



UNIVERSITY *of*
WEST FLORIDA

Review of General Linear Models

Statistics for Data Science II

Recall the general linear model,

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$

This is a multiple regression model because it has multiple predictors (x_i).

A special case is simple linear regression, when there is a single predictor.

β_0 is the y -intercept, or the average outcome (y) when all $x_i = 0$.

β_i is the slope for predictor i and describes the relationship between the predictor and the outcome, after adjusting (or accounting) for the other predictors in the model.

Constructing the Model in R

We will use the `lm()` function to construct the linear model,

```
m <- lm([outcome] ~ [pred1] + [pred2] + [pred3] + ...,  
        data = [dataset])
```

Then we run the model results through the `summary()` function to obtain information about the model,

```
summary(m)
```

Constructing the Model in R

Example

Consider the data from the `palmerpenguin` package. Let's create a dataset with the variables `body_mass_g`, `bill_length_mm`, and `flipper_length_mm`.

```
data <- as_tibble(penguins %>% select(body_mass_g,  
                                     bill_length_mm,  
                                     flipper_length_mm))  
  
head(data)
```

```
## # A tibble: 6 x 3  
##   body_mass_g bill_length_mm flipper_length_mm  
##         <int>         <dbl>         <int>  
## 1      3750          39.1           181  
## 2      3800          39.5           186  
## 3      3250          40.3           195  
## 4         NA          NA             NA  
## 5      3450          36.7           193  
## 6      3650          39.3           190
```

```
m1 <- lm(bill_length_mm ~ body_mass_g + flipper_length_mm,  
         data = data)  
summary(m1)
```

```
##  
## Call:  
## lm(formula = bill_length_mm ~ body_mass_g + flipper_length_mm,  
##     data = data)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -8.8064 -2.5898 -0.7053  1.9911 18.8288   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  -3.4366939   4.5805532   -0.750    0.454      
## body_mass_g    0.0006622   0.0005672    1.168    0.244      
## flipper_length_mm 0.2218655   0.0323484    6.859 3.31e-11 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 4.124 on 339 degrees of freedom  
## (2 observations deleted due to missingness)  
## Multiple R-squared:  0.4329, Adjusted R-squared:  0.4295   
## F-statistic: 129.4 on 2 and 339 DF,  p-value: < 2.2e-16
```

Interpretation of Slope

We want to put the slope into perspective for whoever we are collaborating with.

Basic interpretation: for every 1 [units of x_i] increase in $[x_i]$, $[y]$ [increases or decreases] by $[|\hat{\beta}_i|]$ [units of y].

We say that y is decreasing if $\hat{\beta}_0 < 0$ and y is increasing if $\hat{\beta}_0 > 0$.

We can also scale our interpretations. e.g.,

For every 7 [units of x_i] increase in $[x_i]$, $[y]$ [increases or decreases] by $[7 \times |\hat{\beta}_i|]$ [units of y].

Example:

```
coefficients(m1)
```

##	(Intercept)	body_mass_g	flipper_length_mm
##	-3.4366939266	0.0006622186	0.2218654584

For a 1 gram increase in body mass, we expect bill length to increase by 0.0007 mm.

For a 1000 gram increase in body mass (i.e., 1 kg or ~ 2.2 lbs), we expect bill length to increase by 0.66 mm.

For a 1 mm increase in flipper length, we expect bill length to increase by 0.22 mm.

Confidence Intervals for β_i

Recall confidence intervals – they allow us to determine how “good” our estimation is.

In general CIs will take the form

$$\text{point estimate} \pm \text{margin of error},$$

where the margin of error is a critical value (e.g., $t_{1-\alpha/2}$) multiplied by the standard error of the point estimate.

Recall that the standard error accounts for the sample size.

In R, we will run the model results through the `confint()` function.

```
confint(m)
```


Example:

```
confint(m1)
```

##		2.5 %	97.5 %
## (Intercept)		-1.244658e+01	5.573192182
## body_mass_g		-4.534709e-04	0.001777908
## flipper_length_mm		1.582365e-01	0.285494420

We have the following CIs:

95% CI for β_{mass} is (-0.0005, 0.0018)

95% CI for β_{flipper} is (0.1582, 0.2855)

Confidence Intervals for β_i

We can change the confidence level by specifying the `level`.

Example:

```
confint(m1, level=0.99)
```

```
##               0.5 %      99.5 %  
## (Intercept)  -1.530220e+01 8.428814954  
## body_mass_g  -8.070812e-04 0.002131518  
## flipper_length_mm 1.380697e-01 0.305661191
```

```
confint(m1, level=0.8914)
```

```
##               5.43 %      94.57 %  
## (Intercept)  -1.080570e+01 3.932309891  
## body_mass_g  -2.502813e-04 0.001574718  
## flipper_length_mm 1.698246e-01 0.273906301
```

Significant Regression Line

Hypotheses

$$H_0 : \beta_1 = \dots = \beta_k = 0$$

$$H_1 : \text{at least one } \beta_i \neq 0$$

Test Statistic and p -Value

F_0 and p from `summary()` (last line)

Rejection Region

Reject H_0 if $p < \alpha$

Significant Regression Line

```
m1 <- lm(bill_length_mm ~ body_mass_g + flipper_length_mm,
         data = data)
summary(m1)

##
## Call:
## lm(formula = bill_length_mm ~ body_mass_g + flipper_length_mm,
##     data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.8064 -2.5898 -0.7053  1.9911 18.8288
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -3.4366939   4.5805532   -0.750    0.454
## body_mass_g     0.0006622   0.0005672    1.168    0.244
## flipper_length_mm 0.2218655   0.0323484    6.859 3.31e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.124 on 339 degrees of freedom
## (2 observations deleted due to missingness)
## Multiple R-squared:  0.4329, Adjusted R-squared:  0.4295
## F-statistic: 129.4 on 2 and 339 DF,  p-value: < 2.2e-16
```

Significant Regression Line

Hypotheses

$$H_0 : \beta_{\text{mass}} = \beta_{\text{flipper}} = 0$$

$$H_1 : \text{at least one } \beta_i \neq 0$$

Test Statistic and p -Value

$$F_0 = 129.4 \ (p < 0.001)$$

Rejection Region

$$\text{Reject } H_0 \text{ if } p < \alpha; \alpha = 0.05$$

Conclusion/Interpretation

Reject H_0 . There is sufficient evidence to suggest that at least one slope is non-zero.

Hypotheses

$$H_0 : \beta_i = 0$$

$$H_1 : \beta_i \neq 0$$

Test Statistic and p -Value

t_0 and p from `summary()` (last two columns)

Rejection Region

Reject H_0 if $p < \alpha$

```
m1 <- lm(bill_length_mm ~ body_mass_g + flipper_length_mm,  
         data = data)  
summary(m1)
```

```
##  
## Call:  
## lm(formula = bill_length_mm ~ body_mass_g + flipper_length_mm,  
##     data = data)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -8.8064 -2.5898 -0.7053  1.9911 18.8288   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  -3.4366939   4.5805532  -0.750    0.454      
## body_mass_g    0.0006622   0.0005672   1.168    0.244      
## flipper_length_mm 0.2218655   0.0323484   6.859 3.31e-11 ***  
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## F-statistic: 129.4 on 2 and 339 DF,  p-value: < 2.2e-16
```

Hypotheses

$$H_0 : \beta_{\text{mass}} = 0$$

$$H_1 : \beta_{\text{mass}} \neq 0$$

Test Statistic and p -Value

$$t_0 = 1.168 \ (p = 0.244)$$

Rejection Region

Reject H_0 if $p < \alpha$; $\alpha = 0.05$

Conclusion / Interpretation

Fail to reject H_0 . There is not sufficient evidence to suggest that body mass significantly predicts bill length.

Hypotheses

$$H_0 : \beta_{\text{flipper}} = 0$$

$$H_1 : \beta_{\text{flipper}} \neq 0$$

Test Statistic and p -Value

$$t_0 = 6.859 \ (p < 0.001)$$

Rejection Region

Reject H_0 if $p < \alpha$; $\alpha = 0.05$

Conclusion / Interpretation

Reject H_0 . There is sufficient evidence to suggest that flipper length significantly predicts bill length.

We can construct basic scatterplots to try to visualize the relationships*.

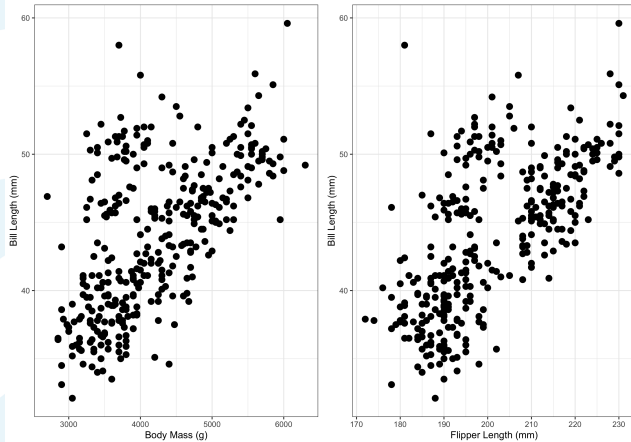
Example:

```
p1 <- data %>% ggplot(aes(x = body_mass_g, y = bill_length_mm)) +  
  geom_point(size=3) +  
  ylab("Bill Length (mm)") +  
  xlab("Body Mass (g)") +  
  theme_bw()
```

```
p2 <- data %>% ggplot(aes(x = flipper_length_mm, y = bill_length_mm)) +  
  geom_point(size=3) +  
  ylab("Bill Length (mm)") +  
  xlab("Flipper Length (mm)") +  
  theme_bw()
```

Visualizing the Data

Example:



We can construct predicted values to overlay the resulting regression line.

To do this, we must pick one predictor to vary. All other predictors must be held constant in order to overlay a regression line.

First, we will plug in the average flipper length and let body mass vary (`p_mass`).

Then, we will plug in the average body mass and let flipper length vary (`p_flip`).

Example:

```
c1 <- coefficients(m1)
```

```
data <- data %>%
```

```
  mutate(p_mass = c1[1] + c1[2]*body_mass_g + c1[3]*mean(data$flipper_length_mm, na.rm = TRUE)
```

```
         p_flip = c1[1] + c1[2]*mean(data$body_mass_g, na.rm = TRUE) + c1[3]*flipper_length_mm)
```

Example:

```
p3 <- data %>% ggplot(aes(x = body_mass_g, y = bill_length_mm)) +  
  geom_point(size=3) +  
  geom_line(aes(y = p_mass)) +  
  ylab("Bill Length (mm)") +  
  xlab("Body Mass (g)") +  
  theme_bw()
```

```
p4 <- data %>% ggplot(aes(x = flipper_length_mm, y = bill_length_mm)) +  
  geom_point(size=3) +  
  geom_line(aes(y = p_flip)) +  
  ylab("Bill Length (mm)") +  
  xlab("Flipper Length (mm)") +  
  theme_bw()
```

Visualizing the Data

Example:

