Assignment 2 Group 26

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Excercise 2.1

2.1a

We first will start with the full multi-regression model

```
model_full = lm(total ~ expend + ratio + salary + takers, data=sat)
```

```
## The AIC score for the full model = 497.3694
```

Step Up method: With the forward selection we will first start with no predictors and add variables one by one based on the lowest AIC

```
model_StepUp = lm(total ~ expend + takers, data=sat)
```

The AIC score for the step-up method = 494.7994

Step-down Method: we start from the full model and iteratively remove variables that worsen AIC the least.

```
model_StepDown <- lm(total ~ expend + takers, data=sat)</pre>
```

The AIC score for the step-down method = 494.7994

Model interpretation: SAT performance is best explained by school spending and participation rate. Other variables (ratio, salary) don't significantly improve model fit.

2.1b

Where the result for the AIC is 473.9 (rounded up from 473.85).

```
## [1] 473.8576
## The AICS without takers2 is:
                                 494.7994
## Analysis of Variance Table
##
## Model 1: total ~ expend + takers
  Model 2: total ~ takers + takers2 + expend
     Res.Df
              RSS Df Sum of Sq
## 1
         47 49520
## 2
         46 31298
                         18222 26.783 4.872e-06 ***
                  1
## ---
                   0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Signif. codes:
```

In a nested-model ANOVA comparing M_1 : total \sim expend+takers to M_2 : total \sim expend+takers+takers², adding the quadratic term reduces the residual sum of squares from 49,520 to 31,298, a drop of 18,222 with one additional parameter (df = 1), yielding F(1, 46) = 26.783 and $p = 4.872 \times 10^{-6}$. This highly significant improvement leads us to reject H_0 : $\beta_{\text{takers}^2} = 0$ and conclude that **takers**² is a useful predictor: it captures curvature in the relationship between SAT scores and participation that the linear-only specification misses.

2.1c

Comparing the reduced model M_1 to the expanded model M_2 , the ANOVA shows a large and statistically significant drop in residual sum of squares as seen previously, where this drop implies the rejection of $H_0: \beta_{\text{takers}^2} = 0$ and confirming that the quadratic term is informative; this statistical improvement is mirrored by information criteria, with AIC falling from ≈ 492.8 for M_1 to ≈ 471.9 for M_2 , indicating that the model including takers² provides a substantially better fit despite its extra parameter.

Excercise 2.2

2.2a

```
data$type <- factor(data$type)
model_a = lm(volume ~ type, data = data)
summary(model_a)</pre>
```

```
##
## Call:
## lm(formula = volume ~ type, data = data)
##
## Residuals:
##
       Min
                 1Q Median
                                  3Q
                                         Max
##
   -19.971
           -9.960
                    -2.771
                              5.940
                                      46.829
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
                  30.171
                               2.539
                                      11.881
                                                <2e-16 ***
## (Intercept)
## typeoak
                   5.079
                               3.686
                                       1.378
                                                 0.174
## ---
```

A one-way ANOVA comparing mean wood volume between Beech and Oak trees (n = 59) found no statistically significant difference in average volume between the species (F = 1.90, p = 0.17); thus, based on these data, we cannot conclude that Oaks are more voluminous than Beeches at the 5% significance level. The estimated mean volumes were approximately $\bar{V}_{\text{Oak}} \approx$ [insert mean] and $\bar{V}_{\text{Beech}} \approx$ [insert mean]; although Oaks appear slightly larger on average, this observed difference is not statistically significant.

2.2b

```
data$type = factor(data$type)
model_b <- lm(volume ~ diameter + height + type, data = data)</pre>
summary(model_b)
##
## Call:
## lm(formula = volume ~ diameter + height + type, data = data)
##
## Residuals:
##
      Min
                1Q Median
                                3Q
                                       Max
## -7.1859 -2.1396 -0.0871 1.7208 7.7010
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -63.78138
                            5.51293 -11.569 2.33e-16 ***
## diameter
                4.69806
                            0.16450 28.559 < 2e-16 ***
## height
                0.41725
                            0.07515
                                     5.552 8.42e-07 ***
                            0.87791 - 1.486
## typeoak
                -1.30460
                                               0.143
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.243 on 55 degrees of freedom
## Multiple R-squared: 0.9509, Adjusted R-squared: 0.9482
## F-statistic: 354.9 on 3 and 55 DF, p-value: < 2.2e-16
anova(model_b)
```

```
## Analysis of Variance Table
##
## Response: volume
            Df Sum Sq Mean Sq F value
## diameter
             1 10826.5 10826.5 1029.5139 < 2.2e-16 ***
                 346.2
                         346.2
                                 32.9192 4.254e-07 ***
## height
                  23.2
                          23.2
## type
             1
                                  2.2083
                                             0.143
## Residuals 55
                 578.4
                          10.5
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
2.2c
```

The volume of a cylinder is given by $V = \pi r^2 H$, where r is the radius of the circular base, H is the height, and π is the mathematical constant (approximately 3.14159).

```
trees$type = factor(trees$type)
trees$calc_vol = pi*((trees$diameter/2)^2)*trees$height
model_c = lm(volume ~ calc_vol + type, data = trees)
summary(model_c)
## Call:
## lm(formula = volume ~ calc_vol + type, data = trees)
## Residuals:
##
      Min
               1Q Median
                               3Q
## -4.6321 -1.4601 -0.3746 1.5045 5.3354
##
## Coefficients:
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5.056e-01 7.843e-01 -0.645
                                               0.522
## calc_vol
               2.723e-03 5.926e-05 45.958
                                              <2e-16 ***
## typeoak
               4.529e-01 6.061e-01
                                      0.747
                                               0.458
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 2.292 on 56 degrees of freedom
## Multiple R-squared: 0.975, Adjusted R-squared: 0.9741
## F-statistic: 1092 on 2 and 56 DF, p-value: < 2.2e-16
anova(model_c)
```

```
## Analysis of Variance Table
##
## Response: volume
            Df Sum Sq Mean Sq
                               F value Pr(>F)
             1 11477.1 11477.1 2183.8014 <2e-16 ***
## calc_vol
                   2.9
                           2.9
                                  0.5583 0.4581
## type
             1
## Residuals 56
                 294.3
                           5.3
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

As $p \le 0.05$, this yields a better result.

Excercise 2.3

2.3a