

Linear system.



CS450: Numerical Analysis

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Solving Linear Systems

- For a square matrix A , how to (systematically) solve for $Ax = b$?
 - Transform it into one whose solution is the same but easier to compute
 - Specifically, eliminate x_1 from $n - 1$ equations to get a smaller system $A_2 x = b_2$ of size $\underbrace{n - 1}$
 - Eventually, reaching the 1 by 1 system $A_n x_n = b_n$ which we know $x_n = b_n/A_n$
 - Working backwards produces x_{n-1}, x_{n-2}, \dots , and eventually x_2 and x_1

$$\begin{array}{l} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2 \\ \vdots \quad \vdots \quad \ddots \quad \vdots \quad \vdots \\ a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n = b_n \end{array} \Rightarrow \begin{array}{c} 0 \\ 0 \\ 0 \\ 0 \\ \vdots \end{array} \left[\begin{array}{c} a_{11} \\ a_{21} \\ \vdots \\ a_{n1} \end{array} \right] \left[\begin{array}{c} x_1 \\ x_2 \\ \vdots \\ x_n \end{array} \right] = \begin{array}{c} b_1 \\ b_2 \\ \vdots \\ b_n \end{array} \Rightarrow \boxed{A_2 x = b_2} \Rightarrow \boxed{A_n x_n = b_n} \quad x_n = \frac{b_n}{A_n}$$

Triangular Linear Systems

- What type of linear system is easy to solve?
 - Systems that form **triangular matrices**

$$a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n = a_{1,n+1}$$

$$a_{22}x_2 + \cdots + a_{2n}x_n = a_{2,n+1}$$

$$\ddots \quad \ddots \quad \ddots \quad \vdots \quad \vdots$$

$$a_{nn}x_n = a_{n,n+1}$$

- Back-substitution

$$x_n = \frac{a_{n,n+1}}{a_{nn}},$$

$$x_i = \frac{a_{i,n+1} - \sum_{j=i+1}^n a_{ij}x_j}{a_{ii}}, \quad i = n-1, \dots, 1$$

$$\boxed{A} \quad \boxed{x = b}$$

$$\left[\begin{array}{c|c} \cancel{M} & \\ \hline 0 & \end{array} \right] x = b$$

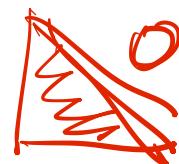
$$a_{n-1,n-1}x_{n-1} + a_{n-1,n}x_n = a_{n,n+1}$$

Triangular Matrices



- Two specific triangular forms are of particular interest
 - Lower triangular: all entries above main diagonal are zero, $a_{ij} = 0$ for $i < j$
 - Upper triangular: all entries below main diagonal are zero, $a_{ij} = 0$ for $i > j$

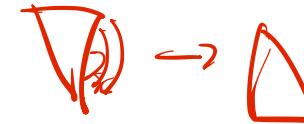
$$\begin{aligned}
 a_{11}x_1 &= b_1 \\
 a_{21}x_1 + a_{22}x_2 &= b_2 \\
 &\vdots \quad \vdots \\
 a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n &= b_m
 \end{aligned}$$



$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= b_1, \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= b_2, \\ &\vdots \\ a_{z1}x_1 + a_{z2}x_2 + \cdots + a_{zn}x_n &= b_z \end{aligned}$$



Triangular Matrices (cont'd)



- Two specific triangular forms are of particular interest
 - Lower triangular: all entries above main diagonal are zero, $a_{ij} = 0$ for $i < j$
 - Upper triangular: all entries below main diagonal are zero, $a_{ij} = 0$ for $i > j$
- Successive substitution process described earlier is especially easy toformulate for lower or upper triangular systems
- Any triangular matrix can be permuted into upper or lower triangular form by suitable row permutation

Elimination

- To transform general linear system into triangular form, we need to replace selected nonzero entries of matrix by zeros
- This can be accomplished by taking linear combinations of rows
- Consider a two-dimensional vector $\underline{a} = [a_1 \ a_2]$
- If $a_1 \neq 0$, then

$$\begin{bmatrix} 1 & 0 \\ -a_2/a_1 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} a_1 \\ 0 \end{bmatrix}$$

$\leftarrow 1 \times a_1 + 0 \times a_2 = a_1$
 $\leftarrow (-\frac{a_2}{a_1}) \times a_1 + a_2 = -a_2 + a_2 = 0$

Elementary Elimination Matrices

$$Ax = b$$

$$M_1 A x = M_1 b$$

$$M_1 \rightarrow$$

$$A = [a_1 \ a_2 \ \dots \ a_n]$$

$$\det(A) = 0$$

- More generally, we can annihilate all entries below k -th in a n -dimensional vector \mathbf{a} by transformation

$$m_{k+1} = -\frac{a_{k+1}}{a_k}$$

at the $(k+1)$ -th column position

$$m_{k+2} = -\frac{a_{k+2}}{a_k}$$

$$M_k$$

$$\text{where } m_i = \frac{a_i}{a_k}, i = k + 1, \dots, n$$

- Divisor a_k , called **pivot**, must be nonzero

$$(-m_{k+1}) \times a_k + 1 \times a_{k+1}$$

$$= -\frac{a_{k+1}}{a_k} \times a_k + a_{k+1} = 0$$

Elementary Elimination Matrices (cont'd)

Example: For a vector $\underline{\underline{a}} = [2, 4, -2]^T$, the elementary elimination matrices M_1

and M_2 are (recall: $m_i = \frac{a_i}{a_k}$, $i = k + 1, \dots, n$)

$$-\frac{a_2}{a_1} = -\frac{4}{2} = -2$$

$$-\frac{a_3}{a_1} = -\frac{-2}{2} = 1$$

$$M_1 \underline{\underline{a}} = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \\ -2 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}$$

$$M_2 \underline{\underline{a}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1/2 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \\ -2 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \\ 0 \end{bmatrix}$$

Elementary Elimination Matrices (cont'd)

- Matrix M_k , called elementary elimination matrix, adds multiple of row k to each subsequent row, with multipliers m_i chosen so that result is zero
- M_k is unit lower triangular and nonsingular
- $M_k = I - m_k e_k^T$, where $m_k = [0, \dots, 0, m_{k+1}, \dots, m_n]^T$ and e_k is the k -th column of identity matrix
- $M_k^{-1} = I + m_k e_k^T$, which means $M_k^{-1} = L_k$ is the same as M_k except signs of multipliers are reversed

$$\begin{bmatrix} 0 & 0 & \dots & 0 & 1 & 0 & \dots & 0 \\ \vdots & & & & k & \cancel{k+1} & & \\ (k-1) & & & & \cancel{k+1} & & & \end{bmatrix}$$

$$e_k^T M_k = \underbrace{\begin{bmatrix} 0 & 0 & \dots & 0 & 1 & 0 & \dots & 0 \end{bmatrix}}_{(k-1) \text{ } k} \underbrace{\begin{bmatrix} 0 & & & & & & & \\ \vdots & & & & & & & \\ m_{k+1} & & & & & & & \\ \vdots & & & & & & & \\ m_n & & & & & & & \end{bmatrix}}_{=0} = 0$$

$$M_k M_k^{-1} = (I - m_k e_k^T)(I + m_k e_k^T)$$

$$= I + \cancel{m_k e_k^T} - \cancel{m_k e_k^T} - \frac{m_k e_k^T m_k e_k^T}{m_k \times 0 \times e_k^T} = 0$$

$$M_k^{-1} = I$$

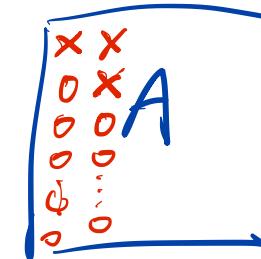
Elementary Elimination Matrices (cont'd)

- If $M_j, j > k$, is another elementary elimination matrix, with vectors of multipliers \mathbf{m}_j , then

$$M_k M_j = (I - \mathbf{m}_k \mathbf{e}_k^T)(I - \mathbf{m}_j \mathbf{e}_j^T)$$

$$= I - \mathbf{m}_k \mathbf{e}_k^T - \mathbf{m}_j \mathbf{e}_j^T + \mathbf{m}_k \mathbf{e}_k^T \mathbf{m}_j \mathbf{e}_j^T$$

$$= \underbrace{I - \mathbf{m}_k \mathbf{e}_k^T}_{\text{---}} - \underbrace{\mathbf{m}_j \mathbf{e}_j^T}_{\text{---}}$$



A

$M_1 M_2 - \sim$

where means product is essentially "union", and similarly for product of inverses, $L_k L_j$

Gaussian Elimination

$$\begin{bmatrix} m_1 \\ m_2 \\ \vdots \\ m_n \end{bmatrix} = M$$



- To reduce a general linear system of equations $\mathbf{A}\mathbf{x} = \mathbf{b}$ into upper triangular form, do the following
 - Choose \mathbf{M}_1 with a_{11} as pivot, annihilate first column of \mathbf{A} below first row: the system becomes $\mathbf{M}_1\mathbf{A}\mathbf{x} = \mathbf{M}_1\mathbf{b}$, but solution remains unchanged
 - Next choose \mathbf{M}_2 with a_{22} as pivot, annihilate second column of $\mathbf{M}_1\mathbf{A}$ below second row: the system becomes $\mathbf{M}_2\mathbf{M}_1\mathbf{A}\mathbf{x} = \mathbf{M}_2\mathbf{M}_1\mathbf{b}$, but the solution still unchanged
 - Process continues for each successive column until all subdiagonal entries have been zeroed, results in upper triangular linear system $\underbrace{\mathbf{M}_{n-1} \cdots \mathbf{M}_1\mathbf{A}}_{\text{Upper triangular matrix}} \mathbf{x} = \underbrace{\mathbf{M}_{n-1} \cdots \mathbf{M}_1\mathbf{b}}_{\text{Upper triangular vector}}$, which can be solved via back-substitution
 - This process is called **Gaussian elimination**

LU Factorization

$$M_{n-1} M_{n-2} \cdots M_2 M_1 A = \Delta$$

$$I + m_k e_k e_k^T \Delta$$

- Denote by $M_k^{-1} = L_k$, then $\underline{L} = M^{-1} = \overbrace{M_1^{-1} \cdots M_{n-1}^{-1}}^{\Delta} = \underbrace{L_1 \cdots L_{n-1}}_{\Delta}$ is lower triangular $(M_{n-1} \cdots M_1) U = A$

- By design, $\underline{U} = \underbrace{M_{n-1} \cdots M_1}_{\sim} A$ is upper triangular

- Therefore, we can factorize matrix A into the product of a lower triangular matrix and an upper triangular matrix

$$\begin{aligned} Ax &= b_1 & Ax &= b_2 \\ LUx &= b_1 & \rightarrow Ux &= L^{-1}b_1 \quad \underline{A = LU} \end{aligned}$$

- Thus, Gaussian elimination produces LU factorization of matrix into triangular factors

Fourier Transform $\boxed{7/1} = 1$

$$\begin{aligned} A &= \overbrace{M_1^{-1} M_2^{-1} \cdots M_{n-1}^{-1}}^{\Delta} U \\ &= LU \end{aligned}$$

$$\square = \Delta \quad \nabla$$

$$\begin{aligned} MAx &= Mb \Rightarrow A = LU \\ \nabla &= 1 \end{aligned}$$

LU Factorization (cont'd)

- The LU factorization can be viewed as a sum of rank-1 matrices

$$A = \underbrace{\begin{bmatrix} 1 \times \bar{r}_1 \\ -m_{21} \times \bar{r}_1 \\ -m_{31} \times \bar{r}_1 \\ \vdots \\ -m_{n1} \times \bar{r}_1 \end{bmatrix}}_{\text{rank-1 matrix}} + \underbrace{\begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & A_2 & & & \\ 0 & & \ddots & & \\ \vdots & & & \ddots & \\ 0 & & & & \bar{r}_1 \end{bmatrix}}_{\text{rank-1 matrix}} = \bar{m}_1 \times \bar{r}_1 + \underbrace{\begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & A_2 & & \\ \vdots & & \ddots & \\ 0 & & & \bar{r}_1 \end{bmatrix}}_{\text{rank-1 matrix}} + \bar{m}_2 \times \bar{r}_2 + \underbrace{\begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}}_{\text{rank-1 matrix}}$$

LU Factorization (cont'd)

$$Ax = b \rightarrow A = LU$$



- With LU factorization, the linear system becomes $\underline{LUx = b}$ → $\underline{Ly = b}$
- Can be solved by forward-substitution in lower triangular system $Ly = b$
- Followed by back-substitution $Ux = y$ in upper triangular system
- Gaussian elimination and LU factorization are two ways of expressing same solution process

- What's the advantage of LU factorization?

of $Ax = b$ is all I need.

of $Ax = b_1$

$Ax = b_2$

$Ax = b_k \dots$

$$\begin{aligned} & a_{11}y_1 = b_1 \\ & a_{12}y_1 + a_{22}y_2 = b_2 \\ & \vdots \\ & a_{n1}y_1 + a_{n2}y_2 + \dots + a_{nn}y_n = b_n \\ & a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = y_1 \\ & a_{22}x_2 + \dots + a_{2n}x_n = y_2 \\ & \vdots \quad \vdots \\ & a_{nn}x_n = y_n \end{aligned}$$

Working Example

- Apply Gaussian elimination to the following system using four-digit arithmetic with rounding, and compare the result to the exact solution

$$x_1 = 10.00 \text{ and } x_2 = 1.000$$

$$M_1 = \begin{bmatrix} 1 & 0 \\ -m_1 & 1 \end{bmatrix} \quad -m_1 = -\frac{a_{21}}{a_{11}}$$

$$= -\frac{5.291}{0.00300}$$

$$= -1763.66$$

$$\approx 1764$$

$$\begin{aligned} E_1 : \quad & 0.003000x_1 + 59.14x_2 = 59.17 \\ E_2 : \quad & \underline{\underline{5.291}}x_1 - 6.130x_2 = 46.78 \end{aligned}$$

$$\begin{bmatrix} 1 & 0 \\ -1764 & 1 \end{bmatrix} \times A \times = \begin{bmatrix} 1 & 0 \\ -1764 & 1 \end{bmatrix} b$$

Working Example

$$A = \begin{bmatrix} 0.003 & 59.14 \\ 5.291 & -6.130 \end{bmatrix}$$

$$R(A) \approx 11.2992$$

- Gaussian elimination using four-digit arithmetic with rounding

$$\boxed{\begin{array}{l} E_1 : 0.003000x_1 + 59.14x_2 = 59.17 \\ E_2 : 5.291x_1 - 6.130x_2 = 46.78 \end{array}}$$

$$5.291x_1 - 6.130x_2 = 46.78$$

$$0.003x_1 + 59.14x_2 = 59.17$$

$$0.00300x_1 + 59.14x_2 = 59.17$$

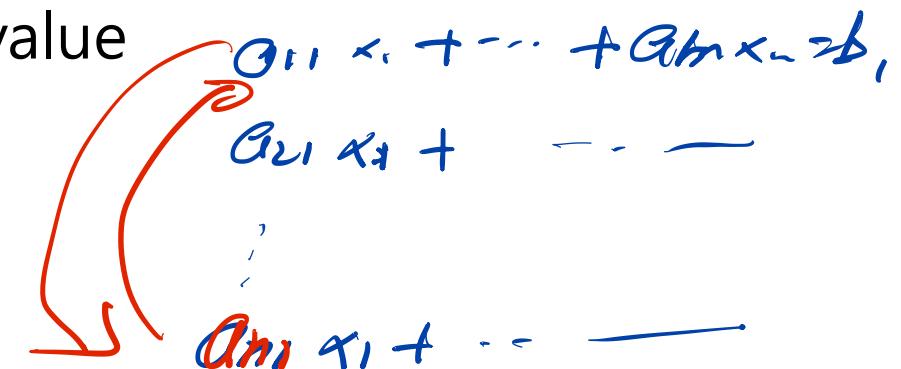
$$-104300x_2 = -104400$$

$$x_2 \approx \frac{-104400}{-104300} \approx 1.001$$

$$x_1 = \frac{59.17 - 59.14 \times 1.001}{0.00300} = -10.00$$

Partial Pivoting

- In principle, any nonzero value can serve as the pivot
- In practice, chose the one that minimizes error propagation
- Approach: select an element in the same column that is below the diagonal and has the largest absolute value


$$\begin{aligned} a_{11}x_1 + \cdots + a_{1n}x_n &= b_1 \\ a_{21}x_1 + \cdots + a_{2n}x_n &= b_2 \\ \vdots & \\ a_{m1}x_1 + \cdots + a_{mn}x_n &= b_m \end{aligned}$$

Working Example (cont'd)

- Apply Gaussian elimination to the following system using partial pivoting and four-digit arithmetic with rounding, and compare the result to the exact solution $x_1 = 10.00$ and $x_2 = 1.000$

$$E_1 : \begin{matrix} \swarrow & 0.003000x_1 + 59.14x_2 = 59.17 \\ E_2 : & 5.291x_1 - 6.130x_2 = 46.78 \end{matrix} \quad \text{J}$$