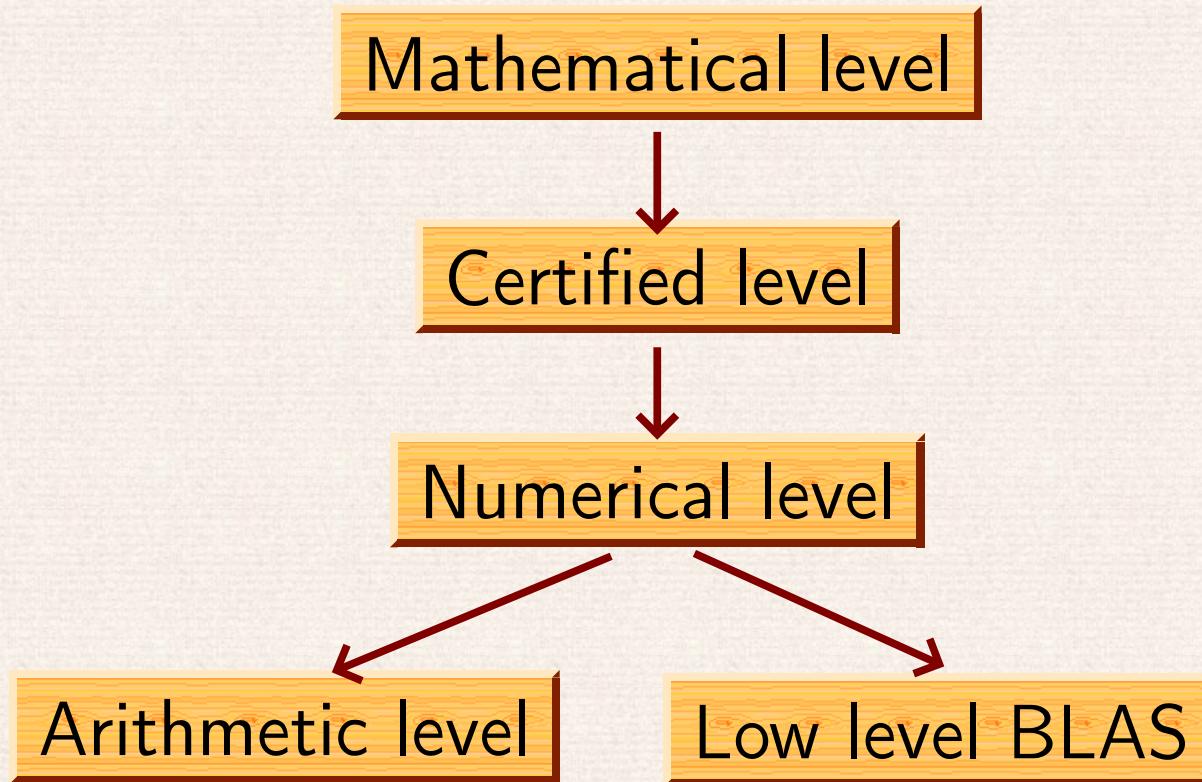
Challenges



- Which problems can be solved, at least theoretically?
Computable analysis, BSS computability, ...
- Automatic computation of error bounds for numerical computations
Interval analysis, ball arithmetic
- Redevelop numerical analysis for multiple precision computations
Runge Kutta \rightsquigarrow Taylor methods
Complexity, conditioning, ...



Numerical hierarchy

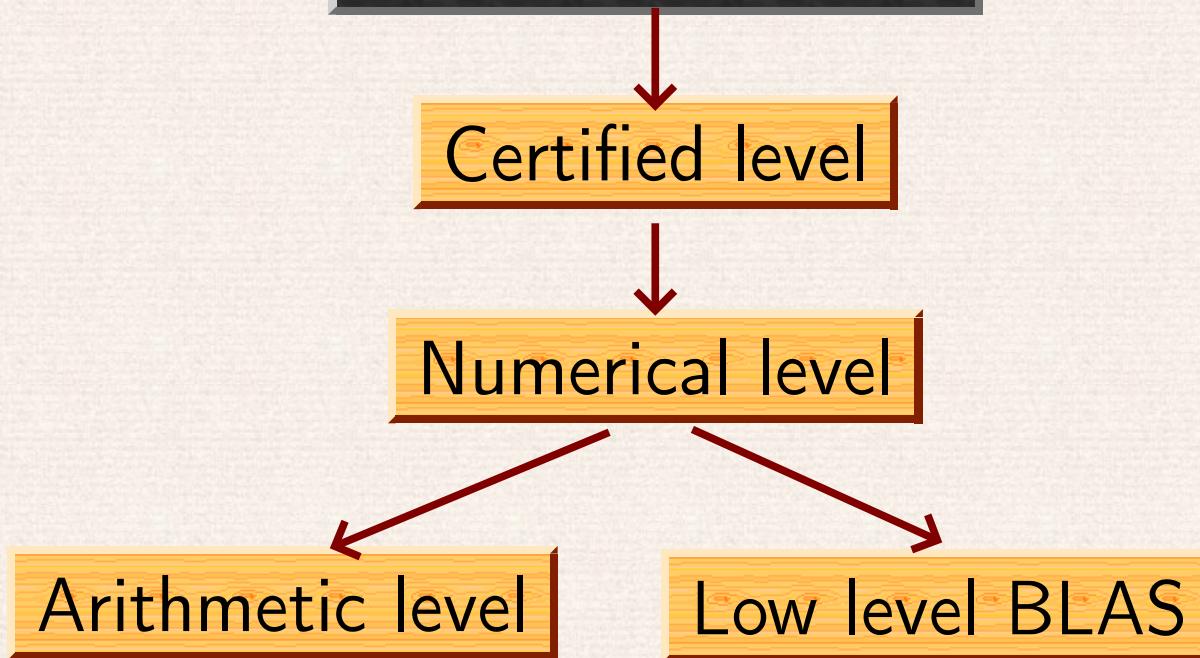




Numerical hierarchy



$$M, N \in (\mathbb{R}^{\text{com}})^{n \times n}$$

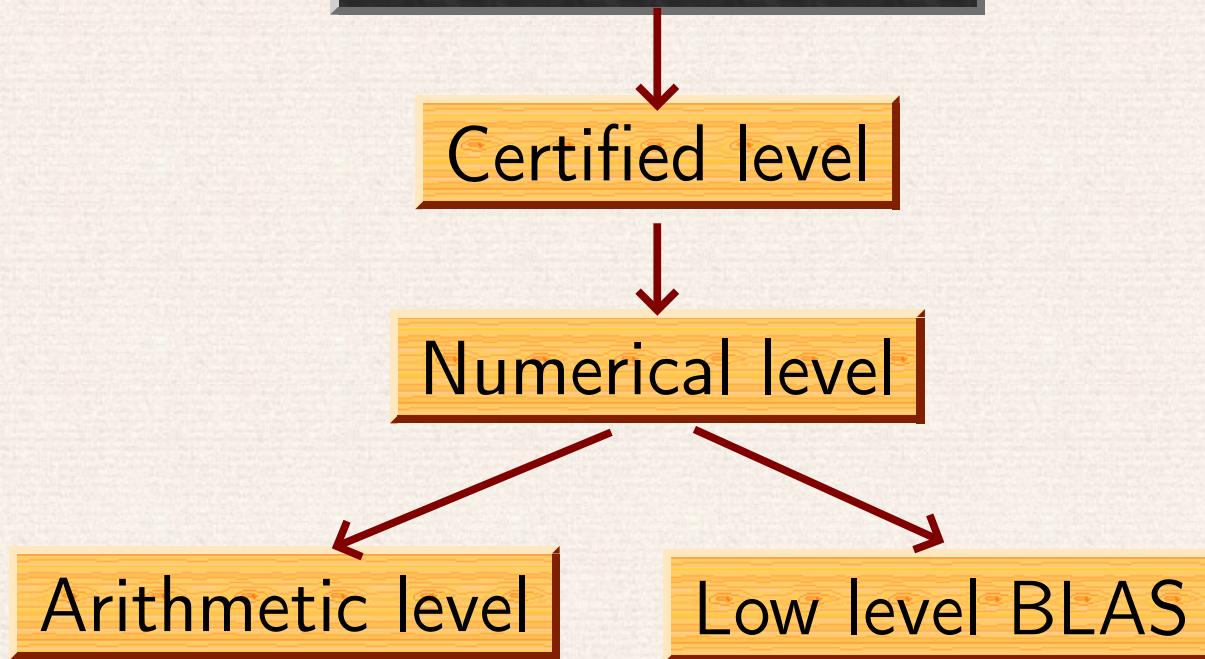




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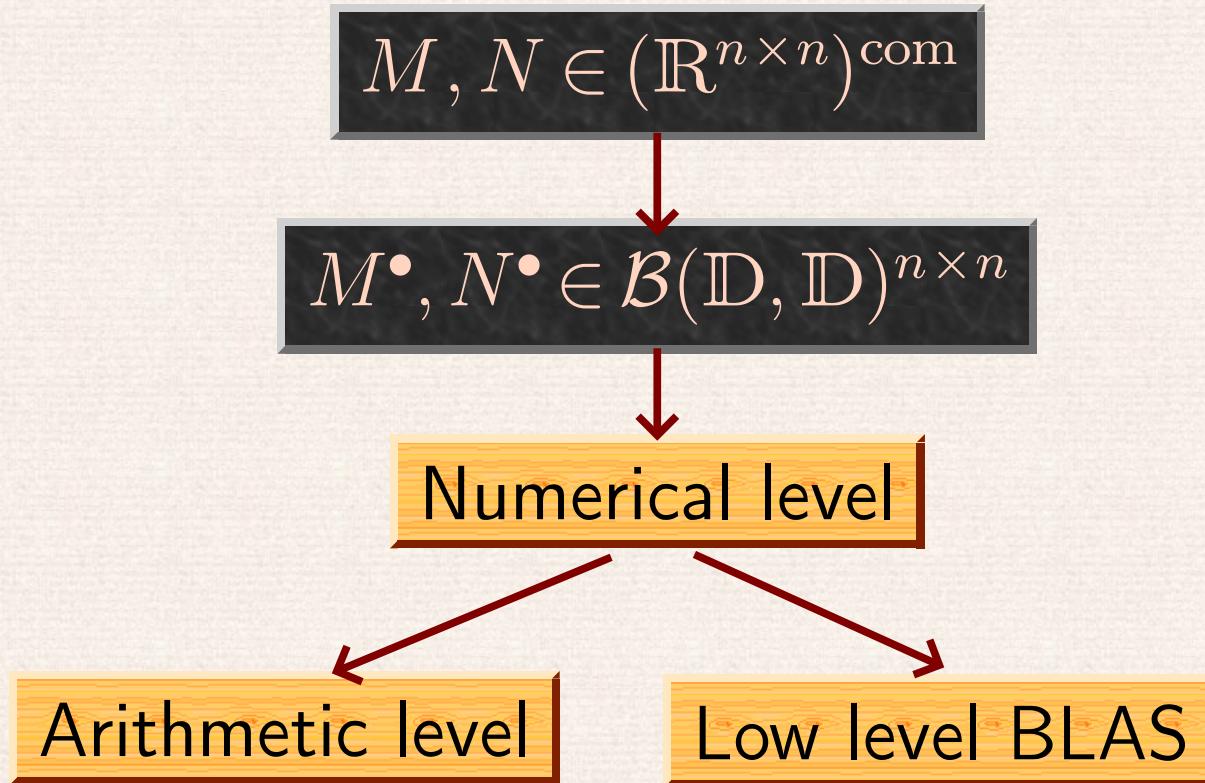


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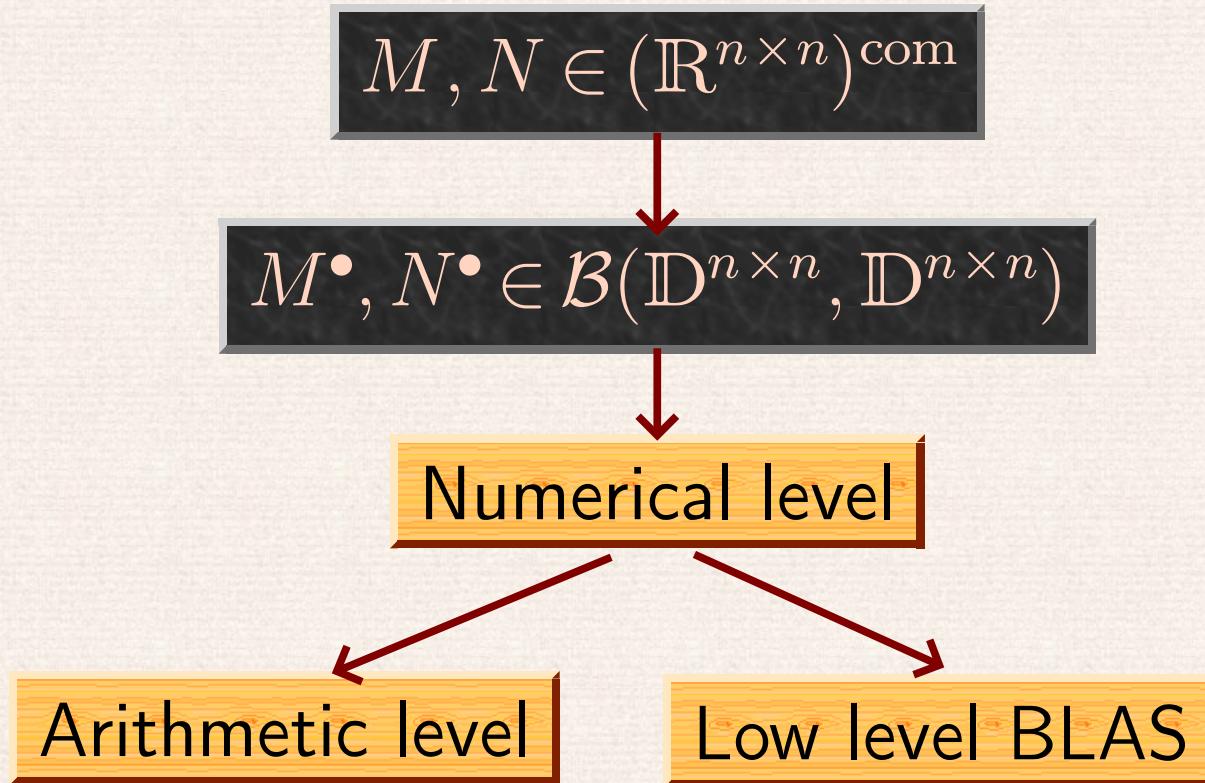


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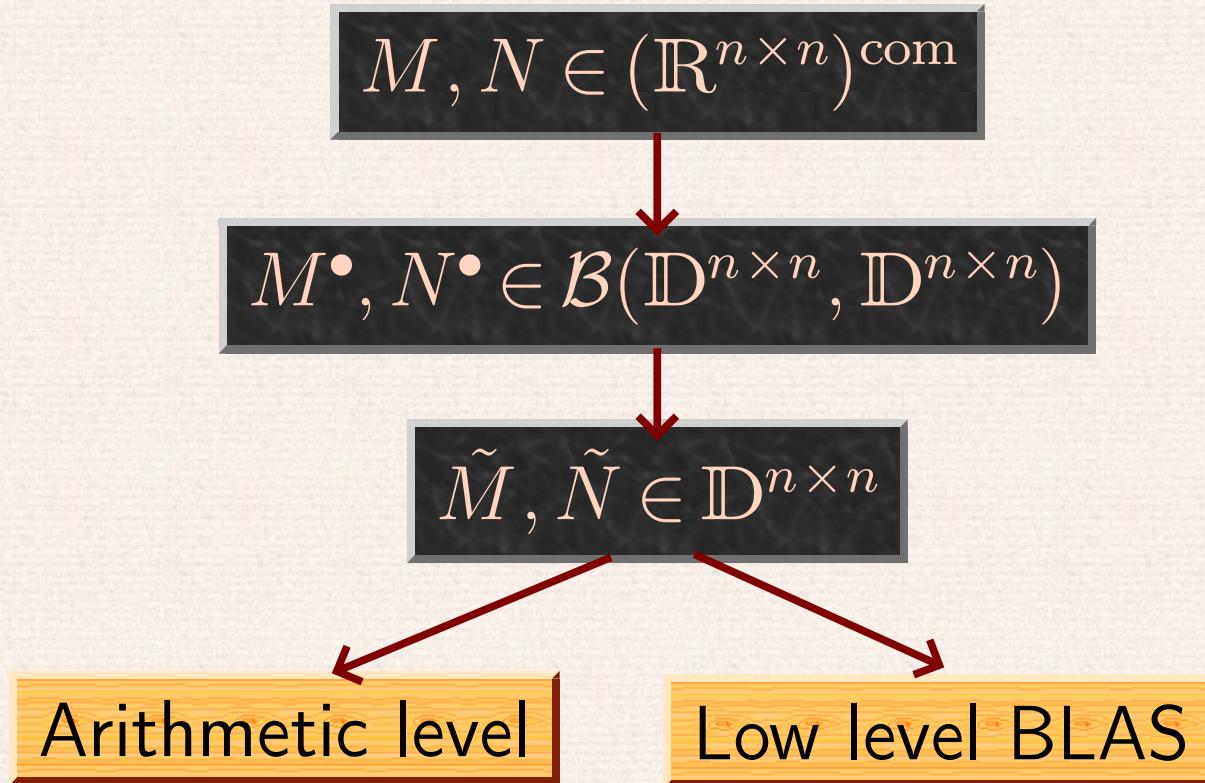


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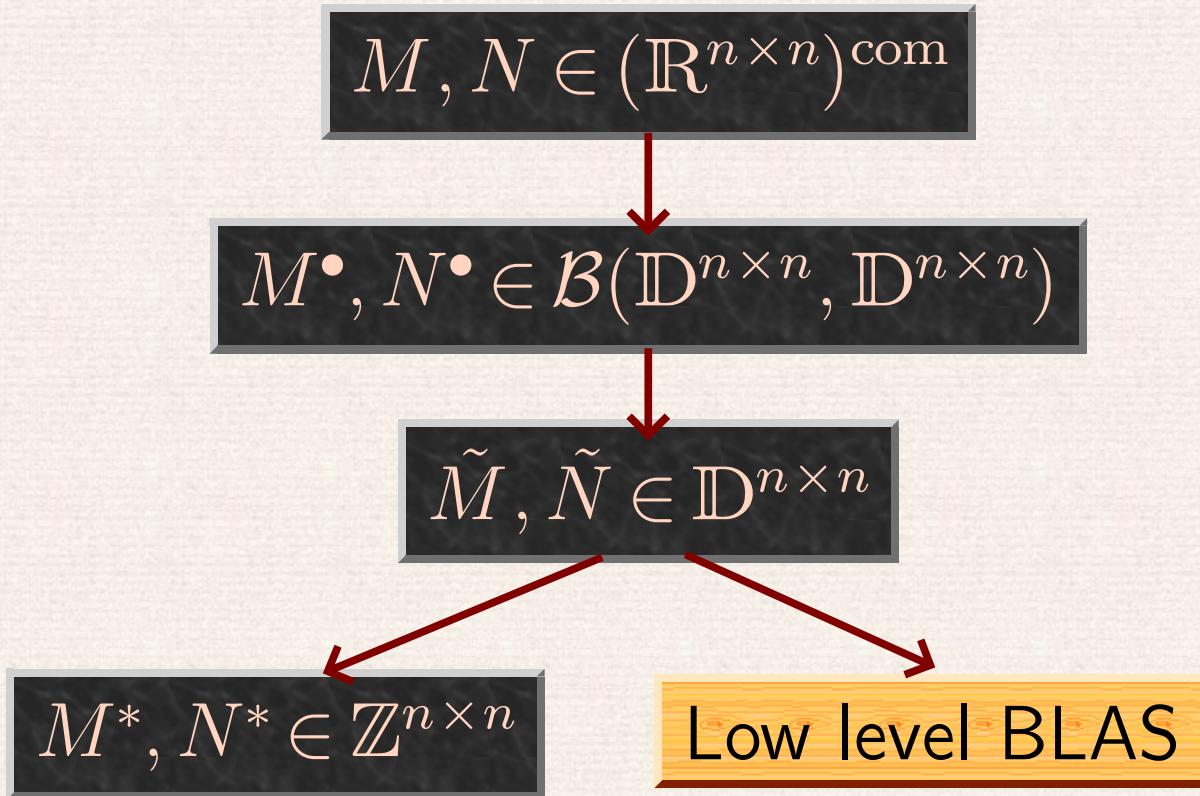


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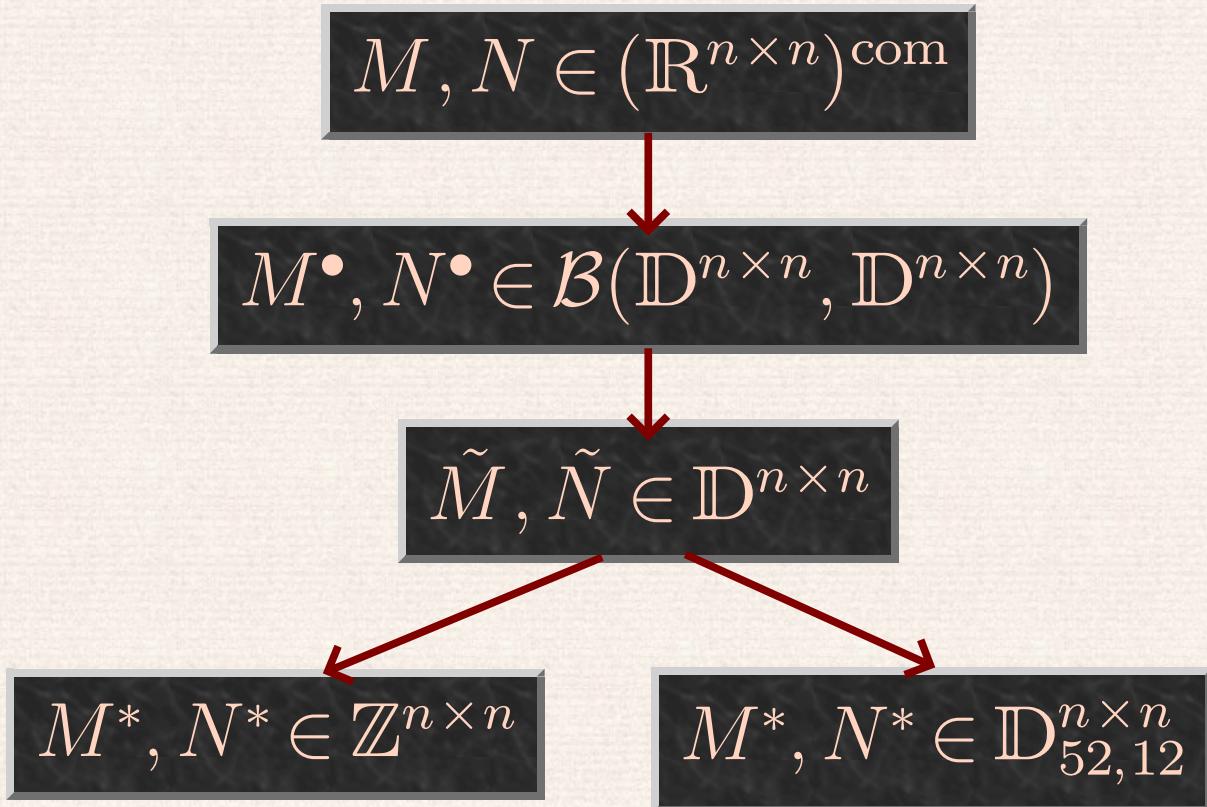


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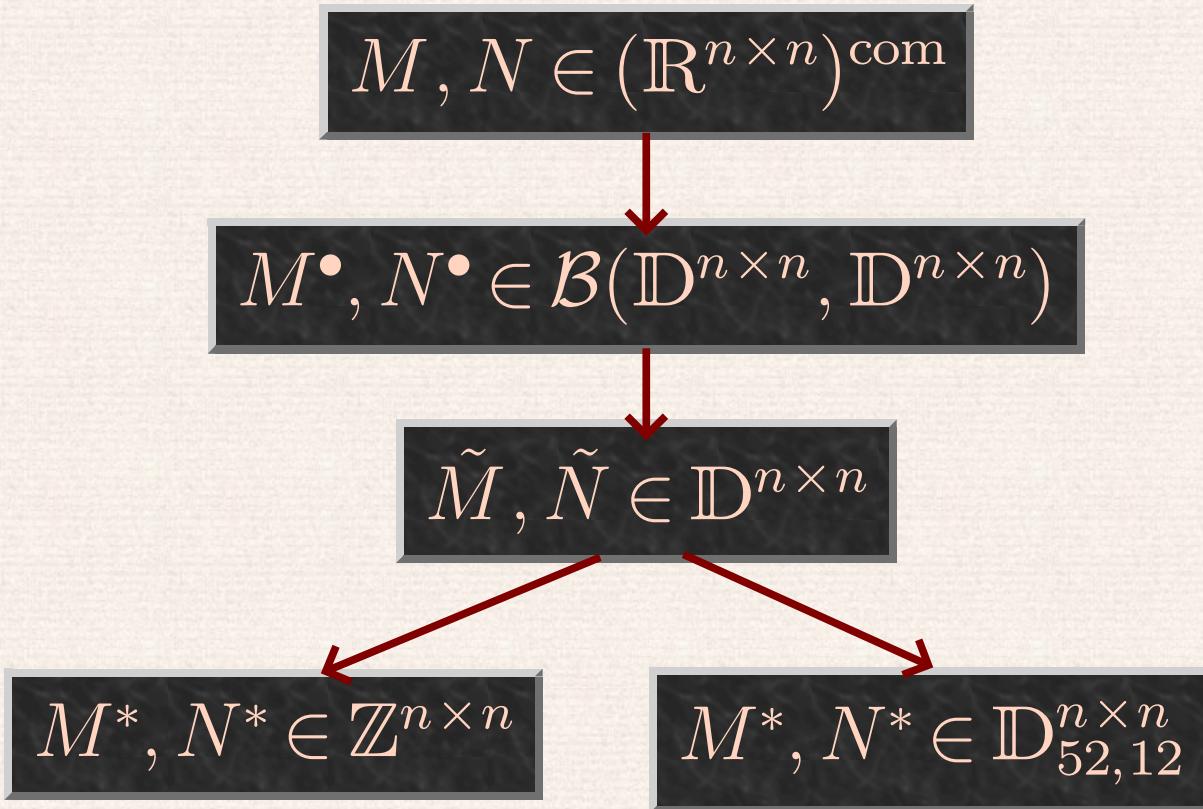


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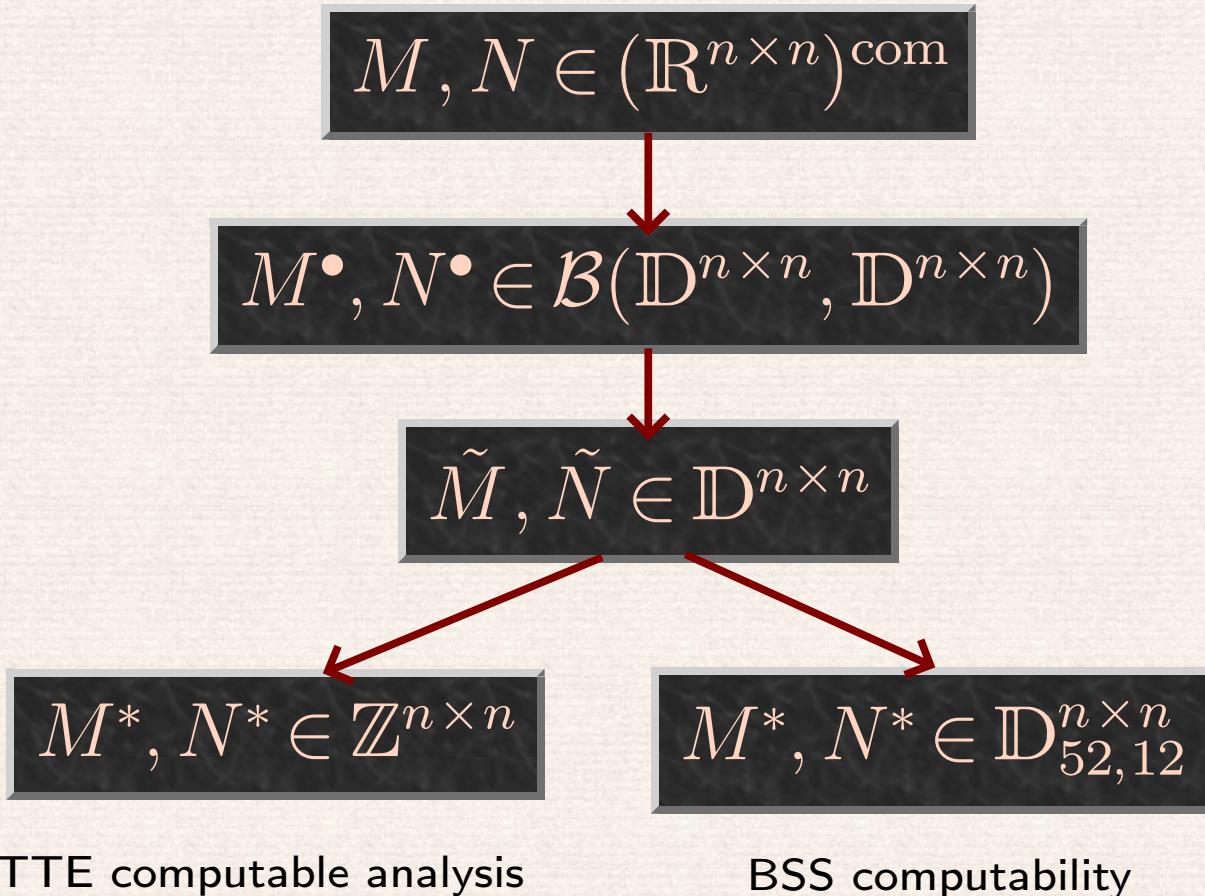
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TTE computable analysis



Numerical hierarchy





Computable real number



Definition. $x \in \mathbb{R}$ is **computable** if there exists an algorithm which takes $\varepsilon \in \mathbb{D}^>$ on input and produces an ε -approximation $\tilde{x} \in \mathbb{D}$ of x with $|\tilde{x} - x| \leq \varepsilon$. We denote \mathbb{R}^{com} to be the set of computable real numbers.

```
Mmx] use "asymptotix"; type_mode? := true;
Mmx] one: Approximator (Floating, Floating) == 1;
Mmx] e == exp one
Mmx] approximate (e, 1.0e-1000)
Mmx]
```



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2.718281828459045235360287471352662497757247093699959574966967627724076630\\
3535475945713821785251664274274663919320030599218174135966290435729003342\\
9526059563073813232862794349076323382988075319525101901157383418793070215\\
4089149934884167509244761460668082264800168477411853742345442437107539077\\
7449920695517027618386062613313845830007520449338265602976067371132007093\\
2870912744374704723069697720931014169283681902551510865746377211125238978\\
4425056953696770785449969967946864454905987931636889230098793127736178215\\
4249992295763514822082698951936680331825288693984964651058209392398294887\\
9332036250944311730123819706841614039701983767932068328237646480429531180\\
2328782509819455815301756717361332069811250996181881593041690351598888519\\
3458072738667385894228792284998920868058257492796104841984443634632449684\\
8756023362482704197862320900216099023530436994184914631409343173814364054\\
6253152096183690888707016768396424378140592714563549061303107208510383750\\
510115747704171898610687396965521267154688957035035402123407848: Floating

Mmx]



Computable power series



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Mmx] use "algebramix"; type_mode? := true;  
Mmx] z == series (0, 1)  
Mmx] B == exp (exp z - 1)  
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$z + O(z^{10})$: Series(Integer)

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6247484776193701794751691765261720408686766315411560885573191072335924586\\
5506869359619719703653924004647854188013036725130580199273179311643313446\\
3929399319082714196961652168013602803041772182448739785880587721883539643\\
696750170168607678730423675712080858884633763266376601388: Rational

```
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```



Principle

Systematic approximation of real numbers $x \in \mathbb{R}$ by closed **balls**

$$x^\bullet = \mathcal{B}(c, r) = c + \mathcal{B}(r) = \{x \in \mathbb{R} : |x - c| \leq r\},$$

with $c \in \mathbb{R}$ and $r \in \mathbb{R}^{\geq}$ (or $c \in \mathbb{D} \cup \{\pm\infty\}$ and $r \in \mathbb{D}^{\geq} \cup \{\infty\}$)

→ while guaranteeing that the « genuine result » x lies in x^\bullet



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Operations

$f^\bullet: \mathcal{B}(\mathbb{R}, \mathbb{R}^{\geq})^d \rightarrow \mathcal{B}(\mathbb{R}, \mathbb{R}^{\geq})$ **extension** of $f: \mathbb{R}^d \rightarrow \mathbb{R}$ if

$$f(x_1^\bullet, \dots, x_d^\bullet) = \{f(x_1, \dots, x_d): x_1 \in x_1^\bullet, \dots, x_n \in x_n^\bullet\} \subseteq f^\bullet(x_1^\bullet, \dots, x_n^\bullet),$$

for all $x_1^\bullet, \dots, x_d^\bullet \in \mathcal{B}(\mathbb{R}, \mathbb{R}^{\geq})$



Computability revisited



Computability = Ultimate approximability using ball arithmetic

Definition. $x \in \mathbb{R}$ is **computable** if there exists an algorithm which takes $p \in \mathbb{N}$ on input and which produces a ball $x_p^\bullet \in \mathcal{B}(\mathbb{D}, \mathbb{D})$ with $\{x\} = \bigcap_p x_p^\bullet$.

Definition. a function $f: \mathbb{R} \rightarrow \mathbb{R}$ is **computable** if there exists an algorithm which takes $p \in \mathbb{N}$ on input and which produces a computable function $f_p^\bullet: \mathcal{B}(\mathbb{D}, \mathbb{D}) \rightarrow \mathcal{B}(\mathbb{D}, \mathbb{D})$ with $f(x^\bullet) \subseteq f_p^\bullet(x^\bullet)$ for all $x^\bullet \in \mathcal{B}(\mathbb{D}, \mathbb{D})$ and such that for each sequence $(x_p^\bullet)_{p \in \mathbb{N}} \in \mathcal{B}(\mathbb{D}, \mathbb{D})^{\mathbb{N}}$ with $\{x\} = \bigcap_p x_p^\bullet$, we have $\{f(x)\} = \bigcap_p f_p^\bullet(x_p^\bullet)$.

Remark. Equivalent to TTE computability,
but relying on ordinary Turing machines



Elementary operations



Exact formulas

$$\mathcal{B}(x, r) + \bullet \mathcal{B}(y, s) = \mathcal{B}(x + y, r + s)$$

$$\mathcal{B}(x, r) - \bullet \mathcal{B}(y, s) = \mathcal{B}(x - y, r + s)$$

$$\mathcal{B}(x, r) \times \bullet \mathcal{B}(y, s) = \mathcal{B}(x \times y, r \times (|y| + s) + |x| \times s)$$



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Approximate formulas

$$x, y, r, s \in \mathbb{D}_{p,e} = \pm\{0, \dots, 2^p - 1\} 2^{\pm\{0, \dots, 2^e - 1\}} \cup \{\pm\infty\}$$

$$\mathcal{B}(x, r) +^\bullet \mathcal{B}(y, s) = \mathcal{B}(x +^{\text{near}} y, r +^\uparrow s +^\uparrow \text{error}_+(x, y))$$

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Interval arithmetic



Interval arithmetic	Ball arithmetic
Good hardware support	Poor hardware support
Natural standardization	Non canonical standardization
Natural for subdivision algorithms	Not natural for subdivision algorithms
Loses factor 2 for multiple precision	Efficient for multiple precision
Less natural for vectorization	Easy to vectorize
Requires total ordering	Natural extension to C and beyond
Not natural under perturbations	Natural for perturbation algorithms
<i>ad hoc</i> theoretical foundations (IEEE)	Well understood ε - δ calculus



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References

Moore (1965): Interval analysis

Alefeld & Herzberger (1983): Introduction to interval analysis

Rump (2010): Verification methods: rigourous results using FP arithmetic



Digression: *a priori* error estimates



Example: computing an ε -approximation for $z = x + y$

Compute $\frac{\varepsilon}{2}$ -approximations \tilde{x} and \tilde{y} for x and y

Return $\tilde{x} + \tilde{y}$



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Problem 1: Horner evaluation of $P_d x^d + \dots + P_0$ at $x = 1$

→ computes $\frac{\varepsilon}{2^{d-k}}$ -approximation of P_k for $k = 0, \dots, d-1$

→ small tolerances and bad complexity



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Problem 2: necessitates « dags » for the intermediate results



The enemy



Overestimation of the error

$$\mathcal{B}(0, 1) - \mathcal{B}(0, 1) = \mathcal{B}(0, 2)$$



The enemy

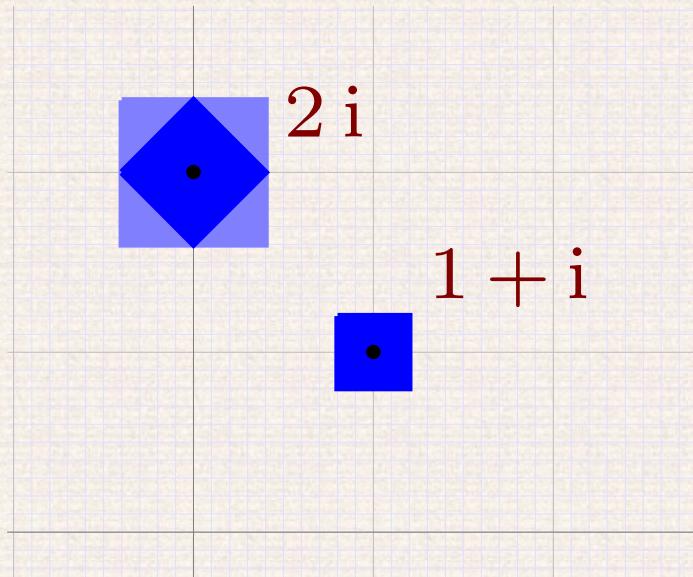


Overestimation of the error

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Wrapping effect

$$([1 - \varepsilon, 1 + \varepsilon] + [1 - \varepsilon, 1 + \varepsilon] i)^2 = [-2\varepsilon, 2\varepsilon] + [2 - 2\varepsilon, 2 + 2\varepsilon] i$$





Example



```
Mmx] use "algebramix";  
Mmx] power (z, n) == if n = 1 then z else z * power (z, n-1);  
Mmx] z == complex (interval (1.0, 1.0000000001),  
                     interval (1.0, 1.0000000001))  
Mmx] [ power (z, 4*n) || n in 1 to 10 ]  
Mmx]
```



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1.000000000 + 1.000000000 i

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```
[ -4.00000000  
 16.0000000  
 -64.000000  
 256.0000  
 -1024.000  
 4096.00  
 -16384.0  
 6.5536e4  
 -2.62e5  
 1.05e6 ]
```

```
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```



Changing the kind of enclosures



```
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 256.000000  
 -1024.00000  
 4096.00000  
 -16384.00000  
 65536.00000  
 -262144.00000  
 1.04857600e6 ]
```

```
Mmx]
```



Minimizing the depth of the computation



```
Mmx] use "algebramix";  
Mmx] power (z, n) ==  
    if n = 1 then z  
    else power (z, n quo 2) * power (z, n - (n quo 2));  
Mmx] z == complex (interval (1.0, 1.0000000001),  
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 65536.000  
 -262144.00  
 1.0485760e6 ]
```

Mmx]

Perturbation method (Hansen)



Algorithm: invert the matrix $M \in \mathcal{B}(\mathbb{D}, \mathbb{D})^{n \times n}$

- Write $M = \mathcal{B}(C, R)$, with $C \in \mathbb{D}^{n \times n}$ et $R \in (\mathbb{D}^>)^{n \times n}$
- Numerically invert $U := C^{-1}$
- Compute $E := C\mathcal{B}(U, 0) - \mathcal{B}(1, 0)$, so that

$$M^{-1} = U(MU)^{-1} = U(1 + E)^{-1}$$

- With $\varepsilon := \|E\|_\infty = \max_{1 \leq i \leq n} (|E_{i1}| + \dots + |E_{in}|)$, we have

$$\|(1 + E)^{-1} - 1\|_\infty = \|-E + E^2 - E^3 + \dots\|_\infty \leq \frac{\varepsilon}{1 - \varepsilon}$$

- Let $\mathbb{1}$ be the matrix with entries $\mathbb{1}_{ij} = 1$
- Return $V := U\mathcal{B}(1, \frac{\varepsilon}{1 - \varepsilon}\mathbb{1})$

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- Return $V := U\mathcal{B}(1, \frac{\varepsilon}{1 - \varepsilon} \mathbb{1})$

More generally \rightsquigarrow

Phase of **guessing** or **prospection**, next phase of **validation**



Example



```
Mmx] use "analyziz"  
Mmx] rnd () == {  
    x == uniform_deviate (0.0, 1.0);  
    return ball (x, 0.00000001);  
};  
Mmx] M == [ rnd () | j in 1 to 7 || i in 1 to 7 ]  
Mmx] row_echelon M  
Mmx]
```



Example



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```
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```

$$\begin{bmatrix} 0.6003643 & 0.3710189 & 0.4791752 & 0.1559513 & 0.4159951 & 0.1407053 & 0.0044911 \\ 0.5120348 & 0.7247114 & 0.1947940 & 0.655922 & 0.9355430 & 0.251486 & 0.2468534 \\ 0.462639 & 0.5648943 & 0.744350 & 0.4275757 & 0.7804102 & 0.9920186 & 0.7571225 \\ 0.2508314 & 0.0131642 & 0.8669620 & 0.6802075 & 0.7552889 & 0.3166660 & 0.3160914 \\ 0.2876469 & 0.988199 & 0.6639689 & 0.303261 & 0.498002 & 0.0277941 & 0.9222224 \\ 0.1304958 & 0.7945297 & 0.7988684 & 0.5890020 & 0.3421886 & 0.0285099 & 0.9893513 \\ 0.3882938 & 0.7500550 & 0.9237840 & 0.594590 & 0.8730709 & 0.5362681 & 0.134547 \end{bmatrix}$$

```
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```

```
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Example



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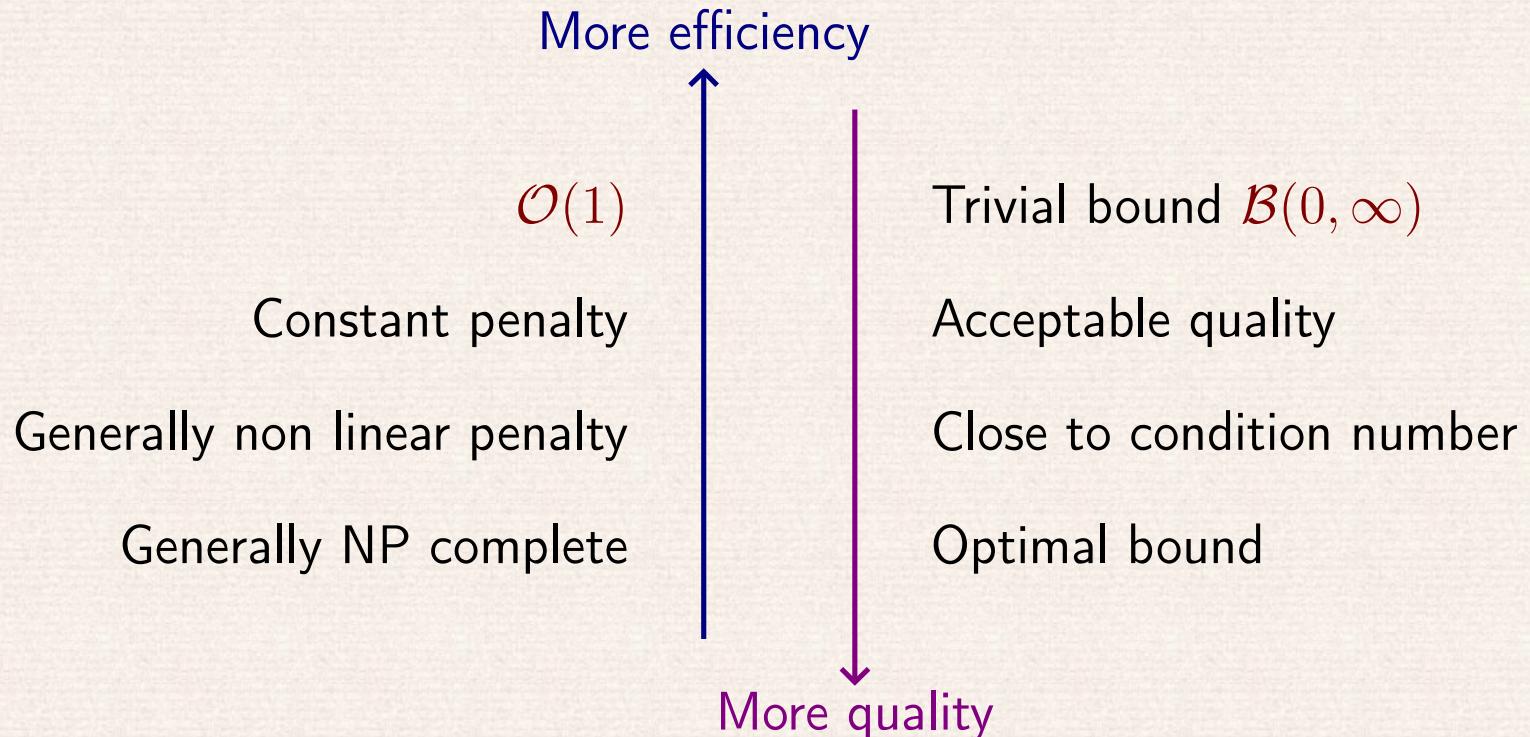
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Mmx]

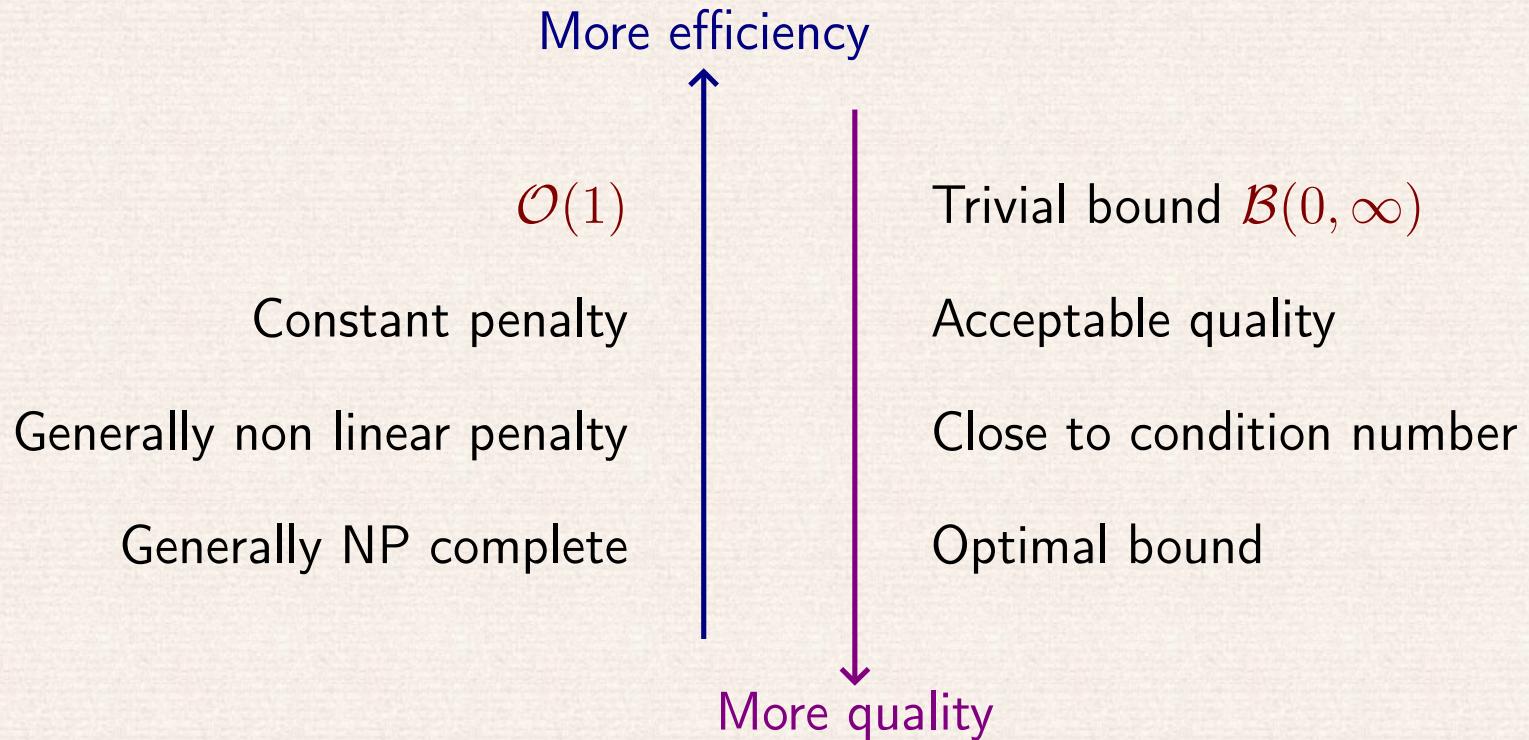


Graal: efficient *and* tight error bounding





Graal: efficient *and* tight error bounding



Early termination: start with fast strategy, but *a priori* of poor quality
Use slower algorithms only if this quality is not enough



Example: matrix multiplication



Majoration $|(MN)_{ij}| \leq [\max |M_{i\cdot}|] [\max |N_{\cdot j}|]$:

1 multiplication in $\mathbb{D}^{n \times n}$ and $\mathcal{O}(n^2)$ majorations, possibly bad quality

Compromise: cut M and N into $k \times k$ matrices for fixed k :

α_k multiplications in $\mathbb{D}^{n \times n}$ with $1 \leq \alpha_k \leq 3$, usually good quality

Compromise: resort to naive multiplication in case of ill conditioning

Between 1 and 3 multiplications in $\mathbb{D}^{n \times n}$, always good quality

Rewrite $M, N \in \mathcal{B}(\mathbb{D}^{n \times n}, \mathbb{D}^{n \times n})$:

3 multiplications in $\mathbb{D}^{n \times n}$ (with 2 multiplications at single precision)

Naive product M, N with $M, N \in \mathcal{B}(\mathbb{D}, \mathbb{D})^{n \times n}$:

$\mathcal{O}(n^3)$ operations in $\mathcal{B}(\mathbb{D}, \mathbb{D})$, always good quality



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General principle (observed in practice):

Validation cost asymptotically negligible for well conditioned operations



Example: polynomial multiplication



$$P, Q \in \mathcal{B}(\mathbb{D}_p, \mathbb{D}_{52})[x]_{<d}$$

FFT multiplication

Cost $\tilde{\mathcal{O}}(dp)$, only good quality if all coefficients of same magnitude

FFT multiplication with scaling $[P(\alpha x) Q(\alpha x)] \circ (x/\alpha)$

Cost $\tilde{\mathcal{O}}(dp)$, good quality for truncated power series

FFT multiplication with scaling and cutting into blocks (VdH, Arb)

(vdH) Cost $\tilde{\mathcal{O}}(dp)$, good quality in terms of roots of polynomials

(Arb) Cost between $\tilde{\mathcal{O}}(dp)$ and $\tilde{\mathcal{O}}(d^2 p)$, optimal quality

Naive multiplication of $P, Q \in \mathcal{B}(\mathbb{D}_p, \mathbb{D}_{52})[x]_{<d}$

Cost $\tilde{\mathcal{O}}(d^2 p)$, optimal quality



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Condition numbers and precision loss



Condition number (intrinsic)

$$f: \mathbb{R}^n \rightarrow \mathbb{R}^k$$

$$\begin{aligned}\kappa_f(x) &= \limsup_{\varepsilon \rightarrow 0} \frac{\|f(x + \varepsilon) - f(x)\|}{\|f(x)\|} \Bigg/ \frac{\|\varepsilon\|}{\|x\|} \\ \kappa(M) &= \|M\| \|M^{-1}\|\end{aligned}$$



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Precision loss (of an algorithm)

$$f_p: \mathbb{D}_p^n \rightarrow \mathbb{D}_p^k$$

$$\chi_{f_p}(x) = \frac{\|f_p(x) - f(x)\|}{\|f(x)\|} / (2^p \kappa_f(x))$$



Optimal extensions and overestimation



Optimal extension (intrinsic)

$$f: \mathbb{R}^n \rightarrow \mathbb{R}^k$$
$$f^*(\mathcal{B}(x, r)) = \mathcal{B}\left(f(x), \sup_{x' \in \mathcal{B}(x, r)} |f(x') - f(x)|\right)$$



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Overestimation and punctual overestimation (of an algorithm)

$$f^\bullet: \mathcal{B}(\mathbb{R}, \mathbb{R})^n \rightarrow \mathcal{B}(\mathbb{R}, \mathbb{R})^k$$

$$\chi_{f^\bullet}(\mathcal{B}(x, r)) = \inf_{\lambda} \{f^\bullet(\mathcal{B}(x, r)) - f(x) \subseteq \lambda (f^*(\mathcal{B}(x, r)) - f(x))\}$$

$$\chi_{f^\bullet}(x) = \limsup_{r \rightarrow 0} \chi_{f^\bullet}(\mathcal{B}(x, r))$$



Optimal extensions and overestimation



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$$\chi_{f^\bullet}(\mathcal{B}(x, r)) = \inf_{\lambda} \{f^\bullet(\mathcal{B}(x, r)) - f(x) \subseteq \lambda (f^*(\mathcal{B}(x, r)) - f(x))\}$$
$$\chi_{f^\bullet}(x) = \limsup_{r \rightarrow 0} \chi_{f^\bullet}(\mathcal{B}(x, r))$$

Question: for f^\bullet constructed using $+\bullet$, $-\bullet$, $\times\bullet$, do we have

$$\chi_{f^\bullet}(\mathcal{B}(x, r)) \leq \sup_{x \in \mathcal{B}(x, r)} \chi_{f^\bullet}(x) ?$$



Overestimation of standard arithmetic



Example

$$f(x) = (x - 1)^2$$

$$f^\bullet(x^\bullet) = (x^\bullet)^2 - \bullet 2x^\bullet + \bullet 1$$

$$f^*(\mathcal{B}(x, \varepsilon)) = \mathcal{B}(f(x), 2|x - 1|\varepsilon + \mathcal{O}(\varepsilon^2))$$

$$f^\bullet(\mathcal{B}(x, \varepsilon)) = \mathcal{B}(f(x), 2|x|\varepsilon + 2\varepsilon + \mathcal{O}(\varepsilon^2))$$

$$\chi_{f^\bullet}(x) = \frac{|x| + 1}{|x - 1|}$$



Overestimation of standard arithmetic



Example

$$\begin{aligned} f(x) &= (x - 1)^2 \\ f^\bullet(x^\bullet) &= (x^\bullet)^2 - \bullet 2x^\bullet + \bullet 1 \end{aligned}$$

$$\begin{aligned} f^*(\mathcal{B}(x, \varepsilon)) &= \mathcal{B}(f(x), 2|x - 1|\varepsilon + \mathcal{O}(\varepsilon^2)) \\ f^\bullet(\mathcal{B}(x, \varepsilon)) &= \mathcal{B}(f(x), 2|x|\varepsilon + 2\varepsilon + \mathcal{O}(\varepsilon^2)) \\ \chi_{f^\bullet}(x) &= \frac{|x| + 1}{|x - 1|} \end{aligned}$$

In general

$$\begin{aligned} \chi_{f^\bullet}(x) &= \limsup_{\varepsilon \neq 0} \frac{(\bar{\nabla} f)(x) \cdot |\varepsilon|}{|(\nabla f)(x)| \cdot |\varepsilon|} \quad \text{or } (d=1) \quad \frac{(\bar{\nabla} f)(x)}{|f'(x)|} \\ \bar{\nabla} c &= (0, \dots, 0) \quad (c \in \mathbb{R}) \\ \bar{\nabla} X_k &= (0, {}^{k-1}\dots, 0, 1, 0, \dots, 0) \quad (k \in \{1, \dots, r\}) \\ \bar{\nabla}(f \pm g) &= \bar{\nabla} f + \bar{\nabla} g \\ \bar{\nabla}(fg) &= (\bar{\nabla} f)|g| + |f|(\bar{\nabla} g), \end{aligned}$$



Taylor models (Berz et Makino)



Taylor model of order n on $\mathcal{B}(0, r)$

$$\mathcal{B}_r(\varphi, K) = \{ f \text{ analytic on } \mathcal{B}(0, r) : \forall |z| \leq r, |f(z) - \varphi(z)| \leq K \}$$

$$\mathcal{B}_r(\mathbb{D}[z]_{<n}, \mathbb{D}) = \{ \mathcal{B}_r(f_0 + \dots + f_{n-1} z^{n-1}, K) : f_0, \dots, f_{n-1}, K \in \mathbb{D} \}$$



Taylor models (Berz et Makino)



Taylor model of order n on $\mathcal{B}(0, r)$

$$\mathcal{B}_r(\varphi, K) = \{ f \text{ analytic on } \mathcal{B}(0, r) : \forall |z| \leq r, |f(z) - \varphi(z)| \leq K \}$$

$$\mathcal{B}_r(\mathbb{D}[z]_{<n}, \mathbb{D}) = \{ \mathcal{B}_r(f_0 + \cdots + f_{n-1} z^{n-1}, K) : f_0, \dots, f_{n-1}, K \in \mathbb{D} \}$$

Product

$$\mathcal{B}_r(f_0 + \cdots + f_{n-1} z^{n-1}, K) \mathcal{B}_r(g_0 + \cdots + g_{n-1} z^{n-1}, L)$$

$$= \mathcal{B}_r(f_0 g_0 + \cdots + (f_0 g_{n-1} + \cdots + f_{n-1} g_0) z^{n-1}, E^{\text{tr}} + E^{\text{rnd}})$$

$$E^{\text{tr}} = |f_1| |g_{n-1}| + |f_2| (|g_{n-1}| + |g_{n-2}|) + \cdots + |f_{n-1}| (|g_1| + \cdots + |g_{n-1}|) \quad (\text{up})$$

$$E^{\text{rnd}} = [|f_0| |g_{n-1}| + \cdots + (|f_0| + \cdots + |f_{n-1}|) |g_0|] C 2^{-p} \quad (\text{up})$$



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Intégration

$$\int \mathcal{B}_r(f_0 + \dots + f_{n-1} z^{n-1}, K) = \mathcal{B}_r(f_1 + \dots + \frac{f_{n-2}}{n-1} z^{n-1}, K r + \frac{|f_{n-1}|}{n} r^n + E^{\text{rnd}})$$



Reduction of overestimation



Example

$$\begin{aligned} f(x) &= (x - 1)^2 \\ f^\bullet(x^\bullet) &= (x^\bullet)^2 - \bullet 2x^\bullet + \bullet 1 \end{aligned}$$

$$\begin{aligned} f^*(\mathcal{B}(x, \varepsilon)) &= \mathcal{B}(f(x), 2|x - 1|\varepsilon + \mathcal{O}(\varepsilon^2)) \\ f^\bullet(\mathcal{B}(x, \varepsilon)) &= \mathcal{B}(f(x), 2|x|\varepsilon + 2\varepsilon + \mathcal{O}(\varepsilon^2)) \\ \chi_{f^\bullet}(x) &= \frac{|x| + 1}{|x - 1|} \end{aligned}$$



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Idea: use a Taylor model of order ≥ 2

$$\begin{aligned} f^{\text{Taylor}}(\mathcal{B}_r(x, 0)) &= \mathcal{B}_r(y_0 + y_1 t, \varepsilon) \\ f^\bullet(\mathcal{B}(x, r)) &= \mathcal{B}(y_0, |y_1|r + \varepsilon) \\ \chi_{f^\bullet}(x) &= 1 \end{aligned}$$



Example challenge



Complexity to solve

$$P(z) = 0,$$

with $P \in \mathbb{C}[z]$, $\deg P = d$, at bit precision p ?

Challenge 1. Optimal complexity, uniformly in p and d



Example challenge



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Challenge 2. Relation to easier question: multipoint evaluation

$$p \gg d \rightsquigarrow \tilde{\mathcal{O}}(p d)$$



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$$p \ll \sqrt[3]{d} \rightsquigarrow \tilde{\mathcal{O}}(d^{3/2} p^{3/2})$$



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Challenge 3. Dependence on condition number



Random polynomials (well conditioned)



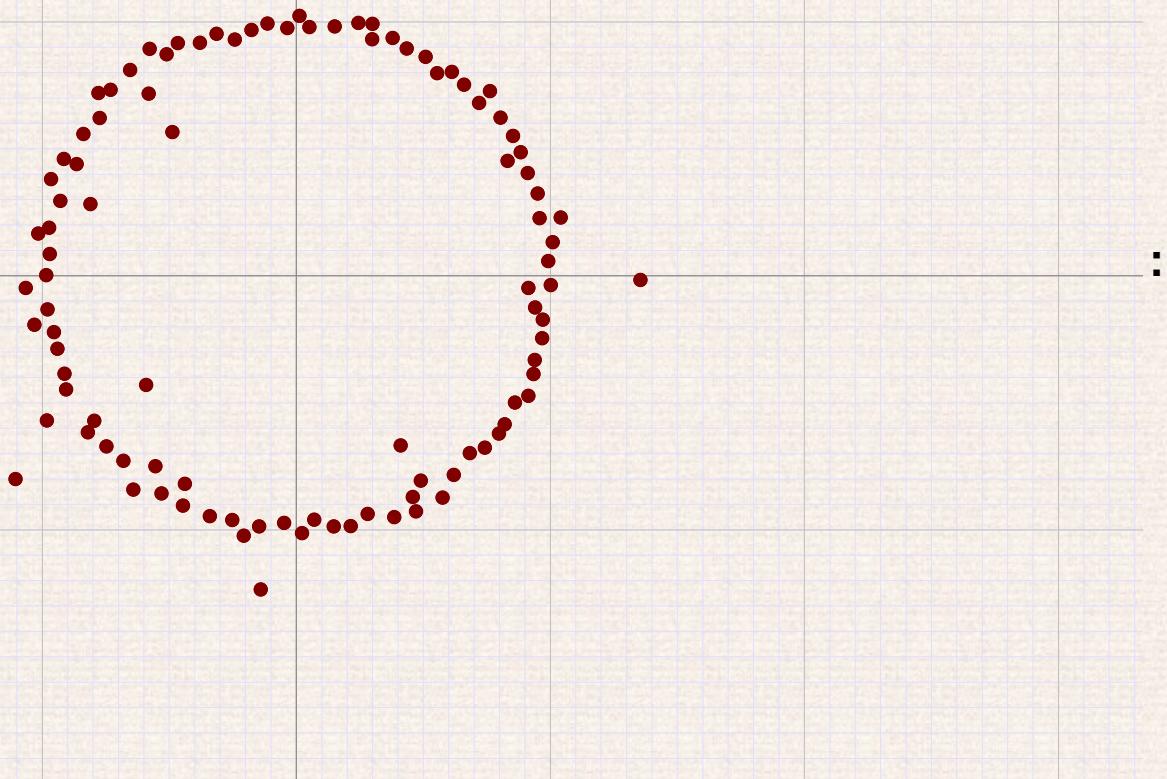
```
Mmx] use "analyziz"; include "graphix/points.mmx";  
Mmx] pi == 4.0 * arctan 1.0;  
Mmx] rnd () == exp (complex (0.0, uniform_deviate (0.0, 2*pi)));  
Mmx] p == polynomial (rnd () | i in 0 to 100);  
Mmx] $points roots p  
Mmx]
```



Random polynomials (well conditioned)



```
Mmx] use "analyziz"; include "graphix/points.mmx";  
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```





Multiple roots



```
Mmx] p == poly (1.0, -1.0)^100; // (1 - z)^100
```

```
Mmx] $points (roots p)
```

```
Mmx]
```

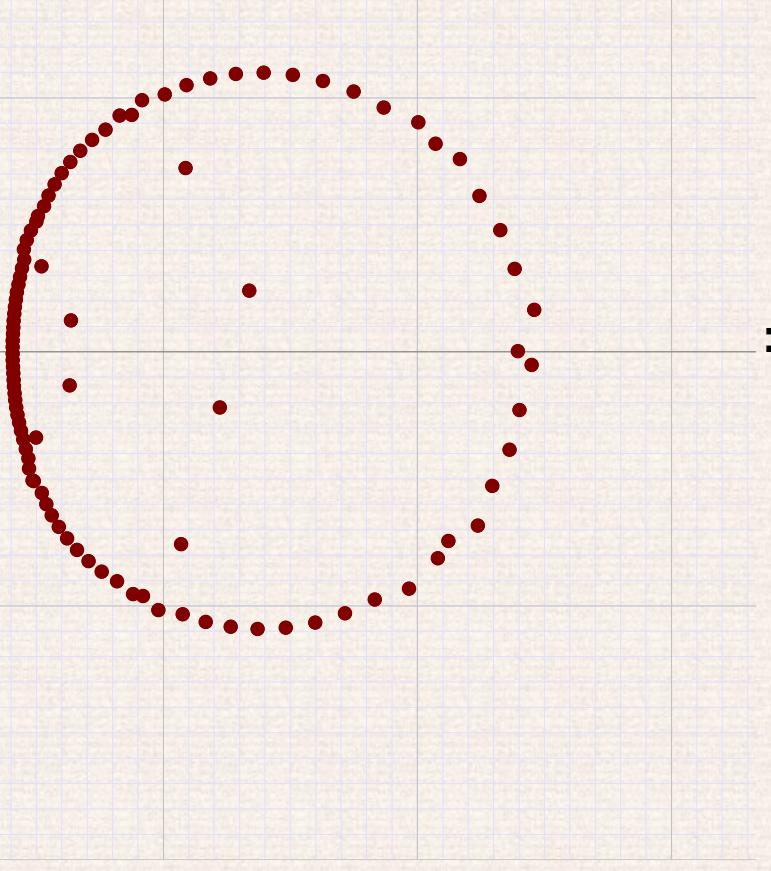


Multiple roots



```
Mmx] p == poly (1.0, -1.0)^100; // (1 - z)^100  
Mmx] $points (roots p)
```

Compound
in 639





Random roots on half circle



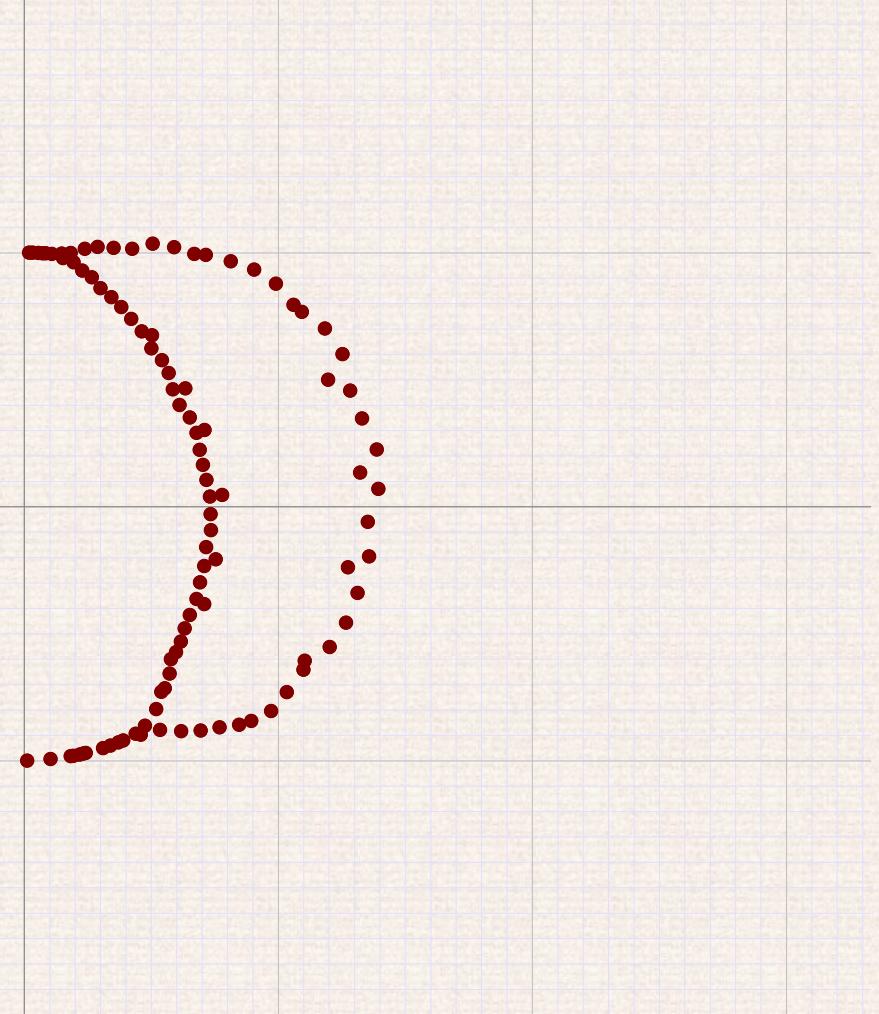
```
Mmx] v == [ rnd () | i in 1 to 100 ];  
Mmx] v == [ sqrt rnd () | i in 1 to 100 ];  
Mmx] p == annulator v;  
Mmx] $points (roots p)  
Mmx]
```



Random roots on half circle



```
Mmx] v == [ rnd () | i in 1 to 100 ];  
Mmx] v == [ sqrt rnd () | i in 1 to 100 ];  
Mmx] p == annulator v;  
Mmx] $points (roots p)
```



Compound
in 641



Truncated power series



```
Mmx] z == series (0.0, 1.0);  
Mmx] B == exp (exp z - 1);  
Mmx] p == B[0,100];  
Mmx] $points (0.5 * roots p)  
Mmx]
```



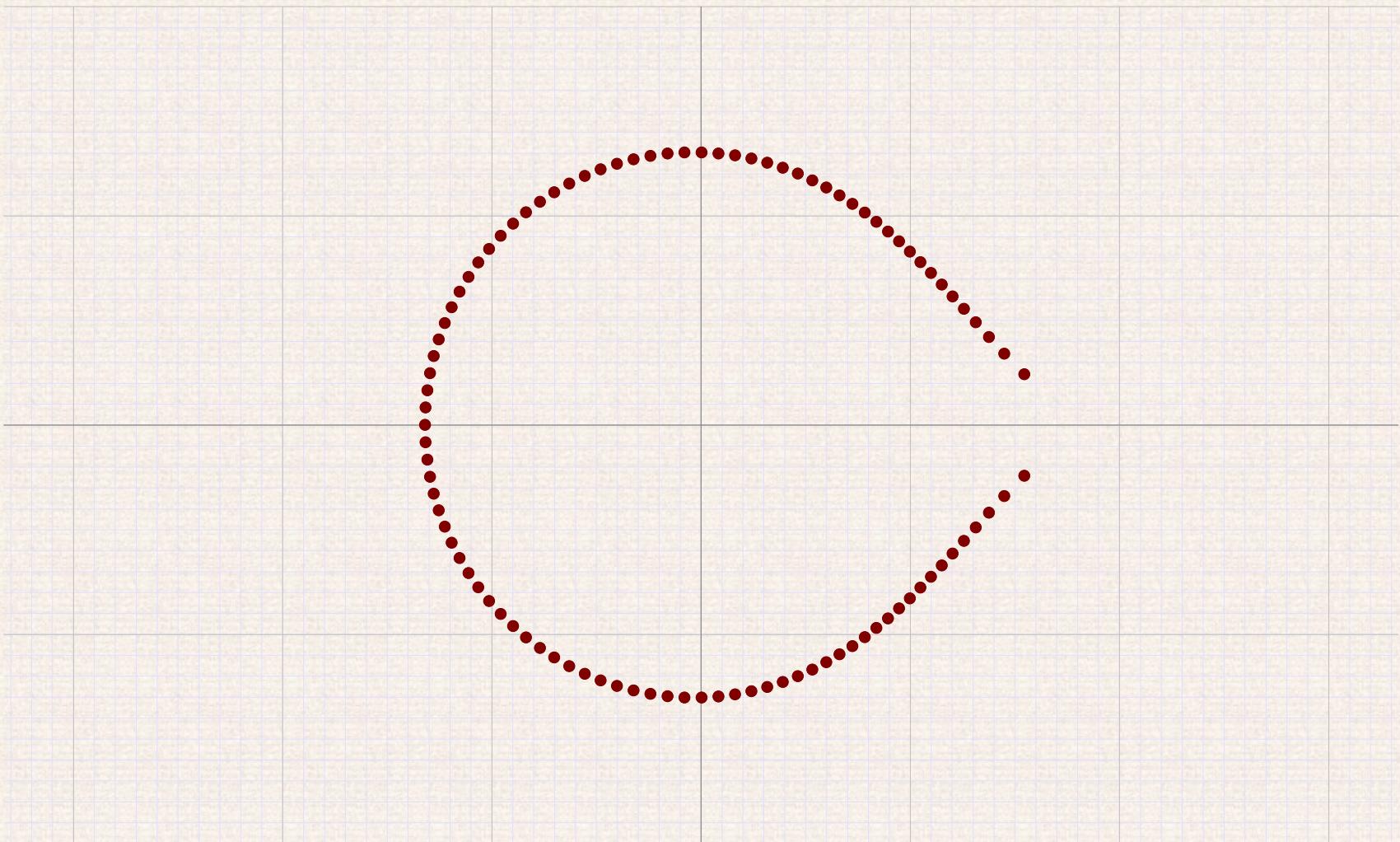
Truncated power series



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Mmx] z == series (0.0, 1.0);  
Mmx] B == exp (exp z - 1);
```

```
Mmx] p == B[0,100];
```

```
Mmx] $points (0.5 * roots p)
```





Truncated power series



```
Mmx] z == series (0.0, 1.0);  
Mmx] f == integrate exp (-z*z);  
Mmx] p == f[0,200];  
Mmx] $points (0.2 * roots p)  
Mmx]
```



Truncated power series



```
Mmx] z == series (0.0, 1.0);  
Mmx] f == integrate exp (-z*z);
```

```
Mmx] p == f[0,200];
```

```
Mmx] $points (0.2 * roots p)
```

