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Fixed-accuracy Randomized Interpolative Decomposition

Exa-SofT General Assembly (September 2025)

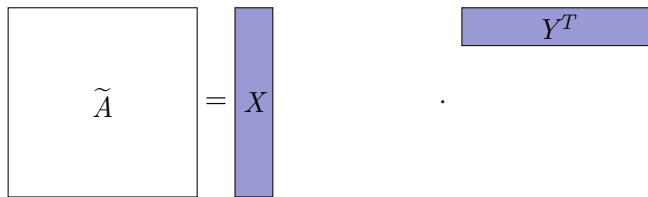
K. Hoogveld[†]

Supervisors: A. Buttari[†], T. Mary^{*}

[†]CNRS-IRIT (Exa-SofT), ^{*}CNRS-LIP6 (Exa-MA)

Fixed-rank *versus* Fixed-accuracy

Let A be a dense matrix of size $m \times n$ with $m \geq n$. Take a target rank k . If k is small enough such that the rank- k approximation

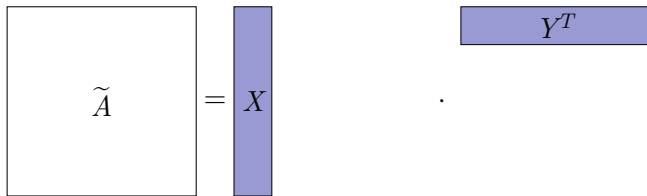


The diagram illustrates the fixed-rank approximation equation $\tilde{A} = XY^T$. On the left, a large white square box labeled $\tilde{A}$ is followed by an equals sign and a tall, narrow purple rectangular box labeled X . To the right of this is a dot, followed by a horizontal purple rectangular box labeled Y^T . The purple boxes represent matrices of size $m \times k$ and $k \times n$ respectively, which are significantly smaller than the $m \times n$ matrix $\tilde{A}$.

requires less storage than the full-rank matrix A , i.e., if $k(m+n) \leq mn$, then XY^T is a low-rank approximation of the original matrix $\Rightarrow$ **fixed-rank strategy**.

Fixed-rank *versus* Fixed-accuracy

Let A be a dense matrix of size $m \times n$ with $m \geq n$.


$$\tilde{A} = X \cdot Y^T$$

In practice such a rank k is often not known. A target accuracy ε is rather chosen and the low-rank approximation algorithm will determine the associated k_ε for which $\|A - \tilde{A}\| \leq \varepsilon \Rightarrow$ **fixed-accuracy strategy**.



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Randomized Interpolative Decomposition *(in literature)*

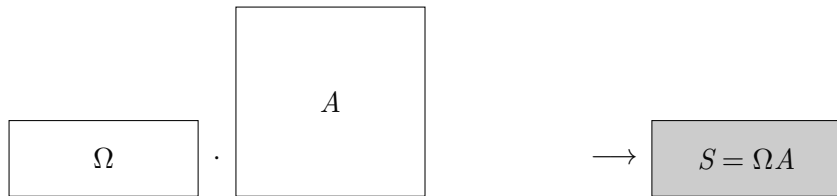
Randomized Interpolative Decomposition (RID)

Fixed-rank



F. Woolfe, E. Liberty, V. Rokhlin and M. Tygert.
"A fast randomized algorithm for the approximation of matrices". In: Elsevier ACHA (2008).

1. **Sampling** Generate the $k \times n$ sketch S for fixed rank k where Ω is a $k \times m$ sampling matrix;



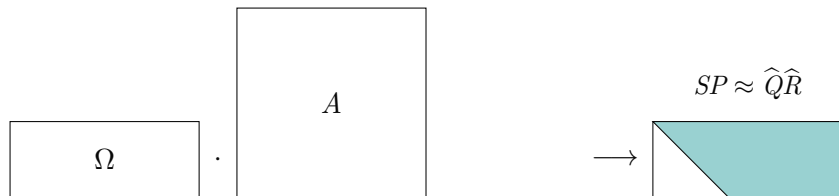
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2. **QRCP** Compute a QRCP factorization of S ;



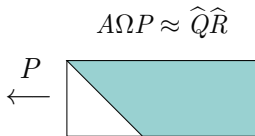
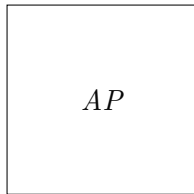
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3. $S \rightarrow A$ Using P .



Randomized Interpolative Decomposition (RID)

Fixed-rank

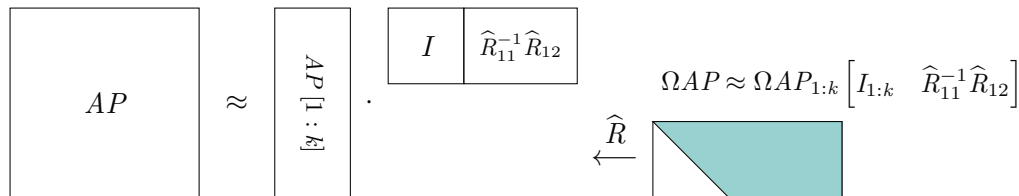


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2. **QRCP** Compute a QRCP factorization of S ;
3. $S \rightarrow A$ Using P and $\hat{R}$.

$$AP \approx \begin{bmatrix} AP[1:k] \end{bmatrix} \cdot \begin{bmatrix} I & \hat{R}_{11}^{-1} \hat{R}_{12} \end{bmatrix}$$

$\xleftarrow{\hat{R}}$

$$\Omega AP \approx \Omega AP_{1:k} \begin{bmatrix} I_{1:k} & \hat{R}_{11}^{-1} \hat{R}_{12} \end{bmatrix}$$


Randomized Interpolative Decomposition (RID)

Fixed-accuracy (*in literature*)



T. Mary, I. Yamazaki, J. Kurzak, P. Luszczek, S. Tomov, and J. Dongarra. "Performance of random sampling for computing low-rank approximations of a dense matrix on GPUs". In: SC (2015).

```
1 repeat
   $S_i = A^T \Omega_i$ 
3   $Q_i, R_i = \text{qr}(S_i, \text{NoPivot})$ 
   $Q_i, R_i = \text{qr}(Q_i - Q Q^T Q_i)$ 
5   $B_i = Q_i^T A^T$ 
   $A^T = A^T - Q_i B_i$ 
7  if  $\text{norm}(A) \leq \varepsilon$  then stop
end
9 return  $S = [S_1 \dots S_i]$ 
```

👍 Reliable

👎 High complexity



P-G. Martinsson and S. Voronin. "A Randomized Blocked Algorithm for Efficiently Computing Rank-revealing Factorizations of Matrices". In: SIAM SISC (2016).

```
1  $S_i = A^T \Omega_i$ 
  repeat
3    $Q_i, R_i = \text{qr}(S_i, \text{NoPivot})$ 
    $S_{i+1} = A^T \Omega_{i+1}$ 
5    $S_{i+1} = S_{i+1} - Q Q^T S_{i+1}$ 
   if  $\text{norm}(S_{i+1}) \leq \varepsilon$  then stop
7 end
return  $S = [S_1 \dots S_i]$ 
```

👍 Low complexity

👎 Unreliable



N. Halko, P-G. Martinsson and J. Tropp. "Finding Structure with Randomness: Probabilistic Algorithms for Constructing Approximate Matrix Decompositions". In: SIAM Review (2011).



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A novel approach

Randomized Interpolative Decomposition (RID)

by E. Agullo, A. Buttari, K. Hoogveld and T. Mary



J. Duersch and M. Gu. "Randomized QR with column pivoting". In: SIAM Journal on Scientific Computing (2017).

Let b be the block size and p the oversampling factor.

$$\Omega_1 \cdot A \longrightarrow S_1 = \Omega_1 A$$

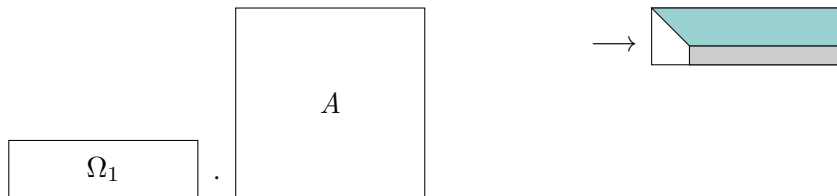
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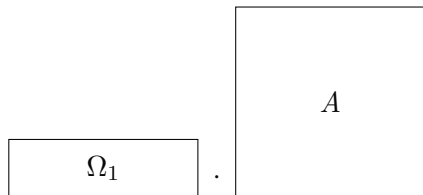
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$$S_1 P \approx \hat{Q} \hat{R}$$

$\|\hat{R}_{22}\| \leq \hat{\epsilon} ?$

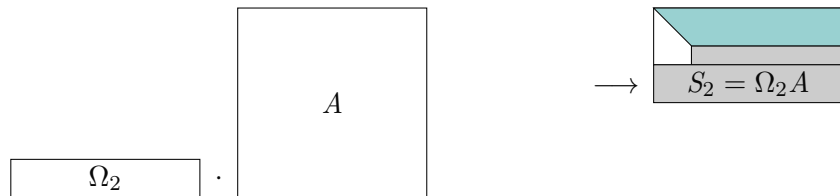
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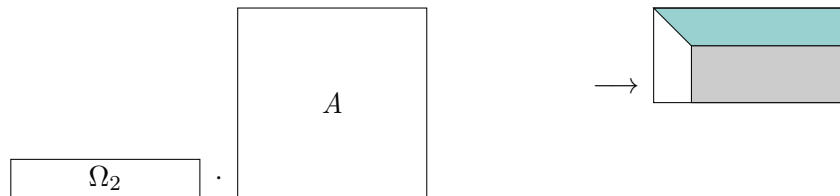
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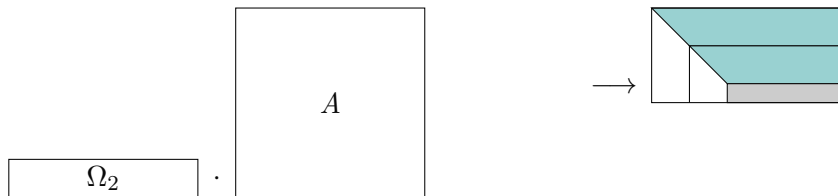
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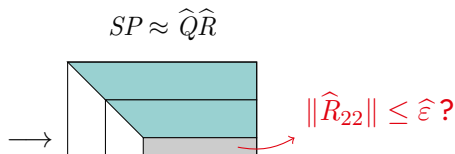
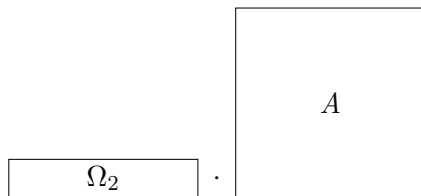
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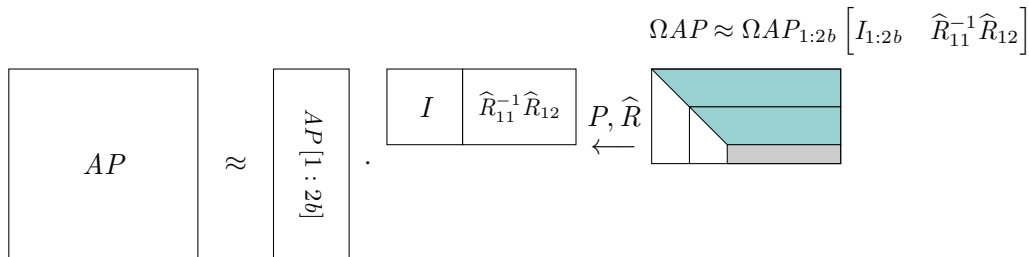
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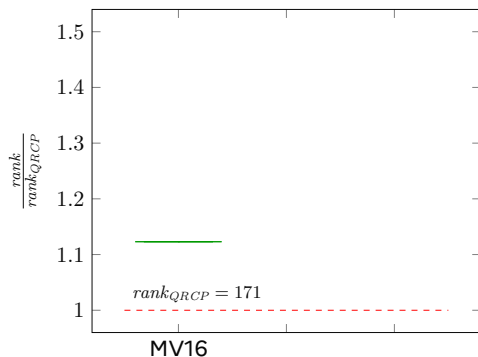
$$AP \approx \begin{bmatrix} AP[1:2b] \\ \vdots \end{bmatrix} \cdot \begin{bmatrix} I & \hat{R}_{11}^{-1} \hat{R}_{12} \end{bmatrix} \begin{matrix} P, \hat{R} \\ \leftarrow \end{matrix}$$


Experimental results

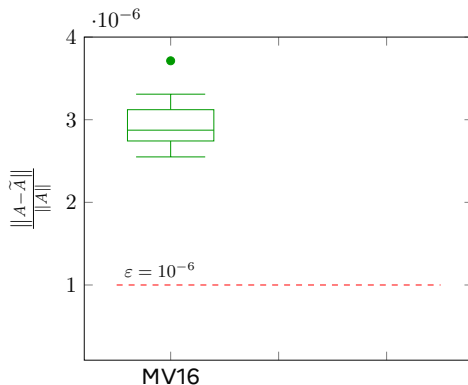
Backward error

Let us assess the numerical behavior of these fixed-accuracy RID variants on a 2048×2048 Heat test matrix using a Gaussian sampling matrix.

Relative truncation rank



Relative backward error

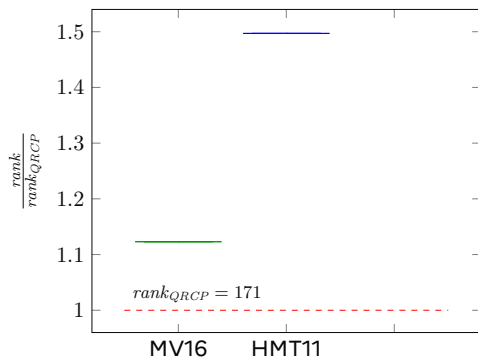


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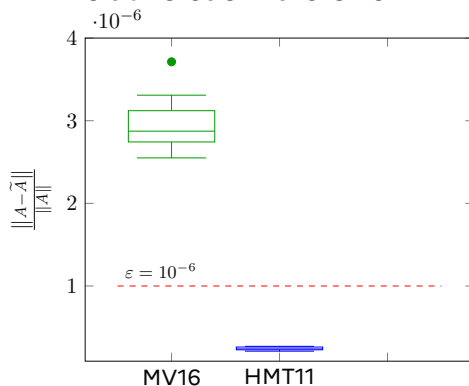
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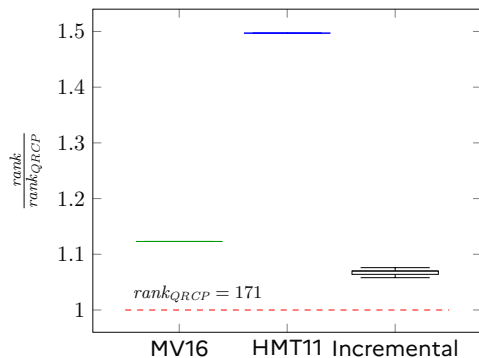


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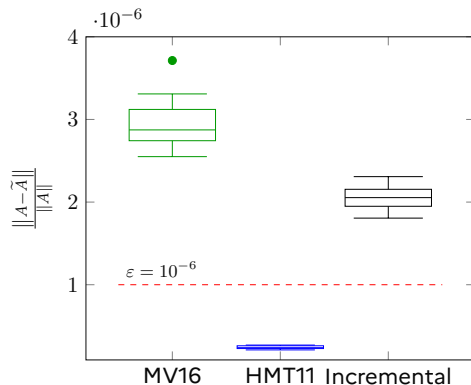
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Variants

Variants

Subsampled Randomized Hadamard Transform (SRHT)

Algorithm	Gaussian sketching	
Incremental RID	$2mnk + 4nk^2 - \frac{8}{3}k^3$	
HMT11 RID	$2mnk + 6nk^2 - \frac{8}{3}k^3$	
MV16 RID	$6mnk + 6nk^2 - \frac{8}{3}k^3$	

Variants

Subsampled Randomized Hadamard Transform (SRHT)

Algorithm	Gaussian sketching	SRHT sketching
Incremental RID	$2mnk + 4nk^2 - \frac{8}{3}k^3$	$2mnk\frac{\log(b)}{b} + 4nk^2 - \frac{8}{3}k^3$
HMT11 RID	$2mnk + 6nk^2 - \frac{8}{3}k^3$	$2mnk\frac{\log(b)}{b} + 6nk^2 - \frac{8}{3}k^3$
MV16 RID	$6mnk + 6nk^2 - \frac{8}{3}k^3$	$2mnk\frac{\log(b)}{b} + 4mnk + 6nk^2 - \frac{8}{3}k^3$

Key Ideas:

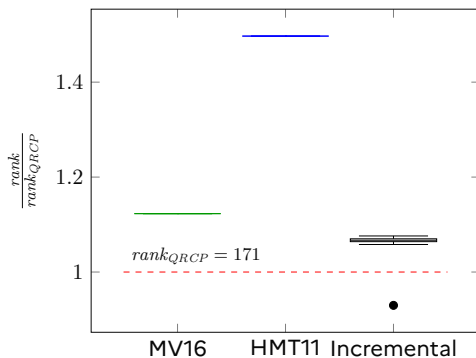
- $\Omega \rightarrow$ Sampling matrix defined as $\Omega = \sqrt{\frac{m}{l}} RHD$;
- $H \rightarrow$ Fast to apply via Fast Hadamard Transform (FHT) in $\mathcal{O}(m \log m)$ time;
- $D \rightarrow$ Random sign flipping spreads out information;
- $R \rightarrow$ Uniform row sampling reduces dimensionality.

Experimental results

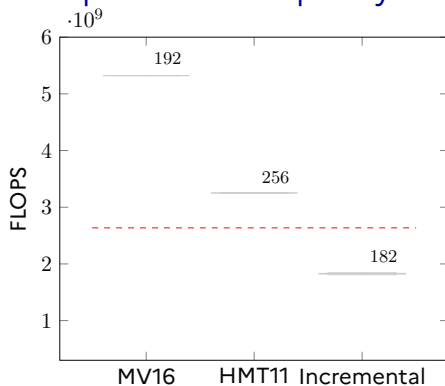
Subsampled Randomized Hadamard Transform (SRHT)

Let us assess the numerical behavior of these fixed-accuracy RID variants on a 2048×2048 Heat test matrix using a SRHT sampling matrix.

Relative truncation rank



Operational complexity

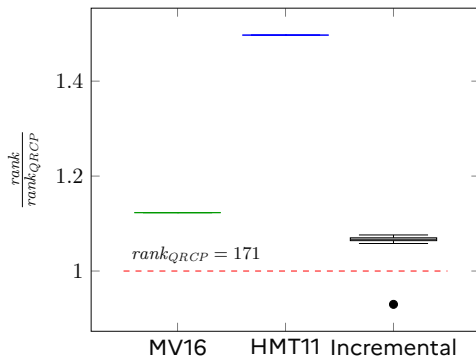


Experimental results

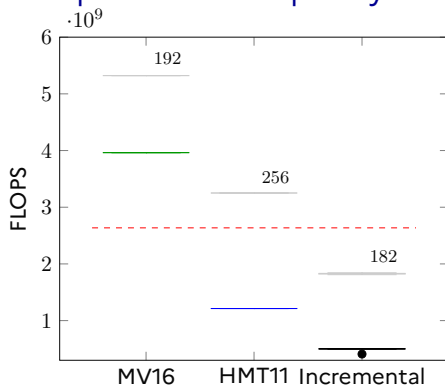
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Operational complexity

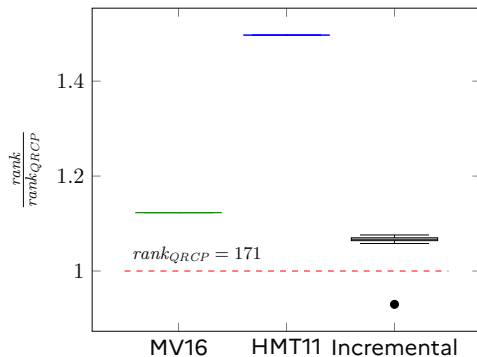


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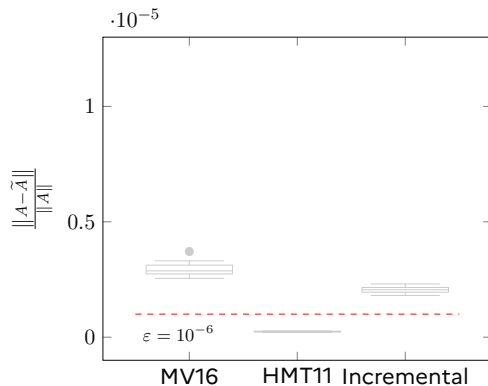
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Relative backward error

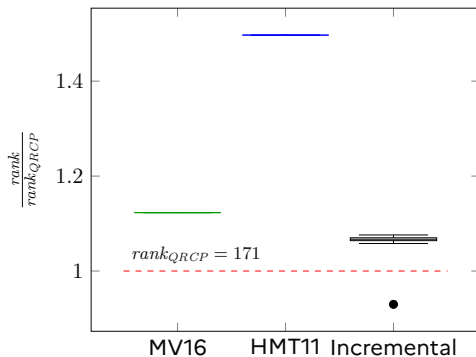


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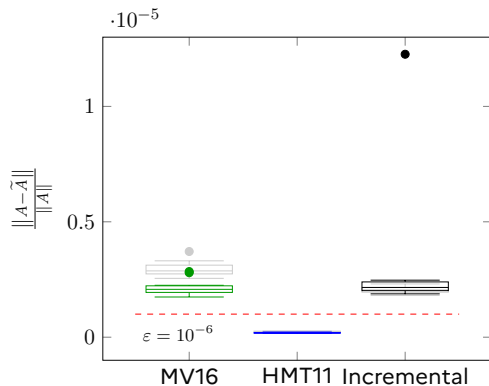
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Relative backward error



Variants

Orthogonal post-processing

Sketch based (ORID_S)

$$\begin{aligned} \tilde{Q}, \tilde{R} &= \text{qr}(A[:, 1:k], \text{NoPivot}()) \\ R &= \tilde{R} [\mathbf{I}(k), \hat{R}_{11}^{-1} \hat{R}_{12}] \end{aligned}$$

👍 Orthogonal basis at a low operational cost

Original matrix based (ORID_A)

$$\begin{aligned} \tilde{Q}, \tilde{R} &= \text{qr}(A[:, 1:k], \text{NoPivot}()) \\ R &= [\tilde{R}, \tilde{Q}^T A_{1:k, k+1:n}] \end{aligned}$$

👍 Orthogonal basis with good approximation quality

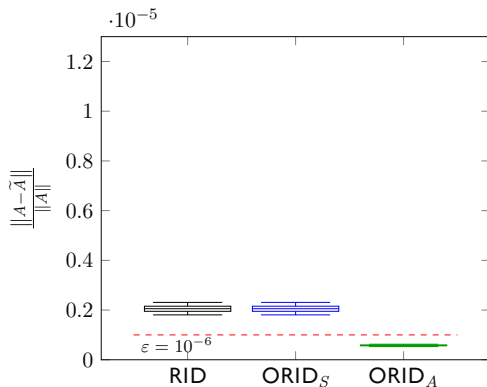
Algorithm	Gaussian sketching
Incremental RID	$2mnk + 4nk^2 - \frac{8}{3}k^3$
Incremental ORID _S	$2mnk + 4nk^2 + 4mk^2 - 2k^3$
Incremental ORID _A	$4mnk + 5nk^2 + 2mk^2 - 3k^3$

Experimental results

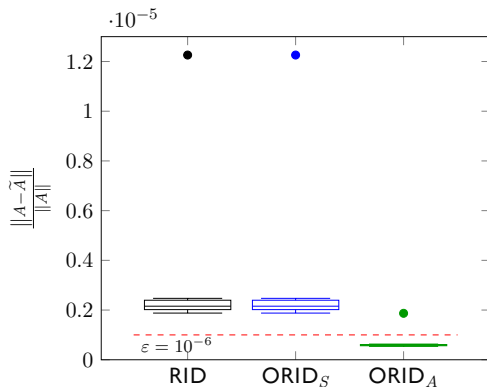
Backward error

Let us compare, using again the Heat test matrix, the post-processing techniques for incremental RID.

Gaussian sketching



SRHT sketching





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Software



Let's take an example where the sketch is partitioned in 4 blocks of size $b \times b$.



Goal: Task-based column selection in a parallel distributed setting in *Chameleon*.

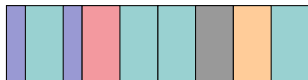


Key Ideas:

- Each task computes QRCP on a block pair;
- Elegant implementation using REDUX from *StarPU*.



Let's take an example where the sketch is partitioned in 4 blocks of size $b \times b$.



Goal: Task-based column selection in a parallel distributed setting in *Chameleon*.

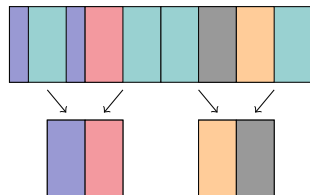


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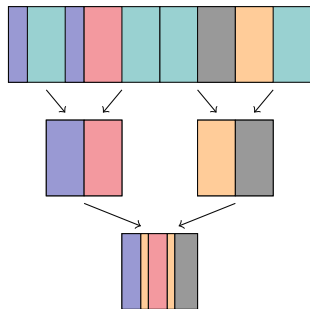


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Key Ideas:

- Each task computes QRCP on a block pair;
- Elegant implementation using REDUX from *StarPU*.

⇒ MR in *StarPU* on SCRATCH data in REDUX.

Goal: Permute columns of a distributed matrix based on the internship work of Matteo Marcos (supervised by Alycia Lisito, Pierre Ramet and Mathieu Faverge).



Key Ideas of his internship:

- Row permutation of matrices with irregular distributions in *Chameleon*;
- Communication volume reduction by use of workspaces;
- **Extension to column permutation.**



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Conclusion

Conclusion and future work

Conclusion

- Extended RID to a novel fixed-accuracy variant;
- Lead a unified operational complexity analysis;
- Julia numerical behavior assessment.

Conclusion and future work

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- Extended RID to a novel fixed-accuracy variant;
- Lead a unified operational complexity analysis;
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Future work

- Write task-based SRHT sketching;
- Consolidate Tournament pivoting implementation;
- Familiarize with the permutation developments by Matteo Marcos.

Thank you for your attention. Any questions ?

As part of the "France 2030" initiative, this work has benefited from a national grant managed by the French National Research Agency (Agence Nationale de la Recherche) attributed to the Exa-SoFT project of the NumPEX PEPR program, under the reference ANR-22-EXNU-0003.