

Tutorial 6 Inner Product Spaces and their Operators

Def. 6.1. An inner product is a function $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{F}$, where $\mathbb{F} = \mathbb{R}$ or \mathbb{C} , s.t.

(IP1) Sesquilinear $\langle ax+ty, z \rangle = a\langle x, z \rangle + t\langle y, z \rangle \quad \forall x, y, z \in V, a, t \in \mathbb{F}$.

linear in first and conjugate linear in second
 $\langle x, ay+tz \rangle = \bar{a}\langle x, y \rangle + \bar{t}\langle x, z \rangle$
 conjugate: $\overline{a+bi} = a-bi$

(IP2) Conjugate symmetric $\langle x, y \rangle = \overline{\langle y, x \rangle} \quad \forall x, y \in V$.

(IP3) positive definite $\langle x, x \rangle \geq 0$ with $=$ iff $x=0$. $\forall x \in V$.

Remark. (i) (IP2) implies $\langle x, x \rangle \in \mathbb{R}$, so (IP3) make sense as \mathbb{R} has a natural order. \Rightarrow

(ii) When $\mathbb{F} = \mathbb{R}$, a function $\langle \cdot, \cdot \rangle$ satisfying (IP1) is called a bilinear form.

a function satisfying (IP1)+(IP2) is called a symmetric bilinear form.

so an inner product is a positive definite symmetric bilinear form.

(a function $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{F}$ is called a form)

They are all very important objects in linear algebra, and appear everywhere in geometry.

When $\mathbb{F} = \mathbb{C}$, we also study Hermitian form: A function $H(\cdot, \cdot) : V \times V \rightarrow \mathbb{F}$ satisfying

(IP1)+(IP2). They are heavily studied in analysis, especially functional

analysis.

(iii) The dictionary:

$\mathbb{F} = \mathbb{R}$	symmetric bilinear form	$\langle Tv, w \rangle = \langle v, Tw \rangle$	\iff	symmetry matrix	$A^T = A$	\iff	$A = [T]_{\beta}$	
$\mathbb{F} = \mathbb{C}$	Hermitian form	$\langle Tv, w \rangle = \langle v, Tw \rangle$	\iff	Hermitian matrix	$A^H = A$	\iff	$A = [T]_{\beta}$	orthonormal basis

(iv) For every symmetry bilinear form B we can associate a quadratic form $q : V \rightarrow \mathbb{F}$ defined by $q(x) = B(x, x)$. A quadratic form is a function $q : V \rightarrow \mathbb{F}$ satisfying

(QF1) $q(ax) = a^2 q(x) \quad \forall x \in V, a \in \mathbb{F}$.

(QF2) $q(x+y) - q(x) - q(y)$ is bilinear $\forall x, y \in V$.

Eg. $q(x) = x^T Q x$, where Q is a matrix corresponding to q if a basis is chosen.

Eg. $q(x, y) = 4x^2 + 2xy - 3y^2 = \begin{pmatrix} x & y \end{pmatrix} \begin{pmatrix} 4 & 1 \\ 1 & -3 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$ so we may just study $Q = \begin{pmatrix} 4 & 1 \\ 1 & -3 \end{pmatrix}$.

Classification of quadratic form gives classification of quadrics in \mathbb{R}^n .

When $n=3$, we may classify all conic sections (圓錐曲線) in high school!

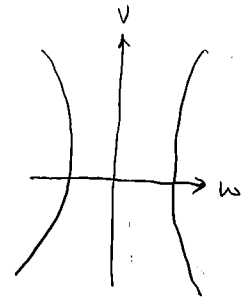
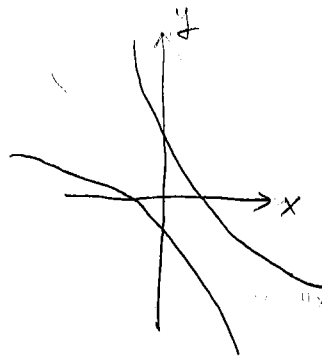
Eg. $q(x,y) = x^2 + 4xy + y^2$

$$= (x \ y) \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

$$= (x \ y) P \begin{pmatrix} 3 & 0 \\ 0 & -1 \end{pmatrix} P^T \begin{pmatrix} x \\ y \end{pmatrix} \quad P = \frac{1}{2} \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix} = \text{rotation by } \frac{\pi}{4}$$

$$= (w \ v) \begin{pmatrix} 3 & 0 \\ 0 & -1 \end{pmatrix} \begin{pmatrix} w \\ v \end{pmatrix} \quad \text{where } (w,v) = (x,y)P$$

$$= 3w^2 - v^2 \quad = \left(\frac{1}{\sqrt{2}}(x+y), \frac{1}{\sqrt{2}}(y-x) \right)$$




(V) A bilinear form $B: V \times V \rightarrow \mathbb{F}$ is equivalent to a linear map $\tilde{B}: V \otimes V \rightarrow \mathbb{F}$.

In this language, we can study multilinear maps: $f: V^{\otimes n} \rightarrow \mathbb{F}$. ↑ tensor product.

This is another generalization of this topic.

* all remarks above are non-examinable except (i).

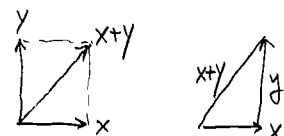
Def. 6.2. An inner product space is a vector space with an inner product on it.

Remark. (i) Recall $\cos \theta = \frac{\langle v, w \rangle}{\sqrt{\langle v, v \rangle \langle w, w \rangle}}$  , $\langle v, w \rangle = v^T w$ here.

$\|v\| = \sqrt{\langle v, v \rangle}$ length of v .

So on inner product space we may talk about "angle" and "length".

(ii) Pythagorean theorem (勾股定理) $\langle x, y \rangle = 0$
 $\|x\|^2 + \|y\|^2 = \|x+y\|^2$ where $x \perp y$



This works for arbitrary dimension!

$$\sum_{i=1}^n \|x_i\|^2 = \left\| \sum_{i=1}^n x_i \right\|^2 \quad \text{if } \langle x_i, x_j \rangle = 0 \text{ for all } i \neq j.$$

(iii). Cauchy inequality (柯西不等式)

$$(x_1^2 + x_2^2)(y_1^2 + y_2^2) \geq (x_1 y_1 + x_2 y_2)^2 \Leftrightarrow \|x\| \|y\| \geq |\langle x, y \rangle| \quad x = (x_1, x_2) \quad y = (y_1, y_2)$$

Again this works for arbitrary dimension! Cauchy-Schwarz inequality.

$$\|x\| \|y\| \geq |\langle x, y \rangle| \quad x = (x_1, x_2, \dots, x_n) \quad y = (y_1, \dots, y_n)$$

$$\begin{aligned} &\Downarrow \\ &\left(\sum_{i=1}^n x_i^2\right) \left(\sum_{i=1}^n y_i^2\right) = \left(\sum_{i=1}^n x_i y_i\right)^2 \end{aligned}$$

(iv). matrix transpose Let $T: V \rightarrow V$ be a linear operator.

When we define $\langle v, w \rangle = v^* w$ the standard inner product.

$$\langle Tv, w \rangle = \langle v, T^* w \rangle \Leftrightarrow (Tv)^* w = v^* T^* w$$

where $*$ is the transpose when $\mathbb{F} = \mathbb{R}$
hermitian where $\mathbb{F} = \mathbb{C}$.
conjugate + transpose

T^* is called the adjoint operator of T .

So we have notion of matrix transpose and matrix Hermitian in our language.

* not all remarks above are examinable, depends on the progress of lecture.

Eg. Frobenius inner product: $\langle A, B \rangle = \text{tr}(AB^H)$. gives a inner product structure on $M_n(\mathbb{C})$.

Euclidean space: \mathbb{R}^n with an inner product, $\mathbb{F} = \mathbb{R}$.

Inner product gives additional structure to a vector space, and such restrictions give many astonishing consequences.

Thm 6.3 Let V be an inner product space, $\mathbb{F} = \mathbb{R}$ or \mathbb{C} . Suppose $\dim V < \infty$. Then

(i). There exist an orthonormal basis, via Gram-Schmidt orthonormalization process.

$w_1 = v_1$
 $w_2 = v_2 - \frac{\langle w_1, v_2 \rangle}{\langle w_1, w_1 \rangle} w_1$
 \vdots
 $w_k = v_k - \sum_{i=1}^{k-1} \frac{\langle w_i, v_k \rangle}{\langle w_i, w_i \rangle} w_i$

orthogonalization

$u_i = \frac{w_i}{\|w_i\|} \quad \|w_i\| = \sqrt{\langle w_i, w_i \rangle}$

normalization

Any basis $\{v_1, \dots, v_n\}$ $\xrightarrow{\text{orthonormalization}}$ Orthonormal basis $\{u_1, \dots, u_n\}$

orthonormal basis

$\langle u_i, u_j \rangle = \delta_{ij} = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases}$ length=1

$v = \sum_{i=1}^n \underbrace{\langle v, u_i \rangle}_{\text{scalar}} u_i$ is the linear combination for any $v \in V$.

$$\Rightarrow [T]_{\beta} = \langle w_i, T(u_j) \rangle$$

(ii). Every subspace $U \subseteq V$ has an orthogonal complement

$$U^\perp := \{ v \in V \mid \langle v, u \rangle = 0 \text{ for all } u \in U \}$$

So that $V = U \oplus U^\perp$

This is direct result from (i); the existence of orthonormal basis.

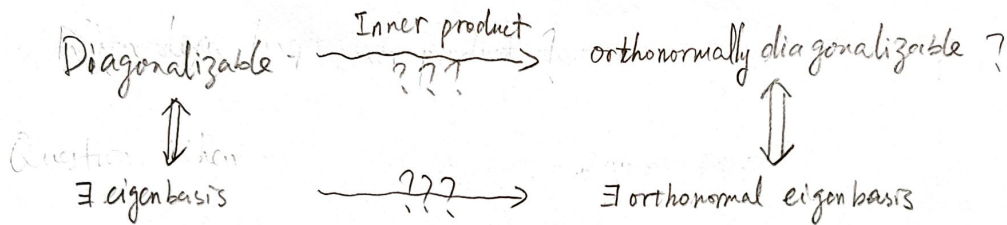
Moreover, one may extend an orthonormal basis in U to a orthonormal basis in V . This is done by an arbitrary extension of basis, and then do Gram-Schmidt. As the basis in U is already orthonormal, this will do nothing to them.

(iii) The adjoint T^* always exists and linear. (T^* always unique if exist).

Spectral Theorem.

← eigenspace

Let $T: V \rightarrow V$ be a linear operator on a finite dimensional vs. V .



The spectral theorem gives the condition when $T: V \rightarrow V$ is orthonormally diagonalizable.

(spectral) Thm 6.4 (i) $\mathbb{F} = \mathbb{R}$. $T = T^*$ ^{self adjoint} $\Leftrightarrow \exists$ orthonormal eigenbasis $\Leftrightarrow T$ is orthonormally diagonalizable.

(ii) $\mathbb{F} = \mathbb{C}$. $TT^* = T^*T$ _{normal} $\Leftrightarrow \exists$ orthonormal eigenbasis $\Leftrightarrow T$ is unitarily diagonalizable.

Thm 6.5 (i) $ST = T^* \Leftrightarrow \langle Tv, v \rangle \in \mathbb{R} \forall v \in V$. \mathbb{R} $\mathbb{F} = \mathbb{C}$.

(ii) $T = T^* \Rightarrow$ all eigenvalues are real. $\mathbb{F} = \mathbb{R}$ or \mathbb{C} .

(iii) $TT^* = T^*T$ and all eigenvalues are real $\Rightarrow T = T^*$ $\mathbb{F} = \mathbb{C}$.

(iv) $TT^* = T^*T \Leftrightarrow \|Tv\| = \|T^*v\| \Leftrightarrow \exists$ orthonormal eigenbasis $\mathbb{F} = \mathbb{C}$.

(v) $TT^* = T^*T \Leftrightarrow \exists$ orthonormal basis β s.t. $[T]_\beta$ is block diagonal with each block is a scalar or $\begin{pmatrix} a & -b \\ b & a \end{pmatrix}$ where $b > 0$. $\mathbb{F} = \mathbb{R}$.

Isometry Let $T: V \rightarrow V$ be a linear operator on a finite dimensional vector space V .

We want to study distance preserving symmetries of space V , this is the notion of isometry. Examples include rotations and reflection. [cf. Artin Algebra.]

Def. 6.6. T is an isometry if $\|Tv\| = \|v\|$ for all $v \in V$.

Lemma 6.7. $\|Tv\| = \|v\| \Leftrightarrow \langle Tv, Tw \rangle = \langle v, w \rangle \Leftrightarrow T^*T = Id \Leftrightarrow \begin{cases} A^t A = I & \text{orthogonal } F = \mathbb{R} \\ A^H A = I & \text{unitary } F = \mathbb{C} \end{cases}$
 \Rightarrow all eigenvalues $|\lambda_i| = 1$. where $A = [T]_{\beta}$ \leftarrow orthonormal basis

Thm. 6.8.(i) $F = \mathbb{R}$. $T^*T = Id \Leftrightarrow \exists$ orthonormal basis β s.t. $[T]_{\beta} = \begin{pmatrix} I & & & \\ & -I & & \\ & & R_{\theta_1} & \\ & & & \ddots \\ & & & & R_{\theta_n} \end{pmatrix}$ $\theta_i \neq 0, \pi$

\swarrow corresponding to $\lambda, \bar{\lambda}$ in \mathbb{C} .
 where $R_{\theta} = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$

(ii) $F = \mathbb{C}$. $T^*T = Id \Leftrightarrow \exists$ orthonormal eigenbasis s.t. $[T]_{\beta} = \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$ \leftarrow eigenvalues with $|\lambda_i| = 1$.
 $\Leftrightarrow T$ is unitarily diagonalizable with eigenvalues $|\lambda_i| = 1$. \leftarrow unitary.

(note that $TT^* = Id$ implies $T^*T = TT^*$ so spectral thm is applicable)

Q. (Unitary matrix v.s. unitarily diagonalizable: unitary matrices when the inner product is $\langle v, w \rangle = v^t w$)

Unitary matrix means $A^H A = I = A A^H$. Unitarily diagonalizable means \exists unitary P s.t. $A = P^T D P$

for diagonal D . By 6.8 (ii), unitary matrix is unitarily diagonalizable with eigenvalues $|\lambda_i| = 1$.

Q. (field normal v.s. unitary. Over \mathbb{C} , all fields include a scalar multiplication and real numbers)

A is normal if $AA^* = A^*A$. By 6.4 (ii) and 6.8 (ii) we see that if we replace the definition of inner product by positive definite symmetric bilinear form, then A is normal iff A is unitary with all eigenvalues $|\lambda_i| = 1$.

Remark 6.1 (i), (ii) Remark 6.2 (i), (ii), (iii) (i), (ii), Thm 6.3, Spectral thm 6.4 (ii),

Thm 6.8 (ii) first three \Leftrightarrow of lemma 6.7 should work for arbitrary F .

Fourier Transform and Hilbert Space.

Eg. Consider $L^2([E, J]) = \{ f: [E, J] \rightarrow \mathbb{R} \mid \int_E^J |f(x)|^2 dx < \infty \}$ \swarrow L^2 -integrable

It is a vector space with $(f_1 + f_2)(x) = f_1(x) + f_2(x) \quad x \in [E, J]$

$(af_1)(x) = a f_1(x) \quad a \in \mathbb{R}.$

Define an inner product on $L^2([E, J])$ by

$$\langle f, g \rangle = \int_E^J f(x)g(x) dx$$

This makes $(L^2([E, J]), \langle, \rangle)$ an inner product space.

For example, for $n, m \in \mathbb{Z}$,

$$\langle \sin m\pi x, \cos n\pi x \rangle = \int_{-1}^1 \sin m\pi x \cos n\pi x dx = 0$$

$$\langle \sin m\pi x, \sin n\pi x \rangle = \int_{-1}^1 \sin m\pi x \sin n\pi x dx = \begin{cases} 0 & \text{if } m \neq n \\ 1 & \text{if } m = n \end{cases}$$

$$\langle \cos m\pi x, \cos n\pi x \rangle = \int_{-1}^1 \cos m\pi x \cos n\pi x dx = \begin{cases} 0 & \text{if } m \neq n \\ 1 & \text{if } m = n \end{cases}$$

$$\begin{aligned} \sin \alpha \cos \beta &= \frac{1}{2} [\sin(\alpha - \beta) + \sin(\alpha + \beta)] \\ \sin \alpha \sin \beta &= \frac{1}{2} [\cos(\alpha - \beta) - \cos(\alpha + \beta)] \\ \cos \alpha \cos \beta &= \frac{1}{2} [\cos(\alpha - \beta) + \cos(\alpha + \beta)] \end{aligned}$$

$\forall m, n \in \mathbb{Z}$

Hence $\{ \sin n\pi x, \cos n\pi x \}_{n \in \mathbb{Z}}$ are orthonormal elements in $(L^2([-1, 1]), \langle, \rangle)$

This is useful for later when we define Fourier transform.

Eg. Let $\{e_i\}_{i=1}^n$ be an orthonormal basis of an inner product space (V, \langle, \rangle) . Let $S = \{v_i\}_{i=1}^n$ be a subset of V s.t.

$$\|v_i - e_i\| \leq \frac{1}{\sqrt{n}}$$

Then S is a basis.

pf. If $\{v_i\}_{i=1}^n$ are linearly dependent, $0 = \sum a_i v_i = \sum a_i (v_i - e_i) + \sum a_i e_i$.

$$\text{Hence } \|\sum a_i (v_i - e_i)\| = \|\sum a_i e_i\|$$

$$\text{But } \|\sum a_i (v_i - e_i)\| \stackrel{\text{triangle}}{\leq} \sum |a_i| \|v_i - e_i\| < \frac{1}{\sqrt{n}} \sum |a_i| =$$

$$\|\sum a_i e_i\| = (\sum |a_i|^2)^{\frac{1}{2}} \text{ since } \{e_i\} \text{ are orthonormal.}$$

As $(\sum |a_i|^2) (\sum 1^2) \stackrel{\text{Cauchy-Schwarz}}{\geq} (\sum |a_i|)^2$, this gives a contradiction unless $a_i = 0$ for all i . \square

Q1. Let $A \in M_n(\mathbb{R})$. Show that

$\exists B \in M_n(\mathbb{R})$ s.t. $A = B^t B \iff A$ is symmetric and all eigenvalues are non-negative.

Pf. (\implies) $A^t = (B^t B)^t = B^t B = A$. Hence A is symmetric.

Suppose λ is any eigenvalue with eigenvector v .

$$\langle Av, v \rangle = \lambda \langle v, v \rangle.$$

$$\langle B^t B v, v \rangle = \langle Bv, Bv \rangle.$$

If $Bv = 0$, then $Av = 0$ so $\lambda = 0$.

If $Bv \neq 0$, $\lambda = \frac{\langle Bv, Bv \rangle}{\langle v, v \rangle} > 0$.

(\impliedby) By spectral theorem, $A = P D P^t$, where P is an orthonormal matrix, D is diagonal with eigenvalues at the diagonal. As eigenvalues are non-negative, \sqrt{D} (all entries are square root of D) exist. Then let $B = P \sqrt{D}$ gives the result as $(\sqrt{D})^t = \sqrt{D}$ and $(\sqrt{D})^2 = D$. \square

Q2. Let $T \in \mathcal{L}(V)$ be a self-adjoint operator on inner product space V over \mathbb{F} .

Suppose $\exists \lambda \in \mathbb{F}$, $\|v\| = 1$, $\varepsilon > 0$ s.t.

$$\|Tv - \lambda v\| < \varepsilon.$$

Show that T has an eigenvalue $\lambda' \in \mathbb{F}$ s.t.

$$|\lambda' - \lambda| < \varepsilon.$$

Pf. It suffices to show for matrix version. Suppose A is self-adjoint and $A = P D P^t$, for P orthogonal. In particular, $\|Pw\| = \|w\|$ for any $w \in V$.

$$\text{Now } \|Tv - \lambda v\| = \|P(D - \lambda I)P^{-1}v\| = \|(D - \lambda I)P^{-1}v\|.$$

Write $D = \begin{pmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \lambda_n \end{pmatrix}$. $P^{-1}v = \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix}$. As $\|P^{-1}v\| = \|v\| = 1$, $\left\| \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix} \right\|^2 = 1$.

Suppose for contradiction that $|\lambda_i - \lambda| \geq \varepsilon$ for all i . Then

$$\varepsilon \geq \|Tv - \lambda v\| = \|(D - \lambda I) \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix}\| = \left\| \begin{pmatrix} (\lambda_1 - \lambda)c_1 \\ \vdots \\ (\lambda_n - \lambda)c_n \end{pmatrix} \right\| > \varepsilon \left\| \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix} \right\| = \varepsilon \quad \text{contradiction.}$$

Hence $\exists \lambda_i$ s.t. $|\lambda_i - \lambda| < \varepsilon$. \square