

Tutorial 5

$$1. \max_{\|\vec{x}\| \neq 0} \frac{\|A\vec{x}\|}{\|\vec{x}\|} = \max_{\|\vec{x}\| \neq 0} \left\| \frac{A\vec{x}}{\|\vec{x}\|} \right\| \quad \text{since } a\|\vec{y}\| = \|a\vec{y}\|$$

← note that $\frac{\vec{x}}{\|\vec{x}\|}$ is a unit vector \hat{x} .

$$= \max_{\|\vec{x}\| \neq 0} \|A\hat{x}\| \quad \leftarrow \hat{x} \text{ is a unit vector so } \|\hat{x}\| = 1$$

$$= \max_{\|\hat{x}\|=1} \|A\hat{x}\|$$

$$\therefore \max_{\|\vec{x}\| \neq 0} \frac{\|A\vec{x}\|}{\|\vec{x}\|} = \max_{\|\vec{x}\|=1} \|A\vec{x}\| \quad \square$$

2. Start with our induced matrix norm definition:

$$① \|A\|_1 = \max_{\|\vec{x}\|=1} \|A\vec{x}\|_1$$

← now let's look at this part:

$$② \|A\vec{x}\|_1 = \left\| \sum_{k=1}^n x_k \vec{A}_k \right\|_1 \quad \begin{array}{l} \text{element in } \vec{x} \\ \text{kth} \end{array}$$

(note that x_k is a number, not a vector)

← kth column of A

$$\leq \sum_{k=1}^n \|x_k \vec{A}_k\|_1 \quad \leftarrow \text{this ensures no subtraction in the summation, so we get "}\leq\text{"}$$

$$= \sum_{k=1}^n |x_k| \|\vec{A}_k\|_1 \quad \leftarrow \text{since } a\|\vec{y}\| = \|a\vec{y}\|$$

③ Putting ① & ② together:

$$\|A\|_1 = \max_{\|\vec{x}\|=1} \|A\vec{x}\|_1 \leq \max_{\|\vec{x}\|=1} \sum_{k=1}^n |x_k| \|\vec{A}_k\|_1$$

ctd

ctd

- ④ If we modify the last result of ③ so that rather than use $\|\vec{A}_k\|_1$ in the summation, it uses $\max_k \|\vec{A}_k\|_1$ (the column with the largest 1-norm), then we get:

$$\max_{\|\vec{x}\|=1} \sum_{k=1}^n |x_k| \|\vec{A}_k\|_1 \leq \left(\max_{k \in [1, n]} \|\vec{A}_k\|_1 \right) \sum_{k=1}^n |x_k|$$

this = 1 since $\|\vec{x}\|_1 = 1$

$$\text{Notice that } \max_k \|\vec{A}_k\|_1 = \max_k \sum_{j=1}^n |A_{jk}|.$$

(both are the maximum absolute column sum)

\therefore we have shown that $\|A\|_1 \leq \max_k \sum_{j=1}^n |A_{jk}|$, but we have to show the converse as well

- ⑤ As with the previous case, we can begin with:

$$\|A\vec{x}\|_1 = \left\| \sum_{k=1}^n x_k \vec{A}_k \right\|_1$$

but now let's pick some \vec{x}' such that $x'_k = \begin{cases} 0 & k \neq l \\ 1 & k = l \end{cases}$ where l is the column in A with the largest absolute column sum.

$$\text{It follows that: } \|A\vec{x}'\|_1 = \left\| \sum_{k=1}^n x'_k \vec{A}_k \right\|_1$$

$$= \|\vec{A}_l\|_1$$

$$= \sum_j |A_{jl}|$$

by definition of the 1-norm for vectors

$$= \max_k \sum_j |A_{jk}|$$

$$\textcircled{6} \|A\|_1 = \max_{\|\vec{x}\|=1} \|A\vec{x}\|_1 \geq \|A\vec{x}'\|_1 = \max_k \sum_j |A_{jk}| \quad \therefore \|A\|_1 \geq \max_k \sum_j |A_{jk}|$$

- ⑦ Since we have shown the inequality in both directions (in ④ and ⑥), we conclude that $\|A\|_1 = \max_k \sum_{j=1}^n |A_{jk}|$ \blacksquare

3. Recall the following definitions

^{symmetric}
1) Positive definite: A is positive definite if $x^T A x > 0 \forall \vec{x} \neq 0$
where A is an $m \times n$ matrix and x is an $n \times 1$ vector

^{symmetric}
2) Positive semi-definite: same as 1) but $x^T A x \geq 0 \forall \vec{x} \neq 0$

We want to show that $A = M^T M$ is symmetric positive definite if M is an $m \times n$ matrix of full-rank and $m > n$.

$$\textcircled{1} x^T A x = x^T M^T M x = (Mx)^T Mx = \|Mx\|^2 \geq 0$$

$\therefore A$ is symmetric positive semi-definite.

Q: Why, if $\vec{x} \neq 0$, is $\|Mx\|^2$ not strictly greater than zero?

A: \vec{x} could be in $\text{null}(M)$ (ex. $\left\| \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\|^2 = 0$)

\rightarrow
 $\textcircled{2}$ Now we will use the fact that M is full-rank to show that this is not possible:

$$\text{full-rank} \Rightarrow \text{rank}(M) = \min(m, n) = n$$

Recall from linear algebra that: ~~$\text{rank}(M) = n$~~

$$\text{null}(M) = n - \text{rank}(M)$$

$$= \text{null}(M) = n - n = 0$$

\therefore since M is full-rank, its null space is empty, so $M\vec{x} = 0$ only if $\vec{x} = 0$
other than the zero vector

Using this with our result from $\textcircled{1}$ we get that

$$x^T A x = \|Mx\|^2 > 0 \forall \vec{x} \neq 0$$

$\therefore A$ is symmetric positive definite \blacksquare

Why is $\text{null}(M) = \{0\}$ if M is full-rank?

In our case, $m=n$, so full-rank implies that all the ~~columns~~ ^{rows} in M are linearly independent. This means that if we row-reduce M , the result is an upper triangular matrix with no empty rows:

$$M = \begin{bmatrix} \sim & \sim & \sim & \sim \\ & \sim & \sim & \sim \\ & & \sim & \sim \\ 0 & & & \sim \end{bmatrix}$$

Now multiply this to some vector $x = \begin{bmatrix} \sim \\ \sim \\ \sim \\ \sim \end{bmatrix}$

Call the resulting vector y : $y = Mx = \begin{bmatrix} \sim & \sim & \sim & \sim \\ & \sim & \sim & \sim \\ & & \sim & \sim \\ 0 & & & \sim \end{bmatrix} \begin{bmatrix} \sim \\ \sim \\ \sim \\ \sim \end{bmatrix} \neq 0$ if $x \neq 0$

Since the last row of M is zero everywhere but the last column, the last element in y can't be zero unless the last element in x is zero. If that is the case, then the second last element in y will only be zero if the second last element in x is zero.

From this we can see that the only way for all the elements in y to be zero is if all the elements in x are zero

$$\therefore \text{If } M \text{ is full rank, } Mx \neq 0 \quad \forall x \neq 0$$

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4. Multiplying the left side (LS) by $(A - \vec{u}\vec{v}^T)$ gives

$$LS = (A - \vec{u}\vec{v}^T)(A - \vec{u}\vec{v}^T)^{-1} = \mathbb{I}$$

Multiplying by the same thing on the right side:

$$\begin{aligned} RS &= (A - \vec{u}\vec{v}^T) \left(A^{-1} + \frac{A^{-1}\vec{u}\vec{v}^T A^{-1}}{1 - \vec{v}^T A^{-1} \vec{u}} \right) \\ &= AA^{-1} - \vec{u}\vec{v}^T A^{-1} + \frac{AA^{-1}\vec{u}\vec{v}^T A^{-1}}{1 - \vec{v}^T A^{-1} \vec{u}} - \frac{\vec{u}\vec{v}^T A^{-1} \vec{u}\vec{v}^T A^{-1}}{1 - \vec{v}^T A^{-1} \vec{u}} \end{aligned}$$

Consider the dimensions of the vectors/matrices involved:

A is $n \times n$ \vec{u} is $n \times 1$ \vec{v}^T is $1 \times n$

$\therefore \vec{v}^T A^{-1} \vec{u}$ has dimensions $(1 \times n) \cdot (n \times n) \cdot (n \times 1) = (1 \times n) \cdot (n \times 1) = 1 \times 1$
ie. it is a number, not a vector or matrix

Replacing $\vec{v}^T A^{-1} \vec{u} = c$ and $AA^{-1} = \mathbb{I}$ we get:

$$RS = \mathbb{I} - \vec{u}\vec{v}^T A^{-1} + \frac{\vec{u}\vec{v}^T A^{-1}}{1 - c} - \frac{c \vec{u}\vec{v}^T A^{-1}}{1 - c}$$

note that c is a number
so $\vec{u}c\vec{v}^T A^{-1}$ was rewritten
as $c\vec{u}\vec{v}^T A^{-1}$

Factoring out $\frac{\vec{u}\vec{v}^T A^{-1}}{1 - c}$ from the last two terms gives:

$$\begin{aligned} RS &= \mathbb{I} - \vec{u}\vec{v}^T A^{-1} + \frac{\vec{u}\vec{v}^T A^{-1}}{1 - c} (1 - c) \\ &= \mathbb{I} - \vec{u}\vec{v}^T A^{-1} + \vec{u}\vec{v}^T A^{-1} \\ &= \mathbb{I} \end{aligned}$$

$$\therefore LS = RS \quad \blacksquare$$