

# ECEn 671: Mathematics of Signals and Systems

Randal W. Beard

Brigham Young University

September 1, 2023

# Section 1

## Orthogonality

# Orthogonality

Let  $x, y \in \mathbb{X}$  where  $\mathbb{X}$  is an inner product space. Then the angle between  $x$  and  $y$  is

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

i.e.

$$\langle x, y \rangle = \|x\| \|y\| \cos \theta$$

# Orthogonality, cont.

## Definition (Colinear)

Two vectors  $x, y \in \mathbb{X}$  are said to be colinear if

$$\theta = 180 * n \quad n = 0, \pm 1, \pm 2, \dots$$

## Definition (Orthogonal)

Two vectors  $x, y \in \mathbb{X}$  are said to be orthogonal if

$$\theta = 90 * n \quad n = \pm 1, \pm 3, \pm 5, \dots$$

i.e.,  $\langle x, y \rangle = 0$ .

If  $\langle x, y \rangle = 0$  we write  $x \perp y$ .

## Orthogonality, cont.

### Example (Vectors in $L_2[0, 2\pi]$ )

The functions  $x = \sin(t)$  and  $y = \cos(t)$  are orthogonal since

$$\langle x, y \rangle = \int_0^{2\pi} \sin(t)\cos(t)dt = 0.$$

### Example (Vectors in $\ell$ )

The sequences

$$x = (1, 1, 1, 1, 0, 0, \dots)$$

$$y = (1, -1, 1, -1, 1, \dots)$$

are orthogonal since

$$\langle x, y \rangle = \sum_{i=1}^{\infty} x_i y_i = 0.$$

# Other useful inner products and norms: Weighting

## Definition (Positive Definite Matrix)

A matrix  $W : \mathbb{R}^k \rightarrow \mathbb{R}^k$  is positive definite (PD) if

$$\forall x \in \mathbb{R}^k \quad x^T W x > 0$$

- ▶  $W$  is positive semi-definite (PSD) if  $x^T W x \geq 0$
- ▶  $W$  is negative definite (ND) if  $x^T W x < 0 \quad \forall x \in \mathbb{R}^k$
- ▶  $W$  is negative semi-definite (NSD) if  $x^T W x \leq 0 \quad \forall x \in \mathbb{R}^k$
- ▶ Otherwise it is indefinite

## Examples of positive definiteness

- ▶  $W = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$  is PD since

$$x^T W x = x_1^2 + x_2^2 > 0 \quad \forall x \in \mathbb{R}^2$$

- ▶  $W = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}$  is PSD since

$$x^T W x = x_1^2 = 0 \quad \forall x = \begin{pmatrix} 0 \\ \alpha \end{pmatrix} \neq 0$$

- ▶  $W = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix}$  is indefinite since

$$x^T W x = -x_1^2 + x_2^2$$

which can be positive or negative depending on  $x$ .

# Examples of Inner Products

## Weighted Inner Products and Norms

If  $W > 0$  then  $\langle x, y \rangle_W = x^H W y$  is a valid inner product which induces the weighted norm  $\|x\|_W = (x^H W x)^{\frac{1}{2}}$

We can define weighted inner products for functions:

$$\langle f, g \rangle_W = \int f(t)g(t)w(t)dt$$

where  $w(t) > 0$  except on a set of measure zero.



# Examples of Inner Products

## Definition (Expectation)

Expectation is a weighted inner product with weight  $f_{\mathbb{X}\mathbb{Y}}(x, y)$

$$\langle \mathbb{X}, \mathbb{Y} \rangle = \int xy f_{\mathbb{X}\mathbb{Y}}(x, y) dx dy = E[\mathbb{X}\mathbb{Y}]$$

if  $\mathbb{X}$  is a zero mean then

$$\langle x, x \rangle = \text{var}(x)$$

is the norm induced by  $E[\cdot]$

# Examples of Inner Products

- ▶ Let  $\mathbb{I}(m, n)$  be the set of grayscale images with  $m \times n$  pixels, each valued between  $[0, 255]$ .
- ▶ A valid inner on  $\mathbb{I}(m, n)$  is given by

$$\langle I, J \rangle = \sum_{u=1}^m \sum_{v=1}^n I(u, v)J(u, v), \quad \forall I, J \in \mathbb{I}(m, n).$$

# Orthogonal Subspaces

## Definition (Orthogonal Subspaces)

Let  $V, W$  be subspaces of  $S$ .  $V \perp W$  if

$$\forall v \in V \text{ and } \forall w \in W, \quad \langle v, w \rangle = 0$$

## Definition (Orthogonal Complement)

$V^\perp$ , called the orthogonal complement of  $V$ , is the set

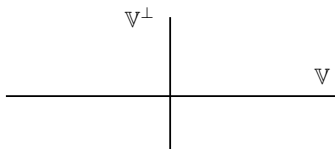
$$V^\perp = \{x \in S : \forall v \in V, \langle x, v \rangle = 0\}$$

# Orthogonal Subspaces, cont.

## Example

Let  $S = \mathbb{R}^2$  and  $V = \left\{ \begin{pmatrix} \alpha \\ 0 \end{pmatrix}, \alpha \in \mathbb{R} \right\}$  then

$$V^\perp = \left\{ \begin{pmatrix} 0 \\ \alpha \end{pmatrix}, \alpha \in \mathbb{R} \right\}$$



# Orthogonal Subspaces, cont.

## Theorem

*Let  $V$  and  $W$  be subspaces of an inner product space  $S$  (not necessarily Hilbert). Then*

1.  $V^\perp$  is a closed subspace of  $S$
2.  $V \subset V^{\perp\perp}$  ( $V = V^{\perp\perp}$  if  $S$  is complete)
3. If  $V \subset W$  then  $W^\perp \subset V^\perp$
4.  $V^{\perp\perp\perp} = V^\perp$
5. If  $x \in V \cap V^\perp$  then  $x = 0$
6.  $\{0\}^\perp = S$  and  $S^\perp = \{0\}$

Prove one in class.

# Inner Sum and Direct Sum

## Definition (Inner Sum)

If  $V$  and  $W$  are linear subspaces then

$$V + W = \{x : x = v + w, v \in V \text{ and } w \in W\}$$

is the inner sum.

## Definition (Orthogonal Sum)

If  $V$  and  $W$  are orthogonal subspaces then the sum

$$V \oplus W = \{x : x = v + w, v \in V \text{ and } w \in W\}$$

is called the orthogonal sum.

## Definition (Disjoint Subspaces)

Two subspaces are said to be disjoint if

$$V \cap W = \{0\}$$

# Inner Sum and Direct Sum, cont.

## Lemma

*Let  $V + W$  be subspaces of  $S$  and let  $x \in V + W$  then the representation  $x = v + w$  is unique iff  $V + W$  are disjoint.*

## Proof.

( $\Leftarrow$ ) Assume  $V, W$  are disjoint but  $x = v + w$  is not unique i.e.  $x = v_1 + w_1 = v_2 + w_2$  where  $v_1 \neq v_2$  and  $w_1 \neq w_2$ . This implies that  $v_1 - v_2 = w_2 - w_1$  but  $v_1 - v_2 \in V$  and  $w_2 - w_1 \in W$  since  $V, W$  are subspaces. Since  $V \cap W = \{0\}$  we must have that  $v_1 - v_2 = w_2 - w_1 = 0$  or  $v_1 = v_2$  and  $w_1 = w_2$  which is a contradiction. □

# Inner Sum and Direct Sum, cont.

## Lemma

*If  $V$  and  $W$  are orthogonal subspaces then the representation of  $x \in V \oplus W$  is unique (i.e.  $x = v + w$ , where  $v \in V$  and  $w \in W$ ).*

## Example

Let  $S = \mathbb{R}^2$ , let  $V = \left\{ \begin{pmatrix} \alpha \\ 0 \end{pmatrix} : \alpha \in \mathbb{R} \right\}$ , let

$W = \left\{ \begin{pmatrix} 0 \\ \alpha \end{pmatrix} : \alpha \in \mathbb{R} \right\}$  Then

$$\begin{pmatrix} 5 \\ 2 \end{pmatrix} = \begin{pmatrix} 5 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ 2 \end{pmatrix}$$

is a unique decomposition.



# Difference between a Hamel basis and a Complete basis.

## Definition

An orthonormal set of basis vectors  $T = \{p_1, p_2, \dots\}$  is said to be a complete basis for a Hilbert space  $S$  if every  $x \in S$  can be represented as

$$x = \sum_{j=1}^{\infty} c_j p_j$$

Examples of complete bases: Fourier functions:  $e^{j\omega t}$

Legendre & Chebyshev polynomials

Difference: A Hamel basis  $\Rightarrow$  every  $x$  can be represented by a finite representation. A complete basis allows functions through a limiting process.