## Sections 6.2 and 6.3

Orthogonal Projections

## Orthogonal Complements

## Definition

Let $W$ be a subspace of $\mathbf{R}^{n}$.
Its orthogonal complement, written $W^{\perp}$ (read " $W$ perp"), is the set of all vectors in $\mathbf{R}^{n}$ which are orthogonal (perpendicular) to $W$. We will focus on when $n=2$ and $n=3$.

## Pictures:

The orthogonal complement of a line in $\mathbf{R}^{2}$ is the perpendicular line.
[interactive]

The orthogonal complement of a line in $\mathbf{R}^{3}$ is the perpendicular plane.
[interactive]

The orthogonal complement of a plane in $\mathbf{R}^{3}$ is the perpendicular line.
[interactive]


## Orthogonal Complements

## Computation

Problem: if $W=\operatorname{Span}\left\{\left(\begin{array}{c}1 \\ 1 \\ -1\end{array}\right),\left(\begin{array}{l}1 \\ 1 \\ 1\end{array}\right)\right\}$, compute $W^{\perp}$.
Let $v_{1}=\left(\begin{array}{c}1 \\ 1 \\ -1\end{array}\right)$ and $v_{2}=\left(\begin{array}{l}1 \\ 1 \\ 1\end{array}\right)$.
A vector $u=\left(\begin{array}{l}x \\ y \\ z\end{array}\right)$ is in $W^{\perp}$ if and only if $u \perp v_{1}$ and $u \perp v_{2}$.
Why? If $u \perp v_{1}$ and $u \perp v_{2}$, then for any scalars $c_{1}$ and $c_{2}$ :

$$
u \cdot\left(c_{1} v_{1}+c_{2} v_{2}\right)=c_{1}\left(u \cdot v_{1}\right)+c_{2}\left(u \cdot v_{2}\right)=c_{1}(0)+c_{2}(0)=0
$$

Therefore, $u$ will be orthogonal to every vector in $\operatorname{Span}\left\{v_{1}, v_{2}\right\}$.

## Computation, continued

Now $u \perp v_{1}$ means $x+y-z=0$ and $u \perp v_{2}$ means $x+y+z=0$. This means $u=\left(\begin{array}{l}x \\ y \\ z\end{array}\right)$ satisfies

$$
\begin{aligned}
& x+y-z=0 \\
& x+y+z=0
\end{aligned}
$$

which means $u$ is in $\operatorname{Nul}\left(\begin{array}{ccc}1 & 1 & -1 \\ 1 & 1 & 1\end{array}\right)$. Therefore,

$$
\begin{aligned}
W^{\perp}=\operatorname{Nul}\left(\begin{array}{ccc}
1 & 1 & -1 \\
1 & 1 & 1
\end{array}\right)= & (\ldots \text { with work } \ldots)=\operatorname{Span}\left\{\left(\begin{array}{c}
-1 \\
1 \\
0
\end{array}\right)\right\} . \\
& {[\text { interactive }] }
\end{aligned}
$$

$$
\operatorname{Span}\left\{v_{1}, v_{2}, \ldots, v_{m}\right\}^{\perp}=\operatorname{Nul}\left(\begin{array}{c}
-v_{1}^{T}- \\
-v_{2}^{T}- \\
\vdots \\
-v_{m}^{T}-
\end{array}\right)
$$

## Best Approximation

Suppose you measure a data point $\times$ which you know for theoretical reasons must lie on a subspace $W$.


Due to measurement error, though, the measured $x$ is not actually in $W$. Best approximation: $y$ is the closest point to $x$ on $W$.

How do you know that $y$ is the closest point? The vector from $y$ to $x$ is orthogonal to $W$ : it is in the orthogonal complement $W^{\perp}$.

## Orthogonal Decomposition

## Theorem

Every vector $x$ in $\mathbf{R}^{n}$ can be written as

$$
x=x_{w}+x_{W \perp}
$$

for unique vectors $x_{W}$ in $W$ and $x_{W \perp}$ in $W^{\perp}$.
The equation $x=x_{W}+x_{W \perp}$ is called the orthogonal decomposition of $x$ (with respect to $W$ ).

The vector $x_{W}$ is the orthogonal projection of $x$ onto $W$.

The vector $x_{W}$ is the closest vector to $x$ on $W$. [interactive 1] [interactive 2]

## Orthogonal Decomposition

## Example

Let $W$ be the $x y$-plane in $\mathbf{R}^{3}$. Then $W^{\perp}$ is the $z$-axis.

$$
\begin{aligned}
& x=\left(\begin{array}{l}
2 \\
1 \\
3
\end{array}\right) \Longrightarrow x_{W}=\left(\begin{array}{l}
2 \\
1 \\
0
\end{array}\right) \quad x_{w \perp}=\left(\begin{array}{l}
0 \\
0 \\
3
\end{array}\right) . \\
& x=\left(\begin{array}{l}
a \\
b \\
c
\end{array}\right) \Longrightarrow x_{w}=\left(\begin{array}{l}
a \\
b \\
0
\end{array}\right)
\end{aligned}
$$

This is just decomposing a vector into a "horizontal" component (in the $x y$-plane) and a "vertical" component (on the $z$-axis).


## Orthogonal Decomposition

Problem: Given $x$ and $W$, how do you compute the decomposition $x=x_{W}+x_{W \perp}$ ?
Observation: It is enough to compute $x_{W}$, because $x_{W \perp}=x-x_{W}$.

## The $A^{T} A$ Trick to compute $x_{W}$ and $x_{W \perp}$

## Theorem (The $A^{T} A$ Trick)

Let $W$ be a subspace of $\mathbf{R}^{n}$, let $v_{1}, v_{2}, \ldots, v_{m}$ be a spanning set for $W$ (e.g., a basis), and let

$$
A=\left(\begin{array}{cccc}
\mid & \mid & & \mid \\
v_{1} & v_{2} & \cdots & v_{m} \\
\mid & \mid & & \mid
\end{array}\right) .
$$

Then for any $x$ in $\mathbf{R}^{n}$, the matrix equation

$$
\left.A^{T} A v=A^{T} x \quad \text { (in the unknown vector } v\right)
$$

is consistent, and $x_{W}=A v$ for any solution $v$.

Recipe for Computing $x=x_{W}+x_{W \perp}$

- Write $W$ as a column space of a matrix $A$.
- Find a solution $v$ of $A^{T} A v=A^{T} x$ (by row reducing).
- Then $x_{w}=A v$ and $x_{W \perp}=x-x_{W}$.


## The $A^{T} A$ Trick

## An Example

Problem: Let

$$
x=\left(\begin{array}{l}
1 \\
2 \\
3
\end{array}\right) \quad W=\left\{\left(\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3}
\end{array}\right) \text { in } \mathbf{R}^{3} \mid x_{1}-x_{2}+x_{3}=0\right\}
$$

Find $x_{W}, x_{W \perp}$, and the distance from $x$ to $W$.
The distance from $x$ to $W$ is $\left\|x_{W} \perp\right\|$, so we need to compute the orthogonal projection. First we need a basis for $W=\operatorname{Nul}\left(\begin{array}{lll}1 & -1 & 1\end{array}\right)$. This matrix is in RREF, so the parametric form of the solution set is

$$
\begin{aligned}
& x_{1}=x_{2}-x_{3} \\
& x_{2}=x_{2} \\
& x_{3}=
\end{aligned} \quad \begin{aligned}
& \text { PVF } \\
& x_{3}
\end{aligned} \quad\left(\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3}
\end{array}\right)=x_{2}\left(\begin{array}{l}
1 \\
1 \\
0
\end{array}\right)+x_{3}\left(\begin{array}{c}
-1 \\
0 \\
1
\end{array}\right) .
$$

Hence we can take a basis to be

$$
\left\{\left(\begin{array}{l}
1 \\
1 \\
0
\end{array}\right),\left(\begin{array}{c}
-1 \\
0 \\
1
\end{array}\right)\right\} \quad \text { пй } \quad A=\left(\begin{array}{cc}
1 & -1 \\
1 & 0 \\
0 & 1
\end{array}\right)
$$

## The $A^{T} A$ Trick

Example, Continued

Problem: Let

$$
x=\left(\begin{array}{l}
1 \\
2 \\
3
\end{array}\right) \quad W=\left\{\left(\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3}
\end{array}\right) \text { in } \mathbf{R}^{3} \mid x_{1}-x_{2}+x_{3}=0\right\}
$$

Compute the distance from $x$ to $W$.
We compute

$$
A^{T} A=\left(\begin{array}{cc}
2 & -1 \\
-1 & 2
\end{array}\right) \quad A^{T} x=\binom{3}{2}
$$

To solve $A^{T} A v=A^{T} x$ we form an augmented matrix and row reduce:

$$
\begin{gathered}
\left(\begin{array}{rr|r}
2 & -1 & 3 \\
-1 & 2 & 2
\end{array}\right) \quad \stackrel{\text { RREF }}{\text { mun }}\left(\begin{array}{lll}
1 & 0 & 8 / 3 \\
0 & 1 & 7 / 3
\end{array}\right) \quad \text { mn } \rightarrow \quad v=\frac{1}{3}\binom{8}{7} . \\
x_{w}=A v=\frac{1}{3}\left(\begin{array}{l}
1 \\
8 \\
7
\end{array}\right) \quad x_{w \perp}=x-x_{w}=\frac{1}{3}\left(\begin{array}{c}
2 \\
-2 \\
2
\end{array}\right) .
\end{gathered}
$$

The distance is $\left\|x_{W \perp}\right\|=\frac{1}{3} \sqrt{4+4+4} \approx 1.155$.

## The $A^{T} A$ Trick

## Proof

Theorem (The $A^{T} A$ Trick)
Let $W$ be a subspace of $\mathbf{R}^{n}$, let $v_{1}, v_{2}, \ldots, v_{m}$ be a spanning set for $W$ (e.g., a basis), and let

$$
A=\left(\begin{array}{cccc}
\mid & \mid & & \mid \\
v_{1} & v_{2} & \cdots & v_{m} \\
\mid & \mid & & \mid
\end{array}\right)
$$

Then for any $x$ in $\mathbf{R}^{n}$, the matrix equation

$$
A^{T} A v=A^{T} x \quad(\text { in the unknown vector } v)
$$

is consistent, and $x_{W}=A v$ for any solution $v$.
Proof: Let $x=x_{W}+x_{W \perp}$. Then $x_{W \perp}$ is in $W^{\perp}=\operatorname{Nul}\left(A^{T}\right)$, so $A^{T} x_{W \perp}=0$. Hence

$$
A^{T} x=A^{T}\left(x_{W}+x_{W \perp}\right)=A^{T} x_{W}+A^{T} x_{W \perp}=A^{T} x_{W} .
$$

Since $x_{W}$ is in $W=\operatorname{Span}\left\{v_{1}, v_{2}, \ldots, v_{m}\right\}$, we can write

$$
x_{W}=c_{1} v_{1}+c_{2} v_{2}+\cdots+c_{m} v_{m} .
$$

If $v=\left(c_{1}, c_{2}, \ldots, c_{m}\right)$ then $A v=x_{W}$, so

$$
A^{T} x=A^{T} x_{w}=A^{T} A v
$$

## Orthogonal Projection onto a Line

Problem: Let $L=\operatorname{Span}\{u\}$ be a line in $\mathbf{R}^{n}$ and let $x$ be a vector in $\mathbf{R}^{n}$.
Compute $x_{L}$.
We have to solve $u^{T} u v=u^{T} x$, where $u$ is an $n \times 1$ matrix. But $u^{T} u=u \cdot u$ and $u^{T} x=u \cdot x$ are scalars, so

$$
v=\frac{u \cdot x}{u \cdot u} \quad \Longrightarrow \quad x_{L}=u v=\frac{u \cdot x}{u \cdot u} u
$$

Projection onto a Line
The projection of $x$ onto a line $L=\operatorname{Span}\{u\}$ is

$$
x_{L}=\frac{u \cdot x}{u \cdot u} u \quad x_{L \perp}=x-x_{L} .
$$



## Orthogonal Projection onto a Line

## Example

Problem: Compute the orthogonal projection of $x=\binom{-6}{4}$ onto the line $L$ spanned by $u=\binom{3}{2}$, and find the distance from $u$ to $L$.

$$
x_{L}=\frac{x \cdot u}{u \cdot u} u=\frac{-18+8}{9+4}\binom{3}{2}=-\frac{10}{13}\binom{3}{2} \quad x_{L \perp}=x-x_{L}=\frac{1}{13}\binom{-48}{72} .
$$

The distance from $x$ to $L$ is

$$
\left\|x_{L \perp}\right\|=\frac{1}{13} \sqrt{48^{2}+72^{2}} \approx 6.656
$$


[interactive]

## Projection Matrix

## Method 1

Let $W$ be a subspace of $\mathbf{R}^{n}$ and let $T: \mathbf{R}^{n} \rightarrow \mathbf{R}^{n}$ be the orthogonal projection with respect to $W$.

How do you compute the standard matrix $A$ for $T$ ?
The same as any other linear transformation:

$$
A=\left(\begin{array}{llll}
T\left(e_{1}\right) & T\left(e_{2}\right) & \cdots & T\left(e_{n}\right)
\end{array}\right) .
$$

## Projection Matrix

## Method 1, Example 1

Problem: Let $L=\operatorname{Span}\left\{\binom{3}{2}\right\}$ and let $T: \mathbf{R}^{2} \rightarrow \mathbf{R}^{2}$ be the orthogonal projection onto $L$. Compute the matrix $A$ for $T$.

It's easy to compute orthogonal projection onto a line:

$$
\left.\begin{array}{l}
T\left(e_{1}\right)=\left(e_{1}\right)_{L}=\frac{u \cdot e_{1}}{u \cdot u} u=\frac{3}{13}\binom{3}{2} \\
T\left(e_{2}\right)=\left(e_{2}\right)_{L}=\frac{u \cdot e_{2}}{u \cdot u} u=\frac{2}{13}\binom{3}{2}
\end{array}\right\} \quad \Longrightarrow \quad A=\frac{1}{13}\left(\begin{array}{ll}
9 & 6 \\
6 & 4
\end{array}\right) .
$$

## Projection Matrix

## Method 1, Example 2

Problem: Let

$$
W=\left\{\left(\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3}
\end{array}\right) \text { in } \mathbf{R}^{3} \mid x_{1}-x_{2}+x_{3}=0\right\}
$$

and let $T: \mathbf{R}^{3} \rightarrow \mathbf{R}^{3}$ be orthogonal projection onto $W$. Compute the matrix $B$ for $T$.

We computed $W=\operatorname{Col} A$ for

$$
A=\left(\begin{array}{cc}
1 & -1 \\
1 & 0 \\
0 & 1
\end{array}\right)
$$

To compute $T\left(e_{i}\right)$ we have to solve the matrix equation $A^{T} A v=A^{T} e_{i}$. We have

$$
A^{T} A=\left(\begin{array}{cc}
2 & -1 \\
-1 & 2
\end{array}\right) \quad A^{T} e_{i}=\text { the } i \text { th column of } A^{T}=\left(\begin{array}{ccc}
1 & 1 & 0 \\
-1 & 0 & 1
\end{array}\right) .
$$

## Projection Matrix

## Another Example, Continued

Problem: Let

$$
W=\left\{\left(\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3}
\end{array}\right) \text { in } \mathbf{R}^{3} \mid x_{1}-x_{2}+x_{3}=0\right\}
$$

and let $T: \mathbf{R}^{3} \rightarrow \mathbf{R}^{3}$ be orthogonal projection onto $W$. Compute the matrix $B$ for $T$.

$$
\begin{aligned}
& \left(\begin{array}{rr|r}
2 & -1 & 1 \\
-1 & 2 & -1
\end{array}\right) \stackrel{\text { RREF }}{\sim m m}\left(\begin{array}{rr|r}
1 & 0 & 1 / 3 \\
0 & 1 & -1 / 3
\end{array}\right) \Longrightarrow T\left(e_{1}\right)=\frac{1}{3} A\binom{1}{-1}=\frac{1}{3}\left(\begin{array}{r}
2 \\
1 \\
-1
\end{array}\right) \\
& \left(\begin{array}{rr|r}
2 & -1 & 1 \\
-1 & 2 & 0
\end{array}\right) \stackrel{\text { RREF }}{\sim \sim \sim m} \rightarrow\left(\begin{array}{ll|l}
1 & 0 & 2 / 3 \\
0 & 1 & 1 / 3
\end{array}\right) \Longrightarrow T\left(e_{2}\right)=\frac{1}{3} A\binom{2}{1}=\frac{1}{3}\left(\begin{array}{l}
1 \\
2 \\
1
\end{array}\right) \\
& \left(\begin{array}{rr|r}
2 & -1 & 0 \\
-1 & 2 & 1
\end{array}\right) \stackrel{\text { RREF }}{\sim \sim \sim} \rightarrow\left(\begin{array}{ll|r}
1 & 0 & 1 / 3 \\
0 & 1 & 2 / 3
\end{array}\right) \Longrightarrow T\left(e_{2}\right)=\frac{1}{3} A\binom{1}{2}=\frac{1}{3}\left(\begin{array}{r}
-1 \\
1 \\
2
\end{array}\right) \\
& \Longrightarrow B=\frac{1}{3}\left(\begin{array}{rrr}
2 & 1 & -1 \\
1 & 2 & 1 \\
-1 & 1 & 2
\end{array}\right) .
\end{aligned}
$$

## Projection Matrix

## Method 2

## Theorem

Let $\left\{v_{1}, v_{2}, \ldots, v_{m}\right\}$ be a linearly independent set in $\mathbf{R}^{n}$, and let

$$
A=\left(\begin{array}{cccc}
\mid & \mid & & \mid \\
v_{1} & v_{2} & \cdots & v_{m} \\
\mid & \mid & & \mid
\end{array}\right) .
$$

Then the $m \times m$ matrix $A^{T} A$ is invertible.
Proof: We'll show $\operatorname{Nul}\left(A^{T} A\right)=\{0\}$. Suppose $A^{T} A v=0$. Then $A v$ is in $\operatorname{Nul}\left(A^{T}\right)=\operatorname{Col}(A)^{\perp}$. But $A v$ is in $\operatorname{Col}(A)$ as well, so $A v=0$, and hence $v=0$ because the columns of $A$ are linearly independent.

## Projection Matrix

## Method 2

## Theorem

Let $\left\{v_{1}, v_{2}, \ldots, v_{m}\right\}$ be a linearly independent set in $\mathbf{R}^{n}$, and let

$$
A=\left(\begin{array}{cccc}
\mid & \mid & & \mid \\
v_{1} & v_{2} & \cdots & v_{m} \\
\mid & \mid & & \mid
\end{array}\right)
$$

Then the $m \times m$ matrix $A^{T} A$ is invertible.
Let $W$ be a subspace of $\mathbf{R}^{n}$ and let $T: \mathbf{R}^{n} \rightarrow \mathbf{R}^{n}$ be the orthogonal projection with respect to $W$. Let $\left\{v_{1}, v_{2}, \ldots, v_{m}\right\}$ be a basis for $W$ and let $A$ be the matrix with columns $v_{1}, v_{2}, \ldots, v_{m}$. To compute $T(x)=x_{W}$ you solve $A^{T} A v=A x$; then $x_{w}=A v$.

$$
v=\left(A^{T} A\right)^{-1}\left(A^{T} x\right) \Longrightarrow T(x)=A v=\left[A\left(A^{T} A\right)^{-1} A^{T}\right] x
$$

If the columns of $A$ are a basis for $W$ then the matrix for $T$ is

$$
A\left(A^{T} A\right)^{-1} A^{T}
$$

## Projection Matrix

## Method 2, Example 1

Problem: Let $L=\operatorname{Span}\left\{\binom{3}{2}\right\}$ and let $T: \mathbf{R}^{2} \rightarrow \mathbf{R}^{2}$ be the orthogonal projection onto $L$. Compute the matrix $A$ for $T$.

The set $\left\{\binom{3}{2}\right\}$ is a basis for $L$, so

$$
A=u\left(u^{T} u\right)^{-1} u^{T}=\frac{1}{u \cdot u} u u^{T}=\frac{1}{13}\binom{3}{2}\left(\begin{array}{ll}
3 & 2
\end{array}\right)=\frac{1}{13}\left(\begin{array}{ll}
9 & 6 \\
6 & 4
\end{array}\right) .
$$

Matrix of Projection onto a Line
If $L=\operatorname{Span}\{u\}$ is a line in $\mathbf{R}^{n}$, then the matrix for projection onto $L$ is

$$
\frac{1}{u \cdot u} u u^{T} .
$$

## Projection Matrix

## Method 2, Example 2

Problem: Let

$$
W=\left\{\left(\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3}
\end{array}\right) \text { in } \mathbf{R}^{3} \mid x_{1}-x_{2}+x_{3}=0\right\}
$$

and let $T: \mathbf{R}^{3} \rightarrow \mathbf{R}^{3}$ be orthogonal projection onto $W$. Compute the matrix $B$ for $T$.

In the slides for the last lecture we computed $W=\operatorname{Col} A$ for

$$
A=\left(\begin{array}{cc}
1 & -1 \\
1 & 0 \\
0 & 1
\end{array}\right)
$$

The columns are linearly independent, so they form a basis for $W$. Hence

$$
\begin{aligned}
B=A\left(A^{T} A\right)^{-1} A^{T}=A\left(\begin{array}{cc}
2 & -1 \\
-1 & 2
\end{array}\right)^{-1} A^{T} & =\frac{1}{3} A\left(\begin{array}{cc}
2 & 1 \\
1 & 2
\end{array}\right) A^{T} \\
& =\frac{1}{3}\left(\begin{array}{ccc}
2 & 1 & -1 \\
1 & 2 & 1 \\
-1 & 1 & 2
\end{array}\right)
\end{aligned}
$$

Let $W$ be a subspace of $\mathbf{R}^{n}$ which is neither the zero subspace nor all of $\mathbf{R}^{n}$.
Poll
Let $A$ be the matrix for $\operatorname{proj}_{W}$. What is/are the eigenvalue(s) of $A$ ?
A. 0
B. 1 C. -1
D. 0,1
E. $1,-1$
F. $0,-1$
G. $-1,0,1$

The 1-eigenspace is $W$.
The 0 -eigenspace is $W^{\perp}$.
We have $\operatorname{dim} W+\operatorname{dim} W^{\perp}=n$, so that gives $n$ linearly independent eigenvectors already.

So the answer is $D$.

## Projection Matrix

## Facts

## Theorem

Let $W$ be an $m$-dimensional subspace of $\mathbf{R}^{n}$, let $T: \mathbf{R}^{n} \rightarrow W$ be the projection, and let $A$ be the matrix for $T$. Then:

1. $\operatorname{Col} A=W$, which is the 1 -eigenspace.
2. Nul $A=W^{\perp}$, which is the 0-eigenspace.
3. $A^{2}=A$.
4. $A$ is similar to the diagonal matrix with $m$ ones and $n-m$ zeros on the diagonal.

Proof of 4: Let $v_{1}, v_{2}, \ldots, v_{m}$ be a basis for $W$, and let $v_{m+1}, v_{m+2}, \ldots, v_{n}$ be a basis for $W^{\perp}$. These are (linearly independent) eigenvectors with eigenvalues 1 and 0 , respectively, and they form a basis for $\mathbf{R}^{n}$ because there are $n$ of them.

Example: If $W$ is a plane in $\mathbf{R}^{3}$, then $A$ is similar to projection onto the $x y$-plane:

$$
\left(\begin{array}{lll}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 0
\end{array}\right)
$$

