

**MSc. Data Science**  
LAA - Homework 1

1. Let  $A$  be an  $m \times n$  matrix. Define

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

- (i) Prove that this is indeed a matrix norm.  
(ii) Evaluate  $\|A\|_1$ ,  $\|A\|_2$ ,  $\|A\|_\infty$  and  $\|A\|_F$  for

$$A = \begin{pmatrix} 4 & -2 & 4 \\ -2 & 1 & -2 \\ 4 & -2 & 4 \end{pmatrix}.$$

(a)  $A$  be an  $m \times n$  matrix and  $\|A\|_F = \left( \sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2 \right)^{\frac{1}{2}}$ . To prove that this is indeed a matrix norm we need to verify the properties of the Matrix Norm.

- First,  $\|A\|_F$  is positive definite as we are squaring all the entries and then taking square root of it. Hence, it is following the positive definite property.
- Second, We need to prove the triangle inequality. Let us take 2 norms,  $\|A\|_F$  and  $\|B\|_F$ . Need to show,  $\|A + B\|_F \leq \|A\|_F + \|B\|_F$ .

$$\|A + B\|_F^2 = \|A\|_F^2 + \|B\|_F^2 + 2\|AB\|_F$$

Now,

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

using Cauchy-Schwartz Inequality,

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

Hence,

$$2\|AB\|_F \leq 2\|A\|_F \|B\|_F$$

So,

$$\|A + B\|_F^2 \leq \|A\|_F^2 + \|B\|_F^2 + 2\|A\|_F \|B\|_F = (\|A\|_F + \|B\|_F)^2$$

By applying Square Root on both side,

$$\|A + B\|_F \leq \|A\|_F + \|B\|_F \text{ (Proved)}$$

- We have already shown by CS inequality that,  $\|AB\|_F \leq \|A\|_F \|B\|_F$

As, it is following all the properties of a Matrix Norm, Frobenius norm is indeed a matrix norm.

(b)

$$A = \begin{pmatrix} 4 & -2 & 4 \\ -2 & 1 & -2 \\ 4 & -2 & 4 \end{pmatrix}.$$

- Calculating 1-Norm,

$$\|A\|_1 = \max_{1 \leq j \leq 3} \left[ \sum_{i=1}^3 |a_{ij}| \right] = \max[10, 5, 10] = 10$$

- Calculating Infinity Norm,

$$\|A\|_{\infty} = \max_{1 \leq i \leq 3} \left[ \sum_{j=1}^3 |a_{ij}| \right] = \max [10, 5, 10] = \mathbf{10}$$

- Calculating Frobenius Norm,

$$\|A\|_F = \left( \sum_{i=1}^3 \sum_{j=1}^3 |a_{ij}|^2 \right)^{\frac{1}{2}} = [4^2 + |-2|^2 + 4^2 + |-2|^2 + 1^2 + |-2|^2 + 4^2 + |-2|^2 + 4^2]^{\frac{1}{2}} = \mathbf{9}$$

- Now for calculating 2-norm, we need to evaluate the matrix  $A^*A$ .

$$A^*A = \begin{pmatrix} 4 & -2 & 4 \\ -2 & 1 & -2 \\ 4 & -2 & 4 \end{pmatrix}^* \begin{pmatrix} 4 & -2 & 4 \\ -2 & 1 & -2 \\ 4 & -2 & 4 \end{pmatrix} = \begin{pmatrix} 36 & -18 & 36 \\ -18 & 9 & -18 \\ 36 & -18 & 36 \end{pmatrix}$$

Now, calculating the eigen value of the  $A^*A$ ,

$$\begin{vmatrix} 36 - \lambda & -18 & 36 \\ -18 & 9 - \lambda & -18 \\ 36 & -18 & 36 - \lambda \end{vmatrix} = 0$$

Solving this equation we get,

$$4\lambda^2 \times (81 - \lambda) = 0$$

Hence, the eigen values are, 0,0,81. As by the definition the 2-norm is the square root of of the maximum eigen value of the matrix  $A^*A$ ,

$$\|A\|_2 = \sqrt{81} = \mathbf{9}$$

2. Evaluate  $\|I_{n \times n}\|_F$ .

According to the definition of Frobenius Norm,

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

As  $I_{n \times n}$  is Identity Matrix, then the diagonal entries are 1 and all the off diagonal entries are 0. Mathematically,  $I_{ii} = 1$  and  $I_{ij} = 0$ , where  $i \neq j$ .

Hence,

$$\|I_{n \times n}\|_F = [1^2 + 1^2 + \dots \text{n times}]^{\frac{1}{2}} = \sqrt{n}$$

3. Prove that for the induced 2-norm and the Frobenius norm on matrices are invariant under multiplication by unitary matrices.

A matrix norm is unitary invariant if,  $\|UAV\| = \|A\| \forall U^*U = I, V^*V = I$ .

- **Induced 2-Norm**

So,

$$(UAV)^*(UAV) = V^*A^*U^*UAV = V^*A^*AV \text{ as, } U^*U = I$$

We know that for an Unitary Matrix,  $V^*V = I = VV^*$ . Hence,  $V^* = V^{-1}$

$$(UAV)^*(UAV) = V^{-1}A^*AV$$

From the above equation, it is clear that,  $(UAV)^*(UAV)$  and  $A^*A$  are similar. Hence both of them will have same eigen values.

So, by definition of 2-Norm,

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

Where,  $\lambda_{\max}$  is the maximum eigen value.

Hence, Induced 2-Norm of a Matrix is Unitary Invariant. (Proved)

- **Frobenius Norm**

According to the definition of Frobenius Norm,

$$\|A\|_F^2 = \sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2 = \sum_{i=1}^m \left( \sum_{j=1}^n a_{ij}^* a_{ij} \right) = \sum_{i=1}^m (A^*A)_{ii} = \text{tr} (A^*A)$$

Again, to show, the Frobenius Norm to be Unitary Invariant,

we need to show,  $\|UAV\|_F = \|A\|_F \forall U^*U = I, V^*V = I$ .

Hence,

$$\text{tr} (UAV)^*(UAV) = \text{tr} (V^*A^*U^*UAV) = \text{tr} (V^*A^*AV) \text{ as, } U^*U = I$$

Since,  $\text{tr} (AB) = \text{tr} (BA)$ ,

$$\text{tr} (UAV)^*(UAV) = \text{tr} (V^*A^*AV) = \text{tr} (VV^*A^*A)$$

As, V is Unitary,  $V^*V = VV^* = I$ .

$$\text{tr} (UAV)^*(UAV) = \text{tr} (VV^*A^*A) = \text{tr} (IA^*A) = \text{tr} (A^*A) = \|A\|_F^2$$

Hence, Frobenius Norm of a Matrix is Unitary Invariant. (Proved)

4. Study Section 1.3 of Strang's book 'Linear Algebra and Learning from Data' (you can find it [here](#)). Then solve problems 1, 2, 4 and 6 from problem set 1.3 (page 20).

(a) **The Null Space of  $AB$  contains the Null Space of  $B$ .**

Let a vector  $v$  is in the Null Space of  $B$ . Then, by the definition of Null Space,  $Bv = 0$ . So, multiplying A on the both side,

$$A(Bv) = 0$$

$$(AB)v = 0$$

Hence,  $v$  is also in the Null Space of  $AB$ . Hence Proved.

- (b) **Find a square matrix with  $\text{rank}(A^2) < \text{rank}(A)$ . Confirm that the  $\text{rank}(A^T A) = \text{rank}(A)$ .**

The nilpotent square matrix of degree 2 will give  $\text{rank}(A^2) < \text{rank}(A)$ . The example of such matrix is,

$$A = \begin{pmatrix} 0 & a \\ 0 & 0 \end{pmatrix}$$

where,  $a \in \mathbb{R}, a \neq 0$ .

$$\text{Hence, } A^2 = \begin{pmatrix} 0 & a \\ 0 & 0 \end{pmatrix} \times \begin{pmatrix} 0 & a \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$

The  $\text{rank}(A) = 1$ , but the  $\text{rank}(A^2) = 0$ . Hence,  $\text{rank}(A^2) < \text{rank}(A)$ .

$$\text{Now, } A^T A = \begin{pmatrix} 0 & 0 \\ a & 0 \end{pmatrix} \times \begin{pmatrix} 0 & a \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & a^2 \end{pmatrix}. \text{ The } \text{rank}(A^T A) = 1$$

Hence,  $\text{rank}(A^T A) = \text{rank}(A)$  (Confirmed).

- (c) **If row space of  $A$  = Column Space of  $A$ , and also  $N(A) = N(A^T)$ , is  $A$  symmetric?**

by the definition of null space  $N(A)$  = Contains all solutions  $x$  to  $Ax = 0$ .

and the definition of Left null space  $N(A^T)$  = Contains all solutions of  $y$  to  $A^T y = 0$ .

As,  $\text{rank}(A) = \text{rank}(A^T)$ , by rank-nullity theorem,  $A$  is a square matrix.

By, the definition of column space  $A = C(A)$  = Contains all combinations of the columns of  $A$ .

and the definition of row space  $A = C(A^T)$  = Contains all combinations of the columns of  $A^T$ .

It is given that, row space of  $A$  = Column Space of  $A$ , then from the above definitions,  $C(A) = C(A^T)$ .

So,  $\dim C(A) = \dim C(A^T) = \text{rank}(A)$ .

Now, here two cases may arise, the rank of  $A$  is equal to the dimension of the matrix, or the rank of  $A$  is less than equals to the dimension of the matrix.

Hence, If  $A$  is of full rank. Then,  $A$  is invertible and the null space and the left null space will have the dimension 0. In this case  $A$  need not to be symmetric.

Example -  $\begin{pmatrix} 1 & 4 \\ 3 & 8 \end{pmatrix}$ . This matrix is not symmetric but the row space of  $A$  = Column Space of  $A$ , and also  $N(A) = N(A^T)$ .

Now, If,  $A$  is not of full rank, then it should be symmetric.

Example -  $\begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}$ .

So,  $A$  doesn't necessarily be a symmetric matrix.

- (d) **Show that  $A^T A$  has the same null space as  $A$ .**

First, let's assume  $x$  is a vector in the null space of  $A$ . So,  $Ax = 0$ .

Multiplying  $A^T$  on both side,

$$A^T(Ax) = 0 = (A^T A)x$$

Hence, null space of  $A^T A$  contains the null space of  $A$ .

Now, Let,  $y$  is a vector in the null space of  $A^T A$ . So,  $A^T A y = 0$ .

Multiplying  $y^T$  on the both side,

$$\begin{aligned} y^T A^T A y &= 0 \\ \implies (y^T A^T) A y &= 0 \end{aligned}$$

$$\implies (Ay)^T Ay = 0$$

$$\implies \|Ay\|^2 = 0$$

$$\implies Ay = 0$$

hence, null space of  $A$  contains the null space of  $A^T A$ .

Finally we can say that,  $A^T A$  has the same null space as  $A$  (proved).

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