



An Introduction to Hierarchical Poincaré-Steklov (HPS) Solvers

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Problem Addressed

This talk concerns numerical methods for boundary value problems of the form

$$\begin{cases} \mathcal{A}u(\boldsymbol{x}) = g(\boldsymbol{x}), & \boldsymbol{x} \in \Omega, \\ \mathcal{B}u(\boldsymbol{x}) = f(\boldsymbol{x}), & \boldsymbol{x} \in \Gamma, \end{cases} \quad (\text{BVP})$$

where Ω is a domain (2D or 3D) with boundary Γ , and where \mathcal{A} is a linear elliptic differential operator; possibly with variable coefficients.

Examples of problems we are interested in:

- The equations of linear elasticity.
- Stokes' equation.
- Helmholtz' equation (at least at low and intermediate frequencies).
- Time-harmonic Maxwell (at least at low and intermediate frequencies).

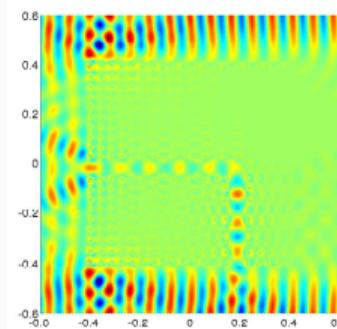
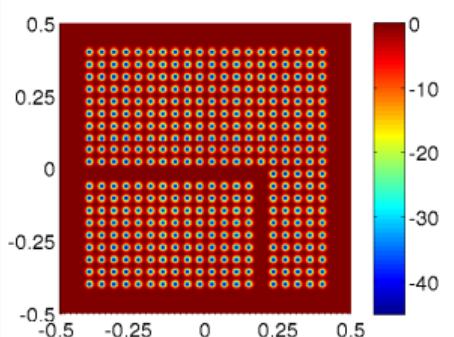
Helmholtz equation governs electromagnetic and acoustic scattering

In a varying medium Ω , the Helmholtz equation takes the form

$$-\Delta u(x) - \kappa^2(1 - b(x))u(x) = f(x), \quad x \in \Omega$$

with appropriate boundary conditions.

κ is roughly # wavelengths in unit domain and $b(x) \leq 1$ describes how the medium varies.



Example: photonic crystal in free space.

The distance between crystals is set to filter certain light frequencies.

Image credit: Gillman, Martinsson, Barnett.
BIT 2014.

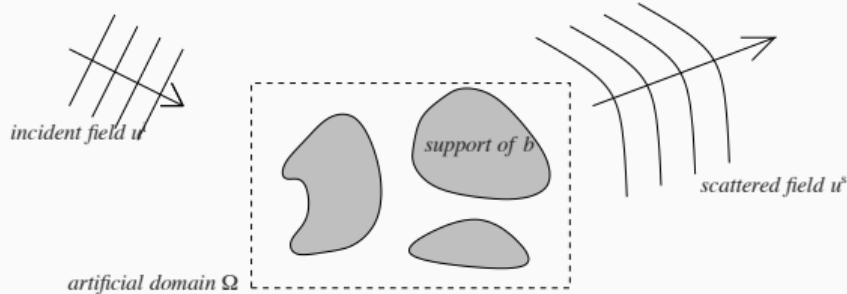


Image credit: Gillman, Martinsson, Barnett.

Standard numerical recipe for (BVP)

- Truncate the domain using absorbing boundary conditions.
- Discretize using FD/FEM.
- Solve the sparse system $\mathbf{A}\mathbf{u} = \mathbf{f}$ with an iterative solver (and possibly a preconditioner).

Challenge 1: Discretization

Large systems $\mathbf{A}\mathbf{u} = \mathbf{f}$

- Typically discretize to ~ 10 points per wavelength.
- As wavenumber κ increases, $N \sim \kappa^d$, $d = 2, 3$.

Pollution effect for large κ

- For low order discretization, we often need *more* points per wavelength as κ increases to avoid phase errors.
- Counteract pollution using local high order discretization.

Challenge 2: Iterative Solvers Struggle

- Because \mathbf{A} is indefinite and ill-conditioned, a preconditioner is needed.

$$\underbrace{-\Delta u(x)}_{\text{positive eigenvalues}} - \underbrace{\kappa^2 u(x)}_{\text{negative shift}}$$

Preconditioners are often problem-specific.

- For strong scattering (e.g. multiple reflections, cavities, trapped rays), no efficient preconditioners are known to exist, and number of iterations may scale with κ .

This workshop:

- Focus on boundary integral formulations on complicated interfaces.
- For variable coefficients PDEs, can formulate a volume integral equation.*

Hierarchical Poincaré Steklov scheme:

- Discretize the (BVP) on the volume with *local* high order discretization.
- Build an *approximate* direct solver that is fast to build and apply.

* A. Gopal, P.G. Martinsson. “An accelerated, high-order accurate direct solver for the Lippmann-Schwinger equation for acoustic scattering in the plane.” *ACOM* 2022.

Outline

- Review classical algorithms for sparse direct solvers and their complexity.
- HPS discretization scheme.
- Applications of HPS, including BIE coupling for exterior scattering problems and time-stepping.
- Ongoing efforts to attain linear complexity solvers in 3D.

Model Problem

Let $\Omega = [0, 1]^2$ and $\Gamma = \partial\Omega$. We seek to solve

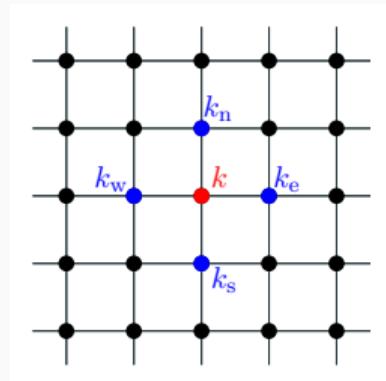
$$\begin{cases} -\Delta u(\mathbf{x}) = g(\mathbf{x}), & \mathbf{x} \in \Omega, \\ u(\mathbf{x}) = f(\mathbf{x}), & \mathbf{x} \in \Gamma, \end{cases}$$

We introduce an $n \times n$ grid on Ω with nodes $\{\mathbf{x}_k\}_{k=1}^N$ where $N = n^2$ and discretize using the five point stencil. We need to solve the sparse system

$$\underset{N \times N}{\mathbf{A}} \mathbf{u} = \mathbf{b}$$

where $\mathbf{u}_k \approx u(\mathbf{x}_k)$

$$[\mathbf{A}\mathbf{u}]_k = \frac{1}{h^2}(4\mathbf{u}_k - \mathbf{u}_{k_s} - \mathbf{u}_{k_e} - \mathbf{u}_{k_n} - \mathbf{u}(k_w)).$$



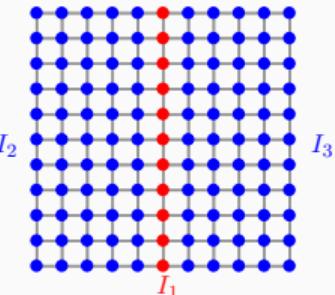
$$h = \frac{1}{n+1}$$

Divide and Conquer

To compute a sparse factorization

$$\mathbf{A}_{N \times N} = \mathbf{L} \mathbf{U},$$

we start by splitting the nodes $I = [I_1, I_2, I_3]$.



The resulting factorization then preserves some sparsity of \mathbf{A}

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_{33} & & \mathbf{A}_{31} \\ & \mathbf{A}_{22} & \mathbf{A}_{21} \\ \mathbf{A}_{13} & \mathbf{A}_{12} & \mathbf{A}_{11} \end{bmatrix} = \begin{bmatrix} \mathbf{L}_{33} & & \\ & \mathbf{L}_{22} & \\ \mathbf{L}_{13} & \mathbf{L}_{12} & \mathbf{L}_{11} \end{bmatrix} \begin{bmatrix} \mathbf{U}_{33} & & \mathbf{U}_{31} \\ & \mathbf{U}_{22} & \mathbf{U}_{21} \\ & & \mathbf{U}_{11} \end{bmatrix},$$

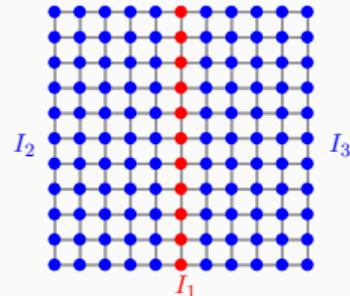
however, the Schur complement on I_1 is **dense**

$$\mathbf{L}_{11} \mathbf{U}_{11} = \mathbf{A}_{11} - \mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21} - \mathbf{A}_{13} \mathbf{A}_{33}^{-1} \mathbf{A}_{31}.$$

Divide and Conquer

To factorize \mathbf{A} , we do the following:

$$\mathbf{A} = \left[\begin{array}{c|c|c} \mathbf{A}_{33} & & \mathbf{A}_{31} \\ \hline & \mathbf{A}_{22} & \mathbf{A}_{21} \\ \hline \mathbf{A}_{13} & \mathbf{A}_{12} & \mathbf{A}_{11} \end{array} \right]$$



- Factorize *sparse* system $\mathbf{L}_{22}\mathbf{U}_{22}$ for volume I_2 .
- Factorize *sparse* system $\mathbf{L}_{33}\mathbf{U}_{33}$ for volume I_3 .
- Factorize **dense** system \mathbf{T}_{11} on interface I_1 .

size $\sim N/2 \times N/2$

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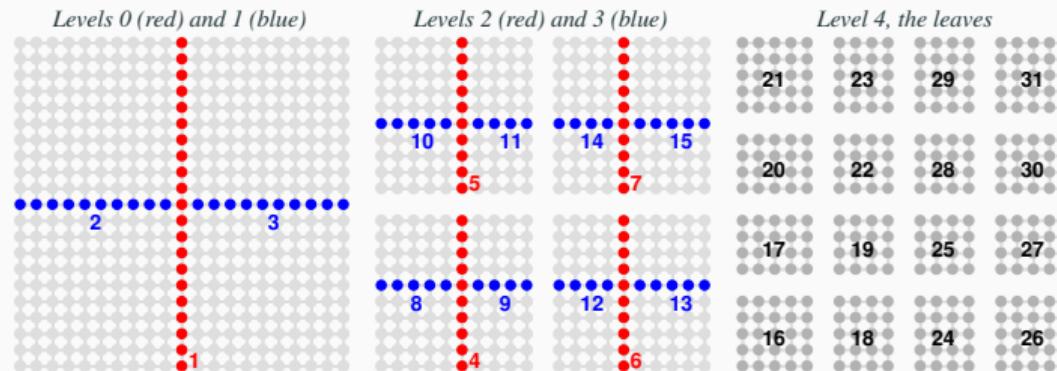
size $\sim \sqrt{N} \times \sqrt{N}$

$$\mathbf{T}_{11} = \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} - \mathbf{A}_{13}\mathbf{A}_{33}^{-1}\mathbf{A}_{31}.$$

Note the obvious recursion!

Algorithm with Multiple Fronts

Nested Dissection Ordering



- The factorization is constructed using an upwards tree traversal.
- First, form sparse direct solvers for the “leaves” .
- Then, factorize resulting dense Schur complements at each level of the tree.

We convert a *sparse* system on a volume into a **dense** system to solve on interfaces.

Nested Dissection Orderings

Typically, the ordering is more complicated.

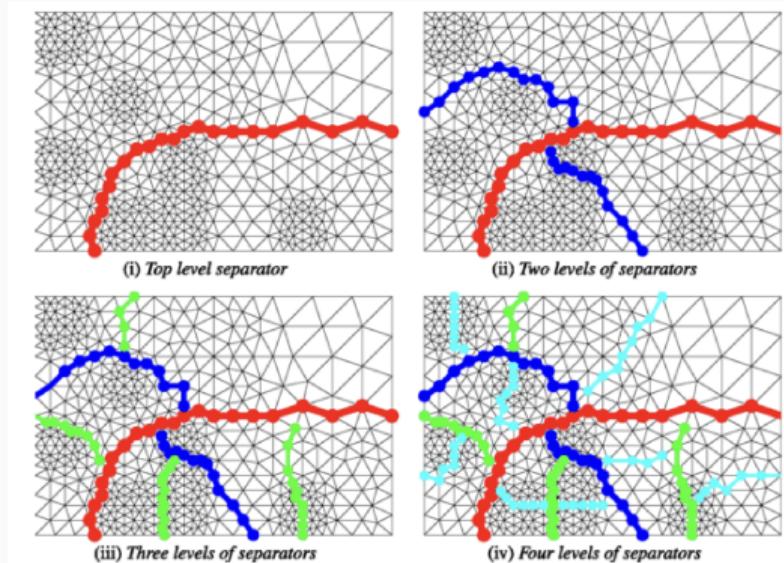
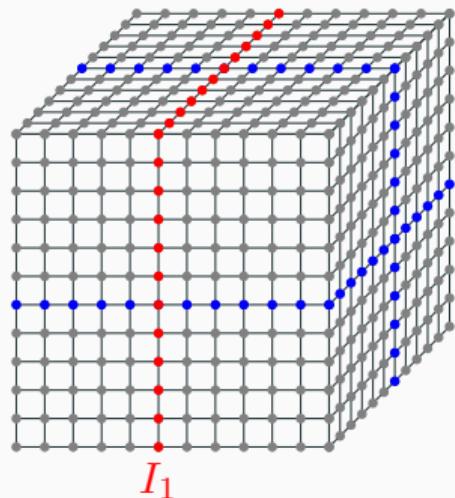


Image credit: Jianlin Xia, "Robust and Efficient Multifrontal Solver for Large Discretized PDEs," 2012.

Nested Dissection in 3D



In 3D, the algorithm transforms a *sparse* matrix on *3D volume* into **dense** matrix on **2D separators**.

The separator I_1 is a surface of size $\sim N^{2/3} \times N^{2/3}$.

We summarize the costs for $d = 2, 3$:

| d | cost to compute | memory for solver |
|-----|-----------------|-------------------|
| 2 | $O(N^{1.5})$ | $O(N \log N)$ |
| 3 | $O(N^2)$ | $O(N^{4/3})$ |

Dimensionality Reduction as Workshop Theme

Key point: When faced with a BVP for a 3D volume, it is often beneficial to instead solve a **dense** problem on the **surface**.

- Constant-coefficient PDE: Reformulate as an integral equation on the boundary.
- Variable-coefficient PDE: Discretize the PDE, then compute a sparse direct solver involving dense Schur complements on surfaces.

Sparse Direct Solvers

An *algebraic* means of reformulating a volume PDE to a *dense* operator on a surface.

Physical interpretation of Schur complement

Consider applying Dirichlet data \mathbf{g}_1 to the Schur complement:

$$\mathbf{T}_{11} \mathbf{g}_1 = \mathbf{A}_{11} \mathbf{g}_1 - \mathbf{A}_{12} \underbrace{\mathbf{A}_{22}^{-1} \mathbf{A}_{21} \mathbf{g}_1}_{\text{solution } \mathbf{u}_2 \text{ in volume}}.$$

The matrix \mathbf{T}_{11} can be viewed as a Dirichlet-to-Neumann map, also known as a Poincaré-Steklov operator.

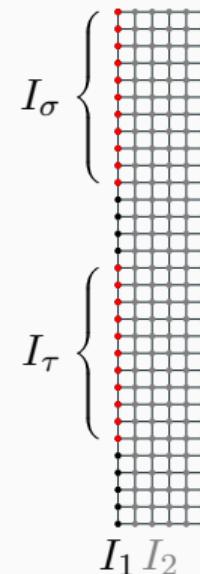
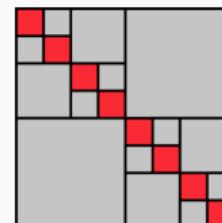
Rank Structure

The matrix \mathbf{T}_{11} is compressible an HSS/HBS matrix.

For a dense matrix of size $n \times n$:

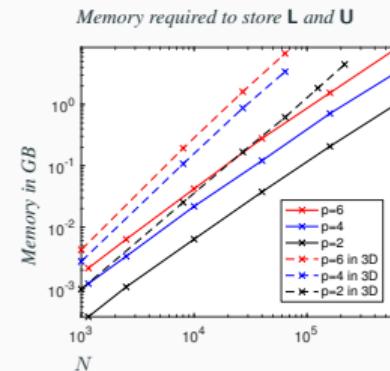
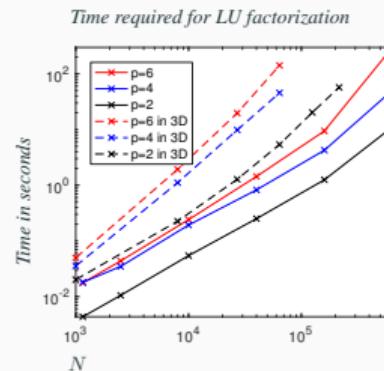
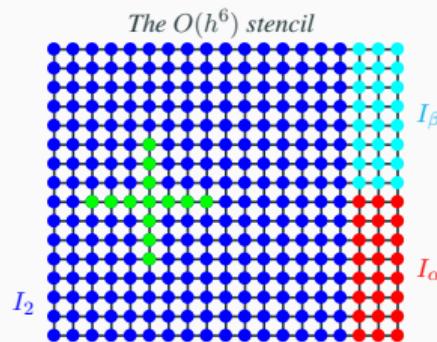
Matrix-vector multiply: $\mathcal{O}(n^2) \searrow \mathcal{O}(n)$

LU factorization: $\mathcal{O}(n^3) \searrow \mathcal{O}(n)$



High order discretization and sparse direct solvers

- Need high order discretizations to resolve the PDE, especially for scattering problems.
- Need direct solvers to resolve ill-conditioned systems.
- **Issue:** Traditional high order discretizations (e.g. 4th or 6th order finite difference) cause performance of multifrontal solvers to plummet.



With increasing p , the separators grow wider.

As p increases, factorization and memory costs increase.

Hierarchical Poincaré-Steklov schemes

Instead of discretizing the domain Ω , we partition into subdomains $\Omega = \dot{\cup}_i \Omega_i$, then use a multidomain discretization.

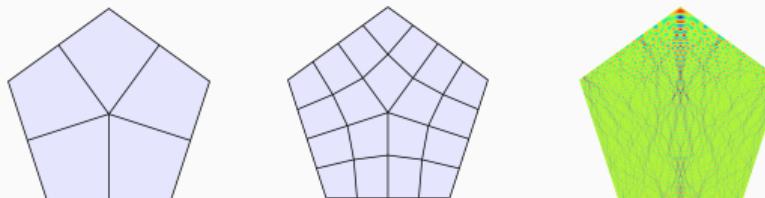


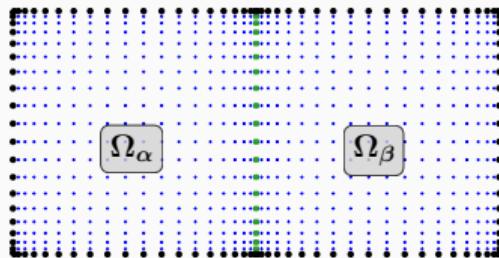
Image credit: Fortunato, Hale, Townsend.
“Ultraspherical spectral element method,” *JCP* 2021.

On each subdomain Ω_i , enforce the PDE on subdomain interior.
Ensure that the computed solutions are consistent by enforcing:

- Continuity of solution across boundaries.
- Continuity of normal derivative across boundaries.

Related work: domain decomposition, non-overlapping Schwarz.

HPS for Two Subdomains



Consider the discretization of $\Omega = \Omega_\alpha \cup \Omega_\beta$ with labeling of the nodes $I = I_1 \cup I_2 \cup I_3$ so that

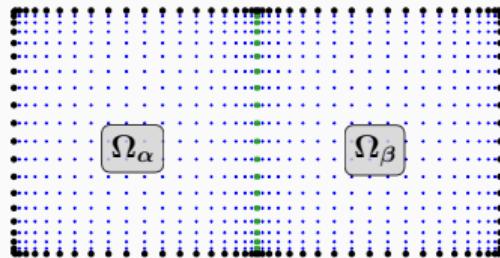
- I_1 : shared boundary, where continuity of $\partial u / \partial x$ enforced
- I_2 : collocation of (BVP) on Ω_α
- I_3 : collocation of (BVP) on Ω_β

The discretized system is

$$\begin{bmatrix} \mathbf{A}_{33} & & & \mathbf{A}_{31} & \mathbf{u}_3 \\ & \mathbf{A}_{22} & & \mathbf{A}_{21} & \mathbf{u}_2 \\ \mathbf{D}_{13}^\alpha & -\mathbf{D}_{12}^\beta & \mathbf{N} & \mathbf{u}_1 & \mathbf{f}_1 \end{bmatrix} = \begin{bmatrix} \mathbf{f}_3 \\ \mathbf{f}_2 \\ \mathbf{f}_1 \end{bmatrix},$$

where $\mathbf{N} = \mathbf{D}_{11}^\alpha - \mathbf{D}_{11}^\beta$. The last equation enforces continuity of $\partial u / \partial x$ on I_1 .

HPS for Two Subdomains



Consider the discretization of $\Omega = \Omega_\alpha \cup \Omega_\beta$ with labeling of the nodes $I = I_1 \cup I_2 \cup I_3$ so that

I_1 : shared boundary, where
continuity of $\partial u / \partial x$ enforced

I_2 : collocation of (BVP) on Ω_α

I_3 : collocation of (BVP) on Ω_β

Factorizing the system to “eliminate” the subdomain interiors leads to a modified system on the interface:

$$\begin{bmatrix} \mathbf{A}_{33} & & \mathbf{A}_{31} \\ & \mathbf{A}_{22} & \mathbf{A}_{21} \\ \mathbf{D}_{13}^\alpha & -\mathbf{D}_{12}^\beta & \mathbf{N} \end{bmatrix} = \mathbf{L} \begin{bmatrix} \mathbf{A}_{33} & & \\ & \mathbf{A}_{22} & \\ & & \mathbf{T}_{11} \end{bmatrix} \mathbf{U},$$

where

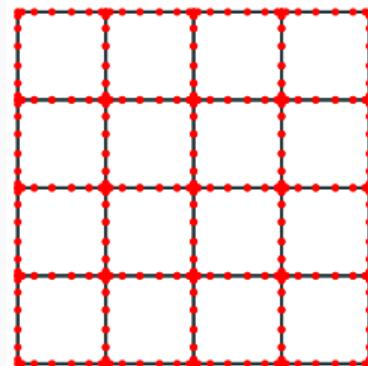
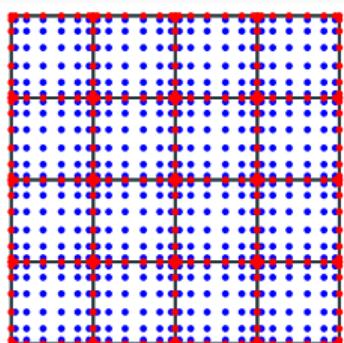
$$\mathbf{T}_{11} = \mathbf{N} - \underbrace{\mathbf{D}_{12}^\alpha \mathbf{A}_{22}^{-1} \mathbf{A}_{21}}_{\text{DtN}_\alpha} + \underbrace{\mathbf{D}_{13}^\beta \mathbf{A}_{33}^{-1} \mathbf{A}_{31}}_{\text{DtN}_\beta}.$$

is a linear combination of DtN maps.

Model Problem for HPS

Consider a model problem on a square domain $\Omega = [0, 1]^2$.

$$\begin{cases} -\Delta u(\boldsymbol{x}) - \kappa^2 u(\boldsymbol{x}) = 0, & \boldsymbol{x} \in \Omega, \\ u(\boldsymbol{x}) = f(\boldsymbol{x}), & \boldsymbol{x} \in \Gamma, \end{cases}$$



Use spectral differentiation to discretize PDE on each patch and to enforce continuity of $\partial u / \partial x$ on interfaces.

Eliminating points in patch interiors leads to modified system on interfaces, involving Poincaré-Steklov operators.

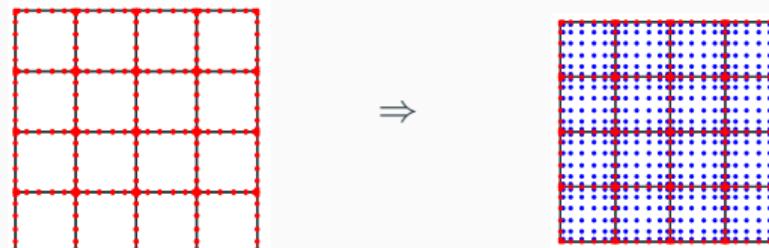
To solve $\mathbf{A}\mathbf{u} = \mathbf{f}$

Step 1: Compute equivalent body load $\tilde{\mathbf{f}}$ on interfaces.



Step 2: Solve sparse system $\mathbf{T}\tilde{\mathbf{u}} = \tilde{\mathbf{f}}$ for the solution on the interfaces using direct solver.

Step 3: Solve [locally] for the solution on patch interior, given the solution on the interface.



Complexity Scaling in p

Using dense spectral differentiation on the leaves, the cost to *build* a solution operator:

| | | |
|----|-------------------------------------|--------------------------------|
| 2D | $\sim \mathcal{O}(p^4 N + N^{3/2})$ | with spectral differentiation* |
| 3D | $\sim \mathcal{O}(p^6 N + N^2)$ | with spectral differentiation. |

P.G. Martinsson, “Fast Direct Solvers for Elliptic PDEs,” SIAM 2019.

- Increasing p leads to increase in *linear*-scaling factor, but does not affect the *pre-factor* cost of computing a direct solver.
- Cost of direct solver can be reduced using \mathcal{H} -matrix algebra.

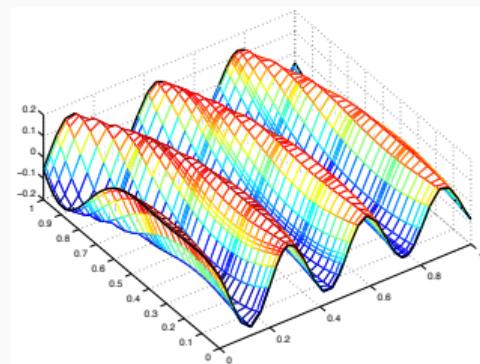
Using ultraspherical polynomials (instead of Chebyshev polynomials) for leaf discretization reduces complexity to $\mathcal{O}(p^2 N + N^{3/2})$ in 2D. See “Ultraspherical Method,” 2021.

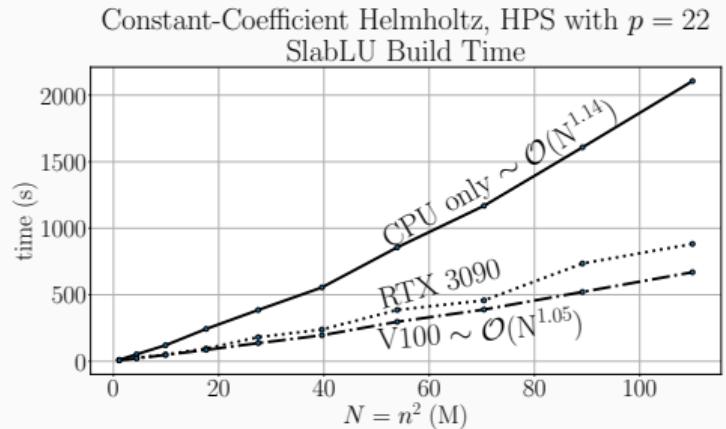
Benchmark problem

On a square domain $\Omega = [0, 1]^2$, we scale κ as N increases to maintain 10 ppw:

$$\begin{cases} -\Delta u(\boldsymbol{x}) - \kappa^2 u(\boldsymbol{x}) = 0, & \boldsymbol{x} \in \Omega, \\ u(\boldsymbol{x}) = f(\boldsymbol{x}), & \boldsymbol{x} \in \Gamma, \end{cases}$$

Let us consider how the discretization performs on the benchmark problem with prescribed Dirichlet data f as the restriction of wave from a point source $\boldsymbol{x} \rightarrow Y_0(\kappa|\boldsymbol{x} - \hat{\boldsymbol{x}}|)$.





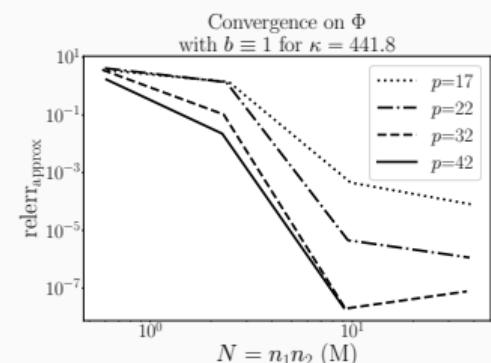
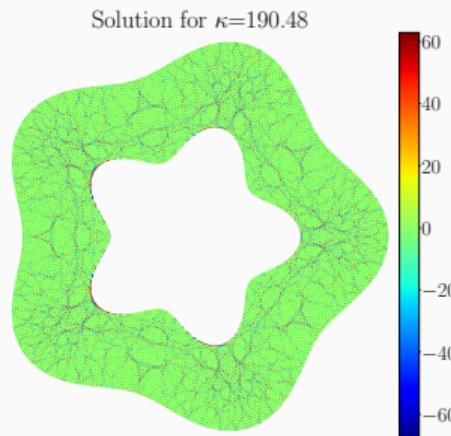
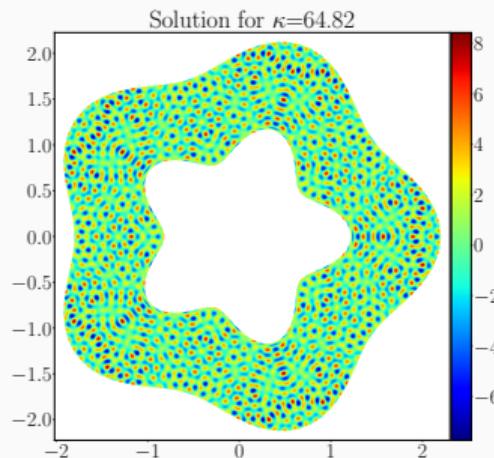
| N | κ | M_{build} | T_{solve} | $\text{relerr}_{\text{true}}$ |
|---------|-----------------------|--------------------|--------------------|-------------------------------|
| 1.1 M | 630.3 | 0.3 GB | 1.0 s | 2.4e-08 |
| 4.4 M | 1258.6 | 1.8 GB | 3.8 s | 9.5e-08 |
| 17.6 M | 2515.3 | 8.9 GB | 13.9 s | 4.0e-07 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 110.0 M | 6285.2 | 80.0 GB | 83.9 s | 7.5e-07 |
| | $\sim 10 \text{ ppw}$ | | | |

Sparsity alone (and some GPU acceleration) is enough to scale to $1000\lambda \times 1000\lambda$ on a gaming desktop, with 7 digits of accuracy compared to known solution.

Yesypenko, Martinsson. "SlabLU: A Two-Level Sparse Direct Solver for Elliptic PDEs,"
ACOM, 2024.

High frequency Helmholtz in curved domain

The flexibility of a multi-domain scheme allows us to handle complicated geometries.



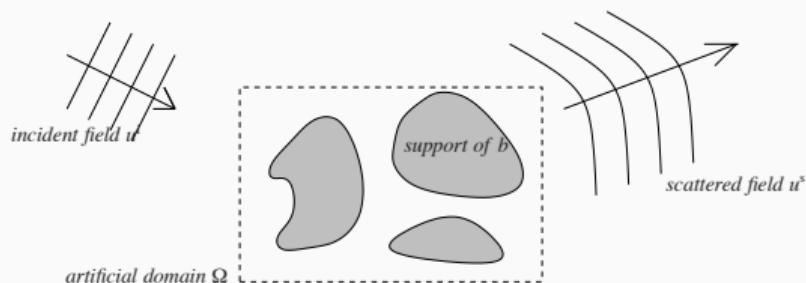
Interior Dirichlet problem with $\partial\Omega \equiv 1$.

Choosing higher p helps avoid numerical pollution and achieve higher accuracy for fixed number of points.

Fast Direct Solvers and BIE Coupling

Consider the free-space acoustic scattering problem

$$\begin{cases} -\Delta u^s(\boldsymbol{x}) - \kappa^2(1 - b(\boldsymbol{x}))u^s(\boldsymbol{x}) = -\kappa^2 b(\boldsymbol{x})u^i(\boldsymbol{x}), & \boldsymbol{x} \in \Omega, \\ \lim_{|\boldsymbol{x}| \rightarrow \infty} (\partial_{|\boldsymbol{x}|} u^s(\boldsymbol{x}) - i\kappa u^s(\boldsymbol{x})) = 0 \end{cases}$$



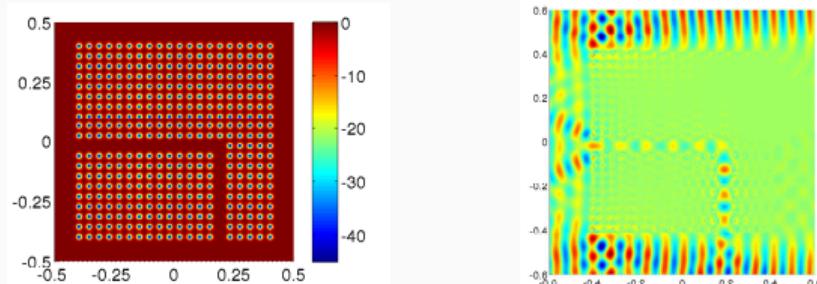
$b(\boldsymbol{x})$ is a smooth scattering potential with compact support

$u^i(\boldsymbol{x})$ is a given ‘incoming potential’

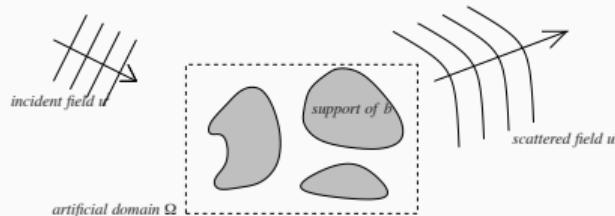
$u^s(\boldsymbol{x})$ is the sought ‘outgoing potential’

Gillman, Martinsson, Barnett. “A spectrally accurate direct solution technique for frequency-domain scattering problems with variable media,” BIT 2015.

Impedance to Impedance operators



Left: Field $-\kappa^2(1 - b(\mathbf{x}))$
Right: Solution $u(\mathbf{x})$



- In the interior, discretize volume PDE.
- On the exterior, use BIE representation, with panel-based quadrature.
- Glue operators together at the interface $\partial\Omega$ using \mathcal{H} -matrix algebra.
- Instead of using Poincaré-Steklov operators, this work uses impedance-to-impedance maps, which avoid internal resonances.

Parabolic PDEs and HPS

The ability to reuse precomputed solution operators allows for efficient implicit time-stepping for parabolic PDEs. For a variable-coefficient operator \mathcal{L} , let

$$\frac{\partial u}{\partial t} = \mathcal{L}u \quad u \in \Omega \times [0, T]$$

Define time step Δt and time points $t_n = n\Delta t$. Let u^n be the solution at time step t_n . Discretizing in time using backward Euler yields a steady-state PDE in u^{n+1}

$$(I - \Delta t \mathcal{L})u^{n+1} = u^n,$$

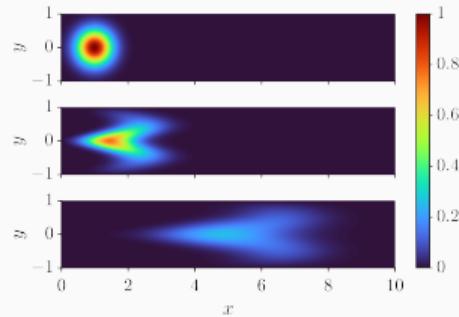
where the equation above must be solved to compute u^{n+1} given u^n . A direct solver can be computed and reused for *multiple right hand sides*.

HPS with time stepping schemes

Backward Euler (first order)

Time-dependent reaction-diffusion equation

$$\frac{\partial u}{\partial t} = \kappa \nabla^2 u - \nabla \cdot (\mathbf{b}(x, y)u)$$

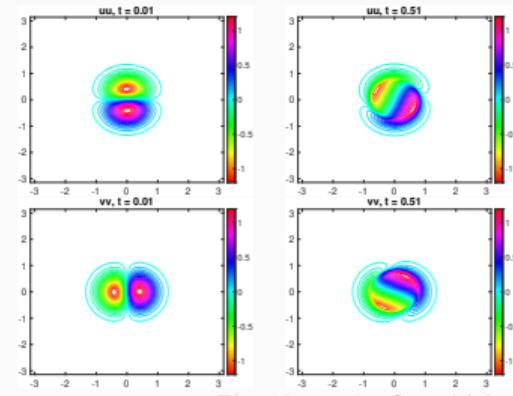


Fortunato, Hale, Townsend. "Ultraspherical spectral element method," *JCP* 2021.

Runge-Kutte (high order)

Regularized non-linear Schrodinger equation

$$i \frac{\partial u}{\partial t} + (1 - ia\epsilon) \Delta u + (1 + ic\epsilon) |u|^2 u = ib\epsilon u$$



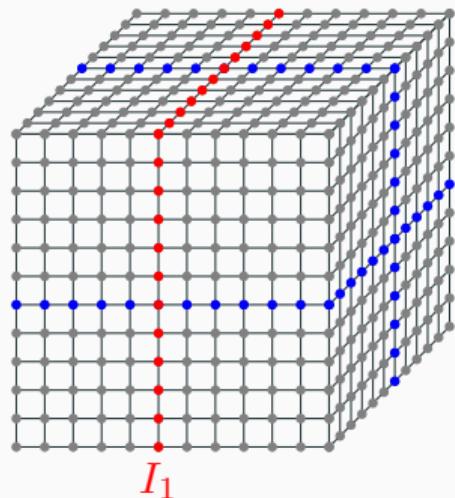
Ke Chen et al. "Fast and high-order approximation of parabolic equations," *arXiv* 2023.

Hierarchical Poincaré Steklov schemes

- Combines high order discretization with sparse direct solvers to solve elliptic PDEs to high accuracy.
- Particularly compelling for indefinite PDEs for combating the effect of pollution *and* solving the discretized system to high accuracy.
- Useful in applications to scattering and solving parabolic PDEs.

Finally, we discuss rank structure related to sparse direct solvers and how it can be used to build a fast (linear scaling for a constant PDE) solver.

Motivation for Using Rank Structure



Though we have reduced the dimensionality from a 3D volume to a 2D surface, the complexity costs for a direct solver are still prohibitively high in 3D.

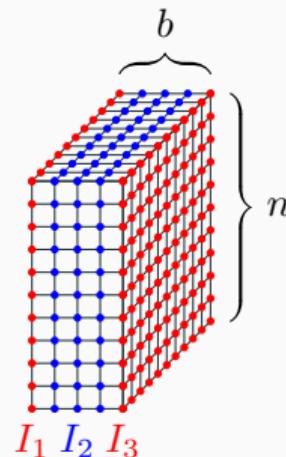
| d | cost to compute | memory to store |
|-----|-----------------|-----------------|
| 2 | $O(N^{1.5})$ | $O(N \log N)$ |
| 3 | $O(N^2)$ | $O(N^{4/3})$ |

Limitations of 3D Sparse Direct Solvers

There is a large literature of fast direct solvers in 2D*, but 3D remains a challenge.

Memory consumption is a particular concern.

- For $N = 100M$ in 2D, sub-block \mathbf{T}_{11} needs <1GB to store.
- For $N = 100M$ in 3D, sub-block \mathbf{T}_{11} needs >300 GB to store.

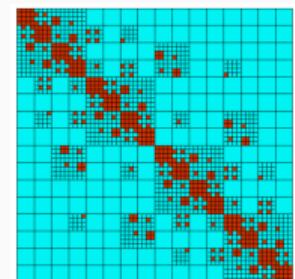
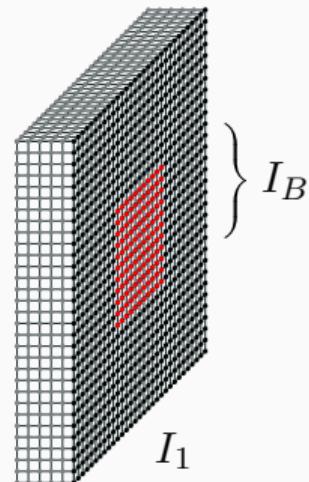
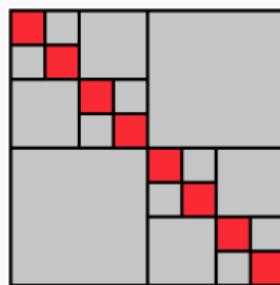
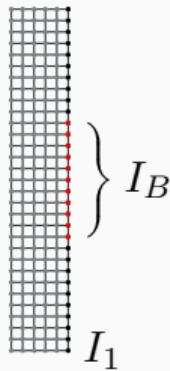


$$\mathbf{T}_{11} = \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21}$$

* Gillman, Martinsson. "A Direct Solver with $O(N)$ Complexity for Variable Coefficient Elliptic PDEs," *SIAM* 2014.

* Gillman, Martinsson, Barnett. "A spectrally accurate direct solution technique for frequency-domain scattering problems," *BIT* 2015.

\mathcal{H} -matrix structure in T_{11}



\mathcal{H}^2 -matrix structures on interfaces in 3D need more complicated data structure to achieve small memory footprint.

Problem Setting

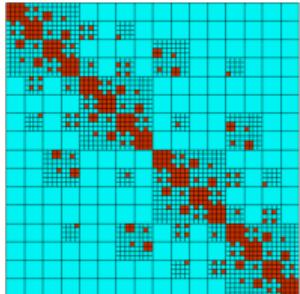


Image credit:

Ambikasaran & Darve, arxiv.org #1407.1572

\mathcal{H}^2 -matrices with a *strong admissibility* condition are for achieving linear scaling direct solvers. For a dense matrix of size $m \times m$:

Matrix-vector product: $\mathcal{O}(m^2) \searrow \mathcal{O}(m)$

LU factorization: $\mathcal{O}(m^3) \searrow \mathcal{O}(m \text{ polylog}(m))$

In practice, there are challenges to using this format...

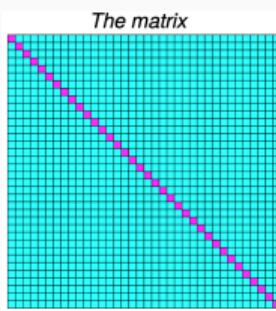
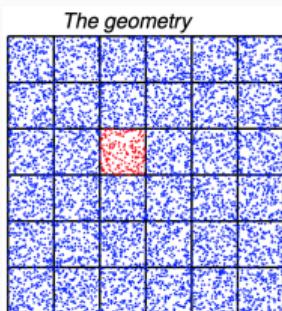
Challenge 1: Compression

For many applications, a fast matrix-vector product $\mathbf{v} \rightarrow \mathbf{T}\mathbf{v}$ is available, but individual entries \mathbf{T}_{ij} may be hard or complicated to access.

$$\mathbf{T}_{11} = \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21}$$

Challenge 2: Computing \mathbf{T}^{-1}

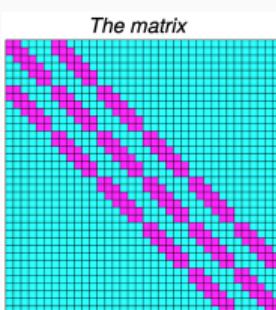
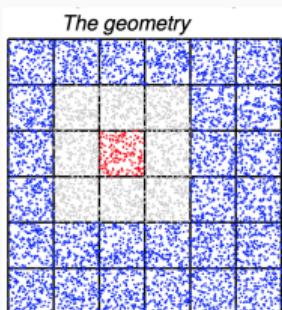
Weak admissibility



Neighbor blocks are compressed as low rank,
leading to simpler algebraic structure.

If you can represent \mathbf{T} , algebraic algorithms for a
factorization \mathbf{T}^{-1} are available.

Strong admissibility (focus for 3D solvers)



Neighbor blocks are stored densely.

Even if you can represent \mathbf{T} , it is not so simple to
construct \mathbf{T}^{-1} (often recompression is needed).

Addressing Challenges

Randomized Sketching

For a *globally low rank* matrix $\mathbf{B} \in \mathbb{R}^{m \times n}$ with rank k , a factorization can be reconstructed matrix-free from sketches

$$\mathbf{Y}_{m \times k} = \mathbf{B}_{m \times n} \mathbf{\Omega}_{n \times k}, \quad \mathbf{Z}_{n \times k} = \mathbf{B}^*_{n \times m} \mathbf{\Psi}_{m \times k},$$

where $\mathbf{\Omega}, \mathbf{\Psi}$ are Gaussian random matrices.

Cheng, Gimbutas, Martinsson, Rokhlin. “On the compression of low-rank matrices,” SIAM 2005.

Linear algorithm for computing \mathbf{T}^{-1}

A promising approach is “strong recursive skeletonization,” but the algorithm is *only* applicable when matrix entries are available.

Minden, Damle, Ho, Ying. “A recursive skeletonization factorization based on strong admissibility,” SIAM 2017.

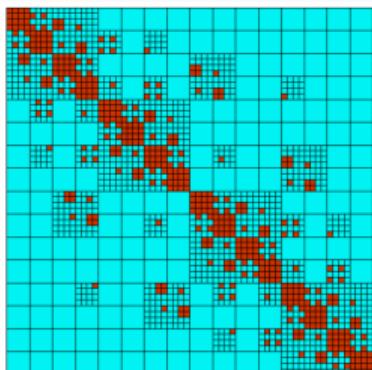


Sushnikova, Greengard, O'Neil, Rachh. “FMM-LU,” SIAM 2023.

Randomized Strong Recursive Skeletonization (RSRS)

Often, a fast matrix-vector product $\mathbf{v} \rightarrow \mathbf{T}\mathbf{v}$ is available for \mathbf{T} and its adjoint.

Suppose we are given $\{\mathbf{Y}, \mathbf{Z}, \boldsymbol{\Omega}, \boldsymbol{\Psi}\}$:



$$\mathbf{Y}_{N \times p} = \mathbf{T}_{N \times N} \boldsymbol{\Omega}_{N \times p}, \quad \mathbf{Z}_{N \times p} = \mathbf{T}^*_{N \times N} \boldsymbol{\Psi}_{N \times p}$$

where $\boldsymbol{\Omega}, \boldsymbol{\Psi}$ are random matrices and $p \ll N$.

RSRS recovers the \mathcal{H}^2 -matrix **and** computes an invertible factorization in-place. Requires *constant* number of samples and *linear* post-processing cost.

A. Yesypenko, P.G. Martinsson. arXiv preprint arXiv:2311.01451

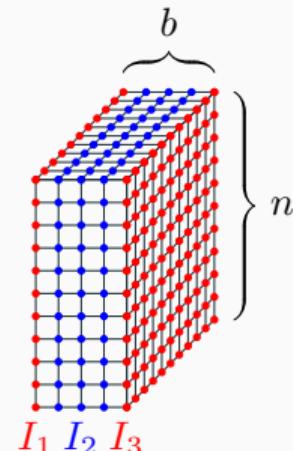
Extends on many previous works on randomized sampling for \mathcal{H}^2 matrices,
notably the dissertation of James Levitt.

Numerical Experiments for 3D SlabLU

We compute \mathbf{T}_{11}^{-1} for a Schur complement arising from a PDE discretization for 3D SlabLU*

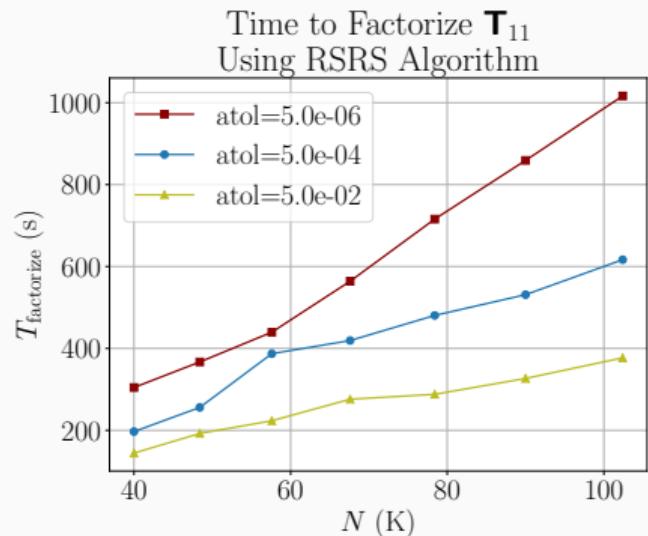
$$\mathbf{T}_{11} = \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21}$$

- PDE is Poisson, discretized with 2nd order finite difference discretization.
- Slab width $b = 10$ fixed, which number of points on slab interface grows as $N = n^2$.
- User supplies compression tolerance ‘atol.’

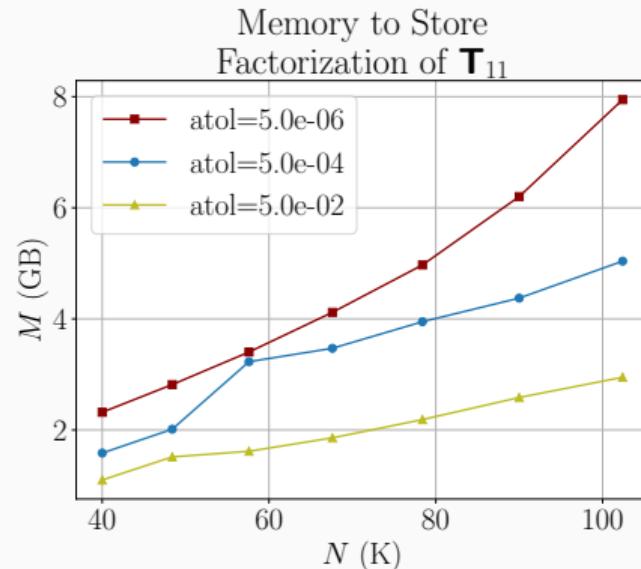


* Yesypenko, Martinsson. "SlabLU: A Two-Level Sparse Direct Solver for Elliptic PDEs." *ACOM*, 2024.

Linear-Time Construction

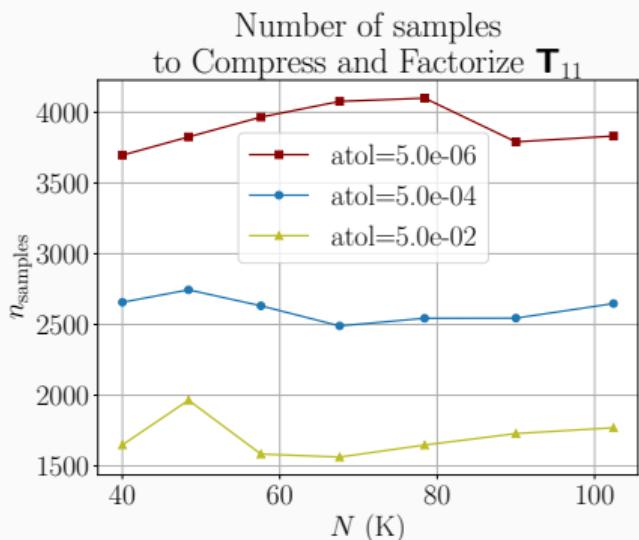


Time to compute \mathbf{T}_{11}^{-1} scales linearly.

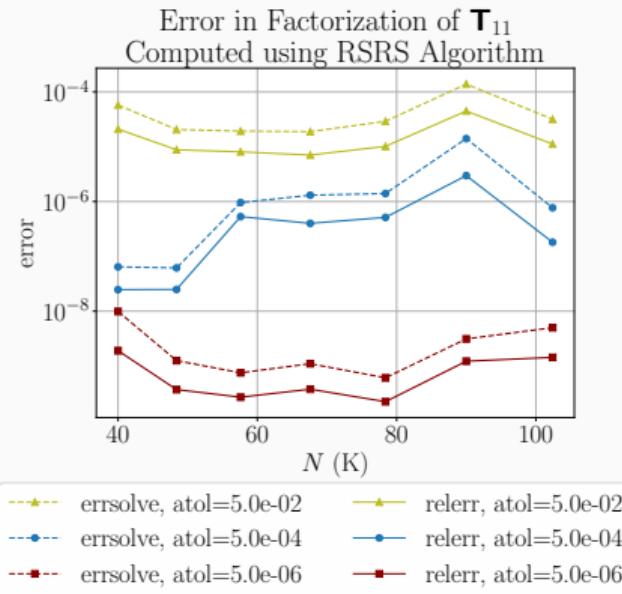


Memory to store \mathbf{T}_{11}^{-1} scales linearly.

Constant Number of Samples



Number of samples needed is independent of N .



The computed factorization is accurate and does not deteriorate with increasing N .

Thank you! Concluding Remarks

The talk today featured:

- Review of sparse direct solvers for PDE discretizations.
- Domain decomposition techniques and efficient high order discretization.
- Applications of HPS to scattering and time-stepping.
- An overview of fast direct solvers which use rank-structure to achieve linear complexity.

