

Linear Regression

Fall 2025

Simple Linear Regression Model

↳ "one predictor & one response"

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \quad i = 1, \dots, n$$

Notation:

- y_i = i^{th} observed value of the response variable Y

RANDOM

- x_i = i^{th} observed value of the predictor variable X

FIXED

$$\{(x_i, y_i)\}_{i=1, \dots, n}$$

- n : sample size

FIXED

- β_0 : unknown intercept parameter

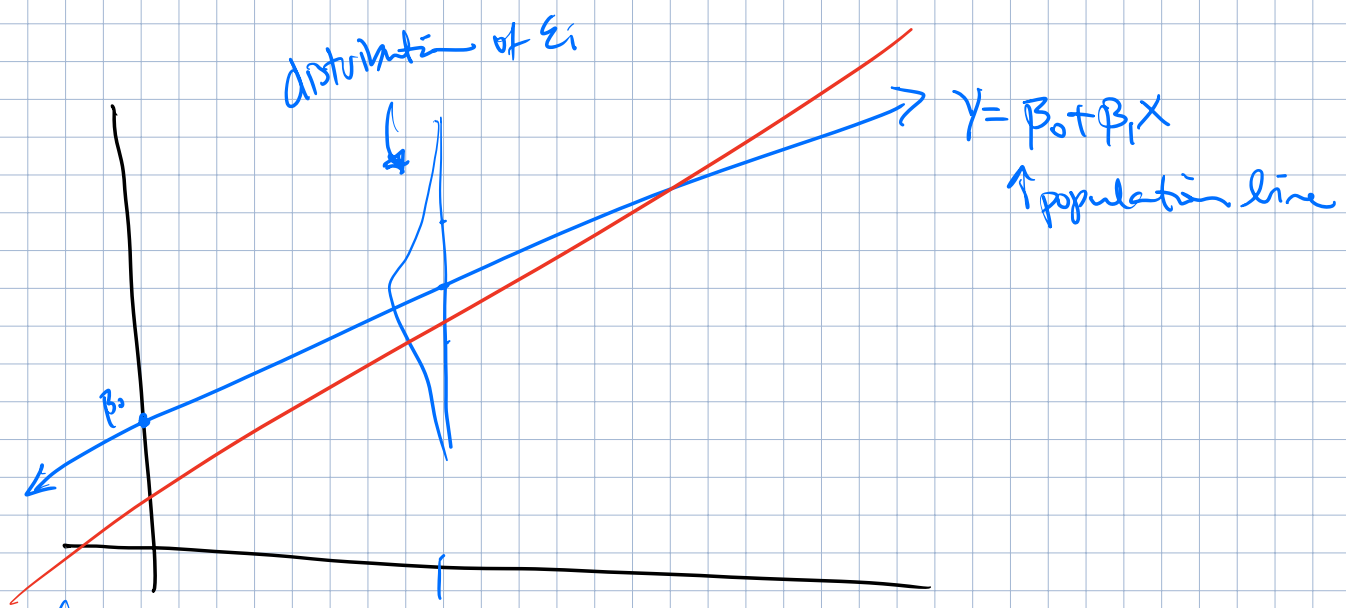
FIXED

- β_1 : unknown slope parameter

FIXED

- ε_i : random error term

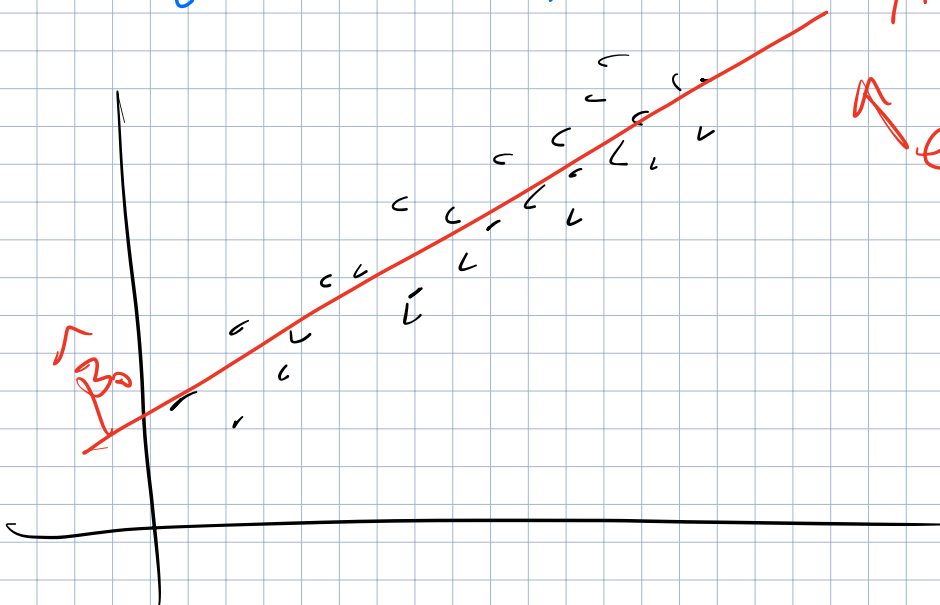
RANDOM



$$\{(x_i, y_i)\}_{i=1, \dots, n}$$

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$$

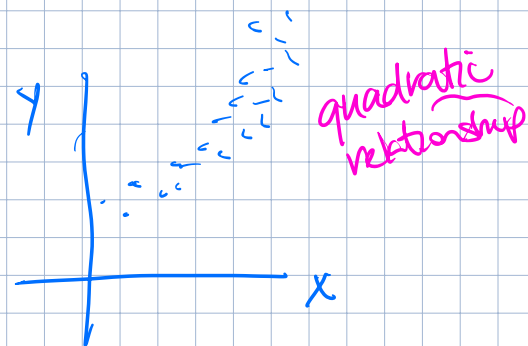
estimated line



Observations:

- ① simple: only 1 predictor var
- ② linear: y_i is a linear fn of its parameters β_0 & β_1

Ex:



$$\textcircled{A} \quad y_i = \beta_0 + \beta_1 x_i^2 + \varepsilon_i$$

Let's let $z_i = x_i^2$

$$\Rightarrow y_i = \beta_0 + \beta_1 z_i + \varepsilon_i \quad \checkmark \text{ linear}$$



$$\textcircled{B} \quad y_i = \beta_0 + \beta_1 \log x_i + \varepsilon_i \quad \checkmark \text{ linear}$$

$$\textcircled{C} \quad y_i = \frac{\beta_0}{\beta_1 + x_i} + \varepsilon_i \quad (x \text{ not linear})$$

Model Assumptions

• ε_i 's are RANDOM variables that satisfy

- BASIC**
- (i) $E(\varepsilon_i) = 0$
 - (ii) $\text{Var}(\varepsilon_i) = \sigma^2 \leftarrow \text{constant w/ respect to } x$
 - (iii) $\text{Cov}(\varepsilon_i, \varepsilon_j) = 0 \text{ for } i \neq j$
 $\hookrightarrow \text{uncorrelated errors}$

assumption
(iv) $\varepsilon_i \stackrel{\text{iid}}{\sim} N(0, \sigma^2)$
↑ useful for inference

- x_i 's are fixed

(If we take x_i 's as random, we need a random effects model.)

Regression Function

The regression function is

$$g(x) = E(y | X=x) \quad \downarrow \text{linear}$$
$$= \beta_0 + \beta_1 x$$

Idea: Always estimating g as our target...

Under some assumptions the form of g changes.

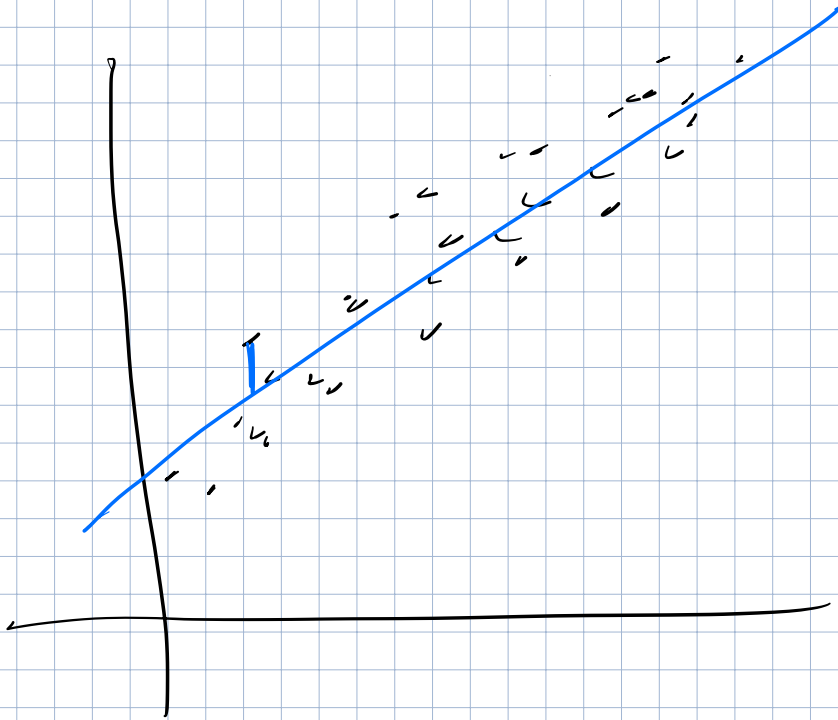
Here g boils down to two parameters: β_0 & β_1 .

This is equivalent (in SLR case) to estimating

① β_0 & ② β_1 .

The Least Squares Principle

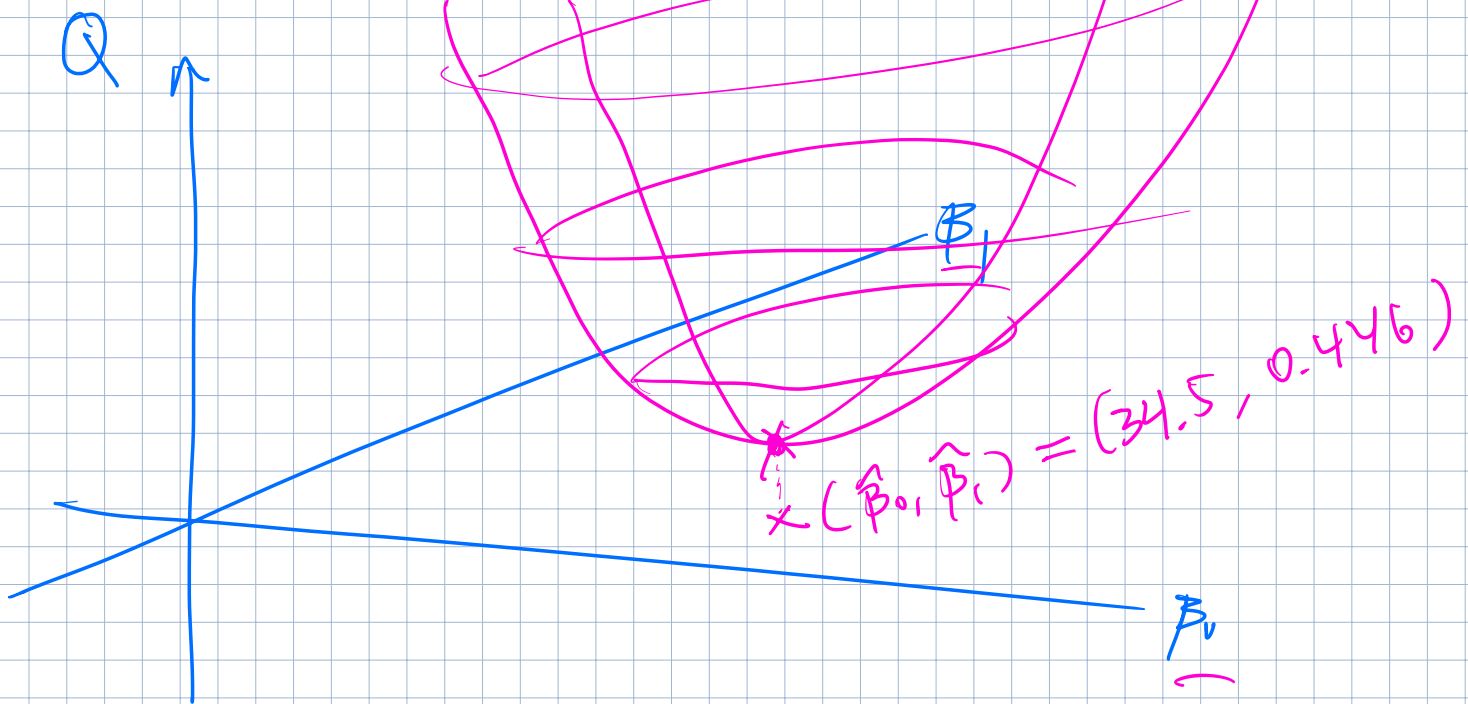
is how we try to solve that problem.



I want to find the line that minimizes
total squared error:

$$\begin{aligned} Q(\beta_0, \beta_1) &= \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2 \\ &= \sum_{i=1}^n e_i^2 \end{aligned}$$

$$= \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$



In other words,

$$(\hat{\beta}_0, \hat{\beta}_1) = \underset{\beta_0, \beta_1}{\operatorname{argmin}} Q(\beta_0, \beta_1)$$

So the estimates $(\hat{\beta}_0, \hat{\beta}_1)$ are the choices of β_0 & β_1 values that satisfy:

$$\textcircled{1} \frac{\partial Q}{\partial \beta_0} \stackrel{!}{=} 0$$

$$\textcircled{2} \frac{\partial Q}{\partial \beta_1} \stackrel{!}{=} 0$$

$$\begin{aligned}
 \textcircled{1} \quad \frac{\partial Q}{\partial \beta_0} &= \frac{\partial}{\partial \beta_0} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2 \\
 &= \sum_{i=1}^n \frac{\partial}{\partial \beta_0} \underbrace{(y_i - \beta_0 - \beta_1 x_i)^2} \\
 &= \sum_{i=1}^n 2(y_i - \beta_0 - \beta_1 x_i)(0 - 1 - 0) \\
 &= \boxed{-2 \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i) \stackrel{!}{=} 0} // \quad \text{A}
 \end{aligned}$$

$$\begin{aligned}
 \textcircled{2} \quad \frac{\partial Q}{\partial \beta_1} &= \frac{\partial}{\partial \beta_1} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2 \\
 &= \sum_{i=1}^n \frac{\partial}{\partial \beta_1} (y_i - \beta_0 - \beta_1 x_i)^2 \\
 &= \sum_{i=1}^n 2(y_i - \beta_0 - \beta_1 x_i)(0 - 0 - x_i) \\
 &= \boxed{-2 \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i) x_i \stackrel{!}{=} 0} \quad \text{B}
 \end{aligned}$$

$$A \quad -2 \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i) = 0$$

$$\bar{y} = \frac{\sum y_i}{n} \Leftrightarrow \sum y_i = n\bar{y}$$

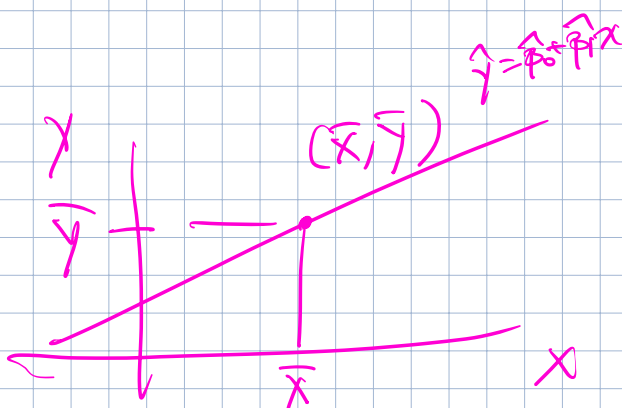
$$\Rightarrow \sum_{i=1}^n y_i - \sum_{i=1}^n \beta_0 - \sum_{i=1}^n \beta_1 x_i = 0$$

$$n\bar{y} - n\beta_0 - \beta_1 (n\bar{x}) = 0$$

$$n\bar{y} = n\beta_0 + n\beta_1 \bar{x}$$

Solutions
($\hat{\beta}_0, \hat{\beta}_1$)
must satisfy:
Condition 1

$$\bar{y} = \hat{\beta}_0 + \hat{\beta}_1 \bar{x}$$



$$B \quad -2 \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i) x_i = 0$$

$$\Rightarrow \sum_{i=1}^n x_i y_i - \beta_0 \sum_{i=1}^n x_i - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

plug into
here

$$\Rightarrow \sum_{i=1}^n x_i y_i - (\bar{y} - \beta_1 \bar{x}) \left[\sum_{i=1}^n x_i \right] - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

$= n\bar{x}$

Solve for β_1 :

$$\sum_{i=1}^n x_i y_i - (n\bar{x}\bar{y} - \beta_1 n\bar{x}^2) - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$\sum_{i=1}^n x_i y_i - n\bar{x}\bar{y} + \beta_1 n\bar{x}^2 - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$\Rightarrow \sum_i x_i y_i - n \bar{x} \bar{y} = \beta_1 \sum_{i=1}^n x_i^2 - \beta_1 n \bar{x}^2$$

$$= \beta_1 \left(\sum_{i=1}^n x_i^2 - n \bar{x}^2 \right)$$

Solution:

$$\Rightarrow \hat{\beta}_1 = \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - n \bar{x}^2}$$

Ans

$$= \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\hat{\text{cov}}(x, y)}{\hat{\text{var}}(x)}$$