

Distributed Dense Linear Algebra on Heterogeneous Architectures

George Bosilca
bosilca@eecs.utk.edu



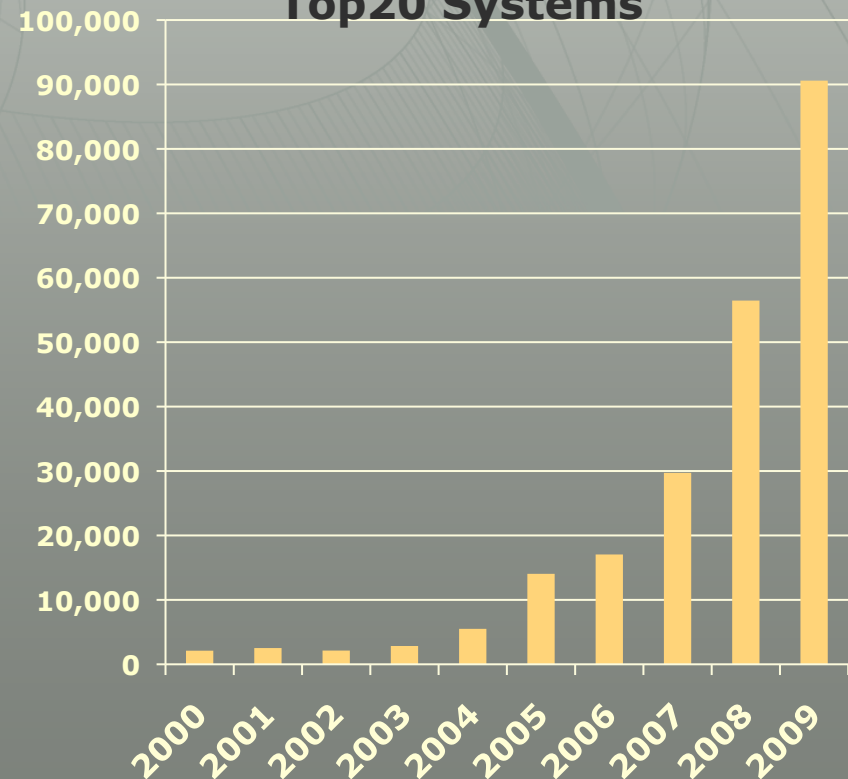
Innovative Computing Laboratory
COMPUTER SCIENCE DEPARTMENT
UNIVERSITY OF TENNESSEE

Centraro, Italy June 2010

Factors that Necessitate to Redesign of Our Software

- » **Steepness of the ascent from terascale to petascale to exascale**
- » Extreme parallelism and hybrid design
 - » Preparing for million/billion way parallelism
- » Tightening memory/bandwidth bottleneck
 - » Limits on power/clock speed implication on multicore
 - » Reducing communication will become much more intense
 - » Memory per core changes, byte-to-flop ratio will change
- » Necessary Fault Tolerance
 - » MTTF will drop
 - » Checkpoint/restart has limitations

Average Number of Cores Per Supercomputer for Top20 Systems

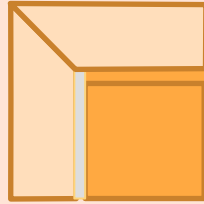


Software infrastructure does not exist today

Linpack Evolution

Software/Algorithms follow hardware evolution in time

LINPACK (70's)
(Vector operations)

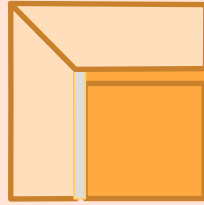


Rely on
- Level-1 BLAS
operations

Linpack (R)Evolution

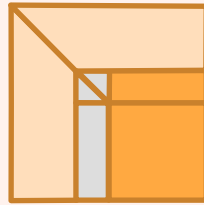
Software/Algorithms follow hardware evolution in time

LINPACK (70's)
(Vector operations)



Rely on
- Level-1 BLAS
operations

LAPACK (80's)
(Blocking, cache
friendly)

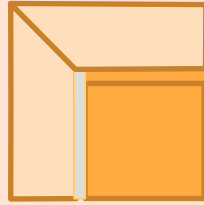


Rely on
- Level-3 BLAS
operations

Linpack Evolution

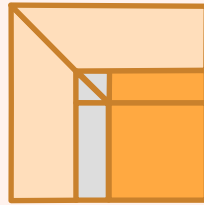
Software/Algorithms follow hardware evolution in time

LINPACK (70's)
(Vector operations)



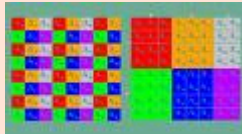
Rely on
- Level-1 BLAS
operations

LAPACK (80's)
(Blocking, cache
friendly)



Rely on
- Level-3 BLAS
operations

ScaLAPACK (90's)
(Distributed Memory)

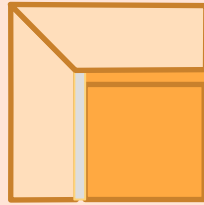


Rely on
- PBLAS Mess
Passing

Linpack Evolution

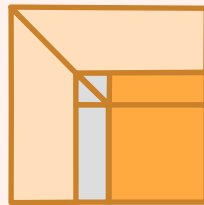
Software/Algorithms follow hardware evolution in time

LINPACK (70's)
(Vector operations)



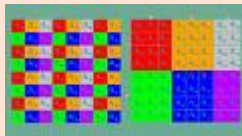
Rely on
- Level-1 BLAS operations

LAPACK (80's)
(Blocking, cache friendly)



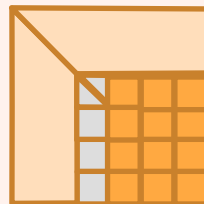
Rely on
- Level-3 BLAS operations

ScaLAPACK (90's)
(Distributed Memory)



Rely on
- PBLAS Mess Passing

PLASMA (00's)
New Algorithms
(many-core friendly)

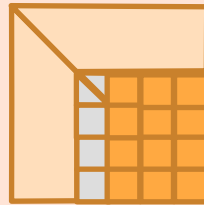


Rely on
- a DAG/scheduler
- block data layout
- some extra kernels

Linpack Evolution

Software/Algorithms follow hardware evolution in time

PLASMA (00's)
New Algorithms
(many-core friendly)



Rely on

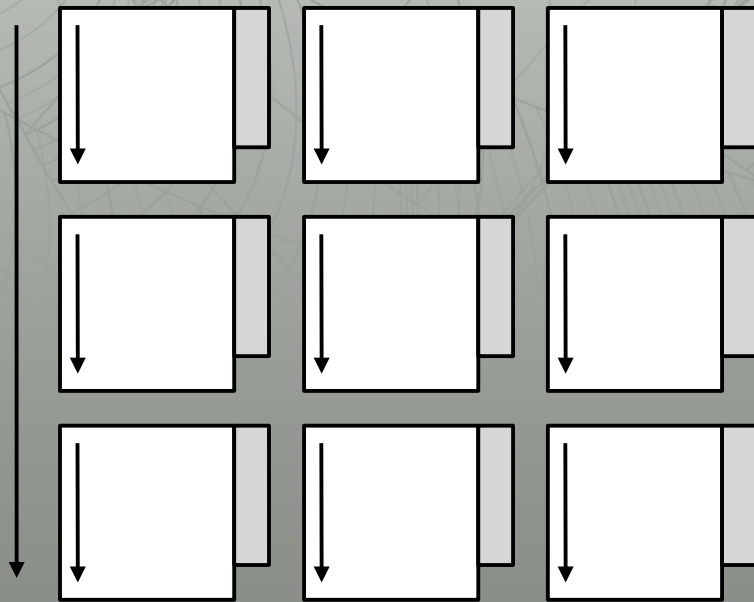
- a DAG/scheduler
- block data layout
- some extra kernels

Those new algorithms

- have a very **low granularity**, they scale very well (multicore, petascale computing, ...)
- **removes of dependencies** among the tasks, (multicore, distributed computing)
- **avoid latency** (distributed computing, out-of-core)
- **rely on fast kernels**

Those new algorithms need new kernels and rely on efficient scheduling algorithms.

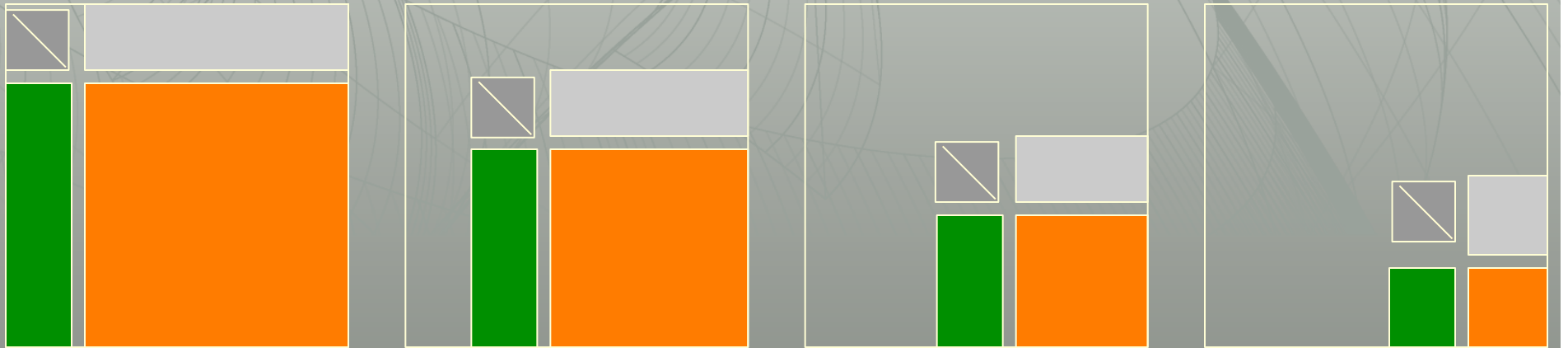
The algorithmic challenge



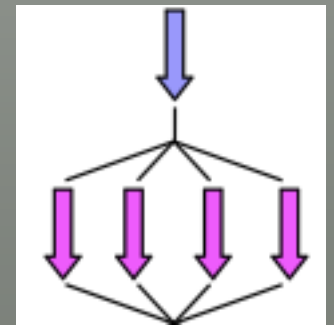
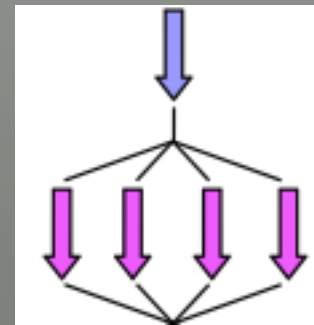
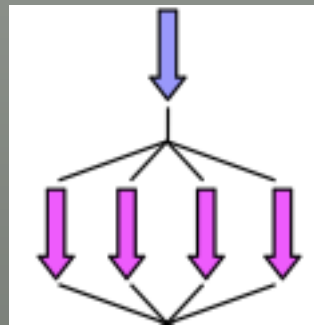
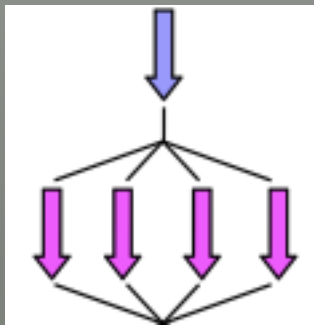
- ◆ Tiled
- ◆ Column-major / column-major
- ◆ Flat (no indirection)

- » Asynchronicity
 - » Avoid fork-join (Bulk sync design)
- » Dynamic Scheduling
 - » Out of order execution
- » Fine Granularity
 - » Independent block operations
- » Locality of Reference
 - » Data storage – Block Data Layout

LAPACK LU

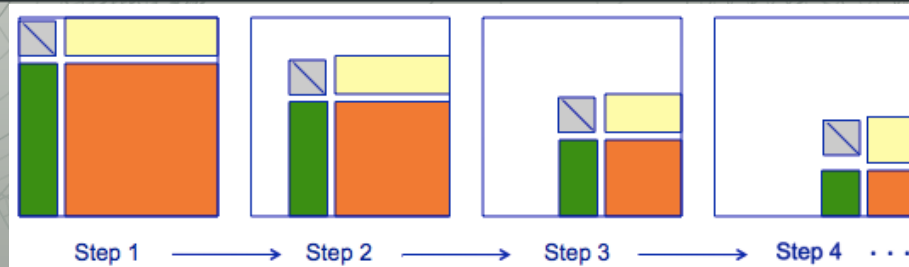


Step 1 → Step 2 → Step 3 → Step 4 . . .

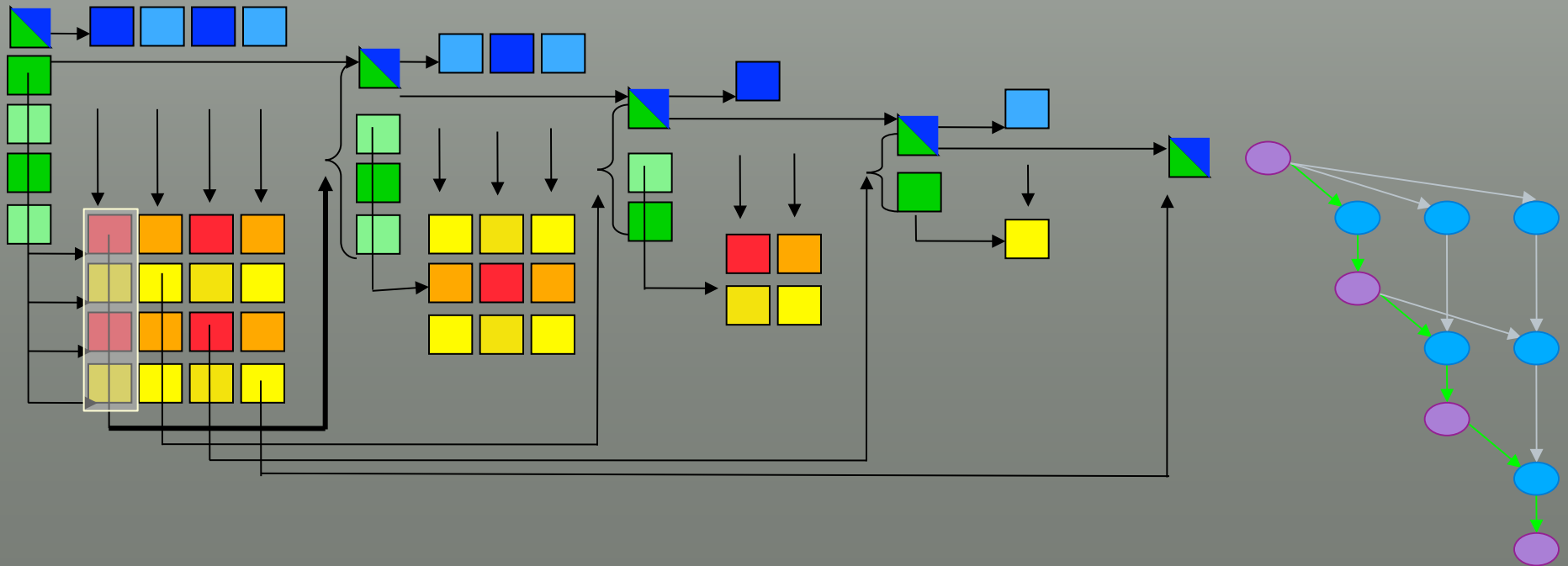


» Fork-join, bulk synchronous processing

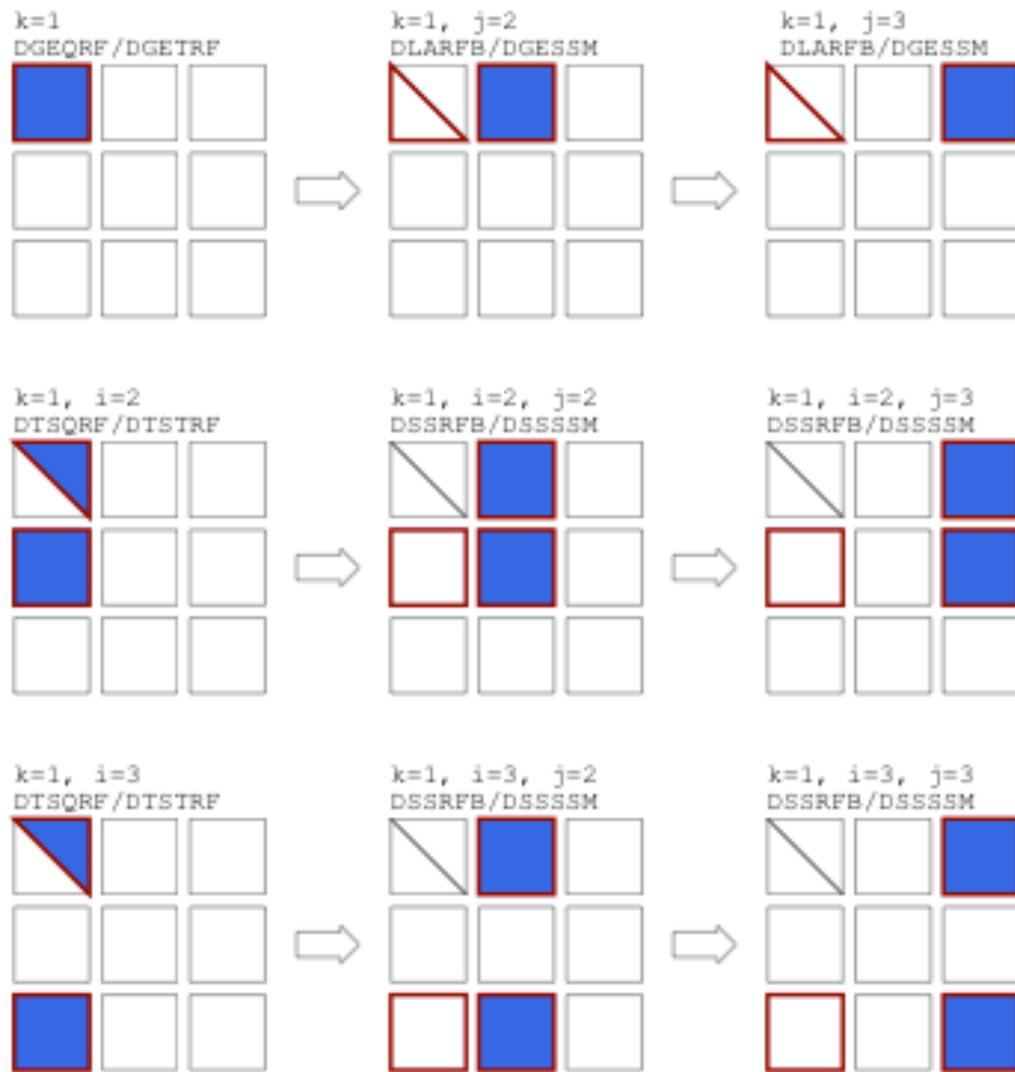
Parallel Tasks in LU



- » Expose the intrinsic parallelism: break into smaller tasks and remove dependencies

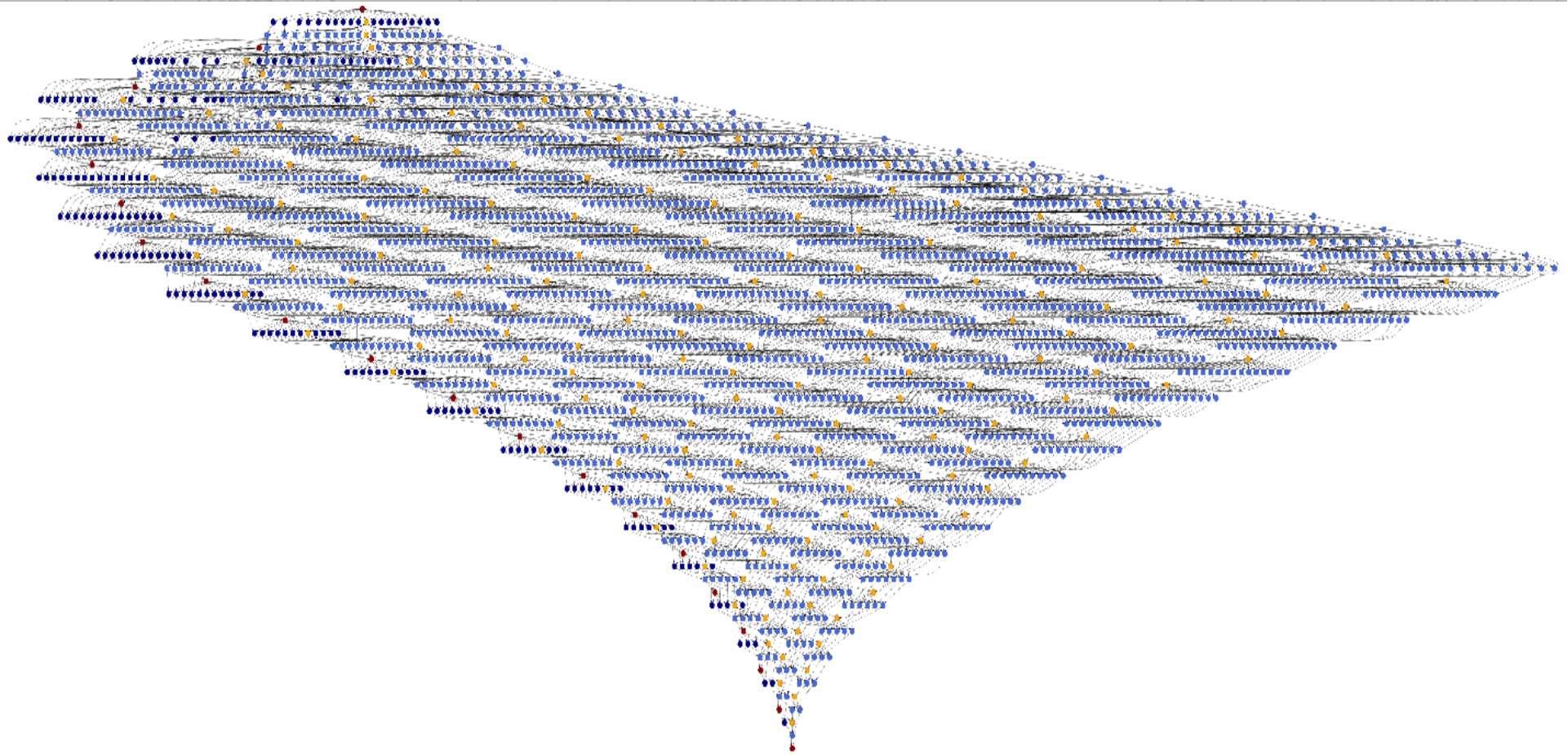


Expose the intrinsic parallelism



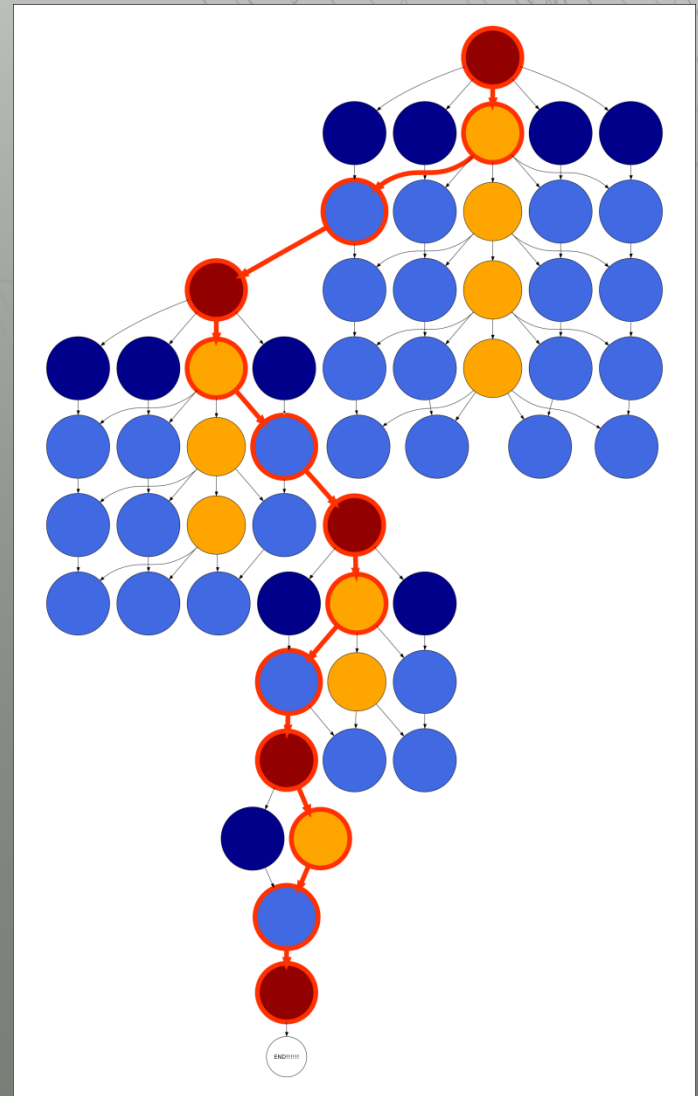
- » The three amigos
- » Example of QR factorization
 - » 4 basic kernels
- » LU identical to QR except using different kernels
- » Cholesky slightly different due to the matrix symmetry

LU DAG representation



A quite simple problem ...

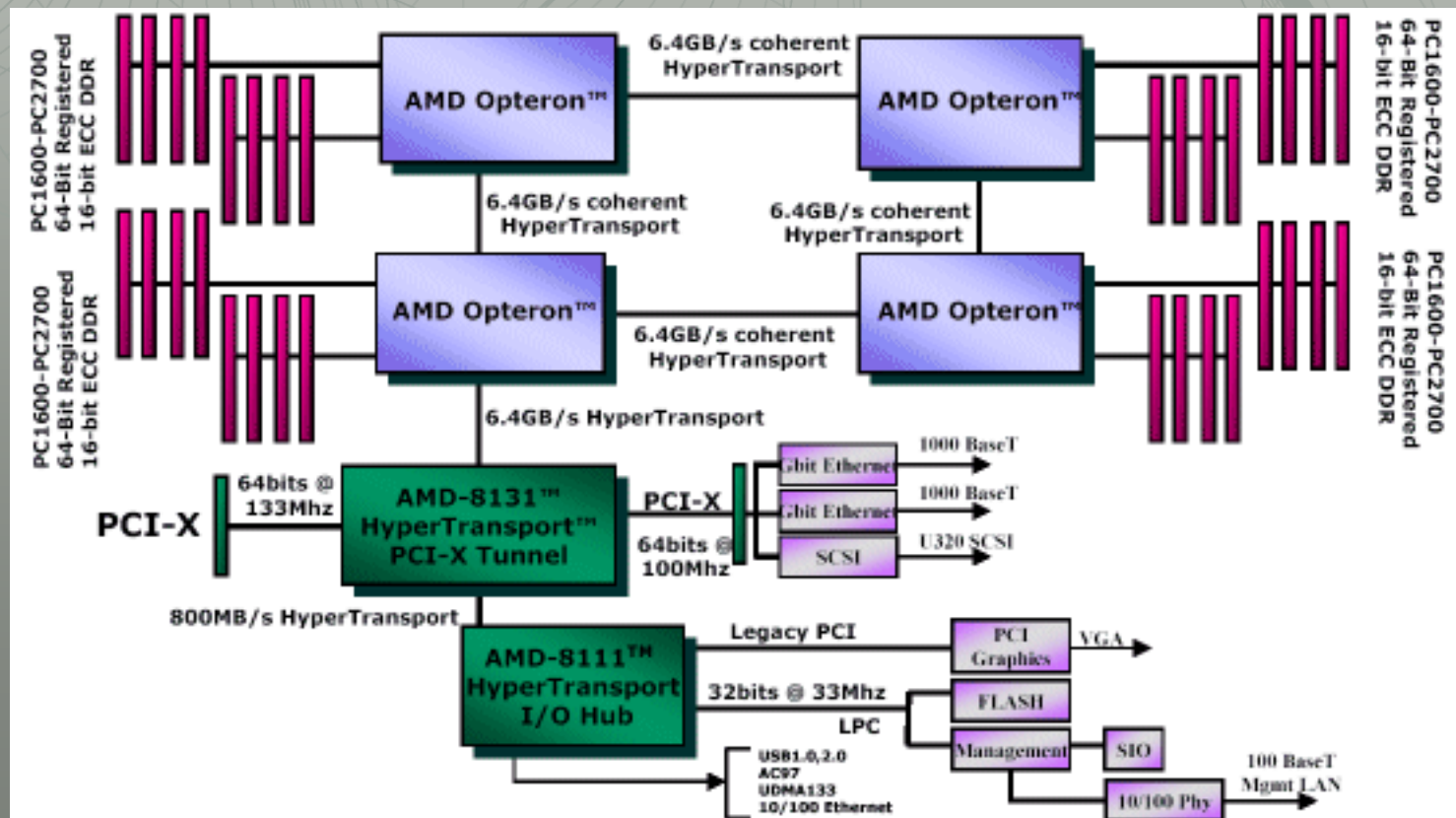
- » We would generate the DAG, find the critical path and execute it.
- » DAG too large to generate ahead of time
 - » Not explicitly generate
 - » Dynamically generate the DAG as we go
- » Machines will have large number of cores in a distributed fashion
 - » Will have to engage in message passing
 - » Distributed management
 - » Locally have a run time system



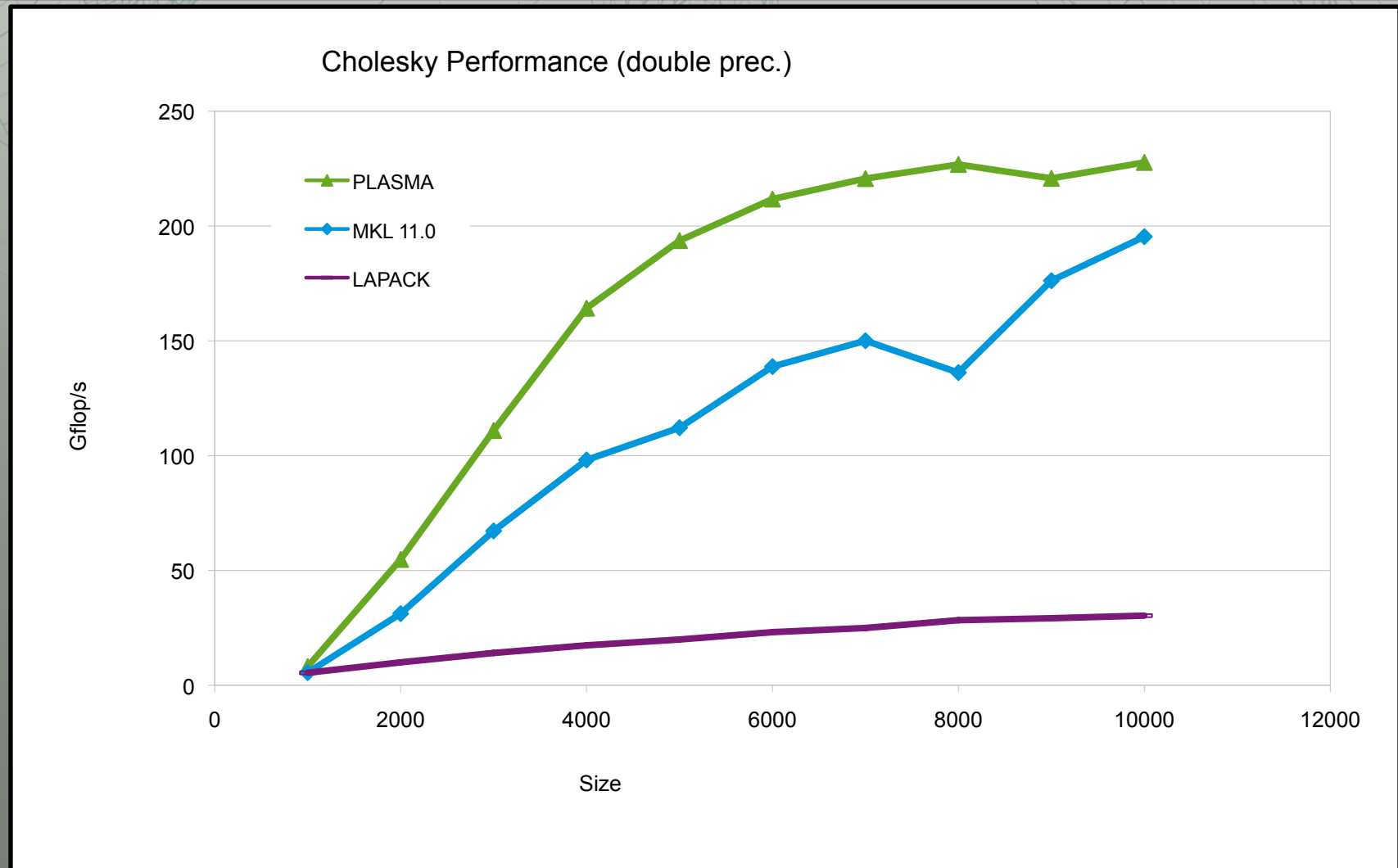
What is PLASMA?

- Dense linear algebra software library
 - Linear systems & least squares (LU, Cholesky, QR/LQ)
 - Eigenvalues & singular values
- Multicore processors
 - Multi-socket multi-core / Shared memory systems
 - NUMA systems
- What is next:
 - GPU acceleration – MAGMA
 - Distributed Memory – DAGuE / DPLASMA

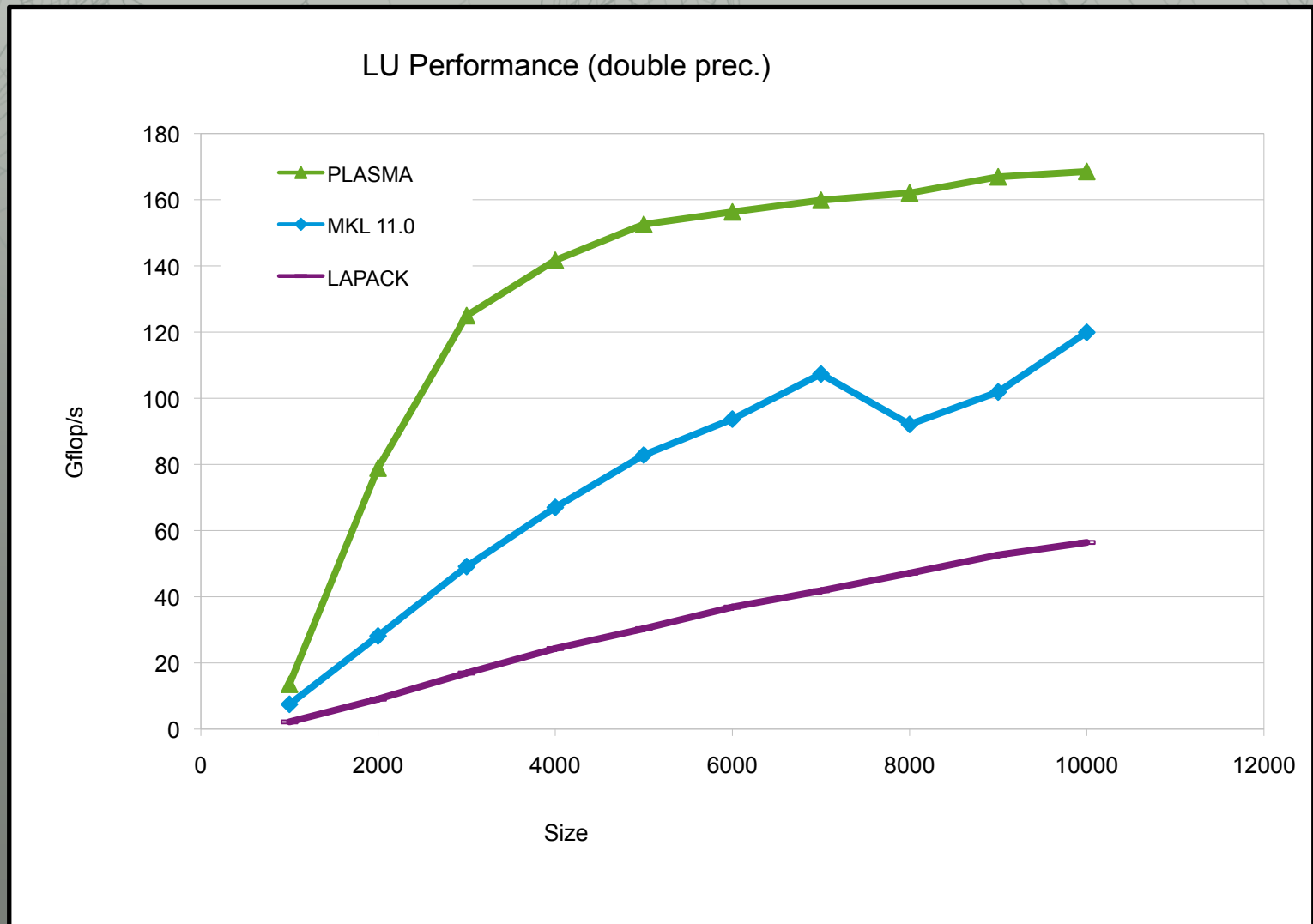
If the current architectures ...



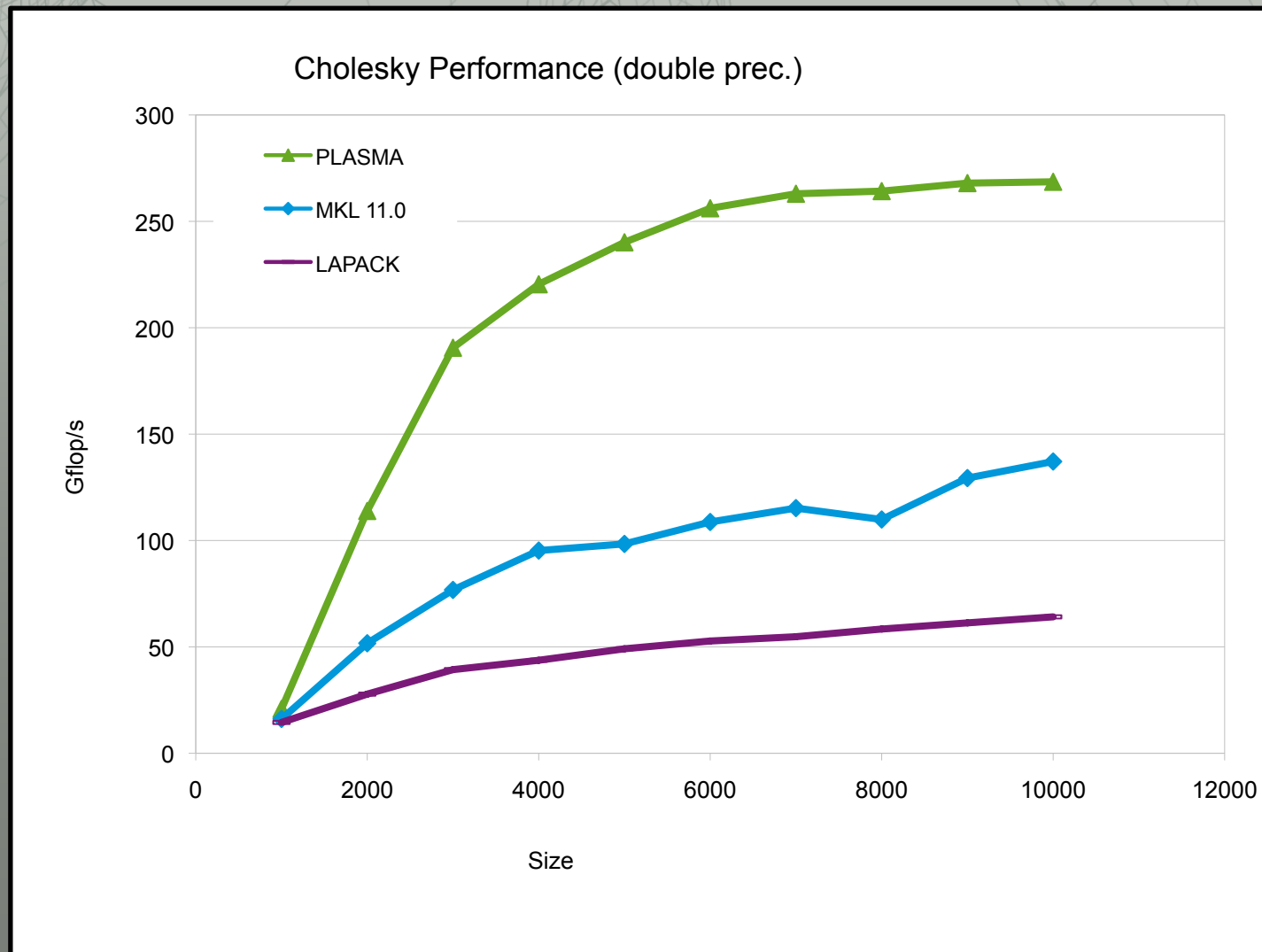
PLASMA Performance (Cholesky, 48 cores)



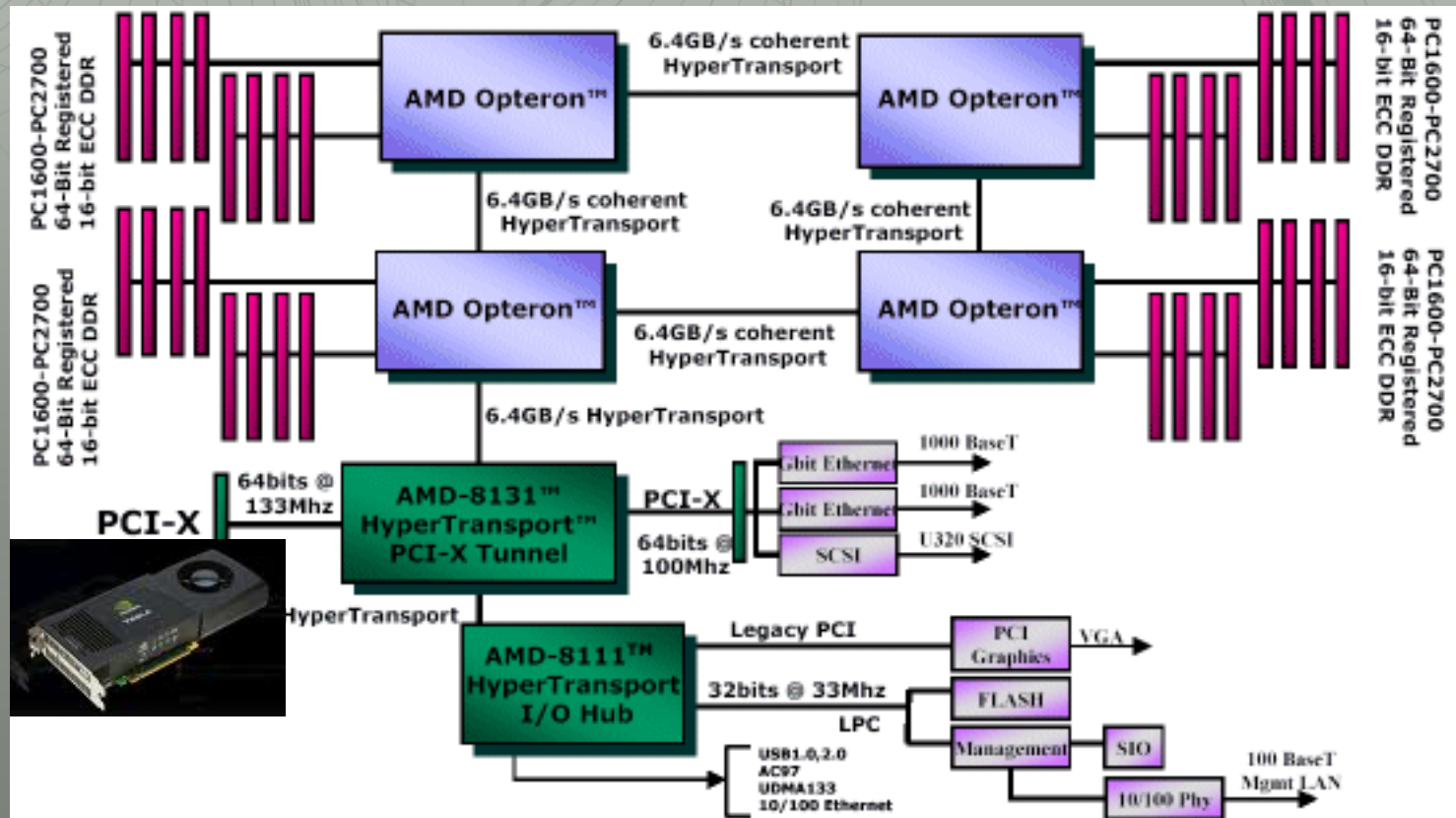
PLASMA Performance (LU, 48 Cores)



PLASMA Performance (QR, 48 cores)



If the current architectures ...



NVIDIA Tesla C2050 (Fermi), GF100 Chip

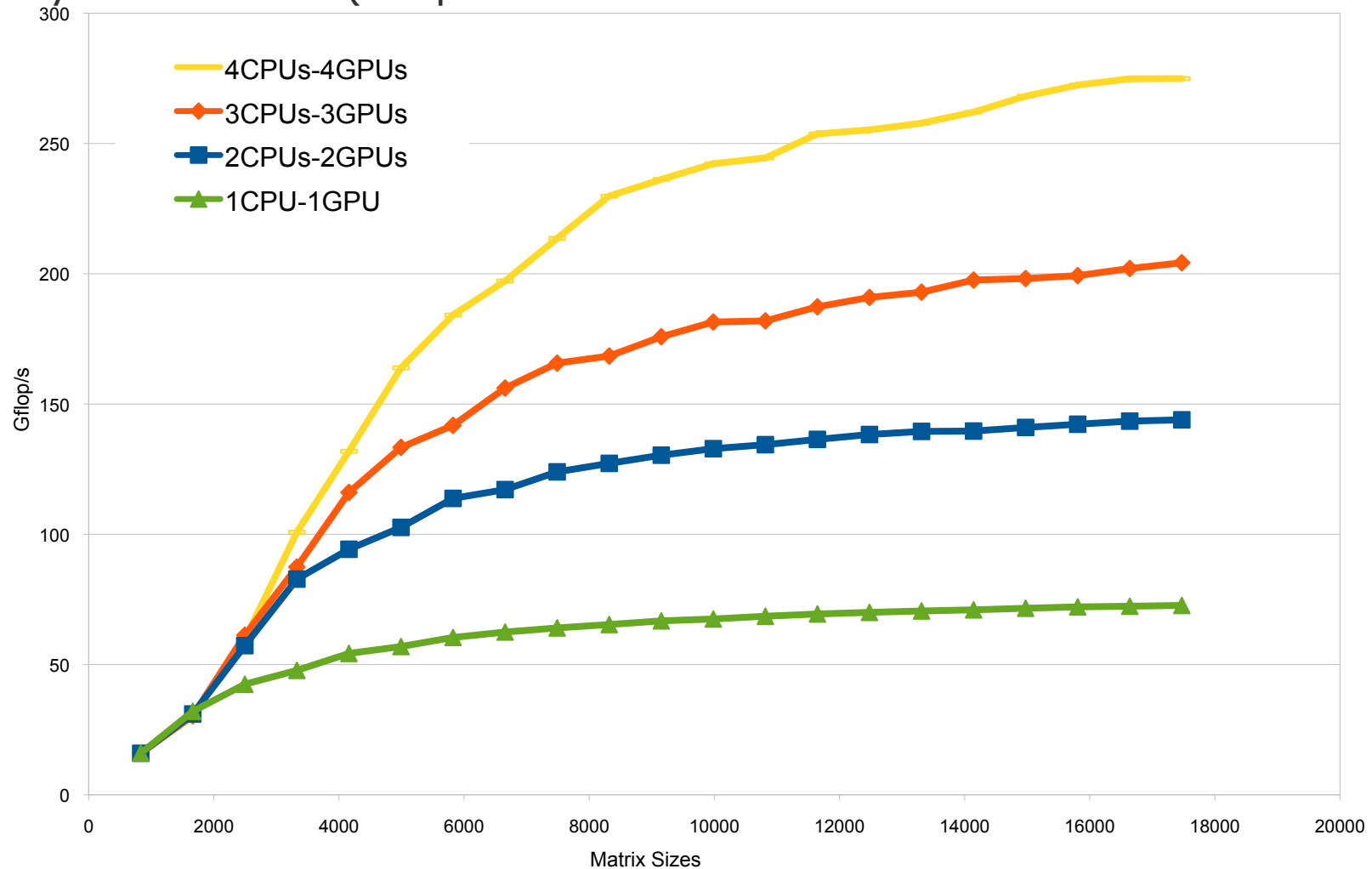
- » Marketing truth
 - » 14 processing cores (448 ALUs)
 - » 32 CUDA Cores (SIMD functional units) per core
 - » 1 mul-add (2 flops) per ALU (2 flops/cycle)
 - » Best case theoretically: 448 mul-adds
 - » 1.15 GHz clock
 - » $14 * 32 * 2 * 1.15 = 1.03 \text{ Tflop/s}$ peak
 - » All this is single precision
 - » Double precision is half this rate, 515 Gflop/s
- » Dense Linear Algebra truth
 - » 144 GB/s bus, 3 GB memory
 - » In SP SGEMM performance 580 Gflop/s
 - » In DP DGEMM performance 300 Gflop/s
 - » Power: 247 W
 - » Interface PCIex16

Processing Core



Cholesky with Multiple GPUs

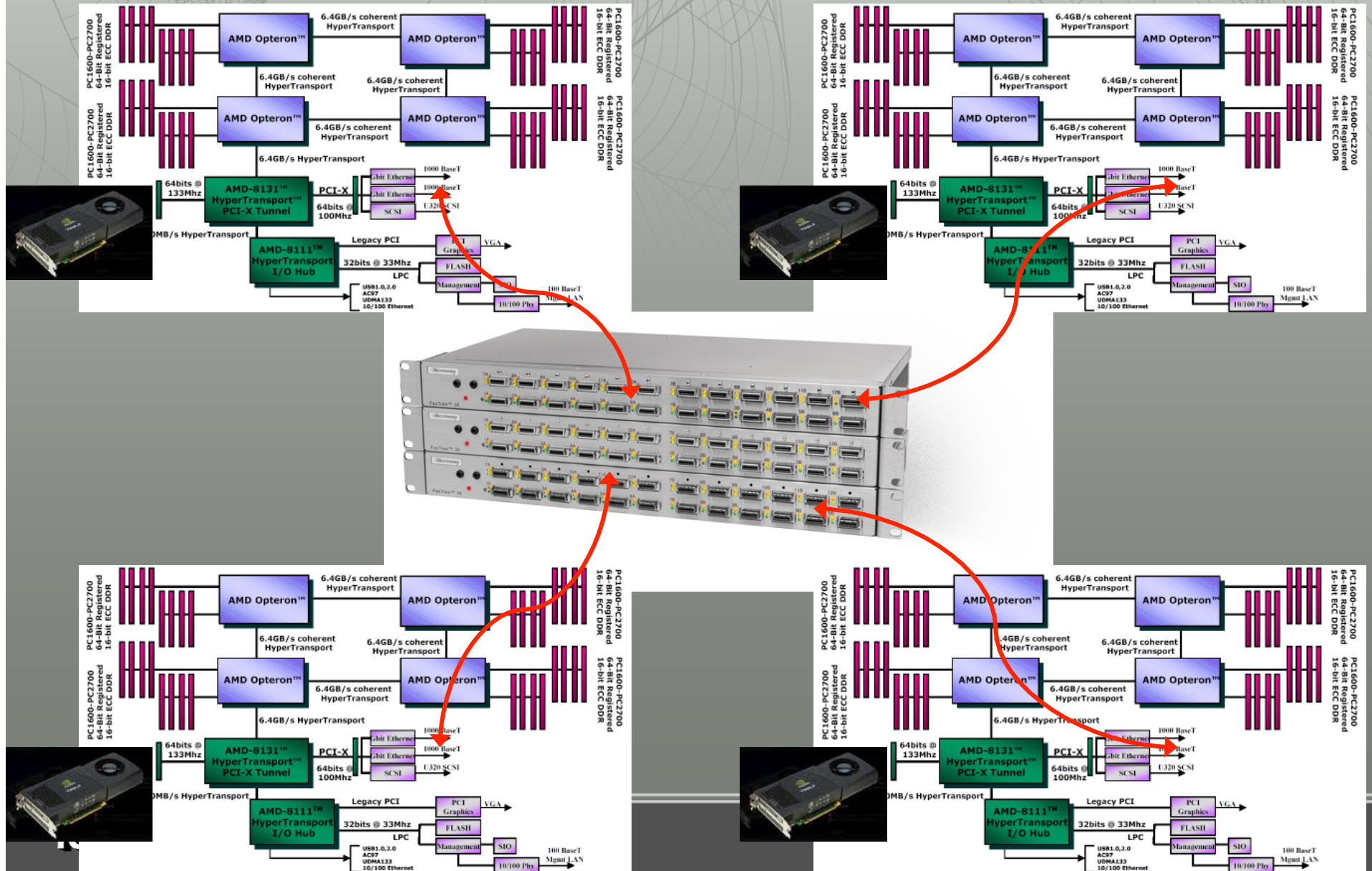
hybrid DPOTRF (4 Opteron 1.8GHz and 4 GPU TESLA C1060 1.44GHz)

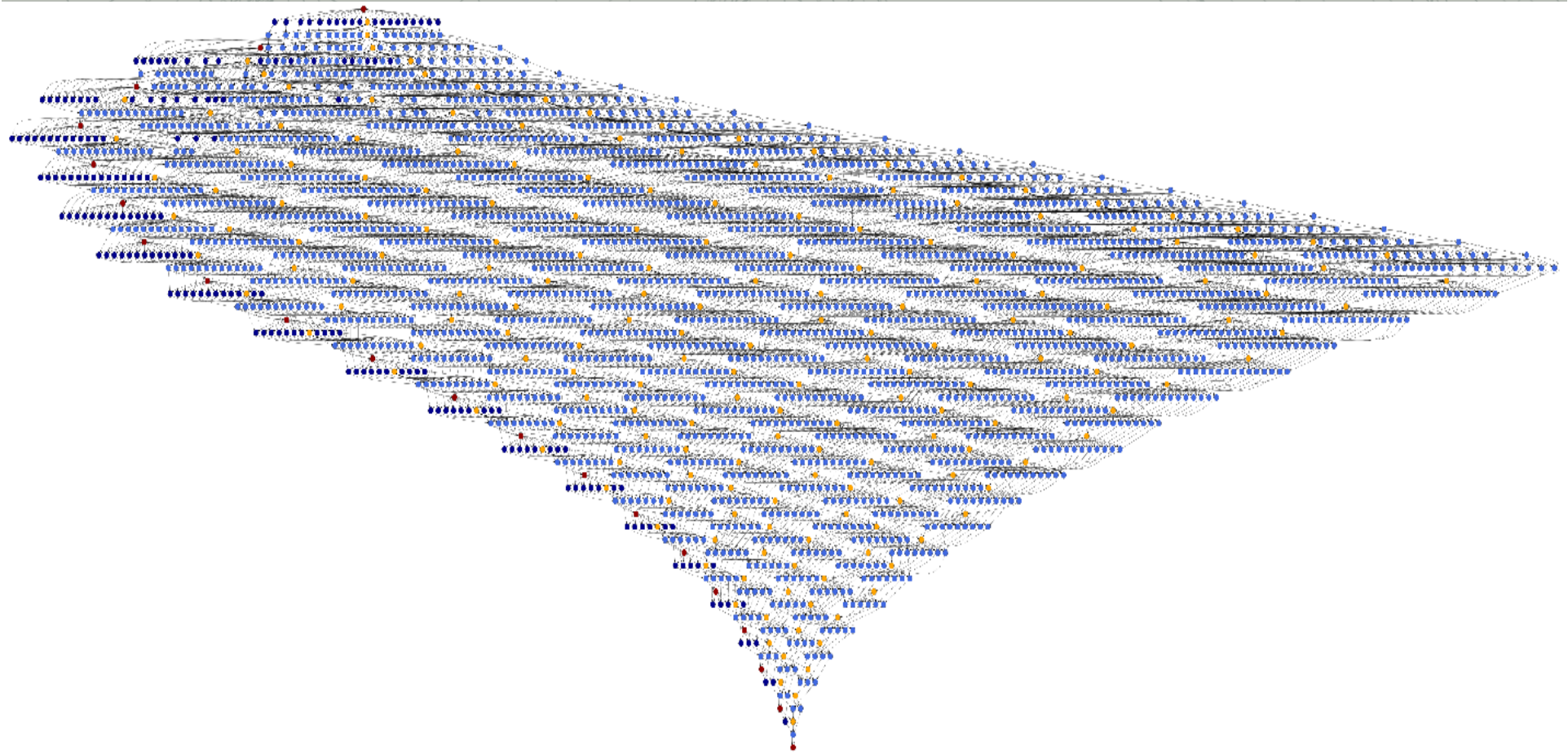


MAGMA Software

- Available through MAGMA's homepage
<http://icl.cs.utk.edu/magma/>
- Included are the 3 one-sided matrix factorizations
- Iterative Refinement Algorithm (Mixed Precision)
- Standard (LAPACK) data layout and accuracy
- Two LAPACK-style interfaces
 - » CPU interface: both input and output are on the CPU
 - » GPU interface: both input and output are on the GPU

Current Architectures





DPLASMA / DAGuE

- » DAGuE: the runtime
 - » Deploy a DAG on a heterogeneous distributed environment
 - » Architecture aware
 - » Minimize data movements (in and out the node)
 - » Enforce data locality (cache / NUMA / GPU)
 - » Move the data across nodes
- » DPLASMA: an algebraic description of a DAG
 - » Define the data distribution
 - » Describe the algorithm at a high level
 - » A powerful description language (?)

Kernels description

```
POTRF(k) (high_priority)
RW T <- type = [tile]
    -> type = [tile]
BODY [core]
    CORE(potrf, (uplo, NB, T, NB,
                &INFO))
END
```

```
SYRK(k,n) (high_priority)
R  A <- type = [tile]
RW T <- type = [tile]
    -> type = [tile]
BODY [core]
    CORE(syrk, (Lower, NoTrans, NB, NB, -1.0,
                A, NB, 1.0, T, NB))
END
```

```
TRSM(k,n) (high_priority)
R  T <- type = [tile]
RW C <- type = [tile]
    -> type = [tile]
BODY [core]
    CORE(trsm, (Right, Lower, Trans, NonUnit,
                NB, NB, 1.0, T, NB, C, NB))
END
```

```
GEMM(k,m,n)
R  A <- type = [tile]
R  B <- type = [tile]
RW C <- type = [tile]
    -> type = [tile]
BODY [core]
    CORE(gemm, (NoTrans, Trans, NB, NB, NB,
                -1.0, B, NB, A, NB, 1.0, C, NB))
END
BODY [cuda]
    ...
END
```

Algebraic dependencies description

```
POTRF(k)
  k = [0 .. SIZE-1]
: (k / rtileSIZE) % GRIDrows == rowRANK
: (k / ctileSIZE) % GRIDcols == colRANK
  T <- (k == 0) ? A(k, k) : T SYRK(k-1, k)
  -> T TRSM(k, k+1..SIZE-1)
  -> A(k, k)

; (k >= (SIZE - PRI_CHANGE)) ? 10 * (SIZE - k)
* (SIZE - k) * (SIZE - k) : 1000000000
```

```
SYRK(k,n)
  k = [0 .. SIZE-1]
  n = [k+1 .. SIZE-1]
: (n / rtileSIZE) % GRIDrows == rowRANK
: (n / ctileSIZE) % GRIDcols == colRANK
  A <- C TRSM(k, n)
  T <- (k == 0) ? A(n,n) : T SYRK(k-1, n)
  -> (n == k+1) ? T POTRF(k+1) : T SYRK(k+1,n)

; (n >= (SIZE - PRI_CHANGE)) ? 10 * (SIZE - n) *
(SIZE - n) * (SIZE - n) + 1 : 1000000000
```

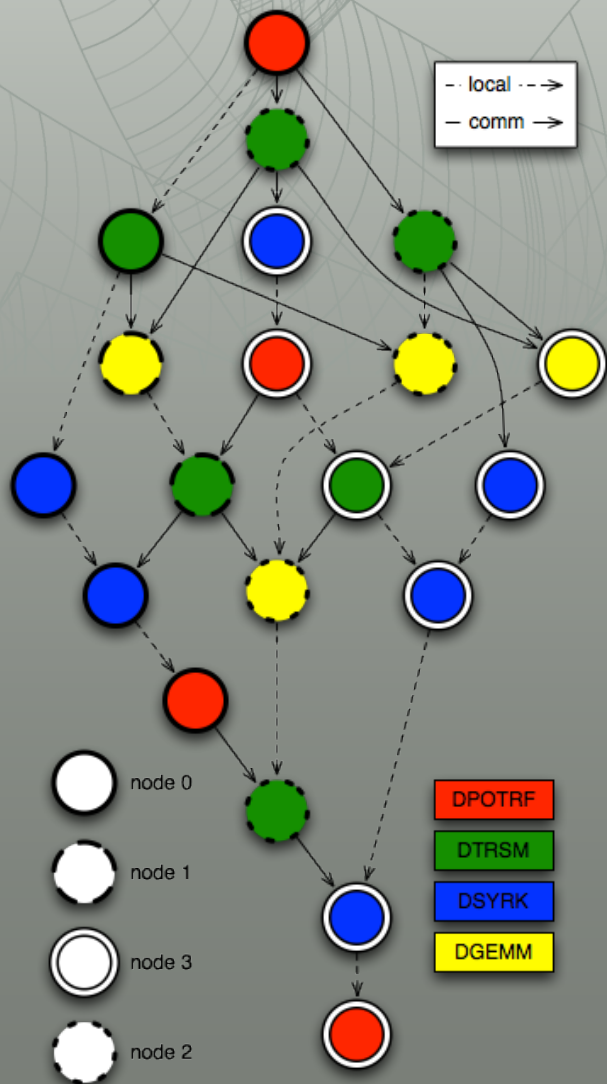
```
TRSM(k,n)
  k = [0 .. SIZE-1]
  n = [k+1 .. SIZE-1]
: (n / rtileSIZE) % GRIDrows == rowRANK
: (k / ctileSIZE) % GRIDcols == colRANK
  T <- T POTRF(k)
  C <- (k == 0) ? A(n, k) : C GEMM(k-1, n, k)
  -> A SYRK(k, n)
  -> A GEMM(k, n+1..SIZE-1, n)
  -> B GEMM(k, n, k+1..n-1)
  -> A(n, k)

; (n >= (SIZE - PRI_CHANGE)) ? 10 * (SIZE - n)
* (SIZE - n) * (SIZE - n) + 2 : 1000000000
```

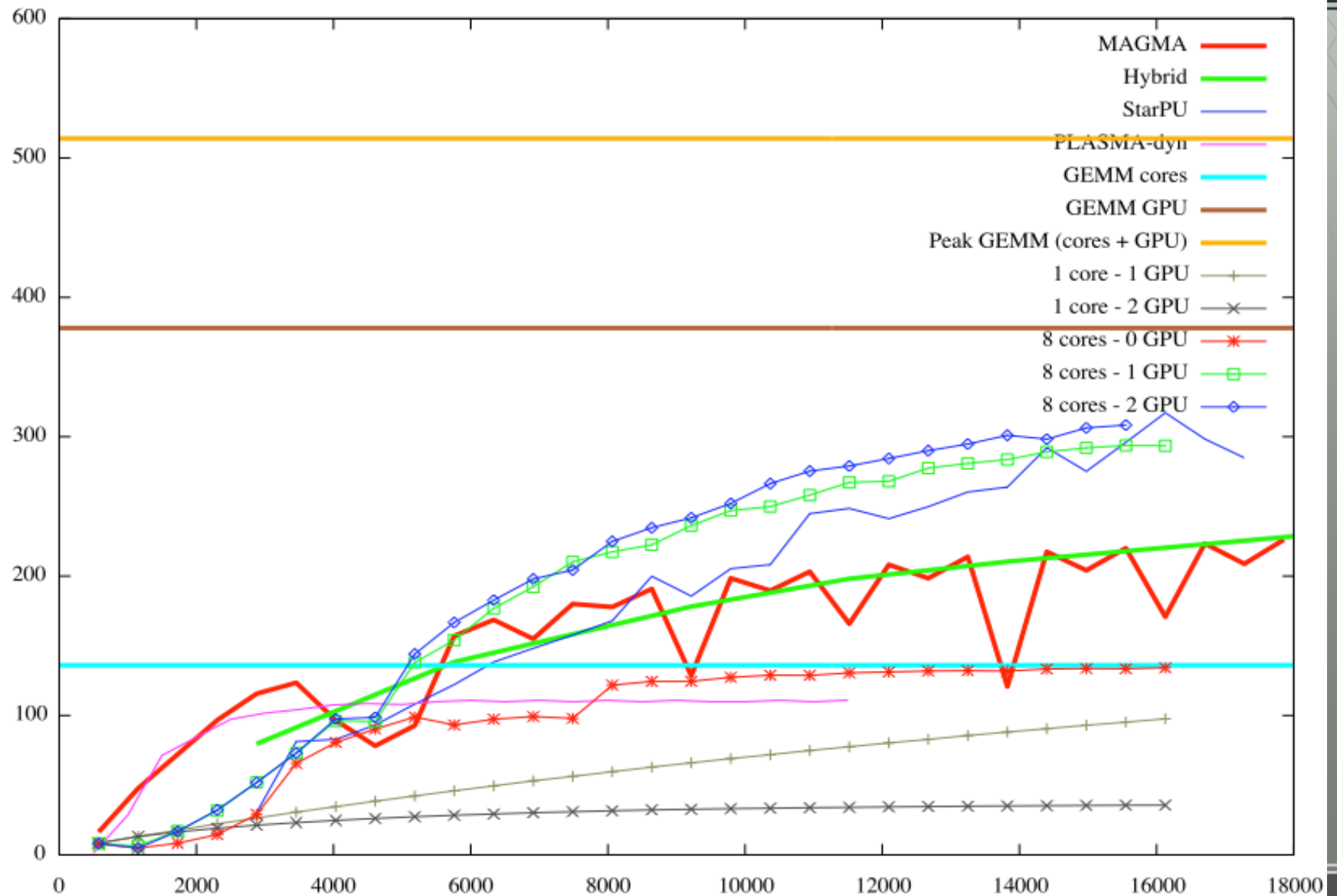
```
GEMM(k,m,n) (assoc(k))
  k = [0 .. SIZE]
  m = [k+2 .. SIZE-1]
  n = [k+1 .. m-1]
: (m / rtileSIZE) % GRIDrows == rowRANK
: (n / ctileSIZE) % GRIDcols == colRANK
  A <- C TRSM(k, n)
  B <- C TRSM(k, m)
  C <- (k == 0) ? A(m, n) : C GEMM(k-1, m, n)
  -> (n == k+1) ? C TRSM(k+1, m) :
      C GEMM(k+1, m, n)

; (m >= (SIZE - PRI_CHANGE)) ? 10 * (SIZE - m)
* (SIZE - m) * (SIZE - m) + 1 : 1000000000
```

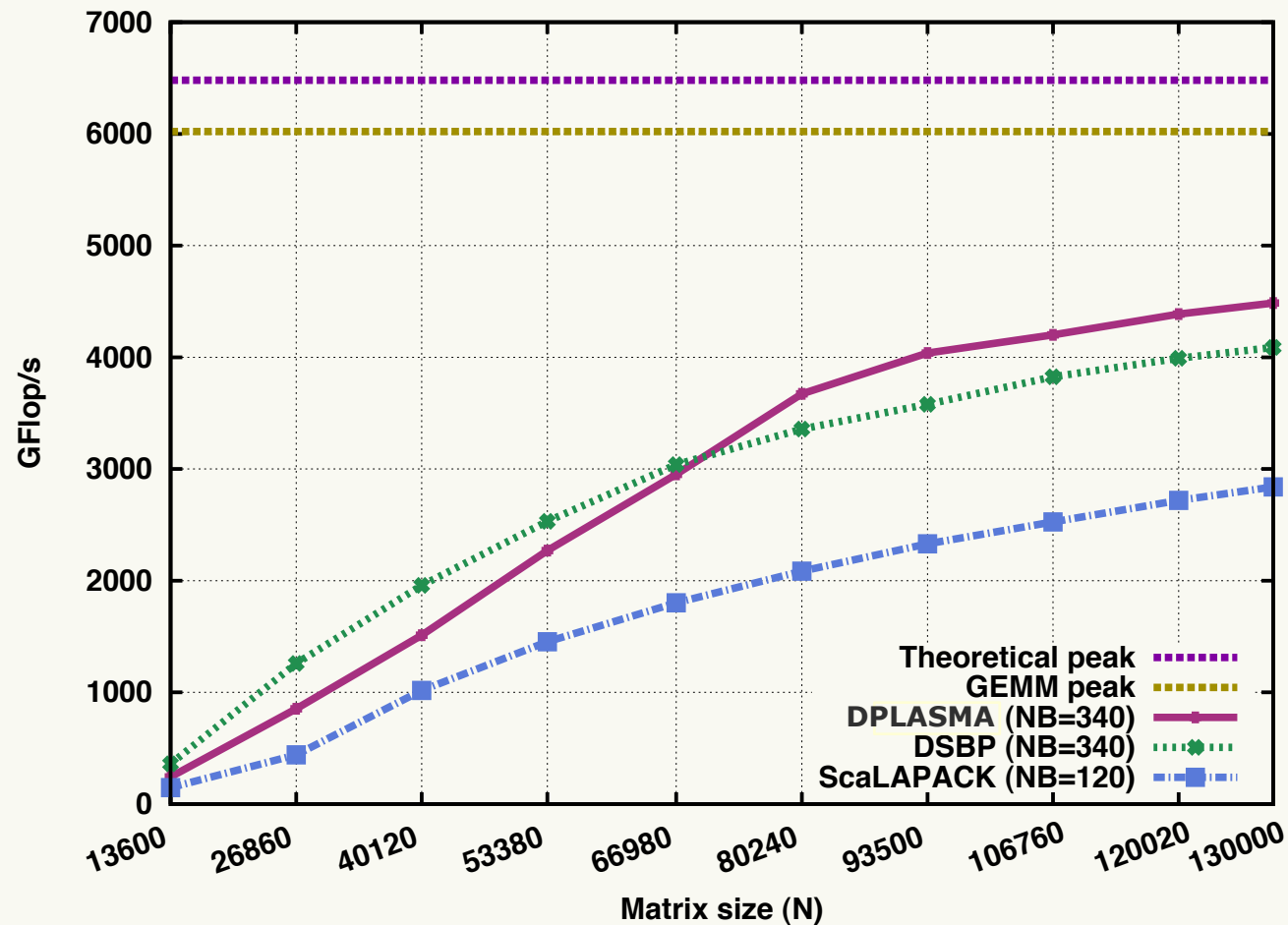
Cholesky (4x4)



Heterogeneous multi-GPU

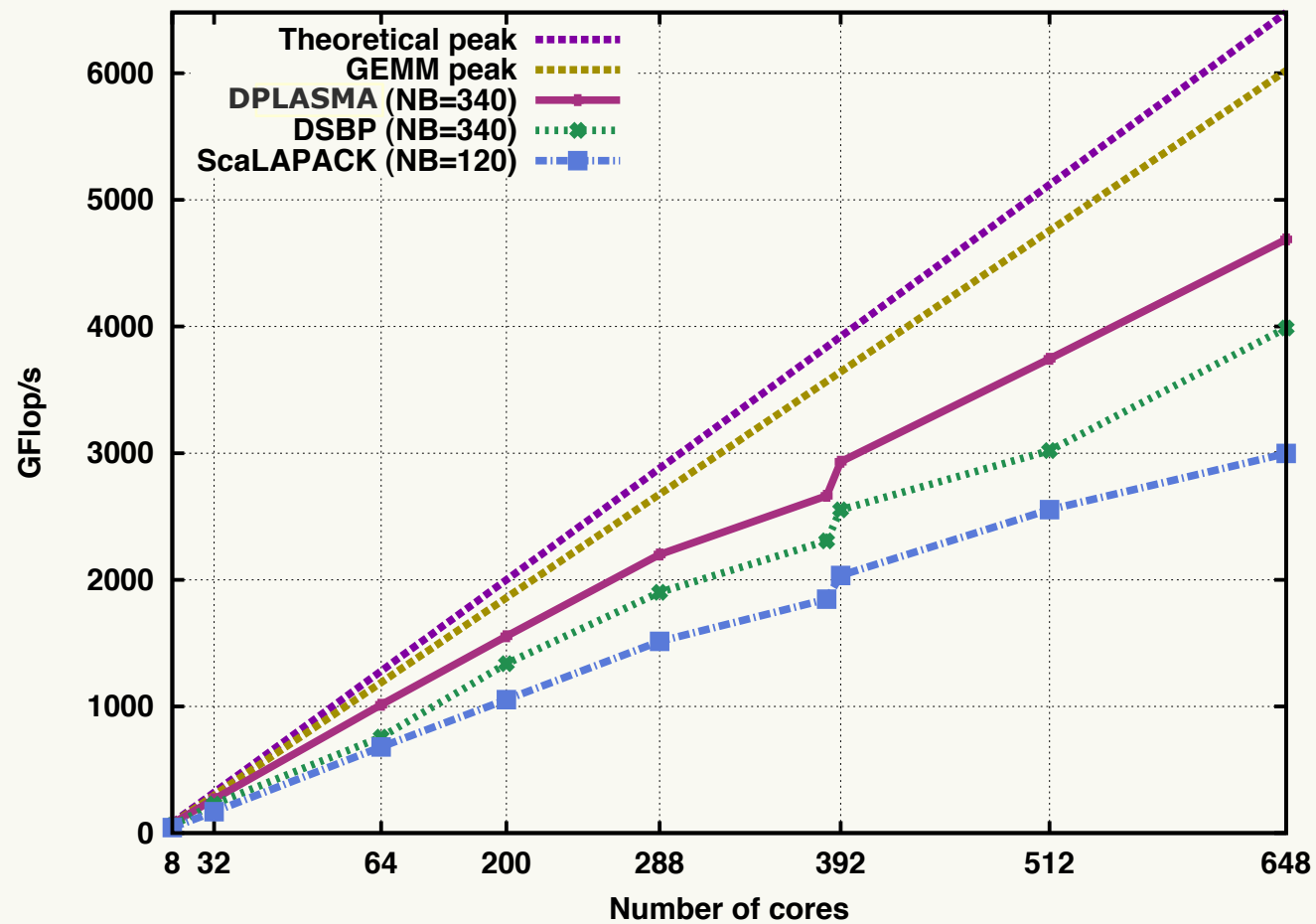


Cholesky (problem size)

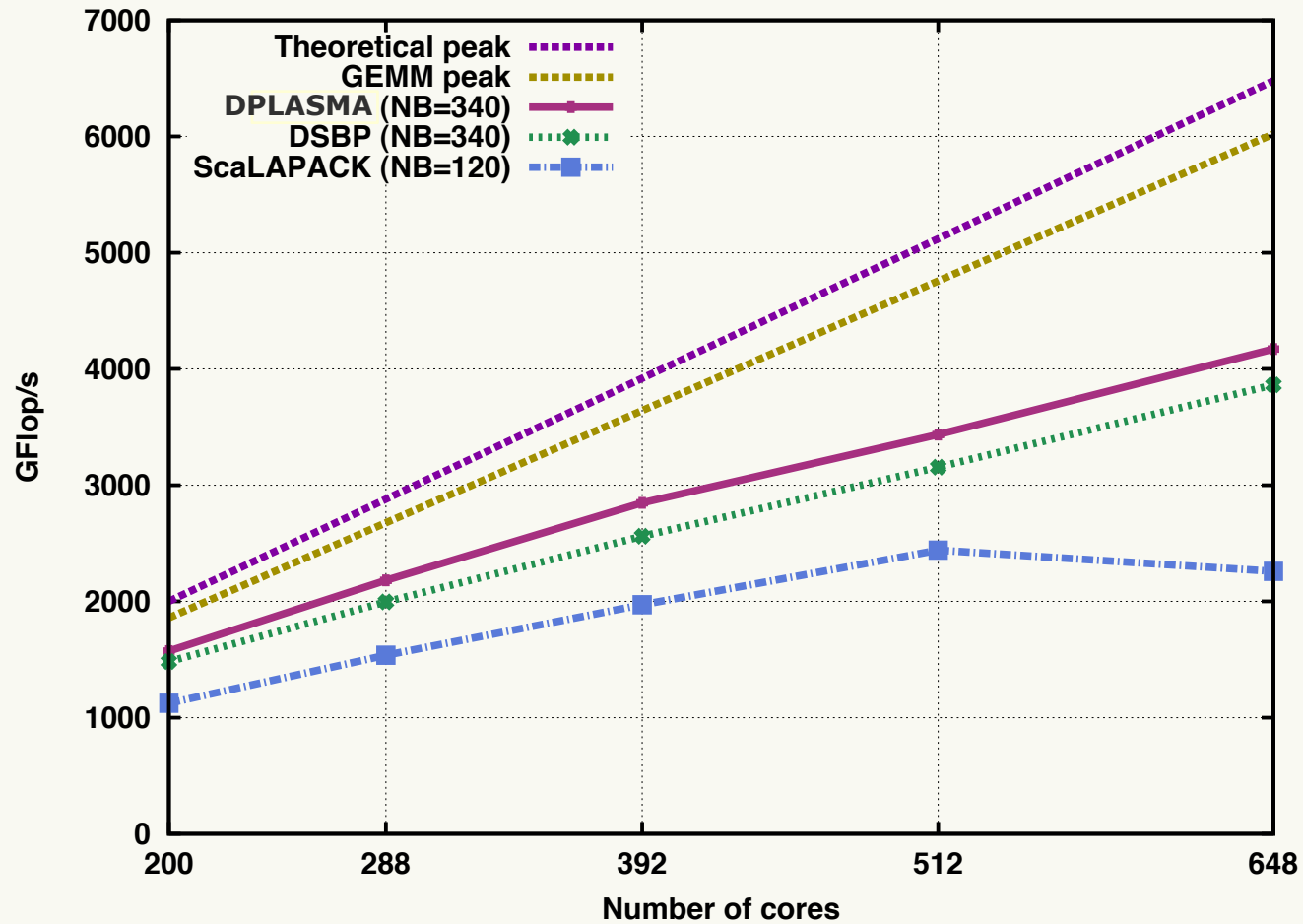


Griffon : 81 nodes, 648 cores, Infiniband 20Gbs

Cholesky (weak scalability)

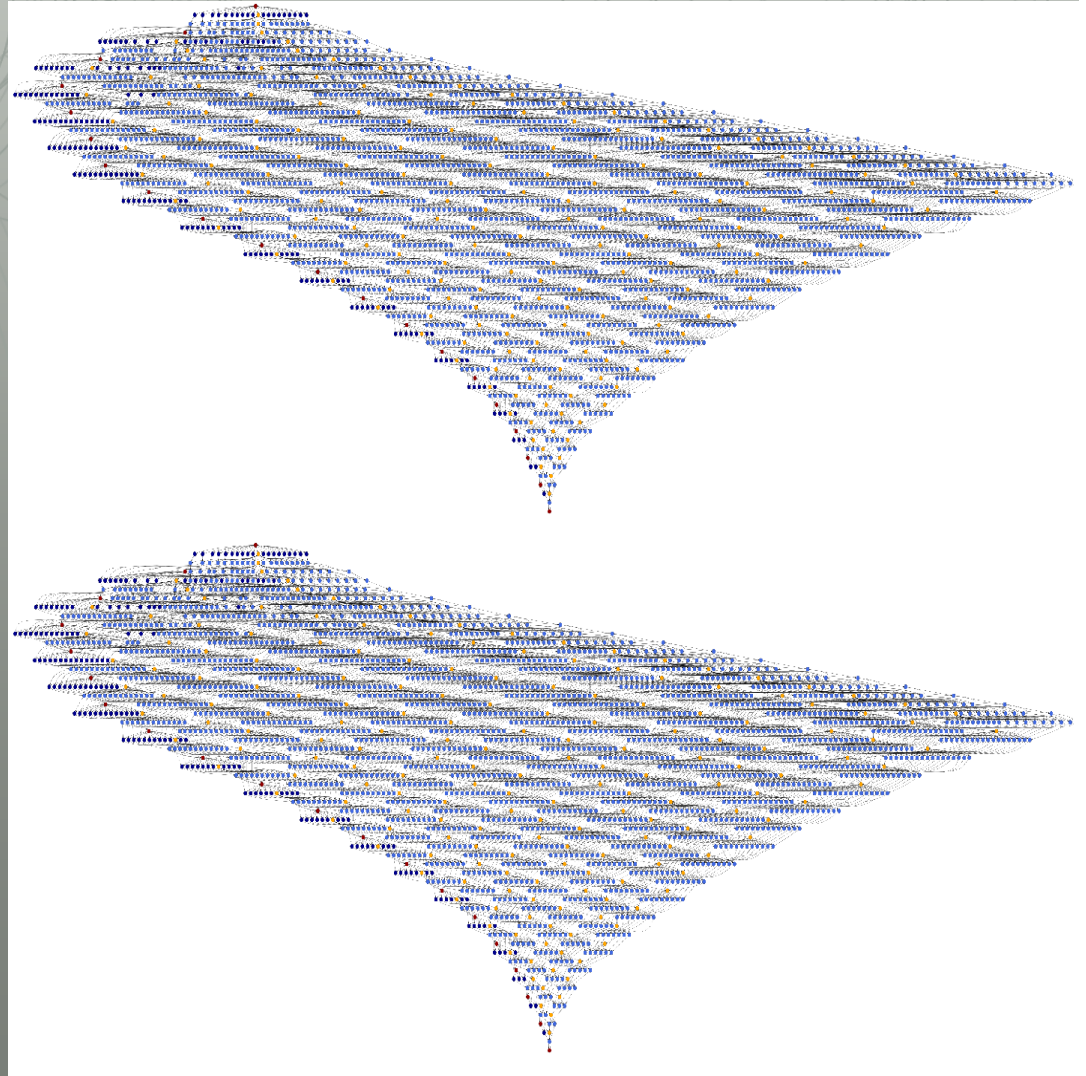


Cholesky (strong scalability)



Composability

- » Totally remove the need for synchronization
- » Follow the data flow between algebraic description of DAGs
- » Shorten the time to completion



Composability

