Hybrid methods, Hybrid architectures, Hybrid compressions for sparse direct solvers

JS MCIA, Pau

P. Ramet
HiePACS team
Inria Bordeaux Sud-Ouest
LaBRI Bordeaux University

February 11, 2014

Guideline

Introduction

Direct sparse factorization

Hybrid methods

Towards sparse factorization on manycore

Low-rank compression - $\mathcal{H}$-matrix

Conclusion

1 Introduction

Motivations

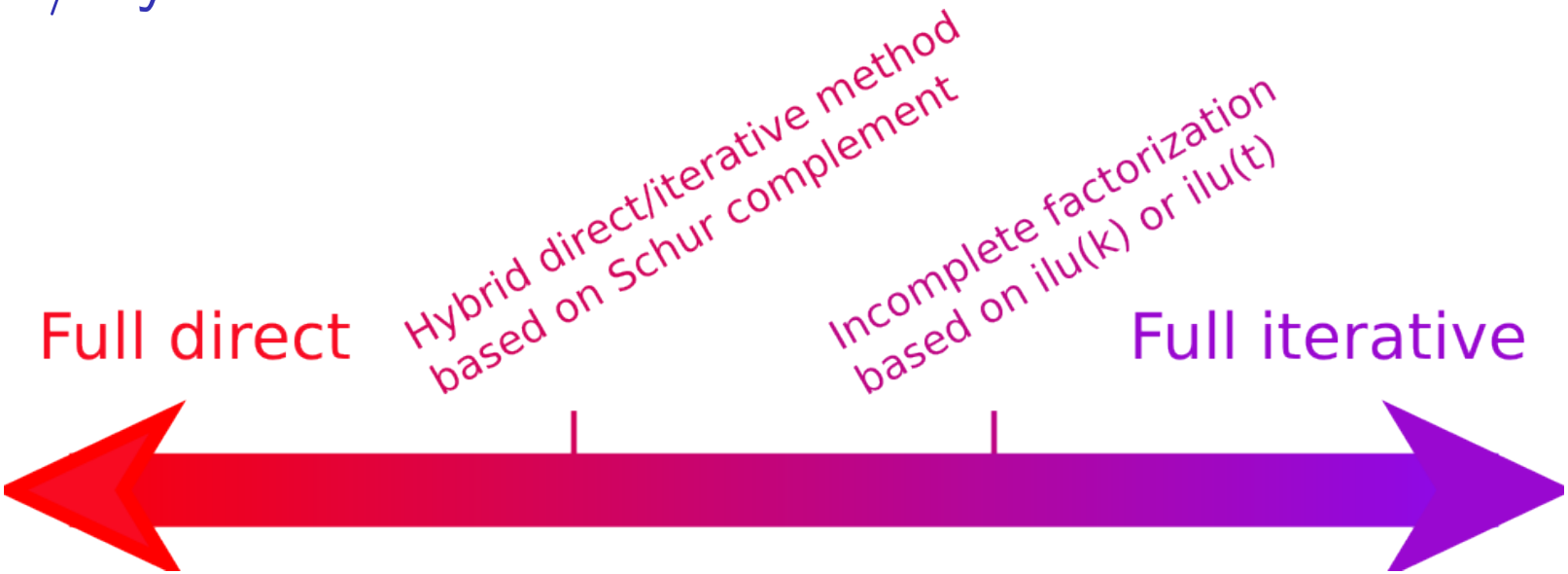
- solve linear systems of equations $\rightarrow$ key algorithmic kernel

$$\textit{Continuous problem}$$
$$\downarrow$$
$$\textit{Discretization}$$
$$\downarrow$$
$$\textit{Solution of a linear system } Ax = b$$

- Main parameters:
  - Numerical properties of the linear system (symmetry, positive definite, conditioning, ...)
  - Size and structure:
    - Large $> 10^6 \times 10^6$ (square / rectangular)
    - Dense or Sparse (structured / unstructured)
    - Target computer (sequential / parallel)

$\rightarrow$ *Algorithmic choices are critical*

Mixed/Hybrid direct-iterative methods



The "spectrum" of linear algebra solvers

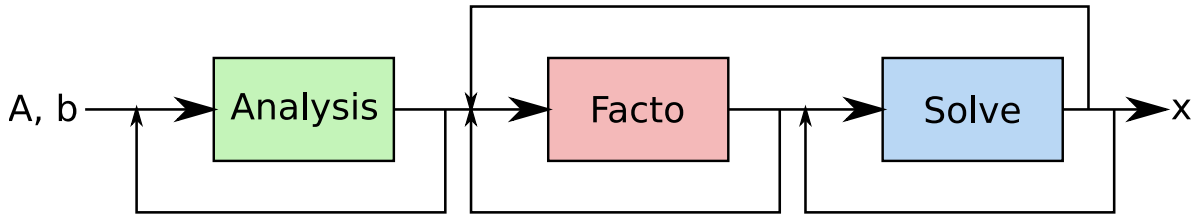
- Robust/accurate for general problems
- BLAS-3 based implementation
- Memory/CPU prohibitive for large 3D problems
- Limited parallel scalability

- Problem dependent efficiency/controlled accuracy
- Only mat-vec required, fine grain computation
- Less memory consumption, possible trade-off with CPU
- Attractive "build-in" parallel features

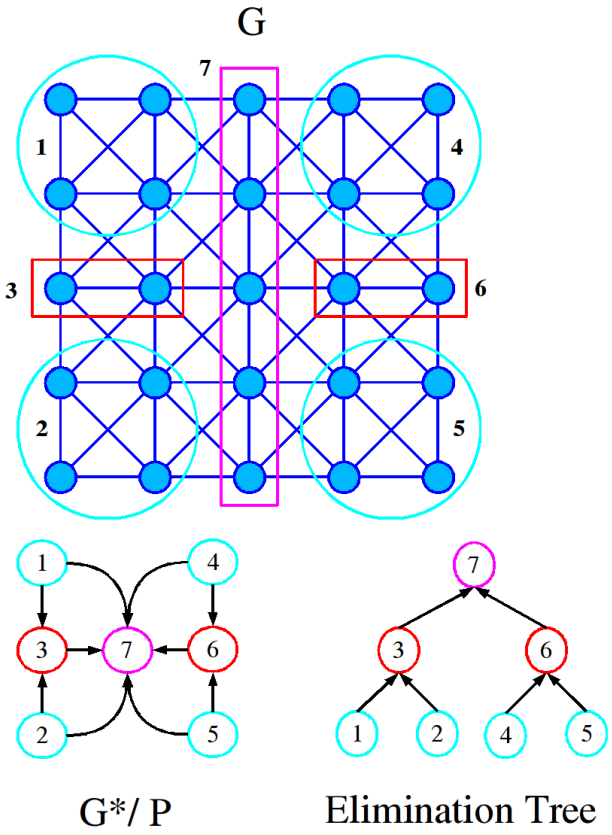
2
Direct sparse factorization

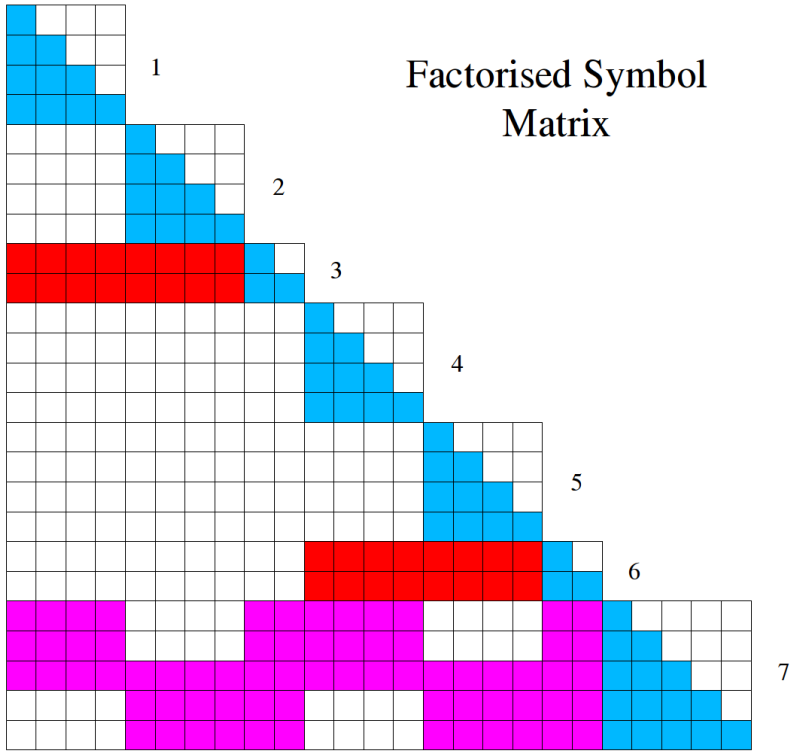
Major steps for solving sparse linear systems

1. Analysis: matrix is preprocessed to improve its structural properties ($A'x' = b'$ with $A' = P_n P D_r A D_c Q P^T$)
2. Factorization: matrix is factorized as $A = LU$, LL^T or LDL^T
3. Solve: the solution x is computed by means of forward and backward substitutions



Direct Method and Nested Dissection [A. George 73]





Symbolic factorization

The goal of this algorithm is to build the non-zero pattern of L (and U). We will consider the symmetric case (graph of $A + A^t$ if A has an unsymmetric NZ pattern). In this case the symbolic factorization is really cheaper than the factorization algorithm.

Fundamental property

The symbolic factorization relies on the elimination tree of A.

Supernodal methods

Definition

A *supernode* (or supervariable) is a set of contiguous columns in the factors **L** that share essentially the same sparsity structure.

- All algorithms (ordering, symbolic factor., factor., solve) generalized to block versions.
- Use of efficient matrix-matrix kernels (improve cache usage).
- Same concept as *supervariables* for elimination tree/minimum degree ordering.
- Supernodes and pivoting: pivoting inside a supernode does not increase fill-in.

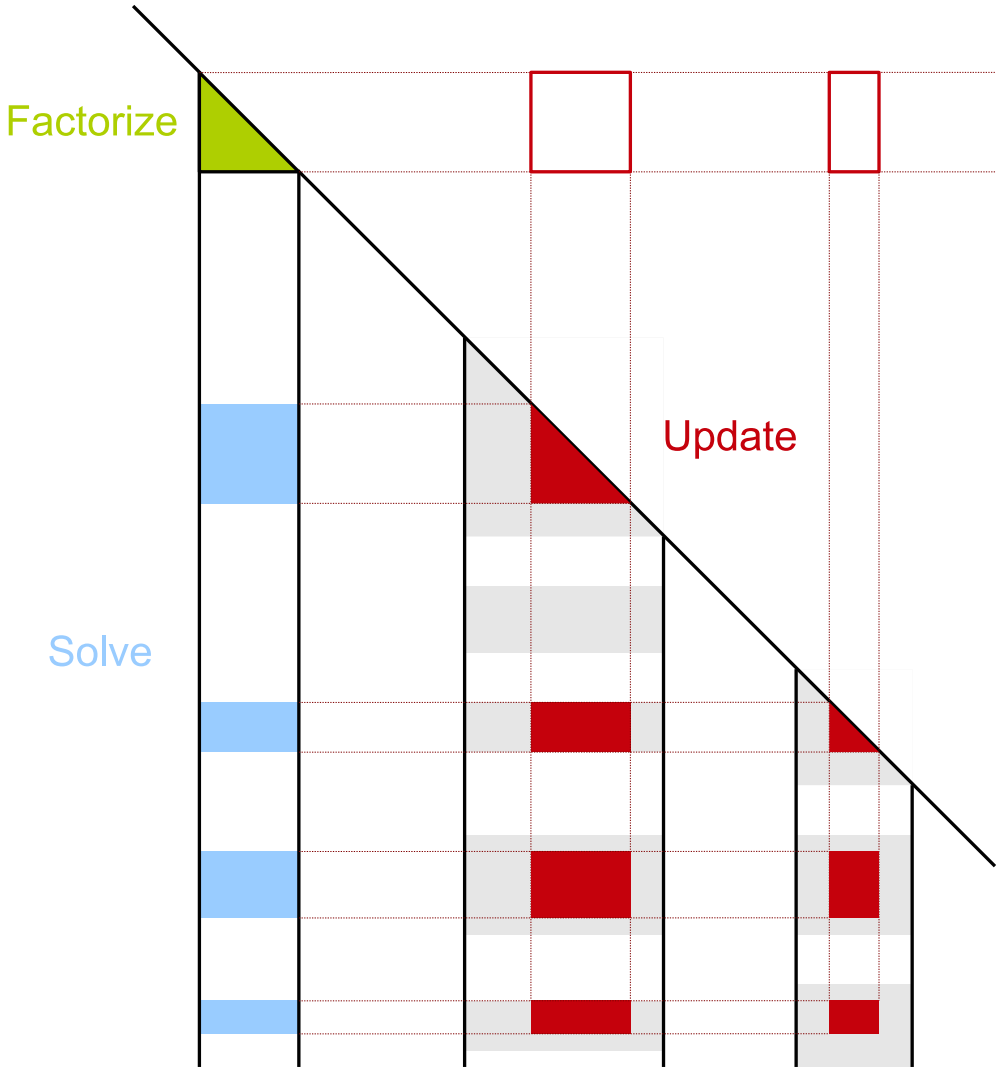
PaStiX Features [P. HENON, P. RAMET, ...]

- LLt, LDLt, LU : supernodal implementation (BLAS3)
- Static pivoting + Refinement: CG/GMRES/BiCGstab
- 1D/2D block distribution
- Simple/Double precision + Float/Complex operations
- **MPI/Threads (Cluster/Multicore/SMP/NUMA)**
- **Multiple GPUs using DAG runtimes**
- Support external ordering library (PT-Scotch/METIS)
- Multiple RHS (direct factorization)
- Incomplete factorization with ILU(k) preconditionner
- Schur computation
- Out-of Core implementation (shared memory only)

Current works

- with Astrid Casadei (PhD student) : memory optimization to build a Schur complement in PaStiX tight coupling between sparse direct and iterative solvers (HIPS)
- with Xavier Lacoste (PhD student) and the MUMPS team : GPU optimizations for sparse factorizations with StarPU
- with Mathieu Faverge (Assistant Professor) : **redesigned** PaStiX static/dynamic scheduling with PaRSEC (George Bosilca's team) in order to get a generic framework for multicore/MPI/GPU/Out-of-Core + **compression**

Supernodal factorization tasks



Static scheduling within PaStiX

forall the *Supernode* S_1 *attributed to* t **do**
  `wait` (S_1);
  `factorize` (S_1);
  forall the *off diagonal blocks* B_i *of* S_1 **do**
    $S_2 \leftarrow$ `supernode_in_front_of` (B_i);
    `lock` (S_2);
    `update` (S_1, S_2);
    `unlock` (S_2);
    if *All updates applied on* S_2 **then**
      `release` (S_2)
    end
  end
end

Direct Solver Highlights (multicore)

SGI 160-cores

Name	**N**	**NNZ_A**	**Fill ratio**	**Fact**
Audi	9.44×10^5	3.93×10^7	31.28	float LL^T
10M	1.04×10^7	8.91×10^7	75.66	complex LDL^T

10M	10	20	40	80	160
Facto (s)	3020	1750	654	356	260
Mem (Gb)	122	124	127	133	146
Solve (s)	24.6	13.5	3.87	2.90	2.89

Audi	128	2x64	4x32	8x16
Facto (s)	17.8	18.6	13.8	**13.4**
Mem (Gb)	**13.4**	2x7.68	4x4.54	8x2.69
Solve (s)	0.40	0.32	0.21	**0.14**

Direct Solver Highlights (cluster of multicore)

RC3 matrix - complex double precision
N=730700 - NNA=41600758 - Fill-in=50

Facto	1 MPI	2 MPI	4 MPI	8 MPI
1 thread	6820	3520	1900	1890
6 threads	1020	639	337	287
12 threads	525	360	155	121
Mem Gb	1 MPI	2 MPI	4 MPI	8 MPI
1 thread	34	19,2	12,5	9,22
6 threads	34,3	19,5	12,8	9,66
12 threads	34,6	19,7	13	9,14
Solve	1 MPI	2 MPI	4 MPI	8 MPI
1 thread	6,97	3,75	1,93	1,03
6 threads	2,5	1,43	0,78	0,54
12 threads	1,33	0,93	0,66	0,59

Dynamic Scheduling for NUMA and multicore architectures [M. FAVERGE]

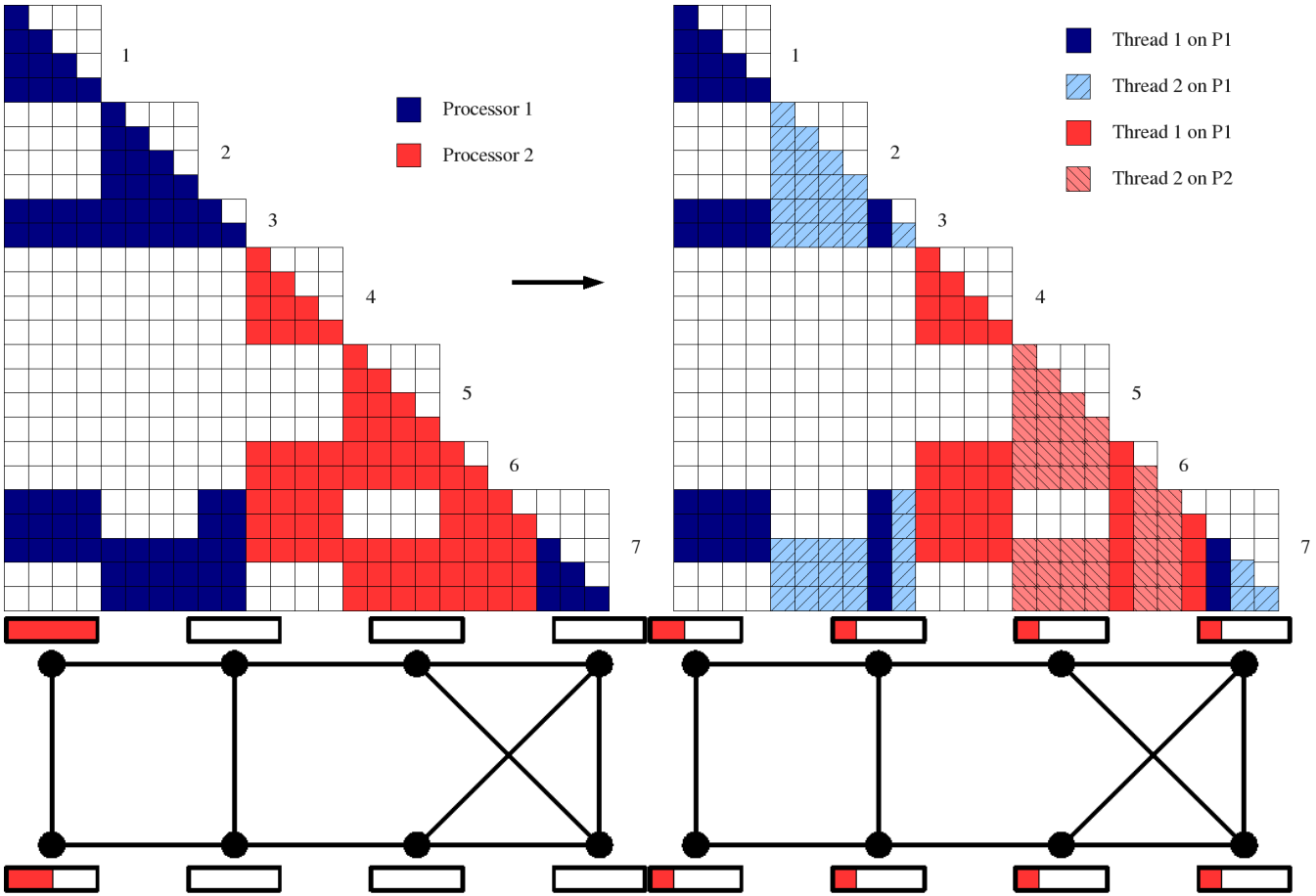
Needs

- Adapt to NUMA architectures
- Improve memory affinity (take care of memory hierarchy)
- Reduce idle-times due to I/O (communications and disk access in future works)

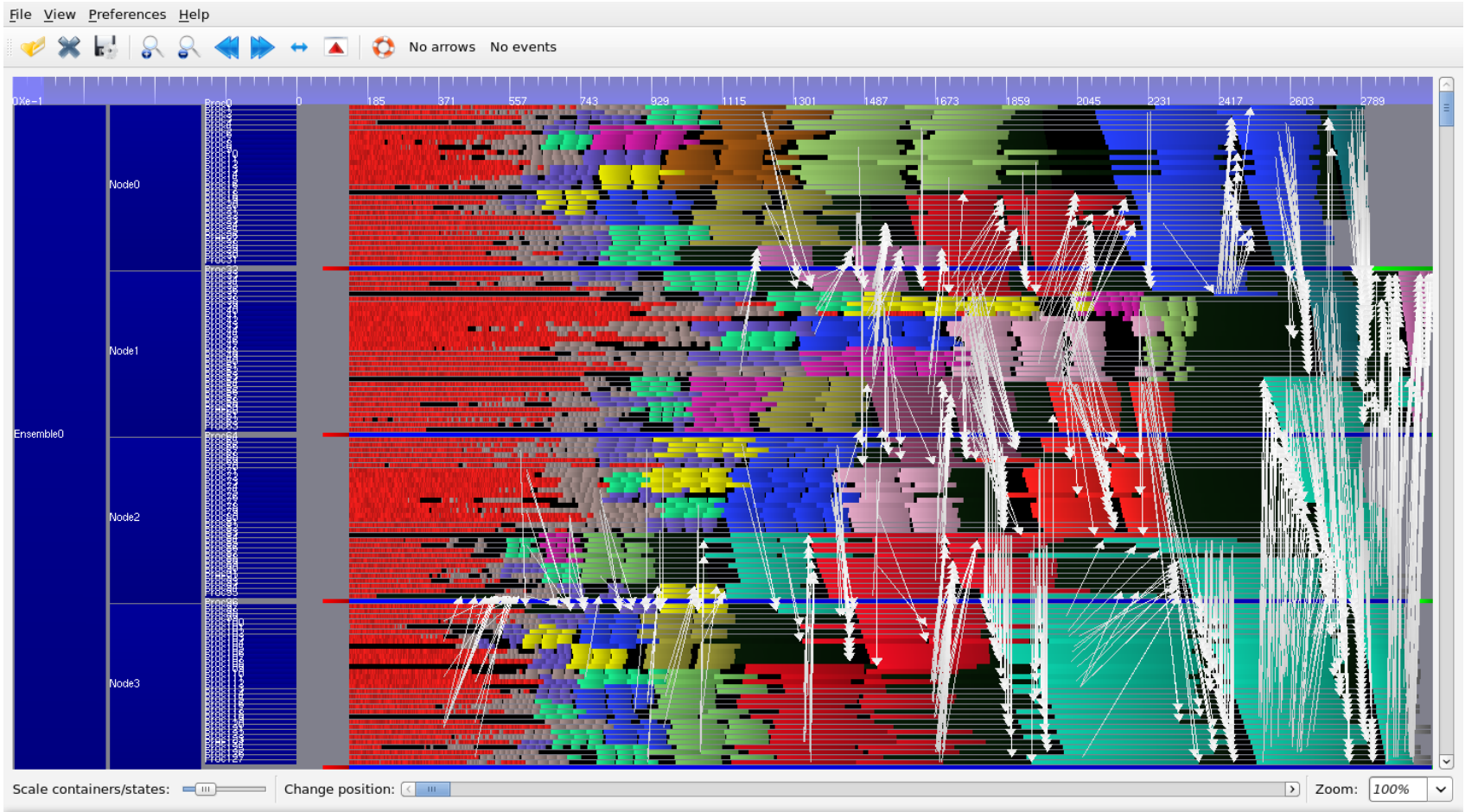
Proposed solution

- Based on a classical work stealing algorithm
- Stealing is limited to preserve memory affinity
- Use dedicated threads for I/O and communication in order to give them an higher priority
- Suitable to GP-GPU programming model

NUMA-Aware Allocation (upto 20% efficiency)

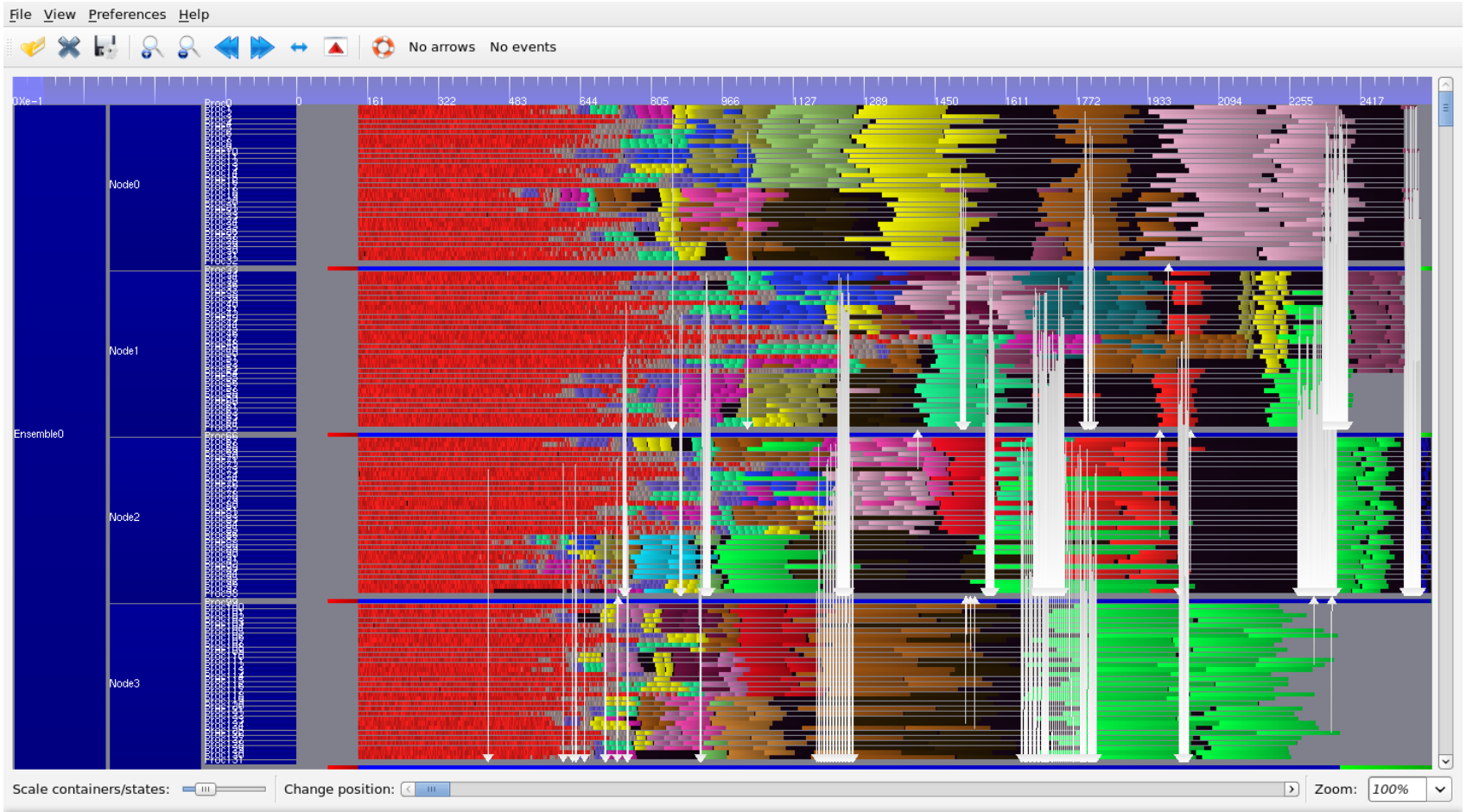


Static Scheduling Gantt Diagram



- *10Million* test case on IDRIS IBM Power6 with 4 MPI process of 32 threads (color is level in the tree)

Dynamic Scheduling Gantt Diagram



- Reduces time by 10-15% on SMP cluster (better results are expected on NUMA clusters)

Block ILU(k): supernode amalgamation algorithm

Derive a block incomplete LU factorization from the supernodal parallel direct solver

- Based on existing package PaStiX
- Level-3 BLAS incomplete factorization implementation
- Fill-in strategy based on level-fill among block structures identified thanks to the quotient graph
- **Amalgamation strategy to enlarge block size**

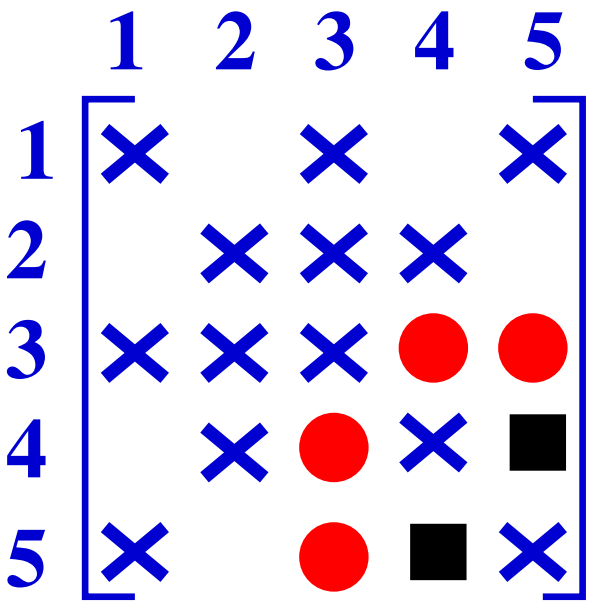
Highlights

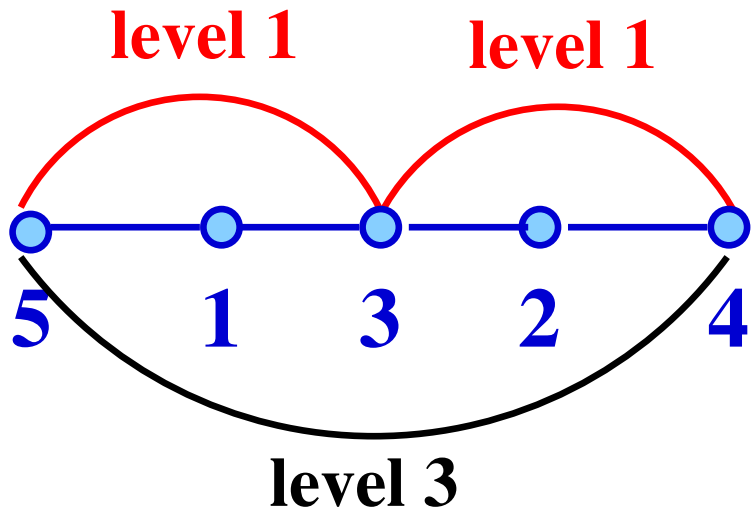
- Handles efficiently high level-of-fill
- Solving time faster than with scalar ILU(k)
- Scalable parallel implementation

Fill-in theorem

Theorem

Any $A_{ij} = 0$ will become a non-null entry L_{ij} or $U_{ij} \neq 0$ in $A = iLU(k)$ if and only if it exists a shortest path of lengh $k+1$ in $G_A(V, E)$ from vertex i to vertex j that only goes through vertices with a lower number than i and j.

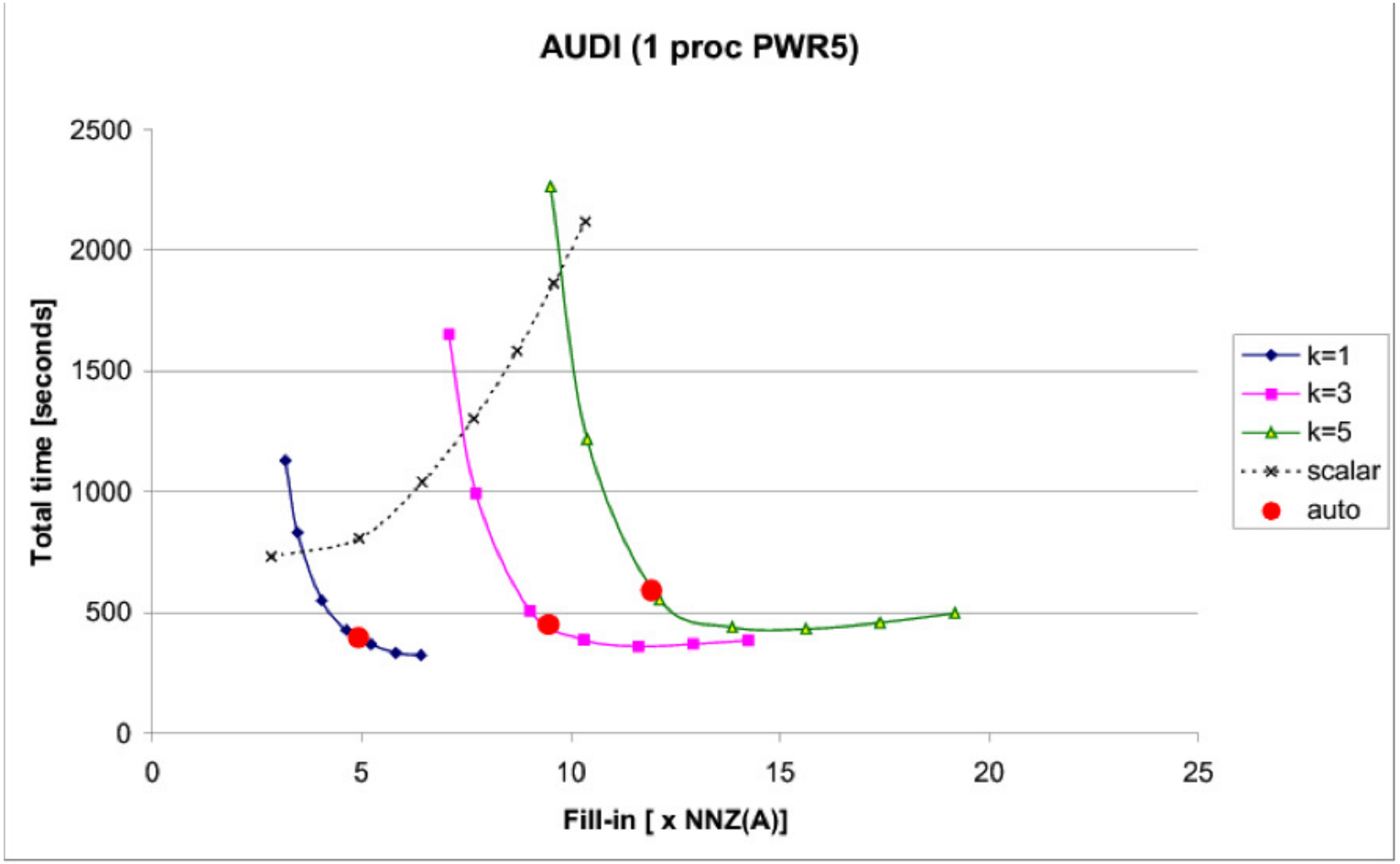




Block ILU(k): some results on AUDI matrix

(N = 943,695, NNZ = 39,297,771)

Total solution time



3
Hybrid methods

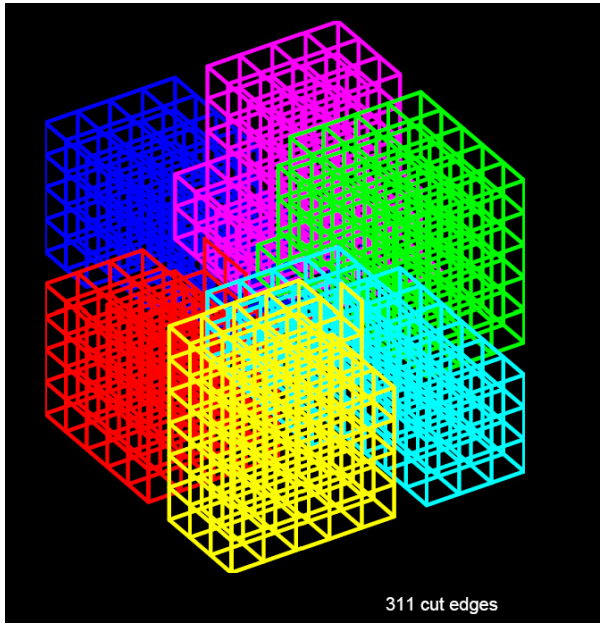
Hybrid Linear Solvers : HIPS or MaPHYS

Develop robust scalable parallel hybrid direct/iterative linear solvers

- Exploit the efficiency and robustness of the sparse direct solvers
- Develop robust parallel preconditioners for iterative solvers
- Take advantage of scalable implementation of iterative solvers

Domain Decomposition (DD)

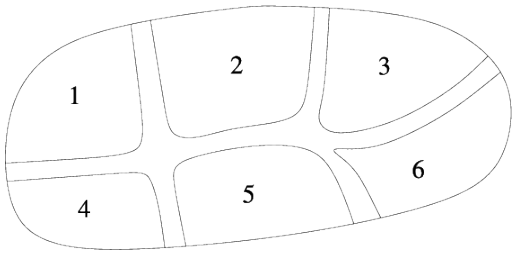
- Natural approach for PDE's
- Extend to general sparse matrices
- Partition the problem into subdomains
- Use a direct solver on the subdomains
- Robust preconditioned iterative solver



HIPS [J. GAIDAMOUR, P. HENON]

Based on a **domain decomposition** : interface one node-wide (no overlap in DD lingo)

$$\begin{pmatrix} A_B & F \\ E & A_C \end{pmatrix}$$

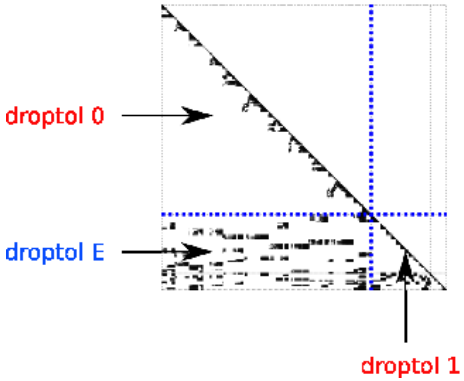


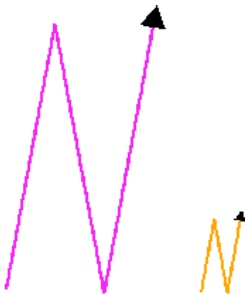
B : Interior nodes of subdomains (direct factorization).

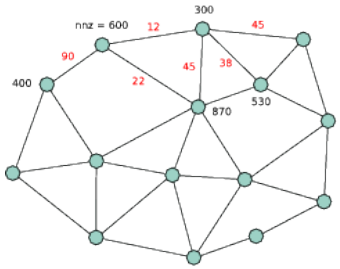
C : Interface nodes.

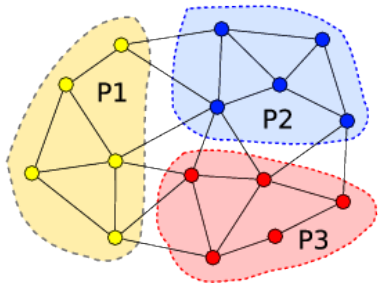
Special decomposition and ordering of the subset C :
Goal : Building a global Schur complement preconditioner (ILU) from the local domain matrices only.

HIPS: hybrid direct-iterative preconditioners









Main features

- Iterative or "hybrid" direct/iterative method are implemented.
- Mix direct supernodal (BLAS-3) and sparse ILUT factorization in a seamless manner.
- Memory/load balancing : distribute the domains on the processors (domains $>$ processors).

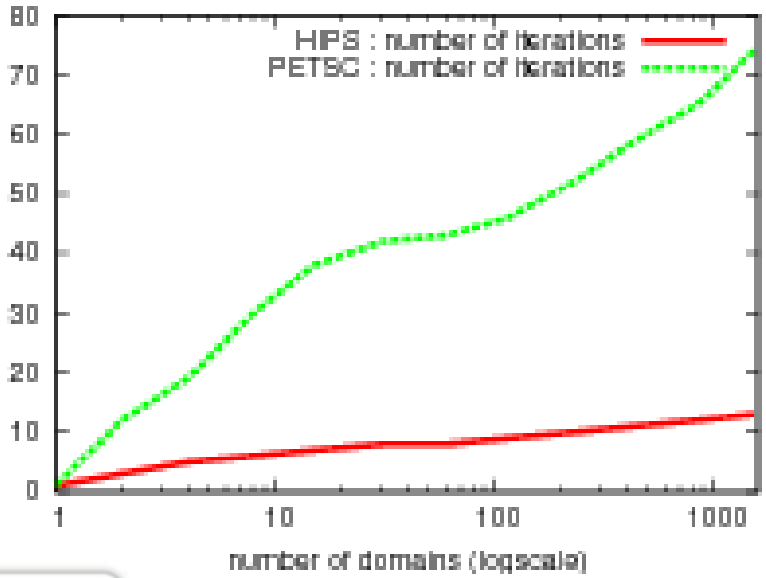
HIPS vs Additive Schwarz (from PETSc)

Experimental conditions

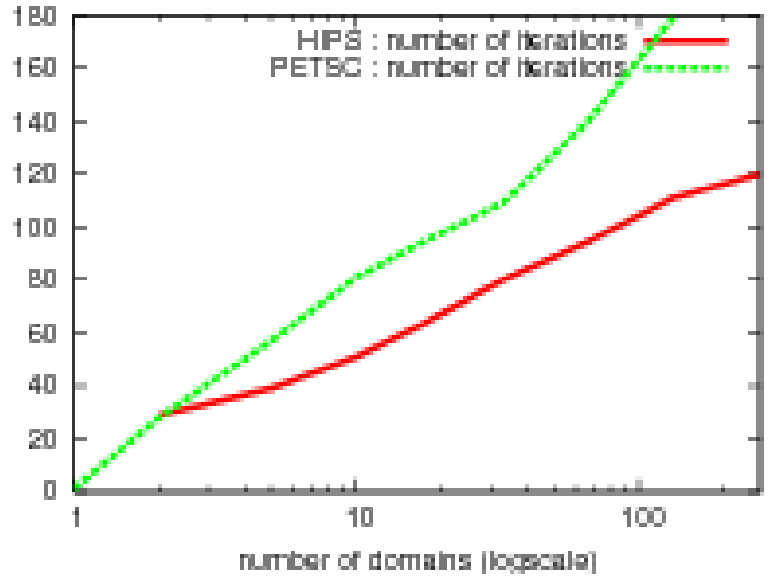
These curves compare HIPS (Hybrid) with Additive Schwarz from PETSc.

Parameters were tuned to compare the result with a very similar fill-in

Haltere

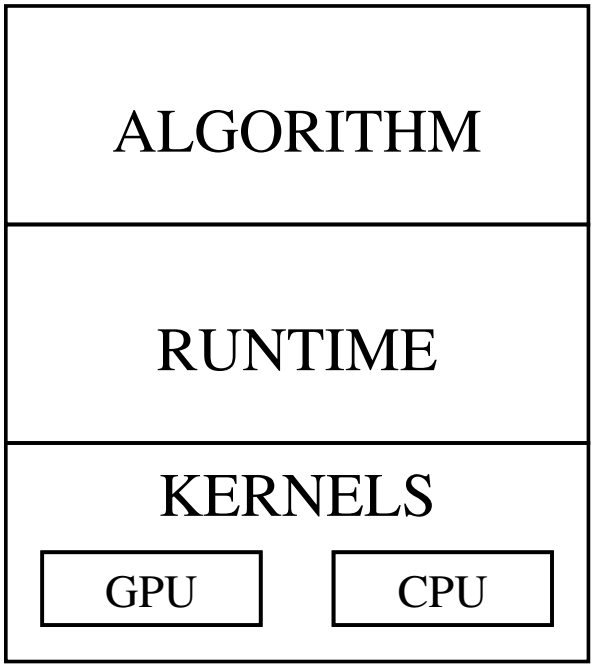


MHD



4
Towards sparse factorization on manycore

Multiple layer approach [X. LACOSTE]



Governing ideas: Enable advanced numerical algorithms to be executed on a scalable unified runtime system for exploiting the full potential of future exascale machines.

Basics:

- Graph of tasks
- Out-of-order scheduling
- Fine granularity

DAG schedulers considered

StarPU

- RunTime Team – Inria Bordeaux Sud-Ouest
- C. Augonnet, R. Namyst, S. Thibault.
- Dynamic Task Discovery
- Computes cost models on the fly
- Multiple kernels on the accelerators
- Heterogeneous First-Time strategy

PaRSEC (formerly DAGuE)

- ICL – University of Tennessee, Knoxville
- G. Bosilca, A. Bouteiller, A. Danalys, T. Herault
- Parameterized Task Graph
- Only the most compute intensive kernel on accelerators
- Simple scheduling strategy based on computing capabilities
- GPU multi-stream enabled

StarPU loop to submit tasks (DTD)

forall the *Supernode* S_1 **do**
  `submit_factorize` (S_1);
  forall the *off diagonal blocks* B_i *of* S_1 **do**
    $S_2 \leftarrow$ `supernode_in_front_of` (B_i);
    `submit_update` (S_1, S_2);
  end
end

PaRSEC's representation (PTG)

```
panel(j) [high_priority = on]
/* execution space */
c = 0 .. cblknbr-1
/* Extra parameters */
firstblock = diagonal_block_of( c )
lastblock = last_block_of( c )
lastbrow = last_brow_of( c )
/* Locality */
:A(c)
RW A ← leaf ? A(c) : C update(lastbrow)
       → A update(firstblock+1..lastblock)
       → A(c)
```

```
update(j)
/* execution space */
b = 0 .. bloknbr-1
/* Extra parameters */
c = get_cblk_of( b )
fc = get_facing_cblk_of( b )
...
/* Locality */
:A(fc)
READ A ← A panel(c)
RW C ← previous ? C update(prev) : A(fc)
       → next ? C update(next) : A panel(fc)
```

Experiments

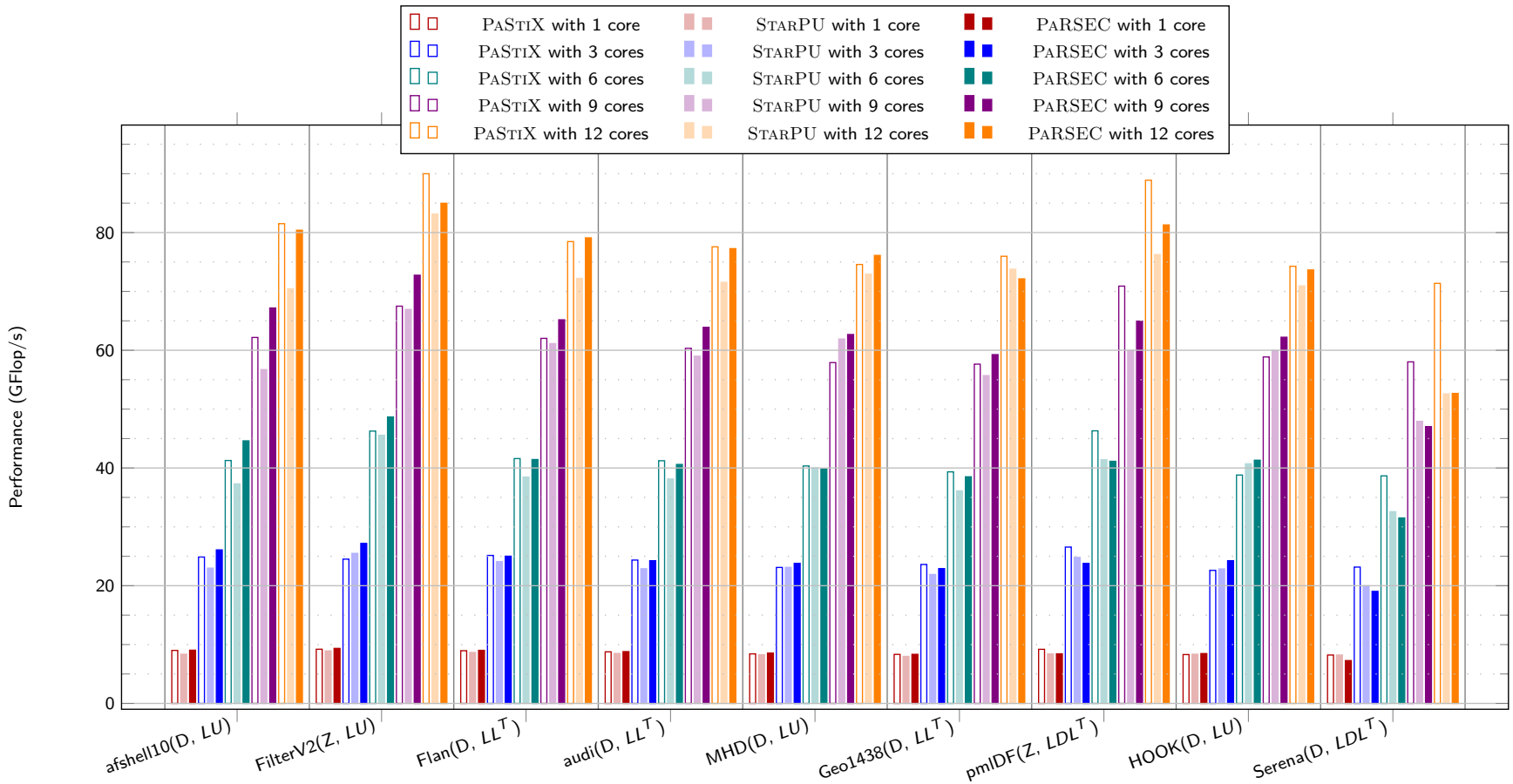
Matrix	Prec	Method	Size	nnz_A	nnz_L	TFlop/s
Afshell10	D	LU	1.5e+6	27e+6	610e+6	0.12
FilterV2	Z	LU	0.6e+6	12e+6	536e+6	3.6
Flan	D	LL^T	1.6e+6	59e+6	1712e+6	5.3
Audi	D	LL^T	0.9e+6	39e+6	1325e+6	6.5
MHD	D	LU	0.5e+6	24e+6	1133e+6	6.6
Geo1438	D	LL^T	1.4e+6	32e+6	2768e+6	23
Pmldf	Z	LDL^T	1.0e+6	8e+6	1105e+6	28
Hook	D	LU	1.5e+6	31e+6	4168e+6	35
Serena	D	LDL^T	1.4e+6	32e+6	3365e+6	47

Table: Matrix description (Z: double complex, D: double).

Machine

- Two hexa-cores Westmere Xeon X5650 (2.67 GHz)
- 32 GB of memory

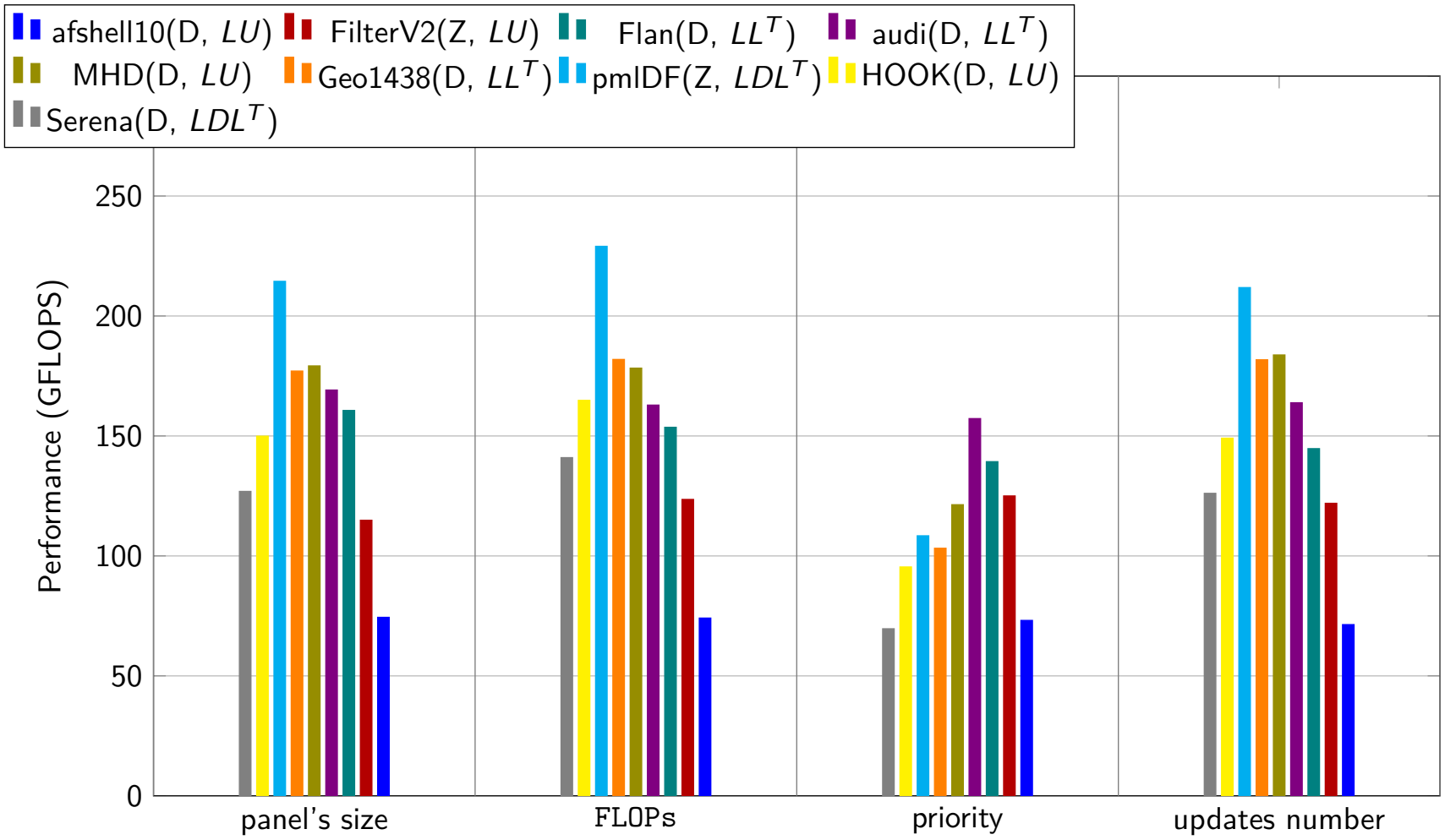
CPU Scaling study



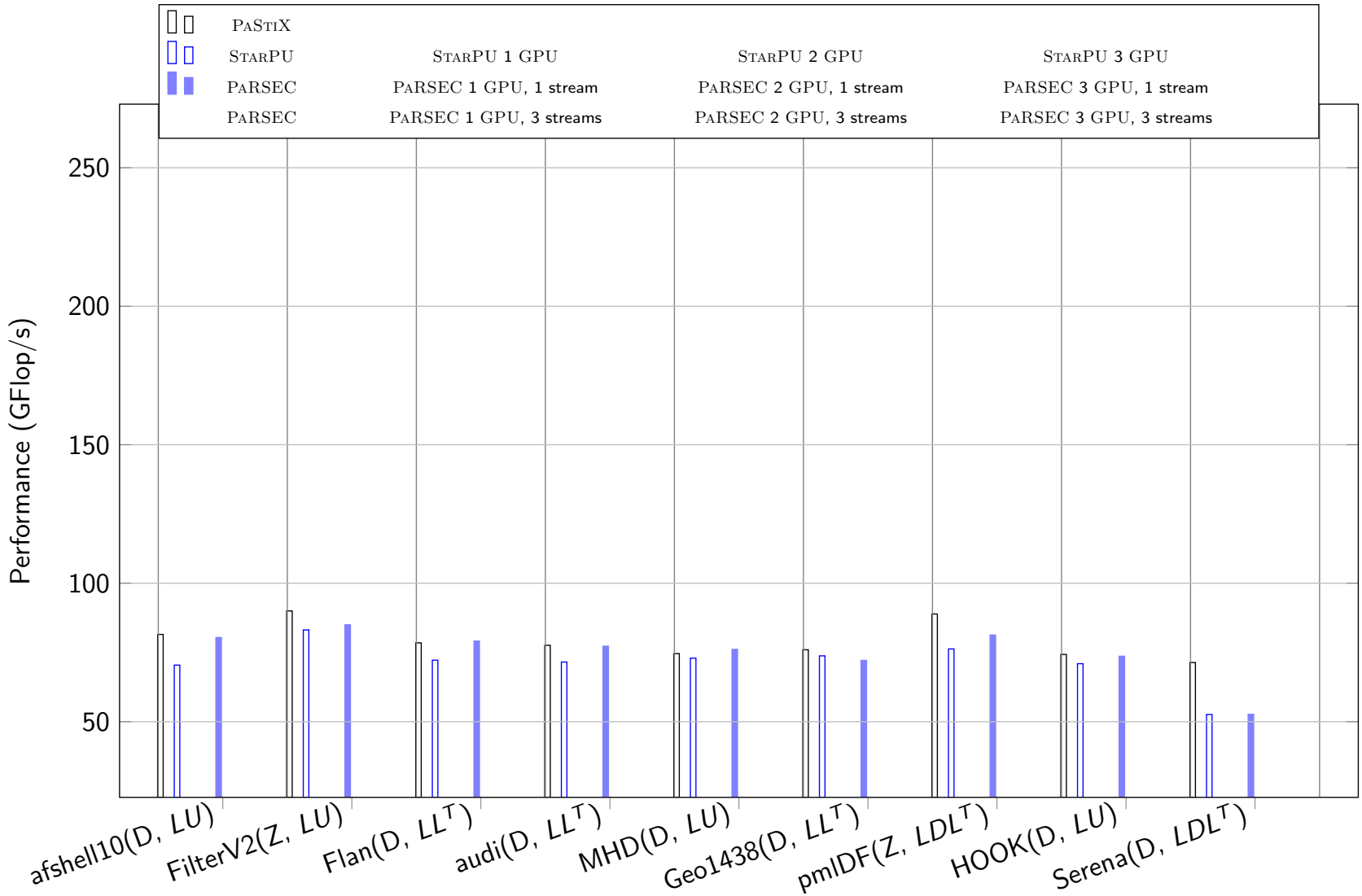
What can be offloaded to the GPU?

- Panel factorization:
  - Call MAGMA kernel?
  - Diagonal block size < 120
  - Panel is done on CPU
  - $\rightarrow$ No GPU kernel for factorization
- Panel update:
  - GEMM variant
  - Highly efficient GEMM source code available
  - $\rightarrow$ existing GEMM can easily be adapted to our problem
  - Extension of ASTRA kernel (J. Kurzak, ICL)

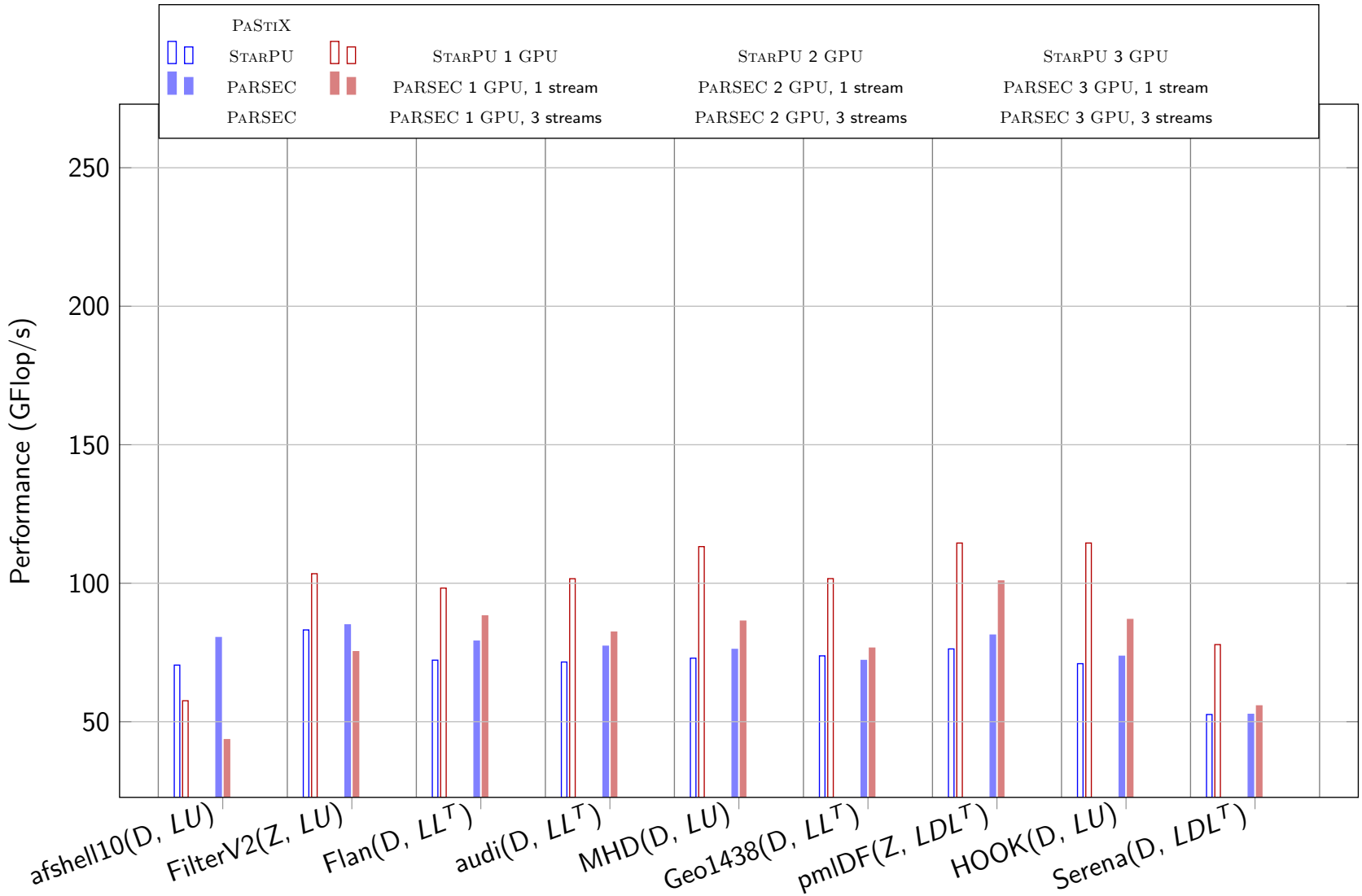
Data mapping over GPU (PaRSEC, 3 Tesla M2070)



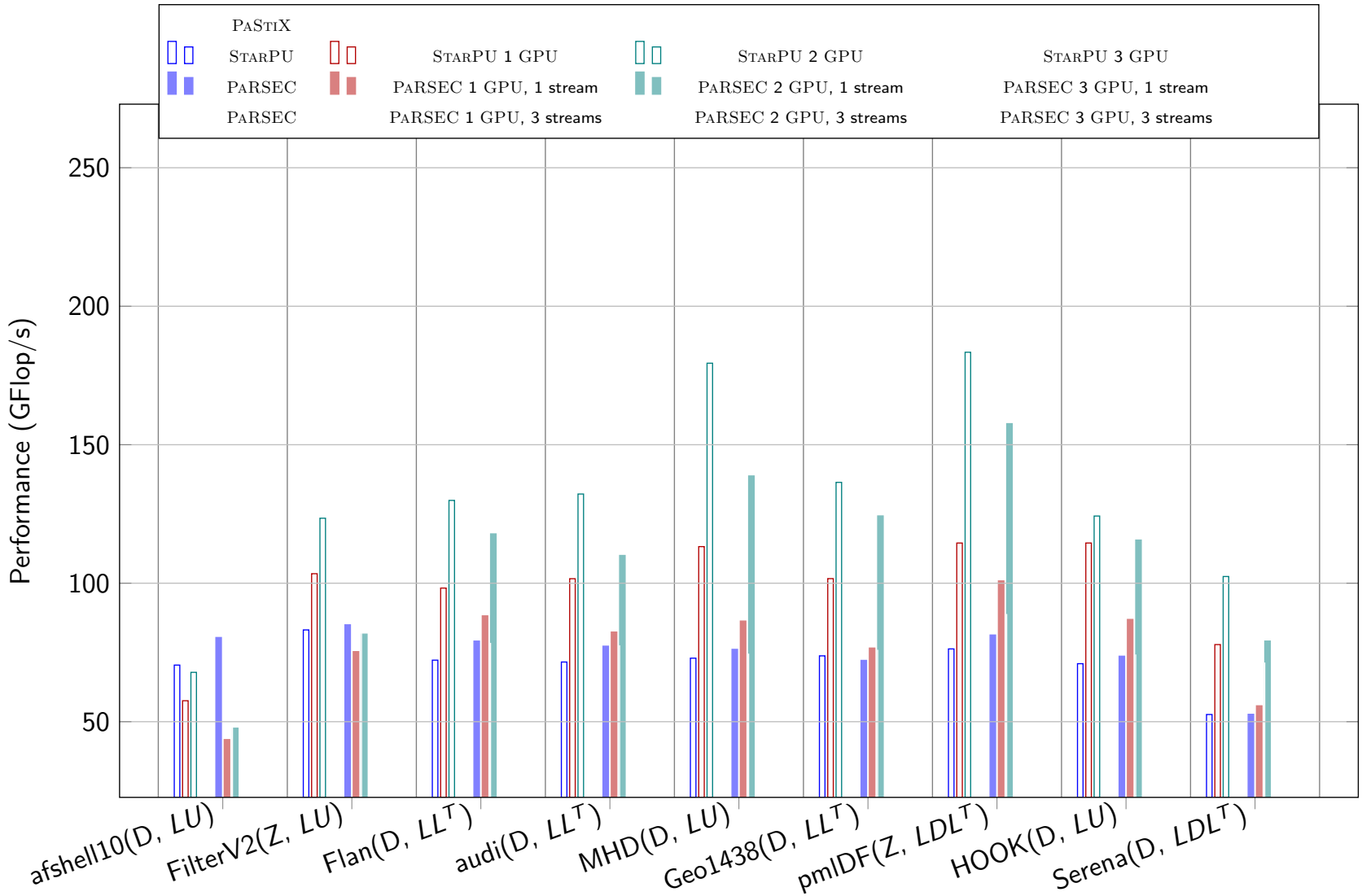
GPU scaling study (No GPU - 12 CPUs)



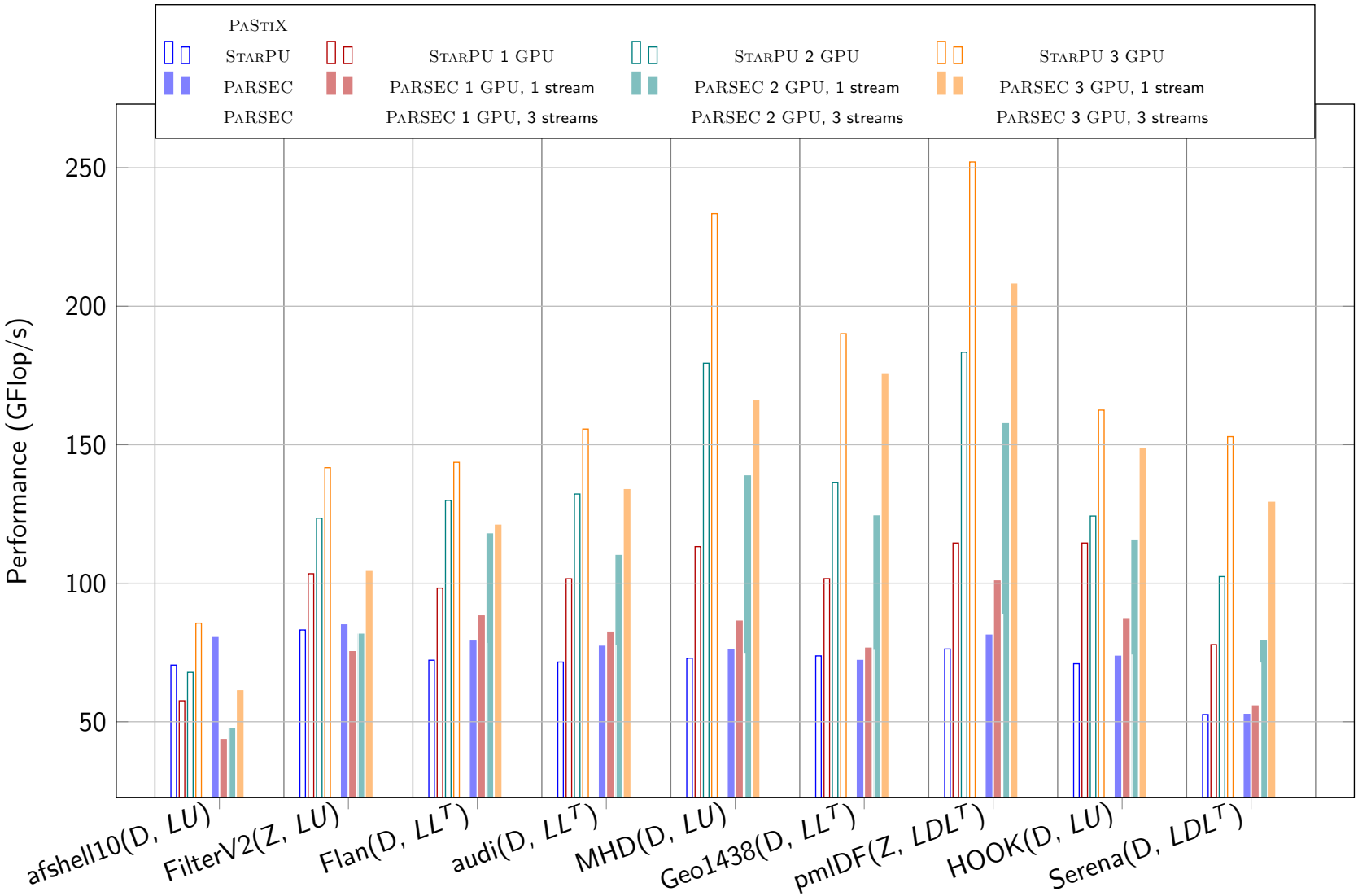
GPU scaling study (1 GPU - 12 CPUs)



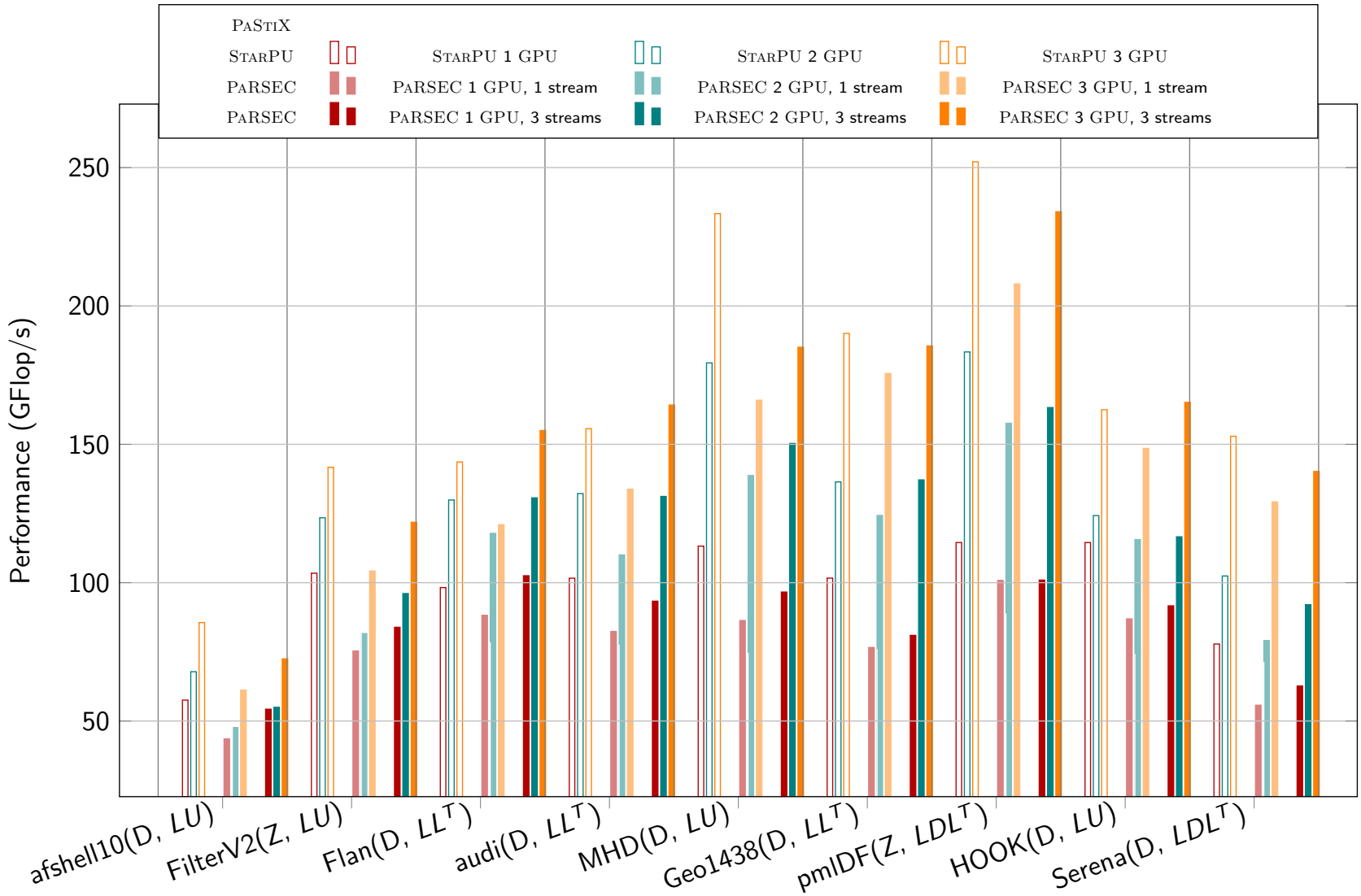
GPU scaling stud (2 GPUs - 12 CPUs)



GPU scaling study (3 GPUs - 12 CPUs)



GPU scaling study (Multi-streams - 12 CPUs)



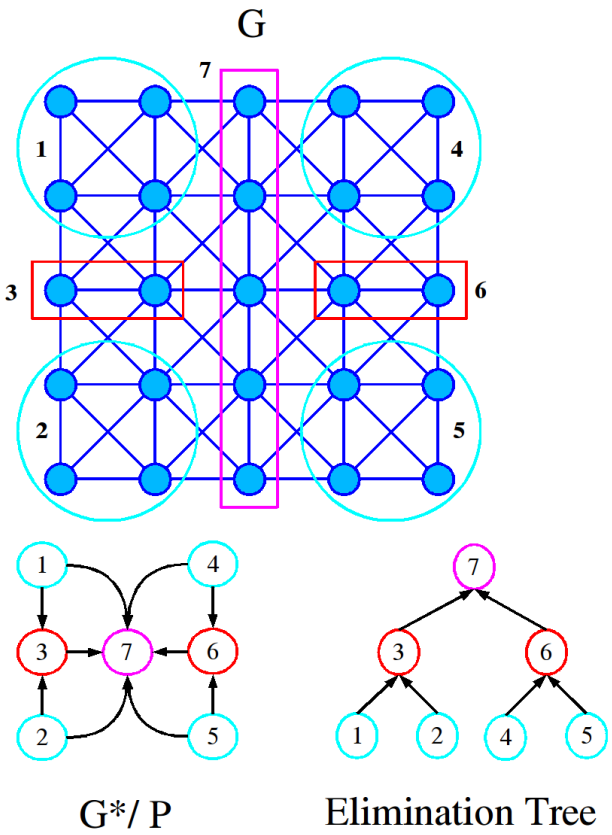
5
Low-rank compression - $\mathcal{H}$-matrix

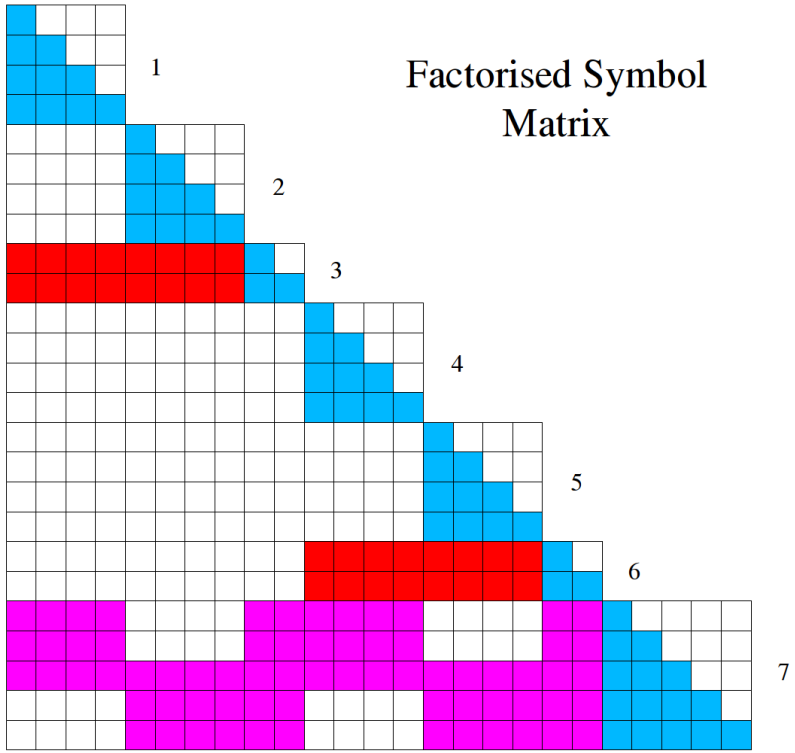
$\mathcal{H}$-PaStiX ?

Many works on hierarchical matrices

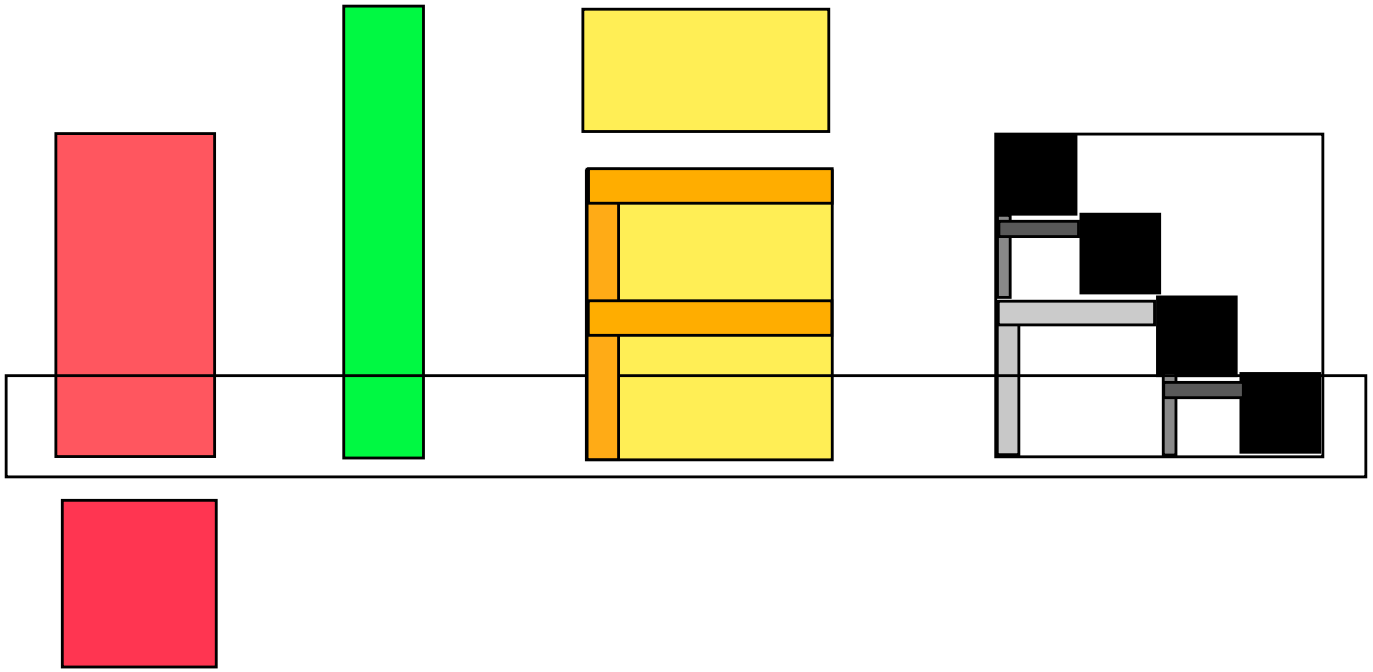
- Eric Darve : Hierarchical matrices classifications (*Building O(N) Linear Solvers Using Nested Dissection*)
- Sherry Li : Multifrontal solver + HSS (*Towards an Optimal-Order Approximate Sparse Factorization Exploiting Data-Sparseness in Separators*)
- David Bindel : CHOLMOD + Low Rank (*An Efficient Solver for Sparse Linear Systems Based on Rank-Structured Cholesky Factorization*)
- Jean-Yves L'Excellent : MUMPS + BLR

Target larger supernodes for compression (top tree)





Forming compressed updates



FastLA associate team between INRIA/Berkeley/Stanford

Workpackages

1. Check the potential compression ratio on top level blocks
2. Develop a prototype with:
   - low-rank compression on the larger supernodes
   - compression tree built at each update
3. Study coupling between nested dissection and compression tree ordering

Which algorithm to find low-rank approximation ?

SVD, RR-LU, RR-QR, ACA, CUR, Random ...

Which family of hierarchical matrix ?

$\mathcal{H}$, $\mathcal{H}^2$, HODLR ...

6 Conclusion

BACCHUS/HiePACS softwares

Graph/Mesh partitioner and ordering :

http://scotch.gforge.inria.fr

Sparse linear system solvers :

http://pastix.gforge.inria.fr

http://hips.gforge.inria.fr

MURGE: a common API to the sparse linear solvers of HiePACS

http://murge.gforge.inria.fr

Features

- Through one interface, access to many solver strategies
- Enter a graph/matrix in a centralized or distributed way
- Simple formats : coordinate, CSR or CSC
- Very easy to implement an assembly step

Thank You

Pierre Ramet

HiePACS

http://www.labri.fr/ ramet