

Class web page

Office hrs: ~~12:30~~ - 1:30pm (4318 Siebel)

<https://bit.ly/fastalg-s24>

today: in this room,  
right after class

contains:

- ▶ Class outline ✓
- ▶ Notes ✓
- ▶ Demos ✓
- ▶ Assignments ✓
- ▶ Discussion forum ✓
- ▶ Grading ✓
- ▶ Video ✓

$$\int k(x,y) \sigma(y) dy$$

## Why study this at all?

- ▶ Finite difference/element methods are inherently
  - ▶ ill-conditioned ←
  - ▶ tricky to get high accuracy with ←
- ▶ Build up a toolset that does *not* have these flaws
- ▶ Plus: An interesting/different analytical and computational point of view
  - ▶ If you're not going to use it to solve PDEs, it (or the ideas behind it) will still help you gain insight.

## FD/FEM: Issues

Idea of these methods:

1. Take differential equations
2. Discretize derivatives
3. Make linear system
4. Solve

So what's wrong with doing that?

# Discretizing Derivatives: Issues?

~ bad conditioning

$$\kappa(A) = \|A\| \|A^{-1}\|$$

$$\|A\|_{\infty} = \sup_{f \in S} \frac{\|Af\|_{\infty}}{\|f\|_{\infty}}$$

$$A = \partial_x$$

$$\|\partial_x f\|_{\infty} \leq ? \leq \|f\|_{\infty}$$
$$\|\partial_x\|_{\infty} = \infty$$

$$\|\partial_x\|_{\infty} = \infty$$

discrete

?

$$(e^{i\alpha x})' = (i\alpha) e^{i\alpha x} \quad \alpha \in \mathbb{R}$$

$$\|e^{i\alpha x}\|_{L^{\infty}(0, 2\pi)} = 1$$
$$\|i\alpha e^{i\alpha x}\|_{\infty} = |\alpha|$$

## Discretizing Derivatives: Issues?

**Result:** The better we discretize (the more points we use), the worse the condition number gets.

**Demo: Conditioning of Derivative Matrices**

**To be fair:** Multigrid works around that (by judiciously using **fewer** points!)  
But there's another issue that's not fixable.

As  $h \rightarrow 0$

$$\frac{f(x+h) - f(x-h)}{2h}$$

Cancellation

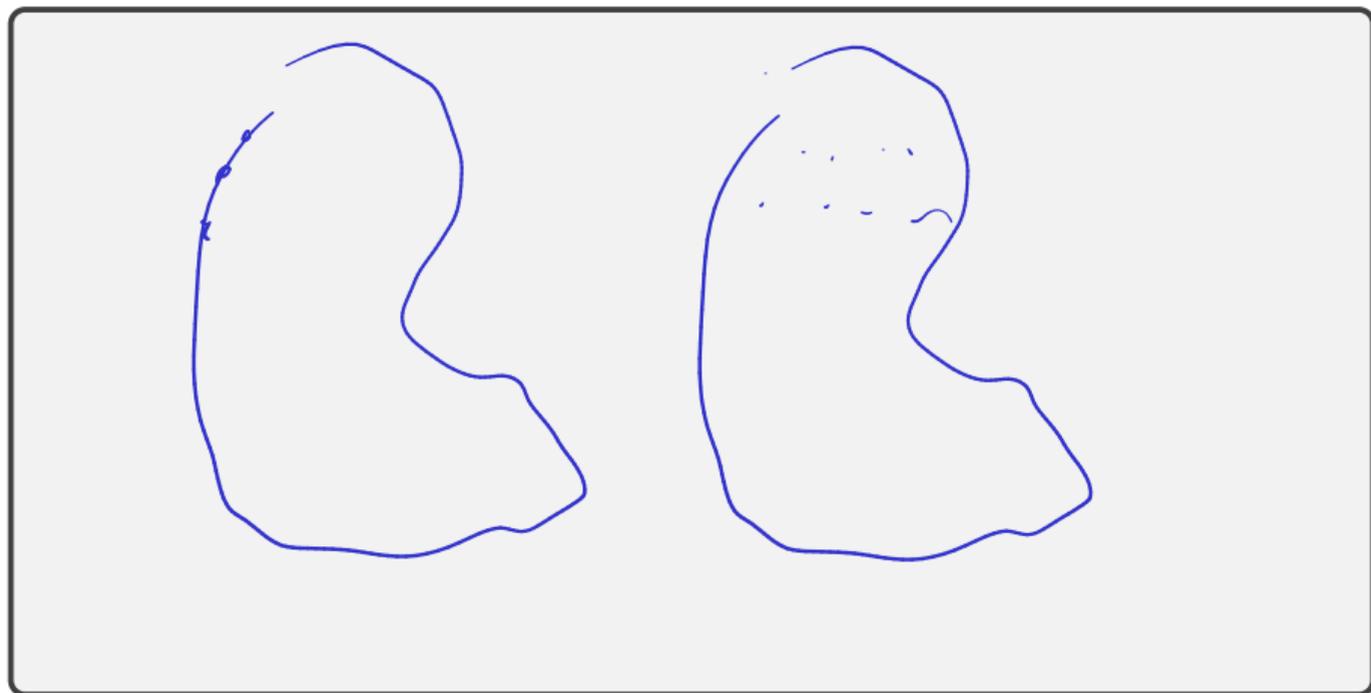
**Q:** Are these problems real?

Poisson  $\Delta u = f \leftarrow$  need MG or other preconditioner

So this class is about starting fresh with methods that (rigorously!) don't have these flaws!

## Bonus Advertising Goodie

Both multigrid and fast/IE schemes ultimately are  $O(N)$  in the number of degrees of freedom  $N$ .



## Open Source <3

These notes (and the accompanying demos) are open-source!

Bug reports and pull requests welcome:

<https://github.com/inducer/fast-alg-ie-notes>

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# Outline

Introduction

**Dense Matrices and Computation**

Tools for Low-Rank Linear Algebra

Rank and Smoothness

Near and Far: Separating out High-Rank Interactions

Outlook: Building a Fast PDE Solver

Going Infinite: Integral Operators and Functional Analysis

Singular Integrals and Potential Theory

Boundary Value Problems

Back from Infinity: Discretization

Computing Integrals: Approaches to Quadrature

Going General: More PDEs

## Matvec: A Slow Algorithm

Matrix-vector multiplication: our first 'slow' algorithm.  
 $O(N^2)$  complexity.

$$\beta_i = \sum_{j=1}^N A_{ij} \alpha_j$$

Assume  $A$  dense.

columns : sources  
rows : targets

# Matrices and Point Interactions

$$A_{ij} = G(x_i, y_j)$$

Does that actually change anything?

$$\psi(x_i) = \sum G(x_i, y_j) \varphi(y_j)$$

$x_i$     $y_j$    points ( $\in \mathbb{R}^2$ ?  $\in \mathbb{R}^3$ )

-  $x_i$  "targets" / "observation points"

-  $y_j$  "sources"

-  $G$  kernel

"where you look"

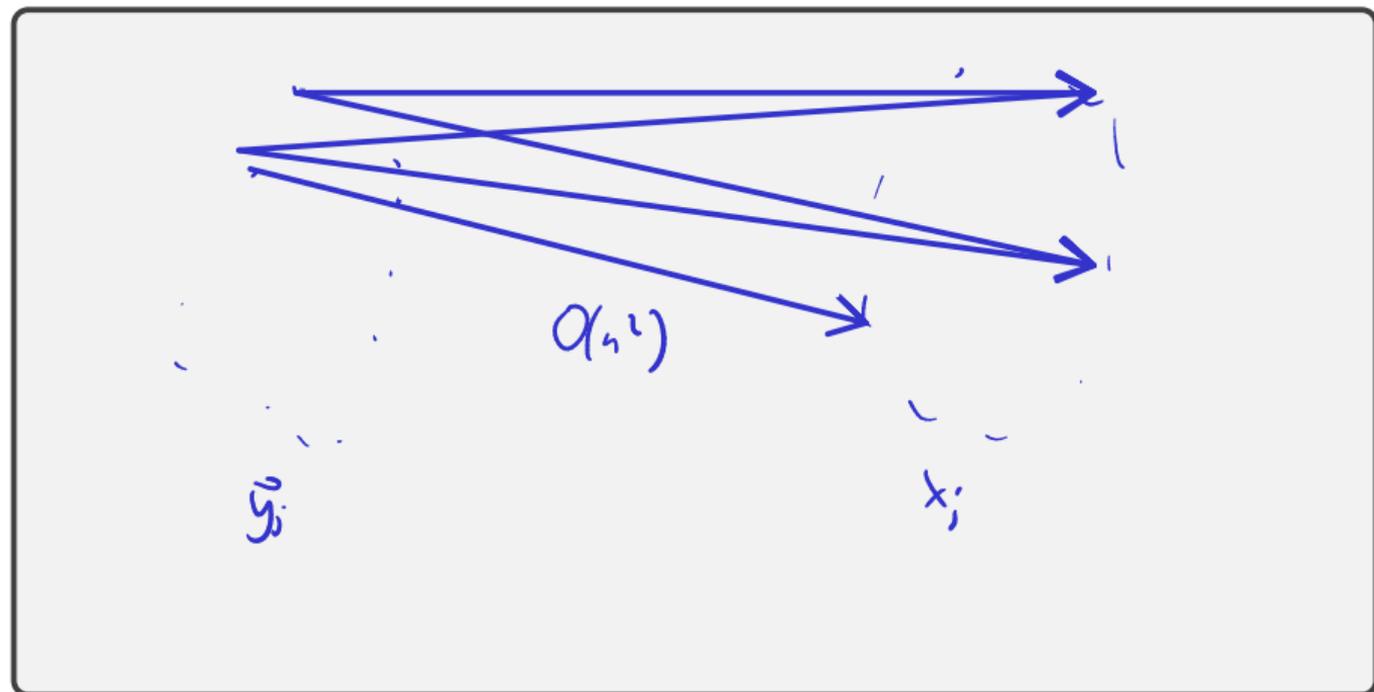
"electrons"

$$G(x, y) = \frac{1}{\|x-y\|_2}$$

# Matrices and Point Interactions

$$A_{ij} = G(x_i, y_j)$$

Graphically, too:



## Matrices and point Interactions

$$\psi(x_i) = \sum_{j=1}^N G(x_i, y_j) \varphi(y_j)$$

This *feels* different.

make  $x$  continuous:  $\Psi(x) = \sum_{j=1}^N G(x, y_j) \varphi(y_j) \leftarrow$  mat inf. tall  
make  $y$  continuous:  $\Psi(x) = \int G(x, y) \varphi(y) dy \leftarrow$  mat. inf. wide

**Q:** Are there enough matrices that come from globally defined  $G$  to make this worth studying?

# Point Interaction Matrices: Examples (I)



- Interpolation

$$\Psi(x) = \sum_{j=1}^n \underbrace{l_j(x)} \varphi(y_j) \quad L$$

- Differentiation

$$\Psi(x) = \sum_{j=1}^n \underbrace{l_j'(x)} \varphi(y_j)$$

- Integration

$$\Psi(x) = \Psi(x) = \sum_{j=1}^n \int_0^x l_j(y) d\zeta_j(y_j)$$

## Point Interaction Matrices: Examples (II)

- Potential evaluation (3D)

$$U(x) = \frac{q_{el}}{4\pi\epsilon_0} \cdot \frac{1}{|x|} \leftarrow \text{electrostatics}$$

$$U(x) = \sum_{j=1}^N \frac{q_{el}}{4\pi\epsilon_0} \frac{1}{|x-y_j|} \varphi(y_j)$$

waves:  $U(x) = C \cdot \frac{e^{ik|x|}}{|x|}$

## Point Interaction Matrices: Examples (III)

• Convolutions

$$\psi(x) = \sum_{j=1}^N G(x - y_j) \varphi(y_j)$$

sub- $O(N^2)$  algorithm? FFT

↳ grid periodic  
equispaced

• Butterfly transform

So yes, there are indeed lots of these things.

## Integral Operators

Why did we go through the trouble of rephrasing matvecs as

$$\psi(x_i) = \sum_{j=1}^N G(x_i, y_j) \varphi(y_j)?$$



## Cheaper Matvecs

$$\psi(x_i) = \sum_{j=1}^N G(x_i, y_j) \varphi(y_j)$$

So what can we do to make evaluating this cheaper?

- sparse (FO / FEM)
- special structure  
    Toeplitz  
    circulant } FFT-based trickery
- low rank

## Fast Dense Matvecs

Consider

$$A_{ij} = u_i v_j,$$

outer product  
 $A = \vec{u} \vec{v}^T$

let  $u = (u_i)$  and  $v = (v_j)$ .

Can we compute  $Ax$  quickly? (for a vector  $x$ )

$$\begin{aligned} A\vec{x} &= \vec{u} \vec{v}^T \vec{x} \\ &= (\vec{u} \vec{v}^T) \vec{x} \quad \textcircled{1} \quad \leftarrow O(n^2) \\ &= \vec{u} (\underbrace{\vec{v}^T \vec{x}}_{O(n)}) \quad \textcircled{2} \quad \leftarrow O(n) \quad \checkmark \end{aligned}$$

## Fast Dense Matvecs (II)

$$A = u_1 v_1^T + \dots + u_K v_K^T$$

$$A \in \mathbb{R}^{N \times N}$$

Does this generalize? What is  $K$  here?

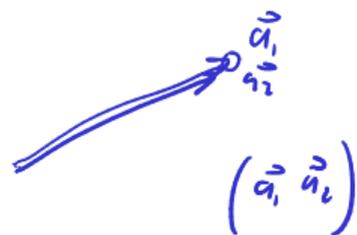
$$\text{rank}(A) = k$$

$$\text{Cost: } O(Nk)$$

## Low-Rank Point Interaction Matrices

Usable with low-rank complexity reduction?

$$\psi(x_i) = \sum_{j=1}^N G(x_i, y_j) \varphi(y_j)$$



$$\psi(x_i) = \sum_{j=1}^N \underbrace{G_1(x_i) G_2(y_j)}_{G(x_i, y_j)} \varphi(y_j)$$

'separation of variables'

$$G(x, y) = \frac{1}{\|x - y\|_2}$$

does not look like this.

rank hard to define numerically because of round-off

## Numerical Rank

What would a *numerical* generalization of 'rank' look like?



# Eckart-Young-Mirsky Theorem

## Theorem (Eckart-Young-Mirsky)

SVD  $A = U\Sigma V^T$ . If  $k < r = \text{rank}(A)$  and

$$A_k = \sum_{i=1}^k \sigma_i u_i v_i^T,$$

then

$$\min_{\text{rank}(B)=k} \|A - B\|_2 = \|A - A_k\|_2 = \sigma_{k+1}.$$

**Q:** What's that error in the Frobenius norm?

So in principle that's good news:

- ▶ We can find the numerical rank.
- ▶ We can also find a factorization that reveals that rank (!)

**Demo:** Rank of a Potential Evaluation Matrix (Attempt 2)

## Constructing a tool

There is still a slight downside, though.

