

# MATH 201: Linear Algebra

Week 11

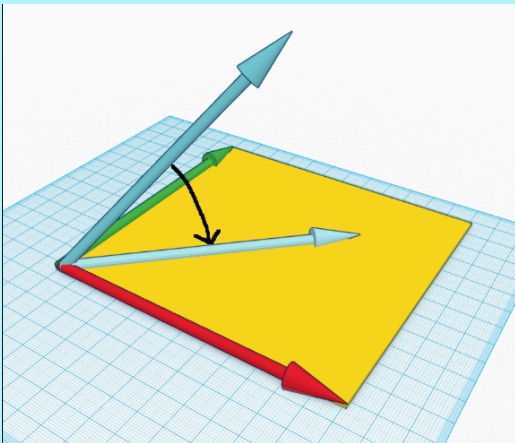
Today: Chapter 5

- \* The Gram-Schmidt Process
- \* QR-Factorization
- \* Orthogonal matrices
- \* The least squares method.

**Theorem:** If  $V \subseteq \mathbb{R}^n$  is a subspace with an orthogonal basis  $\{\vec{u}_1, \dots, \vec{u}_k\}$

Then

$$\text{proj}_V(\vec{x}) = \sum_{i=1}^k \frac{\vec{u}_i \cdot \vec{x}}{\vec{u}_i \cdot \vec{u}_i} \vec{u}_i$$



$$\text{ex: } \vec{u}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \vec{u}_2 = \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \vec{x} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$$

$$\vec{u}_1 \cdot \vec{u}_2 = 0$$

$$\vec{u}_1 \cdot \vec{x} = 3$$

$$\vec{u}_2 \cdot \vec{x} = -1$$

$$\vec{u}_1 \cdot \vec{u}_1 = 1$$

$$\vec{u}_2 \cdot \vec{u}_2 = 1$$

$$\text{proj}_V(\vec{x}) = \frac{3}{1} \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \frac{1}{1} \begin{bmatrix} -1 \\ 0 \end{bmatrix}$$

$$\Rightarrow = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

**Theorem (Cauchy-Schwarz):** For all  $\vec{x}, \vec{y} \in \mathbb{R}^n$ ,

$$|\vec{x} \cdot \vec{y}| \leq \|\vec{x}\| \|\vec{y}\|$$

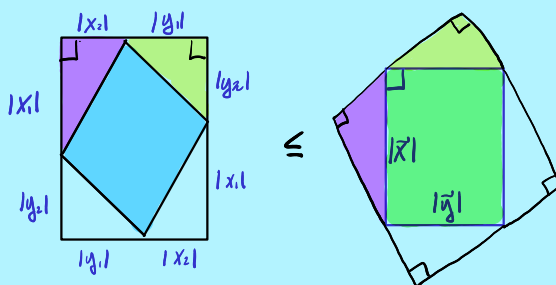
with equality if and only if  $\vec{x} \parallel \vec{y}$ .

**Theorem:**  $\|\text{proj}_V(\vec{x})\| \leq \|\vec{x}\|$  with equality iff  $\vec{x} \in V$

"proof" for  $n=2$ . Let  $\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$   $\vec{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$ .

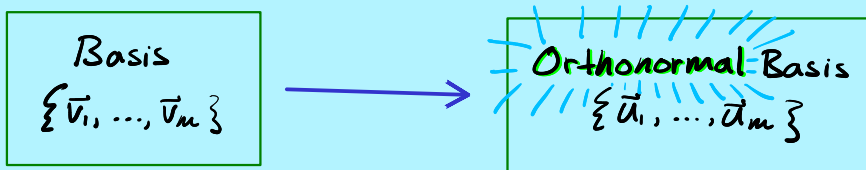
Then  $\vec{x} \cdot \vec{y} = x_1 y_1 + x_2 y_2$

and  $\|\vec{x}\| \|\vec{y}\| = \sqrt{x_1^2 + x_2^2} \sqrt{y_1^2 + y_2^2}$



## 5.2: The Gram-Schmidt Process and QR Factorization.

Goal: Make an algorithm



$$\vec{w}_1 = \vec{v}_1$$

$$\vec{w}_2 = \vec{v}_2 - \text{proj}_{\vec{w}_1}(\vec{v}_2)$$

## The Process

Given  $k$  nonzero, linearly-independent vectors  $\vec{v}_1, \dots, \vec{v}_k$ , do

$$\vec{w}_1 = \vec{v}_1$$

$$\vec{w}_2 = \vec{v}_2 - \text{proj}_{\vec{w}_1}(\vec{v}_2)$$

$$\vec{w}_3 = \vec{v}_3 - \text{proj}_{\vec{w}_1}(\vec{v}_3) - \text{proj}_{\vec{w}_2}(\vec{v}_3)$$

$$\vec{w}_4 = \vec{v}_4 - \text{proj}_{\vec{w}_1}(\vec{v}_4) - \text{proj}_{\vec{w}_2}(\vec{v}_4) - \text{proj}_{\vec{w}_3}(\vec{v}_4)$$

$\vdots$

$$\vec{w}_k = \vec{v}_k - \sum_{j=1}^{k-1} \text{proj}_{\vec{w}_j}(\vec{v}_k)$$

Result:  $k$  orthogonal vectors  $\{\vec{w}_k\}$

## Normalize

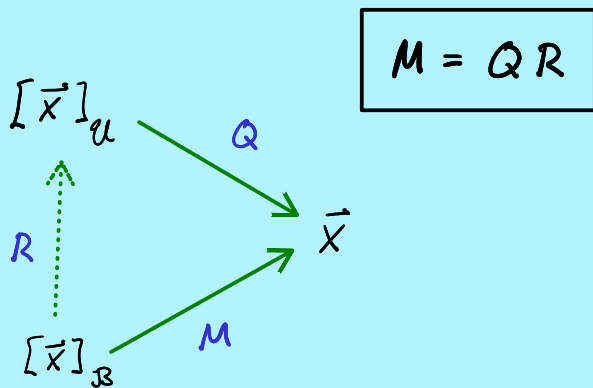
Then set  $\vec{u}_i = \frac{\vec{w}_i}{\|\vec{w}_i\|}$

•  $\mathcal{B}$  = old basis

•  $\mathcal{U}$  = new basis



# The QR-Factorization



Old basis:

$$\mathcal{B} = \{\vec{v}_1, \dots, \vec{v}_m\}$$

$$M = \begin{bmatrix} | & & | \\ \vec{v}_1 & & \vec{v}_m \\ | & & | \end{bmatrix}$$

New (orthonormal basis):

$$\mathcal{U} = \{\vec{u}_1, \dots, \vec{u}_m\}$$

$$Q = \begin{bmatrix} | & & | \\ \vec{u}_1 & & \vec{u}_m \\ | & & | \end{bmatrix}$$

**Theorem:** Suppose that  $M$  is an  $n \times m$  matrix with linearly independent columns  $\vec{v}_1, \dots, \vec{v}_m$ . Then there exists an  $n \times m$  matrix  $Q$  whose columns  $\vec{u}_1, \dots, \vec{u}_m$  are orthonormal and an upper triangular matrix  $R$  with positive diagonal entries such that

$$M = QR.$$

This representation is unique.

•  $r_{ij} = \vec{u}_i \cdot \vec{v}_j$  for  $i < j$

$$R = Q^T M$$

$$r_{ij} = \vec{q}_i^T \vec{b}_j = \vec{q}_i \cdot \vec{b}_j$$

If  $i > j$  then  $\vec{q}_i \perp \text{span}\{\vec{b}_1, \dots, \vec{b}_j\}$

but  $\vec{b}_j \in \text{span}\{\vec{b}_1, \dots, \vec{b}_j\}$

$$\Rightarrow \vec{q}_i \cdot \vec{b}_j = 0 \Rightarrow r_{ij} = 0 \text{ for } i > j.$$

$\Rightarrow R$  is upper-triangular.

$(\vec{b}_1, \dots, \vec{b}_n)$  (old)  $[M]$

$(\vec{q}_1, \dots, \vec{q}_n)$  (new)  $[Q]$

Example: Find an orthonormal basis  $\vec{u}_1, \vec{u}_2$  of the subspace  $V = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 9 \\ 1 \end{bmatrix} \right\}$ .

Example: Find the QR-factorization of the matrix  $M = \begin{bmatrix} 2 & 2 \\ 1 & 7 \\ -2 & -8 \end{bmatrix}$ .

Definition: A linear transformation  $T: \mathbb{R}^n \rightarrow \mathbb{R}^n$  is called orthogonal if

$$\|T(\vec{x})\| = \|\vec{x}\| \quad \forall \vec{x} \in \mathbb{R}^n$$

Facts:

1.  $T: \mathbb{R}^n \rightarrow \mathbb{R}^n$  is orthogonal  $\Leftrightarrow$  the columns of  $T(\vec{x}) = A\vec{x}$  form an orthonormal basis for  $\mathbb{R}^n$ .
2. If  $A$  and  $B$  are orthogonal, so is  $AB$ .
3. If  $A$  is orthogonal, so is  $A^{-1}$ .
4.  $A$  is orthogonal  $\Leftrightarrow A^{-1} = A^T$ .

Theorem: Let  $V \subseteq \mathbb{R}^n$  have orthonormal basis  $\mathcal{B} = \{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_m\}$ .  
The matrix representing orthogonal projection onto  $V$  is  $QQ^T$   
where

$$Q = \begin{bmatrix} | & & | \\ \vec{u}_1 & \cdots & \vec{u}_m \\ | & & | \end{bmatrix}$$