

ESO208A: Computational Methods in Engineering

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Recap

- Direct Methods:
 - Gauss Elimination,
 - Gauss-Jordan Elimination,
 - LU-Decomposition,
 - Thomas Algorithm (for tri-diagonal banded matrix)
 - Cholesky Decomposition



LU decomposition

Error Analysis

Forward Error Analysis

Recall

$$f(x)$$

$$x + \Delta x$$

$$C_p = \frac{|\Delta f / f|}{|\Delta x / x|}$$

$$|x|$$

$$|\Delta x|$$

$$\Rightarrow \frac{|\Delta f|}{|f|} = C_p \left| \frac{\Delta x}{x} \right|$$

Linear system

$$Ax = b$$

$$x = A^{-1}b$$

What would be the relative changes in x , i.e. $\frac{\Delta x}{x}$, due to small perturbations in A , $\frac{\Delta A}{A}$, or b , $\frac{\Delta b}{b}$.



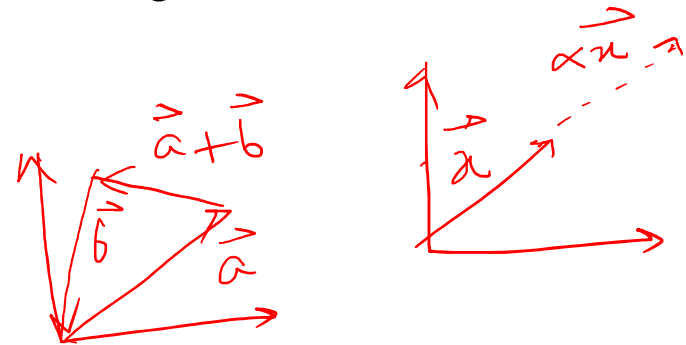
LU decomposition

For Error Analysis, we need to first understand vector and matrix norms

Vector Norm

A vector norm is a measure (in some sense) of the size or “length” of a vector

- Properties of Vector Norm:
 - $\|\mathbf{x}\| > 0$ for $\mathbf{x} \neq \mathbf{0}$; $\|\mathbf{x}\| = 0$ iff $\mathbf{x} = \mathbf{0}$
 - $\|\alpha\mathbf{x}\| = |\alpha|\|\mathbf{x}\|$ for a scalar α
 - $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$



- L_p -Norm of a vector \mathbf{x} :

$$\|\mathbf{x}\|_p = (|x_1|^p + |x_2|^p \dots + |x_n|^p)^{1/p}$$

- Example Norms:

- $p = 1$: sum of the absolute values
- $p = 2$: Euclidean norm
- $p \rightarrow \infty$: maximum absolute value, $\|\mathbf{x}\|_\infty = \max_{0 \leq i \leq n} |x_i|$

$$\mathbf{x} = \begin{bmatrix} 4 \\ 2 \\ 1 \end{bmatrix}$$
$$L_\infty = 4$$



LU decomposition

Matrix Norm: A matrix norm is a measure of the size of a matrix

- Properties of Matrix norm:
 - $\|A\| > 0$ for $A \neq \mathbf{0}$; $\|A\| = 0$ iff $A = \mathbf{0}$
 - $\|\alpha A\| = |\alpha| \|A\|$ for a scalar α
 - $\|A + B\| \leq \|A\| + \|B\|$
 - $\|AB\| \leq \|A\| \|B\|$
 - $\|Ax\| \leq \|A\| \|x\|$ for consistent matrix and vector norms
- L_p Norm of a matrix A :

$$\|A\|_p = \max_{x \neq 0} \frac{\|Ax\|_p}{\|x\|_p}$$



LU decomposition

Matric Norm:

- *Column-Sum* norm: $\|\mathbf{A}\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^n |a_{ij}|$
- *Spectral norm*: $\|\mathbf{A}\|_2 = \left(\max_{1 \leq j \leq n} |\lambda_j| \right)^{1/2}$ where, λ_j are the eigenvalues of the square symmetric matrix $\mathbf{A}^T \mathbf{A}$.
- *Row-Sum* norm: $\|\mathbf{A}\|_\infty = \max_{1 \leq i \leq n} \sum_{j=1}^n |a_{ij}|$
- *Frobenius* norm: $\|\mathbf{A}\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n a_{ij}^2} = \sqrt{\text{trace}(\mathbf{A}^T \mathbf{A})}$

Trace of a matrix is the sum of elements on the main diagonal



LU decomposition

Matrix Norm

- Spectral Radius: largest absolute eigenvalue of matrix A denoted by $\rho(A)$
 - If there are m distinct eigenvalues of A : $\rho(A) = \max_{1 \leq i \leq m} |\lambda_i|$
 - Lower bound of all matrix norms: $\rho(A) \leq \|A\|$

$$\boxed{Ax_i = \lambda_i x_i} \quad \begin{array}{l} \lambda_i - \text{eigen} \\ \text{values} \\ x_i - \text{eigen} \\ \text{vectors} \end{array}$$

Spectral radius provides a lower bound
on the matrix norms

$$\|Ax_i\| = \|\lambda_i x_i\|$$
$$\|Ax_i\| = |\lambda_i| \|x_i\|$$

But $\|Ax_i\| \leq \|A\| \|x_i\|$

$$\Rightarrow \|A\| \|x_i\| \geq |\lambda_i| \|x_i\|$$
$$\Rightarrow \boxed{\|A\| \geq |\lambda_i|} \quad \max |\lambda_i|$$

- For any norm of matrix A : $\rho(A) = \lim_{n \rightarrow \infty} \|A^n\|^{1/n}$



LU decomposition

Matric Norm:

Example $A = \begin{bmatrix} -2 & 3 \\ 4 & -5 \end{bmatrix} \quad \begin{bmatrix} 5 \\ 9 \end{bmatrix}$

$$\|A\|_{\infty} = 9$$
$$\|A\|_1 = 8 \quad [6 \ 8]$$



LU decomposition

Condition Number

Condition number

$$Ax = b$$

(a) Perturb A

$$(A + \Delta A)(x + \Delta x) = b$$

$$\cancel{Ax} + \Delta Ax + A\Delta x + \Delta A\Delta x = \cancel{b}$$

$$\Rightarrow \Delta x = -A^{-1}\Delta A(x + \Delta x)$$

Norm

$$\|\Delta x\| = \|A^{-1}\Delta A(x + \Delta x)\|$$

$$\leq \|A^{-1}\| \|\Delta A(x + \Delta x)\|$$

$$\leq \|A^{-1}\| \|\Delta Ax\| + \|A^{-1}\| \|\Delta A\Delta x\|$$

we assume

$$\|\Delta A\Delta x\| \leq$$

$$\|\Delta x\| \leq \|A^{-1}\| \|\Delta A\| \|x\|$$

$$\Rightarrow \frac{\|\Delta x\|}{\|x\|} \leq \underbrace{\|A^{-1}\| \|A\|}_{C(A)} \frac{\|\Delta A\|}{\|A\|}$$

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

(b) Perturb b

$$A(x + \Delta x) = (b + \Delta b)$$

$$\Rightarrow \Delta x = A^{-1}\Delta b$$

$$\Rightarrow \|\Delta x\| \leq \|A^{-1}\| \|\Delta b\|$$

$$\leq \|A^{-1}\| \|b\| \frac{\|\Delta b\|}{\|b\|}$$

$$\leq \|A^{-1}\| \|A\| \|x\| \frac{\|\Delta b\|}{\|b\|}$$

$$\Rightarrow \frac{\|\Delta x\|}{\|x\|} \leq \|A^{-1}\| \|A\| \frac{\|\Delta b\|}{\|b\|} \quad C(A) = \|A^{-1}\| \|A\|$$



LU decomposition

Condition Number

Example

$$x_1 + 2x_2 = 10 \quad (443)$$

$$1.1x_1 + 2x_2 = 10.4 \quad \begin{matrix} \text{841} \\ \text{1.05} \end{matrix}$$

$$\| \Delta x \|_0 = 4$$

$$A = \begin{bmatrix} 1 & 2 \\ 1.1 & 2 \end{bmatrix}$$

$$\| A \|_{\infty} = 3.1$$

$$A^{-1} = \begin{bmatrix} -10 & 10 \\ 5.5 & -5 \end{bmatrix}$$

$$\| A^{-1} \|_{\infty} = 20$$

$$\begin{aligned} C(A) &= \| A^{-1} \|_{\infty} \| A \|_{\infty} \\ &= 3.1 \times 20 = \underline{\underline{62}} \end{aligned}$$

ill. conditioned

Smallest condition number
 $A = I \quad C(A) = 1$



LU decomposition

Condition Number

If we change 1.1 to 1.05, what would be the corresponding change in x

$$\frac{\|\Delta x\|}{\|x\|} \leq C_p \frac{\|\Delta A\|}{\|A\|}$$
$$\leq 62 \cdot \frac{0.05}{3.1}$$

$$\frac{\|\Delta x\|}{\|x\|} \leq 1$$

$$\|\Delta x\| \leq \|x\|_\infty$$

$$\|\Delta x\| \leq \underline{\underline{4}}$$

$$x = \begin{bmatrix} 4 \\ 3 \end{bmatrix}$$



Condition Number

Condition Number

Recall: Determinant is not a good measure of the ill or well conditioning of the matrix

$$\begin{array}{l} A = \begin{bmatrix} 1 & 2 \\ 1.1 & 2 \end{bmatrix} \quad \det(A) = -0.2 \\ \downarrow C(A)=62 \\ A = \begin{bmatrix} 1000 & 2000 \\ 1100 & 2000 \end{bmatrix} \quad \det(A) = 2 \times 10^5 \\ \|A\|_{\infty} = 3100 \\ A^{-1} = \begin{bmatrix} -0.01 & 0.01 \\ 0.0055 & -0.005 \end{bmatrix} \quad \|A^{-1}\|_{\infty} = 0.02 \\ C(A) = \|A^{-1}\|_{\infty} \|A\|_{\infty} \\ = \underline{\underline{62}} \quad \underline{\underline{\text{invariant}}} \end{array}$$

Measure of $C(A)$ is independent of the scaling, which is a good thing



Condition Number

Question: It is always recommended that after estimating X , substitute it in the equation and see whether the equation is satisfied or not. Is the residual $r = b - \tilde{b}$ a good measure for $e = x - \tilde{x}$

$$\begin{aligned} Ax &= b \\ \text{Instead of } x \text{ we estimated } \tilde{x} \\ A\tilde{x} &= \tilde{b} \\ r = b - \tilde{b} \text{ is small, then the} \\ &\text{estimate } \tilde{x} \text{ is good?} \end{aligned}$$



Condition Number

Question: It is always recommended that after estimating X, substitute it in the equation and see whether the equation is satisfied or not.

$$e = x - \tilde{x}$$

$$r = b - \tilde{b}$$

$$Ax - A\tilde{x} = r$$

$$\Rightarrow A(x - \tilde{x}) = r$$

$$\Rightarrow e = A^{-1}r$$

$$\Rightarrow \|e\| \leq \|A^{-1}\| \|r\| \quad \text{--- (1)}$$

$$Ax = b$$

$$\|b\| = \|Ax\|$$

$$\|b\| \leq \|A\| \|x\|$$

$$\Rightarrow \|x\| \geq \frac{\|b\|}{\|A\|} \quad \text{--- (2)}$$

$$\frac{\|e\|}{\|x\|} \leq \frac{\|A^{-1}\| \|r\|}{\|b\| \|A\|}$$

$$\leq \|A^{-1}\| \|A\| \frac{\|r\|}{\|b\|}$$

$$\Rightarrow \boxed{\frac{\|e\|}{\|x\|} \leq \underline{\underline{C(A)}} \frac{\|r\|}{\|b\|}}$$



Iterative Refinement or Improvement

Iterative Refinement or Improvement

$$\boxed{Ax = b}$$

$$A\tilde{x} = \tilde{b}$$

$$Ax - A\tilde{x} = b - \tilde{b}$$

$$A(x - \tilde{x}) = r$$

$$\Rightarrow \boxed{Ae = r}$$

Unknown "e" can be estimated by $O(n^2)$

$$e = x - \tilde{x}$$

$$\Rightarrow \boxed{x = \tilde{x} + e}$$

Example

$$A = \begin{bmatrix} 3 & 1 \\ 2 & 4 \end{bmatrix} \quad b = \begin{bmatrix} 5 \\ 10 \end{bmatrix} \quad x = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$\tilde{x} = \begin{bmatrix} 0.5 \\ 1.5 \end{bmatrix}$$

$$A\tilde{x} = \tilde{b} = \begin{bmatrix} 3 \\ 7 \end{bmatrix}$$

$$r = b - \tilde{b} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$$

$$Ae = r \longrightarrow e = \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$$

$$\begin{aligned} x &= \tilde{x} + e \\ &= \begin{bmatrix} 0.5 \\ 1.5 \end{bmatrix} + \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \end{aligned}$$



Summary

- Forward error analysis
- Vector norm and matrix norm
- Condition number of a matrix

