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Amortizing AMG Components Across Problem Sequences

Ray Tuminaro, Sandia National Labs

Collaborators:

Hu, Prokopenko, Siefert, Tsuji (Sandia)

Boman, Cyr, Lin, Shadid (Sandia), Gee, Wiesner (TU Munich), Olson (U. Illinois), Schroder (LLNL), Keyes (KAUST), Gaidamour (CNRS), Maclachlan, Benson (Tufts), Shank (Temple), Waisman (Columbia U), Hiriyr(Weidlinger), Gerstenberg (Rolls Royce)

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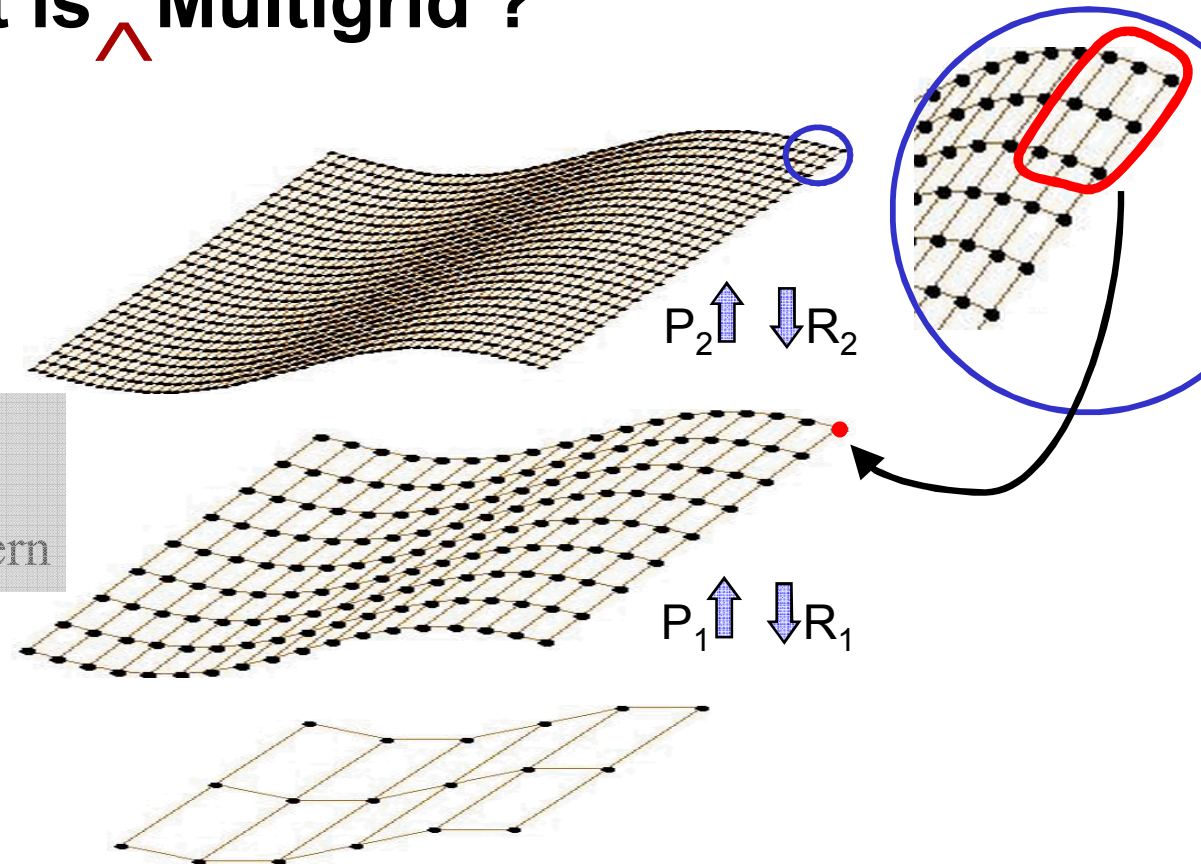
Outline

- AMG background
 - popular approaches: inexpensive, often effective, but rigid
- Energy minimization AMG
 - arbitrary coarsening, flexible coarse basis function support
- Energy minimization costs & amortization
 - Reuse & initial guess choice
- Leveraging flexibility
 - structured AMG for exascale architectures
 - mixed finite elements,
 - extended finite elements & anisotropic PDEs

Algebraic What is \wedge Multigrid ?

Solve $A_3 u_3 = f_3$

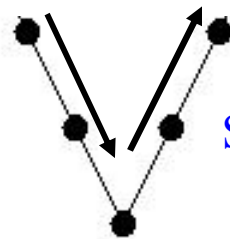
- Construct Graph & Coarsen
- Determine P_i & R_i sparsity pattern
- Determine P_i & R_i 's coefs
- Project: $A_i = R_i A_{i+1} P_i$



Smooth $A_3 u_3 = f_3$. Set $f_2 = R_2 r_3$.

Smooth $A_2 u_2 = f_2$. Set $f_1 = R_1 r_2$.

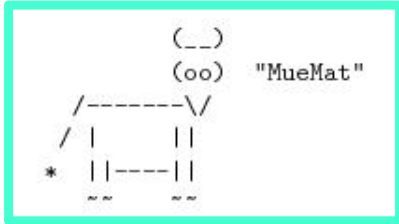
Solve $A_1 u_1 = f_1$ directly.



Set $u_3 = u_3 + P_2 u_2$. Smooth $A_3 u_3 = f_3$.

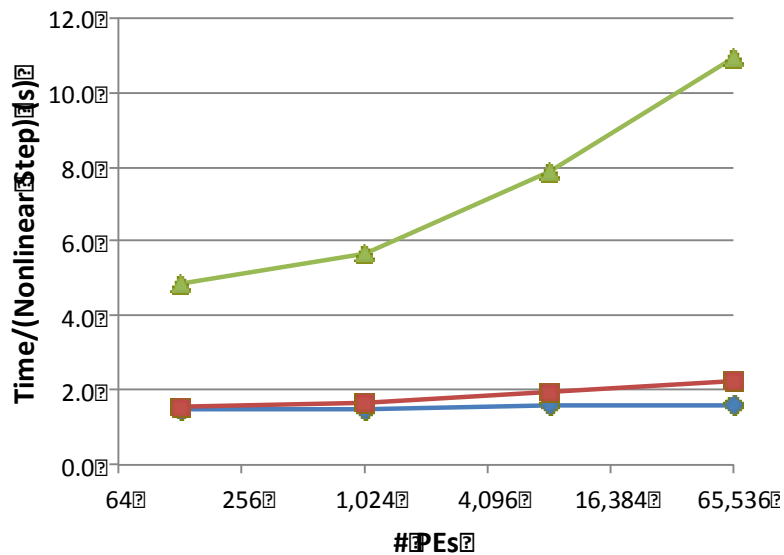
Set $u_2 = u_2 + P_1 u_1$. Smooth $A_2 u_2 = f_2$.

MueMat/ MueLu

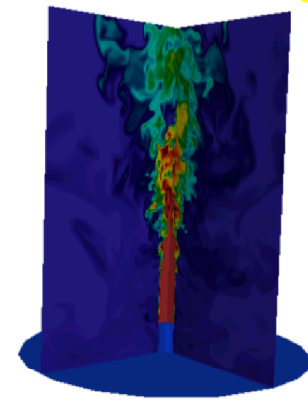
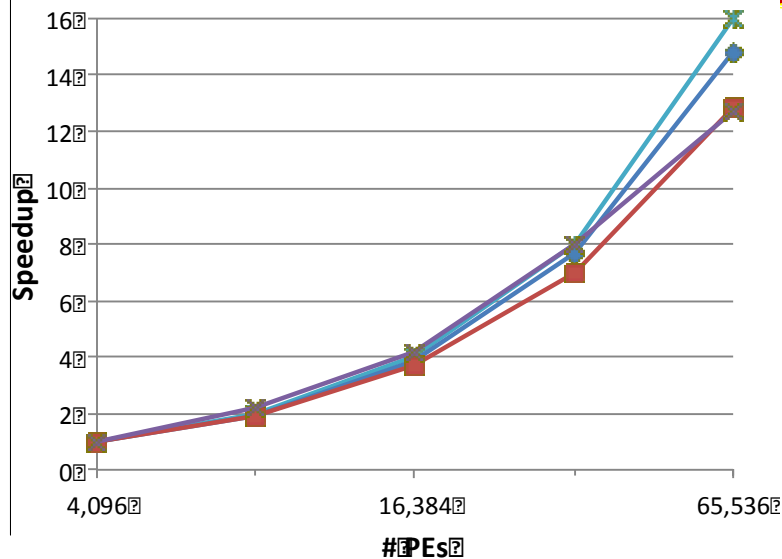


- new AMG algorithms, e.g. energy minimization
- leverages Trilinos/Kokkos for multi-core/GPU performance
- templating for mixed precision
- designed for flexibility
 - *special* application circumstances
 - architecture considerations
 - reuse

137k Elem/Core PPE1 (Multigrid)



1.12B Elem, PPE1 (Multigrid)



9 billion dofs

* Ideal
 ◆ Assemble
 ■ Assem+Load+Comp
 × Solve-psetup
 ▲ Apply+prec+GMRES

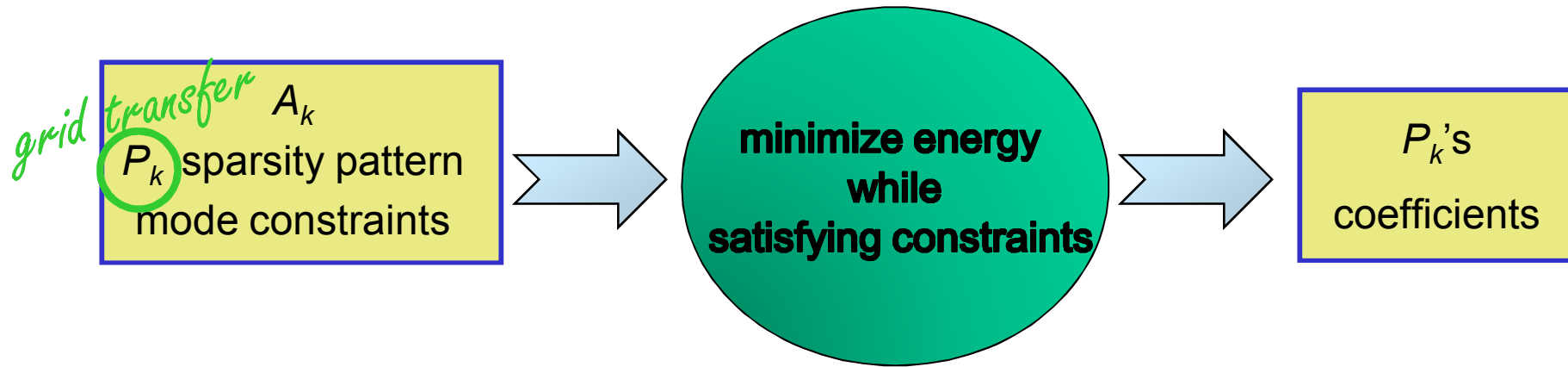
AMG limitations ...

Best understood theoretically for
scalar elliptic PDEs with *standard* discretizations
(e.g. linear nodal FE & finite differences),
but often works on broader range of systems.

Deficiency: **Classical AMG & smoothed aggregation are rigid & not easily adapted to *advanced* situations.**

- ❑ coarsening rules: diameter 3 aggregates or
 - (C1) for each $i \in F$, each point $j \in S_i$ should either be in C , or should be strongly connected to at least one point in $C \cap S_i$
 - (C2) C should be a maximal subset of all points with the property that no two C-points are strongly connected to each other
- ❑ coarsening, P sparsity pattern, p_{ij} choices are often tied together
- ❑ strong/weak decisions influence multiple phases of algorithm
- ❑ accurate interpolation of constants automatically addressed, but considering other important modes can be problematic

AMG & Energy Minimization



Tradeoffs:

+ flexibility

- any coarsening
- any sparsity pattern
- constraints
- important modes
requiring accurate interpolation

+ robustness

$$\min_P p_1^T A p_1 + p_2^T A p_2 + p_3^T A p_3 + \dots$$

$$P = [p_1 \ p_2 \ p_3 \ \dots]$$

Brandt, Brannick, Brezina, Chan, Gee, Kahl,
Kolev, Livshits, Mandel, Olson, Schroder,
Smith, T, Vanek, Vassilevski, Wagner, Wall,
Wan, Wiesner, Xu, Zikatanov



“Solve” $AP = 0$

- 1) with minimization algorithm
- 2) in space satisfying constraints

or equivalently

“solve” $\hat{A} \mathbf{P} = 0$ where $\hat{A} = \begin{pmatrix} A & & \\ & A & \\ & & A \\ & & & \ddots \end{pmatrix}$ $\mathbf{P} = \begin{pmatrix} p_1 \\ p_2 \\ p_3 \\ \vdots \end{pmatrix}$

and $P = [p_1 \ p_2 \ \cdots \ p_m]$

Minimization candidates include *CG & Chebyshev, GMRES & CGNR*

Constraints

– $P B_c = B \Rightarrow X \mathbf{P} = g$ via $Q = (I - X^T (X X^T)^{-1} X)$

Constraint Satisfying Space *might* be

$Q \hat{A} \mathbf{P}_0, (Q \hat{A})^2 \mathbf{P}_0, (Q \hat{A})^3 \mathbf{P}_0, (Q \hat{A})^4 \mathbf{P}_0, \dots$

Prolongator construction cost

- Costs:

1 Krylov iteration $\left\{ \begin{array}{l} \text{Matrix-matrix multiply: } A P \\ \text{Remove nnzs beyond desired sparsity pattern} \\ \text{Apply } Q = I - X^T (X X^T)^{-1} X \end{array} \right.$

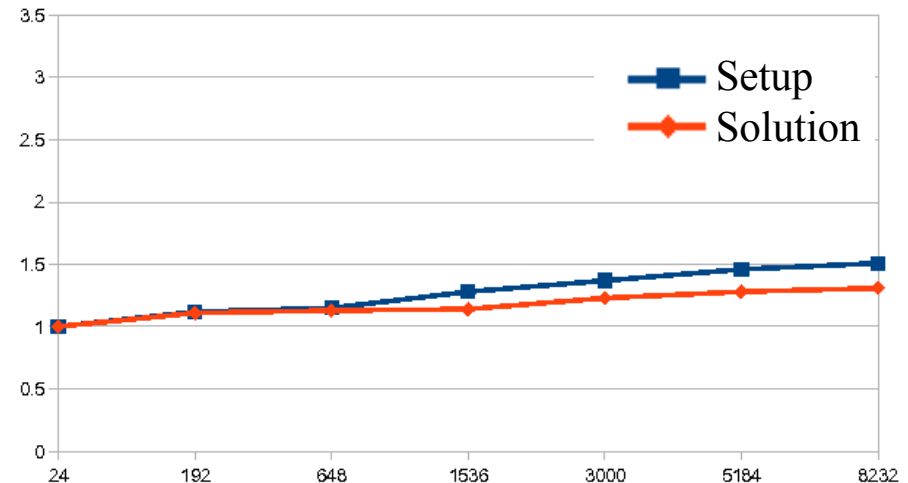
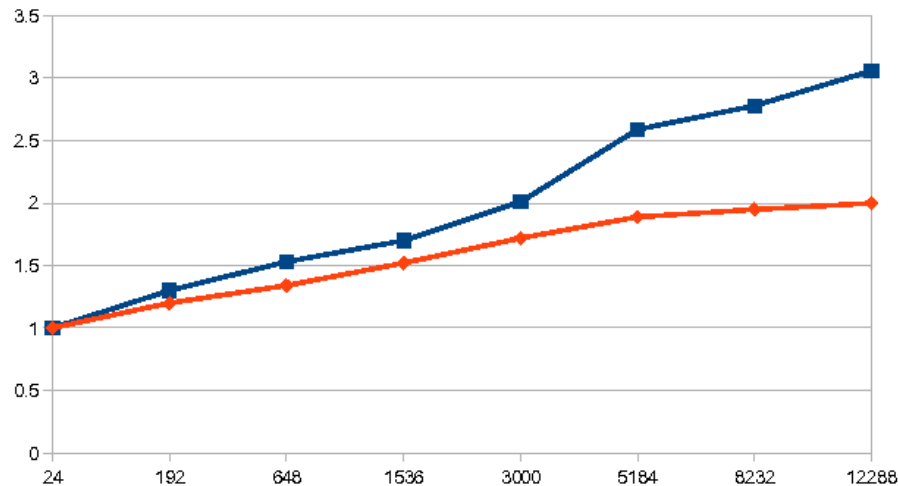
- Practical algorithms follow ...

- Few iterations needed, e.g. Smoothed Aggregation
- *Computation of $(X X^T)^{-1}$ easy as*

$$X X^T = \begin{pmatrix} \text{yellow square} & & & & \\ & \text{yellow square} & & & \\ & & \text{yellow square} & & \\ & & & \text{yellow square} & \\ & & & & \text{yellow square} \end{pmatrix}$$

- Amortization opportunities: init. guess, reuse of $X X^T$

MueLu E_{min} Setup Scaling



3D Laplace via 7 pt stencil

- 2 CG E_{min} iterations
- P_0 via tentative prolongator
- same sparsity pattern as SA

3D elasticity with Poisson ratio .25

- 2 CG E_{min} iterations
- P_0 via tentative prolongator
- same sparsity pattern as SA

2 E_{min} iterations typically fine for AMG convergence

SA sparsity pattern \Rightarrow solver cost comparable with SA

1 E_{min} iter. \Rightarrow Setup cost $\approx 1.5-2x >$ SA setup \Rightarrow not too significant



Setup Amortization

- E_{min} generally more expensive than SA
- Typically solve a sequence of related linear systems
 - time stepping, Newton, continuation, inverse problems, UQ, ...
- Many setup components can often be reused
 - P_0 , sparsity pattern, matrix graphs, constraint builder, even some substeps of matrix-matrix multiply
 - depends on changes to ...
mesh & matrix coefficients and strength-of-connection
- Previous P_{final} can be used for next $P_0 \Rightarrow$ fewer E_{min} iterations

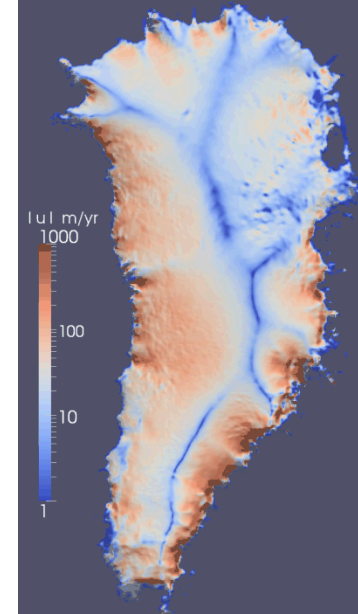
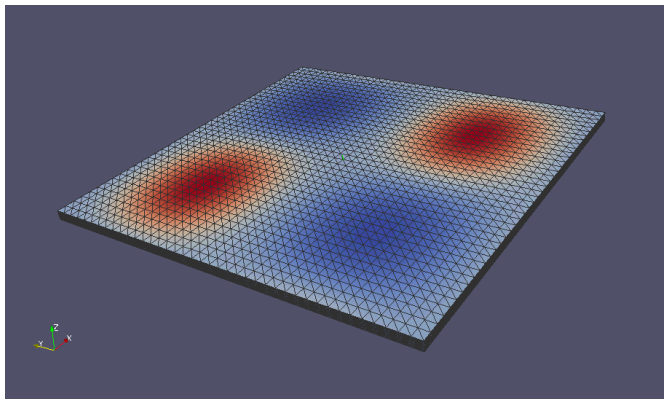
Ice Sheet Amortization Test Case

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

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



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

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

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

A = flow rate factor

n = Glen's law exponent = 3

γ = regularization parameter

β = sliding coefficient ≥ 0

Newton's method & continuation used



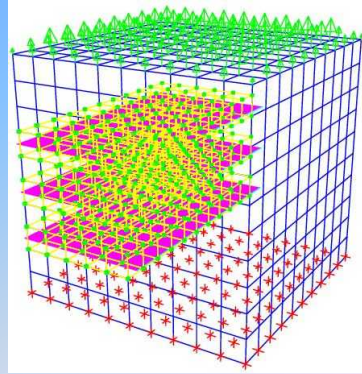
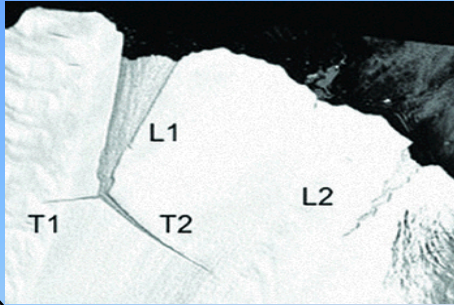
Ice Sheet Results

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

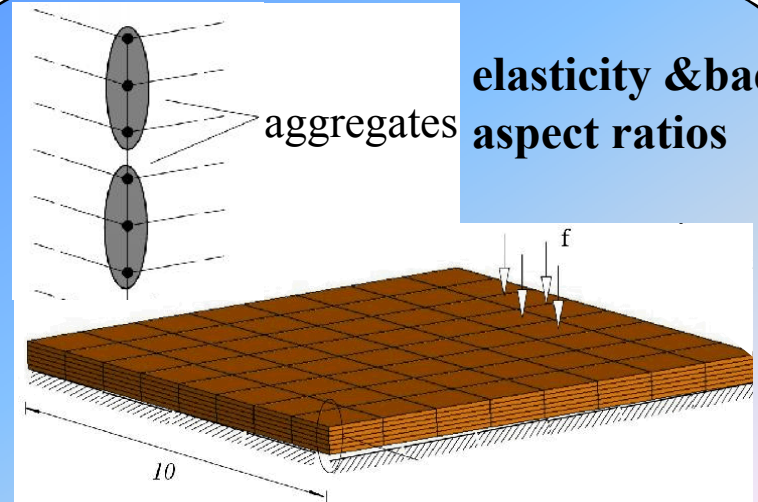
- Emin(k): k E_{min} iterations, no reuse
- Emin(k,1) k E_{min} iterations
- Solve times comparable for Emin(6) and Emin(6,1)
- Emin(6,1) setup times 4x better than Emin(6)

Exploiting Energy Minimization's Flexibility

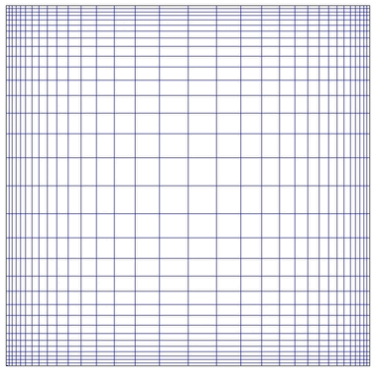
extended FE



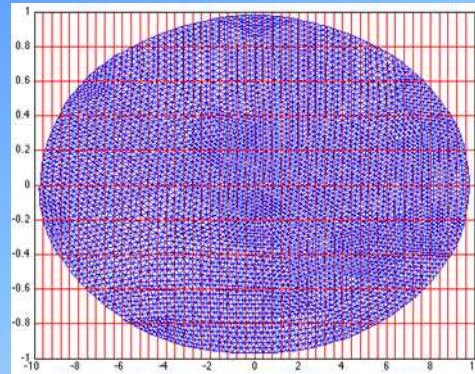
elasticity & bad aspect ratios



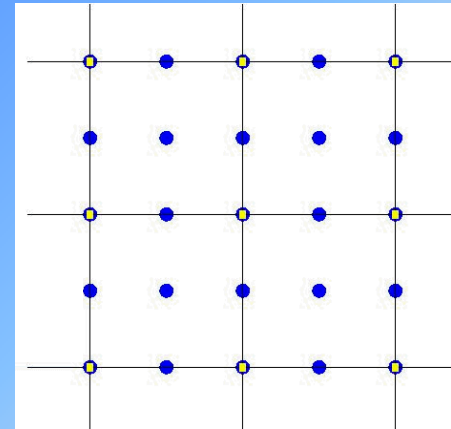
stretched meshes



unstructured to structured



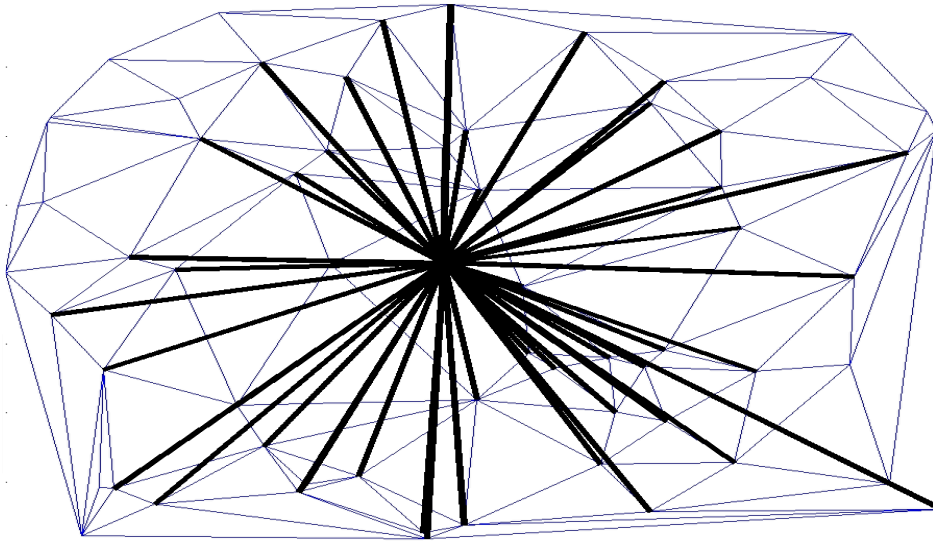
mixed finite elements



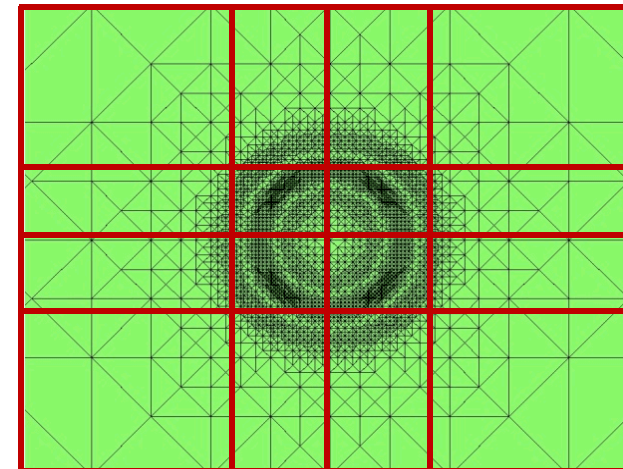
Unstructured \Rightarrow Structured

Why?

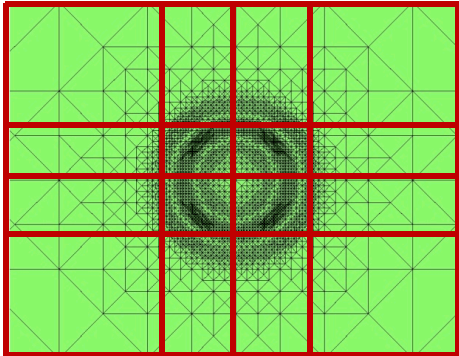
computational efficiency ... on large parallel systems



- Overlay unstructured grid with structured grid.
- **Coarse DOFs** on structured mesh, interpolate from **fine DOFs** within rectangles.
- Interpolation weights found with energy minimization.

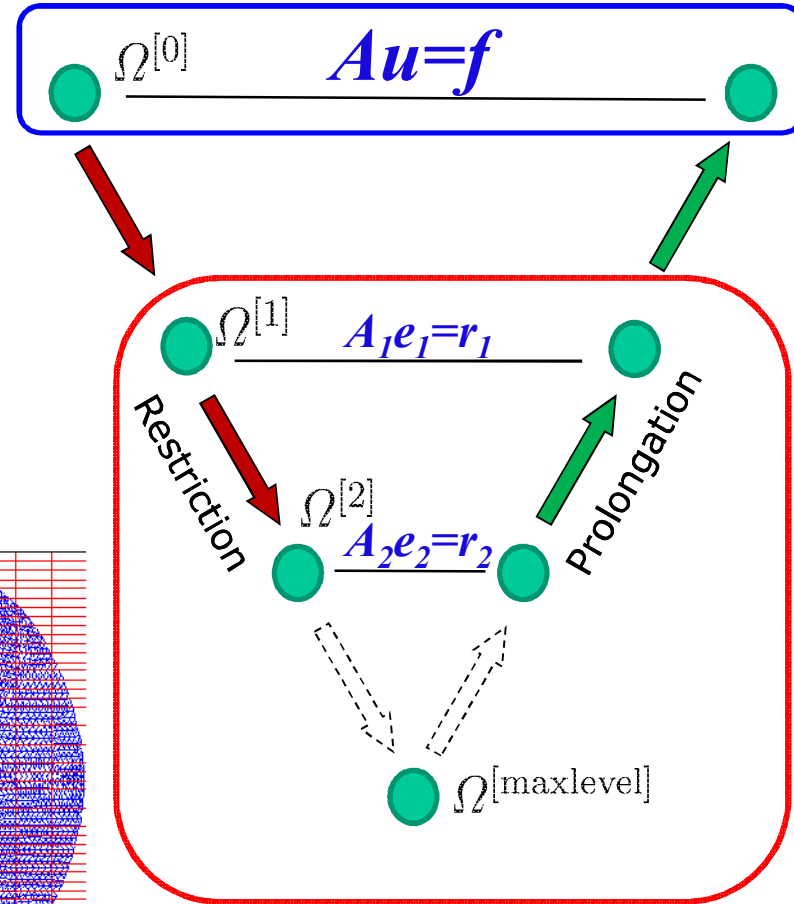


Unstructured \Rightarrow Structured

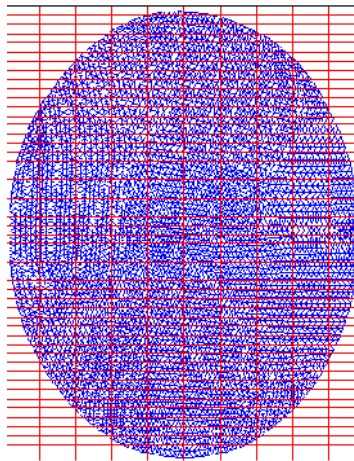


<i>domains</i>	<i>Emin its</i>
4×4	12
8×8	11
12×12	10
16×16	10

Unstructured mesh



Structured meshes



#DOFs	Unstructured AMG		Unstruct /struct AMG
	SA	Emin	Emin
69185	77 (1.95)	59 (1.95)	31 (1.59)
277633	112 (1.93)	84 (1.93)	38 (1.61)

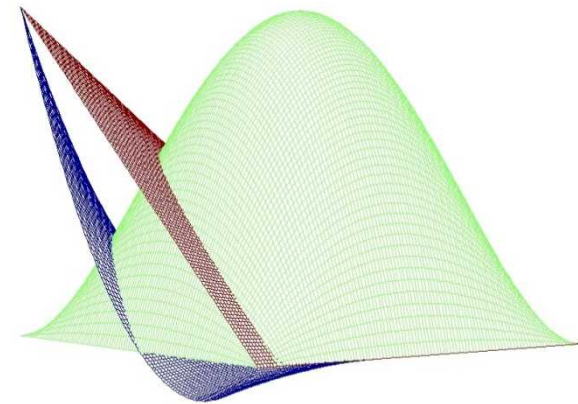
- caveat: **unstr.** is 3-level, **unstr.** to **struct.** is 2-level

Mixed Finite Elements

Stokes flow

$$\begin{pmatrix} \mu\Delta & \nabla \\ \nabla \bullet & \end{pmatrix} \begin{pmatrix} u \\ p \end{pmatrix} = \begin{pmatrix} f \\ 0 \end{pmatrix}$$

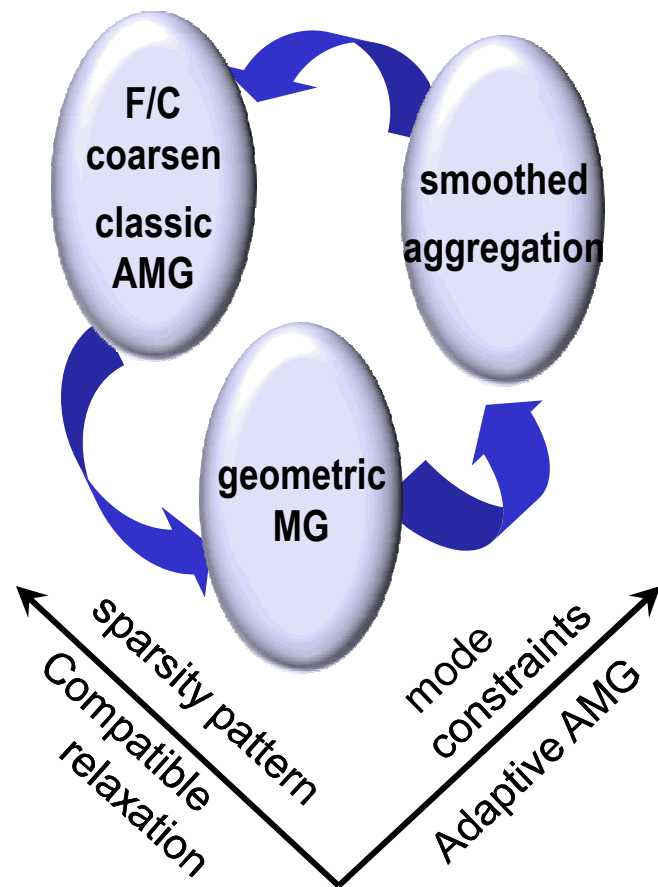
Q2-Q1 elements due to Inf-Sup conditions



Mesh	Iters	complexity
9 x 9	20	2.01
17 x 17	25	1.81
65 x 65	Xx	Xx
257 x 257	29	1.91

Concluding Remarks

- Energy Minimization AMG provides great flexibility
- Parallel practical variants definitely possible
 - a couple of Krylov sweeps
 - careful implementation of constraints
 - amortization
- Many situations arise where flexibility is useful
 - large scale parallel computations
 - advanced discretizations
 - stretched meshes
- Research needed to steer through some of the choices

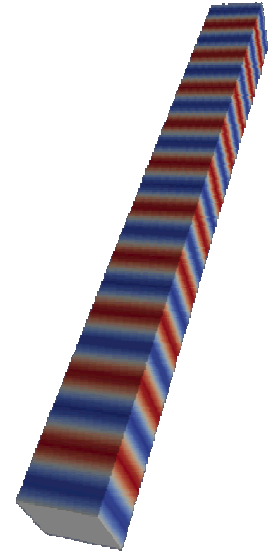




Related & Future Work

Helmholtz solvers

- Implemented parallel shifted-Laplacian AMG solver
 - tested on acoustic weapons problem
- Analyzed strengths/weaknesses of shifted-Laplacian
- Developed 2nd projection to accelerate shifted-Laplacian



Smoothers for MHD based on physics-based preconditioning

- Trilinos code under development
- Will be combined with Q2-Q1 AMG work

Coarsening/sparsity pattern scheme mimicking compatible relaxation idea

- Analyze intermediate E_{min} prolongators & correct deficiencies.