

STAT 88: Lecture 37

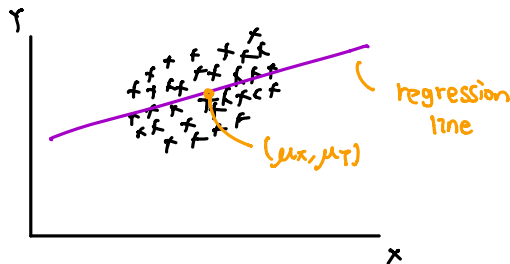
Contents

Section 11.5: The Error in Regression

Section 12.1: The Simple Linear Regression Model

Warm up:

Let (X, Y) be a random pair. The average of this pair is (μ_X, μ_Y) , called the point of averages. Show that the point of averages lies on the regression line.



Last time

Least squares regression

Let (X, Y) be a random pair. We write

- $E(X) = \mu_X$, $SD(X) = \sigma_X$.
- $E(Y) = \mu_Y$, $SD(Y) = \sigma_Y$.
- Correlation

$$r = \frac{E((X - \mu_X)(Y - \mu_Y))}{\sigma_X \sigma_Y}.$$

The regression line $\hat{Y} = \hat{a}X + \hat{b}$ is the best fitting line, in the sense that it minimizes the mean squared error

$$MSE(a, b) = E((Y - (aX + b))^2).$$

We showed that

$$\hat{a} = r \frac{\sigma_Y}{\sigma_X} \text{ and } \hat{b} = \mu_Y - \hat{a} \cdot \mu_X.$$

Correlation

Let X^* be X in standard units and Y^* be Y in standard units:

$$X^* = \frac{X - \mu_X}{\sigma_X} \text{ and } Y^* = \frac{Y - \mu_Y}{\sigma_Y}.$$

Then

$$r = r(X, Y) = \frac{E((X - \mu_X)(Y - \mu_Y))}{\sigma_X \sigma_Y} = E\left(\frac{X - \mu_X}{\sigma_X} \cdot \frac{Y - \mu_Y}{\sigma_Y}\right) = E(X^* Y^*).$$

The correlation satisfies the following properties:

- $-1 \leq r(X, Y) \leq 1$.
- $r(X, Y) = r(Y, X)$.
- $r(aX + b, cY + d) = \begin{cases} r(X, Y) & \text{if } ac > 0 \\ -r(X, Y) & \text{if } ac < 0 \end{cases}$

11.5. The Error in Regression

r As a Measure of Linear Association The error in the regression estimate is called the residual and is defined as

$$D = Y - \hat{Y}.$$

We showed

$$E(D) = 0 \text{ and } SD(D) = \sqrt{1 - r^2}\sigma_Y.$$

So if r is close to ± 1 , $SD(D)$ is close to 0, which implies that Y is close to \hat{Y} . In other words, Y is close to being a linear function of X . $\leftarrow r$ measures strength of linear relationship between X and Y

In the extreme case $r = \pm 1$, $SD(D) = 0$ and Y is a perfectly linear function of X .

The Residual is Uncorrelated with X We will show that the correlation between X and residual D is zero. Note that

$$r(D, X) = \frac{E((D - \mu_D)(X - \mu_X))}{\sigma_D \sigma_X} = \frac{1}{\sigma_D \sigma_X} E(DD_X),$$

because $\mu_D = 0$. We thus show $E(DD_X) = 0$:

$$\begin{aligned} E(DD_X) &= E((D_Y - \hat{a}D_X)D_X) \\ &= E(D_X D_Y) - \hat{a}E(D_X^2) \\ &= r\sigma_X\sigma_Y - r\frac{\sigma_Y}{\sigma_X}\sigma_X^2 \\ &= 0. \end{aligned}$$

Example: (Exercise 11.6.11) Let X have the uniform distribution on the three points -1 , 0 , and 1 . Let $Y = X^2$.

(a) Show that X and Y are uncorrelated.

(b) Are X and Y independent?

12.1. The Simple Linear Regression Model

The model involves a variable called the **response** and another called a **predictor variable** or **feature**.

Y = response and x = predictor variable/covariate/feature

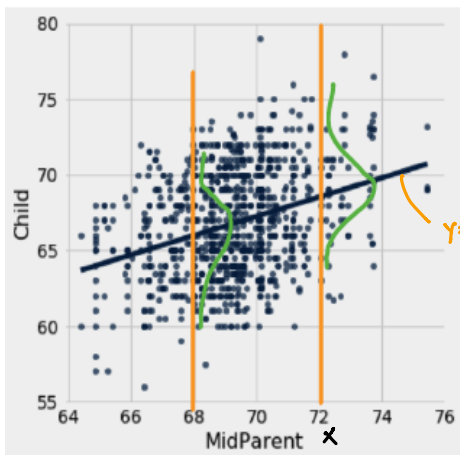
\leftarrow big Y (random) \leftarrow Small x (fixed / not random)

We observe the response and the predictor variable of n individuals, i.e. $(x_1, Y_1), \dots, (x_n, Y_n)$. Our assumption is

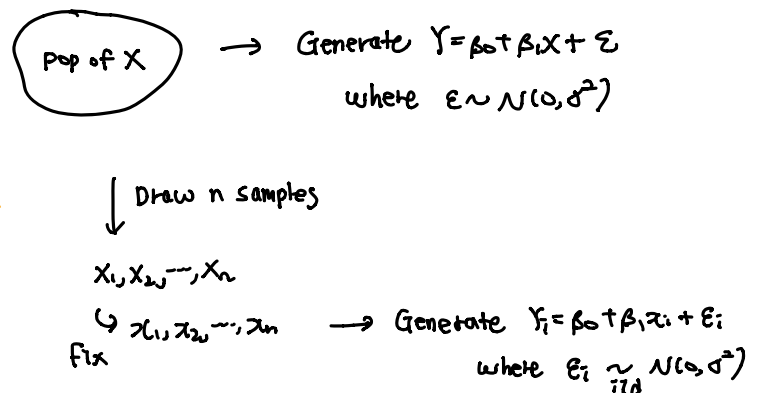
$$Y_i = \underbrace{\beta_0 + \beta_1 x_i}_{\text{signal}} + \underbrace{\epsilon_i}_{\text{noise}},$$

where

- β_0 and β_1 are unobservable constant parameters.
- x_i is the value of the predictor variable for individual i and is assumed to be constant (that is, not random).
- The errors $\epsilon_1, \epsilon_2, \dots, \epsilon_n$ are i.i.d. normal $\mathcal{N}(0, \sigma^2)$ random variables.
- The error variance σ^2 is an unobservable constant parameter, and is assumed to be the same for all individuals i .



Data generation process



Individual Responses Fix x_i , then

$$Y_i = \beta_0 + \beta_1 x_i + \epsilon_i \sim \mathcal{N}(\quad, \quad).$$

Y_1, Y_2, \dots, Y_n are independent because $\epsilon_1, \epsilon_2, \dots, \epsilon_n$ are independent.

Average Response Let $\bar{Y} = \frac{1}{n} \sum_{i=1}^n$ denote the average response of the n individuals.

What distribution does \bar{Y} follow?

Find $E(\bar{Y})$.

Find $\text{Var}(\bar{Y})$.