

Argonne Training Program on Extreme-Scale Computing



ATPESC 2024

Krylov Solvers and Algebraic Multigrid with hypre

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Outline

- Interfaces and Data Structures
 - IJ interface / ParCSR data structure
 - Structured interface / Struct data structure
- Iterative Solvers
 - Krylov Solvers
 - Multigrid solvers
- Some hands-on examples

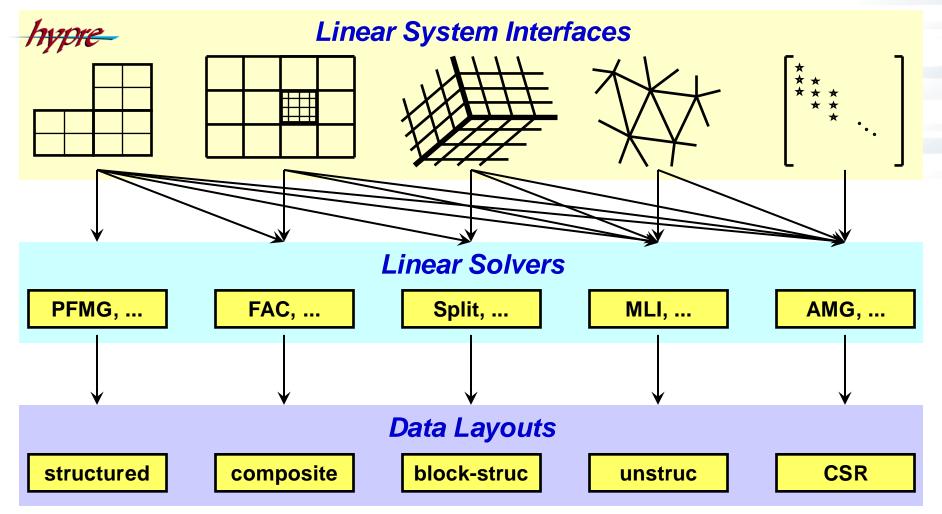
https://www.github.com/LLNL/hypre

	System Interfaces			
Solvers	Struct	SStruct	FEI	IJ
Jacobi	Χ	Х		
SMG	Χ	X		
PFMG	Χ	Х		
Split		Х		
SysPFMG		Х		
FAC		Х		
Maxwell		Х		
BoomerAMG		Х	Х	Х
AMS		Х	Х	Х
ADS		Х	Х	Х
MLI		Х	Х	X
MGR				Х
FSAI				Х
ParaSails		X	Х	X
ILU				Х
Euclid		Х	Х	Х
PILUT		Х	Х	X
PCG	Χ	X	Х	X
GMRES	Χ	X	Х	Х
FlexGMRES	Χ	X	Х	Х
LGMRES	Χ	X		Х
BICGSTAB	Х	X	Х	Х
Hybrid	Χ	X	Х	Х
LOBPCG	X	X		Х





(Conceptual) linear system interfaces are necessary to provide "best" solvers and data layouts





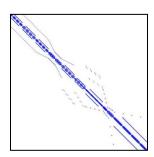


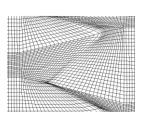
hypre supports these system interfaces

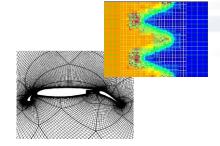
- Structured-Grid (Struct)
 - logically rectangular grids

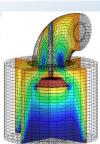


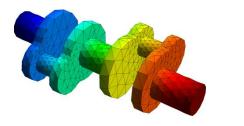
- grids that are mostly structured
- Examples: block-structured grids, structured adaptive mesh refinement grids, overset grids
- Finite elements
- Linear-Algebraic (IJ)
 - general sparse linear systems















Why multiple interfaces? The key points

- Provides natural "views" of the linear system
- Eases some of the coding burden for users by eliminating the need to map to rows/columns
- Provides for more efficient (scalable) linear solvers
- Provides for more effective data storage schemes and more efficient computational kernels





ParCSRMatrix data structure

- Based on compressed sparse row (CSR) data structure
- Consists of two CSR matrices:
 - One containing local coefficients connecting to local column indices
 - The other (Offd) containing coefficients with column indices pointing to off processor rows
- Also contains a mapping between local and global column indices for Offd
- Requires much indirect addressing, integer computations, and computations of relationships between processes etc,





Proc 0

Proc 1

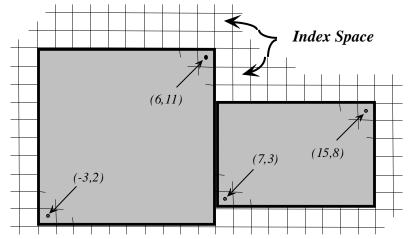
Proc p

Structured-Grid System Interface (Struct)

- Appropriate for scalar applications on structured grids with a fixed stencil pattern
- Grids are described via a global d-dimensional index space (singles in 1D, tuples in 2D, and triples in 3D)
- A box is a collection of cell-centered indices, described by its "lower" and "upper" corners
- The grid is a collection of boxes
- Matrix coefficients are defined via stencils

$$\begin{bmatrix} S4 \\ S1 S0 S2 \end{bmatrix} = \begin{bmatrix} -1 \\ -1 & 4 & -1 \end{bmatrix}$$

$$S3$$







StructMatrix data structure

• Stencil
$$\begin{bmatrix} $4 \\ $1 $ $0 $ $2 \end{bmatrix} = \begin{bmatrix} -1 \\ -1 $ 4 $ -1 \end{bmatrix}$$

- Grid boxes: [(-3,1), (-1,2)] [(0,1), (2,4)]
- Data Space: grid boxes + ghost layers:
 [(-4,0), (0,3)], [(-1,0), (3,5)]
- Data stored



 Operations applied to stencil entries per box (corresponds to matrix (off) diagonals from a matrix point of view)

(-1,2)

(-4,0)-

(0,3)

(-3, 1)





(-1,0)

(3,5)

Iterative Solvers

- Solve linear system Ax = b, where A is a large sparse matrix of size n
- Direct solvers (e.g., Gaussian elimination) too expensive
- Iterative solvers
- Richardson iteration:

$$x^{n+1} = x^n + (b - Ax^n)$$

 $e^{n+1} = (I - A)e^n$

• Introduce a preconditioner *B*:

$$x^{n+1} = x^n + B(b - Ax^n)$$

$$e^{n+1} = (I - BA)e^n$$

• Jacobi: $B = D^{-1}$; Richardson: $B = \lambda I$





Generalized Minimal Residual (GMRES)

$$\bullet \ x^{n+1} = x^n + B(b - Ax^n)$$

•
$$\Rightarrow x^{n+1} = \sum_{i=0}^{n} \alpha_i (BA)^i Bb$$

- $x^{n+1} \in K^n = span\{Bb, (BA)Bb, (BA)^2Bb, \dots, (BA)^nBb\}$ Krylov space
- Construct a new basis for K^n through orthonormalization $\{q_0 = \frac{Bb}{\|Bb\|}, q_1, \dots, q_n\}$
- q_i also called search directions
- Now optimize by defining x^{n+1} through $\min_{x^{n+1} \in K^n} \lVert B(Ax^{n+1} b) \rVert$





Some comments on GMRES

- GMRES consists of fairly simple operations:
 - Inner products and norms (global reductions)
 - Vector updates (embarrassingly parallel)
 - Matvecs (nearest neighbor updates)
 - Residual decreases monotonically at each step
- Often used restarted as GMRES(k), i.e., after k iterations throw out q_i and start again using latest approximation
- Many variants to reduce and/or overlap communication (pipelined GMRES, etc)





Other Krylov solvers

- Conjugate Gradient (CG)
 - For symmetric positive definite matrices
 - Possesses like GMRES an orthogonality property
 - Uses a three-term concurrence
 - Requires only two inner products and a norm per iteration
- BiCGSTAB (Biconjugate Gradient Stabilized)
 - Like CG uses a three-term recurrence relation
 - No orthogonality property, can break down
 - Requires several inner products and a norm at each iteration (and two matvecs)
 - More erratic convergence than GMRES, but needs generally less memory



Hands-on Exercises: Krylov methods (First Set of Runs)

• Go to https://xsdk-project.github.io/MathPackagesTraining2024/lessons/krylov_amg_hypre/

• Poisson equation: $-\Delta \varphi = RHS$ with Dirichlet boundary conditions $\varphi = 0$

• Grid: cube



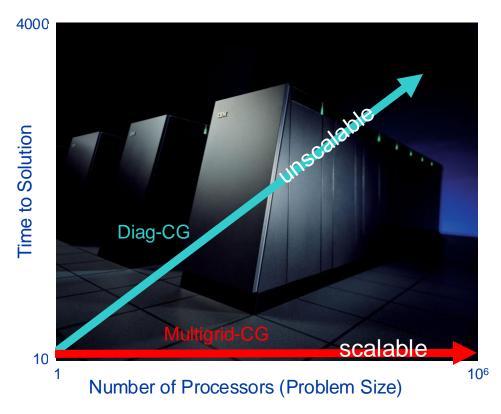
- Finite difference discretization:
 - Central differences for diffusion term
 - 7-point stencil







Multigrid linear solvers are optimal (O(N) operations), and hence have good scaling potential

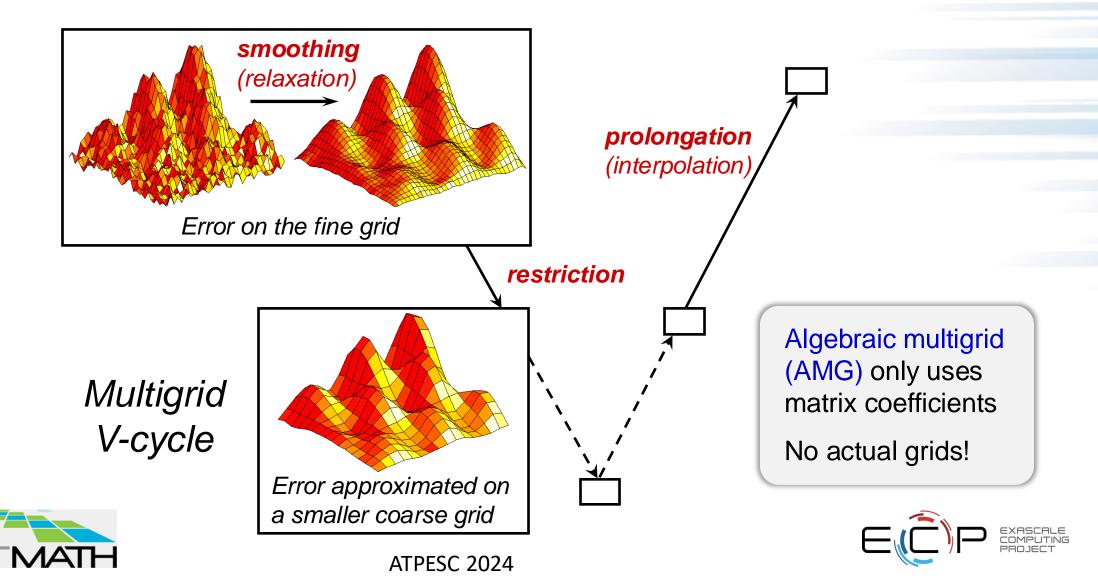


 Weak scaling – want constant solution time as problem size grows in proportion to the number of processors





Multigrid (MG) uses a sequence of coarse grids to accelerate the fine grid solution



AMG Building Blocks

Setup Phase:

- Select coarse "grids"
- Define interpolation: $P^{(m)}$, m = 1,2,...
- Define restriction: $R^{(m)}$, m = 1,2,..., often $R^{(m)} = (P^{(m)})^T$
- Define coarse-grid operators: $A^{(m+1)} = R^{(m)}A^{(m)}P^{(m)}$

Galerkin product

Solve Phase:

Relax
$$A^{(m)}u^m = f^m$$

Compute $r^m = f^m - A^{(m)}u^m$

Restrict $r^{m+1} = R^{(m)}r^m$

Correct $u^m \leftarrow u^m + e^m$

Solve
$$A^{(m+1)}e^{m+1} = r^{m+1}$$





Multigrid software

• ML, MueLu included in



- GAMG in **PETSc**
- The hypre—library provides various algebraic multigrid solvers, including multigrid solvers for special problems e.g., Maxwell equations, ...

•

- All of these provide different flavors of multigrid and provide excellent performance for suitable problems
- Focus here on hypre

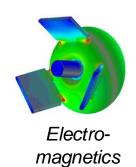




The hypre software library provides structured and unstructured multigrid solvers

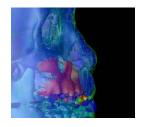
Used in many applications



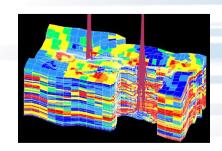




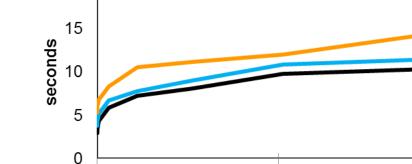
hydrodynamics



Facial surgery



Subsurface simulations



0.5

No of cores

Quantum Chromodynamics

20





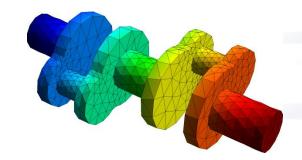


1 Million

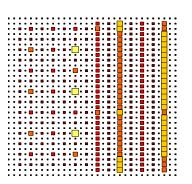
BoomerAMG is an algebraic multigrid method for unstructured grids

• Interface: SStruct, IJ

• Matrix Class: ParCSR



- Originally developed as a general matrix method (i.e., assumes given only A, x, and b)
- Various coarsening, interpolation and relaxation schemes
- Automatically coarsens "grids"
- Can solve systems of PDEs if additional information is provided
- Can also be used through PETSc and Trilinos
- Can be used on GPUs (CUDA, HIP, SYCL)



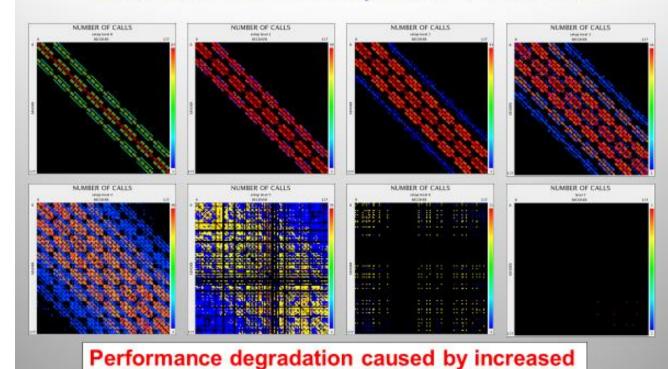




Complexity issues

- Coarse-grid selection in AMG can produce unwanted side effects
- Operator (RAP) "stencil growth" reduces efficiency
- For BoomerAMG, we will also consider complexities:
 - Operator complexity: $C_{op} = (\sum_{i=0}^{L} nnz(A_i))/nnz(A_0)$
 - Affects flops and memory
 - Generally, would like C_{op} < 2, close to 1
- Can control complexities in various ways
 - varying strength threshold
 - more aggressive coarsening
 - Operator sparsification (interpolation truncation, non-Galerkin approach)
- Needs to be done carefully to avoid excessive convergence deterioration

AMG Communication patterns, 128 cores



communication complexity on coarser grids!

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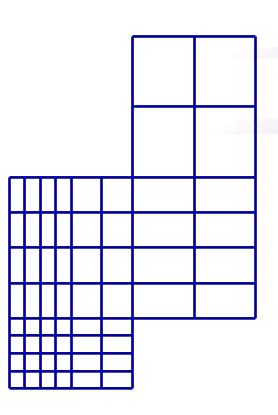
SMG and PFMG are semicoarsening multigrid methods for structured grids

• Interface: Struct

• Matrix Class: Struct

- SMG uses plane smoothing in 3D, where each plane "solve" is affected by one 2D V-cycle
- SMG is very robust
- PFMG uses simple pointwise smoothing, and is less robust
- Note that stencil growth is limited for SMG and PFMG (to at most 27 points per stencil in 3D)
- Constant-coefficient versions
- Can be used on GPUs (CUDA, HIP, SYCL, RAJA, Kokkos)

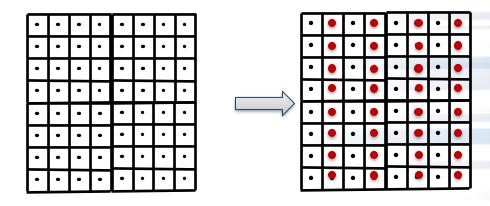






PFMG is an algebraic multigrid method for structured grids

- Matrix defined in terms of grids and stencils
- Uses semicoarsening
- Simple 2-point interpolation
 - → limits stencil growth to at most 9pt (2D), 27pt (3D)
- Optional non-Galerkin approach (Ashby, Falgout), uses geometric knowledge, preserves stencil size
- Pointwise smoothing
- Highly efficient for suitable problems

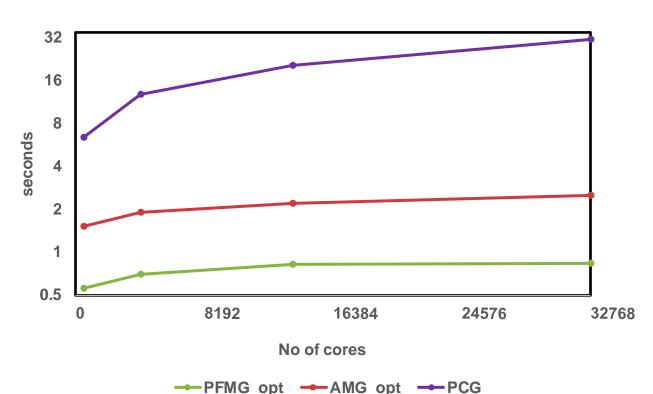




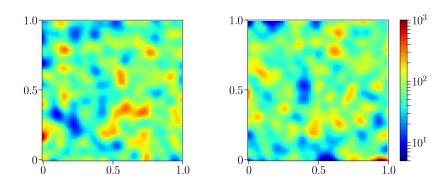


Algebraic multigrid as preconditioner

- Generally algebraic multigrid methods are used as preconditioners to Krylov methods, such as conjugate gradient (CG) or GMRES
- This often leads to additional performance improvements



Classic porous media diffusion problem: $-\nabla \cdot \kappa \nabla u = f$ with κ having jumps of 2-3 orders of magnitude



Weak scaling: 32x32x32 grid points per core, BG/Q





Hands-on Exercises: Algebraic multigrid (Second Set of Runs)

• Go to https://xsdk-project.github.io/MathPackagesTraining2024/lessons/krylov_amg_hypre/

- Poisson equation: $-\Delta \varphi = RHS$ with Dirichlet boundary conditions $\varphi = 0$
- Grid: cube



- Finite difference discretization:
 - Central differences for diffusion term
 - 7-point stencil







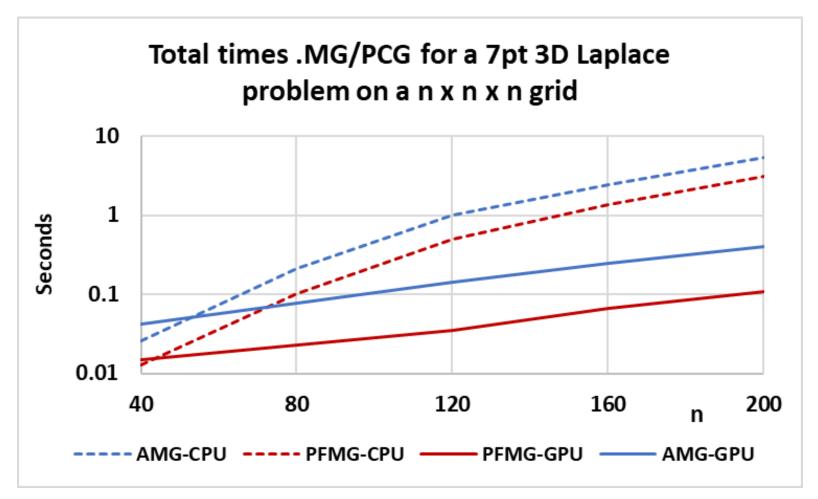
Porting to GPUs required inclusion of new programming models and different strategies for structured/unstructured interfaces

- Strategy for structured interface and solvers
 - Include new programming models (CUDA, HIP, RAJA, Kokkos, OMP, and SYCL) in hypre_BoxLoops (macros that operate on data in loops).
- Strategy for unstructured interface and solvers (CSR-based data structures)
 - Modularize into smaller chunks/kernels to be ported to CUDA for Nvidia GPUS initially
 - Convert CUDA kernels to HIP for AMD GPUs and SYCL for Intel GPUs
 - Develop new algorithms for portions not suitable for GPUs (interpolation operators, smoothers)
 - → different defaults for CPU and GPU use
 - Various special solvers (e.g., Maxwell solver AMS, ADS, AME, pAIR, MGR) built on BoomerAMG benefit from this strategy





Structured multigrid methods perform significantly better than unstructured ones on CPUs and - even more - on GPUs



ThetaGPU

GPU: 1 Nvidia A100 CPU: 16 MPI tasks

Used optimal settings for AMG, which are different for CPU and GPU!

Speedups at n=200

Speedup GPU/CPU 13.2 CPU Speedup PFMG/AMG 1 7

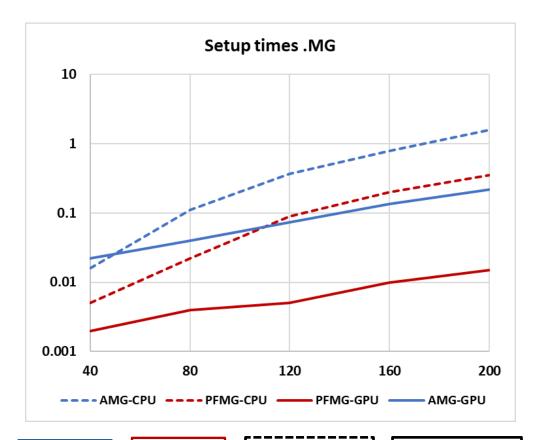
Speedup GPU/CPU 28.5

GPU Speedup PFMG/AMG 3.8



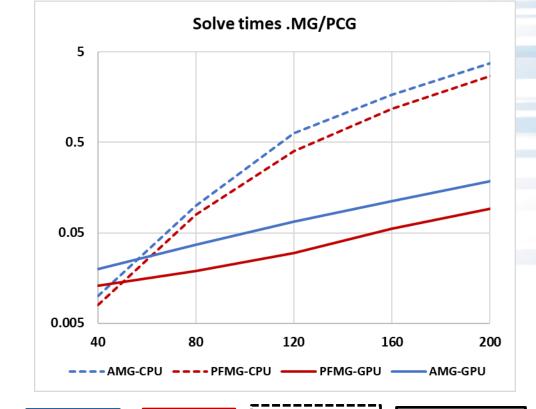


Most gains of PFMG over AMG in setup phase



Speedup GPU/CPU 7.2 Speedup GPU/CPU 23.3 CPU Speedup PFMG/AMG 4.5

GPU Speedup PFMG/AMG 14.5



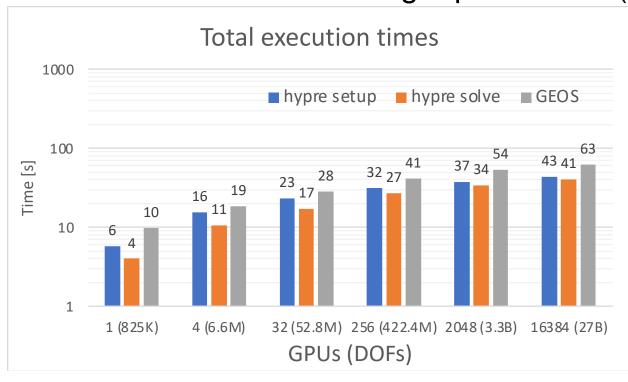
Speedup GPU/CPU 20.1 Speedup GPU/CPU 29.3 CPU Speedup PFMG/AMG 1.4 GPU Speedup PFMG/AMG 2.0

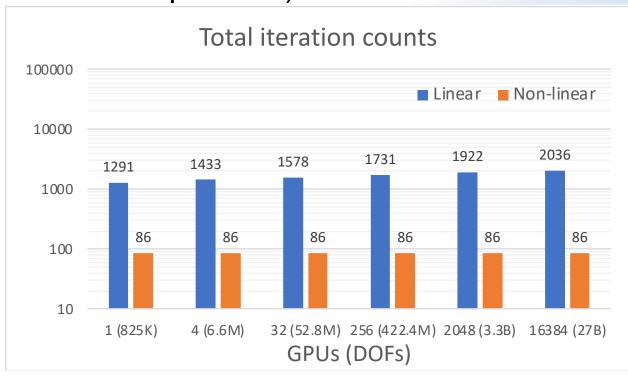




Successfully used hypre on Frontier (AMD GPUs) for solving complex multiphysics simulations

Single-phase flow (Poisson-like problem)





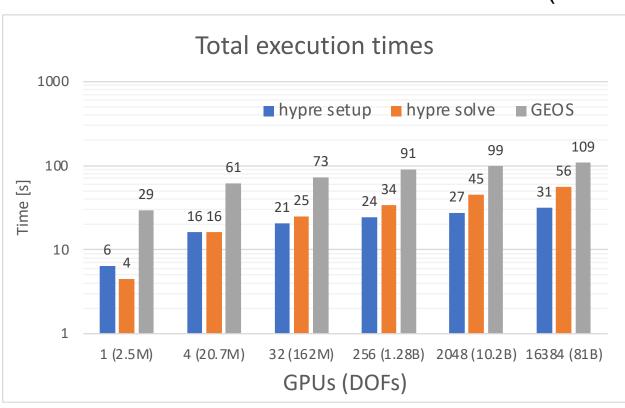
- Weak scaling with BoomerAMG/GMRES(50)
- Time complexity ~ O(log(N)); Iteration counts ~ O(1).
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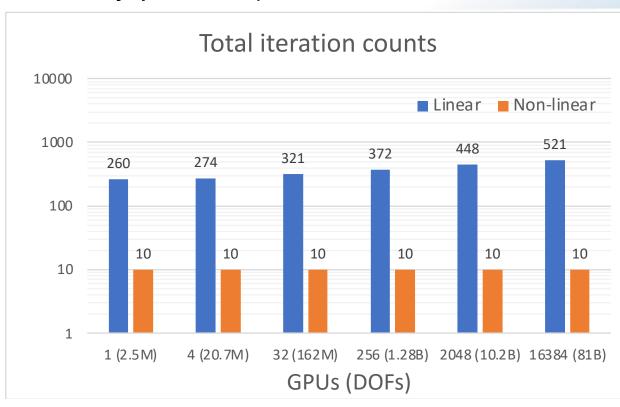




Frontier (AMD GPUs) results - Solved system with 80B DOFs using less than 25% of the machine

Mechanics (linear elasticity problem)







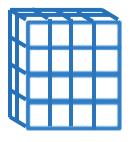




Hands-on Exercises: Comparing GPU to CPU Performance Algebraic Multigrid methods (Third Set of Runs)

• Go to https://xsdk-project.github.io/MathPackagesTraining2024/lessons/krylov_amg_hypre/

- Poisson equation: $-\Delta \varphi = RHS$
 - with Dirichlet boundary conditions $\varphi = 0$
- Grid: cube



- Finite difference discretization:
 - Central differences for diffusion term
 - 7-point stencil

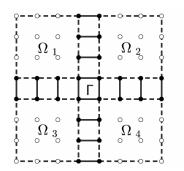


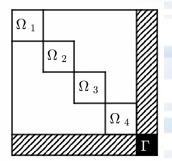




Some special general purpose solvers in hypre

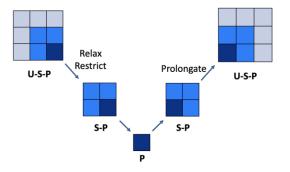
- Incomplete LU factorization
 - Based on a domain decomposition framework
 - Local ILU solve with global Schur complement solve
 - Various combinations of local ILU and global Schur solvers
 - GPU support available (for certain options)





- Multigrid reduction for PDE systems and Multiphysics applications
 - Reduction-based solver in a multigrid framework
 - Utilizes BoomerAMG as coarse solver
 - Effective Multiphysics preconditioner
 - GPU support available

$$\begin{pmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \\ u_3 \end{pmatrix} = \begin{pmatrix} f_1 \\ f_2 \\ f_3 \end{pmatrix}$$









Thank you!







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