

Lecture 17 (§7.3 continued)

Thm: Let $(V, \|\cdot\|)$ be normed vector space, let W be a finite dimensional subspace of V . Then for $\forall v \in V$, \exists at least closest pt $w^* \in W$ to v . (That is $\exists w^* \in W$ st. $\|v - w^*\| = \inf \{ \|v - w\| : w \in W \}$)

Proof: W is a subspace of V . Therefore, $0 \in W$.

$$\|v - 0\| = \|v\|$$

$$\inf \{ \|v - w\| : w \in W \} \leq \|v\| = M$$

Sps W satisfies $\|v - w\| < \|v\|$

$$\|w\| \leq \|w - v\| + \|v\| \leq M + M = 2M$$

$$\text{Then } \inf \{ \|v - w\| : w \in W \} = \inf \{ \|v - w\| : w \in W \}$$

If we define $K = \{w \in W : \|w\| \leq 2M\}$

Claim: K is compact. K is bdd (by $2M$)

Let v_k be a cvgt. seq of pts in K .

$$v_k \rightarrow v$$

$$\|v\| \leq \|v - v_k\| + \|v_k\| \leq \epsilon + \|v_k\| \leq \epsilon + \|v_k\| \leq \epsilon + 2M \text{ for } \forall \epsilon$$

$$\Rightarrow \|v\| \leq 2M, v \in W, v \in K \Rightarrow K \text{ is closed}$$

$$f(w) = \|v - w\|$$

Lipschitz with constant $\|f(w) - f(x)\| = \|v - w\| - \|v - x\| \leq \|w - x\|$

By EVT, $\exists \min w^* \in K$, so w^* is a closest pt to v .

→ and it is not always unique.

§7.4 Inner Product Spaces

Def'n: Any inner product on a vector space V is a function $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{R}$ s.t.

① positive definite

$$\langle x, x \rangle \geq 0 \quad \forall x \in V$$

$$\langle x, x \rangle = 0 \text{ iff } x = 0$$

② symmetric $\langle x, y \rangle = \langle y, x \rangle, \forall x, y \in V$

③ bi-linearity:

$$\forall x, y, z \in V, \alpha, \beta \in \mathbb{R}$$

$$\langle \alpha x + \beta y, z \rangle = \alpha \langle x, z \rangle + \beta \langle y, z \rangle$$

$$\langle x, \alpha y + \beta z \rangle = \alpha \langle x, y \rangle + \beta \langle x, z \rangle$$

An inner product space is a vector space,
inner product space

↓
norm

$$\|x\| = \langle x, x \rangle^{\frac{1}{2}}$$

↓
metric

Ex: $C[a, b]$

$$\langle f, g \rangle = \int_a^b f(x) \cdot g(x) dx$$

$$\|f\| = [\int_a^b f^2 dx]^{\frac{1}{2}} \text{ — L}_2 \text{ norm}$$

Ex: $A: \mathbb{R}^n \rightarrow \mathbb{R}^n$ A is a matrix $A = [a_{ij}]$

$$\langle x, y \rangle_A = \langle Ax, y \rangle$$

A has positive eigenvalues, A must be symmetric.

7.4.4 Cauchy-Schwarz Inequality.

For all vectors x, y in the inner product space

$$|\langle x, y \rangle| \leq \|x\| \cdot \|y\| \dots (*)$$

equality holds iff x, y are co-linear

Proof: ① if either x or $y = 0$.

(*) is equality. x, y are colinear

② neither is 0

$$x - ty, t \in \mathbb{R}$$

$$\langle x - ty, x - ty \rangle \geq 0$$

$$\langle x, x \rangle - 2t \langle x, y \rangle + t^2 \langle y, y \rangle = \|x\|^2 - 2t \langle x, y \rangle + t^2 \|y\|^2$$

$$\text{take } t = \frac{\langle x, y \rangle}{\|y\|^2}$$

$$0 \leq \|x\|^2 - 2 \cdot \frac{\langle x, y \rangle}{\|y\|^2} \cdot \langle x, y \rangle + \frac{\langle x, y \rangle^2}{\|y\|^2} = \|x\|^2 - \frac{\langle x, y \rangle^2}{\|y\|^2}$$

$$\langle x, y \rangle^2 \leq \|x\|^2 \cdot \|y\|^2$$

$$|\langle x, y \rangle| \leq \|x\| \cdot \|y\|$$

If equality holds $|\langle x, y \rangle| = \|x\| \cdot \|y\|$

Let $t = \frac{\|x\|}{\|y\|}$, in this case $\|x - ty\| = 0$

$$x - ty = 0 \Rightarrow x = ty$$

If x, y is colinear $\Rightarrow x = ty$

$$|\langle x, y \rangle| = |\langle ty, y \rangle|$$

$\langle x - ty, x - ty \rangle \leftarrow$ compute this & get equality.

Corollary: for $f, g \in C[a, b]$

$$\left| \int_a^b f \cdot g \, dx \right| \leq (\int_a^b f^2 \, dx)^{1/2} (\int_a^b g^2 \, dx)^{1/2}$$

Corollary: triangle inequality. $\|x+y\| \leq \|x\| + \|y\|$

Moreover, if equality holds, x, y are colinear:

$$\langle x+y, x+y \rangle = \|x+y\|^2 = \langle x, x \rangle + 2\langle x, y \rangle + \langle y, y \rangle$$

$$\leq \|x\|^2 + 2\|x\| \cdot \|y\| + \|y\|^2$$

$$\leq \langle x, x \rangle + 2|\langle x, y \rangle| + \langle y, y \rangle$$

$$= (\|x\| + \|y\|)^2$$

by Cauchy-Schwarz

Def'n: 2 vectors x, y are orthogonal if $\langle x, y \rangle = 0$. A collection of vectors $\{e_i : i \in S\}$ in V :

$$\langle e_i, e_j \rangle = 0, i \neq j$$

$$\|e_i\| = 1, \forall i \in S$$

Orthonormal

Ex: \mathbb{R}^n : $e_1 = (1, 0, \dots, 0)$, $e_2 = (0, 1, 0, \dots, 0)$, \dots , $e_n = (0, 0, \dots, 1)$

Lemma: Let $\{e_1, e_2, \dots, e_n\}$ be a finite orthonormal set & d_1, \dots, d_n be real numbers
 If w is $\sum_{i=1}^n d_i e_i \Rightarrow d_i = \langle w, e_i \rangle$
 Also for $\forall v, v - \sum_{i=1}^n \langle v, e_i \rangle e_i$ is orthogonal to each $e_j, \forall j = 1, 2, \dots, n$

$$\begin{aligned} \text{Proof: } & \langle v - \sum_{i=1}^n \langle v, e_i \rangle e_i, e_j \rangle \\ &= \langle v, e_j \rangle - \sum_{i=1}^n \langle v, e_i \rangle \langle e_i, e_j \rangle \\ &= \langle v, e_j \rangle - \cancel{\langle v, e_j \rangle} \quad \leftarrow \text{Q1} \checkmark \text{ j is an index, not variable} \quad i=j \\ &= 0 \end{aligned}$$

Corollary: $\{e_1, \dots, e_n\}$ be finite orthonormal set. If x is in $\text{span}\{e_1, \dots, e_n\}$, then x can be uniquely written as $\sum_{i=1}^n \langle x, e_i \rangle e_i$. Also, all orthonormal sets are L.I.

Cor: In a finite-dimensional vector space, an orthonormal set is a basis iff it is maximized w.r.t. being a orthonormal set.

Gram-Schmidt Process.

L.I. set $\{x_1, \dots, x_n\} \Rightarrow$ orthonormal basis.

$$f_1 = \frac{x_1}{\|x_1\|}$$

:

Sps we have f_1, \dots, f_k orthonormal vectors.

$$y_{k+1} = x_{k+1} - \sum_{i=1}^k \langle x_{k+1}, f_i \rangle f_i$$

$$f_{k+1} = \frac{y_{k+1}}{\|y_{k+1}\|}$$

Lemma:

Let $\{e_1, \dots, e_n\}$ be an orthonormal set in $(V, \langle \cdot, \cdot \rangle)$. If $x = \sum_{j=1}^n \alpha_j e_j$, $y = \sum_{j=1}^n \beta_j e_j$ ($\langle y, e_j \rangle = \beta_j$) then $\langle x, y \rangle = \sum_{j=1}^n \alpha_j \beta_j$

$$\|x\|^2 = \sum_{j=1}^n \alpha_j^2$$

on inner-product space V

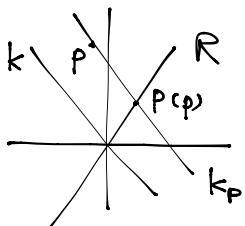
Cor:

If $(V, \langle \cdot, \cdot \rangle)$ of dimension n , then it has an orthonormal basis with n elements

& the inner product is given by $\langle \sum_{i=1}^n \alpha_i e_i, \sum_{j=1}^n \beta_j e_j \rangle = \sum_{i=1}^n \alpha_i \beta_i$

Def'n: A projection is a linear map $P: V \rightarrow V$, $P^2 = P$

Ex: I, O.



$$\begin{aligned} P(p) &= p \\ \text{so } P^2(p) &= P(p) = p \end{aligned}$$

Def'n: P is an orthogonal projection if $\ker P$ is orthogonal to $\text{Im } P$.
 $\ker P = \{v \in V : Pv = 0\}$

Prop:

If P is a projection on a normal Vector space then

$$1) \ker P = \text{Range}(I - P)$$

If, V is an inner product space and P is an orthogonal projection, then

$$2) \forall x \in V, \|x\|^2 = \|Px\|^2 + \|(I - P)x\|^2$$

3) P is uniquely determined by its range

Proof: 1) Sps $x \in \ker P \Rightarrow Px = 0$

$$\text{Then } (I - P)x = Ix - Px = x \Rightarrow x \in \text{Range}(I - P)$$

Sps $y \in \text{Im}(I - P)$

$$x = (I - P)y$$

$$\Rightarrow Px = (P - P^2)y = 0$$

$$((I - P)x = Ix - Px = x - Px = x \Rightarrow Px = 0 \Rightarrow x \in \ker P)$$

2). by our assumption, $\underbrace{\text{range}(I - P)}_{-\ker P} \text{ & range } P$ are orthogonal

$$x = Px + (I - P)x$$

$$\|x\|^2 = \langle x, x \rangle$$

$$= \langle Px + (I - P)x, Px + (I - P)x \rangle$$

$$= \langle Px, Px \rangle + 2\langle Px, (I - P)x \rangle + \langle (I - P)x, (I - P)x \rangle$$

$$= \|Px\|^2 + \|(I - P)x\|^2$$

Proof of 3) as an exercise

Projection Thm:

Let M be a finite-dimensional subspace of an inner product space V and P . The orthogonal projection with $P(M) = M$. Then for all $y \in V$, all $x \in M$.

$$\|y - x\|^2 = \|y - Py\|^2 + \|Py - x\|^2$$

In particular, Py is the closest vector in M to y . If $\{e_1, \dots, e_n\}$ is an orthonormal basis for M , then $Py = \sum_{j=1}^n \langle y, e_j \rangle e_j$ for $\forall y \in V$

Further, $\|y\|^2 \geq \sum_{j=1}^n \langle y, e_j \rangle^2$

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$$f(x, y) = \begin{cases} (1+xy)^{1/x}, & x \neq 0 \\ e^y, & x = 0 \end{cases}$$

$$(0, y_0)$$

$$f(x, y) = e^{g(x, y)}$$

$$g(x, y) = \begin{cases} \ln(1+xy), & x \neq 0 \\ y, & x = 0 \end{cases}$$

when $xy > -1$, $|x| < \frac{1}{|y|+1}$. enough to show $g(x, y)$ is cont.

wts $g(x, y) - g(0, y_0)$ can be made arbitrarily small by making (x, y) close to $(0, y_0)$

$$\begin{aligned}
 g(x,y) - g(0,y_0) &= \frac{\ln(1+xy)}{x} - y_0 \\
 &= \frac{\ln(1+xy)}{x} - y + y - y_0 \\
 &= \frac{\ln(1+xy) - xy}{x} + y - y_0 \\
 &= y \cdot \frac{\ln(1+xy) - xy}{xy} + y - y_0
 \end{aligned}$$

if $xy \rightarrow 0$, $\frac{\ln(1+xy) - xy}{xy} \rightarrow 0$

Can assume by making $|y - y_0| < \frac{|y_0|}{2}$, $|y| < \frac{3|y_0|}{2}$
 Take x much smaller compared to $\frac{3|y_0|}{2}$

$\frac{\ln(1+xy) - xy}{xy} \rightarrow 0$, $y - y_0 \rightarrow 0 \Rightarrow$ function is continuous.