## HW9

#### 2024-11-11

Stat 5000 Homework #9

Fall 2024 due Fri, November 15th @ 11:59 pm Name: Sam Olson

COLLABORATORS: The Hatman

### $\mathbf{Q}\mathbf{1}$

Suppose that six observations of the yield (Y) of a chemical process were taken at each of four temperature levels (X) for running the process, but you are only given information on the sample means and standard deviations for the observed yields at each temperature. The summary data are

Temperature (°C)	Sample Mean	Sample Variance	Sample Size
150	66	1.15	6
200	81	1.00	6
250	89	1.35	6
300	92	0.90	6

(a)

Use this information to compute the least squares estimates of  $\beta_0$  and  $\beta_1$  for the simple linear regression model:

$$Y_{ij} = \beta_0 + \beta_1 x_i + \epsilon_{ij}$$

Report values for the estimated coefficients  $(b_0 \text{ and } b_1)$  and their standard errors  $(S_{b_0} \text{ and } S_{b_1})$ .

```
# Given data
temperature <- c(150, 200, 250, 300)
sample_mean <- c(66, 81, 89, 92)
sample_variance <- c(1.15, 1.00, 1.35, 0.90)
sample_size <- c(6, 6, 6, 6)

# Compute the weights based on sample variances and sample sizes
weights <- sample_size / sample_variance

# Weighted means of temperature and yield
weighted_mean_x <- sum(weights * temperature) / sum(weights)
weighted_mean_y <- sum(weights * sample_mean) / sum(weights)
# Weighted sums of squares</pre>
```

```
SS_xy <- sum(weights * (temperature - weighted_mean_x) * (sample_mean - weighted_mean_y))
SS_xx <- sum(weights * (temperature - weighted_mean_x)^2)
# Compute b1 and b0
b1 <- SS_xy / SS_xx
b0 <- weighted_mean_y - b1 * weighted_mean_x</pre>
# Calculate standard errors for b0 and b1
s_squared <- sum(weights * (sample_mean - b0 - b1 * temperature)^2) / (sum(weights) - 2)
Sb1 <- sqrt(s_squared / SS_xx)</pre>
Sb0 <- sqrt(s_squared * (1 / sum(weights) + weighted_mean_x^2 / SS_xx))
# Display results
list(
  "Estimated Intercept (b0)" = b0,
 "Estimated Slope (b1)" = b1,
 "Standard Error of b0 (Sb0)" = Sb0,
  "Standard Error of b1 (Sb1)" = Sb1
## $'Estimated Intercept (b0)'
## [1] 44.44479
##
## $'Estimated Slope (b1)'
## [1] 0.1662539
## $'Standard Error of b0 (Sb0)'
## [1] 2.733743
```

### (b)

##

Complete the following ANOVA table:

## \$'Standard Error of b1 (Sb1)'

## [1] 0.01162316

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square			
Regression on X	1	2022.0969	2022.096857			
Residuals	22	200.9148	9.132492			
- Lack-of-fit	2	178.9148	89.457413			
- Pure error	20	22.0000	1.100000			
Total	23	2223.0117	NA			

```
# Given data and results from previous calculations
sample_size <- c(6, 6, 6, 6)
sample_mean <- c(66, 81, 89, 92)
sample_variance <- c(1.15, 1.00, 1.35, 0.90)

# Total sample size and number of groups
N <- sum(sample_size)
r <- length(sample_size)</pre>
```

```
# Weighted mean for sample means
weights <- sample_size / sample_variance</pre>
overall_weighted_mean <- sum(weights * sample_mean) / sum(weights)</pre>
# SST: Total Sum of Squares
SST <- sum(weights * (sample_mean - overall_weighted_mean)^2)
# Regression SS (SSR) using previously computed b1 and SS xy
SSR <- b1 * SS_xy
# Residual SS (SSE)
SSE <- SST - SSR
# Pure Error SS (SSPE)
SSPE <- sum((sample_size - 1) * sample_variance)</pre>
# Lack-of-Fit SS (SSLF)
SSLF <- SSE - SSPE
# Degrees of Freedom
df total <- N - 1
df_regression <- 1</pre>
df residual <- N - 2
df_lack_of_fit <- r - 2</pre>
df_pure_error <- N - r</pre>
# Mean Squares
MSR <- SSR / df_regression
MSE <- SSE / df_residual
MSLF <- SSLF / df_lack_of_fit
MSPE <- SSPE / df_pure_error</pre>
# ANOVA Table
anova_table <- data.frame(</pre>
  "Source of Variation" = c("Regression on X", "Residuals", " - Lack-of-fit", " - Pure error", "Total
  "Degrees of Freedom" = c(df_regression, df_residual, df_lack_of_fit, df_pure_error, df_total),
  "Sum of Squares" = c(SSR, SSE, SSLF, SSPE, SST),
  "Mean Square" = c(MSR, MSE, MSLF, MSPE, NA)
anova_table
     Source.of.Variation Degrees.of.Freedom Sum.of.Squares Mean.Square
##
                                                   2022.0969 2022.096857
## 1
        Regression on X
                                           1
```

(c)

Compute the F-statistic for the lack-of-fit test and report the corresponding degrees freedom. Suppose the p-value is 0.0001, then interpret this result in the context of the study

$$F = \frac{\text{MSLF}}{\text{MSPE}} == \frac{89.457413}{1.100000} \approx 81.32$$

MSLF (Mean Square for Lack of Fit) = 89.457413 MSPE (Mean Square for Pure Error) = 1.100000

Numerator degrees of freedom (for Lack of Fit) = 2 Denominator degrees of freedom (for Pure Error) = 20

So, the computed **F-statistic for the lack-of-fit test** is approximately **81.32** with degrees of freedom (2, 20).

A p-value of 0.0001 is very small (much less than a typical significance level, such as 0.05). This indicates strong evidence against the null hypothesis of the lack-of-fit test, which states that the simple linear regression model is adequate for the data.

## $\mathbf{Q2}$

The Berkeley Guidance Study enrolled children born in Berkeley, California, between January 1928 and June 1929, and then measure each child periodically until age 18. The data for all of the girls in the study who were measured at age 18 are posted in the file BGSgirls.dat in our course's shared folder on SAS Studio. There is one line for each girl in this data file, with the subject identification number, weight (in kilograms), and height (in centimeters), in that order from left to right

#### (a)

Compute least square estimates of the intercept  $(\beta_0)$  and slope  $(\beta_1)$  of a simple linear regression model for predicting weight (Y) from height (x). Report the parameter estimates and their standard errors. Is height a significant predictor of weight (yes or no)? Briefly justify your choice.

			[	M	REG   lodel: I lent Va	MOD		ht				
		Number of Observations Read							70			
		Number of Observations Used						69				
		Number of Observations with Missing Values					1					
				Ana	llysis o							
Soul	rce				Sum o Square		Mean Square		F Va	/alue I		> F
Mod	lel		1	150	5.2418	0 1	1505.241	180	45	45.52		001
Erro	г	67 221		5.55472 33.067		798						
Corr	Corrected Total		68	372	3720.79652							
		Root MSE			5.750		8 R-Square		0.4	045		
		Depender		Mean	59.23478		Adj R-Sq		0.3	3957		
	Coeff Var			9.7079								
		Parameter Estimates										
	Var			meter Sta		ndard Error	t Va	lue	Pr >  t			
	Inte	ercept	1	-69.2	1339	19	9.05090 -		.63	3 0.000		
	Hai	ght 1 0.77100		0	11428	6.75		<.00	101			

Figure 1: CocoMelon

(b)

Plot weight versus height and insert the estimated regression line on the plot, and include the plot in your submission. What does this plot suggest?

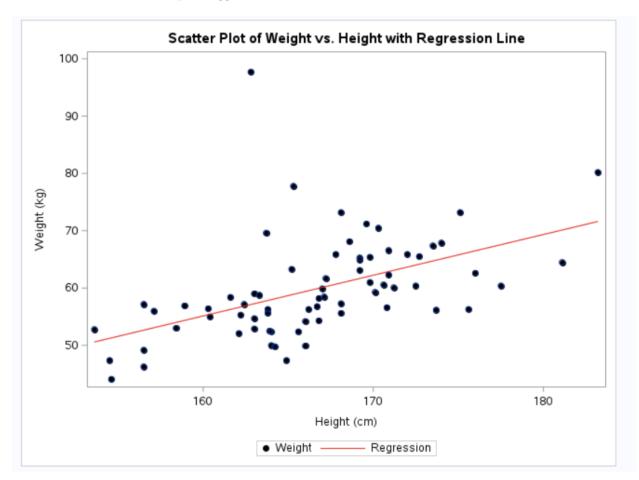


Figure 2: CocoMelon

(c)

Construct a plot of the studentized residuals versus  $\hat{Y}_i$ , where  $\hat{Y}_i = b_0 + b_1 x_i$ , and include the plot in your submission. What does this plot indicate?

(d)

The diagnostic plots should indicate that there is one 18 year-old girl who is extremely heavy given her height. This observation may involve a value for either height or weight that was not properly recorded, or it may just correspond to an unusually heavy girl. You can delete this observation by replacing the value of the weight with a period. Because this is the only girl with weight exceeding 90 kg, you can delete this case in a data step by inserting the code:

if(weight > 90) then weight=.;

Or you can use only the subset of data by

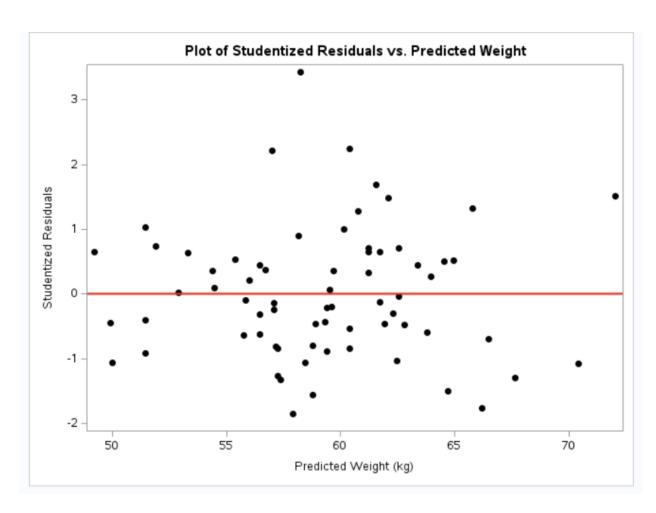


Figure 3: CocoMelon

#### where weight le 90;

Re-fit the simple linear regression model. Do the diagnostic plots now appear to show that the data conform to the assumptions of the proposed regression model? If not, what problems remain? Include all relevant plots in your submission.

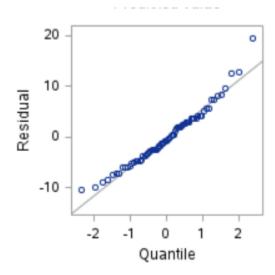


Figure 4: CocoMelon

(e)

Plot the estimated regression lines with the extreme observation included and the extreme observation removed on the same plot. Include the plot in your submission. Did deleting the observation in part (d) have a large effect on any of the parameter estimates? Briefly justify your response.

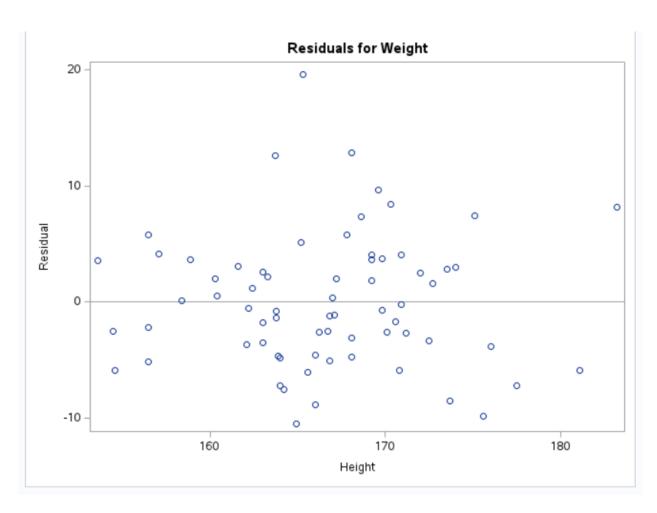


Figure 5: CocoMelon

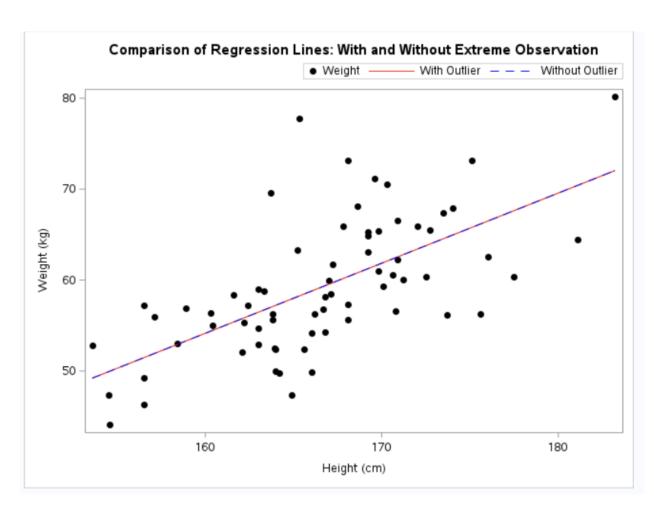


Figure 6: CocoMelon

#### Q3

One factor that may explain the price of a diamond is the weight of the diamond. Data were collected for a sample of 48 diamonds, including the weight in grams (g) and the price (in Singapore dollars) of each diamond. These data are located in the file diamonds.csv posted in Canvas. The R code that generated the output below is included in Canvas in the diamonds Hmwk9.R file for your reference.

#### (a)

Write the simple linear regression model for this problem (including assumptions). Give the definition of the parameter values  $\beta_0$ ,  $\beta_1$ , and  $\sigma^2$  in the context of the response and explanatory variables.

### (b)

Write the simple linear regression model for this problem in vector-matrix notation. Give the first 4 rows of the design matrix  $\mathbf{X}$ .

#### (c)

Describe the scatterplot, shown below, of the weight and price of the 48 diamonds in this sample. What do you notice about the relationship between these two values?

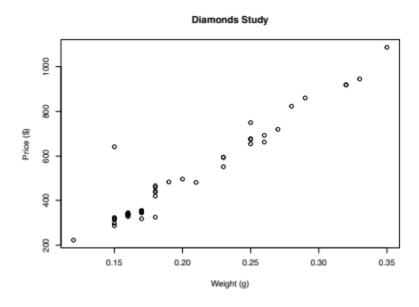


Figure 7: CocoMelon

# (d)

The output below includes the sample correlation coefficient between the weight and price of the diamonds. How does the value of the correlation reinforce your description from part (c).

```
> cor(diamonds$weight, diamonds$price)
[1] 0.9622006
```

Figure 8: CocoMelon

(e)

Using the output shown below, give the equation for the least squares regression line to predict the price of a diamond from its weight.

```
lm(formula = price ~ weight, data = diamonds)
Residuals:
  Min
          1Q Median
                        3Q
                              Max
-95.31 -26.37 -7.56 10.32 330.07
Coefficients:
           Estimate Std. Error t value Pr(>ItI)
(Intercept) -229.94
                         31.63 -7.271 3.58e-09 ***
                        150.76 23.962 < 2e-16 ***
weight
            3612.50
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
Residual standard error: 58.81 on 46 degrees of freedom
Multiple R-squared: 0.9258,
                               Adjusted R-squared: 0.9242
F-statistic: 574.2 on 1 and 46 DF, p-value: < 2.2e-16
```

Figure 9: CocoMelon

(f)

Use the ANOVA Table shown below to conduct a test of significance for the linear regression model

```
Df Sum Sq Mean Sq F value Pr(>F)
weight 1 1986120 1986120 574.2 <2e-16 ***
Residuals 46 159112 3459
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
```

Figure 10: CocoMelon

(g)

A 95% confidence interval for the slope parameter in the simple linear regression model is shown below. Give an interpretation of this interval.

```
2.5 % 97.5 % (Intercept) -293.6016 -166.2819 weight 3309.0375 3915.9530
```

Figure 11: CocoMelon

## (h)

A 95% confidence interval for the conditional mean price of all diamonds in the population with a weight of 0.2 grams is shown below. Give the interpretation of this interval.

fit lwr upr 492.5573 475.4583 509.6563

Figure 12: CocoMelon

### (i)

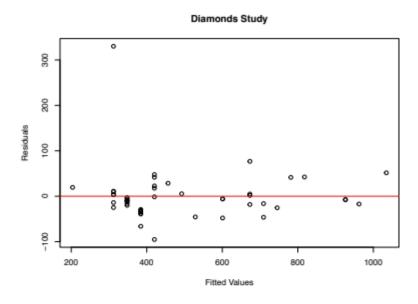
A 95% prediction interval for the price of a diamond in the population with a weight of 0.3 grams is shown below. Give the interpretation of this interval.

fit lwr upr 853.8068 730.5604 977.0533

Figure 13: CocoMelon

# (j)

Examine the residual plots shown below. Is there any reason to suspect the model assumptions do not hold or that there are influence points?



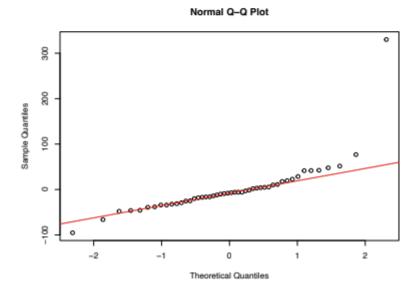


Figure 14: CocoMelon