Vector operations, tiled operations, distributed execution, task graphs, ...

What next ?

Samuel Thibault, University of Bordeaux
Inria STORM Team

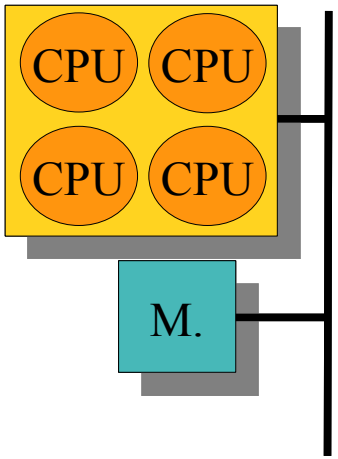
High-Performance Computing

- Frontier supercomputer
- #1 on top500.org LINPACK benchmark
- 1.102 EFlop/s
- 9472 nodes
  - 1 AMD Epyc CPU
  - 4 AMD Instinct 250X GPUs
  - 4TB flash memory
  - Infinity Fabric interconnect
- Slingshot 100GB/s network
- 21.1 MW
- Also #1 Green 500

High-Performance Computing

Classical parallel programming

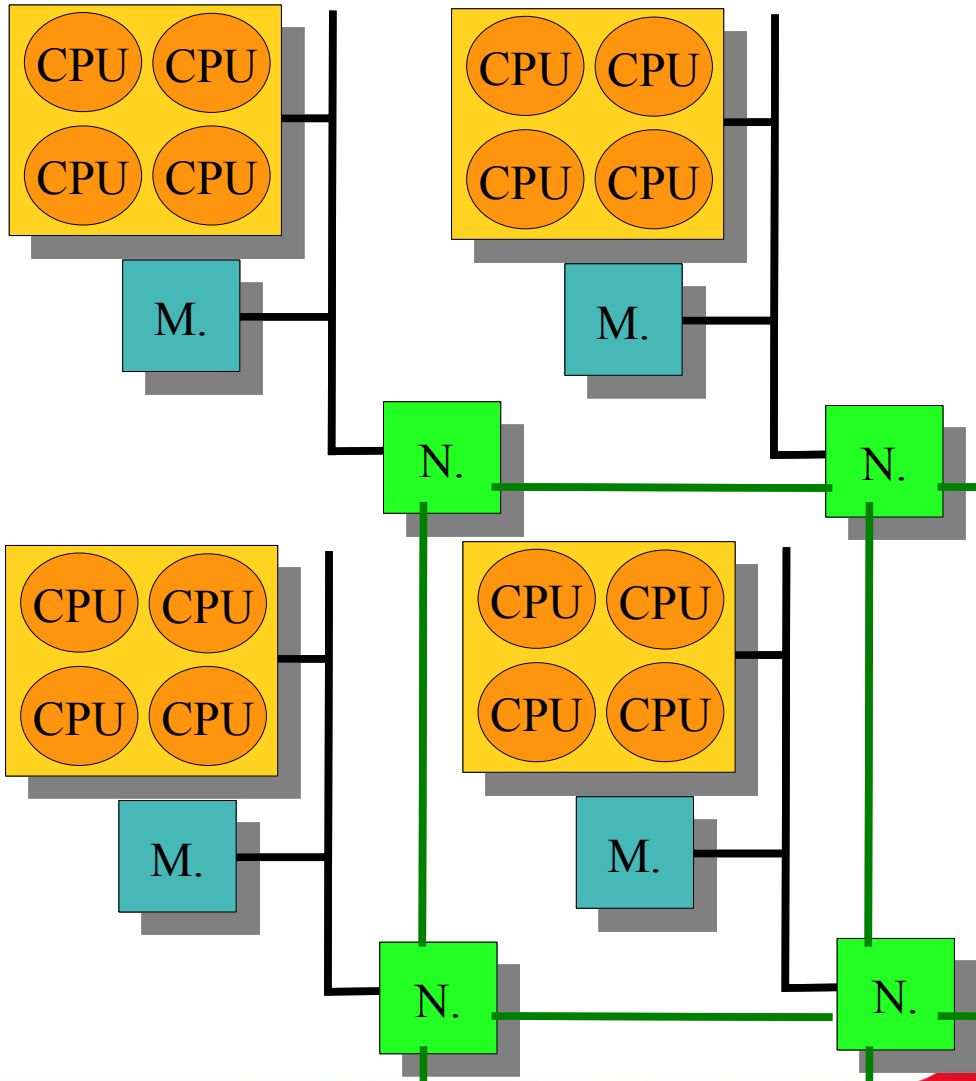
- threads



High-Performance Computing

Classical parallel programming

- threads
- MPI+threads



High-Performance Computing

Classical parallel programming

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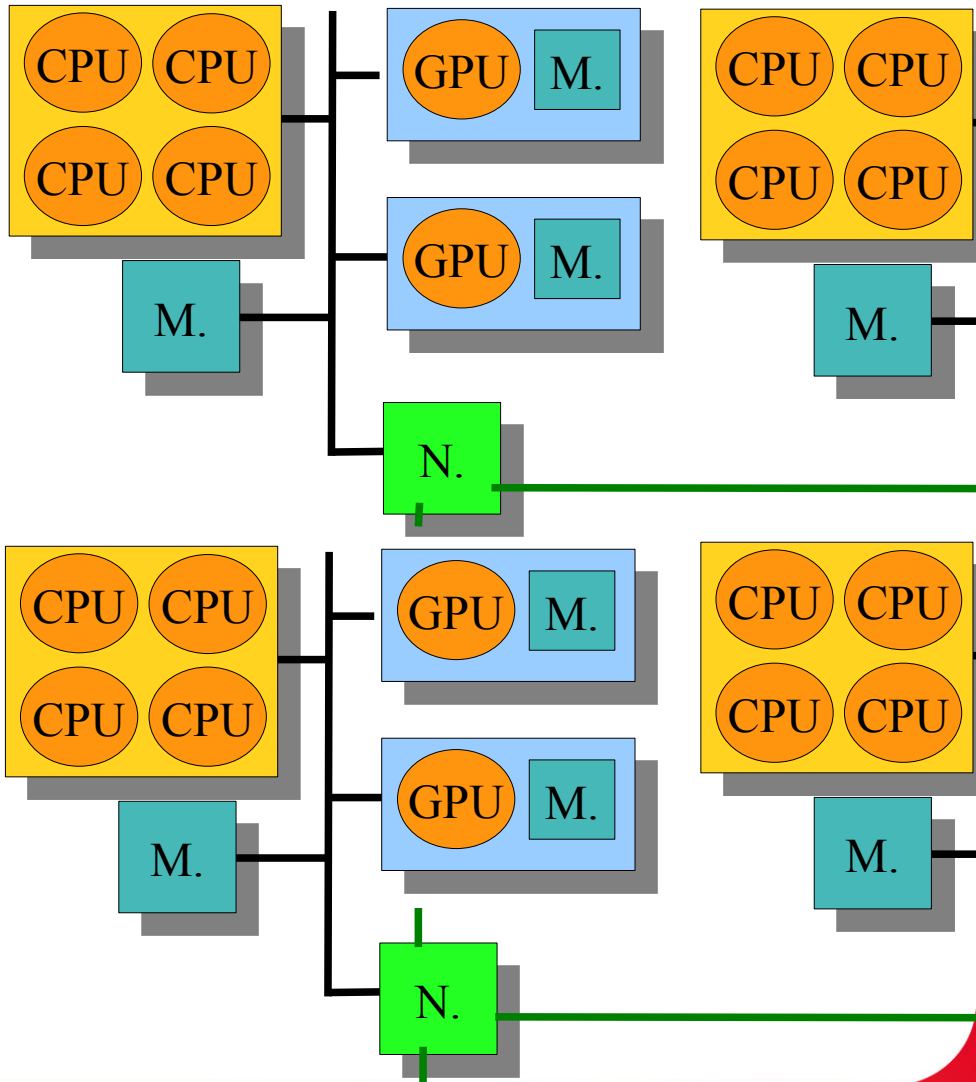
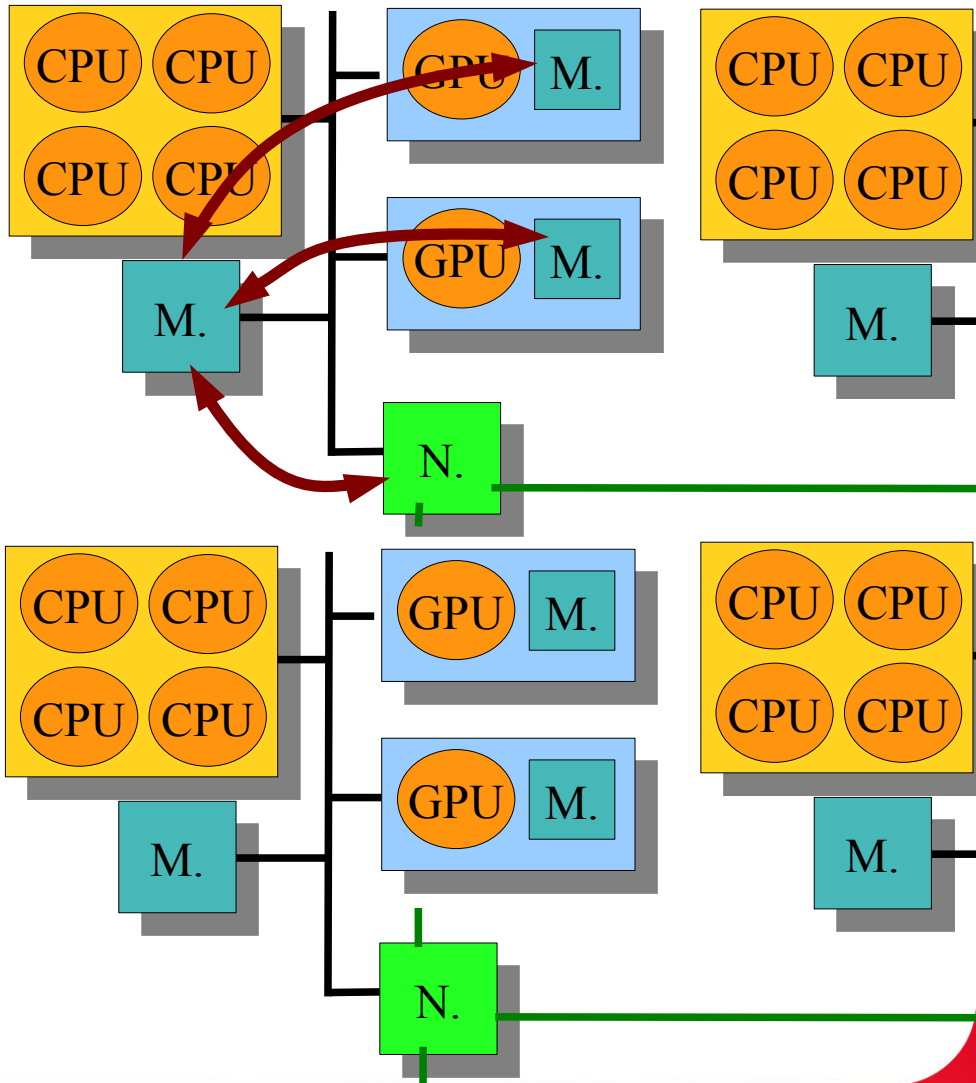
- MPI+threads+GPU



High-Performance Computing

Classical parallel programming

- threads
- MPI+threads
- MPI+threads+GPU
- Data transfers



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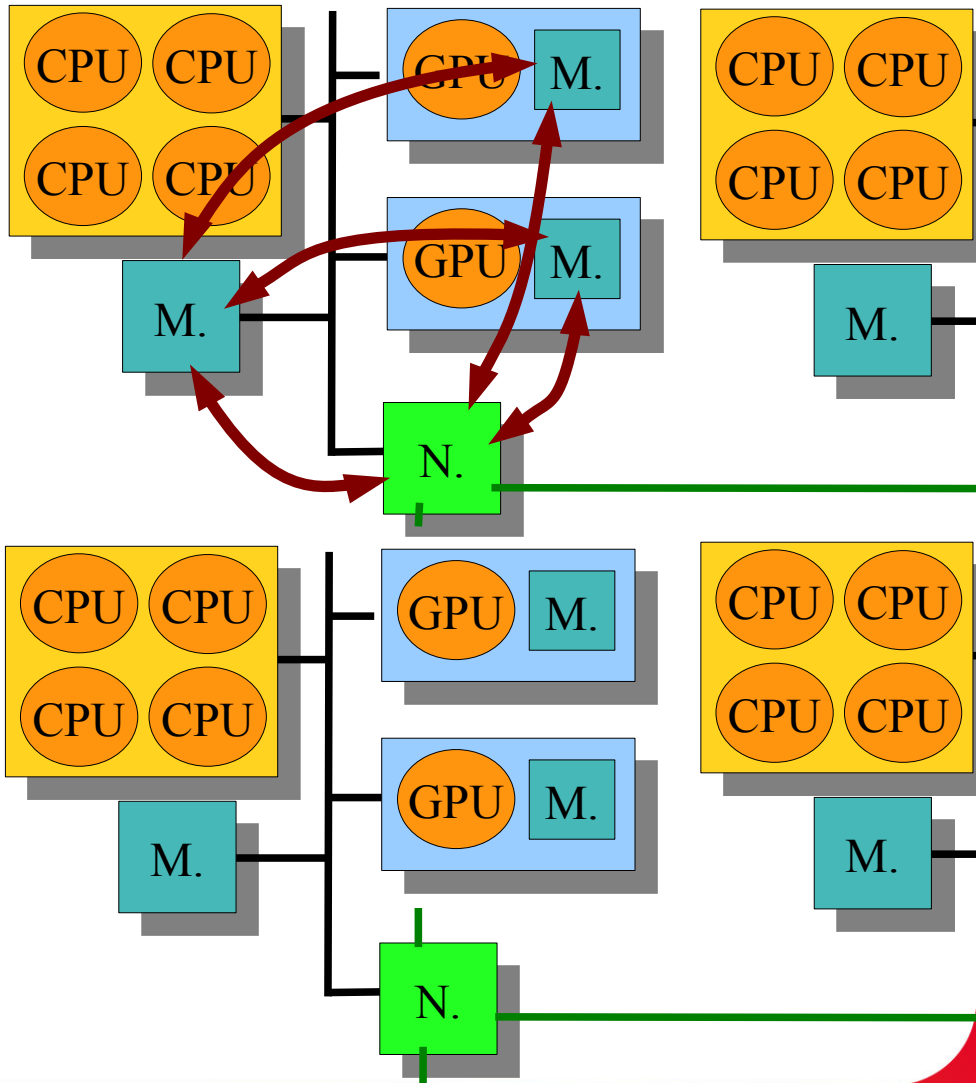

High-Performance Computing

Classical parallel programming

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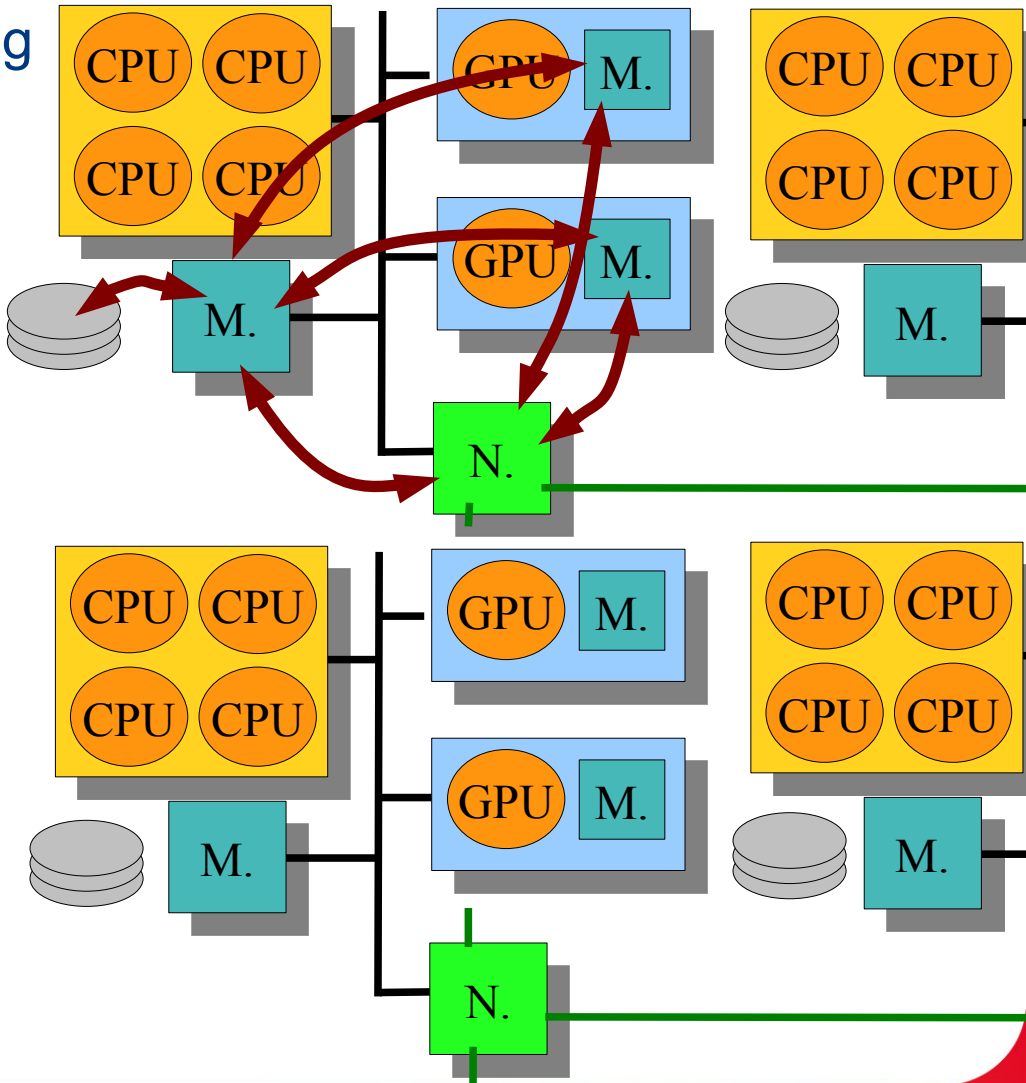
- Data transfers
- Disk storage



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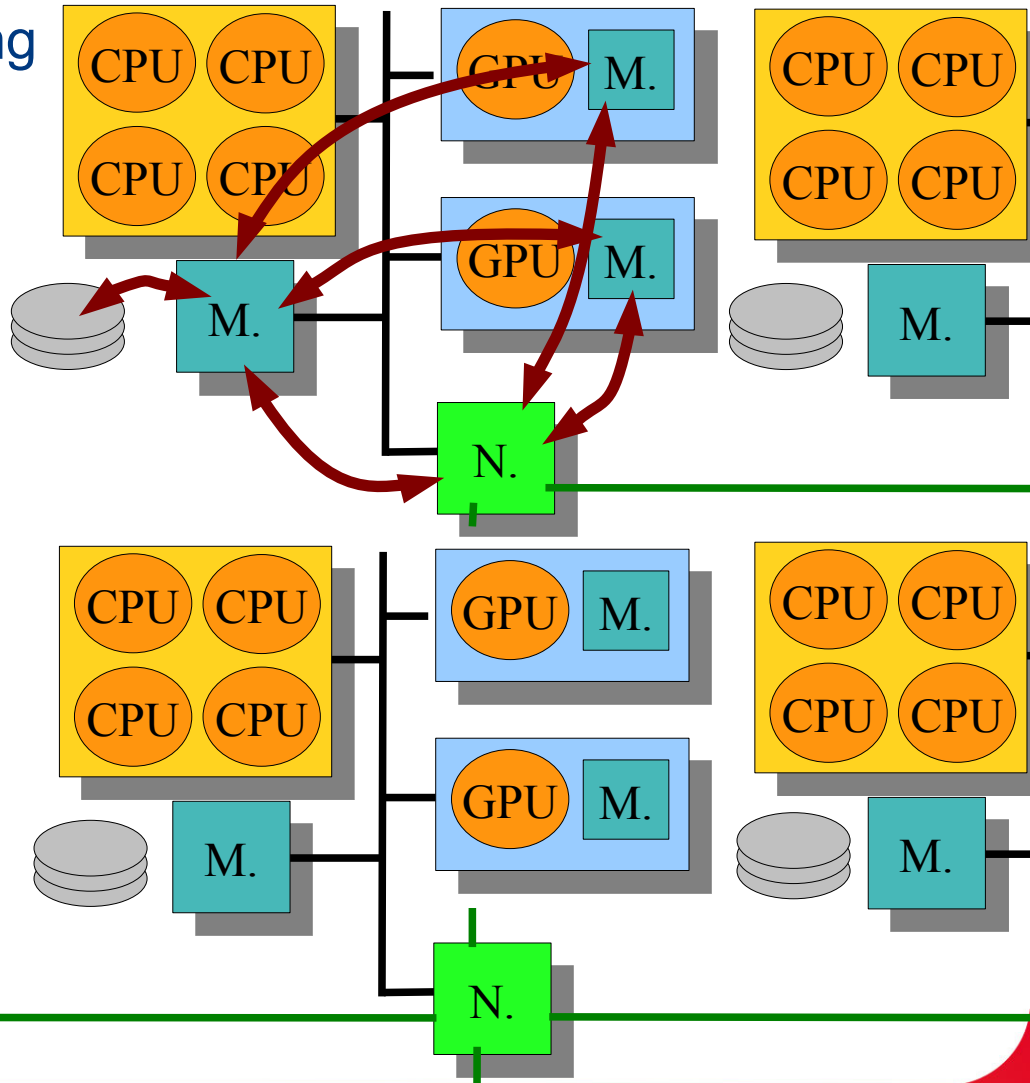

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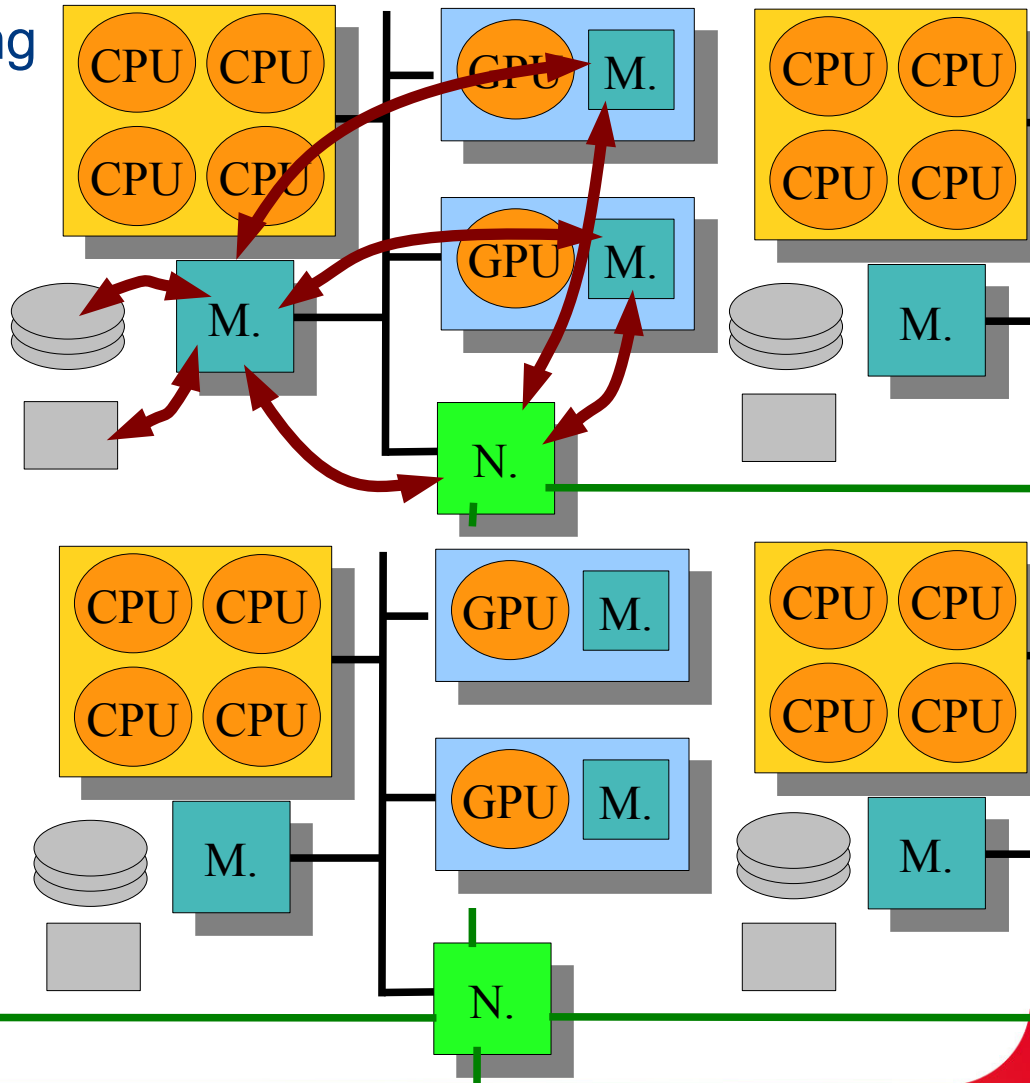

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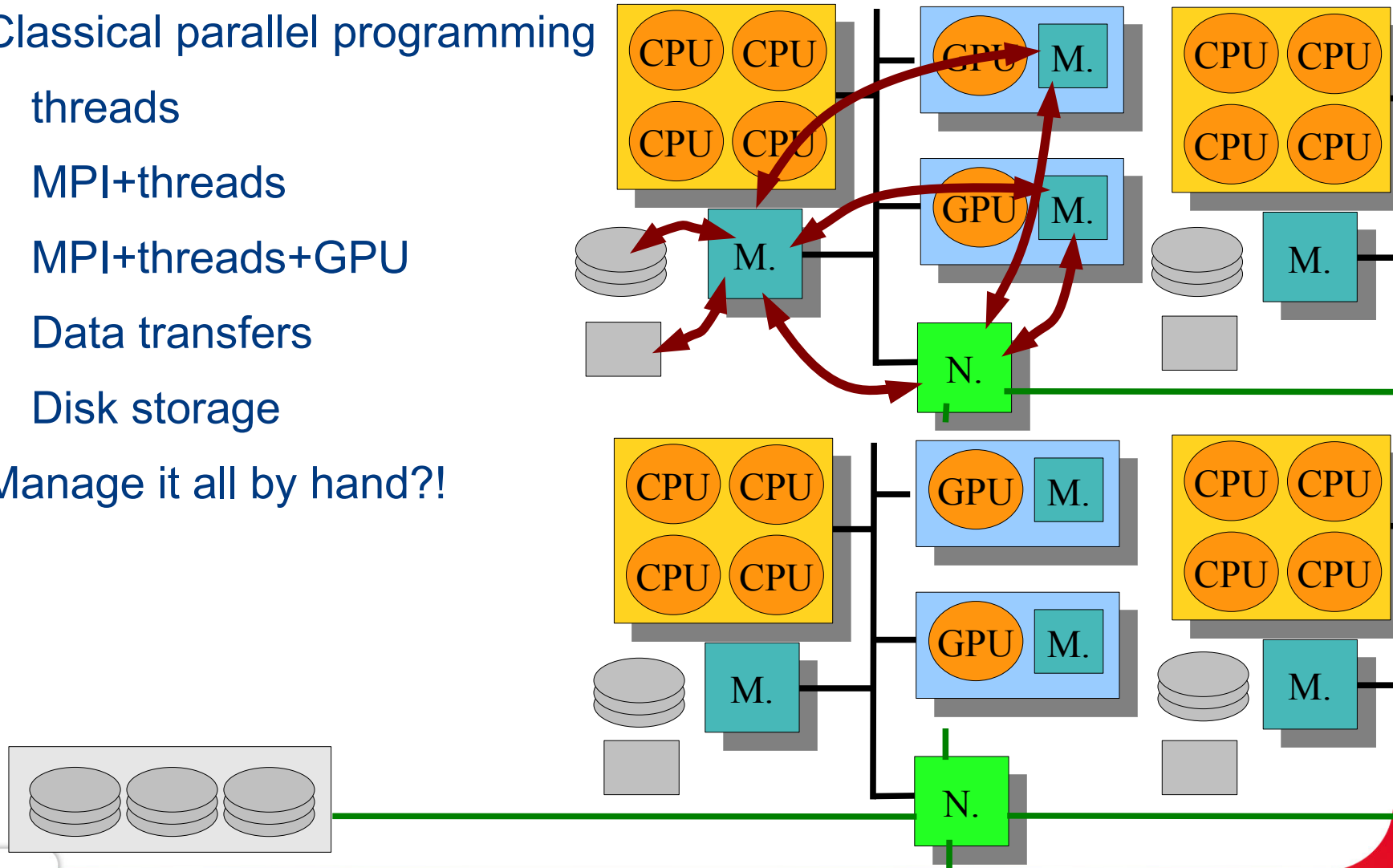
Manage it all by hand?!



High-Performance Computing

Classical parallel programming

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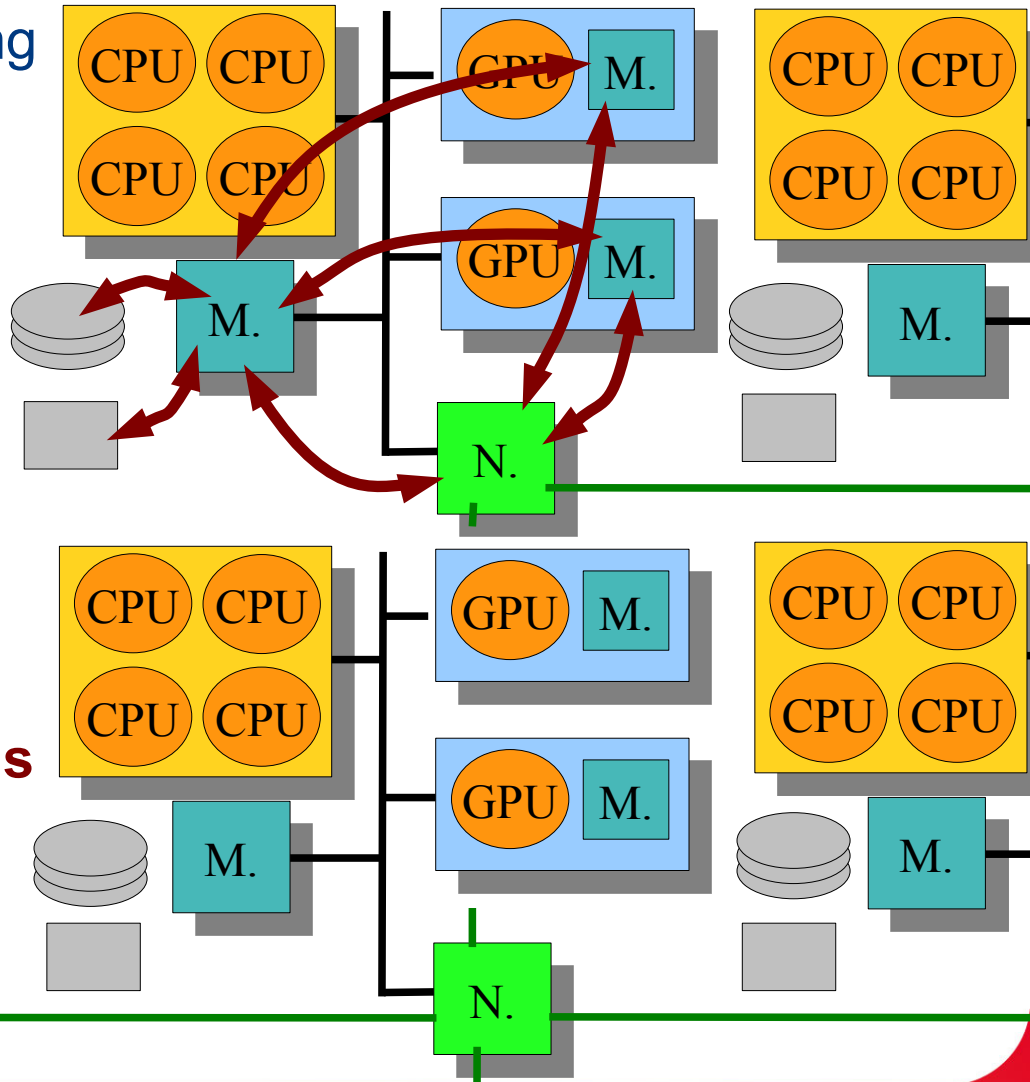
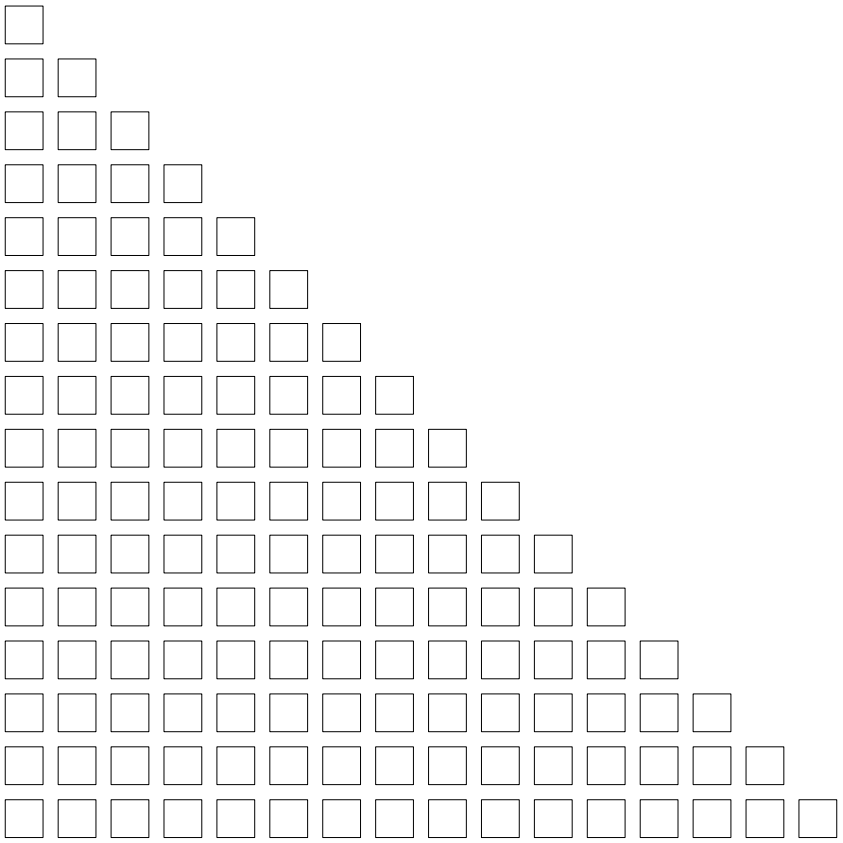
Manage it all by hand?!

Need high-level abstractions



Cholesky ($A = L.L^T$)



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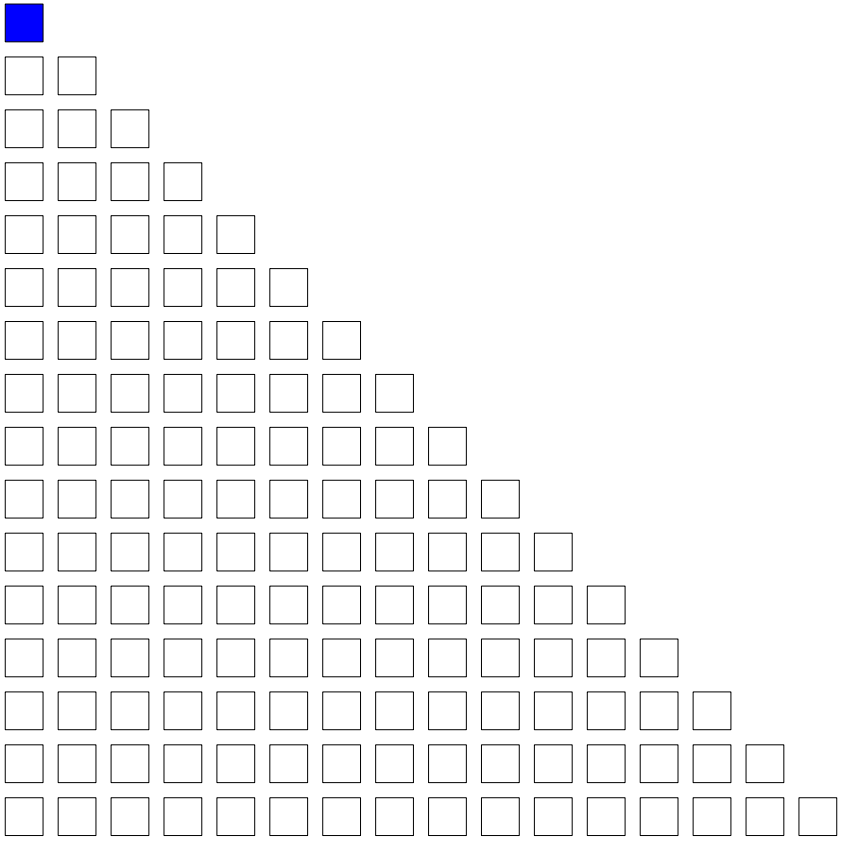

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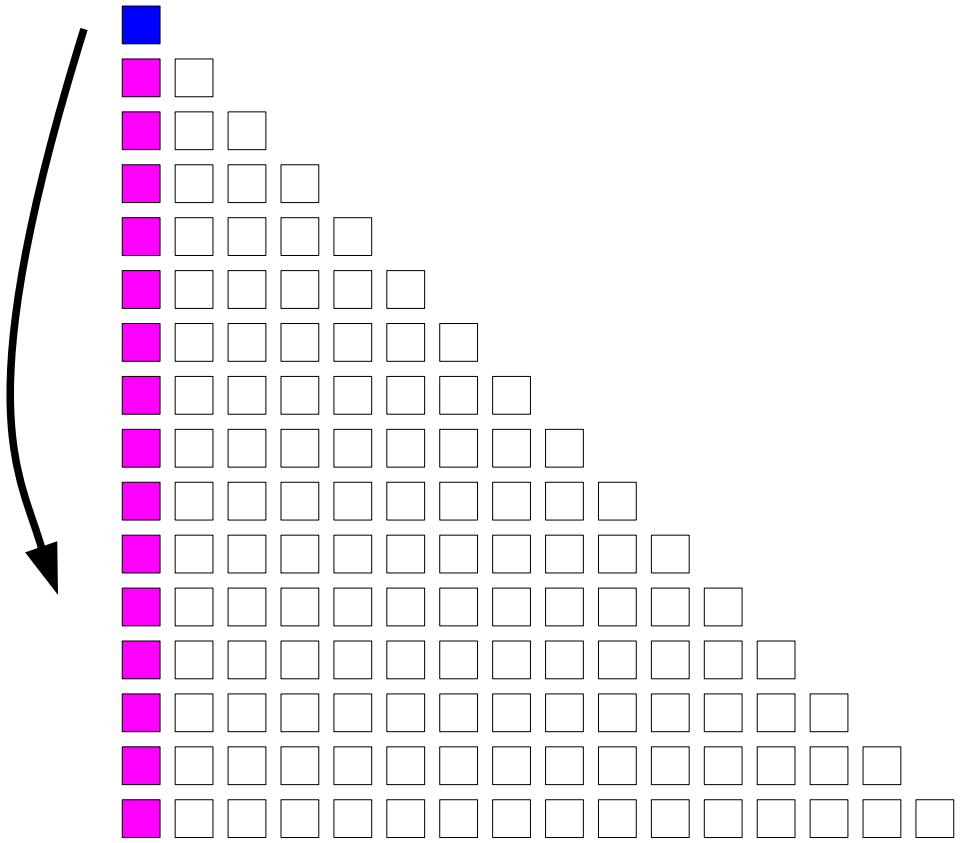

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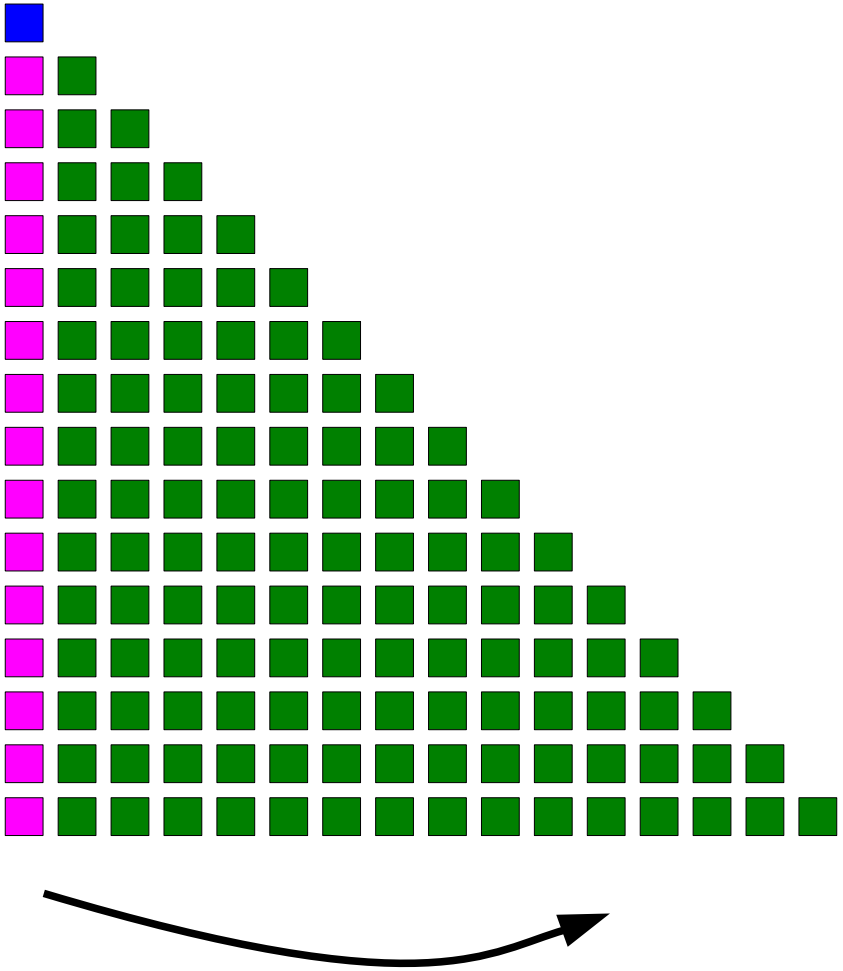

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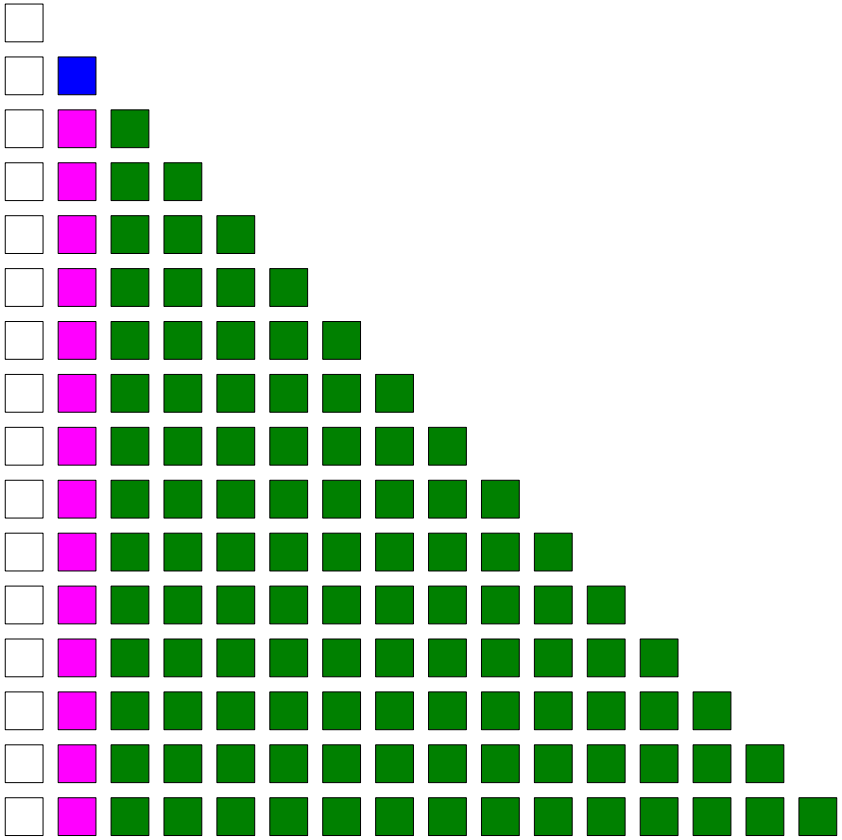

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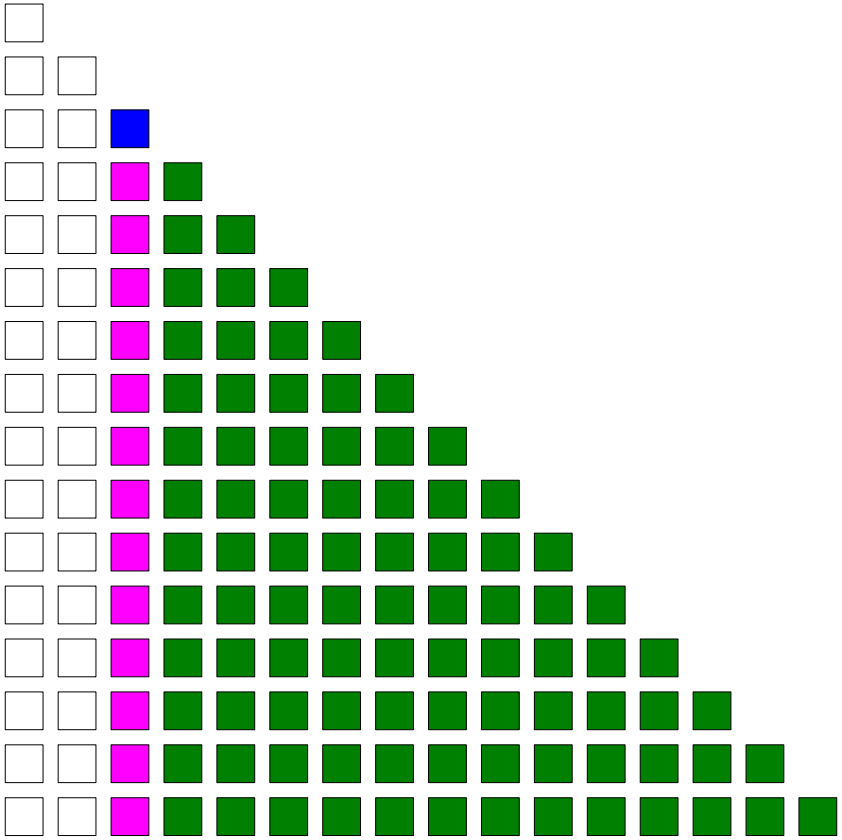

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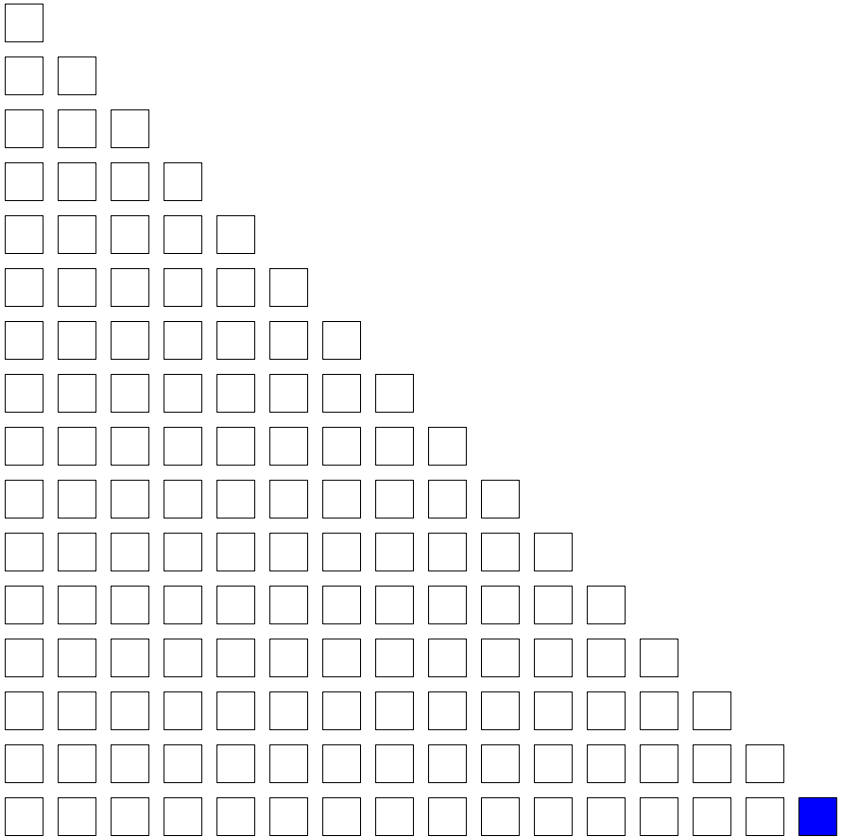
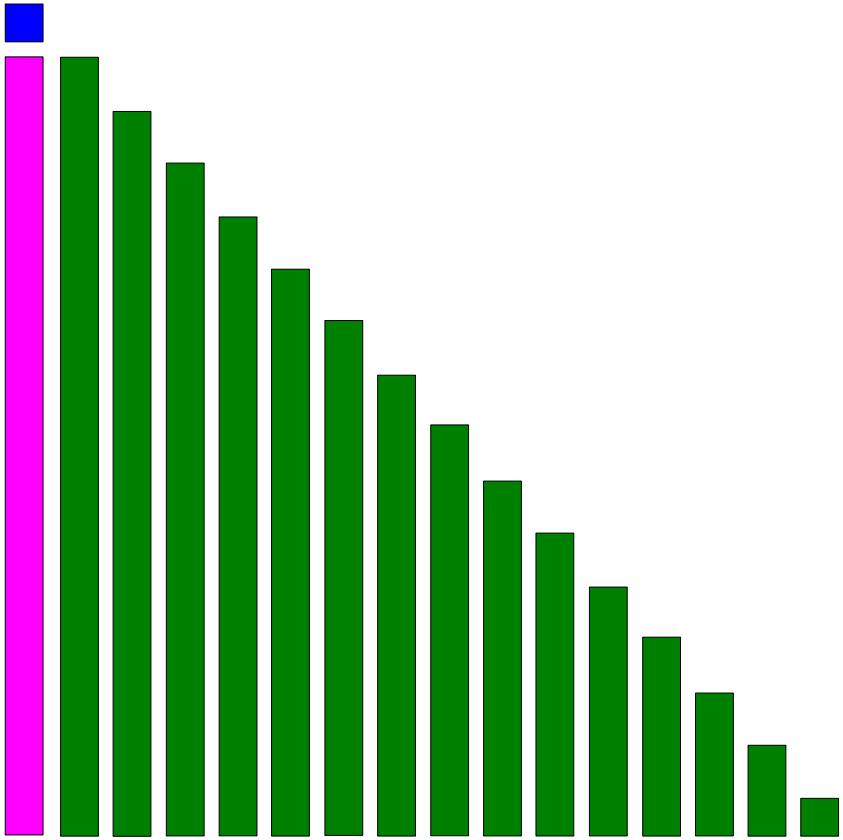


Cholesky, LINPACK

Vector computers (end ‘70s, ‘80s)



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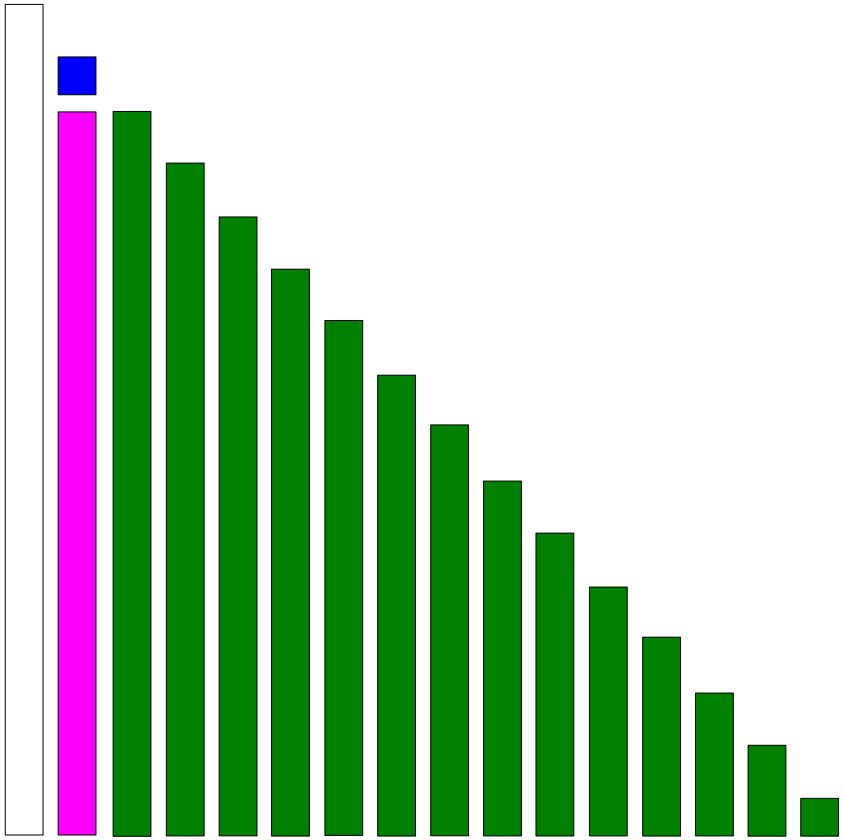

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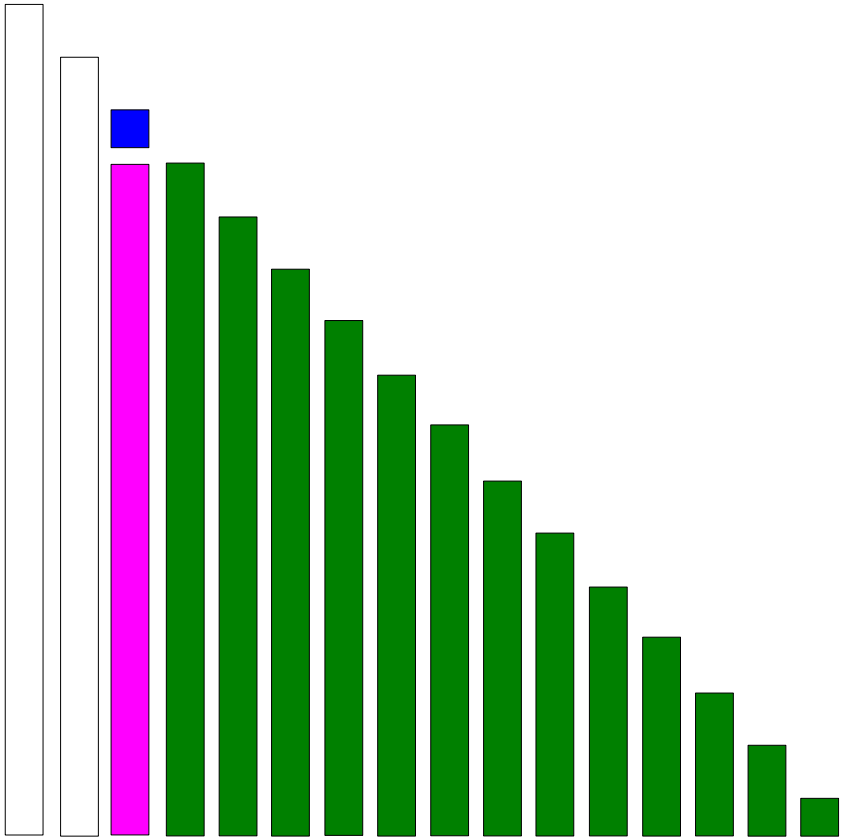

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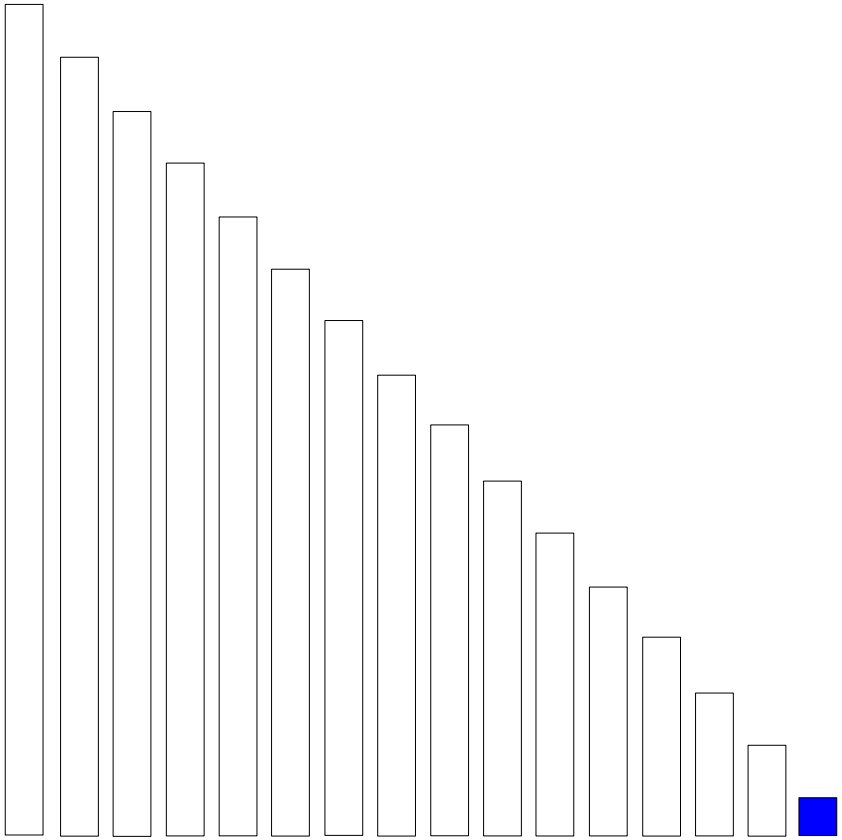
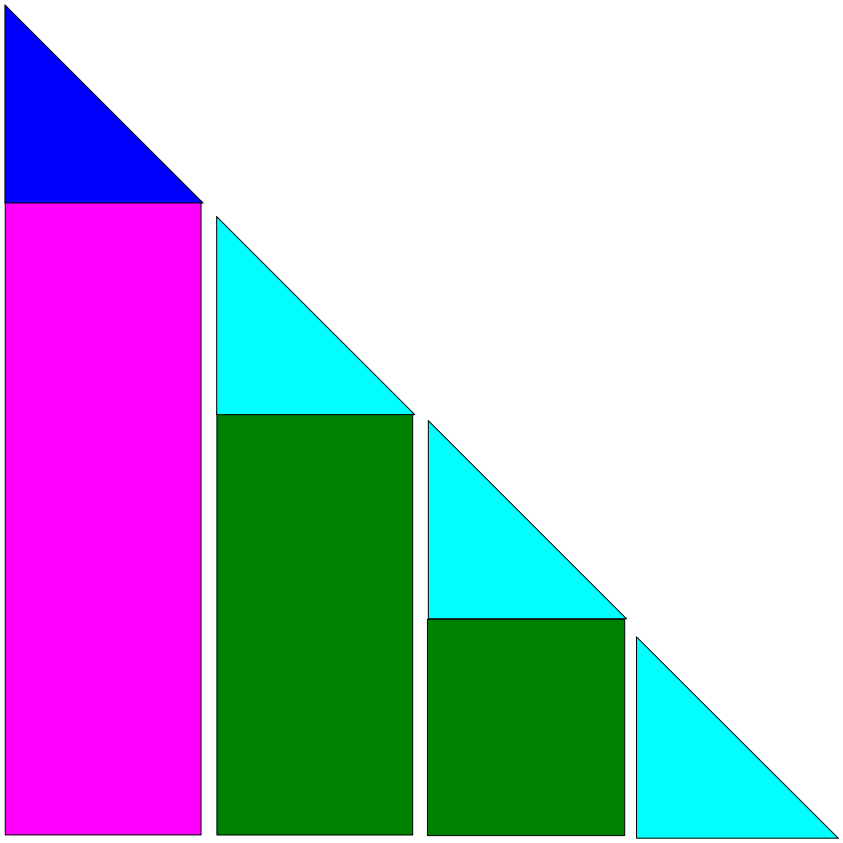


Cholesky, LAPACK

Computers with cache (early ‘90s-today), blocked operations : BLAS



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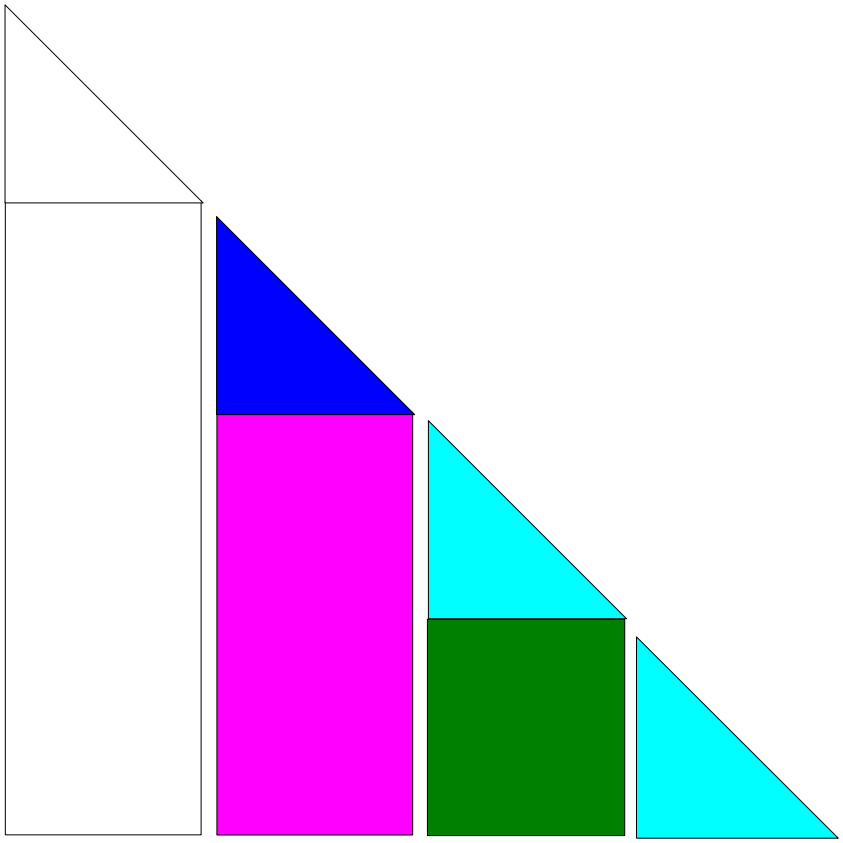

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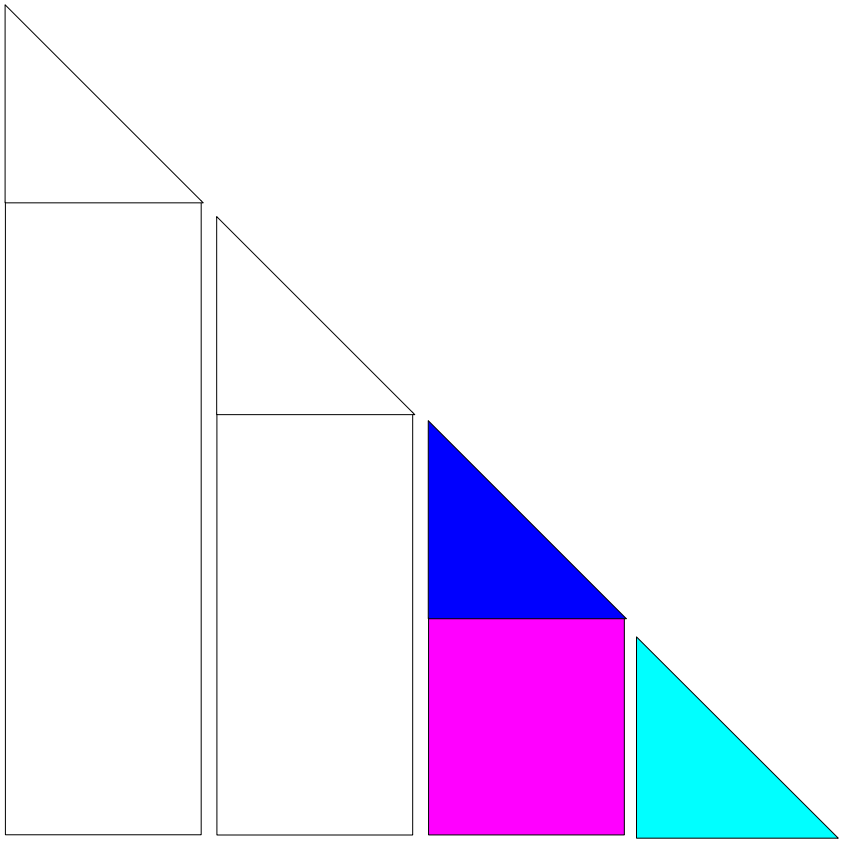

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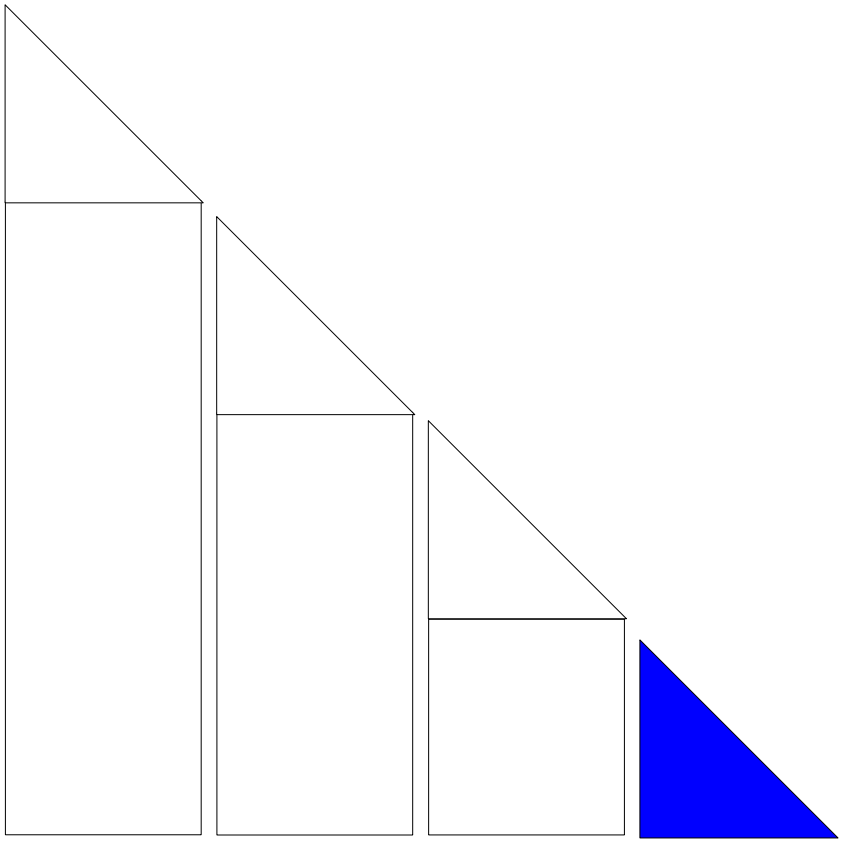
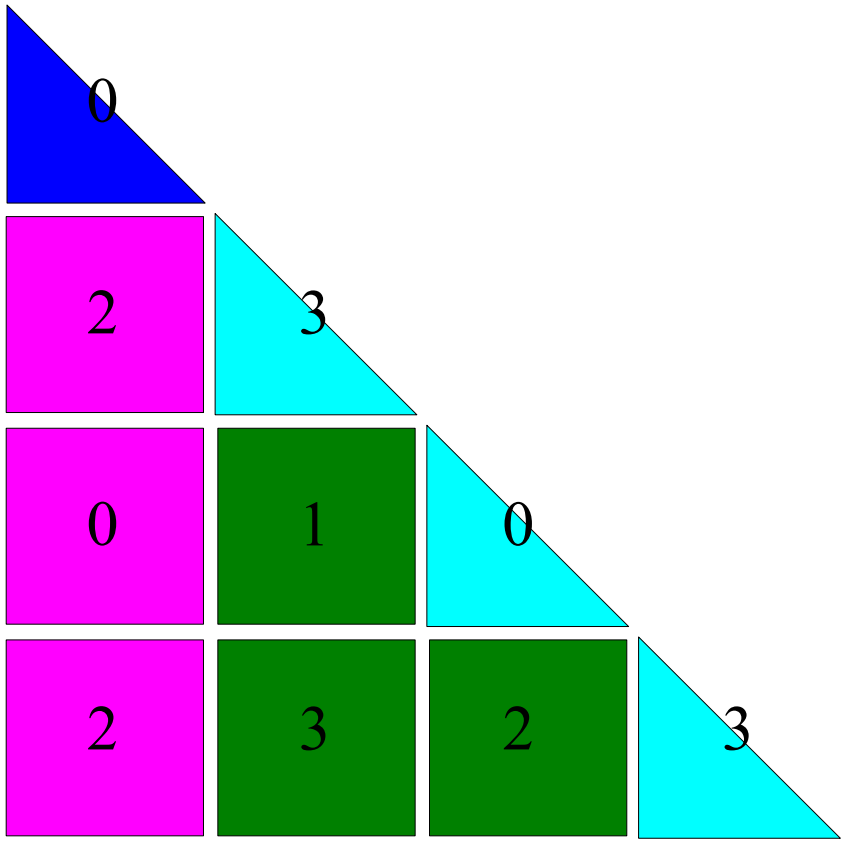


Cholesky, ScaLAPACK

Distributed Computers (late ‘90s-today), 2D-block-cyclic distribution



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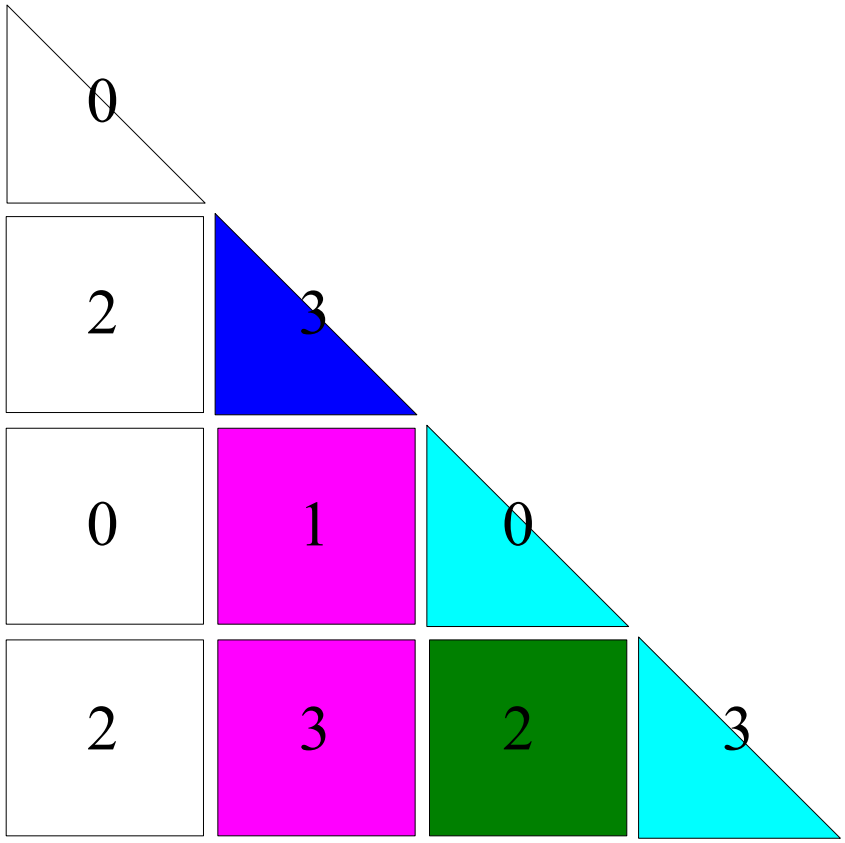

Cholesky, ScaLAPACK

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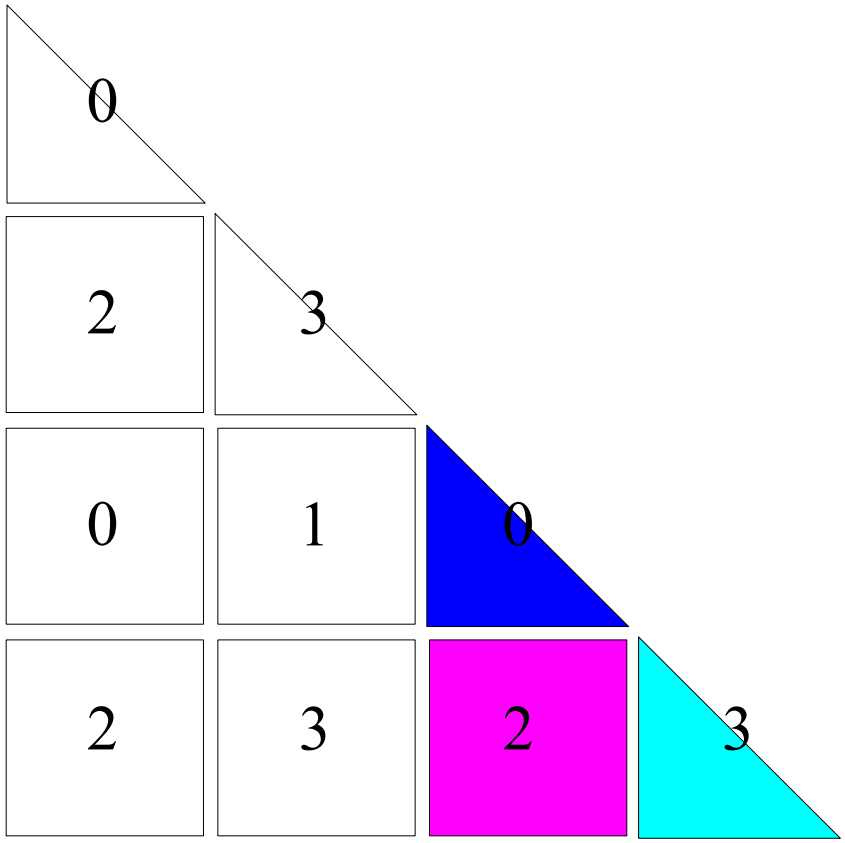

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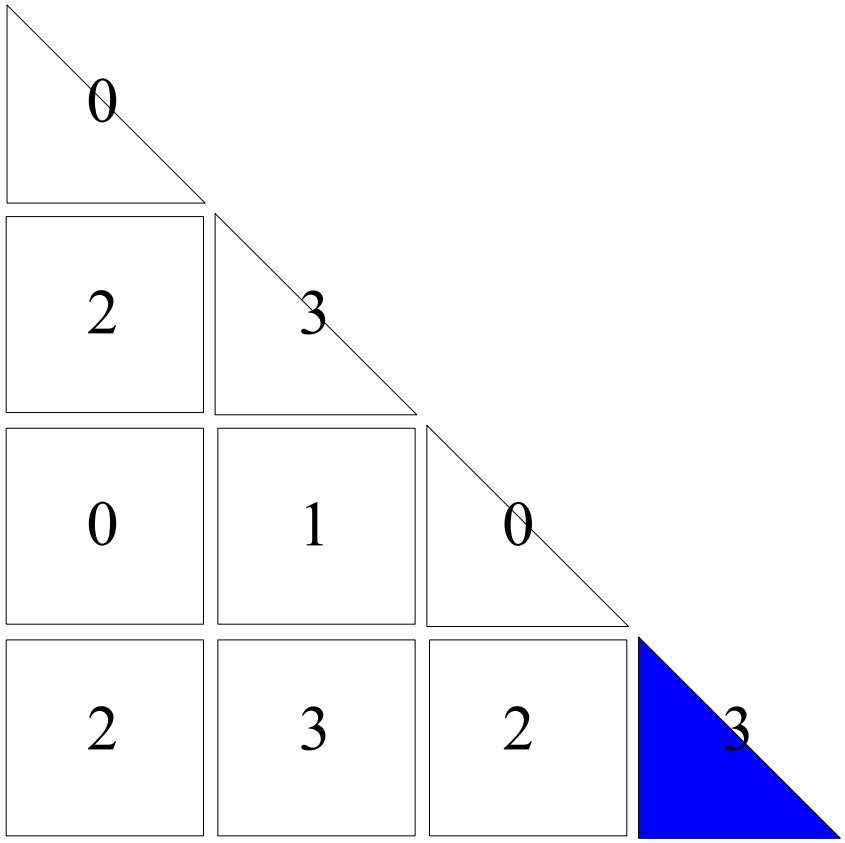
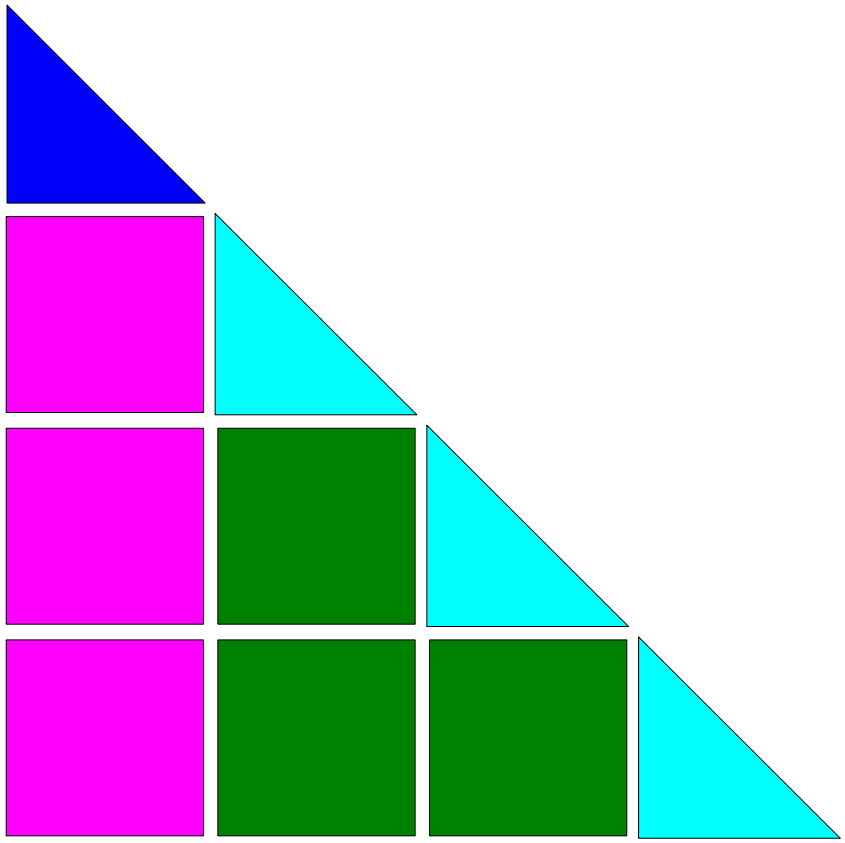


Cholesky, PLASMA

Task graph (~'08-today)



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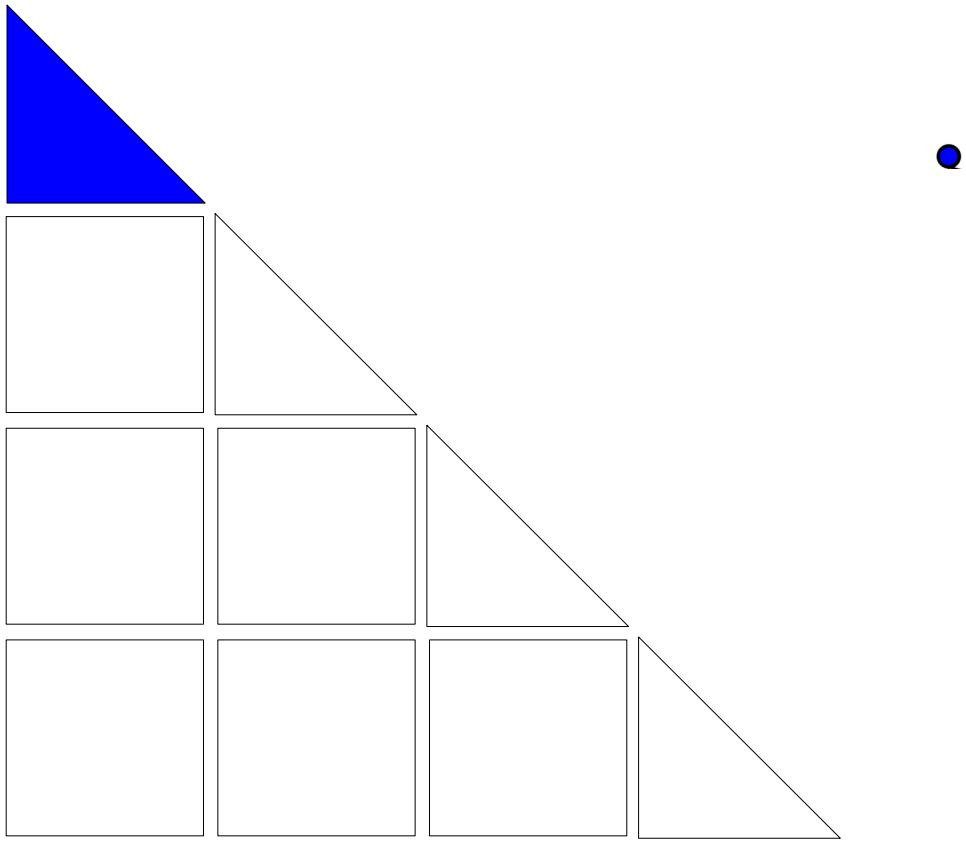

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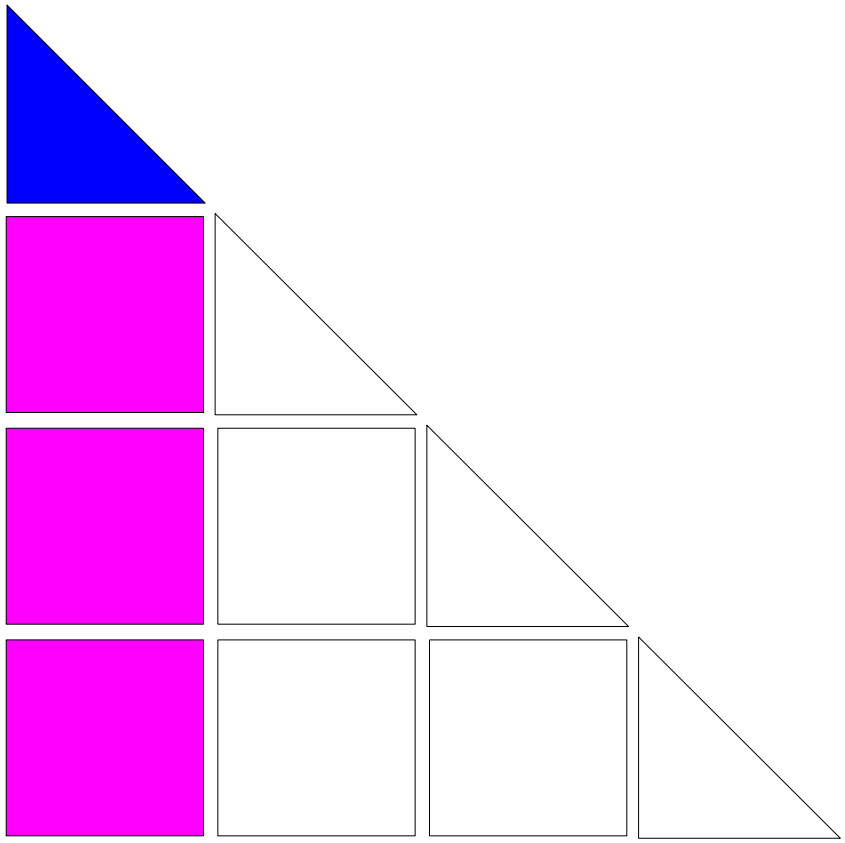

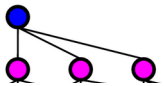

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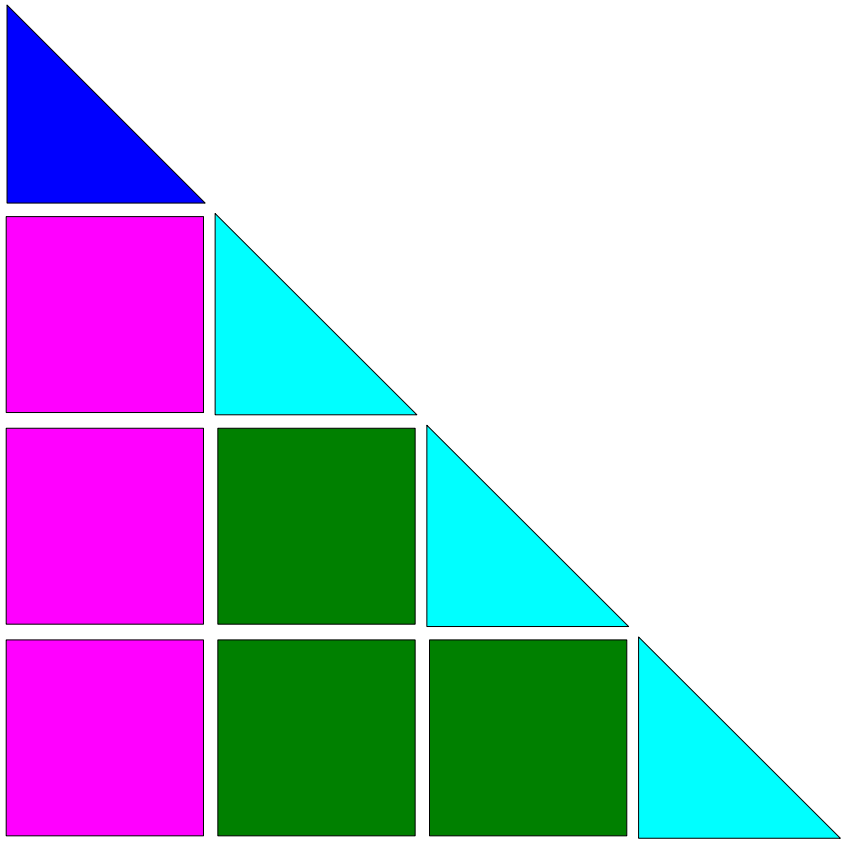

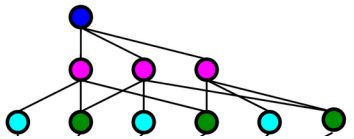

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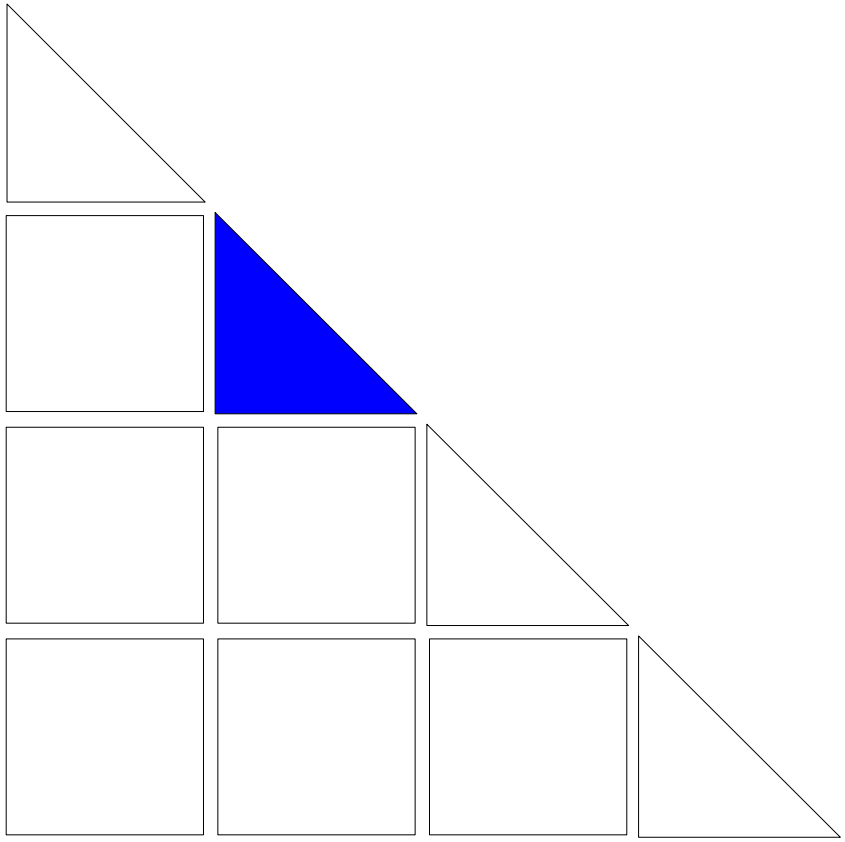

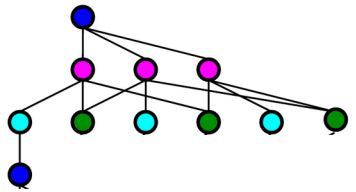

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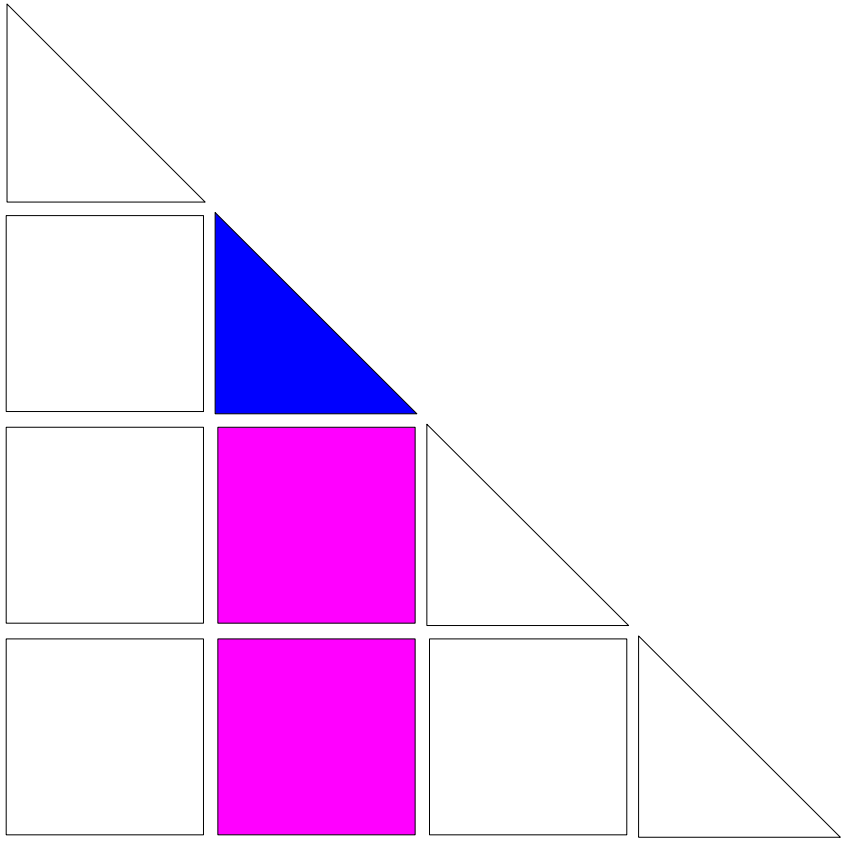

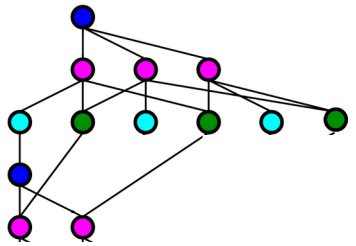

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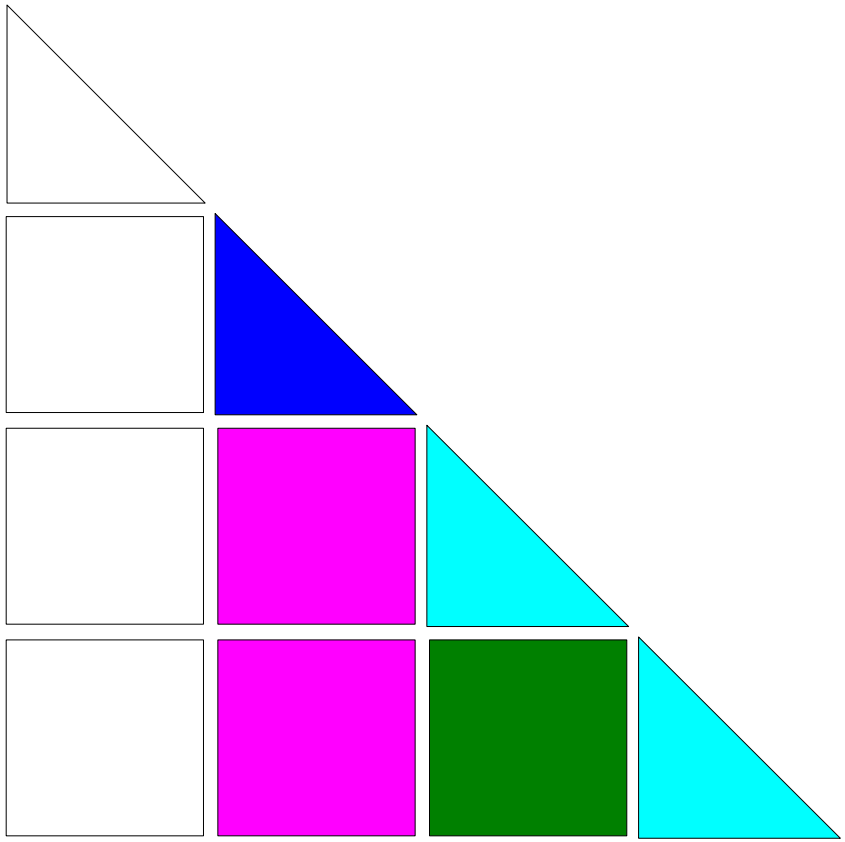

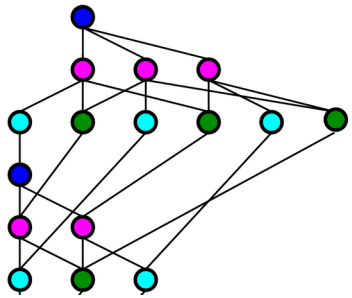

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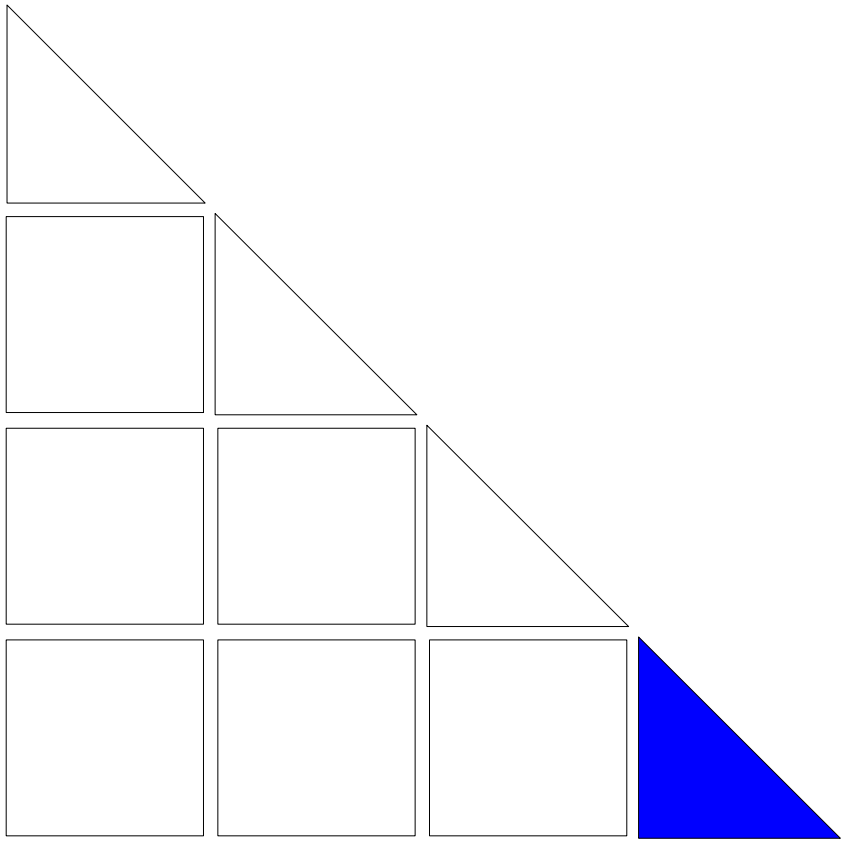
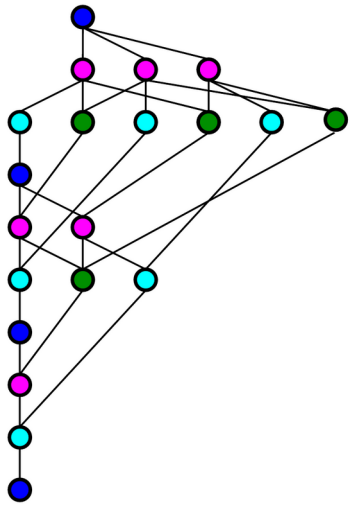
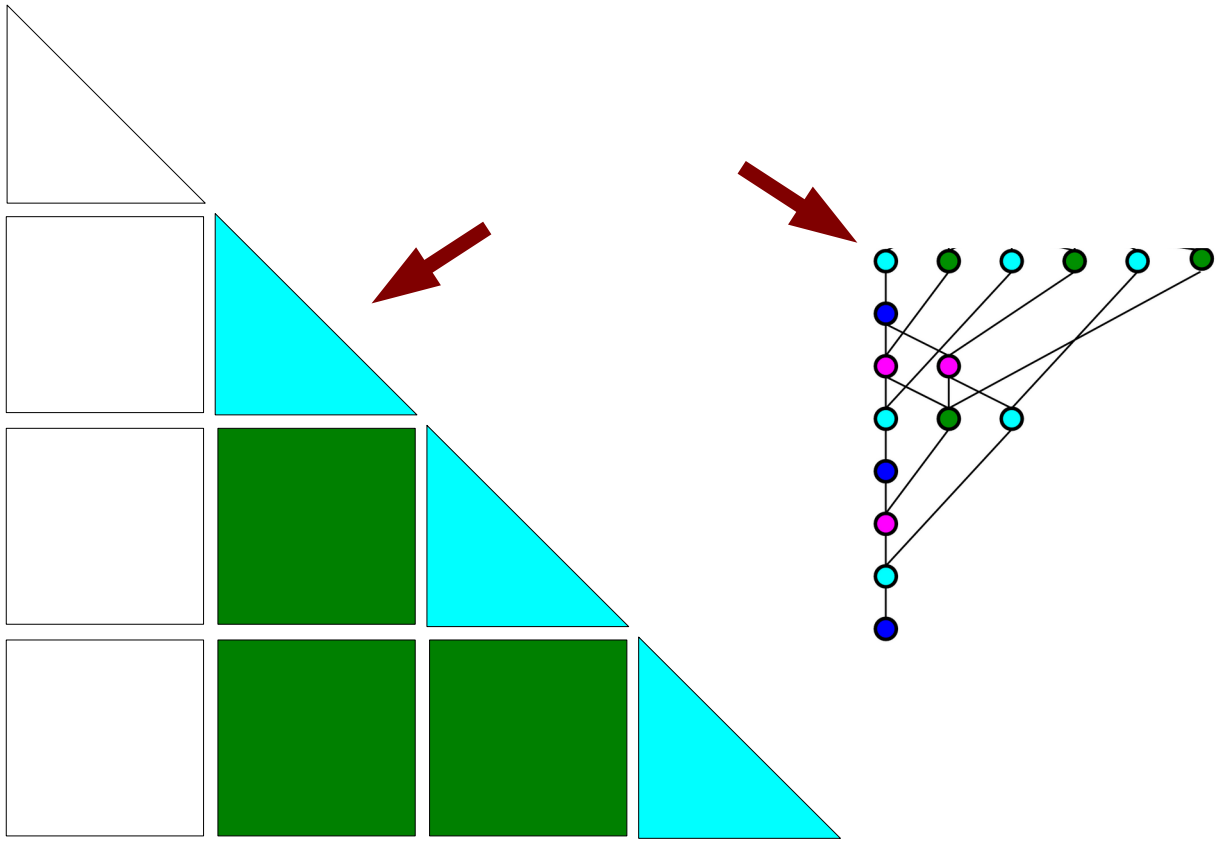




Cholesky, PLASMA

Task graph (~'08-today), **priorities**



Cholesky, PLASMA

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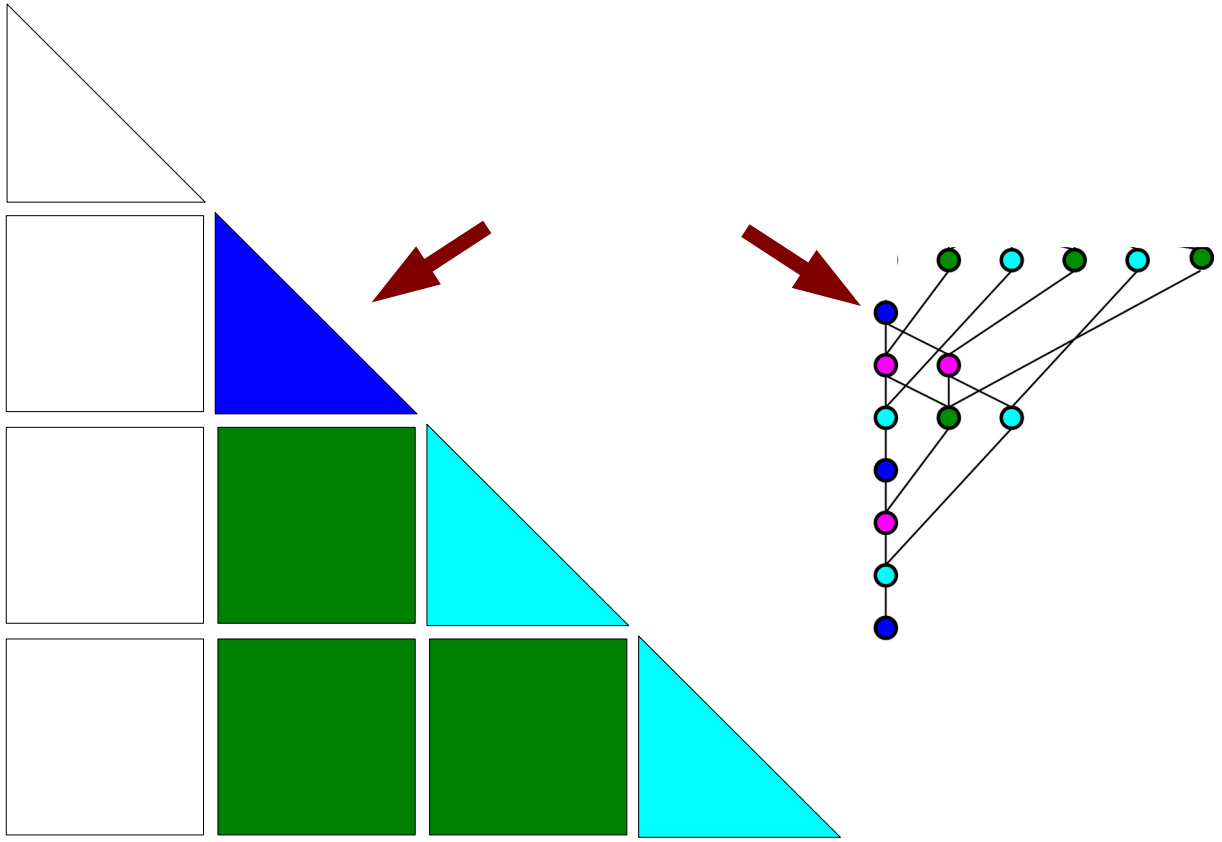

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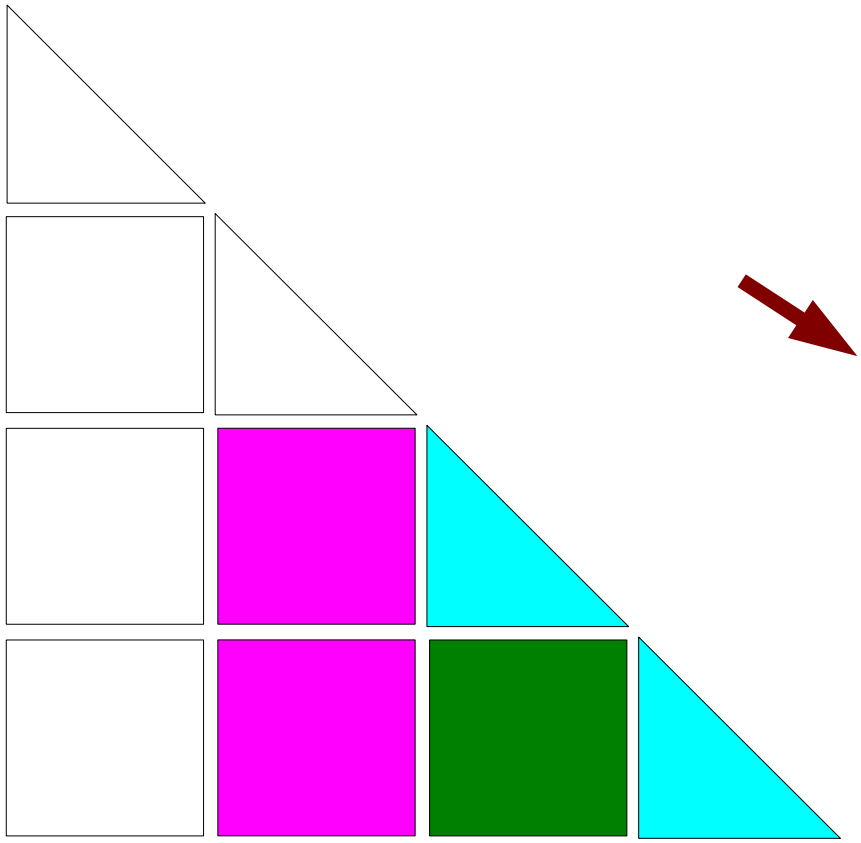
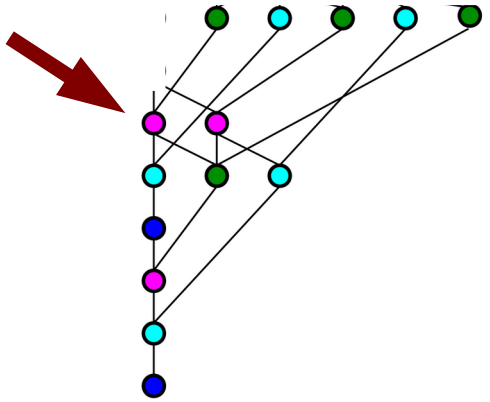




Task graphs in HPC

Runtime systems

- OmpSs, PARSEC, StarPU, SuperGlue/DuctTeip, XKaapi...

Standards

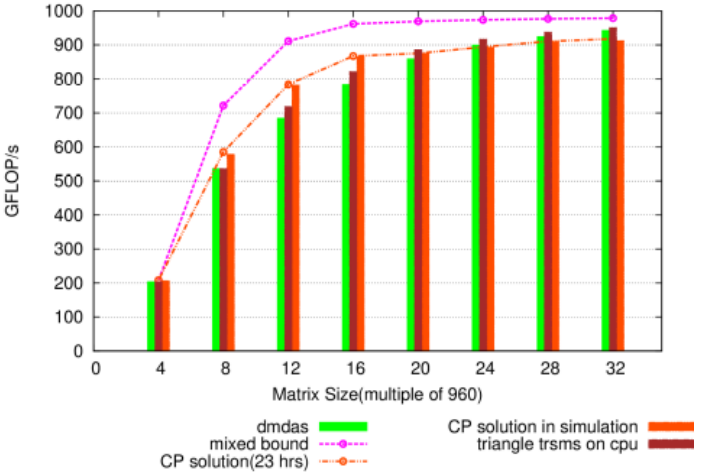
- OpenMP4.0 introduced task dependencies

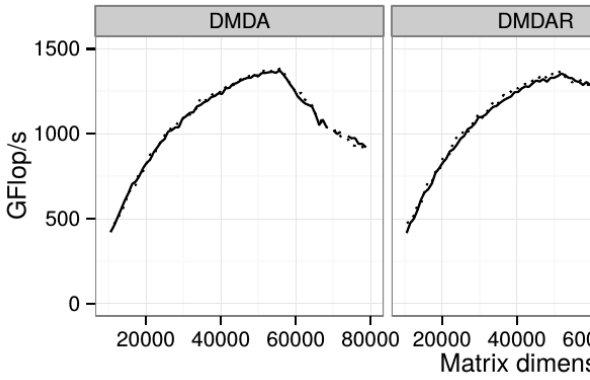
Applications

- Chameleon, DPLASMA, SLATE for dense linear algebra
- qr_mumps, PaStiX for sparse linear algebra
- ScalFMM for FMM
- …

Task-based support

- Task/data scheduling
  - Load balancing
  - Data prefetching
  - Pipelining
  - GPU memory limitation management
- Distributed execution through MPI
- Out-of-core: optimized swapping to disk
- High-level performance analysis
- Performance bounds
- Debugging sequential execution
- Reproducible performance simulation

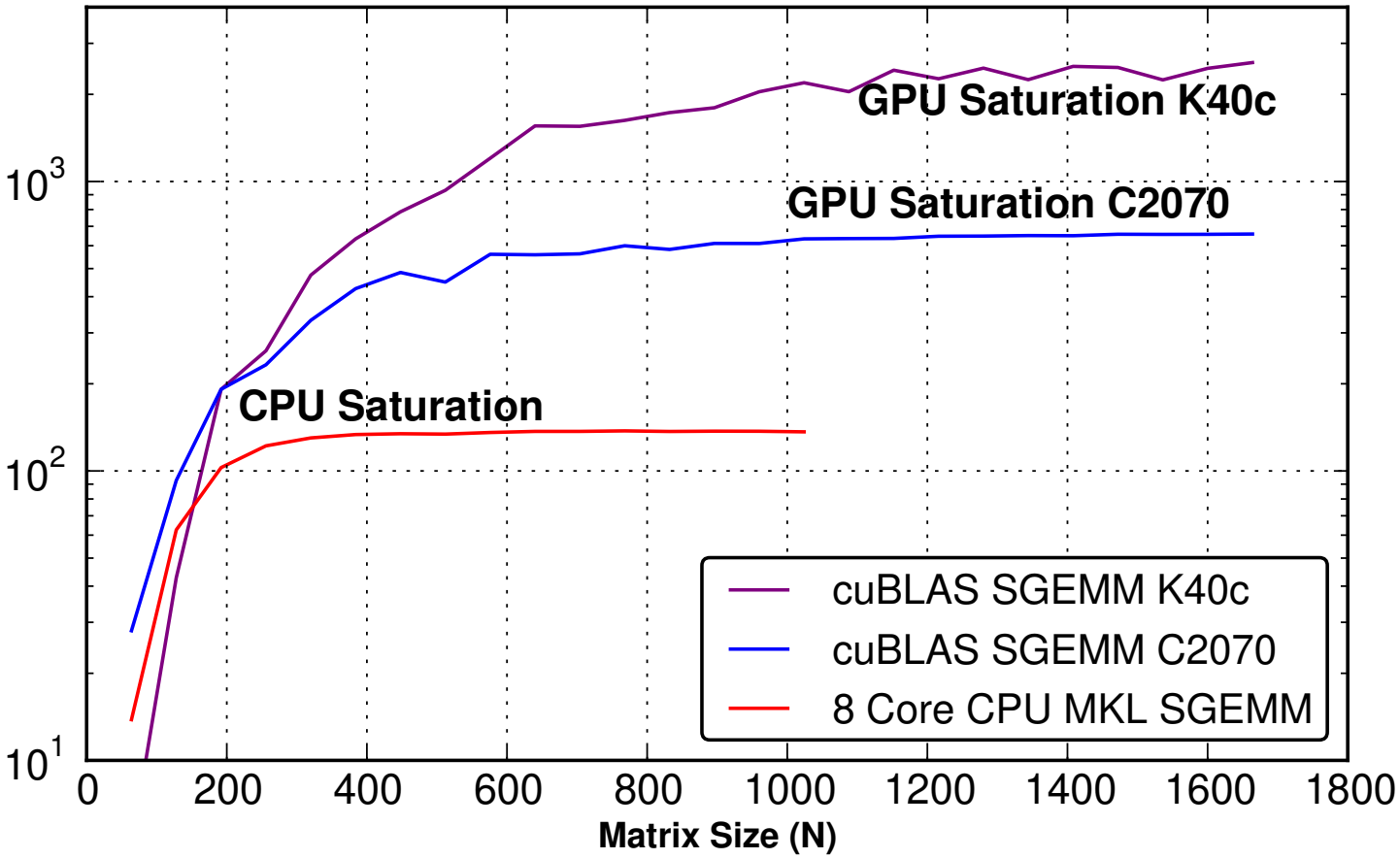




How big should a task be?

- Small enough to get parallelism to **feed** all processing units
- Large enough to **efficiently** use the processing units

How big should a task be?



From PARSEC : « Hierarchical DAG Scheduling for Hybrid Distributed Systems », Wu, Bouteiller, Bosilca, Faverge, Dongarra

How big should a task be?

GPUs

- Efficient only with large tile sizes

CPUs

- Need many tasks

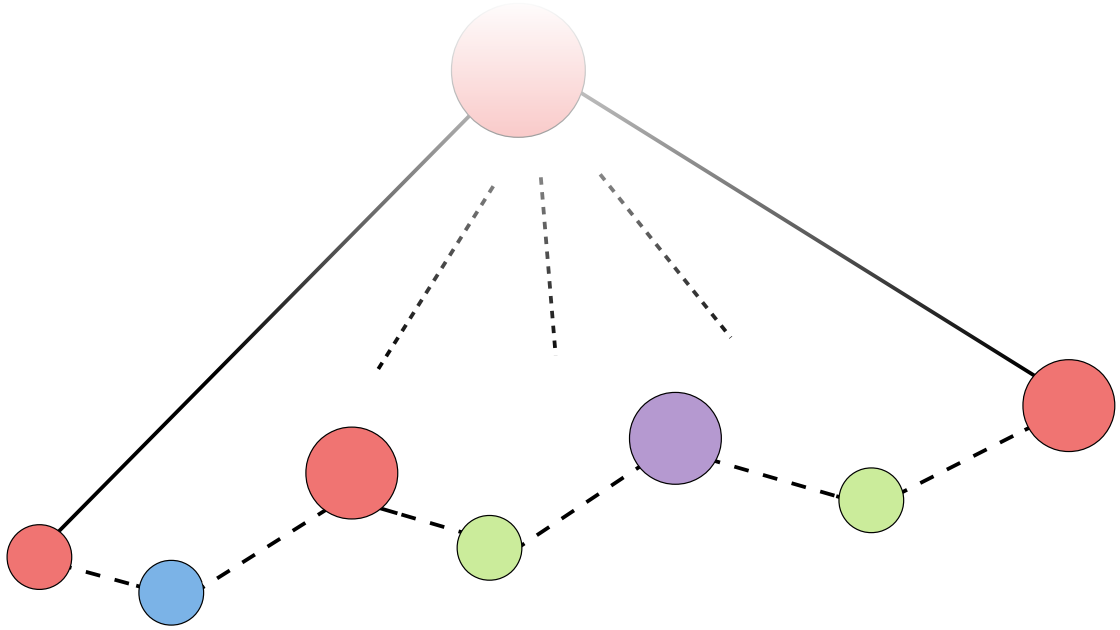
→ **Hybrid** task size

More generally, **hierarchical** task graphs

- Seen in CEA, OmpSs, PaRSEC, StarPU

Outline

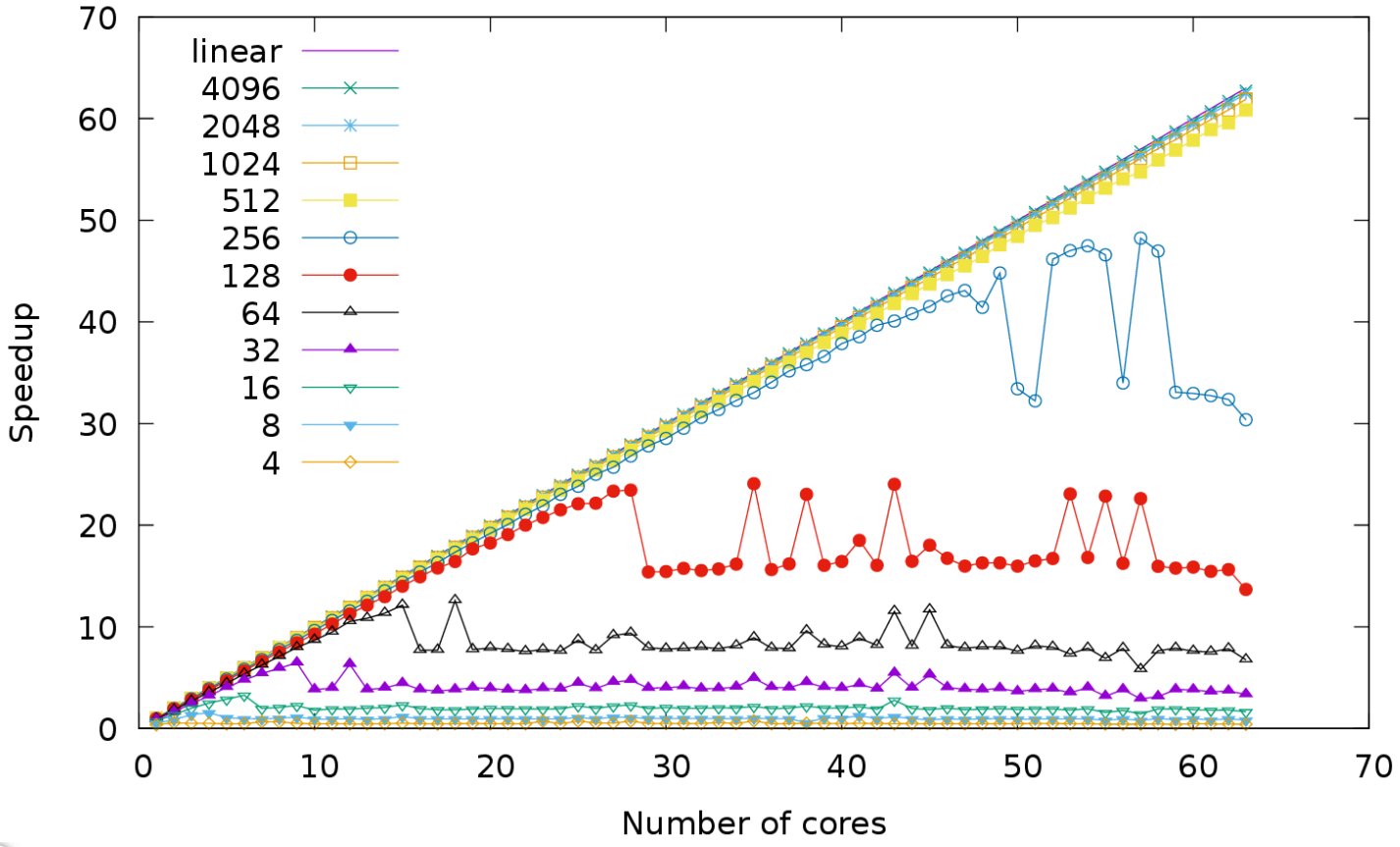
- How big should a task be?
- Hierarchical task graphs
- Opportunities



How big should a task be?

How big should a task be?

- Lower bound due to runtime overhead
  - Proposed by Martin Tillenius for DuctTeip (U. Uppsala)



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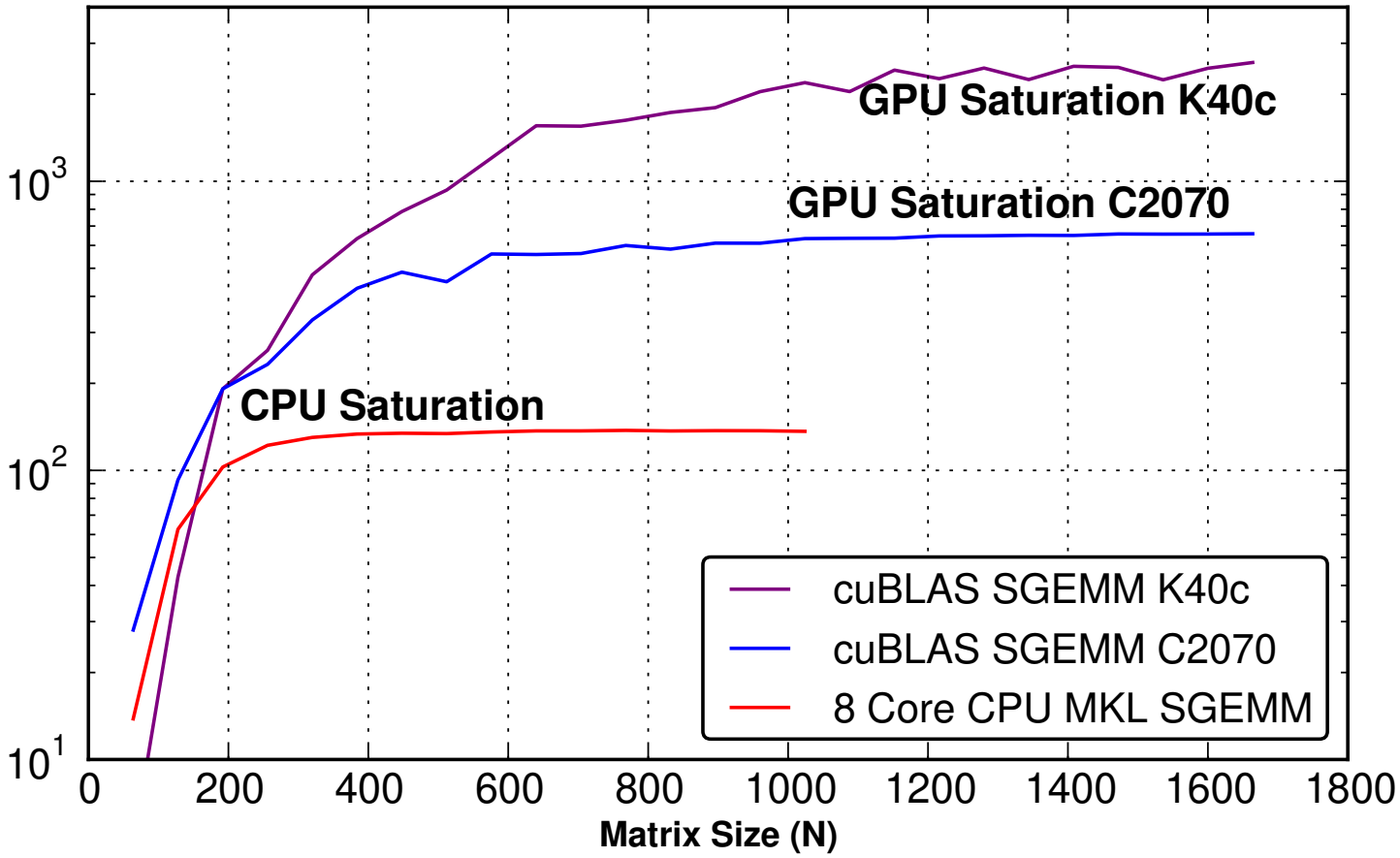


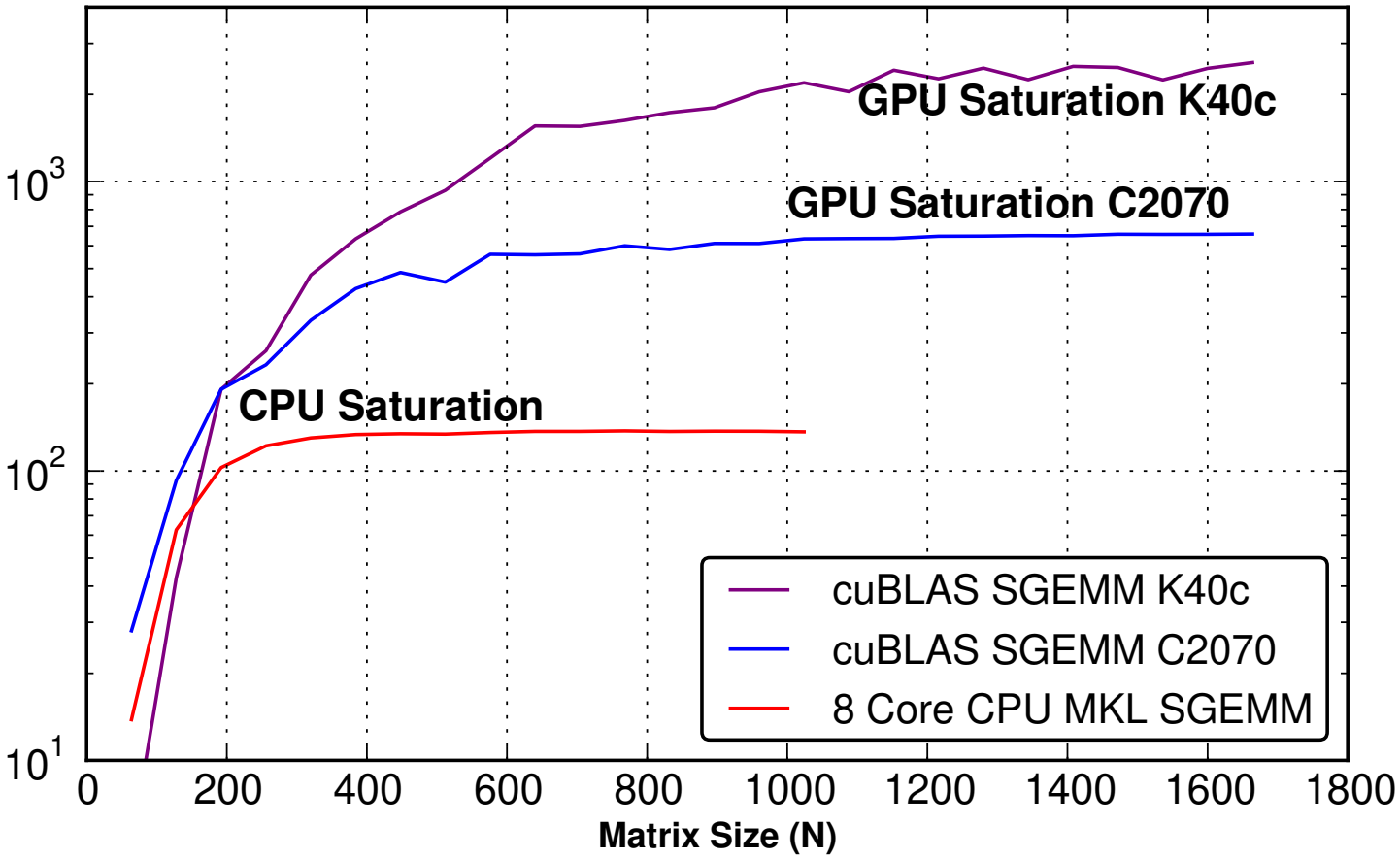
From PARSEC : « Hierarchical DAG Scheduling for Hybrid Distributed Systems », Wu, Bouteiller, Bosilca, Faverge, Dongarra

How big should a task be?

GPUs

- Have **thousands** for cores to feed
- Newer generations require yet larger sizes
- Can run several kernels at the same time
  - Still limited

How big should a task be?



From PARSEC : « Hierarchical DAG Scheduling for Hybrid Distributed Systems », Wu, Bouteiller, Bosilca, Faverge, Dongarra

How big should a task be?

CPUs

- Have many independent cores

  → Need many tasks
- Can use parallel implementations (e.g. from MKL)
  - But better have subtasks to interleave them

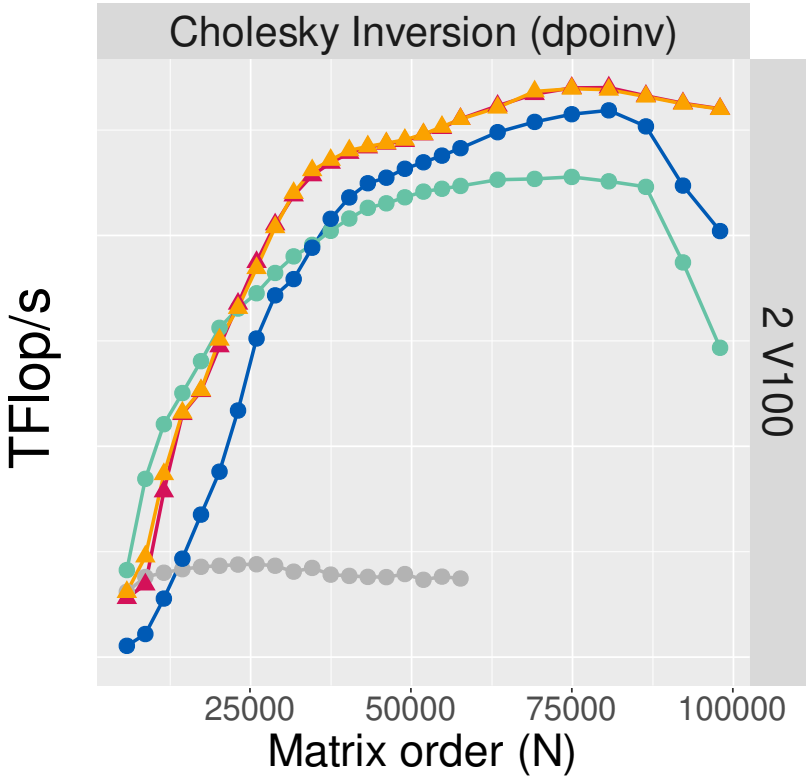
How big should a task be?

How size does not fit all

Gwenolé Lucas experimented with Chameleon

- Cholesky inversion
- 2 NVIDIA V100
- 2 Xeon Gold 6142
- Different matrix tile sizes : 2880 / 960 / 320

Hybrid tile sizes



Version: Tile sizes

- Non-Hierarchical: 2880
- Non-Hierarchical: 960
- Non-Hierarchical: 320
- Hierarchical: 2880 / 960
- Hierarchical: 2880 / 960 / 320

How big should a task be?

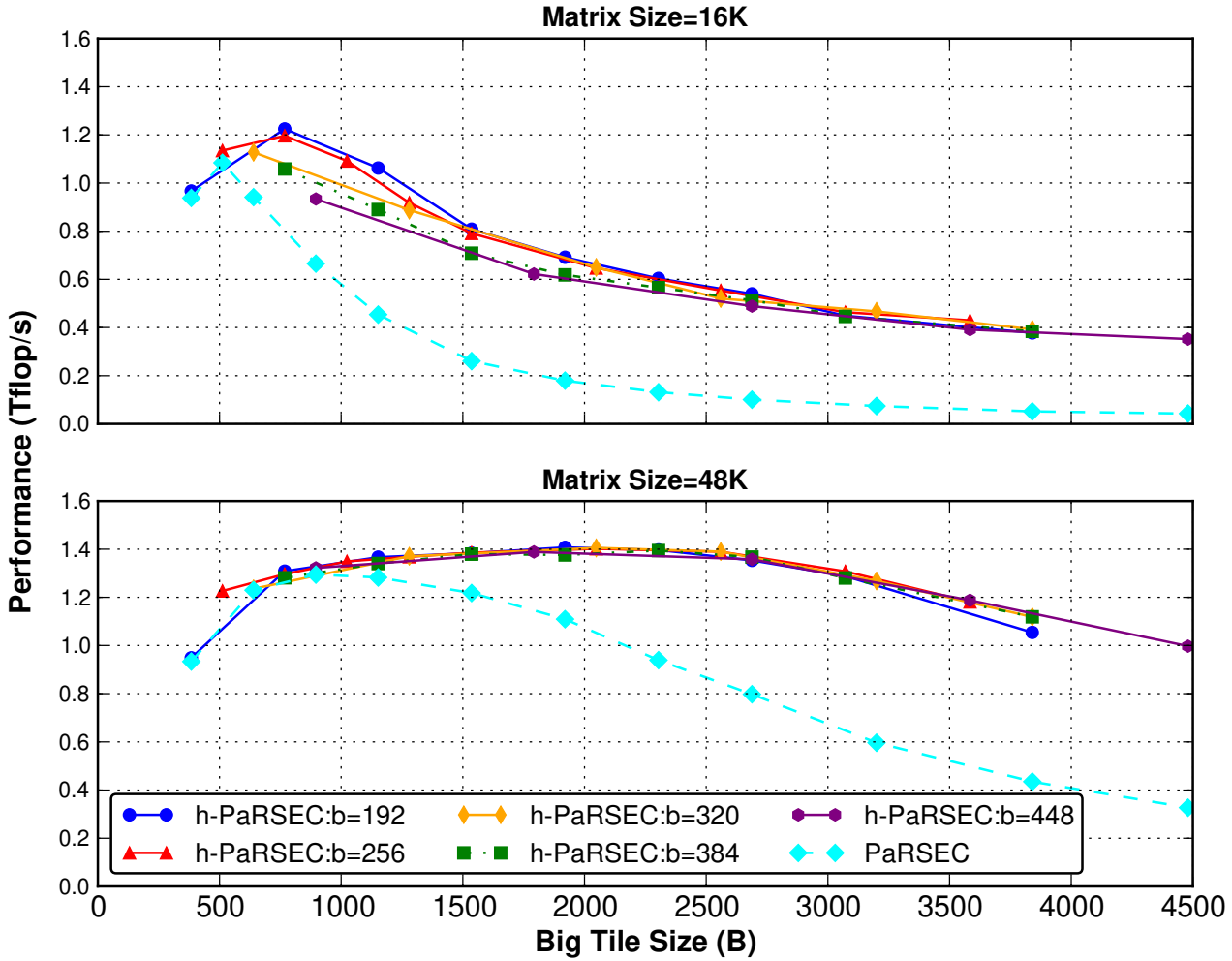
Tuning the tile size?

- B = “big” tile size, for GPUs
  - Large enough for GPUs
  - Not too large for parallelism

- b = “small” tile size, for CPUs
  - Large enough for CPUs
  - Not too large for parallelism

With Parsec, Wu, Bouteiller, Bosilca, Faverge and Dongarra experimented tuning

How big should a task be?



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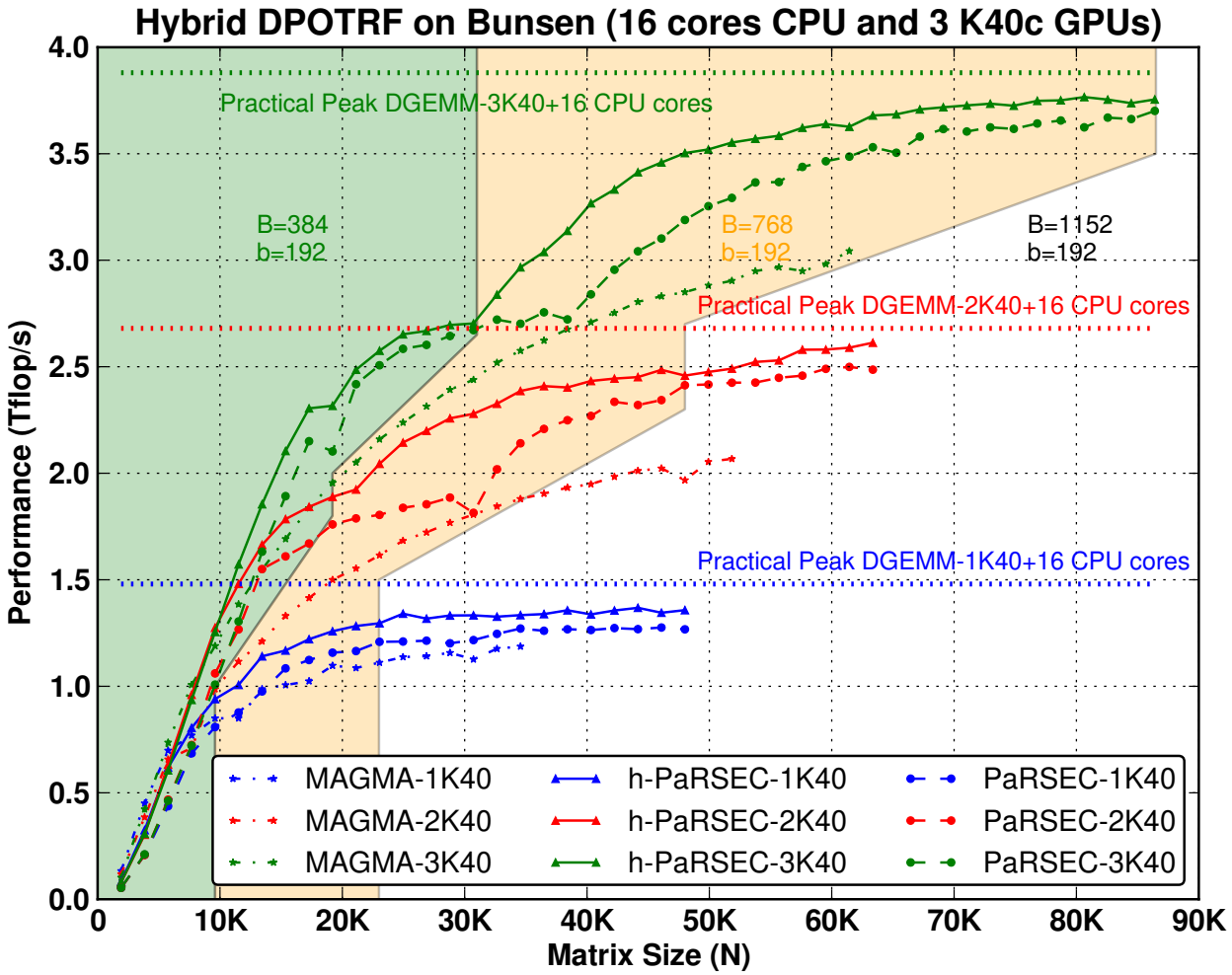

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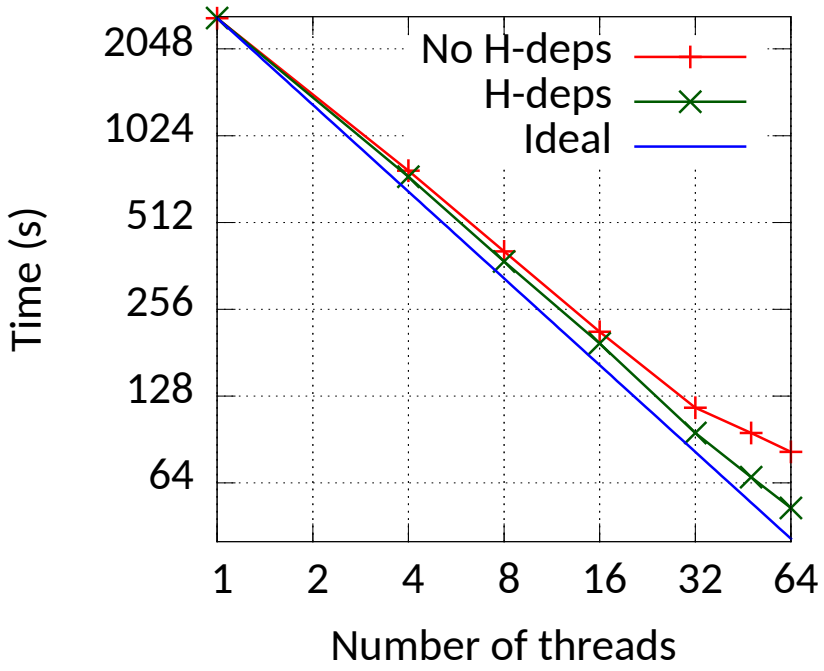
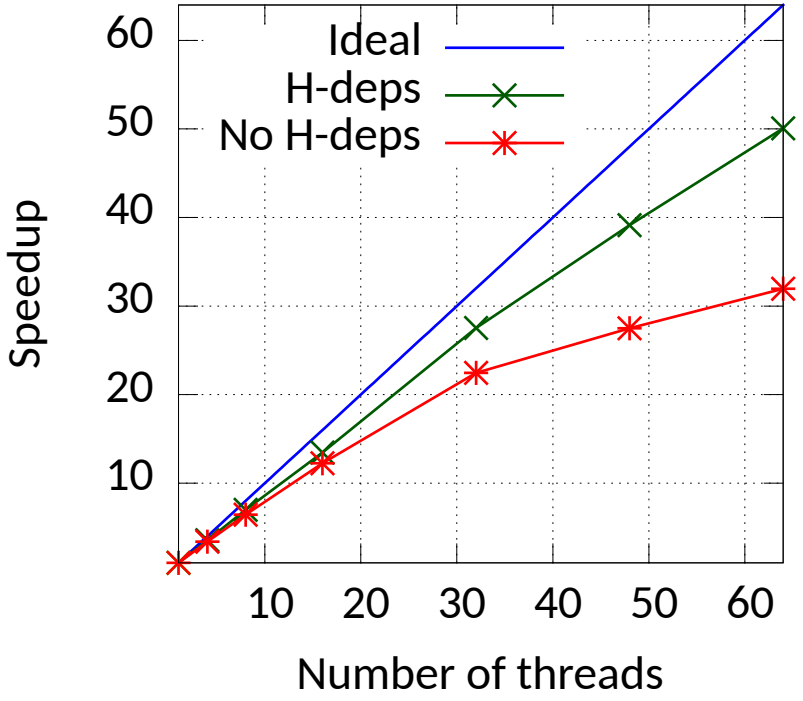




From CEA : « A hierarchical fast direct solver for distributed memory machines with manycore nodes », Augonnet, Goudin, Kuhn, Lacoste, Namyst, Ramet

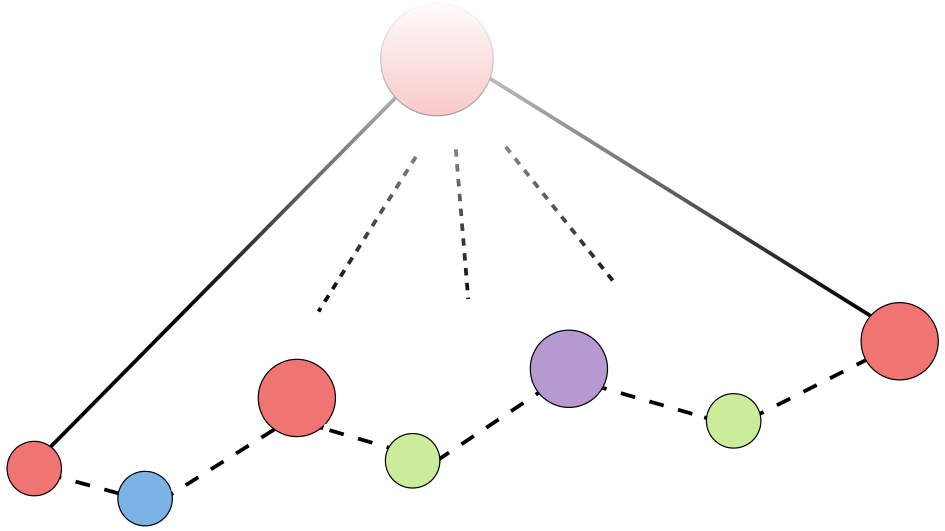
How big should a task be?

Multiple answers

- Depends on available platform parallelism
- Depends on available application parallelism
- Depends on application phases

Automatically adapt?

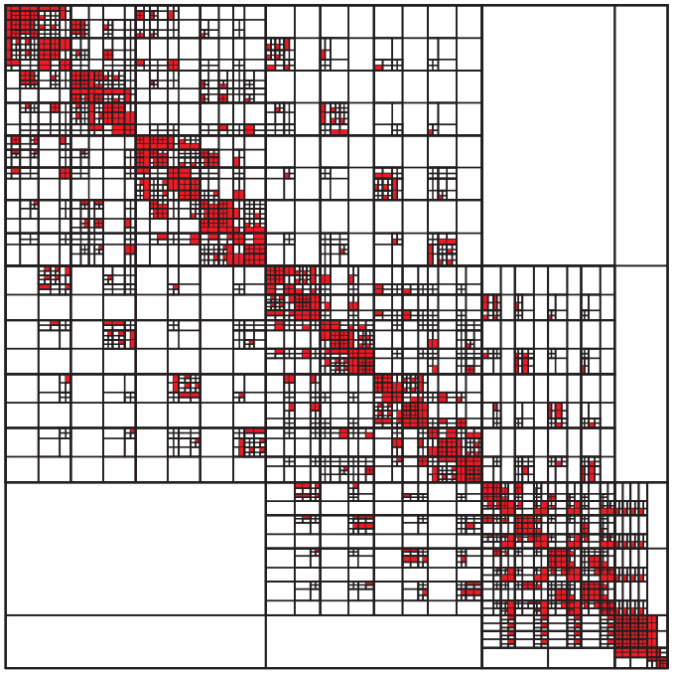
Hierarchical task graphs



Hierarchical task graphs

Applications themselves are recursive

- e.g. h-matrices



From Airbus Group

Hierarchical task graphs

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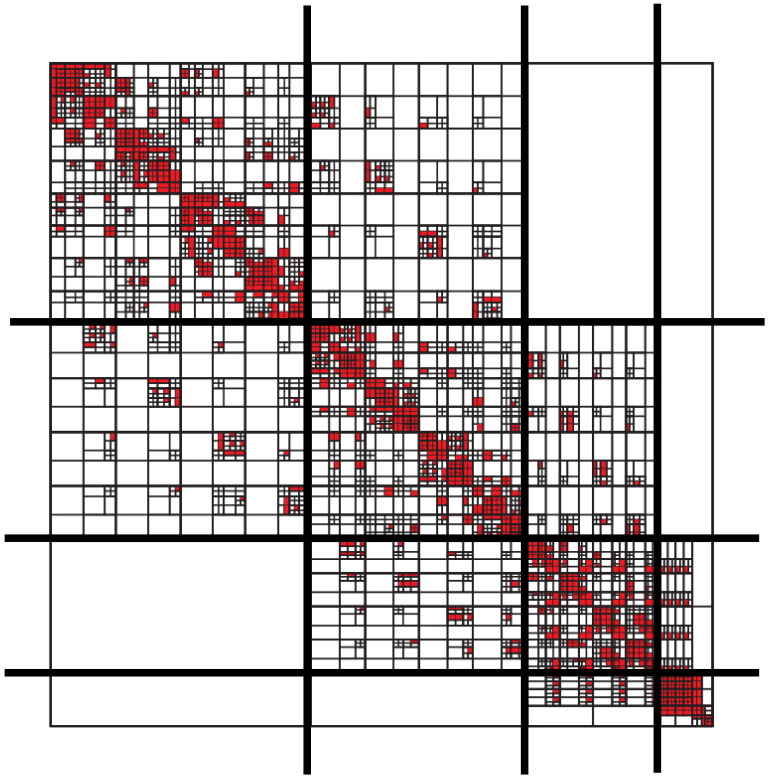

From Airbus Group

Hierarchical task graphs

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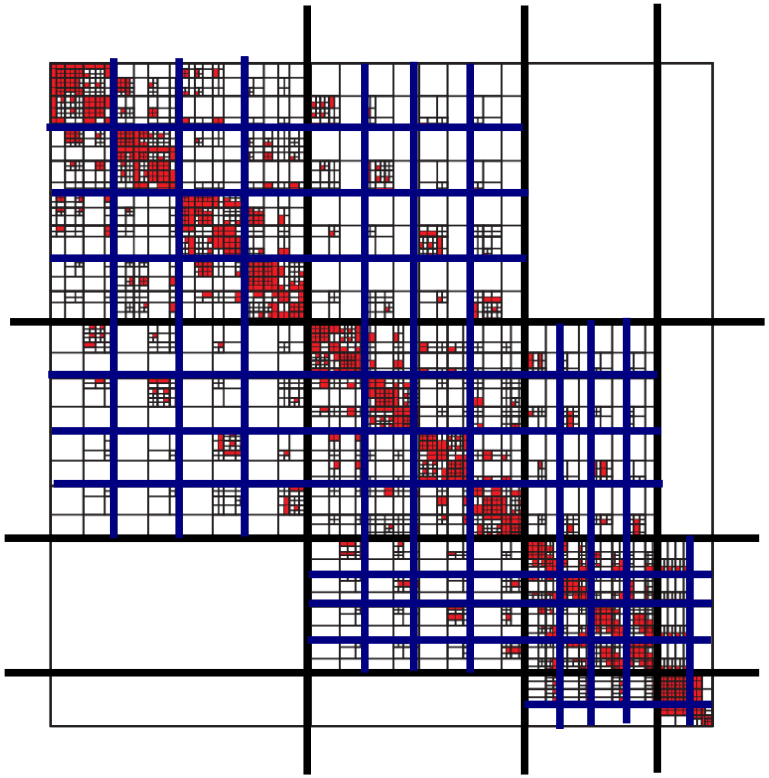
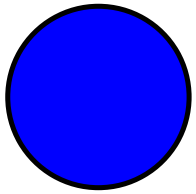


From Airbus Group

Hierarchical task graphs

Ideally, should just start with one huge task, and split



Hierarchical task graphs

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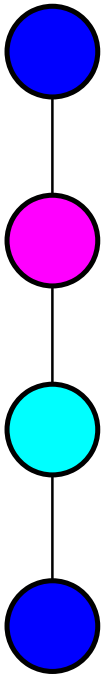

Hierarchical task graphs

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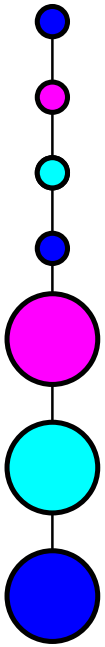

Hierarchical task graphs

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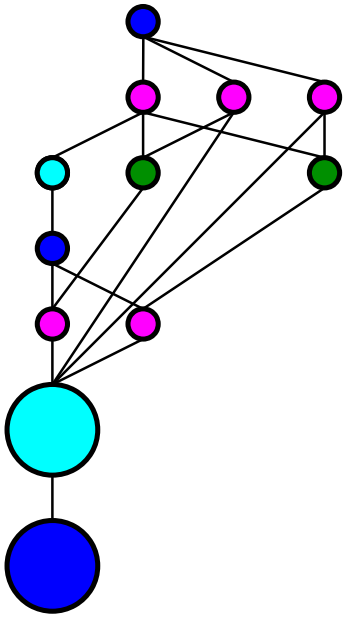

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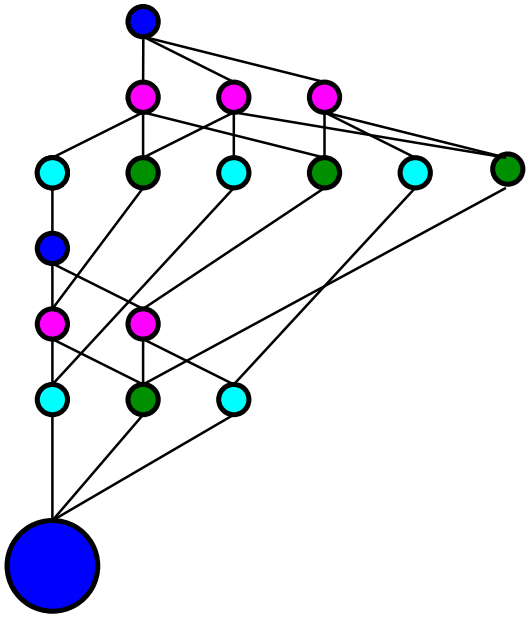
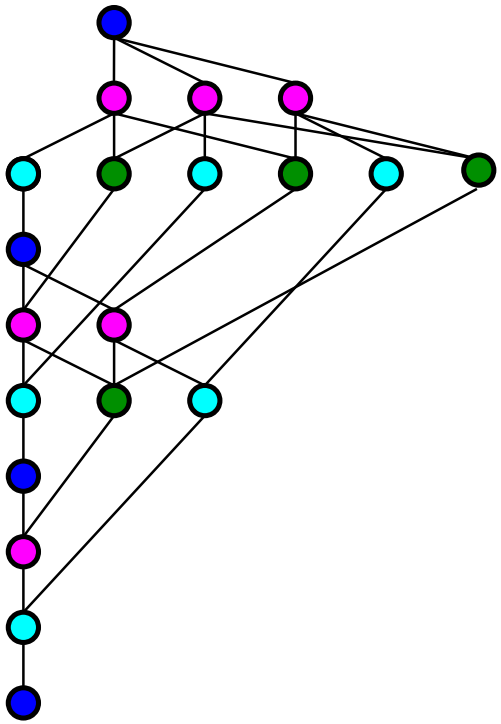


Hierarchical task graphs

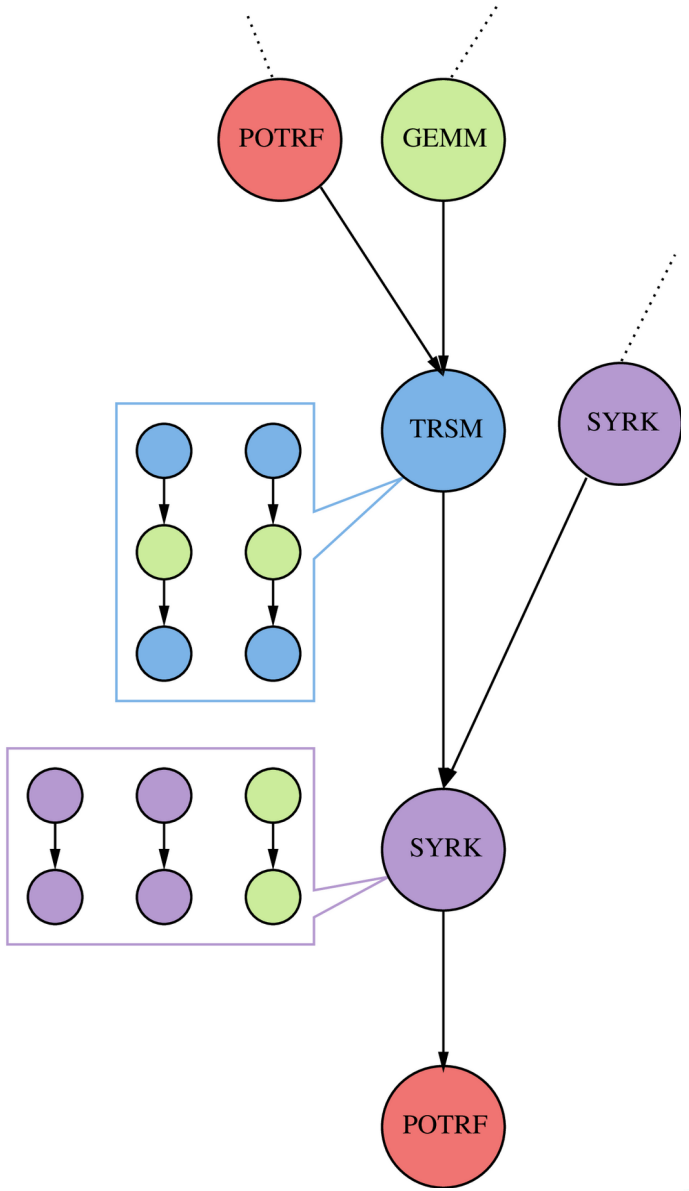
Ideally, should just start with one huge task, and split



Hierarchical task graphs

- In OpenMP?

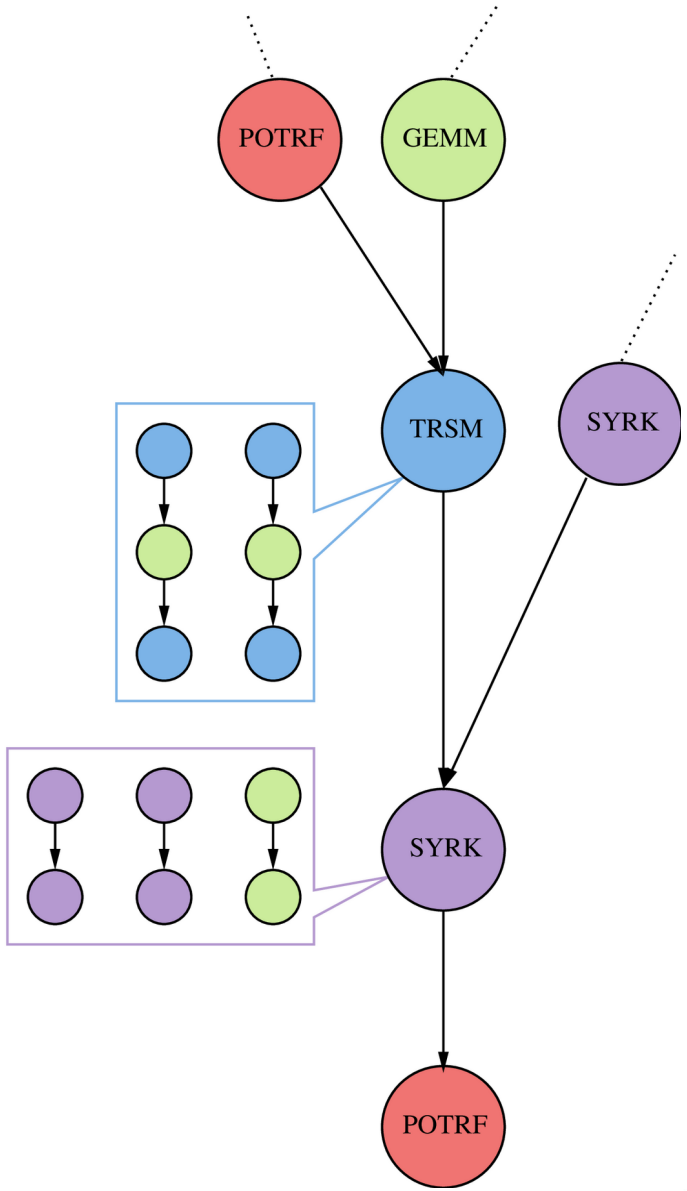
```
TRSM(A, B) {
#pragma omp task depend(in:A, inout:B) wait
{
    #pragma omp task \
            depend(in:A[0][0], inout:B[0][0])
        TRSM(A[0][0], B[0][0])
    #pragma omp task \
            depend(in:A[0][0], inout:B[1][0])
        TRSM(A[0][0], B[1][0])
    #pragma omp task \
            depend(in:A[1][0], in:B[0][0], inout:B[0][1])
        GEMM(A[1][0], B[0][0], B[0][1])
    ...
```



Hierarchical task graphs

Synchronization concerns

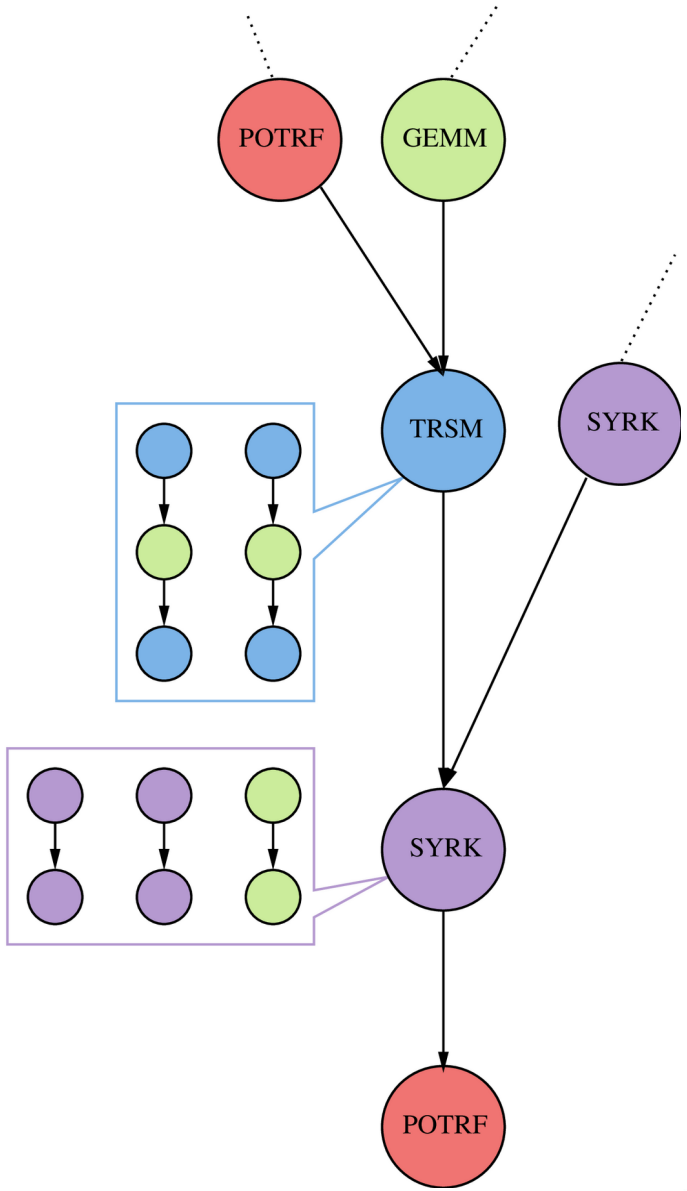
- Fork-join parallelism
- Hindered by synchronization induced by task graph



Hierarchical task graphs

- OmpSs introduced weak dependencies

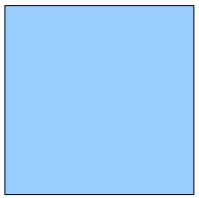
```
TRSM(A, B) {
#pragma omp task depend(weakin:A, weakinout:B) \
                    weakwait
{
   #pragma omp task \
         depend(in:A[0][0], inout:B[0][0])
        TRSM(A[0][0], B[0][0])
   #pragma omp task \
        depend(in:A[0][0], inout:B[1][0])
         TRSM(A[0][0], B[1][0])
   #pragma omp task \
        depend(in:A[1][0], in:B[0][0], inout:B[0][1])
         GEMM(A[1][0], B[0][0], B[0][1])
   ...
```



Hierarchical task graphs

In StarPU

- Explicit data registration
- Recursive partitioning



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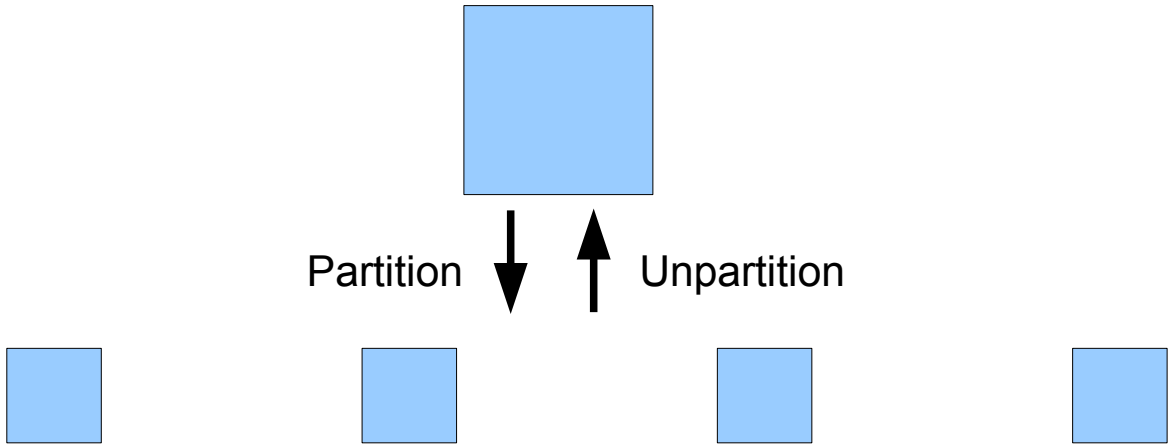

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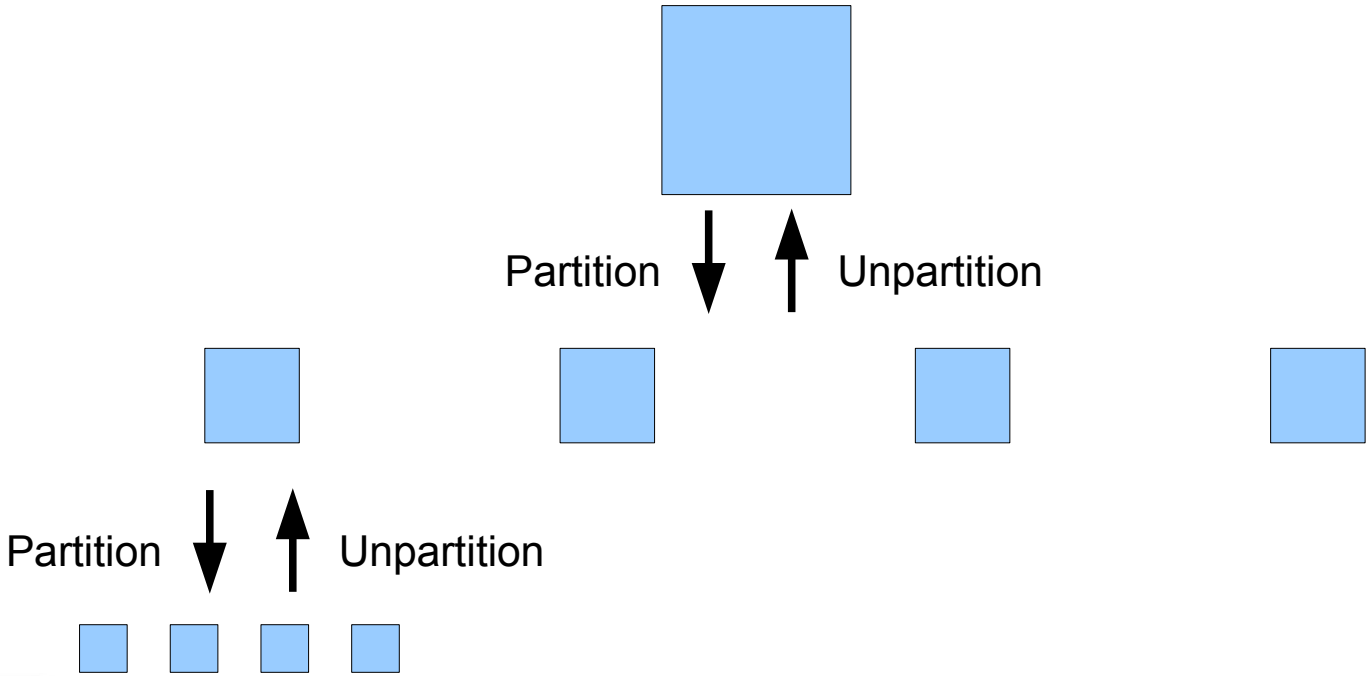

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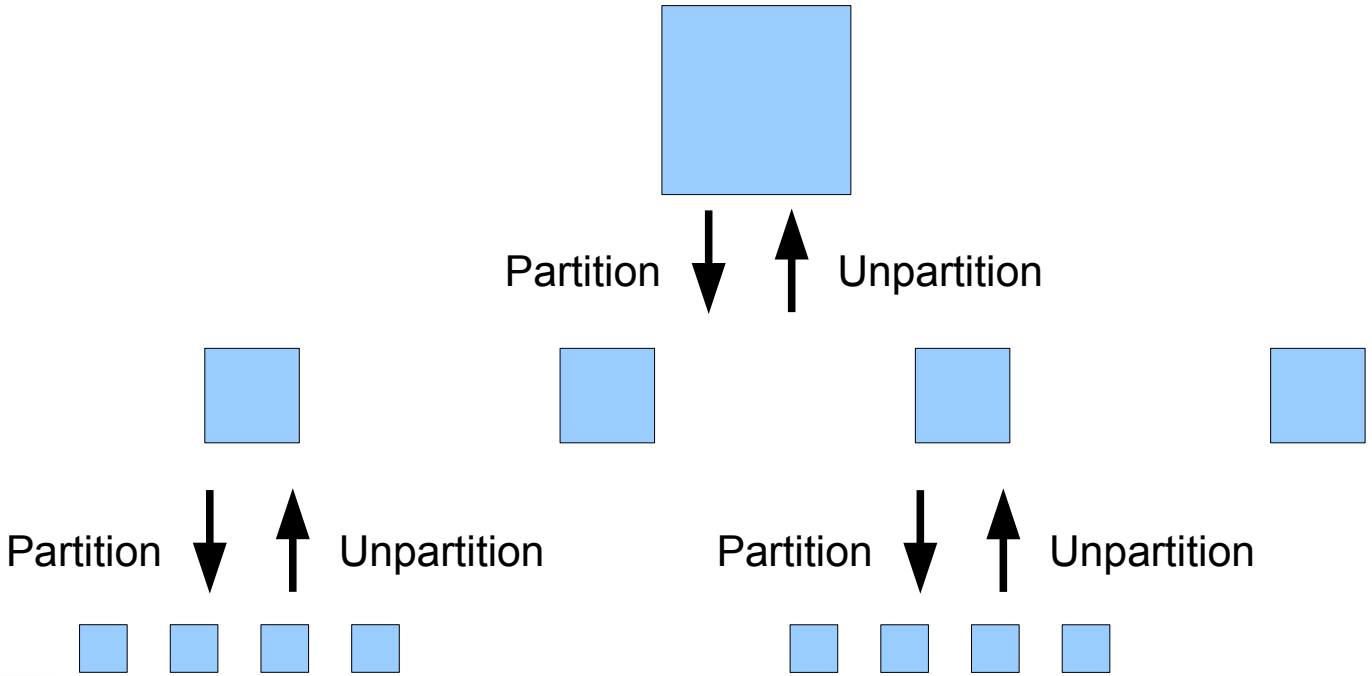

Hierarchical task graphs

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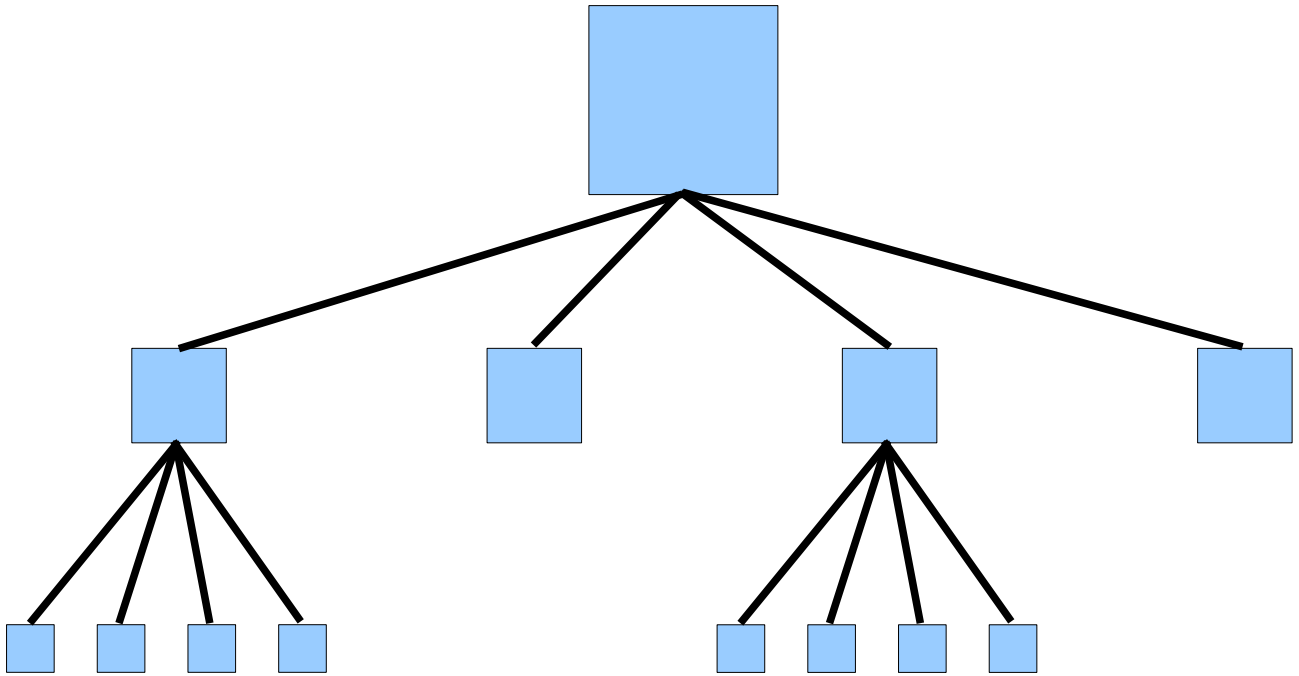
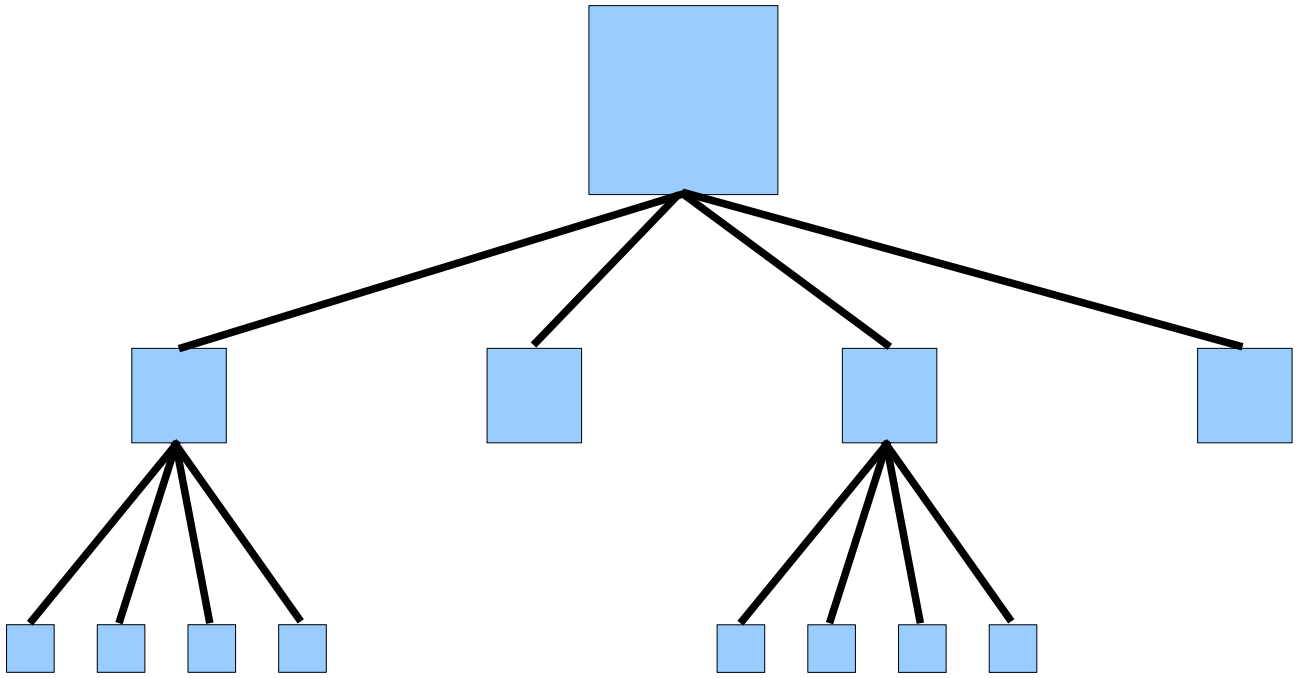


Hierarchical task graphs

In StarPU

- Multi-level data coherency, among CPUs-GPUs-disk
- Enables seamless recursive tasks
- More details in Gwenolé Lucas' talk Thursday 14:40

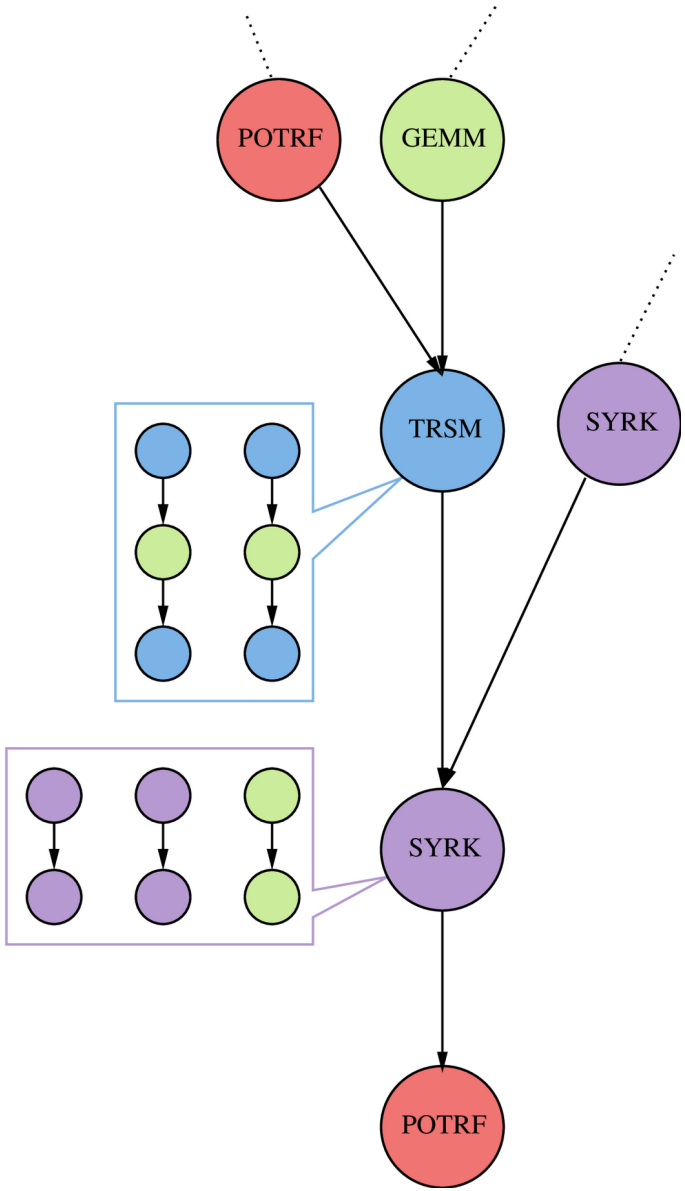


Hierarchical task graphs

Multi-level data coherency

- Synchronization pseudo-tasks
  - Only when needed
- Result is exactly as appropriate

→ Just split at will!



Hierarchical task graphs

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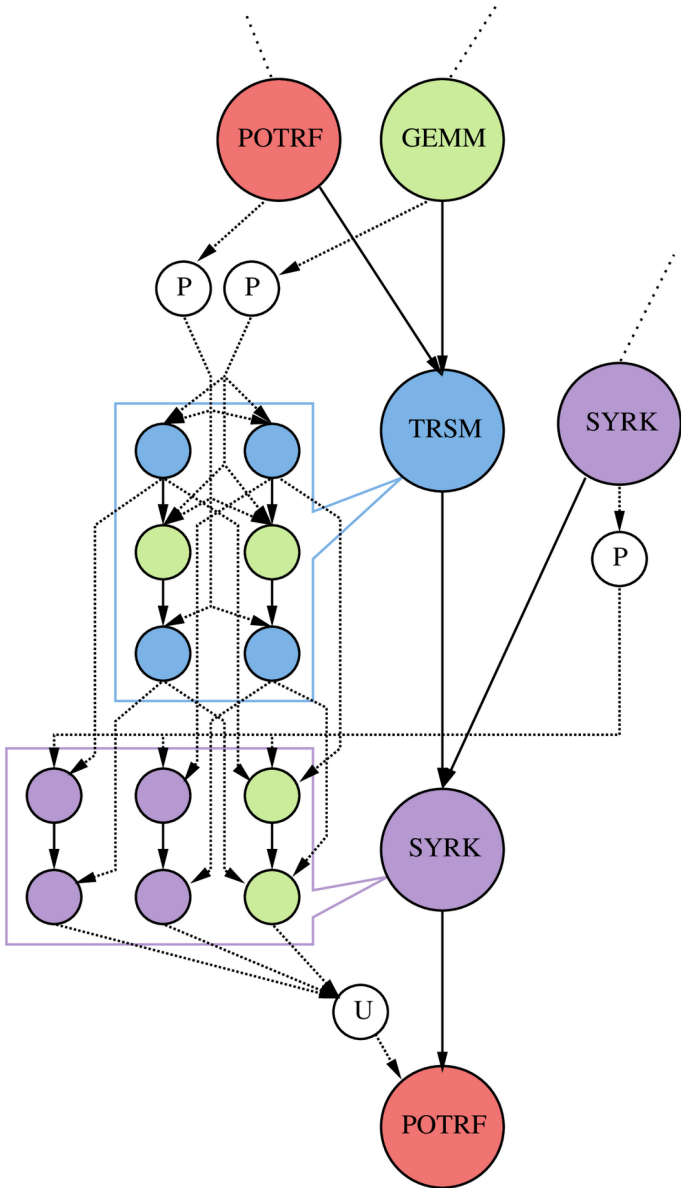

Dividing tasks

No extra synchronization

→ Can consider task graph subdivision as a tree

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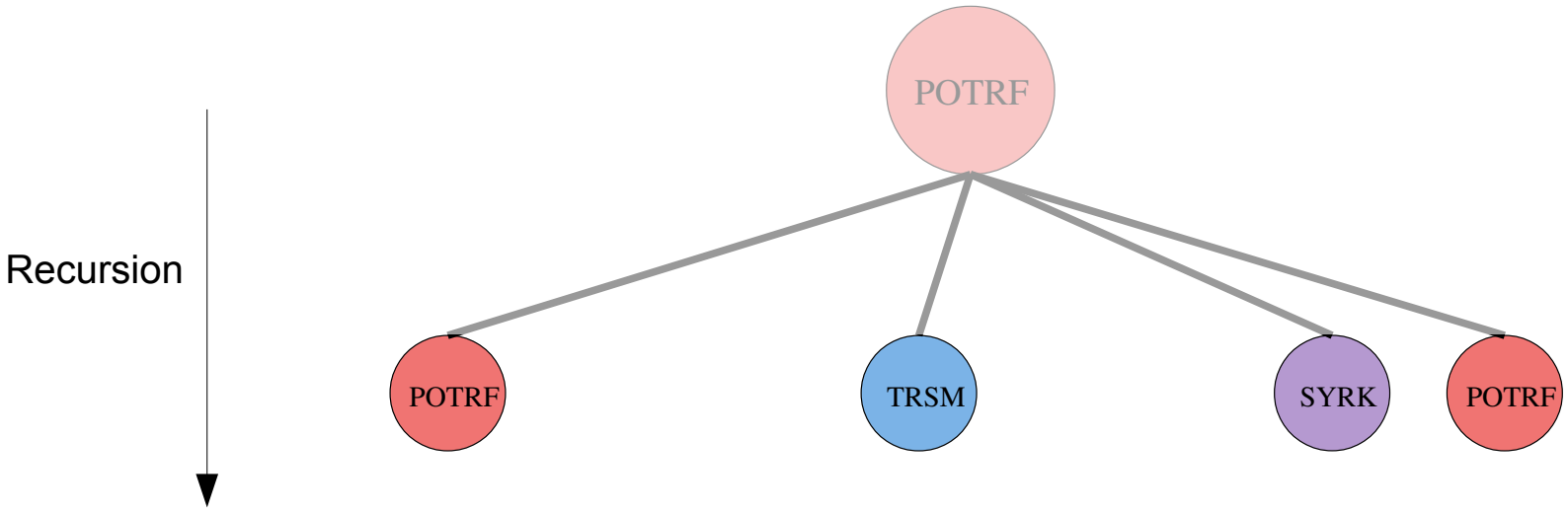

Dividing tasks

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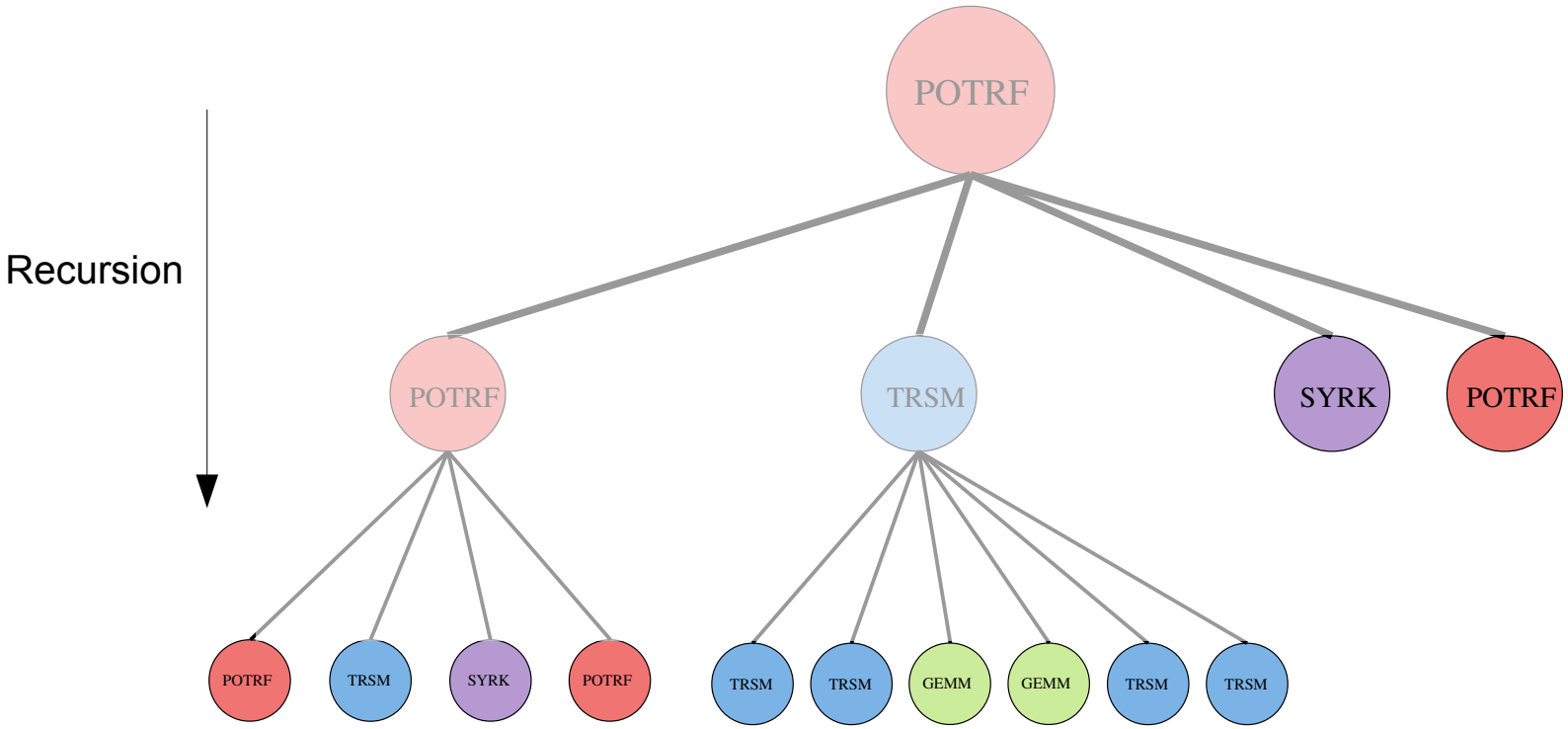
→ Can consider task graph subdivision as a tree

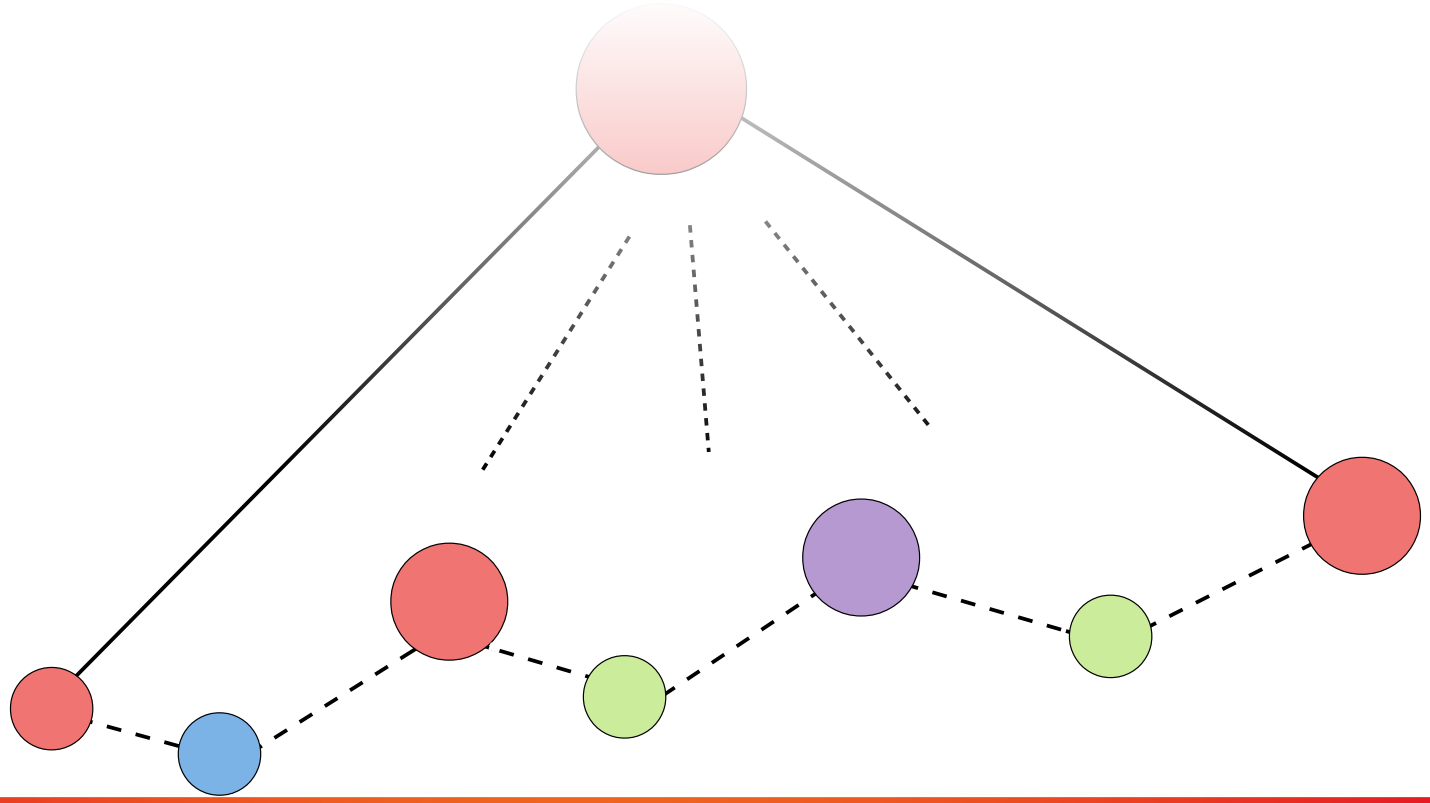


Dividing tasks

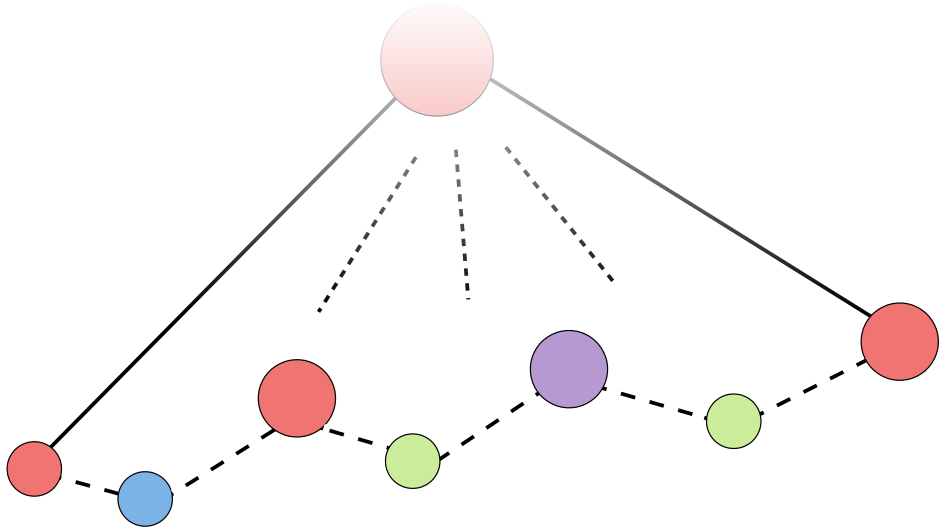
No extra synchronization

→ Can consider task graph subdivision as a tree

→ Decide at will where and when to stop recursing



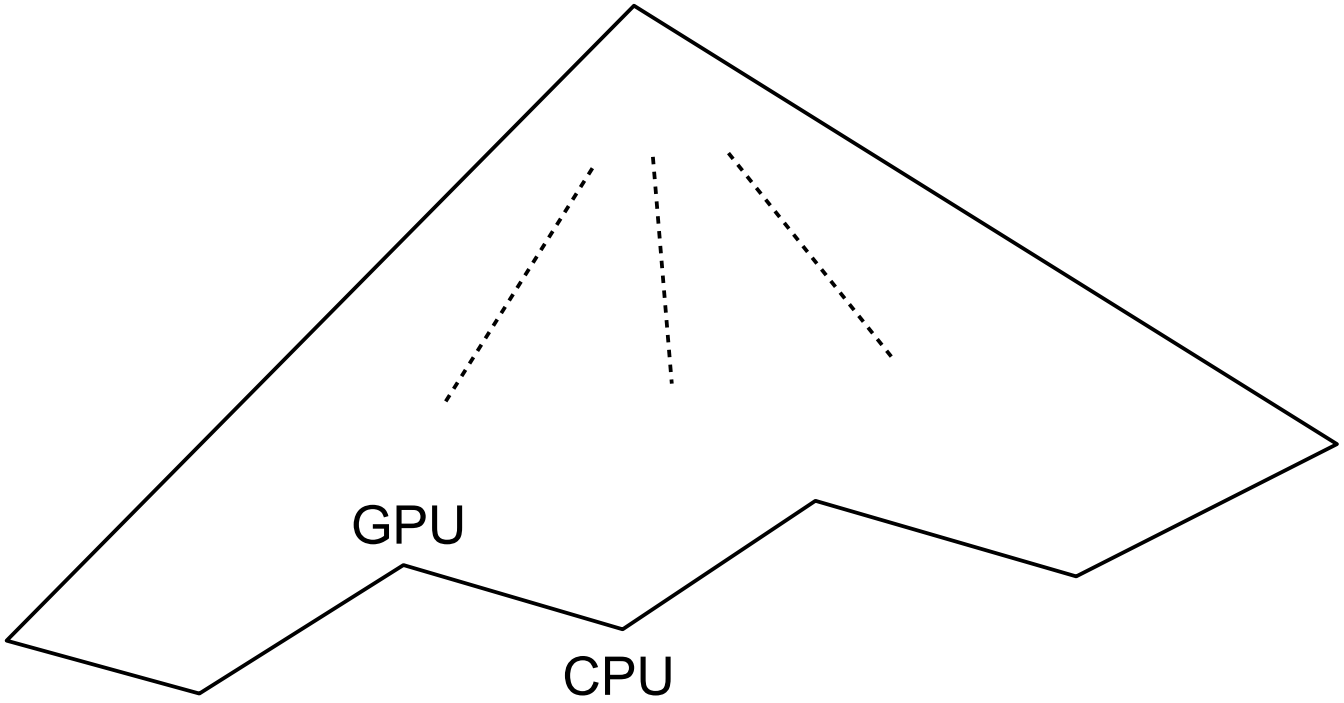
Opportunities



Opportunities

GPU / CPU efficiency management

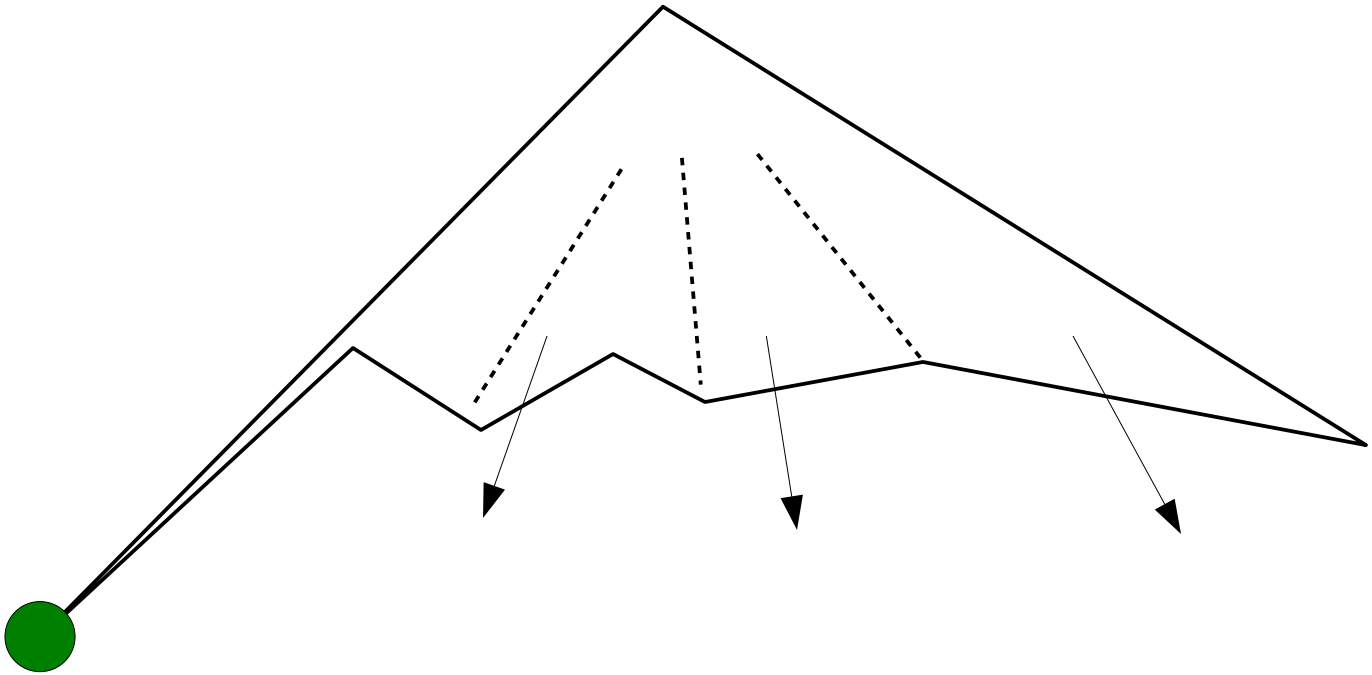
- Stop recursing at desired tile size
- Care for latency of the task graph critical path



Opportunities

Parallel submission

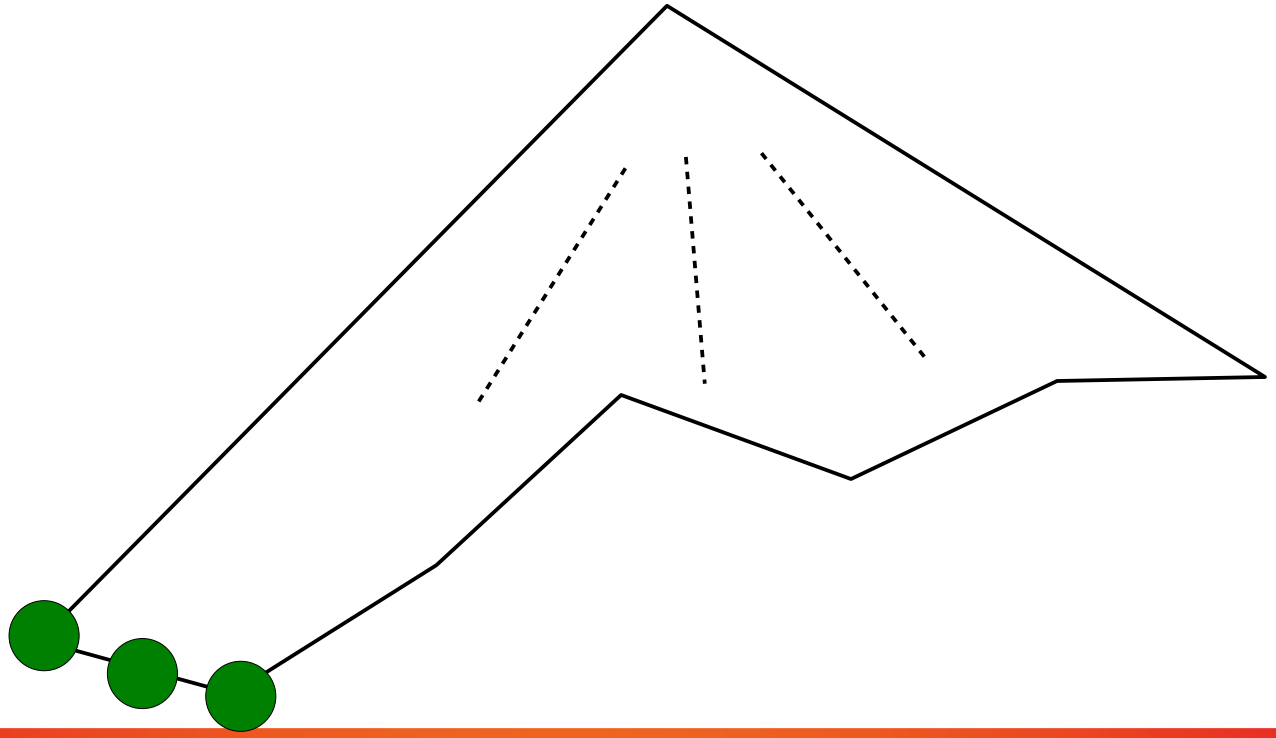
- Unroll the graph in parallel
- While one PU is computing the first task



Opportunities

Delay unrolling

- Observe behavior before unrolling the rest accordingly
- Decorrelate submission and execution



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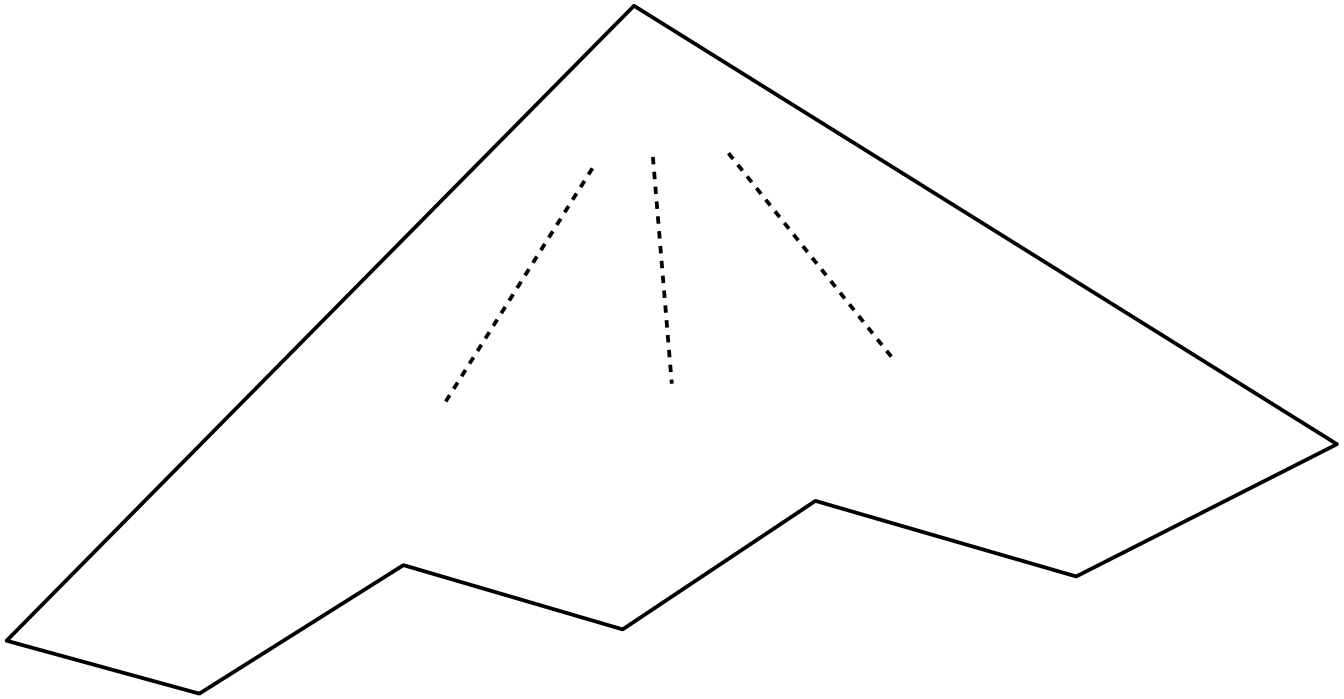
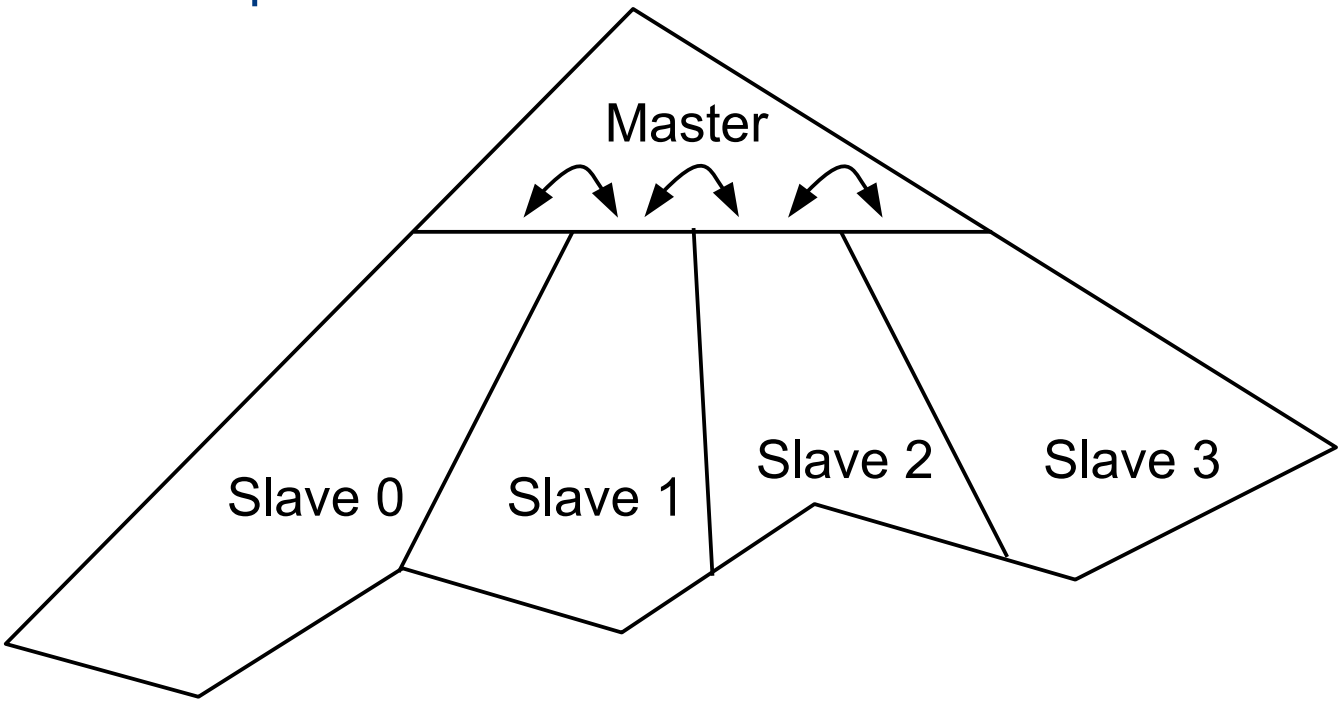


Opportunities

Scaling at large

- Master unrolls higher recursion levels, schedules result
- Slaves unroll the rest
- Master still contention point

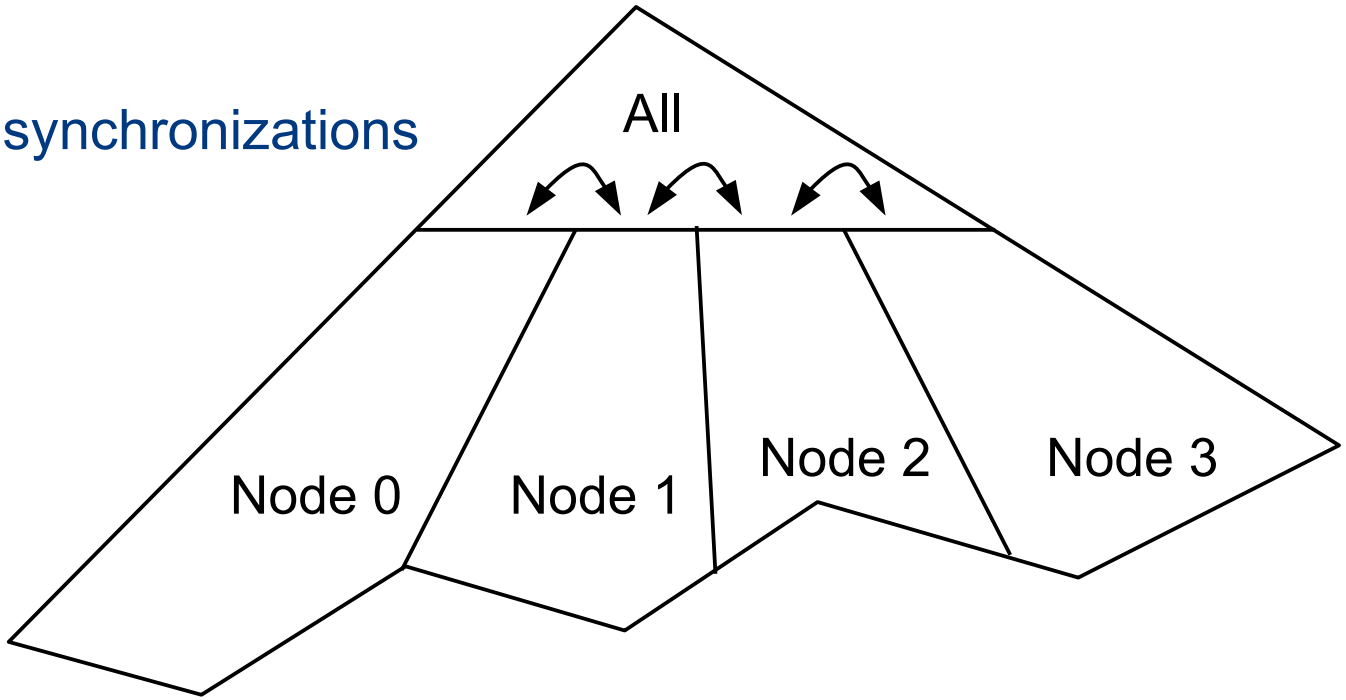


Opportunities

Scaling at large

- All nodes unroll higher recursion levels, determine task mapping
- Nodes unroll their own remaining recursion
- Network communication quite coarse

  → Spurious synchronizations

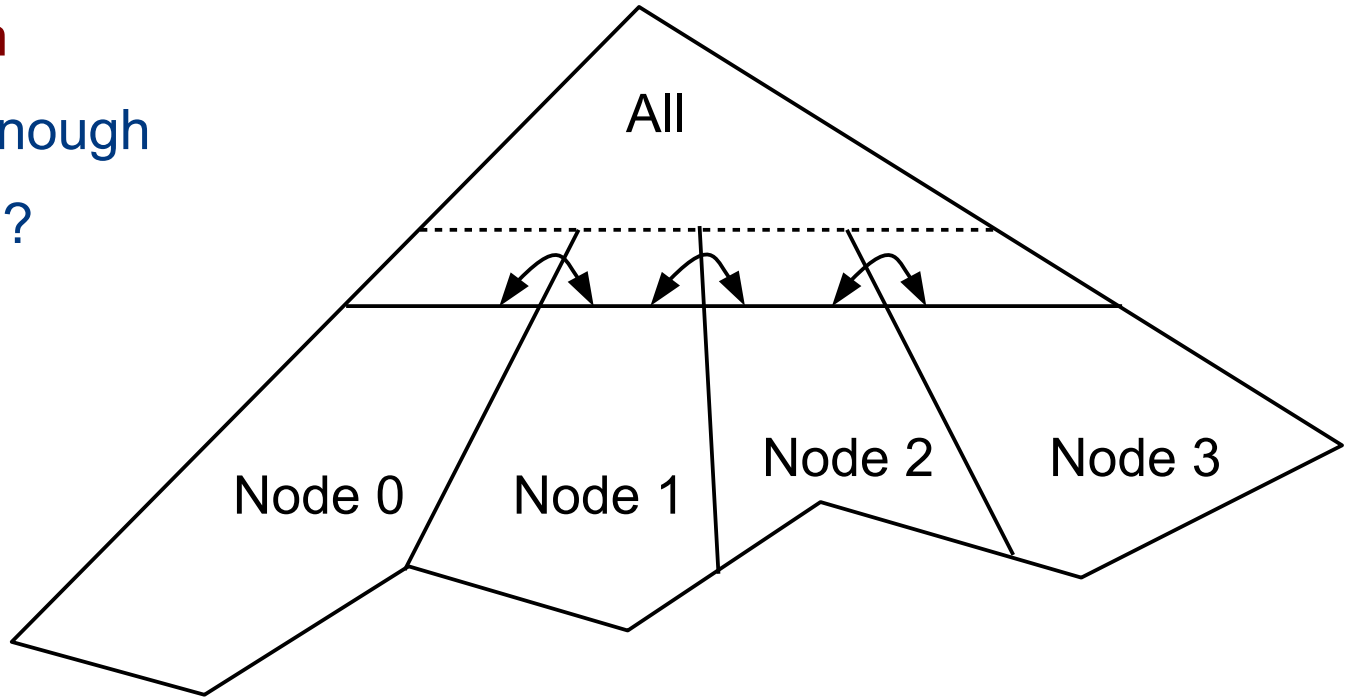


Opportunities

Scaling at large

- All nodes unroll higher recursion levels, determine task mapping
- Nodes unroll their own remaining recursion
- Network communication at finer grain
- Fine-grain enough

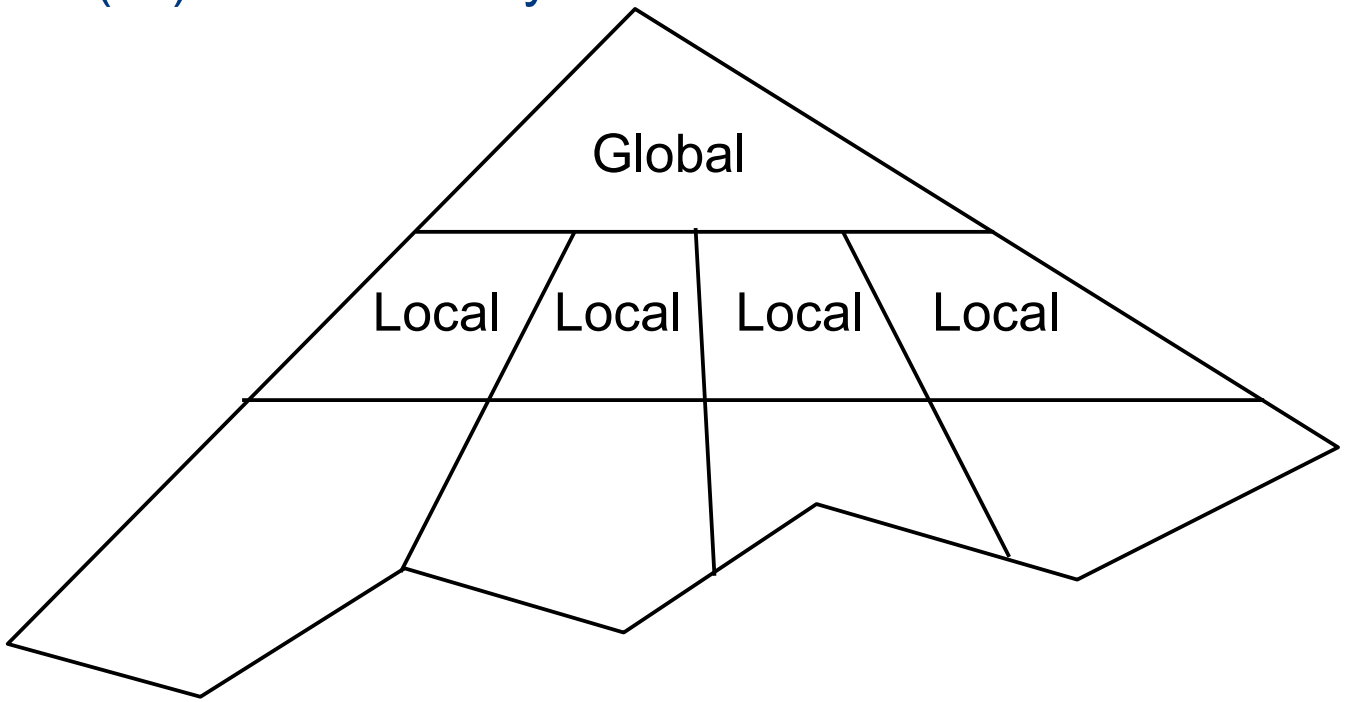
  vs overhead?



Opportunities

Scheduling at large

- High-level global task graph scheduling, e.g. mapping, critical path
- High-level local task graph scheduling, e.g. memory-based ordering
- $O(N^2)$ or even $O(N^3)$ not that costly



Opportunities

- Computation efficiency
- Scaling at large
- Scheduling at large

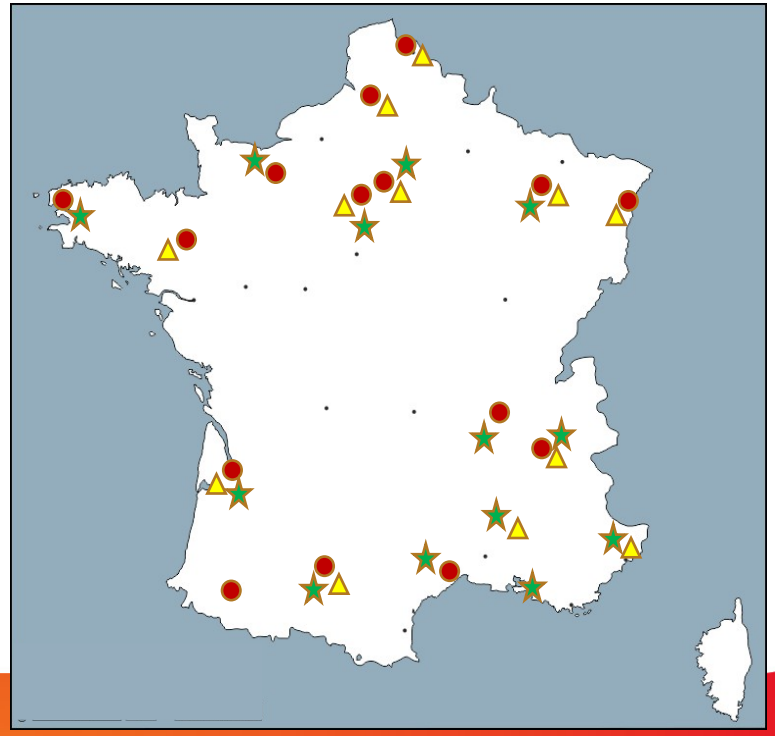
NumPEx PEPR project

NumPEx project

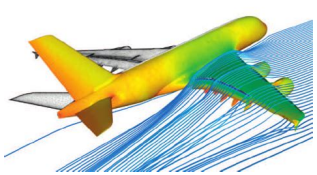
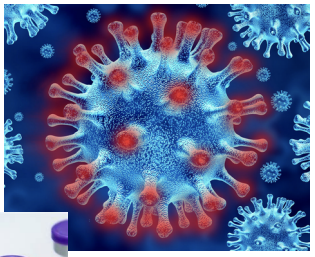
Building a national ecosystem for the future exaflops machine hosted in France

- Facilitate conception, deployment, and monitoring of composite applications at large scale
- Efficiently exploit a heterogeneous architecture with many accelerators
- Control the energy envelope

80 teams in France



NumPEx project






PC1-ExaMA

Methods/Algorithms for the Exascale

PC2-ExaSoft

HPC softwares/tools for the Exascale

PC5-ExaDIP

Application co-design Integration and productivity

PC3-ExaDost

Data-oriented softwares/tools for the Exascale

PC4-ExaATaW

Architectures/tools for large-scale workflows

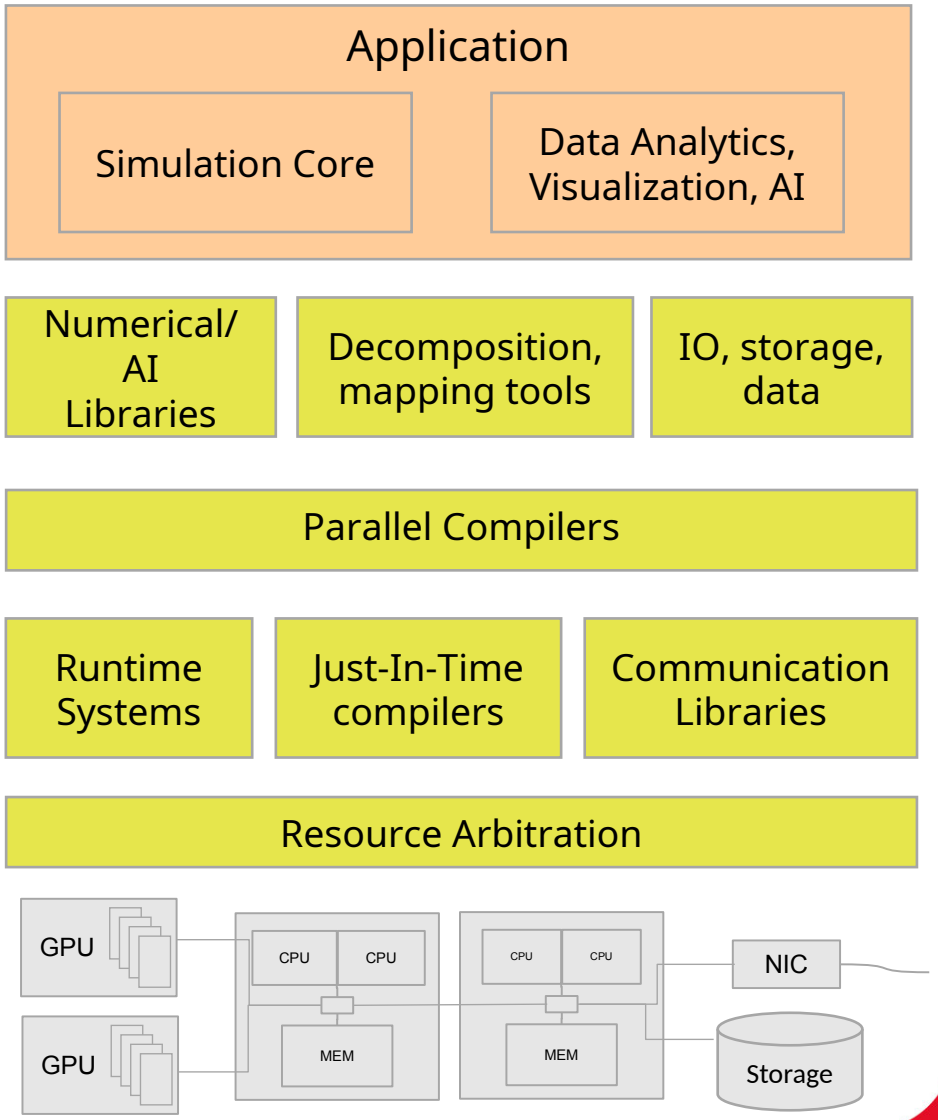
A Software Forge

Integration and productivity

NumPEx project

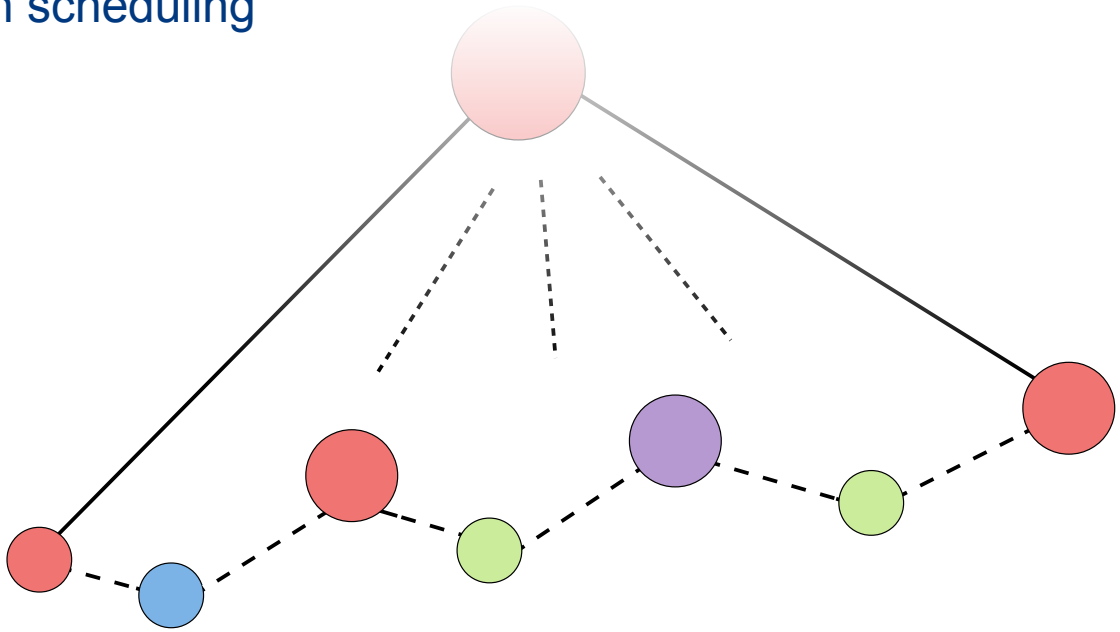
PC2-ExaSoft

- Holistic approach
  - Contribute to a sound, consistent software stack
  - Most components should fit together!
  - Bridge the gap between existing languages/software/tools
  - Integrate state-of-the-art research results
  - Demonstrate relevance on representative applications
- WP3 : Runtime Systems at Exascale



Conclusion

- Programming large systems requires abstraction
- Recursive applications are there
- Hierarchical task graphs seems an opportunity for
  - Controlling task size
  - Controlling task submission
  - High-level task graph scheduling



The StarPU runtime system

Development context

- History
  - Started in 2008
    - PhD Thesis of Cédric Augonnet
  - StarPU main core ≈ 70k lines of code
  - Written in C
- Open Source
  - Released under LGPL
  - Sources freely available
    - git repository and nightly tarballs
    - See https://starpu.gitlabpages.inria.fr/
  - Open to external contributors
- [HPPC'08]
- [Europar'09] – [CCPE'11],... >1500 citations

Features

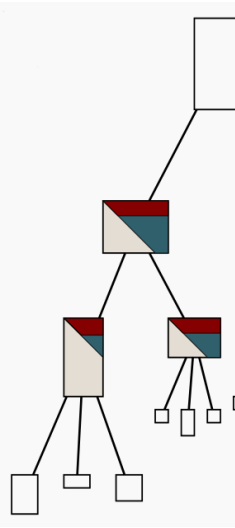
- C, OpenMP, OpenCL APIs
- CPUs, GPUs, Phi
- Advanced task mapping & scheduling
- Optimized data transfers
- Cluster Support through MPI
- Out-Of-Core support
- Simulation support
- Performance analysis tools

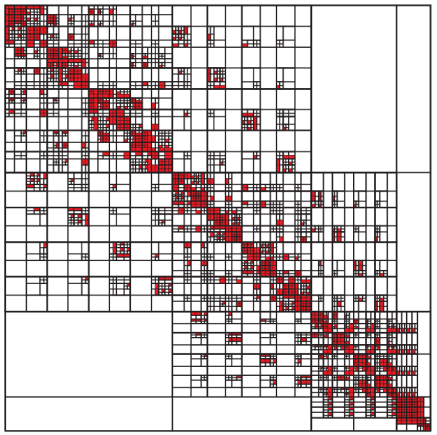
The StarPU runtime system

Success stories

Task-based programming actually makes things easier!

- QR-Mumps (sparse linear algebra)
  - Non-task version: only 1D decomposition
  - Task version: 2D decomposition, flurry of parallelism
    - With seamless memory control
- H-Matrices (compressed linear algebra, AirBus)
  - Out-of-core support
    - Could run cases unachievable before
    - e.g. 1600 GB matrix with 256 GB memory
  - Shipped to AirBus customers
- Implemented CFD, FMM, CG, stencils, …





The StarPU runtime system

Supported platforms

- Supported architectures
  - Multicore CPUs (x86, PPC, ...)
  - NVIDIA GPUs
  - OpenCL devices (eg. AMD cards)
  - HIP
  - FPGA (ongoing)
  - Old Intel Xeon Phi (MIC), SCC, Kalray MPPA, Cell (decommissioned)
- Supported Operating Systems
  - Linux
  - Mac OS
  - Windows

Applications on top of StarPU

Using CPUs, GPUs, distributed, out of core, ...

- Dense linear algebra
  - Cholesky, QR, LU, ... : Chameleon (based on Plasma/Magma)
- Sparse linear algebra
  - QR_MUMPS
  - PaStiX
- Compressed linear algebra
  - BLR, h-matrices
- Fast Multipole Method
  - ScalFMM
- Conjugate Gradient
- Other programming models : Data flow, skeletons
  - SignalPU, SkePU
- ...