QR Factorization of Tall and Skinny Matrices in a Grid Computing Environment

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Can we speed up dense linear algebra applications using a computational grid ?

Building blocks

Tremendous computational power of grid infrastructures

- ★ BOINC: 2.4 Pflop/s,
- ★ Folding@home: 7.9 Pflop/s.

MPI-based linear algebra libraries

- ⋆ ScaLAPACK;
- ★ HP Linpack.

Grid-enabled MPI middleware

- ★ MPICH-G2;
- ★ PACX-MPI;
- ★ GridMPI.

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Can we speed up dense linear algebra applications using a computational grid ?

- * GrADS project [Petitet et al., 2001]:
 - © Grid enables to process larger matrices;
 - For matrices that can fit in the (distributed) memory of a cluster, the use of a single cluster is optimal.
- Study on a cloud infrastructure [Napper et al., 2009] Linpack on Amazon EC2 commercial offer:
 - © Under-calibrated components;
 - Grid costs too much

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Our approach

Principle

Confine intensive communications (ScaLAPACK calls) within the different geographical sites.

Method

Articulate:

- * Communication-Avoiding algorithms [Demmel et al., 2008];
- * with a topology-aware middleware (QCG-OMPI).

Focus

- * QR factorization;
- ★ Tall and Skinny matrices.

Outline

1. Background

2. Articulation of TSQR with QCG-OMPI

3. Experiments

- ScaLAPACK performance
- TSQR performance
- TSQR vs ScaLAPACK performance

4. Conclusion and future work

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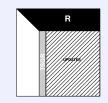
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TSQR / CAQR

Communication-Avoiding QR (CAQR) [Demmel et al., 2008]

Tall and Skinny QR (TSQR)





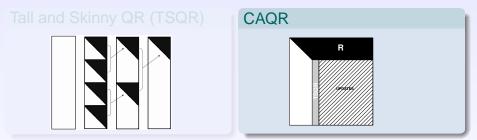
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Examples of applications for TSQR

- panel factorization in CAQR;
- block iterative methods (iterative methods with multiple right-hand sides or iterative eigenvalue solvers);
 - linear least squares problems with a number of equations
 - tremely larger than the number of unknowns.

TSQR / CAQR

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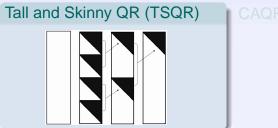
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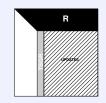
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QCG-OMPI

Topology-aware MPI middleware for the Grid

MPICH-G2

- * description of the topology through the concept of colors:
 - used to build topology-aware MPI communicators;
 - It he application has to adapt itself to the discovered topology;
- ★ based on MPICH.

QCG-OMPI

- resource-aware grid meta-scheduler (QosCosGrid);
- allocation of resources that match requirements expressed in a "JobProfile" (amount of memory, CPU speed, network properties between groups of processes, ...)
 - application always executed on an appropriate resource topology.
- based on OpenMPI.

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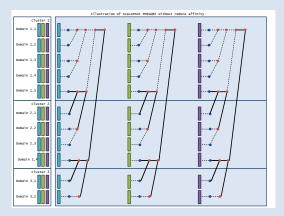
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- TSQR performance
- TSQR vs ScaLAPACK performance

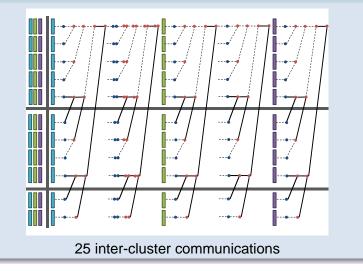
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ScaLAPACK (panel factorization routine) - non optimized tree

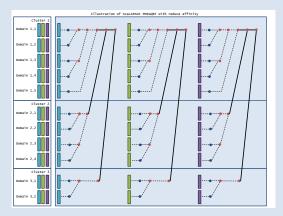


25 inter-cluster communications

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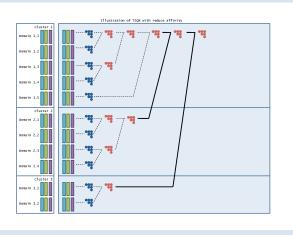


ScaLAPACK (panel factorization routine) - optimized tree



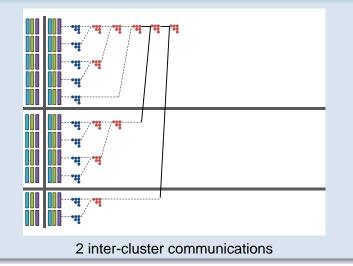
10 inter-cluster communications

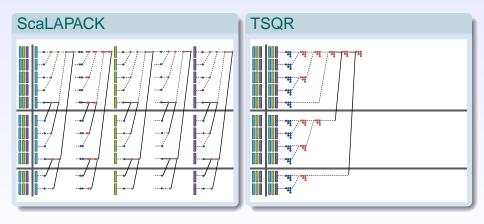
TSQR - optimized tree



2 inter-cluster communications

TSQR - optimized tree





Articulation of TSQR with QCG-OMPI

ScaLAPACK-based TSQR

- * each domain is factorized with a ScaLAPACK call;
- * the reduction is performed by pairs of communicators;
- the number of domains per cluster may vary from 1 to 64 (number of cores per cluster).

QCG JobProfile

- * processes are split into groups of equivalent computing power;
- good network connectivity inside each group (low latency, high bandwidth);
- ★ lower network connectivity between the groups.

 \rightarrow Classical cluster of clusters approach (with a constraint on the relative size of the clusters to facilitate load balancing).

Computing R

	# inter-cluster msg	inter-cluster vol. exchanged	# FLOPs
ScaLAPACK QR2	$2N \log_2(C)$	$\log_2(C)(N^2/2)$	$(2MN^2 - 2/3N^3)/C$
TSQR	$log_2(C)$	$\log_2(C)(N^2/2)$	$(2MN^2 - 2/3N^3)/C + 2/3\log_2(C)N^3$

Computing Q and R (on C clusters)

- ★ C: number of clusters;
- ★ 1 domain per cluster is assumed for these tables.

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$4N \log_2(C)$	
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Experimental environment: Grid'5000

- ★ Four clusters 32 nodes per cluster 2 cores per node.
- AMD Opteron 246 (2 GHz/ 1MB L2 cache) up to AMD Opteron 2218 (2.6 GHz / 2MB L2 cache).
- * Linux 2.6.30 ScaLAPACK 1.8.0 GotoBlas 1.26.
- ★ 256 cores total (theoretical peak 2048 Gflop/s dgemm upperbound 940 Gflop/s).

Orsay
Bordeaux
Antipolis Toulouse

Network

tothonk .									
	-	-							
Latency (ms)	Orsay	Toulouse	Bordeaux	Sophia					
Orsay	0.07	7.97	6.98	6.12					
Toulouse		0.03	9.03	8.18					
Bordeaux			0.05	7.18					
Sophia				0.06					
Throughput (Mb/s)	Orsay	Toulouse	Bordeaux	Sophia					
moughput (MD/3)	Oisay	louiouse	Donacaux						
Orsay	890	78	90	102					
	, ,								
Orsay	, ,	78	90	102					
Orsay Toulouse	, ,	78	90 77	102 90					

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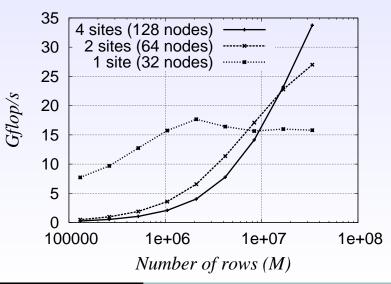
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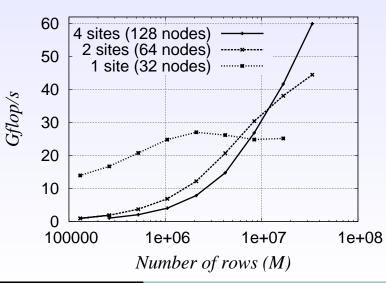
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ScaLAPACK - N = 64



Experiments

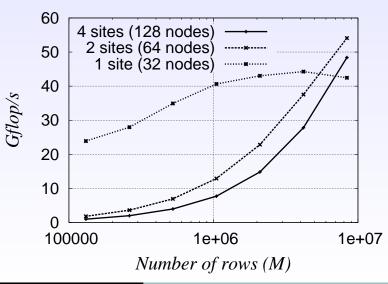
ScaLAPACK - N = 128



Experiments

ScaLAPACK performance

ScaLAPACK - N = 256

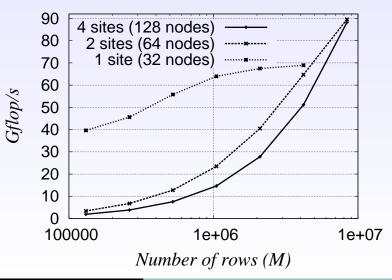


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Experiments

ScaLAPACK - N = 512



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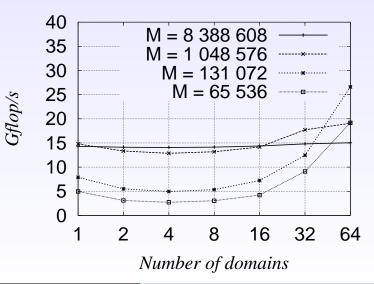
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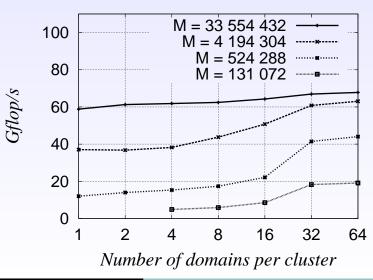
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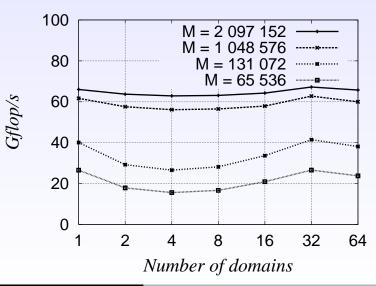
TSQR - N = 64 - one cluster



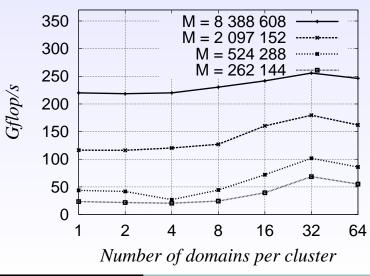
TSQR - N = 64 - all four clusters



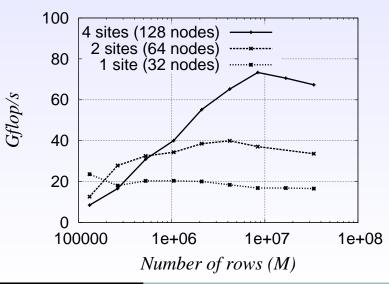
TSQR - N = 512 - one cluster



TSQR - N = 512 - all four clusters



TSQR - N = 64



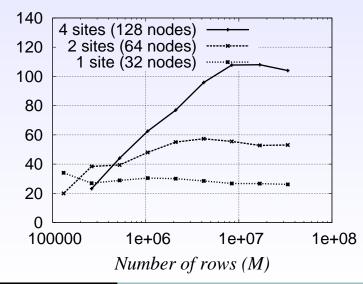
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QR Factorization of Tall and Skinny Matrices in a Grid Computing Environment

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Experiments TSQR performance (optimum configuration)

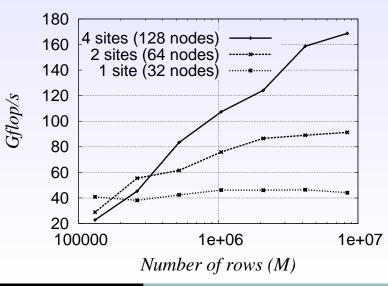
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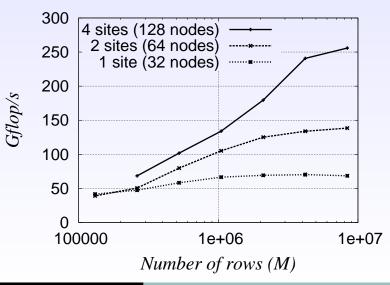
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Gflop/s

TSQR - N = 256



TSQR - N = 512



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QR Factorization of Tall and Skinny Matrices in a Grid Computing Environment 29

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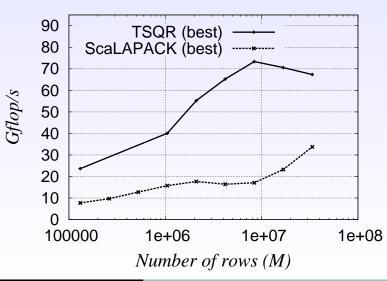
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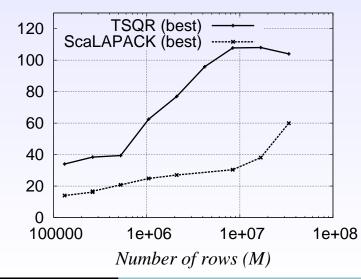
TSQR vs ScaLAPACK - N = 64



Experiments

TSQR vs ScaLAPACK performance

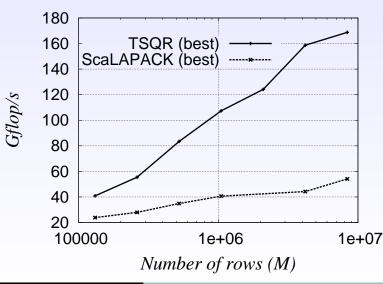
TSQR vs ScaLAPACK - N = 128



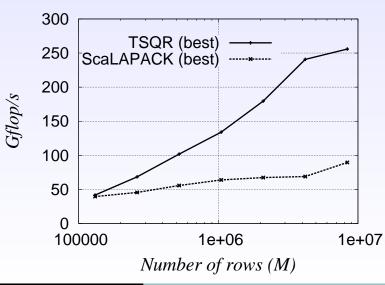
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Conclusion

Can we speed up dense linear algebra applications using a computational grid ?

Yes,

at least for applications based on the QR factorization of Tall and Skinny matrices.

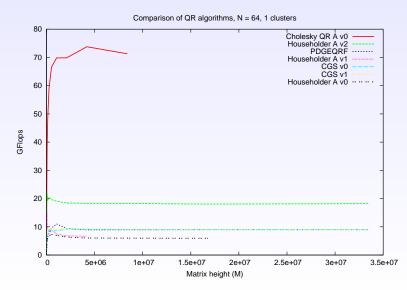
Future directions

* What about square matrices (CAQR) ?

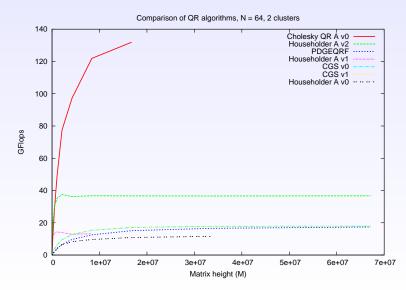
* LU and Cholesky factorizations ?

* Can we benefit from recursive kernels ?

N = 64 - one cluster

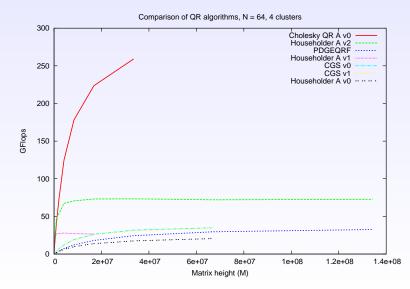


N = 64 - two clusters

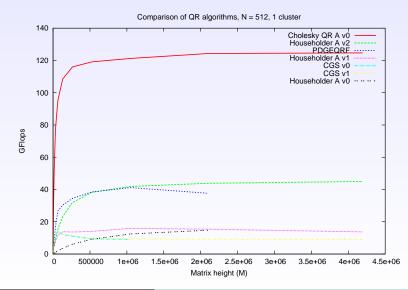


Conclusion and future work

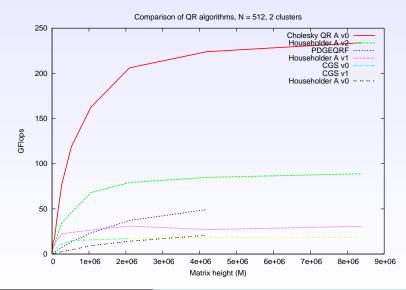
N = 64 - all four clusters



N = 512 - one cluster



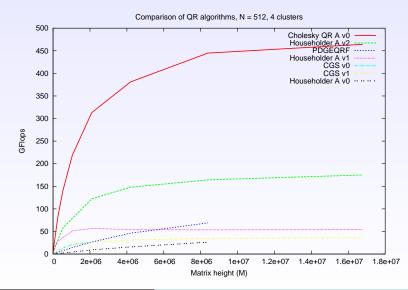
N = 512 - two clusters



Conclusion and future work

current investigations

N = 512 - all four clusters





★ Questions ?