



**Iterative methods: from theory to practice**  
**(A tutorial)**

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## **SOFTWARE, APPLICATIONS AND DEMOS**

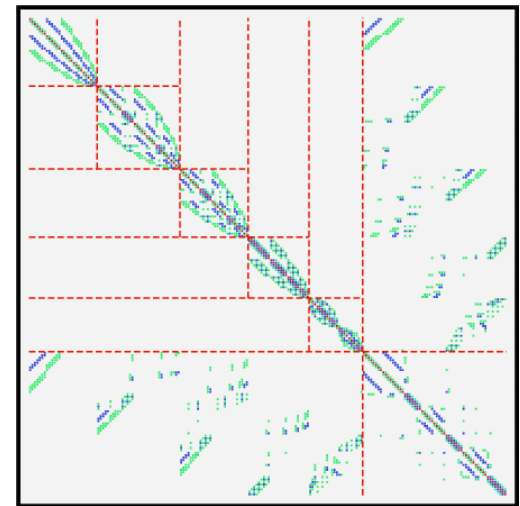
# ITSOL and ZITSOL

## ➤ Preconditioners for general sparse linear systems

$$Ax = b, \quad A \in \mathbb{R}^{n \times n} \text{ (ITSOL)}, \quad \mathbb{C}^{n \times n} \text{ (ZITSOL)}$$

## ➤ “Sequential” preconditioners (in v2.0)

- ILUK (ILU preconditioner with level of fill)
- ILUT (ILU preconditioner with threshold)
- ILUC (Crout version of ILUT)
- VBILU (Variable block ILU; Automatic block detection)
- ARMS (Algebraic Recursive Multilevel Solvers; Standard and ddPQ versions)



## ➤ Demos

<https://www-users.cse.umn.edu/~saad/software/ITSOL/index.html>

# pARMS: Parallel solvers for sparse linear systems

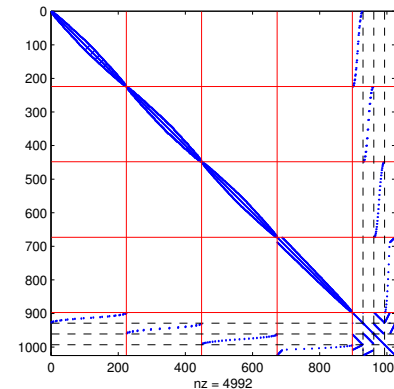
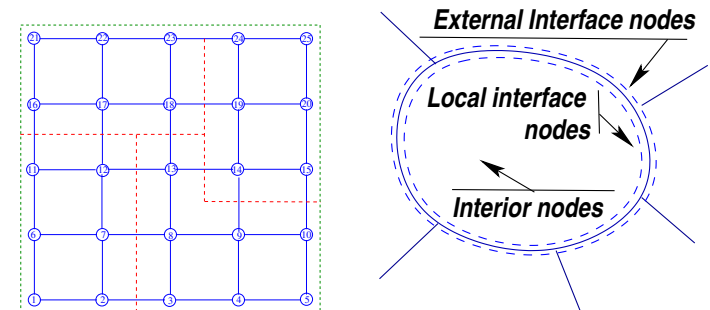
- MPI-based with Domain Decomposition (DD)
- Also available from PETSc: PCPARMS. v2.2 and v3.2

## Local preconditioner

- ILU0, ILUK, ILUT
- ARMS

## Global preconditioner

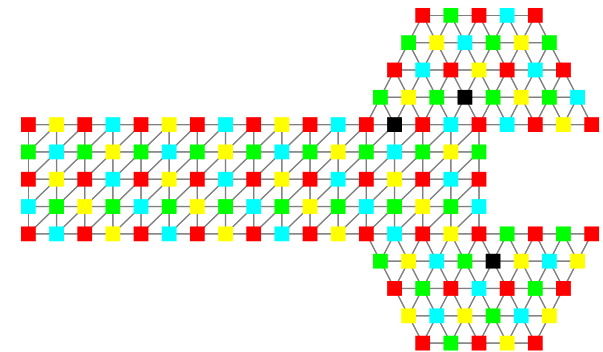
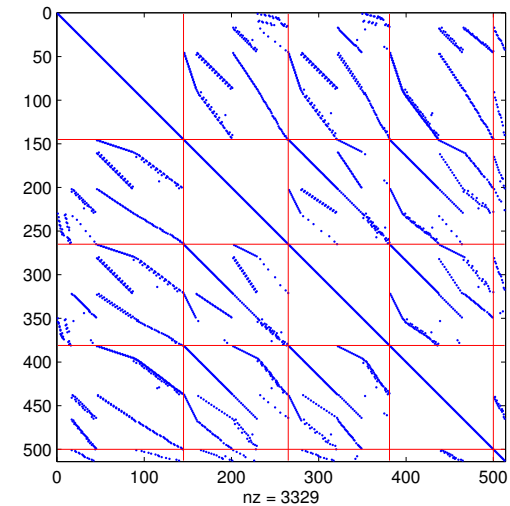
- Restricted additive Schwarz (RAS)
- Block Jacobi (BJ)
- Schur complement
- Distributed ILU(0)/SSOR (v2.2)



<https://www-users.cse.umn.edu/~saad/software/pARMS/index.html>

# CUDA-ITSOL: ITSOL for single CUDA GPU

- **Sparse matrix kernels**
  - SpMV in DIA, ELL, JAD, CSR
  - Level-scheduling SpTrSV
- **GPU-friendly preconditioners**
  - Block Jacobi ILU
  - Multicolor SSOR/ILU(0)
  - Least-squares polynomial
- **Krylov subspace methods**
  - CG
  - GMRES



<https://www-users.cse.umn.edu/~saad/software/>

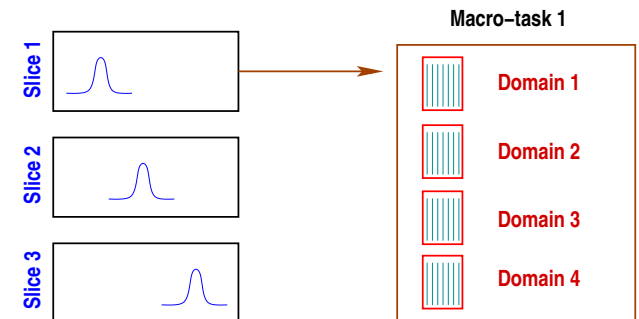
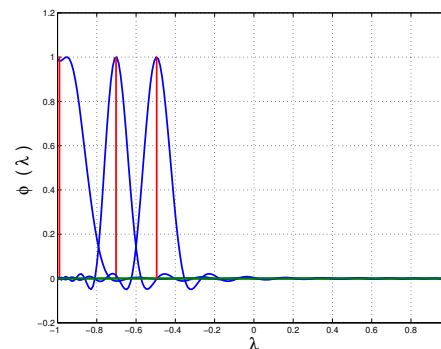
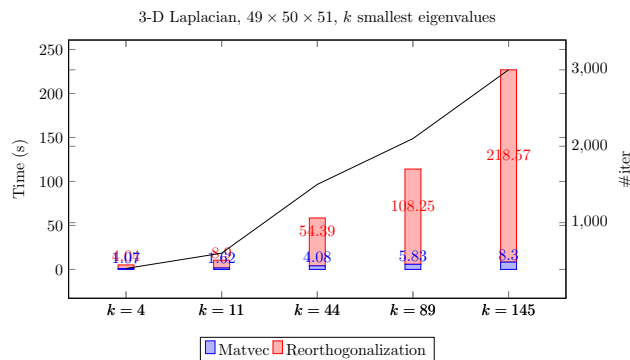
# EVSL: Solvers for symmetric eigenvalue problems

## EigenValues Slicing Library (v1.1.1)

- Compute (interior) eigenvalues of  $(A, B)$ ,  $A$  is symmetric,  $B$  is SPD
- Spectral slicing by Kernel Polynomial Method or Stochastic Lanczos
  - Reduces memory cost for storing basis
  - Reduces orthogonalization cost
  - Enables parallelism

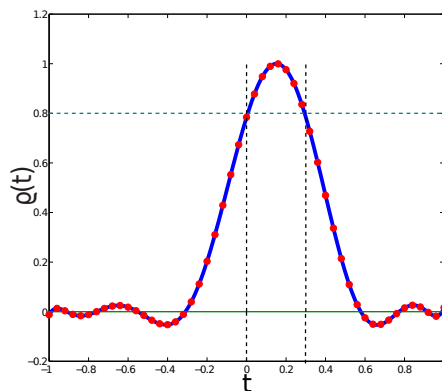
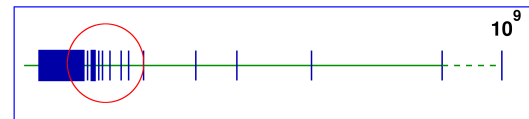
 3-D Laplacian  $n = 49^3$ . Compute all the 1,971 eigenvalues in  $[0, 1]$

`eigs(A,1971,'sa')`: 4 hours; EVSL with 5 slices, less than 300 sec in total!

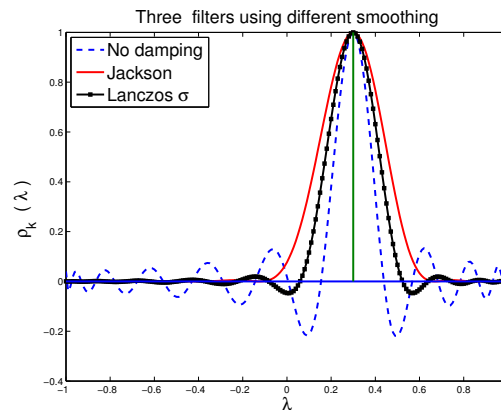


# EVSL: Solvers for symmetric eigenvalue problems

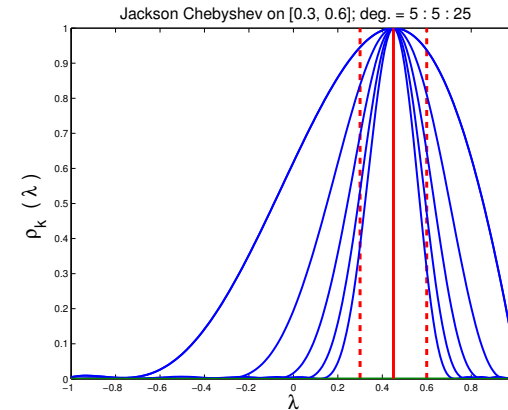
- Compute (interior) eigenvalues of  $(A, B)$ ,  $A$  is symmetric,  $B$  is SPD
- Polynomial and rational filtering
  - Extract eigenvalues at any location of the spectrum
  - Least-squares Chebyshev polynomial filtering
    - \* does not require expensive matrix factorizations
  - Least-squares rational filtering
    - \* handles stretched spectra better 🖱️



Expansion to  $\delta(t - \gamma)$



Removing oscillations



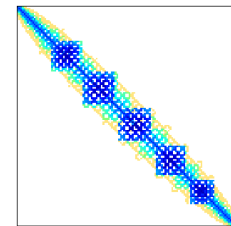
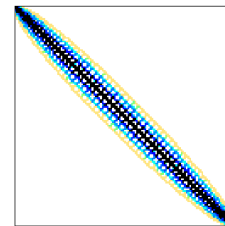
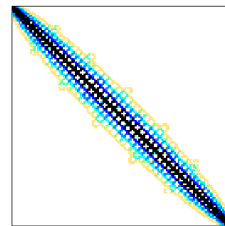
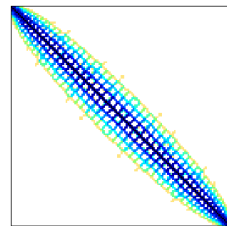
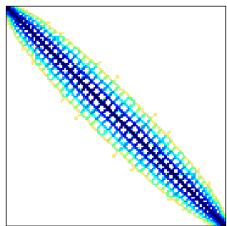
Automatically determine degrees

# Application of EVSL: Kohn-Sham equation

- $\hat{H}\Psi = E\Psi$   $n_0$  is corresponding to the Fermi level
- SEVP: compute all the eigenpairs in  $[0.5n_0, 1.5n_0]$

## ► SuiteSparse Matrix Collection: PARSEC

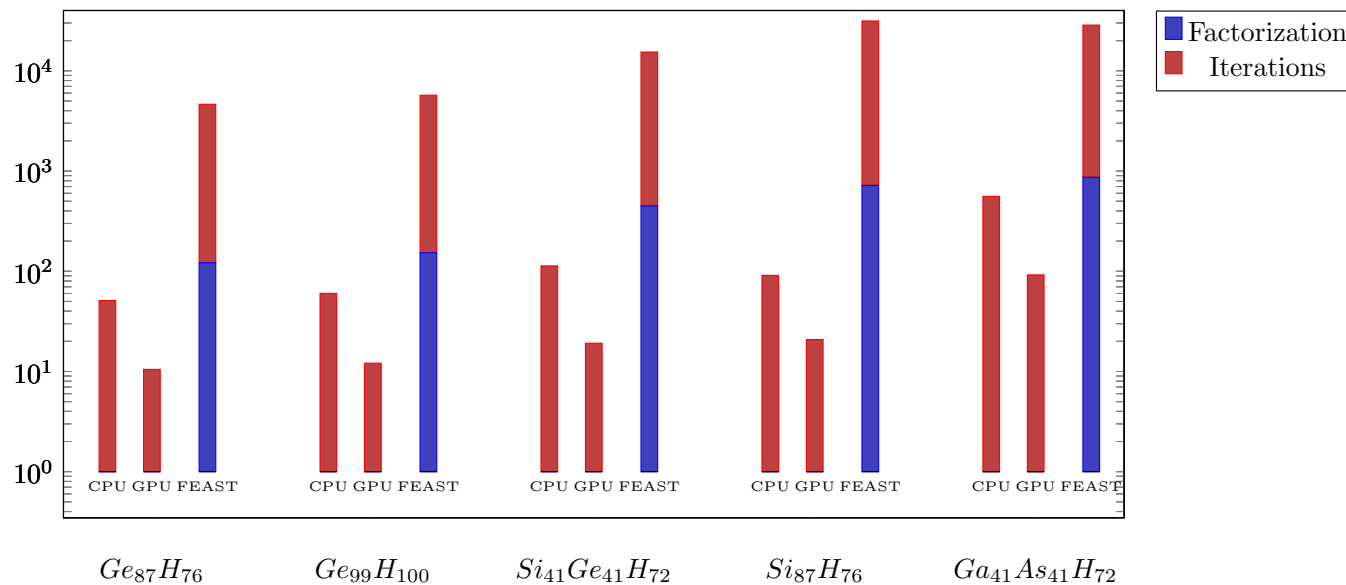
Hamiltonian	n	nnz	$[a, b]$	$[\xi, \eta]$	$\nu_{[\xi, \eta]}$
Ge <sub>87</sub> H <sub>76</sub>	112, 985	7, 892, 195	$[-1.214, 32.764]$	$[-0.645, -0.0053]$	212
Ge <sub>99</sub> H <sub>100</sub>	112, 985	8, 451, 295	$[-1.226, 32.703]$	$[-0.650, -0.0096]$	250
Si <sub>41</sub> Ge <sub>41</sub> H <sub>72</sub>	185, 639	15, 011, 265	$[-1.121, 49.818]$	$[-0.640, -0.0028]$	218
Si <sub>87</sub> H <sub>76</sub>	240, 369	10, 661, 631	$[-1.196, 43.074]$	$[-0.660, -0.0300]$	213
Ga <sub>41</sub> As <sub>41</sub> H <sub>72</sub>	268, 096	18, 488, 476	$[-1.250, 1300.9]$	$[-0.640, -0.0000]$	201





# Application of EVSL: Kohn-Sham equation

- Shift-and-invert: extremely expensive LU factorization
- Polynomial filtering is much more efficient
- And can be accelerated by GPUs: 7x speedup

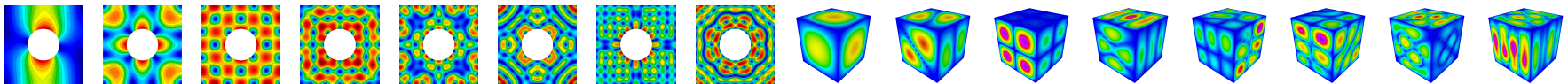


Intel Xeon E5-2695 CPU (24 cores) and NVIDIA P100 GPU

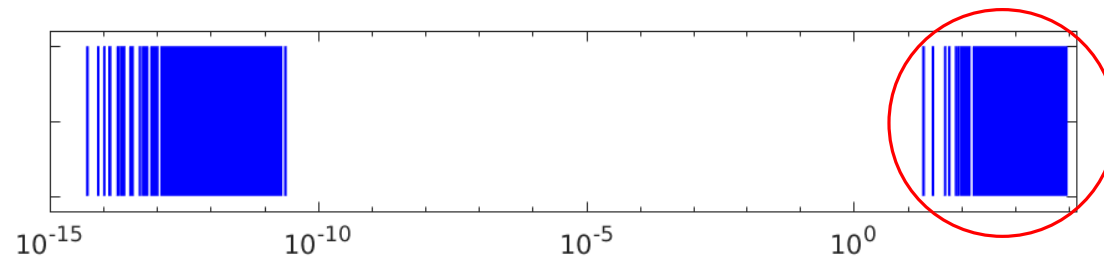
# Application of EVSL: Maxwell eigenproblem

$$\nabla \times \nabla \times \vec{E} = \lambda \vec{E}, \quad \nabla \cdot \vec{E} = 0 \text{ in } \Omega, \quad \vec{E} \times \vec{n} = 0 \text{ on } \partial\Omega$$

- $\vec{E}$ : electric field intensity. Discretized by 2nd order Nédélec FEM



- $B^{-1}$  with **simple** iterative methods
- Interior GEVP: interested in nonzero eigenvalues



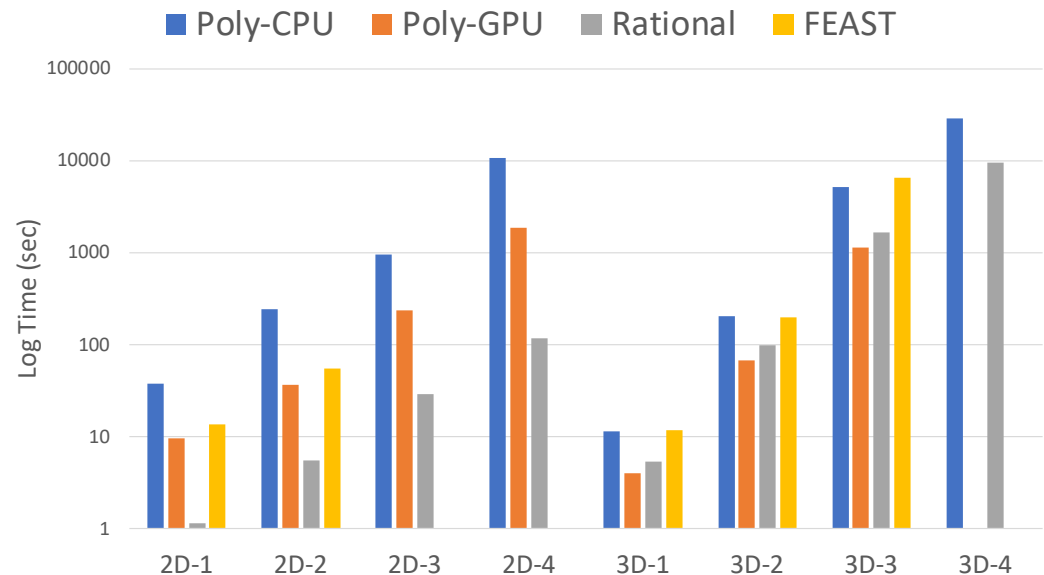
- Algebraic method: without knowing the discretized gradient

# Application of EVSL: Maxwell eigenproblem

- Rational filtering is more efficient for 2-D. Polynomial filtering is more efficient for 3-D with GPUs

$$(\xi, \eta) = (19.5, 250)$$

Prob	n	(a, b)	$\nu_{[\xi, \eta]}$
3D-1	10,800	(0, 9e3)	115
3D-2	92,256	(0, 3.7e4)	121
3D-3	762,048	(0, 1.5e5)	121
3D-4	2,599,200	(0, 3.3e5)	121



- Rational filtering requires much more memory to store the factors; 68 GB for the 3D-4 problem

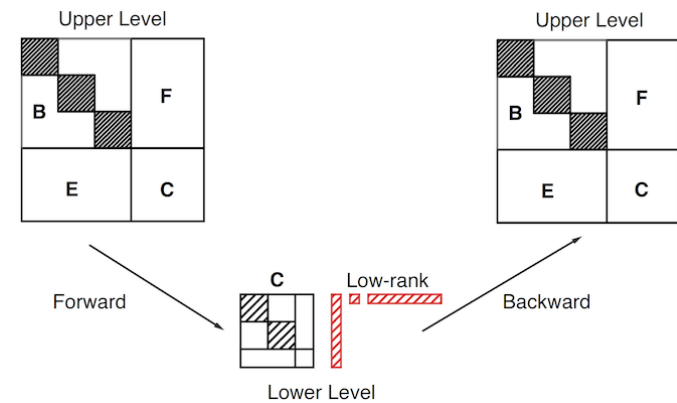
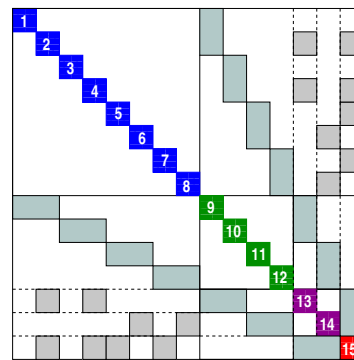
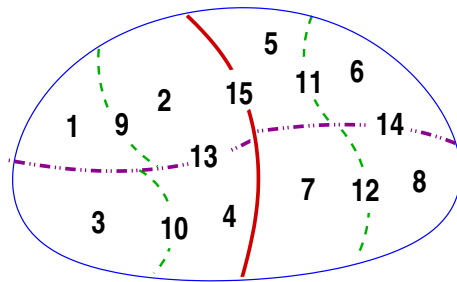


**Demos**

<https://github.com/eigs/EVSL>

# ParGeMSLR: Generalized Multilevel Schur Low-Rank

- Parallel preconditioner for distributed linear systems
- Recursive multilevel DD with low-rank corrections
- $S^{-1} \approx C^{-1} + \text{Low-Rank Correction}$
- Nonsymmetric systems and complex systems
- Fully parallel: MPI-based library with OpenMP and CUDA



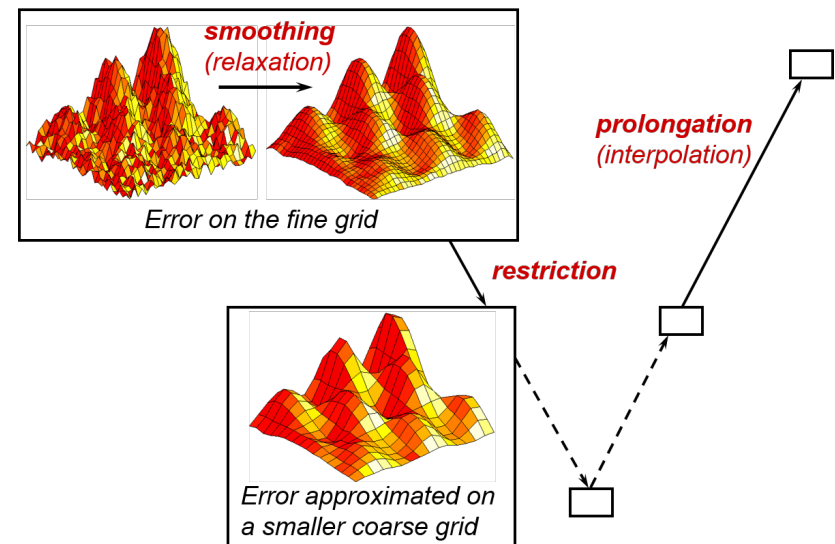
**Demos**

<https://github.com/hitenze/pargemslr.git>

# BoomerAMG: Parallel Algebraic Multigrid Method

- Various parallel coarsening techniques, interpolation and relaxation schemes
- More advanced approaches to increase efficiency and scalability: aggressive coarsening, Non-Galerkin coarse-grid operator
- AMG for systems of PDEs
- Special additive V-cycles
- Full GPU-support
- Available in hypre

➤ **Demos**



<https://github.com/hypre-space/hypre>