

On Parallelization of Energy Minimizing Multigrid

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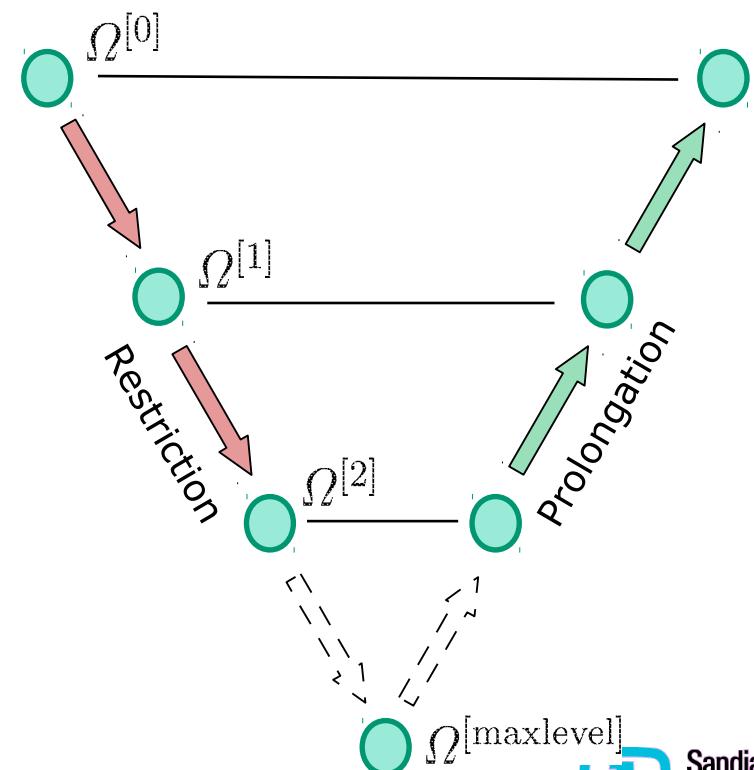
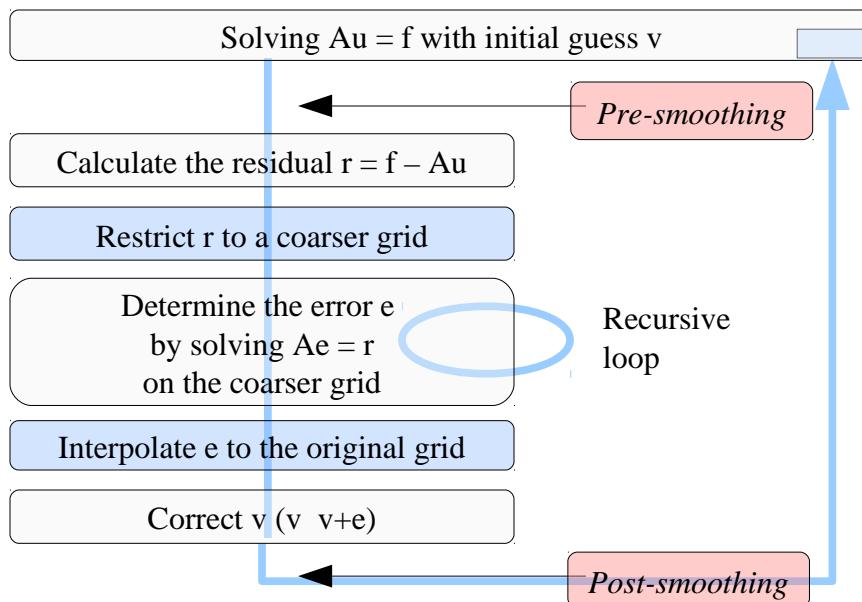
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Outline

- Introduction
- Energy-minimization based AMG
 - Motivations
 - Algorithm
- Parallel implementation
- Setup amortization
- Conclusion

- Iterative method for solving linear equations
- Commonly used as a preconditioner
- Idea: capture error at multiple resolutions using grid transfer operator:
 - **Smoothing** damps the oscillatory error (high energy)
 - **Coarse grid correction** reduces the smooth error (low energy)





Prolongator requirements

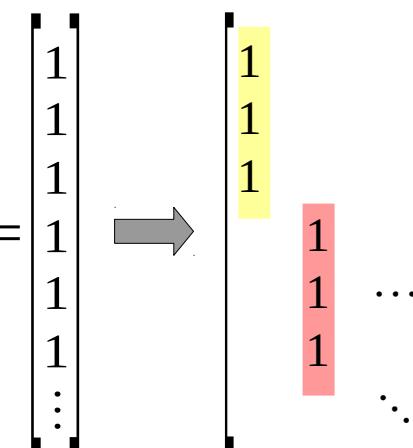
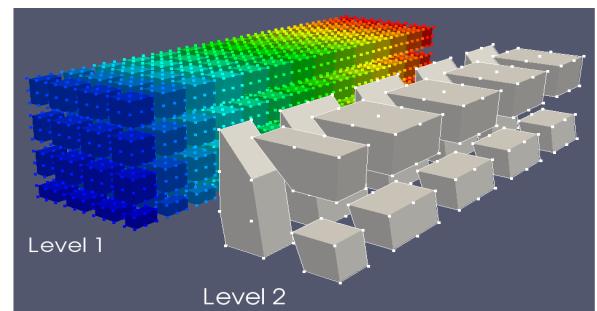
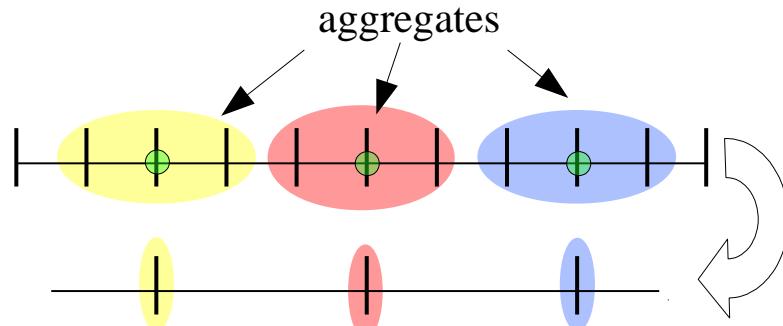
Few desired properties

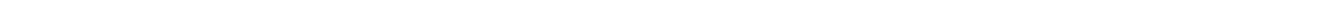
- **preservation of null space**: the span of basis functions on each coarse level should contain zero energy modes
- **minimization of energy**: basis functions on the coarse levels should have as small energy as possible
- **bounded intersection**: the supports of the basis functions on the coarse levels should overlap as little as possible.

Smoothed Aggregation

SA prolongator is constructed in a few steps

- Construct aggregates
 - Select a set of root nodes
 - Group unknowns into aggregates
- Construct tentative prolongator and coarse nullspace
 - Restrict fine nullspace onto aggregates
 - Do QR decomposition
We satisfy $P_{tent}B_c = B$
- Decrease energy of P_{tent} by smoothing
 $P = (I - \omega D^{-1}A)P_{tent}$
May not satisfy $P_{SA}B_c = B$





Energy minimization



Energy minimization

Energy minimization is a general framework.

Idea: construct the prolongator P by minimizing the energy of each column P_k while enforcing constraints.

Find P :

$$P = \operatorname{argmin} \sum \|P_k\|_\chi$$

subject to

- specified sparsity pattern;
- nullspace preservation.

Advantages:

- Flexibility (input):
 - accept any sparsity pattern (arbitrary basis function support)
 - enforce constraints: important modes requiring accurate interpolation
 - choice of norm for minimization and search space
- Robustness

Constraint matrix

- Sparsity pattern
- B, B_c fine and coarse mode(s) requiring accurate interpolation

Preservation of the nullspace: for instance $P\mathbf{1} = \mathbf{1}$

} inputs

$$N = \begin{bmatrix} * & * \\ * & 0 \\ * & * \\ 0 & * \end{bmatrix} \quad PB_c = B \Leftrightarrow \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \\ p_{31} & p_{32} \\ p_{41} & p_{42} \end{bmatrix} \begin{bmatrix} b_{11}^c \\ b_{21}^c \end{bmatrix} = \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ b_{41} \end{bmatrix}$$

- Representation of the constraints in the algorithm:

$$XP = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ b_{11}^c & 0 & 0 & 0 & b_{21}^c & 0 & 0 & 0 \\ 0 & b_{11}^c & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{11}^c & 0 & 0 & 0 & b_{21}^c & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & b_{21}^c \end{bmatrix} \begin{bmatrix} p_{11} \\ p_{21} \\ p_{31} \\ p_{41} \\ p_{12} \\ p_{22} \\ p_{32} \\ p_{42} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ b_{11} \\ b_{21} \\ b_{31} \\ b_{41} \end{bmatrix}$$

Constraint matrix

Two nullspace vectors:

$$P \begin{bmatrix} b_{11}^c & b_{12}^c \\ b_{21}^c & b_{22}^c \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \\ b_{31} & b_{32} \\ b_{41} & b_{42} \end{bmatrix}$$

$$\begin{bmatrix} b_{11}^c & 0 & 0 & b_{21}^c & 0 & 0 \\ 0 & b_{11}^c & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{11}^c & 0 & b_{21}^c & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{21}^c \end{bmatrix} \begin{bmatrix} p_{11} \\ p_{21} \\ p_{31} \\ p_{12} \\ p_{32} \\ p_{42} \end{bmatrix} = \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ b_{41} \\ b_{12} \\ b_{22} \\ b_{32} \\ b_{42} \end{bmatrix}$$



Energy-minimization algorithm

Find P :

$$P = \operatorname{argmin} \sum \|P_k\|_x$$

subject to

- specified sparsity pattern;
- nullspace preservation.

Solve $AP = 0$
in a constrained Krylov space

- Definition of energy $\|\cdot\|_x$ depends on Krylov method
 - A for CG
 - $A^T A$ for GMRES



Energy minimization algorithm

Construct aggregates

$$\mathcal{N} = |A||P^{(0)}|$$

▷ Select sparsity pattern

$$D = \text{diag}(A)$$

▷ Diagonal preconditioner

$$R = -AP^{(0)}$$

▷ Initial residual

$$R = \text{enforce}(R, \mathcal{N})$$

▷ Enforce sparsity on R

$$R = \text{project}(R, X)$$

▷ Enforce $RB_c = \mathbf{0}$

for i to iter **do**

$$Z = D^{-1}R$$

$$\gamma = \langle R, Z \rangle_F$$

if i is 1 **then**

$$Y = Z$$

else

$$\beta = \gamma / \gamma_{old};$$

$$Y = Z + \beta Y$$

▷ New search direction

end if

$$\gamma_{old} = \gamma$$

$$Y_A = AY$$

$$Y_A = \text{enforce}(Y_A, \mathcal{N})$$

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$$Y_A = \text{project}(Y_A, B_c)$$

▷ Enforce $Y_A B_c = \mathbf{0}$

$$\alpha = \gamma / \langle Y, Y_A \rangle_F$$

$$P^{(i)} = P^{(i-1)} + \alpha Y$$

▷ Update prolongator

$$R = R - \alpha Y_A$$

▷ Update residual

Comparison with Smoothed Aggregation

- SA: 6 DOFs/node
- Energy Minimization: 3 DOFs/node, 6 nullspace vectors

Tab. : Iteration count and *complexity* (lower complexity = faster run time) for increasing mesh sizes and stretch factors.

Mesh	$\epsilon = 1$		$\epsilon = 10$		$\epsilon = 100$	
	SA	Emin	SA	Emin	SA	Emin
10^3	6 1.30	7 1.07	8 2.81	8 1.22	9 3.21	8 1.24
15^3	8 1.19	9 1.05	10 2.32	10 1.15	12 2.54	12 1.16
20^3	8 1.24	9 1.06	10 2.59	9 1.18	13 3.05	10 1.20
25^3	9 1.26	8 1.07	11 2.76	9 1.20	14 3.04	10 1.20
30^3	10 1.22	11 1.05	12 2.52	12 1.17	15 3.06	13 1.19
35^3	10 1.24	10 1.06	12 2.66	12 1.18	16 3.03	13 1.19
40^3	10 1.26	9 1.06	12 2.77	12 1.19	16 3.21	11 1.21

3.85x

$$\text{complexity: } \frac{\sum_i \text{nnz}(A_i)}{\text{nnz}(A)}$$

Parallel implementation



Energy minimization algorithm

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Energy minimization algorithm

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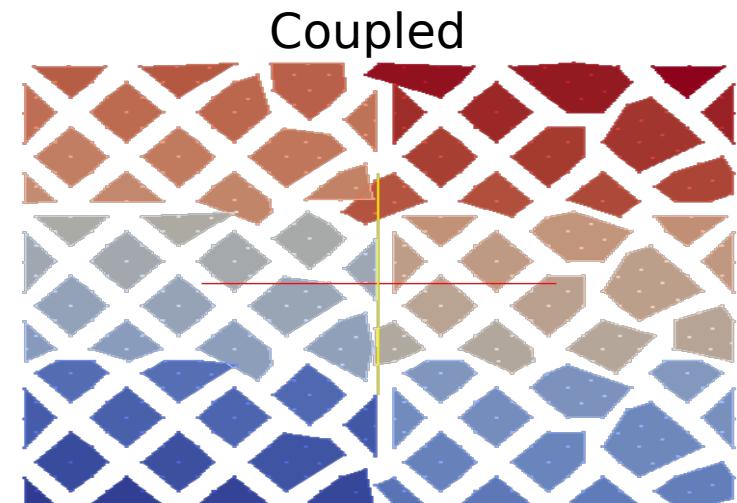
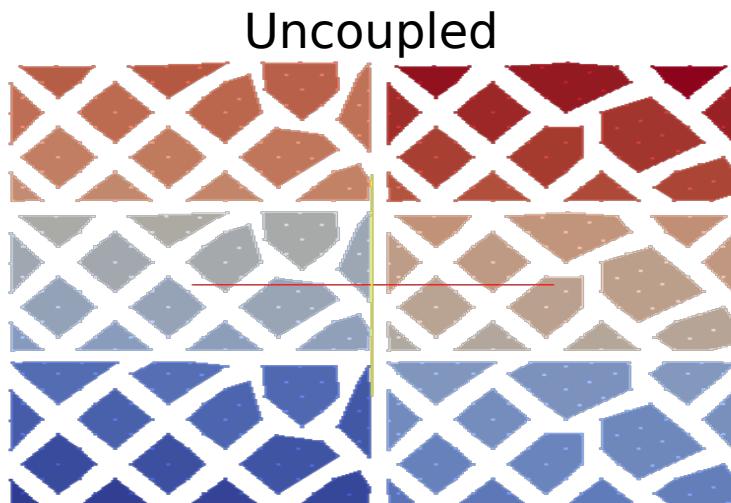
▷ Update residual



Parallel aggregation

Two choices: coupled and uncoupled aggregation

- Uncoupled aggregation aggregates only inside a subdomain
- Coupled aggregation allows aggregates to cross subdomain boundary
- Coupled aggregation is more expensive, but has convergence similar to the serial case



Constraints in parallel

Let P have the following pattern and nullspace consist of two vectors

$$P \begin{bmatrix} b_{11}^c & b_{12}^c \\ b_{21}^c & b_{22}^c \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \\ b_{31} & b_{32} \\ b_{41} & b_{42} \end{bmatrix} \quad P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & 0 \\ p_{31} & p_{32} \\ 0 & p_{41} \end{bmatrix}$$

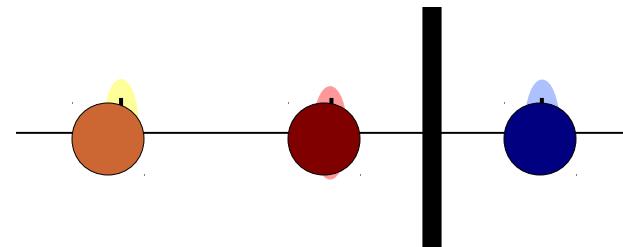
$$\begin{bmatrix} b_{11}^c & 0 & 0 & b_{21}^c & 0 & 0 \\ 0 & b_{11}^c & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{11}^c & 0 & b_{21}^c & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{21}^c \\ \hline b_{12}^c & 0 & 0 & b_{22}^c & 0 & 0 \\ 0 & b_{12}^c & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{12}^c & 0 & b_{22}^c & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{22}^c \end{bmatrix} \begin{bmatrix} p_{11} \\ p_{21} \\ p_{31} \\ p_{12} \\ p_{32} \\ p_{42} \end{bmatrix} = \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ b_{41} \\ b_{12} \\ b_{22} \\ b_{32} \\ b_{42} \end{bmatrix}$$

$$\begin{bmatrix} b_{11}^c & b_{21}^c & 0 & 0 & 0 & 0 \\ b_{12}^c & b_{22}^c & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & b_{11}^c & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{22}^c & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & b_{11}^c & b_{21}^c \\ 0 & 0 & 0 & 0 & b_{12}^c & b_{22}^c \\ \hline 0 & 0 & 0 & 0 & 0 & b_{21}^c \\ 0 & 0 & 0 & 0 & 0 & b_{22}^c \end{bmatrix} \begin{bmatrix} p_{11} \\ p_{12} \\ p_{21} \\ p_{32} \\ p_{41} \\ p_{42} \end{bmatrix} = \begin{bmatrix} b_{11} \\ b_{12} \\ b_{21} \\ b_{22} \\ b_{31} \\ b_{32} \\ b_{41} \\ b_{42} \end{bmatrix}$$



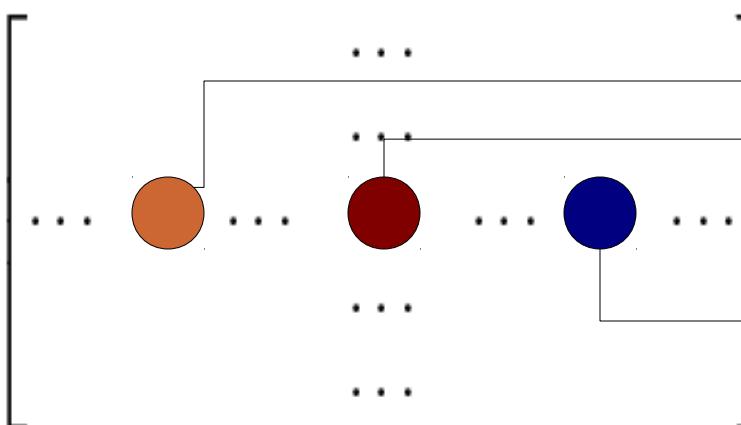
Constraints in parallel

What does each block correspond to?

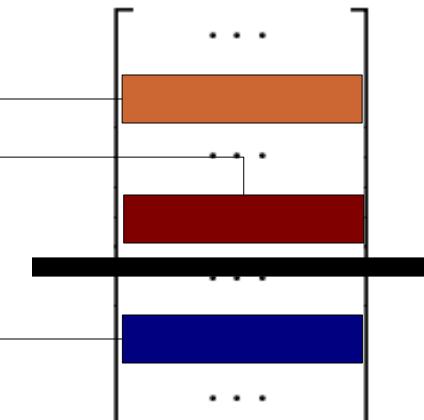


Consider a row of P with three nonzeros

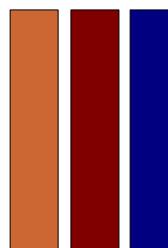
Prolongator row



Coarse nullspace



Block of the constraint corresponding to the row



Energy minimization algorithm (updated)

Construct aggregates

$$\mathcal{N} = |A||P^{(0)}|$$

Import ghost components of nullspace vectors

$$D = \text{diag}(A)$$

▷ Select sparsity pattern

$$R = -AP^{(0)}$$

▷ Diagonal preconditioner

$$R = \text{enforce}(R, \mathcal{N})$$

▷ Initial residual

$$R = \text{project}(R, X)$$

▷ Enforce sparsity on R

▷ Enforce $RB_c = \mathbf{0}$

for i to iter **do**

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end if

$$\gamma_{old} = \gamma$$

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▷ New search direction

$$Y_A = \text{project}(Y_A, B_c)$$

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▷ Enforce $Y_A B_c = \mathbf{0}$

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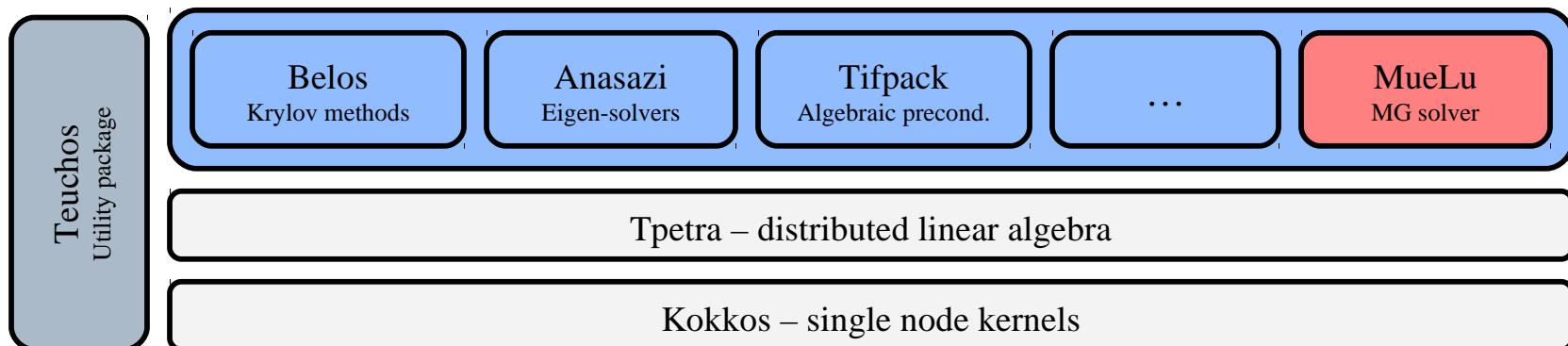
▷ Update prolongator

$$P^{(i)} = P^{(i-1)} + \alpha Y$$

▷ Update residual

$$R = R - \alpha Y_A$$

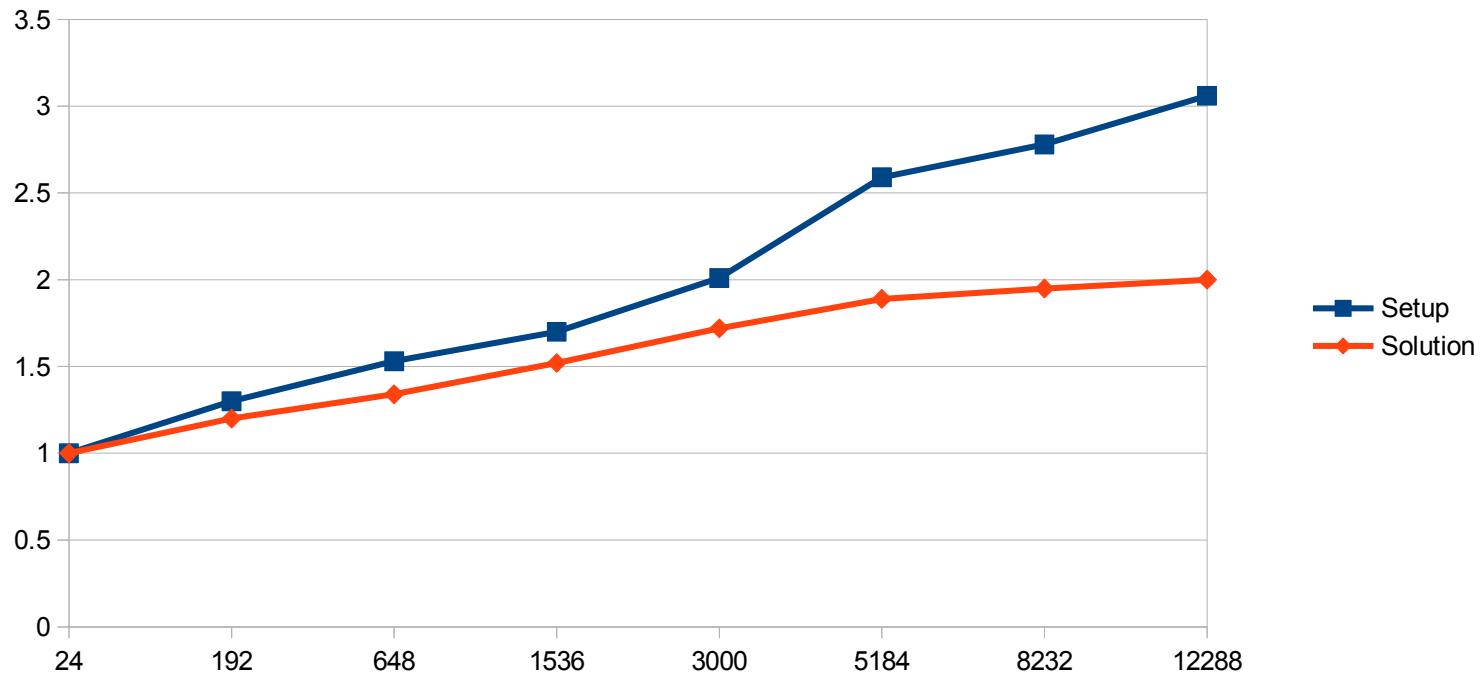
- Future package of the Trilinos project (to replace ML)
 - Massively parallel
 - Multicore and GPU aware
 - Templatized types for mixed precision calculation (32-bit – 64-bit) and type complex
- Objective is to solve problem with billions of DOF on 100Ks of cores...
- Leverage the Trilinos software stack:



- Currently in development...

Numerical results - Laplace 3D

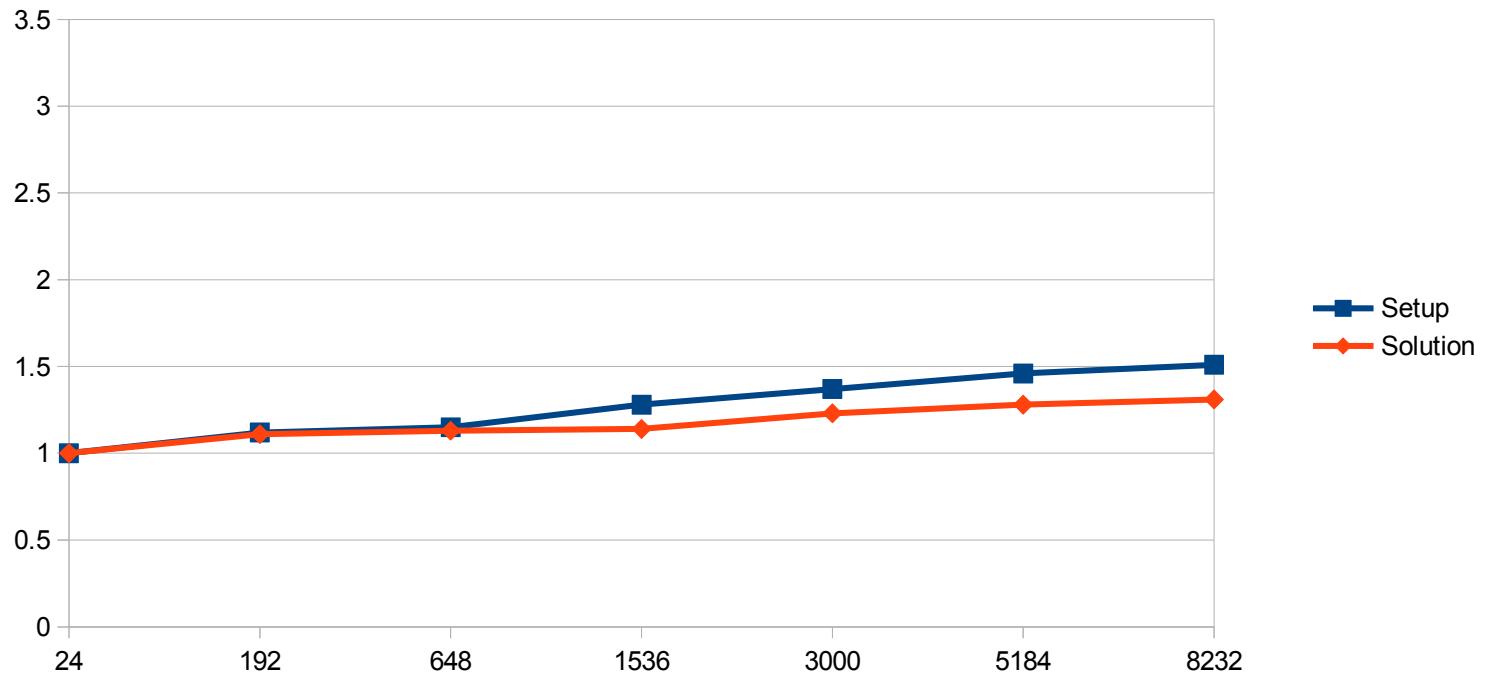
- Laplace 3D, 7 point stencil
- Energy minimization
 - 2 CG iterations
 - Initial guess: tentative prolongator
 - Sparsity pattern: same as SA





Numerical results - Elasticity 3D

- Elasticity 3D, Poisson ratio 0.25
- Energy minimization
 - 2 CG iterations
 - Initial guess: tentative prolongator
 - Sparsity pattern: same as SA



Setup amortization



Setup amortization: reuse

- Emin setup may be expensive (several times that of SA)
- Typically, we need multigrid for each linear iteration of Newton, therefore it is reasonable to assume that the system does not change too much
- Many components of the setup phase can be reused
 - Initial prolongator
 - Sparsity patterns (assuming no filtering)
 - Matrix graphs (assuming fixed mesh)



Strategies for a sequence of systems

- **No reuse**: construct multigrid anew for each iteration
- **Simple reuse**: construct multigrid only for the first iteration, and then use the same preconditioner for all iteration
- **Fast reuse**: construct multigrid with multiple iterations on the first step, and use fewer iterations for consecutive step, reusing constructed prolongators and graphs

Numerical example: icesheet model

System of two coupled non-linear PDEs

$$\begin{cases} -\nabla \cdot (2\mu \dot{\epsilon}_1) = -\rho g \frac{\partial s}{\partial x}, \\ -\nabla \cdot (2\mu \dot{\epsilon}_2) = -\rho g \frac{\partial s}{\partial y} \end{cases}$$

with Glen's law viscosity

$$\mu = \frac{1}{2} A^{-\frac{1}{n}} (\dot{\epsilon}_{xx}^2 + \dot{\epsilon}_{yy}^2 + \dot{\epsilon}_{xx}\dot{\epsilon}_{yy} + \dot{\epsilon}_{xy}^2 + \dot{\epsilon}_{xz}^2 + \dot{\epsilon}_{yz}^2 + \gamma)^{\left(\frac{1}{2n} - \frac{1}{2}\right)}$$

$$\dot{\epsilon}_1^T = \left(2\dot{\epsilon}_{xx} + \dot{\epsilon}_{yy}, \quad \dot{\epsilon}_{xy}, \quad \dot{\epsilon}_{xz} \right)$$

$$\dot{\epsilon}_2^T = \left(\dot{\epsilon}_{xy}, \quad \dot{\epsilon}_{xx} + 2\dot{\epsilon}_{yy}, \quad \dot{\epsilon}_{yz} \right)$$

$$\dot{\epsilon}_{ij} = \frac{1}{2} \left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right)$$

A = flow rate factor

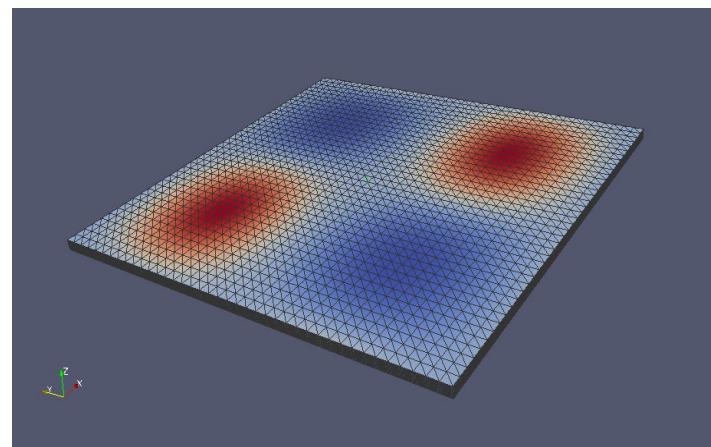
n = Glen's law exponent = 3

γ = regularization parameter

β = sliding coefficient ≥ 0

Discretization: classical Galerkin FEM with structured or unstructured mesh.

Nonlinear solver: Newton's method





Numerical results: icesheet model

Step	Emin(6)	Emin(1)	Emin(6,1)
2	17	30	17
8	16	32	17
12	17	33	18
18	17	36	18
23	17	36	18
28	17	34	18



Summary

- Energy minimization AMG is flexible
- Energy minimization AMG is suitable for parallelization
 - Standard parallel operations ($M \times M$, BLAS1) are well known
 - Constraint application could be done locally storing ghost info
- Preliminary results show promise
- There are ways to reduce setup cost