## October 24 Math 3260 sec. 57 Fall 2017

## Recall the Law of Cosines

For triangle with angles $A, B, C$ and opposite sides of lengths $a, b$, and $c$, respectively,

$$
c^{2}=a^{2}+b^{2}-2 a b \cos (C)
$$



## Geometry of the Dot Product



Figure: We can use the law of cosines to show that in $\mathbb{R}^{2}$ that $\mathbf{u} \cdot \mathbf{v}$ is related to the angle between the two (nonzero) vectors. This holds in $\mathbb{R}^{n}$. We're just restricting $n$ to 2 for ease of computation.

By the low of Cosines

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

We car note that $\|\vec{h}-\vec{v}\|^{2}=(\vec{G}-\vec{v}) \cdot(\vec{u}-\vec{v})$

$$
\begin{gathered}
\vec{u} \cdot \vec{u}-\vec{u} \cdot \vec{v}-\vec{v} \cdot \vec{u}+\vec{v} \cdot \vec{v}=\|\vec{u}\|^{2}+\|\vec{v}\|^{2}-2\|\vec{u}\|\|\vec{v}\| \cos \theta \\
\|\vec{i}\|^{2}-2 \vec{u} \cdot \vec{v}+\|\vec{v}\|^{2}=\|\vec{i}\|^{2}+\|\vec{v}\|^{2}-2\|\vec{u}\|\|\vec{v}\| \cos \theta \\
-2 \vec{u} \cdot \vec{v}=-2\|\vec{u}\|\|\vec{v}\| \cos \theta \\
\vec{u} \cdot \vec{v}=\|\vec{u}\|\|\vec{v}\| \cos \theta
\end{gathered}
$$

## Section 6.2: Orthogonal Sets

Remark: We know that if $\mathcal{B}=\left\{\mathbf{b}_{1}, \ldots, \mathbf{b}_{p}\right\}$ is a basis for a subspace $W$ of $\mathbb{R}^{n}$, then each vector $\mathbf{x}$ in $W$ can be realized (uniquely) as a sum

$$
\mathbf{x}=c_{1} \mathbf{b}_{2}+\cdots+c_{p} \mathbf{b}_{p}
$$

If $n$ is very large, the computations needed to determine the coefficients $c_{1}, \ldots, c_{p}$ may require a lot of time (and machine memory).

Question: Can we seek a basis whose nature simplifies this task? And what properties should such a basis possess?

## Orthogonal Sets \& Orthogonal Bases

Definition: An indexed set $\left\{\mathbf{u}_{1}, \ldots, \mathbf{u}_{p}\right\}$ in $\mathbb{R}^{n}$ is said to be an orthogonal set provided each pair of distinct vectors in the set is orthogonal. That is, provided

$$
\mathbf{u}_{i} \cdot \mathbf{u}_{j}=0 \quad \text { whenever } \quad i \neq j
$$

Definition: An orthogonal basis for a subspace $W$ of $\mathbb{R}^{n}$ is a basis that is also an orthogonal set.

Theorem: Let $\left\{\mathbf{u}_{1}, \ldots, \mathbf{u}_{p}\right\}$ be an orthogonal basis for a subspace $W$ of $\mathbb{R}^{n}$. Then each vector $\mathbf{y}$ in $W$ can be written as the linear combination

$$
\begin{aligned}
& \mathbf{y}=c_{1} \mathbf{u}_{1}+c_{2} \mathbf{u}_{2}+\cdots+c_{p} \mathbf{u}_{p}, \quad \text { where the weights } \\
& \qquad c_{j}=\frac{\mathbf{y} \cdot \mathbf{u}_{j}}{\mathbf{u}_{j} \cdot \mathbf{u}_{j}} .
\end{aligned}
$$

## Projection

Given a nonzero vector u, suppose we wish to decompose another nonzero vector $\mathbf{y}$ into a sum of the form

$$
\mathbf{y}=\hat{\mathbf{y}}+\mathbf{z}
$$

in such a way that $\hat{\mathbf{y}}$ is parallel to $\mathbf{u}$ and $\mathbf{z}$ is perpendicular to $\mathbf{u}$.


$$
\vec{z}=\vec{y}-\hat{y}
$$

## Projection

Since $\hat{\mathbf{y}}$ is parallel to $\mathbf{u}$, there is a scalar $\alpha$ such that

$$
\hat{\mathbf{y}}=\alpha \mathbf{u} .
$$

We determined last time that the scalar

$$
\alpha=\frac{\mathbf{y} \cdot \mathbf{u}}{\mathbf{u} \cdot \mathbf{u}}=\frac{\mathbf{y} \cdot \mathbf{u}}{\|\mathbf{u}\|^{2}}
$$

so that

$$
\hat{\mathbf{y}}=\frac{\mathbf{y} \cdot \mathbf{u}}{\|\mathbf{u}\|^{2}} \mathbf{u} \quad \text { and } \quad \mathbf{z}=\mathbf{y}-\hat{\mathbf{y}} .
$$

## Projection onto the subspace $L=\operatorname{Span}\{\mathbf{u}\}$

$$
\text { Notation: } \quad \hat{\mathbf{y}}=\operatorname{proj}_{L}=\left(\frac{\mathbf{y} \cdot \mathbf{u}}{\mathbf{u} \cdot \mathbf{u}}\right) \mathbf{u}
$$

Example: Let $\mathbf{y}=\left[\begin{array}{l}7 \\ 6\end{array}\right]$ and $\mathbf{u}=\left[\begin{array}{l}4 \\ 2\end{array}\right]$. Write $\mathbf{y}=\hat{\mathbf{y}}+\mathbf{z}$ where $\hat{\mathbf{y}}$ is in $\operatorname{Span}\{\mathbf{u}\}$ and $\mathbf{z}$ is orthogonal to $\mathbf{u}$.

$$
\begin{aligned}
& \hat{y}=\frac{\vec{y} \cdot \vec{u}}{\|\vec{u}\|^{2}} \vec{u}=\left(\frac{7(4)+6(2)}{4^{2}+2^{2}}\right) \vec{u}=\frac{40}{20} \vec{u}=2 \vec{u}=\left[\begin{array}{l}
8 \\
4
\end{array}\right] \\
& \vec{z}=\vec{y}-\hat{y}=\left[\begin{array}{l}
7 \\
6
\end{array}\right]-\left[\begin{array}{l}
8 \\
4
\end{array}\right]=\left[\begin{array}{l}
-1 \\
2
\end{array}\right]
\end{aligned}
$$

So

$$
\vec{y}=\left[\begin{array}{l}
8 \\
4
\end{array}\right]+\left[\begin{array}{c}
-1 \\
2
\end{array}\right]
$$

Example Continued...
Determine the distance between the point $(7,6)$ and the line $\operatorname{Span}\{\mathbf{u}\}$.

The shortest distance is $\|\vec{z}\|$.

The distance is $\sqrt{(-1)^{2}+2^{2}}=\sqrt{5}$

## Orthonormal Sets

Definition: A set $\left\{\mathbf{u}_{1}, \ldots, \mathbf{u}_{p}\right\}$ is called an orthonormal set if it is an orthogonal set of unit vectors.

Definition: An orthonormal basis of a subspace $W$ of $\mathbb{R}^{n}$ is a basis that is also an orthonormal set.

Example: Show that $\left\{\left[\begin{array}{l}3 \\ 5 \\ 4 \\ 5\end{array}\right],\left[\begin{array}{c}-\frac{4}{5} \\ \frac{3}{5}\end{array}\right]\right\}$ is an orthonormal basis for
$\mathbb{R}^{2}$.

$$
\begin{aligned}
& \vec{u}_{1} \cdot \vec{u}_{2}=\frac{3}{5}\left(\frac{-4}{5}\right)+\left(\frac{4}{5}\right)\left(\frac{3}{5}\right)^{u_{1}}=\frac{-16+16}{25}=0 \quad \text { They are orthogond } \\
& \left\|\vec{u}_{1}\right\|^{2}=\left(\frac{3}{5}\right)^{2}+\left(\frac{4}{5}\right)^{2}=\frac{16+9}{25}=\frac{25}{25}=1,\left\|\vec{u}_{2}\right\|^{2}=\left(\frac{-4}{5}\right)^{2}+\left(\frac{3}{5}\right)^{2}=\frac{16+9}{25}=1
\end{aligned}
$$

They one also unit vectors.

If the vectors ane lineally independent, they span $\mathbb{R}^{2}$ (since the ne an 2 of them).

$$
\begin{aligned}
& c_{1} \vec{u}_{1}+c_{2} \vec{u}_{2}=\overrightarrow{0} \\
& \vec{u}_{1}=\left[\begin{array}{l}
\frac{3}{5} \\
\frac{4}{s}
\end{array}\right] \quad \vec{u}_{2}=\left[\begin{array}{c}
\frac{-4}{s} \\
\frac{3}{5}
\end{array}\right], \begin{array}{l}
\vec{u}_{1} \text { is not } a \\
\text { scaled version } \\
\text { on } \vec{u}_{2}
\end{array}
\end{aligned}
$$

Hence they are lin. independent and $\left\{\vec{u}_{1}, \vec{u}_{2}\right\}$ is an or tho normal basis for $\mathbb{R}^{2}$.

## Orthogonal Matrix

Consider the matrix $U=\left[\begin{array}{cc}\frac{3}{5} & -\frac{4}{5} \\ 5 & \frac{3}{5}\end{array}\right]$ whose columns are the vectors in the last example. Compute the product
$U^{T} U=\left[\begin{array}{cc}\frac{3}{5} & \frac{4}{5} \\ \frac{-4}{5} & \frac{3}{5}\end{array}\right]\left[\begin{array}{cc}\frac{3}{5} & \frac{-4}{5} \\ \frac{4}{5} & \frac{3}{5}\end{array}\right]=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]$
This shows that $u^{\top}=U^{-1}$
What does this say about $U^{-1}$ ?

## Orthogonal Matrix

Definition: A square matrix $U$ is called an orthogonal matrix if $U^{T}=U^{-1}$.

Theorem: An $n \times n$ matrix $U$ is orthogonal if and only if it's columns form an orthonormal basis of $\mathbb{R}^{n}$.

The linear transformation associated to an orthogonal matrix preserves lenghts and angles in the following sense:

## Theorem: Orthogonal Matrices

Let $U$ be an $n \times n$ orthogonal matrix and $\mathbf{x}$ and $\mathbf{y}$ vectors in $\mathbb{R}^{n}$. Then
(a) $\|U \mathbf{x}\|=\|\mathbf{x}\|$
(b) $(U \mathbf{x}) \cdot(U \mathbf{y})=\mathbf{x} \cdot \mathbf{y}$, in particular
(c) $(U \mathbf{x}) \cdot(U \mathbf{y})=0$ if and only if $\mathbf{x} \cdot \mathbf{y}=0$.

Proof (of (a)):
Recall $\|u \vec{x}\|^{2}=(u \vec{x}) \cdot(u \vec{x})$
$=(u \vec{x})^{\top}(U \vec{x})$

$$
\begin{gathered}
\text { This is how we } \\
\text { defining the } \\
\text { dol product }
\end{gathered}
$$

$$
\begin{aligned}
& =\left(\vec{x}^{\top} U^{\top}\right)(U \vec{x}) \\
& \text { Recall } \\
& (A B)^{\top}=B^{\top} A^{\top} \\
& =x^{\top}\left(U^{\top} U\right) \vec{x} \\
& =\vec{x}^{\top} I \vec{x} \\
& =\vec{x}^{\top} \vec{x}=\|\vec{x}\|^{2}
\end{aligned}
$$

so

$$
\|U \vec{x}\|=\|\vec{x}\|
$$

## Section 6.3: Orthogonal Projections

Equating points with position vectors, we may wish to find the point $\hat{\mathbf{y}}$ in a subspace $W$ of $\mathbb{R}^{n}$ that is closest to a given point $\mathbf{y}$.


Figure: Illustration of an orthogonal projection. Note that $\operatorname{dist}(\mathbf{y}, \hat{\mathbf{y}})$ is the shortest distance between $\mathbf{y}$ and the points on $W$.

## Orthogonal Decomposition Theorem

Let $W$ be a subspace of $\mathbb{R}^{n}$. Each vector $\mathbf{y}$ in $\mathbb{R}^{n}$ can be written uniquely as a sum

$$
\mathbf{y}=\hat{\mathbf{y}}+\mathbf{z}
$$

where $\hat{\mathbf{y}}$ is in $W$ and $\mathbf{z}$ is in $W^{\perp}$.
If $\left\{\mathbf{u}_{1}, \ldots, \mathbf{u}_{p}\right\}$ is any orthogonal basis for $W$, then

$$
\hat{\mathbf{y}}=\sum_{j=1}^{p}\left(\frac{\mathbf{y} \cdot \mathbf{u}_{j}}{\mathbf{u}_{j} \cdot \mathbf{u}_{j}}\right) \mathbf{u}_{j}, \quad \text { and } \quad \mathbf{z}=\mathbf{y}-\hat{\mathbf{y}} .
$$

Remark: Note that the basis must be orthogonal, but otherwise the vector $\hat{\mathbf{y}}$ is independent of the particular basis used!

Remark: The vector $\hat{\mathbf{y}}$ is called the orthogonal projection of $\mathbf{y}$ onto $W$. We can denote it

$$
\operatorname{proj}_{W} \mathbf{y} .
$$

## Example

Let $\mathbf{y}=\left[\begin{array}{l}4 \\ 8 \\ 1\end{array}\right]$ and

$$
\begin{aligned}
& \text { col these } \\
& i_{i} \quad \vec{u}_{2} \\
& W=\operatorname{Span}\left\{\left[\begin{array}{l}
2 \\
1 \\
2
\end{array}\right],\left[\begin{array}{c}
-2 \\
2 \\
1
\end{array}\right]\right\} .
\end{aligned}
$$

(a) Verify that the spanning vectors for $W$ given are an orthogonal basis for $W$.

$$
\vec{u}_{1} \cdot \vec{u}_{2}=2(-2)+1(2)+2(1)=-4+2+2=0
$$

Thy an orthosond. This implies
that they one also lineal, indiperdeact hence as orthogond basis.

Example Continued...

$$
W=\operatorname{Span}\left\{\left[\begin{array}{l}
2 \\
1 \\
2
\end{array}\right],\left[\begin{array}{c}
-2 \\
2 \\
1
\end{array}\right]\right\} \quad \text { and } \quad \mathbf{y}=\left[\begin{array}{l}
4 \\
8 \\
1
\end{array}\right]
$$

(b) Find the orthogonal projection of $\mathbf{y}$ onto $W$.

$$
\begin{aligned}
& \hat{y}=\frac{\vec{y} \cdot \vec{u}_{1}}{\| \vec{u}_{1} 1^{2}} \vec{u}_{1}+\frac{\vec{y} \cdot \vec{u}_{2}}{\left\|\vec{u}_{2}\right\|^{2}} \vec{u}_{2} \\
& \left\|\vec{u}_{1}\right\|^{2}=2^{2}+1^{2}+2^{2}=9 \Rightarrow\left\|\vec{u}_{1}\right\|=3 \\
& \left\|\vec{u}_{2}\right\|^{2}=(-2)^{2}+2^{2}+1^{2}=9 \Rightarrow\left\|\vec{u}_{2}\right\|=3 \\
& \vec{y} \cdot \vec{u}_{1}=2 \cdot 4+1 \cdot 8+2 \cdot 1=18, \quad \vec{y}^{2} \cdot \vec{u}_{2}=-2(4)+2(8)+1=9
\end{aligned}
$$

$$
\begin{aligned}
\hat{y} & =\frac{18}{9} \vec{u}_{1}+\frac{9}{9} \vec{u}_{2}=2 \vec{u}_{1}+\vec{u}_{2} \\
& =2\left[\begin{array}{l}
2 \\
1 \\
2
\end{array}\right]+\left[\begin{array}{c}
-2 \\
2 \\
1
\end{array}\right]=\left[\begin{array}{c}
4-2 \\
2+2 \\
4+1
\end{array}\right]=\left[\begin{array}{l}
2 \\
4 \\
5
\end{array}\right]
\end{aligned}
$$

(c) Find the shortest distance between $y$ and the subspace $W$.
wt $\vec{z}=\vec{y}-\hat{y}=\left[\begin{array}{l}4 \\ 0 \\ 1\end{array}\right]-\left[\begin{array}{l}2 \\ y \\ 5\end{array}\right]=\left[\begin{array}{c}2 \\ 4 \\ -4\end{array}\right]$
The shortest distance is

$$
\|\vec{z}\|=\sqrt{2^{2}+4^{2}+(-1)}=\sqrt{4+16+16}=6
$$

