## **Chapter 6 Inner Product Spaces**

## 6.1 Inner Products and Norms

**Definition.** Inner Product Let V be a vector space over F. An inner product on V is a function that assigns, to every ordered pair of vectors x and y in V, a scalar in F, denoted  $\langle x,y\rangle$ , such that for all  $x,y,z\in VE$  and all  $c\in F$ ,

- 1.  $\langle x+z,y\rangle = \langle x,y\rangle + \langle z,y\rangle$
- 2.  $\langle cx, y \rangle = c \langle x, y \rangle$
- 3.  $\overline{\langle x, y \rangle} = \langle y, x \rangle$
- 4.  $\langle x, x \rangle > 0$  if  $x \neq 0$

First two condition requires inner product be linear in the first component. Also

$$\langle \sum_{i} a_i v_i, y \rangle = \sum_{i} a_i \langle v_i, y \rangle$$

**Definition.** Conjugate Transpose or Adjoint of a Matrix Let  $A \in M_{m \times n}(F)$ , the conjugate transpose or adjoint of A is an  $n \times m$  matrix  $A^*$  such that  $(A^*)_{ij} = \overline{A_{ji}}$  for all i, j. For  $F = \mathbb{R}$ ,  $A^* = A^T$ 

Definition. Inner Product Definition Example

1. Standard Inner Product on  $F^n$  For  $x = (a_1, a_2, \dots, a_n)$  and  $y = (b_1, b_2, \dots, b_n)$  in  $F^n$ , the standard inner product on  $F^n$  is given by

$$\langle x, y \rangle = \sum_{i=1}^{n} a_i \bar{b}_i$$

2. Inner Product for Real-valued Continuous Functions on [0,1] Let V = C([0,1]),  $f,g \in V$ , define

$$\langle f, g \rangle = \int_0^1 f(t)g(t)dt$$

3. Frobenius Inner Product for Matrices Let  $V = M_{n \times n}(F)$ ,  $A, B \in V$ , then

$$\langle A, B \rangle = tr(B^*A) = \sum_{i=1}^{n} (B^*A)_{ii}$$

**Definition.** Inner Product Space A vector space over F endowed with a specific inner product is called an inner product space. If F = C, V is a complex inner product space; if  $F = \mathbb{R}$ , then V is a real inner product space

**Theorem.** 6.1 Properties From Inner Product Conditions Let V be an inner product space. Then for  $x, y, z \in V$  and  $c \in F$ , the following statements are true

1. 
$$\langle x, y + z \rangle = \langle x, y \rangle + \langle x, z \rangle$$

2. 
$$\langle x, cy \rangle = \overline{c} \langle x, y \rangle$$

3. 
$$\langle x, 0 \rangle = \langle 0, x \rangle = 0$$

4. 
$$\langle x, x \rangle = 0$$
 if and only if  $x = 0$ 

5. If 
$$\langle x, y \rangle = \langle x, z \rangle$$
 for all  $x \in V$ , then  $y = z$ 

The inner product is conjugate linear in the second argument

**Definition.** Norm/Length Let V be an inner product space. For  $x \in V$ , define norm or length of x by

$$||x|| = \sqrt{\langle x, x \rangle}$$

**Definition.** 6.2 Properties of Norm Let V be an inner product space over F. Then for all  $x, y \in V$  and  $c \in F$ , the following statements are true

1. 
$$||cx|| = |c| \cdot ||x||$$

2. 
$$||x|| = 0$$
 if and only if  $x = 0$ . In any case,  $||x|| \ge 0$ 

3. Cauchy-Schwarz Inequality 
$$|\langle x,y\rangle| \leq ||x|| \cdot ||y||$$

4. Triangular Inequality 
$$||x+y|| \le ||x|| + ||y||$$

**Definition.** Angle For  $F = \mathbb{R}$ ,  $x, y \neq 0$ , and  $\theta$  be angle between x and y

$$\cos \theta = \frac{\langle x, y \rangle}{\|x\| \|y\|} \qquad \theta = \cos^{-1} \left( \frac{\langle x, y \rangle}{\|x\| \|y\|} \right)$$

Note

$$\left| \frac{\langle x, y \rangle}{\|x\| \|y\|} \right| \le 1$$

So valid input to arccos function

**Definition.** Orthogonal Vectors Let V be an inner product space. Vectors x and y in V are orthogonal (perpendicular) if  $\langle x, y \rangle = 0$ .

**Definition.** Orthogonal Sets and Orthonormal Sets A subset S of V is orthogonal if any two distinct vectors in S are orthogonal. A vector x in V is a unit vector if ||x|| = 1. A subset S of V is orthonormal if S is orthogonal and consists entirely of unit vectors.

1. 
$$S = \{v_1, v_2, \dots\}$$
, then S is orthonormal if and only if  $\langle v_i, v_j \rangle = \delta_{ij}$ 

2. We can **normalize** an orthogonal set S, by multiplying 1/||x|| for each  $x \in S$ 

**Definition.** Orthonormal Set Property Let V be inner product space and  $S = \{s_1, s_2, \dots\} \subseteq V$  be an orthonormal set. Let  $v \in span(S)$ , then  $v = a_1s_1 + \dots + a_ks_k$ . Then

$$\langle v, s_i \rangle = a_i$$

by

$$\langle v, s_j \rangle = \langle \sum_i a_i s_i, s_j \rangle = \sum_i a_i \langle s_i, s_j \rangle = \sum_i a_i \delta_{ij} = a_j$$

#### Gram-Schmidt Orthogonalization Process and Orthogonal Complements

**Definition.** Orthonormal Basis Let V be an inner product space. A subset of V is an orthonormal basis for V if it is an ordered basis that is orthonormal

**Definition.** Every Inner Product Space has n Orthogonal Basis Let V be an inner product space and  $S = \{v_1, v_2, \dots, v_k\}$  be an orthogonal subset of V consisting of nonzero vectors. If  $y \in span(S)$ , then

$$y = \sum_{i=1}^{k} \frac{\langle y, v_i \rangle}{\|v_i\|^2} v_i$$

Corollary. Special case for Orthonormal Set If, in addition to hypotheses of previous theorem, S is orthonormal and  $y \in S$ , then

$$y = \sum_{i=1}^{k} \langle y, v_i \rangle v_i$$

Corollary. Nonzero Orthonormal Set is Linearly Independent Let V be an inner product space, and flet S be an orthogonal subset of V consisting of nonzero vectors. Then S is linearly independent

**Theorem. 6.4 Gram-Schmidt Process** Let V be an inner product space and  $S = \{w_1, w_2, \dots, w_n\}$  be a linearly independent subset of V. Define  $S' = \{v_1, v_2, \dots, v_n\}$ , where  $v_1 = w_1$  and

$$v_k = w_k - \sum_{j=1}^{k-1} \frac{\langle w_k, v_j \rangle}{\|v_j\|^2} v_j \qquad 2 \le k \le n$$

Then S' is an orthogonal set of nonzero vectors such that span(S') = span(S)

Theorem. 6.5 Every Finite Dimensional I.P.S has an Orthonormal Basis Let V be a nonzero finite-dimensional inner product space. Then V has an orthonormal basis  $\beta$ . Furthermore, if  $\beta = \{v_1, v_2, \dots, v_n\}$  and  $x \in V$ , then

$$x = \sum_{x=1}^{n} \langle x, v_i \rangle v_i$$

Corollary. Expression for Matrix Representation of Transformation on Orthonormal Basis Let V be a finite-dimensional inner product space with an orthonormal basis  $\beta = \{v_1, v_2, \dots, v_n\}$ . Let T be a linear operator on V, and let  $A = [T]_{\beta}$ . Then for any i and j,  $A_{ij} = \langle T(v_j), v_i \rangle$ , i.e.

$$T(v_j) = \sum_{i=1}^{n} \langle T(v_j), v_i \rangle v_i$$

**Definition.** Fourier Coefficients Let  $\beta$  be an orthonormal subset (possibly infinite) of an inner product space V, and let  $x \in V$ . We define the Fourier coefficients of x relative to  $\beta$  to be the scalars  $\langle x, y \rangle$ , where  $y \in \beta$ 

### **Orthogonal Complements**

**Definition.** Orthogonal Complements Let S be a nonempty subset of an inner product space V. We define  $S^{\perp} = \{x \in V : \langle x, y \rangle = 0 \text{ for all } y \in S\}$ . The set  $S^{\perp}$  is called the orthogonal complement of S

1. 
$$\{0\}^{\perp} = V \text{ and } V^{\perp} = \{0\}$$

**Theorem.** 6.6 Finding Projection of a Vector onto a Subspace Let W be a finite-dimensional subspace of an inner product space V, and let  $y \in V$ . Then there exist unique vectors  $u \in W$  and  $z \in W^{\perp}$  such that y = u + z. Furthermore, if  $\{v_1, v_2, \dots, v_k\}$  is an orthonormal basis for W, then

$$u = \sum_{i=1}^{k} \langle y, v_i \rangle v_i$$

where u is the orthogonal projection of y on W.

Corollary. Orthogonal Projection is Unique and Closest to Projected Vector In the notation of previous theorem, the vector u the unique vector in W that is closest to y; that is, for any  $x \in W$ ,  $||y - x|| \ge ||y - u||$ , and this inequality is an equality if and only if x = u

**Theorem.** 6.7 Orthonormal Basis and Subspaces Suppose that  $S = \{v_1, v_2, \dots, v_k\}$  is an orthonormal set in an n-dimensional inner product space V. Then

- 1. S can be extended to an orthonormal basis  $\{v_1, v_2, \dots, v_k, v_{k+1}, \dots, v_n\}$  for V.
- 2. If W = span(S), then  $S_1 = \{v_{k+1}, \dots, v_n\}$  is an orthonormal basis for  $W^{\perp}$
- 3. If W is any subspace of V, then  $dim(V) = dim(W) + dim(W^{\perp})$

## 6.3 The Adjoint of a Linear Operator

**Definition.** Dual Space is a space of all linear transformations from a vector space V to its field F.

**Theorem.** 6.8 Every Linear Transformation from V to F Can Be Written as a Inner Product Let V be a finite-dimensional inner product space over F, and let  $g: V \to F$  be a linear transformation. Then there exists a unique vector  $y \in V$  such that  $g(x) = \langle x, y \rangle$  for all  $x \in V$ , where

$$y = \sum_{i} \overline{g(v_i)}v_i$$
  $\beta = \{v_1, \dots, v_n\}$  is orthonormal basis

**Definition.** Adjoint Linear Operator Given inner product space V, let T be a linear operator on V. The adjoint of operator T,  $T^*$ , is the unique operator on V satisfying

$$\langle T(x), y \rangle = \langle x, T^*(y) \rangle$$
 for all  $x, y \in V$ 

**Theorem.** 6.9 Adjoint of an Linear Operator Exist for f.d. Inner Product Space Let V be a finite-dimensional inner product space, and let T be a linear operator on V. Then there exists a unique function, called the adjoint of T,  $T^*: V \to V$  such that

$$\langle T(x), y \rangle = \langle x, T^*(y) \rangle$$

for all  $x, y \in V$ . Furthermore,  $T^*$  is linear.

Theorem. 6.10 Adjoint of a Linear Operator in Matrix Form is the Adjoint of Matrix Form of that Linear Operator Let v be a finite-dimensional inner product space. Let  $\beta$  be an orthonormal basis for V. If T is a linear operator on V, there

$$[T^*]_{\beta} = [T]_{\beta}^*$$

Corollary. For Left-Matrix Transformation Let A be  $n \times n$  matrix, then  $L_{A^*} = (L_A)^*$ . ( theorem 2.16 )

Theorem. 6.11 Properties of Adjoint of Linear Operators

Let V bewr an inner product space, and let T, U be linear operators on V, then

- 1.  $(T+U)^* = T^* + U^*$
- 2.  $(cT)^* = \overline{c}T^*$  for any  $c \in F$
- 3.  $(TU)^* = U^*T^*$
- 4.  $T^{**} = T$
- 5.  $I^* = I$

assuming adjoints always exists.

## Corollary. For Matrix

Let A and B be  $n \times n$  matrix, then

1. 
$$(A+B)^* = A^* + B^*$$

2. 
$$(cA)^* = \overline{c}A^*$$
 for all  $c \in F$ 

3. 
$$(AB)^* = B^*A^*$$

4. 
$$A^{**} = A$$

5. 
$$I^* = I$$

# **Least Squares Approximation**

**Definition.** Some notation Fort  $x, y \in F^n$ 

- 1.  $\langle x,y\rangle_n$  is the standard inner product of x and y in  $F^n$
- 2. If x and y are column vectors, then  $\langle x, y \rangle_n = y^*x$

**Lemma.** Let  $A \in M_{m \times n}(F)$ ,  $x \in F^n$  and  $y \in F^m$ , then

$$\langle Ax, y \rangle_m = \langle x, A^*y \rangle_n$$

**Lemma.** Let  $A \in M_{m \times n}(F)$ . Then  $rank(A^*A) = rank(A)$ 

**Corollary.** If A is  $m \times n$  matrix such that rank(A) = n, then  $A^*A$  is invertible

**Theorem.** 6.12 Close Form Solution for Least Squared Problem Let  $A \in M_{m \times n}(F)$  and  $y \in F^m$ . Then there exists  $x_0 \in F^n$  such that  $(A^*A)x_0 = A^*y$  and  $||Ax_0 - y|| \le ||Ax - y||$  for all  $x \in F^n$ . Furthermore, if rank(A) = n, then  $x_0 = (A^*A)^{-1}A^*y$