

## 5.1: Orthogonal Projections & Orthonormal Bases

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class summary to date.

Three main motivations  
for linear algebra

course outline  
↔ date

- (1) applications
- (2) challenge common  
conceptions in math.
- (3) Intro to mathematical  
abstraction & reasoning.

- (1) Linear Equations
- (2) Linear Transformations
- (3) Subspaces of  $\mathbb{R}^n$  and  
their dimension.
  - image & kernel  
of a L.T.
  - bases & L.I.
  - Dimension
  - coordinates.

So where are we going? In our next chapter  
we will focus on a special type/class of  
bases (orthonormal), how to find them, and  
their applications (least squares).

Basic vector concepts.

- (a) perpendicular/orthogonal vectors.
- (b) length/magnitude/norm
- (c) unit vectors
- (d) finding unit vectors.
- (e) orthonormal vectors.

$\vec{u}_1, \dots, \vec{u}_m \in \mathbb{R}^n$  are orthonormal if

$$\vec{u}_i \cdot \vec{u}_j = \begin{cases} 1 & , i = j \\ 0 & , i \neq j \end{cases}$$

ex1: The standard vecs.

ex2: The cols of the 2D rotation matrix

ex3:  $\begin{bmatrix} 2/\sqrt{3} \\ 1/\sqrt{3} \\ 1/\sqrt{3} \end{bmatrix}, \begin{bmatrix} -2/\sqrt{3} \\ 1/\sqrt{3} \\ 2/\sqrt{3} \end{bmatrix}, \begin{bmatrix} 1/\sqrt{3} \\ -2/\sqrt{3} \\ 2/\sqrt{3} \end{bmatrix}$  (show they are orthonormal)

Thm: properties of orthonormalvecs.

- (a) orthonormal vecs are L.I.
- (b) orthonormal vecs  $\vec{u}_1, \dots, \vec{u}_r$  in  $\mathbb{R}^n$  form a basis for  $\mathbb{R}^n$ .

□ proof.

Suppose  $\vec{u}_1, \dots, \vec{u}_n \in \mathbb{R}^n$  are L.I. orthonormalvecs.

To show that these are L.I. we must show

$$c_1\vec{u}_1 + \dots + c_n\vec{u}_n = \vec{0} \quad \text{has only the trivial sol.}$$

□ proof

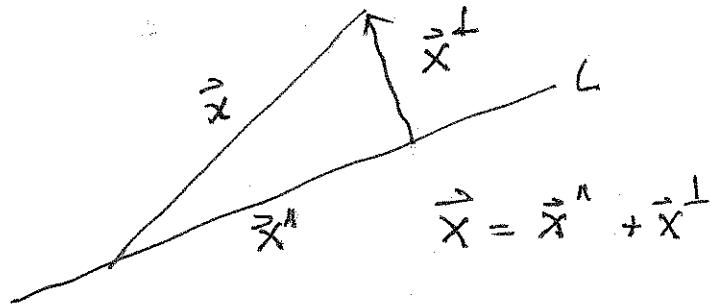
$$\text{consider } u_i \cdot (c_1\vec{u}_1 + \dots + c_n\vec{u}_n) = \vec{u}_i \cdot \vec{0} \quad \text{for } i=1, \dots, n$$

$$\Rightarrow c_1 u_{i1} u_1 + \dots + c_{i-1} u_{i-1} u_{i-1} + c_i u_i \cdot u_i + c_{i+1} u_i \cdot u_{i+1} + \dots + c_n u_i u_n = \vec{0}$$

$$\Rightarrow c_i = 0 \quad \text{for } i=1, \dots, n$$

Hence  $\vec{u}_1, \dots, \vec{u}_n$  are L.I. QED ■

orthogonal projections



Thm: consider a vector  $\vec{x} \in \mathbb{R}^n$  and a subspace V of  $\mathbb{R}^n$ . Then we can write  $\vec{x} = \vec{x}'' + \vec{x}'^\perp$  where  $\vec{x}'' \in V$  and  $\vec{x}'^\perp$  is orthogonal to V. This representation is unique.

□ proof.

Consider an orthonormal basis  $\vec{u}_1, \dots, \vec{u}_n$  of  $V$ .

If  $\vec{x} = \vec{x}'' + \vec{x}^\perp$  exists, then

$$\vec{x}'' = c_1 \vec{u}_1 + \dots + c_i \vec{u}_i + \dots + c_n \vec{u}_n$$

for yet to be determined coefficients.

$$\Rightarrow \vec{x}^\perp = \vec{x} - \vec{x}'' = \vec{x} - c_1 \vec{u}_1 - \dots - c_i \vec{u}_i - \dots - c_n \vec{u}_n$$

is orthogonal to all  $u_i \in V$ .

$$\Rightarrow 0 = \vec{u}_i \cdot (\vec{x} - c_1 \vec{u}_1 - \dots - c_i \vec{u}_i - \dots - c_n \vec{u}_n)$$

$$\Rightarrow 0 = u_i \cdot \vec{x} - c_i$$

$$\Rightarrow c_i = u_i \cdot \vec{x}$$

$$\Rightarrow \vec{x}'' = (\vec{u}_1 \cdot \vec{x}) \vec{u}_1 + \dots + (\vec{u}_n \cdot \vec{x}) \vec{u}_n$$

$$\text{and } \vec{x}^\perp = \vec{x} - \vec{x}''.$$

It is unique by construction. ■

Thus if  $V$  is a subspace of  $\mathbb{R}^n$  w/ orthonormal basis

$\vec{u}_1, \dots, \vec{u}_m$  then  $\text{proj}_V(\vec{x}) = \vec{x}'' = (\vec{u}_1 \cdot \vec{x}) \vec{u}_1 + \dots + (\vec{u}_m \cdot \vec{x}) \vec{u}_m$   
for all  $\vec{x}$  in  $\mathbb{R}^n$ .

ex 4: consider the subspace  $V = \text{im}(A)$  of  $\mathbb{R}^3$  where

$$A = \begin{bmatrix} 2 & -2 \\ 2 & 1 \\ 1 & 2 \end{bmatrix}. \text{ Find } \text{proj}_V(\vec{x}) \text{ for } \vec{x} = \begin{bmatrix} 3 \\ 3 \\ 1 \end{bmatrix}$$

$$\vec{u}_1 = \begin{bmatrix} 2/3 \\ 2/3 \\ 1/3 \end{bmatrix} \text{ and } \vec{u}_2 = \begin{bmatrix} -2/3 \\ 1/3 \\ 2/3 \end{bmatrix} \quad \vec{x}'' = (5) \begin{bmatrix} 2/3 \\ 2/3 \\ 1/3 \end{bmatrix} + (1) \begin{bmatrix} -2/3 \\ 1/3 \\ 2/3 \end{bmatrix} = \begin{bmatrix} 8/3 \\ 11/3 \\ 7/3 \end{bmatrix}$$

check that  $\vec{x}^\perp$  is  $\perp$  to  $\vec{u}_1$  &  $\vec{u}_2$

Thm: Consider an orthonormal basis  $\vec{u}_1, \dots, \vec{u}_n \in \mathbb{R}^n$ .

Then  $\vec{x} = (\vec{u}_1 \cdot \vec{x}) \vec{u}_1 + \dots + (\vec{u}_n \cdot \vec{x}) \vec{u}_n$  for all  $\vec{x} \in \mathbb{R}^n$ .

Recall, if  $\vec{v}_1, \dots, \vec{v}_n \in \mathbb{R}^n$  is a basis for  $\mathbb{R}^n$ ,

then  $c_1, \dots, c_n$  s.t.  $\vec{x} = c_1 \vec{v}_1 + \dots + c_n \vec{v}_n$  are the coordinates of  $\vec{x}$ .

If  $\vec{u}_1, \dots, \vec{u}_n \in \mathbb{R}^n$  are an orthonormal basis, then the coords are easy to find:  $c_i = \vec{u}_i \cdot \vec{x}$

Dfn: Consider a subspace  $V$  of  $\mathbb{R}^n$ . The orthogonal complement  $V^\perp$  of  $V$  is the set of those vectors  $\vec{x} \in \mathbb{R}^n$  that are orthogonal to all vcs in  $V$ .

$$V^\perp = \{\vec{x} \in \mathbb{R}^n \mid \vec{v} \cdot \vec{x} = 0 \text{ for all } \vec{v} \in V\}$$

Note:  $V^\perp$  is the kernel of the orthogonal projection onto  $V$ .

Thm: Consider a subspace  $V$  of  $\mathbb{R}^n$ .

(a) the orthogonal complement  $V^\perp$  of  $V$  is a subspace of  $\mathbb{R}^n$ .

(b) The intersection  $V \cap V^\perp = \{\vec{0}\}$  —

(c)  $\dim(V) + \dim(V^\perp) = n$  (see pics).

(d)  $(V^\perp)^\perp = V$  —

# Derivation of the Cauchy-Schwarz Inequality.

Let  $\vec{y}$  be a vector in the direction of the line  $L$ , and  $\vec{u} = \frac{\vec{y}}{\|\vec{y}\|}$ .

$$\begin{aligned}\|\vec{x}\| &\geq \|\text{proj}_L \vec{x}\| \\ &= \|(\vec{x} \cdot \vec{u}) \vec{u}\| \\ &= |\vec{x} \cdot \vec{u}| \|\vec{u}\| \\ &= |\vec{x} \cdot \vec{u}| \\ &= \left| \vec{x} \cdot \frac{\vec{y}}{\|\vec{y}\|} \right| \\ &= \frac{1}{\|\vec{y}\|} |\vec{x} \cdot \vec{y}|\end{aligned}$$

$$\Rightarrow \|\vec{x}\| \|\vec{y}\| \geq |\vec{x} \cdot \vec{y}| \quad (\text{equal only if } \vec{x} \text{ & } \vec{y} \text{ are parallel}).$$

The angle between vectors.

$$\vec{x} \cdot \vec{y} = \|\vec{x}\| \|\vec{y}\| \cos \theta$$

$$\Rightarrow \theta = \arccos \left[ \frac{\vec{x} \cdot \vec{y}}{\|\vec{x}\| \|\vec{y}\|} \right]$$

This is always defined by Cauchy-Schwarz