

## Gaussian elimination without Pivoting

The basic gaussian elimination without pivoting (no row interchanges) is redundant due to roundoff error.

Example:

recall machine eps  $\epsilon = 2^{-52}$

roundoff errors in machines:

$2 + \epsilon = 2$  (in a machine next largest number after 2 is  $2 + 2\epsilon$ ).

$4 - \epsilon = 4$  (similarly, next largest number after 4 is  $4 + 4\epsilon$ ).

say we have:  $\epsilon x_1 + 2x_2 = 4 \rightarrow$   $\epsilon x_1$  is very small  $\therefore x_2 = \frac{4}{2} = 2$   
 $x_1 - x_2 = 1 \rightarrow$  since  $x_2 = 2 \rightarrow x_1 = 3$

our 'theoretical' numerical simulation should give this answer

$$\text{augmented matrix} \rightarrow \begin{pmatrix} \epsilon & 2 & 4 \\ 1 & -1 & 1 \end{pmatrix} \xrightarrow{-\frac{1}{\epsilon}r_1 + r_2} \begin{pmatrix} \epsilon & 2 & 4 \\ 0 & -\frac{2}{\epsilon} - 1 & 1 - \frac{4}{\epsilon} \end{pmatrix}$$

$\therefore$  Multiply by  $-\epsilon$ :

$$(2 + \epsilon)x_2 = 4 - \epsilon$$

$$\text{or, } 2x_2 = 4 \rightarrow x_2 = 2$$

$$\epsilon x_1 + 2x_2 = 4$$

$$\text{put in } x_2 = 2$$

$$\therefore \epsilon x_1 = 0 \rightarrow x_1 = 0$$

Sol 2

solutions does not match up!

this is because of roundoff errors that occurred when we said numbers with  $\epsilon$  are equal to 0.

$$\begin{aligned} \epsilon x_1 + 2x_2 &= 4 \\ \left(-\frac{2}{\epsilon} - 1\right)x_2 &= 1 - \frac{4}{\epsilon} \end{aligned}$$

Example: Consider the equations

$$\begin{aligned} 2\epsilon x_1 + 2x_2 &= 4 \\ x_1 - x_2 &= 1 \end{aligned} \quad \left[ \begin{array}{cc|c} 2\epsilon & 2 & 4 \\ 1 & -1 & 1 \end{array} \right] \text{ augmented matrix}$$

solve in matlab without pivoting  $\rightarrow x_1 = 3, x_2 = 2$

solving analytically:  $2\epsilon x_1 + 2x_2 = 4 \rightarrow 2\epsilon x_1$  is small

$$\therefore x_2 = 2$$

$$\therefore x_1 = 1 + 2 = 3$$

Partial pivoting  $\rightarrow$  row interchanges

$$\text{System: } \begin{aligned} \epsilon x_1 + 2x_2 &= 4 \\ x_1 - x_2 &= 1 \end{aligned} \quad \left[ \begin{array}{cc|c} 2\epsilon & 2 & 4 \\ 1 & -1 & 1 \end{array} \right]$$

$$\left[ \begin{array}{cc|c} 1 & -1 & 1 \\ 0 & 2 + \epsilon & 4 - \epsilon \end{array} \right] \xleftarrow{-\epsilon r_1 + r_2} \left[ \begin{array}{cc|c} 1 & -1 & 1 \\ \epsilon & 2 & 4 \end{array} \right]$$

$$\therefore x_2 = \frac{4 - \epsilon}{2 + \epsilon} = 2$$

$$x_1 = 1 + \frac{4 - \epsilon}{2 + \epsilon} = 3$$

solution with good pivoting

go down a column and look for number with largest magnitude. Here 1 is largest in column 1. Interchange this row ✓

## LU decomposition with partial pivots

$$A = \begin{bmatrix} -2 & 2 & -1 \\ 6 & -6 & 7 \\ 3 & -8 & 4 \end{bmatrix} \xrightarrow[\text{pivot in 1st column}]{\substack{r1 \leftrightarrow r2 \\ \text{row-wise}}} \begin{bmatrix} 6 & -6 & 7 \\ -2 & 2 & -1 \\ 3 & -8 & 4 \end{bmatrix} \xrightarrow[r3 - r1]{\substack{r2 + \frac{r1}{3} \\ \text{row-wise}}} \begin{bmatrix} 6 & -6 & 7 \\ 0 & 0 & \frac{4}{3} \\ 0 & -5 & \frac{1}{2} \end{bmatrix}$$

$P_{12}A$   $M_2M_1P_{12}A$

\*  $P_{12}, P_{23}$  are transformation matrices. Multiplication by  $P_{12}/P_{23}$  on right side to any matrix interchanges columns. Multiplication by  $P_{12}/P_{23}$  on left to any matrix interchanges rows

$$\begin{bmatrix} 6 & -6 & 7 \\ 0 & -5 & \frac{1}{2} \\ 0 & 0 & \frac{4}{3} \end{bmatrix} \xleftarrow{\text{row-wise pivot in 2nd column}} P_{23}M_2M_1P_{12}A = \text{Upper triangular matrix}$$

Now to compute  $L$  from the upper triangle, we use the LU decomposition formula:

In our case:  $(P_{23}M_2M_1P_{23})P_{23}P_{12}A = U$

or,  $P_{23}P_{12}A = (P_{23}M_2M_1P_{23})^{-1}U$

here,  $(P_{23}M_2M_1P_{23})^{-1} = L$

where  $P_{12} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ ,  $M_2 = \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{3} & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ ,  $M_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -\frac{1}{2} & 0 & 1 \end{bmatrix}$

and  $P_{23} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$

$M_2M_1 = \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{3} & 1 & 0 \\ -\frac{1}{2} & 0 & 1 \end{bmatrix}$

$\therefore P_{23}M_2M_1P_{23}$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{3} & 1 & 0 \\ -\frac{1}{2} & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ -\frac{1}{2} & 0 & 1 \\ \frac{1}{3} & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -\frac{1}{2} & 1 & 0 \\ \frac{1}{3} & 0 & 1 \end{bmatrix}$$

$$(P_{23}M_2M_1P_{23})^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{2} & 1 & 0 \\ -\frac{1}{3} & 0 & 1 \end{bmatrix} = L$$

Matlab saves this  $L$  matrix as  $P_{12}P_{23}L$  and calls it "a psychologically lower triangular matrix". All the decomposition algos completed till now is how Matlab handles matrices. It is faster to deduce LU decomposition of  $A$  in  $AX=B$  and find solution than it is to find solution of  $AX=B$  using Gaussian elimination.