

Parallel Symbolic Cholesky Factorization

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Sparse Direct Solvers

- Sparse linear system Ax = b, solved via factorization $A = L \cdot U$
- Factorization adds *fill-in* to sparsity pattern of *A*
- Fill-in reducing heuristics like Approximate Minimum Degree (AMD) and Nested Dissection reordering
- Reordered matrix PAP^T has fewer fill-in entries \rightarrow less storage, faster factorization
- Reordering → Symbolic Factorization → Numerical Factorization → Triangular Solve

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Sparse Factorizations: Symbolic Phase

- General criterion: For non pattern-symmetric A, (L + U)_{ij} is nonzero if and only if there is a path i → k₁ → … → k_n → j, k_l < min(i, j) through A
- Symmetric case: L_{ij} nonzero if and only if there is a path $i \rightarrow k_1 \rightarrow \cdots \rightarrow k_n \rightarrow j, k_l < j$
- *L* has a compact representation through the Elimination Tree *T* (transitive reduction)
- *T* can be computed in almost linear time (size and number of nonzeros of *A*)
- Sparsity pattern of row L_{i*} consists of all pairwise paths between A_{i*} through T

Symbolic Cholesky: Enumerating Fill-in

Theorem: The entry l_{ij} in L is (symbolically) nonzero if and only if the row subtree of i contains j, i.e. there is a nonzero a_{ik} in A such that j lies on the path from k to i in the elimination tree T

 \rightarrow we need to identify lowest common ancestors (LCAs) between pairs k_1, k_2 belonging to nonzeros a_{ik_1}, a_{ik_2}

Theorem: In a post-ordered tree *T*, the LCA between any pair of nodes u < v is the first node *w* on the path from *u* towards the root that fulfills $v \le w$

 \rightarrow we can limit ourselves to LCA search between consecutive nonzeros of A in postorder

Theorem: After postordering the matrix, the ordered lower nonzeros of a row a_{ij_k} , $j_1 < \cdots < j_n = i$ give a path decomposition of the row subtree of row i via $[j_k, LCA(j_k, j_{k+1}))$, plus the root i.

Symbolic Cholesky: Enumerating Fill-in



Symbolic Cholesky: Algorithmic Framework

- Copy A to the CPU (optional)
- CPU: Compute Elimination Tree *T*
- CPU: Compute post-ordering of *T*
- Copy *T* to the device (optional)
- Device: Reorder rows of *A* with post-order column indices
- Device: Count number of nonzeros for each row
- Device: Allocate memory
- Device: Generate nonzeros for each row
- Device: Sort rows by column index (optional)

Symbolic Cholesky: Computing the Elimination Tree



transpose(children, parents);

Symbolic Cholesky: Enumerating

```
// Map column indices to postorder
parfor j = 0, ..., m - 1 do
   post_columns[j] = postorder<sup>-1</sup>[columns[j]];
end
// Sort postorder column indices
parfor i = 0, ..., n - 1 do
   sort(post_columns[row_ptrs[i], ..., diag_idx[i]]);
end
// Traverse row subtrees
parfor i = 0, ..., n - 1 do
   parfor j = row_ptrs[i], \ldots, diag_idx[i] do
        u_{post} \leftarrow \text{post\_columns}[j];
       v_{post} \leftarrow \text{post\_columns}[j+1];
       while u_{post} < v_{post} do
           u = postorder[u_{post}];
           u_{post} = post_parent[u_{post}];
           // Output or count nonzero l_{iu}
       end
    end
end
```

Performance Evaluation: Setup

- Code available in the Ginkgo HPC library https://github.com/ginkgo-project/ginkgo
- Comparison against symbolic part of CHOLMOD
- Compiled using gcc 11.3.0, CUDA 11.8, ROCM 5.1.1 with –O3 flags
- Inputs: (almost) all pattern-symmetric matrices from SuiteSparse with between 10⁴ and 10⁷ rows/columns
- Benchmarks with input ordering (*natural*), AMD and Nested Dissection (*nd*) ordering
- Removed all inputs that overflow 32 bit indices in row pointers

•	Validated as correct for small sample of matrices					NVIDIA	AMD
	validated as confect for sinal sample of matrices					Intel	AMD
					CPU	Xeon Platinum 8368	EPYC 7543
					Sockets	2	2
		natural	AMD	ND	Cores/Socket	38	32
•	#matrices	458	579	601	L3 Cache/Socket	57 MB	256 MB
	median fill-in	131x	8.5x	7.7x			
			•		GPU	NVIDIA A100	AMD MI210
					VRAM	40 GB	64 GB
					Memory BW	1555 GB/s	1600 GB/s
11/	11/13/23 Ribizel and Anzt, Parallel Symbolic Cholesky Factorization				FP32 FLOPS	19.5 TFLOPS/s	22.6 TFLOP/s

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Performance Evaluation: Results Intel CPU (Speedup)



Performance Evaluation: Results AMD MI210 (Speedup)



Performance Evaluation: Results NVIDIA A100 (Speedup)



Performance Evaluation: Throughput



A100

MI210

Intel CPU

Sparsity Pattern generation only on Nested Dissection ordering

Performance Evaluation: Breakdown







A100

MI210

Intel CPU

Performance Evaluation: Scaling on Intel CPU



Future Work in Progress: Near-Symmetric LU

- If we symmetrize via $A_{symm} = A + A^T$, then the fill-in of A is a subset of the factors $L_{symm} + L_{symm}^T$ of A_{symm} \rightarrow Follow Symbolic Cholesky on A_{symm} with "numerical factorization" with A stored inside 0/1 binary A_{symm} \rightarrow Result tells us which fill-in entries in $L_{symm} + L_{symm}^T$ are actually present in factors $L + L^T$ of A
- First results (A100 vs. sequential baseline):
 - 3.5x speedup for AMD-ordered matrix
 - 18x speedup for input-ordered matrix

Future Work

- Performance optimization of fill-in kernels (faster LCA lookup, parallel path traversal)
- Reduced data movement cost by computing skeleton graph of A
- Fully on-GPU elimination tree computation
- Fully on-GPU symbolic factorization
- Tuning numerical factorizations

References

- Joseph W.H. Liu. 1990. The Role of Elimination Trees in Sparse Factorization, SIAM J. Matrix Anal. Appl, https://doi.org/10.1137/0611010
- Timothy A. Davis. 2006. Direct methods for sparse linear systems, SIAM
- Yanqing Chen, Timothy A. Davis, William W. Hager, and Sivasankaran Rajamanickam. 2008. Algorithm 887: CHOLMOD, Supernodal Sparse Cholesky Factorization and Update/Downdate. ACM TOMS, <u>https://doi.org/10.1145/1391989.1391995</u>
- Timothy A. Davis and Yifan Hu. 2011. The University of Florida sparse matrix collection. ACM TOMS, https://doi.org/10.1145/2049662.2049663
- Hartwig Anzt, Terry Cojean, Goran Flegar, Fritz Göbel, Thomas Grützmacher, Pratik Nayak, Tobias Ribizel, Yuhsiang Mike Tsai, and Enrique S. Quintana-Ortí. 2022. Ginkgo: A Modern Linear Operator Algebra Framework for High Performance Computing. ACM TOMS, <u>https://doi.org/10.1145/3480935</u>

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