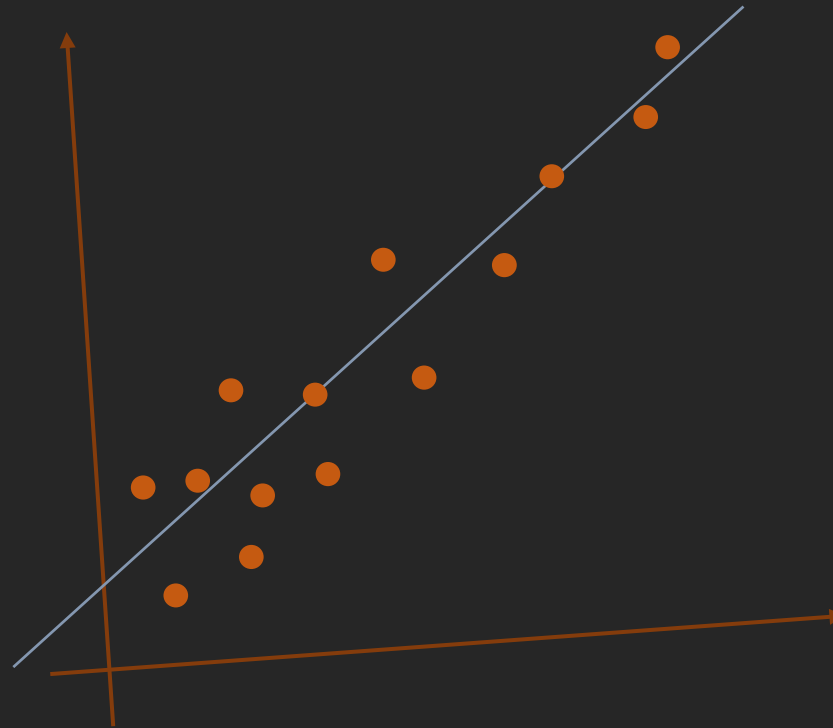


# Applied Regression Analysis

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STAT 4043/ STAT 5543



Introduction to simple linear  
regression – The model

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# Simple linear regression

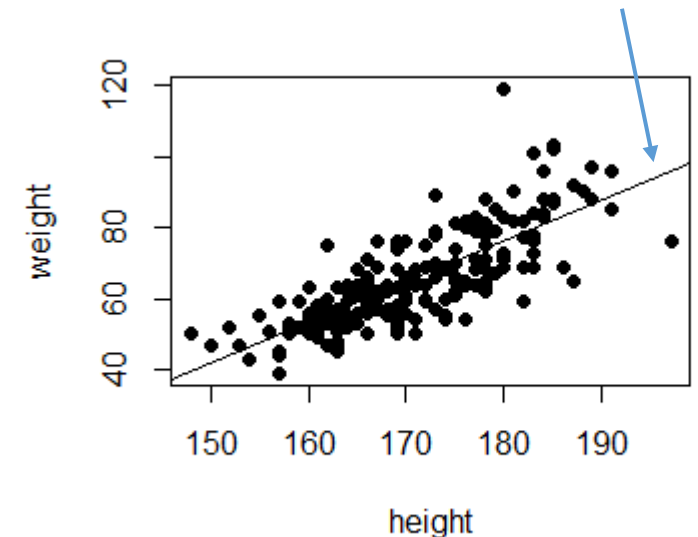
How good is a linear model (equation for a straight line) to explain the relationship of two variables?

# Simple linear regression model – an example

- $y = \beta_0 + \beta_1 x + \epsilon$
- Here,  $y$  is weight and  $x$  is height.
- $y$ : Dependent variable/**Response**/Outcome
- $x$ : Independent variable/**predictor**/explanatory variable
- $\epsilon$ : statistical error
- $\beta_0$ : intercept,  
 $\beta_1$ : slope/ regression coefficient.

True regression line, not known in practice.

Distance of the points from the line are errors.



# Simple Linear Regression (SLR) model

- Because the model holds for all data points  $(x_i, y_i)$ , we can write the model also as:

The diagram shows the equation  $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$  with red arrows pointing to each term and its label. The labels are: "Response/Dependent variable" for  $y_i$ , "Intercept" for  $\beta_0$ , "Slope" for  $\beta_1$ , "Predictor/Independent variable" for  $x_i$ , and "Error" for  $\epsilon_i$ .

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i,$$

Labels and arrows:

- Response/Dependent variable (points to  $y_i$ )
- Intercept (points to  $\beta_0$ )
- Slope (points to  $\beta_1$ )
- Predictor/Independent variable (points to  $x_i$ )
- Error (points to  $\epsilon_i$ )

$$i = 1, 2, \dots, n.$$

# The model

- $y_i = \beta_0 + \beta_1 x_i + \epsilon_i, i = 1, 2, \dots, n.$
- The unknown parameters are  $\beta_0$  and  $\beta_1$  which need to be estimated.
- Estimating them involves finding the line that is ‘best fit’ through the points. What is best fit? We will see.
- Thus the estimation is also called “fitting the line”. These estimates are denoted by  $\hat{\beta}_0$  and  $\hat{\beta}_1$ .

# True model vs fitted model?

Boardwork

# The SLR model revisited

- True model

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad i = 1, 2, \dots, n.$$

Diagram illustrating the True model equation with labels:

- $y_i$ : Response/Dependent variable
- $\beta_0$ : Intercept
- $\beta_1$ : Slope
- $x_i$ : Predictor/Independent variable
- $\epsilon_i$ : Error

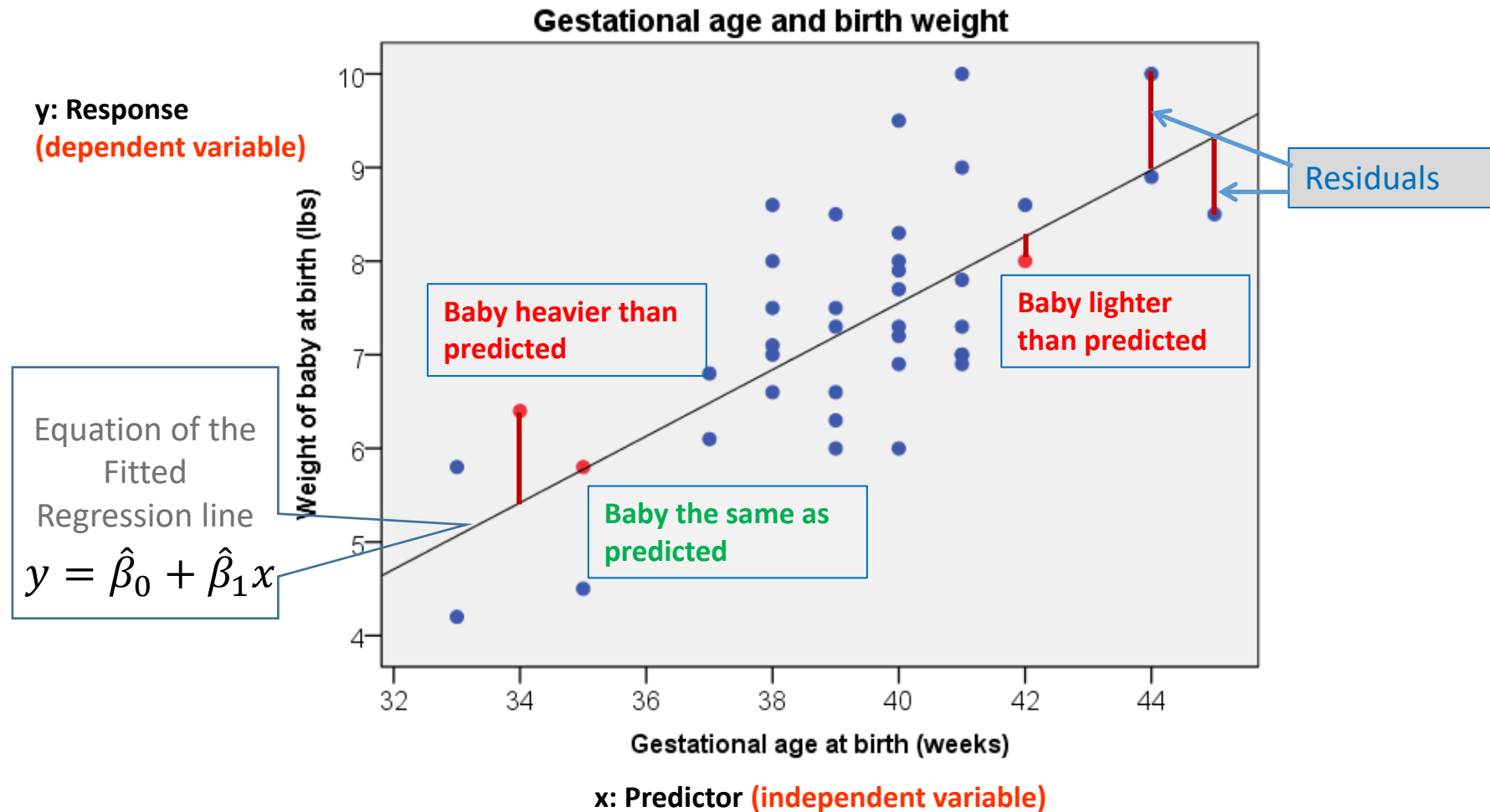
- Fitted model

$$y_i = \hat{\beta}_0 + \hat{\beta}_1 x_i + e_i, \quad i = 1, 2, \dots, n.$$

Diagram illustrating the Fitted model equation with labels:

- $e_i$ : Residuals

# Residuals (deviation from the fitted line)





# The concept of statistical error ( $\epsilon_i$ )

- Functional vs statistical relationships.
  - Tax calculation – functional.
  - Calculating your final grades – functional.
  - Relation between height and weight – statistical.
- Random component, uncertainty.
- ‘Error’ does not mean mistake, it is an inherent part of statistical model.
- The unsystematic or unexplained part of the variability belongs to the random error component.

# How much is random and how much can be explained?

- Why is the relationship between height and weight not exact?
- What are the other factors that result in variation in weight among people who have the same height?
- Can we explain some of this variability using other variables?
- Sure, but in most cases, we cannot explain all of it.

# Assumptions about the two variables

- We assume that the response ( $y$ ) is a **continuous random variable**.
- The predictor ( $x$ ) can be continuous, discrete or even categorical.
- But the predictor is assumed to be **non-random/fixed**.

# More examples

- An experiment was conducted to study the effectiveness of different dosage of a drug to reduce blood pressure. A random sample of 500 hypertension patients was chosen and everyone received one of the 10 different dosages. The dosage ( $x$ ) and reduction in blood pressure ( $y$ ) after taking the drug for a month was measured for each patient.
- An instructor wanted to see if there is any relationship of the final exam score ( $y$ ) of students in his statistics class with whether the student had taken a linear algebra class ever ( $x$ ).
- A study was conducted to find the effect of body mass index ( $x$ ) of a person on whether the person ends up having a heart attack or not ( $y$ ).

# Many more examples in chapter 2 and 3 of your textbook

The examples also come with data sets. I have posted the data sets on Canvas for your convenience.

# Assumptions about the error term

- It is reasonable to think that the error will be 0, on average.
- In fact, the idea is to model the average value of  $y$  as a function of  $x$ .

$$E(y) = \beta_0 + \beta_1 x$$

- It is assumed that the error term  $\epsilon_i$  follows a normal distribution with mean 0 and variance  $\sigma^2$ .
- It is assumed that the  $\epsilon_i$  terms are independent, implying that observations ( $y_i$ ) are independent of each other.

# Multiple Linear Regression

- If we want to include other variables that might have effect on the response, we will end up with a model like

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \epsilon_i$$

- This is called a multiple linear regression (MLR).
- Simple linear regression (SLR) is a special case. We will develop the techniques for the SLR first and study MLR later.

# Fitting SLR model using R