

# Inner Products and Norms (part II)

Prof. Dan A. Simovici

UMB

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# Dissimilarities

## Definition

A *dissimilarity on a set  $S$*  is a function  $d : S^2 \rightarrow \mathbb{R}_{\geq 0}$  satisfying the following conditions:

- i  $d(x, x) = 0$  for all  $x \in S$ ;
- ii  $d(x, y) = d(y, x)$  for all  $x, y \in S$ .

The pair  $(S, d)$  is a **dissimilarity space**.

The set of dissimilarities defined on a set  $S$  is denoted by  $\mathcal{D}_S$ .

## Other Properties of Dissimilarities

- ①  $d(x, y) = 0$  implies  $d(x, z) = d(y, z)$  for every  $x, y, z \in S$  (**evenness**);
- ②  $d(x, y) = 0$  implies  $x = y$  for every  $x, y$  (**definiteness**);
- ③  $d(x, y) \leq d(x, z) + d(z, y)$  for every  $x, y, z$  (**triangular inequality**);
- ④  $d(x, y) \leq \max\{d(x, z), d(z, y)\}$  for every  $x, y, z$  (**the ultrametric inequality**);
- ⑤  $d(x, y) + d(u, v) \leq \max\{d(x, u) + d(y, v), d(x, v) + d(y, u)\}$  for every  $x, y, u, v$  (**Buneman's inequality**, also known as the **four-point condition**).

If  $d : S^2 \longrightarrow \mathbb{R}$  is a function that satisfies the properties of dissimilarities and the triangular inequality, then the values of  $d$  are nonnegative numbers. Indeed, by taking  $x = y$  in the triangular inequality, we have

$$0 = d(x, x) \leq d(x, z) + d(z, x) = 2d(x, z),$$

for every  $z \in S$ .

# Classes of Dissimilarities

## Definition

A dissimilarity  $d \in \mathcal{D}_S$  is

- i a **pseudo-metric** if it satisfies the triangular inequality;
- ii a **metric** if it satisfies the definiteness property and the triangular inequality,
- iii a **tree metric** if it satisfies the definiteness property and Buneman's inequality, and
- iv an **ultrametric** if it satisfies the definiteness property and the ultrametric inequality.

The set of metrics on a set  $S$  is denoted by  $\mathcal{M}_S$ . The sets of tree metrics and ultrametrics on a set  $S$  are denoted by  $\mathcal{T}_S$  and  $\mathcal{U}_S$ , respectively.

# Metrics

A function  $d : S^2 \rightarrow \mathbb{R}_{\geq 0}$  is a **metric** if it has the following properties:

- i  $d(x, y) = 0$  if and only if  $x = y$  for  $x, y \in S$ ;
- ii  $d(x, y) = d(y, x)$  for  $x, y \in S$ ;
- iii  $d(x, y) \leq d(x, z) + d(z, y)$  for  $x, y, z \in S$ .

If the first property is replaced by the weaker requirement that  $d(x, x) = 0$  for  $x \in S$ , then we refer to  $d$  as a **semimetric** on  $S$ . Thus, if  $d$  is a semimetric  $d(x, y) = 0$  does not necessarily imply  $x = y$  and we can have for two distinct elements  $x, y$  of  $S$ ,  $d(x, y) = 0$ .

### Example

Let  $S$  be a nonempty set. Define the mapping  $d : S^2 \longrightarrow \mathbb{R}_{\geq 0}$  by

$$d(u, v) = \begin{cases} 1 & \text{if } u \neq v, \\ 0 & \text{otherwise,} \end{cases}$$

for  $x, y \in S$ . It is clear that  $d$  satisfies the definiteness property. The triangular inequality,  $d(x, y) \leq d(x, z) + d(z, y)$  is satisfied if  $x = y$ . Therefore, suppose that  $x \neq y$ , so  $d(x, y) = 1$ . Then, for every  $z \in S$ , we have at least one of the inequalities  $x \neq z$  or  $z \neq y$ , so at least one of the numbers  $d(x, z)$  or  $d(z, y)$  equals 1. Thus  $d$  satisfies the triangular inequality. The metric  $d$  introduced here is the **discrete metric** on  $S$ .



## Example

Consider the mapping  $d_h : (\text{Seq}_n(S))^2 \longrightarrow \mathbb{R}_{\geq 0}$  defined by

$$d_h(\mathbf{p}, \mathbf{q}) = |\{i \mid 0 \leq i \leq n-1 \text{ and } \mathbf{p}(i) \neq \mathbf{q}(i)\}|$$

for all sequences  $\mathbf{p}, \mathbf{q}$  of length  $n$  on the set  $S$ .

Clearly,  $d_h$  is a dissimilarity that is both even and definite. Moreover, it satisfies the triangular inequality. Indeed, let  $\mathbf{p}, \mathbf{q}, \mathbf{r}$  be three sequences of length  $n$  on the set  $S$ . If  $\mathbf{p}(i) \neq \mathbf{q}(i)$ , then  $\mathbf{r}(i)$  must be distinct from at least one of  $\mathbf{p}(i)$  and  $\mathbf{q}(i)$ . Therefore,

$$\begin{aligned} & \{i \mid 0 \leq i \leq n-1 \text{ and } \mathbf{p}(i) \neq \mathbf{q}(i)\} \\ & \subseteq \{i \mid 0 \leq i \leq n-1 \text{ and } \mathbf{p}(i) \neq \mathbf{r}(i)\} \cup \{i \mid 0 \leq i \leq n-1 \text{ and } \mathbf{r}(i) \neq \mathbf{q}(i)\} \end{aligned}$$

which implies the triangular inequality. This distance is known as the **Hamming distance** on  $\text{Seq}_n(S)$ .

If we need to compare sequences of unequal length, we can use an extended metric  $d'_h$  defined by

$$d'_h(\mathbf{x}, \mathbf{y}) = \begin{cases} |\{i \mid 0 \leq i \leq |\mathbf{x}| - 1, x_i \neq y_i\}| & \text{if } |\mathbf{x}| = |\mathbf{y}|, \\ \infty & \text{if } |\mathbf{x}| \neq |\mathbf{y}|. \end{cases}$$

### Example

Define the mapping  $d : \mathbb{R} \times \mathbb{R} \longrightarrow \mathbb{R}_{\geq 0}$  as  $d(x, y) = |x - y|$  for  $x, y \in \mathbb{R}$ . It is clear that  $d(x, y) = 0$  if and only if  $x = y$  and that  $d(x, y) = d(y, x)$  for  $x, y \in S$ ;

To prove the triangular inequality suppose that  $x \leq y \leq z$ . Then,  $d(x, z) + d(z, y) = z - x + z - y = 2z - x - y$  and we have  $2z - x - y > y - x = d(x, y)$  because  $z > y$ . The triangular inequality is similarly satisfied no matter what the relative order of  $x, y, z$  is.

# Open and Closed Spheres

## Definition

Let  $(S, d)$  be a metric space. The **closed sphere** centered in  $x \in S$  of radius  $r$  is the set

$$B_d[x, r] = \{y \in S \mid d(x, y) \leq r\}.$$

The **open sphere** centered in  $x \in S$  of radius  $r$  is the set

$$B_d(x, r) = \{y \in S \mid d(x, y) < r\}.$$

The **spherical surface** centered in  $x \in S$  of radius  $r$  is the set

$$S_n(x, r) = \{y \in S \mid d(x, y) = r\}.$$

If the metric  $d$  is clear from context we drop the subscript  $d$  and replace  $B_d[x, r]$  and  $B_d(x, r)$  by  $B[x, r]$  and  $B(x, r)$ , respectively.

## Definition

Let  $(S, d)$  be a metric space. The **diameter** of a subset  $U$  of  $S$  is the number  $diam_{S,d}(U) = \sup\{d(x, y) \mid x, y \in U\}$ . The set  $U$  is *bounded* if  $diam_{S,d}(U)$  is finite.

The **diameter** of the metric space  $(S, d)$  is the number

$$diam_{S,d} = \sup\{d(x, y) \mid x, y \in S\}.$$

If the metric space is clear from the context, then we denote the diameter of a subset  $U$  just by  $diam(U)$ .

If  $(S, d)$  is a finite metric space, then  $diam_{S,d} = \max\{d(x, y) \mid x, y \in S\}$ .

## Definition

Let  $(S, d)$  and  $(T, d')$  be two metric spaces. An isometry between these spaces is a function  $f : S \rightarrow T$  that satisfies the equality

$$d'(f(x), f(y)) = d(x, y)$$

for every  $x, y \in S$ .

If an isometry exists between  $(S, d)$  and  $(T, d')$  we say that these metric spaces are **isometric**.

Note that if  $f : S \rightarrow T$  is an isometry, then  $f(x) = f(y)$  implies  $d(f(x), f(y)) = d(x, y) = 0$ , which yields  $x = y$  for  $x, y \in S$ . Therefore, every isometry is injective.

A surjective isometry is, therefore, a bijection.

### Theorem

*Each norm  $\nu : L \longrightarrow \mathbb{R}_{\geq 0}$  on a linear space  $L$  generates a metric on the set  $L$  defined by  $d_\nu(\mathbf{x}, \mathbf{y}) = \nu \mathbf{x} - \mathbf{y}$  for  $\mathbf{x}, \mathbf{y} \in L$ .*

# Proof

Note that if  $d_\nu(\mathbf{x}, \mathbf{y}) = \nu\mathbf{x} - \mathbf{y} = 0$ , it follows that  $\mathbf{x} - \mathbf{y} = \mathbf{0}_L$ , so  $\mathbf{x} = \mathbf{y}$ . The symmetry of  $d_\nu$  is obvious and so we need to verify only the triangular axiom. Let  $\mathbf{x}, \mathbf{y}, \mathbf{z} \in L$ . We have

$$\nu(\mathbf{x} - \mathbf{z}) = \nu(\mathbf{x} - \mathbf{y} + \mathbf{y} - \mathbf{z}) \leq \nu(\mathbf{x} - \mathbf{y}) + \nu(\mathbf{y} - \mathbf{z})$$

or, equivalently,  $d_\nu(\mathbf{x}, \mathbf{z}) \leq d_\nu(\mathbf{x}, \mathbf{y}) + d_\nu(\mathbf{y}, \mathbf{z})$ , for every  $\mathbf{x}, \mathbf{y}, \mathbf{z} \in L$ , which concludes the argument.

We refer to  $d_\nu$  as the **metric induced by the norm  $\nu$  on the linear space  $L$** .



# Norms Generated by Translation-Invariant Metrics

The metric  $d_\nu$  on  $L$  induced by a norm is translation invariant, that is,  $d_\nu(x + z, y + z) = d_\nu(x, y)$  for every  $z \in L$ . Also, for every  $a \in \mathbb{R}$  and  $x, y \in L$  we have the homogeneity property  $d_\nu(ax, ay) = |a|d_\nu(x, y)$  for  $x, y \in L$ .

## Theorem

*Let  $L$  be a real linear space and let  $d : L \times L \longrightarrow \mathbb{R}_{\geq 0}$  be a metric on  $L$ . If  $d$  is translation invariant and homogeneous, then there exists a norm  $\nu$  of  $L$  such that  $d = d_\nu$ .*

**Proof:** Let  $d$  be a metric on  $L$  that is translation invariant and homogeneous. Define  $\nu(x) = d(x, 0_L)$ . It follows immediately that  $\nu$  is a norm on  $L$ .

# Minkowski Metrics

For  $p \geq 1$ , then  $d_p$  denotes the metric  $d_{\nu_p}$  induced by the norm  $\nu_p$  on the linear space  $(\mathbb{R}^n, +, \cdot)$  known as the **Minkowski metric** on  $\mathbb{R}^n$ .

The metrics  $d_1, d_2$  and  $d_\infty$  defined on  $\mathbb{R}^n$  are given by

$$d_1(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^n |x_i - y_i|,$$

$$d_2(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i=1}^n |x_i - y_i|^2},$$

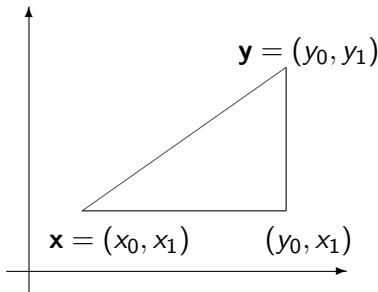
$$d_\infty(\mathbf{x}, \mathbf{y}) = \max\{|x_i - y_i| \mid 1 \leq i \leq n\},$$

for  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ .

If

$$\mathbf{x} = \begin{pmatrix} x_0 \\ x_1 \end{pmatrix} \text{ and } \mathbf{y} = \begin{pmatrix} y_0 \\ y_1 \end{pmatrix},$$

then  $d_1(\mathbf{x}, \mathbf{y})$  is the sum of the lengths of the two legs of the triangle,  $d_2(\mathbf{x}, \mathbf{y})$  is the length of the hypotenuse of the right triangle and  $d_\infty(\mathbf{x}, \mathbf{y})$  is the largest of the lengths of the legs.



The distances  $d_1(\mathbf{x}, \mathbf{y})$ ,  $d_2(\mathbf{x}, \mathbf{y})$  and  $d_\infty(\mathbf{x}, \mathbf{y})$ .

### Lemma

*Let  $a_1, \dots, a_n$  be  $n$  positive numbers. If  $p$  and  $q$  are two positive numbers such that  $p \leq q$ , then  $(a_1^p + \dots + a_n^p)^{\frac{1}{p}} \geq (a_1^q + \dots + a_n^q)^{\frac{1}{q}}$ .*

# Proof

Let  $f : \mathbb{R}^{>0} \rightarrow \mathbb{R}$  be the function defined by  $f(r) = (a_1^r + \cdots + a_n^r)^{\frac{1}{r}}$ .  
Since

$$\ln f(r) = \frac{\ln(a_1^r + \cdots + a_n^r)}{r},$$

it follows that

$$\frac{f'(r)}{f(r)} = -\frac{1}{r^2} (a_1^r + \cdots + a_n^r) + \frac{1}{r} \cdot \frac{a_1^r \ln a_1 + \cdots + a_n^r \ln a_n}{a_1^r + \cdots + a_n^r}.$$

To prove that  $f'(r) < 0$ , it suffices to show that

$$\frac{a_1^r \ln a_1 + \cdots + a_n^r \ln a_n}{a_1^r + \cdots + a_n^r} \leq \frac{\ln(a_1^r + \cdots + a_n^r)}{r}.$$

# Proof (cont'd)

This last inequality is easily seen to be equivalent to

$$\sum_{i=1}^n \frac{a_i^r}{a_1^r + \cdots + a_n^r} \ln \frac{a_i^r}{a_1^r + \cdots + a_n^r} \leq 0,$$

which holds because

$$\frac{a_i^r}{a_1^r + \cdots + a_n^r} \leq 1$$

for  $1 \leq i \leq n$ .

## Theorem

*Let  $p$  and  $q$  be two positive numbers such that  $p \leq q$ . We have  $\| \mathbf{u} \|_p \geq \| \mathbf{u} \|_q$  for  $\mathbf{u} \in \mathbb{R}^n$ .*

This follows from the previous Lemma.

### Corollary

*Let  $p, q$  be two positive numbers such that  $p \leq q$ . For every  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ , we have  $d_p(\mathbf{x}, \mathbf{y}) \geq d_q(\mathbf{x}, \mathbf{y})$ .*



## Theorem

Let  $p \geq 1$ . We have  $\| \mathbf{x} \|_{\infty} \leq \| \mathbf{x} \|_p \leq n \| \mathbf{x} \|_{\infty}$  for  $\mathbf{x} \in \mathbb{R}^n$ .

**Proof:** The first inequality is an immediate consequence of Theorem ??.  
The second inequality follows by observing that

$$\| \mathbf{x} \|_p = \left( \sum_{i=1}^n |x_i|^p \right)^{\frac{1}{p}} \leq n \max_{1 \leq i \leq n} |x_i| = n \| \mathbf{x} \|_{\infty} .$$

## Corollary

Let  $p$  and  $q$  be two numbers such that  $p, q \geq 1$ . For  $\mathbf{x} \in \mathbb{R}^n$  we have:

$$\frac{1}{n} \|\mathbf{x}\|_q \leq \|\mathbf{x}\|_p \leq n \|\mathbf{x}\|_q.$$

**Proof:** Since  $\|\mathbf{x}\|_\infty \leq \|\mathbf{x}\|_p$  and  $\|\mathbf{x}\|_q \leq n \|\mathbf{x}\|_\infty$ , it follows that  $\|\mathbf{x}\|_q \leq n \|\mathbf{x}\|_p$ . Exchanging the roles of  $p$  and  $q$ , we have  $\|\mathbf{x}\|_p \leq n \|\mathbf{x}\|_q$ , so

$$\frac{1}{n} \|\mathbf{x}\|_q \leq \|\mathbf{x}\|_p \leq n \|\mathbf{x}\|_q$$

for every  $\mathbf{x} \in \mathbb{R}^n$ .

## Corollary

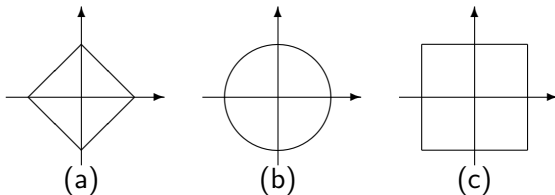
*For every  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$  and  $p \geq 1$ , we have  $d_\infty(\mathbf{x}, \mathbf{y}) \leq d_p(\mathbf{x}, \mathbf{y}) \leq n d_\infty(\mathbf{x}, \mathbf{y})$ . Further, for  $p, q > 1$ , there exist  $c, c' \in \mathbb{R}_{>0}$  such that*

$$c d_q(\mathbf{x}, \mathbf{y}) \leq d_p(\mathbf{x}, \mathbf{y}) \leq c' d_q(\mathbf{x}, \mathbf{y})$$

*for  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ .*

If  $p \leq q$ , then the closed sphere  $B_{d_p}[\mathbf{x}, r]$  is included in the closed sphere  $B_{d_q}[\mathbf{x}, r]$ . For example, we have

$$B_{d_1}[\mathbf{0}, 1] \subseteq B_{d_2}[\mathbf{0}, 1] \subseteq B_{d_\infty}[\mathbf{0}, 1].$$



Spheres  $B_{d_p}[\mathbf{0}, 1]$  for  $p = 1, 2, \infty$ .

# Examples

- The set of real number sequences **Seq**( $\mathbb{R}$ ) is a real linear space where the sum of the sequences  $\mathbf{x} = (x_n)$  and  $\mathbf{y} = (y_n)$  is defined as  $\mathbf{x} + \mathbf{y} = (x_n + y_n)$  and the product of a real with  $\mathbf{x}$  is  $a\mathbf{x} = (ax_n)$ .
- The subspace  $\ell^1(\mathbb{R})$  of **Seq**( $\mathbb{R}$ ) consists of all sequences  $\mathbf{x} = (x_n)$  such that  $\sum_{n \in \mathbb{N}} |x_n|$  is convergent. Note that a norm exists on  $\ell^1$  defined by  $\|\mathbf{x}\| = \sum_{n \in \mathbb{N}} |x_n|$ .
- The set of sequences  $\mathbf{x} \in \mathbf{Seq}_\infty(\mathbb{R})$  such that  $\|\mathbf{x}\|_p$  is finite is a real normed linear space.

- Let  $\mathbf{x}, \mathbf{y} \in \mathbf{Seq}_\infty(\mathbb{R})$  be two sequences such that  $\|\mathbf{x}\|_p$  and  $\|\mathbf{y}\|_p$  are finite. By Minkowski's inequality, if  $p \geq 1$  we have

$$\left( \sum_{i=1}^n |x_i + y_i|^p \right)^{\frac{1}{p}} \leq \left( \sum_{i=1}^n (|x_i| + |y_i|)^p \right)^{\frac{1}{p}} \leq \left( \sum_{i=1}^n |x_i|^p \right)^{\frac{1}{p}} + \left( \sum_{i=1}^n |y_i|^p \right)^{\frac{1}{p}}$$

When  $n$  tends to  $\infty$  we have  $\|\mathbf{x} + \mathbf{y}\|_p \leq \|\mathbf{x}\|_p + \|\mathbf{y}\|_p$ , so the function  $\|\cdot\|_p$  is indeed a norm.

- If  $S_p(\mathbb{R})$  is the set of all sequences  $\mathbf{x}$  in  $\mathbf{Seq}_\infty(\mathbb{R})$  such that  $\|\mathbf{x}\|_p < \infty$ , then  $(S_p(\mathbb{R}), \|\cdot\|_p)$  is a normed space denoted by  $\ell^p(\mathbb{R})$ . The space  $\ell^\infty(\mathbb{R})$  consists of bounded sequences in  $\mathbf{Seq}_\infty(\mathbb{R})$ .

# The angle between vector

The Cauchy-Schwarz Inequality implies that  $|(\mathbf{x}, \mathbf{y})| \leq \|\mathbf{x}\|_2 \|\mathbf{y}\|_2$ . Equivalently, this means that

$$-1 \leq \frac{(\mathbf{x}, \mathbf{y})}{\|\mathbf{x}\|_2 \|\mathbf{y}\|_2} \leq 1.$$

This double inequality allows us to introduce the notion of **angle** between two vectors  $\mathbf{x}, \mathbf{y}$  of a real linear space  $L$ .

## Definition

The **angle** between the vectors  $\mathbf{x}$  and  $\mathbf{y}$  is the number  $\alpha \in [0, \pi]$  defined by

$$\cos \alpha = \frac{(\mathbf{x}, \mathbf{y})}{\|\mathbf{x}\|_2 \|\mathbf{y}\|_2}.$$

This angle will be denoted by  $\angle(\mathbf{x}, \mathbf{y})$ .

### Example

Let  $\mathbf{u} = \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \in \mathbb{R}^2$  be a unit vector. Since  $u_1^2 + u_2^2 = 1$ , there exists  $\alpha \in [0, 2\pi]$  such that  $u_1 = \cos \alpha$  and  $u_2 = \sin \alpha$ . Thus, for any two unit vectors in  $\mathbb{R}^2$ ,  $\mathbf{u} = (\cos \alpha, \sin \alpha)$  and  $\mathbf{v} = (\cos \beta, \sin \beta)$  we have  $(\mathbf{u}, \mathbf{v}) = \cos \alpha \cos \beta + \sin \alpha \sin \beta = \cos(\alpha - \beta)$ , where  $\alpha, \beta \in [0, 2\pi]$ . Consequently,  $\angle(\mathbf{u}, \mathbf{v})$  is the angle in the interval  $[0, \pi]$  that has the same cosine as  $\alpha - \beta$ .



## Theorem

**(The Cosine Theorem)** *Let  $\mathbf{x}$  and  $\mathbf{y}$  be two vectors in  $\mathbb{R}^n$  equipped with the Euclidean inner product. We have:*

$$\|\mathbf{x} - \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 - 2 \|\mathbf{x}\| \|\mathbf{y}\| \cos \alpha,$$

where  $\alpha = \angle(\mathbf{x}, \mathbf{y})$ .

## Proof

Since the norm is induced by the inner product we have

$$\begin{aligned}
 \| \mathbf{x} - \mathbf{y} \|^2 &= (\mathbf{x} - \mathbf{y}, \mathbf{x} - \mathbf{y}) \\
 &= (\mathbf{x}, \mathbf{x}) - 2(\mathbf{x}, \mathbf{y}) + (\mathbf{y}, \mathbf{y}) \\
 &= \| \mathbf{x} \|^2 - 2 \| \mathbf{x} \| \| \mathbf{y} \| \cos \alpha + \| \mathbf{y} \|^2,
 \end{aligned}$$

which is the desired equality.

### Definition

Let  $L$  be an inner product space. Two vectors  $\mathbf{x}$  and  $\mathbf{y}$  of  $L$  are **orthogonal** if  $(\mathbf{x}, \mathbf{y}) = 0$ .

A pair of orthogonal vectors  $(\mathbf{x}, \mathbf{y})$  is denoted by  $\mathbf{x} \perp \mathbf{y}$ .

### Definition

An **orthogonal set of vectors** in an inner product space  $L$  is a subset  $W$  of  $L$  such that for every distinct  $u, v \in W$  we have  $u \perp v$ .

If, in addition,  $\|u\| = 1$  for every  $u \in W$ , then we say that  $W$  is **orthonormal**.

## Theorem

*If  $W$  is a set of non-zero orthogonal vectors in an inner product space  $(V, (\cdot, \cdot))$ , then  $W$  is linearly independent.*

**Proof:** Let  $a_1 \mathbf{w}_1 + \cdots + a_n \mathbf{w}_n = \mathbf{0}$  for a linear combination of elements of  $W$ . This implies  $a_i \|\mathbf{w}_i\|^2 = 0$ , so  $a_i = 0$  because  $\|\mathbf{w}_i\|^2 \neq 0$ , and this holds for every  $i$ , where  $1 \leq i \leq n$ . Thus,  $W$  is linearly independent.

## Corollary

*Let  $L$  be an  $n$ -dimensional linear space. If  $W$  is an orthonormal set and  $|W| = n$ , then  $W$  is an orthonormal basis of  $L$ .*

For an arbitrary subset  $T$  of an inner product space  $L$  the set  $T^\perp$  is defined by:

$$T^\perp = \{\mathbf{v} \in L \mid \mathbf{v} \perp \mathbf{t} \text{ for every } \mathbf{t} \in T\}$$

Note that  $T \subseteq U$  implies  $U^\perp \subseteq T^\perp$ .

If  $S, T$  are two subspaces of an inner product space, then  $S$  and  $T$  are **orthogonal** if  $\mathbf{s} \perp \mathbf{t}$  for every  $\mathbf{s} \in S$  and every  $\mathbf{t} \in T$ . This is denoted as  $S \perp T$ .

### Theorem

*Let  $L$  be an inner product space and let  $T$  be a subset of an inner product  $\mathbb{F}$ -linear space  $L$ . The set  $T^\perp$  is a subspace of  $L$ .*

# Proof

Let  $x$  and  $y$  be two members of  $T$ . We have  $(x, t) = (y, t) = 0$  for every  $t \in T$ . Therefore, for every  $a, b \in \mathbb{F}$ , by the linearity of the inner product we have  $(ax + by, t) = a(x, t) + b(y, t) = 0$ , for  $t \in T$ , so  $ax + by \in T^\perp$ . Thus,  $T^\perp$  is a subspace of  $L$ .

## Theorem

*Let  $L$  be an inner product space and let  $T$  be a subset of an inner product  $\mathbb{F}$ -linear space  $L$ . The set  $T^\perp$  is a subspace of  $L$ .*

**Proof:** Let  $x$  and  $y$  be two members of  $T$ . We have  $(x, t) = (y, t) = 0$  for every  $t \in T$ . Therefore, for every  $a, b \in \mathbb{F}$ , by the linearity of the inner product we have  $(ax + by, t) = a(x, t) + b(y, t) = 0$ , for  $t \in T$ , so  $ax + by \in T^\perp$ . Thus,  $T^\perp$  is a subspace of  $L$ .



## Theorem

Let  $L$  be a finite-dimensional inner product  $\mathbb{F}$ -linear space and let  $T$  be a subset of  $L$ . We have  $\langle T \rangle^\perp = T^\perp$ .

**Proof:** By a previous observation, since  $T \subseteq \langle T \rangle$ , we have  $\langle T \rangle^\perp \subseteq T^\perp$ . To prove the converse inclusion, let  $z \in T^\perp$ .

If  $y \in \langle T \rangle$ ,  $y$  is a linear combination of vectors of  $T$ ,  $y = a_1 t_1 + \cdots + a_m t_m$ , so  $(y, z) = a_1(t_1, z) + \cdots + a_m(t_m, z) = 0$ .

Therefore,  $z \perp y$ , which implies  $z \in \langle T \rangle^\perp$ . This allows us to conclude that  $\langle T \rangle^\perp = T^\perp$ .

We refer to  $T^\perp$  as the **orthogonal complement** of  $T$ .

Note that  $T \cap T^\perp \subseteq \{0\}$ . If  $T$  is a subspace, then this inclusion becomes an equality, that is,  $T \cap T^\perp = \{0\}$ .

### Theorem

*Let  $T$  be a subspace of the finite-dimensional linear space  $L$ . We have  $L = T \boxplus T^\perp$ .*

**Proof:** We observed that  $T \cap T^\perp = 0_L$ . Suppose that  $B$  and  $B'$  are two orthonormal bases in  $T$  and  $T^\perp$ , respectively. The set  $B \cup B'$  is a basis for  $S = T \boxplus T^\perp$ .

Suppose that  $S \subset L$ . The set  $B \cup B'$  can be extended to a orthonormal basis  $B \cup B' \cup B''$  for  $L$ . Note that  $B'' \perp B$ , so  $B'' \perp T$ , which implies  $B'' \subseteq T^\perp$ . This is impossible because  $B \cup B' \cup B''$  is linearly independent. Therefore,  $B \cup B'$  is a basis for  $L$ , so  $L = T \boxplus T^\perp$ .

### Example

Let  $A \in \mathbb{C}^{n \times n}$ . We have

$$(A) = (\text{Ran}(A^H))^{\perp}. \quad (1)$$

Indeed, if  $\mathbf{x} \in (A)$  we have  $A\mathbf{x} = \mathbf{0}_n$ . Since  $(A\mathbf{x}, \mathbf{x}) = (\mathbf{x}, A^H\mathbf{x})$  it follows that  $\mathbf{x}$  is orthogonal on  $A^H\mathbf{x}$ , so  $\mathbf{x} \in (\text{Ran}(A^H))^{\perp}$ .

To prove the converse inclusion, suppose that  $\mathbf{x} \in (\text{Ran}(A^H))^{\perp}$ . Then,  $\mathbf{x} \perp \mathbf{z}$  for every  $\mathbf{z} \in \text{Ran}(A^H)$ . In particular, for  $\mathbf{z} = A^H(A\mathbf{x})$  we have Thus,

$$0 = (\mathbf{x}, \mathbf{z}) = (\mathbf{x}, A^H A\mathbf{x}) = (A\mathbf{x}, A\mathbf{x}),$$

which implies  $A\mathbf{x} = \mathbf{0}_n$ , that is,  $\mathbf{x} \in \text{NullSp}(A)$ .

# Pythagora's Theorem

## Theorem

Let  $x_1, \dots, x_n$  be a finite orthogonal set on  $n$  distinct elements in an inner product space  $L$ . We have

$$\left\| \sum_{i=1}^n x_i \right\|^2 = \sum_{i=1}^n \|x_i\|^2.$$

**Proof:** By applying the definition of the norm induced by the inner product we have

$$\begin{aligned} \left\| \sum_{i=1}^n x_i \right\|^2 &= \left( \sum_{i=1}^n x_i, \sum_{j=1}^n x_j \right) \\ &= \sum_{i=1}^n \sum_{j=1}^n (x_i, x_j) = \sum_{i=1}^n (x_i, x_i) \\ &\quad (\text{because } (x_i, x_j) = 0 \text{ for } i \neq j) \end{aligned}$$