

On some robust solvers and their scalable implementation

Pierre Jolivet
ETH Zürich

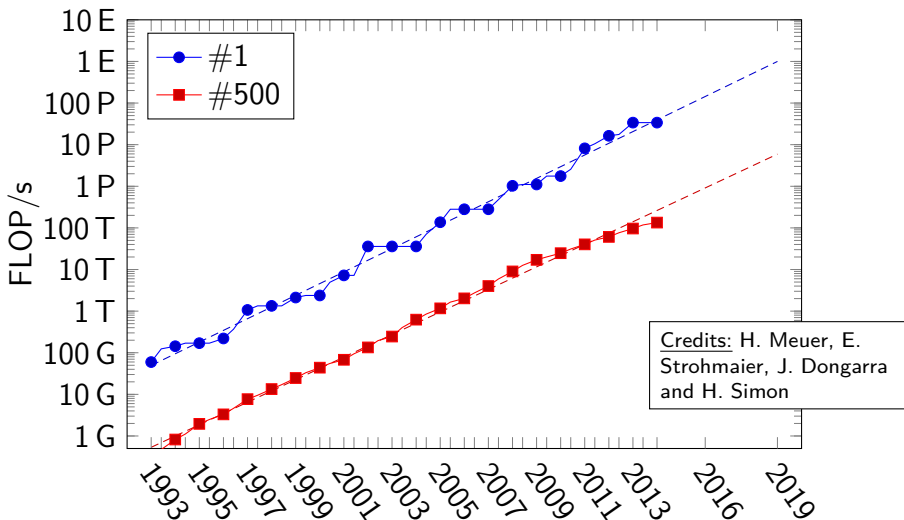
Journée DDM - parallélisation

June 11, 2015



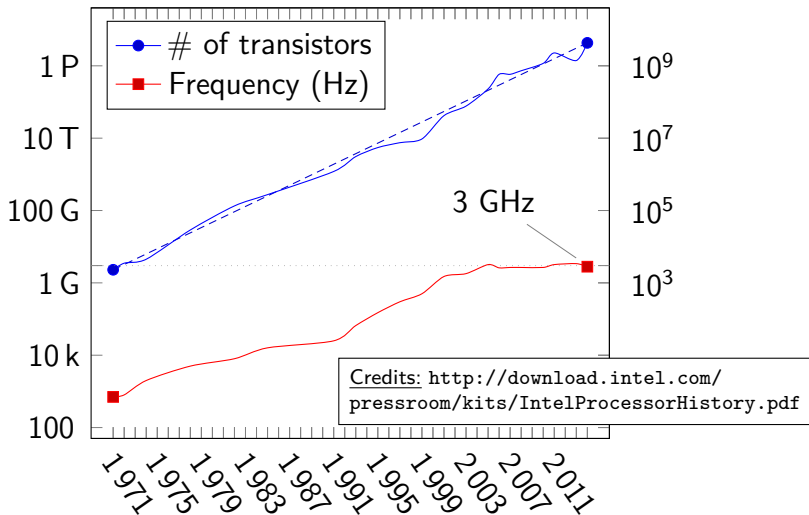
High-performance computing context

Today's large-scale supercomputers are tomorrow's desktops:



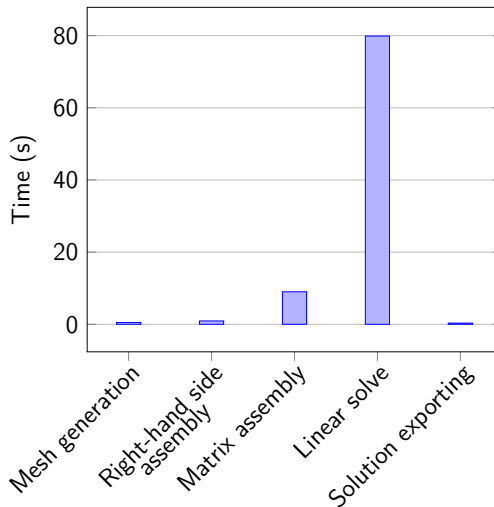


2005 and the end of f -scaling





The big picture of implicit methods





State of the art

Many theoretical work on DDM. [Mathew 2008; Pechstein 2012; Quarteroni and Valli 1999; Smith, Bjørstad, and Gropp 2004; Toselli and Widlund 2005]



State of the art

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Not many available implementations:

- Klawonn & Rheinbach,
- Badia & Principe,
- Šístek, Mandel, and Sousedík,
- Trilinos SALINAS.

Mostly application dependant solvers.



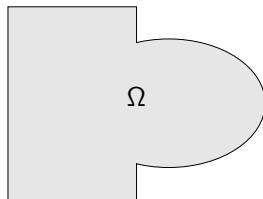
High-Performance DDM

- <https://github.com/hpddm/hpddm> [Jolivet and Nataf 2014],
- C++ open-source,
- supported by many work [Dolean, Jolivet, and Nataf 2015; Jolivet, Hecht, Nataf, and Prud'homme 2013; Spillane, Dolean, et al. 2013; Spillane and Rixen 2013]...
- interfaced with FE libraries (FreeFem++ and Feel++),
- scales on 16k threads to solve billion d.o.f. problems,
- Stokes equation, Maxwell equations...



Overlappings methods I

Consider the linear system: $Au = f \in \mathbb{R}^n$.



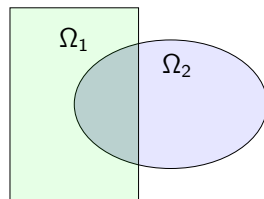


Overlappings methods I

Consider the linear system: $Au = f \in \mathbb{R}^n$.

Given a decomposition of $\llbracket 1; n \rrbracket$, $(\mathcal{N}_1, \mathcal{N}_2)$, define:

- the restriction operator R_i from $\llbracket 1; n \rrbracket$ into \mathcal{N}_i ,
- R_i^T as the extension by 0 from \mathcal{N}_i into $\llbracket 1; n \rrbracket$.





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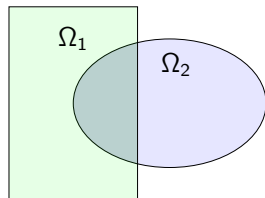
- the restriction operator R_i from $\llbracket 1; n \rrbracket$ into \mathcal{N}_i ,
- R_i^T as the extension by 0 from \mathcal{N}_i into $\llbracket 1; n \rrbracket$.

Then solve concurrently:

$$u_1^{m+1} = u_1^m + A_{11}^{-1} R_1(f - Au^m) \quad u_2^{m+1} = u_2^m + A_{22}^{-1} R_2(f - Au^m)$$

where $u_i = R_i u$ and $A_{ij} := R_i A R_j^T$.

[Schwarz 1870]



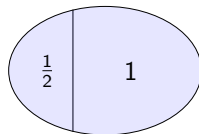
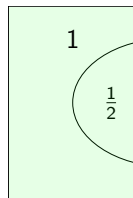


Overlappings methods II

Problem is effectively divided, but yet to be conquered.

Duplicated unknowns coupled via a *partition of unity*:

$$I = \sum_{i=1}^N R_i^T D_i R_i.$$



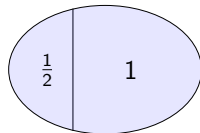
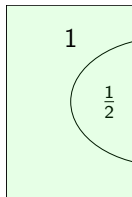


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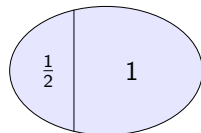
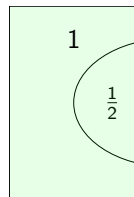
$$\text{Then, } u^{m+1} = \sum_{i=1}^N R_i^T D_i u_i^{m+1}.$$

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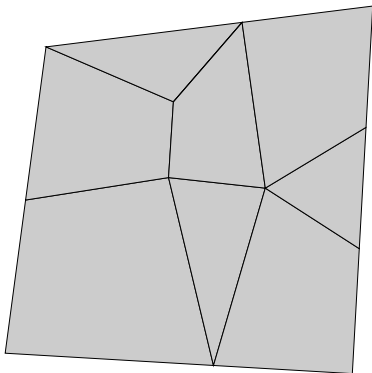


Then, $u^{m+1} = \sum_{i=1}^N R_i^T D_i u_i^{m+1}.$

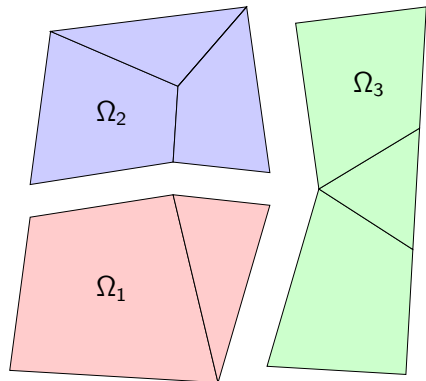
$$M_{\text{RAS}}^{-1} = \sum_{i=1}^N R_i^T D_i A_{ii}^{-1} R_i$$

[Cai and Sarkis 1999]

Substructuring preconditioners I

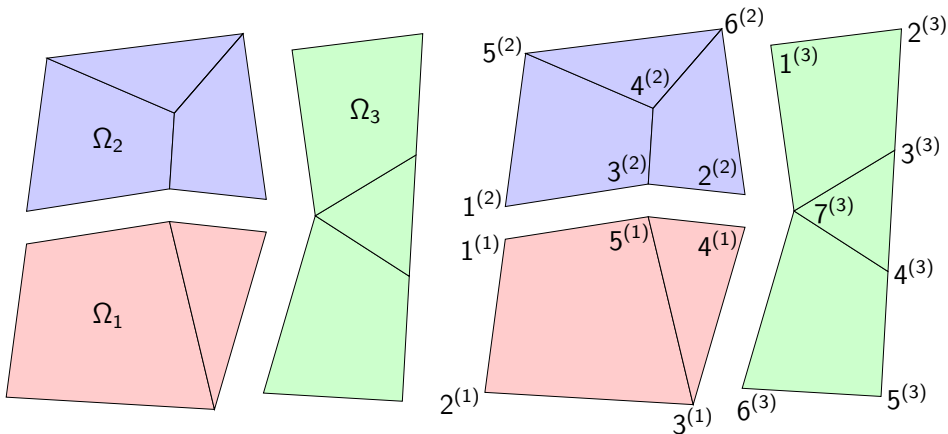


[Gosselet and Rey 2006]



Subdomain tearing

Substructuring preconditioners I

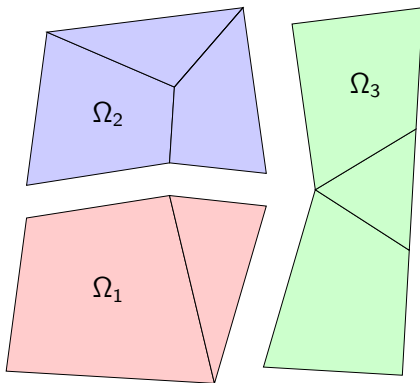


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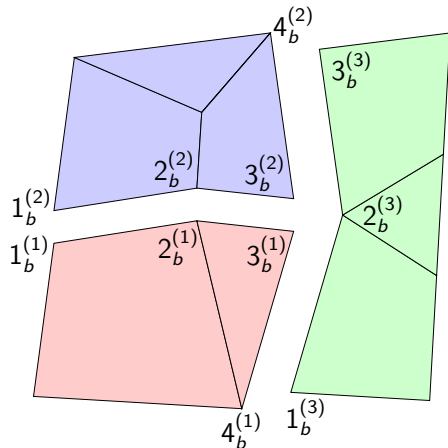
Local numbering

$$A^{(k)} = \begin{bmatrix} A_{ii} & A_{ib} \\ A_{bi} & A_{bb} \end{bmatrix}$$

Substructuring preconditioners I



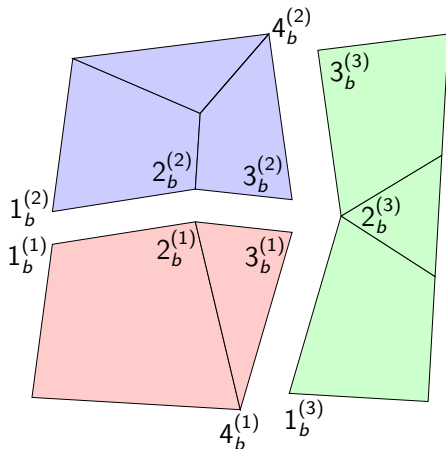
[Gosselet and Rey 2006]



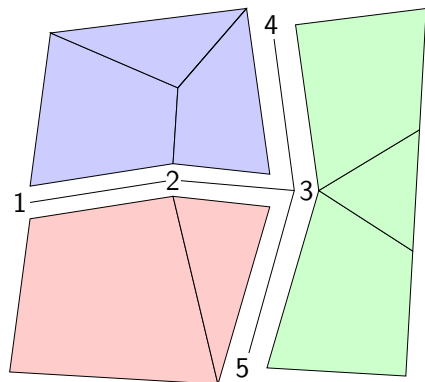
Elimination of interior d.o.f.

$$S^{(k)} = A_{bb} - A_{bi}A_{ij}^{-1}A_{ib}$$

Substructuring preconditioners I

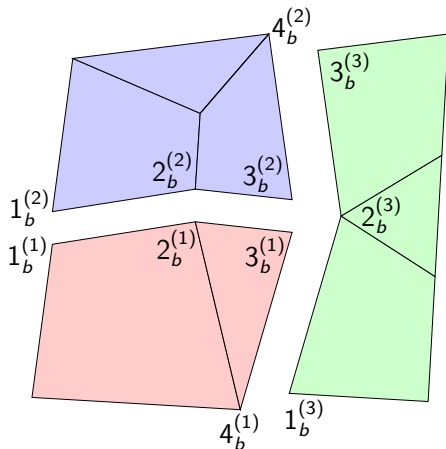


Jump operators: $\{B^{(i)}\}_{i=1}^3$

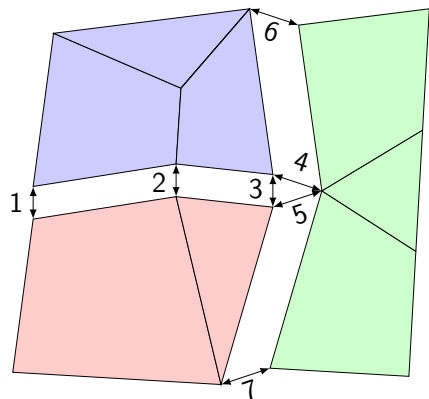


Primal constraints
[Mandel 1993]

Substructuring preconditioners I



Jump operators: $\{\underline{B}^{(i)}\}_{i=1}^3$



Dual constraints
[Farhat and Roux 1991]



Substructuring preconditioners II

The new system reads:

$$\forall i \in \llbracket 1; N \rrbracket, S^{(i)} u_b^{(i)} = g_i + \lambda_b^{(i)}$$



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$$\sum_{i=1}^N B^{(i)} \lambda_b^{(i)} = 0.$$

Efficient preconditioners (based on scaled sum):

[Dohrmann 2003; Farhat, Mandel, and Roux 1994; Rixen and Farhat 1997]



Limitations of one-level methods

One-level methods don't require exchange of global information.

This hampers numerical scalability of such preconditioners:

$$\kappa(M^{-1}A) \leq C \frac{1}{H^2} \left(1 + \frac{H}{\delta} \right)$$

- level of overlap δ ,
- characteristic size of a subdomain H .

[Le Tallec 1994; Toselli and Widlund 2005]



Two-level preconditioners

A common technique in the field of DDM, MG, deflation:

introduce an auxiliary “coarse” problem.

Let Z be a rectangular matrix. Define

$$E := Z^T A Z.$$

Z has $\mathcal{O}(N)$ columns, hence E is much smaller than A .



Two-level preconditioners

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Enrich the original preconditioner, e.g. additively

$$P^{-1} = M^{-1} + Z E^{-1} Z^T,$$

cf. [Tang, Nabben, Vuik, and Erlangga 2009].



Formal definition of Z

The convergence is hindered by extreme eigenvalues.

↔ use the associated eigenvectors for the deflation matrix.



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A local threshold criterion selects γ_i local vectors $\{\Lambda_{i_k}\}_{k=1}^{\gamma_i}$.



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$$W_i = \begin{bmatrix} D_i \Lambda_{i_1} & D_i \Lambda_{i_2} & \cdots & D_i \Lambda_{i_{\gamma_i}} \end{bmatrix}.$$



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Then, define the global deflation matrix as:

$$Z = \begin{cases} \begin{bmatrix} R_1^T W_1 & R_2^T W_2 & \cdots & R_N^T W_N \end{bmatrix} & \text{for Schwarz,} \\ \begin{bmatrix} B_1 W_1 & B_2 W_2 & \cdots & B_N W_N \end{bmatrix} & \text{for BDD,} \\ \begin{bmatrix} \underline{B}_1 W_1 & \underline{B}_2 W_2 & \cdots & \underline{B}_N W_N \end{bmatrix} & \text{for FETI.} \end{cases}$$

Not in assembled in reality since they require a global ordering.



Construction of Z

GenEO for Schwarz methods

Solved by ARPACK concurrently:

$$A_i^N \Lambda_{i_k} = \lambda_{i_k} D_i R_{i,0}^T R_{i,0} A_i^N R_{i,0} R_{i,0}^T D_i \Lambda_{i_k},$$

where

- A_i^N is the local unassembled matrix (bilinear form with Neumann boundary conditions on the interfaces),
- $R_{i,0}$ is the restriction from Ω_i to $\Omega_i \cap \left(\bigcup_{j \in \mathcal{O}_i} \Omega_j \right)$.



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The “algebraicity” of Schwarz methods is lost here.



Construction of Z

GenEO for Optimized Schwarz methods

Same framework as in [St-Cyr, Gander, and Thomas 2007].



Construction of Z

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$$A_i^N \Lambda_{i_k} = \lambda_{i_k} B_i \Lambda_{i_k},$$

where

- A_i^N is the local unassembled matrix (bilinear form with Neumann boundary conditions on the interfaces),
- B_i is the local matrix with optimized interface conditions.

Cf. [Conen, Dolean, Krause, and Nataf 2014; Haferssas, Jolivet, and Nataf 2015].



Construction of Z

GenEO for substructuring methods

For BDD, solved by LAPACK concurrently:

$$S^{(i)}\Lambda_{i_k} = \lambda_{i_k} D_i B^{(i)T} S B^{(i)} D_i \Lambda_{i_k}.$$



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The Schur complement S is never assembled:

$$B^{(i)T} S B^{(i)} = B^{(i)T} \sum_{j \in \bar{\mathcal{O}}_i} B^{(j)} S^{(j)} B^{(j)T} B^{(i)}$$



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With both GEVP, null eigenvalues yield rigid body modes.
No efficient solution for FETI.



Distribution of E

How can one apply E^{-1} to a vector in \mathbb{R}^m ?

Some constraints:

- ① E can't be centralized on one MPI process, cf. DD 20 proceedings,
- ② E can't be distributed on all MPI processes,
- ③ the solution must be computed fast and reliably.



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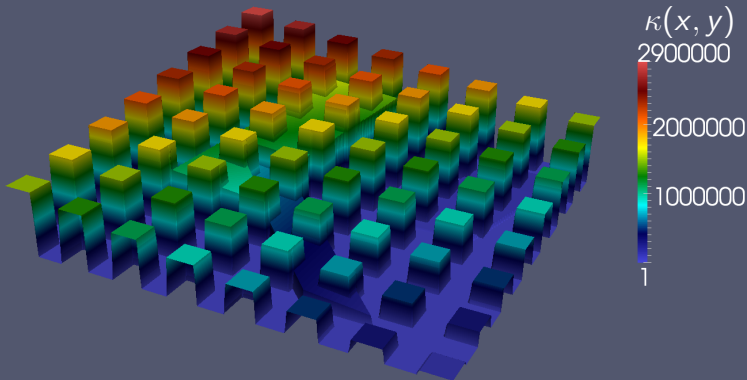
\implies use a direct solver with a distributed matrix on few *master* processes (number chosen at runtime).

SC13 best paper award nominee [Jolivet et al. 2013].

Example of heterogeneous coefficients

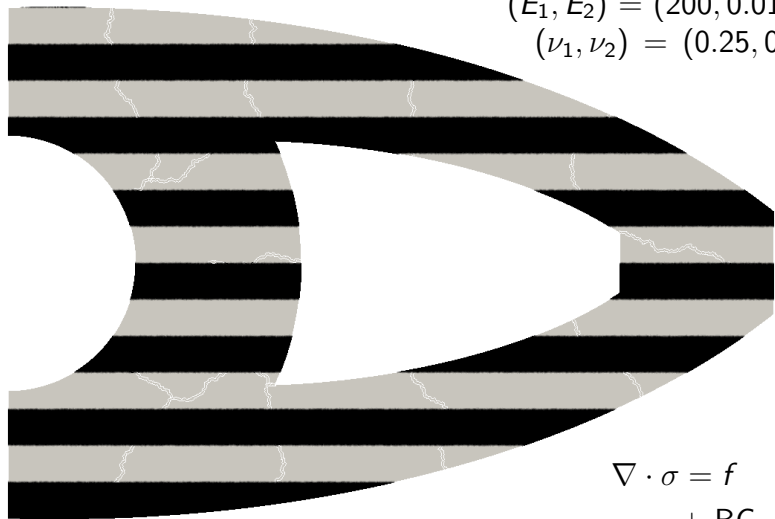
$$\nabla \cdot (\kappa \nabla u) = f$$

$$+ \text{BC}$$





2D geometry

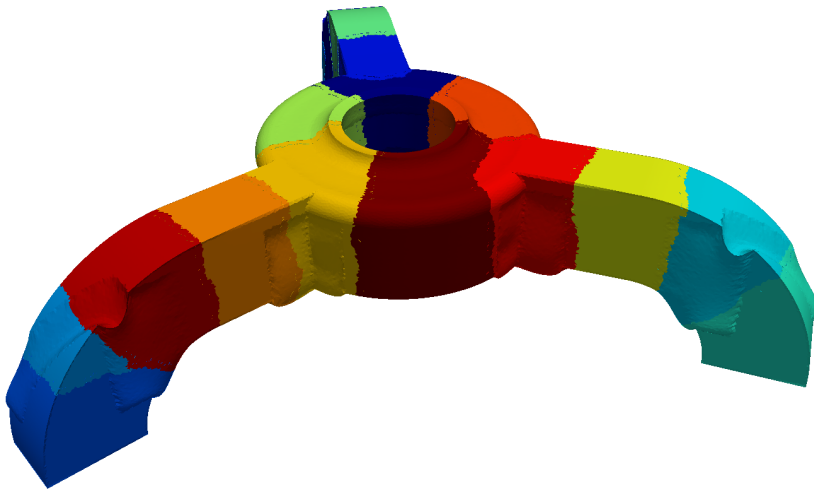


$$(E_1, E_2) = (200, 0.01) \text{ GPa}$$
$$(\nu_1, \nu_2) = (0.25, 0.45)$$

$$\nabla \cdot \sigma = f$$
$$+ \text{BC}$$



3D geometry



Machines used for scaling runs

Curie Thin Nodes

- 5 040 compute nodes (2 eight-core Intel Sandy Bridge).
- IB QDR full fat-tree.
- BullxMPI based on an old OpenMPI (1.6.x).

Turing

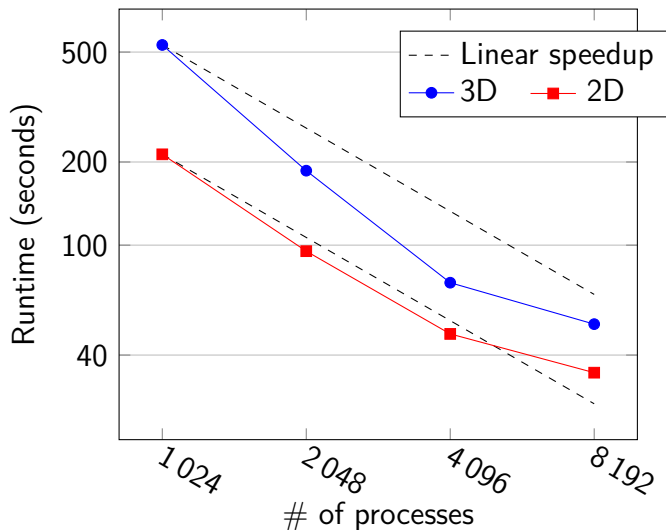
- 6 BlueGene/Q racks.





Strong scaling (linear elasticity)

1 subdomain/MPI process, 2 OpenMP threads/MPI process.

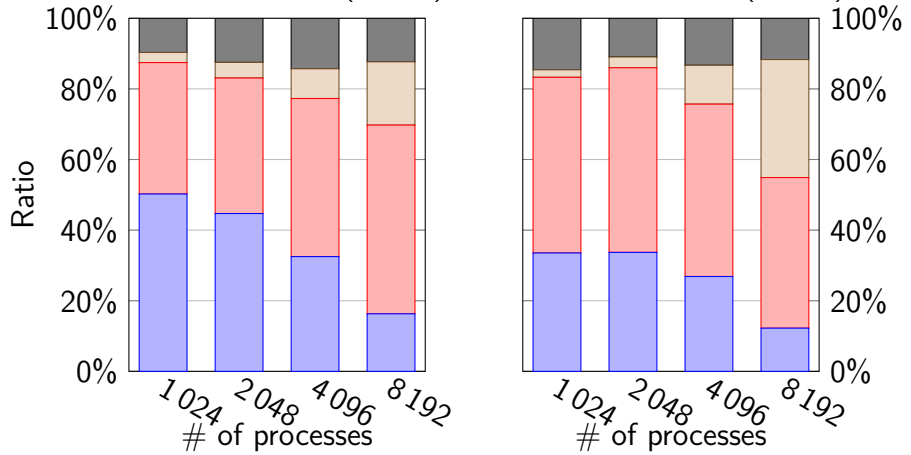


Strong scaling (linear elasticity)

1 subdomain/MPI process, 2 OpenMP threads/MPI process.

2.1B d.o.f. in 2D (\mathbb{P}_3 FE)

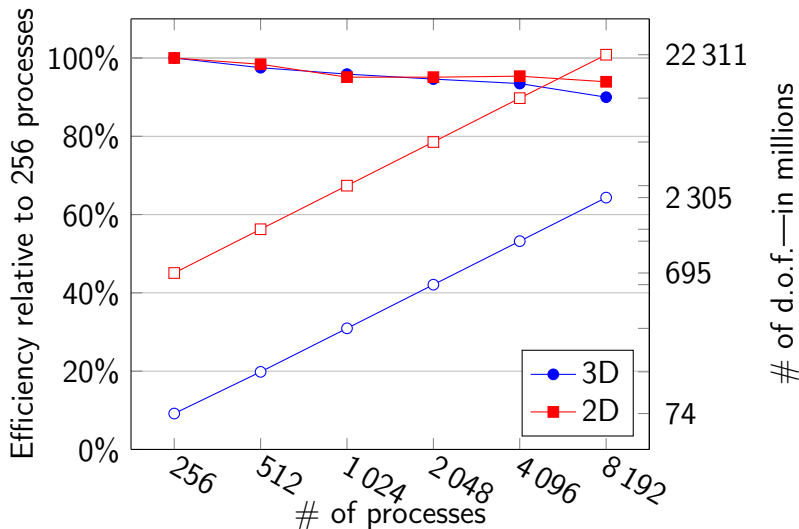
300M d.o.f. in 3D (\mathbb{P}_2 FE)





Weak scaling (scalar diffusion equation)

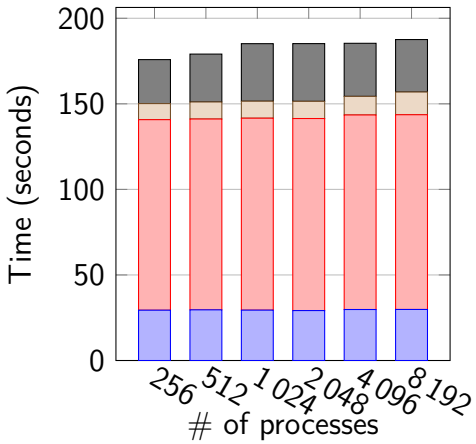
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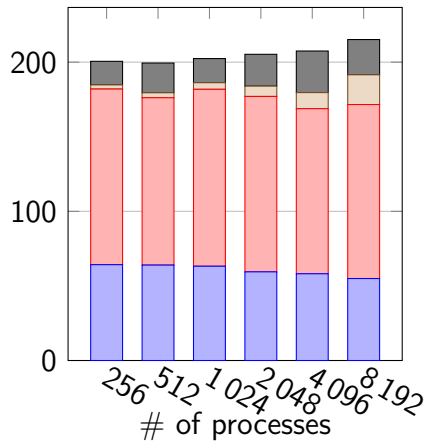
Weak scaling (scalar diffusion equation)

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2.1M $\frac{\text{d.o.f.}}{\text{sbdmn}}$ in 2D (\mathbb{P}_4 FE)



280k $\frac{\text{d.o.f.}}{\text{sbdmn}}$ in 3D (\mathbb{P}_2 FE)





Schwarz preconditioners vs. MG solvers

Performance of setup and solution phases of algebraic solvers:

- Hypre BoomerAMG, selective algebraic multigrid (LLNL)

- GAMG, aggregative algebraic multigrid (ANL/LBL)

and:

- Schwarz GenEO



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↔ number of deflation vectors (increasing it only “improves” the preconditioner).



Schwarz preconditioners vs. MG solvers

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- Hypre BoomerAMG, selective algebraic multigrid (LLNL)

↪ `-pc_hypre_boomeramg_agg_n1 2 -pc_hypre_boomeramg_P_max 4`

`-pc_hypre_boomeramg_coarsen_type HMIS -pc_hypre_boomeramg_interp_type`

`ext+i -pc_hypre_boomeramg_no_CF`

- GAMG, aggregative algebraic multigrid (ANL/LBL)

↪ `-pc_gamg_agg_nsmooths 1 -mg_levels_pc_type jacobi -mg_levels_ksp_type`

`chebyshev -mg_levels_ksp_max_it 1 -pc_gamg_threshold 0.1 -`

`mg_coarse_pc_type svd -mg_coarse_pc_svd_monitor -gamg_est_ksp_type`

`gmres -gamg_est_pc_type jacobi`

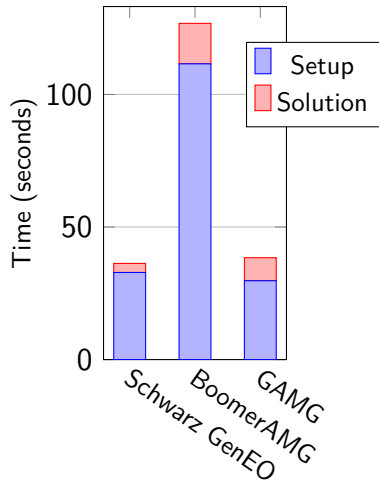
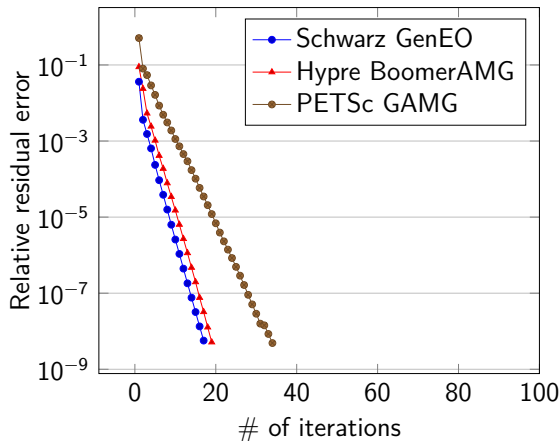
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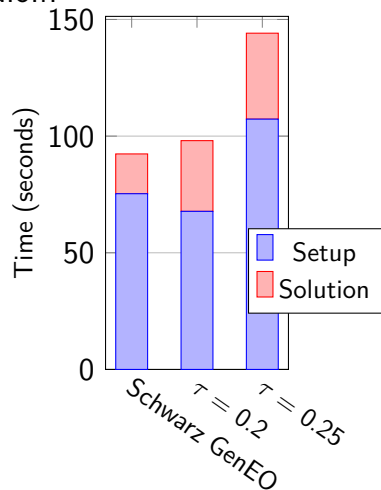
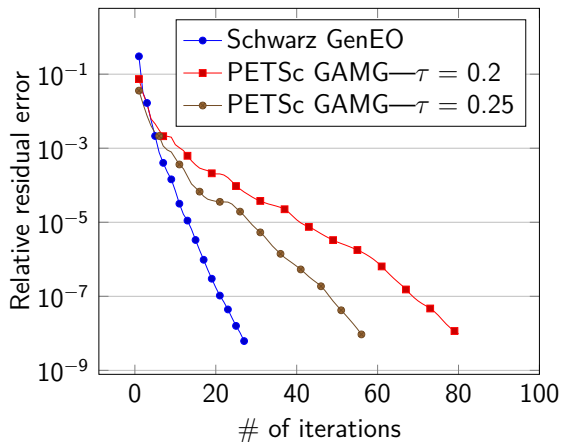
Solution of a linear system I

Homogeneous 3D Poisson equation discretized by \mathbb{P}_1 FE solved on 4 096 MPI processes, 217M d.o.f.



Solution of a linear system II

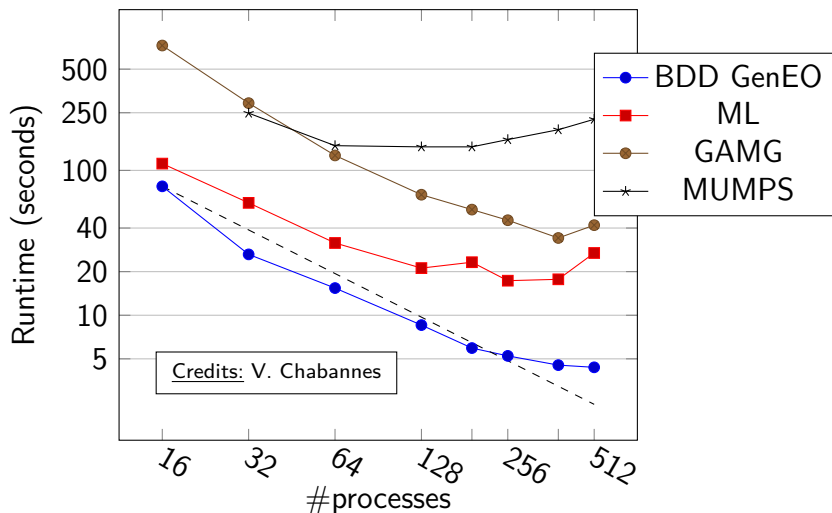
Heterogeneous 3D linear elasticity equation discretized by \mathbb{P}_2 FE solved on 4 096 MPI processes, 262M d.o.f.





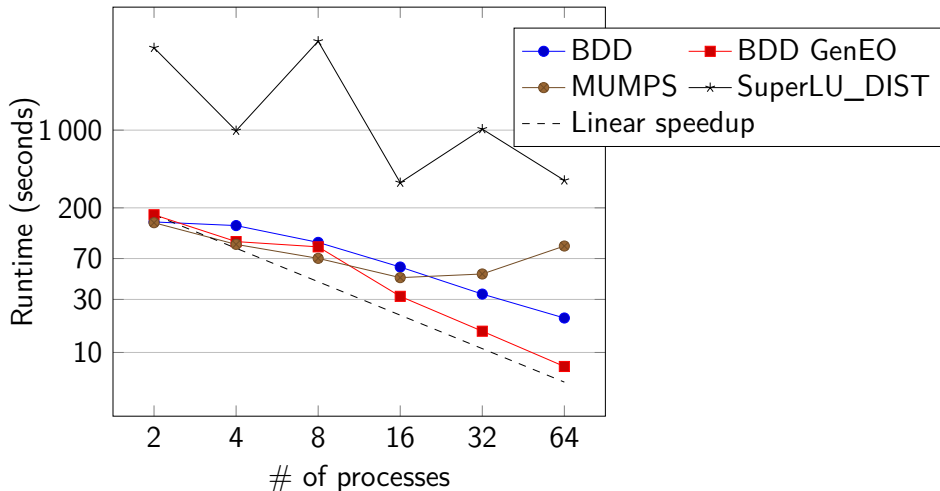
Substructuring preconditioners vs. MG solvers

Homogeneous 2D elasticity discretized by \mathbb{P}_3 FE, 23M d.o.f.



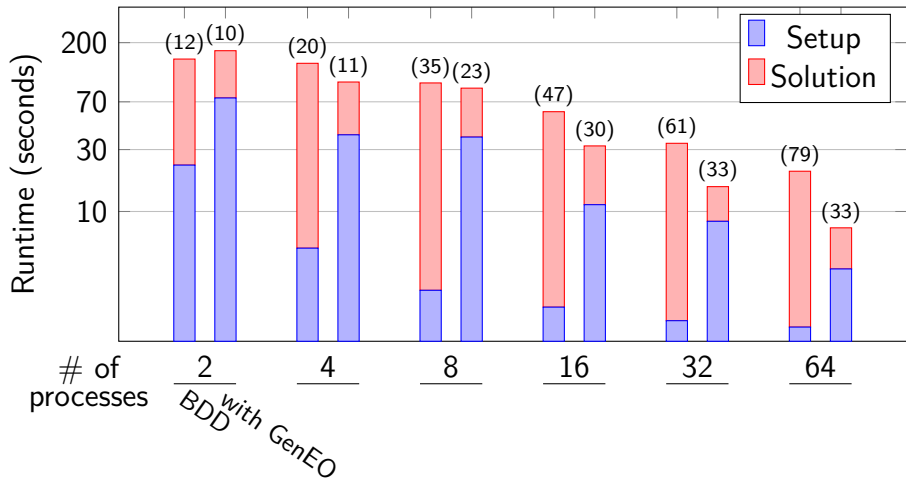
Substructuring preconditioners vs. direct solvers

Homogeneous 2D Poisson equation discretized by \mathbb{P}_4 FE, 5M d.o.f.





Effect of the GenEO deflation vectors





Final words

Summary:

- scalable framework for building two-level preconditioners for both Schwarz or substructuring methods (FETI, BDD),
- wide range of applications,
- still many ongoing projects:
 - assembly of Z^*A^*AZ ,
 - systems with multiple RHS,
 - multilevel extension.



Perspectives

Outlooks:

- adaptive construction of the coarse operator,
- recycling for nonlinear problems.











Perspectives






Outlooks:





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Thank you !

-  Cai, X-C. and M. Sarkis (1999). “Restricted additive Schwarz preconditioner for general sparse linear systems”. In: *SIAM Journal on Scientific Computing* 21.2, pp. 792–797.
-  Conen, L., V. Dolean, R. Krause, and F. Nataf (2014). “A coarse space for heterogeneous Helmholtz problems based on the Dirichlet-to-Neumann operator”. In: *Journal of Computational and Applied Mathematics* 271, pp. 83–99.
-  St-Cyr, A., M. Gander, and S. Thomas (2007). “Optimized multiplicative, additive, and restricted additive Schwarz preconditioning”. In: *SIAM Journal on Scientific Computing* 29.6, pp. 2402–2425.
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