Parallel Sparse Matrix Computations Parallel Sparse BLAS 2 Matrix Multiplication

Like dense matrix multiplications, sparse matrix time vector multiplication can be blocked:

```
DOALL II = 1, M1

DOALL JJ = 1, M2

DO I = II, II + N/M1 - 1

DO J = JJ, JJ + N/M2 - 1

C(I) = C(I) + A(I,J) * B(J)

ENDDO

ENDDO

ENDDO

ENDDO
```

However, this can lead to uneven load balance!!!!!!!



This can (partly) be prevented by only row slicing/partitioning:

```
DOALL II = 1, M1
DO I = II, II + N/M1 - 1
DO J = 1, N
C(I) = C(I) + A(I,J) * B(J)
ENDDO
ENDDO
ENDDO
```

Mostly the number of NNZ per row/column is rather constant.

Each processor needs a full copy of the B vector!!

Column slicing/partitioning:

```
DOALL JJ = 1, M1

DO J = JJ, JJ + N/M1 - 1

DO I = 1, N

C(I) = C(I) + A(I,J) * B(J)

ENDDO

ENDDO

ENDDO
```

Each processor just has a part of the B vector. But every processor needs a full copy of the C vector plus the processors need to communicate their changes to C!!

Solution:

Let NNZ be the number of non-zero elements of the sparse matrix. Assume we want to compute in parallel on PxQ processors.

→ Divide the rows into P partitions: $R_1R_2...R_{P-1}R_P$ such that for all k: NNZ (R_k) ≈ NNZ/P, then partition every row partition R_k into Q partitions: $C_1^k C_2^k...C_{Q-1}^k C_Q^k$ columns, such that for every m: NNZ (C_m^k) ≈ NNZ (R_k) / Q.

By doing so, we have for all k, m: NNZ $(C_m^k) \approx NNZ / PQ$

In a picture:



Parallel Sparse (Upper) Triangular Solver

$$Ux = c$$

Levelization:

Take a DFS spanning tree of the associated symmetric graph of U+U^T, and group all nodes at the same level of the tree together



- ➔ the nodes within each group are not connected, i.e. will not have an edge in common
- → in other words each group will form a diagonal, diagonal block
- ➔ in fact the associated digraph of a (block) triangular matrix can be seen as a "partially ordered" set (poset) and a diagonal block as an incomparable subset of elements



So, not only do we have easily invertible U_{kk} blocks, this operation can be executed in parallel or as a vector operation.

In fact not only do we have parallelism on a block level but also on column/row level



- 1. Solve $U_4 x_4 = c_4$
- 2. $c_3 = c_3 \tilde{U}_3 \cdot x_4$

3. Solve
$$U_3 x_3 = c_3$$

4.
$$c_2 = c_2 - \tilde{U}_2 \cdot \begin{bmatrix} x_3 \\ x_4 \end{bmatrix}$$

5. Solve
$$U_2 x_2 = c_2$$

6.
$$c_1 = c_1 - \tilde{U}_1 \cdot \begin{bmatrix} x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

7. Solve $U_1 x_1 = c_1$

Orderings to Special Form

An ordering of a sparse matrix A to a sparse matrix B is called asymmetric if

$$B = PAQ^T,$$

with *P* and *Q* permutation matrices If P = Q, then the ordering is symmetric.

Note that the levelization ordering is symmetric. Partial Pivoting is asymmetric!!

- ➔ With a symmetric ordering the associated digraphs of A and B are isomorphic.
- Properties like diagonal dominant and eigenvalues do not changes with symmetric orderings

Example

	х	х		х		х	х		х	
	х	х		х		x	х		х	
row			х	х	\uparrow	x	х	х	х	
interchange	х	х	х	х	\downarrow			х	х	





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Block Triangular Form for Parallel LU



Based on finding strongly connected components O(n+m)
 Symmetric ordering
 Unique decomposition
 Every diagonal block can be factured in parallel

Banded Structure



Better Storage Opportunities (Diagonal Storage)
 Minimization of fill-in in LU factorization
 Better exploitation of spatial locality (stride 1 accesses)
 In some cases convergence of iterative methods are enhanced if nnz's are located near the diagonal

Banded structure through Cuthill-McKee



- Start with an arbitrary node α . Let $S_1 = \{ \alpha \}$.
- Let S_i = { nodes, which are not contained in any S_j with j < i }. The nodes in S_i are ordered such that first nodes are the nodes which are neighbors of the first node in S_{i-1}, the following nodes are neighbors of the second node in S_{i-1}, etc.

(Basically a **BFS** tree is constructed of $A + A^{T}$)

This results in:



BTW As a side effect: Reversing Cuthill-McKee leads in many cases to minimization of fill-in

Banded Structure through One-Way/ Nested Dissection

One way dissection is based on Cuthill-KcKee:

Let S₁ S₂ ... S_k be the levelization sets obtained by Cuthill-McKee on the associated graph of a (symmetric) matrix A

Compute

 $m = \lfloor (\Sigma_{i=1,2..,k} S_i) / k \rfloor$, the average number of elements per set.

≻ Let

 $\delta = \sqrt{\left(\left(3m + 13\right)/2\right)}$

Take all the nodes from sets S_j with $j = \lfloor i\delta + 0.5 \rfloor$, i = 1, 2, ...Number these nodes last

The choice of δ is based on experiments run on regular grid matrices.

This results in the following matrix



The same result can be obtained by nested dissection



And recursively computing separator sets for B and C, and so on, and so on....

Number the nodes of these separator sets last

➔ As a result we have a more general method, not only suited for grid matrices.

Tearing Techniques



A large grain decomposition for computing LU factorization in parallel

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The desired form is bordered upper block triangular form

Hellerman-Rarick



- Unsymmetric Ordering
- Diagonal elements are assigned pivots
- > The q columns are called spikes and will form the border

The algorithm

- 1. p=0, q=0 and the whole matrix is active
- 2. *m* is the minimum NNZ entries in any row of the active (sub)matrix. Choose m columns, by choosing first the column with most NNZ's in rows with NNZ-count of *m*, then the column is chosen with most NNZ's in rows with NNZ-count of *m-1*, and so on.
- 3. If the last column has *s* rows with a singleton NNZ then these rows are permuted to the beginning of the active (sub) matrix and these rows are assigned pivot rows
- 4. The last *s* columns chosen are also permuted to the front of the active (sub) matrix and these columns are assigned pivot columns
- 5. The remaining *m*-*s* columns are permuted to the border
- 6. p = p + s and q = q + m s
- 7. If p + q = n then stop else goto 2

Example



Column 1 is chosen first: it has most entries in rows of count 3. Then column 4 is chosen, because it has most entries in rows with new count 2.

Then column 6 is chosen because it has singletons in rows 2 and 4 .

→ Rows 2 and 4 are permuted to the front

Example 2



Now columns 6 and 4 are permuted to the front and column 1 is permuted to the back As a results we have:

DENSE



Tearing based on nested dissection

Remark: Separator sets were constructed on A + A^T



Edges from the separators can go both directions to B and C

For nodes u in S with only incoming edges from B, move u to C



For nodes v in S with only outgoing edges to C, move v to B



➔ As a result the size of the separator sets (border) is reduced, while there are NNZ introduced in the upper triangular part

A Hybrid Reordering H*

- H0: Through an asymmetric ordering $A' = PAQ^T$ permute "large values to the diagonal", i.e. for each k find the largest a_{mn} such that $|a_{mn}| \ge |a_{ij}|$, for all $a_{ij} \in A_{kk}$. Permute row k and row m, permute column k and column n.
- H1: Find strongly connected components using Tarjan's algorithm, and permute the matrix with a symmetric ordering into block upper triangular form: A '' = VA 'V^T
- H2: Use tearing based on nested dissection on each diagonal block, and number all nodes of the separator sets last. As a results the (block upper triangular) matrix is transformed into a bordered block upper triangular matrix: $A^{""} = WA^{""}W^T$
- So A''' = WVPAQ^TV^TW^T and the L and U factors can be computed in parallel using the diagonal elements as pivots