Communication avoiding algorithms for LU and QR factorizations

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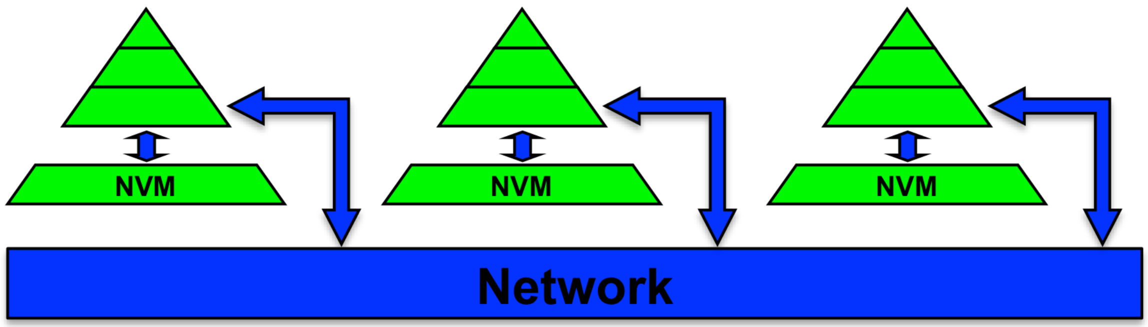
Plan

- Motivation
- Communication complexity of linear algebra operations
- Communication avoiding for dense linear algebra
  - LU, QR, Rank Revealing QR factorizations
  - Progressively implemented in ScaLAPACK, LAPACK
  - Algorithms for multicore processors
- Conclusions

Motivation - the communication wall

- Runtime of an algorithm is the sum of:
  - #flops x **time_per_flop**
  - #words_moved / **bandwidth**
  - #messages x **latency**

- Time to move data >> time per flop
  - Gap steadily and exponentially growing over time



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  - #words_moved / **bandwidth**
  - #messages x **latency**

- Time to move data >> time per flop
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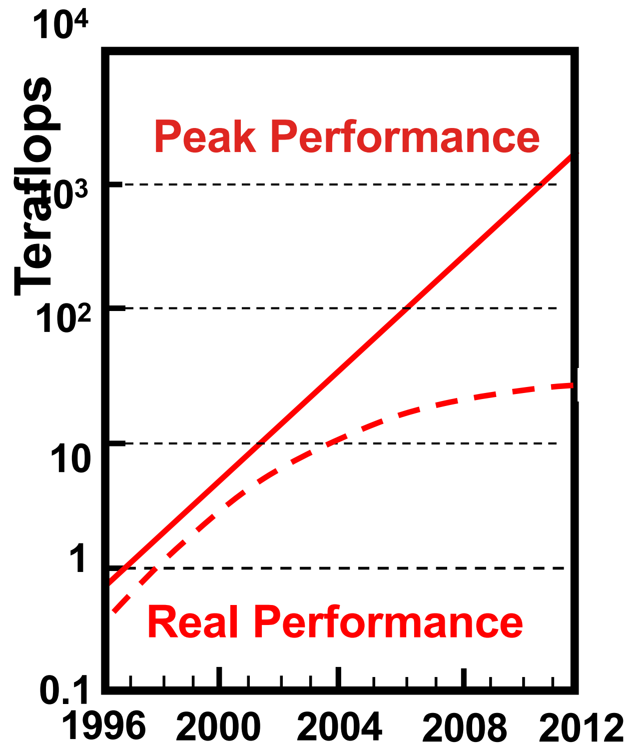
Annual improvements			
Time/flop		Bandwidth	Latency
59%	Network	**26%**	**15%**
	DRAM	**23%**	**5%**



Adapted from J. Demmel

- Performance of an application is less than 10% of the peak performance

"We are going to hit the ***memory wall****, unless something basic changes"*
[W. Wulf, S. McKee, 95]

Compelling numbers

DRAM latency:

- DDR2 (2007) ~ 120 ns 1x
- DDR4 (2014) ~ 45 ns 2.6x in 7 yrs
- Stacked memory ~ similar to DDR4

Time/flop

- 2008 Intel Nehalem 3.2GHz × 4 cores (51.2 GFlops/socket) 1x
- 2017 Intel Skylake XP 2.1GHz × 28 cores (1.8 TFlops/socket) 35x in 9 yrs

Network latency

- Interconnect (example one machine today): 0.25μs to 3.7μs MPI latency

Source: G. Bosilca (UTK), S. Knepper (Intel), J. Shalf (LBL)

Selected past work on reducing communication

- Only few examples shown, many references available

A. Tuning

- Overlap communication and computation, at most a factor of 2 speedup

B. Ghosting

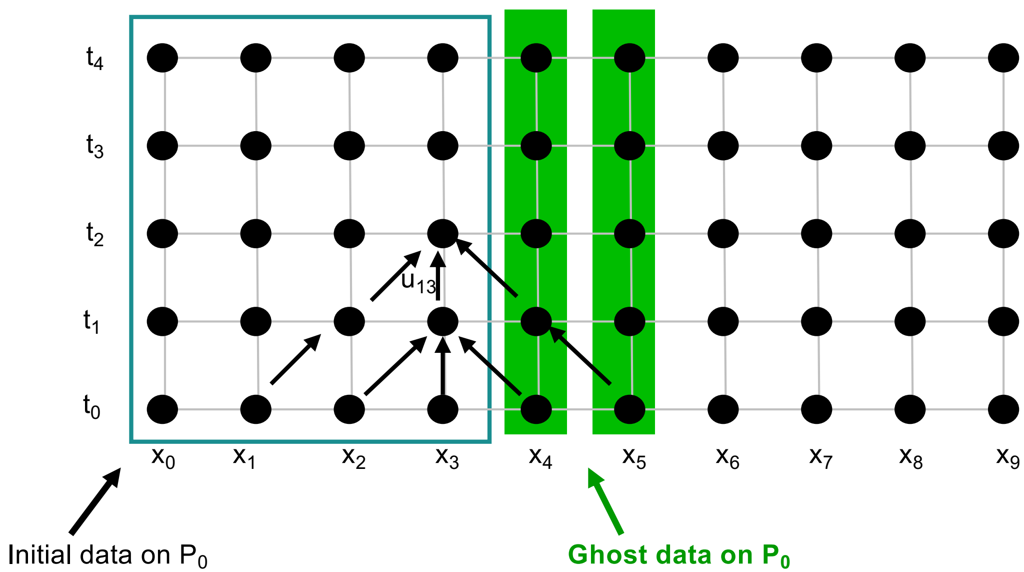
- Standard approach in *explicit methods*
- Store redundantly data from neighboring processors for future computations

Example of a parabolic PDE

$$u_t = \alpha \Delta u$$

with a finite difference,
the solution at a grid point is:

$$u_{i,j+1} = u(x_i, t_{j+1})$$
$$= f(u_{i-1,j}, u_{ij}, u_{i+1,j})$$



Selected past work on reducing communication

C. Same operation, different schedule of the computation

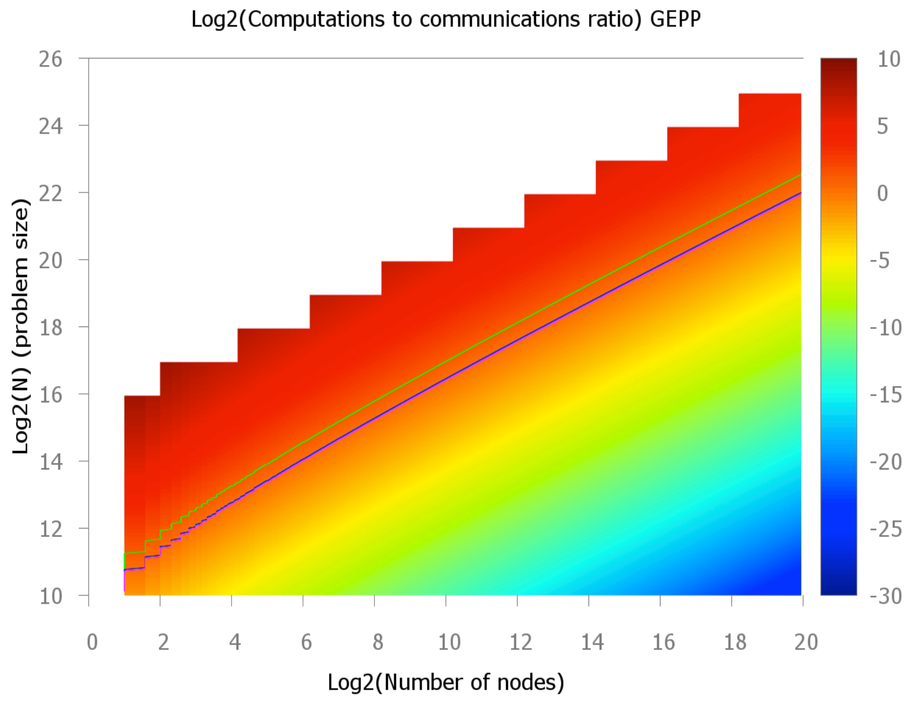
Block algorithms for dense linear algebra

- Barron and Swinnerton-Dyer, 1960
  - LU factorization used to solve a system with 31 equations - first subroutine written for EDSAC 2
  - Block LU factorization used to solve a system with 100 equations using an auxiliary magnetic-tape
  - The basis of the algorithm used in LAPACK

Cache oblivious algorithms

- recursive Cholesky, LU, QR

(Gustavson ‘97, Toledo ‘97,
Elmroth and Gustavson ‘98,
Frens and Wise ’03,
Ahmed and Pingali ‘00)



Selected past work on reducing communication

D. Same algebraic framework, different numerical algorithm

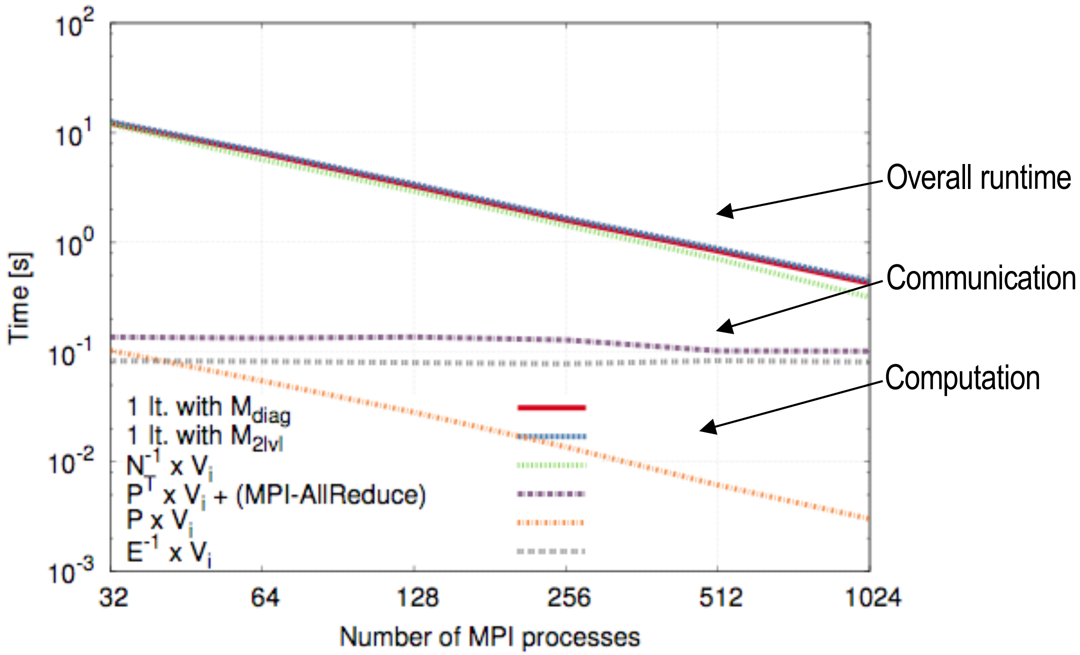
More opportunities for reducing communication, may affect stability

Dense LU-like factorization (Barron and Swinnerton-Dyer, 60)

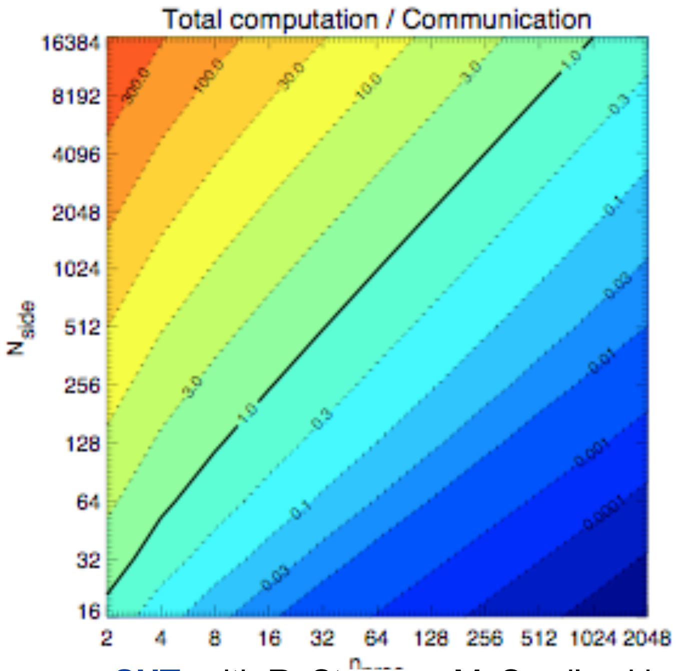
- LU-like factorization based on pairwise pivoting and its block version
  $PA = L_1 L_2 \ldots L_n U$
- With small modifications, minimizes communication between two levels of fast-slow memory
- Stable for small matrices, unstable for nowadays matrices

Communication in CMB data analysis

- Map-making problem
  - Find the best map *x* from observations *d*, scanning strategy *A*, and noise N^{-1}
  - Solve generalized least squares problem involving sparse matrices of size 10^{12}-by-10^{7}
- Spherical harmonic transform (SHT)
  - Synthesize a sky image from its harmonic representation
    - Computation over rows of a 2D object (summation of spherical harmonics)
    - Communication to transpose the 2D object
    - Computation over columns of the 2D object (FFTs)



Map making, with R. Stompor, M. Szydlarski
Results obtained on Hopper, Cray XE6, NERSC



SHT, with R. Stompor, M. Szydlarski
Simulation on a petascale computer

Motivation

- The communication problem needs to be taken into account higher in the computing stack

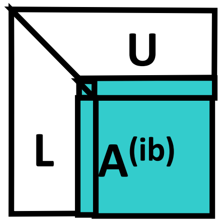
- A paradigm shift in the way the numerical algorithms are devised is required

- Communication avoiding algorithms - a novel perspective for numerical linear algebra
  - Minimize volume of communication
  - Minimize number of messages
  - Minimize over multiple levels of memory/parallelism
  - Allow redundant computations (preferably as a low order term)

Evolution of numerical libraries

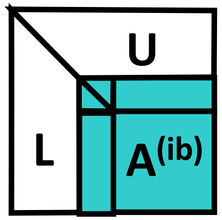
LINPACK (70's)

- vector operations, use BLAS1
- HPL benchmark based on Linpack LU factorization



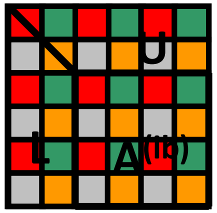
LAPACK (80's)

- Block versions of the algorithms used in LINPACK
- Uses BLAS3



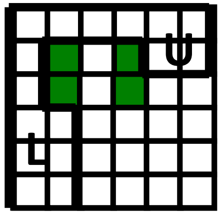
ScaLAPACK (90's)

- Targets distributed memories
- 2D block cyclic distribution of data
- PBLAS based on message passing



PLASMA (2008): new algorithms

- Targets many-core
- Block data layout
- Low granularity, high asynchronicity



Project developed by U Tennessee Knoxville, UC Berkeley, other collaborators.

Source: inspired from J. Dongarra, UTK, J. Langou, CU Denver

Communication Complexity of Dense Linear Algebra

- Matrix multiply, using $2n^3$ flops (sequential or parallel)
  - Hong-Kung (1981), Irony/Tishkin/Toledo (2004)
  - Lower bound on Bandwidth = Ω (#flops / $M^{1/2}$)
  - Lower bound on Latency = Ω (#flops / $M^{3/2}$)

- Same lower bounds apply to LU using reduction
  - Demmel, LG, Hoemmen, Langou 2008

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

- And to almost all direct linear algebra [Ballard, Demmel, Holtz, Schwartz, 09]

Lower bounds for linear algebra

- Computation modelled as an n-by-n-by-n set of lattice points (i,j,k) represents the operation $c(i,j) \mathrel{+}= f_{ij}(\, g_{ijk}\, (\, a(i,k)*b(k,j))\,)\,)$
- The computation is divided in S phases
- Each phase contains exactly M (the fast memory size) load and store instructions
- Determine how many flops the algorithm can compute in each phase, by applying discrete Loomis-Whitney inequality:

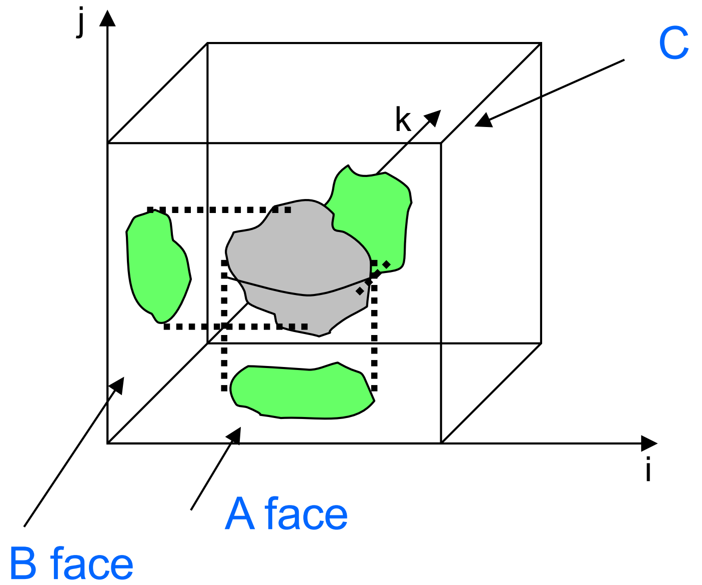
$$w^2 \leq N_A N_B N_C$$

Algorithms in direct linear alg

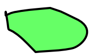
$for\ i,j,k = 1:n$

$\quad c(i,j) = f_{ij}(g_{ijk}(a(i,k),b(k,j)))$

$endfor$




- set of points in R^3, represent w arithmetics


- orthogonal projections of the points onto coordinate planes N_A, N_B, N_C represent values of A, B, C

Lower bounds for matrix multiplication (contd)

- Discrete Loomis-Whitney inequality:

$$w^2 \le N_A N_B N_C$$

- Since there are at most 2M elements of A, B, C in a phase, the bound is:

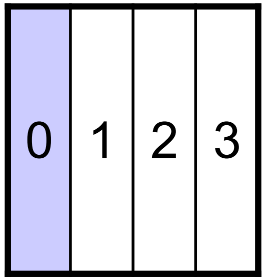
$$w \le 2\sqrt{2}M^{3/2}$$

- The number of phases S is #flops/w, and hence the lower bound on communication is:

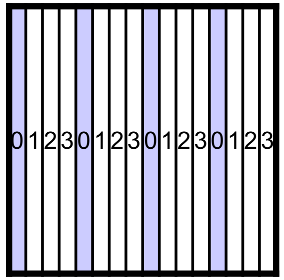
$$\#messages(S) \ge \frac{\#\ flops}{w} = \Omega\left(\frac{\#\ flops}{M^{3/2}}\right)$$

$$\#loads/stores \ge \Omega\left(\frac{\#\ flops}{M^{1/2}}\right)$$

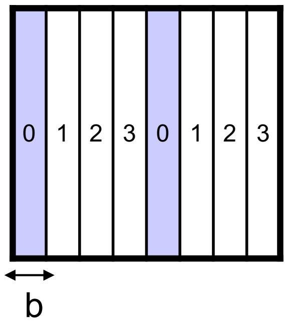
Matrix distributions



1) 1D Column Blocked Layout

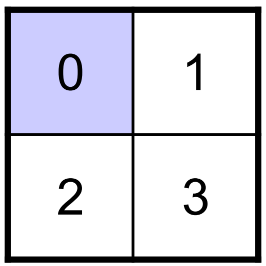


2) 1D Column Cyclic Layout

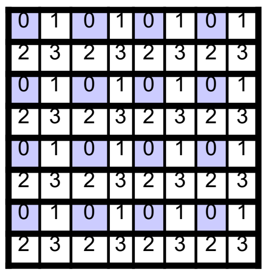


3) 1D Column Block Cyclic Layout

4) Row versions of the previous layouts



5) 2D Row and Column Blocked Layout



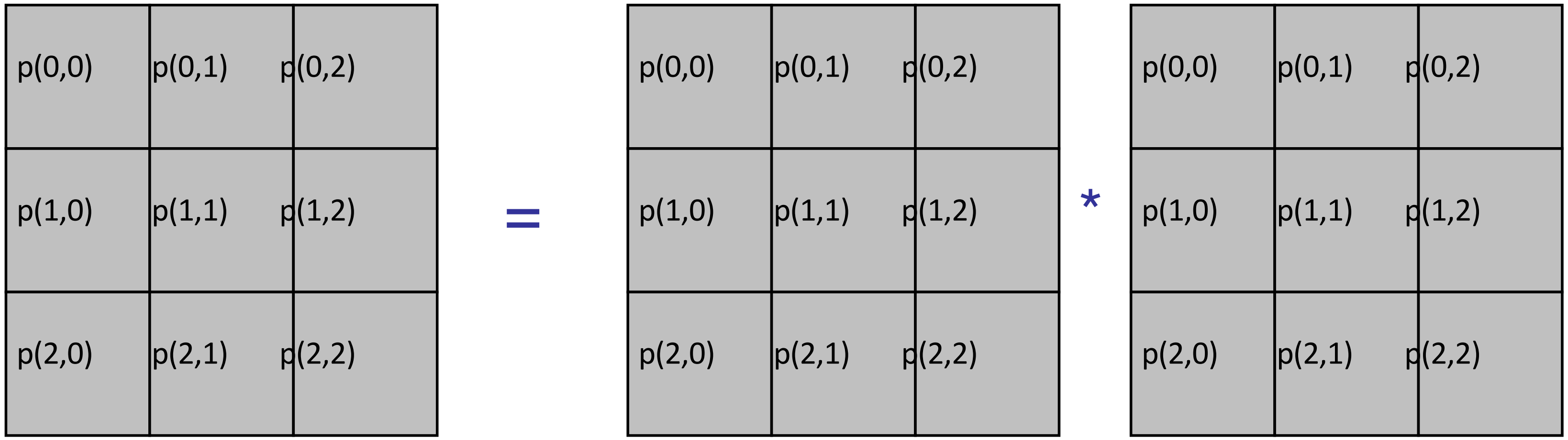
Generalizes others

6) 2D Row and Column Block Cyclic Layout

Source slide: J. Demmel

MatMul with 2D Layout

- Consider processors in 2D grid (physical or logical)
- Processors can communicate with 4 nearest neighbors
  - Broadcast along rows and columns



- Assume p processors form square s x s grid, $s = p^{1/2}$

Source slide: J. Demmel

Cannon's Algorithm

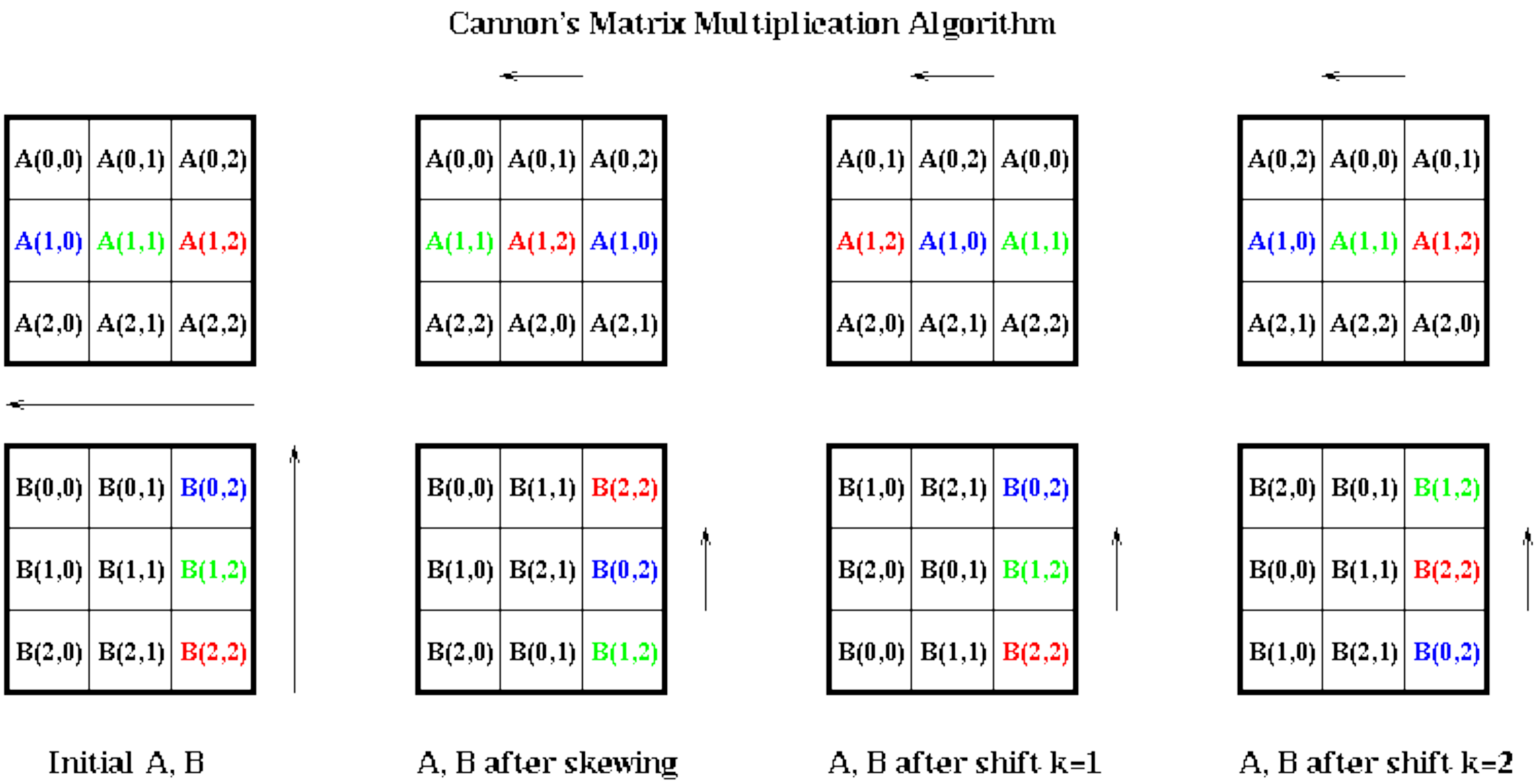
… $C(i,j) = C(i,j) + \sum_k A(i,k)*B(k,j)$

… assume s = sqrt(p) is an integer

```
forall  i=0 to s-1                 …  "skew" A
    left-circular-shift row i of A by i
    … so that A(i,j) overwritten by A(i,(j+i)mod s)
forall  i=0 to s-1                 …  "skew" B
    up-circular-shift column i of B by i
    … so that B(i,j) overwritten by B((i+j)mod s), j)
for k=0 to s-1        … sequential
    forall i=0 to s-1 and j=0 to s-1    … all processors in parallel
        C(i,j) = C(i,j) + A(i,j)*B(i,j)
        left-circular-shift each row of A by 1
        up-circular-shift each column of B by 1
```

Source slide: J. Demmel

Cannon’s Matrix Multiplication



C(1,2) = A(1,0) * B(0,2) + A(1,1) * B(1,2) + A(1,2) * B(2,2)

Source slide: J. Demmel

Cost of Cannon's Algorithm

forall i=0 to s-1 … recall s = sqrt(p)

    left-circular-shift row i of A by i … cost $\le$ s*(α + β*n^2/p)

forall i=0 to s-1

    up-circular-shift column i of B by i … cost $\le$ s*(α + β*n^2/p)

for k=0 to s-1

    forall i=0 to s-1 and j=0 to s-1

        C(i,j) = C(i,j) + A(i,j)*B(i,j) … cost = 2*$(n/s)^3$ = 2*$n^3/p^{3/2}$

        left-circular-shift each row of A by 1 … cost = α + β*n^2/p

        up-circular-shift each column of B by 1 … cost = α + β*n^2/p

- Total Time = 2*n^3/p + 4* s*α + 4*β*n^2/s - Optimal!
- Parallel Efficiency = 2*n^3 / (p * Total Time)

  = 1/(1 + α * 2*$(s/n)^3$ + β * 2*(s/n))

  = 1/(1 + O(sqrt(p)/n))
- Grows to 1 as n/s = n/sqrt(p) = sqrt(data per processor) grows

Source slide: J. Demmel

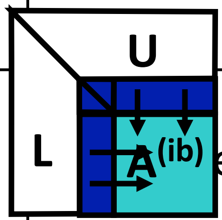
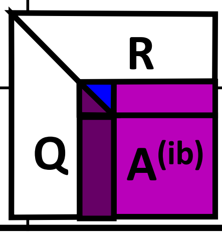
Sequential algorithms and communication bounds

Algorithm	Minimizing #words (not #messages)	Minimizing #words and #messages
Cholesky	LAPACK	[Gustavson, 97] [Ahmed, Pingali, 00]
LU	LAPACK (few cases) [Toledo,97], [Gustavson, 97] both use partial pivoting	[LG, Demmel, Xiang, 08] [Khabou, Demmel, LG, Gu, 12] uses tournament pivoting
QR	LAPACK (few cases) [Elmroth,Gustavson,98]	[Frens, Wise, 03], 3x flops [Demmel, LG, Hoemmen, Langou, 08] [Ballard et al, 14]
RRQR		[Demmel, LG, Gu, Xiang 11] uses tournament pivoting, 3x flops

- Only several references shown for block algorithms (LAPACK), cache-oblivious algorithms and communication avoiding algorithms
- CA algorithms exist also for SVD and eigenvalue computation

2D Parallel algorithms and communication bounds

- If memory per processor = n^2 / P, the lower bounds become
  #words_moved ≥ Ω (n^2 / $P^{1/2}$), #messages ≥ Ω ($P^{1/2}$)

Algorithm	Minimizing #words (not #messages)	Minimizing #words and #messages
Cholesky	ScaLAPACK	ScaLAPACK
LU	 ScaLAPACK es partial pivoting	[LG, Demmel, Xiang, 08] [Khabou, Demmel, LG, Gu, 12] uses tournament pivoting
QR	ScaLAPACK	[Demmel, LG, Hoemmen, Langou, 08] [Ballard et al, 14]
RRQR	 ScaLAPACK	[Demmel, LG, Gu, Xiang 13] uses tournament pivoting, 3x flops

- Only several references shown, block algorithms (ScaLAPACK) and communication avoiding algorithms
- CA algorithms exist also for SVD and eigenvalue computation

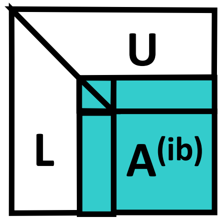
LU factorization (as in ScaLAPACK pdgetrf)

LU factorization on a $P = P_r \times P_c$ grid of processors

For ib = 1 to n-1 step b

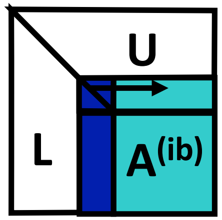
$A^{(ib)} = A(ib:n, ib:n)$

#messages



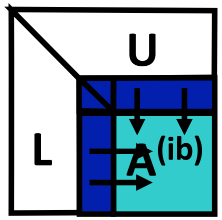
(1) Compute panel factorization — $O(n \log_2 P_r)$

- find pivot in each column, swap rows



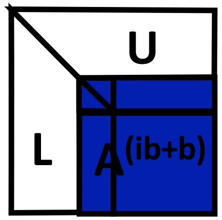
(2) Apply all row permutations — $O(n/b(\log_2 P_c + \log_2 P_r))$

- broadcast pivot information along the rows
- swap rows at left and right



(3) Compute block row of U — $O(n/b \log_2 P_c)$

- broadcast right diagonal block of L of current panel



(4) Update trailing matrix — $O(n/b(\log_2 P_c + \log_2 P_r))$

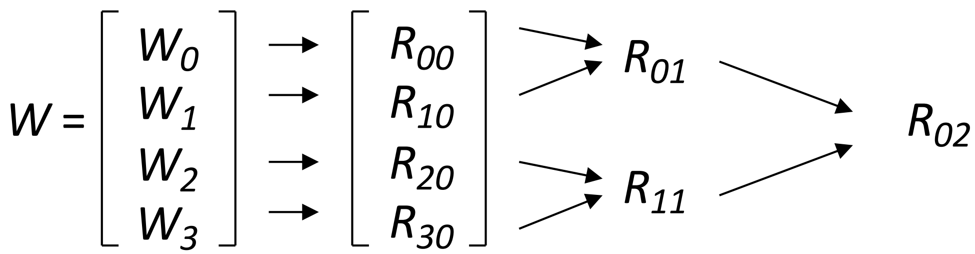
- broadcast right block column of L
- broadcast down block row of U

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

- QR decomposition of m x b matrix W, m >> b
  - P processors, block row layout

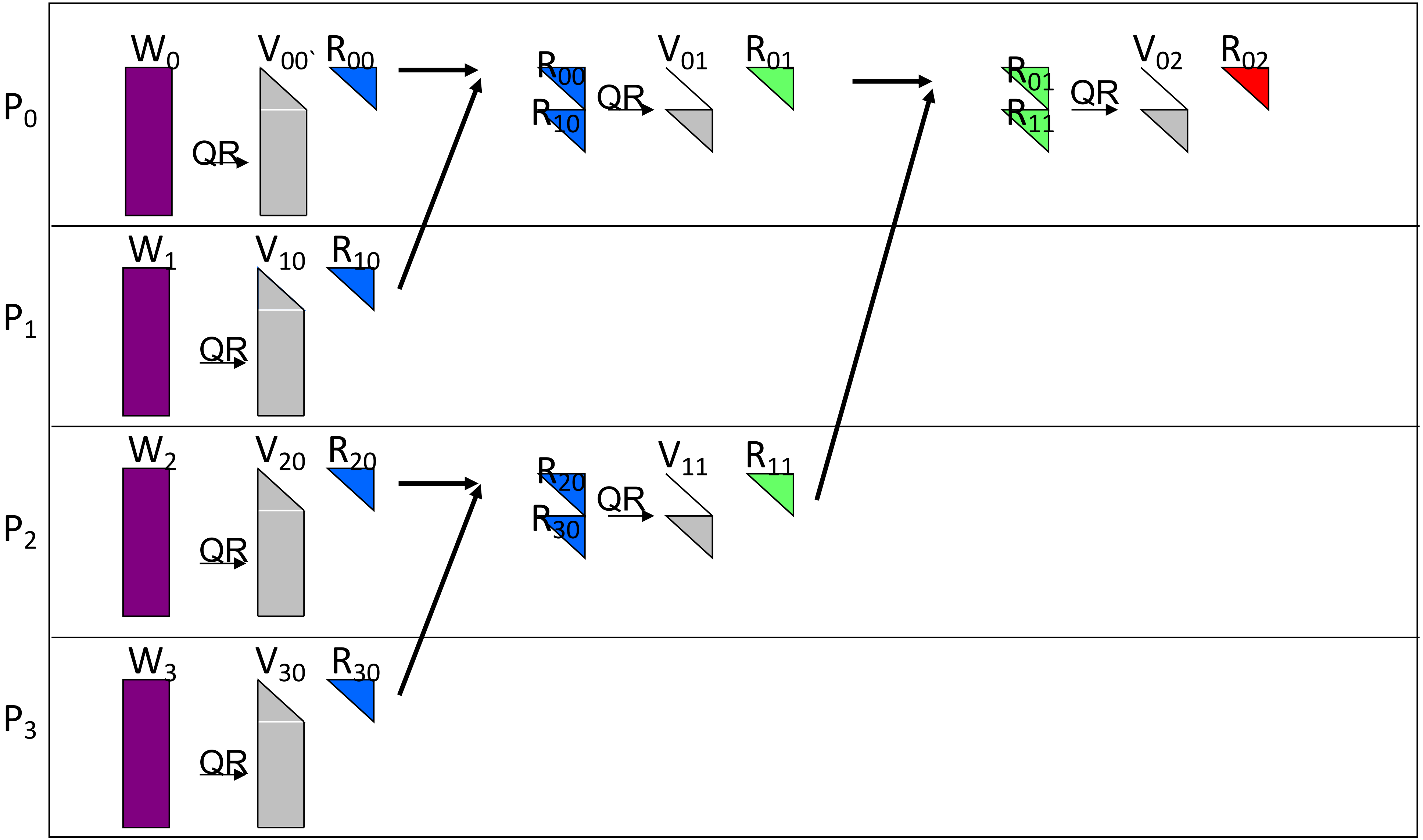
- Classic Parallel Algorithm
  - Compute Householder vector for each column
  - Number of messages ∝ b log P

- Communication Avoiding Algorithm
  - Reduction operation, with QR as operator
  - Number of messages ∝ log P



J. Demmel, LG, M. Hoemmen, J. Langou, 08

Parallel TSQR



References: Golub, Plemmons, Sameh 88, Pothen, Raghavan, 89, Da Cunha, Becker, Patterson, 02

Algebra of TSQR

Parallel:

$$
\begin{tikzcd}[row sep=tiny]
W = \begin{bmatrix} W_0 \\ W_1 \\ W_2 \\ W_3 \end{bmatrix}
\end{tikzcd}
\qquad
\begin{tikzcd}[row sep=small]
W_0 \arrow[r] & R_{00} \arrow[dr] & & \\
W_1 \arrow[r] & R_{10} \arrow[r] & R_{01} \arrow[dr] & \\
W_2 \arrow[r] & R_{20} \arrow[dr] & & R_{02} \\
W_3 \arrow[r] & R_{30} \arrow[r] & R_{11} \arrow[ur] &
\end{tikzcd}
$$

$$
W = \begin{pmatrix} W_0 \\ W_1 \\ W_2 \\ W_3 \end{pmatrix} = \begin{pmatrix} Q_{00}R_{00} \\ \hline Q_{10}R_{10} \\ \hline Q_{20}R_{20} \\ \hline Q_{30}R_{30} \end{pmatrix} = \begin{pmatrix} Q_{00} & & & \\ \hline & Q_{10} & & \\ \hline & & Q_{20} & \\ \hline & & & Q_{30} \end{pmatrix} \cdot \begin{pmatrix} R_{00} \\ \hline R_{10} \\ \hline R_{20} \\ \hline R_{30} \end{pmatrix}
$$

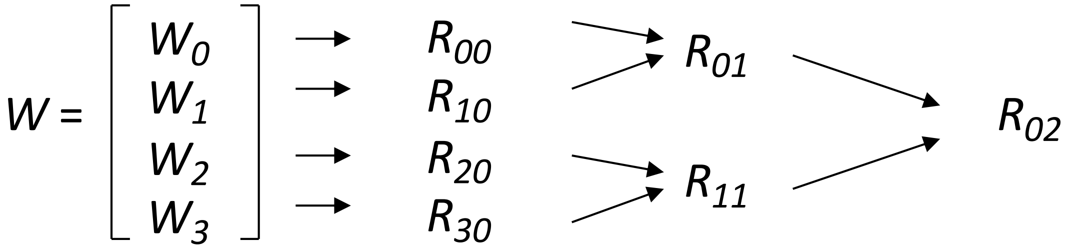
$$
\begin{pmatrix} R_{00} \\ R_{10} \\ \hline R_{20} \\ R_{30} \end{pmatrix} = \begin{pmatrix} Q_{01}R_{01} \\ \hline Q_{11}R_{11} \end{pmatrix} = \begin{pmatrix} Q_{01} & \\ \hline & Q_{11} \end{pmatrix} \cdot \begin{pmatrix} R_{01} \\ \hline R_{11} \end{pmatrix} \qquad \begin{pmatrix} R_{01} \\ \hline R_{11} \end{pmatrix} = Q_{02}R_{02}
$$

Q is represented implicitly as a product

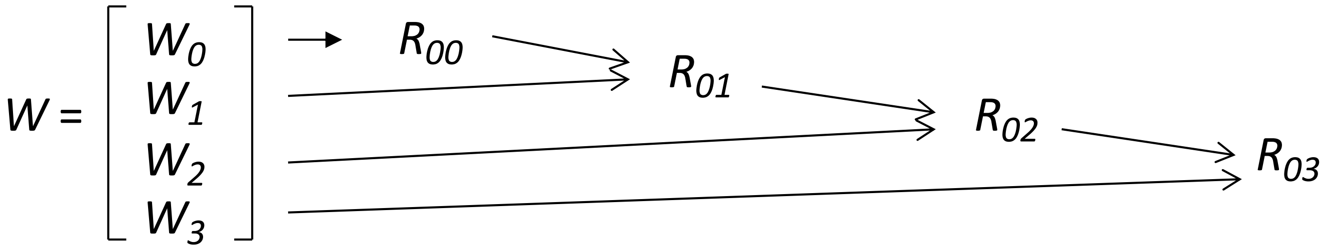
Output: $\{Q_{00}, Q_{10}, Q_{00}, Q_{20}, Q_{30}, Q_{01}, Q_{11}, Q_{02}, R_{02}\}$

Flexibility of TSQR and CAQR algorithms

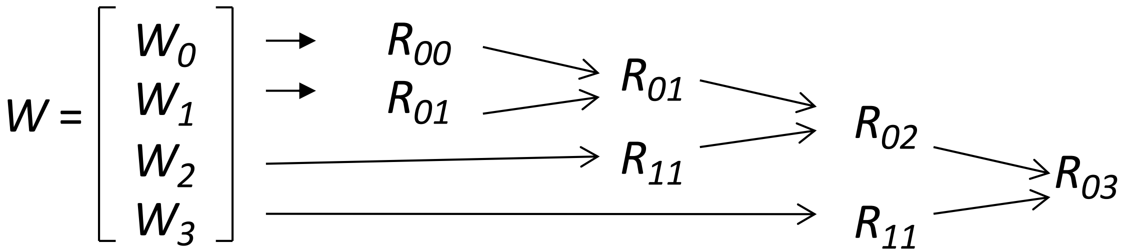
Parallel:



Sequential:



Dual Core:



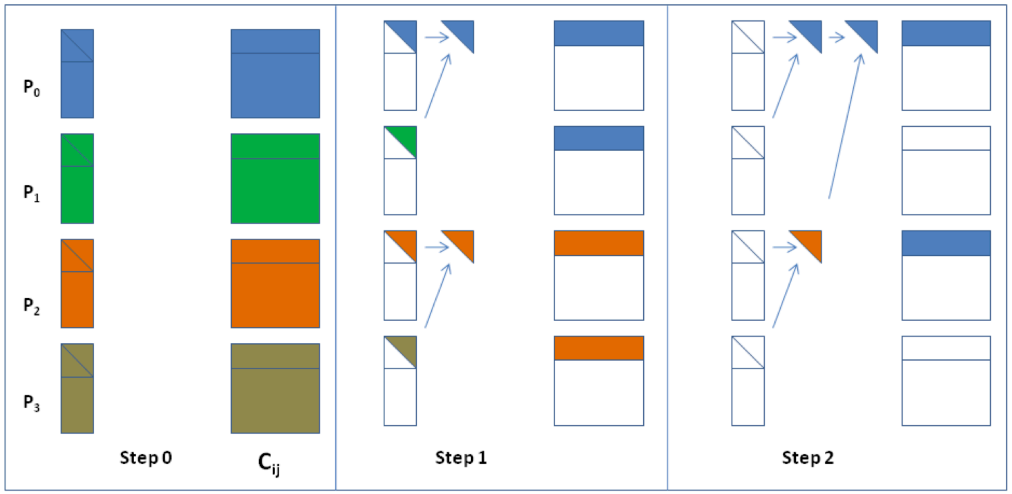
Reduction tree will depend on the underlying architecture, could be chosen dynamically

Algebra of TSQR

Parallel:

$$W = \begin{bmatrix} W_0 \\ W_1 \\ W_2 \\ W_3 \end{bmatrix} \begin{matrix} \rightarrow \\ \rightarrow \\ \rightarrow \\ \rightarrow \end{matrix} \begin{matrix} R_{00} \\ R_{10} \\ R_{20} \\ R_{30} \end{matrix} \begin{matrix} \searrow \\ \nearrow \\ \searrow \\ \nearrow \end{matrix} \begin{matrix} R_{01} \\ \\ R_{11} \end{matrix} \begin{matrix} \searrow \\ \nearrow \end{matrix} R_{02}$$

CAQR



QR for General Matrices

- Cost of CAQR vs ScaLAPACK's PDGEQRF
  - n x n matrix on $P^{1/2}$ x $P^{1/2}$ processor grid, block size b
  - Flops: $(4/3)n^3/P + (3/4)n^2 b \log P/P^{1/2}$ vs $(4/3)n^3/P$
  - Bandwidth: $(3/4)n^2 \log P/P^{1/2}$ vs same
  - Latency: 2.5 n log P / **b** vs 1.5 n log P

- Close to optimal (modulo log P factors)
  - Assume: $O(n^2/P)$ memory/processor, $O(n^3)$ algorithm,
  - Choose b near $n / P^{1/2}$ (its upper bound)
  - Bandwidth lower bound:

    $\Omega(n^2 / P^{1/2})$ – just log(P) smaller
  - Latency lower bound:

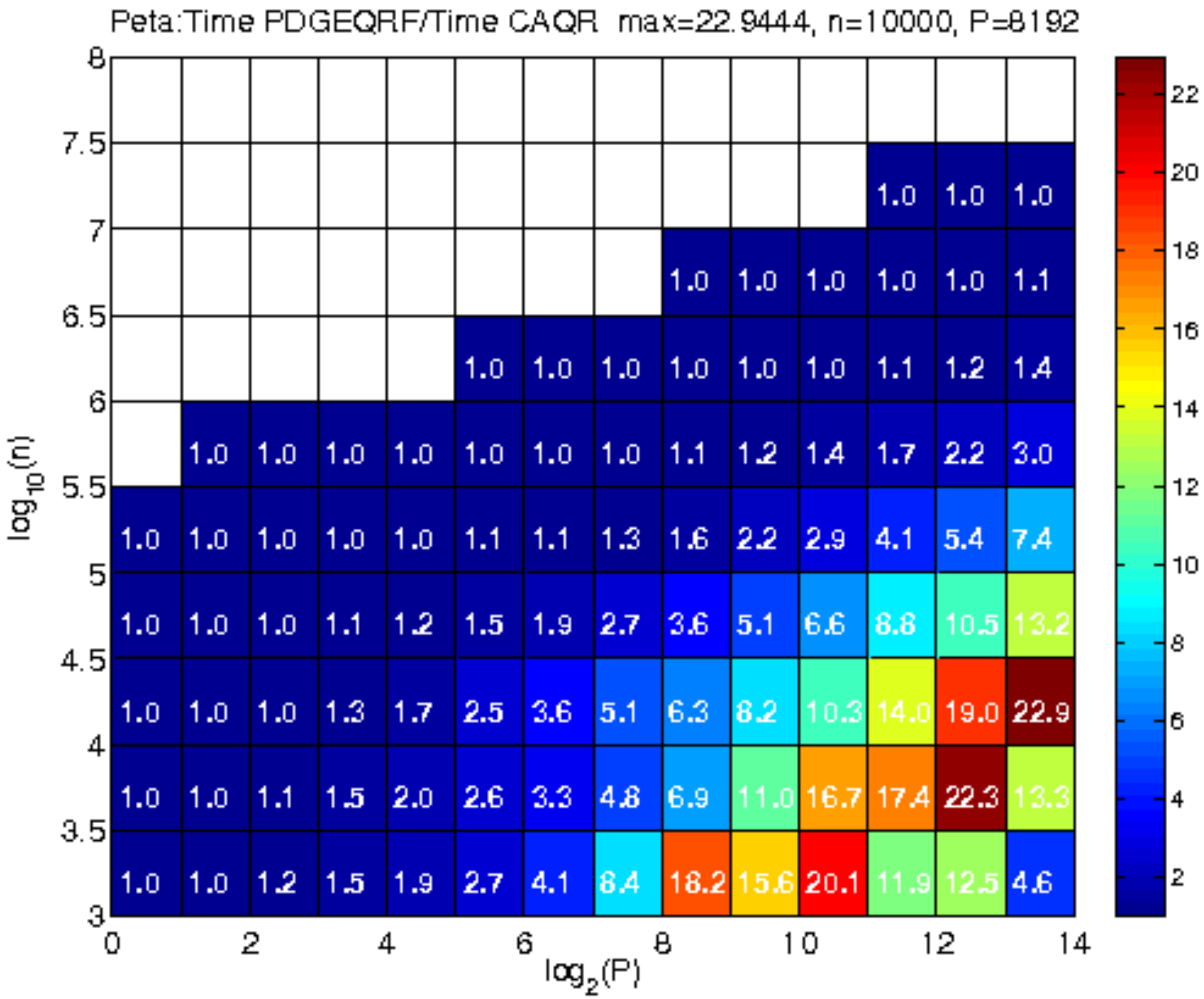
    $\Omega(P^{1/2})$ – just polylog(P) smaller

Performance of TSQR vs Sca/LAPACK

- Parallel
  - Intel Xeon (two socket, quad core machine), 2010
    - Up to **5.3x speedup** (8 cores, 10^5 x 200)
  - Pentium III cluster, Dolphin Interconnect, MPICH, 2008
    - Up to **6.7x speedup** (16 procs, 100K x 200)
  - BlueGene/L, 2008
    - Up to **4x speedup** (32 procs, 1M x 50)
  - Tesla C 2050 / Fermi (Anderson et al)
    - Up to **13x** (110,592 x 100)
  - Grid – **4x** on 4 cities vs 1 city (Dongarra, Langou et al)
  - QR computed locally using recursive algorithm (Elmroth-Gustavson) – enabled by TSQR

- Results from many papers, for some see [Demmel, LG, Hoemmen, Langou, SISC 12], [Donfack, LG, IPDPS 10].

Modeled Speedups of CAQR vs ScaLAPACK



Petascale
up to 22.9x

IBM Power 5
up to 9.7x

"Grid"
up to 11x

Petascale machine with 8192 procs, each at 500 GFlops/s, a bandwidth of 4 GB/s.

$$\gamma = 2 \cdot 10^{-12} s, \alpha = 10^{-5} s, \beta = 2 \cdot 10^{-9} s/word$$

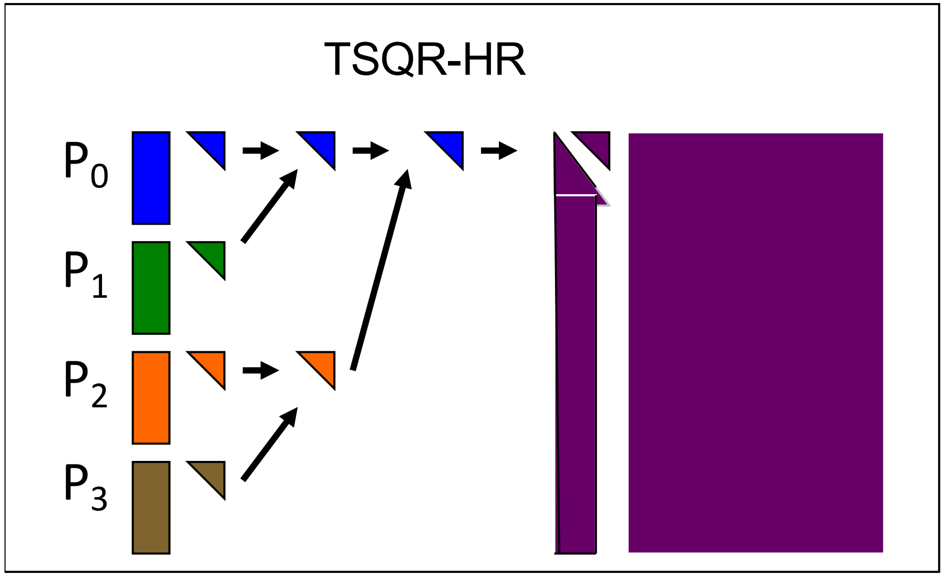
Impact

- TSQR/CAQR implemented in
  - Intel Data analytics library
  - GNU Scientific Library
  - ScaLAPACK
  - Spark for data mining
- CALU implemented in
  - Cray's libsci
  - To be implemented in lapack/scapalack

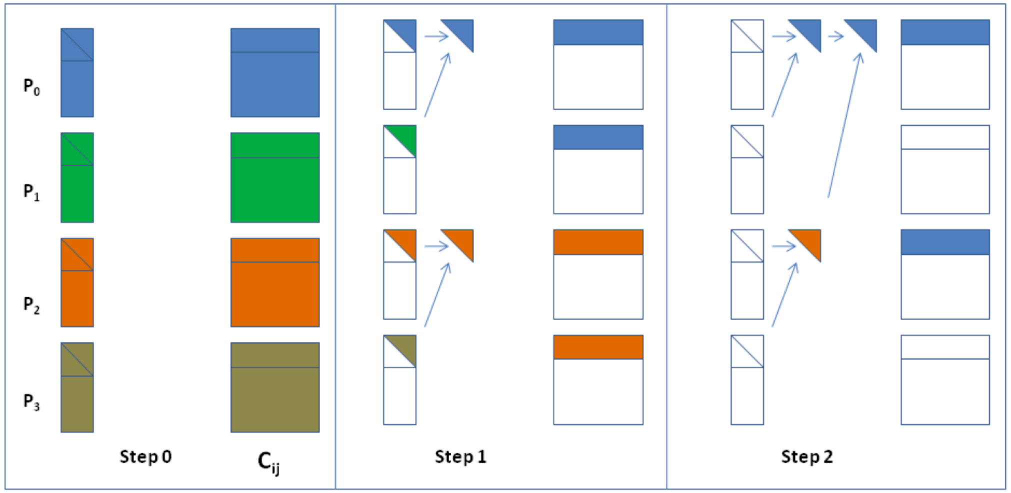
Algebra of TSQR

Parallel:

$$W = \begin{bmatrix} W_0 \\ W_1 \\ W_2 \\ W_3 \end{bmatrix} \begin{matrix} \rightarrow \\ \rightarrow \\ \rightarrow \\ \rightarrow \end{matrix} \begin{matrix} R_{00} \\ R_{10} \\ R_{20} \\ R_{30} \end{matrix} \begin{matrix} \searrow \\ \nearrow \\ \searrow \\ \nearrow \end{matrix} \begin{matrix} R_{01} \\ \\ R_{11} \end{matrix} \begin{matrix} \searrow \\ \nearrow \end{matrix} R_{02}$$



CAQR



Reconstruct Householder vectors from TSQR

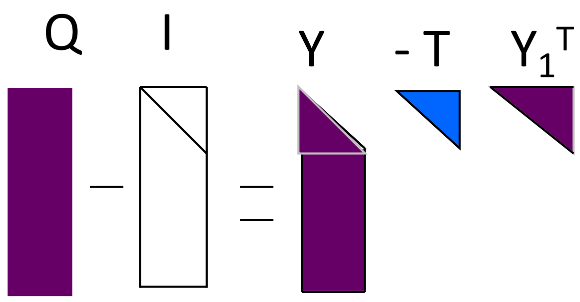
The QR factorization using Householder vectors

$$W = QR = (I - YTY_1^T)R$$

can be re-written as an LU factorization

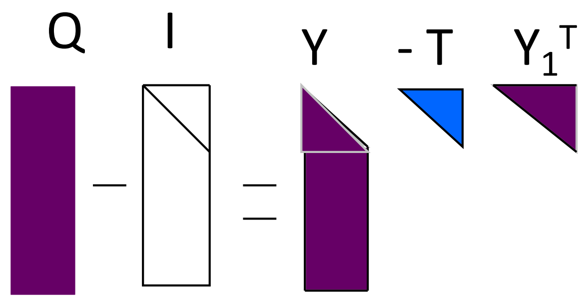
$$W - R = Y(-TY_1^T)R$$

$$Q - I = Y(-TY_1^T)$$



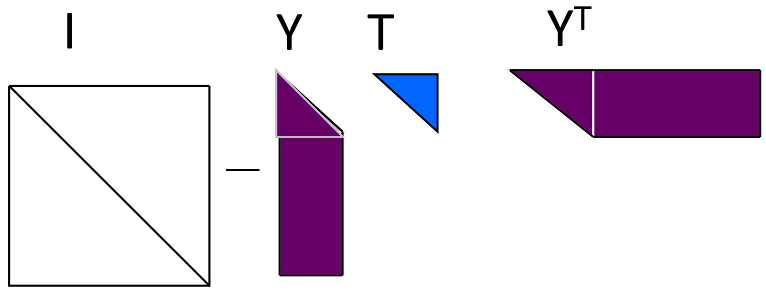
Reconstruct Householder vectors TSQR-HR

1. Perform TSQR
2. Form Q explicitly (tall-skinny orthonormal factor)
3. Perform LU decomposition: $Q - I = LU$

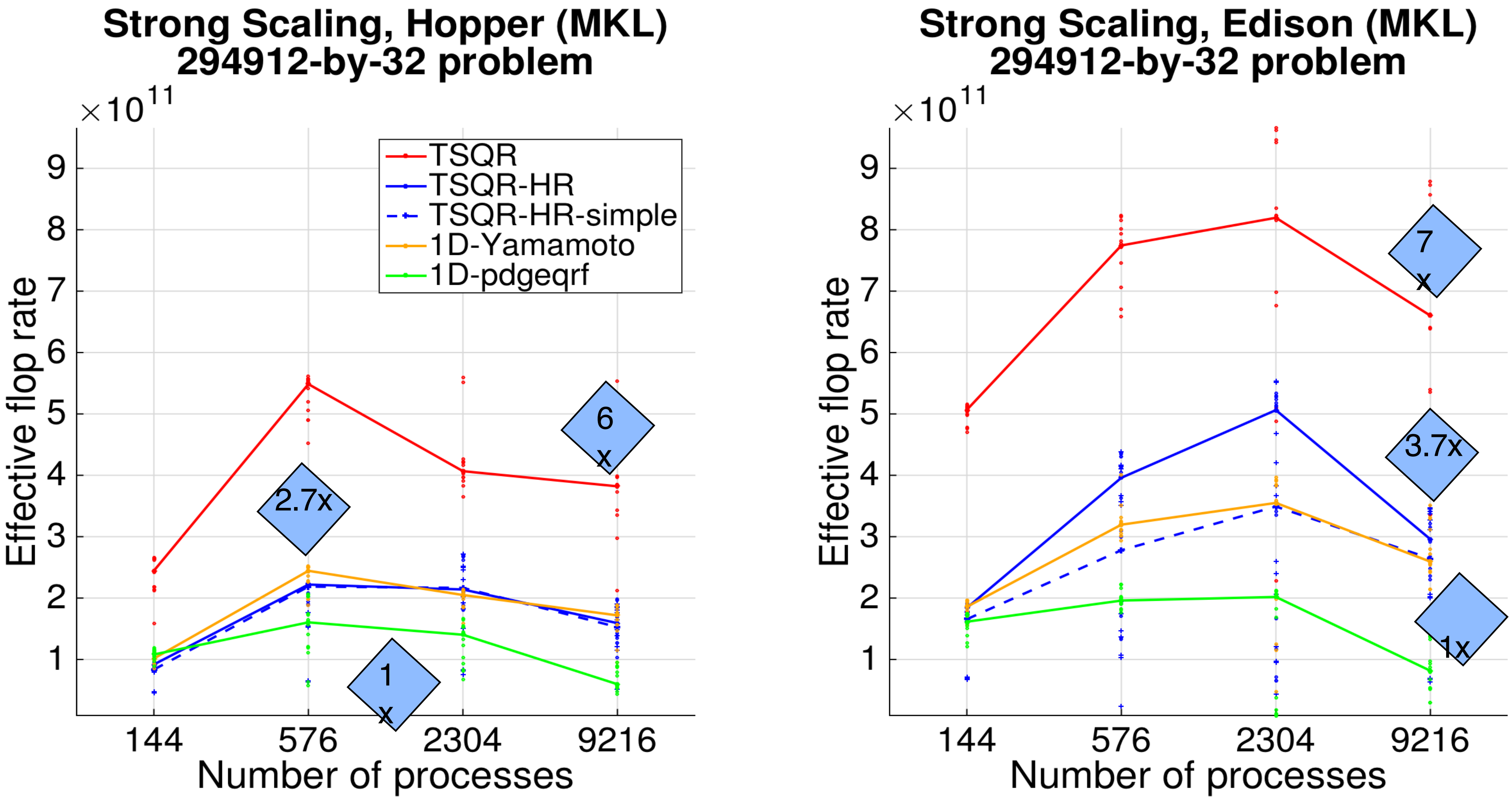


4. Set $Y = L$
5. Set $T = -U\, Y_1^{-T}$

$$I - YTY^T = I - \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} T \begin{bmatrix} Y_1^T & Y_2^T \end{bmatrix}$$



Strong scaling



- Hopper: Cray XE6 (NERSC) – 2 x 12-core AMD Magny-Cours (2.1 GHz)
- Edison: Cray CX30 (NERSC) – 2 x 12-core Intel Ivy Bridge (2.4 GHz)
- Effective flop rate, computed by dividing $2mn^2 - 2n^3/3$ by measured runtime

Ballard, Demmel, LG, Jacquelin, Knight, Nguyen, and Solomonik, 2015.

The LU factorization of a tall skinny matrix

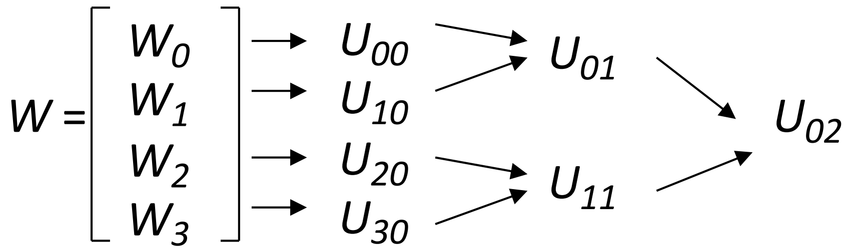
First try the obvious generalization of TSQR.

$$W = \begin{pmatrix} W_0 \\ W_1 \\ W_2 \\ W_3 \end{pmatrix} = \underbrace{\begin{pmatrix} \Pi_{00} & & & \\ & \Pi_{10} & & \\ & & \Pi_{20} & \\ & & & \Pi_{30} \end{pmatrix}}_{\Pi_0} \cdot \begin{pmatrix} L_{00} & & & \\ & L_{10} & & \\ & & L_{20} & \\ & & & L_{30} \end{pmatrix} \cdot \begin{pmatrix} U_{00} \\ U_{10} \\ U_{20} \\ U_{30} \end{pmatrix}$$

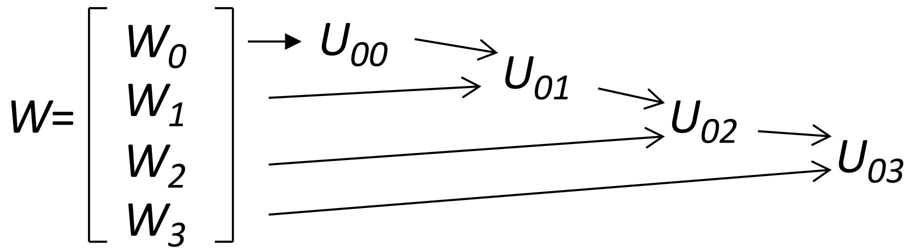
$$\begin{pmatrix} U_{00} \\ U_{10} \\ U_{20} \\ U_{30} \end{pmatrix} = \underbrace{\begin{pmatrix} \Pi_{01} & \\ & \Pi_{11} \end{pmatrix}}_{\Pi_1} \cdot \begin{pmatrix} L_{01} & \\ & L_{11} \end{pmatrix} \cdot \begin{pmatrix} U_{01} \\ U_{11} \end{pmatrix}$$

Obvious generalization of TSQR to LU

- Block parallel pivoting:
  - uses a binary tree and is optimal in the parallel case



- Block pairwise pivoting:
  - uses a flat tree and is optimal in the sequential case
  - introduced by Barron and Swinnerton-Dyer, 1960: block LU factorization used to solve a system with 100 equations on EDSAC 2 computer using an auxiliary magnetic-tape
  - used in PLASMA for multicore architectures and FLAME for out-of-core algorithms and for multicore architectures



Stability of the LU factorization

- The backward stability of the LU factorization of a matrix A of size n-by-n

$$\left\| |\hat{L}| \cdot |\hat{U}| \right\|_\infty \leq (1 + 2(n^2 - n) g_w) \|A\|_\infty$$

depends on the growth factor

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

- $g_W \leq 2^{n-1}$, attained for Wilkinson matrix

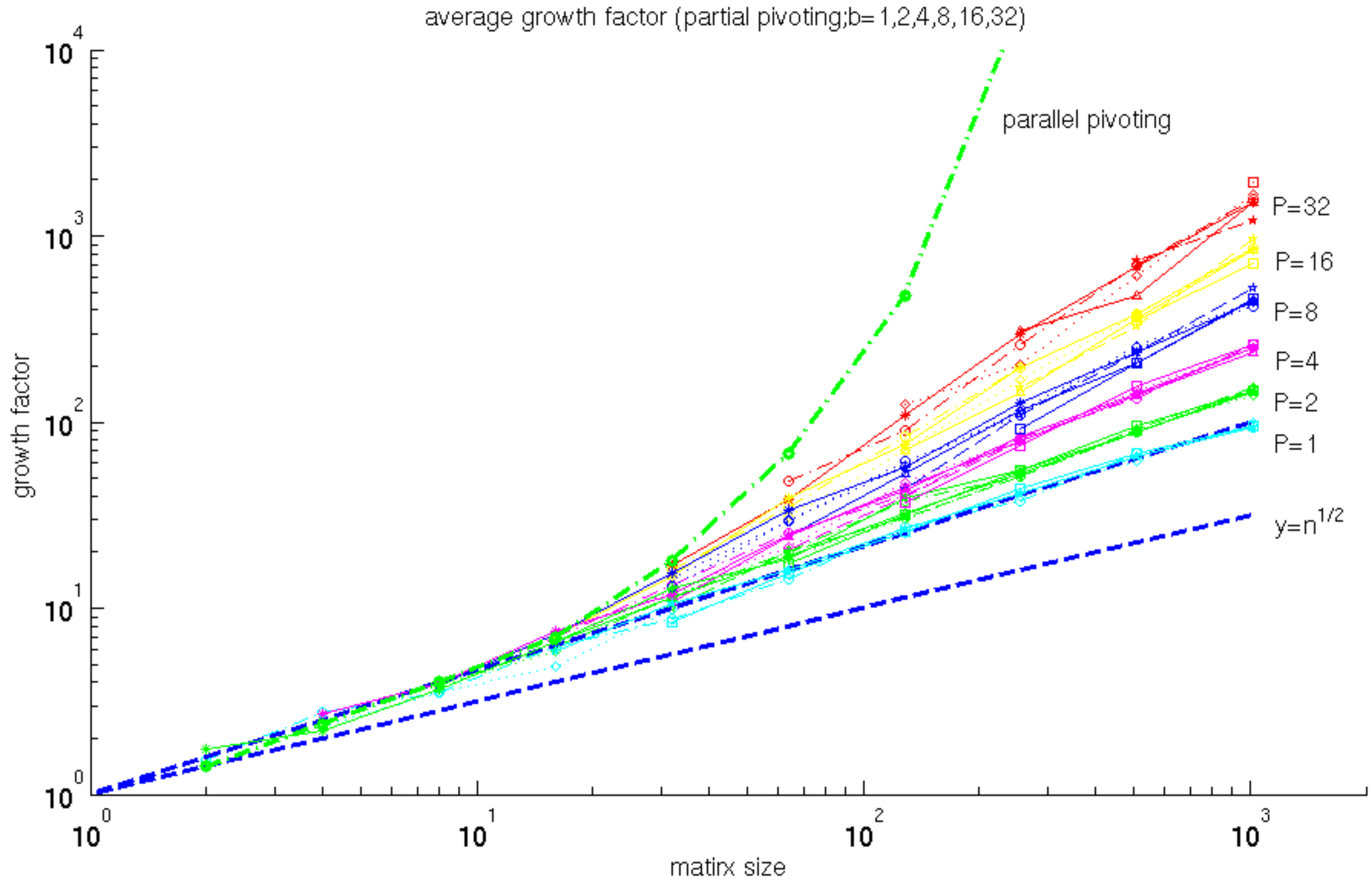
  but in practice it is on the order of $n^{2/3}$ -- $n^{1/2}$

- Two reasons considered to be important for the average case stability [Trefethen and Schreiber, 90] :

- the multipliers in L are small,

- the correction introduced at each elimination step is of rank 1.

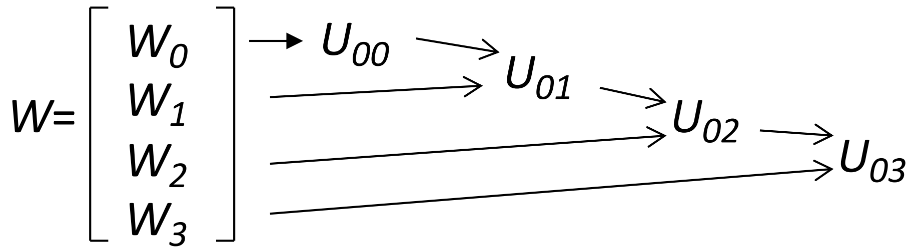
Block parallel pivoting

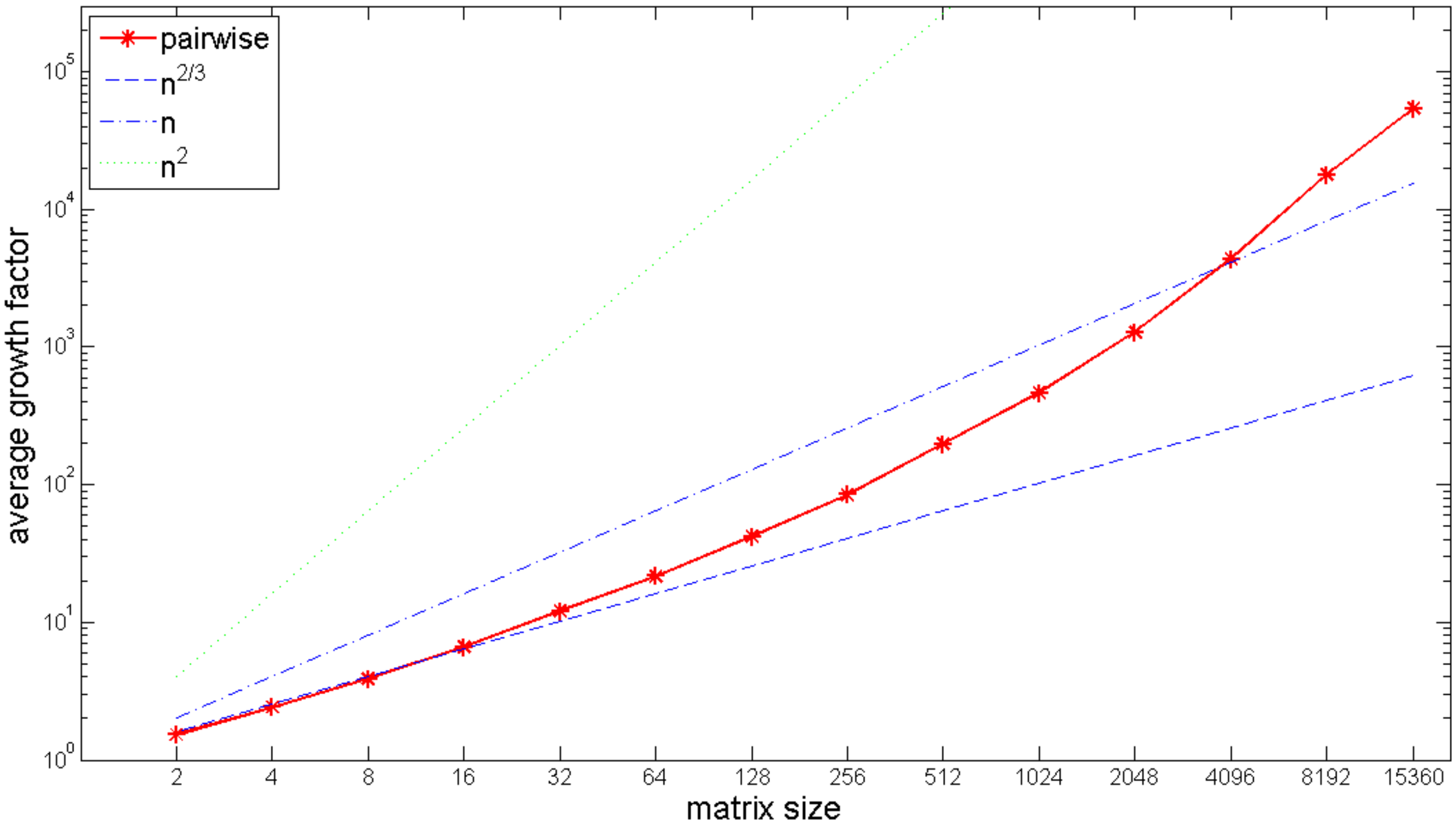


- Unstable for large number of processors P
- When P=number rows, it corresponds to parallel pivoting, known to be unstable (Trefethen and Schreiber, 90)

Block pairwise pivoting

- Results shown for random matrices
- Will become unstable for large matrices





Tournament pivoting - the overall idea

- At each iteration of a block algorithm

$$A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{matrix} \}\ b \\ \}\ n-b \end{matrix}, \text{ where } \quad W = \begin{pmatrix} A_{11} \\ A_{21} \end{pmatrix}$$

  - Preprocess W to find at low communication cost good pivots for the LU factorization of W, return a permutation matrix P.
  - Permute the pivots to top, ie compute PA.
  - Compute LU with no pivoting of W, update trailing matrix.

$$PA = \begin{pmatrix} L_{11} & \\ L_{21} & I_{n-b} \end{pmatrix} \begin{pmatrix} U_{11} & U_{12} \\ & A_{22} - L_{21} U_{12} \end{pmatrix}$$

Tournament pivoting for a tall skinny matrix

1) Compute GEPP factorization of each $W_{i.}$, find permutation Π_0

$$W = \begin{pmatrix} W_0 \\ \hline W_1 \\ \hline W_2 \\ \hline W_3 \end{pmatrix} = \begin{pmatrix} \Pi_{00} L_{00} U_{00} \\ \hline \Pi_{10} L_{10} U_{10} \\ \hline \Pi_{20} L_{20} U_{20} \\ \hline \Pi_{30} L_{30} U_{30} \end{pmatrix},$$

Pick b pivot rows, form A_{00}

Same for A_{10}

Same for A_{20}

Same for A_{30}

2) Perform $\log_2(P)$ times GEPP factorizations of 2b-by-b rows, find permutations Π_1, Π_2

$$\begin{pmatrix} A_{00} \\ A_{10} \\ \hline A_{20} \\ A_{30} \end{pmatrix} = \begin{pmatrix} \Pi_{01} L_{01} U_{01} \\ \hline \Pi_{11} L_{11} U_{11} \end{pmatrix}$$

Pick b pivot rows, form A_{01}

Same for A_{11}

3) Compute LU factorization with no pivoting of the permuted matrix:

$$\Pi_2^T \Pi_1^T \Pi_0^T W = LU$$

Tournament pivoting

P_0: $W_0 = \begin{pmatrix} 2 & 4 \\ 0 & 1 \\ 2 & 0 \\ 1 & 2 \end{pmatrix} = \Pi_0 L_0 U_0$, $\quad \Pi_0^T W_0 = \begin{pmatrix} 2 & 4 \\ 2 & 0 \end{pmatrix}$

P_1: $W_1 = \begin{pmatrix} 2 & 0 \\ 0 & 0 \\ 4 & 1 \\ 1 & 0 \end{pmatrix} = \Pi_1 L_1 U_1$, $\quad \Pi_1^T W_1 = \begin{pmatrix} 4 & 1 \\ 2 & 0 \end{pmatrix}$

P_2: $W_2 = \begin{pmatrix} 0 & 1 \\ 1 & 4 \\ 0 & 0 \\ 0 & 2 \end{pmatrix} = \Pi_2 L_2 U_2$, $\quad \Pi_2^T W_2 = \begin{pmatrix} 1 & 4 \\ 0 & 2 \end{pmatrix}$

P_3: $W_3 = \begin{pmatrix} 2 & 1 \\ 0 & 2 \\ 1 & 0 \\ 4 & 2 \end{pmatrix} = \Pi_3 L_3 U_3$, $\quad \Pi_3^T W_3 = \begin{pmatrix} 4 & 2 \\ 0 & 2 \end{pmatrix}$

$\overline{W_0} = \begin{pmatrix} 2 & 4 \\ 2 & 0 \\ 4 & 1 \\ 2 & 0 \end{pmatrix} = \overline{\Pi}_0 \overline{L}_0 \overline{U}_0$, $\quad \overline{\Pi}_0^T \overline{W}_0 = \begin{pmatrix} 4 & 1 \\ 2 & 4 \end{pmatrix}$

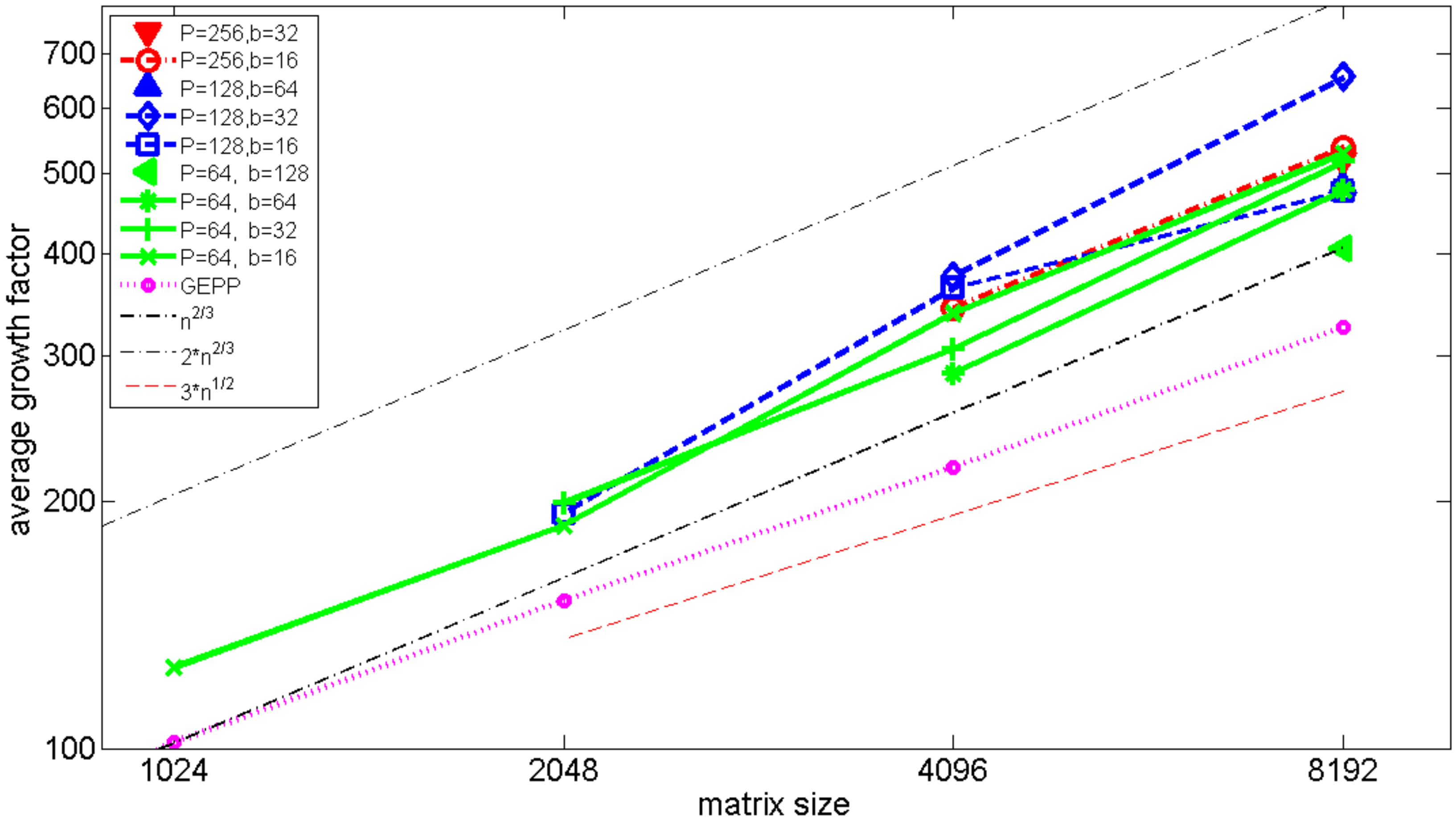
$\overline{W_2} = \begin{pmatrix} 1 & 4 \\ 0 & 2 \\ 4 & 2 \\ 0 & 2 \end{pmatrix} = \overline{\Pi}_2 \overline{L}_2 \overline{U}_2$, $\quad \overline{\Pi}_2^T \overline{W}_2 = \begin{pmatrix} 4 & 2 \\ 1 & 4 \end{pmatrix}$

$\underline{W}_0 = \begin{pmatrix} 4 & 1 \\ 2 & 4 \\ 4 & 2 \\ 1 & 4 \end{pmatrix} = \underline{\Pi}_0 \underline{L}_0 \underline{U}_0$, $\quad \underline{\Pi}_0^T \underline{W}_0 = \begin{pmatrix} 4 & 1 \\ 1 & 4 \end{pmatrix}$

Good pivots for factorizing W

time $\longrightarrow$

Growth factor for binary tree based CALU



- Random matrices from a normal distribution
- Same behaviour for all matrices in our test, and |L| <= 4.2

Our “proof of stability” for CALU

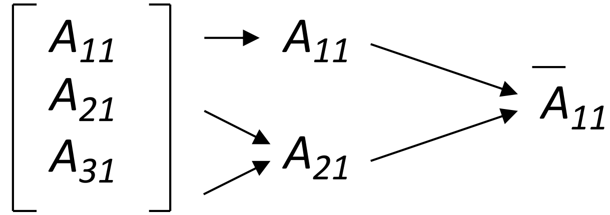
- CALU as stable as GEPP in following sense:

  In exact arithmetic, CALU process on a matrix A is equivalent to GEPP process on a larger matrix G whose entries are blocks of A and zeros.

- Example of one step of tournament pivoting:

$$A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \\ A_{31} & A_{32} \end{pmatrix}$$

tournament pivoting:

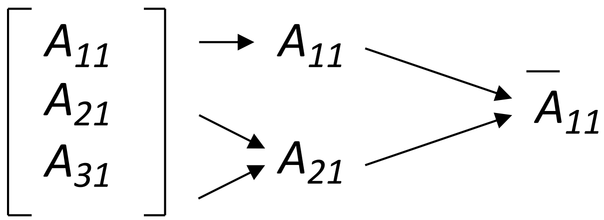


$$G = \begin{pmatrix} \bar{A}_{11} & & \bar{A}_{12} \\ A_{21} & A_{21} & \\ & -A_{31} & A_{32} \end{pmatrix}$$

- Proof possible by using original rows of A during tournament pivoting (not the computed rows of U).

Outline of the proof of stability for CALU

- Consider $A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \\ A_{31} & A_{32} \end{pmatrix}$, and the result of TSLU as



- After the factorization of first panel by CALU, A^s_{32} (the Schur complement of A_{32}) is not bounded as in GEPP,

$$\begin{pmatrix} \Pi_{11} & \Pi_{12} & \\ \Pi_{21} & \Pi_{22} & \\ & & I \end{pmatrix} \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \\ A_{31} & A_{32} \end{pmatrix} = \begin{pmatrix} \bar{A}_{11} & \bar{A}_{12} \\ \bar{A}_{21} & \bar{A}_{22} \\ A_{31} & A_{32} \end{pmatrix} = \begin{pmatrix} \bar{L}_{11} & & \\ \bar{L}_{21} & I & \\ \bar{L}_{31} & & I \end{pmatrix} \begin{pmatrix} \bar{U}_{11} & \bar{U}_{12} \\ & A^s_{22} \\ & A^s_{32} \end{pmatrix}$$

- but A^s_{32} can be obtained by GEPP on larger matrix G formed from blocks of A

$$G = \begin{pmatrix} \bar{A}_{11} & & \bar{A}_{12} \\ A_{21} & A_{21} & \\ & -A_{31} & A_{32} \end{pmatrix} = \begin{pmatrix} \bar{L}_{11} & & \\ A_{21}\bar{U}_{11}^{-1} & L_{21} & \\ & -L_{31} & I \end{pmatrix} \begin{pmatrix} \bar{U}_{11} & & \bar{U}_{12} \\ & U_{21} & -L_{21}^{-1}A_{21}\bar{U}_{11}^{-1}\bar{U}_{12} \\ & & A^s_{32} \end{pmatrix}$$

- GEPP on G does not permute and

$$L_{31}L_{21}^{-1}A_{21}\bar{U}_{11}^{-1}\bar{U}_{12} + A^s_{32} = L_{31}U_{21}\bar{U}_{11}^{-1}\bar{U}_{12} + A^s_{32} = A_{31}\bar{U}_{11}^{-1}\bar{U}_{12} + A^s_{32} = \bar{L}_{31}\bar{U}_{12} + A^s_{32} = A_{32}$$

Growth factor in exact arithmetic

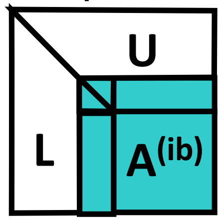
- Matrix of size m-by-n, reduction tree of height H=log(P).
- (CA)LU_PRRP select pivots using strong rank revealing QR (A. Khabou, J. Demmel, LG, M. Gu, SIMAX 2013)
- "In practice" means observed/expected/conjectured values.

	CALU	GEPP
Upper bound	$2^{n(\log(P)+1)-1}$	2^{n-1}
In practice	$n^{2/3}$ -- $n^{1/2}$	$n^{2/3}$ -- $n^{1/2}$

Better bounds

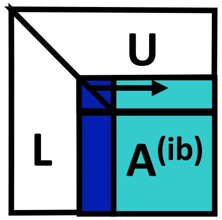
CALU – a communication avoiding LU factorization

- Consider a 2D grid of P processors P_r-by-P_c, using a 2D block cyclic layout with square blocks of size b.



For ib = 1 to n-1 step b
    $A^{(ib)} = A(ib:n, ib:n)$

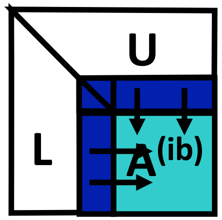
(1) Find permutation for current panel using TSLU $O(n/b \log_2 P_r)$



(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)

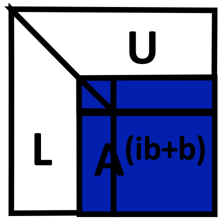


$O(n/b \log_2 P_c)$

(4) Compute block row of U (pdtrsm)

- broadcast right diagonal part of L of current panel

(5) Update trailing matrix (pdgemm) $O(n/b(\log_2 P_c + \log_2 P_r))$



- broadcast right block column of L
- broadcast down block row of U

LU for General Matrices

- Cost of CALU vs ScaLAPACK's PDGETRF
  - n x n matrix on $P^{1/2}$ x $P^{1/2}$ processor grid, block size b
  - Flops: $(2/3)n^3/P + (3/2)n^2b / P^{1/2}$ vs $(2/3)n^3/P + n^2b/P^{1/2}$
  - Bandwidth: $n^2 \log P/P^{1/2}$ vs same
  - Latency: $3 n \log P / \mathbf{b}$ vs $1.5 n \log P + 3.5n \log P / b$

- Close to optimal (modulo log P factors)
  - Assume: $O(n^2/P)$ memory/processor, $O(n^3)$ algorithm,
  - Choose b near $n / P^{1/2}$ (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

Performance vs ScaLAPACK

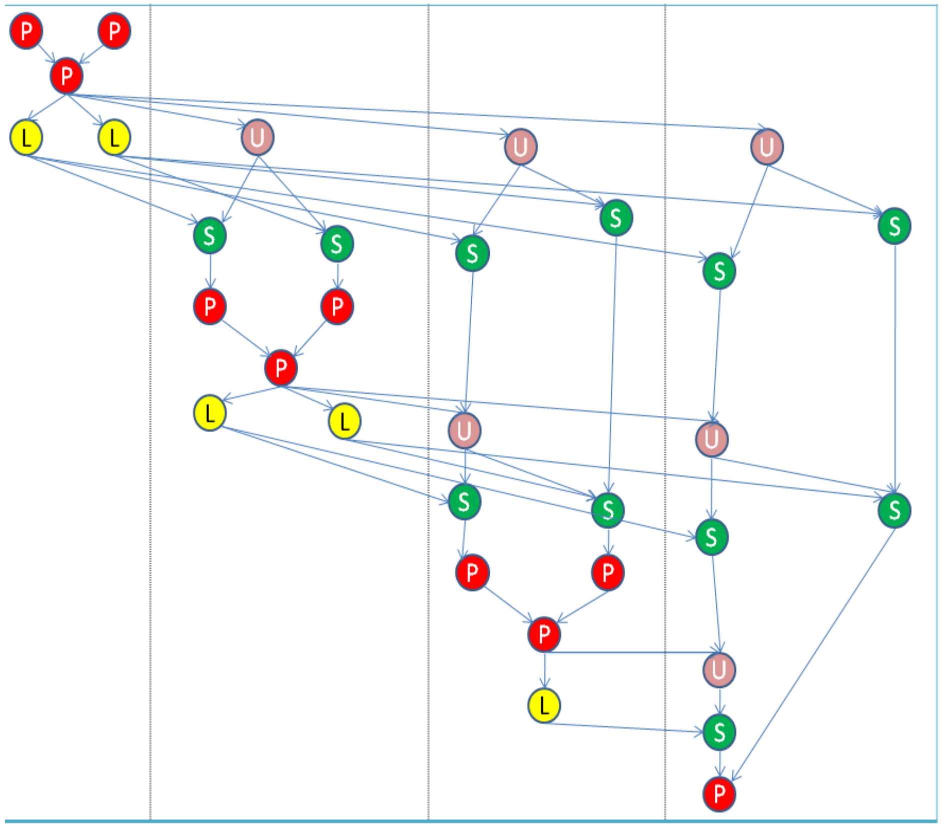
- Parallel TSLU (LU on tall-skinny matrix)
  - IBM Power 5
    - Up to **4.37x** faster (16 procs, 1M x 150)
  - Cray XT4
    - Up to **5.52x** faster (8 procs, 1M x 150)

- Parallel CALU (LU on general matrices)
  - Intel Xeon (two socket, quad core)
    - Up to **2.3x** faster (8 cores, 10^6 x 500)
  - 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)

- Details in SC08 (LG, Demmel, Xiang), IPDPS'10 (S. Donfack, LG).

CALU and its task dependency graph

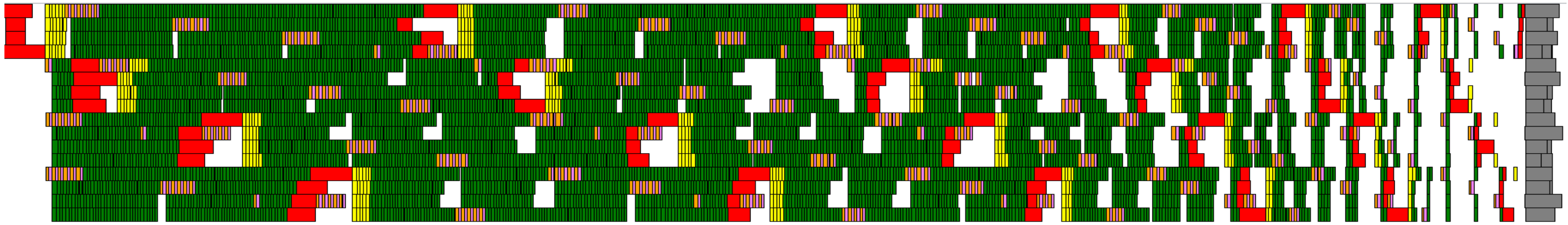
- The matrix is partitioned into blocks of size T x b.
- The computation of each block is associated with a task.



Scheduling CALU's Task Dependency Graph

- Static scheduling

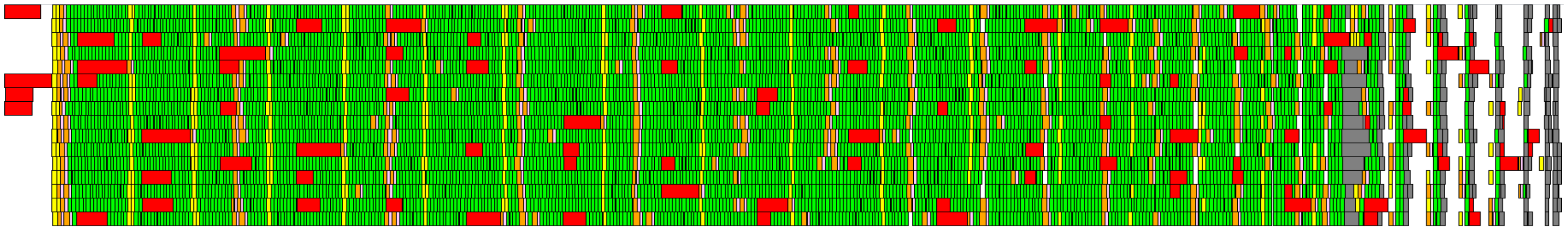
  \+ Good locality of data - Ignores noise



- Dynamic scheduling

  \+ Keeps cores busy - Poor usage of data locality

  \- Can have large dequeue overhead



Lightweight scheduling

- Emerging complexities of multi- and mani-core processors suggest a need for self-adaptive strategies
  - One example is work stealing
- Goal:
  - Design a tunable strategy that is able to provide a good trade-off between load balance, data locality, and dequeue overhead.
  - Provide performance consistency
- Approach: combine static and dynamic scheduling
  - Shown to be efficient for regular mesh computation [B. Gropp and V. Kale]

	Design space		
Data layout/scheduling	Static	Dynamic	Static/(%dynamic)
Column Major Layout (CM)		√	
Block Cyclic Layout (BCL)	√	√	√
2-level Block Layout (2l-BL)	√	√	√

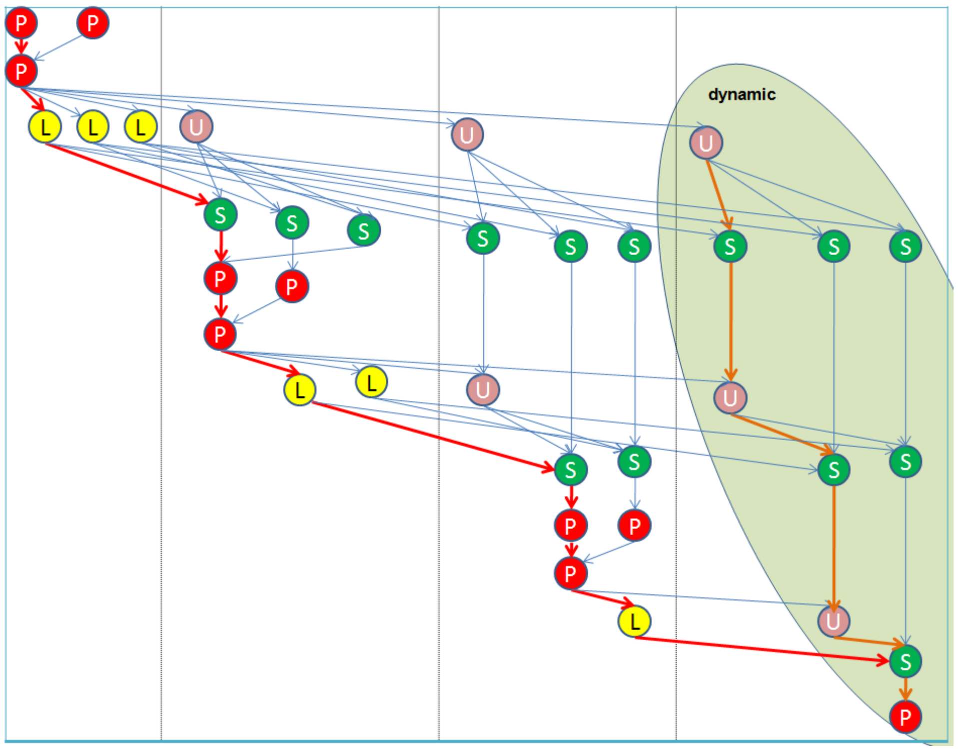
S. Donfack, LG, B. Gropp, V. Kale,IPDPS 2012

Lightweight scheduling

- A self-adaptive strategy to provide
  - A good trade-off between load balance, data locality, and dequeue overhead.
  - Performance consistency
  - Shown to be efficient for regular mesh computation [B. Gropp and V. Kale]

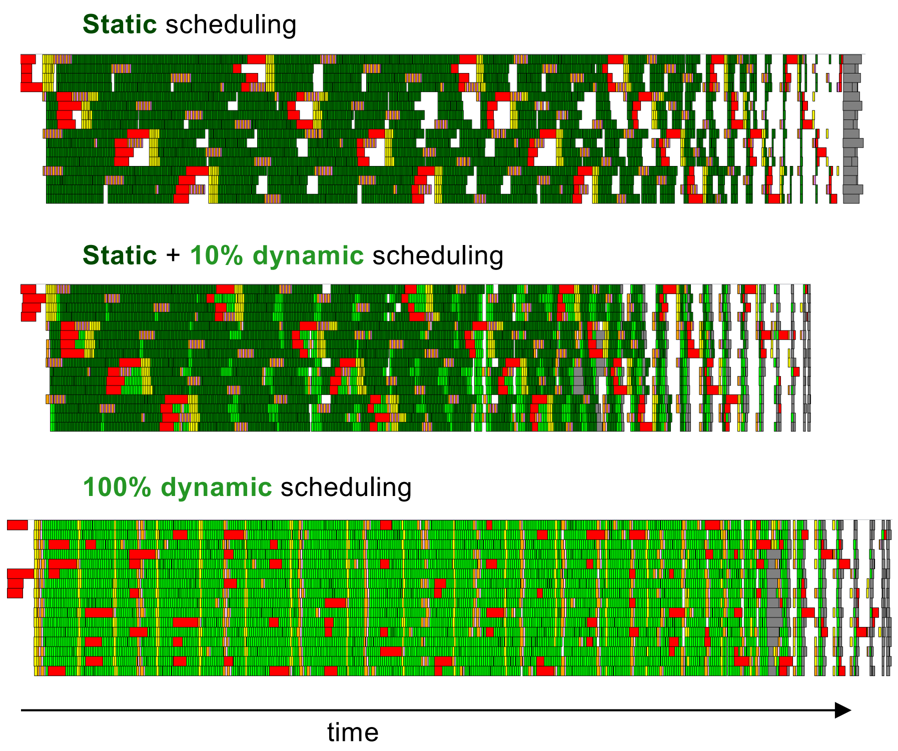
Combined static/dynamic scheduling:

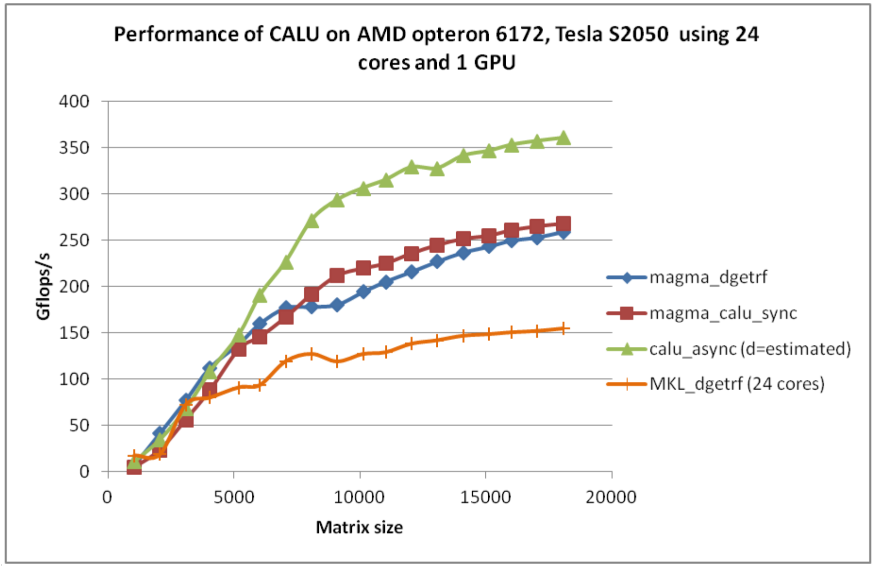
- A thread executes in priority its statically assigned tasks
- When no task ready, it picks a ready task from the dynamic part
- The size of the dynamic part is guided by a performance model

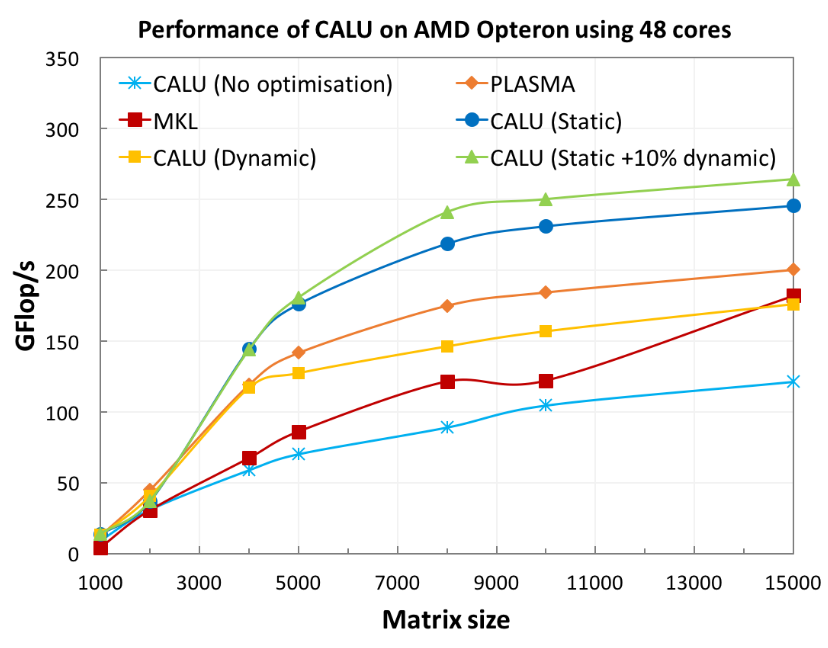


S. Donfack, LG, B. Gropp, V. Kale, 2012

Best performance of CALU on multicore architectures







- Reported performance for PLASMA uses LU with block pairwise pivoting.
- GPU data courtesy of S. Donfack