## Computing OLS, CIs, Hypothesis Testing, Plots

### PSTAT 126

#### Lab 2

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

## Contents

Computing OLS estimators	1
The $\operatorname{lm}()$ function	3
Confidence Intervals for intercept and slope estimates	5
Hypothesis Testing	5
Coefficient of Determination $R^2$	6
Plots	7

#### Computing OLS estimators

Dataset: Adelie and Gentoo Penguins

ggplot(data = penguins\_noChinstrap,

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

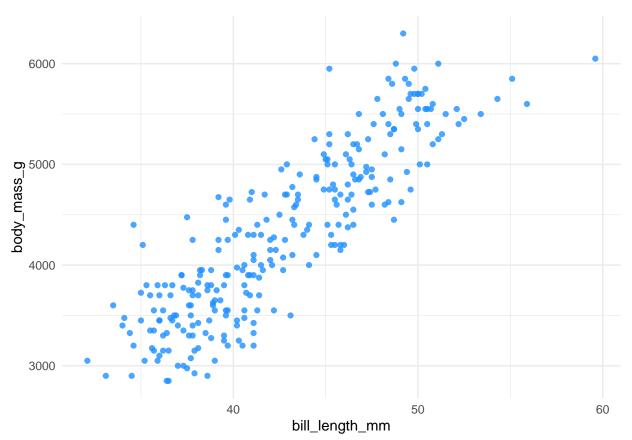
```
data("penguins")

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

summary(penguins_noChinstrap)
```

```
##
         species
                          island
                                    bill_length_mm
                                                    bill_depth_mm
##
             :151
                                                            :13.10
   Adelie
                    Biscoe
                             :167
                                    Min.
                                            :32.10
                                                     Min.
   Chinstrap: 0
                    Dream
                             : 56
                                     1st Qu.:38.35
                                                     1st Qu.:15.00
            :123
                    Torgersen: 51
                                    Median :42.00
##
   Gentoo
                                                     Median :17.00
##
                                    Mean
                                            :42.70
                                                     Mean
                                                            :16.84
##
                                     3rd Qu.:46.67
                                                     3rd Qu.:18.50
##
                                                            :21.50
                                    Max.
                                            :59.60
                                                     Max.
##
  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
           :202.2
                             :4318
                                                          :2008
## Mean
                      Mean
                                                   Mean
   3rd Qu.:215.0
                      3rd Qu.:4950
                                                   3rd Qu.:2009
## Max.
           :231.0
                      Max.
                             :6300
                                                   Max.
                                                          :2009
# plot of data
```

```
aes(x = bill_length_mm, y = body_mass_g)) +
geom_point(color = "dodgerblue", alpha = 0.8, size = 1.5) +
theme_minimal()
```



```
x <- penguins_noChinstrap$bill_length_mm
y <- penguins_noChinstrap$body_mass_g</pre>
```

First obtain means of x and y

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

```
Sxx <- sum((x - x_bar)^2)
Sxx</pre>
```

## [1] 7369.338

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

```
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</pre>
```

## [1] 1039728

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

b1 <- Sxy / Sxx

## [1] 141.0884

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

b0 <- y\_bar - b1\*x\_bar

## [1] -1706.821

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

 $y_hat \leftarrow b0 + b1*x$ 

#### **Estimation of Residuals**

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

e <- y - y\_hat

$$\hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^n e_i^2$$

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

## [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)
##</pre>
```

## lm(formula = body\_mass\_g ~ bill\_length\_mm, data = penguins\_noChinstrap)
##

## Residuals:

## Call:

```
10 Median
                                  3Q
       Min
## -891.91 -272.91 -0.82 282.47 1279.63
##
## Coefficients:
##
                    Estimate Std. Error t value Pr(>|t|)
                   -1706.821
                                 201.712 -8.462 1.65e-15 ***
## (Intercept)
## bill_length_mm 141.088
                                   4.689 30.088 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 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 beta0 and beta1
##
       (Intercept) bill_length_mm
##
       -1706.8209
                          141.0884
model $ coefficients
##
       (Intercept) bill_length_mm
       -1706.8209
##
                          141.0884
head(model$residuals) # residuals
##
                         2
                                     3
             1
## -59.73552 -66.17088 -729.04160 -21.12337 -187.95320 -156.51784
head(model$fitted.values) # y_hat values
                              3
##
## 3809.736 3866.171 3979.042 3471.123 3837.953 3781.518
summary(model$residuals) # first line in summary output.
        Min.
                1st Qu.
                            Median
                                         Mean
                                                 3rd Qu.
## -891.9123 -272.9122
                           -0.8239
                                       0.0000 282.4722 1279.6252
\hat{se}(\hat{\beta}_1) = \sqrt{\frac{\hat{\sigma}^2}{S_{xx}}} \ \hat{se}(\hat{\beta}_0) = \sqrt{\hat{\sigma}^2(\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}})}
# Standard errors
summary(model)$coef
##
                     Estimate Std. Error
                                             t value
                                                          Pr(>|t|)
## (Intercept)
                   -1706.8209 201.71210 -8.461668 1.648813e-15
## bill_length_mm 141.0884
                                  4.68916 30.088202 1.590571e-88
coef(summary(model))[, "Std. Error"]
##
       (Intercept) bill_length_mm
##
        201.71210
                           4.68916
sqrt(sigma_2_hat/Sxx)
## [1] 4.68916
sqrt(sigma_2_hat*(1/n + (x_bar^2)/Sxx))
## [1] 201.7121
```

```
# 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 simple linear regression are identical.
```

```
summary(model)$sigma
```

## [1] 402.5402

#### 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

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

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

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

## [1] -2039.742 -1373.900</pre>
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 \text{ vs. } H_1: \hat{\beta}_0 \neq 0
H_0: \hat{\beta}_1 = 0 \text{ 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 \leftarrow 2*(1 - pt(abs(t_b0), df = n-2))
p1 \leftarrow 2*(1 - pt(abs(t_b1), df = n-2))
p0
## [1] 1.776357e-15
р1
## [1] 0
```

## Coefficient of Determination $R^2$

• A goodness-of-fit measure

Reject null hypothesis for both  $\hat{\beta}_0, \hat{\beta}_1$ 

$$R^2 = 1 - \frac{RSS}{S_{yy}}$$
 
$$R_{adj}^2 = 1 - \frac{RSS/df}{S_{yy}/(n-1)}$$

```
b0 <- summary(model)$coef[1,1] # Intercept
b1 <- summary(model)$coef[2,1] # Slope
y_hat <- b0 + b1*x # Fitted values
e <- y - y_hat # Residuals

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

r_2 <- 1 - (sum(e^2)/Syy)
r_2

## [1] 0.7689629

summary(model)$r.squared

## [1] 0.7689629

r <- cor(x,y)
r^2

## [1] 0.7689629
```

```
adj_r2 <- 1 - (sum(e^2)/(n-2))/(Syy/(n-1))
adj_r2
## [1] 0.7681135
summary(model)$adj.r.squared</pre>
```

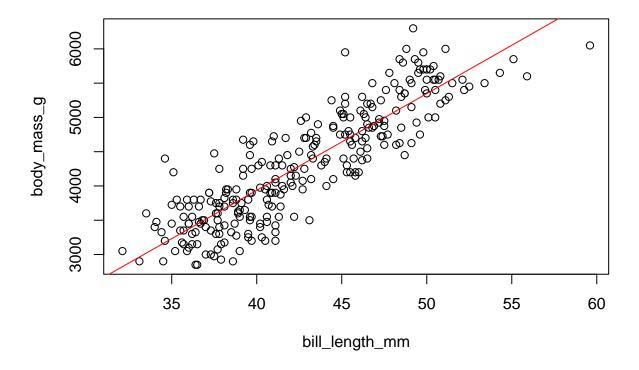
## [1] 0.7681135

Notes on  $\mathbb{R}^2$ 

- Always between 0 and 1
- Can interpret as  $R^2 \times 100$  percent of the variation in Y is explained by the variation in the predictor x.

## Plots

## Plot with fitted values



# Plot with fitted values

