## Math 313 Lecture #25 §6.1: Inner Product, Length, and Orthogonality

We will now impose on the vector space  $\mathbb{R}^n$  a structure that enables us to define geometric notions of length and angle between vectors.

We define the **inner product** of two vectors  $\vec{u}, \vec{v}$  in  $\mathbb{R}^n$  to be the scalar quantity

$$\vec{u} \cdot \vec{v} = \vec{u}^T \vec{v} = [u_1 \ u_2 \ \dots \ u_n] \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} = u_1 v_1 + u_2 v_2 + \dots + u_n v_n = \sum_{i=1}^n u_i v_i.$$

This inner product is also known as the **dot product** in  $\mathbb{R}^n$ .

Theorem 1. The inner product  $\vec{u} \cdot \vec{v}$  on  $\mathbb{R}^n$  satisfies

- a.  $\vec{u} \cdot \vec{v} = \vec{v} \cdot \vec{u}$ ,
- b.  $(\vec{u} + \vec{v}) \cdot \vec{w} = \vec{u} \cdot \vec{w} + \vec{v} \cdot \vec{w}$ ,
- c.  $(c\vec{u}) \cdot \vec{v} = c(\vec{u} \cdot \vec{v})$ , and
- d.  $\vec{u} \cdot \vec{u} \ge 0$  and  $\vec{u} \cdot \vec{u} = 0$  if and only if  $\vec{u} = 0$ .

The **length**, or **norm** of a vector  $\vec{x}$  in  $\mathbb{R}^n$  is the nonnegative quantity

$$\|\vec{u}\| = \sqrt{(\vec{u} \cdot \vec{u})} = \sqrt{u_1^2 + u_2^2 + \dots + u_n^2}.$$

An important variation of this is the equation

$$\|\vec{u}\|^2 = \vec{u} \cdot \vec{u}$$

For any scalar c, the length of  $c\vec{u}$  is

$$||c\vec{u}|| = \sqrt{(cu_1)^2 + (cu_2)^2 + \dots + (cu_n)^2} = |c| ||\vec{u}||.$$

A vector whose length is one is called a **unit vector**.

We always get a unit vector from a nonzero vector when we multiply the vector by the reciprocal of its length:

$$\left\|\frac{1}{\|\vec{u}\|}\vec{u}\right\| = \frac{1}{\|\vec{u}\|}\|\vec{u}\| = 1$$

The **distance** between two vectors  $\vec{u}$  and  $\vec{v}$  in  $\mathbb{R}^n$  is the quantity

$$\|\vec{u} - \vec{v}\| = \sqrt{(u_1 - v_1)^2 + (u_2 - v_2)^2 + \dots + (u_n - v_n)^2}.$$

Two vectors  $\vec{u}$  and  $\vec{v}$  form an angle  $0 \le \theta \le \pi$ . How do we measure  $\theta$ ? Theorem. The angle  $\theta$  between two vectors  $\vec{u}$  and  $\vec{v}$  in  $\mathbb{R}^n$  satisfies

$$\vec{u} \cdot \vec{v} = \|\vec{u}\| \|\vec{u}\| \cos \theta.$$

Proof. The vectors  $\vec{u}$ ,  $\vec{v}$ , and  $\vec{v} - \vec{u}$  form the sides a triangle that lies in the subspace  $\text{Span}\{\vec{u}, \vec{v}\}$  (a plane, a line, or a point, all of which lie in a plane).

The law of cosines applies to this triangle:

$$\|\vec{v} - \vec{u}\|^2 = \|\vec{u}\|^2 + \|\vec{v}\|^2 - 2\|\vec{u}\| \|\vec{v}\| \cos\theta$$

It follows that

$$\begin{aligned} \|\vec{u}\| \|\vec{v}\| &\cos\theta = \frac{1}{2} \left( \|\vec{u}\|^2 + \|\vec{v}\|^2 - \|\vec{v} - \vec{u}\|^2 \right) \\ &= \frac{1}{2} \left( \vec{u} \cdot \vec{u} + \vec{v} \cdot \vec{v} - (\vec{v} - \vec{u}) \cdot (\vec{v} - \vec{u}) \right) \\ &= \frac{1}{2} \left( \vec{u} \cdot \vec{u} + \vec{v} \cdot \vec{v} - \vec{v} \cdot \vec{v} + \vec{v} \cdot \vec{u} + \vec{u} \cdot \vec{v} - \vec{u} \cdot \vec{u} \right) \\ &= \frac{1}{2} \left( \vec{v} \cdot \vec{u} + \vec{u} \cdot \vec{v} \right) \\ &= \frac{1}{2} \left( \vec{u} \cdot \vec{v} + \vec{u} \cdot \vec{v} \right) \\ &= \vec{u} \cdot \vec{v}. \end{aligned}$$

This gives the formula that  $\theta$  satisfies.

Definition. Two vectors  $\vec{u}$  and  $\vec{v}$  in  $\mathbb{R}^n$  are said to be **orthogonal** if the angle between them is  $\pi/2$ , which is to say that their inner product is 0, and we write  $\vec{u} \perp \vec{v}$ .

Remember the Pythagorean Theorem that says in a right-angle triangle, the square of the hypothenuse equals the sum of the squares of the other sides?

Theorem 2 (The Pythagorean Theorem). Two vectors  $\vec{u}$  and  $\vec{v}$  in  $\mathbb{R}^n$  are orthogonal if and only if  $\|\vec{u} + \vec{v}\|^2 = \|\vec{u}\|^2 + \|\vec{v}\|^2$ .

Proof. For two vectors  $\vec{u}$  and  $\vec{v}$  in  $\mathbb{R}^n$ , we have

$$\|\vec{u} + \vec{v}\|^2 = (\vec{u} + \vec{v}) \cdot (\vec{u} + \vec{v}) = \vec{u} \cdot \vec{u} + 2\vec{u} \cdot \vec{v} + \vec{v} \cdot \vec{v} = \|\vec{u}\|^2 + 2\vec{u} \cdot \vec{v} + \|\vec{v}\|^2.$$

By this *identity*, if  $\vec{u} \perp \vec{v}$ , then  $\vec{u} \cdot \vec{v} = 0$ , and so  $\|\vec{u} + \vec{v}\|^2 = \|\vec{u}\|^2 + \|\vec{v}\|^2$ .

On the other hand, by the identity, if  $\|\vec{u} + \vec{v}\|^2 = \|\vec{u}\|^2 + \|\vec{v}\|^2$ , then  $\vec{u} \cdot \vec{v} = 0$ , and so  $\vec{u} \perp \vec{v}$ .

Example. In 
$$\mathbb{R}^4$$
, let  $\vec{x} = \begin{bmatrix} 1\\2\\-1\\4 \end{bmatrix}$ ,  $\vec{y} = \begin{bmatrix} -2\\3\\8\\1 \end{bmatrix}$ , and  $\vec{z} = \begin{bmatrix} 1\\1\\-1\\1 \end{bmatrix}$ .

Although we can not sketch these vectors, we can use the inner product to get useful information about them.

The inner products of pairs of these vectors are

$$\vec{x} \cdot \vec{y} = -2 + 6 - 8 + 4 = 0,$$
  
$$\vec{x} \cdot \vec{z} = 1 + 2 + 1 + 4 = 8,$$
  
$$\vec{y} \cdot \vec{z} = -2 + 3 - 8 + 1 = -6.$$

So  $\vec{x} \perp \vec{y}$ , while  $\vec{x}$  is not orthogonal to  $\vec{z}$ , and  $\vec{y}$  is not orthogonal to  $\vec{z}$ .

The lengths of these vectors are

$$\begin{split} \|\vec{x}\| &= \sqrt{1+4+1+16} = \sqrt{22}, \\ \|\vec{y}\| &= \sqrt{4+9+64+1} = \sqrt{78}, \\ \|\vec{z}\| &= \sqrt{1+1+1+1} = 2. \end{split}$$

So  $\vec{z}$  is the shortest of these three, while  $\vec{y}$  is the longest. Unit vectors in the direction of  $\vec{x}$ ,  $\vec{y}$ , and  $\vec{z}$  respectively are

$$\frac{1}{\|\vec{x}\|}\vec{x} = \begin{bmatrix} 1/\sqrt{22} \\ 2/\sqrt{22} \\ -1/\sqrt{22} \\ 4/\sqrt{22} \end{bmatrix}, \ \frac{1}{\|\vec{y}\|}\vec{y} = \begin{bmatrix} -2/\sqrt{78} \\ 3/\sqrt{78} \\ 8/\sqrt{78} \\ 1/\sqrt{78} \end{bmatrix}, \ \frac{1}{\|\vec{z}\|}\vec{z} = \begin{bmatrix} 1/2 \\ 1/2 \\ -1/2 \\ 1/2 \\ 1/2 \end{bmatrix}.$$

Now since  $\vec{x} \perp \vec{y}$ , the Pythagorean Law should hold for  $\vec{x}$  and  $\vec{y}$ . We can verify this:

$$\|\vec{x} + \vec{y}\|^2 = \|[-1, 5, 7, 5]^T\|^2 = 1 + 25 + 49 + 25 = 100$$

while

$$\|\vec{x}\|^2 + \|\vec{y}\|^2 = 22 + 78 = 100.$$

Orthogonal Complements. We extend the notion of orthogonality between two vectors to between a vector and a subspace of vectors.

A vector  $\vec{z}$  in  $\mathbb{R}^n$  is orthogonal to a subspace W of  $\mathbb{R}^n$  if  $\vec{z}$  is orthogonal to every vector of W.

The **orthogonal complement** of W, denoted by  $W^{\perp}$ , is the set of all vectors  $\vec{z}$  in  $\mathbb{R}^n$  that are orthogonal to W.

Example. Every line L through the origin in  $\mathbb{R}^3$  is a one dimensional subspace.

The orthogonal complement of L is a plane W through the origin that makes a right angle with L.

The orthogonal complement of a plane W through the origin is a line L through the origin that makes a right angle with W.

Theorem. Let W be a subspace of  $\mathbb{R}^n$ . A vector  $\vec{x}$  in  $\mathbb{R}^n$  is orthogonal to W if and only if  $\vec{x}$  is orthogonal to every vector in a spanning set for W. The orthogonal complement  $W^{\perp}$  is a subspace of  $\mathbb{R}^n$ .

You will provide a proof of this theorem in the homework.

An  $m \times n$  matrix A has several subspaces associated to it: its null space, its row space, and its column space.

Are any of these the orthogonal complement of others?

Theorem 3. For an  $m \times n$  matrix A, there holds

 $(\operatorname{Row} A)^{\perp} = \operatorname{Nul}(A), \text{ and } (\operatorname{Col} A)^{\perp} = \operatorname{Nul}(A^T).$ 

Proof. By the row-column rule for computing  $A\vec{x}$ , we see that for each  $\vec{x}$  in Nul(A) is orthogonal to each row of A.

Since the rows of A are a spanning set for  $\operatorname{Row}(A)$ , we have that every  $\vec{x}$  in  $\operatorname{Nul}(A)$  is orthogonal to  $\operatorname{Row}(A)$ .

Conversely, if  $\vec{x}$  is orthogonal to Row(A), then  $\vec{x}$  is orthogonal to each row of A, and hence  $A\vec{x} = 0$ .

Hence  $\vec{x}$  is in Nul(A).

This shows that  $(\operatorname{Row} A)^{\perp} = \operatorname{Nul}(A)$ .

This works for any matrix, so it work for  $A^T$  which gives  $(\operatorname{Row} A^T)^{\perp} = \operatorname{Nul}(A^T)$ .

Since  $\operatorname{Row}(A^T) = \operatorname{Col}(A)$ , we have that  $(\operatorname{Col} A)^{\perp} = \operatorname{Nul}(A^T)$ .

Example. Let  $A = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$ .

The null space of A is a one dimensional subspace of  $\mathbb{R}^3$ :

$$\operatorname{Nul}(A) = \operatorname{Span}\left\{ \begin{bmatrix} 1\\ -1\\ 0 \end{bmatrix} \right\}.$$

The row space of A is a two dimensional subspace of  $\mathbb{R}^3$ :

$$\operatorname{Row}(A) = \operatorname{Span}\left\{ \begin{bmatrix} 1\\1\\0 \end{bmatrix}, \begin{bmatrix} 0\\0\\2 \end{bmatrix} \right\}.$$

Notice that the basis vector for Nul(A) is orthogonal to each basis vector for Row(A), so indeed  $(Row A)^{\perp} = Nul(A)$ .

The null space of  $A^T$  is the zero dimensional subspace of  $\mathbb{R}^2$ :

$$\operatorname{Nul}(A^T) = \{\vec{0}\}.$$

The column space of A is the two dimensional subspace of  $\mathbb{R}^2$ :

$$\operatorname{Col}(A) = \operatorname{Span}\left\{ \begin{bmatrix} 1\\ 0 \end{bmatrix}, \begin{bmatrix} 0\\ 2 \end{bmatrix} \right\}.$$

Notice that the zero vector is orthogonal to every vector in  $\operatorname{Col}(A)$ , so indeed  $(\operatorname{Col} A)^{\perp} = \operatorname{Nul}(A^T)$ .