

Accurate Matrix Computations in the Presence of Roundoff Errors

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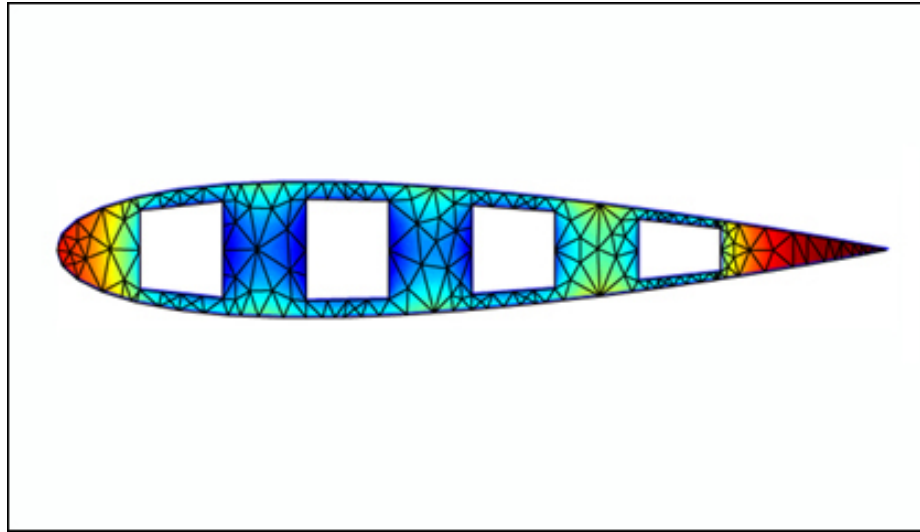
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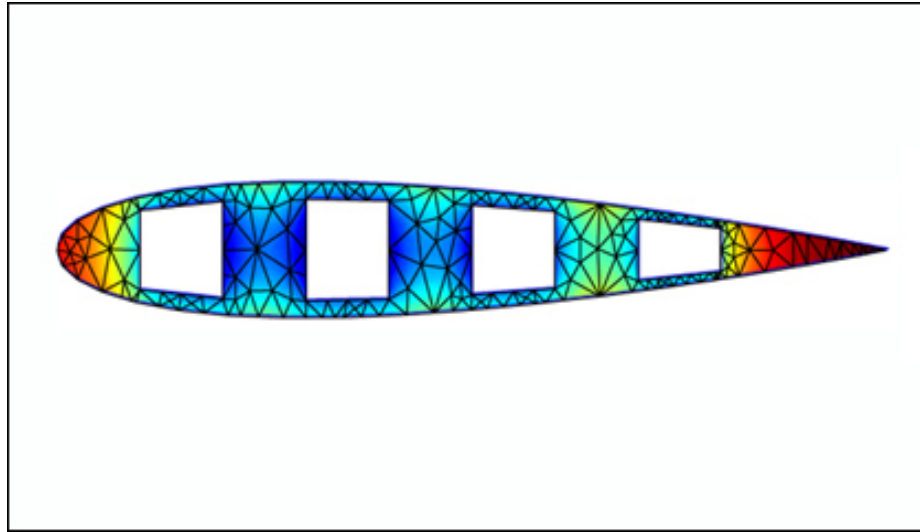
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$$Ax = b, \quad Ax = \lambda x$$

- Solved in *finite precision arithmetic*

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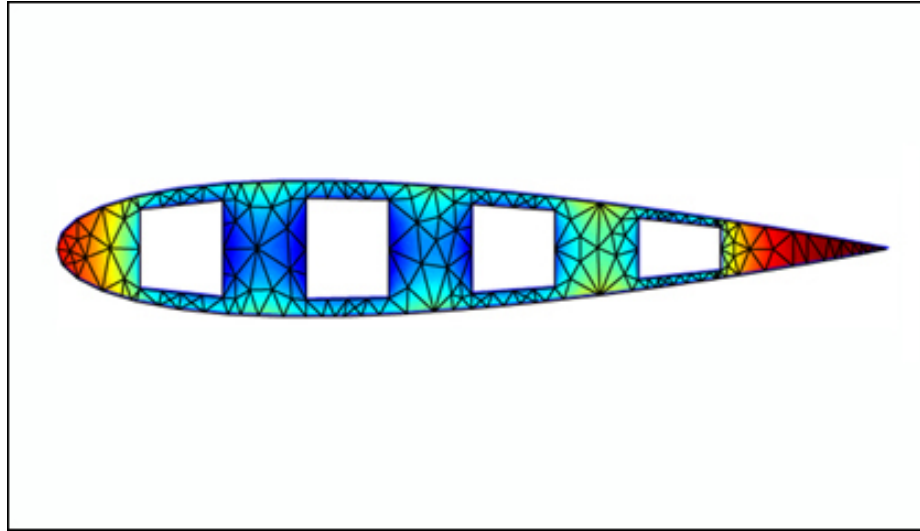


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- **Roundoff Errors** affect the accuracy:

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- The quantity $\varepsilon = 1.1102e - 16 \approx 10^{-16}$ is called **Machine Precision**

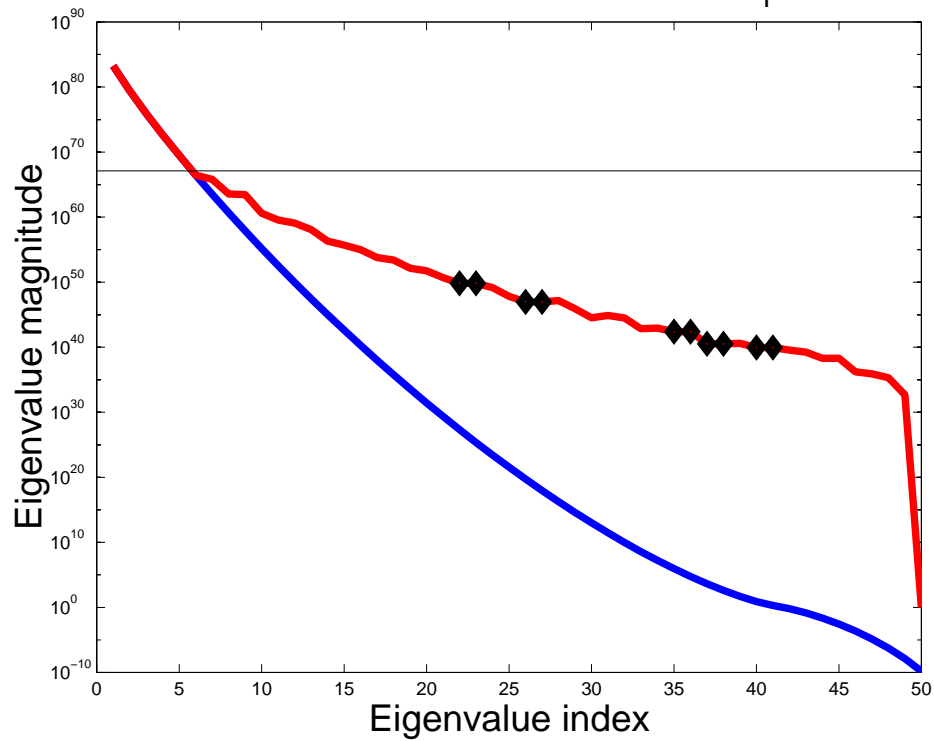
Example: 50×50 Vandermonde Matrix $V = [i^{j-1}]_{i,j=1}^{50}$

$$V = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & 2 & 2^2 & \dots & 2^{49} \\ \vdots & & & & \\ 1 & 50 & 50^2 & & 50^{49} \end{bmatrix}$$

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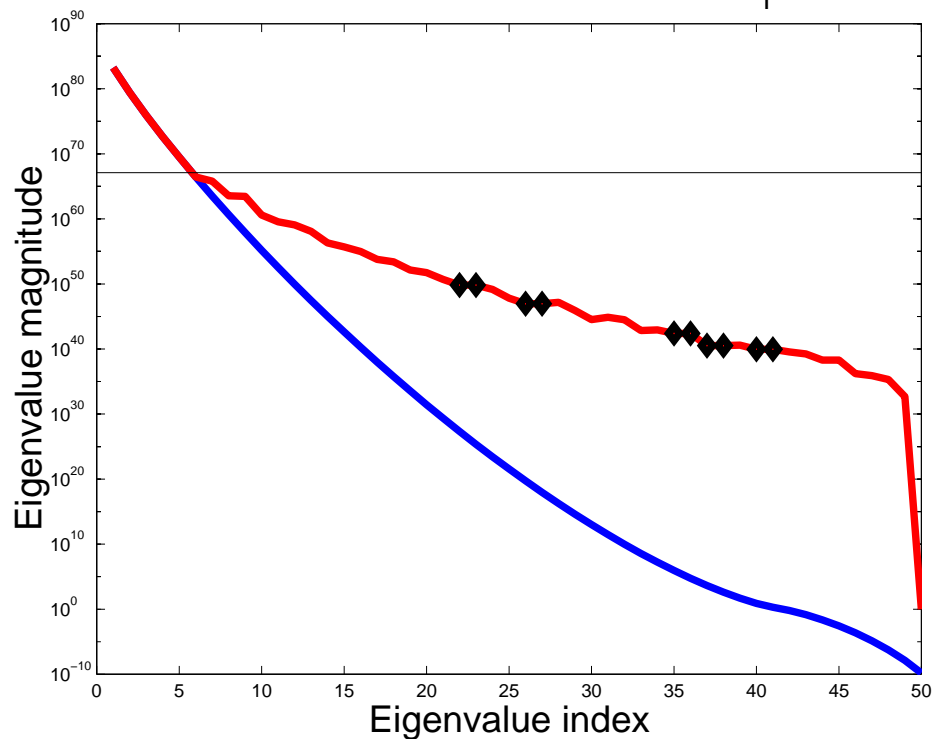
50-by-50 Vandermonde matrix, $x_i=i$



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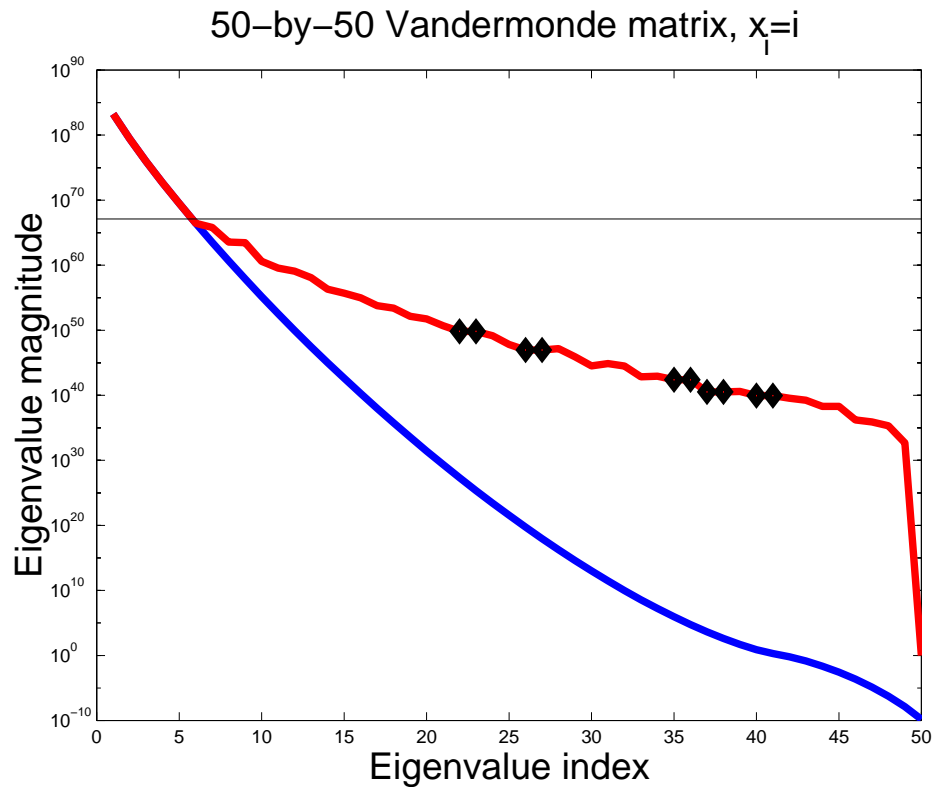
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- **Blue=Accurate Algorithm**, **Red=Traditional Algorithm**
- With traditional algorithm:
Only **eigenvalues** $\geq \|V\|\epsilon \approx 10^{83} \cdot 10^{-16} = 10^{67}$ are accurate

What is the Problem?

- We are computing “small” quantities (e.g., eigenvalues), when the norm of the matrix is “large” ($\|V\| \approx 10^{83}$)
- The quantity $\kappa(V) \equiv \|V\| \cdot \|V^{-1}\|$ is called *Condition number*
- $\kappa(A) \geq 1$ for all A . Equality for A – orthogonal
- When $\kappa(A)$ is “small” (e.g., < 1000), A is *Well Conditioned*
- Otherwise *Ill Conditioned*
- A – well conditioned \Rightarrow traditional algorithms *Always Accurate*
- A – ill conditioned \Rightarrow likely inaccurate

Problem in Computing with Ill Conditioned Matrices

—Subtractive Cancellation

- **Subtractive Cancellation** means:

“small” = “LARGE” – “LARGE”

- if $\hat{a} \approx a > 0$ and $\hat{b} \approx b > 0$ to (say) 9 digits, then

$$\left. \begin{array}{l} \hat{a} \cdot \hat{b} \approx a \cdot b \\ \hat{a} + \hat{b} \approx a + b \\ \hat{a}/\hat{b} \approx a/b \end{array} \right\} \text{ to about 9 digits}$$

BUT

$$\hat{a} - \hat{b}$$

may have **no correct digits** if $a \approx b$:

$$\begin{array}{r} .123456789xxx \\ - .123456789yyy \\ \hline .000000000zzz \end{array}$$

- So: **NO SUBTRACTIONS \implies ACCURACY!**

Accurate Computations with Matrices

- Not always possible:
 - if A is *unstructured*, then general theory applies
- If A is *structured*, accurate computations are possible when:
 - The structure is explicitly revealed
 - The quantities of interest are accurately determined
 - Subtraction-free computation is possible

Examples of Structures Revealed Explicitly

• Vandermonde $V = [x_i^{j-1}]_{i,j=1}^n$, **parameters:** x_i

• Cauchy $V = \left[\frac{1}{x_i + y_j} \right]$, **parameters:** x_i, y_j

• M-matrices

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \dots & a_{3n} \\ \vdots & \vdots & \vdots & \dots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{nn} \end{bmatrix}; \quad \begin{array}{l} a_{ii} \geq 0 \\ a_{ij} \leq 0, \quad i \neq j \\ \sum_{j=1}^n a_{ij} \geq 0 \end{array}$$

parameters: a_{ij} , $i \neq j$ and $s_i = \sum_{j=1}^n a_{ij}$ (but NOT a_{ii} !!!)

• Other classes of structured matrices also possible:

- Generalized and Polynomial Vandermonde
- Green's matrices
- Oscillatory, Totally Positive, Sign-regular
- ...

Gaussian Elimination of a Diagonally Dominant M-matrix

- Traditional Gaussian elimination:

$$a'_{ij} = a_{ij} - \frac{a_{ik}a_{kj}}{a_{kk}}, \quad i \neq j;$$

(NO subtractive cancellation!)

$$a'_{ii} = a_{ii} - \frac{a_{ik}a_{ki}}{a_{kk}}$$

(possible subtractive cancellation)

- Schur complement is also a Diagonally Dominant M-matrix

- **New Algorithm:**

– Diagonal elements: $a_{kk} = s_k - \sum_{j \neq k} a_{kj}$

– Off diagonals: $a'_{ij} = a_{ij} - \frac{a_{ik}a_{kj}}{a_{kk}}$

– Row sums: $s'_i = s_i - \frac{a_{ik}}{a_{kk}} s_k$

- Schur complement determined accurately by a'_{ij}, s'_i

- No subtractive cancellation \implies Accuracy!

Conclusions

- Accurate computations with structured matrices are possible when
 - The matrix structure is revealed explicitly
 - The computed quantities are well determined
 - Subtractive cancellation is avoided
- Works for many classes of structured matrices
- Many open problems remain
- This talk, MATLAB software and papers:
`math.mit.edu/~plamen`