

$(V, \langle \cdot, \cdot \rangle)$  an inner product space over  $F = \mathbb{R}$  or  $\mathbb{C}$ .

$W \subseteq V$  fin-dim'l subspace  $\Rightarrow V = W \oplus W^\perp$ , so every  $y \in V$  has a unique expression of the form  $y = u + z$ ,  $u \in W$ ,  $z \in W^\perp$ .

If  $\{u_1, \dots, u_k\}$  is an orthonormal basis for  $W$ , then

$$u = \sum_{i=1}^k \langle y, u_i \rangle u_i$$

and  $u$  is the point in  $W$  closest to  $y$ .

e.g. In  $\mathbb{R}^3$ , find the line closest to the three points  $(0, 0, 1)$ ,  $(1, 0, 0)$ ,  $(2, 0, 0)$ . For  $y = ax + b$

to pass through the pts, we would need

$$\begin{pmatrix} 0 & 1 \\ 1 & 1 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

$$A \quad x \quad y$$



There is no  $x$  satisfying this eq'n, so instead we look for  $x = (a, b)$  minimizing the error  $e := \|y - Ax\|$ .

Define  $W := \text{im}(A)$ . Then to minimize  $e$ , we need to compute the projection of  $y = (0, 0, 0)$  onto  $W$ . For this, we need an orthonormal basis of  $W$ . Begin w/ columns of  $A$  & apply Gram-Schmidt:  $v_1 = (0, 1, 2)$

$$\begin{aligned} v_2 &= (1, 1, 1) - \frac{(1, 1, 1) \cdot (0, 1, 2)}{(0, 1, 2) \cdot (0, 1, 2)} (0, 1, 2) \\ &= (1, 1, 1) - \frac{3}{5} (0, 1, 2) \\ &= \left(1, \frac{2}{5}, -\frac{1}{5}\right). \end{aligned}$$

Then  $u_1 = \frac{v_1}{\|v_1\|} = \frac{1}{\sqrt{5}} (0, 1, 2)$

$u_2 = \frac{v_2}{\|v_2\|} = \frac{\sqrt{5}}{6} \left(1, \frac{2}{5}, -\frac{1}{5}\right)$  form an orthonormal basis of  $W$ .

The projection of  $y$  onto  $W$  is

$$\begin{aligned} u &= \langle y, u_1 \rangle u_1 + \langle y, u_2 \rangle u_2 \\ &= (6, 0, 0) \cdot \frac{1}{\sqrt{5}} (0, 1, 2) u_1 + (6, 0, 0) \cdot \sqrt{\frac{5}{6}} \left(1, \frac{2}{5}, -\frac{1}{5}\right) u_2 \\ &= 6 \sqrt{\frac{5}{6}} u_2 \\ &= 6 \sqrt{\frac{5}{6}} \sqrt{\frac{5}{6}} \left(1, \frac{2}{5}, -\frac{1}{5}\right) \\ &= (5, 2, -1). \end{aligned}$$

Since  $(5, 2, -1) \in W = \text{im } A$ , we can solve

$$\begin{pmatrix} 0 & 1 \\ 1 & 1 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} 5 \\ 2 \\ -1 \end{pmatrix} \quad \text{and get } a = -3, b = 5.$$

So the line of best fit is  $\boxed{y = -3x + 5}$ .

Adjoint (w/o proof)

If  $f \in \mathcal{L}(V)$ ,  $\exists! f^t \in \mathcal{L}(V)$ , the adjoint of  $f$  satisfying

$$\langle f(x), y \rangle = \langle x, f^t(y) \rangle$$

$\forall x, y \in V$ . If  $f$  is ~~rep~~ represented by a matrix  $A$  wrt some ordered basis, then  $f^t$  is rep'd by  $A^t$  (i.e.  $A^t$ ), the conjugate transpose of  $A$ :  $\langle Ax, y \rangle = \langle x, A^t y \rangle$ .

Utility: given  $A \in M_{m \times n}(F)$  and  $y \in F^m$ , want to compute  $x \in F^n$  minimizing  $\|y - Ax\|$ .

Lemma,  $\text{rank}(A^t A) = \text{rank}(A)$ .

Pf Note  $A^t A \in M_{n \times n}(F)$ . By rank-nullity,

$$\text{rank}(A) = n - \dim(\ker A)$$

$$\text{rank}(A^t A) = n - \dim(\ker A^t A)$$

so it suffices to show  $\dim \ker A = \dim \ker A^t A$ .

If  $x \in \ker A$ , then  $Ax = 0 \Rightarrow A^T Ax = A^T 0 = 0$  so  $x \in \ker A^T A$ .

Thus  $\ker A \subseteq \ker A^T A$ .

If  $x \in \ker A^T A$ , then  $A^T Ax = 0 \Rightarrow 0 = \langle x, 0 \rangle = \langle x, A^T Ax \rangle = \langle Ax, Ax \rangle$ .

By pos def,  $Ax = 0$ , so  $x \in \ker A$ , proving the opposite inclusion.  $\square$

Cor If  $A \in M_{m \times n}(F)$  has rank  $n$ , then  $A^T A$  is invertible.  $\square$

Prop Given  $A \in M_{m \times n}(F)$  and  $y \in F^m$ , there exists  $x_0 \in F^n$  such that  $\|y - Ax_0\| \leq \|y - Ax\| \quad \forall x \in F^n$ . For this  $x_0$ , we have  $A^T A x_0 = A^T y$ . If  $\text{rank}(A) = n$ , then  $x_0 = (A^T A)^{-1} A^T y$ .

Pf Want  $Ax_0$  closest to  $y$  so looking for the proj'n of  $y$  onto  $\text{im}(A) \subseteq F^m$ . This proves existence. Now want to find  $x_0 \in F^n$

s.t.  $y = Ax_0 + z$  with  $z = y - Ax_0 \in (\text{im } A)^\perp$ .

$$y - Ax_0 \in (\text{im } A)^\perp \iff \langle Ax, y - Ax_0 \rangle = 0 \quad \forall x \in F^n$$

$$\iff \langle x, A^T(y - Ax_0) \rangle = 0 \quad \forall x \in F^n$$

$$\iff A^T(y - Ax_0) = 0$$

$$\iff A^T A x_0 = A^T y. \quad \square$$

Ex.  $A = \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix}$ ,  $y = \begin{pmatrix} 6 \\ 0 \end{pmatrix}$ ,  $\text{rank } A = 2$ .

$$A^T A = \begin{pmatrix} 0 & 1 & 2 \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix} = \begin{pmatrix} 5 & 3 \\ 3 & 3 \end{pmatrix}, \quad (A^T A)^{-1} = \frac{1}{6} \begin{pmatrix} 3 & -3 \\ -3 & 5 \end{pmatrix}$$

$$\Rightarrow x_0 = (A^T A)^{-1} A^T y = \frac{1}{6} \begin{pmatrix} 3 & -3 \\ -3 & 5 \end{pmatrix} \begin{pmatrix} 0 & 1 & 2 \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} 6 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} -3 \\ 5 \end{pmatrix} \quad \checkmark$$

Remark This method avoids computing an orthonormal basis (as before).

Least Squares Minimizing  $\|y - Ax\|$  is called the method of least squares. Imagine that at time  $t_i$  we are measuring a quantity  $y_i \in F$ ,  $i = 1, \dots, n$ . Want the "best" line  $y = ax + b$ . Then we want  $a, b \in F$  s.t.  $y_i = at_i + b$  for each  $i$ , i.e.

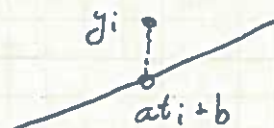
$$\begin{pmatrix} t_1 & 1 \\ \vdots & \vdots \\ t_n & 1 \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$$

$$A \quad x \quad y$$

Seek to minimize error  $\|y - Ax\|$ , or equivalently  $\|y - Ax\|^2$ . But

$$\|y - Ax\|^2 = \sum_{i=1}^n (y_i - (at_i + b))^2.$$

The terms  $y_i - (at_i + b)$  are vertical distances



and we are minimizing their squares.