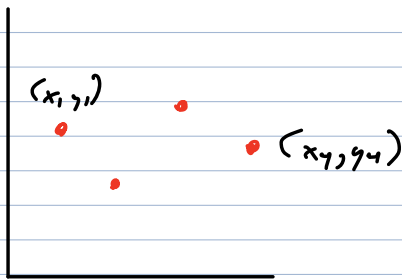


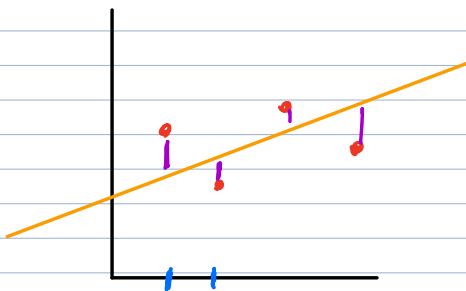
Section 6.6

Recall intro from last time. (Will introduce some different notation along the way)

Have data (measurements/observations) with coordinates (x_i, y_i)



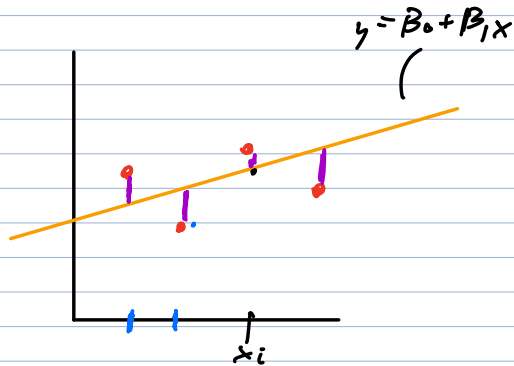
Would like a line (function) that best explains data



Instead of $y = mx + b$
will use notation

$$y = \beta_0 + \beta_1 x$$

Distance from line to point is called the residual



As in last section
we want to minimize
error

Again measure error using
square terms

line at specific pt x_i

$$\star (\beta_0 + x_i \beta_1) - (y_i) = \text{residual}_i$$

i.e. predicted y value
at x_i Actual/observed
value of y at x_i

$$\text{Error} = \sum (\text{residual}_i)^2$$

Goal: Choose line (so choose β_0, β_1)
so as to minimize error, i.e. find the
least squares line / linear regression

Note: β_0, β_1 are called **regression coefficients**

If every point was on a line, we would
have system of equations

$$\begin{cases} \text{predicted } y\text{-value} & \text{observed } y\text{-value} \\ \beta_0 + \beta_1 x_1 = y_1 \\ \beta_0 + \beta_1 x_2 = y_2 \\ \vdots \\ \beta_0 + \beta_1 x_n = y_n \end{cases}$$

Write as matrix equation

$$\begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \quad \text{Inconsistent?}$$

$n \times 2$
matrix

2×1
vector
regression
coefficients

$n \times 1$ vector
observed y 's

New Notation:

$$X \vec{\beta} = \vec{y} \quad \text{instead of} \quad A \vec{x} = \vec{b}$$

Real world situation: Will have data, no line
Want to find line of best fit, i.e. find
 β_0, β_1

Ideally, want β_0, β_1 that solve matrix equation:

$$\star \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

$\uparrow \quad \uparrow \quad \uparrow$
1's known inputs known outputs

What if system is inconsistent? Section 6.5!

Now this is a least squares problem we
know how to solve

Short Story:

Solve system $X^T X \vec{\beta} = X^T \vec{y}$

★ Example / Problem break

Survey of Topres

A modification: In design matrix X , may change the first column to get "nicer" matrix

① Let \bar{x} = average of observed inputs x_1, x_2, \dots, x_n

② Then consider equations

$$y = \beta_0 \bar{x} + \beta_1 (\bar{x} - x_i) \quad \star$$

③ Get matrix equation

$$\begin{bmatrix} \bar{x} & (\bar{x} - x_1) \\ \bar{x} & (\bar{x} - x_2) \\ \bar{x} & \vdots \\ \bar{x} & (\bar{x} - x_n) \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

Why? Columns will be orthogonal, and orthogonal nice to work with.

General Linear Model

Have been considering $\vec{y} = X\vec{\beta}$ as an approximation, and this is accurate, want to minimize error

Another way to write this:

$$\vec{y} = X\vec{\beta} + \vec{E}$$

error term
called "residual vector"

Then by rearranging see that E is

$$\vec{E} = (\vec{y} - X\vec{\beta}) \downarrow$$

residual vector = observed values - predicted values

$$\text{error} = \|\text{residual vector}\| = \|\vec{y} - X\vec{\beta}\| \quad \text{minimize this}$$

If we start with system of equations

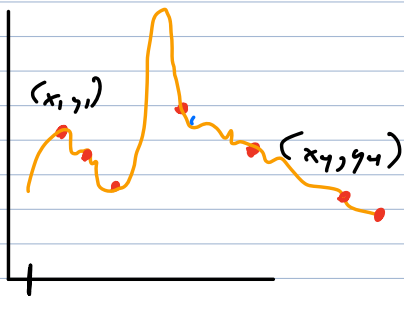
$$y_1 = \beta_0 + \beta_1 x_1$$

\vdots

$$y_n = \beta_0 + \beta_1 x_n$$

then nothing has changed. It is exactly
set up we had before, just slightly
different notation.

But maybe we want to begin from different
set up.



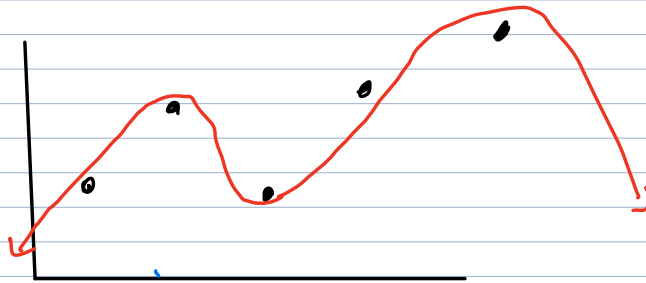
Sometimes no line is a
good approximation to
the "real" function that
governs our data

a

D

Output Input

$$\begin{aligned} y_1 &= \beta_0 + \beta_1 f(x_1) + \beta_2 g(x_1) + \beta_3 h(x_1) + \beta_4 i(x_1) \\ &\vdots \\ y_n &= \beta_0 + \beta_1 + \beta_2 x_1^2 + \beta_3 x_1^3 + \beta_4 x_1^4 \end{aligned} \quad \left. \vphantom{\begin{aligned} y_1 &= \beta_0 + \beta_1 f(x_1) + \beta_2 g(x_1) + \beta_3 h(x_1) + \beta_4 i(x_1) \\ &\vdots \\ y_n &= \beta_0 + \beta_1 + \beta_2 x_1^2 + \beta_3 x_1^3 + \beta_4 x_1^4 \end{aligned}} \right\}$$



$$\begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ 1 & x_3 \\ 1 & x_4 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix}$$

$$\left[\begin{array}{c|ccc|c} 1 & x_1 & x_1^2 & x_1^3 & x_1^4 & \beta_0 \\ 1 & x_2 & x_2^2 & x_2^3 & x_2^4 & \beta_1 \\ 1 & x_3 & x_3^2 & x_3^3 & x_3^4 & \beta_2 \\ 1 & x_4 & x_4^2 & x_4^3 & x_4^4 & \beta_3 \end{array} \right] = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix}$$

polynomial of form

$$y = \underline{\beta_0} + \underline{\beta_1} x + \underline{\beta_2} x^2 + \underline{\beta_3} x^3 + \underline{\beta_4} x^4$$

$$\begin{bmatrix} X^T X & | & X^T y \end{bmatrix}$$

Weierstrass Approximation Theorem:

Any continuous function on interval $[a, b]$ can be approximated arbitrarily well by a polynomial.

$$(x_1, y_1)$$

$$(x_1, y_1, (z_1))$$