

Lecture 18: Quick review from previous lecture

- **Triangle Inequality** holds:

$$\|\mathbf{v} + \mathbf{w}\| \leq \|\mathbf{v}\| + \|\mathbf{w}\| \quad \text{for all } \mathbf{v}, \mathbf{w} \in V.$$

- **Definition:** A **norm** on a vector space V assigns a non-negative real number $\|\mathbf{v}\|$ to each vector $\mathbf{v} \in V$, such that for every $\mathbf{v}, \mathbf{w} \in V$ and $c \in \mathbb{R}$, the following axioms holds:

(1) Positivity: $\|\mathbf{v}\| \geq 0$; $\|\mathbf{v}\| = 0$ if and only if $\mathbf{v} = 0$.

(2) Homogeneity: $\|c\mathbf{v}\| = |c|\|\mathbf{v}\|$.

(3) Triangle inequality: $\|\mathbf{v} + \mathbf{w}\| \leq \|\mathbf{v}\| + \|\mathbf{w}\|$.

- We have saw the following norm on \mathbb{R}^n :

– (2 norm) $\|\mathbf{x}\| = \left(\sum_{i=1}^n x_i^2\right)^{1/2}$ is the norm induced from the dot product on \mathbb{R}^n .

– (1 norm) $\|\mathbf{x}\| = \sum_{i=1}^n |x_i|$

Today we will discuss Norms.

Jesse(TA): No office hours on March 17th (Tues.) and March 19th.

Instead, March 24 (Tues.) and March 26 (Thur.) from 8:05 am to 12:05 pm

- Midterm 1 solutions are on Canvas now.

There is a generalization of these norms:

If $p \geq 1$, we define:

$$\|\mathbf{x}\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p}$$

This is often called the p **norm**.

Example. (1) Compute the 3 norm of $\mathbf{x} = (2, -1, 3)^T$:

$$\|\mathbf{x}\|_3 = \left(2^3 + |-1|^3 + 3^3 \right)^{1/3} = (8 + 1 + 27)^{1/3} = (36)^{1/3}$$

(2) Compute the p norm of $\mathbf{x} = (1, \dots, 1)^T$ in \mathbb{R}^n :

$$\|\mathbf{x}\|_p = \left(\underbrace{1^p + \dots + 1^p}_{n \text{ terms}} \right)^{1/p} = n^{1/p}$$

2. L^p norm on $C^0[a, b]$.

We define the L^p norms on $C^0([a, b])$, for $p \geq 1$:

$$\|f\|_p = \left(\int_a^b |f(x)|^p dx \right)^{1/p}$$

Check the three conditions to make sure this is a norm:

- ① Positivity: $\|f\|_p = 0 \iff f = 0.$
 - ② Homogeneity: $\|cf\|_p = |c| \|f\|_p$
 - ③ triangular inequality is tricky, we will skip it.
- } Exercise.

Example. Compute the $3/2$ norm of $f(x) = x^2$ on $[0, 1]$.

$$\begin{aligned} \|f\|_{3/2} &= \left(\int_0^1 |f|^{3/2} dx \right)^{2/3} = \left(\int_0^1 |x|^3 dx \right)^{2/3} \\ &= \left(\int_0^1 x^3 dx \right)^{2/3} \\ &= \left(\frac{x^4}{4} \Big|_0^1 \right)^{2/3} = \left(\frac{1}{4} \right)^{2/3} \\ &= 2^{-4/3} \end{aligned}$$

3. $p = \infty$.

when $p = \infty$, we define ∞ norm on \mathbb{R}^n by:

$$\|\mathbf{x}\|_{\infty} = \max_{1 \leq i \leq n} |x_i|$$

Example. If $\mathbf{x} = (1, -5, 3)^T$, then $\|\mathbf{x}\|_{\infty} = 5$.

Similarly,

when $p = \infty$, on $C^0([a, b])$ we define

$$\|f\|_{\infty} = \max_{x \in [a, b]} |f(x)|$$

Example. If $f(x) = -x^3$, then on $[-1, 1]$, $\|f\|_{\infty} = \max_{x \in [-1, 1]} |f| = \max_{x \in [-1, 1]} |-x^3|$
 $= \max_{x \in [-1, 1]} |x^3|$
 $= 1$. #

3. Distance. Every norms defines a **distance** between vector space elements, that is,

$$d(\mathbf{v}, \mathbf{w}) = \|\mathbf{v} - \mathbf{w}\|.$$

It satisfies

1. Symmetry: $d(\mathbf{v}, \mathbf{w}) = d(\mathbf{w}, \mathbf{v})$
2. Positivity: $d(\mathbf{v}, \mathbf{w}) = 0$ iff $\mathbf{v} = \mathbf{w}$.
3. Triangle inequality: $d(\mathbf{v}, \mathbf{w}) \leq d(\mathbf{v}, \mathbf{z}) + d(\mathbf{z}, \mathbf{w})$

Recall $M_{m \times n} = \{m \times n \text{ matrix}\}$

4. Matrix Norms.

If $\|\mathbf{v}\|$ is any norm on \mathbb{R}^n , it induces a natural norm on $M_{n \times n}$, the vector space of n -by- n matrices.

The **matrix norm** (with respect to the norm $\|\cdot\|$ on \mathbb{R}^n) is defined as follows. If A is any n -by- n matrix, then

$$\|A\| = \max\{\|A\mathbf{u}\| : \|\mathbf{u}\| = 1\}$$

Proof. To show it is a norm, see pages 153–154 in the book for the proof. \square

* In other words, $\|A\|$ is the maximum amount that A can change the norm of a unit vector \mathbf{u} (one with $\|\mathbf{u}\| = 1$) when we apply A to \mathbf{u} .

* The book calls $\|A\|$ the **natural matrix norm** associated to the vector norm $\|\mathbf{v}\|$. It is also often called the **operator norm** of A .

Fact:

(1) $\|A\mathbf{v}\| \leq \|A\|\|\mathbf{v}\|$, for all $n \times n$ matrices A , $\mathbf{v} \in \mathbb{R}^n$,

(2) $\|AB\| \leq \|A\|\|B\|$, for all $n \times n$ matrices A and B .

[To see these:]

(1) $u \neq 0$, unit vector $w = \frac{u}{\|u\|}$, $\|w\| = 1$.

$$\|Aw\| = \left\| A \frac{u}{\|u\|} \right\| \leq \|A\| \Rightarrow \frac{\|Au\|}{\|u\|} \leq \|A\|$$

(2) $\|u\| = 1$.

$$\|ABu\| = \|A(Bu)\| \stackrel{(1)}{\leq} \|A\| \|Bu\| \stackrel{(2)}{\leq} \|A\| \|B\| \|u\| = \|A\| \|B\|$$

$\|AB\| = \max\{\|ABu\|; \|u\|=1\} \leq \|A\| \|B\|$

The 2nd inequality implies that

Fact: If A a square matrix, then

$$\|A^k\| \leq \|A\|^k$$

3.4 Positive Definite Matrices

We have seen that the following inner products on \mathbb{R}^n :

- standard inner product $\langle \mathbf{x}, \mathbf{y} \rangle = x_1y_1 + \dots + x_ny_n = (x_1, \dots, x_n) \begin{pmatrix} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \end{pmatrix} \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$
- For $c_1 > 0, \dots, c_n > 0$, $= \mathbf{x}^T \mathbf{I}_n \mathbf{y}$.

$$\langle \mathbf{x}, \mathbf{y} \rangle = c_1x_1y_1 + \dots + c_nx_ny_n = \mathbf{x}^T \mathbf{D} \mathbf{y}, \quad \mathbf{D} = \text{diag}(c_1, \dots, c_n)$$

- For nonsingular matrix A ,

$$\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T (A^T A) \mathbf{y}$$

is also an inner product

They all have been of the following form:

$$\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T K \mathbf{y}$$

for some symmetric matrix K .

Q: Are there any other types of inner products on \mathbb{R}^n ?

Ans: In fact, all inner products on \mathbb{R}^n are of the form $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T K \mathbf{y}$, for some symmetric matrix K .

However, it is not true that any symmetric matrix K defines an inner product! Only a special type of matrix K can do this.

Recall: inner product.

① Bilinearity

② Symmetry: $\langle x, y \rangle = \langle y, x \rangle$

③ Positivity: $\langle x, x \rangle \geq 0$; $\langle x, x \rangle = 0$

\Downarrow
 $x = 0$.