

PSTAT 126

Lab 2

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```
library(tidyverse) # Easily Install and Load the 'Tidyverse'
library(palmerpenguins) # Palmer Archipelago (Antarctica) Penguin Data
```

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Computing OLS estimators in simple linear regression (without lm())

Dataset: Adelie and Gentoo Penguins

- Question: Can we predict body mass in grams by a penguins bill length in mm?

```
data("penguins")

penguins_noChinstrap <- penguins %>%
  filter(species != "Chinstrap") %>%
  drop_na(bill_length_mm, body_mass_g)

str(penguins_noChinstrap)

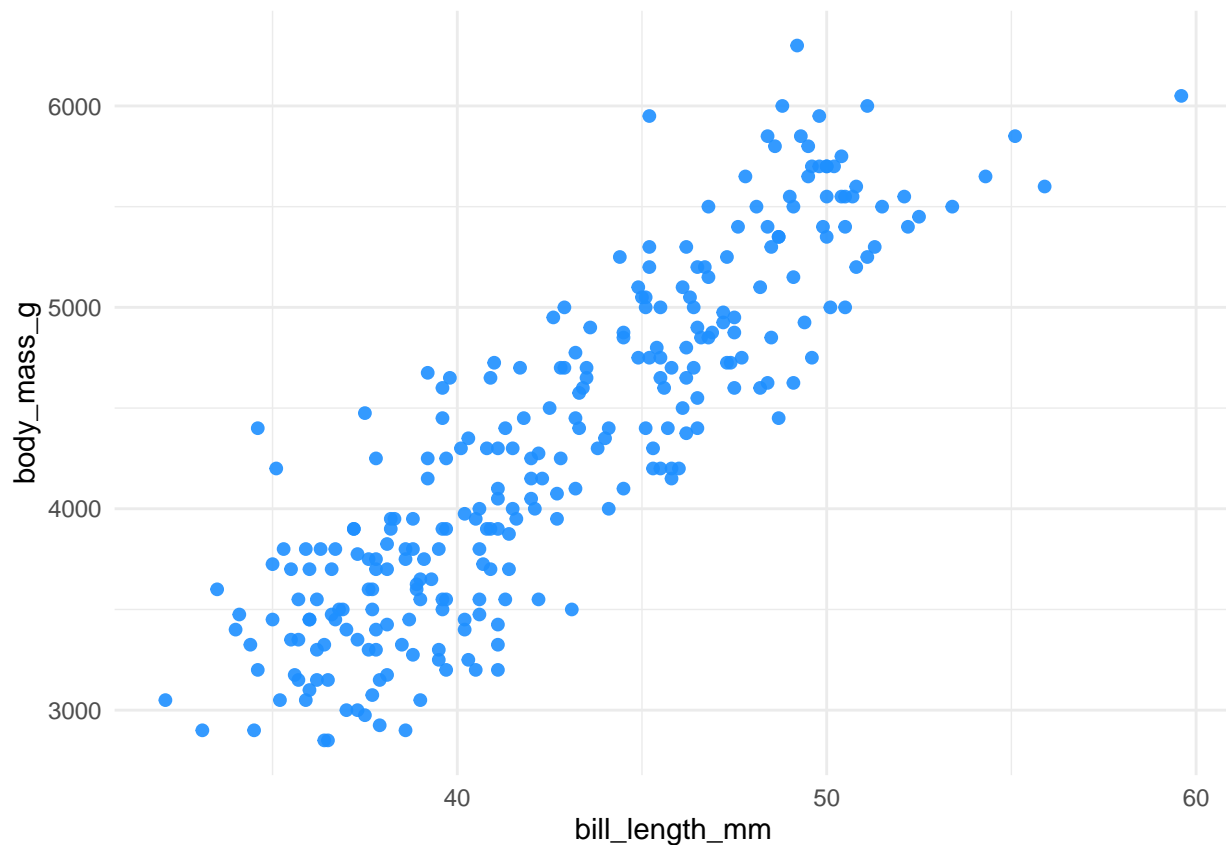
## tibble [274 x 8] (S3: tbl_df/tbl/data.frame)
## $ species      : Factor w/ 3 levels "Adelie","Chinstrap",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ island       : Factor w/ 3 levels "Biscoe","Dream",...: 3 3 3 3 3 3 3 3 3 3 ...
## $ bill_length_mm : num [1:274] 39.1 39.5 40.3 36.7 39.3 38.9 39.2 34.1 42 37.8 ...
## $ bill_depth_mm : num [1:274] 18.7 17.4 18 19.3 20.6 17.8 19.6 18.1 20.2 17.1 ...
## $ flipper_length_mm: int [1:274] 181 186 195 193 190 181 195 193 190 186 ...
## $ body_mass_g    : int [1:274] 3750 3800 3250 3450 3650 3625 4675 3475 4250 3300 ...
## $ sex           : Factor w/ 2 levels "female","male": 2 1 1 1 2 1 2 NA NA NA ...
## $ year          : int [1:274] 2007 2007 2007 2007 2007 2007 2007 2007 2007 2007 ...

summary(penguins_noChinstrap)

##      species      island  bill_length_mm  bill_depth_mm
## Adelie      :151   Biscoe      :167   Min.      :32.10   Min.      :13.10
## Chinstrap:  0    Dream       : 56   1st Qu.:38.35   1st Qu.:15.00
```

```
## Gentoo :123 Torgersen: 51 Median :42.00 Median :17.00
## Mean :42.70 Mean :16.84
## 3rd Qu.:46.67 3rd Qu.:18.50
## Max. :59.60 Max. :21.50
## flipper_length_mm body_mass_g sex year
## Min. :172.0 Min. :2850 female:131 Min. :2007
## 1st Qu.:190.0 1st Qu.:3600 male :134 1st Qu.:2007
## Median :198.0 Median :4262 NA's : 9 Median :2008
## Mean :202.2 Mean :4318 Mean :2008
## 3rd Qu.:215.0 3rd Qu.:4950 3rd Qu.:2009
## Max. :231.0 Max. :6300 Max. :2009
```

```
# plot of data
ggplot(data = penguins_noChinstrap,
  aes(x = bill_length_mm, y = body_mass_g)) +
  geom_point(color = "dodgerblue", alpha = 0.9, size = 1.75) +
  theme_minimal()
```



```
x <- penguins_noChinstrap$bill_length_mm
y <- penguins_noChinstrap$body_mass_g
```

First obtain means of x and y

```
x_bar <- mean(x)
y_bar <- mean(y)
```

$$S_{xx} : \sum_{i=1}^n (x_i - \bar{x})^2$$

```
Sxx <- sum((x - x_bar)^2)
Sxx
```

```
## [1] 7369.338
```

$$S_{yy} : \sum_{i=1}^n (y_i - \bar{y})^2$$

```
Syy <- sum((y - y_bar)^2)
Syy
```

```
## [1] 190768075
```

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

```
Sxy <- sum((x - x_bar)*(y - y_bar))
Sxy
```

```
## [1] 1039728
```

$$\hat{\beta}_1 = S_{xy}/S_{xx}$$

```
b1 <- Sxy / Sxx
b1
```

```
## [1] 141.0884
```

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

```
b0 <- y_bar - b1*x_bar
b0
```

```
## [1] -1706.821
```

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 x$$

```
y_hat <- b0 + b1*x
```

Estimation of Residuals

$$e_i = y_i - \hat{y}$$

```
e <- y - y_hat
```

$$\hat{\sigma}^2 = \frac{1}{N-2} \sum_{n=1}^n e_n^2$$

```
n <- length(y)
sigma_2_hat <- sum(e^2) / (n-2)
sigma_2_hat

## [1] 162038.6
sqrt(sigma_2_hat) # Residual Standard Error (RSE)

## [1] 402.5402
```

The `lm()` function

```
model <- lm(body_mass_g ~ bill_length_mm , data = penguins_noChinstrap)
```

```
summary(model)
```

```
##
## Call:
## lm(formula = body_mass_g ~ bill_length_mm, data = penguins_noChinstrap)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -891.91 -272.91   -0.82   282.47 1279.63
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1706.821    201.712  -8.462 1.65e-15 ***
## bill_length_mm   141.088      4.689   30.088 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 402.5 on 272 degrees of freedom
## Multiple R-squared:  0.769, Adjusted R-squared:  0.7681
## F-statistic: 905.3 on 1 and 272 DF, p-value: < 2.2e-16
```

```
coef(model) # Estimates for b0 and b1
```

```
##      (Intercept) bill_length_mm  
##      -1706.8209      141.0884
```

```
model$coefficients
```

```
##      (Intercept) bill_length_mm  
##      -1706.8209      141.0884
```

```
head(residuals(model)) # residuals
```

```
##           1           2           3           4           5           6  
## -59.73552 -66.17088 -729.04160 -21.12337 -187.95320 -156.51784
```

```
head(fitted(model)) # y_hat values
```

```
##           1           2           3           4           5           6  
## 3809.736 3866.171 3979.042 3471.123 3837.953 3781.518
```

```
summary(residuals(model)) # First line in summary output.
```

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.  
## -891.9123 -272.9122   -0.8239    0.0000  282.4722 1279.6252
```

```
# Standard errors
```

```
summary(model)$coef[,2]
```

```
##      (Intercept) bill_length_mm  
##      201.71210      4.68916
```

```
coef(summary(model))[, "Std. Error"]
```

```
##      (Intercept) bill_length_mm  
##      201.71210      4.68916
```

```
# p-values for intercept and slope
```

```
summary(model)$coef[,4]
```

```
##      (Intercept) bill_length_mm  
## 1.648813e-15 1.590571e-88
```

p-values for t-test and F-test in SLR are identical.

```
summary(model)$sigma^2
```

```
## [1] 162038.6
```

Confidence Intervals for intercept and slope estimates

Can calculate a 90% confidence interval by entering values into formula:

- Intercept

$$\hat{\beta}_0 \pm (t_{\alpha/2, N-2} SE(\hat{\beta}_0))$$

- Slope

$$\hat{\beta}_1 \pm (t_{\alpha/2, N-2} SE(\hat{\beta}_1))$$

```
n <- length(x)
sigma_2_hat <- sum(e^2) / (n-2)
sigma_hat <- sqrt(sigma_2_hat)
Sxx <- sum((x - x_bar)^2)

se_b0 <- sqrt(sigma_2_hat*(1/n +
                        (x_bar^2)/Sxx)) # se of intercept
se_b1 <- sqrt(sigma_2_hat/Sxx) # se of slope

t_pct <- qt(p = 0.95, df = n - 2) # t-statistic

CI_b0_90 <- c(b0 - t_pct*se_b0, b0 + t_pct*se_b0) # 90% CI for b0
CI_b1_90 <- c(b1 - t_pct*se_b1, b1 + t_pct*se_b1) # 90% CI for b1
CI_b0_90

## [1] -2039.742 -1373.900
CI_b1_90
```

```
## [1] 133.3491 148.8277
```

Can also use the `confint` function

```
?confint
confint(model, level = 0.95) # 95% CI

##                2.5 %      97.5 %
## (Intercept)   -2103.9363 -1309.7054
## bill_length_mm  131.8567  150.3201

confint(model, level = 0.90) # 90% CI

##                5 %       95 %
## (Intercept)   -2039.7416 -1373.9001
## bill_length_mm  133.3491  148.8277
```

Hypothesis Testing

Hypothesis testing of $\hat{\beta}_0, \hat{\beta}_1$

Want to test:

$H_0 : \hat{\beta}_0 = 0$ vs. $H_1 : \hat{\beta}_0 \neq 0$

$H_0 : \hat{\beta}_1 = 0$ vs. $H_1 : \hat{\beta}_1 \neq 0$

Let $\alpha = 0.05$

```
t_b0 <- (b0-0)/se_b0  
t_b1 <- (b1-0)/se_b1  
t_b0
```

```
## [1] -8.461668
```

```
t_b1
```

```
## [1] 30.0882
```

- For distributions in R, p stands for “probability”, the cumulative distribution function (c. d. f.).

```
p0 <- 2*(1 - pt(abs(t_b0), df = n-2))  
p1 <- 2*(1 - pt(abs(t_b1), df = n-2))
```

```
alpha <- 0.05  
p0 > alpha
```

```
## [1] FALSE
```

```
p1 > alpha
```

```
## [1] FALSE
```

```
p0
```

```
## [1] 1.776357e-15
```

```
p1
```

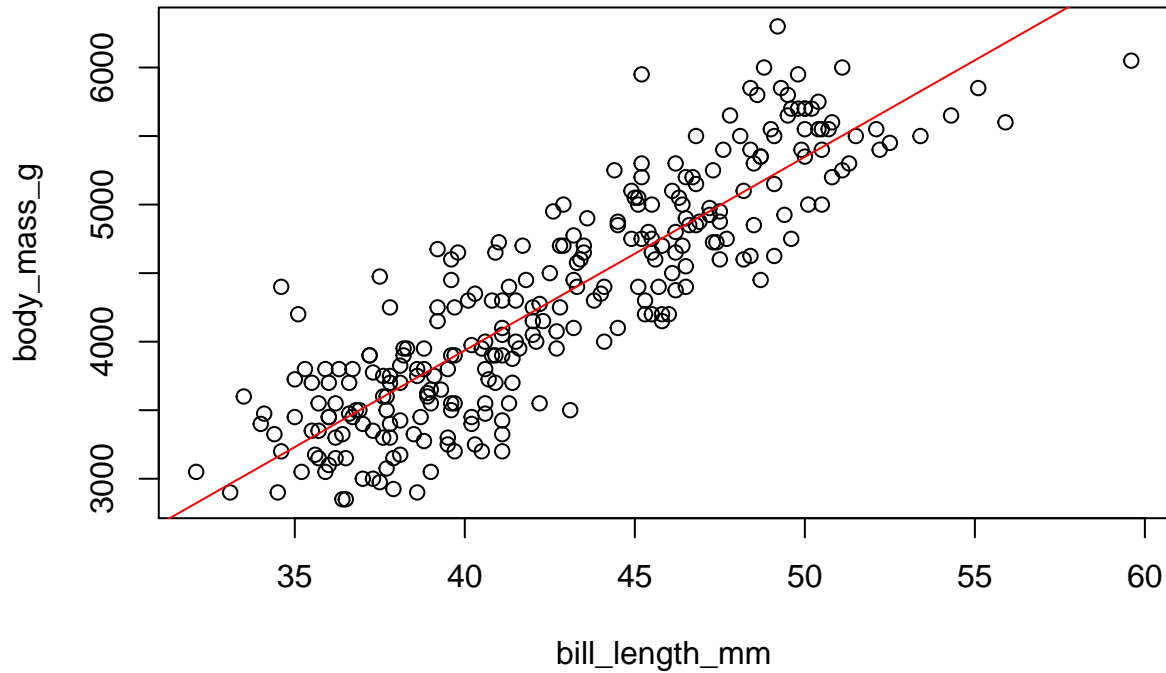
```
## [1] 0
```

Reject Null Hypothesis for both $\hat{\beta}_0, \hat{\beta}_1$

Plots

```
plot(body_mass_g ~ bill_length_mm, data = penguins_noChinstrap,  
      main = "Plot with fitted values")  
abline(model, col = "Red")
```

Plot with fitted values



```
ggplot(data = penguins_noChinstrap) +  
  geom_point(aes(x = bill_length_mm, y = body_mass_g), color = "dodgerblue", alpha = 0.95) +  
  geom_abline(aes(intercept = model$coefficients[[1]],  
                  slope = model$coefficients[[2]]),  
              color = "red") +  
  labs(x = "bill length (mm)",  
        y = "body mass (grams)",  
        title = "Plot with fitted values") +  
  theme_minimal()
```

Plot with fitted values

