STAT2170 - Assignment 1

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Due Date: 2023-10-27

Question 1

Load the traffic data

```
traffic <- read.csv("traffic.csv")
```

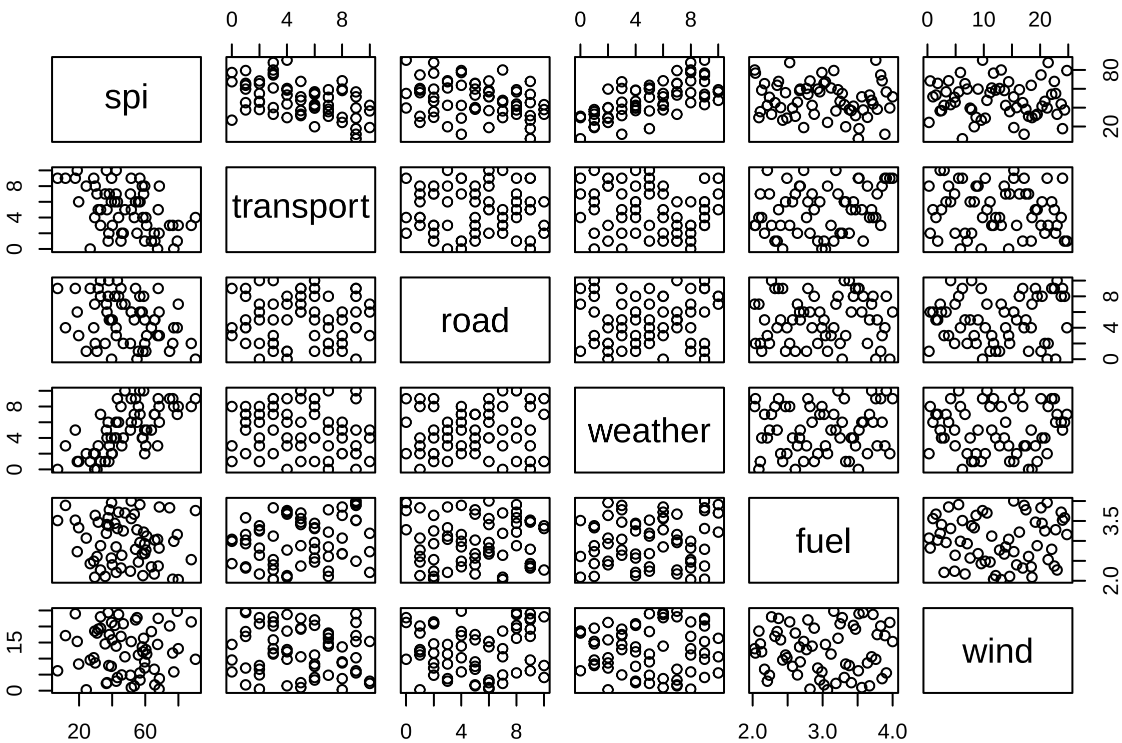
Part A

Calculate correlation matrix and create a scatterplot matrix

```
cor(traffic)
```

```
##                   spi    transport         road     weather         fuel
## spi        1.00000000 -0.472909967 -0.303836850  0.66672345 -0.138153417
## transport -0.47290997  1.000000000 -0.005714728 -0.16971072  0.240947972
## road      -0.30383685 -0.005714728  1.000000000  0.12495993  0.043675635
## weather    0.66672345 -0.169710717  0.124959926  1.00000000  0.110531767
## fuel      -0.13815342  0.240947972  0.043675635  0.11053177  1.000000000
## wind      -0.03466263 -0.131014749  0.080481857  0.00751783  0.006532832
##                  wind
## spi       -0.034662632
## transport -0.131014749
## road       0.080481857
## weather    0.007517830
## fuel       0.006532832
## wind       1.000000000
```

```
pairs(traffic)
```



Part B

Fit a linear regression model

```
fit <- lm(spi ~ ., data = traffic)
summary(fit)
```

```
##
## Call:
## lm(formula = spi ~ ., data = traffic)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18.1596  -4.9415   0.1278   5.1686  21.7415
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  62.8071     7.4080   8.478 1.27e-11 ***
## transport    -2.1750     0.4611  -4.717 1.63e-05 ***
## road         -2.4097     0.4365  -5.520 9.04e-07 ***
## weather       4.2456     0.4473   9.492 2.92e-13 ***
## fuel         -3.6145     2.2759  -1.588    0.118
## wind         -0.1358     0.1764  -0.769    0.445
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.913 on 56 degrees of freedom
## Multiple R-squared:  0.7405, Adjusted R-squared:  0.7174
## F-statistic: 31.96 on 5 and 56 DF,  p-value: 3.039e-15
```

Calculate confidence interval for the 'weather' variable

```
confint(fit, 'weather', level = 0.95)
```

```
##            2.5 %   97.5 %
## weather 3.349648 5.141639
```

Looking at the Confidence Interval: 0 is not included, therefore it is significant.

Part C

Display the summary of the linear regression model

```
summary(fit)
```

```
##
## Call:
## lm(formula = spi ~ ., data = traffic)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18.1596  -4.9415   0.1278   5.1686  21.7415
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  62.8071     7.4080   8.478 1.27e-11 ***
## transport    -2.1750     0.4611  -4.717 1.63e-05 ***
## road         -2.4097     0.4365  -5.520 9.04e-07 ***
## weather       4.2456     0.4473   9.492 2.92e-13 ***
## fuel         -3.6145     2.2759  -1.588    0.118
## wind         -0.1358     0.1764  -0.769    0.445
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.913 on 56 degrees of freedom
## Multiple R-squared:  0.7405, Adjusted R-squared:  0.7174
## F-statistic: 31.96 on 5 and 56 DF,  p-value: 3.039e-15
```

Present the model equation

$spi = 62.8071 - 2.1750 * transport - 2.4097 * road + 4.2456 * weather - 3.6145 * fuel - 0.1358 * wind$

Null hypothesis: $Beta1 = Beta2 = ... = BetaN = 0$

Alternate hypothesis: $Atleast1Beta(i)! = 0$

Anova table for model comparison

```
traffic$null <- mean(traffic$spi)
null_fit <- lm(spi ~ null, data = traffic)
summary(null_fit)
```

```
##
## Call:
## lm(formula = spi ~ null, data = traffic)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -41.694 -12.086  -1.479  11.471  41.656
##
## Coefficients: (1 not defined because of singularities)
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   48.694      2.368   20.56   <2e-16 ***
## null              NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18.65 on 61 degrees of freedom
```

```
anova(null_fit, fit)
```

```
## Analysis of Variance Table
##
## Model 1: spi ~ null
## Model 2: spi ~ transport + road + weather + fuel + wind
##   Res.Df     RSS Df Sum of Sq      F    Pr(>F)
## 1     61 21206.2
## 2     56  5502.6  5     15704 31.963 3.039e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The null distribution is the mean value of SPI

With such a small p-value, the null hypothesis (H0) can be rejected. The F-statistic provides strong evidence that at least one of the predictor variables has a significant linear relationship with the dependent variable (spi).The perdictor variables being; transport, road, weather, fuel, wind.

Part D

Goodness of fit

```
summary(fit)
```

```
##
## Call:
## lm(formula = spi ~ ., data = traffic)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18.1596  -4.9415   0.1278   5.1686  21.7415
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  62.8071     7.4080   8.478 1.27e-11 ***
## transport    -2.1750     0.4611  -4.717 1.63e-05 ***
## road         -2.4097     0.4365  -5.520 9.04e-07 ***
## weather       4.2456     0.4473   9.492 2.92e-13 ***
## fuel         -3.6145     2.2759  -1.588    0.118
## wind         -0.1358     0.1764  -0.769    0.445
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.913 on 56 degrees of freedom
## Multiple R-squared:  0.7405, Adjusted R-squared:  0.7174
## F-statistic: 31.96 on 5 and 56 DF,  p-value: 3.039e-15
```

Re-run the model without 'fuel' and 'wind'

```
fit_updated <- lm(spi ~ transport + road + weather, data = traffic)
summary(fit_updated)
```

```
##
## Call:
## lm(formula = spi ~ transport + road + weather, data = traffic)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -21.672  -5.643   1.067   4.656  23.164
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  51.7370     4.1027  12.611  < 2e-16 ***
## transport    -2.3216     0.4449  -5.218 2.54e-06 ***
## road         -2.4563     0.4394  -5.590 6.40e-07 ***
## weather       4.1450     0.4463   9.286 4.48e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.02 on 58 degrees of freedom
## Multiple R-squared:  0.7256, Adjusted R-squared:  0.7114
## F-statistic: 51.12 on 3 and 58 DF,  p-value: 2.724e-16
```

Since fuel and wind are not significant variables it could be ideal to removed them from the model. This makes the model clearer by only showing useful data.

Part E

R-squared is a measure of the model fit and explained variability

```r
summary(fit)
```

```
##
## Call:
## lm(formula = spi ~ ., data = traffic)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18.1596  -4.9415   0.1278   5.1686  21.7415
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  62.8071     7.4080   8.478 1.27e-11 ***
## transport    -2.1750     0.4611  -4.717 1.63e-05 ***
## road         -2.4097     0.4365  -5.520 9.04e-07 ***
## weather       4.2456     0.4473   9.492 2.92e-13 ***
## fuel         -3.6145     2.2759  -1.588    0.118
## wind         -0.1358     0.1764  -0.769    0.445
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.913 on 56 degrees of freedom
## Multiple R-squared:  0.7405, Adjusted R-squared:  0.7174
## F-statistic: 31.96 on 5 and 56 DF,  p-value: 3.039e-15
```

Note: The R-Squared value here is 0.7405

Part F (Stepwise Selection)

Backwards stepwise selection

```r
fit <- lm(spi ~ transport + road + weather + fuel, data = traffic)
summary(fit)
```

```
##
## Call:
## lm(formula = spi ~ transport + road + weather + fuel, data = traffic)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18.9347  -4.2440   0.0528   5.0544  21.4515
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  61.1610     7.0669   8.655 5.69e-12 ***
## transport    -2.1257     0.4550  -4.672 1.86e-05 ***
## road         -2.4372     0.4335  -5.622 5.92e-07 ***
## weather       4.2565     0.4454   9.555 1.94e-13 ***
## fuel         -3.6853     2.2659  -1.626    0.109
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 9.877 on 57 degrees of freedom
## Multiple R-squared:  0.7378, Adjusted R-squared:  0.7194
## F-statistic: 40.09 on 4 and 57 DF,  p-value: 5.959e-16
```

Backward stepwise selection (removing 'fuel')

```
fit <- lm(spi ~ transport + road + weather, data = traffic)
summary(fit)
```

```
##
## Call:
## lm(formula = spi ~ transport + road + weather, data = traffic)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -21.672  -5.643   1.067   4.656  23.164
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  51.7370     4.1027  12.611  < 2e-16 ***
## transport    -2.3216     0.4449  -5.218 2.54e-06 ***
## road         -2.4563     0.4394  -5.590 6.40e-07 ***
## weather       4.1450     0.4463   9.286 4.48e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.02 on 58 degrees of freedom
## Multiple R-squared:  0.7256, Adjusted R-squared:  0.7114
## F-statistic: 51.12 on 3 and 58 DF,  p-value: 2.724e-16
```

Part G

Adjusted R^2 takes into account the number of variables in the dataset. The adjusted R-Squared is close to the multiple R squared in the final model, meaning the model is not over fitting based on superfluous variables

Question 2

```
cake <- read.csv("cake.csv")
```

Part A

```
table(cake$Temp, cake$Recipe)
```

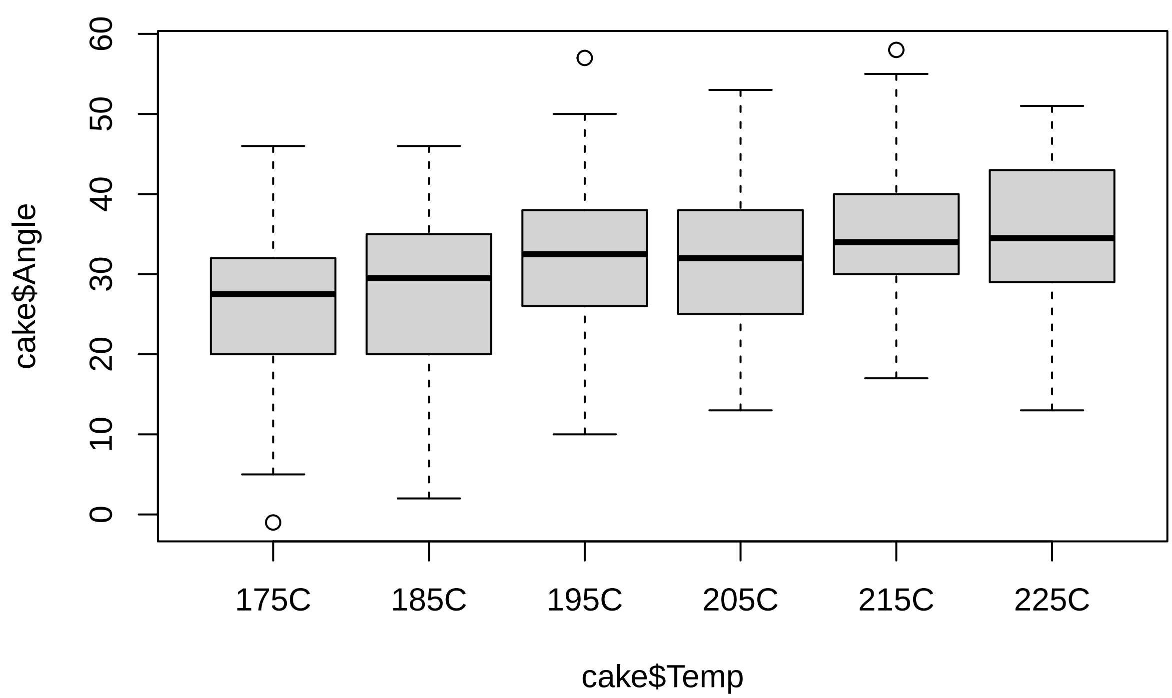
```
##
##          A  B  C
```

```
##   175C 14 14 14
##   185C 14 14 14
##   195C 14 14 14
##   205C 14 14 14
##   215C 14 14 14
##   225C 14 14 14
```

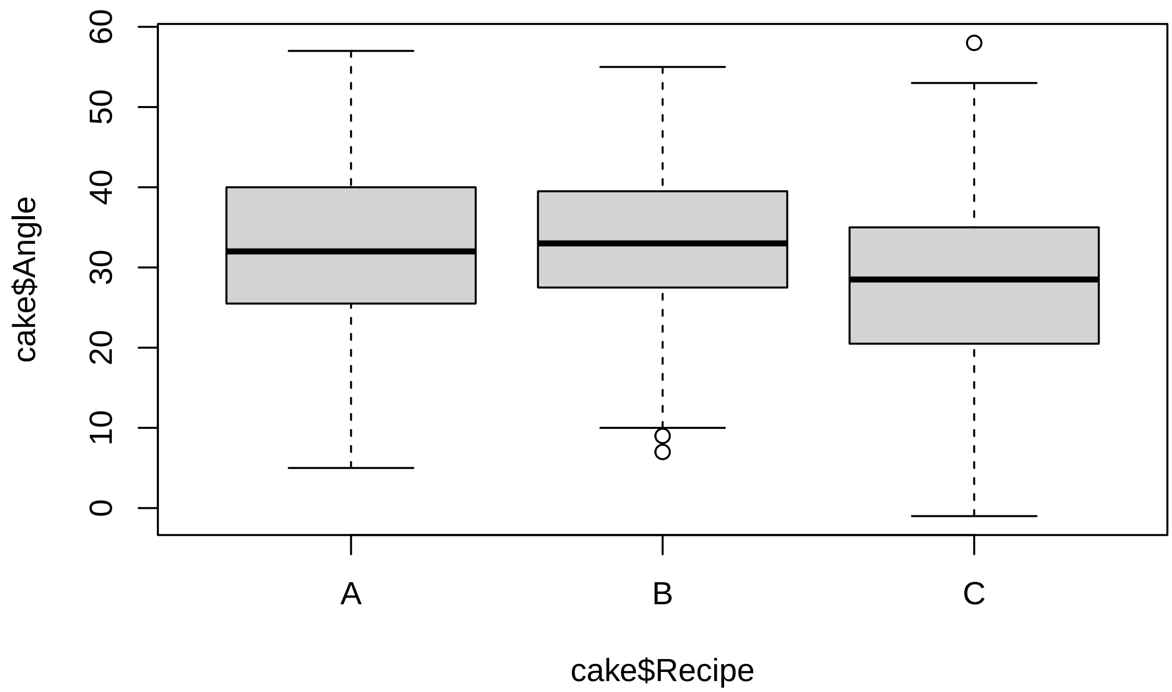
It is balanced - there is the same number of subjects in each cohort

Part B

```r
boxplot(cake$Angle~cake$Temp)
```




```r
boxplot(cake$Angle~cake$Recipe)
```



Temp and recipe do have an impact on the angle the cake broke but the interaction variable is insignificant

Part C

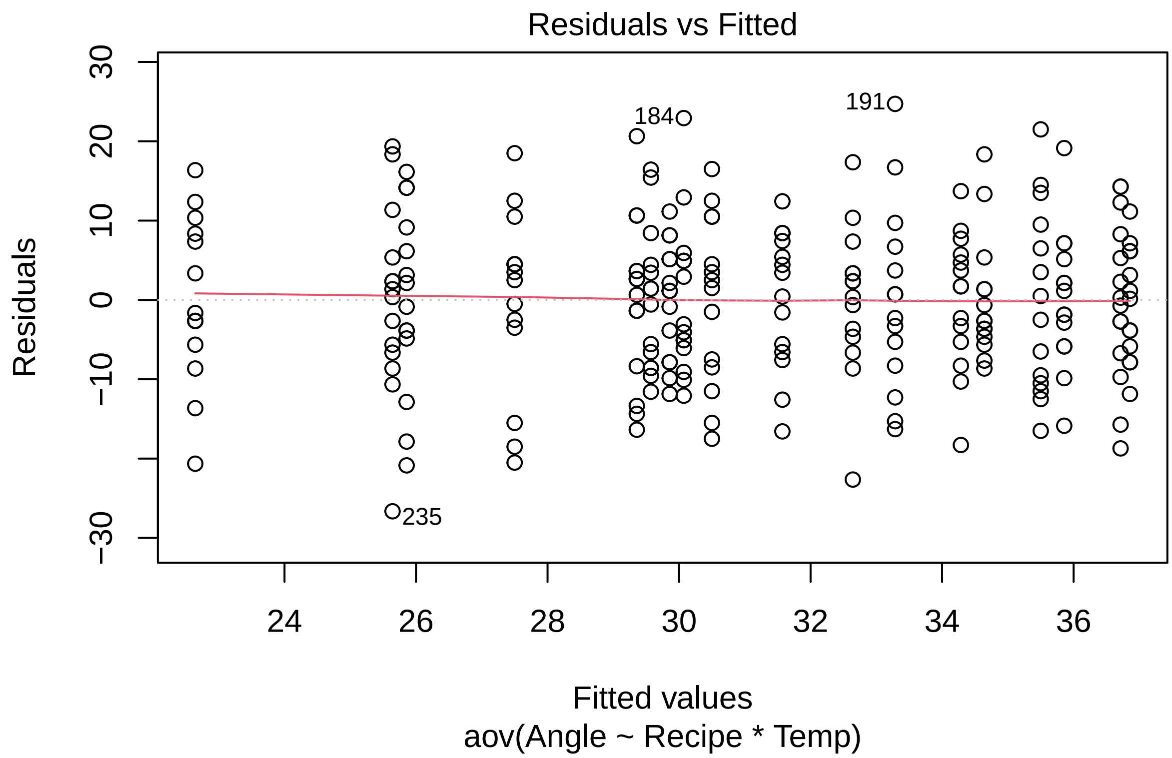
```
av = aov(formula = Angle~Recipe*Temp, data = cake)
```

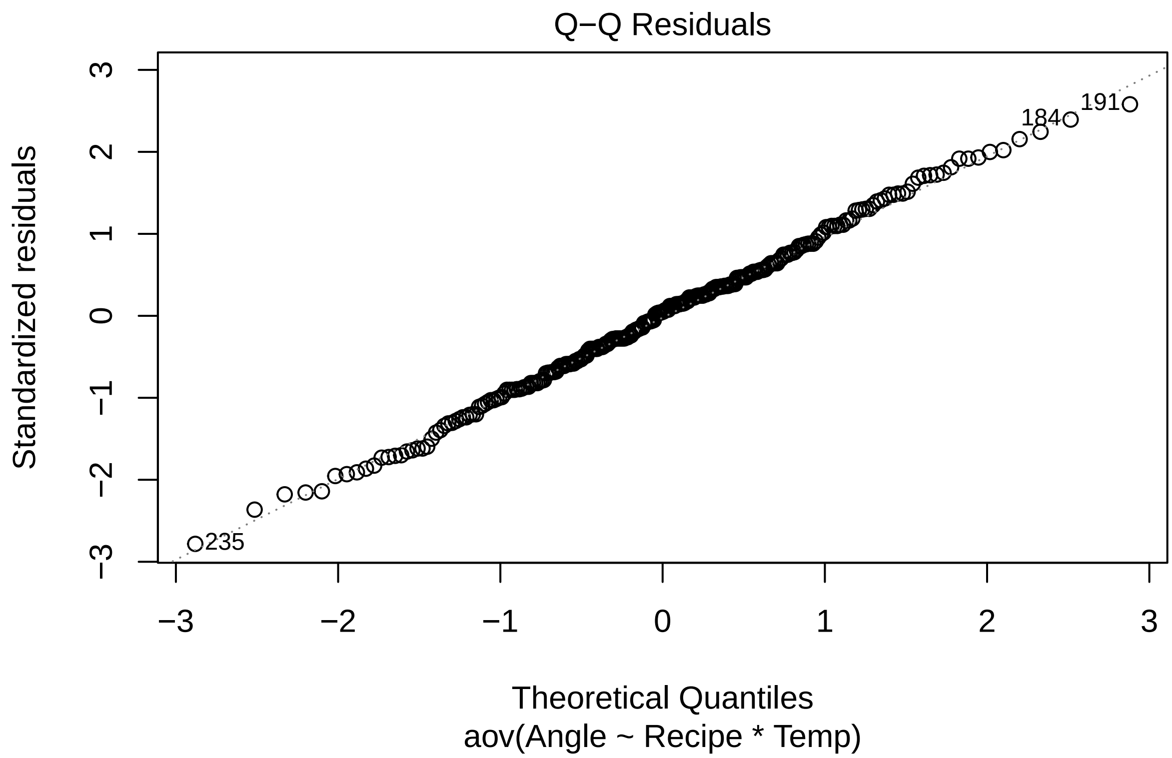
Part D

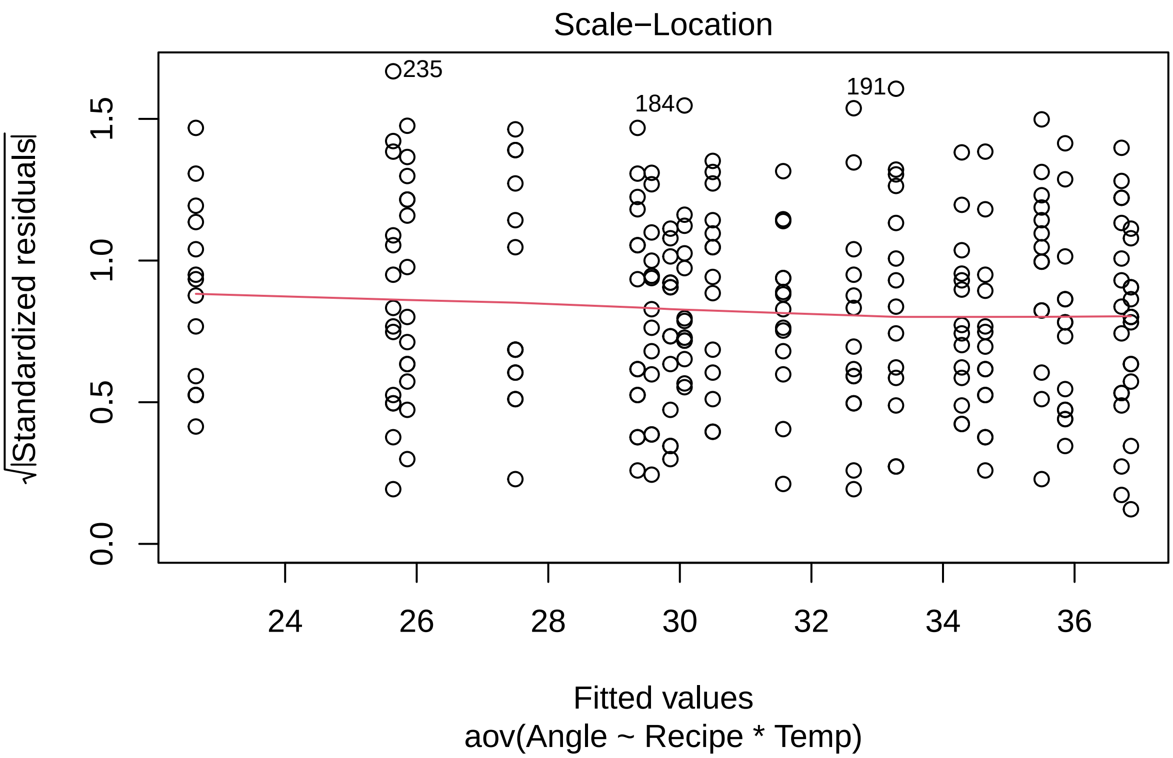
```
summary(av)
```

```
##                Df Sum Sq Mean Sq F value   Pr(>F)
## Recipe          2    845   422.4   4.276 0.014998 *
## Temp            5   2530   506.0   5.123 0.000177 ***
## Recipe:Temp    10    636    63.6   0.643 0.775632
## Residuals     234  23114    98.8
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

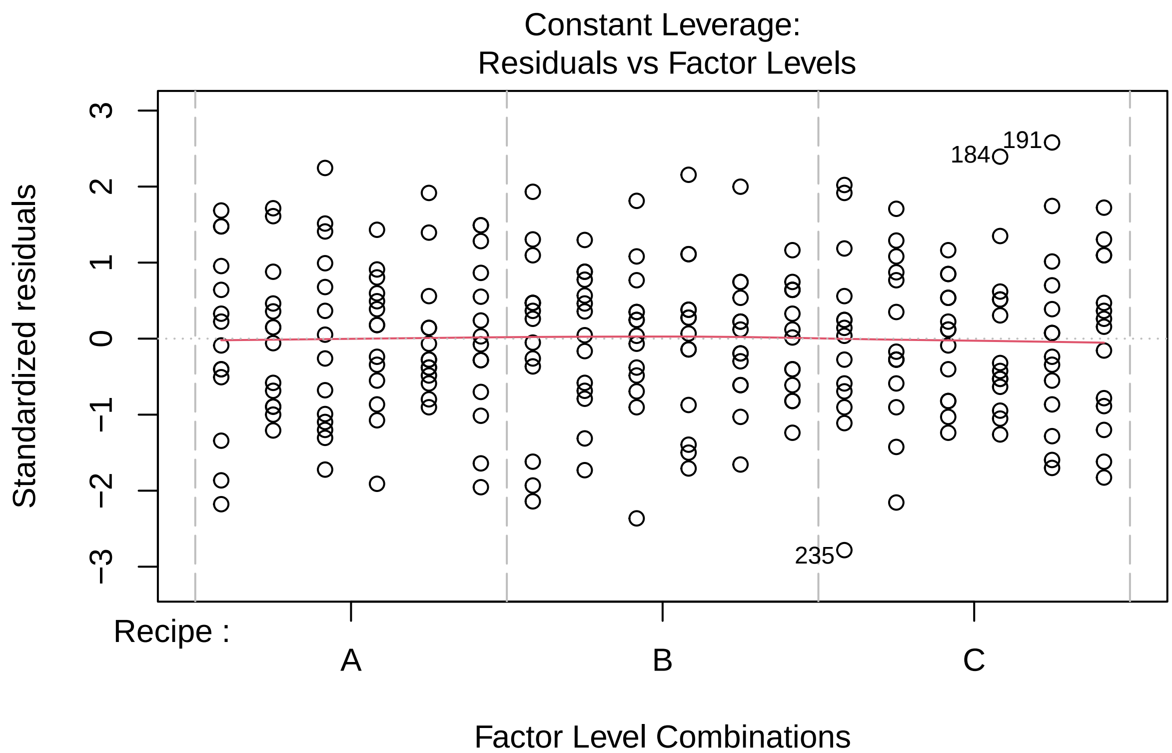
```
plot(av)
```


Residuals vs Fitted
Residuals
Fitted values
aov(Angle ~ Recipe * Temp)
184
191
235
30
20
10
0
−10
−30
24
26
28
30
32
34
36


Q−Q Residuals
Standardized residuals
Theoretical Quantiles
aov(Angle ~ Recipe * Temp)
235
184
191
−3
−2
−1
0
1
2
3



Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
235
184
191
24
26
28
30
32
34
36
Fitted values
aov(Angle ~ Recipe * Temp)



Null Hypothesis: There is no significant effect of either the "Recipe" factor, the "Temp" factor, or their interaction ("Recipe:Temp") on the dependent variable.

Alternate Hypothesis: At least one of the factors ("Recipe" or "Temp") or their interaction ("Recipe:Temp") has a significant effect on the dependent variable.

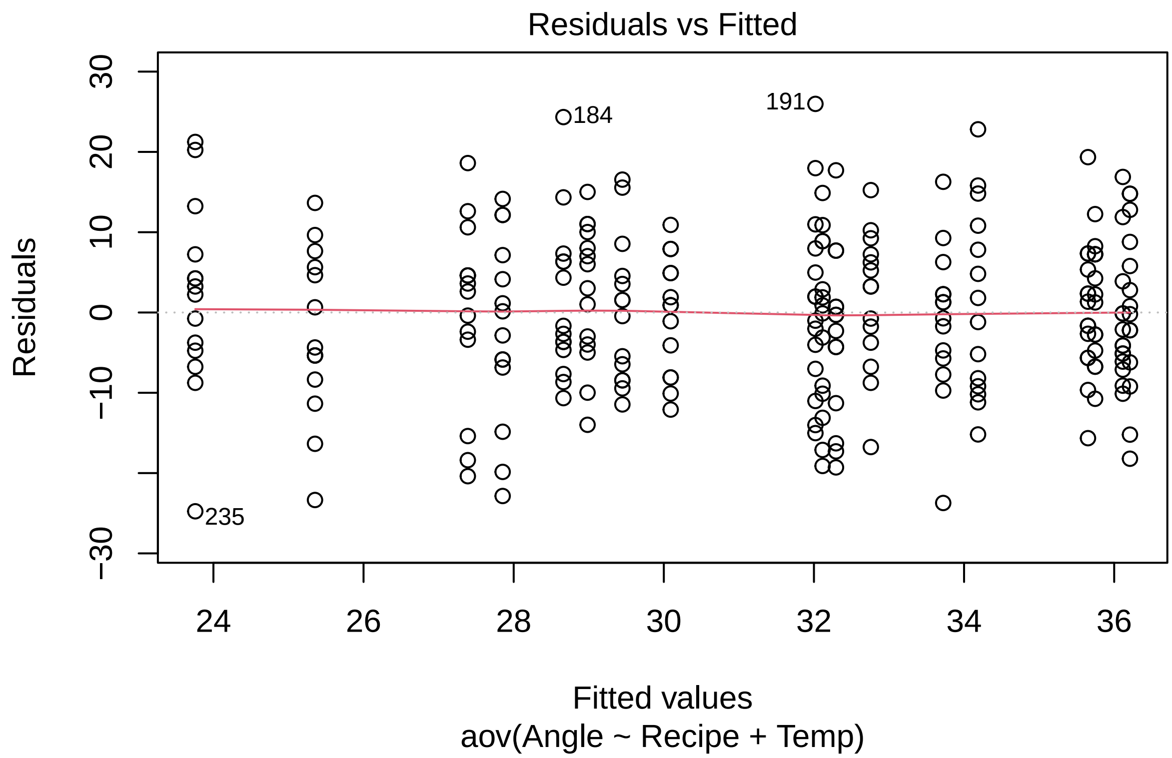
In conclusion, the findings show that although their interaction does not significantly affect the dependent variable, the "Recipe" and "Temp" factors do. The data and the model fit each other well.

Part E

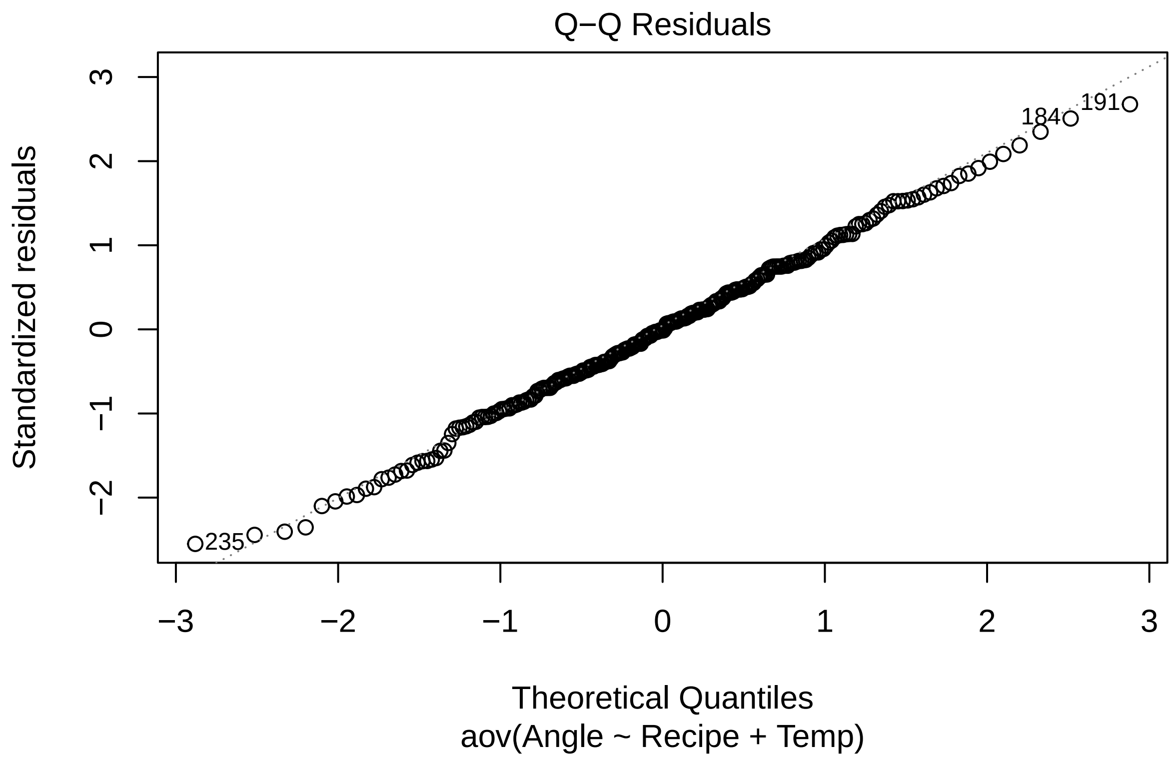
```
me <- aov(formula = Angle~Recipe+Temp, data = cake)
summary(me)
```

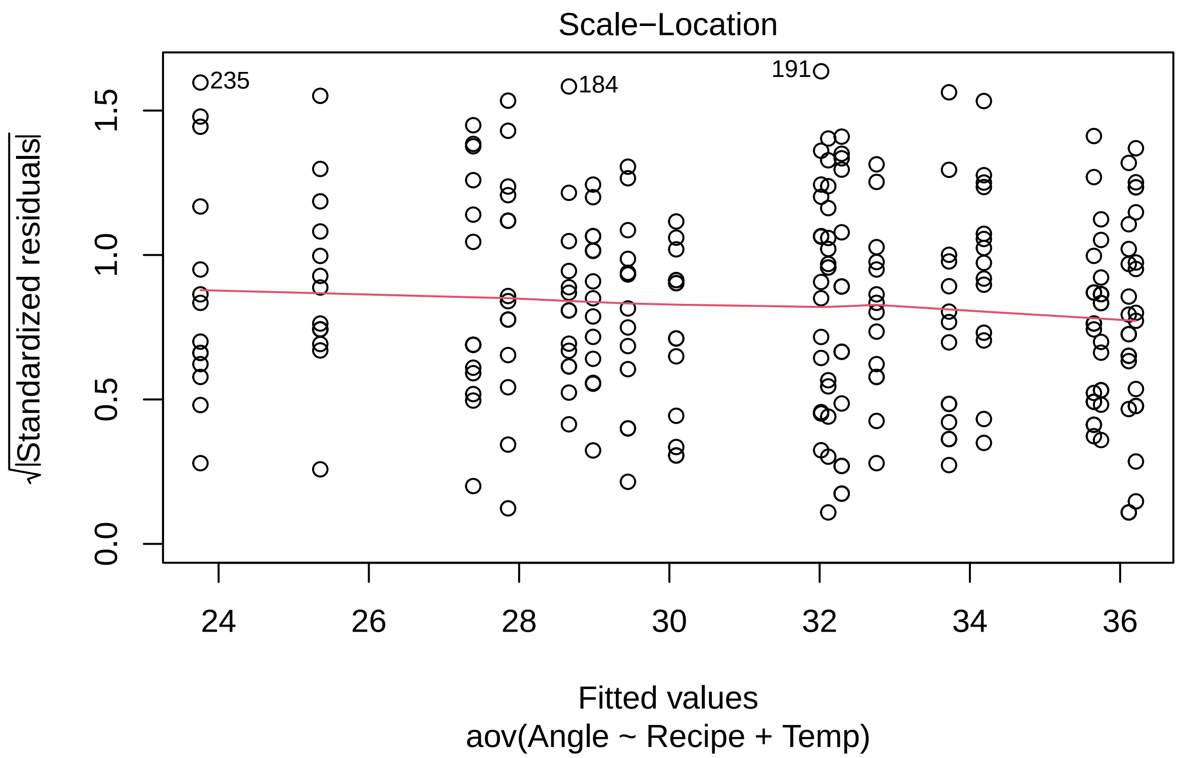
```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## Recipe        2    845   422.4   4.340 0.014064 *
## Temp          5   2530   506.0   5.199 0.000149 ***
## Residuals   244  23749    97.3
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

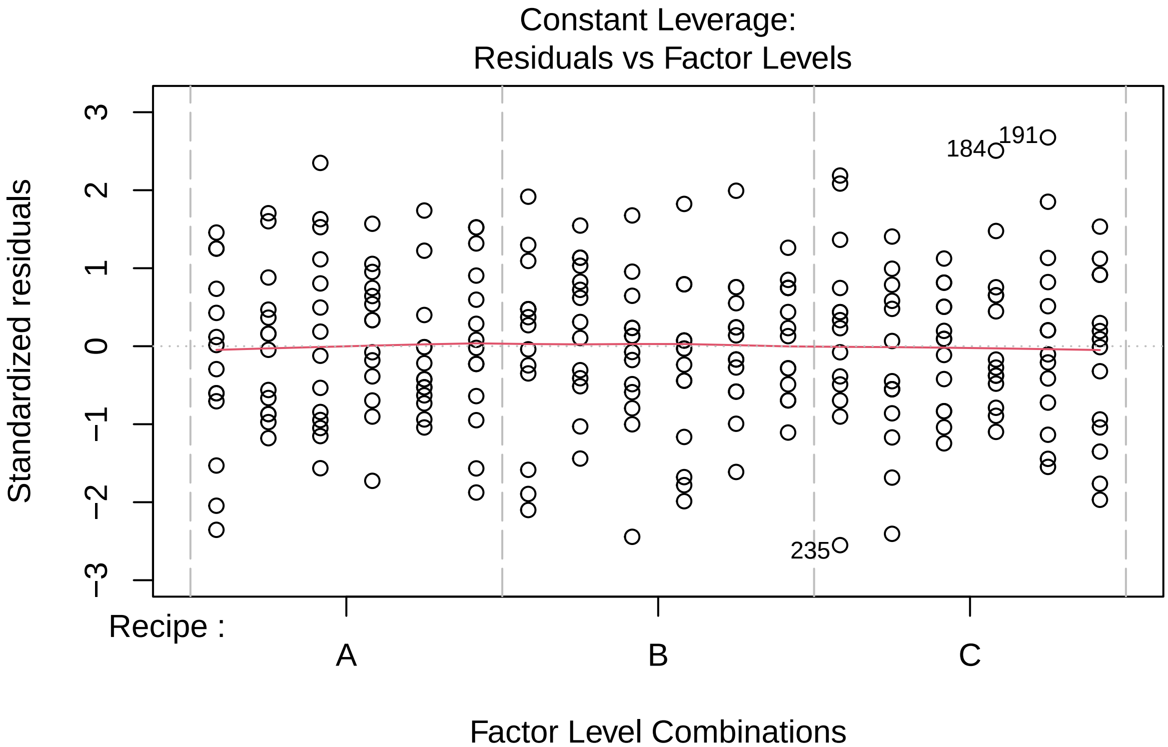
```
plot(me)
```



Residuals vs Fitted
Residuals
30
20
10
0
−10
−30
184
191
235
24
26
28
30
32
34
36
Fitted values
aov(Angle ~ Recipe + Temp)


Q−Q Residuals
Standardized residuals
Theoretical Quantiles
aov(Angle ~ Recipe + Temp)
−3
−2
−1
0
1
2
3
235
184
191


Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
235
184
191
24
26
28
30
32
34
36
Fitted values
aov(Angle ~ Recipe + Temp)



Null Hypothesis: There are no appreciable variations in the means of the groups that are characterised by the "Temp" component, the "Recipe" factor, or their combination on the dependent variable "Angle." It asserts the equality of all group means.

Alternative Hypothesis: Among the groups identified by the "Recipe" component, the "Temp" factor, or their interaction on the dependent variable "Angle," at least one group mean differs from the others. It suggests that there are differences in group means.

Part F

Temp (Temperature) Effect: The "Temp" factor has a very significant effect on the "Angle" response variable, as seen by the extremely small p-value (0.000177) connected with it. This implies that the angle at which the cake splits is significantly influenced by the temperature at which it is baked. In particular, it seems that varying temperatures produce varying "Angle" results.

Recipe Effect:

"Recipe" has a p-value of 0.014998, which is less than 0.05. This suggests that the "Angle" response variable is significantly impacted by the "Recipe" component. As a result, the angle at which the cake splits depends on the recipe that is baked.

Interaction Effect (Recipe:Temp): The interaction term "Recipe:Temp" has a p-value of 0.775632, which is higher than 0.05. This implies that the "Recipe" and "Temp" do not significantly interact to affect the "Angle" reaction. Put another, there is no statistically significant difference between the combined impact of "Recipe" and "Temp" on the "Angle" variable.

In conclusion, the angle at which the cake splits is significantly influenced by both "Temp" and "Recipe" alone. It matters which recipe and temperature you use. Nevertheless, temperature and recipe do not significantly interact, which means that the combined effect of both is not substantially different from what would be predicted based on each of their independent effects.