Lab Assignment 3

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```
library(GGally)
```

```
## Loading required package: ggplot2
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```

```
library(car)
```

```
## Loading required package: carData
```

```
library(ggplot2)
library(lattice)
library(MASS)
library(leaps)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following object is masked from 'package:MASS':
##
##     select
```

```
## The following object is masked from 'package:car':
##
##     recode
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(tidyr)
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
library(GGally)
library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✔ forcats   1.0.0     ✔ readr     2.1.4
## ✔ lubridate 1.9.2     ✔ stringr   1.5.0
## ✔ purrr     1.0.1     ✔ tibble    3.2.0
```

```
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ✖ dplyr::recode() masks car::recode()
## ✖ dplyr::select() masks MASS::select()
## ✖ purrr::some()   masks car::some()
## ℹ Use the ]8;;http://conflicted.r-lib.org/ conflicted package ]8;; to force all co
nflicts to become errors
```

```
library(ggpubr)
library(agricolae)
```

Question 1.

The tensile strength of Portland cement is being studied. Four different mixing techniques can be used economically. A completely randomized experiment was conducted, and the following data were collected:

```
cement <- data.frame(Mixing_Technique = c(1,1,1,1,2,2,2,2,3,3,3,3,4,4,4,4),
                     Tensile_Strength = c(3129, 3000, 2865, 2890, 3200, 3300, 2975, 3
150, 2800, 2900, 2985, 3050, 2600, 2700, 2600, 2765))

head(cement)
```

```
##   Mixing_Technique Tensile_Strength
## 1                1             3129
## 2                1             3000
## 3                1             2865
## 4                1             2890
## 5                2             3200
## 6                2             3300
```

1.a.

H0: Mixing techniques do not affect the strength of cement H1: Mixing techniques do affect the strength of cement

```
cement$Mixing_Technique <- as.factor(cement$Mixing_Technique)
str(cement)
```

```
## 'data.frame':    16 obs. of  2 variables:
##  $ Mixing_Technique: Factor w/ 4 levels "1","2","3","4": 1 1 1 1 2 2 2 2 3 3 ...
##  $ Tensile_Strength: num  3129 3000 2865 2890 3200 ...
```

```
cement %>% group_by(Mixing_Technique) %>% summarise(mean = mean(Tensile_Strength, na.
rm = TRUE),
                                                    sd = sd(Tensile_Strength, na.rm =
TRUE))
```

```
## # A tibble: 4 × 3
##   Mixing_Technique  mean    sd
##   <fct>            <dbl> <dbl>
## 1 1                2971  121.
## 2 2                3156. 136.
## 3 3                2934. 108.
## 4 4                2666.  81.0
```

```
aov.cement <- aov(formula = Tensile_Strength ~ Mixing_Technique, data = cement)
anova(aov.cement)
```

```
## Analysis of Variance Table
##
## Response: Tensile_Strength
##                  Df Sum Sq Mean Sq F value    Pr(>F)
## Mixing_Technique  3 489740  163247  12.728 0.0004887 ***
## Residuals        12 153908   12826
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

By creating a linear model of the data and using the anova() function to analyse it, the p-value of the model outputs to 0.0005 which is less than the significance level of 0.05. Therefore, the null hypothesis can be rejected and it can be concluded that mixing techniques do affect the strength of cement.

1.b.

```
Tukey.tensilestrength.factors = aov(Tensile_Strength ~ factor(Mixing_Technique), data
= cement)
TukeyHSD(Tukey.tensilestrength.factors)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = Tensile_Strength ~ factor(Mixing_Technique), data = cement)
##
## $`factor(Mixing_Technique)`
##        diff        lwr        upr     p adj
## 2-1  185.25  -52.50029  423.00029 0.1493561
## 3-1  -37.25 -275.00029  200.50029 0.9652776
## 4-1 -304.75 -542.50029  -66.99971 0.0115923
## 3-2 -222.50 -460.25029   15.25029 0.0693027
## 4-2 -490.00 -727.75029 -252.24971 0.0002622
## 4-3 -267.50 -505.25029  -29.74971 0.0261838
```

```
LSD.test(y = aov.cement, trt = "Mixing_Technique", DFerror = aov.cement$df.residual,
MSerror = deviance(aov.cement)/aov.cement$df.residual, alpha = 0.05, group = FALSE, c
onsole = TRUE)
```

```
##
## Study: aov.cement ~ "Mixing_Technique"
##
## LSD t Test for Tensile_Strength
##
## Mean Square Error:  12825.69
##
## Mixing_Technique,  means and individual ( 95 %) CI
##
##   Tensile_Strength       std r      LCL      UCL  Min  Max
## 1          2971.00 120.55704 4 2847.624 3094.376 2865 3129
## 2          3156.25 135.97641 4 3032.874 3279.626 2975 3300
## 3          2933.75 108.27242 4 2810.374 3057.126 2800 3050
## 4          2666.25  80.97067 4 2542.874 2789.626 2600 2765
##
## Alpha: 0.05 ; DF Error: 12
## Critical Value of t: 2.178813
##
## Comparison between treatments means
##
##       difference pvalue signif.        LCL       UCL
## 1 - 2    -185.25 0.0392       * -359.72984 -10.77016
## 1 - 3      37.25 0.6501         -137.22984 211.72984
## 1 - 4     304.75 0.0025      **  130.27016 479.22984
## 2 - 3     222.50 0.0167       *   48.02016 396.97984
## 2 - 4     490.00 0.0001     ***  315.52016 664.47984
## 3 - 4     267.50 0.0059      **   93.02016 441.97984
```

1.c.

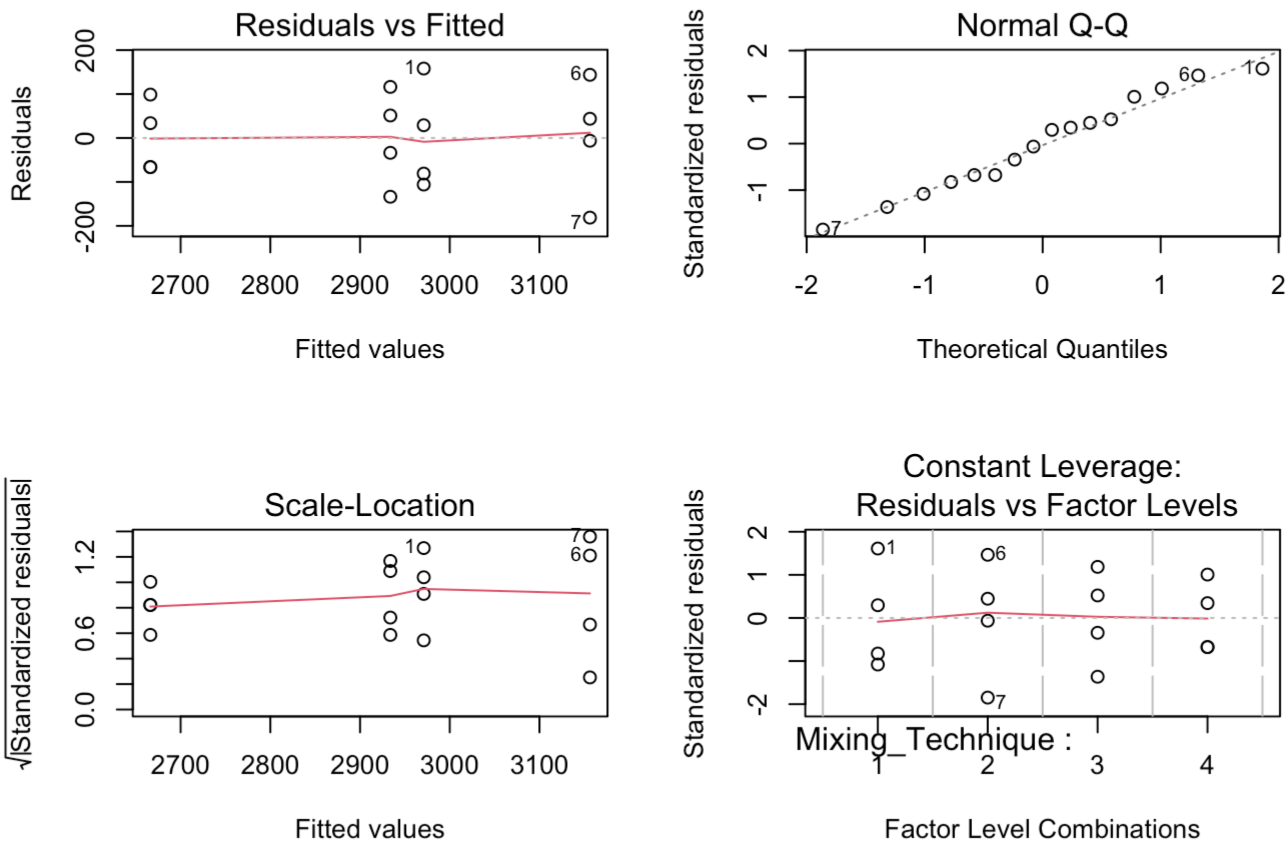
Yes, both tests give very similar results and hence give similar conclusions.

1.d.

The LSD test and Tukey tests are similar except the LSD test uses a t-value whereas the Tukey test uses a studentised range value.

1.e and f.

```
par(mfrow = c(2,2))
plot(aov.cement)
```



The normal probability plot of the residuals shows no outliers with the residuals all close to the straight diagonal line. This can lead to the conclusion that the validity of the normality assumption is good and the residuals are normally distributed.

The residuals versus the predicted tensile strength values plot highlights the constant variance of the residuals with the points being evenly distributed between values less than 0 and values greater than 0. This allows me to conclude that the residuals are randomly distributed.

Question 2.

A consumer products company relies on direct mail marketing pieces as a major component of its advertising campaigns. The company has four different designs for a new brochure and wants to evaluate their effectiveness, as there are substantial differences in costs between the three designs. The company decides to test the four designs by mailing 5000 samples of each to potential customers in four different regions of the country. Since there are known regional differences in the customer base, regions are considered as blocks. The number of responses to each mailing is as follows.

```
mail <- data.frame(Design = c(1,1,1,1,2,2,2,2,3,3,3,3,4,4,4,4),
                   Region = c("QLD", "NSW", "VIC", "WA", "QLD", "NSW", "VIC", "WA","Q
LD", "NSW", "VIC", "WA","QLD", "NSW", "VIC", "WA"),
                   Responses = c(250, 350, 330, 219, 290, 495, 480, 230, 275, 340, 32
0, 200, 240, 490, 326, 165))

head(mail)
```

```
##   Design Region Responses
## 1      1    QLD       250
## 2      1    NSW       350
## 3      1    VIC       330
## 4      1     WA       219
## 5      2    QLD       290
## 6      2    NSW       495
```

2.a.

RCB Design. The different regions have an influence on the number of responses received, however the influence is not of interest and therefore they are considered as a blocks, creating an RCB design.

2.a. part 2

H0: $\tau 1 = \tau 2 = \tau 3 = \tau 4 = 0$ H1: one or more of $\tau i = 0$

```
mail <- mail %>% mutate(Design = factor(Design), Region = factor(Region))
str(mail)
```

```
## 'data.frame':    16 obs. of  3 variables:
##  $ Design   : Factor w/ 4 levels "1","2","3","4": 1 1 1 1 2 2 2 2 3 3 ...
##  $ Region   : Factor w/ 4 levels "NSW","QLD","VIC",..: 2 1 3 4 2 1 3 4 2 1 ...
##  $ Responses: num  250 350 330 219 290 495 480 230 275 340 ...
```

The region and design variables need to be converted to the factor data type.

```
mail %>% group_by(Design) %>%  summarise(n = n(),
                                          mean = mean(Responses, na.rm = TRUE),
                                          sd = sd(Responses, na.rm = TRUE),
                                          stderr = sd/sqrt(n),
                                          LCL = mean - qt(1 - (0.05 / 2), n - 1) * st
derr,
                                          UCL = mean + qt(1 - (0.05 / 2), n - 1) * st
derr,
                                          median = median(Responses, na.rm = TRUE),
                                          min = min(Responses, na.rm = TRUE),
                                          max = max(Responses, na.rm = TRUE),
                                          IQR = IQR(Responses, na.rm = TRUE))
```

```
## # A tibble: 4 × 11
##   Design     n  mean    sd stderr   LCL   UCL median   min   max   IQR
##   <fct>  <int> <dbl> <dbl>  <dbl> <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl>
## 1 1          4  287.  62.7   31.4 187.   387.   290    219   350  92.8
## 2 2          4  374. 134.    66.9 161.   587.   385    230   495 209. 
## 3 3          4  284.  62.1   31.0 185.   383.   298.   200   340  68.8
## 4 4          4  305. 140.    69.8  83.1  527.   283    165   490 146.
```

From the statistical summary, the mean of the second design is much higher than the other 3 designs which initially suggests the second design has a higher response rate. Further analysis will be done to either confirm or deny this.

```
lm.mail <- lm(formula = Responses ~ Design + Region, data = mail)
anova(lm.mail)
```

```
## Analysis of Variance Table
##
## Response: Responses
##           Df Sum Sq Mean Sq F value    Pr(>F)
## Design     3  21073    7024  2.7797 0.1023919
## Region     3 112796   37599 14.8784 0.0007803 ***
## Residuals  9  22743    2527
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
qf(p=.05, df1 = 3, df2 = 9, lower.tail = FALSE)
```

```
## [1] 3.862548
```

F0 = 2.78 < 3.86, therefore the null hypothesis is rejected.

2.b.

```
summary(lm.mail)
```

```
##
## Call:
## lm(formula = Responses ~ Design + Region, data = mail)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -50.00 -32.12 -12.00  28.94  78.50
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   393.50      33.25  11.834 8.67e-07 ***
## Design2        86.50      35.55   2.433 0.037768 *
## Design3        -3.50      35.55  -0.098 0.923722
## Design4        18.00      35.55   0.506 0.624759
## RegionQLD    -155.00      35.55  -4.361 0.001822 **
## RegionVIC     -54.75      35.55  -1.540 0.157886
## RegionWA     -215.25      35.55  -6.056 0.000189 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 50.27 on 9 degrees of freedom
## Multiple R-squared:  0.8548, Adjusted R-squared:  0.758
## F-statistic: 8.829 on 6 and 9 DF,  p-value: 0.002354
```

$\tau 1 = 393.5$ $\tau 2 = 86.5$ $\tau 3 = -3.5$ $\tau 4 = 18.0$

2.c.

```
LSD.test(y = lm.mail, trt = "Design", DFerror = lm.mail$df.residual, MSerror = devian
ce(lm.mail)/lm.mail$df.residual, alpha = 0.05, group = TRUE, console = TRUE)
```

```
##
## Study: lm.mail ~ "Design"
##
## LSD t Test for Responses
##
## Mean Square Error:  2527.056
##
## Design,  means and individual ( 95 %) CI
##
##   Responses       std r      LCL      UCL Min Max
## 1    287.25  62.74485 4 230.3909 344.1091 219 350
## 2    373.75 133.75195 4 316.8909 430.6091 230 495
## 3    283.75  62.09871 4 226.8909 340.6091 200 340
## 4    305.25 139.63136 4 248.3909 362.1091 165 490
##
## Alpha: 0.05 ; DF Error: 9
## Critical Value of t: 2.262157
##
## least Significant Difference: 80.41095
##
## Treatments with the same letter are not significantly different.
##
##   Responses groups
## 2    373.75      a
## 4    305.25     ab
## 1    287.25      b
## 3    283.75      b
```

Design 2 appears to be have a significantly different mean response rate to the other 3 designs.

2.d.

The Latin Square design should be employed if a third factor (different workplaces A, B, C and D) is added to the design. The extra block variable (workplace) causes another source of variation which results in the degrees of freedom being less which is a limitation to this particular design.

Question 3.

An industrial engineer is investigating the effects of four assembly methods (A, B, C, and D) on the assembly time for a color television component. Four operators are selected for the study. Furthermore, the engineer knows that each assembly method produces such fatigue that the time required for the last assembly may be greater than the time required for the first, regardless of the method. That is, a trend develops in the required assembly time. The engineer suspects that the workplaces used by the four operators may represent an additional source of variation. A fourth factor, workplace (α, β, γ, δ) needs to be considered and another experiment is conducted. The layout of the experiment and the data are given in the following.

```
television_component <- data.frame(Order_of_Assembly = c(1,1,1,1,2,2,2,2,3,3,3,3,4,4,
4,4),
                                   Operator = c(1,1,1,1,2,2,2,2,3,3,3,3,4,4,4,4),
                                   Assembly_Method = c("C", "B", "D", "A", "B", "C",
"A", "D","A", "D", "B", "C","D", "A", "C", "B"),
                                   Workplace = c("β", "γ", "δ", "α", "α", "δ", "γ",
"β","δ", "α", "β", "γ","γ", "β", "α", "δ"),
                                   Time = c(11, 10, 14, 8, 8, 12, 10, 12, 9, 11, 7, 1
5, 9, 8, 18, 6))

head(television_component)
```

```
##   Order_of_Assembly Operator Assembly_Method Workplace Time
## 1                 1        1               C         β   11
## 2                 1        1               B         γ   10
## 3                 1        1               D         δ   14
## 4                 1        1               A         α    8
## 5                 2        2               B         α    8
## 6                 2        2               C         δ   12
```

3.a.

The design of this experiment is a Graeco-Latin square design as the design contains blocks in 3 directions. This 4x4 design contains four factors. The two obvious factors are the rows and columns (Order of Assembly and Operator respectively). The two other factors are the Latin Letters representing the 4 different assembly methods and the Greek letters representing the 4 different work places.

3.b.

```
television_component <- television_component %>% mutate(Order_of_Assembly = factor(Or
der_of_Assembly), Operator = factor(Operator), Assembly_Method = factor(Assembly_Meth
od), Workplace = factor(Workplace))
str(television_component)
```

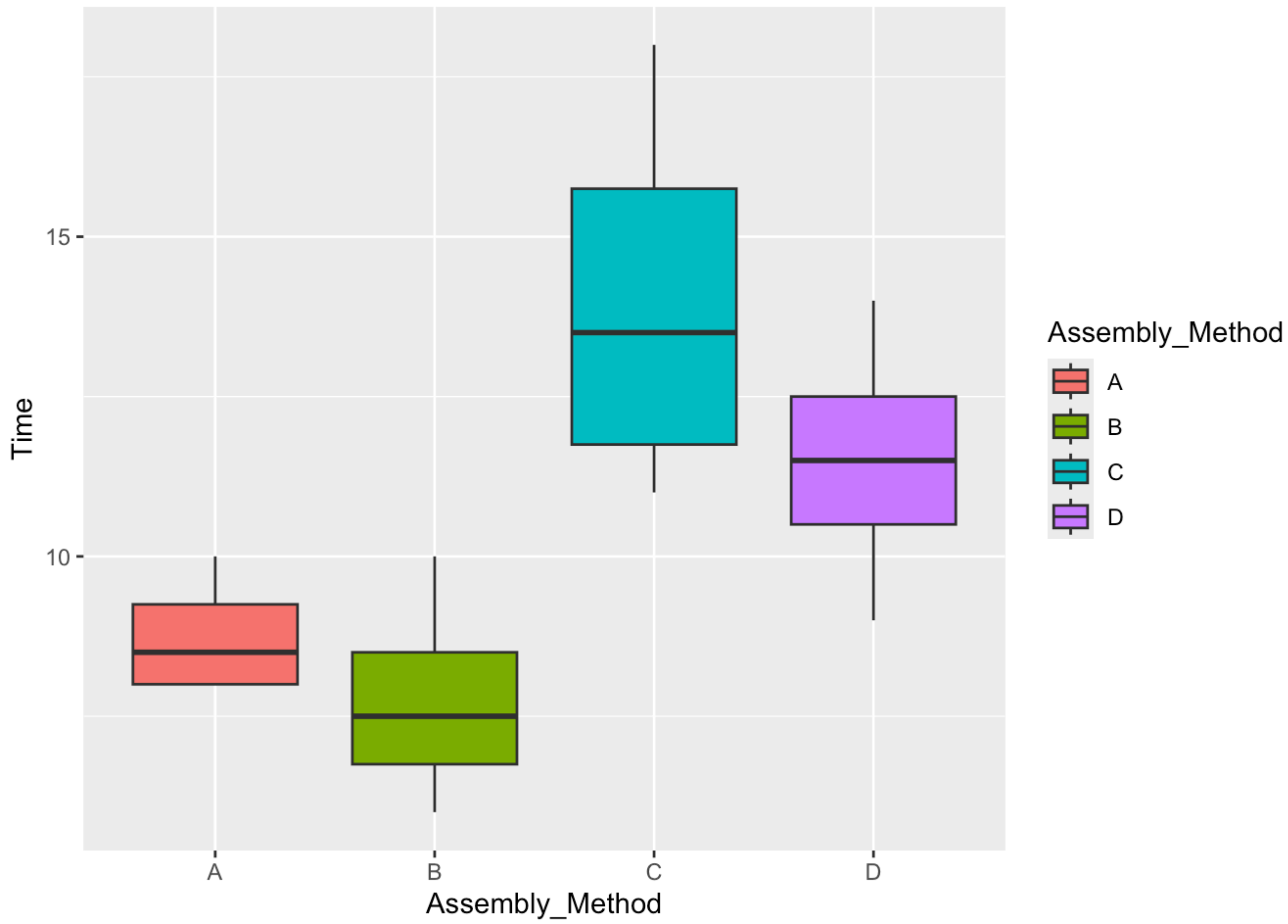
```
## 'data.frame':    16 obs. of  5 variables:
##  $ Order_of_Assembly: Factor w/ 4 levels "1","2","3","4": 1 1 1 1 2 2 2 2 3 3 ...
##  $ Operator         : Factor w/ 4 levels "1","2","3","4": 1 1 1 1 2 2 2 2 3 3 ...
##  $ Assembly_Method  : Factor w/ 4 levels "A","B","C","D": 3 2 4 1 2 3 1 4 1 4 ...
##  $ Workplace        : Factor w/ 4 levels "α","β","γ","δ": 2 3 4 1 1 4 3 2 4 1 ...
##  $ Time             : num  11 10 14 8 8 12 10 12 9 11 ...
```

H0: Four assembly methods are not different H1: Four assembly methods are different

```
television_component %>% group_by(Assembly_Method) %>%  summarise(n = n(),
                                                          mean = mean(Time, na.rm = TRUE),
                                                          sd = sd(Time, na.rm = TRUE),
                                                          stderr = sd/sqrt(n),
                                                          LCL = mean - qt(1 - (0.05 / 2), n - 1) * st
derr,
                                                          UCL = mean + qt(1 - (0.05 / 2), n - 1) * st
derr,
                                                          median = median(Time, na.rm = TRUE),
                                                          min = min(Time, na.rm = TRUE),
                                                          max = max(Time, na.rm = TRUE),
                                                          IQR = IQR(Time, na.rm = TRUE))
```

```
## # A tibble: 4 × 11
##   Assembly_Method     n  mean    sd stderr   LCL   UCL median   min   max   IQR
##   <fct>           <int> <dbl> <dbl>  <dbl> <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl>
## 1 A                   4  8.75 0.957  0.479  7.23  10.3    8.5     8    10  1.25
## 2 B                   4  7.75 1.71   0.854  5.03  10.5    7.5     6    10  1.75
## 3 C                   4 14    3.16   1.58   8.97  19.0   13.5    11    18  4
## 4 D                   4 11.5  2.08   1.04   8.19  14.8   11.5     9    14  2
```

```
ggplot(television_component, aes(x = Assembly_Method, y = Time, fill = Assembly_Metho
d)) + geom_boxplot()
```



The boxplot suggests that there is a difference in completion time between the four assembly methods with C or D taking the longest and B or A taking the shortest amount of time.

```
aov.television <- aov(formula = Time ~ Assembly_Method, data = television_component)
anova(aov.television)
```

```
## Analysis of Variance Table
##
## Response: Time
##                 Df Sum Sq Mean Sq F value   Pr(>F)
## Assembly_Method  3   95.5  31.833  7.0092 0.005595 **
## Residuals       12   54.5   4.542
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The anova() function on the created model outputs a p-value of 0.006 which is less than the significance level of 0.05 and therefore the null hypothesis is rejected. This means it can be cocluded that there is a difference in the completion time between at least one of the assembly methods and the rest.

3.c.

```
model2 <- lm(formula = Time ~ Assembly_Method + Order_of_Assembly + Workplace + Opera
tor, data = television_component)
summary(model2)
```

```
##
## Call:
## lm(formula = Time ~ Assembly_Method + Order_of_Assembly + Workplace +
##     Operator, data = television_component)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.7500 -1.3750  0.3750  0.9375  3.5000
##
## Coefficients: (3 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)            9.750      2.201   4.430  0.00442 **
## Assembly_MethodB      -1.000      1.968  -0.508  0.62958
## Assembly_MethodC       5.250      1.968   2.667  0.03717 *
## Assembly_MethodD       2.750      1.968   1.397  0.21190
## Order_of_Assembly2    -0.250      1.968  -0.127  0.90309
## Order_of_Assembly3    -0.250      1.968  -0.127  0.90309
## Order_of_Assembly4    -0.500      1.968  -0.254  0.80798
## Workplaceβ            -1.750      1.968  -0.889  0.40823
## Workplaceγ            -0.250      1.968  -0.127  0.90309
## Workplaceδ            -1.000      1.968  -0.508  0.62958
## Operator2                 NA         NA      NA       NA
## Operator3                 NA         NA      NA       NA
## Operator4                 NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.784 on 6 degrees of freedom
## Multiple R-squared:   0.69,  Adjusted R-squared:  0.225
## F-statistic: 1.484 on 9 and 6 DF,  p-value: 0.3251
```

The estimates of the treatment effects can be found from the output of the summary() function in the first column of the output under “Estimate”

3.d.

```
TukeyTV <- aov(formula = Time ~ Assembly_Method + Order_of_Assembly + Workplace + Ope
rator, data = television_component)
TukeyHSD(TukeyTV)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = Time ~ Assembly_Method + Order_of_Assembly + Workplace + Operat
or, data = television_component)
##
## $Assembly_Method
##      diff        lwr       upr     p adj
## B-A -1.00 -7.8143857  5.814386 0.9541951
## C-A  5.25 -1.5643857 12.064386 0.1284170
## D-A  2.75 -4.0643857  9.564386 0.5439589
## C-B  6.25 -0.5643857 13.064386 0.0698871
## D-B  3.75 -3.0643857 10.564386 0.3178553
## D-C -2.50 -9.3143857  4.314386 0.6109794
##
## $Order_of_Assembly
##      diff       lwr      upr     p adj
## 2-1 -0.25 -7.064386 6.564386 0.9991839
## 3-1 -0.25 -7.064386 6.564386 0.9991839
## 4-1 -0.50 -7.314386 6.314386 0.9936450
## 3-2  0.00 -6.814386 6.814386 1.0000000
## 4-2 -0.25 -7.064386 6.564386 0.9991839
## 4-3 -0.25 -7.064386 6.564386 0.9991839
##
## $Workplace
##      diff       lwr      upr     p adj
## β-α -1.75 -8.564386 5.064386 0.8111004
## γ-α -0.25 -7.064386 6.564386 0.9991839
## δ-α -1.00 -7.814386 5.814386 0.9541951
## γ-β  1.50 -5.314386 8.314386 0.8686348
## δ-β  0.75 -6.064386 7.564386 0.9794772
## δ-γ -0.75 -7.564386 6.064386 0.9794772
```

3.e.

Residual Test

```
mean(model2$residuals)
```

```
## [1] 2.775558e-17
```

Approximately equal to 0 as required.

Equality of Variances

H0: Equal variance H1: Not equal variance for at least one

```
ncvTest(model2)
```

```
## Non-constant Variance Score Test
## Variance formula: ~ fitted.values
## Chisquare = 3.457518, Df = 1, p = 0.062965
```

The p-value of 0.06 is greater than the significance level of 0.05 so the null hypothesis of equal variance is not rejected.

Normality of Residuals

H0: Normally distributed residuals H1: Not normally distributed residuals

```
y=rstudent(model2)
shapiro.test(y)
```

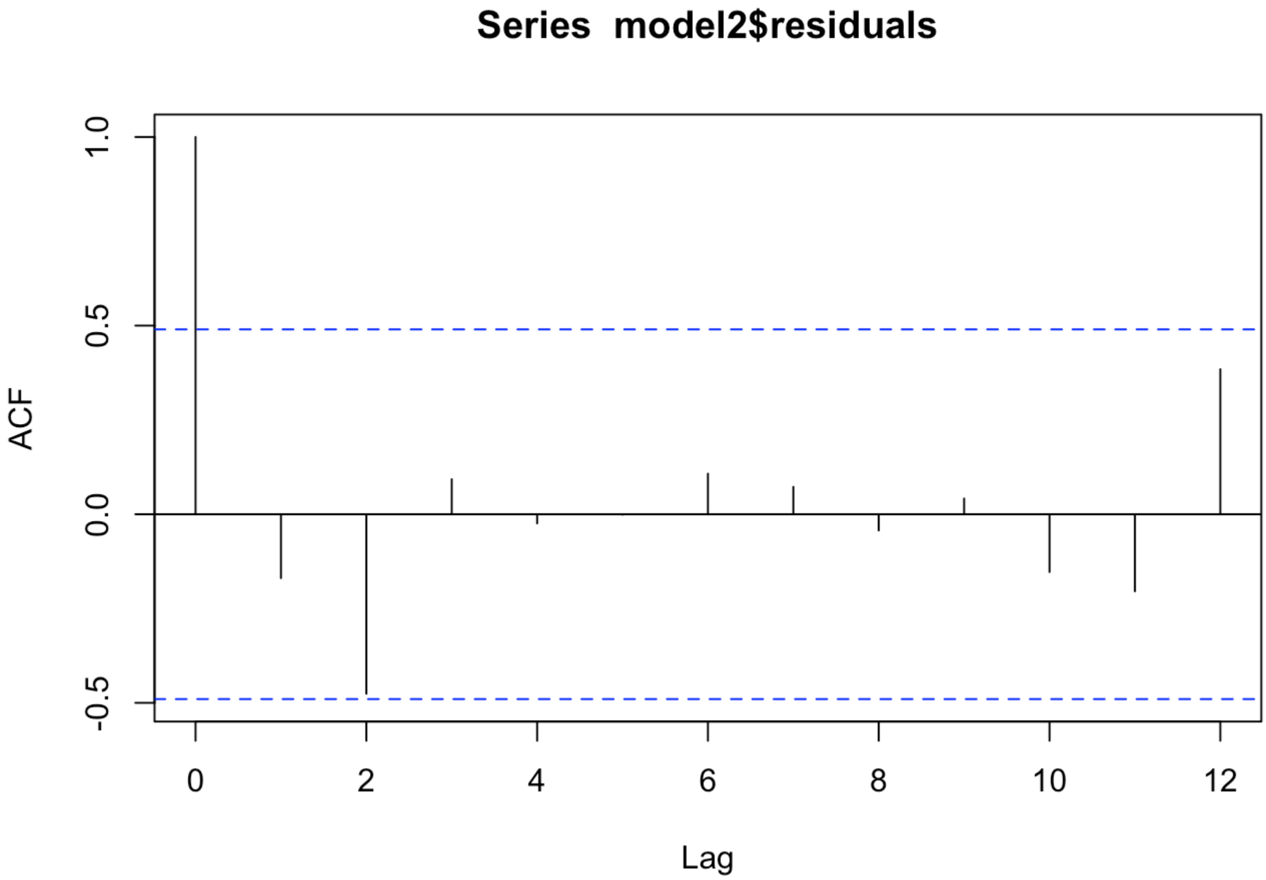
```
##
##  Shapiro-Wilk normality test
##
## data:  y
## W = 0.93647, p-value = 0.308
```

The p-value of 0.308 is greater than the significance level of 0.05 so the null hypothesis of normally distributed residuals is not rejected.

Correlated errors

H0: Correlation between errors H1: No correlation between errors

```
acf(model2$residuals)
```



One lag crosses the horizontal line on the ACF plot which means the null hypothesis of a correlation between errors can be rejected.

```
summary(model2)
```

```
##
## Call:
## lm(formula = Time ~ Assembly_Method + Order_of_Assembly + Workplace +
##     Operator, data = television_component)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.7500 -1.3750  0.3750  0.9375  3.5000
##
## Coefficients: (3 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)            9.750      2.201   4.430  0.00442 **
## Assembly_MethodB      -1.000      1.968  -0.508  0.62958
## Assembly_MethodC       5.250      1.968   2.667  0.03717 *
## Assembly_MethodD       2.750      1.968   1.397  0.21190
## Order_of_Assembly2    -0.250      1.968  -0.127  0.90309
## Order_of_Assembly3    -0.250      1.968  -0.127  0.90309
## Order_of_Assembly4    -0.500      1.968  -0.254  0.80798
## Workplaceβ            -1.750      1.968  -0.889  0.40823
## Workplaceγ            -0.250      1.968  -0.127  0.90309
## Workplaceδ            -1.000      1.968  -0.508  0.62958
## Operator2                 NA         NA      NA       NA
## Operator3                 NA         NA      NA       NA
## Operator4                 NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.784 on 6 degrees of freedom
## Multiple R-squared:   0.69,  Adjusted R-squared:  0.225
## F-statistic: 1.484 on 9 and 6 DF,  p-value: 0.3251
```

Finally, the p-value of 0.3251 is greater than the significance level of 0.05 which suggest the model is insignificant.