



2.29 Numerical Fluid Mechanics

Spring 2015 – Lecture 6

REVIEW Lecture 5:

Systems of Linear Equations

- Direct Methods for solving Linear Equation Systems

- Determinants and Cramer's Rule
- Gauss Elimination

- Algorithm

- Forward Elimination/Reduction to Upper Triangular System
- Back-Substitution
- Number of Operations: $O(\frac{2}{3}n^3 + n^2) + O(n^2)$

- Numerical implementation and stability

- Partial Pivoting
- Equilibration
- Full pivoting
- Well suited for dense matrices
- Issues: round-off, cost, does not vectorize/parallelize well

- Special cases, Multiple RHSs, Operation count $O(n^3 + pn^2) + O(pn^2)$



TODAY's Lecture: Systems of Linear Equations II

- Direct Methods
 - Cramer's Rule
 - Gauss Elimination
 - Algorithm
 - Numerical implementation and stability
 - Partial Pivoting
 - Equilibration
 - Full Pivoting
 - Well suited for dense matrices
 - Issues: round-off, cost, does not vectorize/parallelize well
 - Special cases, Multiple right hand sides, Operation count
 - LU decomposition/factorization
 - Error Analysis for Linear Systems
 - Condition Number
 - Special Matrices: Tri-diagonal systems
- Iterative Methods
 - Jacobi's method
 - Gauss-Seidel iteration
 - Convergence



Reading Assignment

- **Chapters 9 and 10 of “Chapra and Canale, Numerical Methods for Engineers, 2006/2010/204.”**
 - Any chapter on “Solving linear systems of equations” in references on CFD that we provided. For example: chapter 5 of “J. H. Ferziger and M. Peric, Computational Methods for Fluid Dynamics. Springer, NY, 3rd edition, 2002”



LU Decomposition/Factorization:

LU Decomposition: Separates time-consuming elimination for A from that for b / B

The coefficient Matrix $\bar{\bar{A}}$ is decomposed as

$$\bar{\bar{A}} = \bar{\bar{L}} \cdot \bar{\bar{U}}$$

where $\bar{\bar{L}}$ is a lower triangular matrix
and $\bar{\bar{U}}$ is an upper triangular matrix

$$\bar{\bar{L}} = [l_{ij}] = \begin{bmatrix} l_{11} & 0 & \cdot & \cdot & \cdot & \cdot & 0 \\ l_{21} & l_{22} & \cdot & \cdot & \cdot & \cdot & \cdot \\ \vdots & \vdots & \cdot & \cdot & \cdot & \cdot & \cdot \\ \vdots & \vdots & \cdot & l_{kk} & \cdot & \cdot & \cdot \\ \vdots & \vdots & \cdot & \cdot & \cdot & \cdot & 0 \\ l_{n1} & \cdot & \cdot & \cdot & \cdot & l_{n,n-1} & l_{nn} \end{bmatrix}$$

Then the solution is performed in two simple steps

1. $\bar{\bar{L}}\vec{y} = \vec{b}$ Forward substitution

2. $\bar{\bar{U}}\vec{x} = \vec{y}$ Back substitution

$$\bar{\bar{U}} = [u_{ij}] =$$

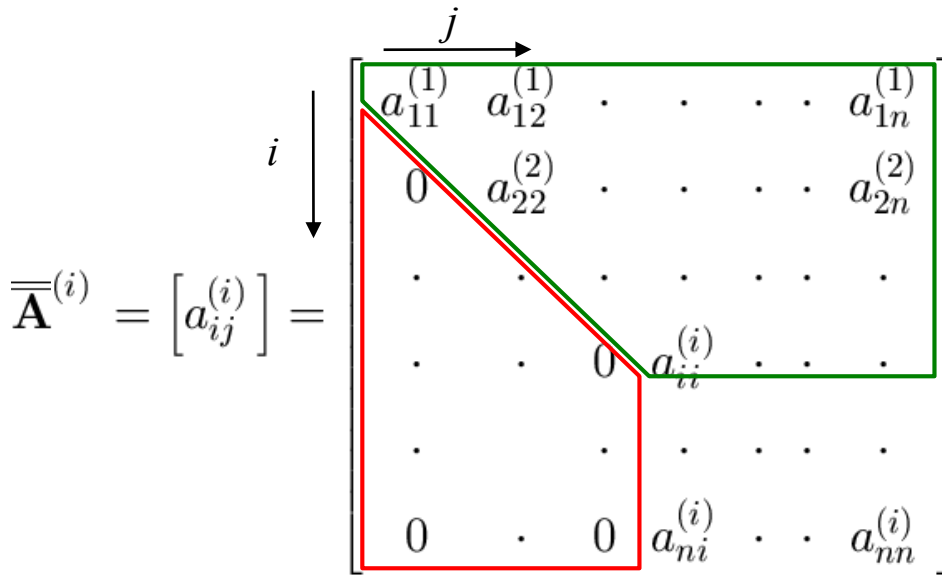
$$\bar{\bar{U}} = \begin{bmatrix} u_{11} & u_{12} & \cdot & \cdot & \cdot & \cdot & u_{1n} \\ 0 & u_{22} & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & u_{kk} & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & u_{n-1,n} \\ 0 & \cdot & \cdot & \cdot & \cdot & 0 & u_{nn} \end{bmatrix}$$

How to determine $\bar{\bar{L}}$ and $\bar{\bar{U}}$?



LU Decomposition / Factorization

via Gauss Elimination, assuming no pivoting needed



Gauss Elimination (GE): iteration eqns. for the reduction at step k are

$$a_{ij}^{(k+1)} = a_{ij}^{(k)} - m_{ik} a_{kj}^{(k)}, \quad m_{ik} = a_{ik}^{(k)} / a_{kk}^{(k)}$$

This gives the final changes occurring in reduction steps $k = 1$ to $k = i-1$

After reduction step $i-1$:

Above and on diagonal: $i \leq j$

Unchanged after step $i-1$: $a_{ij}^{(n)} = \dots a_{ij}^{(i)}$

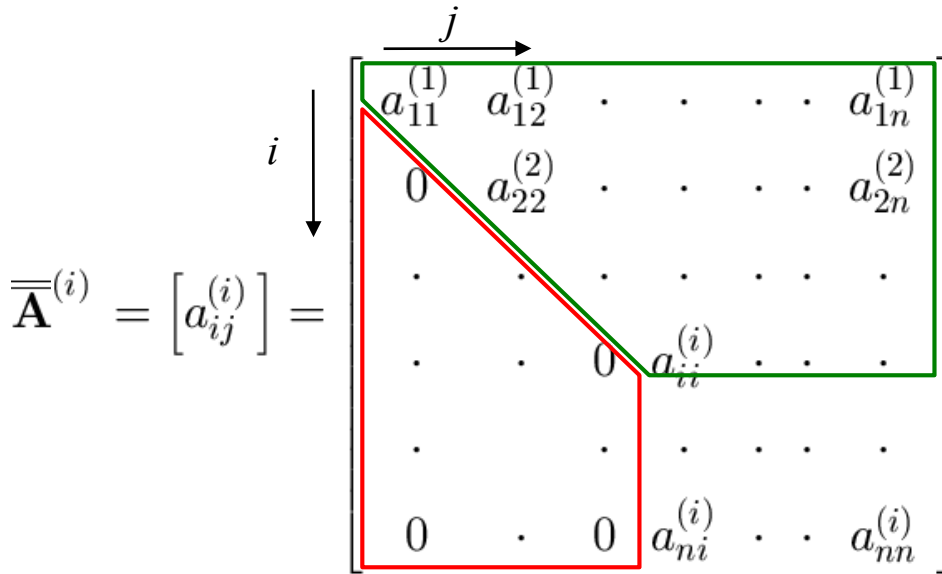
Below diagonal: $j < i$

Become and remain 0 in step j : $a_{ij}^{(n)} = \dots a_{ij}^{(j+1)} = 0$



LU Decomposition / Factorization

via Gauss Elimination, assuming no pivoting needed



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Above and on diagonal: $i \leq j$

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Now, to evaluate the changes that accumulated from when one started the elimination, let's try to sum this iteration equation, from:

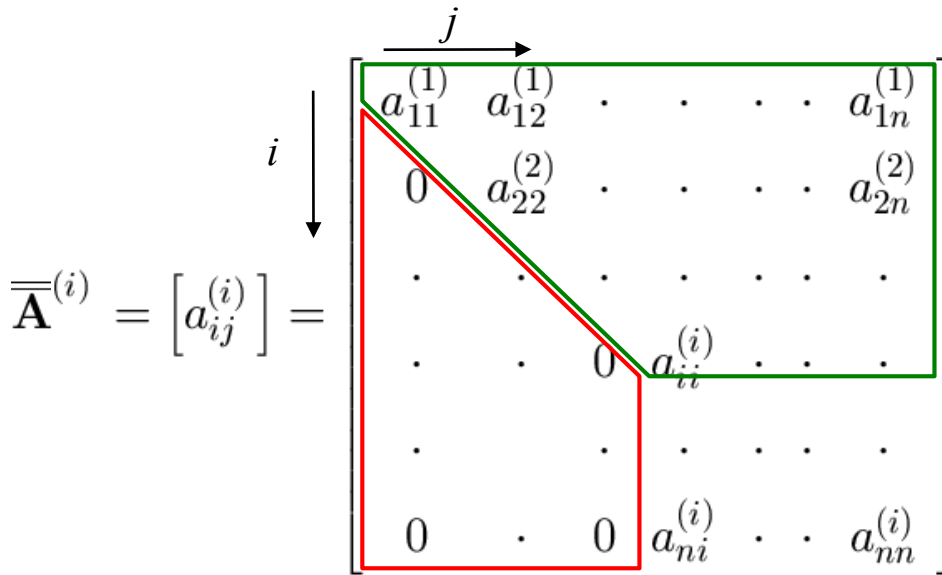
- 1 to $i-1$ for above and on diagonal
- 1 to j for below diagonal

As done in class, you can also sum up to an arbitrary r and see which terms remain.



LU Decomposition / Factorization

via Gauss Elimination, assuming no pivoting needed



After reduction step $i-1$:

Above and on diagonal: $i \leq j$

Unchanged after step $i-1$: $a_{ij}^{(n)} = \dots a_{ij}^{(i)}$

Below diagonal: $j < i$

Become and remain 0 in step j : $a_{ij}^{(n)} = \dots a_{ij}^{(j+1)} = 0$

Gauss Elimination (GE): iteration eqns. for the reduction at step k are

$$a_{ij}^{(k+1)} = a_{ij}^{(k)} - m_{ik} a_{kj}^{(k)}, \quad m_{ik} = a_{ik}^{(k)} / a_{kk}^{(k)}$$

This gives the final changes occurring in reduction steps $k = 1$ to $k = i-1$

Σ these step- k eqns. from $(k=1$ to $i-1) \Rightarrow$
Gives the total change above diagonal:

$$i \leq j : a_{ij}^{(i)} = a_{ij} - \sum_{k=1}^{i-1} m_{ik} a_{kj}^{(k)}$$

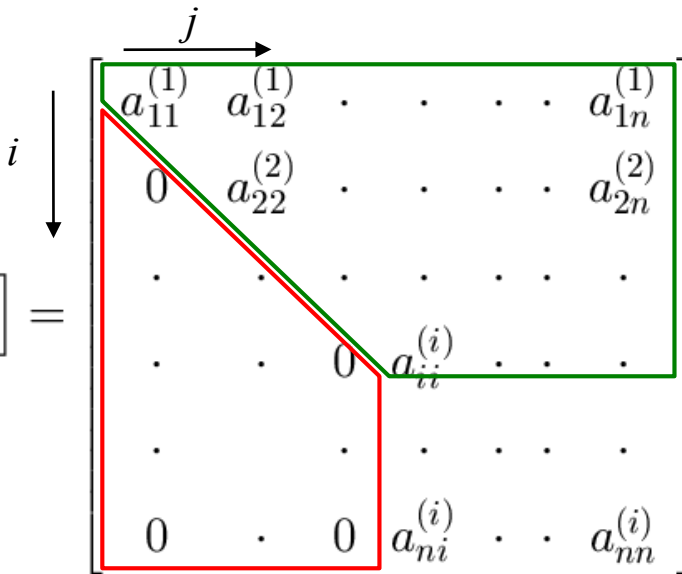
Σ this step- k eqns. from $(k=1$ to $j) \Rightarrow$
Gives the total change below diagonal:

$$i > j : a_{ij}^{(i)} = 0 = a_{ij} - \sum_{k=1}^j m_{ik} a_{kj}^{(k)}$$



LU Decomposition / Factorization

via Gauss Elimination, assuming no pivoting needed



After reduction step $i-1$:

Above and on diagonal: $i \leq j$

Unchanged after step $i-1$: $a_{ij}^{(n)} = \dots a_{ij}^{(i)}$

Below diagonal: $j < i$

Become and remain 0 in step j : $a_{ij}^{(n)} = \dots a_{ij}^{(j+1)} = 0$

Summary: summing the changes in reduction steps $k = 1$ to $k = i-1$:

$$a_{ij}^{(k+1)} = a_{ij}^{(k)} - m_{ik} a_{kj}^{(k)}, \quad m_{ik} = a_{ik}^{(k)} / a_{kk}^{(k)}$$

We obtained: Total change above diagonal

$$i \leq j : a_{ij}^{(i)} = a_{ij} - \sum_{k=1}^{i-1} m_{ik} a_{kj}^{(k)} \quad (1)$$

We obtained: Total change below diagonal

$$i > j : a_{ij}^{(i)} = 0 = a_{ij} - \sum_{k=1}^j m_{ik} a_{kj}^{(k)} \quad (2)$$

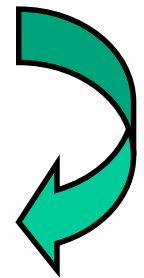
→ Now, if we define:

$$m_{ii} = 1, \quad i = 1, \dots, n$$

and use them in equations (1) and (2) =>

$$\left\{ \begin{array}{l} i \leq j : a_{ij} = \sum_{k=1}^i m_{ik} a_{kj}^{(k)} \\ i > j : a_{ij} = \sum_{k=1}^j m_{ik} a_{kj}^{(k)} \end{array} \right.$$

$$\Rightarrow a_{ij} = \sum_{k=1}^{\min(i,j)} m_{ik} a_{kj}^{(k)}$$





LU Decomposition / Factorization

via Gauss Elimination, assuming no pivoting needed

Result seems to be a 'Matrix product': $a_{ij} = \sum_{k=1}^{\min(i,j)} m_{ik} a_{kj}^{(k)}$ Sum stops at diagonal

Lower triangular

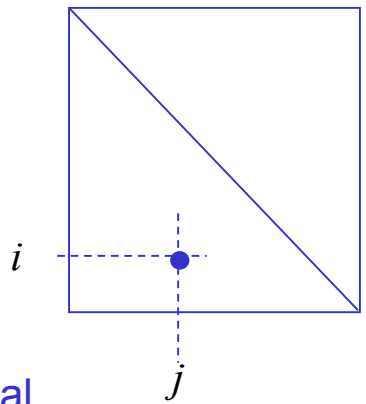
Upper triangular

Below diagonal
 a_{ij}

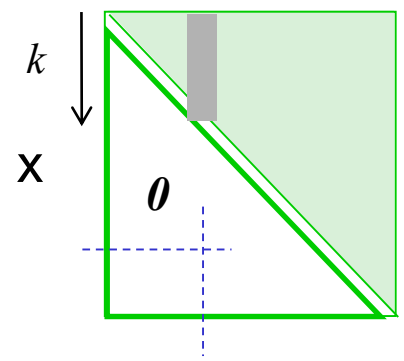
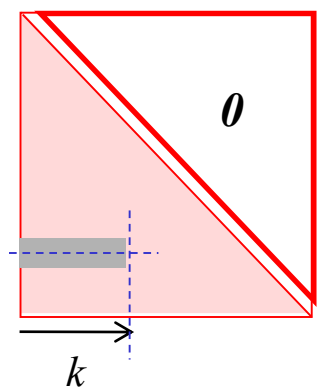
m_{ik}

$a_{kj}^{(k)}$

$i > j :$
 $i > j : a_{ij} = \sum_{k=1}^j m_{ik} a_{kj}^{(k)}$

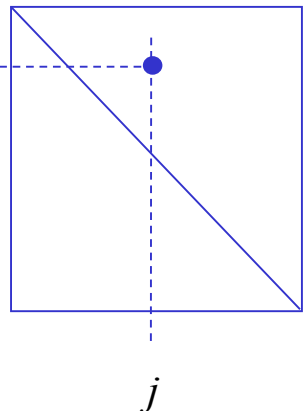


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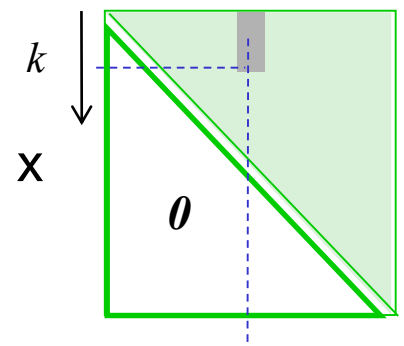
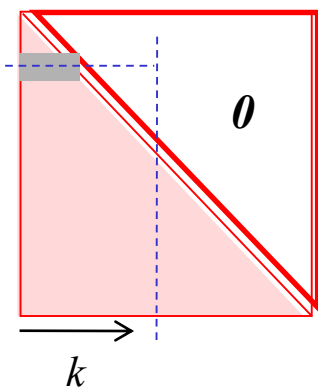


Above diagonal

$i \leq j :$
 $i \leq j : a_{ij} = \sum_{k=1}^i m_{ik} a_{kj}^{(k)}$



=





LU Decomposition / Factorization

via Gauss Elimination, assuming no pivoting needed

GE reduction directly yields LU factorization

$$\overline{\overline{\mathbf{A}}} = \overline{\overline{\mathbf{L}}} \cdot \overline{\overline{\mathbf{U}}}$$

Lower triangular

$$\overline{\overline{\mathbf{L}}} = l_{ij} = \begin{cases} 0 & i < j \\ 1 & i = j \\ m_{ij} & i > j \end{cases}$$

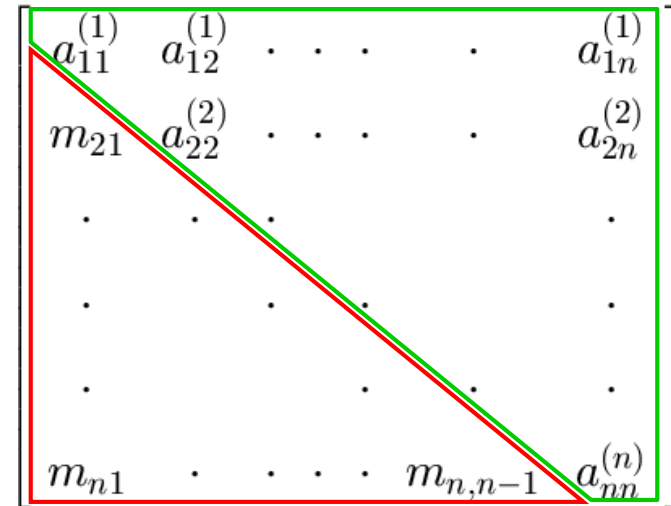
Upper triangular

$$\overline{\overline{\mathbf{U}}} = u_{ij} = \begin{cases} a_{ij}^{(i)} & i \leq j \\ 0 & i > j \end{cases}$$

Number of Operations for LU?

Compact storage:

no need for additional memory (the unitary diagonal of L does not need to be stored)



Lower diagonal implied

$$m_{ii} = 1, \quad i = 1, \dots, n$$

(referred to as the Doolittle decomposition)



LU Decomposition / Factorization

via Gauss Elimination, assuming no pivoting needed

GE Reduction directly yields LU factorization

$$\overline{\overline{\mathbf{A}}} = \overline{\overline{\mathbf{L}}} \cdot \overline{\overline{\mathbf{U}}}$$

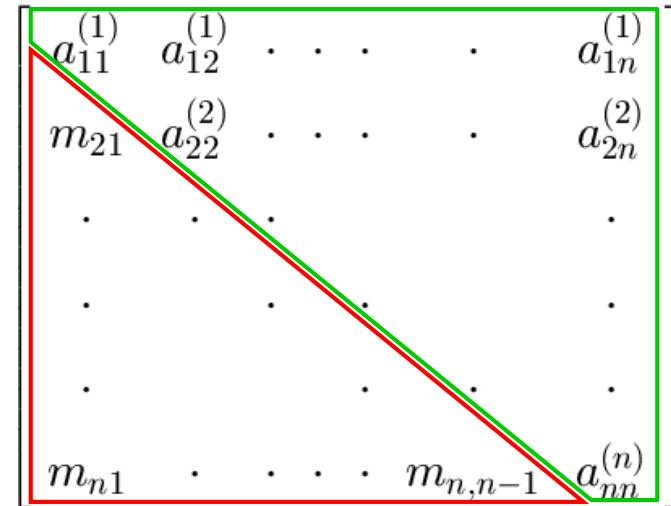
Lower triangular

$$\overline{\overline{\mathbf{L}}} = l_{ij} = \begin{cases} 0 & i < j \\ 1 & i = j \\ m_{ij} & i > j \end{cases}$$

Upper triangular

$$\overline{\overline{\mathbf{U}}} = u_{ij} = \begin{cases} a_{ij}^{(i)} & i \leq j \\ 0 & i > j \end{cases}$$

Compact storage



Lower diagonal implied

$$m_{ii} = 1, \quad i = 1, \dots, n$$

Number of Operations for LU?

Same as Gauss Elimination:

less in Elimination phase (no RHS operations), but more in double back-substitution phase



Pivoting in LU Decomposition / Factorization

Before reduction, step k

$$\begin{bmatrix}
 a_{11}^{(1)} & a_{12}^{(1)} & \cdot & \cdot & \cdot & \cdot & a_{1n}^{(1)} \\
 m_{21} & a_{22}^{(2)} & \cdot & \cdot & \cdot & \cdot & a_{2n}^{(2)} \\
 \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
 \cdot & \cdot & m_{k,k-1} & a_{kk}^{(k)} & \cdot & \cdot & \cdot \\
 \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
 m_{n1} & \cdot & m_{n,k-1} & a_{nk}^{(k)} & \cdot & \dots & a_{nn}^{(k)}
 \end{bmatrix}$$

Pivoting if

$$|a_{ik}^{(k)}| \gg |a_{kk}^{(k)}|, \quad i > k$$

To do this interchange of rows i and k ,

use a pivot vector: $\begin{cases} p_k = i \\ \text{or else} \\ p_k = k \end{cases}$

Pivot element vector

$$p_i, \quad i = 1, \dots, n$$

Forward substitution, step k

$$\bar{\bar{L}}\vec{y} = \vec{b}$$

Interchange rows i and k

$$\begin{bmatrix}
 b_1 \\
 \cdot \\
 \cdot \\
 b_k \\
 \cdot \\
 b_i \\
 \cdot \\
 b_n
 \end{bmatrix}$$

Dummy var.

In code, use $b(p(k))$, which amounts to:

$$\text{If } p_k = i \Rightarrow \begin{cases} b_i^{(k)} = b_k \\ b_k = b_i \\ b_i = b_i^{(k)} \end{cases}$$



LU Decomposition / Factorization: Variations

- Doolittle decomposition:
 - $m_{ii}=1$ (implied but could be stored in **L**)
- Crout decomposition:
 - Directly impose diagonal of **U** equal to 1's (instead of **L**)
 - Sweeps both by columns and rows (columns for **L** and rows for **U**)
 - Reduce storage needs
 - Each element of **A** only employed once
- Matrix inverse: $\mathbf{AX}=\mathbf{I} \Rightarrow (\mathbf{LU})\mathbf{X}=\mathbf{I}$

– Numbers of ops: $O \left(\begin{array}{ccc} \frac{2n^3}{3} & + & pn^2 & + & pn^2 \\ \text{LU Decomp.} & & \text{Forward} & & \text{Backward} \\ & & \text{Substitution} & & \text{Substitution} \end{array} \right)$ for $p = n$, $\Rightarrow \frac{2n^3}{3} + 2n^3 = \frac{8n^3}{3}$



Recall Lecture 3: The Condition Number

- The *condition* of a mathematical problem relates to its sensitivity to changes in its input values
- A computation is *numerically unstable* if the uncertainty of the input values are magnified by the numerical method
- Considering x and $f(x)$, the *condition number* is the ratio of the relative error in $f(x)$ to that in x .

- Using first-order Taylor series $f(\bar{x}) = f(\bar{x}) + f'(\bar{x})(x - \bar{x})$

- Relative error in $f(x)$: $\frac{f(x) - f(\bar{x})}{f(\bar{x})} \cong \frac{f'(\bar{x})(x - \bar{x})}{f(\bar{x})}$

- Relative error in x : $\frac{(x - \bar{x})}{\bar{x}}$

- Condition Nb = Ratio of relative errors:

$$K_p = \left| \frac{\bar{x} f'(\bar{x})}{f(\bar{x})} \right|$$



Linear Systems of Equations Error Analysis

Function of one variable

$$y = f(x)$$

Condition number

$$\left| \frac{f(\bar{x}) - f(x)}{f(x)} \right| = K \left| \frac{\bar{x} - x}{x} \right|, \quad \bar{x} = x + \delta x$$

$$\left| \frac{\delta y}{y} \right| = K \left| \frac{\delta x}{x} \right|$$

The condition number K is a measure of the **amplification** of the **relative error** by the function $f(x)$

Linear systems

How is the relative error of $\bar{\mathbf{x}}$ dependent on errors in $\bar{\mathbf{b}}$?

$$\bar{\mathbf{A}}\bar{\mathbf{x}} = \bar{\mathbf{b}}$$

Example

$$\bar{\mathbf{A}} = \begin{bmatrix} 1.0 & 1.0 \\ 1.0 & 1.0001 \end{bmatrix}, \quad \det(\bar{\mathbf{A}}) = 0.0001$$

Using MATLAB with different $\bar{\mathbf{b}}$'s (see tbt8.m):

$$\bar{\mathbf{b}} = \begin{Bmatrix} 2 \\ 2 \end{Bmatrix} \Rightarrow \bar{\mathbf{x}} = \begin{Bmatrix} 2 \\ 0 \end{Bmatrix}$$

$$\bar{\mathbf{b}} = \begin{Bmatrix} 2 \\ 2.0001 \end{Bmatrix} \Rightarrow \bar{\mathbf{x}} = \begin{Bmatrix} 1 \\ 1 \end{Bmatrix}$$

Small changes in $\bar{\mathbf{b}}$ give large changes in $\bar{\mathbf{x}}$
The system is **ill-Conditioned**



Linear Systems of Equations: Norms

Vector and Matrix Norms:

$$\left\{ \begin{array}{l} \|\bar{\mathbf{x}}\|_{\infty} = \max_i |x_i| \\ \|\bar{\bar{\mathbf{A}}}\|_{\infty} = \max_i \sum_{j=1}^n |a_{ij}| \end{array} \right.$$

Evaluation of Condition Numbers requires use of Norms

Properties:

$$\bar{\bar{\mathbf{A}}} \neq \bar{\mathbf{0}} \Rightarrow \|\bar{\bar{\mathbf{A}}}\| > 0$$

$$\|\alpha \bar{\bar{\mathbf{A}}}\| = |\alpha| \|\bar{\bar{\mathbf{A}}}\|$$

$$\|\bar{\bar{\mathbf{A}}} + \bar{\bar{\mathbf{B}}}\| \leq \|\bar{\bar{\mathbf{A}}}\| + \|\bar{\bar{\mathbf{B}}}\|$$

Sub-multiplicative / Associative Norms (n-by-n matrices with such norms form a Banach Algebra/space)

$$\left\{ \begin{array}{l} \|\bar{\bar{\mathbf{A}}}\bar{\bar{\mathbf{B}}}\| \leq \|\bar{\bar{\mathbf{A}}}\| \|\bar{\bar{\mathbf{B}}}\| \\ \|\bar{\bar{\mathbf{A}}}\bar{\mathbf{x}}\| \leq \|\bar{\bar{\mathbf{A}}}\| \|\bar{\mathbf{x}}\| \end{array} \right.$$



Examples of Matrix Norms

$$\|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^m |a_{ij}|$$

“Maximum Column Sum”

$$\|A\|_\infty = \max_{1 \leq i \leq m} \sum_{j=1}^n |a_{ij}|$$

“Maximum Row Sum”

$$\|A\|_F = \left(\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2 \right)^{1/2}$$

“The Frobenius norm” (also called Euclidean norm)”, which for matrices differs from:

$$\|A\|_2 = \sqrt{\lambda_{\max}(A^*A)}$$

“The l-2 norm” (also called spectral norm)



Linear Systems of Equations

Error Analysis: Perturbed Right-hand Side

Vector and Matrix Norms

$$\|\bar{\mathbf{x}}\|_\infty = \max_i |x_i|$$

$$\|\bar{\mathbf{A}}\|_\infty = \max_i \sum_{j=1}^n |a_{ij}|$$

Properties

$$\bar{\mathbf{A}} \neq \bar{\mathbf{0}} \Rightarrow \|\bar{\mathbf{A}}\| > 0$$

$$\|\alpha \bar{\mathbf{A}}\| = |\alpha| \|\bar{\mathbf{A}}\|$$

$$\|\bar{\mathbf{A}} + \bar{\mathbf{B}}\| \leq \|\bar{\mathbf{A}}\| + \|\bar{\mathbf{B}}\|$$

$$\|\bar{\mathbf{A}}\bar{\mathbf{B}}\| \leq \|\bar{\mathbf{A}}\| \|\bar{\mathbf{B}}\|$$

$$\|\bar{\mathbf{A}}\bar{\mathbf{x}}\| \leq \|\bar{\mathbf{A}}\| \|\bar{\mathbf{x}}\|$$

Perturbed Right-hand Side implies

$$\bar{\mathbf{A}}\bar{\mathbf{x}} = \bar{\mathbf{b}}$$



$$\bar{\mathbf{A}}(\bar{\mathbf{x}} + \delta\bar{\mathbf{x}}) = \bar{\mathbf{b}} + \delta\bar{\mathbf{b}}$$

Subtract original equation

$$\bar{\mathbf{A}}\delta\bar{\mathbf{x}} = \delta\bar{\mathbf{b}}$$

$$\delta\bar{\mathbf{x}} = \bar{\mathbf{A}}^{-1}\delta\bar{\mathbf{b}}$$



$$\left. \begin{aligned} \|\delta\bar{\mathbf{x}}\| &\leq \|\bar{\mathbf{A}}^{-1}\| \|\delta\bar{\mathbf{b}}\| \\ \|\bar{\mathbf{b}}\| = \|\bar{\mathbf{A}}\bar{\mathbf{x}}\| &\leq \|\bar{\mathbf{A}}\| \|\bar{\mathbf{x}}\| \end{aligned} \right\} \Rightarrow$$

Relative Error Magnification

$$\frac{\|\delta\bar{\mathbf{x}}\|}{\|\bar{\mathbf{x}}\|} \leq \|\bar{\mathbf{A}}^{-1}\| \|\bar{\mathbf{A}}\| \frac{\|\delta\bar{\mathbf{b}}\|}{\|\bar{\mathbf{b}}\|}$$

Condition Number

$$K(\bar{\mathbf{A}}) = \|\bar{\mathbf{A}}^{-1}\| \|\bar{\mathbf{A}}\|$$



Linear Systems of Equations

Error Analysis: Perturbed Coefficient Matrix

Vector and Matrix Norms

$$\|\bar{\mathbf{x}}\|_\infty = \max_i |x_i|$$

$$\|\bar{\mathbf{A}}\|_\infty = \max_i \sum_{j=1}^n |a_{ij}|$$

Properties

$$\bar{\mathbf{A}} \neq \bar{\mathbf{0}} \Rightarrow \|\bar{\mathbf{A}}\| > 0$$

$$\|\alpha \bar{\mathbf{A}}\| = |\alpha| \|\bar{\mathbf{A}}\|$$

$$\|\bar{\mathbf{A}} + \bar{\mathbf{B}}\| \leq \|\bar{\mathbf{A}}\| + \|\bar{\mathbf{B}}\|$$

$$\|\bar{\mathbf{A}}\bar{\mathbf{B}}\| \leq \|\bar{\mathbf{A}}\| \|\bar{\mathbf{B}}\|$$

$$\|\bar{\mathbf{A}}\bar{\mathbf{x}}\| \leq \|\bar{\mathbf{A}}\| \|\bar{\mathbf{x}}\|$$

Perturbed Coefficient Matrix implies

$$(\bar{\mathbf{A}} + \delta\bar{\mathbf{A}})(\bar{\mathbf{x}} + \delta\bar{\mathbf{x}}) = \bar{\mathbf{b}}$$

Subtract unperturbed equation

$$\bar{\mathbf{A}}\delta\bar{\mathbf{x}} + \delta\bar{\mathbf{A}}(\bar{\mathbf{x}} + \delta\bar{\mathbf{x}}) = \bar{\mathbf{0}}$$

$$\delta\bar{\mathbf{x}} = -\bar{\mathbf{A}}^{-1} \delta\bar{\mathbf{A}}(\bar{\mathbf{x}} + \delta\bar{\mathbf{x}}) \simeq -\bar{\mathbf{A}}^{-1} \delta\bar{\mathbf{A}}\bar{\mathbf{x}}$$

(Neglect 2nd order)

$$\|\delta\bar{\mathbf{x}}\| \leq \|\bar{\mathbf{A}}^{-1}\| \|\delta\bar{\mathbf{A}}\| \|\bar{\mathbf{x}}\|$$

Relative Error Magnification

$$\frac{\|\delta\bar{\mathbf{x}}\|}{\|\bar{\mathbf{x}}\|} \leq \|\bar{\mathbf{A}}^{-1}\| \|\bar{\mathbf{A}}\| \frac{\|\delta\bar{\mathbf{A}}\|}{\|\bar{\mathbf{A}}\|}$$

Condition Number

$$K(\bar{\mathbf{A}}) = \|\bar{\mathbf{A}}^{-1}\| \|\bar{\mathbf{A}}\|$$



Example: Ill-Conditioned System

$$\begin{bmatrix} 1.0 & 1.0 \\ 1.0 & 1.0001 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

4-digit Arithmetic

$$\det(\overline{\overline{\mathbf{A}}}) = 0.0001$$

Using Cramer's rule:

$$\left. \begin{aligned} a_{11} &= \frac{1.0001}{0.0001} = 10,001 \\ a_{12} &= \frac{-1}{0.0001} = -10,000 \\ a_{21} &= \frac{-1}{0.0001} = -10,000 \\ a_{22} &= \frac{1.0}{0.0001} = 10,000 \end{aligned} \right\}$$

$$\left. \begin{aligned} \|\overline{\overline{\mathbf{A}}}\|_{\infty} &= 2.0001 \\ \|\overline{\overline{\mathbf{A}}}^{-1}\|_{\infty} &= 20,001 \end{aligned} \right\} \Rightarrow K(\overline{\overline{\mathbf{A}}}) \simeq \boxed{40,000}$$

Ill-conditioned system

```
n=4
a = [ [1.0 1.0]' [1.0 1.0001] ] tbt6.m
b= [1 2]'

ai=inv(a);
a_nrm=max( abs(a(1,1)) + abs(a(1,2)) ,
           abs(a(2,1)) + abs(a(2,2)) )
ai_nrm=max( abs(ai(1,1)) + abs(ai(1,2)) ,
           abs(ai(2,1)) + abs(ai(2,2)) )
k=a_nrm*ai_nrm

r=ai * b

x=[0 0];
m21=a(2,1)/a(1,1);
a(2,1)=0;
a(2,2) = radd(a(2,2), -m21*a(1,2), n);
b(2)   = radd(b(2), -m21*b(1), n);

x(2)   = b(2)/a(2,2);
x(1)   = (radd(b(1), -a(1,2)*x(2), n))/a(1,1);
x'
```



Example: Better-Conditioned System

$$\begin{bmatrix} 0.0001 & 1.0 \\ 1.0 & 1.0 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

4-digit Arithmetic

$$\det(\overline{\overline{\mathbf{A}}}) = 0.9999$$

$$\left. \begin{aligned} a_{11} &= \frac{-1}{0.9999} = -1.0001 \\ a_{12} &= \frac{1}{0.9999} = 1.0001 \\ a_{21} &= \frac{1}{0.9999} = 1.0001 \\ a_{22} &= \frac{-0.0001}{0.9999} = -0.0001 \end{aligned} \right\}$$

Using Cramer's rule:

```
n=4
a = [ [0.0001 1.0]' [1.0 1.0]' ]      tbt7.m
b= [1 2]'

ai=inv(a);
a_nrm=max( abs(a(1,1)) + abs(a(1,2)) ,
           abs(a(2,1)) + abs(a(2,2)) )
ai_nrm=max( abs(ai(1,1)) + abs(ai(1,2)) ,
           abs(ai(2,1)) + abs(ai(2,2)) )
k=a_nrm*ai_nrm

r=ai * b

x=[0 0];
m21=a(2,1)/a(1,1);
a(2,1)=0;
a(2,2) = radd(a(2,2), -m21*a(1,2), n);
b(2)   = radd(b(2), -m21*b(1), n);

x(2)   = b(2)/a(2,2);
x(1)   = (radd(b(1), -a(1,2)*x(2), n))/a(1,1);
x'
```

$$\left. \begin{aligned} \|\overline{\overline{\mathbf{A}}}\|_{\infty} &= 2.0 \\ \|\overline{\overline{\mathbf{A}}}^{-1}\|_{\infty} &= 2.0002 \end{aligned} \right\} \Rightarrow K(\overline{\overline{\mathbf{A}}}) \simeq \boxed{4}$$

Relatively Well-conditioned system



Recall Lecture 3: The Condition Number

- The *condition* of a mathematical problem relates to its sensitivity to changes in its input values
- A computation is *numerically unstable* if the uncertainty of the input values are magnified by the numerical method
- Considering x and $f(x)$, the *condition number* is the ratio of the relative error in $f(x)$ to that in x .

• Using first-order Taylor series f

• Relative error in $f(x)$:
$$\frac{f(x) - f(\bar{x})}{f(\bar{x})} \cong \frac{f'(\bar{x})(x - \bar{x})}{f(\bar{x})}$$

• Relative error in x :
$$\frac{(x - \bar{x})}{\bar{x}}$$

• Condition Nb = Ratio of relative errors:

$$K_p = \left| \frac{\bar{x} f'(\bar{x})}{f(\bar{x})} \right|$$

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2.29 Numerical Fluid Mechanics

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