

Simultaneous computation of the row and column rank profiles

J-G. DUMAS, C. PERNET and Z. SULTAN

University J. Fourier (Grenoble), INRIA, CNRS, LIG, LJK

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Gaussian elimination in computer algebra

Swiss army knife for applications:

Matrix factorization

(LU decomposition)

- Solving linear systems
- Computing determinants

Computing linear dependencies

(Echelon structure)

- Basis of vector spaces (Krylov iteration)
- Echelon structure of the Macaulay matrix (Gröbner basis)

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Linear dependencies and row/column rank profiles

Definition (Row Rank Profile: RowRP)

Given $A \in K^{m \times n}$, $r = \text{rank}(A)$.

informally: *first r* linearly independent rows

formally: lexico-minimal sub-sequence of $(1, \dots, m)$ of r indices
of linearly independant rows.

Example

$$\begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

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$$\begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\begin{aligned} \text{Rank} &= 3 \\ \text{RowRP} &= \{1, 2, 4\} \end{aligned}$$

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RowRP = {1,2,4}

ColRP = {1,2,3}

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Generic Row Rank Profile : if it equals $\{1, \dots, r\}$.

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Rank = 3

RowRP = {1,2,4}

ColRP = {1,2,3} → Generic ColRP.

Generic Row Rank Profile : if it equals $\{1, \dots, r\}$.

Generic rank profile

Definition (Generic Rank Profile)

First r leading principal minors $\neq 0$

Example

$$\begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

Rank = 4

RowRP = ColRP = {1,2,3,4}

Generic rank profile

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Rank = 4

RowRP = ColRP = {1,2,3,4}

But $|A_{1..2,1..2}| = 0$

→ Generic row and column rank profiles $\not\Rightarrow$ Generic rank profile

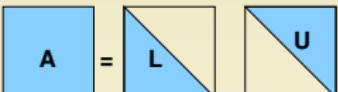
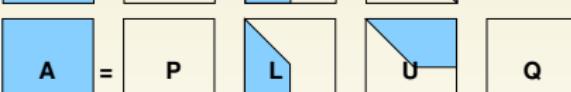
Triangular Matrix decompositions

Decomposition	Exists for	Unique
$A = L U$	Generic rank profile	Y

Triangular Matrix decompositions

Decomposition	Exists for	Unique
$A = L \begin{pmatrix} U & \\ & U \end{pmatrix}$	Generic rank profile	Y
$A = L \begin{pmatrix} U & \\ & U \end{pmatrix} P$	Generic row rank profile	N
$A = P \begin{pmatrix} L & \\ & U \end{pmatrix}$	Generic col rank profile	N

Triangular Matrix decompositions

Decomposition	Exists for	Unique
	Generic rank profile	Y
	Generic row rank profile	N
	Generic col rank profile	N
	Any matrix	N

Triangular Matrix decompositions

Decomposition	Exists for	Unique
$A = L \begin{pmatrix} U & \\ & U \end{pmatrix}$	Generic rank profile	Y
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$A = P \begin{pmatrix} L & \\ & U \end{pmatrix}$	Generic col rank profile	N
$A = P \begin{pmatrix} L & \\ & U \end{pmatrix} Q$	Any matrix	N

→ P, Q may reveal row and/or col rank profiles.

PLUQ decomposition

PLUQ decomposition is not unique:
→ the **pivoting strategy** impacts P, Q .

Numerical linear algebra: *full pivoting*

- choosing the largest pivot (numerical stability)
- increasing data locality
- reducing fill-in (sparse elimination)

Exact linear algebra

- No stability issue: a pivot just has to be invertible
- Some pivoting strategies can reveal the row or the col rank profile

Rank profile revealing PLUQ decomp.: state of the art

Row Rank profile

Pivoting strategy: **row-major** search for a pivot

- equiv. to LSP, LQUP decompositions [Ibarra et al., 1982]
- equiv. to CUP decomposition [Jeannerod et al., 2013]
- $\mathcal{O}(mnr^{\omega-2})$, in-place

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Column rank profile

Pivoting strategy: **column-major** search for a pivot

- Searching for a pivot in a column-major fashion
- equvi. to PLE decomposition [Jeannerod & Al. 13]
- $\mathcal{O}(mnr^{\omega-2})$, in-place

Contribution

A new pivoting strategy for PLUQ

- revealing Row **and** Column rank profiles **at the same time**
- also revealing the RowRP and ColRP of **all n^2** leading sub-matrices.

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Algorithms

- Two rank sensitive algorithms:
 - Quad-recursive in $O(mnr^{\omega-2})$
 - Iterative in $O(mnr)$ (to be used as a base case)
- Time, memory and nb of mod reductions at least as good as state of the art CUP/PLE decompositions.
- Fast implementation

Outline

- 1 A new pivoting strategy
- 2 PLUQ algorithms
 - An iterative algorithm
 - A quad-recursive algorithm
- 3 Computing rank profiles
 - From PLUQ to LEU
 - Computing rank profiles
- 4 Experiments
- 5 Conclusion and perspective

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A new pivoting strategy

Key features:

CUP, LSP, ...

Search for pivot: Row after row

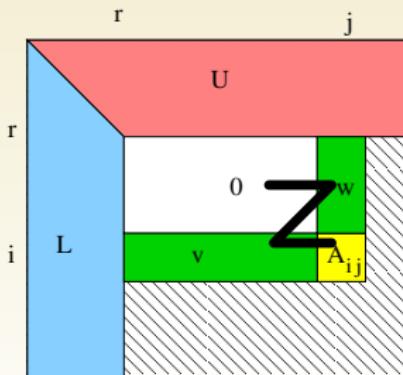
Pivot Permutation: swap

A new pivoting strategy

Key features:

CUP, LSP, ...	New strategy
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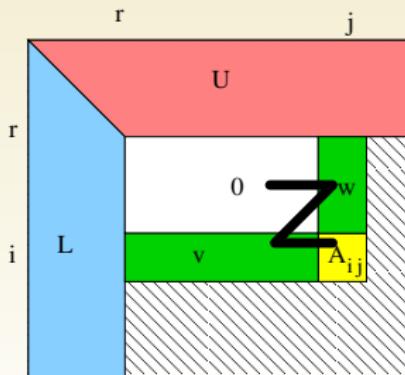
Search for pivot:	Row after row	increasing leading sub-matrix
Pivot Permutation:	swap	



A new pivoting strategy

Key features:

	CUP, LSP, ...	New strategy
Search for pivot:	Row after row	increasing leading sub-matrix
Pivot Permutation:	swap	order 1 rotation



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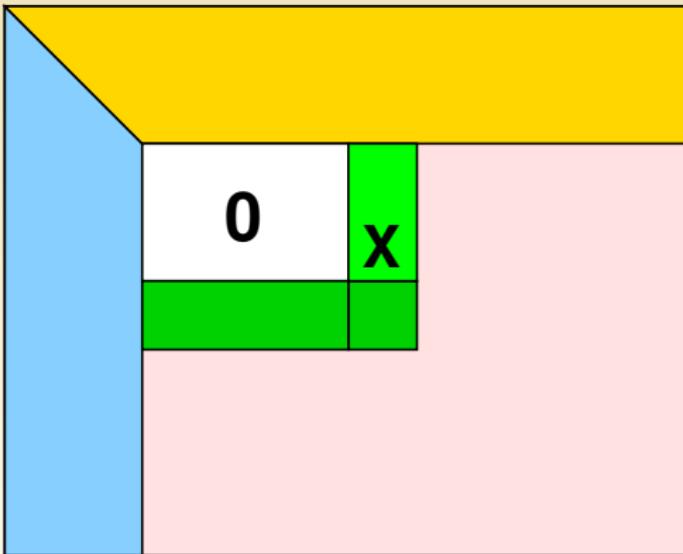
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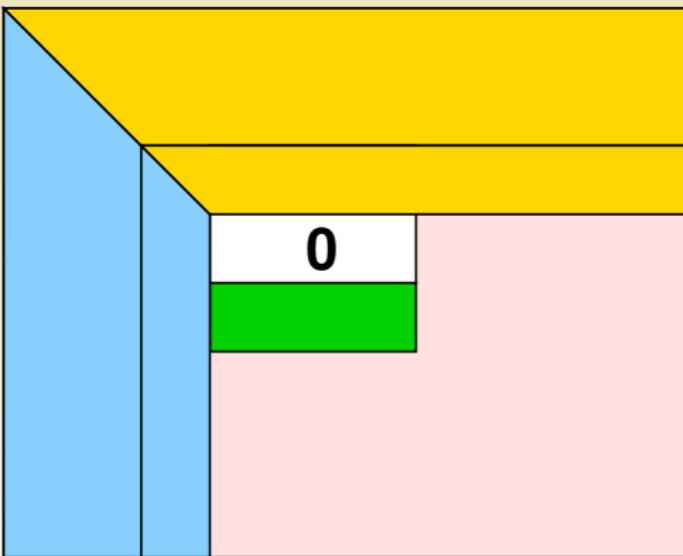


PLUQ iterative version



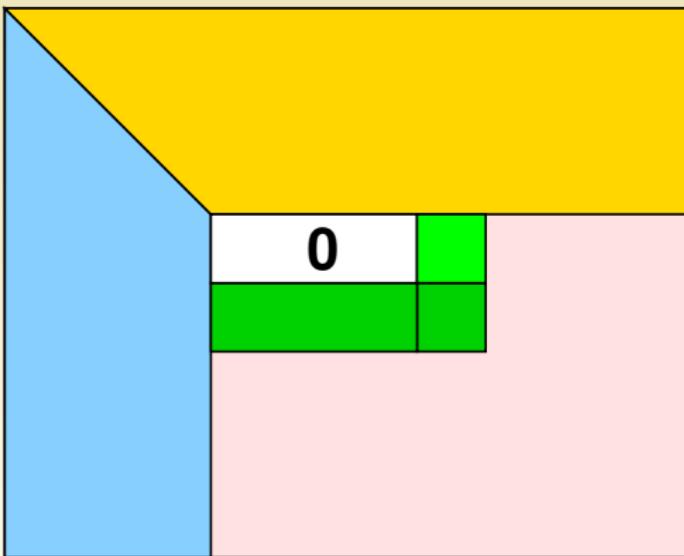


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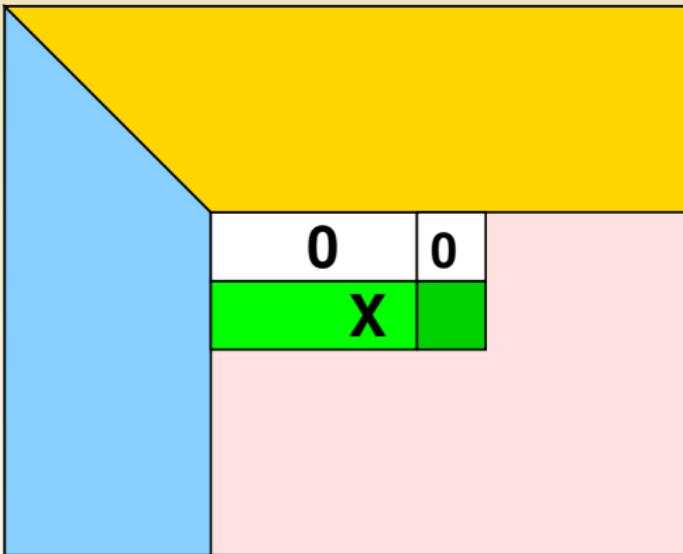


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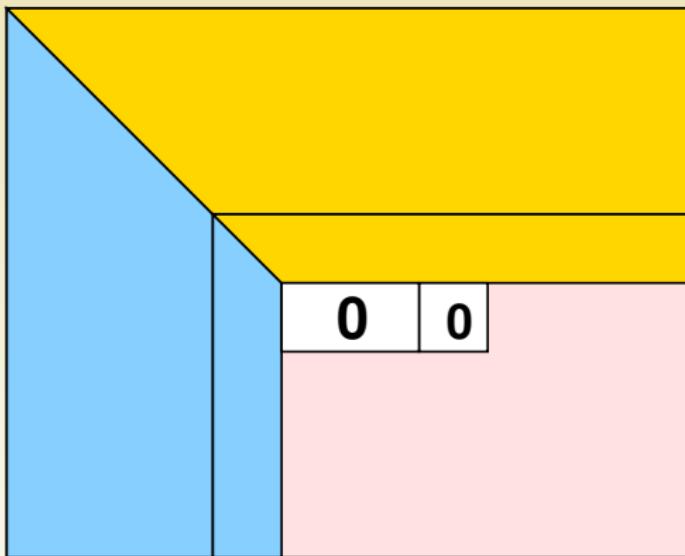


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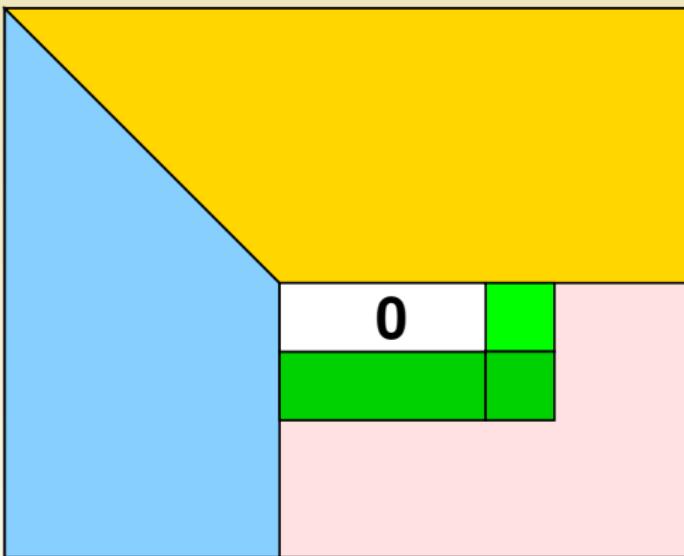


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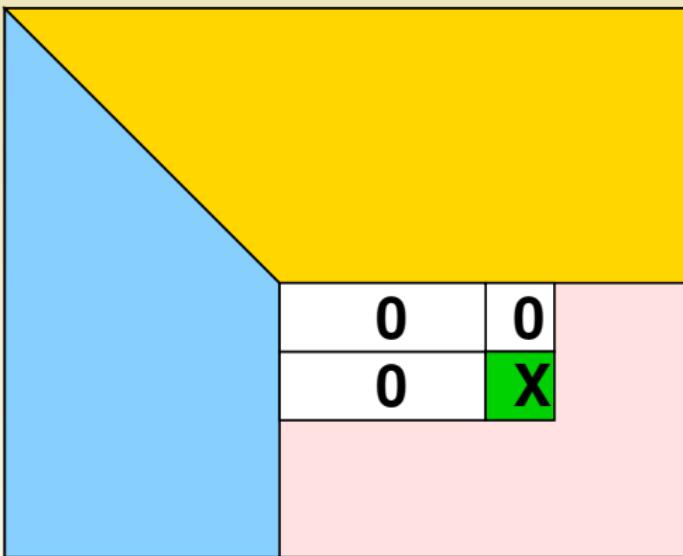


PLUQ iterative version

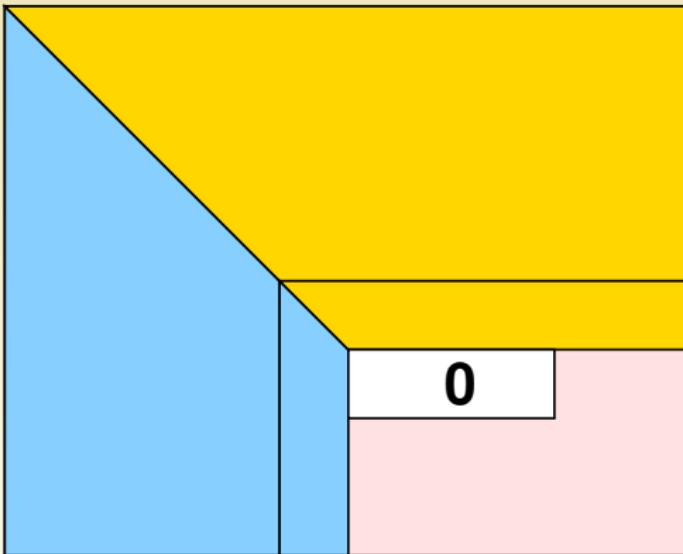




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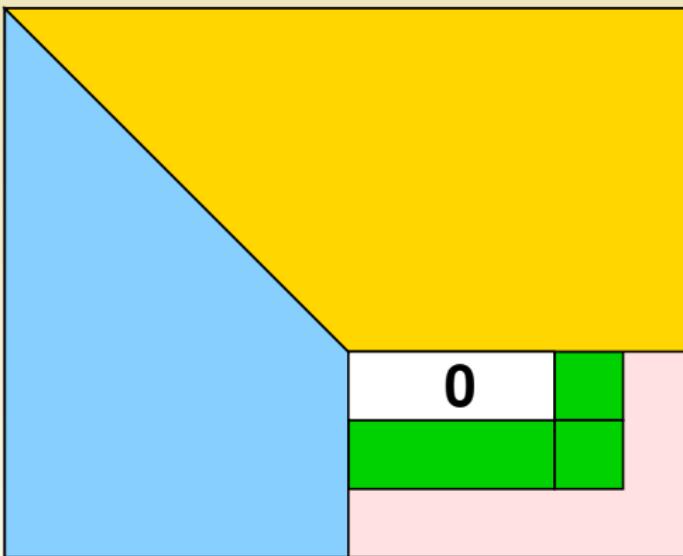


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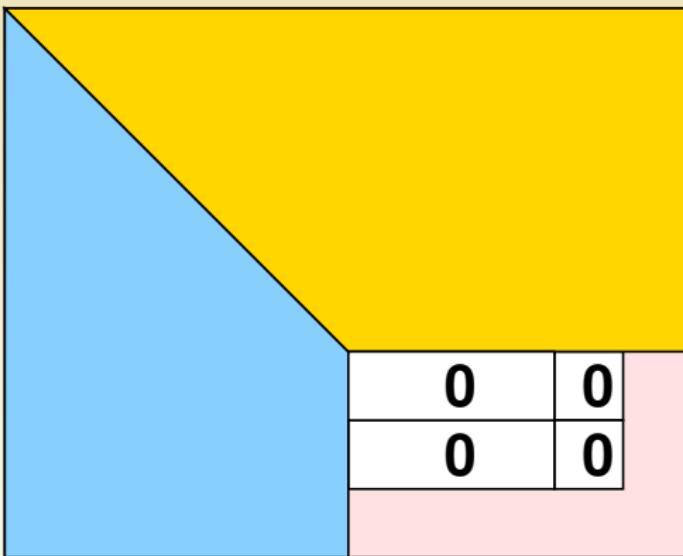




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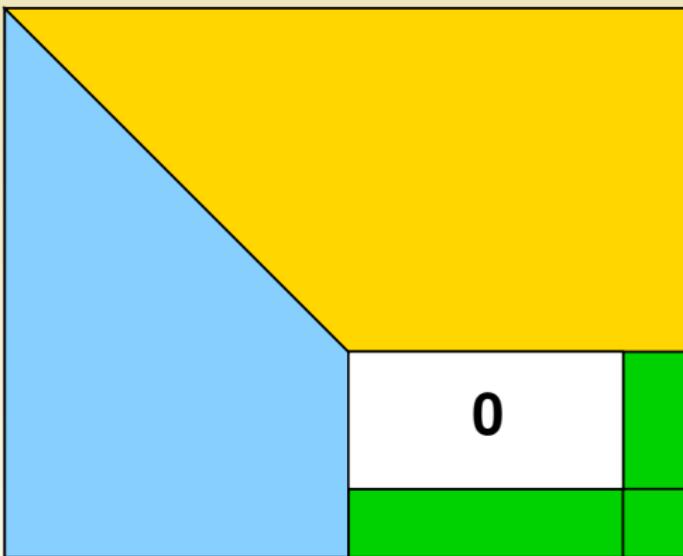


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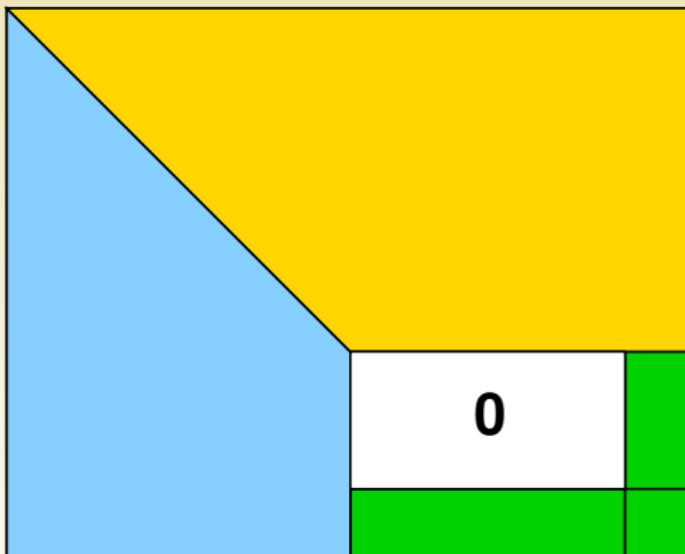




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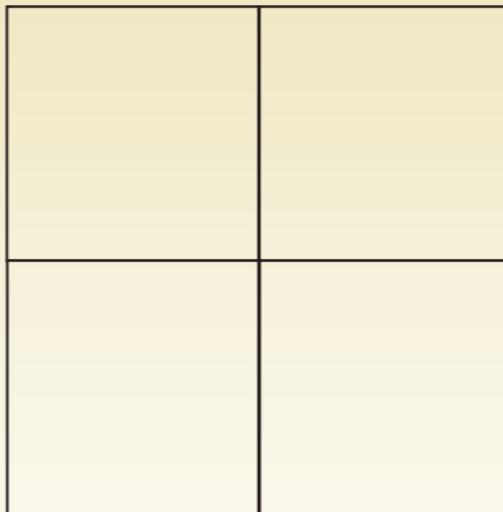


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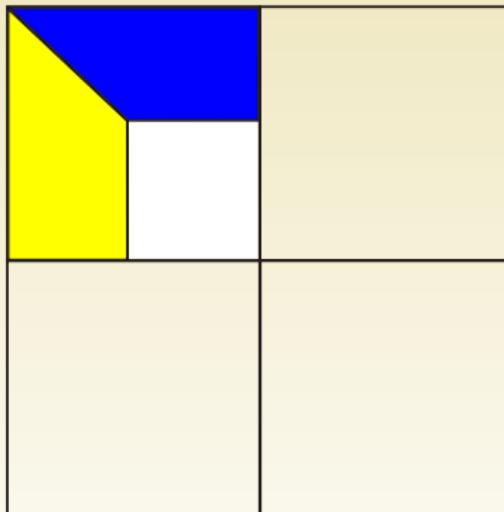
- Complexity $\mathcal{O}(mnr)$
- Further optimizations:
 - Left-looking variant
 - All permutations delayed to the end
- To be used as a base case

Quad-recursive PLUQ algorithm



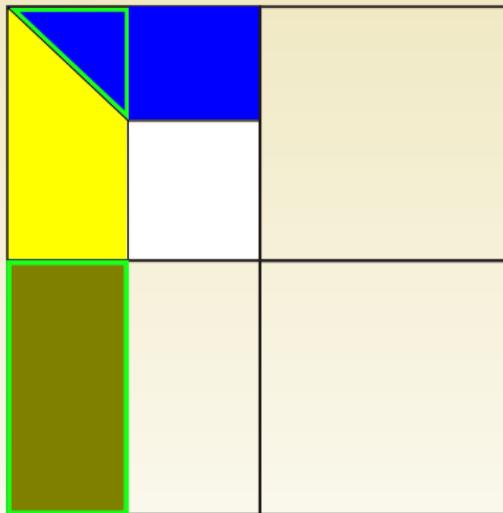
2×2 block splitting

Quad-recursive PLUQ algorithm



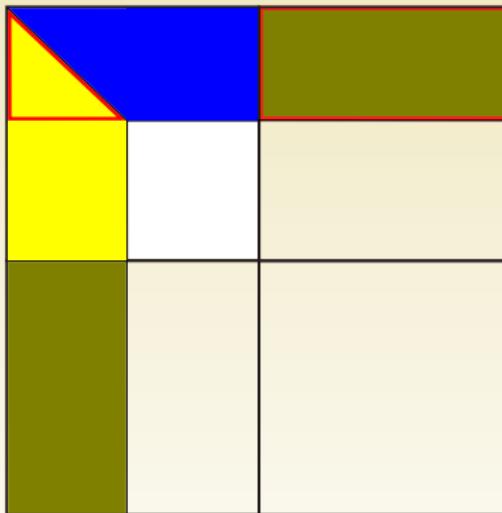
Recursive call

Quad-recursive PLUQ algorithm



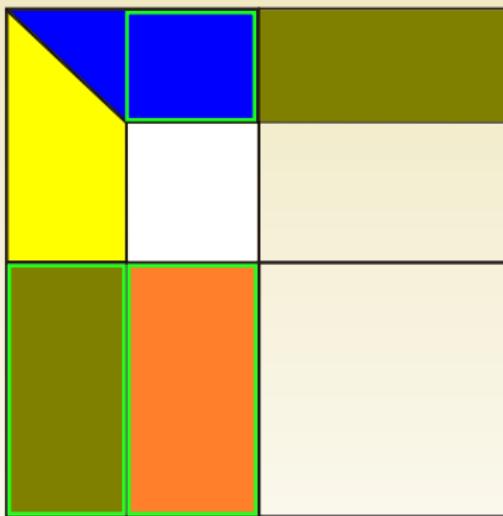
TRSM: $B \leftarrow BU^{-1}$

Quad-recursive PLUQ algorithm



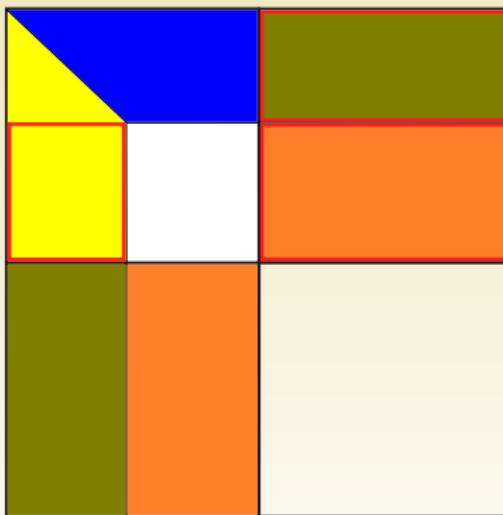
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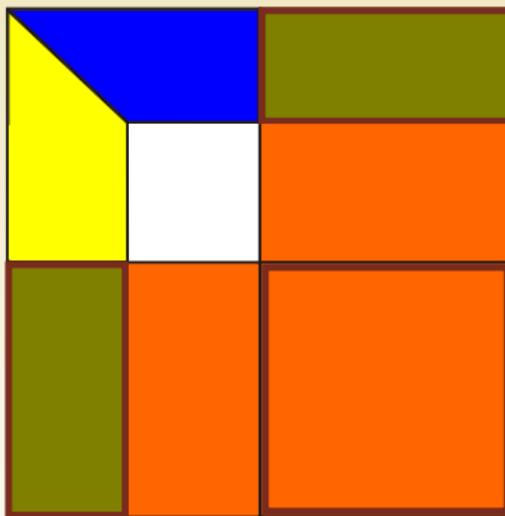
MatMul: $C \leftarrow C - A \times B$

Quad-recursive PLUQ algorithm



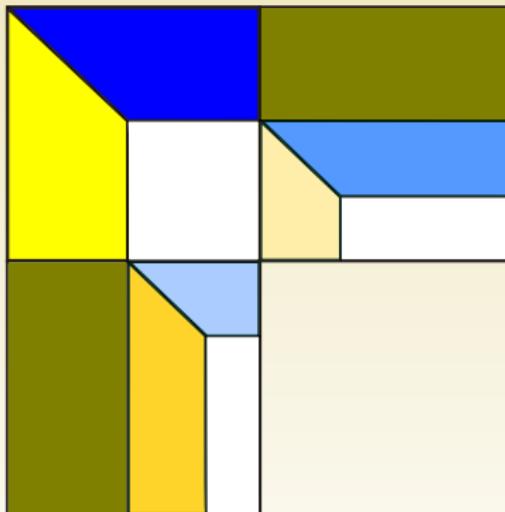
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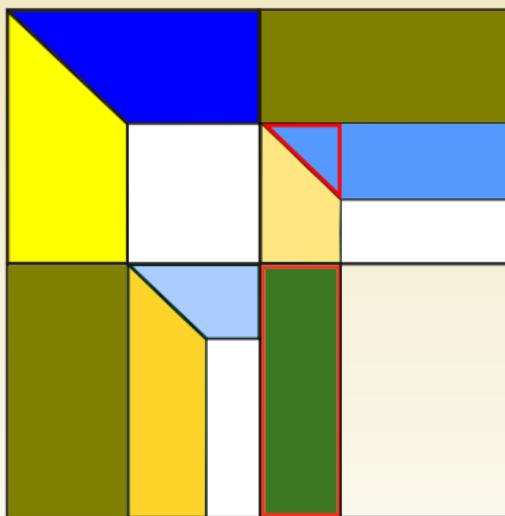
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Quad-recursive PLUQ algorithm



2 independent recursive calls

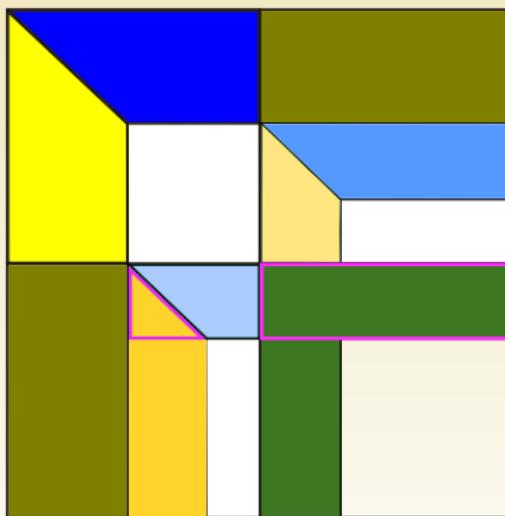
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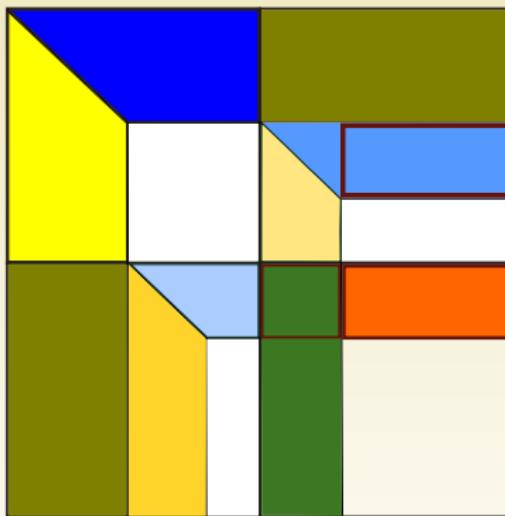


Quad-recursive PLUQ algorithm



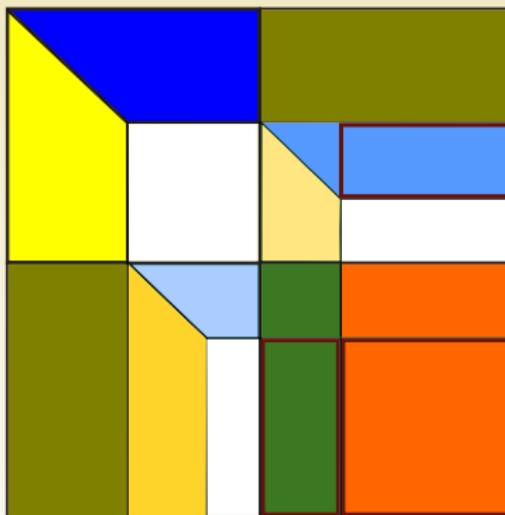
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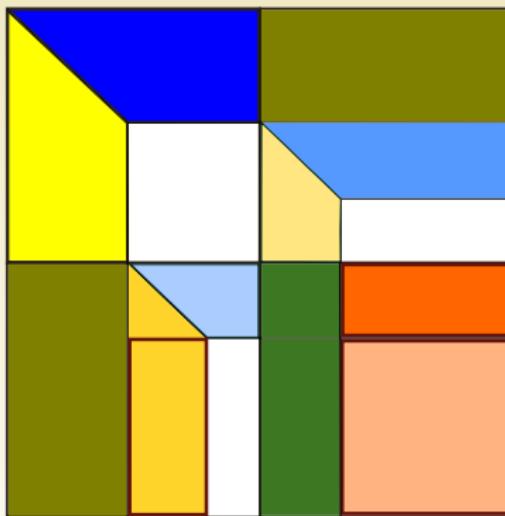
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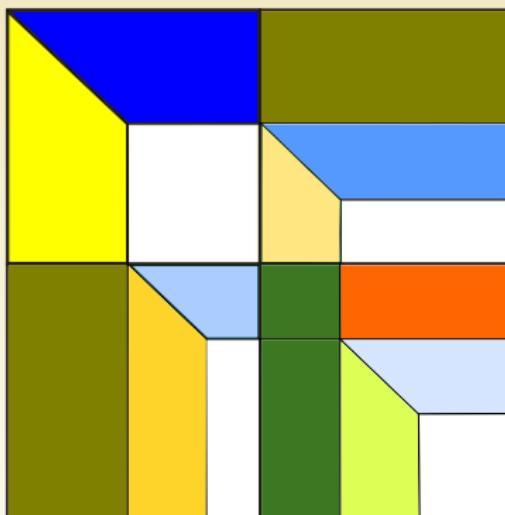
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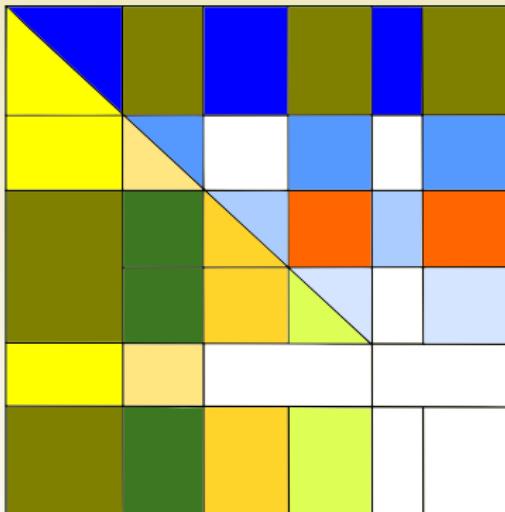
Quad-recursive PLUQ algorithm



Recursive call



Quad-recursive PLUQ algorithm



Puzzle game (block permutations)

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LEU decomposition

LEU decomposition [Malaschonok, 2010]: for any matrix A

$$\begin{matrix} A \\ = \\ \end{matrix} \begin{matrix} L \\ \diagdown \\ \end{matrix} \begin{matrix} E \\ \quad \\ \end{matrix} \begin{matrix} U \\ \diagup \\ \end{matrix}$$

E is a permutation matrix with $n - r$ rows zeroed out.

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From PLUQ to LEU

$$P \begin{bmatrix} L & \\ M & 0 \end{bmatrix} \begin{bmatrix} U & V \\ & 0 \end{bmatrix} Q = P \begin{bmatrix} L & 0 \\ M & I_{m-r} \end{bmatrix} \quad \begin{bmatrix} I_r & \\ & 0 \end{bmatrix} \quad \begin{bmatrix} U & V \\ & I_{n-r} \end{bmatrix} Q$$

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Theorem

\exists pivoting strategy s.t. \bar{L} is lower triangular and \bar{U} is upper triangular.

Computing Rank Profiles from

Lemma

- ① RowRP and ColRP of A and E are identical
- ② RowRP and ColRP of any leading submatrix of A and E are identical

Example

$$\begin{array}{c} A \\ \boxed{\begin{array}{cccc} 1 & 2 & 3 & 4 \\ 2 & 4 & 5 & 8 \\ 1 & 2 & 3 & 4 \\ 3 & 5 & 9 & 12 \end{array}} \end{array} \rightarrow \begin{array}{c} E \\ \boxed{\begin{array}{cccc} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{array}} \end{array}$$

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Example

$$\begin{array}{c} A \\ \hline \boxed{1} & 2 & 3 & 4 \\ 2 & \boxed{4} & 5 & 8 \\ 1 & 2 & 3 & 4 \\ 3 & 5 & 9 & 12 \end{array} \longrightarrow \begin{array}{c} E \\ \hline 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{array}$$

$$\begin{aligned} \text{RowRP} &= \{1\} \\ \text{ColRP} &= \{1\} \end{aligned}$$

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$$\begin{aligned} \text{RowRP} &= \{1, 2\} \\ \text{ColRP} &= \{1, 3\} \end{aligned}$$

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Example

A	E
---	---

1	2	3	4
2	4	5	8
1	2	3	4
3	5	9	12



1	0	0	0
0	0	1	0
0	0	0	0
0	1	0	0

$$\begin{aligned} \text{RowRP} &= \{1, 4\} \\ \text{ColRP} &= \{1, 2\} \end{aligned}$$

Algorithm: Row and Col Rank Profiles from (P,Q)

$\text{RowRP}(A) = \text{sort}(\{i \in \{1 \dots m\} | P_{i,j} = 1 \text{ for } j \in \{1 \dots r\}\})$

$\text{ColRP}(A) = \text{sort}(\{j \in \{1 \dots n\} | Q_{i,j} = 1 \text{ for } i \in \{1 \dots r\}\})$

Computing Rank Profiles from

Lemma

- ① RowRP and ColRP of A and E are identical
- ② RowRP and ColRP of any leading submatrix of A and E are identical

Example

A		E	
1	2	3	4
2	4	5	8
1	2	3	4
3	5	9	12



E			
1	0	0	0
0	0	1	0
0	0	0	0
0	1	0	0

$$\begin{aligned} \text{RowRP} &= \{1, 4\} \\ \text{ColRP} &= \{1, 2\} \end{aligned}$$

Algorithm: Row and Col Rank Profiles from (P,Q)

$$\begin{aligned} \text{RowRP}(A_{1\dots c, 1\dots d}) &= \text{sort}(\{i \in \{1 \dots c\} | P_{i,j} = 1 \text{ for } j \in \{1 \dots r\}\}) \\ \text{ColRP}(A_{1\dots c, 1\dots d}) &= \text{sort}(\{j \in \{1 \dots d\} | Q_{i,j} = 1 \text{ for } i \in \{1 \dots r\}\}) \end{aligned}$$

Outline

- 1 A new pivoting strategy
- 2 PLUQ algorithms
 - An iterative algorithm
 - A quad-recursive algorithm
- 3 Computing rank profiles
 - From PLUQ to LEU
 - Computing rank profiles
- 4 Experiments
- 5 Conclusion and perspective

Implementation

In `fflas-ffpack` (`LinBox` kernel for dense `linalg mod p`)

`LinBox`: exact linear algebra

- **LGPL**, <http://linalg.org/>
- Floating point storage of word size finite field elements.
- Matrix Multiplication: numerical BLAS & Strassen-Winograd

Implementation

In `fflas-ffpack` (`LinBox` kernel for dense `linalg mod p`)

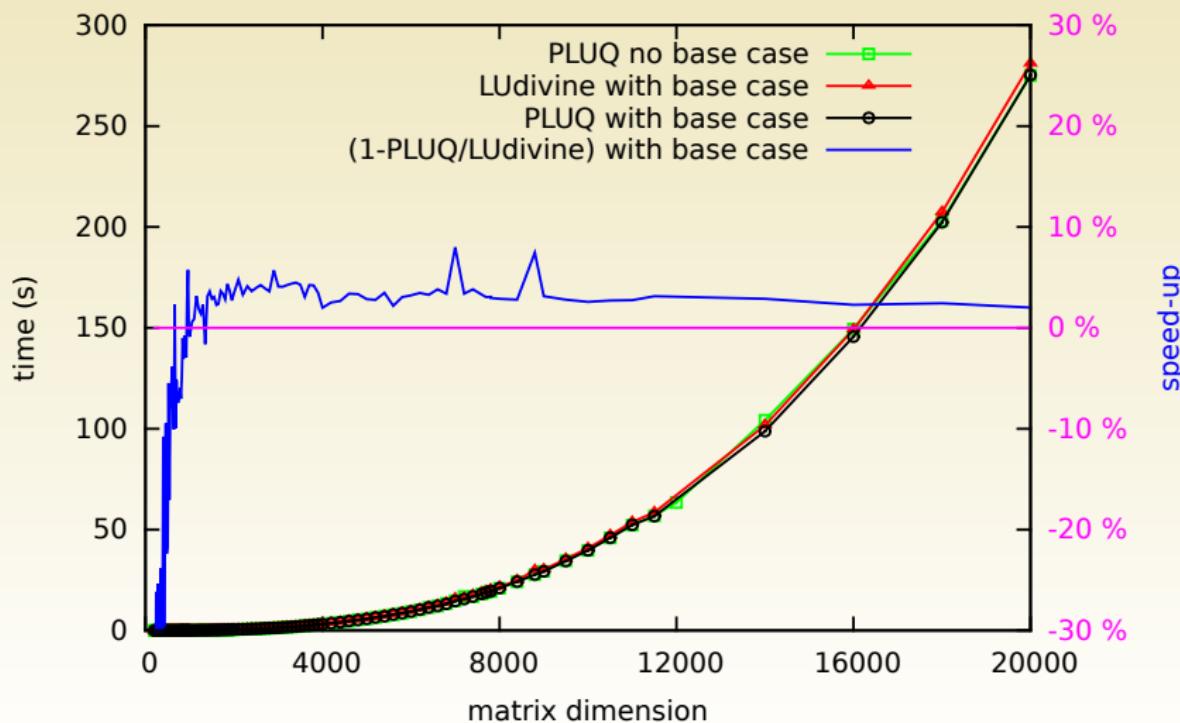
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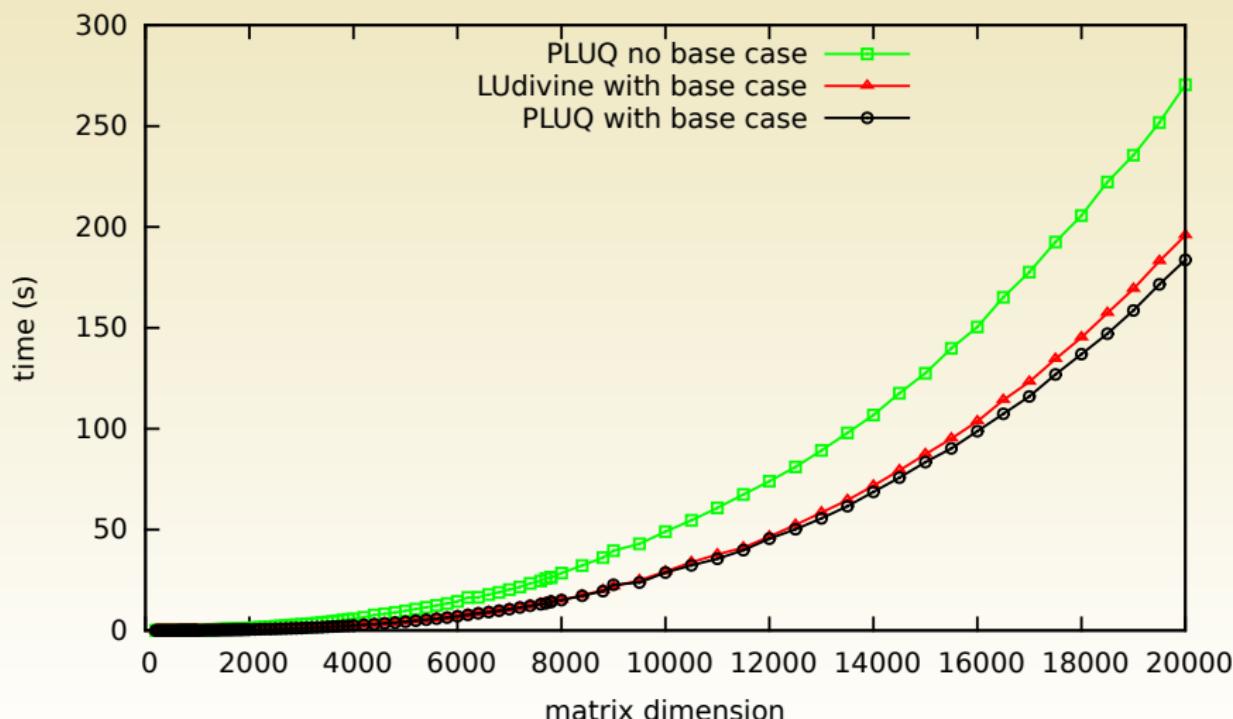
Experiments

- compared to state of the art implementation of CUP (`LUDivine`)
- Experimentally tuned base-case threshold.
- Intel SandyBridge E5-4620 2.2Ghz, 32 cores, L3(16MB).
- gcc-4.7.3, OpenBLAS-93dd133
- Two classes of square matrices over $\mathbb{Z}/1009\mathbb{Z}$
 - generic rank profiles,
 - arbitrary rank profiles: from LEU with rank = $n/2$, and pivots of E uniformly distributed

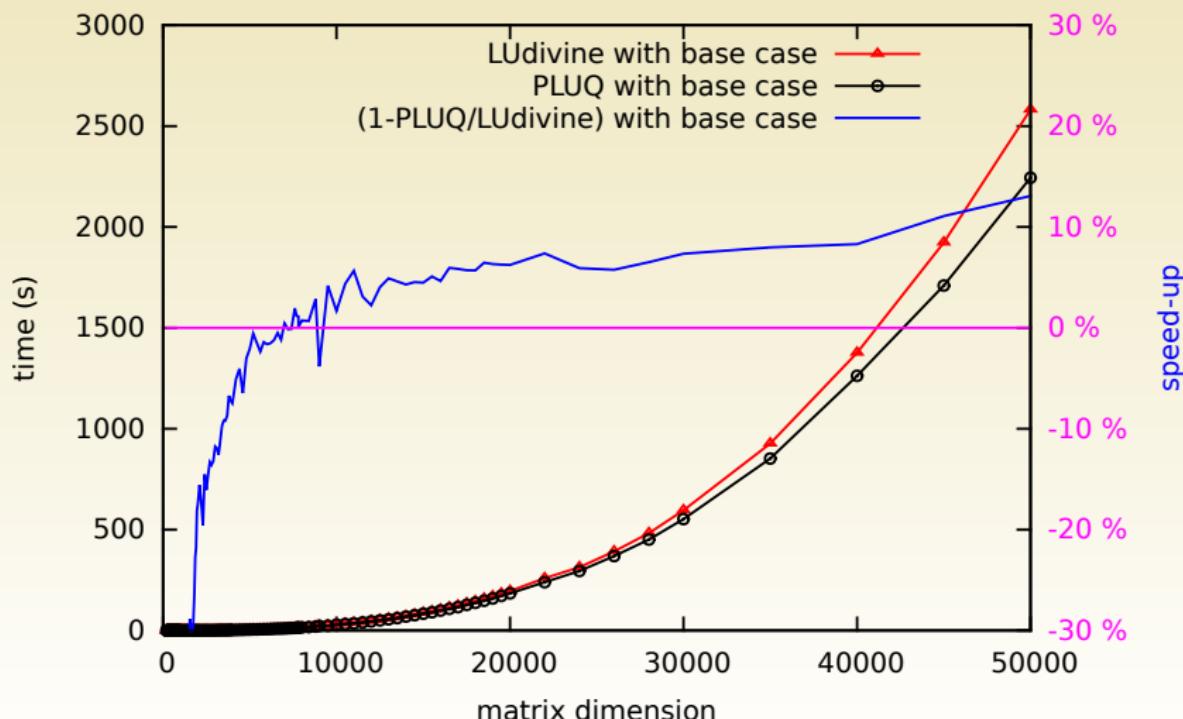
Generic rank profile matrices



Arbitrary rank profile matrices



Arbitrary rank profile matrices (larger dimension)



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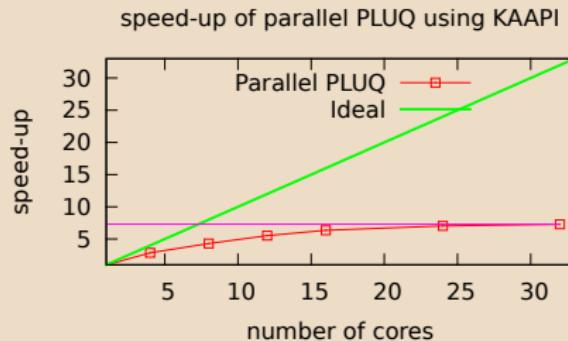
Conclusion

- A new pivoting strategy
- Two algorithms
 - $\mathcal{O}(mnr^{\omega-2})$ quad-recursive algorithm
 - $\mathcal{O}(mnr)$ base case
- Rank profile recovery:
 - all rank profiles in just one elimination,
 - first reduction of **computing RowRP and ColRP of all leading submatrices to matrix multiplication.**
- Faster in practice than previous eliminations:
 - data locality,
 - fewer modular reductions.

Perspective

Parallelization

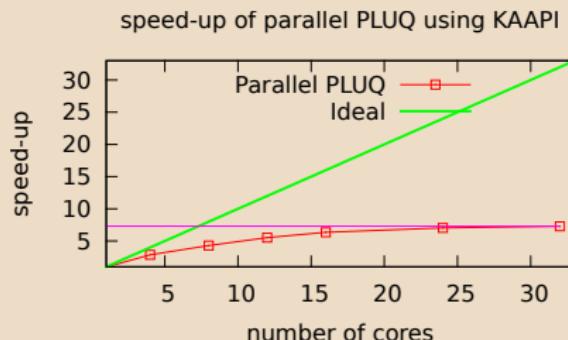
- Rank deficiency becomes an advantage:
- First toy implementation with tasks:



Perspective

Parallelization

- Rank deficiency becomes an advantage:
- First toy implementation with tasks:



Next step

- Tiled iterative version
 - less synchronizations
 - Challenge:** n^4 tasks, most of which are empty
- Data-flow task dependencies in the recursive algorithm

Thank you

References

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