

Lecture 19

Curve Fitting

Problem: Consider the following data points in \mathbb{R}^2

x	y
1	0.3
2	0.7
3	1
4	1.3

We say a linear function

$$f(x) = ax + b$$

is a best fit line for

this data set if it
minimizes the distance

between its predicted values $f(x_i)$ and the experimental values y_i ,

$$E := \sqrt{\sum (f(x_i) - y_i)^2} \text{ over}$$

all linear functions.

Before we find the answer
let's guess.

$$\text{guess } f(x) = \frac{1}{3}x$$

x	$\frac{1}{3}f(x)$
1	0.3333
2	0.666..
3	1
4	1.3333

What is the error
(distance) for our guess

$$\begin{aligned} \epsilon &:= \sqrt{(0.033)^2 + \dots} \\ &= (0.00333)^{1/2} \end{aligned}$$

Can we do better than
this?

How is this a linear algebra problem?

We are trying to:

Find the closest ~~matrix~~

vector

$$\begin{bmatrix} f(x_1) \\ f(x_2) \\ f(x_4) \end{bmatrix} = \begin{bmatrix} f(1) \\ f(2) \\ f(3) \\ f(4) \end{bmatrix}$$

obtained by evaluating a linear function ~~at~~ to the vector of experimental values

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 0.3 \\ 0.7 \\ 1 \\ 1.3 \end{bmatrix}.$$

We know how to find
the closest vector in
a subspace V to a
fixed vector v (its v'').

Are vectors of the form

$$\begin{bmatrix} f(1) \\ f(2) \\ f(3) \\ f(4) \end{bmatrix}$$

obtained by
evaluating linear
functions a
subspace?

Observe:

$$f(x) = ax + b$$

$$f(1) = a \cdot 1 + b$$

$$= [1 \ 1] \begin{bmatrix} a \\ b \end{bmatrix}$$

$$f(2) = a \cdot 2 + b$$

$$= [2 \ 1] \begin{bmatrix} a \\ b \end{bmatrix}$$

$$f(x_i) = a \cdot x_i + b$$

$$= [x_i \ 1] \begin{bmatrix} a \\ b \end{bmatrix}.$$

So:

$$\begin{bmatrix} f(1) \\ f(2) \\ f(3) \\ f(4) \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \\ \vdots \\ 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}$$

$$\begin{bmatrix} f(x_i) \\ \vdots \end{bmatrix} = \begin{bmatrix} x_i \\ \vdots \\ 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}.$$

Fact: Vectors of the

form $\begin{bmatrix} f(1) \\ f(2) \\ f(4) \end{bmatrix}$ are

the image of $A = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \\ \vdots \\ 1 \end{bmatrix}$.

So finding the best fit line is equivalent to finding the closest

vector in the image

of $A = \begin{bmatrix} 1 \\ 2 \\ 3 \\ \vdots \end{bmatrix}$ to

$$\vec{b} = \begin{bmatrix} 0.3 \\ 0.7 \\ 1 \\ 1.3 \end{bmatrix}.$$

This is a problem we know how to do.

★ Find the ~~to~~ Approximate
(least squares solution)

$$\text{to } Ax = \vec{b}, \quad x = \begin{bmatrix} a \\ b \end{bmatrix}.$$

Solution to original problem:

Want approx. solution to $Ax = \vec{b}$.

① Multiply both sides by A^T

$$A^T A x = A^T \vec{b}$$

(consistent).

$$A^T A = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \\ \vdots \\ \vdots \end{bmatrix}$$

$$= \begin{bmatrix} 30 & 10 \\ 10 & 4 \end{bmatrix}$$

$$A^T b = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0.3 \\ 0.7 \\ 1 \\ 1.3 \end{bmatrix}$$

$$= \begin{bmatrix} 9.9 \\ 3.3 \end{bmatrix}$$

② Solve

$$A^T A x = A^T b$$

$$\begin{bmatrix} 30 & 10 \\ 10 & 4 \end{bmatrix} \begin{bmatrix} 9 \\ 6 \end{bmatrix} = \begin{bmatrix} 9.9 \\ 3.3 \end{bmatrix}.$$

Observe $\det(A^T A) = 20 \neq 0$

$$\text{so } (A^T A)^{-1} = \frac{1}{20} \begin{bmatrix} 4 & -10 \\ -10 & 30 \end{bmatrix}.$$

$$x = \frac{1}{20} \begin{bmatrix} 4 & -10 \\ -10 & 30 \end{bmatrix} \begin{bmatrix} 9.9 \\ 3.3 \end{bmatrix}$$

$$= \frac{1}{20} \begin{bmatrix} 6.6 \\ 0 \end{bmatrix} = \begin{bmatrix} 9 \\ 6 \end{bmatrix}$$

$$= \begin{bmatrix} 0.33 \\ 0 \end{bmatrix} = \begin{bmatrix} 9 \\ 6 \end{bmatrix}.$$

Unpacking

$$f(x) = ax + b = 0.33x.$$

What's the error

$$E = \sqrt{\sum_{i=1}^4 (0.33x_i - y_i)^2}$$

$$= \sqrt{(0.03)^2 + \dots}$$

$$= \sqrt{0.003}$$

We did better than our guess.

Key ingredient for using
Linear algebra to solve
this problem was that
the space of vectors
of the form

$$\begin{bmatrix} f(x_1) \\ \vdots \\ f(x_n) \end{bmatrix} \text{ as } \mathbf{F}$$

varies over our class
of functions is a subspace.

What classes of functions
can we use for curve
fitting?

Example: Polynomials of degree
 $\leq k$.

★ Problem: Find a quadratic
polynomial $f(x) = ax^2 + bx + c$
which best fits the
data points:

x	y
-1	8
0	8
1	4
2	16

i.e.

(Minimizes

$$E := \left(\sum (f(x_i) - y_i)^2 \right)^{1/2}$$

over all quadratics.

To use least
squares we need

$$\left\{ \begin{bmatrix} f(x_1) \\ \vdots \\ f(x_n) \end{bmatrix} : f \text{ quadratic} \right\}$$

to be a subspace.

We can show its the
image of the following
transformation

$$\begin{bmatrix} f(x_1) \\ \vdots \\ f(x_n) \end{bmatrix} = \begin{bmatrix} f(-1) \\ f(0) \\ f(1) \\ f(2) \end{bmatrix} = \begin{bmatrix} (-1)^2 & -1 & 1 \\ 0^2 & 0 & 0 \\ 1^2 & 1 & 1 \\ 2^2 & 2 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

$$f(x) = ax^2 + bx + c$$

(More generally for f
a polynomial of degree $\leq n$)

$$\begin{bmatrix} f(x_1) \\ \vdots \\ f(x_n) \end{bmatrix} = \begin{bmatrix} x_1^n & x_1^{n-1} & x_1^{n-2} & \dots & x_1 & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ x_n^n & x_n^{n-1} & x_n^{n-2} & \dots & x_n & 1 \end{bmatrix} \begin{bmatrix} c_n \\ \vdots \\ c_1 \\ c_0 \end{bmatrix}$$

Problem 13 equivalent to minimizing
the distance between

$$\text{Im} \left(\begin{bmatrix} (-1)^2 & -1 & 1 \\ 0 & 0 & 1 \\ 4 & 2 & 1 \end{bmatrix} \right)$$

and $A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 1 \\ 4 & 2 & 1 \end{bmatrix}$
and $b = \begin{bmatrix} 1 \\ 4 \\ 16 \end{bmatrix}$:

What is the solution?

① Compute

$$A^T A = \begin{bmatrix} 17 & 8 & 6 \\ 8 & 6 & 2 \\ 6 & 2 & 4 \end{bmatrix}.$$

$$A^T b = \begin{bmatrix} 76 \\ 29 \\ 36 \end{bmatrix}.$$

②

Solve

$$A^T A x = A^T b$$

(by row reduction)

$$\left[\begin{array}{ccc|c} 1 & 3 & 6 & 76 \\ 3 & 6 & 2 & 28 \\ 6 & 2 & 4 & 36 \end{array} \right]$$

row
reduction \Rightarrow

$$\left[\begin{array}{ccc|c} 1 & 0 & 0 & 31 \\ 0 & 1 & 0 & 5 \\ 0 & 0 & 1 & 5 \end{array} \right].$$

Unpack

$$f(x) = 3x^2 - x + 5$$

Compare experimental + predicted values:

x	F(x)	y
-1	9	8
0	5	8
1	7	4
2	15	16

$$\begin{aligned} E &:= \sqrt{1^2 + 3^2 + 3^2 + 1^2} \\ &= \sqrt{20} \sim 4.47. \end{aligned}$$

The most general class
of functions for which
this ^{technique} works is
the set of functions

$$f = a_1 g_1(x) + a_2 g_2(x) \\ + \dots + a_n g_n(x)$$

for g_1, \dots, g_n some fixed
functions. (Span g_1, \dots, g_n).

Ex: degree 1 polynomials
 $g_1(x) = 1$ $g_2(x) = x$.