

# Parallelization and Pivoting in a Block-Low Rank Multifrontal Solver

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**LSTC**

Livermore Software  
Technology Corp.

## Large sparse linear system $Ax = b$

Often a keystone in scientific computing (discretization of PDEs, step of an optimization method, regression...).

## Sparsity

- ▶ A **sparse matrix** is “any matrix with enough zeros that it pays to take advantage of them” (Wilkinson).

## Multifrontal direct methods

- ▶ rely on dense kernels
- ▶ goal: factorization of  $A = LU$ ,  $A = LDL^T$  or  $A = LL^T$
- ▶ then: forward and backward substitutions  $Ly = b$  and  $Ux = y$

Regular problems	2D $N \times N$ grid	3D $N \times N \times N$ grid
Nonzeros in factors	$O(N^2 \log n)$	$O(N^4)$
Floating-point ops	$O(N^3)$	$O(N^6)$

$\Rightarrow$  extrapolation on a  $1000 \times 1000 \times 1000$  grid:

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- ▶ pivoting for numerical stability
- ▶ distributed-memory parallelism

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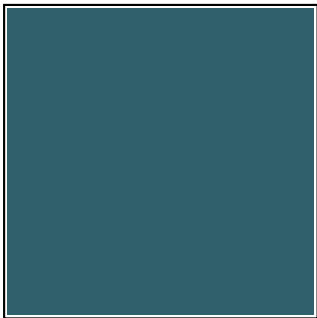
- memory and operations reduction
- numerical parameter  $\varepsilon$  for the approximation
- theory [Bebendorf, Chandrasekaran, Hackbusch, ...] available

Part I

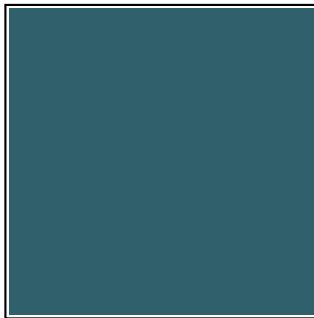
Block Low-Rank format

- ▶ **Many representations:**  $\mathcal{H}, \mathcal{H}^2$  [Bebendorf, Börm, Hackbush, Grasedyck,...], HSS/SSS [Chandrasekaran, Dewilde, Gu, Li, Xia,...]
- ▶ Simpler representations apply to broader classes of problems but provide less potential gain in memory/operations.

**Hierarchically Semi-Separable (HSS):**



**Block Low-Rank (BLR):**

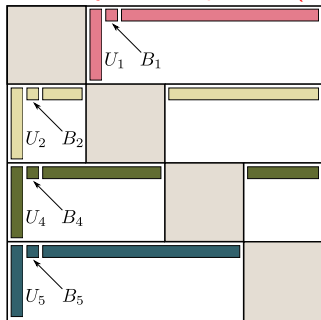




# Low-rank approximations – representations

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## Hierarchically Semi-Separable (HSS):



Recursive partitioning where off-diag blocks are low-rank and nested.

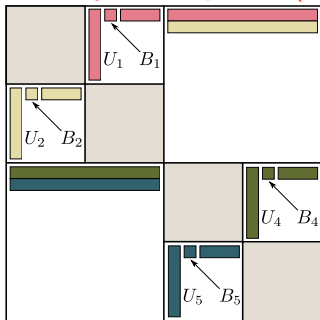
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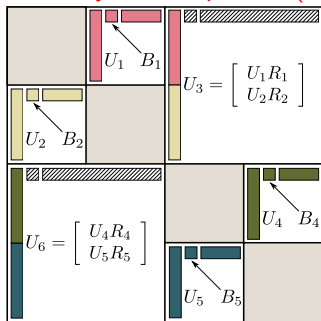
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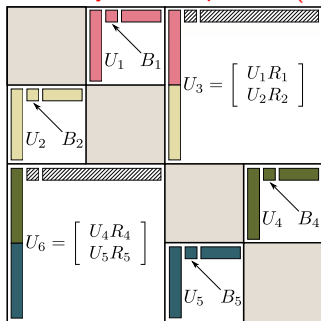
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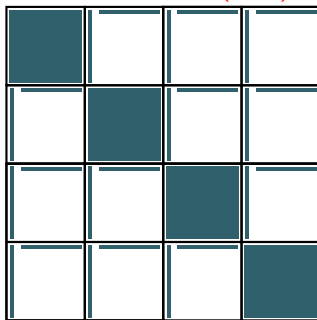
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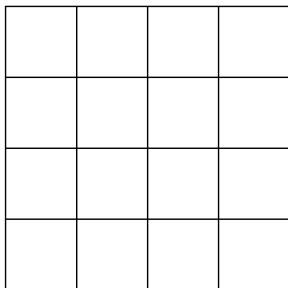
## Block Low-Rank (BLR):



2D partitioning where off-diag blocks are low-rank and do not interact.

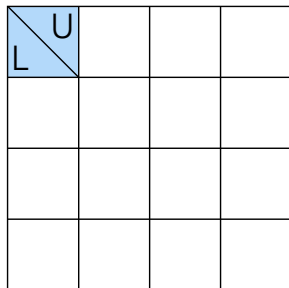
task	operation type	dense	low-rank
Factor (F)	$B = LU^T$	$(2/3)r^3$	$(2/3)r^3$
Solve (S)	$D = X(YL^{-1})$	$r^3$	$kr^2$
Update (U)	$D = D - X_1(Y_1X_2)Y_2$	$2r^3$	$2kr^2$

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► **FACTOR**

► SOLVE

► UPDATE

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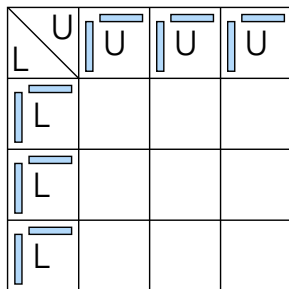
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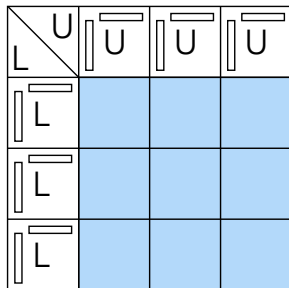
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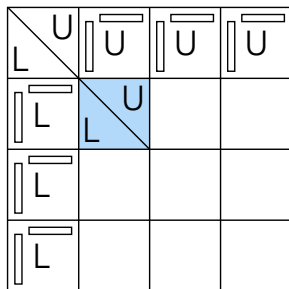
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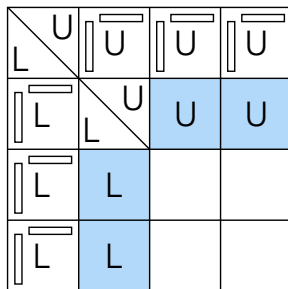
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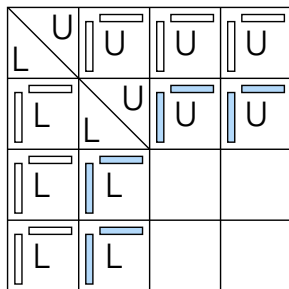
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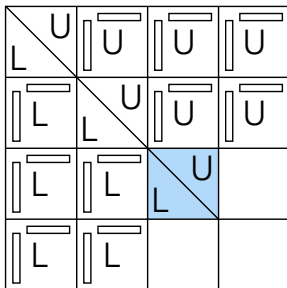
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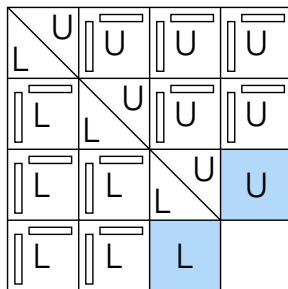
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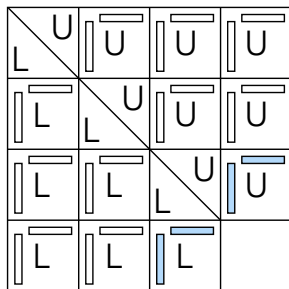
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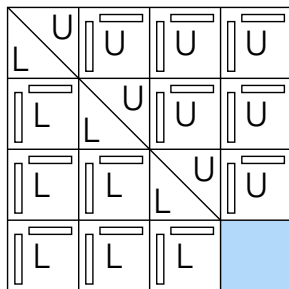
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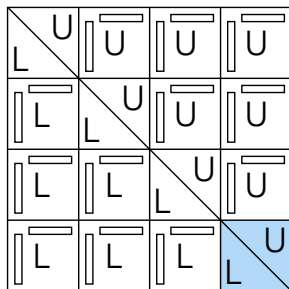
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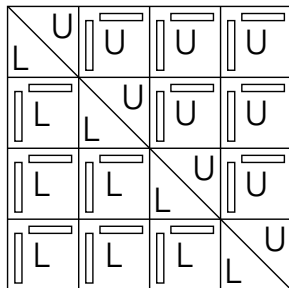
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[Demmel et al. 1995] proposed a bound for  $\|\Delta A\| = \|A - \hat{L}\hat{U}\|$  in the FR case:

$$\|\Delta A\| \leq u \left( \delta(n, r) \|A\| + \theta(n, r) \|\hat{L}\| \|\hat{U}\| \right) + O(u^2)$$

where  $r$  is the block size,  $\delta(n, r)$  and  $\theta(n, r)$  are polynomial constants, and  $u$  the unit roundoff.

For the FSCU algorithm, we proved that:

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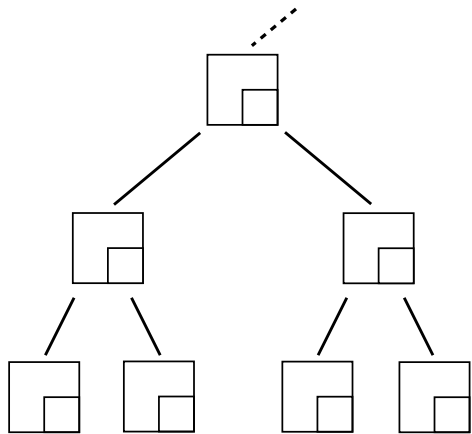
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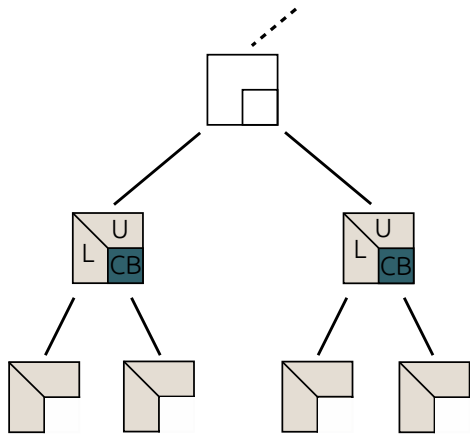
## Part II

### Block Low-Rank multifrontal method



Elimination tree

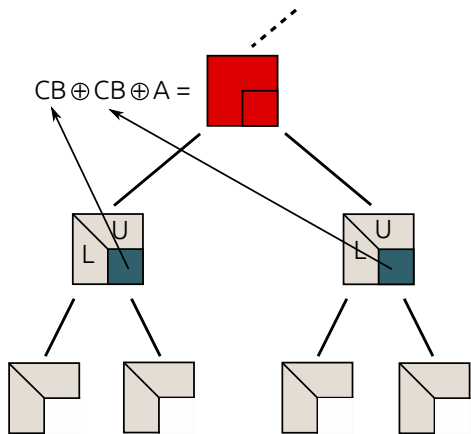




Partial factorizations yield

- rows of U
- columns of L
- contribution blocks (CB)

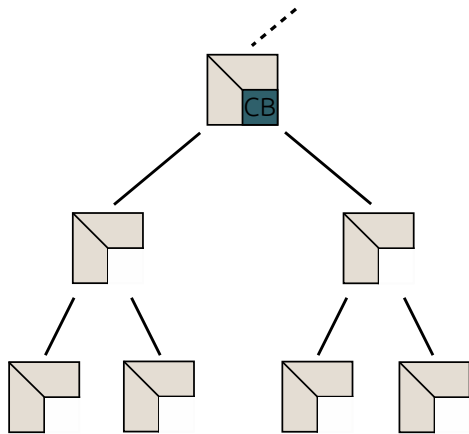
Elimination tree



Elimination tree

Assembly:

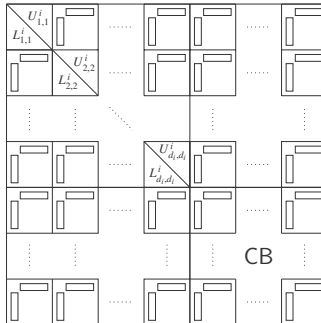
CBs are "summed" with values in A to form a new front



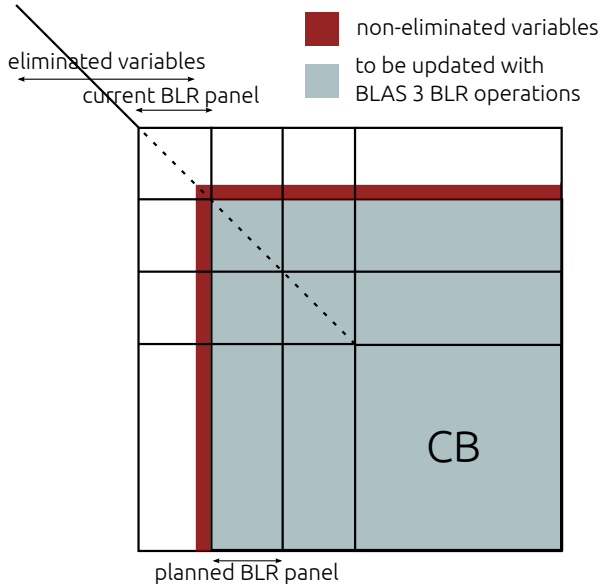
A new front is processed

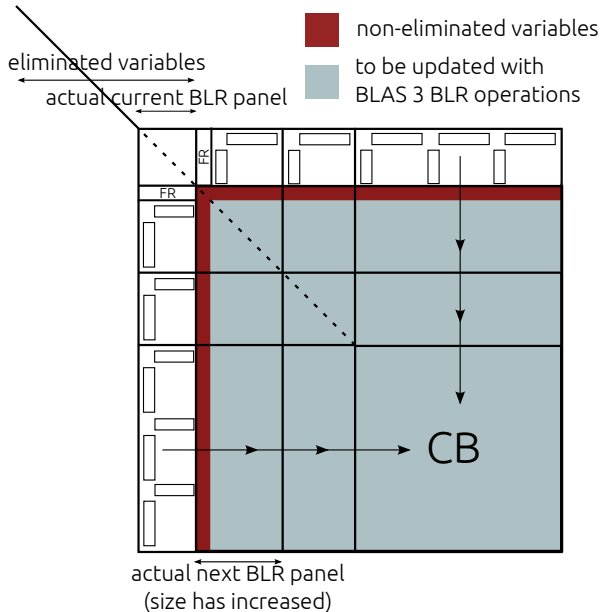
Elimination tree

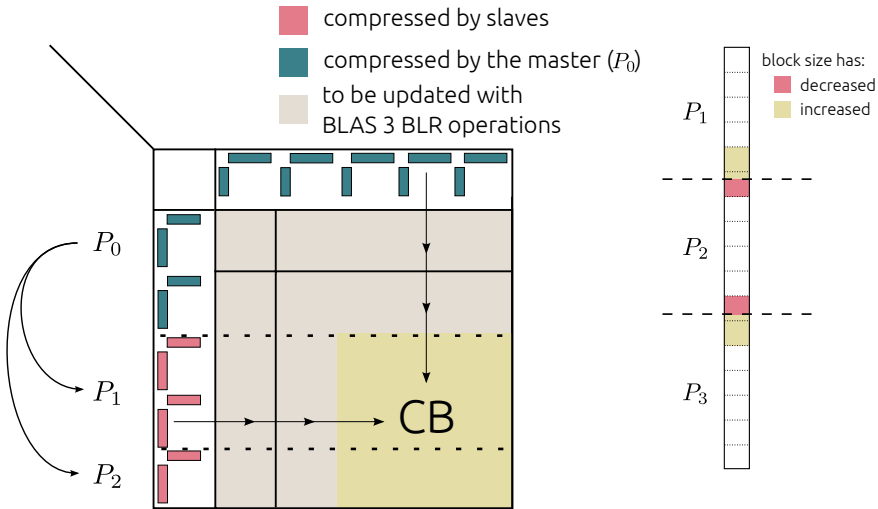
Fronts are not low-rank but have low-rank subblocks [Chandrasekaran et al. 2010, Hackbusch 1999]



- ⇒ blocks must be numerically meaningful to be low-rank
- ⇒ dense algorithm (FSCU) adapts to partial factorization
- ⇒ only larger fronts are processed with BLR







⇒ clustering adapted dynamically to the distribution among processors of MUMPS

The background of the slide features a pattern of light blue, wavy, concentric lines that resemble topographical contour lines or ripples in water. The lines are thin and spaced out, creating a subtle, textured effect across the entire page.

Part III

Results



## metrics:

- ▶  $|\mathbf{L}|$ : fraction of FR factors storage obtained with BLR (%)
- ▶ **ops**: operations for BLR factorization (including compression)
- ▶ **time**: time for BLR factorization (including compression)

## Standard operators:

- ▶ **poisson**:  $\Delta u = f$  with Dirichlet conditions (sym, real)
- ▶ **helmholtz**:  $\left(-\Delta - \frac{\omega^2}{v(x)^2}\right) u(x, \omega) = s(x, \omega)$  (unsym, complex)

## Other matrices:

- ▶ applicative problems from Prof. Davis's collection and EDF

## Accuracy:

- ▶ CSR = Componentwise Scaled Residual =  $\max_i \left( \frac{|A\tilde{x}-b|_i}{(|A||\tilde{x}|+|b|)_i} \right)$

- ▶ preliminary results on a small problem ( $128^3$ )

# procs	Poisson	Helmholtz
	L	
1	53.3%	72.0%
4	54.5%	n/a
8	54.5%	n/a
16	54.6%	73.6%
32	54.9%	73.6%
64	55.3%	73.7%
128	56.0%	74.1%

⇒ factor compression well maintained (slight increase)

- ▶ preliminary results on a small problem ( $128^3$ )

# procs	ops	execution time	
		BLR	MUMPS
1	52.3%	n/a	n/a
16	56.4%	3133s.	4905s.
32	56.5%	2125s.	2648s.
64	56.7%	1409s.	1537s.
128	57.3%	1014s.	979s.

(Helmholtz only)

- ⇒ ops compression well maintained (slight increase)
- ⇒ timings need to be improved (+ too many procs)

name	struct	n ( $\times 10^6$ )	NZ	application
cont-300	sym	0.18	0.53	optimization (linear, UFL)
kkt_power	sym	2	8	optimal power flow (nonlinear, UFL)
d-plan-inco	nonsym	2	21	nonlinear mechanics (EDF)

- ▶ three different applications
- ▶ very large amount of pivoting
- ▶ static pivoting: if  $|a_{k,k}| < \sqrt{\epsilon_{mach}} \cdot \|A\|$ , then  $a_{k,k} \leftarrow \sqrt{\epsilon_{mach}} \cdot \|A\|$
- ▶ Why is partial pivoting needed with BLR applications ?

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cont-300	kkt_power	d-plan-inco
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	cont-300	kkt_power	d-plan-inco
MUMPS FR partial	5.68E-8	3.05E-10	1.90E-12
MUMPS FR static	5.71E-3	4.66E-4	8.88E-7

- ▶ partial pivoting needed in FR

	cont-300	kkt_power	d-plan-inco
MUMPS FR partial	5.68E-8	3.05E-10	1.90E-12
MUMPS FR static	5.71E-3	4.66E-4	8.88E-7
BLR ( $10^{-14}$ ) static	5.91E-3	7.90E-5	1.04E-6
Compressions ( $ L  - f$ )	98 - 116	75 - 64	46 - 8
BLR ( $10^{-14}$ ) partial	2.06E-8	2.65E-9	2.37E-12
Compressions ( $ L  - f$ )	92 - 82	70 - 57	47 - 8

- ▶ partial pivoting needed in FR
- ▶ pivoting does not decrease the compression rates

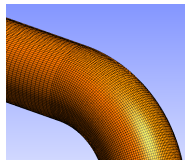
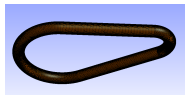
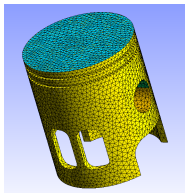
	cont-300	kkt_power	d-plan-inco
MUMPS FR partial	5.68E-8	3.05E-10	1.90E-12
MUMPS FR static	5.71E-3	4.66E-4	8.88E-7
BLR ( $10^{-14}$ ) static	5.91E-3	7.90E-5	1.04E-6
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BLR ( $10^{-14}$ ) partial	2.06E-8	2.65E-9	2.37E-12
Compressions ( $ L  - f$ )	92 - 82	70 - 57	47 - 8
BLR ( $\varepsilon$ ) partial	1.59E-3( $10^{-9}$ )	9.77E-4( $10^{-8}$ )	6.28E-7( $10^{-7}$ )
Compressions ( $ L  - f$ )	86 - 67	54 - 31	44 - 7

- ▶ partial pivoting needed in FR
- ▶ pivoting does not decrease the compression rates
- ▶ two choices: better solution or same solution but faster



	cont-300	kkt_power	d-plan-inco
MUMPS FR partial	5.68E-8	3.05E-10	1.90E-12
MUMPS FR static	5.71E-3	4.66E-4	8.88E-7
BLR ( $10^{-14}$ ) static	5.91E-3	7.90E-5	1.04E-6
Compressions ( $ L  - f$ )	98 - 116	75 - 64	46 - 8
BLR ( $10^{-14}$ ) partial	2.06E-8	2.65E-9	2.37E-12
Compressions ( $ L  - f$ )	92 - 82	70 - 57	47 - 8
BLR ( $\varepsilon$ ) partial	1.59E-3( $10^{-9}$ )	9.77E-4( $10^{-8}$ )	6.28E-7( $10^{-7}$ )
Compressions ( $ L  - f$ )	86 - 67	54 - 31	44 - 7
Time MUMPS FR partial	4 s.	4090 s.	321 s.
Time BLR partial ( $10^{-14}$ )	3 s.	560 s.	82 s.
Time BLR partial ( $\varepsilon$ )	2 s. ( $10^{-9}$ )	484 s. ( $10^{-8}$ )	78s. ( $10^{-7}$ )

- ▶ partial pivoting needed in FR
- ▶ pivoting does not decrease the compression rates
- ▶ two choices: better solution or same solution but faster



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	n	NZ	Cond.	application
piston	1.3E+6	54.7E+6	5.1E+5	external pressure force on the top
perf	2.0E+6	75.8E+6	1.5E+11	"cavity" hook subjected to internal pressure force (challenging for EDF)

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- ▶ CG preconditioned with MUMPS single precision with BLR

FR SP = 3 iterations

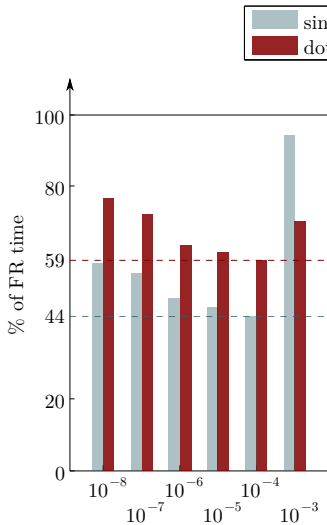
$\varepsilon$	BLR SP			BLR DP		
	#it	L	ops	#it	L	ops
$10^{-8}$	4	66.4%	31.0%	2	65.6%	29.5%
$10^{-7}$	3	63.4%	27.5%	2	62.5%	26.2%
$10^{-6}$	3	60.1%	24.0%	3	59.1%	22.9%
$10^{-5}$	4	56.3%	20.5%	4	55.1%	19.6%
$10^{-4}$	6	51.7%	17.0%	7	50.4%	16.3%
$10^{-3}$	66	45.9%	13.2%	24	44.5%	12.8%
$10^{-2}$	no convergence in 1000s.					

⇒ convergence slightly improved in DP with similar compressions

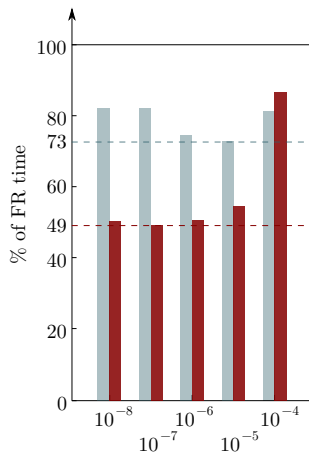
FR SP = 68 iterations

$\varepsilon$	BLR SP			BLR DP		
	#it	L	ops	#it	L	ops
$10^{-8}$	67	59.4%	26.7%	3	58.7%	25.5%
$10^{-7}$	68	56.9%	24.3%	4	56.4%	23.4%
$10^{-6}$	66	52.4%	20.2%	8	51.9%	19.7%
$10^{-5}$	67	49.1%	17.1%	19	48.6%	17.0%
$10^{-4}$	81	45.1%	14.1%	68	44.4%	14.1%
$10^{-3}$	no convergence in 1000s.					
$10^{-2}$						

⇒ convergence substantially improved in DP with similar compressions



piston / FR SP = 373s.  
 $\Rightarrow$  best is SP!



perf / FR SP = 815s.  
 $\Rightarrow$  best is DP!

## A BLR multifrontal solver that is ...

- ▶ algebraic, parallel, general purpose
- ▶ numerically stable
- ▶ efficient (extrapolation on a  $1000 \times 1000 \times 1000$  problem: 40 times less operations, 3 times less factor entries, even more for active memory)

## Perspectives and challenges

- ▶ improve parallelism
- ▶ BLR forward and backward substitutions
- ▶ further study preconditioning
- ▶ BLAS3 efficiency

# Thank you for your attention!

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## More details in ...

- ▶ “*Improving multifrontal methods by means of block low-rank representations*”, Amestoy et al., 2012, submitted to SIAM SISC
- ▶ “*Improving multifrontal solvers by means of algebraic block low-rank representations*”, Weisbecker, 2013, Ph.D. thesis