SI231 - Matrix Computations, Fall 2020-21

Homework Set #2

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Acknowledgements:

1) Deadline: **2020-10-11 23:59:00**
2) Submit your homework at **Gradescope**. Entry Code: **MY3XBJ**. Also, make sure that your gradescope account is your **school e-mail**. Homework #2 contains two parts, the theoretical part the and the programming part.
3) About the the theoretical part:
   (a) Submit your homework in **Homework 2** in gradescope. Make sure that you have assigned the correct pages for the problems in the outline.
   (b) Your homework should be uploaded in the **PDF** format, and the naming format of the file is not specified.
   (c) No handwritten homework is accepted. You need to use LaTeX. (If you have difficulty in using LaTeX, you are allowed to use **Word** for the first and the second homework to accommodate yourself.)
   (d) Use the given template and give your solution in English. Solution in Chinese is not allowed.
4) About the programming part:
   (a) Submit your codes in **Homework 2 Programming part** in gradescope.
   (b) Details of requirements in programming are listed in remarks of Problem 6, please read it carefully before you start to program.
5) **No late submission is allowed.**“‘

I. GENERAL LINEAR SYSTEM

Problem 1 (6 points + 9 points)

Let $\mathbf{A} = \begin{bmatrix} 1 & 0 & 1 & 2 \\ -2 & 4 & -6 & 0 \\ 3 & 1 & 14 & -1 \\ -1 & 7 & -5 & 3 \end{bmatrix} \in \mathbb{R}^{4\times 4}$ and $\mathbf{B} = \begin{bmatrix} 1 & 2 & 3 & -1 \\ 2 & 3 & 1 & 1 \\ 2 & 2 & 2 & -1 \\ 5 & 5 & 2 & 3 \end{bmatrix} \in \mathbb{R}^{4\times 4}$.

1) For $\mathbf{A}$ and $\mathbf{b} = (-1, 2, 5, 3)^T \in \mathbb{R}^4$, find $\mathcal{N}(\mathbf{A})$, $\mathcal{R}(\mathbf{A})$, then solve $\mathbf{Ax} = \mathbf{b}$.
2) For $\mathbf{B}$ and $\mathbf{b} = (1, 1, 1, 2)^T \in \mathbb{R}^4$, solve the linear equation system $\mathbf{Bx} = \mathbf{b}$ with Gauss Elimination, LU decomposition, and LU decomposition with partial pivoting, respectively. (Although not required, you are highly encouraged to write down your solution procedures in detail.)

Solution.

1) To find $\mathcal{N}(A), is$ equal to solve : $Ax = \begin{bmatrix} 1 & 0 & 1 & 2 \\ -2 & 4 & -6 & 0 \\ 3 & 1 & 14 & -1 \\ -1 & 7 & -5 & 3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = 0$

then $\begin{bmatrix} 1 & 0 & 1 & 2 \\ -2 & 4 & -6 & 0 \\ 3 & 1 & 14 & -1 \\ 1 & 7 & -5 & 3 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 1 & 2 \\ 0 & 4 & -4 & 4 \\ 0 & 1 & 11 & -7 \\ 0 & 7 & -4 & 5 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 1 & 2 \\ 0 & 1 & -1 & 1 \\ 0 & 0 & 12 & -8 \\ 0 & 0 & 3 & -2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 1 & 2 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 3 & -2 \\ 0 & 0 & 0 & 0 \end{bmatrix}$

$We\ get \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} -8 \\ -1 \\ 2 \\ 3 \end{bmatrix} k, \quad k \in R.\ so\ \mathcal{N}(A) = span\left(\begin{bmatrix} -8 \\ -1 \\ 2 \\ 3 \end{bmatrix} \right)$

To find $R(A)$,is equal to solve : $Ax = \begin{bmatrix} 1 & 0 & 1 & 2 \\ -2 & 4 & -6 & 0 \\ 3 & 1 & 14 & -1 \\ -1 & 7 & -5 & 3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ 5 \\ 3 \end{bmatrix}$

then $\left[\begin{array}{cccc|c} 1 & 0 & 1 & 2 & 1 \\ -2 & 4 & -6 & 0 & \\ 3 & 1 & 14 & -1 & 5 \\ 1 & 7 & -5 & 3 & 3 \end{array}\right] \rightarrow \left[\begin{array}{cccc|c} 1 & 0 & 1 & 2 & -1 \\ 0 & 4 & -4 & 4 & 0 \\ 0 & 1 & 11 & -7 & 8 \\ 0 & 7 & -4 & 5 & 2 \end{array}\right] \rightarrow \left[\begin{array}{cccc|c} 1 & 0 & 1 & 2 & -1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 12 & -8 & 8 \\ 0 & 0 & 3 & -2 & 2 \end{array}\right] \rightarrow \left[\begin{array}{cccc|c} 1 & 0 & 1 & 2 & -1 \\ 0 & 1 & -1 & 1 & 0 \\ 0 & 0 & 3 & -2 & 2 \\ 0 & 0 & 0 & 0 & 0 \end{array}\right]$

$so\ \mathcal{R}(A) = span\left(\begin{bmatrix} 1 \\ -2 \\ 3 \\ -1 \end{bmatrix} \begin{bmatrix} 0 \\ 4 \\ 1 \\ 7 \end{bmatrix} \begin{bmatrix} 1 \\ -6 \\ 14 \\ 5 \end{bmatrix} \right)$

2) **Gauss Elimination** : Gauss Elimination: $\begin{bmatrix} B & b \end{bmatrix} = \left[\begin{array}{cccc|c} 1 & 2 & 3 & -1 & 1 \\ 2 & 3 & 1 & 1 & 1 \\ 2 & 2 & 2 & 1 & 1 \\ 5 & 5 & 2 & 3 & 2 \end{array}\right] \to \left[\begin{array}{cccc|c} 1 & 2 & 3 & -1 & 1 \\ 0 & -1 & -5 & 3 & -1 \\ 0 & -2 & -4 & 1 & -1 \\ 0 & -5 & -13 & 8 & -3 \end{array}\right] \to$

$$\left[\begin{array}{cccc|c} 1 & 2 & 3 & -1 & 1 \\ 0 & 1 & 5 & -3 & 1 \\ 0 & 0 & 6 & -5 & 1 \\ 0 & 0 & 12 & -7 & 2 \end{array}\right] \to \left[\begin{array}{cccc|c} 1 & 2 & 3 & -1 & 1 \\ 0 & 1 & 5 & -3 & 1 \\ 0 & 0 & 6 & -5 & 1 \\ 0 & 0 & 0 & 3 & 0 \end{array}\right]$$

so we get $\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} \frac{1}{6} \\ \frac{1}{6} \\ \frac{1}{6} \\ 0 \end{bmatrix}$

LU decomposition : solve $B = LU$ Use the previous derivation,we know that $U = \begin{bmatrix} 1 & 2 & 3 & -1 \\ 0 & -1 & -5 & 3 \\ 0 & 0 & 6 & -5 \\ 0 & 0 & 0 & 3 \end{bmatrix}$

$$M_1 = \begin{bmatrix} 1 & & & \\ -2 & 1 & & \\ -2 & & 1 & \\ -5 & & & 1 \end{bmatrix}, \quad M_2 = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & -2 & 1 & \\ & -5 & & 1 \end{bmatrix} M_3 = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & -2 & 1 \end{bmatrix}$$

then $L = M_1^{-1} M_2^{-1} M_3^{-1} = \begin{bmatrix} 1 & & & \\ 2 & 1 & & \\ 2 & 2 & 1 & \\ 5 & 5 & 2 & 1 \end{bmatrix}$

so solve $Bx = b \Leftrightarrow LUx = b \Leftrightarrow Lz = b, \quad Ux = z$

firstly, solve $Lz = b$,then because $[L\ b] = \left[\begin{array}{cccc|c} 1 & & & & 1 \\ 2 & 1 & & & 1 \\ 2 & 2 & 1 & & 1 \\ 5 & 5 & 2 & 1 & 2 \end{array}\right] \Rightarrow \quad z = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{bmatrix} = \begin{bmatrix} 1 \\ -1 \\ 1 \\ 0 \end{bmatrix}$

Secondly, solve $Ux = z$,then because $[U\ z] = \left[\begin{array}{cccc|c} 1 & 2 & 3 & -1 & 1 \\ 0 & -1 & -5 & 3 & -1 \\ 0 & 0 & 6 & -5 & 1 \\ 0 & 0 & 0 & 3 & 0 \end{array}\right] \Rightarrow x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} \frac{1}{6} \\ \frac{1}{6} \\ \frac{1}{6} \\ 0 \end{bmatrix}$

LU decomposition with partial pivoting :

$$B=\begin{bmatrix}1&2&3&1\\2&3&1&1\\2&2&2&1\\5&5&2&3\end{bmatrix}\to\begin{bmatrix}5&5&2&3\\2&3&1&1\\2&2&2&1\\1&2&3&-1\end{bmatrix}\to\begin{bmatrix}5&5&2&3\\0&1&\frac{1}{5}&-\frac{1}{5}\\0&0&\frac{6}{5}&-\frac{1}{5}\\0&1&\frac{13}{5}&-\frac{8}{5}\end{bmatrix}\to\begin{bmatrix}5&5&2&3\\0&1&\frac{1}{5}&-\frac{1}{5}\\0&0&\frac{6}{5}&-\frac{1}{5}\\0&0&\frac{12}{5}&-\frac{7}{5}\end{bmatrix}\to\begin{bmatrix}5&5&2&3\\0&1&\frac{1}{5}&-\frac{1}{5}\\0&0&\frac{12}{5}&-\frac{7}{5}\\0&0&\frac{6}{5}&-\frac{1}{5}\end{bmatrix}\to$$
$$\begin{bmatrix}5&5&2&3\\0&1&\frac{1}{5}&-\frac{1}{5}\\0&0&\frac{12}{5}&-\frac{7}{5}\\0&0&0&\frac{1}{2}\end{bmatrix}$$

$$\therefore \Pi_1=\begin{bmatrix}0&0&0&1\\0&1&0&0\\0&0&1&0\\1&0&0&0\end{bmatrix},M_1=\begin{bmatrix}1&0&0&0\\-\frac{2}{5}&1&0&0\\-\frac{2}{5}&0&1&0\\-\frac{1}{5}&0&0&1\end{bmatrix}$$

$$\pi_2=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&0&0&1\end{bmatrix},M_2=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&-1&0&1\end{bmatrix}$$

$$\pi_3=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&0&1\\0&0&1&0\end{bmatrix},M_3=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&0&-\frac{1}{2}&1\end{bmatrix}$$

$$\widetilde{M_1}=\Pi_3\Pi_2M_1\Pi_2\Pi_3=\begin{bmatrix}1&0&0&0\\-\frac{2}{5}&1&0&0\\-\frac{1}{5}&0&1&0\\-\frac{2}{5}&0&0&1\end{bmatrix},\ \widetilde{M_2}=\Pi_3M_2\Pi_3=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&-1&1&0\\0&0&0&1\end{bmatrix},\ \widetilde{M_3}=M_3$$

$$P=\Pi_3\Pi_2\Pi_1=\begin{bmatrix}0&0&0&1\\0&1&0&0\\1&0&0&0\\0&0&1&0\end{bmatrix},L=\widetilde{M_1}^{-1}\widetilde{M_2}^{-1}\widetilde{M_3}^{-1}=\begin{bmatrix}1&0&0&0\\\frac{2}{5}&1&0&0\\\frac{1}{5}&0&1&0\\\frac{2}{5}&1&\frac{1}{2}&1\end{bmatrix},U=\begin{bmatrix}5&5&2&3\\0&1&\frac{1}{5}&-\frac{1}{5}\\0&0&\frac{12}{5}&-\frac{7}{5}\\0&0&0&\frac{1}{2}\end{bmatrix}$$

$Bx=b\Leftrightarrow PBx=Pb\Leftrightarrow LUx=Pb$ and we can know $Pb=\begin{bmatrix}0&0&0&1\\0&1&0&0\\1&0&0&0\\0&0&1&0\end{bmatrix}\begin{bmatrix}1\\1\\1\\2\end{bmatrix}=\begin{bmatrix}2\\1\\1\\1\end{bmatrix}$

$$\text{solve } Lz = Pb \text{ ,we get } [L, Pb] = \left[\begin{array}{cccc|c} 1 & 0 & 0 & 0 & 2 \\ \frac{2}{5} & 1 & 0 & 0 & 1 \\ \frac{1}{5} & 1 & 1 & 0 & 1 \\ \frac{2}{5} & 0 & \frac{1}{2} & 1 & 1 \end{array}\right] \Rightarrow z = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{bmatrix} = \begin{bmatrix} 2 \\ \frac{1}{5} \\ z \\ \xi \\ 0 \end{bmatrix}$$

$$\text{solve } Ux = z \text{ ,we get } [U \ \ z] = \left[\begin{array}{cccc|c} 5 & 5 & 2 & 3 & 2 \\ 0 & 1 & \frac{1}{5} & -\frac{1}{5} & \frac{1}{5} \\ 0 & 0 & \frac{12}{5} & -\frac{7}{5} & \frac{2}{5} \\ 0 & 0 & 0 & \frac{1}{2} & 0 \end{array}\right] \Rightarrow x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} \frac{1}{6} \\ \frac{1}{6} \\ \frac{1}{6} \\ 0 \end{bmatrix}$$

II. Understanding Various Matrix Decompositions

Problem 2 (10 points)

Consider the following symmetric matrix $\mathbf{A} \in \mathbb{R}^{4\times 4}$,

$$\mathbf{A} = \begin{bmatrix} a & a & a & a \\ a & b & b & b \\ a & b & c & c \\ a & b & c & d \end{bmatrix}.$$

Give the LU decomposition of $\mathbf{A}$. Then describe under which conditions $\mathbf{A}$ is nonsingular, according to the results of LU decomposition.

Solution. Please insert your solution here ...

$$A = \begin{bmatrix} a & a & a & a \\ a & b & b & b \\ a & b & c & c \\ a & b & c & d \end{bmatrix} \rightarrow \begin{bmatrix} a & a & a & a \\ 0 & b-a & b-a & b-a \\ 0 & b-a & c-a & c-a \\ 0 & b-a & c-a & d-a \end{bmatrix} \rightarrow \begin{bmatrix} a & a & a & a \\ 0 & b-a & b-a & b-a \\ 0 & 0 & c-b & c-b \\ 0 & 0 & c-b & d-b \end{bmatrix} \Rightarrow \begin{bmatrix} a & a & a & a \\ 0 & b-a & b-a & b-a \\ 0 & 0 & c-b & c-b \\ 0 & 0 & 0 & d-c \end{bmatrix}$$

$$M_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -1 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ -1 & 0 & 0 & 1 \end{bmatrix} \quad M_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & -1 & 0 & 1 \end{bmatrix} \quad M_3 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & -1 & 1 \end{bmatrix}$$

so $L = M_1^{-1}M_2^{-1}M_3^{-1} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix} \quad U = \begin{bmatrix} a & a & a & a \\ 0 & b-a & b-a & b-a \\ 0 & 0 & c-b & c-b \\ 0 & 0 & 0 & d-c \end{bmatrix}$

if A is nonsingular,we need $r(A) = 4 \Leftrightarrow r(LU) = 4 \Leftrightarrow r(L) = r(u) = 4$

It's easy to know $r(L) = 4$, so we need $r(U) = 4 \therefore det(U) \neq 0 \Leftrightarrow a(b-a)(c-b)(d-c) \neq 0$

$\Leftrightarrow a \neq 0$ and $b \neq a$ and $c \neq b$ and $d \neq c$

Problem 3 (5 points + 10 points)

1) Consider a 3×3 matrix

$$\mathbf{A} = \begin{bmatrix} 2 & 2 & 4 \\ 1 & 5 & 1 \\ 1 & 1 & 8 \end{bmatrix},$$

find the LDM (also called LDU) decomposition of $\mathbf{A}$, i.e., factor $\mathbf{A}$ as $\mathbf{A} = \mathbf{LDM}^T$ (or $\mathbf{A} = \mathbf{LDU}$), where $\mathbf{L} \in \mathbb{R}^{3\times 3}$ is lower triangular with unit diagonal entries, $\mathbf{D} \in \mathbb{R}^{3\times 3}$ is a diagonal matrix, and $\mathbf{M} \in \mathbb{R}^{3\times 3}$ is lower triangular with unit diagonal entries ($\mathbf{U} \in \mathbb{R}^{3\times 3}$ is upper triangular with unit diagonal entries).

2) Consider a 3×3 matrix

$$\mathbf{B} = \begin{bmatrix} 8 & 1 & 1 \\ 1 & 5 & 1 \\ 4 & 2 & 2 \end{bmatrix},$$

find the UL decomposition of $\mathbf{B}$, i.e., factor $\mathbf{B}$ as $\mathbf{B} = \mathbf{UL}$, where $\mathbf{U} \in \mathbb{R}^{3\times 3}$ is upper triangular with unit diagonal entries and $\mathbf{L} \in \mathbb{R}^{3\times 3}$ is lower triangular.

Hint: $\mathbf{B} = \mathbf{PAP}$, where $\mathbf{P}$ is a unit anti-diagonal matrix [1].

Solution.

1) $A = \begin{bmatrix} 2 & 2 & 4 \\ 1 & 5 & 1 \\ 1 & 1 & 8 \end{bmatrix} \to \begin{bmatrix} 2 & 2 & 4 \\ 0 & 4 & -1 \\ 0 & 0 & 6 \end{bmatrix} \therefore M_1 = \begin{bmatrix} 1 & 0 & 0 \\ -\frac{1}{2} & 1 & 0 \\ -\frac{1}{2} & 0 & 1 \end{bmatrix}, \quad L = M_1^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{2} & 1 & 0 \\ \frac{1}{2} & 0 & 1 \end{bmatrix}$

$U = \begin{bmatrix} 2 & 2 & 4 \\ 0 & 4 & -1 \\ 0 & 0 & 6 \end{bmatrix} \therefore A = LU = LDD^{-1}U$

$including \quad D = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 6 \end{bmatrix}$ and $P^{-1} = \begin{bmatrix} \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{4} & 0 \\ 0 & 0 & \frac{1}{6} \end{bmatrix}$

$\therefore M^T = D^{-1}u = \begin{bmatrix} \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{4} & 0 \\ 0 & 0 & \frac{1}{6} \end{bmatrix} \begin{bmatrix} 2 & 2 & 4 \\ 0 & 4 & -1 \\ 0 & 0 & 6 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 2 \\ 0 & 1 & -\frac{1}{4} \\ 0 & 0 & 1 \end{bmatrix}$

2) $B = UL \quad U^{-1}B = L$

[1] **Anti-diagonal matrix:** An anti-diagonal matrix is a square matrix where all the entries are zero except those on the diagonal going from the lower left corner to the upper right corner, known as the anti-diagonal. For example,

$$\text{adiag}(a_1, \ldots, a_n) = \begin{bmatrix} 0 & 0 & \cdots & 0 & a_1 \\ 0 & 0 & \cdots & a_2 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_n & 0 & \cdots & \cdots & 0 \end{bmatrix},$$

and consequently, unit anti-diagonal matrix means $\text{adiag}(1, \ldots, 1)$, also known as the **exchange matrix** or the **permutation matrix**.

$$B=\begin{bmatrix}8&1&1\\1&5&1\\4&2&2\end{bmatrix}\rightarrow\begin{bmatrix}6&0&0\\-1&4&0\\4&2&2\end{bmatrix}$$

$$\therefore M_1=\begin{bmatrix}1&0&-\frac{1}{2}\\0&1&-\frac{1}{2}\\0&0&1\end{bmatrix},\quad U=M_1^{-1}=\begin{bmatrix}1&0&\frac{1}{2}\\0&1&\frac{1}{2}\\0&0&1\end{bmatrix},\quad L=\begin{bmatrix}6&0&0\\-1&4&0\\4&2&2\end{bmatrix}\text{ then }B=UL$$

Problem 4 (7 points + 6 points + 7 points + 5 points)

Given a matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$, suppose that the LDM (LDU) decomposition of $\mathbf{A}$ exists, prove that

1) the LDM (LDU) decomposition of $\mathbf{A}$ is *uniquely* determined;
2) if $\mathbf{A}$ is a symmetric matrix, then its LDM (LDU) decomposition must be $\mathbf{A} = \mathbf{LDL}^T$, which is called LDL (LDL^T) decomposition in this case;
3) $\mathbf{A}$ is a symmetric and positive definite matrix if and only if its Cholesky decomposition exists (i.e., there exists a matrix $\mathbf{G} \in \mathbb{R}^{n\times n}$ such that $\mathbf{A} = \mathbf{GG}^T$, where $\mathbf{G}$ is lower triangular with *positive* diagonal entries);
4) if $\mathbf{A}$ is a symmetric and positive definite matrix, then its Cholesky decomposition is *uniquely* determined.

Hints:

1) The existence of the LDM (LDU) decomposition implies the non-singularity of the matrix.
2) You can directly utilize the following lemmas,
   - the inverse (if it exists) of a lower (resp. upper) triangular matrix is also lower (resp. upper) triangular;
   - the product of two lower (resp. upper) triangular matrices is lower (resp. upper) triangular;
   - also, if such two lower (resp. upper) triangular matrices have unit diagonal entries, then their product also has unit diagonal entries.

Solution.

1) To prove the uniqueness, suppose $A = LDM^T = L_1 D_1 M_1^T$ are two different LDM ^{T} decompositions. Note that all the matrices here are invertible, because A is non-singular. By the uniqueness of the LU decomposition , we have $L = L_1$, hence, $DM = D_1 M_1^T$ and $D_1^{-1} D = M_1^T \left(M^T\right)^{-1}$. since both M^T and M_1^T are unit upper triangular, so is $M_1^T \left(M^T\right)^{-1}$. On the other hand, $D_1^{-1} D$ is diagonal. The only matrix that is unit lower triangular and diagonal is the identity matrix. Thus $M_1^T \left(M^T\right)^{-1} = I$ and $D_1^{-1} D = I$, which implies $M^T = M_1^T$ and $D = D_1$
2) Suppose that the symmetric matrix A has the unique LDU decomposition $\mathbf{A} = \mathbf{LDU}$. Then, $\mathbf{A} = \mathbf{A}^T = \mathbf{U}^T\mathbf{DL}^T$, implying (since $\mathbf{U}^T$ is unit lower triangular and $\mathbf{L}^T$ is unit upper triangular) that $\mathbf{A} = \mathbf{U}^T\mathbf{DL}^T$ is an LDU decomposition of A and hence in light of the uniqueness of the LDU decomposition that $\mathbf{L} = \mathbf{U}^T$ (or equivalently $\mathbf{U} = \mathbf{L}^T$).
3) $\mathbf{Prove\ sufficiency\ first}$: According to the eigenvalue decomposition of the symmetric matrix,we get $A = Q \operatorname{diag}(\lambda_1, \lambda_2, \cdots, \lambda_n) Q^T$ according to the above formula,

$$A = \underbrace{\left[Q \operatorname{diag}\left(\sqrt{\lambda_1}, \sqrt{\lambda_2}, \cdots, \sqrt{\lambda_n}\right)\right.}_{V} \underbrace{\left[\text{Qdiag}\left(\sqrt{\lambda_1}, \sqrt{\lambda_2}, \cdots, \sqrt{\lambda_n}\right)\right]^T}_{V} = VV^T$$

do the RQ decomposition to V, we get $V = \widetilde{K}Q$, in which $\widetilde{K}$ is upper triangular matrix and Q is orthogonal matrix,then

$$A = VV^T = \widetilde{K}QQ^T\widetilde{K}^T = \widetilde{K}\widetilde{K}^T$$

Command $D = \operatorname{diag}(\operatorname{sign} k_{11}, \operatorname{sign} k_{22}, \cdots, \operatorname{sign} k_m)$, then $K = \tilde{K}D$ is an upper triangular matrix with positive diagonal elements. As a result,

$$A = \widetilde{K}\widetilde{K}^T = \left(KD^{-1}\right)\left(KD^{-1}\right)^T = KK^T$$

Prove necessity :G is a lower triangular with positive diagonal entries, then $A^T = GG^T = A$. So $A = GG^T$ is a symmetic matrix obviously. And for $\forall x \neq 0, x^T Ax = x^T GG^T x = \left(G^T x\right)^T G^T x = \left\|G^T x\right\|_2^2 > 0$. So A is a positive definite matrix.

4) let's prove uniqueness: if exist K_1, K_2 can make $K_1 K_1^T = A = K_2 K_2^T$,there must be

$$K_2^{-1}K_1 = K_2^T K_1^{-T} = \left(K_2^{-1}K_1\right)^{-T}$$

Since both sides of the above equation are lower triangular and upper triangular matrices respectively, they are the same diagonal matrix, then

$$K_2^{-1}K_1 = \left(K_2^{-1}K_1\right)^{-T} = \left(K_2^{-1}K_1\right)^{-1}$$

so there must be $K_2^{-1}K_1 = I, \quad$ so $K_1 = K_2$

Problem 5 (10 points + 5 points)

Consider matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$ in the following form,

$$\mathbf{A} = \begin{bmatrix} b_1 & c_1 & 0 & 0 & 0 & 0 \\ a_2 & b_2 & c_2 & 0 & 0 & 0 \\ 0 & a_3 & b_3 & c_3 & 0 & 0 \\ 0 & 0 & \ddots & \ddots & \ddots & 0 \\ \vdots & \vdots & \ddots & a_{n-1} & b_{n-1} & c_{n-1} \\ 0 & 0 & \cdots & 0 & a_n & b_n \end{bmatrix},$$

where a_j, b_j, and c_j are non-zero entries. The matrix in such form is known as a **Tridiagonal Matrix** in the sense that it contains three diagonals.

1) LU decomposition is particularly efficient in the case of tridiagonal matrices. Find the LU decomposition of $\mathbf{A}$ (derivation is expected) and try to complete the Algorithm 1.

Algorithm 1: LU decomposition for tridiagonal matrices

Input : Tridiagonal matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$.

Output: LU decomposition of $\mathbf{A}$.

Complete the algorithm here...

```
N=length(A);
z = zeros(N,1);
L=eye(N);%Let the L matrix be an identity matrix at first
for i=1:N-1
    for j=i+1:N
            L(j,i)=A(j,i)/A(i,i);
            A(j,:)=A(j,:)-(A(j,i)/A(i,i))*A(i,:);
    end
end
L
U=A
```

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2) Consider symmetric tridiagonal matrices

$$\mathbf{A} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix} \quad \text{and } \mathbf{B} = \begin{bmatrix} a & a & 0 \\ a & a+b & b \\ 0 & b & b+c \end{bmatrix},$$

and give the LU decompositions and the LDL^T (also known as the LDL) decompositions of $\mathbf{A}$ and $\mathbf{B}$ respectively.

Solution.

1)

$$A=\begin{bmatrix} b_1 & c_1 & 0 & 0 & 0 & 0 \\ a_2 & b_2 & c_2 & 0 & 0 & 0 \\ 0 & a_3 & b_3 & c_3 & 0 & 0 \\ 0 & 0 & \ddots & \ddots & \ddots & 0 \\ \vdots & \vdots & \ddots & a_{n-1} & b_{n-1} & c_{n-1} \\ 0 & 0 & \cdots & 0 & a_n & b_n \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ v_2 & 1 & 0 & \cdots & 0 \\ 0 & v_3 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 1 & 0 \\ 0 & \cdots & 0 & v_n & 1 \end{bmatrix} \begin{bmatrix} \beta_1 & c_1 & 0 & \cdots & 0 \\ 0 & \beta_2 & c_2 & \ddots & \vdots \\ 0 & 0 & \ddots & \ddots & 0 \\ \vdots & \vdots & \ddots & \beta_{n-1} & c_{n-1} \\ 0 & 0 & \cdots & 0 & \beta_n \end{bmatrix} = LU$$

To determine L, U :

$$b_1 = \beta_1 \Rightarrow \beta_1 = b_1$$

$$a_k = v_k \beta_{k-1} \Rightarrow v_k = a_k/\beta_{k-1}$$

$$b_k = v_k c_{k-1} + \beta_k \Rightarrow \beta_k = b_k - v_k c_{k-1}, \quad k = 2, \dots, n$$

2) $$A = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} = Lu = LDL^\top$$

$$B = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} a & a & 0 \\ 0 & b & b \\ 0 & 0 & c \end{bmatrix} = LH$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} = LDL^T$$

III. Programming

Problem 6 (5 points + 15 points)

In this problem, we explore the efficiency of the LU method together with the classical linear system solvers we have learnt in linear algebra.

1) Derive the complexity of the LU decomposition. Particularly, how many flops does the LU decomposition require? The corresponding pseudo code (in Matlab) is provided as follows:

```
function [L,U]= Naive_lu(A)
    n = size(A,1)
    L = eye(n)
    U = A
    for k=1:n-1
        for j=k+1:n
            L(j,k)=U(j,k)/U(k,k)
            U(j,k:n)=U(j,k:n)-L(j,k)*U(k,k:n)
        end
    end
    for k=2:n
        U(k,1:k-1)=0
    end
end
```

2) **Programming part:** Randomly generate a non-singular matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$ and a vector $\mathbf{b} \in \mathbb{R}^{n\times 1}$, then program the following methods to solve $\mathbf{A}\mathbf{x} = \mathbf{b}$:

- **The inverse method:** Use the inverse of $\mathbf{A}$ to solve the problem, which can be written as,

$$\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}\,.$$

- **Cramer rule:** Suppose $\mathbf{x} = [x_1, \ldots, x_n]^T$, and we denote $\mathbf{A}_{-i}(\mathbf{b})$ the matrix that we replace the i-th column of $\mathbf{A}$ with $\mathbf{b}$. Then we have

$$x_i = \frac{\det(\mathbf{A}_{-i}(\mathbf{b}))}{\det(\mathbf{A})}, i = 1, \ldots, n\,.$$

- **Gauss Elimination:** We perform row operations on the augmented matrix $[\mathbf{A}|\mathbf{b}]$, and use back substitution to obtain the solution $\mathbf{x}$.
- **LU decomposition.** We first find the LU decomposition of $\mathbf{A}$, then we solve $\mathbf{L}\mathbf{y} = \mathbf{b}$ and $\mathbf{U}\mathbf{x} = \mathbf{y}$.

In your homework, you are required to submit the time-consuming plot (**one figure**) of given methods against the size of matrix $\mathbf{A}$ (i.e., n), where $n = 100, 150, \ldots, 1000$ (You can try larger n and see what will happen, but be careful with the memory use of your PC!).

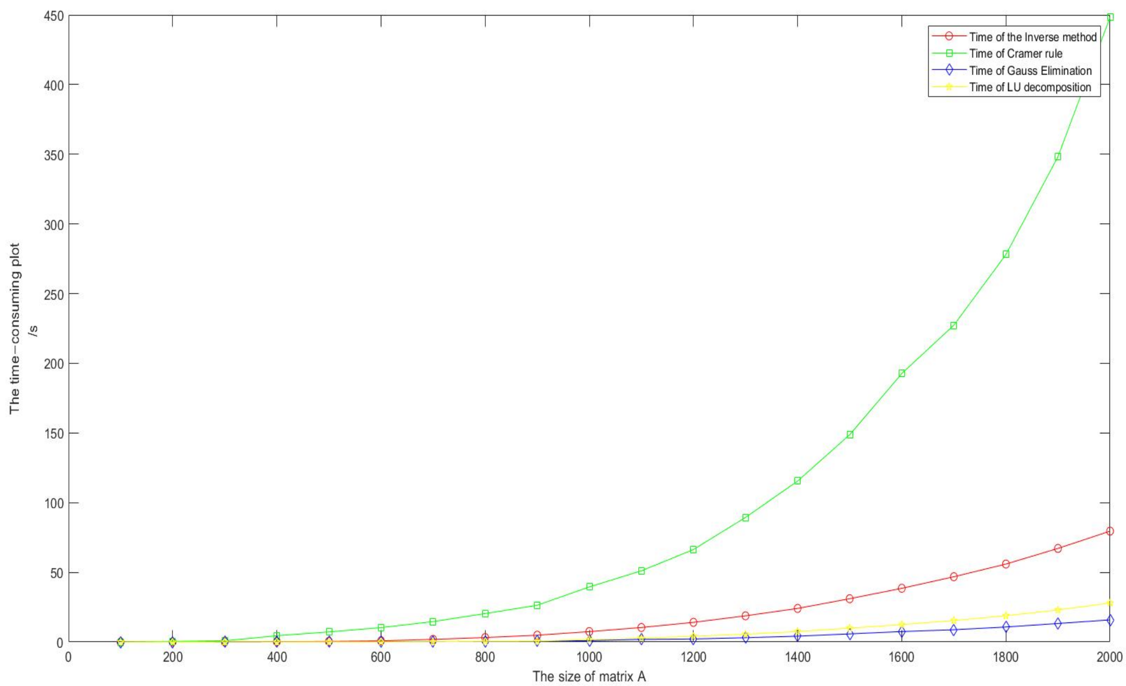

Figure 1. This is an inserted JPG graphic

Remarks: (Important!)

- Coding languages are restricted, but do not use any bulit-in function. For example, do not use Matlab functions such as A/b, inv(A) or lu(A). Otherwise, your results will contradict the complexity analysis, and your scores will be discounted. You can implement the simplest version of these methods by yourself.
- When handing in your homework in gradescope, package all your codes into your_student_id+hw2_code.zip and upload. In the package, you also need to include a file named README.txt/md to clearly identify the function of each file.
- Make sure that your codes can run and are consistent with your solutions.

Solution.

1) $\sum_{k=1}^{n-1}[1+2(n-k+1)](n-k)$
$= \sum_{k=1}^{n-1} 2(n-k)^2+3(n-k)$
$= \sum_{k=1}^{n-1} 2\left(n^2-2nk+k^2\right)+3 \mid n-k\big)$
$= 2n^2(n-1)-4n\sum_{k=1}^{n-1} k+2\sum_{k=1}^{n-1} k^2+3n(n-1)-3\sum_{k=1}^{n-1} k$
$= 2n^3-2n^2-(4n+3)\frac{n(n-1)}{2}+2\frac{(2n-1)n(n-1)}{6}+3n^2-3n$
$= \frac{2}{3}n^3 \quad (n>>0)$

2)
```
dimention = 100:100:2000;
```

```
compute_time=zeros(4,length(dimention));
for n=100:100:2000
    A=round(10*rand(n,n));
    b=round(10*rand(n,1));

    t1=cputime;
    method_1=INVERSE(A,b);
    compute_time(1,n/100)=cputime-t1

    t2=cputime;
    method_2=CRAMER(A,b);
    compute_time(2,n/100)=cputime-t2

    t3=cputime;
    method_3=GAUSS(A,b);
    compute_time(3,n/100)=cputime-t3

    t4=cputime;
    method_4=LU(A,b);
    compute_time(4,n/100)=cputime-t4
end
plot(dimention,compute_time(1,:),'ro-');hold on;
plot(dimention,compute_time(2,:),'gs-');hold on;
plot(dimention,compute_time(3,:),'bd-');hold on;
plot(dimention,compute_time(4,:),'yp-');hold off;
```

```
function inverse_ans =INVERSE(A,b)
N=length(A);
%get the upper triangular matrix
B=eye(N);
for i=1:N
    max=A(i,i);
    M=i;
    for j=i+1:N
        if(abs(A(j,i))>abs(max))%To find the maximum
            max=A(j,i);
```

```
                M=j;
            end
        end
        for m=1:N
            temp1=A(i,m);%Swap the row where the maximum value is and the current row
            A(i,m)=A(M,m);
            A(M,m)=temp1;
            temp2=B(i,m);
            B(i,m)=B(M,m);
            B(M,m)=temp2;
        end
        for k=i+1:N
            xishu=A(k,i)/A(i,i);%The other rows are weighted to give you the upper triangle
            for n=1:N
                A(k,n)=A(k,n)-xishu*A(i,n);
                B(k,n)=B(k,n)-xishu*B(i,n);
            end
        end
end
temp3=A;
%get the identity matrix
for s=N:-1:1
        xishu1 =A(s,s);
        for p=s:N
            A(p,s)=A(p,s)/xishu1;
        end
        for q=1:N
            B(s,q)=B(s,q)/xishu1;
        end
        for w=s-1:-1:1
            xishu=A(w,s);
            A(w,s)=0;
            for t=1:N
                B(w,t)=B(w,t)-xishu*B(s,t);
            end
        end
```

```
end
temp2=A;
inverse_ans=B*b;
```

```
function cramer_ans = CRAMER(A,b)
N=length(A);
cramer_ans=zeros(N,1);
D_det=zeros(N,1);
D=det(A);
A0=A;
for i=1:N
    for j=1:N
        A0(j,i)=b(j);
    end
    D_det(i)=det(A0);
    A0=A;
end
for k=1:N
    cramer_ans(k)=D_det(k)/D;
end
```

```
function Gauss_ans=GAUSS(A,b)
N=length(A);
for i=1:N
    max=A(i,i);
    M=i;
    for j=i+1:N
        if(abs(A(j,i))>abs(max))%Look for the i th column maximum
            max=A(j,i);
            M=j;
        end
    end
    for m=i:N
        temp1=A(i,m);%Swap the row where the maximum value is and the current row
        A(i,m)=A(M,m);
        A(M,m)=temp1;
    end
```

```
            temp2=b(i);
            b(i)=b(M);
            b(M)=temp2;

        for k=i+1:N
            xishu=A(k,i)/A(i,i);%The other rows are weighted to give you the upper triangle
            for n=i:N
                A(k,n)=A(k,n)-xishu*A(i,n);
            end
            b(k)=b(k)-xishu*b(i);
        end
end
Gauss_ans=zeros(N,1);
% Gauss_ans(N)=b(N)/A(N,N);
for p=N:-1:1
    Gauss_ans(p)=b(p)/A(p,p);
    for q=N:-1:p+1
        Gauss_ans(p)=Gauss_ans(p)-Gauss_ans(q)*A(p,q)/A(p,p);
    end
end
```

```
function LU_ans = LU(A,b)
N=length(A);
z = zeros(N,1);
LU_ans = zeros(N,1);
L=eye(N);%Let the L matrix be an identity matrix at first
for i=1:N-1
    for j=i+1:N
            L(j,i)=A(j,i)/A(i,i);
            A(j,:)=A(j,:)-(A(j,i)/A(i,i))*A(i,:);
    end
end

for p=1:1:N
    z(p)=b(p)/L(p,p);
    for q=1:1:p-1
```

```
        z(p)=z(p)-z(q)*L(p,q)/L(p,p);
    end
end
for p_2=N:-1:1
    LU_ans(p_2)=z(p_2)/A(p_2,p_2);
    for q_2=N:-1:p_2+1
        LU_ans(p_2)=LU_ans(p_2)-LU_ans(q_2)*A(p_2,q_2)/A(p_2,p_2);
    end
end
```

IV. ROUNDOFF ERROR

Problem 7 (Bonus Problem: 10 points + 8 points + 2 points)

Given a matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$, consider the roundoff error in the process of solving $\mathbf{Ax} = \mathbf{b}$ by Gaussian elimination in three stages:

1. Decompose $\mathbf{A}$ into $\mathbf{LU}$, in a machine with roundoff error $\mathbf{E}$, $\bar{\mathbf{L}}$ and $\bar{\mathbf{U}}$ are computed instead, i.e.,
$$\mathbf{A} + \mathbf{E} = \bar{\mathbf{L}}\bar{\mathbf{U}}\,.$$
2. Solving $\mathbf{Ly} = \mathbf{b}$, numerically with roundoff error $\delta\bar{\mathbf{L}}$, $\hat{\mathbf{y}} = \mathbf{y} + \delta\mathbf{y}$ are computed instead, i.e.,
$$(\bar{\mathbf{L}} + \delta\bar{\mathbf{L}})(\mathbf{y} + \delta\mathbf{y}) = \mathbf{b}\,.$$
3. Solving $\mathbf{Ux} = \mathbf{y}$, numerically with roundoff error $\delta\bar{\mathbf{U}}$, $\hat{\mathbf{x}} = \mathbf{x} + \delta\mathbf{x}$ are computed instead, i.e.,
$$(\bar{\mathbf{U}} + \delta\bar{\mathbf{U}})(\mathbf{x} + \delta\mathbf{x}) = \hat{\mathbf{y}}\,.$$

Finally, we can get the computed solution $\hat{\mathbf{x}}$ and
$$\begin{aligned}\mathbf{b} =& (\bar{\mathbf{L}} + \delta\bar{\mathbf{L}})(\bar{\mathbf{U}} + \delta\bar{\mathbf{U}})(\mathbf{x} + \delta\mathbf{x})\\ =& (\mathbf{A} + \delta\mathbf{A})(\mathbf{x} + \delta\mathbf{x})\,.\end{aligned}$$

1) Prove that the relative error of $\mathbf{x}$ has an upper bound as follows,
$$\frac{\|\hat{\mathbf{x}} - \mathbf{x}\|}{\|\mathbf{x}\|} = \frac{\|\delta\mathbf{x}\|}{\|\mathbf{x}\|} \leq \frac{1}{1 - \kappa(\mathbf{A})\frac{\|\delta\mathbf{A}\|}{\|\mathbf{A}\|}}\kappa(\mathbf{A})\frac{\|\delta\mathbf{A}\|}{\|\mathbf{A}\|},$$
where $\kappa(\mathbf{A}) = \|\mathbf{A}\|\|\mathbf{A}^{-1}\|$ denotes the condition number of matrix $\mathbf{A}$ (Suppose $\mathbf{A}$ and $\mathbf{A}+\delta\mathbf{A}$ are nonsingular and $\|\mathbf{A}^{-1}\|\|\delta\mathbf{A}\| < 1$), and $\|\cdot\|$ can be any norm.
Hint: The following equation might be useful,
$$\|(\mathbf{I} - \mathbf{B})^{-1}\| = \|\sum_{k=0}^{\infty}\mathbf{B}^k\| \leq \sum_{k=0}^{\infty}\|\mathbf{B}\|^k \leq \frac{1}{1 - \|\mathbf{B}\|}\,.$$
where $\mathbf{I} - \mathbf{B}$ is nonsingular and $\lim_{n\to\infty}\mathbf{B}^n = \mathbf{0}$.
2) Consider a linear system $\mathbf{Ax} = \mathbf{b}$, where
$$\mathbf{A} = \begin{bmatrix} 2 & -1 & 1\\ -1 & 10^{-10} & 10^{-10}\\ 1 & 10^{-10} & 10^{-10}\end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 2(1+10^{-10})\\ -10^{-10}\\ 10^{-10}\end{bmatrix}$$
find the solution $\mathbf{x}$, and calculate the condition number of $\mathbf{A}$ with the matrix infinite norm[2], i.e. $\kappa_\infty(\mathbf{A}) = \|\mathbf{A}\|_\infty\|\mathbf{A}^{-1}\|_\infty$. Suppose $|\delta\mathbf{A}| < 10^{-18}|\mathbf{A}|$[3], use $\kappa_\infty(\mathbf{A})$ to verify that
$$\|\delta\mathbf{x}\| < 10^{-7}\|\mathbf{x}\|.$$

[2]If $\mathbf{A} \in \mathbb{R}^{n\times n}$, then the matrix infinite norm is $\|\mathbf{A}\|_\infty = \max_{1<i<n}\sum_{j=1}^{n}|a_{i,j}|$.
[3]$|\mathbf{A}| \leq |\mathbf{B}|$ means each element in $\mathbf{A}$ is relative smaller to the corresponding element of $\mathbf{A}$

3) Discuss what you have observed from the previous 2 questions. What are the main factors that influence the relative error of the computed solution? Does the ill-conditioned matrix (i.e. the condition number is large) always lead to a large error of the solution?

Solution.

1) Because $\left\|A^{-1}A\right\| < 1$.then $\left\|A^{-1}\delta A\right\| < 1$. We have

$$A + \delta A = A\left(I + A^{-1}\delta A\right) = A(I + A^{-1}\delta A)$$

From the manipulations

$$\begin{aligned}(A+\delta A)^{-1}\mathbf{b} - A^{-1}\mathbf{b} &= \left(I + A^{-1}\delta A\right)^{-1} A^{-1}\mathbf{b} - A^{-1}\mathbf{b} \\ &= \left(I + A^{-1}\delta A\right)^{-1}\left(A^{-1} - \left(I + A^{-1}\delta A\right)A^{-1}\right)\mathbf{b} \\ &= \left(I + A^{-1}\delta A\right)^{-1}\left(-A^{-1}(\delta A)A^{-1}\right)\mathbf{b}\end{aligned}$$

and use the condition of question stem,we get

$$\left\|(I + A^{-1}\delta A)^{-1}\right\| \leq \frac{1}{1 - \|A^{-1}\delta A\|}$$

we obtain

$$\frac{\|\delta \mathrm{x}\|}{\|\mathrm{x}\|} = \frac{\|(\mathrm{x} + \delta\mathrm{x}) - \mathrm{x}\|}{\|\mathrm{x}\|}$$

$$\begin{aligned}\therefore \frac{\|\delta x\|}{\|x\|} = \frac{\|\hat{x} - x\|}{\|x\|} &= \frac{\left\|-\left(\mathbf{I} + A^{-1}\delta A\right)^{-1} A^{-1}\delta A x\right\|}{\|x\|} \\ &\leq \frac{\left\|\left(\mathbf{I} + A^{-1}\delta A\right)^{-1} A^{-1}\delta A\right\| \|x\|}{\|x\|} \\ &\leq \left\|\left(I + A^{-1}\delta A\right)^{-1}\right\| \left\|A^{-1}\right\| \|\delta A\| \\ &\leq \frac{1}{1 - \|A^{-1}\delta A\|}\left\|A^{-1}\right\| \|\delta A\| \\ &\leq \frac{\left\|A^{-1}\right\| \|\delta A\|}{1 - \|A^{-1}\| \|\delta A\|} \\ &= \frac{1}{1 - \kappa(A)\frac{\|\delta A\|}{\|A\|}}\kappa(A)\frac{\|\delta A\|}{\|A\|}\end{aligned}$$

2)

$$A = \mathbf{LU} = \begin{bmatrix} 1 & 0 & 0 \\ -\frac{1}{2} & 1 & 0 \\ \frac{1}{2} & \frac{10^{-10}+\frac{1}{2}}{10^{-10}-\frac{1}{2}} & 1 \end{bmatrix} \begin{bmatrix} 2 & -1 & 1 \\ 0 & 10^{-10} - \frac{1}{2} & 10^{-10} + \frac{1}{2} \\ 0 & 0 & -\frac{2\times 10^{-10}}{10^{-10}-\frac{1}{2}} \end{bmatrix}$$

we can get $y = \left(2\left(1+10^{-10}\right), \quad 1, \quad -\frac{2\times10^{-10}}{10^{-10}-\frac{1}{2}}\right)^\top, x = \left(10^{-10}, -1, 1\right)^\top$

$$\therefore A^{-1} = \begin{bmatrix} 0 & -\frac{1}{2} & \frac{1}{2} \\ -\frac{1}{2} & \frac{\frac{1}{2}-10^{-10}}{2\times10^{-10}} & \frac{\frac{1}{2}+10^{-10}}{2\times10^{-10}} \\ \frac{1}{2} & \frac{\frac{1}{2}+10^{-10}}{2\times10^{-10}} & \frac{\frac{1}{2}-10^{-10}}{2\times10^{-10}} \end{bmatrix}$$

$$\therefore \kappa_\infty(\mathbf{A}) = \|\mathbf{A}\|_\infty \left\|\mathbf{A}^{-1}\right\|_\infty = 4\times\frac{10^{10}+1}{2} = 2\left(10^{10}+1\right)$$

$$\therefore \frac{\|\delta \mathrm{x}\|}{\|\mathrm{x}\|} \le \frac{1}{1-\kappa(\mathbf{A})\frac{\|\delta\mathbf{A}\|}{\|\mathbf{A}\|}}\kappa(\mathbf{A})\frac{\|\delta\mathbf{A}\|}{\|\mathbf{A}\|} = \frac{2\left(10^{10}+1\right)\frac{\|\delta\mathbf{A}\|}{\|\mathbf{A}\|}}{1-2\left(10^{10}+1\right)\frac{\|\delta\mathbf{A}}{\|\mathbf{A}\|}} = \frac{1}{\frac{|\mathbf{A}|}{2(10^{10}+1)|\delta\mathbf{A}|}-1}$$

$$< \frac{1}{\frac{\|\mathbf{A}\|}{2(10^{10}+1)\|\delta\mathbf{A}\|}-1} < \frac{1}{\frac{10^{18}}{2(10^{10}+1)}-1} < \frac{1}{\frac{10^{18}}{5\times10^{10}}-1} = \frac{1}{2\times10^{7}-1} < 10^{-7}$$

So we get $\|\delta\mathbf{x}\| < 10^{-7}\|\mathbf{x}\|$.

3) condition number of $\mathbf{A}$ influence the relative error of the computed solution.