



Practical Manycore Pivoting

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* Thanks also to Jeremy Appleyard of NVIDIA

Introduction

Solve: $Ax = b$

A is:

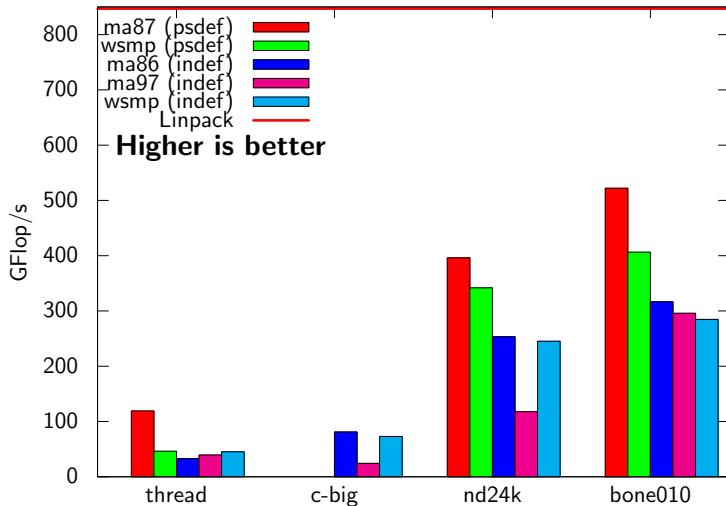
- ▶ Sparse
- ▶ Large
- ▶ Symmetric
- ▶ Indefinite

Algorithm should be:

- ▶ Fast
- ▶ Accurate
- ▶ Numerically Stable
- ▶ Bitwise-reproducible?



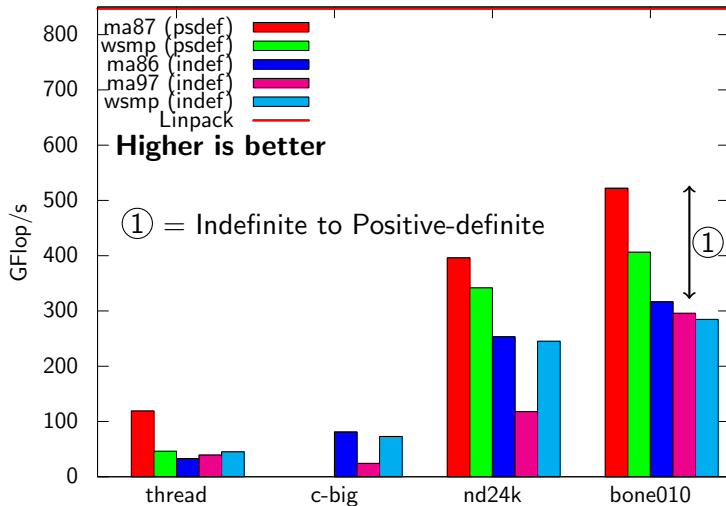
Current Performance Gaps



2×E5-2695 v3 (Haswell-EP) = 28 cores



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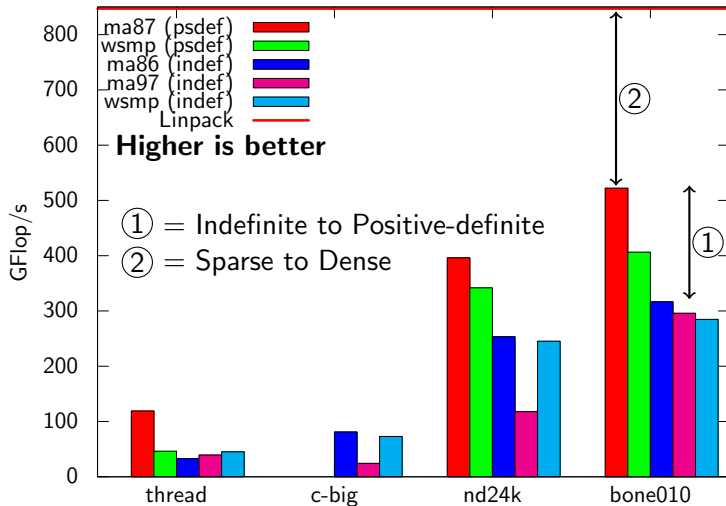


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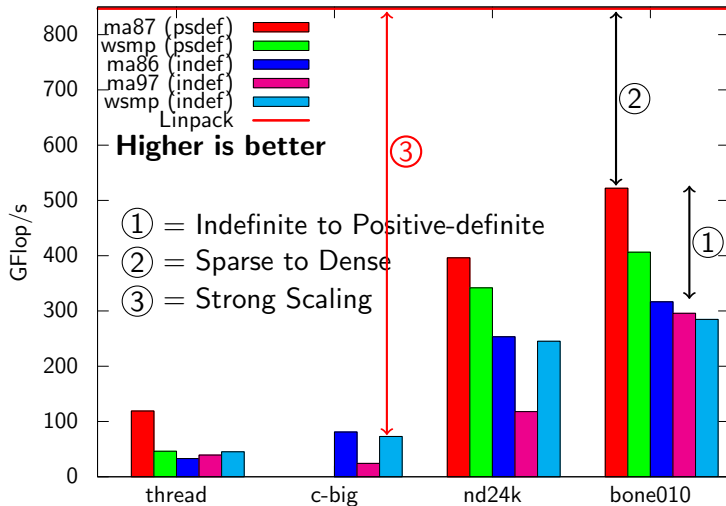
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Main focus of this talk

Indefinite to Positive-definite Performance Gap

⇒ 20–60% depending on problem

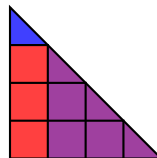


So what's the problem?

Pivoting!

Cholesky pattern:

1. Factor diagonal $A_{jj} = L_{jj}L_{jj}^{-T}$ (Factor)
2. Apply pivot $L_{ij} = L_{ij}L_{jj}^{-T}$ (TRSM)
3. Update uneliminated $A_{ik} \leftarrow A_{ik} - L_{ij}L_{kj}^T$ (GEMM)



Main difference:

- ▶ For LDL^T pivoting requires all blocks in column
- ▶ Cholesky starts Factor/Apply/Update as soon as ready

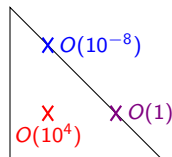
Stability

The problem

- ▶ Need to avoid loss of accuracy
- ▶ (achieve small backward errors)

Root cause

- ▶ “Small” number on diagonal
- ▶ “Big” number below diagonal
- ▶ Divide one by the other in floating point
- ▶ Add to something “small”
- ▶ \Rightarrow Lose accuracy
- ▶ Resultant large values have large “growth”



Solution

- ▶ Don't do this (pivoting)

What's been done before?

Traditional Partial Pivoting (TPP)

- ▶ Used in eg MA27, BCSLIB
- ▶ “Gold standard” numerical stability
- ▶ Not designed with parallelism in mind



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Block Bunch-Kaufman (Richardson '89)

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- ▶ Just apply dense pivoting in diagonal block
- ▶ Potentially unstable
- ▶ Preprocessing (scaling, reordering) to alleviate problem

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A posteriori pivoting (Kim and Eijkhout '12)

- ▶ Apply pivot, then check growth factor
- ▶ Can start Factor before entire column is ready
- ▶ Can't start updates until pivot test passed

Our solutions

A posteriori pivoting

- ▶ Kim and Eijkhout beat us to publishing the idea.
- ▶ Already limited version in SPRAL/SSIDS.
- ▶ But we want to take it further.



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- ▶ Set in Cholesky task-DAG context
- ▶ Run updates speculatively
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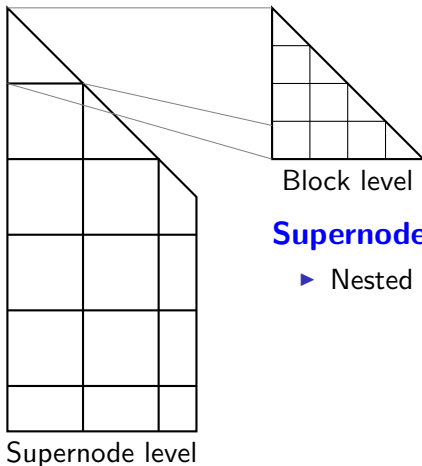
...with speculative execution

- ▶ Set in Cholesky task-DAG context
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...and fallback

- ▶ Detect (subtrees of) matrices with lots of delays
- ▶ Handle with new fallback strategy: **compressed TPP**

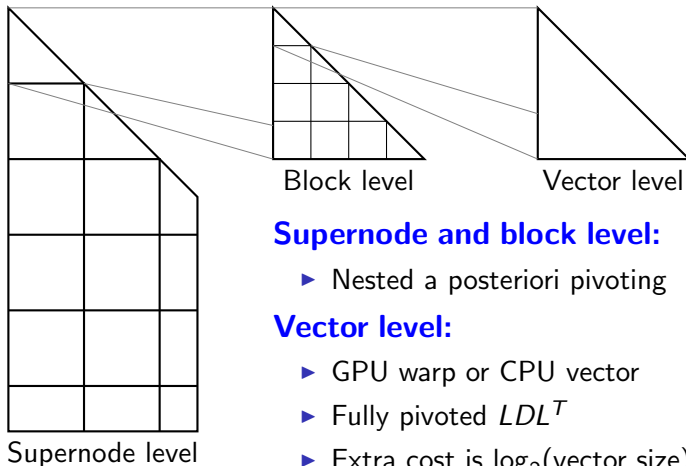
Multi-level approach



Supernode and block level:

- Nested a posteriori pivoting

Multi-level approach



Supernode and block level:

- ▶ Nested a posteriori pivoting

Vector level:

- ▶ GPU warp or CPU vector
- ▶ Fully pivoted LDL^T
- ▶ Extra cost is $\log_2(\text{vector size})$
- ▶ Equivalent to TPP with $u = 0.25$.

Fail in place?

Traditional approach:

- ▶ Column fails \Rightarrow search for column that works
- ▶ Swap good pivot with failed pivot and continue
- ▶ Lots of data movement. Bad!
- ▶ Need to keep collection of failed columns up-to-date.



Fail in place?

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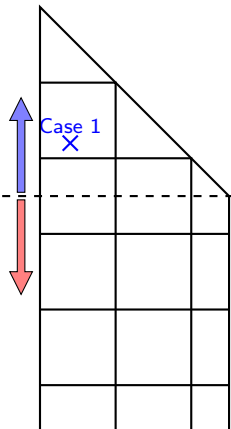
Our approach:

- ▶ Fail in place. Leave failed columns where they are.
- ▶ Swapping occurs only at end
- ▶ Still need to keep failed columns up-to-date
- ▶ But fits better with task-based method \Rightarrow no swaps between blocks!

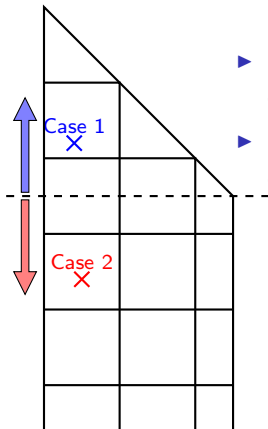
Coping with failure

Case 1:

- ▶ Row should be eliminated at this node
- ▶ Just swap into a diagonal block and rerun



Coping with failure



Case 1:

- ▶ Row should be eliminated at this node
- ▶ Just swap into a diagonal block and rerun

Case 2:

- ▶ Row can not be eliminated at this node
- ▶ Heuristic decision:
 1. Make other swaps and try again
 2. Swap to end and delay

How much swapping?

Terminology

- ▶ One iteration = Multiple passes + one round of swapping

Across 25 difficult problems: Matching scaling

- ▶ 289 variables eliminated on second or later pass
- ▶ 2 variables eliminated on second or later iteration
- ▶ (But quite a few delayed to next node)



How much swapping?

Terminology

- ▶ One iteration = Multiple passes + one round of swapping

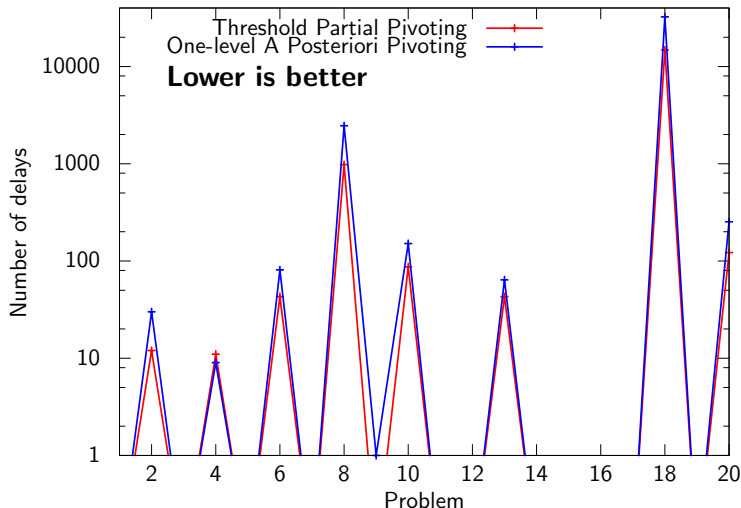
Across 25 difficult problems: Matching scaling

- ▶ 289 variables eliminated on second or later pass
- ▶ 2 variables eliminated on second or later iteration
- ▶ (But quite a few delayed to next node)

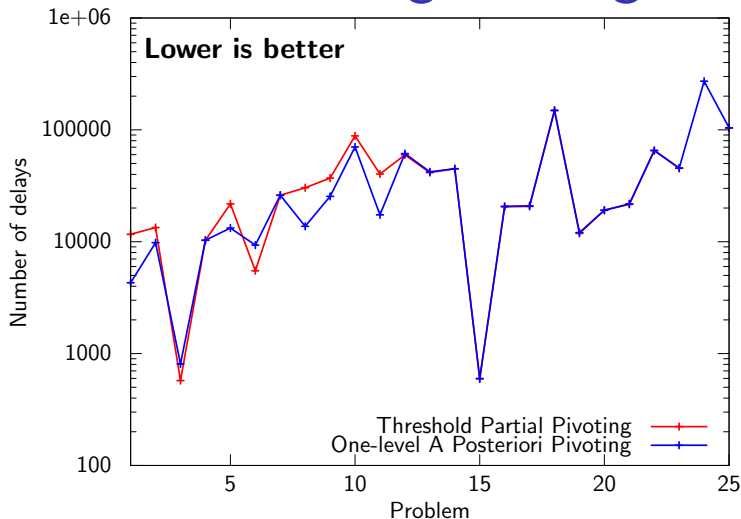
Might as well just delay them?

- ▶ Or consolidate and use TPP

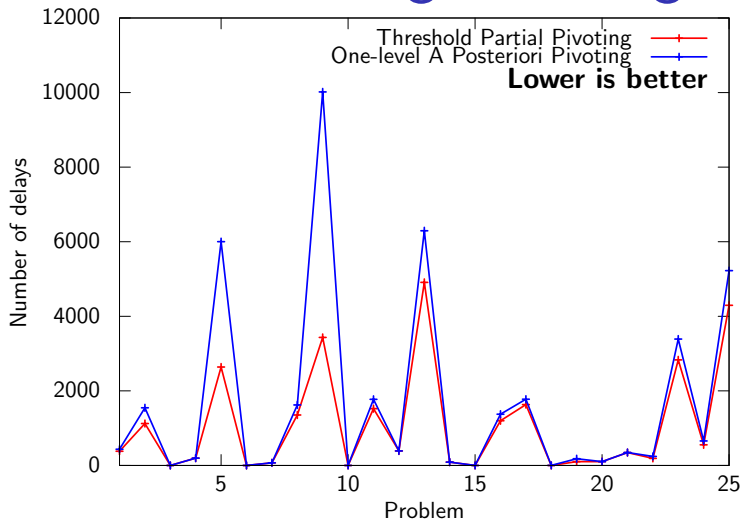
Straightforward: no scaling



Difficult: Matching Scaling



Difficult: Matching Ordering



Numerical Accuracy

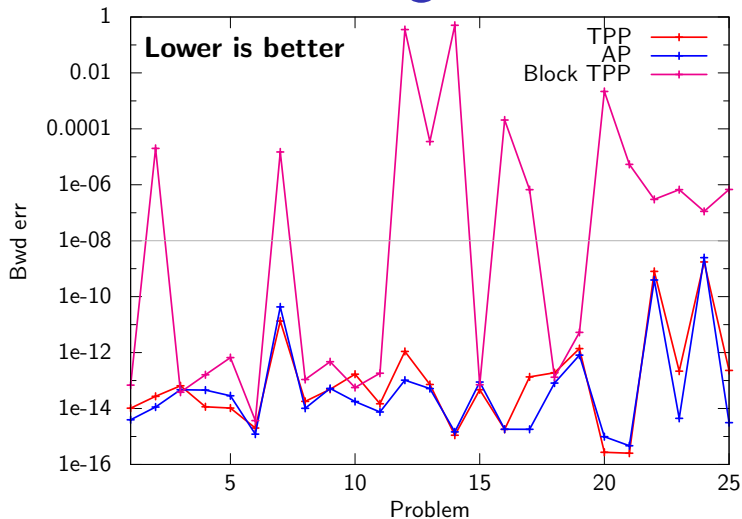
Consider scaled residual:

$$\frac{\|Ax - b\|_{\infty}}{\|A\|_{\infty}\|x\|_{\infty} + \|b\|_{\infty}}$$

- ▶ Results with best preprocessing (Matching-based ordering)
- ▶ Anything $< 10^{-8}$ will *probably* converge using IR



Difficult: Matching-based ordering



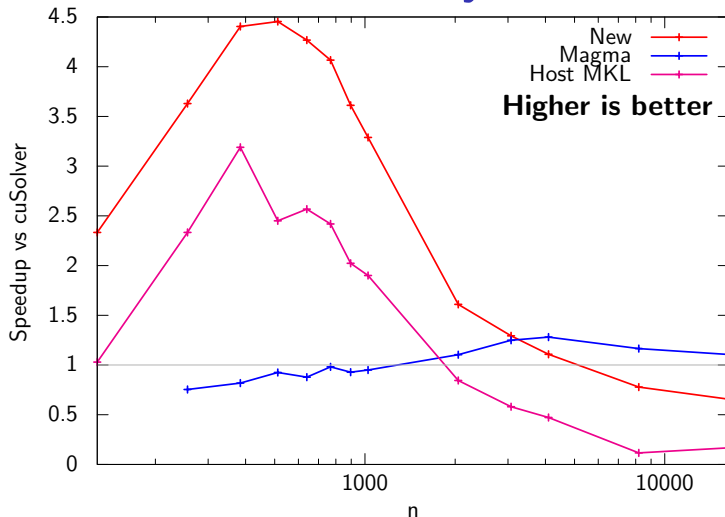
GPU implementation

Still a work in progress...

- ▶ Dense Cholesky “prototype” finished
- ▶ Dense LDL^T version currently being developed
- ▶ Sparse versions pending:
 - ▶ “Drop in” to existing solver straightforward
 - ▶ Fully task-driven with dynamic parallelism for the future
 - ▶ Fully hybrid/multi-GPU code final target



GPU Dense Cholesky: K40



Conclusions: A Posteriori Pivoting

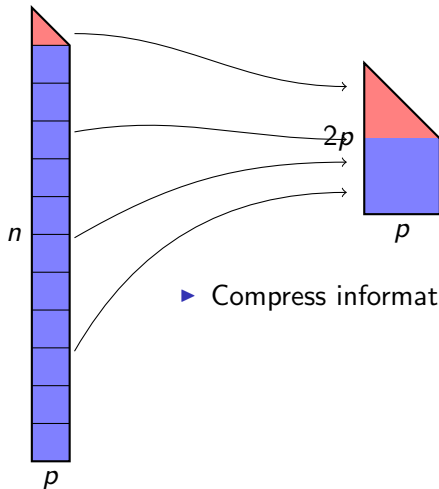
Aim: Symmetric Indefinite to be as cheap as Cholesky

- ▶ For many practical problems stability isn't an issue
- ▶ ... so check it a posteriori
- ▶ Even for numerically difficult problems cost isn't high

Codes will be forthcoming

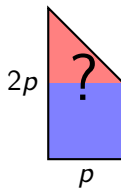
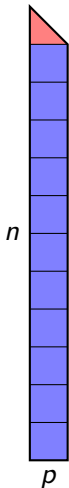
- ▶ GPU code takes longer to develop than I would like
- ▶ <http://www.numerical.rl.ac.uk/spral>

Fallback: Compressed pivoting



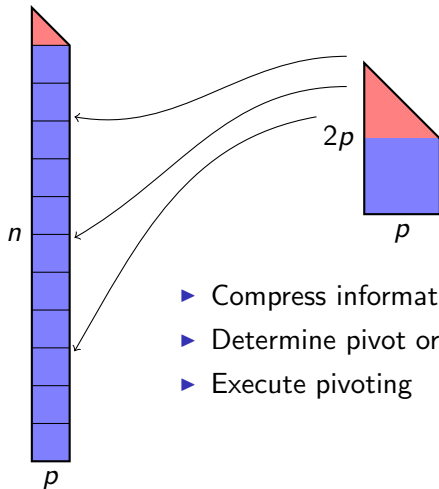
- Compress information into small matrix

Fallback: Compressed pivoting



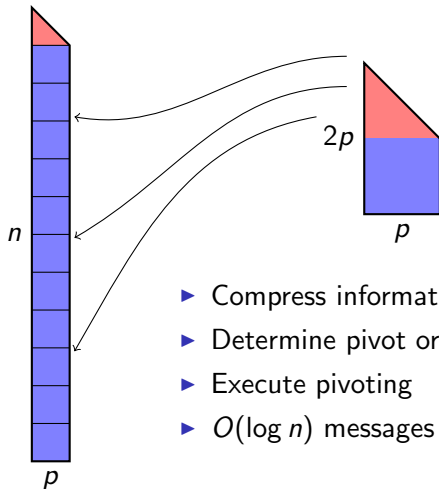
- ▶ Compress information into small matrix
- ▶ Determine pivot order

Fallback: Compressed pivoting



- ▶ Compress information into small matrix
- ▶ Determine pivot order
- ▶ Execute pivoting

Fallback: Compressed pivoting



- ▶ Compress information into small matrix
- ▶ Determine pivot order
- ▶ Execute pivoting
- ▶ $O(\log n)$ messages rather than $O(p \log n)$

Strategies

Strict Compressed Pivoting

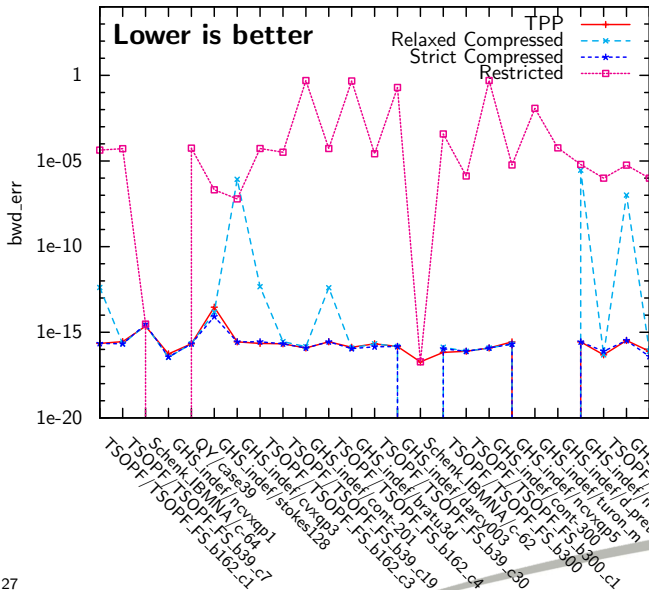
- ▶ Provably numerically stable
- ▶ Expect worst case growth
- ▶ Very pessimistic \Rightarrow more delays

Relaxed Compressed Pivoting

- ▶ Demonstrably unstable on pathological examples
- ▶ Stable in practice — see results
- ▶ Similar performance to traditional TPP



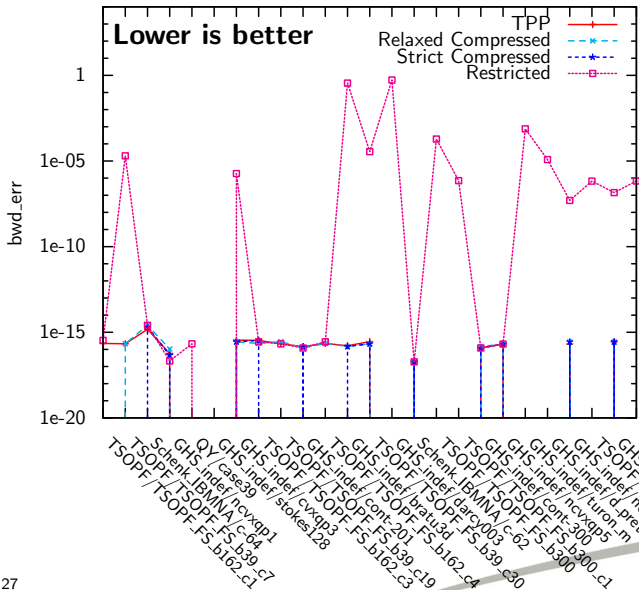
Results: numerical stability



25 difficult problems

- ▶ Strict and TPP always good
- ▶ Relaxed better than restricted

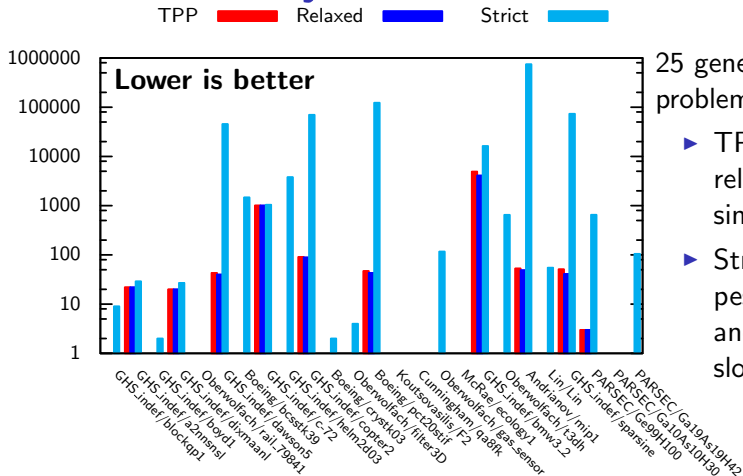
Results: numerical stability



25 difficult problems

- ▶ Strict and TPP always good
- ▶ Relaxed better than restricted
- ▶ Matching-based ordering helps

Results: delays



25 general problems

- ▶ TPP and relaxed very similar
- ▶ Strict very pessimistic and hence slow

Compressed Pivoting: Conclusions

Summary

- ▶ CPU compressed pivoting 2+ times faster on large problems
- ▶ Restricted pivoting not good enough for all problems
- ▶ Strict compressed pivoting guarantees backwards stability
- ▶ Relaxed compressed pivoting works well and cheaper in practice
- ▶ Good fallback method for when a posteriori pivoting encounters lots of delays



Thanks for listening!

Questions?

<http://www.numerical.rl.ac.uk/spral>

Tasks

Cholesky-like

- ▶ Factor Diagonal Block
- ▶ Apply Block Pivot
- ▶ Update to Right

Revisit nodes

- ▶ Apply permutation to left
- ▶ Apply pivot to left (unelim only) + test?
- ▶ Consolidate uneliminated pivots



Strict Compressed Pivoting

1. Partition rows into sets by column of maximum $|a_{ij}|$

$$\begin{pmatrix} \textcircled{12} & 10 & 10 \\ 2 & 3 & \textcircled{4} \\ \textcircled{10} & -3 & \\ 4 & \textcircled{-5} & 4 \\ -6 & \textcircled{8} & \end{pmatrix}$$

Partitioned rows

Strict Compressed Pivoting

1. Partition rows into sets by column of maximum $|a_{ij}|$
2. Represent each set by single row: take maximum $|a_{ij}|$

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Partitioned rows

$$\begin{pmatrix} \boxed{12} & 10 & 10 \\ \boxed{4} & 10 & \boxed{4} \\ \boxed{2} & 6 & 8 \end{pmatrix}$$

Compressed matrix

Strict Compressed Pivoting

1. Partition rows into sets by column of maximum $|a_{ij}|$
2. Represent each set by single row: take maximum $|a_{ij}|$
3. Update using a “worst-case” formula

12	10	10
2	3	4
10		-3
4	-5	4
	-6	8

Partitioned rows

12	10	10
4	10	4
2	6	8

Compressed matrix

- ▶ Provably backwards stable
- ▶ Sometimes too pessimistic

Relaxed example

1. For each column, pick a “representative” row: largest $|a_{ij}|$
2. Apply standard threshold partial pivoting.

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Compressed matrix

- ▶ Not backwards stable!
- ▶ Stable in practice (see results)