

# Fréchet Derivatives of Matrix Functions and Applications

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# Outline

- Matrix Functions, their Derivatives, and the Condition Number
- Elementwise Sensitivity
- Physics: Nuclear Activation Sensitivity Problem
- Differential Equations: Predicting Algebraic Error in the FEM

# Matrix Functions

We are interested in functions  $f : \mathbb{C}^{n \times n} \mapsto \mathbb{C}^{n \times n}$  e.g.

**Matrix Exponential**  $e^A = \sum_{k=0}^{\infty} \frac{A^k}{k!}$

**Matrix Cosine**  $\cos(A) = \sum_{k=0}^{\infty} \frac{(-1)^k A^{2k}}{(2k)!}$

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- Define  $f(A)$  by Taylor series when  $f$  is analytic
- If  $A = XDX^{-1}$  then  $f(A) = Xf(D)X^{-1}$
- Differential equations:  $\frac{du}{dt} = Au(t)$ ,  $u = e^{tA}u(0)$
- Use  $\cos(A)$  and  $\sin(A)$  for second order ODEs

# Fréchet Derivatives

Let  $f : \mathbb{C}^{n \times n} \mapsto \mathbb{C}^{n \times n}$  be a matrix function.

## Definition (Fréchet derivative)

The **Fréchet derivative** of  $f$  at  $A$  is the unique linear function  $L_f(A, \cdot) : \mathbb{C}^{n \times n} \mapsto \mathbb{C}^{n \times n}$  such that for all  $E$

$$f(A + E) - f(A) - L_f(A, E) = o(\|E\|).$$

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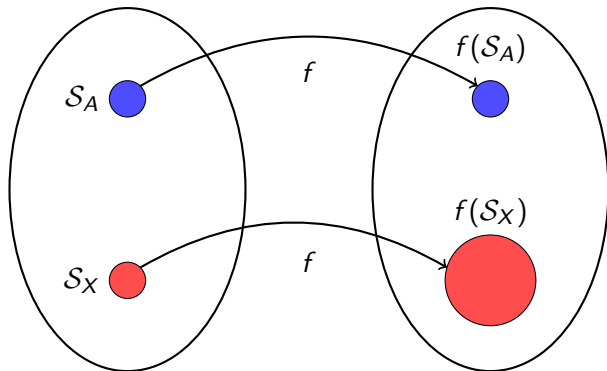
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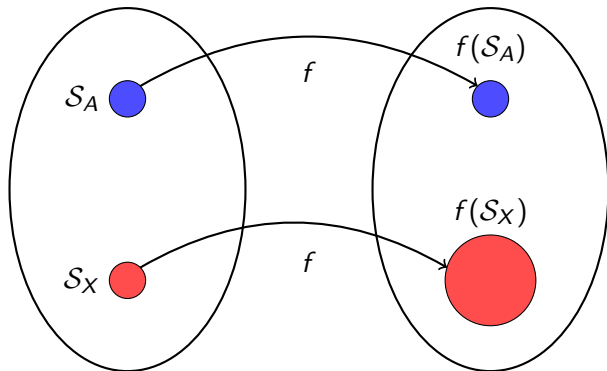
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- **Applications** include manifold optimization, Markov models, bladder cancer, image processing, and network analysis
- **Higher order derivatives** recently analyzed (Higham & R., 2014)

# Sensitivity of Matrix Functions



# Sensitivity of Matrix Functions



The function  $f$  is **well conditioned** at  $A$  and **ill conditioned** at  $X$



# The Norm-wise Condition Number

The two condition numbers for a matrix function are:

$$\text{cond}_{\text{abs}}(f, A) = \max_{\|E\|=1} \|L_f(A, E)\|,$$

$$\text{cond}_{\text{rel}}(f, A) = \max_{\|E\|=1} \|L_f(A, E)\| \frac{\|A\|}{\|f(A)\|}.$$

# Elementwise Sensitivity

If we change just one element  $A_{ij}$ , how is  $f(A)$  affected?

Let  $E_{ij} = [\delta_{ij}]$ , then the difference between  $f(A)$  and  $f(A + \epsilon E_{ij})$  is

$$\|f(A) - f(A + \epsilon E_{ij})\| \approx \epsilon \|L_f(A, E_{ij})\|.$$

- $\|L_f(A, E_{ij})\|$  gives the **sensitivity in  $(i, j)$  component**
- Sometimes we want the  **$t$  most sensitive** elements for  $t = 5: 20$

# A simple algorithm

To compute the most sensitive  $t$  entries of  $A$ :

```
1 for  $i = 1:n$ 
2     for  $j = 1:n$ 
3         if  $A_{ij} \neq 0$ 
4             Compute and store  $\|L_f(A, E_{ij})\|$ 
5         end if
6     end for
7 end for
8 Take the largest  $t$  values of  $\|L_f(A, E_{ij})\|$ 
```

**Cost:** Up to  $O(n^5)$  flops since computing  $L_f(A, E)$  costs  $O(n^3)$  flops

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- **Trivially parallel** but still very expensive when  $A$  is large
- **Speed this up** using block norm estimation (work in progress)

# The Nuclear Activation Sensitivity Problem

- Chemical reactions:  $u'(t) = Au(t)$
- $u(t) = e^{At}u(0)$  tells us the **concentration** of each element at time  $t$
- $q^T u(t)$  is the **dosage** at time  $t$
- $A_{ij}$  represents the **reaction between elements**  $i$  and  $j$  (so ignore  $A_{ij} = 0$ )
- $A_{ij}$  is subject to **measurement error**  
What happens to  $q^T u(t)$  when it changes?



Implications for safety in radiation exposure models etc.

# Nuclear Activation Solution - 1

If  $A_{ij}$  is perturbed, this introduces a **relative error** in  $q^T u(t)$  of

$$\frac{|q^T (e^{tA+\epsilon E_{ij}} - e^{tA}) u(0)|}{|q^T e^{tA} u(0)|} \approx \epsilon \frac{|q^T L_{e^x}(tA, E_{ij}) u(0)|}{|q^T e^{tA} u(0)|}$$

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We note that:

- The denominator is the same for all perturbations
- This requires computing a derivative in all directions  $A_{ij} \neq 0$
- Can we improve upon this?

## Nuclear activation solution - 2

Using  $\text{vec}(AXB) = (B^T \otimes A)\text{vec}(X)$  we see the sensitivity in direction  $E_{ij}$  is

$$|q^T L_{e^x}(tA, E_{ij})u(0)| = |(u(0)^T \otimes q^T)K_{e^x}(tA) \text{vec}(E_{ij})|.$$

Therefore the sensitivity in **ALL  $n^2$  directions** is

$$|[(u(0)^T \otimes q^T)K_{e^x}(tA)]^T| = |\text{vec}(L_{e^x}(tA, \text{unvec}(u(0) \otimes q)^T))^T|.$$

- Only **1 derivative needed** for all sensitivities
- Found **2 bugs** in existing commercial software!
- Extend for time dependent coefficients  $A = A(t)$



# Predicting Algebraic Error in an ODE

Let's solve the model ODE

$$-u'' = f(x), \quad x \in (0, 1), \quad u(0) = u(1) = 0$$

with the finite element method using piecewise linear basis functions  $\phi_i$ .

- Exact solution  $u(x) = e^{-5(x-0.5)^2} - e^{5/4}$  determines  $f(x)$
- Generate a grid of  $n = 19$  equally spaced points  $x_i$
- Generate system  $Ax = b$  where  $A_{ij} = \int_0^1 \phi_i \phi_j$  and  $b_i = f(x_i)$ .  
 $A = \text{diag}(-1, 2, -1)$  in this case
- Solve with CG iteration

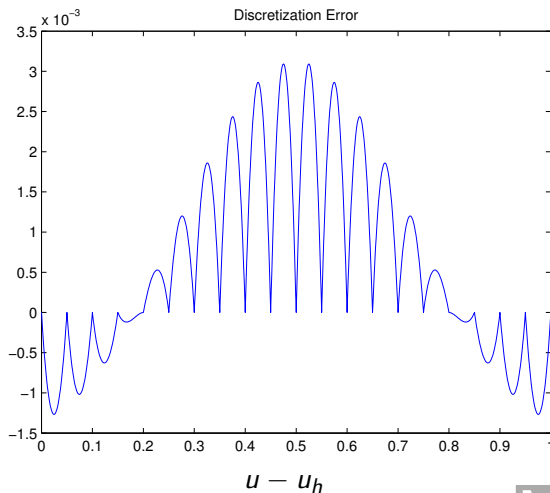
# Algebraic and discretization errors

- Let  $V_h$  be our finite element space (dimension 19)
- Let  $u_h \in V_h$  be the best solution possible from  $V_h$
- Let  $u_{est}^k$  be our numerical solution corresponding to  $k$  iterations of CG

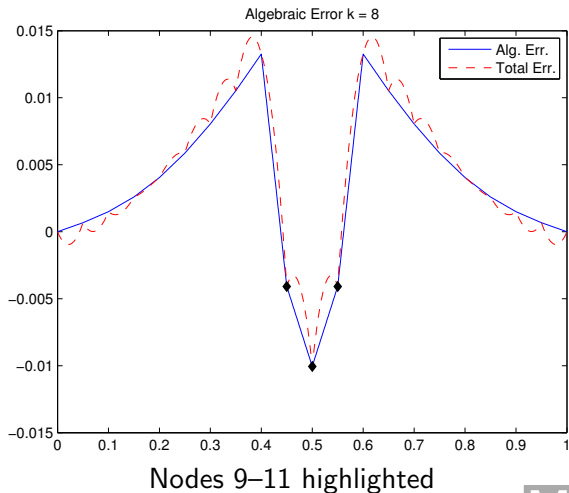
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- The **discretization error** is  $u - u_h$
- The **algebraic error** is  $u_h - u_{est}^k$
- The **total error** is  $u - u_{est}^k = \text{alg. err.} + \text{disc. err.}$
- Sometimes **alg err** dominates the **total err**, how do we detect this?

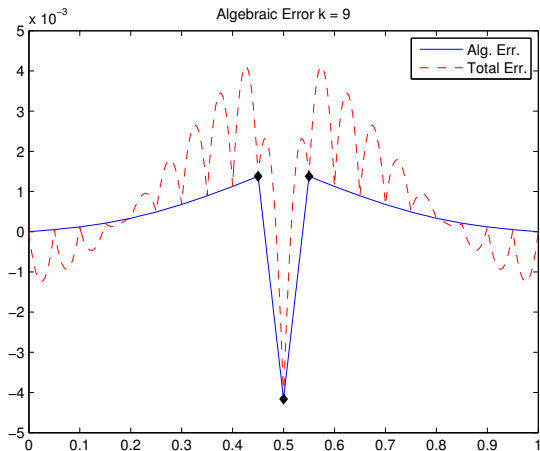
# Discretization error



# Algebraic Error - 8 CG iterations



# Algebraic Error - 9 CG iterations

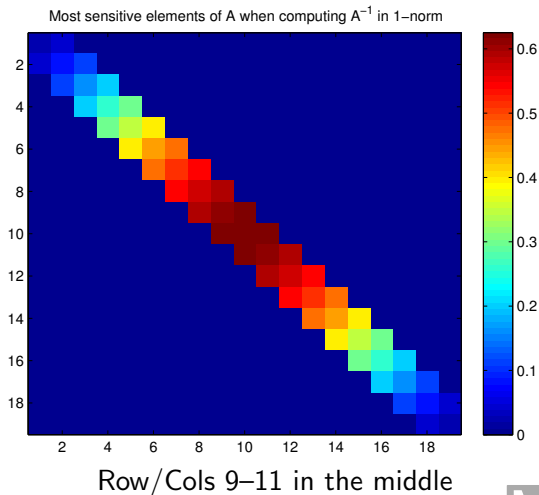


Nodes 9–11 highlighted

# Elementwise sensitivity analysis

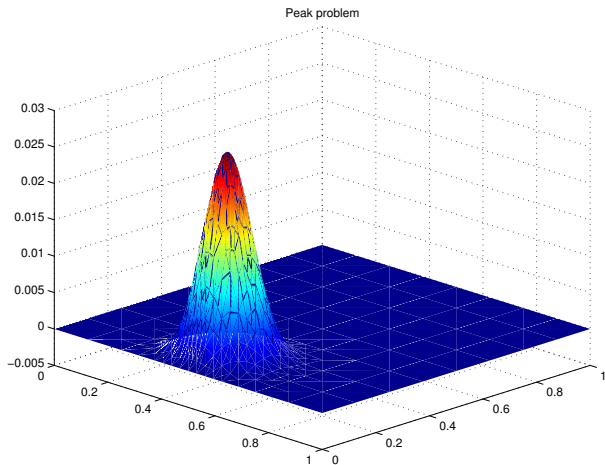
- Taking  $f(A) = A^{-1}$  we can calculate the sensitivity of each element
- $L_f(A, E) = -A^{-1}EA^{-1}$  so easily computed
- Ignore  $A_{ij} = 0$  since the two basis elements don't overlap
- Results plotted on the following heat map

# Elementwise sensitivity analysis

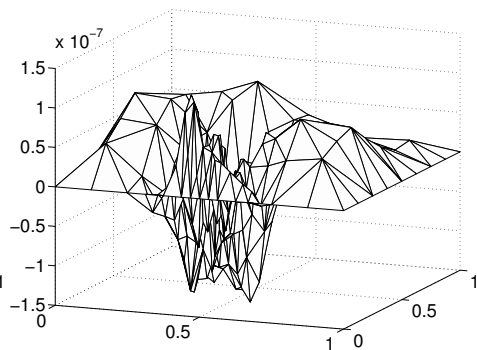
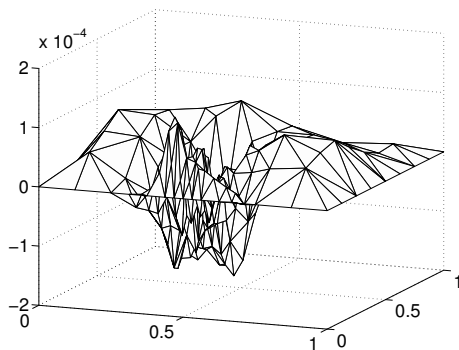




# 2D Peak Problem



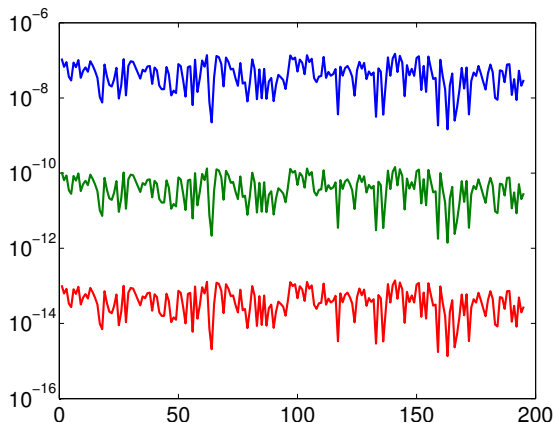
# Algebraic Error Estimation



Left: True algebraic error using 7 CG iterations.

Right: Error in estimated algebraic error using 1st Fréchet derivative.

# Higher Order Derivatives to Estimate Alg. Err.



Componentwise error using  $k$ th order derivatives,  $k = 1, 3, 5$ .

## Possible extensions

- Can this be used to **modify the discretization mesh** to obtain better accuracy? (See Papez, Liesen, and Strakos 2014)
- Currently too expensive: can we **estimate** the sensitivities?
- Can this be extended to  $f(A) = e^A$  (**exponential integrators**)?

# Conclusions

- Explained elementwise sensitivity of matrix functions
- New applications in nuclear physics and FEM analysis
- Former is basically solved, latter needs to be cheaper

## Future work:

- **Estimate** sensitivities more efficiently (block norm estimation)
- **Further comparison** of nuclear physics solution to commercial alternative
- **Further analysis** of ODE problem

# Higher Order Fréchet Derivatives

Higher order derivatives can be defined recursively:

$$L_f^{(k)}(A + E_{k+1}, E_1, \dots, E_k) - L_f^{(k)}(A, E_1, \dots, E_k) = L_f^{(k+1)}(A, E_1, \dots, E_k, E_{k+1}) + o(\|E_{k+1}\|)$$

Also have a simple method to compute them. For example:

$$f \left( \begin{bmatrix} A & E_1 & E_2 & 0 \\ 0 & A & 0 & E_2 \\ 0 & 0 & A & E_1 \\ 0 & 0 & 0 & A \end{bmatrix} \right) = \begin{bmatrix} f(A) & L_f(A, E_1) & L_f(A, E_2) & L_f^{(2)}(A, E_1, E_2) \\ 0 & f(A) & 0 & L_f(A, E_2) \\ 0 & 0 & f(A) & L_f(A, E_1) \\ 0 & 0 & 0 & f(A) \end{bmatrix}$$

More info in Higham & Relton, SIMAX 35(4), 2014.