

## MA 1B RECITATION 02/26/15

### 1. INNER PRODUCT SPACES, NORMS, ORTHOGONAL/ORTHONORMAL VECTORS

Recall that a real vector space  $V$  is said to have an inner product  $(, ) : V \times V \rightarrow \mathbf{R}$  if the function  $(, )$  taking ordered pairs to the scalar field satisfies

- $(x, y) = (y, x)$
- $(x, y + z) = (x, y) + (x, z)$
- $c(x, y) = (cx, y)$
- $(x, x) > 0$  if  $x \neq 0$

For complex vector spaces, we usually replace the first condition by Hermitian symmetry:

$$(x, y) = \overline{(y, x)}.$$

where the bar indicates complex conjugation.

**Example 1.** The standard example is the dot product on  $\mathbf{R}^n$ :

$$\langle v, w \rangle = v \cdot w = v_1 w_1 + v_2 w_2 + \cdots + v_n w_n.$$

The definition of inner product is just the generalization of the notion of dot product. We'll see some other examples on the homework assignments.

*Remark 2.* We often use  $\langle , \rangle$  to denote inner products instead of  $(, )$  to avoid confusion with ordered pairs or tuples.

*Remark 3.* Apostol uses the physics convention for inner product. Specifically, linearity in the second coordinate of an inner product is the physics convention for Hermitian inner products; it corresponds well to the bra-ket notation that you use in quantum mechanics, for example.

Usually, mathematicians use the opposite convention (linearity in the first coordinate).

Inner products allow you to define a **norm**

$$\|x\| = (x, x)^{1/2}$$

which gives us a notion of length, and also allow us to talk about orthogonality. For  $\mathbf{R}^n$ , this just corresponds to the usual length, i.e.

$$\|x\| = \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2}$$

We say two vectors  $v, w \in V$  are **orthogonal** if

$$\langle v, w \rangle = 0.$$

A subset  $S \subset V$  is an **orthogonal set** if for any two distinct elements  $v, w \in S$ , we have  $\langle v, w \rangle = 0$ . An orthogonal set is said to be **orthonormal** if  $\|v\| = 1$  for all  $v \in S$ .

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Here's an example of an orthonormal basis in  $\mathbf{R}^4$  with respect to the dot product:

$$\left\{ \left( \frac{1}{2}, \frac{1}{2}, \frac{1}{2}, \frac{1}{2} \right), \left( \frac{1}{2}, \frac{1}{2}, -\frac{1}{2}, -\frac{1}{2} \right), \left( \frac{1}{2}, -\frac{1}{2}, -\frac{1}{2}, \frac{1}{2} \right), \left( -\frac{1}{2}, \frac{1}{2}, -\frac{1}{2}, \frac{1}{2} \right) \right\}$$

## 2. GRAM-SCHMIDT: FINDING AN ORTHONORMAL BASIS

Let  $V$  be an inner product space.

**Gram-Schmidt process:** takes in a finite linearly independent set  $S = \{v_1, \dots, v_n\}$  in an inner product space and generates an orthogonal set  $S' = \{w_1, \dots, w_n\}$  such that

$$\text{span}(S) = \text{span}(S').$$

How do we do this? Let  $\vec{u} \in V$  be any vector. We define the projection operator on  $V$  by

$$\text{proj}_{\vec{u}}(\vec{v}) = \frac{\langle \vec{v}, \vec{u} \rangle}{\langle \vec{u}, \vec{u} \rangle} \vec{u}.$$

We call this “the (orthogonal) projection of  $\vec{v}$  onto  $\vec{u}$ .” It projects the vector  $\vec{v}$  orthogonally onto the line spanned by the vector  $\vec{u}$ , as you might expect.

We then generate the orthogonal set as follows:

$$\begin{aligned} w_1 &= v_1 \\ w_2 &= v_2 - \text{proj}_{w_1}(v_2) \\ w_3 &= v_3 - \text{proj}_{w_1}(v_3) - \text{proj}_{w_2}(v_3) \\ &\dots \\ w_n &= v_n - \sum_{j=1}^{n-1} \text{proj}_{w_j}(v_n). \end{aligned}$$

Essentially, to get orthogonal vectors, we simply subtract off the parts that would make the new vector non-orthogonal to the old ones.

*Remark 1.* We can even get *orthonormal* vectors from the Gram-Schmidt process by normalizing the resulting vectors, i.e. taking  $e_k = \frac{w_k}{\|w_k\|}$  as the vectors.

**Example 2.** Consider the inner product on  $P_2$ , the real vector space of (real) polynomials of degree at most 2, given by

$$\langle p, q \rangle = \int_0^1 p(x)q(x) dx.$$

What is an orthonormal basis for  $(P_2, \langle \cdot, \cdot \rangle)$ ?

Recall that  $(1, x, x^2)$  is a basis. We can use this to produce an orthonormal basis by the Gram-Schmidt process.

After some work, we get

$$(1, \sqrt{3}(-1 + 2x), \sqrt{5}(1 - 6x + 6x^2)).$$

## 3. ORTHOGONAL PROJECTIONS

The projection operator can be defined for a general subspace as follows. Let  $U$  be a subspace of  $V$ . We have a decomposition

$$V = U \oplus U^\perp$$

where  $U^\perp$  is the set of vectors orthogonal to  $U$ , that is

$$U^\perp = \{v \in V \mid \langle v, u \rangle = 0 \text{ for all } u \in U\}.$$

Therefore, we can write any  $v \in V$  uniquely as

$$v = u + u'$$

where  $u \in U$  and  $u' \in U^\perp$ . Then we have the orthogonal projection of  $V$  onto  $U$ , denoted by  $\text{proj}_U : V \rightarrow U$ , given by

$$\text{proj}_U(v) = u$$

with the notation as above.

**Example 1.** Consider the case  $V = \mathbf{R}^2$ . Let  $U$  be the subspace generated by  $e_1 = (1, 0)$ . Then  $U^\perp$  is the  $y$ -axis, i.e. the subspace generated by  $e_2 = (0, 1)$ . Consider the point  $(3, 2) \in V$ . We have

$$(3, 2) = 3e_1 + 2e_2 \in V = U \oplus U^\perp$$

and so

$$\text{proj}_U(3, 2) = 3e_1 = (3, 0).$$

Here are some basic facts about the projection operator:

- $\text{proj}_U \in \mathcal{L}(V)$
- $\text{range } \text{proj}_U = U$
- $\text{nullspace } \text{proj}_U = U^\perp$
- $v - \text{proj}_U(v) \in U^\perp$  for all  $v \in V$
- $\text{proj}_U^2 = \text{proj}_U$
- $\|\text{proj}_U(v)\| \leq \|v\|$  for all  $v \in V$

The orthogonal projection allows us to solve the following minimization problem.

**Question 2.** Let  $U$  be a subspace of  $V$  and  $v \in V$ . What is the “distance” from  $U$  to  $v$ ? What’s the closest point in  $U$  to  $v$ ? In other words, what is the point  $u \in U$  such that  $\|v - u\|$  is minimized?

Orthogonal projections give a simple answer to this question.

**Proposition 3.** Let  $U$  be a subspace of  $V$  and  $v \in V$ . Then

$$\|v - \text{proj}_U(v)\| \leq \|v - u\|$$

for any  $u \in U$ . Moreover, if  $u \in U$  and the inequality above is an equality, then  $u = \text{proj}_U(v)$ .

In other words,  $\text{proj}_U(v)$  is always the “closest” point in  $U$  to  $v$ .

**Example 4.** We can see this in our simple example above. Is there any point on the  $x$ -axis closer to  $(3, 2)$  than  $(3, 0)$ ? No. For example, you can see this by forming a right triangle along vertices  $(3, 2)$ ,  $(3, 0)$ , and any point  $(d, 0)$  on the  $x$ -axis. The hypotenuse will always be between  $(3, 2)$  and  $(d, 0)$ .

The same idea holds in the general case.

**Proposition 5.** *If  $(e_1, \dots, e_m)$  is an orthonormal basis of  $U$ , then*

$$\text{proj}_U(v) = \langle v, e_1 \rangle e_1 + \dots + \langle v, e_m \rangle e_m.$$

*Proof.* We have  $V = U \oplus U^\perp$ . For  $v \in V$ , we have

$$v = (\langle v, e_1 \rangle e_1 + \dots + \langle v, e_m \rangle e_m) + v - \langle v, e_1 \rangle e_1 - \dots - \langle v, e_m \rangle e_m$$

and note that the terms in the parentheses are in  $U$ . We claim that the remaining terms

$$w = v - \langle v, e_1 \rangle e_1 - \dots - \langle v, e_m \rangle e_m$$

are in  $U^\perp$ . Since  $(e_1, \dots, e_m)$  is an orthonormal set, for all  $j = 1, \dots, m$ , we have

$$\begin{aligned} \langle w, e_j \rangle &= \langle v - \langle v, e_1 \rangle e_1 - \dots - \langle v, e_m \rangle e_m, e_j \rangle \\ &= \langle v, e_j \rangle - \langle v, e_j \rangle \langle e_j, e_j \rangle \\ &= \langle v, e_j \rangle - \langle v, e_j \rangle \\ &= 0. \end{aligned}$$

Therefore,  $w \in U^\perp$ . Our formula then follows.  $\square$

**Example 6.** In  $\mathbf{R}^4$ , let

$$U = \text{span}\{(1, 1, 0, 0), (1, 1, 1, 2)\}.$$

Find  $u \in U$  such that  $\|u - (1, 2, 3, 4)\|$  is as small as possible.

*Solution.* We first find an orthonormal basis of  $U$  by applying the Gram–Schmidt procedure to the generating set of  $U$ . We obtain

$$\begin{aligned} e_1 &= (1/\sqrt{2}, 1/\sqrt{2}, 0, 0) \\ e_2 &= (0, 0, 1/\sqrt{5}, 2/\sqrt{5}). \end{aligned}$$

Thus,  $\{e_1, e_2\}$  is an orthonormal basis of  $U$ .

By the two propositions above, the closest point  $u \in U$  to  $(1, 2, 3, 4)$  is

$$\langle (1, 2, 3, 4), e_1 \rangle e_1 + \langle (1, 2, 3, 4), e_2 \rangle e_2 = (3/2, 3/2, 11/5, 22/5).$$

$\square$