# Towards Optimal Toom-Cook Matrices 

for Integer and Polynomial Multiplication

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(1) Toom-Cook multiplication methods

- Multiplication algorithms and complexity
- Toom-Cook algorithm for polynomials, revisited
- Extension to unbalanced factors
(2) Toom matrices
- The working model
- Operations and costs
- Graph searching
(3) Results
- Toom-2.5 and Toom-3
- Higher Toom-Cook methods
- Some graphics


## Long integer and polynomial multiplication

## Some notation

Let $\mathbf{R}$ be $\mathbb{Z}$ or $\mathbb{Z}[X]$,

$$
a(x)=\sum_{i=0}^{d_{a}} a_{i} x^{i} \quad, \quad b(x)=\sum_{i=0}^{d_{b}} b_{i} x^{i} \in \mathbf{R}[x]
$$

We want to compute their product

$$
c(x)=\sum_{i=0}^{d_{c}} c_{i} x^{i} \in \mathbf{R}[x]
$$

$$
\operatorname{deg}(a)=d_{a} \quad ; \quad \operatorname{deg}(b)=d_{b} \quad ; \quad \operatorname{deg}(c)=d_{c}=d_{a}+d_{b}
$$

## Long integer and polynomial multiplication

The classical Тоом-Cook approach

- Тоом-Cook methods concern univariate polynomials multiplication.
- Тоом- $n$ method refers to factors having $n$ parts each (degrees $d_{a}=d_{b}=n-1$ ).
- It is an absolutely standard procedure to apply these methods to general univariate polynomials and long integers multiplication by a simple base changing.


## Multiplication algorithms

## Many algorithms are known for polynomial multiplication.

- Naïve $\mathrm{O}\left(d^{2}\right)$

Each one has a different complexity, and its own range where it is the fastest one.

## Multiplication algorithms

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- Naïve
- Karatsuba (1962)
$\mathrm{O}\left(d^{2}\right)$
$\mathrm{O}\left(d^{\log _{2} 3}\right)$

Each one has a different complexity, and its own range where it is the fastest one.

## Multiplication algorithms

Many algorithms are known for polynomial multiplication.

- Naïve
- Karatsuba (1962)
- Schönhage-Strassen (1971)
$\mathrm{O}(d \log d \log \log d)$
Each one has a different complexity, and its own range where it is the fastest one.

In 2007, Martin Fürer announced a new algorithm that should have
a better asymptotic complexity.

## Multiplication algorithms

Many algorithms are known for polynomial multiplication.

- Naïve
- Karatsuba (Тоом-2) (1962)
- Тоом-Cook-n (1963)
- Schönhage-Strassen (1971)

$$
\begin{array}{r}
\mathrm{O}\left(d^{2}\right) \\
\mathrm{O}\left(d^{\log _{2} 3}\right) \\
\mathrm{O}\left(d^{\log _{n}(2 n-1)}\right) \\
\mathrm{O}(d \log d \log \log d)
\end{array}
$$

Each one has a different complexity, and its own range where it is the fastest one.

We aim to analyse the optimality of Тоом-Cook methods within their respective ranges of applicability.

## Recall on Toom- $n$ algorithm <br> 3 (core) phases

(1) Splitting: choose a base and split
(2) Evaluation
(9) Recomposition: shift and add.

Phase 2, some linear algebra
Evaluate polynomials $a(x), b(x)$ in $2 n-1$ different points $\left\{v_{i}\right\} \in \mathbb{Z}$.
This can be obtained by multiplying a (non square) Vandermonde matrix by the vector of coefficients.

## Recall on Тоом- $n$ algorithm

(1) Splitting: choose a base and split
(2) Evaluation: $2 \times$ matrix-vector multiplication
(3) Multiplication

## (3) Recomposition: shift and add.

## Phase 3, recursive application

Evaluate the product by multiplying factors evaluations.
$c\left(v_{i}\right)=a\left(v_{i}\right) \cdot b\left(v_{i}\right)$
(degree $n-1$ ) $\times$ (degree $n-1$ ) $\rightsquigarrow$ degree $2 n-2$.
( $n$ parts) $\times(n$ parts $) \rightsquigarrow 2 n-1$ parts. $\Rightarrow 2 n-1$ multiplications.

## Recall on Тоом- $n$ algorithm

(1) Splitting: choose a base and split
(2) Evaluation: $2 \times$ matrix-vector multiplication
(3) Multiplication: $(2 n-1) \times$ smaller multiplication
(9) Interpolation
(9) Recomposition: shift and add.

## Phase 4, some more linear algebra

Interpolate to obtain coefficient of the product polynomial.
Obtain this by multiplying the inverse of a (square) Vandermonde matrix by the vector of evaluations.

## Recall on Тоом- $n$ algorithm

## 3 (core) phases

(1) Splitting: choose a base and split
(2) Evaluation: $2 \times$ matrix-vector multiplication
(3) Multiplication: $(2 n-1) \times$ smaller multiplication
(9) Interpolation: inverse matrix-vector multiplication
(0) Recomposition: shift and add.

## Phases 2 and 4 are critical

Splitting order $n$ results in $(2 n-1)$ multiplications in phase 3, and asymptotic behaviour $\Theta\left(d^{\log _{n}(2 n-1)}\right)$. Rigidly.
The hidden constant is determined by the evaluation/interpolation points and operation sequences for phases 2 and 4 .

## Unbalanced operands

## Factors with different degrees

Тоом-(n+m)/2
(degree $n-1) \times($ degree $m-1) \rightsquigarrow$ degree $n+m-2$ ( $n$ parts) $\times(m$ parts $) \rightsquigarrow n+m-1$ parts

Тоом methods can thus be applied also to polynomials with different degrees. The evaluation phase depends on $m$ and $n$ separately, while the interpolation phase only on $n+m$.

Тоом-2.5
Unbalanced Тоом-3
$(\operatorname{deg} 2) \times(\operatorname{deg} 1) \rightsquigarrow \operatorname{deg} 3$
(3 parts) $\times(2$ parts $) \rightsquigarrow 4$ parts
$(\operatorname{deg} 3) \times(\operatorname{deg} 1) \rightsquigarrow \operatorname{deg} 4$
(4 parts) $\times(2$ parts $) \rightsquigarrow 5$ parts

## Some examples for basic cases

The matrices of Тоом-2.5 and Тоом-3 interpolation phase are

$$
A_{2.5}=\left(\begin{array}{rrrr}
1 & 0 & 0 & 0 \\
-1 & 1 & -1 & 1 \\
1 & 1 & 1 & 1 \\
0 & 0 & 0 & 1
\end{array}\right) \quad ; \quad A_{3}=\left(\begin{array}{rrrrr}
1 & 0 & 0 & 0 & 0 \\
16 & 8 & 4 & 2 & 1 \\
1 & -1 & 1 & -1 & 1 \\
1 & 1 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 1
\end{array}\right)
$$

## Theorem

For $n \geqslant 3, \operatorname{det}\left(A_{n}\right)$ is not a power of 2 (one division is needed).

## Theorem

Let $A_{n}$ be generated by $\left\{\infty, 1,-1, v_{4}, \ldots, v_{2 n-2}, 0\right\}$. At most $2 n-5$ divisions are needed in the interpolation phase.

## The setting

GOAL: we want the best (most efficient) sequence of elementary operations on rows to transform matrix $A_{n}$ into identity.

- There are $\infty$ possible inversion sequences (IS).
- We restrict the admissible operations by defining two criteria.
- They define a finite "model" such that an exhaustive search is possible.
- We describe this model as a weighted graph.
- The goal is reached by solving a shortest path problem on the graph.


## Some useful definitions

For a square matrix $M$ :
$M[i, j]$ : the entry in position $(i, j)$
$M^{(i)} \quad$ : the $i^{\text {th }}$ line
$M^{[j]} \quad$ : the $j^{\text {th }}$ column

## Definition

The support of $M^{(i)}$ is the set $s\left(M^{(i)}\right)$ of column indexes $j \in \mathbb{N}$ such that $M[i, j] \neq 0$. Similarly for $M^{[i]}$.
The support of $M$ is the set $s(M)$ of pairs $(i, j) \in \mathbb{N} \times \mathbb{N}$ such that $M[i, j] \neq 0$.
${ }^{\#} M^{(i)}=$ cardinality of $s\left(M^{(i)}\right)$. Similarly for ${ }^{\#} M^{[i]}$ and ${ }^{\#} M$.

## The model criteria

$$
\cdots \rightarrow M \xrightarrow{(i)} \widetilde{M} \rightarrow \cdots \rightarrow I
$$

(A) Support reduction :

$$
\left(\# \widetilde{M}^{(i)}<\# M^{(i)}\right) \wedge(M[i, j]=0 \Rightarrow \widetilde{M}[i, j]=0)
$$

At least one more zero entry. "Old" 0 entries are not modified.
(B) Regularisation: $\widetilde{M}[i, j] / M\left[i^{\prime}, j\right]=\widetilde{M}\left[i, j^{\prime}\right] / M\left[i^{\prime}, j^{\prime}\right]$.

More entries differing from the corresponding ones in another line by a common multiplicative factor than before.
Example ( $\mathrm{A}, \mathrm{B}$ ): in $A_{3}$,

$$
(168421)+2\left(\begin{array}{llll}
1 & -1 & 1 & -1
\end{array}\right) \rightarrow\left(\begin{array}{rll}
1 8 \longdiv { 6 6 } & 0 & 3
\end{array}\right)
$$

## Operations we count on for linear algebra

## Linear combinations

$l_{i} \leftarrow\left(c_{i} \cdot l_{i}+c_{j} \cdot l_{j}\right) / d_{i}$, where $c_{i}, c_{j}, d_{i}$ are "small" constants. "small" actually means fixed: asymptotically small. Typically fits in 1 WORD.

Basic on long operands: linear operations

|  | $\left\|c_{i}\right\|$ | $\left\|c_{j}\right\|$ | $d_{i}$ | cost |
| :--- | :---: | :---: | :---: | :--- |
| Add/Sub | 1 | 1 | 1 | STEP |
| I.c of first type | 1 | $2^{k}$ | 1 | STEP + (_1_2) |
|  | $2^{k}$ | 1 | 1 | STEP + (_1_2) |
| I.c of second type | 1 | $\neq 2^{k}$ | 1 | STEP + (_1X) |
|  | $\neq 2^{k}$ | 1 | 1 | STEP + (_1 X) |
| Division by $2^{k}($ shift $)$ | 1 | 0 | $2^{k}$ | SHIFT |
| Exact division | 1 | 0 | $\neq 2^{k}$ | DIV |

## The Тоом graph

Let $G=(V, E, w)$ the weighted graph such that
(1) $V$ is the set of matrices obtained by $A_{n}$ with $\rightarrow^{*}$ subject to criteria (A) and (B).
(2) $E$ is the set of edges such that $(M, \widetilde{M}) \in E \Leftrightarrow \widetilde{M}$ can be obtained by $M$ by means of an admissible linear combination.

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## Definition (weight function)

For $\varepsilon \in E, w(\varepsilon)$ is the cost of the corresponding linear combination. For a chain $\mathcal{C}, w(\mathcal{C})=\sum_{\varepsilon \in \mathcal{C}} w(\varepsilon)$.

$$
w(M)=\min _{\mathcal{C}(M, I)}\{w(\mathcal{C})\}
$$

Example (Karatsuba graph): Let $\left(v_{1}=\infty, v_{2}=1, v_{3}=0\right)$

$$
\begin{aligned}
& \left(\begin{array}{lll}
1 & 0 & 0 \\
1 & 1 & 1 \\
0 & 0 & 1
\end{array}\right) \xrightarrow{\varepsilon_{1}}\left(\begin{array}{lll}
1 & 0 & 0 \\
0 & 1 & 1 \\
0 & 0 & 1
\end{array}\right) \\
& \varepsilon_{2} \downarrow \quad \downarrow \varepsilon_{3} \\
& \left(\begin{array}{lll}
1 & 0 & 0 \\
1 & 1 & 0 \\
0 & 0 & 1
\end{array}\right) \xrightarrow{\varepsilon_{4}} \quad \text { / }
\end{aligned}
$$

Example (Knuth graph): Let $\left(v_{1}=\infty, v_{2}=-1, v_{3}=0\right)$

$$
\begin{gathered}
\left(\begin{array}{rrr}
1 & 0 & 0 \\
1 & -1 & 1 \\
0 & 0 & 1
\end{array}\right) \xrightarrow{\varepsilon_{1}}\left(\begin{array}{rrr}
1 & 0 & 0 \\
0 & -1 & 1 \\
0 & 0 & 1
\end{array}\right) \\
\varepsilon_{2} \downarrow \\
\left(\begin{array}{rrr}
1 & 0 & 0 \\
1 & -1 & 0 \\
0 & 0 & 1
\end{array}\right) \xrightarrow{\varepsilon_{3}}
\end{gathered}
$$

## Heuristics for search pruning

We use a recursive function $f$ to visit $G$, keeping some vertexes for some time to benefit from already made evaluations.

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- We make estimates (from below) e(M) of $w(M)$ by exploiting various heuristics (matrix support cardinality, determinant value, submatrices, etc).
- We introduce a threshold $t$ (parameter for $f$ ) to avoid analysing not interesting subgraphs. If $e(M)>t$ the subgraph under $M$ is not analysed (no better IS can be drawn from it).
- $t$ is updated while $f$ visits $G$ : if $M \underset{ }{\varepsilon} \widetilde{M}$ and $f(M, t)$ calls itself, then the recursive call is $f(\widetilde{M}, t-w(\varepsilon))$.


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## Тоом-2.5 optimal IS

$A_{2.5}$ generated by $\{\infty,-1,1,0\}$, with $\operatorname{det}\left(A_{2.5}\right)=2$.
A Тоом-graph with 17 nodes was built. The weight is

$$
\begin{gathered}
4 \cdot \text { STEP }+ \text { SHIFT } \\
A_{2.5}=\left(\begin{array}{rrrr}
1 & 0 & 0 & 0 \\
-1 & 1 & -1 & 1 \\
1 & 1 & 1 & 1 \\
0 & 0 & 0 & 1
\end{array}\right) \stackrel{2-=3}{\Longrightarrow}\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 2 & 0 & 2 \\
1 & 1 & 1 & 1 \\
0 & 0 & 0 & 1
\end{array}\right) \underset{3-=1}{2 \gg(1)}\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 1 \\
0 & 1 & 1 & 1 \\
0 & 0 & 0 & 1
\end{array}\right) \underset{2-=4}{3-=2} I
\end{gathered}
$$

There are 16 minimal equivalent IS.

## Toom-3 optimal IS

$A_{3}$ generated by $\{\infty, 2,-1,1,0\}$, with $\operatorname{det}\left(A_{3}\right)=12$. The IS implemented in GMP 4.2.1 uses both criteria. Its weight is

$$
w_{G M P}=8 \cdot \text { STEP }+ \text { DIV }+2 \cdot \text { SHIFT }+2 \cdot\left(\_1 \_2\right)
$$

## Тоом-3 optimal IS

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$$
w_{G M P}=8 \cdot \text { STEP }+ \text { DIV }+2 \cdot \text { SHIFT }+2 \cdot\left(\_1-2\right)
$$

The solution we found uses only criterion (A) and its weight is

$$
w_{B Z}=8 \cdot \text { STEP }+ \text { DIV }+ \text { SHIFT }+\min \left(\_1 \_X, \text { SHIFT }\right)+\_1 \_2
$$

depending on which of _1_X, SHIFT is smaller.

## Tоом-3 optimal IS, when SHIFT < _1_X

$$
\begin{aligned}
& A_{3}=\left(\begin{array}{rrrrr}
1 & 0 & 0 & 0 & 0 \\
16 & 8 & 4 & 2 & 1 \\
1 & 1 & 1 & 1 & 1 \\
1 & -1 & 1 & -1 & 1 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \stackrel{2-=4}{\Longrightarrow}\left(\begin{array}{rrrrr}
1 & 0 & 0 & 0 & 0 \\
15 & 9 & 3 & 3 & 0 \\
1 & 1 & 1 & 1 & 1 \\
1 & -1 & 1 & -1 & 1 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \stackrel{4=3-4}{\Longrightarrow}\left(\begin{array}{rrrrr}
1 & 0 & 0 & 0 & 0 \\
15 & 9 & 3 & 3 & 0 \\
1 & 1 & 1 & 1 & 1 \\
0 & 2 & 0 & 2 & 0 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \xrightarrow{3-=5} \\
& \left(\begin{array}{rrrrr}
1 & 0 & 0 & 0 & 0 \\
15 & 9 & 3 & 3 & 0 \\
1 & 1 & 1 & 1 & 0 \\
0 & 2 & 0 & 2 & 0 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \underset{4 \gg(1)}{2 /=(3)}\left(\begin{array}{lllll}
1 & 0 & 0 & 0 & 0 \\
5 & 3 & 1 & 1 & 0 \\
1 & 1 & 1 & 1 & 0 \\
0 & 1 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \xrightarrow{2-=3}\left(\begin{array}{lllll}
1 & 0 & 0 & 0 & 0 \\
4 & 2 & 0 & 0 & 0 \\
1 & 1 & 1 & 1 & 0 \\
0 & 1 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \xrightarrow{2 \gg(1)} \\
& \left(\begin{array}{lllll}
1 & 0 & 0 & 0 & 0 \\
2 & 1 & 0 & 0 & 0 \\
1 & 1 & 1 & 1 & 0 \\
0 & 1 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \stackrel{3-=4}{\Longrightarrow}\left(\begin{array}{lllll}
1 & 0 & 0 & 0 & 0 \\
2 & 1 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \underset{3-=1}{2-=(2) 1}\left(\begin{array}{lllll}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{array}\right) \xrightarrow{4-=2} I
\end{aligned}
$$

## Toom-3.5 ( $4 \times 3$ or $5 \times 2$ unbalanced multiplications)

$A_{3.5}$ generated by $\{\infty, 2,-2,1,-1,0\}$. The weight is

$$
\begin{aligned}
& 12 \cdot \text { STEP }+2 \cdot \text { DIV }+2 \cdot \text { SHIFT }+2 \cdot\left(\_1 \_2\right) \\
& A_{3.5}=\left(\begin{array}{rrrrrr}
1 & 0 & 0 & 0 & 0 & 0 \\
32 & 16 & 8 & 4 & 2 & 1 \\
-32 & 16 & -8 & 4 & -2 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 \\
-1 & 1 & -1 & 1 & -1 & 1 \\
0 & 0 & 0 & 0 & 0 & 1
\end{array}\right)
\end{aligned}
$$

One regularisation step (B) is needed.

## ( $4 \times 4$ or $5 \times 3$ or $6 \times 2$ )

$A_{4}$ generated by $\left\{\infty, 2,1,-1, \frac{1}{2},-\frac{1}{2}, 0\right\}$. The weight is
$18 \cdot$ STEP $+3 \cdot$ DIV + SHIFT $+\min \left(\_1 \_X\right.$, SHIFT $)+2 \cdot\left(\_1 \_X\right)+4 \cdot\left(\_1 \_2\right)$

$$
A_{4}=\left(\begin{array}{rrrrrrr}
1 & 0 & 0 & 0 & 0 & 0 & 0 \\
64 & 32 & 16 & 8 & 4 & 2 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & -1 & 1 & -1 & 1 & -1 & 1 \\
1 & 2 & 4 & 8 & 16 & 32 & 64 \\
1 & -2 & 4 & -8 & 16 & -32 & 64 \\
0 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right)
$$

One regularisation step (B) is used.

## Тоом-4.5 $(5 \times 4$ or $6 \times 3$ or $7 \times 2)$

$A_{4.5}$ generated by $\left\{\infty,-1,-2, \frac{1}{2}, 1,2,-\frac{1}{2}, 0\right\}$. The weight is

$$
22 \cdot \text { STEP }+4 \cdot \text { DIV }+ \text { SHIFT }+3 \cdot\left(\_1 \_X\right)+6 \cdot\left(\_1 \_2\right)
$$

$$
A_{4.5}=\left(\begin{array}{rrrrrrrr}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\
-128 & 64 & -32 & 16 & -8 & 4 & -2 & 1 \\
1 & 2 & 4 & 8 & 16 & 32 & 64 & 128 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
128 & 64 & 32 & 16 & 8 & 4 & 2 & 1 \\
1 & -2 & 4 & -8 & 16 & -32 & 64 & -128 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right)
$$

## Тоом-5 <br> ( $5 \times 5$ or $6 \times 4$ or $7 \times 3$ or $8 \times 2$ )

$A_{5}$ generated by $\left\{\infty,-2, \frac{1}{2}, 4,2,-1,1,-\frac{1}{2}, 0\right\}$. The weight is

$$
32 \cdot \text { STEP }+5 \cdot \text { DIV }+2 \cdot \text { SHIFT }+6 \cdot\left(\_1 \_ \text {X }\right)+8 \cdot\left(\_1 \_2\right)
$$

$$
A_{5}=\left(\begin{array}{rrrrrrrrr}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
256 & -128 & 64 & -32 & 16 & -8 & 4 & -2 & 1 \\
1 & 2 & 4 & 8 & 16 & 32 & 64 & 128 & 256 \\
4^{8} & 4^{7} & 4^{6} & 4^{5} & 256 & 64 & 16 & 4 & 1 \\
256 & 128 & 64 & 32 & 16 & 8 & 4 & 2 & 1 \\
1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & -2 & 4 & -8 & 16 & -32 & 64 & -128 & 256 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right)
$$

## Тоом-3 gain

We implemented new GMP code for Тоом-3 with the new IS.



## Related results

Complete matrix inversion sequences for
Тоом-3.5, Тоом-4, Тоом-4.5, Тоом-5 in
What about Toom-Cook matrices optimality ?
Technical Report 605, Centro "Vito Volterra", Università di Roma "Tor Vergata", October 2006.
http://bodrato.it/papers/\#CIVV2006.

Analysis for evaluation sequences,
result for Тоом-3 in
Towards Optimal Toom-Cook Multiplication for Univariate and Multivariate Polynomials in Characteristic 2 and 0 presented at WAIFI 2007, Madrid, España, June 21-22, 2007. http://bodrato.it/papers/\#WAIFI2007.

## That's all folks!

Thank you very much for your very kind attention

## Questions ?

## Presentation will be available on the web: http://bodrato.it/papers/\#ISSAC2007, released under a CreativeCommons BY-NC-SA licence. @(®)(-)

