

Designing sparse direct solvers for multicore architectures

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Outline of talk

How to efficiently solve $A\mathbf{x} = \mathbf{b}$ on **multicore** machines

(A symmetric)

- Dense positive-definite systems
- Large sparse **positive-definite** systems
- Large sparse **indefinite** systems

Dense positive-definite systems

Factorize $A = LL^T$ using simple block algorithm:

For $k = 1, 2, \dots$:

- $A_{kk} = L_{kk}L_{kk}^T$ (Factor)
- For $i > k$: $L_{ik} = A_{ik}L_{kk}^{-T}$ (Triangular Solve)
- For $i, j > k$: $A_{ij} \leftarrow A_{ij} - L_{ik}L_{jk}^T$ (Update)

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What do we need to synchronise?

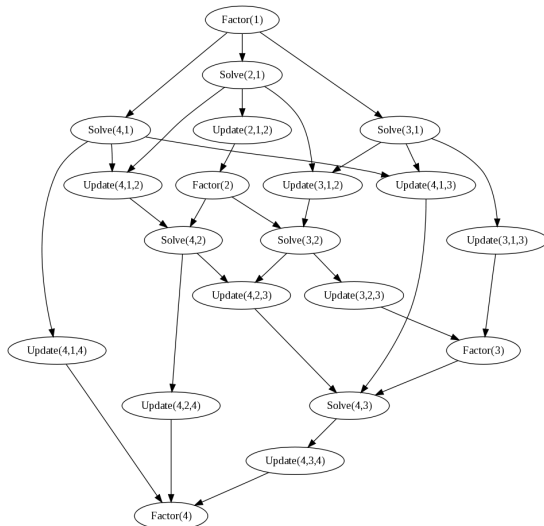
Consider each block operation as a **task**.

Tasks have **dependencies**.

Represent implicitly as a Directed Acyclic Graph (DAG).

Approach of Buttari, Dongarra, Kurzak, Langou, Luszczek, Tomov '06

Task DAG (4 blocks)



Speedup for dense case

Results on machine with 2 Intel E5420 quad core processors.

n	Speedup
500	3.2
2500	5.7
10000	7.2
20000	7.4

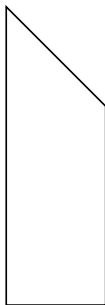
Dense DAG code HSL_MP54 available in HSL 2007.

Sparse case?

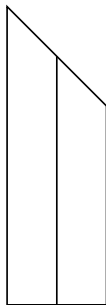
How to generalise to **sparse** factorizations?

Nodal matrix

Hold set of contiguous cols of sparse L with (nearly) same pattern as a dense trapezoidal matrix, referred to as **nodal matrix**.

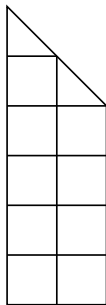


Nodal matrix



Divide nodal matrix into block columns

Nodal matrix



Divide each block column into (square) dense blocks

- Basic operation unit is the block.
- Tasks are performed using these blocks

Tasks in sparse positive-definite case

Express sparse Cholesky factorization using 4 basic operations

`factor_block(L_{diag})`. Computes dense Cholesky factor L_{diag} of block on diagonal.

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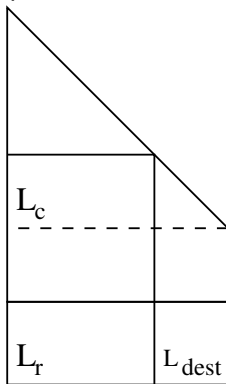
`solve_block(L_{dest})`. Performs triangular solve of off-diagonal block L_{dest} by Cholesky factor L_{diag} of block on its diagonal.

$$L_{dest} \Leftarrow L_{dest} L_{diag}^{-T}$$

Tasks in sparse positive-definite case

`update_internal(L_{dest} , col)`

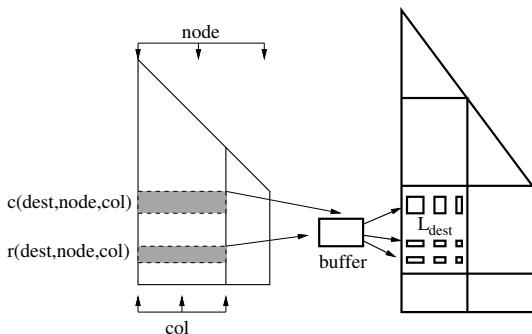
Within *node*, performs update



$$L_{dest} \Leftarrow L_{dest} - L_r L_c^T$$

Tasks in sparse DAG

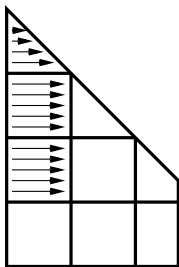
`update_between(L_{dest} , node, col)`



1. Form outer product $L_r L_c^T$ into a buffer.
2. Distribute results into destination block L_{dest} .

Storage of nodal matrix

- Use full storage on diagonal to allow use of efficient BLAS and LAPACK
- Store each block by rows contiguously ... removes discontinuities at row block boundaries and facilitates update tasks.



1				
4	5			
7	8	9		
10	11	12	25	
13	14	15	27	28
16	17	18	29	30
19	20	21	31	32
22	23	24	33	34

Dependency count

During analyse, calculate number of tasks to be performed for each block of L .

During factorization, keep running count of outstanding tasks for each block.

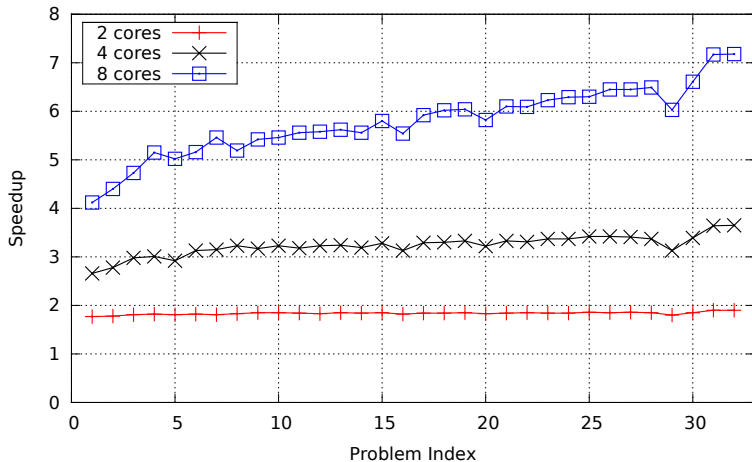
When count reaches 0, a task is stacked.

Each cache keeps small **stack** of tasks that are intended for use by threads sharing this cache.

Tasks added to or drawn from top of local stack. If becomes full, move bottom half to **global task pool**

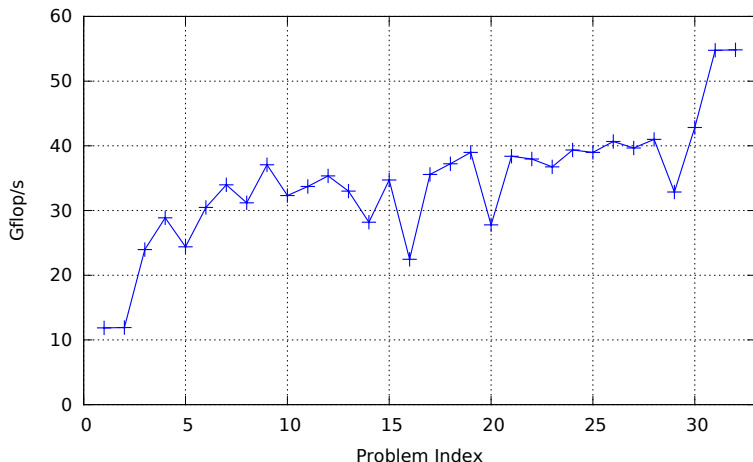
Sparse positive-definite DAG results

Speedups for factorize phase.



Sparse positive-definite DAG results

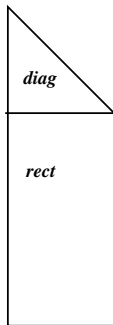
The speed of factorize phase in Gflop/s on 8 cores.
(dgemm peak 72.8 Gflop/s)



Sparse indefinite systems

Extra challenge: need to accommodate pivoting for stability

Do **not** want to restrict pivoting to within block on diagonal



Large entries in *rect* could cause problems.

Implications

- Cannot factorize the diagonal block independently of the off-diagonal blocks.
- The diagonal block and the off-diagonal blocks must all have zero dependency counts.
- Necessary to combine `factor_block` and **all** `solve_block` tasks for a block column L_{col} .
- Separate kernel code written to perform this efficiently, incorporating threshold partial pivoting with 1×1 and 2×2 pivots.

Effects

- Parallelism less fine-grained (large `factorize_col` task replaces smaller `factor_block` and `solve_block` tasks so we use smaller default block size)
- May need to expand storage determined during analyse

$$L_{col} \rightarrow L_{col}^{new}$$

(L_{col}^{new} includes `delayed` columns from child nodes)

- More data movement/copying
- Pivot search requires access by columns (recall: block column stored by rows)

Indefinite results: serial runs

Factorize times on single core. OOM indicates out of memory.

Problem	MA57	HSL_MA77	New code
Schenk_IBMNA/c-56	0.404	0.130	0.163
Simon/olafu	0.559	0.234	0.244
Koutsovasilis/F2	4.48	2.42	2.57
Oberwolfach/t3dh	20.2	11.7	12.1
Schenk_AFE/af_shell110	100	76.2	72.8
Oberwolfach/bone010	877	637	590
PARSEC/Ga41As41H72	OOM	9241	7290

Indefinite results: good news

Factorize times on 1 and 8 cores.

Problem	1	8	speedup
Boeing/crystk03	1.29	0.36	3.58
Koutsovasilis/F2	2.57	0.57	4.51
Cunningham/qa8fk	4.23	0.88	4.79
Oberwolfach/t3dh	12.1	2.17	5.58
Schenk_AFE/af_shell10	72.8	11.7	6.22
Oberwolfach/bone010	590	88.3	6.68
PARSEC/Ga41As41H72	7290	1141	6.39

Conclude: very good results for some large problems

Indefinite results: tough problems

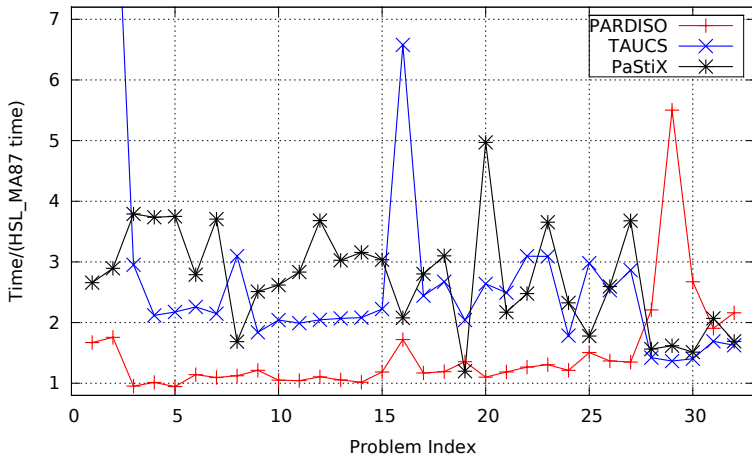
Many delayed pivots cause performance hit.

Problem	num_delay	1	8	speedup
GHS_indef/sparsine	16	250	44.4	5.65
Schenk_IBMA/c-62	28728	9.07	4.93	1.84
GHS_indef/aug3d	144955	36.5	25.9	1.41

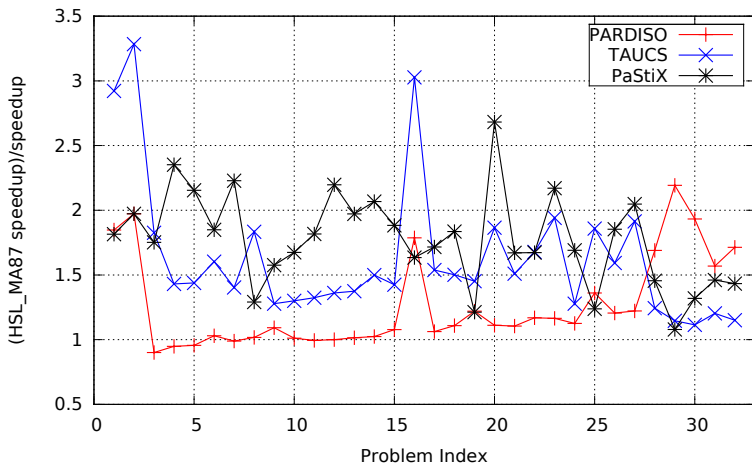
Concluding remarks

- Extended DAG approach from dense positive-definite systems to sparse systems
- Very good results for factorizing positive-definite matrices on our 8-core machine
- Also good results for large indefinite problems provided there are few delayed pivots
- For some tough indefinite problems, further work needed to improve performance while maintaining stability.

Positive-definite case: comparison with other solvers



Positive-definite case: speedup ratios



Indefinite case: comparison with PARDISO

Wall-clock times for factorization phase on 8 cores.

Problem	PARDISO	New code
Schenk_IBMNA/c-56	0.055	0.152
Boeing/crystk03	0.269	0.359
Cunningham/qa8fk	0.704	0.882
Schenk_AFE/af_shell10	13.2	11.7
Oberwolfach/bone010	174	88.3
GSH_indef/sparsine	159	44.4
PARSEC/Ga41As41H72	3020	1141