

Linear algebra for AI and ML

September-8

(Lecture - 9)



$$Ax = b$$

- Existence & uniquenesses of soln x
- LU / QR - compute x
- Sensitivity analysis.

Matrix norms:

Matrices $\begin{matrix} m \times n \\ \mathbb{R} \end{matrix}$ — view as a vectors in \mathbb{R}^m (vectorization)

\ Linear transformation from \mathbb{R}^n to \mathbb{R}^m

$$x \in \mathbb{R}^n \mapsto Ax \in \mathbb{R}^m$$

$$\|\cdot\| : \mathbb{R}^{n \times n} \rightarrow \mathbb{R}$$

Norm: $\forall A, B \in \mathbb{R}^{n \times n}, \alpha, \beta \in \mathbb{R}$

(i) $\|A\| \geq 0$ and $\|A\| = 0 \Leftrightarrow A = 0$

(ii) $\|\alpha A\| = |\alpha| \|A\|$ (iii) $\|A + B\| \leq \|A\| + \|B\|$

(iv) $\|AB\| \leq \|A\| \|B\|$ - ... (submultiplicativity)

Ex: Frobenius norm:

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

(This norm is basically 2-norm of a vector of size n^2 .)

Since 2-norm is a norm on \mathbb{R}^{n^2} , first three properties of matrix-norm are automatically satisfied. For submultiplicativity, we use C.S.I.

$$\underline{C = AB}$$

$$C_{ij} = \sum_{k=1}^n a_{ik} b_{kj}$$

$$A = [a_{ij}]$$

$$B = [b_{ij}]$$

$$C = [c_{ij}]$$

$$\begin{aligned}
\|AB\|_F^2 &= \|C\|_F^2 = \sum_{i=1}^n \sum_{j=1}^n |c_{ij}|^2 \\
&= \sum_{i=1}^n \sum_{j=1}^n \left| \sum_{k=1}^n a_{ik} b_{kj} \right|^2 \quad \begin{array}{l} \text{Cauchy} \\ \text{Schwarz} \\ \text{inequality} \end{array} \\
&\leq \sum_{i=1}^n \sum_{j=1}^n \left(\sum_{k=1}^n |a_{ik}|^2 \sum_{k=1}^n |b_{kj}|^2 \right) \\
&= \left(\sum_{i=1}^n \sum_{k=1}^n |a_{ik}|^2 \right) \left(\sum_{j=1}^n \sum_{k=1}^n |b_{kj}|^2 \right) \\
&= \|A\|_F^2 \|B\|_F^2 \quad \square
\end{aligned}$$

$\Rightarrow \|\cdot\|_F$ is a matrix norm.

Ex: Viewing the matrix as a linear operator.

$$\underbrace{\|A\|_2} = \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$$

$\forall A \in \mathbb{R}^{n \times n}$ $1 \leq p \leq \infty$
 $p = 1, \infty, \textcircled{2}$
(induced-norm)

Is $\|\cdot\|_2$ a norm?? (operator norm)

$$x \in \mathbb{R}^n \xrightarrow{\quad} Ax \in \mathbb{R}^n$$
$$\|x\|_2 \qquad \|Ax\|_2$$

Ratio = $\frac{\|Ax\|_2}{\|x\|_2}$ \leftarrow magnification induced by A in x (by action Ax)

$\|A\|_2$: maximum magnification

$$A \in \mathbb{R}^{2 \times 2}$$

$$A = \begin{bmatrix} 10 & 9 \\ 9 & 8 \end{bmatrix} \in \mathbb{R}^{2 \times 2}$$

$$x = \begin{pmatrix} 1 \\ 1 \end{pmatrix} ; \|x\|_2 = \sqrt{2}$$

$$Ax = \begin{pmatrix} 19 \\ 17 \end{pmatrix} ; \|Ax\|_2 = \sqrt{19^2 + 17^2} = \sqrt{650}$$

$$\frac{\|Ax\|_2}{\|x\|_2} = \frac{\sqrt{650}}{\sqrt{2}} = \sqrt{325} \approx 18$$

$$x = \begin{pmatrix} 1 \\ -1 \end{pmatrix} ; \|x\|_2 = \sqrt{2}$$

$$Ax = \begin{pmatrix} 1 \\ 1 \end{pmatrix} ; \|Ax\|_2 = \sqrt{2}$$

$$\frac{\|Ax\|_2}{\|x\|_2} = \frac{\sqrt{2}}{\sqrt{2}} = 1$$

Thm: $\|Ax\|_2 \leq \|A\|_2 \|x\|_2$ ←

where $\|A\|_2 = \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$

Pf: For $x=0$, trivially true.

For any $x \neq 0$,

$$\boxed{\frac{\|Ax\|_2}{\|x\|_2}} \leq \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = \|A\|_2$$

$$\Rightarrow \frac{\|Ax\|_2}{\|x\|_2} \leq \|A\|_2$$

$$\Rightarrow \|Ax\|_2 \leq \|A\|_2 \|x\|_2 \quad \checkmark$$

This result helps in proving submultiplicative property for $\|\cdot\|_2$ norm. □

To prove: $\|A\|_2 = \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$ is a norm.

i) $\|A\|_2 \geq 0 \quad \forall A$

$$\|A\|_2 = \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} \geq 0$$

in fact, if $A \neq 0$, then \exists a nonzero vector \hat{x} s.t. $A\hat{x} \neq 0$.

$$\|A\|_2 = \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} \geq \frac{\|A\hat{x}\|_2}{\|\hat{x}\|_2} > 0$$

ii) $\| \alpha A \|_2 = |\alpha| \|A\|_2$

iii) triangle inequality:

$$\|A+B\|_2 = \max_{x \neq 0} \frac{\|(A+B)x\|_2}{\|x\|_2} = \max_{x \neq 0} \frac{\|Ax + Bx\|_2}{\|x\|_2}$$

triangle inequality

of $\|\cdot\|_2$

vector norm

$$\leq \max_{x \neq 0} \frac{\|Ax\|_2 + \|Bx\|_2}{\|x\|_2}$$

$$\leq \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} + \max_{x \neq 0} \frac{\|Bx\|_2}{\|x\|_2}$$

$$= \|A\|_2 + \|B\|_2$$

iv) Replace x by Bx in the previous thm:

$$\|ABx\|_2 \leq \|A\|_2 \|Bx\|_2 \leq \|A\|_2 \|B\|_2 \|x\|_2$$

$$\|AB\|_2 = \max_{x \neq 0} \frac{\|ABx\|_2}{\|x\|_2} \leq \|A\|_2 \|B\|_2$$



Ex: $I \in \mathbb{R}^{n \times n}$ identity matrix.

$$\|I\|_F = \sqrt{n}$$

$$\|I\|_2 = 1$$

$$\|Q\|_2 = 1$$

(where $Q \in \mathbb{R}^{n \times n}$ is orthogonal).

$$\forall x \in \mathbb{R}^n; \quad \|Qx\|_2 = \|x\|_2$$

↓

$$\|Q\|_2 = \max_{x \neq 0}$$

$$\frac{\|Qx\|_2}{\|x\|_2}$$

=

$$\max_{x \neq 0} \frac{\|x\|_2}{\|x\|_2}$$

$$= \max_{x \neq 0} 1$$

$$= 1$$

Suppose $A \in \mathbb{R}^{n \times n}$, $b \in \mathbb{R}^n$ and A is invertible.

We know that \exists a unique x s.t.

$$Ax = b \quad \text{--- (1)}$$

Assume that b is perturbed to $b + \delta b$.

then \exists a unique \hat{x} s.t.

$$A\hat{x} = b + \delta b \quad \text{--- (2)}$$

suppose define $\delta x \in \mathbb{R}^n$ s.t. $\hat{x} = x + \delta x$

$$A(x + \delta x) = b + \delta b$$

$$\Rightarrow Ax + A\delta x = b + \delta b$$

From (1)

$$\Rightarrow A\delta x = \delta b \Rightarrow \delta x = A^{-1} \delta b \quad \text{--- (3)}$$

from (3),

$$\|\delta x\|_2 = \|A^{-1} \delta b\|_2$$

$$\|\delta x\|_2 \leq \|A^{-1}\|_2 \|\delta b\|_2 \quad \text{--- (4)}$$

Further, from (1), $b = Ax$

$$\Rightarrow \|b\|_2 = \|Ax\|_2$$

$$\Rightarrow \|b\|_2 \leq \|A\|_2 \|x\|_2$$

$$\Rightarrow \frac{1}{\|x\|_2} \leq \|A\|_2 \frac{1}{\|b\|_2} \quad \text{--- (5)}$$

from (4) & (5);

$$\frac{\|\delta x\|_2}{\|x\|_2} \leq \|A\|_2 \|A^{-1}\|_2 \frac{\|\delta b\|_2}{\|b\|_2}$$

$\kappa_2(A)$: condition number.