Due September 20th 2024, Friday, 11:59pm. See the submission instructions on Canvas.

(1) (6 points) Recalled that  $S_{xy}$  is defined as

$$S_{xy} = \sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y}).$$

Show that  $S_{xy}$  can also be written as

$$S_{xy} = \sum_{i=1}^{n} (x_i - \overline{x})y_i$$

therefore

$$\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}} = \frac{\sum_{i=1}^n (x_i - \overline{x})y_i}{S_{xx}} = \sum_{i=1}^n c_i y_i$$

where

$$c_i = \frac{x_i - \overline{x}}{S_{xx}}, \quad i = 1, \dots, n.$$

(2) (6 points) In our class discussion and on pages 37 and 38 of the August 19th version of the notes, we established that  $\widehat{\beta}_0$  and  $\widehat{\beta}_1$  are unbiased estimators of  $\beta_0$  and  $\beta_1$ , respectively. This means that:

$$E(\widehat{\beta}_0) = \beta_0$$
 and  $E(\widehat{\beta}_1) = \beta_1$ .

In the proof, we assumed that  $E(\epsilon_i) = E(\epsilon \mid x_i) = 0$ . However, what if  $E(\epsilon_i) = E(\epsilon \mid x_i) = \alpha$ , where  $\alpha$  is a non-zero constant? How would this assumption affect the expectations of  $\widehat{\beta}_0$  and  $\widehat{\beta}_1$ ?

To receive full credit, you need to support your claim with a clear and rigorous mathematical proof.

3. (6 points) This exercise involves using R. Start by opening R Studio and navigating to File -> New File -> R Script to create a new R script. In the R script, enter the code below to generate a simulated data set with 1000 data points. Save this data set as a CSV file named simulated\_data.csv.

```
# Set seed for reproducibility
 2
    set.seed(123)
 3
 4
    # Number of data points
 5
    n <- 1000
    # Generate x values (you can specify the range or generate random values)
 7
 8
    x \leftarrow runif(n, min = 0, max = 10) # Random values between 0 and 10
10 # Generate epsilon values (normally distributed with mean 0 and variance 3)
11
    epsilon \leftarrow rnorm(n, mean = 0, sd = sqrt(3))
12
   # Compute y values based on the equation y = 2 + 7x + epsilon
13
   y \leftarrow 2 + 7 * x + epsilon
14
15
16
   # Combine x and y into a data frame
17
   data \leftarrow data.frame(x = x, y = y)
18
19 # Write data to a CSV file
20 write.csv(data, "simulated_data.csv", row.names = FALSE)
21
22
   # Confirmation
23 cat("Data saved to 'simulated_data.csv'")
24
```

Figure 1: Note: In line 8, we use a uniform distribution to generate values for x ranging from 0 to 10. Once x is generated and recorded in the CSV file, it is treated as fixed and non-random. This fixed x value is a key assumption in our regression model.

Based on the code from Homework 2, Problem 5, please complete the following tasks:

- (a) Create an R Markdown document and load the CSV file simulated\_data.csv.
- (b) Set up a least squares regression model using the lm() function.
- (c) Use the summary function to display the results of the regression model.
- (d) Plot the data using the plot() function.
- (e) Add the least squares regression line to the plot using the abline() function.

4. (6 points) Repeat the steps in Question 3 and enter the code below to generate another simulated data set with 1000 data points. Save this data set as a CSV file named simulated\_data\_nonconstant\_variance.CSV.

```
# Set seed for reproducibility
    set.seed(123)
3
4
    # Number of data points
 5
 6
 7
    # Generate x values (you can specify the range or generate random values)
   x \leftarrow runif(n, min = 0, max = 10) # Random values between 0 and 10
 8
   # Generate epsilon values (normally distributed with mean 0 and variance x^2)
10
    epsilon \leftarrow rnorm(n, mean = 0, sd = x^2)
    # Compute y values based on the equation y = 2 + 7x + epsilon
13
    y \leftarrow 2 + 7 * x + epsilon
15
16
    # Combine x and y into a data frame
17
    data \leftarrow data.frame(x = x, y = y)
18
    # Write data to a CSV file
19
    write.csv(data, "simulated_data_nonconstant_variance.csv", row.names = FALSE)
20
21
22
    # Confirmation
    cat("Data saved to 'simulated_data_nonconstant_variance.csv'")
23
```

Figure 2: Note: In line 11, we observe that the variance of the error term is no longer constant. Instead, it increases as x increases, following the relationship  $Var(\epsilon) = x^2$ .

Based on the code from Homework 2, Problem 5, please complete the following tasks:

- (a) Create an R Markdown document and load simulated\_data\_nonconstant\_variance.CSV.
- (b) Set up a least squares regression model using the lm() function.
- (c) Use the summary function to display the results of the regression model.
- (d) Plot the data using the plot() function.
- (e) Add the least squares regression line to the plot using the abline() function.
- (f) Describe how the plot in 3(e) differ from 4(e). Write this comment on your R Markdown document.

5. (6 points) Consider the true relationship between x and y given by

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

When we collect a data set  $(x_i, y_i)$ ,  $i = 1, \dots, n$ , this relationship can be expressed as

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

What assumptions about the error terms  $\epsilon_i$  are necessary to obtain the following results?

- (a)  $E(\widehat{\beta}_0) = \beta_0$
- (b)  $\operatorname{Var}(\widehat{\beta}_1) = \sigma^2 / S_{xx}$
- (c)  $\widehat{\beta}_1 \sim N(\beta_1, \sigma^2/S_{xx})$