

## 1 Review: Minimisation

Recall that  $V = W \oplus W^\perp$ .

Therefore, if  $x \in V$ , then  $x = x_W + x_{W^\perp}$ , where  $x_W$  is the vector in  $W$  closest to  $x \in V$ , the unique vector in  $W$  such that  $x - x_W \in W^\perp$ .

## 2 Adjoints

### Theorem 2.1

Let  $V, W$  be finite dimensional inner product spaces. Let  $T \in \text{Hom}(V, W)$ .

Then there exists a unique homomorphism  $T^* \in \text{Hom}(W, V)$  such that  $\langle T(x), y \rangle_W = \langle x, T^*y \rangle_V$  for all  $x \in V$  and  $y \in W$ .

*Proof.* Fix  $y \in W$ . Note that the function  $f_y : W \rightarrow \mathbb{F}$ , where  $x \mapsto \langle x, y \rangle_W$  is linear.

### Lemma 2.2

If  $f \in \text{Hom}(W, \mathbb{F})$ , then  $f = f_y$  for a unique  $y \in W$ , i.e.  $f(x) = \langle x, y \rangle_W$ .

Fix  $y \in W$ .

Consider  $f : V \rightarrow \mathbb{F}$ , with  $x \mapsto \langle Tx, y \rangle_W$ .

This is linear:  $f$  is in the composition  $f_y \circ T$  of two linear functions.

By Lemma 2.2, there exists a unique vector  $T^*y \in V$  such that  $f(x) = \langle x, T^*y \rangle_V$  for all  $x \in V$ . Thus, we define a function  $T^* : W \rightarrow V$  such that Theorem 2.1 holds, and thus  $f(x) = \langle Tx, y \rangle$ .

**Claim.**  $T^*$  is unique.

Fix  $y \in W$ . Then  $T^*y \in V$  is unique by the uniqueness of a vector given by Lemma 2.2.

**Claim.**  $T^*$  is linear.

Observe the following:

$$\langle x, T^*(cy_1 + y_2) \rangle_V = \langle Tx, cy_1 + y_2 \rangle_W \quad (1)$$

$$= c\langle Tx, y_1 \rangle_W + \langle Tx, y_2 \rangle_W \quad (2)$$

$$= c\langle x, T^*y_1 \rangle_V + \langle x, T^*y_2 \rangle_V \quad (3)$$

$$= \langle x, cT^*y_1 + T^*y_2 \rangle \quad (4)$$

Therefore,  $T^*(cy_1 + y_2) = cT^*y_1 + T^*y_2$

□

**Remark 2.3.**  $\langle y, Tx \rangle_W = \langle T^*y, x \rangle_V$

**Remark 2.4.** If  $V$  is not finite-dimensional, then  $T^*$  may not exist.

### Theorem 2.5

Let  $\beta$  be an orthonormal basis of  $V$ , a finite-dimensional vector space.

Let  $\gamma$  be an orthonormal basis of  $W$ , a finite-dimensional vector space.

Then  $[T^*]_\gamma^\beta = ([T]_\beta^\gamma)^*$ .

*Proof.* Let  $A = [T]_\beta^\gamma$  and  $B = [T^*]_\gamma^\beta$ , where  $\beta = (v_1, \dots, v_n)$  and  $\gamma = (w_1, \dots, w_m)$ .

Therefore,

$$B_{ij} = \langle T^* w_j, v_i \rangle_V = \langle w_j, T v_i \rangle = \overline{\langle T v_i, w_j \rangle} = \overline{A_{ji}}.$$

Therefore,  $B = A^*$ . □

**Theorem 2.6** a) If  $T \in \text{Hom}(V, W)$ ,  $U \in \text{Hom}(V, W)$ , and  $c \in \mathbb{F}$ , then  $(cT + U)^* = \bar{c}T^* + U^*$ .

b) If  $T : V \rightarrow W$  and  $U : W \rightarrow Z$ , where  $V, W, Z$  are finite-dimensional vector spaces, then  $(UT)^* = T^*U^*$ .

c)  $T^{**} = T$

d)  $I^* = I$ , if the inner product is the same.

*Proof.* 2.6, b) and c) are left as exercises.

a) can be deduced as follows, for all  $x \in V$  and  $y \in Z$ :

$$\langle x, (TU)^* y \rangle = \langle TUx, y \rangle_Z = \langle Ux, T^* y \rangle_W = \langle x, U^* T^* y \rangle_V$$

□

### Corollary 2.7

If  $A \in M_{m \times n}(\mathbb{F})$ , then  $L_A : \mathbb{F}^n \rightarrow \mathbb{F}^m$  and  $(L_A)^* = L_{A^*}$ , where standard inner products are used.

Moreover,

a)  $(cA + B)^* = \bar{c}A^* + B^*$

b)  $(AB)^* = B^*A^*$

c)  $A^{**} = A$

*Proof.* Let  $L_A : \mathbb{F}^n \rightarrow \mathbb{F}^m$ , and let  $\beta, \gamma$  be standard bases for  $\mathbb{F}^n, \mathbb{F}^m$  respectively.

Therefore,  $[L_A^*]_\gamma^\beta = ([L_A]_\beta^\gamma)^* = A^* = [L_{A^*}]_\gamma^\beta$ . Therefore,  $L_A^* = L_{A^*}$ .

Then we can deduce (a)-(d) from Theorem 2.6. □

### 3 Least Square Approximation

Let  $A \in M_{m \times n}(\mathbb{F})$ ,  $y \in \mathbb{F}^m$ .

**Problem.** Devise a method to find  $x_0 \in \mathbb{F}^n$  such that  $\|Ax_0 - y\| \leq \|Ax - y\|$  for all  $x \in \mathbb{F}^n$ .

#### Lemma 3.1

$$\langle Ax, y \rangle_{\mathbb{F}^m} = \langle x, A^*y \rangle_{\mathbb{F}^n}.$$

*Proof.* Apply Corollary 2.7. □

#### Lemma 3.2

$$\text{rank } A^*A = \text{rank } A$$

*Proof.* It is enough to show that  $\ker A^*A = \ker A$ .

If  $Ax = 0$ , then  $A^*Ax = 0$ , and hence  $\ker A \subseteq \ker A^*A$ .

If  $A^*Ax = 0$ , then  $\langle x, A^*Ax \rangle = \langle Ax, Ax \rangle = \|Ax\|^2$ . Therefore,  $Ax = 0$ , and hence  $\ker A^*A \subseteq \ker A$ , and thus  $\ker A^*A = \ker A$ . □

#### Theorem 3.3

- a)  $\exists x_0 \in \mathbb{F}^n$  such that  $\|Ax_0 - y\| \leq \|Ax - y\|$  for all  $x \in \mathbb{F}^n$ .
- b)  $x_0$  satisfies (a)  $\Leftrightarrow A^*Ax_0 = A^*y$ .
- c) If  $\text{rank } A = n$ , then  $A^*A$  is invertible, so there's a unique  $x_0$  in (a).

*Proof.*

- a) Let  $W = \text{Im}(A)$ . We know that there exists  $w_0$  in any  $W$  such that  $\|w_0 - y\| \leq \|w - y\|$  for all  $W \in W$ .

Write  $w_0 = Ax_0$  for some  $x_0$ . Therefore,  $\|Ax_0 - y\| \leq \|Ax - y\|$  for all  $x \in \mathbb{F}^n$ .

- b) We also know that  $Ax_0 \in W$  is the closest vector to  $y$  if and only if  $y - Ax_0 \in W^\perp$ .

Therefore, for any  $x \in \mathbb{F}^n$  we have that  $\langle Ax, y - Ax_0 \rangle = 0$ . Equivalently,  $\langle x, A^*(y - Ax_0) \rangle = 0$  for any  $x$ . Thus,  $A^*(y - Ax_0) = 0$ , which means that  $A^*y = A^*Ax_0$ .

- c) If  $\text{rank } A = n$ , then Lemma 3.2 shows that  $\text{rank } A^*A = n$ .

Therefore,  $A^*A$  is invertible.

Hence,  $x_0 = (A^*A)^{-1}A^*y$ . □

**Remark 3.4.** Note that a) shows that  $A^*Ax_0 = A^*y$  has a solution  $x_0$  for any  $y$ .

Therefore,  $\text{Im}(A^*A) = \text{Im } A^*$ .

Suppose now some data points  $(t_i, y_i)$  are given for  $i \in [1, n] \cap \mathbb{N}$ .

Suppose also some line is drawn in the plane of the scatterplot representing the data.

One way to measure how well the line  $y = ax + b$  approximates the data is to compute the sum of the squares of the differences between the data points and the corresponding values given by drawing perpendiculars to the line:

$$\delta = \sum_{i=1}^n (y_i - at_i - b)^2$$

This method is called the least square approximation.

Let  $A = \begin{pmatrix} t_1 & y_1 \\ t_2 & y_2 \\ \vdots & \vdots \\ t_n & y_n \end{pmatrix}$ ,  $x = \begin{pmatrix} a \\ b \end{pmatrix}$  and  $y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$ .

If  $t_1, \dots, t_n$  contain at least 2 different values,  $\text{rank } A \geq 2$ , so Theorem 3.3 implies there exists the unique best approximation.

## 4 Normal and Self-Adjoint Operators

Let  $V$  be a finite-dimensional inner product space.

**Question.** When does  $T \in \text{Hom}(V, V)$  have an orthonormal basis of eigenvectors?

**Answer.** If  $V$  has such a basis  $\beta$ , then  $[T]_\beta = \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$  for  $\lambda_i \in \mathbb{F}$ .

By Theorem 2.5,

$$\begin{pmatrix} \overline{\lambda_1} & & \\ & \ddots & \\ & & \overline{\lambda_n} \end{pmatrix}, \text{ since } \beta \text{ is orthonormal.}$$

Therefore,  $[TT^*]_\beta = [T^*T]_\beta$ , and thus  $TT^* = T^*T$

**Definition 4.1.**  $T \in \text{Hom}(V, V)$  is **normal** if  $TT^* = T^*T$  and **self-adjoint** if  $T^* = T$ .

Similarly,  $A \in M_{n \times n}(\mathbb{F})$  can be defined to be normal or self-adjoint.

### Theorem 4.2

If  $\mathbb{F} = \mathbb{C}$ ,  $V$  has an orthonormal basis of eigenvectors if and only if  $T$  is normal.

If  $\mathbb{F} = \mathbb{R}$ ,  $V$  has an orthonormal basis of eigenvectors if and only if  $T$  is self-adjoint.