## April 22 Math 3260 sec. 51 Spring 2024

Section 6.3: Orthogonal Projections


Figure: Given a subspace $W$ of $\mathbb{R}^{n}$ and a vector $\mathbf{y}$ in $\mathbb{R}^{n}$, we can express $\mathbf{y}$ uniquely as a $\operatorname{sum}_{\operatorname{proj}_{W}}^{\mathbf{y}}+\mathbf{z}$ where $\operatorname{proj}_{W} \mathbf{y}$ is in $W$ and $\mathbf{z}$ is in $W^{\perp}$. Note that $\operatorname{proj}_{W} \mathbf{y}$ is the point in $W$ closest to $\mathbf{y}$ and $\|\mathbf{z}\|$ is the distance between $\mathbf{y}$ and $W$.

## 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: The formula for $\hat{\mathbf{y}}$ is the sum of the projections of $\mathbf{y}$ onto each line Span $\left\{\mathbf{u}_{j}\right\}$.

$$
\operatorname{proj}_{w} \mathbf{y}=\operatorname{proj}_{\mathbf{u}_{1}} \mathbf{y}+\operatorname{proj}_{\mathbf{u}_{2}} \mathbf{y}+\cdots+\operatorname{proj}_{\mathbf{u}_{p}} \mathbf{y}
$$

## Example

Let $\mathbf{y}=\left[\begin{array}{l}4 \\ 8 \\ 1\end{array}\right], \mathbf{u}_{1}=\left[\begin{array}{l}2 \\ 1 \\ 2\end{array}\right], \mathbf{u}_{2}=\left[\begin{array}{r}-2 \\ 2 \\ 1\end{array}\right]$ and $W=\operatorname{Span}\left\{\mathbf{u}_{1}, \mathbf{u}_{2}\right\}$.
We verified that $\left\{\mathbf{u}_{1}, \mathbf{u}_{2}\right\}$ is orthogonal basis for $W$, and we found that

$$
\operatorname{proj}_{W} \mathbf{y}=\left(\frac{\mathbf{y} \cdot \mathbf{u}_{1}}{\mathbf{u}_{1} \cdot \mathbf{u}_{1}}\right) \mathbf{u}_{1}+\left(\frac{\mathbf{y} \cdot \mathbf{u}_{2}}{\mathbf{u}_{2} \cdot \mathbf{u}_{2}}\right) \mathbf{u}_{2}=\left[\begin{array}{l}
2 \\
4 \\
5
\end{array}\right]
$$

The orthogonal part was

$$
\mathbf{y}-\operatorname{proj}_{w} \mathbf{y}=\left[\begin{array}{l}
4 \\
8 \\
1
\end{array}\right]-\left[\begin{array}{l}
2 \\
4 \\
5
\end{array}\right]=\left[\begin{array}{c}
2 \\
4 \\
-4
\end{array}\right]
$$

The distance between $y$ and $W$ was found to be

$$
\operatorname{dist}(W, \mathbf{y})=\left\|\mathbf{y}-\operatorname{proj}_{W} \mathbf{y}\right\|=\sqrt{2^{2}+4^{2}+(-4)^{2}}=6
$$

## Computing Orthogonal Projections

## Theorem

If $\left\{\mathbf{u}_{1}, \ldots, \mathbf{u}_{p}\right\}$ is an orthonormal basis of a subspace $W$ of $\mathbb{R}^{n}$, and $\mathbf{y}$ is any vector in $\mathbb{R}^{n}$ then

$$
\operatorname{proj}_{W} \mathbf{y}=\sum_{j=1}^{p}\left(\mathbf{y} \cdot \mathbf{u}_{j}\right) \mathbf{u}_{j} .
$$

And, if $U$ is the matrix $U=\left[\begin{array}{lll}\mathbf{u}_{1} & \cdots & \mathbf{u}_{p}\end{array}\right]$, then the above is equivalent to

$$
\operatorname{proj}_{W} \mathbf{y}=U U^{T} \mathbf{y} .
$$

Remark: In general, $U$ is not square; it's $n \times p$. So even though $U U^{\top}$ will be a square matrix, it is not the same matrix as $U^{\top} U$ and it is not the identity matrix.

Example
Let $\mathbf{v}_{1}=\left[\begin{array}{l}2 \\ 1 \\ 2\end{array}\right], \mathbf{v}_{2}=\left[\begin{array}{c}-2 \\ 2 \\ 1\end{array}\right]$ and $W=\operatorname{Span}\left\{\mathbf{v}_{1}, \mathbf{v}_{2}\right\}$. Find an orthonormal basis $\left\{\mathbf{u}_{1}, \mathbf{u}_{2}\right\}$ for $W$. Then compute the matrices $U^{\top} U$ and $U U^{T}$ where $U=\left[\begin{array}{ll}\mathbf{u}_{1} & \mathbf{u}_{2}\end{array}\right]$.

$$
\begin{aligned}
& \vec{u}_{1}=\frac{1}{\left\|\vec{v}_{1}\right\|} \vec{v}_{1}, \vec{u}_{2}=\frac{1}{\left\|\vec{v}_{2}\right\|} \vec{v}_{2} \\
& \left\|\vec{v}_{1}\right\|^{2}=2^{2}+1^{2}+2^{2}=9 \Rightarrow\left\|\vec{v}_{1}\right\|=3 \\
& \left\|\vec{v}_{2}\right\|^{2}=(-2)^{2}+2^{2}+1^{2}=9 \Rightarrow\left\|\vec{v}_{2}\right\|^{2}=3 \\
& \vec{u}_{1}=\frac{1}{3}\left[\begin{array}{l}
2 \\
1 \\
2
\end{array}\right]=\left[\begin{array}{c}
2 / 3 \\
1 / 3 \\
2 / 3
\end{array}\right], \vec{u}_{2}=\frac{1}{3}\left[\begin{array}{c}
-2 \\
2 \\
1
\end{array}\right]=\left[\begin{array}{c}
-2 / 3 \\
2 / 3 \\
1 / 3
\end{array}\right]
\end{aligned}
$$

$$
\begin{aligned}
& U=\left[\begin{array}{cc}
2 / 3 & -2 / 3 \\
1 / 3 & 2 / 3 \\
2 / 3 & 1 / 3
\end{array}\right]=\frac{1}{3} \cdot\left[\begin{array}{cc}
2 & -2 \\
1 & 2 \\
2 & 1
\end{array}\right] \\
& \underbrace{U^{\top} U}_{2 \times 2} U=\frac{1}{3} \cdot \frac{1}{3}\left[\begin{array}{lll}
2 \times 2 & 1 & 2 \\
-2 & 2 & 1
\end{array}\right]\left[\begin{array}{cc}
2 & -2 \\
1 & 2 \\
2 & 1
\end{array}\right]=\frac{1}{9}\left[\begin{array}{ll}
9 & 0 \\
0 & 9
\end{array}\right] . \\
& \\
& =\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right] \\
& \underbrace{U \times 2}_{3 \times 3} U^{\top}=\frac{1}{3} \cdot \frac{1}{3}\left[\begin{array}{cc}
2 & -2 \\
1 & 2 \\
2 & 1
\end{array}\right]\left[\begin{array}{ccc}
2 & 1 & 2 \\
-2 & 2 & 1
\end{array}\right]=\frac{1}{9}\left[\begin{array}{ccc}
8 & -2 & 2 \\
-2 & 5 & 4 \\
2 & 4 & 5
\end{array}\right]
\end{aligned}
$$

Note: $\left(U U^{\top}\right)^{\top}=\left(U^{\top}\right)^{\top} U^{\top}=U U^{\top}$

This is why $U$ has the sort of symmetry across the moin dias ond.

FYI: Such a matrix is called a "symmetric" matrix

Example

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

Use the matrix formulation to find $\operatorname{proj}_{W} \mathbf{y}$.

$$
\begin{gathered}
\text { proj}{ }_{w} \vec{y}=u u^{\top} \vec{y} \\
u u^{\top} \vec{y}=\frac{1}{9}\left[\begin{array}{ccc}
8 & -2 & 2 \\
-2 & 5 & 4 \\
2 & 4 & 5
\end{array}\right]\left[\begin{array}{l}
4 \\
8 \\
1
\end{array}\right]
\end{gathered}
$$

where $U=\left[\begin{array}{ll}\vec{u} & \vec{u}_{z}\end{array}\right]$ and $\vec{u}_{1}, \vec{u}_{2}$ are the nor nalized basis llemouts.

$$
=\frac{1}{9}\left[\begin{array}{l}
8(4)-2(8)+2(1) \\
-2(4)+5(8)+4(1) \\
2(4)+4(8)+5(1)
\end{array}\right]=\frac{1}{9}\left[\begin{array}{c}
18 \\
36 \\
45
\end{array}\right]=\left[\begin{array}{l}
2 \\
4 \\
5
\end{array}\right]
$$

## Section 6.4: Gram-Schmidt Orthogonalization

## Big Question:

Given any-old basis for a subspace $W$ of $\mathbb{R}^{n}$, can we construct an orthogonal basis for that same space?

Example: Let $W=\operatorname{Span}\left\{\mathbf{x}_{1}, \mathbf{x}_{2}\right\}=\operatorname{Span}\left\{\left[\begin{array}{l}1 \\ 1 \\ 1\end{array}\right],\left[\begin{array}{c}0 \\ -1 \\ -1\end{array}\right]\right\}$. Find an orthogonal basis $\left\{\mathbf{v}_{1}, \mathbf{v}_{2}\right\}$ that spans $W$.

$$
\begin{aligned}
\text { Since } & \vec{v}_{1} \text { and } \vec{v}_{2} \text { are in } W \text {, } \\
\vec{V}_{1} & =a_{1} \vec{x}_{1} a_{2} \vec{x}_{2} \quad \text { Let's set } a_{1}=1, a_{2}=0 \\
\vec{v}_{2} & =b_{1} \vec{x}_{1}+b_{2} \vec{x}_{2} \quad \text { Let's take } b_{2}=1
\end{aligned}
$$

so for, $\vec{v}_{1}=\vec{x}_{1}$ and $\vec{v}_{2}=b_{1} \vec{x}_{1}+\vec{x}_{2}$
we need $\vec{V}_{1} \cdot \vec{V}_{2}=0$

$$
\begin{aligned}
& \vec{v}_{1} \cdot \vec{V}_{2}= \vec{x}_{1} \cdot\left(b_{1} \vec{x}_{1}+\vec{x}_{2}\right)=0 \\
& b_{1} \vec{x}_{1} \cdot \vec{x}_{1}+\vec{x}_{1} \cdot \vec{x}_{2}=0 \\
& \Rightarrow \quad b_{1} \cdot \vec{x}_{1} \cdot \vec{x}_{1}=-\vec{x}_{1} \cdot \vec{x}_{2} \\
& b_{1}=\frac{-\vec{x}_{1} \cdot \vec{x}_{2}}{\vec{x}_{1} \cdot \vec{x}_{1}}>_{x_{2}}
\end{aligned}
$$

Ss

$$
\begin{aligned}
& \vec{V}_{1}=\vec{x}_{1} \\
& \vec{V}_{2}=\vec{x}_{2}-\frac{\vec{V}_{1} \cdot \vec{x}_{2}}{\vec{V}_{1} \cdot \vec{v}_{1}} \vec{V}_{1}
\end{aligned}
$$

$$
\begin{aligned}
& \vec{x}_{1}=\left[\begin{array}{l}
1 \\
1 \\
1
\end{array}\right], \vec{x}_{2}=\left[\begin{array}{c}
0 \\
-1 \\
-1
\end{array}\right] \quad \begin{array}{l}
\vec{v}_{1} \cdot \vec{x}_{-2}=-2 \\
\vec{v}_{1} \cdot \vec{v}_{1}=3
\end{array} \\
& \vec{V}_{1}=\vec{x}_{1}=\left[\begin{array}{l}
1 \\
1 \\
1
\end{array}\right] \\
& \vec{V}_{2}=\vec{X}_{2}-\frac{\vec{X}_{2} \cdot \vec{V}_{1}}{\vec{V}_{1} \cdot \vec{V}_{1}} \vec{V}_{1}=\left[\begin{array}{c}
0 \\
-1 \\
-1
\end{array}\right]-\frac{-2}{3}\left[\begin{array}{l}
1 \\
1 \\
1
\end{array}\right]=\left[\begin{array}{c}
2 / 3 \\
-1 / 3 \\
-1 / 3
\end{array}\right]
\end{aligned}
$$

The new basis is

$$
\left\{\left[\begin{array}{l}
1 \\
1 \\
1
\end{array}\right],\left[\begin{array}{c}
2 / 3 \\
-1 / 3 \\
-1 / 3
\end{array}\right]\right\}
$$

## Theorem: Gram Schmidt Process

Let $\left\{\mathbf{x}_{1}, \ldots, \mathbf{x}_{p}\right\}$ be any basis for the nonzero subspace $W$ of $\mathbb{R}^{n}$. Define the set of vectors $\left\{\mathbf{v}_{1}, \ldots, \mathbf{v}_{p}\right\}$ via

$$
\begin{aligned}
\mathbf{v}_{1} & =\mathbf{x}_{1} \\
\mathbf{v}_{2} & =\mathbf{x}_{2}-\left(\frac{\mathbf{x}_{2} \cdot \mathbf{v}_{1}}{\mathbf{v}_{1} \cdot \mathbf{v}_{1}}\right) \mathbf{v}_{1} \\
\mathbf{v}_{3} & =\mathbf{x}_{3}-\left(\frac{\mathbf{x}_{3} \cdot \mathbf{v}_{1}}{\mathbf{v}_{1} \cdot \mathbf{v}_{1}}\right) \mathbf{v}_{1}-\left(\frac{\mathbf{x}_{3} \cdot \mathbf{v}_{2}}{\mathbf{v}_{2} \cdot \mathbf{v}_{2}}\right) \mathbf{v}_{2} \\
& \vdots \\
\mathbf{v}_{p} & =\mathbf{x}_{p}-\sum_{j=1}^{p-1}\left(\frac{\mathbf{x}_{p} \cdot \mathbf{v}_{j}}{\mathbf{v}_{j} \cdot \mathbf{v}_{j}}\right) \mathbf{v}_{j} .
\end{aligned}
$$

Then $\left\{\mathbf{v}_{1}, \ldots, \mathbf{v}_{p}\right\}$ is an orthogonal basis for $W$. Moreover, for each $k=1, \ldots, p$
$\operatorname{Span}\left\{\mathbf{v}_{1}, \ldots, \mathbf{v}_{k}\right\}=\operatorname{Span}\left\{\mathbf{x}_{1}, \ldots, \mathbf{x}_{k}\right\}$.

