

## § 10.1 Inner product

Motivation: dot product on  $\mathbb{R}^n$  is useful  
e.g. if  $\{\alpha_1, \dots, \alpha_k\}$  is an orthogonal basis for  $W \subseteq \mathbb{R}^n$   
then the closest point in  $W$  to  $\beta$  / best approximation in  $W$

$$\text{to } \beta \text{ is } \text{Proj}_W(\beta) = \frac{\beta \cdot \alpha_1}{\alpha_1 \cdot \alpha_1} \alpha_1 + \dots + \frac{\beta \cdot \alpha_k}{\alpha_k \cdot \alpha_k} \alpha_k$$

Want to similarly approximate functions in other vector spaces,  
i.e. want to define  $\alpha \cdot \beta$  for  $\alpha, \beta \in V$  — use a symmetric bilinear form

that's positive definite.

Def 10.1.1 Let  $V$  be a vector space over  $\mathbb{R}$ .

$\langle , \rangle$  is an inner product on  $V$  if:

- a. symmetric  $\langle \alpha, \beta \rangle = \langle \beta, \alpha \rangle$
- b. bilinear  $\langle \alpha, \alpha_1\beta_1 + \beta_2 \rangle = \alpha \langle \alpha_1\beta_1 \rangle + \langle \alpha, \beta_2 \rangle$

c. consequence of a and b:

$$\langle a\alpha_1 + \alpha_2, \beta \rangle = a\langle \alpha_1, \beta \rangle + \langle \alpha_2, \beta \rangle$$

d. positive definite  $\langle \alpha, \alpha \rangle > 0 \quad \forall \alpha \neq 0$ .

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Ex:

Ex.: dot product on  $\mathbb{R}^n$ :  $\langle \alpha, \beta \rangle = \alpha \cdot \beta$

• weighted dot product

e.g. in  $\mathbb{R}^3$   $\left\langle \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}, \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} \right\rangle = x_1y_1 + 2x_2y_2 + 5x_3y_3$

• in  $C^0([a, b])$ :  $\langle f, g \rangle = \int_a^b w(x) f(x)g(x) dx$

where  $w(x)$  is a positive weight function on  $(a, b)$

e.g.  $\langle f, g \rangle = \int_{-1}^1 (1+x) f(x)g(x) dx$   
( $w(x) = 1+x$ )

• in  $M_{n,n}(\mathbb{R})$ :

Def. the trace of  $X \in M_{nn}(\mathbb{R})$  is  $\text{Tr}(X) = X_{11} + X_{22} + \dots + X_{nn}$

e.g.  $\text{Tr} \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix} = a + e + i$

$$\langle A, B \rangle = \text{Tr}(A^T B)$$

e.g. On  $M_{2,2}(\mathbb{R})$ :

$$\left\langle \begin{pmatrix} a & a_2 \\ a_3 & a_4 \end{pmatrix}, \begin{pmatrix} b & b_2 \\ b_3 & b_4 \end{pmatrix} \right\rangle = \text{Tr} \begin{pmatrix} (a, a_3) & (b, b_3) \\ (a_2, a_4) & (b_2, b_4) \end{pmatrix} = \text{Tr} \begin{pmatrix} a_1b_1 + a_3b_3 & a_1b_2 + a_3b_4 \\ a_2b_1 + a_4b_3 & a_2b_2 + a_4b_4 \end{pmatrix} = (a_1b_1 + a_3b_3) + (a_2b_2 + a_4b_4)$$

dot product  
on  $\mathbb{R}^4$

In general  $\langle A, B \rangle = [A]_A \cdot [B]_A$  if  $A = \{E^1, E^2, \dots, E^n\}$   
is the standard basis of  $M_{n,n}(\mathbb{R})$ .

Over  $\mathbb{C}$ , we have to define inner products differently, because  
the condition  $\langle \alpha, \alpha \rangle > 0 \quad \forall \alpha \neq \vec{0}$  does not make sense if  $\langle \alpha, \alpha \rangle \in \mathbb{C} \setminus \mathbb{R}$ .

Def 10.1.1 / 9.6.1 Let  $V$  be a vector space over  $\mathbb{C}$ .  
 $\langle , \rangle$  is an inner product on  $V$  if:

a. Hermitian  $\overline{\langle \alpha, \beta \rangle} = \langle \beta, \alpha \rangle$  where — means complex conjugation

(e.g.  $\overline{2+i} = 2-i$ )  
(then  $\overline{\langle \alpha, \alpha \rangle} = \langle \alpha, \alpha \rangle$  so  $\langle \alpha, \alpha \rangle \in \mathbb{R}$ )

b. sesquilinear  $\langle \alpha, \alpha_1 + \alpha_2 \rangle = a\langle \alpha, \alpha_1 \rangle + \langle \alpha, \alpha_2 \rangle$

c. consequence of a and b:  $\langle a\alpha_1 + \alpha_2, \beta \rangle = \overline{a}\langle \alpha_1, \beta \rangle + \langle \alpha_2, \beta \rangle$

d. positive definite  $\langle \alpha, \alpha \rangle > 0 \quad \forall \alpha \neq \vec{0}$ .

(There is a theory for Hermitian sesquilinear forms,  
like the one for symmetric bilinear forms

e.g. polarisation identity,  
diagonalisation theorem and  
algorithm,  
classification by definiteness,  
... - see §9.6.)

Ex: Dot product on  $\mathbb{C}^n$

$$\left\langle \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}, \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \right\rangle = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \cdot \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} = \overline{x_1}y_1 + \dots + \overline{x_n}y_n$$

e.g. on  $\mathbb{C}^2$ :  $\begin{pmatrix} 1 \\ 1+i \end{pmatrix} \cdot \begin{pmatrix} 3 \\ -2i \end{pmatrix} = 1 \cdot 3 + (1-i)(-2i) = 3 - 2i - 2 = 1 - 2i$

Ex:  $V = \{f: \mathbb{R} \rightarrow \mathbb{C} \text{ continuous on } [a, b]\}$

$$\langle f, g \rangle = \int_a^b \overline{f(x)}g(x) dx$$

(computation not examinable)

No inner product over other fields

$$e.g. \{0, 1\} = \mathbb{F}_2$$

Define the length or norm of

$$\alpha \in V \text{ to be } \|\alpha\| = \sqrt{\langle \alpha, \alpha \rangle}$$

$$\text{Then } \|\alpha\|^2 = \langle \alpha, \alpha \rangle$$

$$= \overline{\alpha} \langle \alpha, \alpha \rangle$$

$$= \overline{\alpha} \alpha \langle \alpha, \alpha \rangle$$

$$= |\alpha|^2 \langle \alpha, \alpha \rangle \text{ so } \|\alpha\| = |\alpha| \|\alpha\|$$