

# Mixing LU and QR on multi-core cluster systems

ICL Friday Lunch

J. Herrmann, M. Faverge, J. Langou, Y. Robert

July 6, 2012

# Outline



- ① How to solve a linear system?
  - LU Factorizations
  - QR Factorizations
- ② Mixing LU and QR kernels
- ③ Hierarchical Partial Pivoting (HPP)
- ④ Accuracy study
- ⑤ Current work
- ⑥ Conclusion



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- 1 How to solve a linear system?  
LU Factorizations  
QR Factorizations
- 2 Mixing LU and QR kernels
- 3 Hierarchical Partial Pivoting (HPP)
- 4 Accuracy study
- 5 Current work
- 6 Conclusion

# How to solve a linear system?



- Goal: Solve a linear system  $Ax = b$  where  $A$  is a  $n \times n$  matrix on large cluster of multicores.
- Existing Solutions:
  - **Factorization  $A = LU$ ,**
    - $\hookrightarrow \frac{2}{3}n^3$  floating-point operations
    - $L$  unit lower triangular and  $U$  upper triangular.
    - Solve  $Ax = b$  by solving successively
    - $Ly = b$  and  $Ux = y$
  - **Factorization  $A = QR$ ,**
    - $\hookrightarrow \frac{4}{3}n^3$  floating-point operations
    - $Q$  orthogonal matrix and  $R$  upper triangular.
    - Solve  $Ax = b$  by solving  $Rx = Q^T b$



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    - Solve  $Ax = b$  by solving  $Rx = Q^T b$



# LU Factorizations



## Tile Algorithms

- Partial pivoting
- Incremental pivoting
- Tournament pivoting

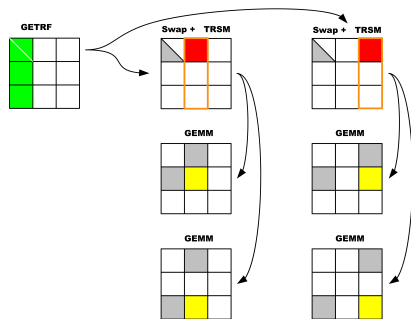


# LU Factorizations

## Partial Pivoting



- 😊 Highly parallel update (GEMM)
- 😊 Good stability
- 😞 Synchronization on each panel to apply the pivots
- 😞 Involves row swapping



DAG for one step of LU  
Partial Pivoting

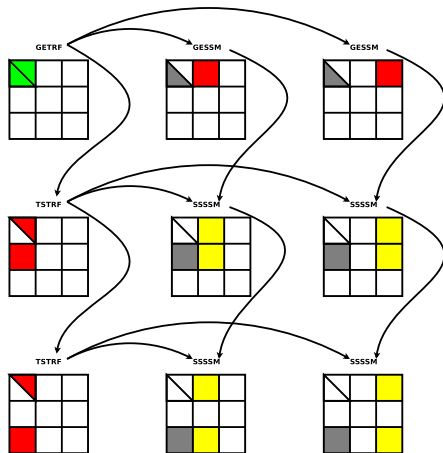


# LU Factorizations

## Incremental Pivoting



- 😊 Updates released before the end of panel factorization
- 😞 Update kernels don't exceed 80% of peak
- 😞 Extra computations compared to LUPP
- 😞 Less stable than LUPP
- 😞 Pipeline of communications on each column



DAG for one step of LU

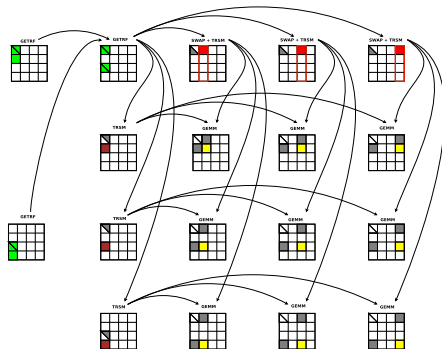


# LU Factorizations

## Tournament Pivoting



- 😊 Highly parallel update (GEMM)
- 😊 Enough stability
- 😊 Reduce the number of synchronisations
- 😞 Synchronization on each panel to apply the pivots
- 😞 Involves row swapping
- 😞 Extra computations compared to LUPP
- 😞 Less stable than LUPP



DAG for one step of LU



# QR Factorizations



## Tile Algorithms

- Flat tree using TS kernels
- Hierarchical trees using TS and TT kernels

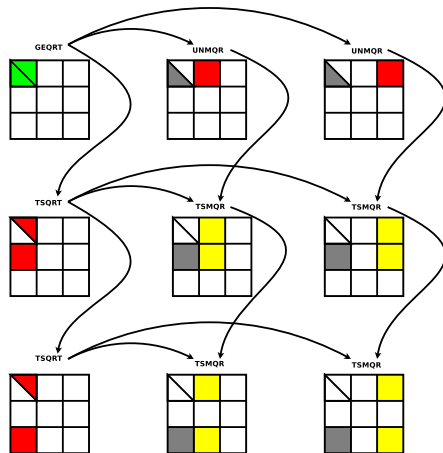


# QR Factorizations



## Flat tree algorithm

- 😊 More stable than LU factorization
- 😊 Some updates are released before the panel factorization is completed
- 😞 Update kernels don't exceed 80% of peak
- 😞 Twice as costly as LU factorization
- 😞 Pipeline of communications on each column



DAG for one step of QR

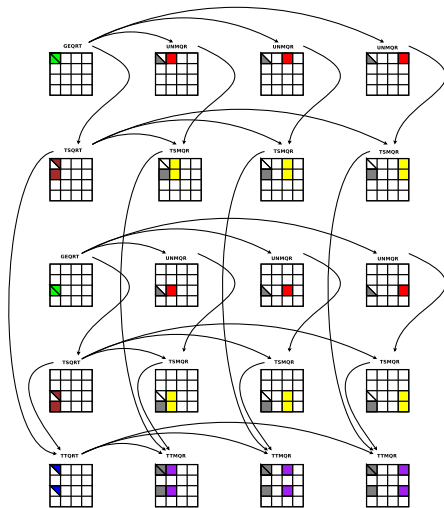


# QR Factorizations

## Hierarchical QR Factorization



- ☺ More stable than LU factorization
- ☺ Updates released before the end of panel factorization
- ☺ Communications reduced
- ☺ Wide space of composability on each panel  
Flat, Greedy, Binary, Fibonacci, ...
- ☹ Update kernels don't exceed 80% of peak
- ☹ Twice as costly as LU factorization



DAG for one step of QR

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# Mixing LU and QR



## Main Idea

- Algorithms have the same pattern:

$$A = \begin{pmatrix} A_{11} & C \\ B & D \end{pmatrix} \Leftrightarrow \begin{pmatrix} \text{factor} & \text{apply} \\ \text{kill} & \text{update} \end{pmatrix}$$

- Keep the flops as close as possible to LU
- Remove the communications along the panel  
Incremental Pivoting or Flat QR
- Panel done as in Tournament pivoting or HQR
- Remove the swap on the trailing submatrix
  - Suppress the synchronization at each step
  - Reduce the number of communications
- Does not give a QR or LU factorization
- We apply all transformations on  $\tilde{A} = (A, b)$

# Mixing LU and QR



## Main Idea

### Diagonal-based algorithms

- One killer per panel
- Killer constructed with 1 or  $f > 1$  tiles
- The killer kills all remaining tiles
- $f$  can be determined dynamically

### Multi-killer algorithms

- Several killers per panel
- In each domain, killer constructed with 1 or  $f > 1$  tiles
- The killer kills the remaining tiles of its own domain
- Use a reduction tree across domains

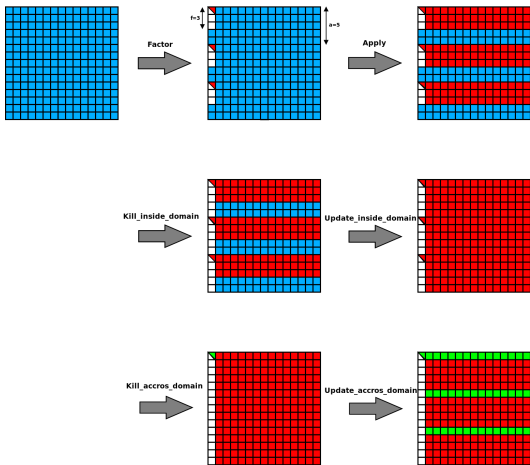


Illustration of the multi-domain approach



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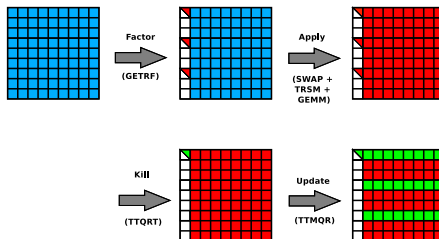


# Hierarchical Partial Pivoting (HPP)

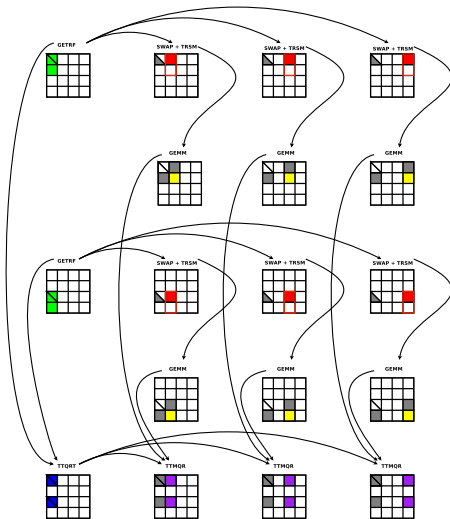


## HPP

- *Factor & Apply*  
↪ LU with Partial pivoting & Swap + TRSM + GEMM
- *Kill\_inside\_domains & Update\_inside\_domains*  
↪ Non-existent since  $f = a$
- *Kill\_accross\_domains & Update\_accross\_domains*  
↪ TTQRT & TTMQR



HPP pattern, on one processor, for a  $9 \times 9$  tiled matrix, and with  $a = 3$



**DAG for one step of the HPP algorithm, on one processor, for a  $4 \times 4$  tiled matrix, and with  $a = 2$**



# Hierarchical Partial Pivoting (HPP)



## Kernels Cost

- LUPP kernels are highly parallel, more performant...
- QR is more stable, but more costly

	LU-based		QR-based	
<i>factor A</i>	2/3	GETRF	4/3	GEQRT
<i>kill B</i>	$(n-1)$	TRSM	$2(n-1)$	TSQRT
<i>apply C</i>	$(n-1)$	TRSM	$2(n-1)$	UNMQR
<i>update D</i>	$2(n-1)^2$	GEMM	$4(n-1)^2$	TSMQR

Table: Computational cost of each kernel. The unit is  $n_b^3$  flops.

# Hierarchical Partial Pivoting (HPP)



## Computational cost

### Proof.

$$\begin{aligned}
 C_{HPP} &= \sum_{k=0}^{n-1} \frac{n-k}{a} \times (C_{GETRF} + (n-k) \times C_{TRSM} + (n-k) \times (a-1) \times C_{GEMM}) \\
 &\quad + \left(\frac{n-k}{a} - 1\right) \times (C_{TTQRT} + (n-k) \times C_{TTMQR}) \\
 &\approx \frac{1}{a} \times \frac{n^3}{3} \times (C_{TRSM} + (a-1) \times C_{GEMM} + C_{TTMQR}) \\
 &\approx \frac{1}{a} \times \frac{n^3}{3} \times (n_b^3 + (a-1) \times 2n_b^3 + 2n_b^3) \\
 &\approx \left(1 + \frac{1}{2a}\right) \times \frac{2}{3} N^3
 \end{aligned}$$





# Hierarchical Partial Pivoting (HPP)



## Computational cost

$$C_{HPP} \approx \left(1 + \frac{1}{2a}\right) \times \frac{2}{3} N^3$$

## Remarks

- When  $a = \infty$ ,  $C_{HPP} \approx C_{LU}$
- When  $a = 1$ ,  $C_{HPP} \approx N^3$ 
  - ↪ computation overhead of 50% as compared LU factorization
  - ↪ still smaller than  $C_{QR} = \frac{4}{3} N^3$



# Hierarchical Partial Pivoting (HPP)



## Implementation

- Use DAGuE runtime
  - ↪ we just specify the task graph
  - ↪ deal with MPI communications and shared memory accesses
- Data flow description of the algorithm
  - ↪ tasks are local
  - ↪ problem with GETRF and SWAP

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# Accuracy study



## Framework

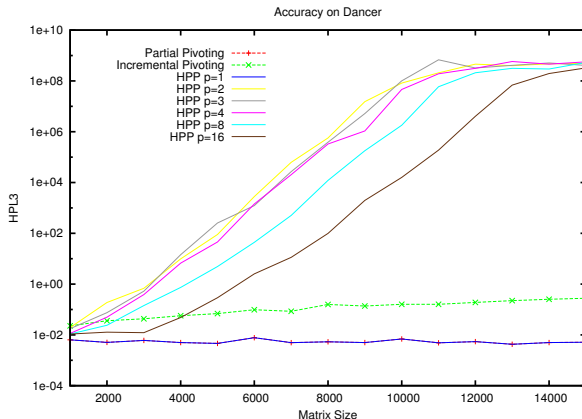
- Every test in distributed memory has been run on *Dancer*  
↪ 16 nodes of 8 cores: Intel(R) Xeon(R) CPU E5520 @ 2.27GHz
- Every test in shared memory has been run on *Remus*  
↪ 48 shared-memory processors: AMD Opteron(tm) Processor 6180 SE
- The algorithm was run with a block size equal to  $n_b = 240$ .
- $A$  and  $b$  are random matrix and vector
- 

$$HPL3 = \frac{\|Ax - b\|_{\infty}}{\|A\|_{\infty} \|x\|_{\infty} \times N \times \epsilon}$$



# Accuracy study

## Distributed memory results

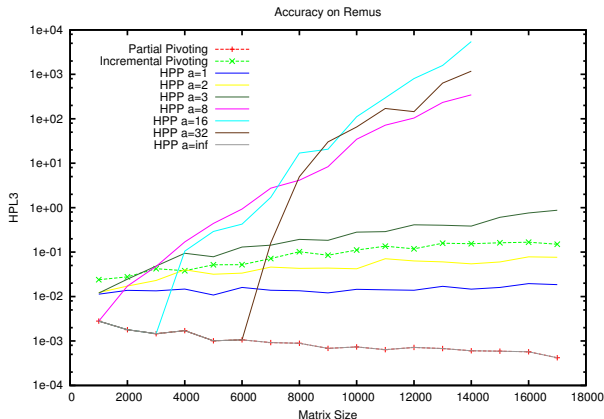


Accuracy of HPP depending on the number of processors  $p$  on Dancer



# Accuracy study

## Shared memory results



Accuracy of HPP depending on the domain size  $a$  on Remus

# Accuracy study

## Growth Factor

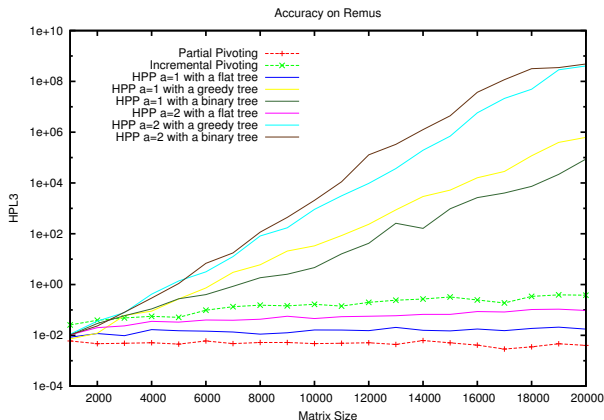


- The worst-case bound growth factor of HPP is the same as that of LU with Partial Pivoting
  - ↪ The domains are factored using LU with Partial Pivoting
  - ↪ The QR reduction across domains is an orthogonal transformation
- So why is HPP unstable?
- Where does the difference of stability between the shared memory and the distributed versions come from?



# Accuracy study

## Impact of the tree



Impact of the reduction tree on the accuracy of HPP

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# Current work



## New version?

- LU factorization on the diagonal domain
- If result **good enough**, update with a Cholesky-like algorithm
- If not, do a QR factorization at this step

## Problem

What is good enough?  $(K * cond_2(A_{k,k}) \geq \sum_{j=k}^{M_t} (\|A_{k,j}\|_1))$



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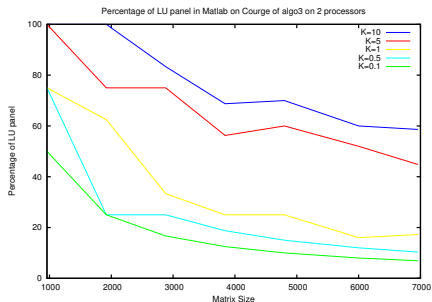
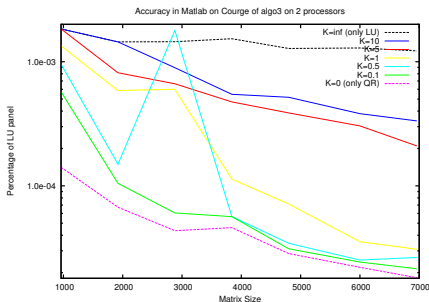
What is good enough? ( $K * \text{cond}_2(A_{k,k}) \geq \sum_{j=k}^{M_t} (\|A_{k,j}\|_1)$ )





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## Accuracy





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# Conclusion



- We introduced a taxonomy for algorithms mixing LU and QR kernels
- We described and implemented one of them
- A second version is in progress
- Results turned out to be less positive than expected
- But encouraging for dynamic algorithms