

7.8 An Application to Least Squares

Eg. *Given points $(1, 1)$, $(3, 2)$, $(4, 3)$ and functions 1 , x . Consider $f(x) = a_0 + a_1x$.*

We want a line $f(x)$ passing through all the points.

But the system
$$\begin{cases} a_0 + a_1 = 1 \\ a_0 + 3a_1 = 2 \\ a_0 + 4a_1 = 3 \end{cases}$$
 has no solution.

Still, there exists a “best-fitting” line for the points.

Eg. $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ $1, x, x^2, \dots, x^m$

We want to determine a “best-fitting” polynomial of the form

$$f(x) = a_0 + a_1x + a_2x^2 + \dots + a_mx^m$$

for the points.

Eg. We may consider more general functions than polynomials.

$$(-1, 0), (0, 1), (1, 4) \quad x, 2^x$$

We want to determine a “best-fitting” function of the form

$$f(x) = a_0x + a_12^x$$

for the points.

Suppose that

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$

are given and suppose that $m + 1$ functions

$$f_0(x), f_1(x), \dots, f_m(x)$$

are specified.

Consider $f(x) = a_0 f_0(x) + a_1 f_1(x) + \dots + a_m f_m(x)$ ($a_i \in \mathbf{R}$).

Problem (in naive form) : Determine a_i 's so that $f(x)$ may be the “best-fitting” function for the points $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$.

$$\text{Let } Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \text{ and } M = \begin{bmatrix} f_0(x_1) & f_1(x_1) & \cdots & f_m(x_1) \\ f_0(x_2) & f_1(x_2) & \cdots & f_m(x_2) \\ \vdots & \vdots & & \vdots \\ f_0(x_n) & f_1(x_n) & \cdots & f_m(x_n) \end{bmatrix}.$$

$$\begin{bmatrix} f(x_1) \\ f(x_2) \\ \vdots \\ f(x_n) \end{bmatrix} = \begin{bmatrix} a_0 f_0(x_1) + a_1 f_1(x_1) + \cdots + a_m f_m(x_1) \\ a_0 f_0(x_2) + a_1 f_1(x_2) + \cdots + a_m f_m(x_2) \\ \vdots \\ a_0 f_0(x_n) + a_1 f_1(x_n) + \cdots + a_m f_m(x_n) \end{bmatrix} = M \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_m \end{bmatrix}$$

$$\begin{bmatrix} y_1 - f(x_1) \\ y_2 - f(x_2) \\ \vdots \\ y_n - f(x_n) \end{bmatrix} = Y - M \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_m \end{bmatrix}.$$

Problem : Choose $Z = [a_0 \ a_1 \ \cdots \ a_m]^T$ such that

$$\|Y - MZ\|^2 = [y_1 - f(x_1)]^2 + [y_2 - f(x_2)]^2 + \cdots + [y_n - f(x_n)]^2$$

is as small as possible.

A function satisfying the above condition is called a **least squares approximating function** of the form $f(x) = a_0 f_0(x) + a_1 f_1(x) + \cdots + a_m f_m(x)$.

Write $U = \{MX \mid X \in \mathbf{R}^m\}$. Then MZ is the closest vector in U to the point Y , so $MZ = \text{proj}_U(Y)$. Thus we have for all $X \in \mathbf{R}^m$

$$\begin{aligned} 0 &= (MX) \cdot (Y - MZ) = (MX)^T (Y - MZ) \\ &= X^T M^T (Y - MZ) = X \cdot [M^T (Y - MZ)]. \end{aligned}$$

Since $M^T(Y - MZ)$ is orthogonal to every vector in \mathbf{R}^m , $M^T(Y - MZ) = O$ and so

$$M^T MZ = M^T Y.$$

Thm. If $Z = [a_0 \ a_1 \ \cdots \ a_m]^T$ is a solution of

$$M^T MZ = M^T Y,$$

then

$$f(x) = a_0 f_0(x) + a_1 f_1(x) + \cdots + a_m f_m(x)$$

is a least squares approximating function of the given form.

Eg. Given $(1, 1), (3, 2), (4, 3)$, find the least squares approximating function of the form $a_0 + a_1x$.

Solution. $f_0(x) = 1, f_1(x) = x$.

$$M = \begin{bmatrix} f_0(x_1) & f_1(x_1) \\ f_0(x_2) & f_1(x_2) \\ f_0(x_3) & f_1(x_3) \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 4 \end{bmatrix}$$

$$M^T M = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 3 & 4 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 4 \end{bmatrix} = \begin{bmatrix} 3 & 8 \\ 8 & 26 \end{bmatrix}, \quad M^T Y = \begin{bmatrix} 6 \\ 19 \end{bmatrix}$$

$$M^T M Z = M^T Y, \quad \begin{bmatrix} 3 & 8 \\ 8 & 26 \end{bmatrix} Z = \begin{bmatrix} 6 \\ 19 \end{bmatrix}, \quad Z = \frac{1}{14} \begin{bmatrix} 4 \\ 9 \end{bmatrix}$$

Now we have

$$f(x) = \frac{2}{7} + \frac{9}{14}x.$$

Observe that $f(x)$ passes through $(1, \frac{13}{14})$, $(3, \frac{31}{14})$, $(4, \frac{40}{14})$.

Eg. Given $(-1, 0), (0, 1), (1, 4)$, find the least squares approximating function of the form $a_0x + a_12^x$.

Solution. $f_0(x) = x, f_1(x) = 2^x$.

$$M = \begin{bmatrix} f_0(x_1) & f_1(x_1) \\ f_0(x_2) & f_1(x_2) \\ f_0(x_3) & f_1(x_3) \end{bmatrix} = \begin{bmatrix} -1 & \frac{1}{2} \\ 0 & 1 \\ 1 & 2 \end{bmatrix}$$

$$M^T M = \begin{bmatrix} 2 & \frac{3}{2} \\ \frac{3}{2} & \frac{21}{4} \end{bmatrix}, \quad M^T Y = \begin{bmatrix} 4 \\ 9 \end{bmatrix}$$

$$M^T M Z = M^T Y, \quad Z = \frac{1}{11} \begin{bmatrix} 10 \\ 16 \end{bmatrix}$$

$$f(x) = \frac{10}{11}x + \frac{16}{11}2^x.$$

5.4 Linear Transformation

Def. A function $T : \mathbf{F}^n \rightarrow \mathbf{F}^m$ is called a *linear transformation* if it satisfies, for all X and Y in \mathbf{F}^n and for all $a \in \mathbf{F}$,

$$T(X + Y) = T(X) + T(Y), \quad T(aX) = aT(X).$$

Observe that $T(O) = O$, $T(-X) = -T(X)$, and

$$T(a_1X_1 + a_2X_2 + \cdots + a_kX_k) = a_1T(X_1) + a_2T(X_2) + \cdots + a_kT(X_k)$$

Eg. $T \left(\begin{bmatrix} x \\ y \end{bmatrix} \right) = \begin{bmatrix} x \\ -y \end{bmatrix}$ and $S \left(\begin{bmatrix} x \\ y \\ z \end{bmatrix} \right) = \begin{bmatrix} y + 2z \\ x \end{bmatrix}$ are linear transformations.

Def. $A : m \times n$ matrix. Define $T_A : \mathbf{F}^n \rightarrow \mathbf{F}^m$ by

$$T_A(X) = AX$$

for $X \in \mathbf{F}^n$. Then T_A is a linear transformation.

Eg. $A = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$, $T_A \left(\begin{bmatrix} x \\ y \end{bmatrix} \right) = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \\ -y \end{bmatrix}$.

$$B = \begin{bmatrix} 0 & 1 & 2 \\ 1 & 0 & 0 \end{bmatrix}, T_B \left(\begin{bmatrix} x \\ y \\ z \end{bmatrix} \right) = \begin{bmatrix} 0 & 1 & 2 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} y + 2z \\ x \end{bmatrix}.$$

Thm. Let $T : \mathbf{F}^n \rightarrow \mathbf{F}^m$ be a linear transformation. Then $T = T_A$ for the unique matrix A given by

$$A = [T(E_1) \quad T(E_2) \quad \cdots \quad T(E_n)],$$

where $\{E_1, E_2, \dots, E_n\}$ is the standard basis of \mathbf{F}^n .

Proof. $X = x_1E_1 + x_2E_2 + \cdots + x_nE_n$

$$\begin{aligned} T(X) &= x_1T(E_1) + x_2T(E_2) + \cdots + x_nT(E_n) \\ &= [T(E_1) \quad T(E_2) \quad \cdots \quad T(E_n)] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = AX. \end{aligned}$$

□

Eg. Let $R_\theta : \mathbf{R}^2 \rightarrow \mathbf{R}^2$ be the rotation through the angle θ . Then R_θ is a linear transformation.

Since $R_\theta(E_1) = \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix}$ and $R_\theta(E_2) = \begin{bmatrix} -\sin \theta \\ \cos \theta \end{bmatrix}$,

$$\begin{bmatrix} R_\theta(E_1) & R_\theta(E_2) \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

induces R_θ .

Eg. Given $N = [1 \ 0 \ 1]$, define a linear transformation $P_N : \mathbf{R}^3 \rightarrow \mathbf{R}^3$ by

$$P_N(X) = X - \frac{X \cdot N}{\|N\|^2} N.$$

Find the matrix of P_N .

Solution.

$$P_N(E_1) = E_1 - \frac{E_1 \cdot N}{\|N\|^2} N = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} - \frac{1}{2} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} \\ 0 \\ -\frac{1}{2} \end{bmatrix}$$

$$P_N(E_2) = E_2 - \frac{E_2 \cdot N}{\|N\|^2} N = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

$$P_N(E_3) = E_3 - \frac{E_3 \cdot N}{\|N\|^2} N = \begin{bmatrix} -\frac{1}{2} \\ 0 \\ \frac{1}{2} \end{bmatrix}$$

$$\begin{bmatrix} P_N(E_1) & P_N(E_2) & P_N(E_3) \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 1 & 0 & -1 \\ 0 & 2 & 0 \\ -1 & 0 & 1 \end{bmatrix}.$$

- Composition

If we have two linear transformations $T : \mathbf{F}^n \rightarrow \mathbf{F}^m$ and $S : \mathbf{F}^m \rightarrow \mathbf{F}^k$, then we can define the **composite** $S \circ T$ of S and T by

$$(S \circ T)(X) = S(T(X)) \text{ for all } X \in \mathbf{F}^n.$$

Thm. *Let $T : \mathbf{F}^n \rightarrow \mathbf{F}^m$ and $S : \mathbf{F}^m \rightarrow \mathbf{F}^k$ be linear transformations with matrices B and A , respectively. The composite $S \circ T : \mathbf{F}^n \rightarrow \mathbf{F}^k$ is the linear transformation with matrix AB .*

Proof. $(S \circ T)(X) = S(T(X)) = S(BX) = (AB)X$ for $X \in \mathbf{F}^n$. \square

Eg. Find the matrix A of reflection in the X axis of \mathbf{R}^2 followed by reflection in the line $y = x$.

Solution The matrix of reflection in the X axis is $\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$,
and the matrix of reflection in the line $y = x$ is $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$.

Hence

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}.$$

- Inverse

Thm. *Let T be a linear transformation with matrix A . Then A is invertible if and only if T has an inverse linear transformation. In this case, T^{-1} is the linear transformation with the matrix A^{-1} .*

Proof. If A is invertible, we define T' by $T'(X) = A^{-1}X$. Then $(T' \circ T)(X) = A^{-1}AX = X$ and $(T \circ T')(X) = AA^{-1}X = X$. Hence, $T' = T^{-1}$.

Conversely, if T^{-1} is the inverse with matrix B , then $T \circ T^{-1} = id$ implies $AB = I$, and $T^{-1} \circ T = id$ implies $BA = I$. Thus $B = A^{-1}$. \square

Eg. Let R_θ be the rotation through the angle θ . Clearly, the inverse is $R_\theta^{-1} = R_{-\theta}$, the rotation through $-\theta$. Since the matrix of R_θ is $A = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$, the matrix of R_θ^{-1} is

$$A^{-1} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} = \begin{bmatrix} \cos(-\theta) & -\sin(-\theta) \\ \sin(-\theta) & \cos(-\theta) \end{bmatrix}.$$

- One-to-one and Onto

Def. A linear transformation T is *one-to-one* (resp. *onto*) if it is one-to-one (resp. onto) as a function.

Def. Let $T : \mathbf{F}^n \rightarrow \mathbf{F}^m$ be a linear transformation with matrix A . Then we define

$$\text{im}T = \{T(X) \mid X \in \mathbf{F}^n\} = \{AX \mid X \in \mathbf{F}^n\} = \text{im}A,$$

$$\text{ker}T = \{X \in \mathbf{F}^n \mid T(X) = O\} = \{X \in \mathbf{F}^n \mid AX = O\} = \text{null}A.$$

Thm. Let $T : \mathbf{F}^n \rightarrow \mathbf{F}^m$ be a linear transformation. Then T is *one-to-one* (resp. *onto*) if and only if $\ker T = \mathbf{0}$ (resp. $\operatorname{im} T = \mathbf{F}^m$).

Rmk. *If follows from*

$$n = \dim(\operatorname{null} A) + \dim(\operatorname{im} A)$$

that

$$n = \dim(\ker T) + \dim(\operatorname{im} T).$$