

## Math 415 Lecture 24

Sec 5.5 (Fri March 14)

Let  $W \subset V$  be a finite dimensional subspace of a vector space  $V$ .

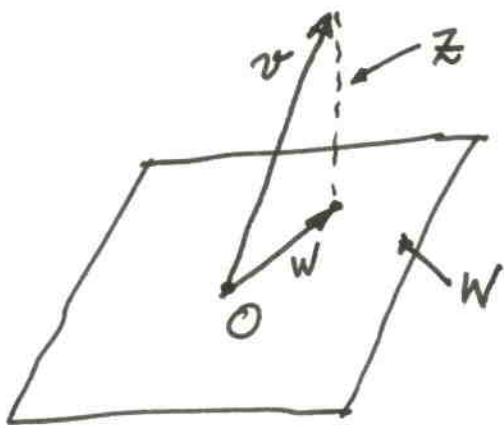
Def'n A vector  $z \in V$  is orthogonal to  $W$  if  $\langle z, w \rangle = 0$  for every vector  $w$  in  $W$ .

Def'n The orthogonal projection of  $v \in V$  onto  $W$  is the element  $w$  in  $W$  for which  $z = v - w$  is orthog to  $W$ .

Observations: If  $W$  has basis  $\{w_1, \dots, w_n\}$ , then  $z$  is orthog to  $W$  iff  $z$  is orthog to each basis vector.

$$w = c_1 w_1 + \dots + c_n w_n$$

so  $0 = \langle z, w \rangle = c_1 \langle z, w_1 \rangle + \dots + c_n \langle z, w_n \rangle$  for all  $c_i$  is  
iff  $\langle z, w_i \rangle = 0, i = 1, \dots, n$ .



Theorem Let  $\{u_1, \dots, u_n\}$  be an orthonormal basis of  $W$ .  
Then the orthog projection of  $v$  onto  $W$  is

$$w = c_1 u_1 + \dots + c_n u_n \quad \text{where } c_i = \langle v, u_i \rangle$$

$$\text{i.e. } w = \langle v, u_1 \rangle u_1 + \dots + \langle v, u_n \rangle u_n$$

if the basis  $\{v_1, \dots, v_n\}$  is just orthogonal, then

$$w = \frac{\langle v, v_1 \rangle}{\|v_1\|^2} v_1 + \dots + \frac{\langle v, v_n \rangle}{\|v_n\|^2} v_n.$$

PS Let orthog proj be

$$w = c_1 u_1 + \dots + c_n u_n.$$

$$\begin{aligned} \text{Then } 0 &= \langle z, u_i \rangle = \langle v, u_i \rangle - \langle c_1 u_1 + \dots + c_n u_n, u_i \rangle \\ &= \langle v, u_i \rangle - c_1 \langle u_1, u_i \rangle - \dots - c_n \langle u_n, u_i \rangle \\ &= \langle v, u_i \rangle - c_i \end{aligned}$$

only the  $i$ -th one is non-zero and equals 1

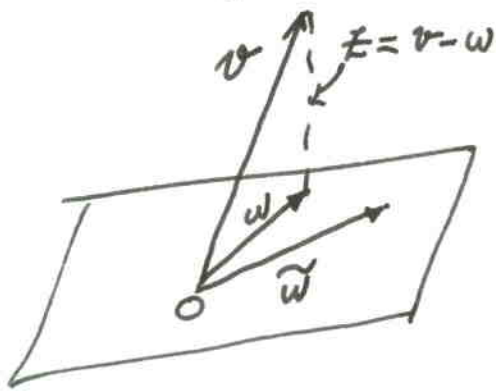
Example. Let  $W = \text{span}\{v_1, v_2\} \subset \mathbb{R}^3$ ,

$$v_1 = \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix}, v_2 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \quad \text{with Euclidean inner prod.}$$

Then, since orthogonal,  $v = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$

$$w = \frac{\langle v, v_1 \rangle}{\|v_1\|^2} v_1 + \frac{\langle v, v_2 \rangle}{\|v_2\|^2} v_2 = \frac{1}{6} \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix} + \frac{1}{3} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} \frac{1}{2} \\ 0 \\ \frac{1}{2} \end{pmatrix}$$

Theorem Given  $v \in V$ , the closest point or least squares minimizer  $w \in W$  to  $v$  is the same as the orthogonal projection of  $v$  onto  $W$ .



$$\begin{aligned} \|v - \tilde{w}\|^2 &= \|z + (w - \tilde{w})\|^2 \\ &= \|w - \tilde{w}\|^2 + 2\langle w - \tilde{w}, z \rangle + \|z\|^2 \end{aligned}$$

Why?  
no

So  $\|v - \tilde{w}\|^2$  is minimized when  $\tilde{w} = w$ . Done.

Example Find the closest point in the span of  $v_1, v_2$  to  $v = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$ .

$$\begin{aligned} p(x) = p(x_1, x_2) &= \left\| \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \right\|^2 \\ &= \text{a quadratic form} \\ &= x^T K x - 2x^T f + c \end{aligned}$$

So solve  $Kx = f$  for the minimizer  $x^*$   
(normal eqns)

Answer (from before)  $w = \begin{pmatrix} \frac{1}{2} \\ 0 \\ \frac{1}{2} \end{pmatrix}$ .

# Data Fitting Again!

$$A^T A x = A^T y$$

$$\text{Fit } y = \alpha + \beta t$$

$$\begin{pmatrix} 1 & \bar{t} \\ \bar{t} & \bar{t}^2 \end{pmatrix} \begin{pmatrix} \alpha \\ \beta \end{pmatrix} = \begin{pmatrix} \bar{y} \\ \bar{t}y \end{pmatrix}$$

↑ invert, etc.

$$\text{Fit } y = p(t) = \alpha_0 + \alpha_1 t + \dots + \alpha_n t^n$$

$$\Rightarrow \alpha_0 \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} + \alpha_1 \begin{pmatrix} t_1 \\ t_2 \\ \vdots \\ t_m \end{pmatrix} + \dots + \alpha_n \begin{pmatrix} t_1^n \\ t_2^n \\ \vdots \\ t_m^n \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix}$$

Thus we have a closest point problem!

Things would be easy if  $\{t_0, t_1, \dots, t_n\}$  were replaced by an orthog set; say  $\{q_0, q_1, \dots, q_n\}$ . These are

$$\text{Use } \langle u, v \rangle = \frac{1}{m} \sum_{i=1}^m u_i v_i = \overline{uv}, \quad \langle \underline{t}_k, \underline{t}_l \rangle = \frac{1}{m} \sum_{i=1}^m t_i^k t_i^l = \overline{t^{k+l}}$$

$$q_0(t) = 1 \quad q_0 = \underline{t}_0, \quad \|q_0\|^2 = 1$$

$$q_1(t) = t \quad q_1 = \underline{t}_1 - \frac{\langle \underline{t}_1, \underline{t}_0 \rangle}{\|q_0\|^2} q_0 = \underline{t}_1, \quad \|q_1\|^2 = \bar{t}^2$$

$$q_2(t) = t^2 - \bar{t}^2 \quad q_2 = \underline{t}_2 - \frac{\langle \underline{t}_2, \underline{q}_0 \rangle}{\|q_0\|^2} q_0 - \frac{\langle \underline{t}_2, \underline{q}_1 \rangle}{\|q_1\|^2} q_1$$

$$q_3(t) = t^3 - \frac{\bar{t}^4}{\bar{t}^2} t = \underline{t}_3 - \bar{t}^2 \underline{t}_1, \quad \|q_2\|^2 = \bar{t}^4 - (\bar{t}^2)^2$$

$$q_3 = \underline{t}_3 - \frac{\bar{t}^4}{\bar{t}^2} \underline{t}_1, \quad \|q_3\|^2 = \bar{t}^6 - \frac{(\bar{t}^4)^2}{\bar{t}^2}, \dots$$

Assume the  $t_i$ 's are equally spaced and if  $t_i$  is there, so is  $-t_i$

Then  $\bar{t} = 0$  i.e.

-3
-2
-1
0
1
2
3

Then the least squares approx is

$$p(t) = a_0 f_0(t) + a_1 f_1(t) + \dots + a_n f_n(t)$$

where

$$a_k = \frac{\langle f_k, y \rangle}{\|f_k\|^2} = \frac{\overline{f_k y}}{f_k^2}, \quad k=1, 2, \dots, n.$$

Can carry this out to any degree without changing previously computed coeffs.

Review Example 5.42.