# Day12

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## Problem 4.13

If the mother is white, then the birth weight will be about 117.87 - 0 + 0 - 0 = 117.87 oz. If the mother is black, then the birth weight will be about 117.87 - 7.31 + 0 - 0 = 110.56 oz. If the mother is Hispanic, then the birth weight will be about 117.87 - 0 + 0.65 - 0 = 118.52 oz. If the mother is other, then the birth weight will be about 117.87 - 0 + 0 - 0.73 = 117.14 oz.

## Problem 4.14

- a) Since the p-values of the Hispanic and Other predictors is greater than 0.05, we can not say that they are significant.
  - b)  $R^2 = 1.9\%$ , so this model explains 1.9% of the variability in the birth weight of a baby.
  - c) p < 0.05, so we can reject the null hypothesis and say that at least one of the predictors is important.

## Probem 4.16

a)  $R^2 = 0.756$ , so about 76% of the variability in log nitrogen assimilation is explained by the model.

```
##
## Call:
## lm(formula = LogNassim ~ LogMass, data = Cater)
##
## Residuals:
##
       Min
                  1Q
                      Median
                                    3Q
                                            Max
## -1.26089 -0.11558 0.02162 0.16725
                                        0.41862
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.88738
                           0.01841 -102.53
## LogMass
                           0.01332
                                     27.85
                                             <2e-16 ***
                0.37096
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.2501 on 251 degrees of freedom
     (14 observations deleted due to missingness)
```

```
## Multiple R-squared: 0.7555, Adjusted R-squared: 0.7545
## F-statistic: 775.6 on 1 and 251 DF, p-value: < 2.2e-16</pre>
```

b)  $R^2 = 0.8348$ , so about 83% of the variability is explained in this model. This is more than the model from before.

```
##
## Call:
## lm(formula = LogNassim ~ I(Instar == 2) + I(Instar == 3) + I(Instar ==
       4) + I(Instar == 5), data = Cater)
##
##
## Residuals:
##
        Min
                  1Q
                      Median
                                    3Q
  -1.08300 -0.06971
                     0.01542 0.10938
                                       0.51487
## Coefficients:
##
                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                      -2.72292
                                  0.03270 -83.261 < 2e-16 ***
## I(Instar == 2)TRUE
                                            3.260 0.00127 **
                      0.15076
                                  0.04625
## I(Instar == 3)TRUE
                      0.30615
                                  0.04495
                                            6.811 7.27e-11 ***
## I(Instar == 4)TRUE 0.69102
                                  0.04169
                                           16.576 < 2e-16 ***
## I(Instar == 5)TRUE 1.24924
                                  0.04169
                                           29.966 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2068 on 248 degrees of freedom
     (14 observations deleted due to missingness)
## Multiple R-squared: 0.8348, Adjusted R-squared: 0.8322
## F-statistic: 313.4 on 4 and 248 DF, p-value: < 2.2e-16
```

- c) When the caterpillar is in stage 2, the log nitrogen assimilation is about -2.572. When it is in stage 3, then the log nitrogen assimilation is about -2.417.
- d)  $R^2 = 0.8361$ , so about 84% of the variability is explained in this model. This is more than the model from before.

```
##
## Call:
## lm(formula = LogNassim ~ LogMass + I(Instar == 2) + I(Instar ==
##
       3) + I(Instar == 4) + I(Instar == 5), data = Cater)
##
## Residuals:
##
                  1Q
                       Median
                                    3Q
                                             Max
## -1.09910 -0.06945
                      0.01555 0.10943 0.49154
##
## Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
                                  0.11702 -21.939 < 2e-16 ***
## (Intercept)
                      -2.56744
## LogMass
                       0.06148
                                  0.04444
                                             1.384 0.16776
                      0.10206
## I(Instar == 2)TRUE
                                  0.05805
                                             1.758 0.07998 .
## I(Instar == 3)TRUE
                                  0.07983
                                            2.691 0.00761 **
                       0.21480
## I(Instar == 4)TRUE
                      0.54611
                                  0.11270
                                            4.846 2.23e-06 ***
## I(Instar == 5)TRUE 1.04876
                                  0.15077
                                            6.956 3.12e-11 ***
## ---
```

```
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2065 on 247 degrees of freedom
## (14 observations deleted due to missingness)
## Multiple R-squared: 0.8361, Adjusted R-squared: 0.8328
## F-statistic: 252 on 5 and 247 DF, p-value: < 2.2e-16</pre>
```

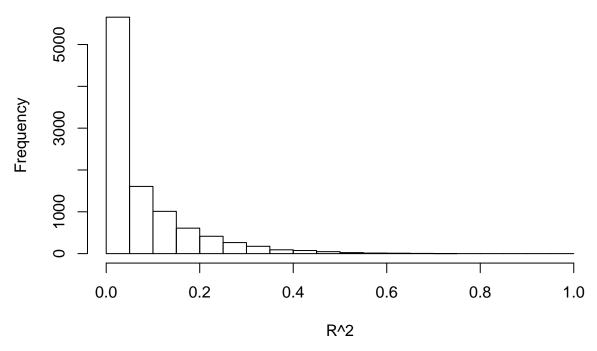
- e) The  $R^2$  is similar for both models, so I would check the *p*-value for the logBodyMass predictor. p = 0.168 > 0.05, so there is not enough evidence to show that logBodyMass is a significant predictor.
- f) There are a lot of predictors to check, so we can use a nested F test using the models found in (a) and (d). The p value is less than 0.05, so the indicators of Instar are important.

```
## Analysis of Variance Table
##
## Model 1: LogNassim ~ LogMass
## Model 2: LogNassim ~ LogMass + I(Instar == 2) + I(Instar == 3) + I(Instar ==
##
       4) + I(Instar == 5)
               RSS Df Sum of Sq
                                     F
                                          Pr(>F)
##
     Res.Df
## 1
        251 15.706
        247 10.528 4
                         5.1776 30.368 < 2.2e-16 ***
## 2
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

#### Problem 4.19

```
a)
##
## Call:
## lm(formula = Time ~ Pitchers + Attendance, data = BB)
##
## Residuals:
##
       Min
                10 Median
                                3Q
                                       Max
## -22.604 -8.248 -3.252
                             5.806 29.074
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.031e+02 2.556e+01
                                      4.032 0.00198 **
               8.109e+00
                          2.557e+00
## Pitchers
                                      3.171 0.00890 **
## Attendance 6.312e-04 3.913e-04
                                      1.613 0.13502
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 16.45 on 11 degrees of freedom
## Multiple R-squared: 0.5307, Adjusted R-squared: 0.4454
## F-statistic: 6.219 on 2 and 11 DF, p-value: 0.0156
 b) Let's use R^2. R^2 = 53.07, so about 53.1\% of the variability is expalined by this model.
 c)
## [1] -0.04047084
```

# **Histogram of Random Samples**



d)

e) Find the number of observations that have an  $R^2$  greater than 0.5307, and this divided by 10,000 is our p-value. This turns out to be p = 0.0045 < 0.05. There is enough evidence to suggest a relationship of predicting Time with Pitchers and Attendance.

#### ## [1] 0.0034

f) The summary output shows a p-value of 0.0156 for the F statistic. This is greater than the p-value from our randomization test, but it is still less than 0.05.