

1) let for any vector  $x \in \mathbb{R}^n$ :

$$x = [x_1 \ x_2 \ \dots \ x_n]^T$$

(a) here,  $y = y_s + y_a$

or,

$$y = [y_{s1} + y_{a1} \ y_{s2} + y_{a2} \ \dots \ y_{sn} + y_{an}]^T$$

or,  $y_i = y_{si} + y_{ai} \ \forall i \in [1, n]$

and,  $y_{n-i+1} = y_{s,n-i+1} + y_{a,n-i+1}$

Since,  $y_{si} = y_{s,n-i+1}$  and  $y_{a,n-i+1} = -y_{ai}$

$$\therefore y_i = y_{si} + y_{ai}$$

and,  $y_{n-i+1} = y_{si} - y_{ai}$

or,  $y_{si} = \frac{y_i + y_{n-i+1}}{2}$ ,  $y_{ai} = \frac{y_i - y_{n-i+1}}{2}$

So, for any  $y \in \mathbb{R}^n$ ,

$$y_s = \left[ \frac{y_1 + y_n}{2} \ \frac{y_2 + y_{n-1}}{2} \ \dots \ \frac{y_n + y_1}{2} \right]^T \text{(symmetric)}$$

$$y_a = \left[ \frac{y_1 - y_n}{2} \ \frac{y_2 - y_{n-1}}{2} \ \dots \ \frac{y_n - y_1}{2} \right]^T \text{(assymmetric)}$$

such that  $y = \underline{y_s + y_a}$

(b) let  $f: \mathbb{R}^n \rightarrow \mathbb{R}^n$  such that for  $y \in \mathbb{R}^n$

$f(y) = y_s$ , where  $y_s$  is the symmetric part

also, let  $g: \mathbb{R}^n \rightarrow \mathbb{R}^n$  such that for  $y \in \mathbb{R}^n$

$g(y) = y_a$ , where  $y_a$  is the asymmetric part.

Now,  $f$  is linear iff:

$$f(\alpha y + \beta x) = \alpha f(y) + \beta f(x) \quad \text{for } x, y \in \mathbb{R}^n \text{ and } \alpha, \beta \in \mathbb{R}$$

LHS

$$f(\alpha y + \beta x) = (\alpha y + \beta x)_s$$

$$= \left[ \underbrace{(\alpha y + \beta x)_1 + (\alpha y + \beta x)_n}_2, \underbrace{(\alpha y + \beta x)_2 + (\alpha y + \beta x)_m}_2, \dots, \underbrace{(\alpha y + \beta x)_h + (\alpha y + \beta x)_i}_T \right]$$

$$= \left[ \underbrace{\alpha y_1 + \beta x_1 + \alpha y_n + \beta x_n}_2, \underbrace{\alpha y_2 + \beta x_2 + \alpha y_m + \beta x_m}_2, \dots, \underbrace{\alpha y_n + \beta x_n + \alpha y_1 + \beta x_1}_T \right]$$

$$= \left[ \underbrace{\beta \frac{(x_1 + x_n)}{2} + \alpha \frac{(y_1 + y_n)}{2}}_2, \dots, \underbrace{\alpha \frac{(y_n + y_1)}{2} + \beta \frac{(x_n + x_1)}{2}}_T \right]$$

$$= \beta \left[ \frac{x_1 + x_n}{2}, \frac{x_2 + x_{n-1}}{2}, \dots, \frac{x_n + x_1}{2} \right]^T +$$

$$\alpha \left[ \frac{y_1 + y_n}{2}, \frac{y_2 + y_{n-1}}{2}, \dots, \frac{y_n + y_1}{2} \right]^T$$

$$= \beta x_s + \alpha y_s = \beta f(x) + \alpha f(y)$$

$\therefore \text{RHS}$

Hence,  $f$  is a linear function

Similarly, we can show that  $g$  is a linear function.

For a linear function, we know

$$f(y) = A_f \cdot y \quad \text{where, } y \in \mathbb{R}^n \\ A_f \in \mathbb{R}^{n \times n}$$

$$\text{and } g(y) = A_g \cdot y$$

$$\text{now, } A_f \cdot y = y_s$$

$$A_f = \begin{bmatrix} y_1 & 0 & 0 & \dots & 0 & y_2 \\ 0 & y_1 & 0 & \dots & y_2 & 0 \\ 0 & 0 & y_1 & \dots & y_2 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & y_1 & y_2 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & y_1 \end{bmatrix}$$

$$\text{now, } A_g \cdot y = y_a$$

$$A_g = \begin{bmatrix} y_1 & 0 & 0 & \dots & 0 & y_2 \\ 0 & y_1 & 0 & \dots & y_2 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & y_1 & y_2 & 0 \\ 0 & 0 & \dots & y_1 & y_2 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & y_1 \end{bmatrix}$$

2.) We have

$$f(u, v) = \theta_0 + \theta_1 u + \theta_2 v + \theta_3 u^2 + \theta_4 u v$$

$$(a) \text{ now, } f(p_{ij}) = f(x_i, y_j)$$

$$= \theta_0 + \theta_1 x_i + \theta_2 y_j + \theta_3 x_i^2 + \theta_4 x_i y_j$$

$$A\theta = b$$

hence,  $A \Rightarrow$

$$\begin{bmatrix} 1 & x_1 & y_1 & x_1 y_1 \\ 1 & x_1 & y_2 & x_1 y_2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_2 & y_1 & x_2 y_1 \\ 1 & x_2 & y_2 & x_2 y_2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_m & y_n & x_m y_n \end{bmatrix} \in \mathbb{R}^{m \times 4}$$

$$\theta = [\theta_0 \ \theta_1 \ \theta_2 \ \theta_3 \ \theta_4]^T \in \mathbb{R}^{4 \times 1}$$

$$b = \begin{bmatrix} f_{11} \\ f_{12} \\ \vdots \\ f_{21} \\ f_{22} \\ \vdots \\ f_{mp} \end{bmatrix} \in \mathbb{R}^{m \times 1}$$

(b) For a unique solution to  $A\theta = b$ ,

the  $A$  matrix should be a tall matrix

i.e.,  $mn \geq 4$

For  $m=1$  or  $n=1$ , it is easy to verify that the columns of  $A$  are not linearly independent.

hence,  ~~$M \geq 2$~~  and  $N \geq 2$ .

minimum values of  $M, N = (2, 2)$

to expect an unique solution to  
 $A\theta = b$ .

3.) We have,

$$A, B \in \mathbb{R}^{n \times n}$$

$\| \cdot \|_2$  - induced 2-norm of matrix

To prove:  $\|AB\|_2 \leq \|A\|_2 \|B\|_2$

We know that

for  $P \in \mathbb{R}^{n \times n}$  and  $x \in \mathbb{R}^n$

$$\|Px\|_2 \leq \|P\|_2 \|x\|_2 \quad (1)$$

Put,  $P = AB$ ,  $x = Bx$

$$\begin{aligned} \text{So, } \|ABx\|_2 &\leq \|A\|_2 \cdot \|Bx\|_2 \\ &\leq \|A\|_2 \cdot \|B\|_2 \|x\|_2 \end{aligned} \quad [\text{From (1)}]$$

Dividing by  $\|x\|_2$ :

$$\frac{\|ABx\|_2}{\|x\|_2} \leq \|A\|_2 \cdot \|B\|_2$$

Taking max both sides:

$$\text{or, } \|AB\|_2 \leq \|A\|_2 \cdot \|B\|_2 \quad = \underline{\text{proved}}$$

Yes, Frobenius norm also follows this property but the proof should follow from Cauchy-Schwarz inequality.

4) We have,  
 $A \in \mathbb{R}^{n \times n}$ ,  $x \in \mathbb{R}^n$

$$A = I_n + ab^T \text{ if } a, b \in \mathbb{R}^n$$

now, suppose we are given  $a$  and  $b$  vectors.

$$\begin{aligned} \text{\# of operations for } ab^T x &\Rightarrow n + n-1 \\ &\Rightarrow \underline{(2n-1)} \end{aligned}$$

$$\text{and } (ab^T) \in \mathbb{R}^{n \times n}$$

$$\begin{aligned} \text{now, } Ax &= (I_n + (ab^T))x \\ &= I_n \cdot x + (ab^T)x \\ &= x + (ab^T)x \\ &= x + a(b^T x) \end{aligned}$$

$$\text{or, } Ax = (I + ab^T)x$$

$$\text{\# of operations for } (I + ab^T)x = \underline{(2n-1)}$$

= 2n-1 operations

$$\begin{aligned} \text{\# of operations for } a(b^T x) &= 3n-1 \text{ operations} \\ \therefore \text{\# of operations for } (I + ab^T)x &= \underline{3n-1} \end{aligned}$$

= 3n-1

= 4n-1 operations

$\therefore Ax$  can be computed in  $\underline{4n-1}$  operations  
 if  $A = I_n + ab^T$ .

5.) we have,

$$x \in \mathbb{R}^n, n \geq 1$$

(a) left inverse:

the columns of the matrix should be linearly independent.

Since,  $n \geq 1$  and  $x$  has 1 column

$\Rightarrow x$  has a left inverse.

For ex:  $x = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$

now, for  $c = \begin{bmatrix} -1 & 1 \end{bmatrix}$ ;

$$cx = I_1 = \begin{bmatrix} 1 \end{bmatrix}$$

(b) Right inverse:

the rows of the matrix should be linearly independent.

Since,  $n \geq 1$  and  $x$  has 1 column

$\Rightarrow$  rows of  $x$  are linearly dependent

$\Rightarrow$  right inverse of  $x$  does not exist.

6) Given:  $I_m + AB$  is invertible  
 $A \in \mathbb{R}^{m \times n}$ ,  $B \in \mathbb{R}^{n \times m}$

now,  $(I_n + BA)B = B + BAB = B(I_m + AB)$

or,  $(I_n + BA)B(I_m + AB)^{-1} = B$

post multiply by  $A$  and add  $I_n$  both sides:

$$I_n + (I_n + BA)B(I_m + AB)^{-1}A = BA + I_n$$

or,  $(I_n + BA)B(I_m + AB)^{-1}A - (I_n + BA) = -I_n$

or,  $(I_n + BA)[I_n - B(I_m + AB)^{-1}A] = I_n$

hence, inverse exists for  $(I_n + BA)$

$\therefore I_n + BA$  is invertible

now,  $(I_n + BA)^{-1} = I_n - B(I_m + AB)^{-1}A$

pre multiply by  $(I_n + BA)$ :

$$\Rightarrow I_n = (I_n + BA) - (I_n + BA)B(I_m + AB)^{-1}A$$

$$(I_m + AB)^{-1}A$$

or,  $BA = (I_n + BA)B(I_m + AB)^{-1}A$

or,  $B = (I_n + BA)B(I_m + AB)^{-1}$  or  $A = 0$

or,  $(I_n + BA)^{-1}B = B(I_m + AB)^{-1}$

~~██████████~~

now, if  $A = 0$ , then  $(I_n + BA)^{-1}B = B$

and  ~~$B(I_m + AB)^{-1} = B$~~

$$\therefore (I_n + BA)^{-1}B = B(I_m + AB)^{-1}$$

proved

7) We have

$$A, B \in \mathbb{R}^{n \times n}$$

(a)  $A+B$ :

$A+B$  may not be invertible

Consider,  $B = -A$

$$\text{or, } [B]_{ij} = -[A]_{ij} \quad \forall i, j \in [1..n]$$

$$\text{So, } A+B = \mathbf{0}$$

which is not invertible.

(b)  $\begin{pmatrix} A & \mathbf{0} \\ \mathbf{0} & B \end{pmatrix} \in \mathbb{R}^{2n \times 2n}$

Since,  $A, B$  are invertible

$\Rightarrow$  columns of  $A, B$  are linearly

independent

$\Rightarrow$  columns of  $\begin{pmatrix} A \\ \mathbf{0} \end{pmatrix}$  and  $\begin{pmatrix} \mathbf{0} \\ B \end{pmatrix}$  will also

be linearly independent

$\Rightarrow \begin{pmatrix} A & \mathbf{0} \\ \mathbf{0} & B \end{pmatrix}$  has linearly independent columns.

$\Rightarrow \begin{pmatrix} A & \mathbf{0} \\ \mathbf{0} & B \end{pmatrix}$  is invertible

$$\Rightarrow \left| \begin{pmatrix} A & \mathbf{0} \\ \mathbf{0} & B \end{pmatrix} \right| \neq 0 - (1)$$

$$(c) \begin{pmatrix} A & A-B \\ 0 & B \end{pmatrix}$$

Now, determinant  $\begin{pmatrix} A & A-B \\ 0 & B \end{pmatrix}$

$$\Rightarrow \begin{vmatrix} A & A-B \\ 0 & B \end{vmatrix}$$

we can do matrix transformations

$$\Rightarrow \begin{vmatrix} A & A-B \\ 0 & B \end{vmatrix} \rightarrow \begin{vmatrix} A & -B \\ 0 & B \end{vmatrix}$$

$$\Rightarrow \begin{vmatrix} A & -B \\ 0 & B \end{vmatrix} \rightarrow \begin{vmatrix} A & 0 \\ 0 & B \end{vmatrix} \quad \begin{matrix} [C_2 \rightarrow C_2 - C_1] \\ [R_1 \rightarrow R_1 + R_2] \end{matrix}$$

From part (b)  $\begin{vmatrix} A & 0 \\ 0 & B \end{vmatrix} \neq 0$

$$\Rightarrow \begin{vmatrix} A & A-B \\ 0 & B \end{vmatrix} \neq 0$$

∴ invertible

(d) ABABA

we know that,  $|A| \neq 0, |B| \neq 0$

$$\text{so, } |ABABA| = |A| \cdot |B| \cdot |A| \cdot |B| \cdot |A| = |A|^3 \cdot |B|^2 \neq 0$$

Property of  
determinants

∴ invertible

8) We have:

$A \in \mathbb{R}^{n \times n}$ , Invertible matrix.

$$\max \text{mag}(A) = \max_{\|x\|_2=1} \|Ax\|_2$$

$$\min \text{mag}(A) = \min_{\|x\|_2=1} \|Ax\|_2$$

$$\text{cond}(A) = \|A\|_2 \|A^{-1}\|_2$$

(a)  $A$  is invertible

$$\text{so, } x \in \mathbb{R}^n \rightarrow Ax = y, y \in \mathbb{R}^n$$

or,  $x = A^{-1}y \in \mathbb{R}^n$

$$\begin{aligned} \text{now, } \max \text{mag}(A) &= \max_{\substack{x \neq 0 \\ \|x\|_2}} \frac{\|Ax\|_2}{\|x\|_2} \\ &= \max_{\substack{y \neq 0 \\ \|y\|_2}} \frac{\|y\|_2}{\|A^{-1}y\|_2} \\ &= \frac{1}{\min_{\substack{y \neq 0 \\ \|y\|_2}} \|A^{-1}y\|_2} \\ &= \frac{1}{\min \text{mag}(A^{-1})} \end{aligned}$$

$$\text{so, } \max \text{mag}(A) = \frac{1}{\min \text{mag}(A^{-1})}$$

proved

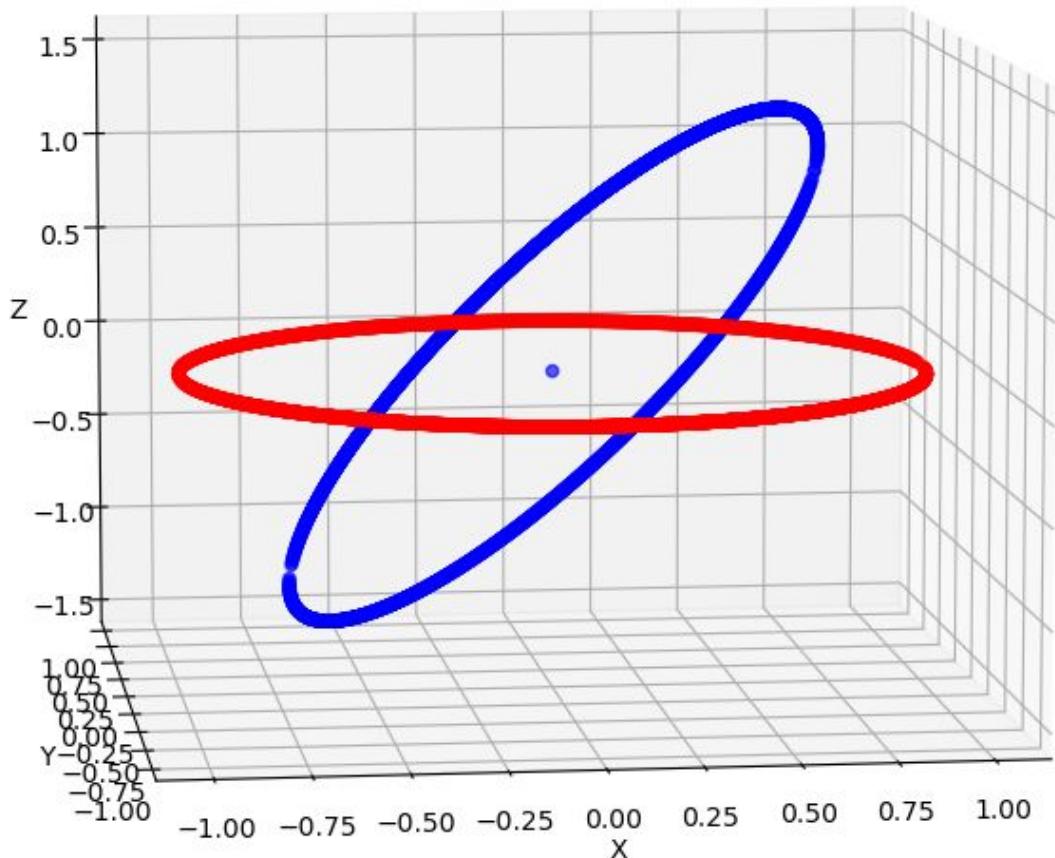
(b)

$$\begin{aligned}\text{Cond}(A) &= \|A\|_2 \cdot \|A^{-1}\|_2 \\ &= \frac{\text{max mag}(A)}{\text{min mag}(A)} \cdot \text{max mag}(A^{-1}) \\ &= \frac{\text{max mag}(A)}{\text{min mag}(A)} \quad [\text{From (a)}] \\ &\quad \Leftarrow \text{proved}\end{aligned}$$

9. In the plots, red - original, blue - transformed

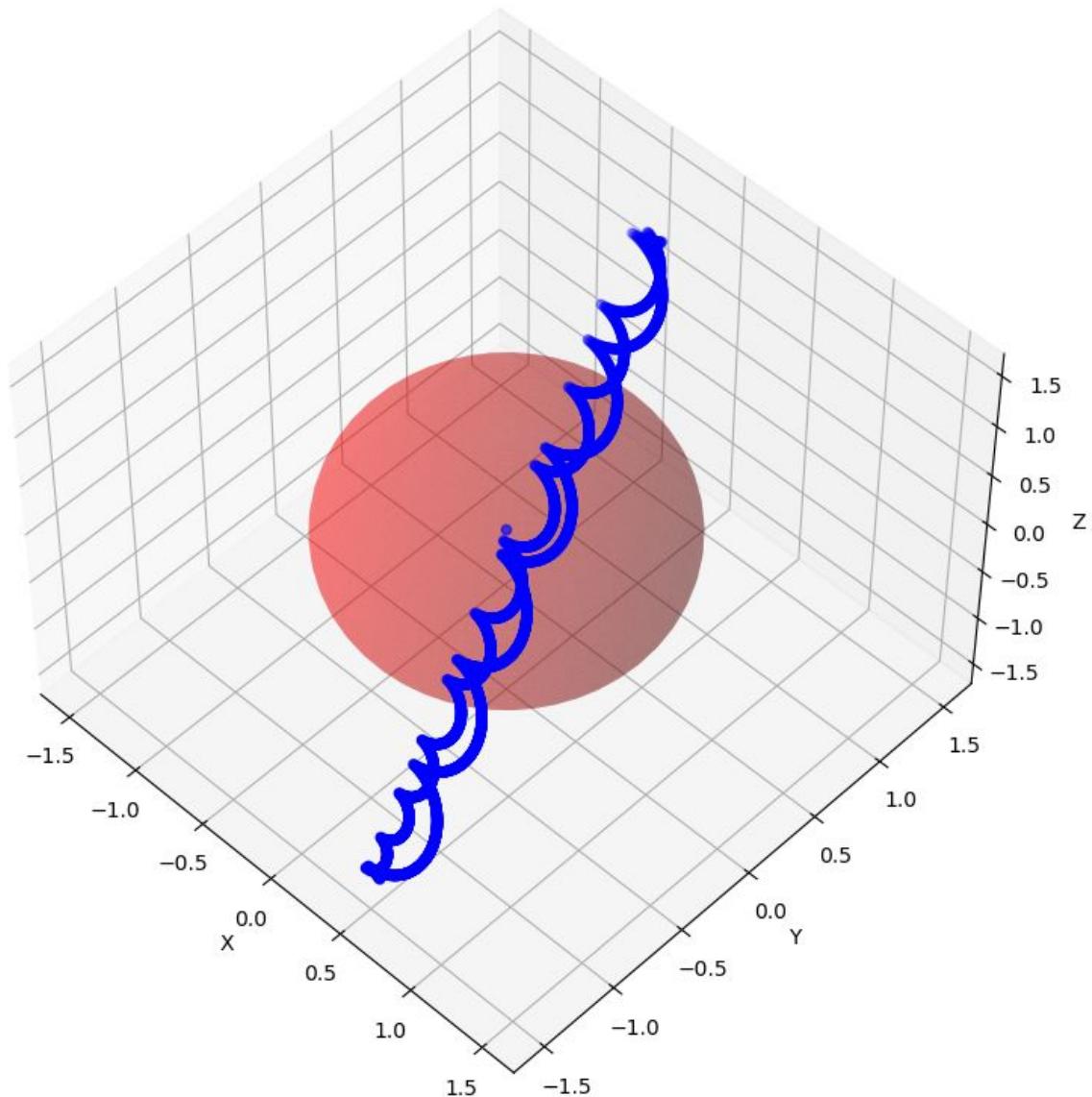
Code: <https://github.com/Deepank308/LA-for-AI/blob/master/assgn3/q9.py>

(a)



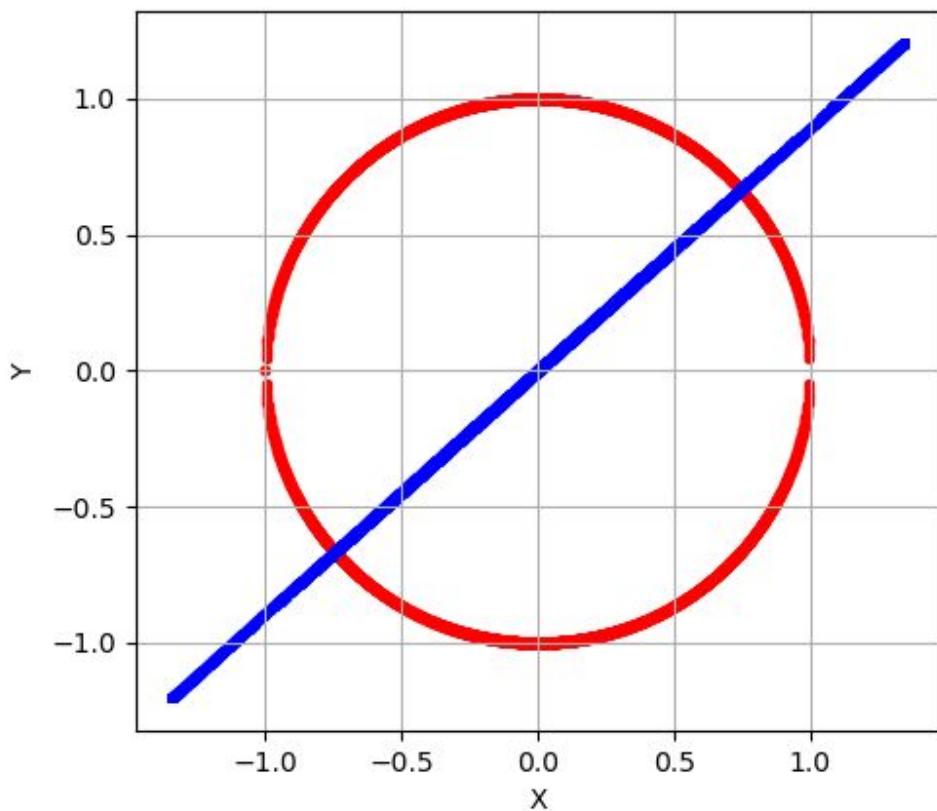
Condition number: 2.23606797749979

(b)



Condition number: 1.715010090561728

(c)

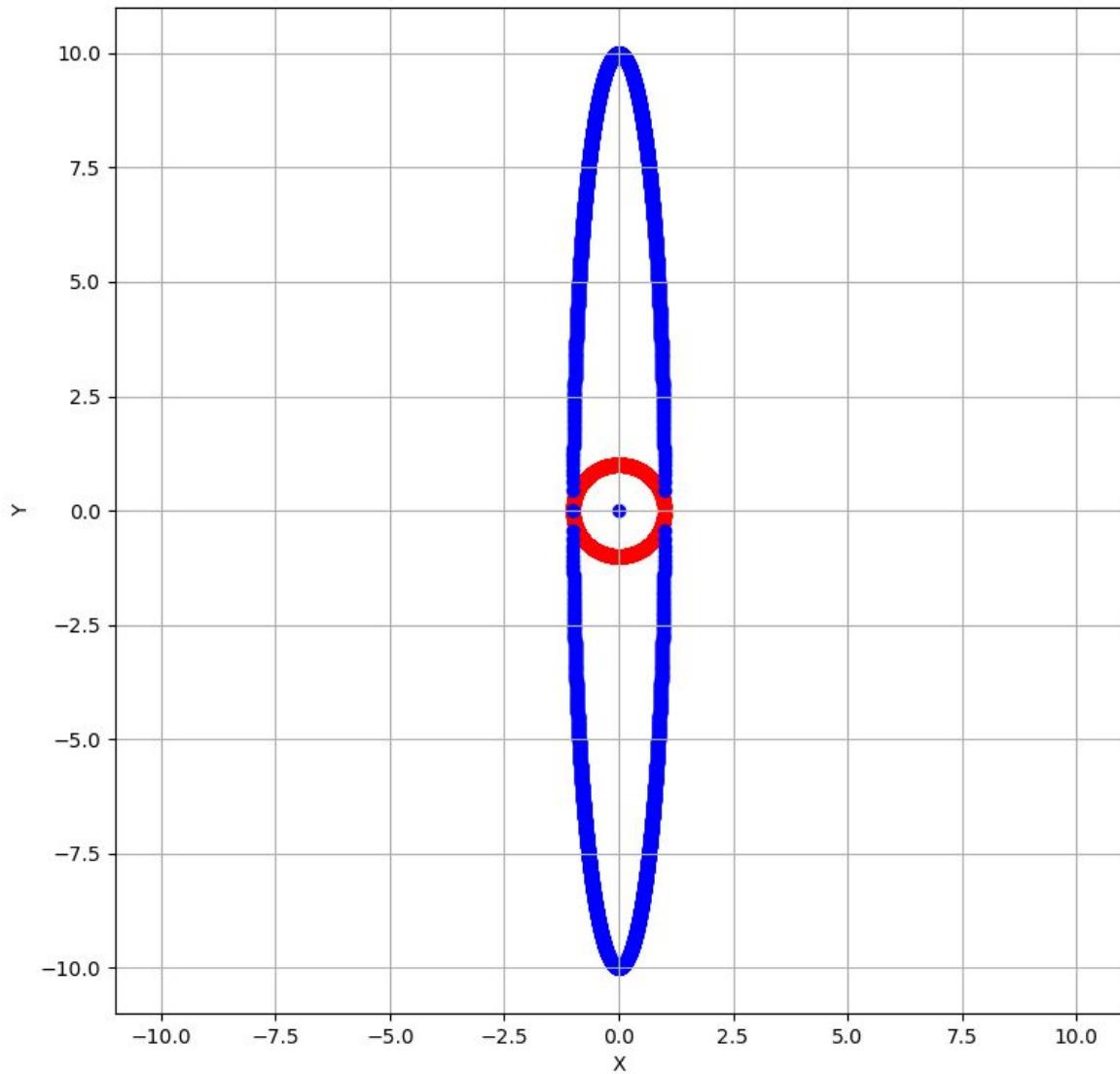


Condition number: 325.99693248647975

Invertible

Determinant: -0.00999999999999995

(d)



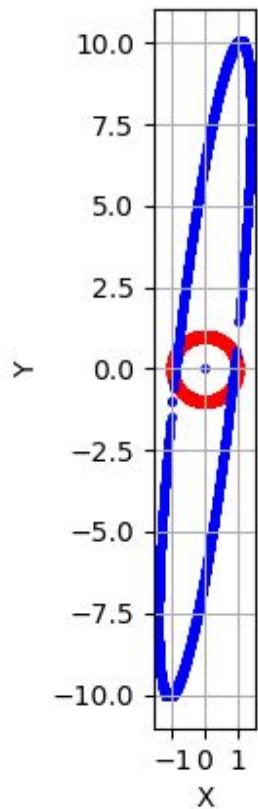
Condition number: 10.0

Invertible

Determinant: -10.000000000000002

(e)

$\varepsilon = 10$

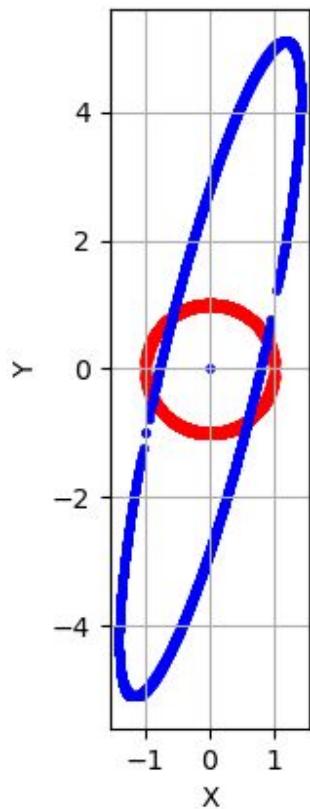


Condition number: 11.35638827945676

Invertible

Determinant: 9.000000000000002

$$\varepsilon = 5$$

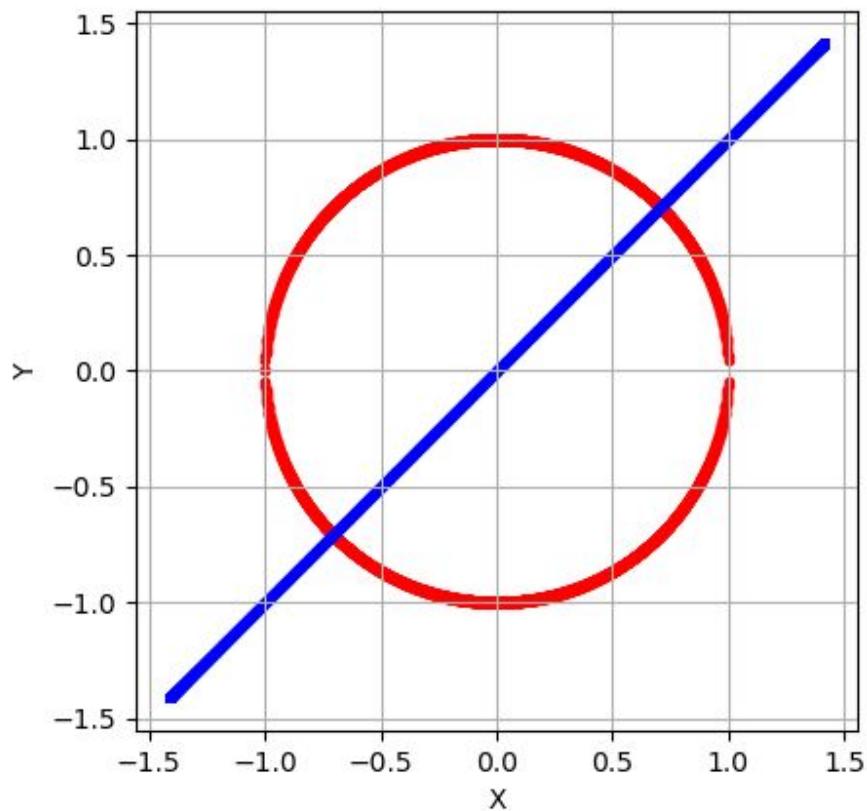


Condition number: 6.854101966249685

Invertible

Determinant: 4.0

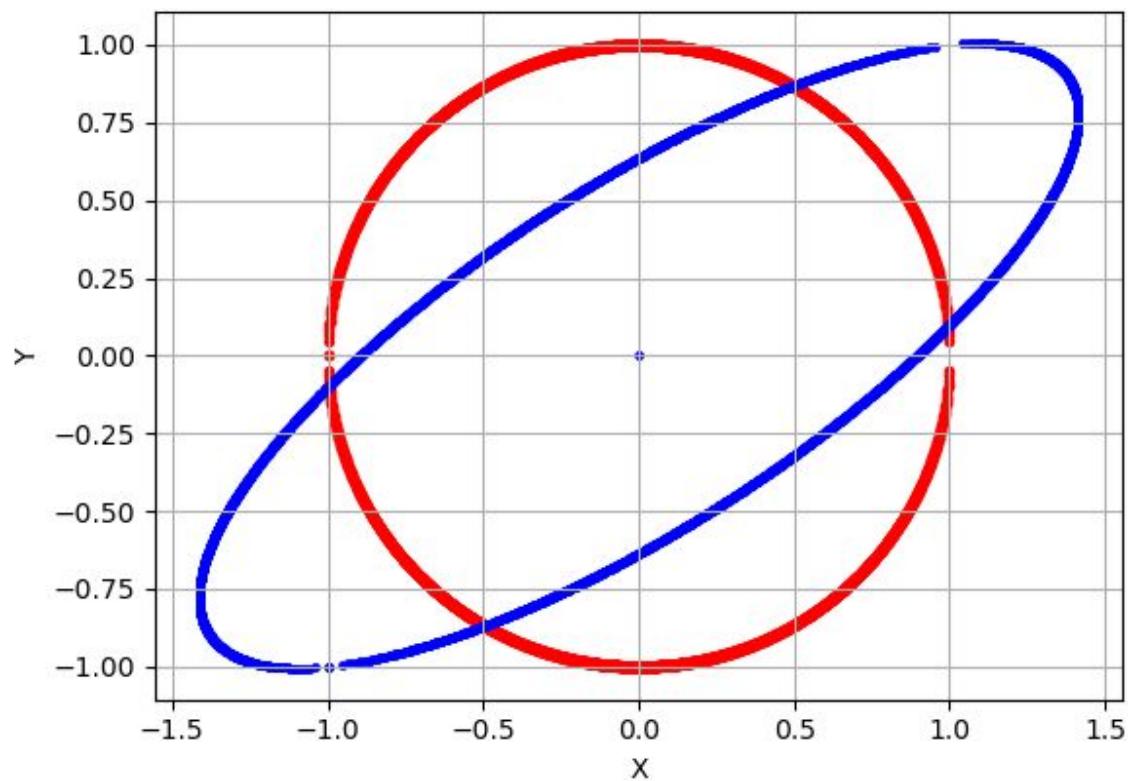
$$\varepsilon = 1$$



Condition number: 5.961777047638983e+16

Not Invertible

$$\varepsilon = 10^{-1}$$

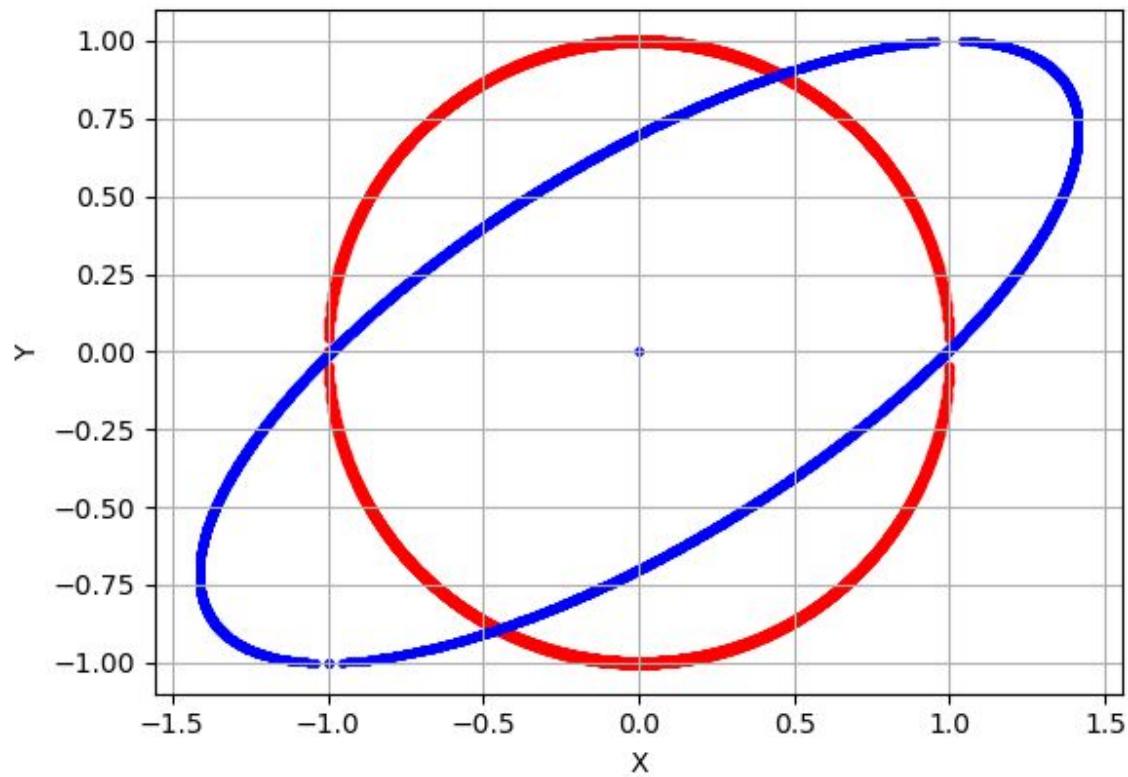


Condition number: 3.0124935233004138

Invertible

Determinant: -0.9

$$\varepsilon = 10^{-2}$$

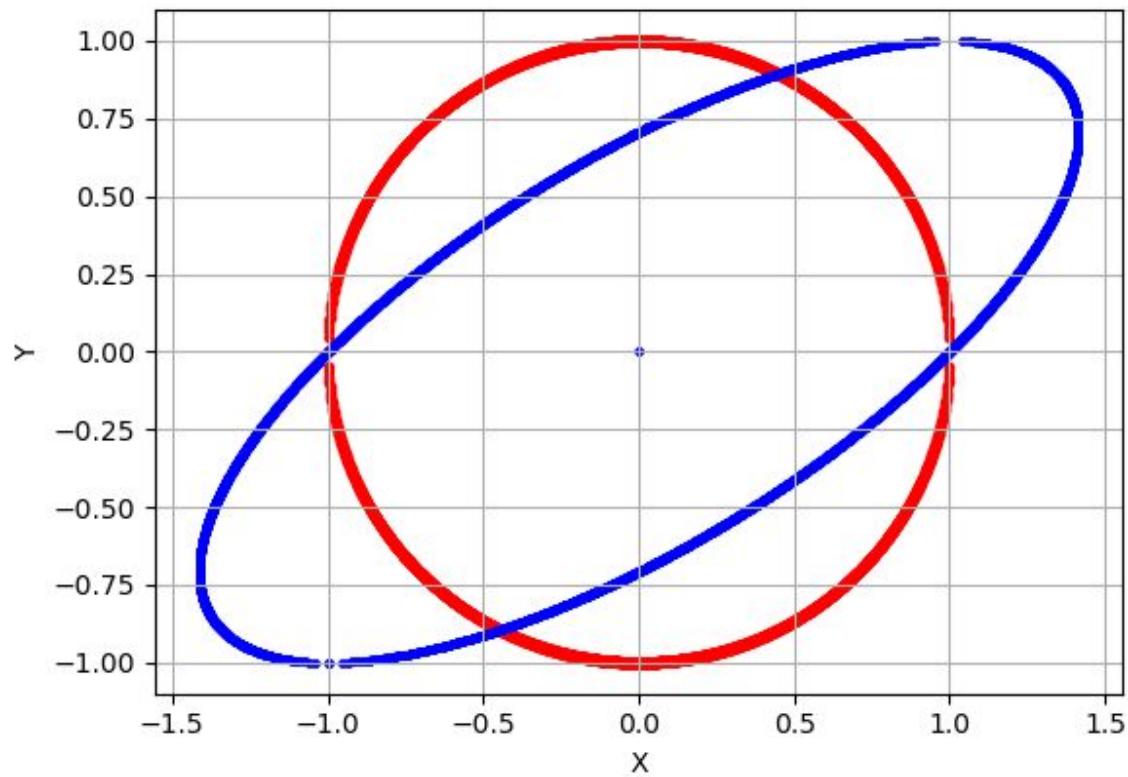


Condition number: 2.6535504563252843

Invertible

Determinant: -0.99

$$\varepsilon = 10^{-4}$$

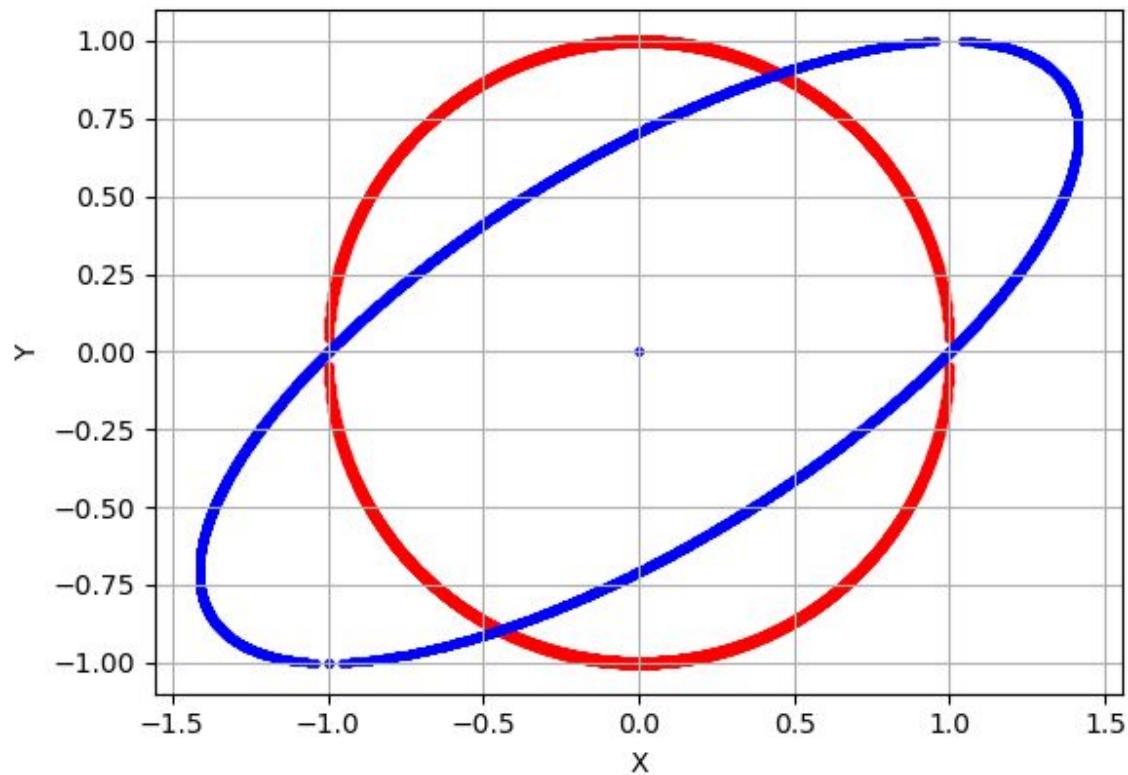


Condition number: 2.618385273654826

Invertible

Determinant: -0.9999

$$\varepsilon = 0$$



Condition number: 2.6180339887498953

Invertible

Determinant: -1.0

As evident from the condition numbers and determinant values, we can say that as condition number becomes larger, determinant approaches 0, i.e., the matrix becomes singular.