

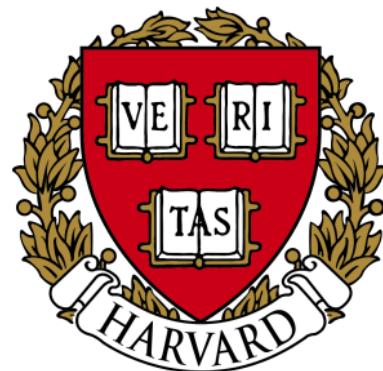
Fast Poisson solvers for spectral methods



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Dan Fortunato
Harvard

IMA Leslie Fox Prize Meeting
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Based on: F. & Townsend, "Fast Poisson solvers for spectral methods," to appear in IMA J. Numer. Anal.

Introduction

A long-standing question

Consider Poisson's equation on $[-1, 1]^2$ with homogeneous Dirichlet conditions,

$$u_{xx} + u_{yy} = f, \quad (x, y) \in [-1, 1]^2, \quad u(\pm 1, \cdot) = u(\cdot, \pm 1) = 0.$$

The classic fast Poisson solver using finite differences:

$$\underbrace{KX + XK^T = F}_{\text{solve with DST-I, } O(n^2 \log n)}, \quad K = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & \\ -1 & \ddots & \ddots & \\ & \ddots & \ddots & -1 \\ & & -1 & 2 \end{bmatrix}$$

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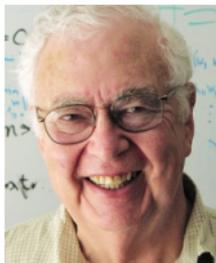
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Bill Buzbee



Gene Golub

- Based on **structured eigenvectors**
- Complexity increases with order of accuracy

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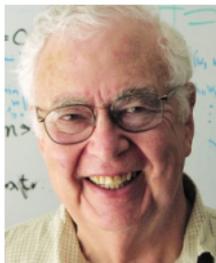
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breaks down for spectral



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Can we make a spectrally-accurate
Poisson solver with $O(n^2 \log n)$ complexity?

A sparse identity

The ultraspherical polynomials

Dirichlet on $[-1, 1]$ \longleftrightarrow Pick a basis that vanishes at ± 1

The classical orthogonal polynomials, f_k , satisfy

$$A(x)f_k''(x) + B(x)f_k'(x) = q_k f_k(x), \quad x \in [-1, 1].$$

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The ultraspherical polynomials of parameter $\lambda > 0$, $C_k^{(\lambda)}$, satisfy [NIST DLMF, 18.8.1]

$$(1 - x^2)C_k^{(\lambda)''}(x) - (2\lambda + 1)x C_k^{(\lambda)'}(x) = -k(k+2\lambda)C_k^{(\lambda)}(x), \quad x \in [-1, 1].$$

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The second derivative of $(1 - x^2)C_k^{(\lambda)}(x)$ is given by

$$\frac{\partial^2}{\partial x^2} \left[(1 - x^2)C_k^{(\lambda)}(x) \right] = (1 - x^2)C_k^{(\lambda)''}(x) - 4x C_k^{(\lambda)'}(x) - 2C_k^{(\lambda)}(x).$$

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Idea: Choose $\lambda = \frac{3}{2}$

A sparse identity

The ultraspherical polynomials

$$\frac{\partial^2}{\partial x^2} \left[(1 - x^2) C_k^{(3/2)}(x) \right] = -(k(k+3)+2) C_k^{(3/2)}(x).$$

$C_k^{(3/2)}(x)$ is an eigenfunction of the differential operator $u \mapsto \frac{\partial^2}{\partial x^2}[(1 - x^2)u]$

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$C_k^{(3/2)}(x)$ is an eigenfunction of the differential operator $u \mapsto \frac{\partial^2}{\partial x^2}[(1-x^2)u]$

$$\begin{aligned} \nabla^2 \left[(1-y^2)(1-x^2) C_j^{(3/2)}(y) C_k^{(3/2)}(x) \right] &= - (j(j+3)+2)(1-x^2) C_j^{(3/2)}(y) C_k^{(3/2)}(x) \\ &\quad - (k(k+3)+2)(1-y^2) C_j^{(3/2)}(y) C_k^{(3/2)}(x) \end{aligned}$$

Therefore, represent the solution in the basis

$$u(x, y) \approx \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} X_{jk} (1-y^2)(1-x^2) C_j^{(3/2)}(y) C_k^{(3/2)}(x), \quad (x, y) \in [-1, 1]^2.$$

A sparse identity

Does it diagonalize Poisson?

$$\nabla^2 u = f$$

A sparse identity

Does it diagonalize Poisson?

$$\nabla^2 \left[\sum_{j,k} X_{jk} (1-y^2)(1-x^2) C_j^{(3/2)}(y) C_k^{(3/2)}(x) \right] = \sum_{j,k} F_{jk} C_j^{(3/2)}(y) C_k^{(3/2)}(x)$$

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We know the action of ∇^2 on this basis:

$$\begin{aligned} \nabla^2 \left[(1-y^2)(1-x^2) C_j^{(3/2)}(y) C_k^{(3/2)}(x) \right] &= -(k(k+3)+2)(1-y^2) C_j^{(3/2)}(y) C_k^{(3/2)}(x) \\ &\quad - (j(j+3)+2)(1-x^2) C_j^{(3/2)}(y) C_k^{(3/2)}(x) \end{aligned}$$

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$$MXD^T + DXM^T = F$$

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A sparse identity

Does it diagonalize Poisson?

diagonal

$$MXD^T + DXM^T = F$$

symmetric pentadiagonal
[NIST DLMF, 18.9.7-8]

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$$AX - XB = D^{-1}FD^{-1}$$
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James Sylvester

A pentadiagonal Sylvester equation



Aleksandr Lyapunov

The alternating direction implicit (ADI) method

Solving Sylvester equations

$$AX - XB = F \quad A, B, F \in \mathbb{C}^{n \times n}$$

- Based on **structured eigenvalues**



Donald Peaceman



Henry Rachford

The alternating direction implicit (ADI) method

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- Based on **structured eigenvalues**

still works for spectral



Donald Peaceman



Henry Rachford

The alternating direction implicit (ADI) method

Solving Sylvester equations

$$AX - XB = F \quad A, B, F \in \mathbb{C}^{n \times n}$$

set $X_0 := 0$

choose shift parameters $p_j, q_j \in \mathbb{C}$

for $j = 0, 1, \dots, J-1$

solve $X_{j+1/2}(B - p_j I) = F - (A - p_j I)X_j$

solve $(A - q_j I)X_{j+1} = F - X_{j+1/2}(B - q_j I)$

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2. How many iterations J do we need?

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$$A, B, F \in \mathbb{C}^{n \times n}$$

set $X_0 := 0$

choose shift parameters $\mathbf{p}_j, \mathbf{q}_j \in \mathbb{C}$

for $j = 0, 1, \dots, J - 1$

solve $X_{j+1/2}(\mathbf{B} - \mathbf{p}_j \mathbf{I}) = F - (A - p_j I)X_j$

solve $(\mathbf{A} - \mathbf{q}_j \mathbf{I})X_{j+1} = F - X_{j+1/2}(\mathbf{B} - q_j \mathbf{I})$

1. What shifts p_j, q_j should we choose?
2. How many iterations J do we need?
3. What is the cost of each iteration?

ADI as a fast direct solver

Three requirements

$$AX - XB = F \quad A, B, F \in \mathbb{C}^{n \times n}$$

Three requirements on A and B will help us answer those three questions:

- P1. A and B are normal matrices.
- P2. There are real, disjoint intervals such that $\sigma(A) \subset [a, b]$, $\sigma(B) \subset [c, d]$.
- P3. For any $p \in \mathbb{C}$, $(A - pl)x = f$ and $(B - pl)x = f$ can be solved in $O(n)$ operations.

ADI as a fast direct solver

Normal matrices

P1. A and B are normal matrices.

Then there is a bound on $\|X - X_J\|_2$ based on the spectra $\sigma(A)$, $\sigma(B)$ and the chosen shifts p_0, \dots, p_{J-1} and q_0, \dots, q_{J-1} :

$$\frac{\|X - X_J\|_2}{\|X\|_2} \leq \frac{\sup_{z \in \sigma(A)} |r(z)|}{\inf_{z \in \sigma(B)} |r(z)|}, \quad r(z) = \frac{\prod_{j=0}^{J-1} (z - p_j)}{\prod_{j=0}^{J-1} (z - q_j)}.$$

Goal: choose shifts p_j, q_j so that the rational function $r(z)$ makes the bound as small as possible:

$$\frac{\sup_{z \in \sigma(A)} |r(z)|}{\inf_{z \in \sigma(B)} |r(z)|} = \inf_{s \in \mathfrak{R}_{J,J}} \frac{\sup_{z \in \sigma(A)} |s(z)|}{\inf_{z \in \sigma(B)} |s(z)|}$$

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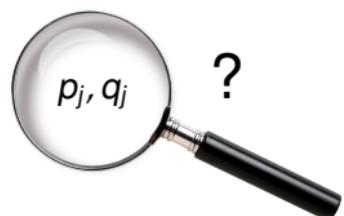
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↑
rational functions



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Normal matrices

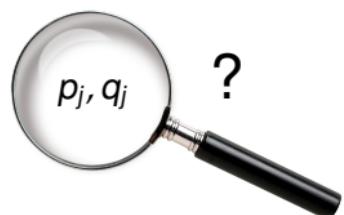
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$$\frac{\|X - X_J\|_2}{\|X\|_2} \leq Z_J(\sigma(A), \sigma(B)), \quad r(z) = \frac{\prod_{j=0}^{J-1}(z - p_j)}{\prod_{j=0}^{J-1}(z - q_j)}.$$

Goal: choose shifts p_j, q_j so that the rational function $r(z)$ makes the bound as small as possible:

$$Z_J(\sigma(A), \sigma(B)) = \underbrace{\inf_{s \in \mathfrak{R}_{J,J}} \frac{\sup_{z \in \sigma(A)} |s(z)|}{\inf_{z \in \sigma(B)} |s(z)|}}_{\begin{array}{l} \text{Zolotarev number} \\ \uparrow \\ \text{rational functions} \end{array}}$$

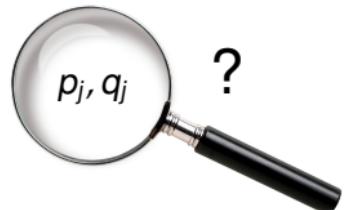


ADI as a fast direct solver

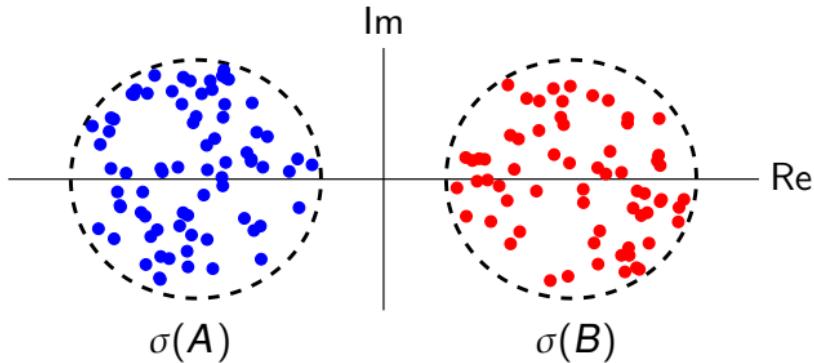
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Yegor Zolotarev



ADI as a fast direct solver

Real separated spectra

P2. There are real, disjoint intervals such that $\sigma(A) \subset [a, b]$, $\sigma(B) \subset [c, d]$.

The **Zolotarev problem** is well-studied for real spectra.

1. Optimal shifts are known: for $[a, b] = [-\alpha, -1]$ and $[c, d] = [1, \alpha]$

$$p_j = -\alpha \operatorname{dn} \left[\frac{2j+1}{2J} K \left(\sqrt{1 - \frac{1}{\alpha^2}} \right), \sqrt{1 - \frac{1}{\alpha^2}} \right]$$

$$q_j = \alpha \operatorname{dn} \left[\frac{2j+1}{2J} K \left(\sqrt{1 - \frac{1}{\alpha^2}} \right), \sqrt{1 - \frac{1}{\alpha^2}} \right]$$

[Zolotarev, 1877]
[Lu & Wachspress, 1991]

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Jacobi elliptic function

complete elliptic integral
of the first kind

[Zolotarev, 1877]
[Lu & Wachspress, 1991]

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1. Optimal shifts are known: Möbius transformations preserve rational functions, so set $\alpha = 2\sqrt{\gamma^2 - \gamma} + 2\gamma + 1$ with $\gamma = \frac{|c-a||d-b|}{|c-b||d-a|}$:

$$p_j = T\left(-\alpha \operatorname{dn}\left[\frac{2j+1}{2J} K\left(\sqrt{1 - \frac{1}{\alpha^2}}\right), \sqrt{1 - \frac{1}{\alpha^2}}\right]\right)$$

$$q_j = T\left(\alpha \operatorname{dn}\left[\frac{2j+1}{2J} K\left(\sqrt{1 - \frac{1}{\alpha^2}}\right), \sqrt{1 - \frac{1}{\alpha^2}}\right]\right)$$

Möbius transformation
 $\{-\alpha, -1, 1, \alpha\} \mapsto [a, b, c, d]$

[Sabino, 2007]

ADI as a fast direct solver

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The **Zolotarev problem** is well-studied for real spectra.

2. There is an upper bound on $Z_J([a, b], [c, d])$:

$$Z_J([a, b], [c, d]) \leq 4 \left[\exp\left(\frac{\pi^2}{2 \log(16\gamma)}\right) \right]^{-2J}$$

[Braess & Hackbusch, 2005]

[Beckermann & Townsend, 2017]

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1. Optimal shifts are known.
2. There is an upper bound on $Z_J([a, b], [c, d])$.

Run ADI with the optimal shifts p_j, q_j . The J^{th} iterate has relative error:

$$\frac{\|X - X_J\|_2}{\|X\|_2} \leq 4 \left[\exp \left(\frac{\pi^2}{2 \log(16\gamma)} \right) \right]^{-2J}$$

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2. There is an upper bound on $Z_J([a, b], [c, d])$.

Run ADI with the optimal shifts p_j, q_j . The J^{th} iterate has relative error:

$$\frac{\|X - X_J\|_2}{\|X\|_2} \leq 4 \left[\exp \left(\frac{\pi^2}{2 \log(16\gamma)} \right) \right]^{-2J}$$

a priori error estimate

ADI as a fast direct solver

Real separated spectra

P2. There are real, disjoint intervals such that $\sigma(A) \subset [a, b]$, $\sigma(B) \subset [c, d]$.

The **Zolotarev problem** is well-studied for real spectra.

1. Optimal shifts are known.
2. There is an upper bound on $Z_J([a, b], [c, d])$.

How does γ scale with n ?

For a given tolerance $0 < \epsilon < 1$, iterate

$$J = \left\lceil \frac{\log(16\gamma) \log(4/\epsilon)}{\pi^2} \right\rceil$$

times. Then $\|X - X_J\|_2 \leq \epsilon \|X\|_2$.

a priori error estimate

ADI as a fast direct solver

Fast shifted linear solves

- P3. For any $p \in \mathbb{C}$, $(A - pl)x = f$ and $(B - pl)x = f$ can be solved in $O(n)$ operations.

set $X_0 := 0$

choose shift parameters $p_j, q_j \in \mathbb{C}$

for $j = 0, 1, \dots, J - 1$

solve $X_{j+1/2}(B - p_j I) = F - (A - p_j I)X_j$

solve $(A - q_j I)X_{j+1} = F - X_{j+1/2}(B - q_j I)$

$\left. \right\} O(n^2)$

Then the total cost of ADI is $O(Jn^2)$. (Is $J = O(\log n)$?)

ADI as a fast direct solver

Three requirements

- P1. A and B are normal matrices.
- P2. There are real, disjoint intervals such that $\sigma(A) \subset [a, b]$, $\sigma(B) \subset [c, d]$.
- P3. For any $p \in \mathbb{C}$, $(A - pl)x = f$ and $(B - pl)x = f$ can be solved in $O(n)$ operations.

1. What shifts p_j , q_j should we choose?
2. How many iterations J do we need?
3. What is the cost of each iteration?

ADI as a fast direct solver

Three requirements

- P1. A and B are normal matrices.
- P2. There are real, disjoint intervals such that $\sigma(A) \subset [a, b]$, $\sigma(B) \subset [c, d]$.
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1. What shifts p_j , q_j should we choose? P1 + P2
2. How many iterations J do we need?
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ADI as a fast direct solver

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- P1. A and B are normal matrices.
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1. What shifts p_j , q_j should we choose? P1 + P2
2. How many iterations J do we need? P1 + P2
3. What is the cost of each iteration? P3

ADI as a fast direct solver

Three requirements

Back to our spectral discretization:

$$AX - XB = D^{-1}FD^{-1} \quad A = D^{-1}M, \\ B = -M^T D^{-1}$$

ADI as a fast direct solver

Three requirements

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ADI as a fast direct solver

Three requirements

Back to our spectral discretization:

$$\tilde{A}\tilde{X} - \tilde{X}\tilde{B} = D^{-1/2}FD^{-1/2}$$

$$\begin{aligned}\tilde{A} &= D^{-1/2}MD^{1/2}, \\ \tilde{B} &= -D^{1/2}M^TD^{-1/2}\end{aligned}$$

P1. A and B are normal matrices.

Transform A and B to normal matrices:

$$\tilde{A} = D^{1/2}AD^{-1/2}$$

$$\tilde{B} = D^{-1/2}BD^{1/2}$$



and recover $X = D^{-1/2}\tilde{X}D^{1/2}$.

ADI as a fast direct solver

Three requirements

Back to our spectral discretization:

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$$\tilde{A} = D^{-1/2}MD^{1/2},$$
$$\tilde{B} = -D^{1/2}M^T D^{-1/2}$$

P2. There are real, disjoint intervals such that $\sigma(\tilde{A}) \subset [a, b]$, $\sigma(\tilde{B}) \subset [c, d]$.

ADI as a fast direct solver

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P2. There are real, disjoint intervals such that $\sigma(\tilde{A}) \subset [a, b]$, $\sigma(\tilde{B}) \subset [c, d]$.

We can prove that

$$\sigma(\tilde{A}) \subset \left[-\frac{1}{2}, -\frac{1}{2n^4}\right], \quad \sigma(\tilde{B}) \subset \left[\frac{1}{2n^4}, \frac{1}{2}\right]$$

by bounding the zeros of $(1 - x^2)C^{(3/2)}(x)$.

Therefore, $\gamma = O(n^4)$ and $J = O(\log \gamma) = O(\log n)$.



ADI as a fast direct solver

Three requirements

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$$\tilde{A}\tilde{X} - \tilde{X}\tilde{B} = D^{-1/2}FD^{-1/2}$$
$$\tilde{A} = D^{-1/2}MD^{1/2},$$
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- P3. For any $p \in \mathbb{C}$, $(\tilde{A} - pl)x = f$ and $(\tilde{B} - pl)x = f$ can be solved in $O(n)$ operations.

ADI as a fast direct solver

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- P3. For any $p \in \mathbb{C}$, $(\tilde{A} - pl)x = f$ and $(\tilde{B} - pl)x = f$ can be solved in $O(n)$ operations.

$(\tilde{A} - pl)$ and $(\tilde{B} - pl)$ are pentadiagonal with zero sub- and super-diagonals.

We can use a variant of the Thomas algorithm to solve in $O(n)$.



A fast spectral Poisson solver on the square

Recipe

For a given error tolerance $0 < \epsilon < 1$:

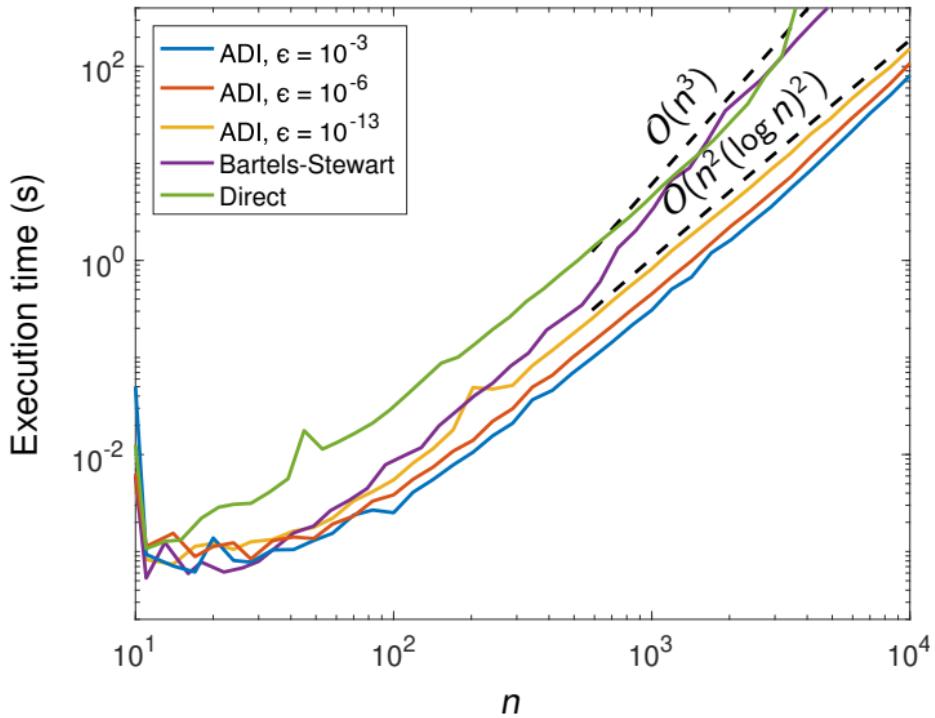
Cost

1. Compute $C^{(3/2)}$ coefficients of f $O(n^2(\log n)^2 \log 1/\epsilon)$ [Townsend, Webb, & Olver, 2018]
2. Solve matrix equation using ADI
 - ▶ $O(n^2)$ per iteration
 - ▶ $O(\log n \log 1/\epsilon)$ iterations $O(n^2 \log n \log 1/\epsilon)$
3. Convert solution to Chebyshev $O(n^2(\log n)^2 \log 1/\epsilon)$ [Townsend, Webb, & Olver, 2018]

$$O(n^2(\log n)^2 \log 1/\epsilon)$$

A fast spectral Poisson solver on the square

Comparison



ADI as a rank-revealing algorithm

Solutions can have low numerical rank

Theorem (F. & Townsend)

The numerical rank of the solution is bounded by

$$\text{rank}_\epsilon(X) \leq \left\lceil \frac{\log(4n^4) \log(4/\epsilon)}{\pi^2} \right\rceil \text{rank}(F),$$

where $\text{rank}_\epsilon(X)$ is the smallest k such that $\sigma_{k+1}(X)/\sigma_1(X) \leq \epsilon$.

ADI as a rank-revealing algorithm

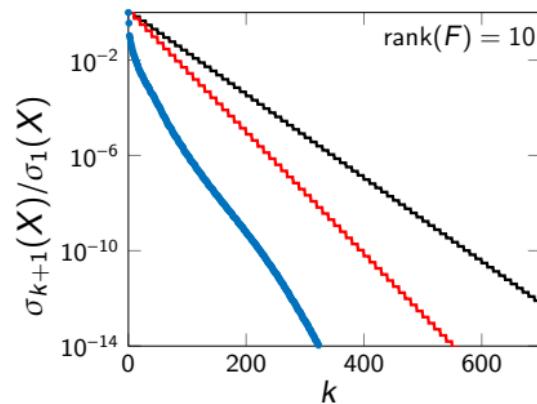
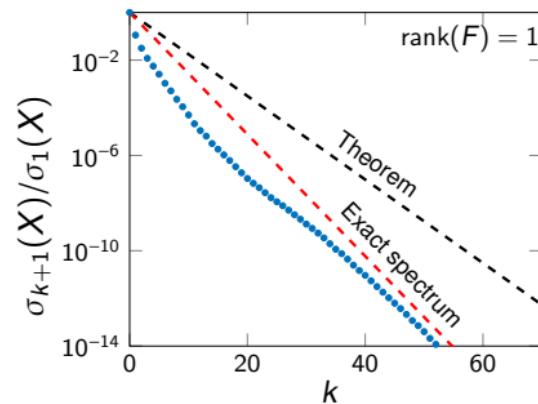
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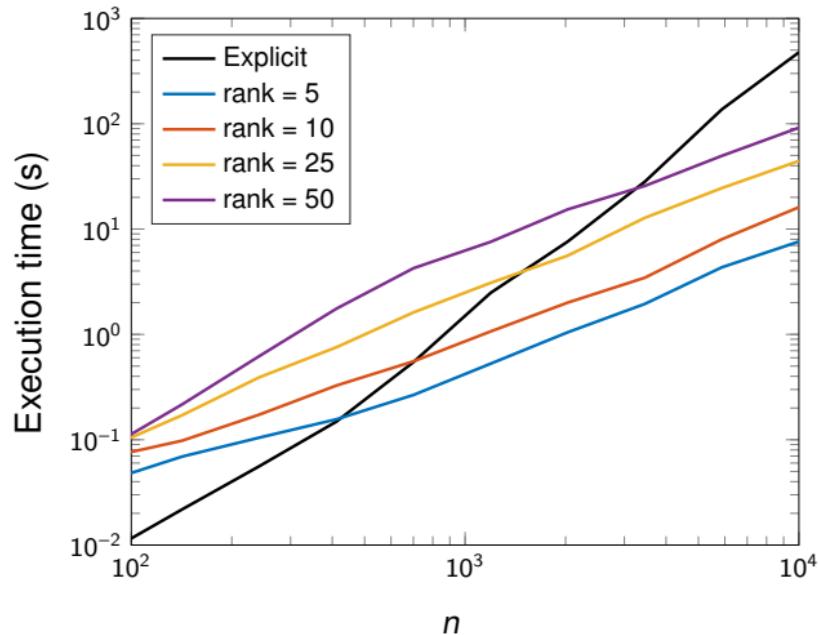
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ADI as a rank-revealing algorithm

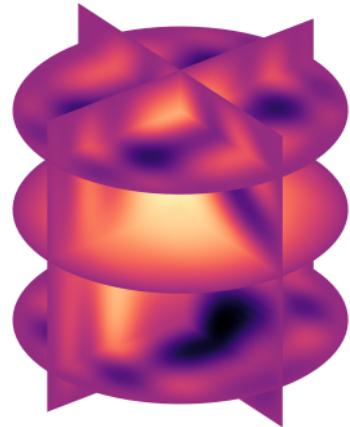
Computing low rank solutions

Factored ADI: given $F = MN^*$, rewrite ADI in terms of low rank factors $X = ZDY^*$

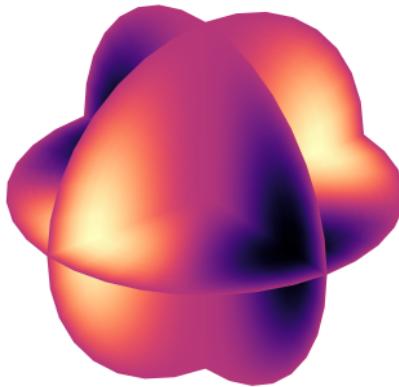


Fast spectral Poisson solvers on more domains

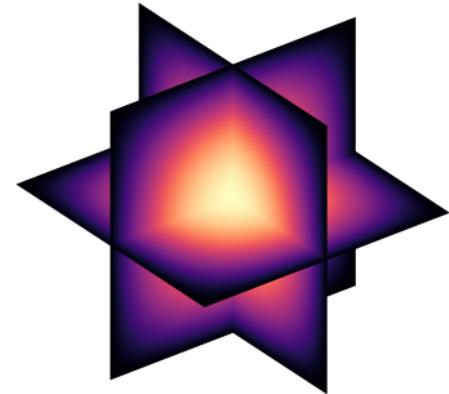
Cylinder, sphere, cube



Chebyshev–Fourier–Chebyshev
Double Fourier sphere
Partial regularity
N decoupled ADI solves
 $O(n^3(\log n)^2)$



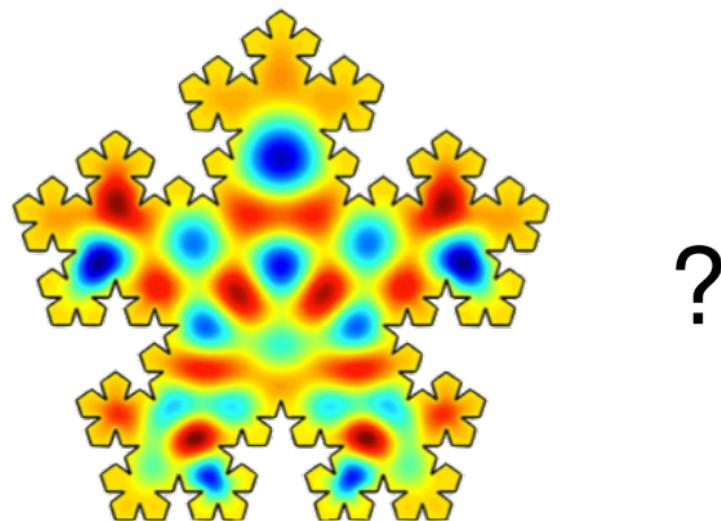
Chebyshev–Fourier–Fourier
Double Fourier sphere
Partial regularity
N decoupled ADI solves
 $O(n^3(\log n)^2)$



Chebyshev–Chebyshev–Chebyshev
Nested ADI iteration
 $O(n^3(\log n)^3)$

Towards more complex geometry

Spectral elements methods and hp -adaptivity

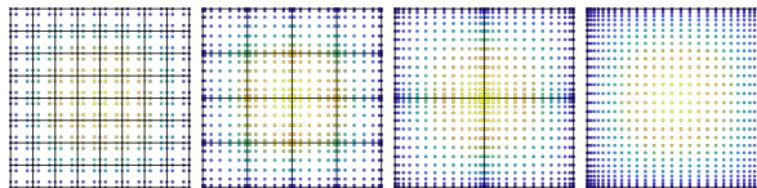


Towards more complex geometry

Spectral elements methods and hp -adaptivity

SEMs combine:

- the flexibility of finite element methods
- the convergence properties of global spectral methods

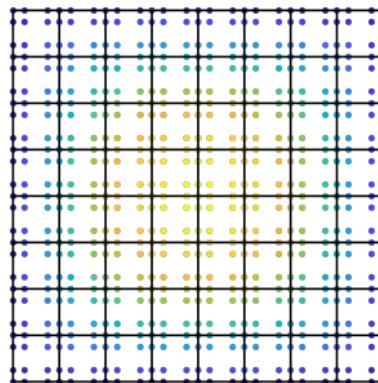
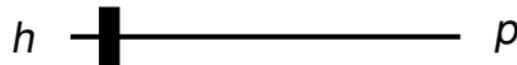


Towards more complex geometry

Spectral elements methods and hp -adaptivity

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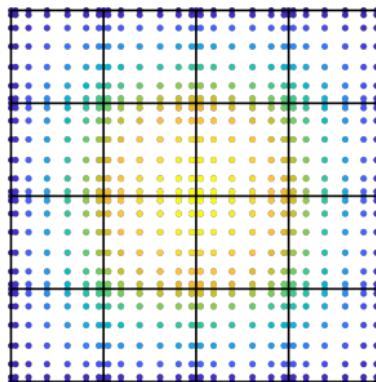
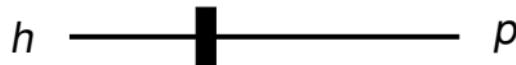


Towards more complex geometry

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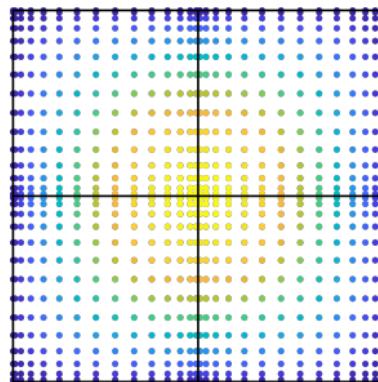
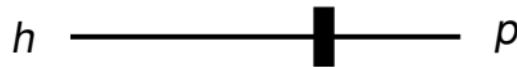


Towards more complex geometry

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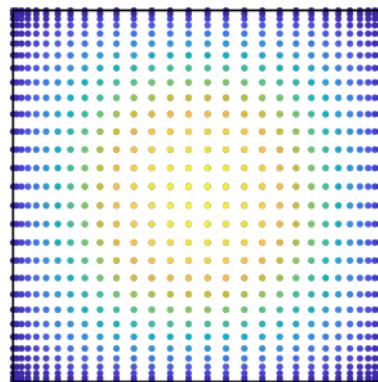
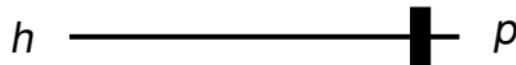


Towards more complex geometry

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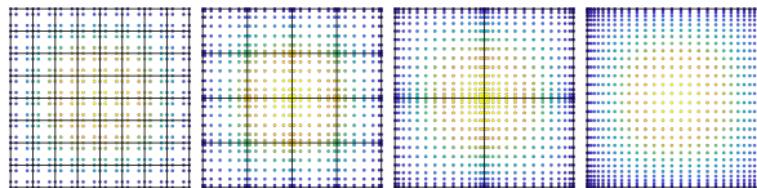


Towards more complex geometry

Spectral elements methods and hp -adaptivity

SEMs combine:

- the flexibility of finite element methods
- the convergence properties of global spectral methods



Most SEMs cost $\mathcal{O}(p^6/h^2) = \mathcal{O}(N p^4)$, so the slider is biased.

“In practice, hp -adaptivity means $p \lesssim 6$.” [Sherwin, 2014]

Towards more complex geometry

A spectral element method for very high p

Hierarchical Poincaré–Steklov method

- Patch operators by imposing C^1 continuity across interface
- Merge squares up the tree



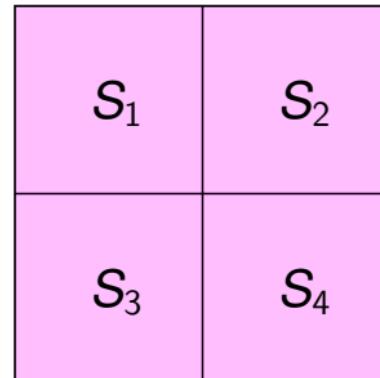
Gunnar Martinsson



Adrianna Gillman

[Martinsson, 2013]

[Gillman & Martinsson, 2014]



Towards more complex geometry

A spectral element method for very high p

Hierarchical Poincaré–Steklov method

- Patch operators by imposing C^1 continuity across interface
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Gunnar Martinsson



Adrianna Gillman

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Towards more complex geometry

A spectral element method for very high p

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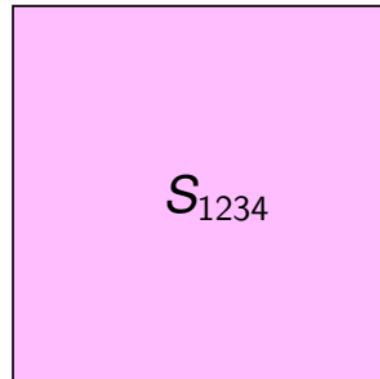
Gunnar Martinsson



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Towards more complex geometry

A spectral element method for very high p

Hierarchical Poincaré–Steklov method

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Gunnar Martinsson



Adrianna Gillman

$$+ \text{ADI} = O(p^3)$$

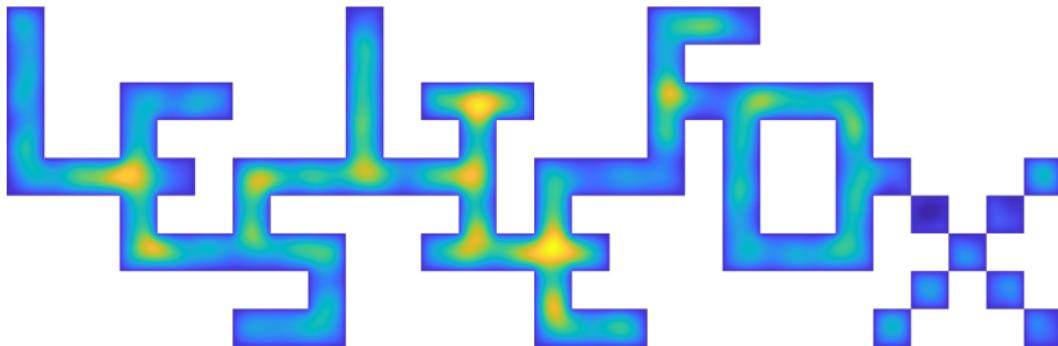
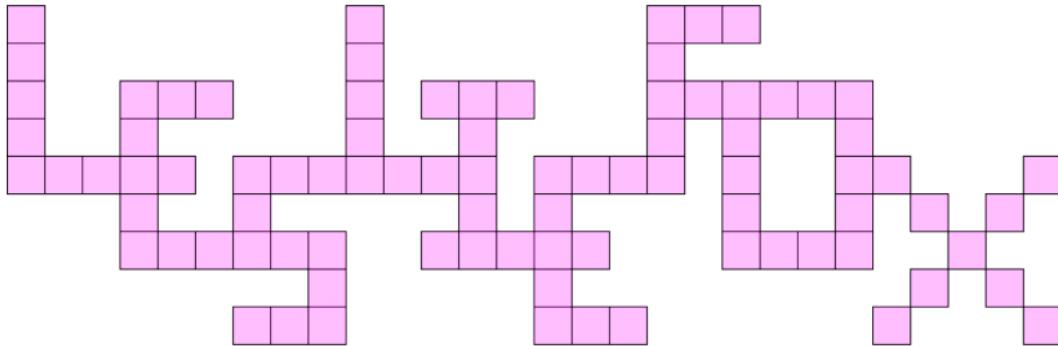
on squares

[Martinsson, 2013]

[Gillman & Martinsson, 2014]

Towards more complex geometry

A spectral element method for very high p



$p = 50$

~ 6 sec



Thank you

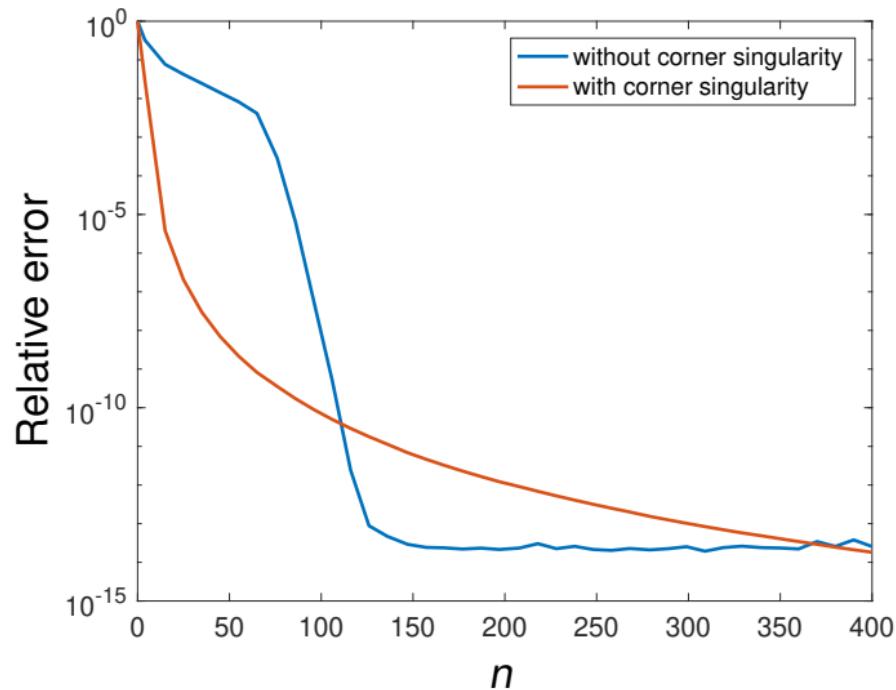


More information in: F. & Townsend, “Fast Poisson solvers for spectral methods,”
to appear in IMA J. Numer. Anal.

Code publicly available:

<https://github.com/danfortunato/fast-poisson-solvers>

Corner singularities



A connection to finite differences

Exploiting structured eigenvalues

$$KX + XK^T = F, \quad K = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & \\ -1 & \ddots & \ddots & \\ & \ddots & \ddots & -1 \\ & & -1 & 2 \end{bmatrix}$$

A connection to finite differences

Exploiting structured eigenvalues

$$KX + XK^T = F, \quad K = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & \\ -1 & \ddots & \ddots & \\ & \ddots & \ddots & -1 \\ & & -1 & 2 \end{bmatrix}$$

P1. A and B are normal matrices.

A connection to finite differences

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P1. A and B are normal matrices.

$A = K$ and $B = -K^T$ are real and symmetric, so are normal.



A connection to finite differences

Exploiting structured eigenvalues

$$KX + XK^T = F, \quad K = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & \\ -1 & \ddots & \ddots & \\ & \ddots & \ddots & -1 \\ & & -1 & 2 \end{bmatrix}$$

P2. There are real, disjoint intervals such that $\sigma(A) \subset [a, b]$, $\sigma(B) \subset [c, d]$.

A connection to finite differences

Exploiting structured eigenvalues

$$KX + XK^T = F, \quad K = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & \\ -1 & \ddots & \ddots & \\ & \ddots & \ddots & -1 \\ & & -1 & 2 \end{bmatrix}$$

P2. There are real, disjoint intervals such that $\sigma(A) \subset [a, b]$, $\sigma(B) \subset [c, d]$.

The eigenvalues of K are

$$-n^2 \sin^2(\pi k / 2n), \quad 1 \leq k \leq n-1$$

Since $(2/\pi)x \leq \sin(x) \leq 1$ for $x \in [0, \pi/2]$, we have:

$$\sigma(A) \subset [-n^2, -1], \quad \sigma(B) \subset [1, n^2].$$



A connection to finite differences

Exploiting structured eigenvalues

$$KX + XK^T = F, \quad K = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & \\ -1 & \ddots & \ddots & \\ & \ddots & \ddots & -1 \\ & & -1 & 2 \end{bmatrix}$$

- P3. For any $p \in \mathbb{C}$, $(A - pI)x = f$ and $(B - pI)x = f$ can be solved in $O(n)$ operations.

A connection to finite differences

Exploiting structured eigenvalues

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- P3. For any $p \in \mathbb{C}$, $(A - pI)x = f$ and $(B - pI)x = f$ can be solved in $O(n)$ operations.

$(A - pI)$ and $(B - pI)$ are tridiagonal. Solve with Thomas algorithm in $O(n)$.



A connection to finite differences

Exploiting structured eigenvalues

