Comunication Optimal Algorithms for Numerical Linear Algebra

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> > June 11, 2009

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#### Plan

- Research context
- Communication-optimal operations for linear algebra, first results in dense LU and QR factorizations
- Conclusions and future work

#### Motivation and challenges

- Running time of an algorithm is sum of 3 terms:
  - # flops \* time\_per\_flop
  - # words moved / bandwidth
  - # messages \* latency
- Exponentially growing gaps between
  - Time\_per\_flop << 1/Network BW << Network Latency</li>
    - Improving 59%/year vs 26%/year vs 15%/year
  - Time\_per\_flop << 1/Memory BW << Memory Latency</li>
    - Improving 59%/year vs 23%/year vs 5.5%/year
- Goal : reorganize linear algebra to *avoid* communication
  - Not just *hiding* communication
  - Arbitrary speedups possible

#### Communication Lower Bounds for Dense Linear Algebra – Summary of theory

- Matrix multiply, using 2n<sup>3</sup> flops (sequential or parallel)
  - Hong-Kung (1981), Irony/Tishkin/Toledo (2004)
  - Lower bound on Bandwidth =  $\Omega$  (#flops / (local/fast memory size)<sup>1/2</sup>)
  - Lower bound on Latency =  $\Omega$  (#flops / (local/fast memory size)<sup>3/2</sup>)
  - Attained by usual block algorithm (sequential), Cannon (parallel)
- Same lower bounds apply to LU, QR and Cholesky
  - Assumption: O(n<sup>3</sup>) algorithms; LU is easy, Cholesky trickier, QR subtle
- LAPACK and ScaLAPACK do not attain these bounds for LU, QR
  - ScaLAPACK attains bandwidth lower bound
    - But sends  $O((mn/P)^{1/2})$  times more messages
  - LAPACK attains neither; O((m<sup>2</sup>/W)<sup>1/2</sup>) times more bandwidth
- But new LU, QR do attain them, mod polylog factors
  - LU requires a new pivoting scheme, still stable
  - QR requires new representation of Q, O(n<sup>2</sup>) more flops
  - Sequential Recursive LU and QR minimize bandwidth, not latency
- Cholesky: ScaLAPACK attains lower bounds, LAPACK just bandwidth
- Joint work with G. Ballard, J. Demmel, L. Grigori, M. Hoemmen, O. Holtz, J. Langou, O. Schwartz

Courtesy of J. Demmel

#### Lower Bounds on Communication for parallel LU

- Matrix multiplication lower bounds on communication bandwidth (Hong,Kung 1981, Irony/Toledo/Tishkin, 2004) extended to provide latency bounds:
  - each processor has  $O(n^2/P)$  memory

$$\# words \ge \Omega\left(\frac{n^2}{\sqrt{P}}\right) \qquad \# messages \ge \Omega\left(\sqrt{P}\right)$$

• Bounds hold for LU using a simple example:

$$\begin{pmatrix} I & -B \\ A & I \\ & I \end{pmatrix} = \begin{pmatrix} I & & \\ A & I \\ & & I \end{pmatrix} \begin{pmatrix} I & -B \\ & I & AB \\ & & I \end{pmatrix}$$

### LU factorization (as in ScaLAPACK pdgetrf)

LU factorization on a Pr by Pc grid of processors For ib = 1 to n-1 step b  $A^{(ib)} = A(ib:n, ib:n)$ 

- (1) Compute panel factorization (pdgetf2)- find pivot in each column, swap rows
- (2) Apply all row permutations (pdlaswp)  $O(n/b(\log_2 P_c + \log_2 P_r))$ 
  - broadcast pivot information along the rows
  - swap rows at left and right
- (3) Compute block row of U (pdtrsm)
  - broadcast right diagonal block of L of current panel
- (4) Update trailing matrix (pdgemm)
  - broadcast right block column of L
  - broadcast down block row of U

$$O(n/b\log_2 P_c)$$
 L

$$O(n/b(\log_2 P_c + \log_2 P_r))$$

 $O(n \log_2 P_r)$ 







TSQR: an approach for QR factorization of a tall skinny matrix using Householder transformations

- QR decomposition of m x n matrix W, m >> n
  - TSQR = "Tall Skinny QR"
  - P processors, block row layout
- Usual Parallel Algorithm
  - Compute Householder vector for each column
  - Number of messages  $\propto$  n log P
- Communication Avoiding Algorithm
  - Reduction operation, with QR as operator
  - Number of messages  $\propto \log P$

$$W = \begin{bmatrix} W_0 \\ W_1 \\ W_2 \\ W_3 \end{bmatrix} \xrightarrow{\bullet} \begin{bmatrix} R_{00} \\ R_{10} \\ R_{20} \\ R_{30} \end{bmatrix} \xrightarrow{\bullet} R_{01} \xrightarrow{\bullet} R_{02}$$

• Joint work with J. Demmel, M. Hoemmen, J. Langou

#### Parallel TSQR



#### Minimizing Communication in TSQR







Multicore / Multisocket / Multirack / Multisite / Out-of-core: ? Choose reduction tree dynamically Page 9

#### Obvious generalization of TSQR to LU



## Stability of the LU factorization

• Consider the growth factor

$$\rho = \frac{\max_{i,j,k} |a_{ij}^k|}{\max_{i,j} |a_{ij}|} \quad \text{where} \quad a_{ij}^{(k)} \text{ are the values at the k-th step.}$$

- Experiments performed for various distribution of matrices with n < 1024 [Trefethen and Schreiber '90] showed that the average growth factor normalized by the standard deviation of the initial matrix elements is:
  - close to  $n^{2/3}$  for partial pivoting,  $n^{1/2}$  for complete pivoting.
- Two reasons considered to be important for the average case stability:
  - the multipliers in L are small,
  - the correction introduced at each elimination step is of rank 1.

Other strategies:

- pairwise pivoting considered reasonably stable (low rank correction).
- TSLU involves a rank-P update at each step.

## Growth factor for TSLU based factorization



- Unstable for large P and large matrices.
- When P equals the number of rows, TSLU is equivalent to parallel pivoting.

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#### Making TSLU stable - preprocessing step to find good pivots $\begin{array}{ccc} \Pi_0^T W_0 \\ \begin{pmatrix} 2 & 4 \\ 2 & 0 \\ \end{pmatrix}$ $\frac{W_0}{4}$ $\overline{W_0}$ $W_0$ $\overline{\Pi}_0^T \overline{W}_0$ $\underline{\Pi}_{0}^{T} \underline{W}_{0}$ 4 1 $\mathsf{P}_0$ 2 0 0 2 4 $=\overline{\Pi}_0\overline{L_0}\overline{U_0}$ 4 2 4 $= \Pi_0 L_0 U_0$ $= \underline{\Pi}_0 \underline{L}_0 \underline{U}_0$ 1 2 4 2 4 Good pivots for 2 2 1 4 0 factorizing W $\Pi_1^T W_1$ $W_1$ <sup>`</sup>0` $P_1$ 0 0 2 0 $= \Pi_1 L_1 U_1$ 0 $\overline{\Pi}_{2}^{T}\overline{W}_{2}$ $\overline{W_2}$ $\Pi_2^T W_2$ $W_2$ 2` *'*4 2 1 4 $P_2$ 0 2, $=\overline{\Pi}_2\overline{L}_2\overline{U}_2$ 4 0 $= \Pi_2 L_2 U_2$ 2 4 0 0 2 0 0 2 $W_3$ $\Pi_3^T W_3$ 2 $\begin{pmatrix} 2\\2 \end{pmatrix}$ $P_3$ 0 2 0 $= \Pi_3 L_3 U_3$ 0 4 2 time Page 13

## Making TSLU stable - the overall idea

- At each node in tree, TSLU selects b pivot rows from 2b candidates from its 2 child nodes
- At each node, do LU on 2b original rows selected by child nodes, not U factors from child nodes
- When TSLU done, permute b selected rows to top of original matrix, redo b steps of LU without pivoting
- CALU Communication Avoiding LU for general A
  - Use TSLU for panel factorizations
  - Apply to rest of matrix
  - Cost: redundant panel factorizations
- Benefit:
  - Stable in practice, but *not* same pivot choice as GEPP
  - b times fewer messages overall faster
- Joint work with J. Demmel, H. Xiang

#### Growth factor for CALU approach



Like threshold pivoting with worst case threshold = .33, so |L| <= 3 Testing shows about same residual as GEPP

## Stability of CALU

• Consider the *m-by-n* matrix W, where  $W_1$  and  $W_3$  are *b-by-b*, and suppose the permutation returned by TSLU is the identity.

$$W = \begin{pmatrix} W_1 & W_5 \\ \frac{W_2 & W_6}{W_3 & W_7} \\ W_4 & W_8 \end{pmatrix} \qquad \text{TSLU:} \qquad \begin{bmatrix} W_1 \\ W_2 \\ W_3 \\ W_4 \end{bmatrix} \xrightarrow{\bullet} W_1 \qquad \qquad W_1$$

• After the factorization of first panel by CALU,  $W_8^s$  (the Schur complement of  $W_8$ ) is not bounded as in GEPP, but:

$$\begin{pmatrix} W_1 & W_1 & W_5 \\ & W_3 & W_3 & W_7 \\ W_3 & 2W_3 & W_7 \\ & -W_4 & -W_8 \end{pmatrix} = \hat{L} \cdot \begin{pmatrix} I_{3b} & I_{n-b} \\ & -W_8^s \end{pmatrix} \cdot \hat{U}$$

• Pivot growth is no worse than PP applied to a different matrix whose entries are the same as the entries of the original matrix.

### CALU – a communication avoiding LU factorization

- Consider a 2D grid of P processors P<sub>r</sub>-by-P<sub>c</sub>, using a 2D block cyclic layout with square blocks of size b.
- For ib = 1 to n-1 step b  $A^{(ib)} = A(ib:n, ib:n)$
- (1) Find permutation for current panel using TSLU  $O(n/b \log_2 P_r)$
- (2) Apply all row permutations (pdlaswp)  $O(n/b(\log_2 P_c + \log_2 P_r))$ - broadcast pivot information along the rows of the grid
- (3) Compute panel factorization (dtrsm)
- (4) Compute block row of U (pdtrsm)
  - broadcast right diagonal part of L of current panel
- (5) Update trailing matrix (pdgemm)
  - broadcast right block column of L
  - broadcast down block row of U

$$O(n/b(\log_2 P_c + \log_2 P_r))$$

 $O(n/b\log, P_c)$ 



∆(ib







# LU for General Matrices

- Cost of CALU vs ScaLAPACK's PDGETRF
  - n x n matrix on P<sup>1/2</sup> x P<sup>1/2</sup> processor grid, block size b
  - Flops:  $(2/3)n^{3}/P + (3/2)n^{2}b / P^{1/2} vs (2/3)n^{3}/P + n^{2}b/P^{1/2}$
  - Bandwidth: n<sup>2</sup> log P/P<sup>1/2</sup>
     vs same
  - Latency: 3 n log P / b vs 1.5 n log P + 3.5n log P / b
- Close to optimal (modulo log P factors)
  - Assume: O(n<sup>2</sup>/P) memory/processor, O(n<sup>3</sup>) algorithm,
  - Choose b near n / P<sup>1/2</sup> (its upper bound)
  - Bandwidth lower bound:  $\Omega(n^2 / P^{1/2}) just \log(P)$  smaller
  - Latency lower bound:  $\Omega(P^{1/2})$  just polylog(P) smaller

#### Evaluation of the performance

• Experiments performed on two platforms at NERSC:

IBM p575 POWER 5 system, 111 compute nodes, 8 processors per node

- each processor is clocked at 1.9 GHz, theoretical peak of 7.6 GFLOPs/sec.
- each node has 32 GB memory.
- MPI Point to Point internode Latency is 5 usec.
- peak Bandwidth is 3100 MB/sec.

**Opteron cluster** with 356 dual-processor nodes

- each node has 6 GB memory
- each processor is clocked at 2.2 GHz, theoretical peak of 4.4 GFLOPs/sec.
- Switch MPI Unidirectional Latency is 4.5 usec.
- peak Switch MPI Unidirectional Bandwidth is 620 MB/sec.

## Performance vs ScaLAPACK

- TSQR
  - Pentium III cluster, Dolphin Interconnect, MPICH
    - Up to 6.7x speedup (16 procs, 100K x 200)
  - BlueGene/L Up to **4x speedup** (32 procs, 1M x 50)
- TSLU
  - IBM Power 5 Up to **4.37x** faster (16 procs, 1M x 150)
  - Cray XT4 Up to **5.52x** faster (8 procs, 1M x 150)
- CALU
  - IBM Power 5 Up to **2.29x** faster (64 procs, 1000 x 1000)
  - Cray XT4 Up to **1.81x** faster (64 procs, 1000 x 1000)
- All use recursive algorithms (Toledo, Elmroth-Gustavson) locally.

#### Speedup prediction for a Petascale machine - up to 81x



Petascale machine with 8192 procs, each at 500 GFlops/s, a bandwidth of 4 GB/s.  $\gamma = 2 \cdot 10^{-12} s, \alpha = 10^{-5} s, \beta = 2 \cdot 10^{-9} s / word.$ 

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#### Conclusions

- Possible to minimize communication complexity of much dense and sparse linear algebra
  - Practical speedups
  - Approaching theoretical lower bounds
- The new algorithms minimize the number of messages exchanged at the cost of some redundant computation.

 Recent work extends the bounds to sparse matrix multiplication and sparse direct factorizations.

#### Conclusions

- *Lots* of prior work, some recent work
  - Idea of binary reduction tree for parallel QR previously studied by
    - Golub, Plemmons, Sameh 1988 first to suggest the idea
    - Pothen, Raghavan, 1989 implement it using logP messages
  - Flat trees algorithms, called tiled algorithms used in the context of
    - Out of core Gunter, van de Geijn 2005
    - Multicore, Cell processors Buttari, Langou, Kurzak and Dongarra (2007, 2008), Quintana-Orti, Quintana-Orti, Chan, van Zee, van de Geijn (2007,2008).
- And some ideas are *new* 
  - Parallel CAQR, CALU
  - Bounds on communication

### Future Work

- Many open problems
- Automatic tuning choose the right communication pattern/tree.
- Extend optimality proofs to general architectures
- Which preconditioners work?