Anebha Bastola, Rachael De Ville
Mikayla Thomas, and Zahra Sodagartojgi
Dr. Withana-Gamage
Math 321
1 May 2022

The Statistical Analysis of *Reading Performance and Visual Fatigue When Using Electronic Displays in Long-Duration Reading Tasks Under Various Lighting Conditions*

The data included in this analysis is from a 2013 study produced by P.-C. Chang, S.-Y. Chou, and K.-K. Shieh. The study is titled "Reading Performance and Visual Fatigue When Using Electronic Displays in Long-Duration Reading Tasks Under Various Lighting Conditions". This data set holds the reading times for 3 devices and 4 lighting conditions (200Lx, 500Lx, 1000Lx, 1500Lx). The experimental unit is the reader, and the response variable is the reading times. There is equal replication used where each treatment used per device is tested five times. There were sixty observations that were made where each reader was tested twenty times, each lighting per device being tested five times. Therefore, each of the factors (light and device) combined had multiple experimental units, which in this case was 5.

The design that would be used to analyze the data the best would be a completely randomized 3 by 4 factorial design. Since the experimental unit is the reader it allows for this design to be used. Four lighting conditions are used and as mentioned earlier each of the 3 reading devices were tested with each condition a total of five times. There's structure in the set,which is why it's not just a completely randomized design rather a completely randomized factorial design. This is a table showing how it would follow this design:

| Factor Combination | Reading Device | Light Setting |
|---|---|---|
| 1 | Reading Device 1 | Lighting Condition 1 |
| 2 | Reading Device 1 | Lighting Condition 2 |
| 3 | Reading Device 1 | Lighting Condition 3 |
| 4 | Reading Device 1 | Lighting Condition 4 |
| 5 | Reading Device 2 | Lighting Condition 1 |
| 6 | Reading Device 2 | Lighting Condition 2 |
| .<br>.<br>. | | |
| 12 | Reading Device 3 | Lighting Condition 4 |

From this table it can be seen that it's a crossed multifactor study which goes by a three by four model that gives us twelve factor level combinations. For this study what is trying to be shown is if there's an effect of the lighting and type of device on how fast someone's reading time is. As mentioned his study uses a completely randomized factorial design and is a crossed multifactor study in which the null hypothesis, that lighting conditions and e-reader device will not affect reading times will be tested.

This study will be using an ANOVA test, specifically a two way test because there are two independent variables in the study that affect one dependent variable. The independent variables are the e-readers and lighting conditions whereas the dependent is the reading times.

The Analysis of variance (ANOVA) test was developed by Sir Ronald Fischer for analyzing the results of agriculture experiments; however today it is used by many people as it can be used for all experimental sciences (Danna 2021). Fischer wanted to separate the factors of his experiment when testing the data and allowing this separation caused there to be many factors within his experiment. Also creating these separations was something also done to test the significance of his data.

The analysis of variance (ANOVA) is a statistical test which helps find if differences in data are statistically significant (Kenton 2021). How this test works is that it looks at the affects of the factors in the data by comparing the means. According to the American Heart Association Journals, ANOVA is used to test equality in means by comparing their variances in groups. The formula used to calculate ANOVA is:

$$F=\frac{MST}{MSE}$$

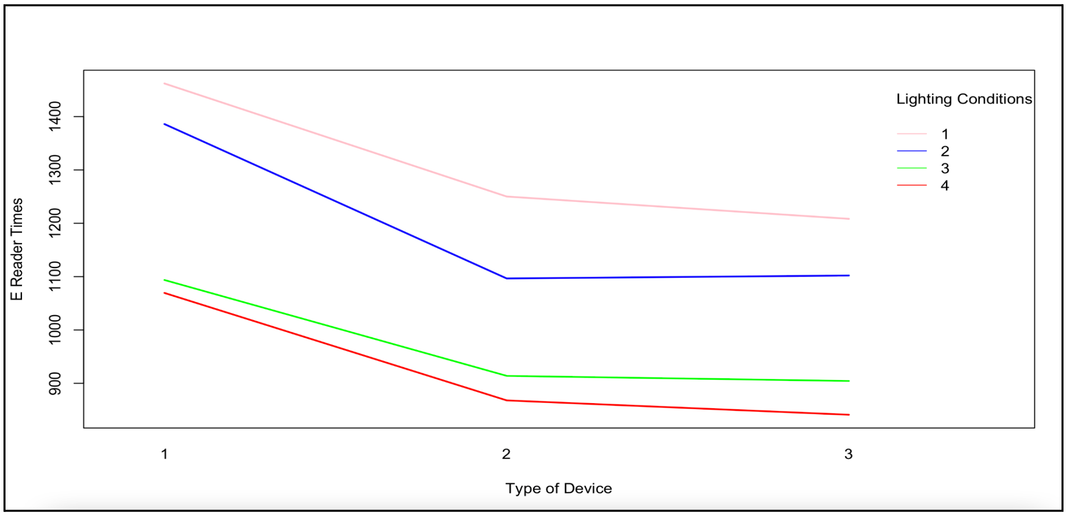
where MST is the mean sum of squares due to treatment and MSE is the mean sum of squares due to error. When the F-ratio statistic is close to one then we fail to reject the null hypothesis as there is no difference between the treatments. An ANOVA table typically looks like is:

| | Degrees of Freedom | Sum Square | Mean Square | F Value |
|---|---|---|---|---|
| Treatment | | | | |
| Residuals | | | | |

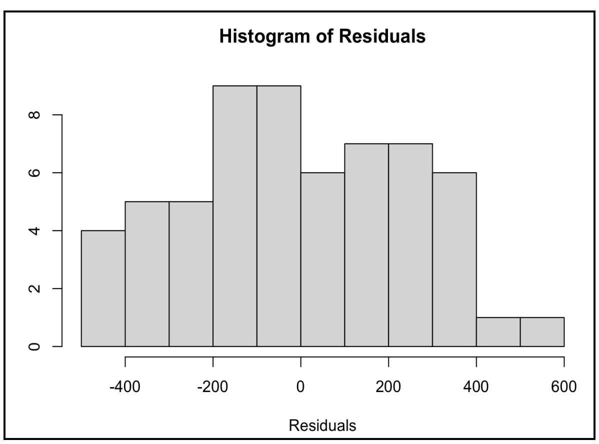
The ANOVA test also led to two other well known statistical tests known as the t-test and z-test. Sometimes it's not known if someone should use a t-test or an ANOVA test however to determine this, a t-test is used when determining the significance in the differences between two populations and ANOVA is determined with three or more populations. Two types of ANOVA tests are commonly used in statistics called the one way-ANOVA and two way ANOVA; two way ANOVA tests are done to test two variables on another variable.

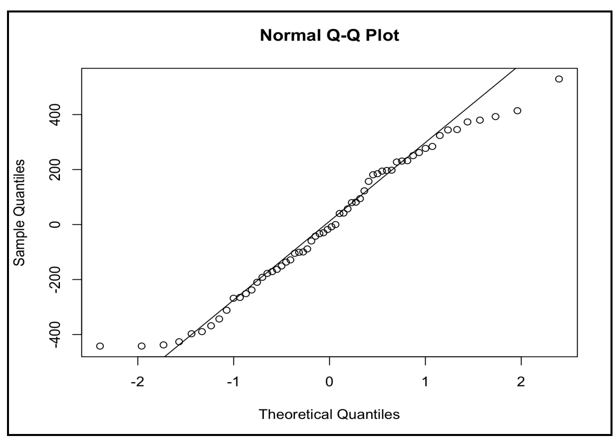
Another test that we will be using to analyze this study will be the tukey's test. Tukey’s test typically evaluates all pairwise comparisons, which for this study will allow for a more detailed comparison within all the factors. Tukey’s method also controls experimentwise error rate as well as shows differences between means compared with critical differences. How this method works with the ANOVA test is that it is used for creating confidence intervals for the pairwise differences between the factor level means. Typically this is what the output in R for tukey's test looks like for each factor:

| | difference | lower | upper | p-adj |
|---|---|---|---|---|
| B-A | | | | |
| C-A | | | | |
| C-B | | | | |



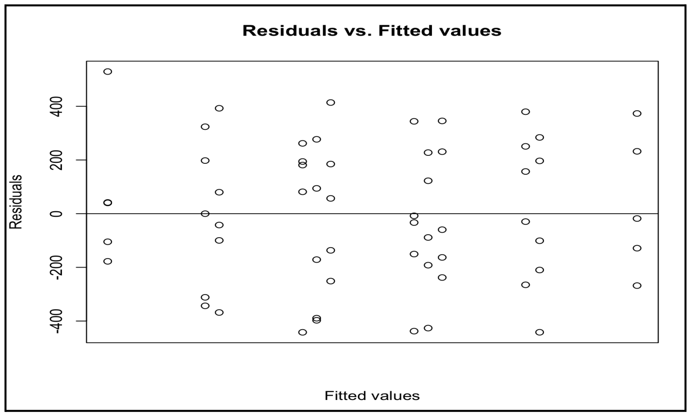

When starting our analysis, we first looked at checking the assumptions of the data. We needed to check the normality and the constant variance assumption. In addition, we looked at determining independence and possible outliers When checking for normality, we looked at the Histogram of Residuals and the Normal Q-Q Plot below.




Based on the Histogram of Residuals, we can see that the distribution of the data is approximately normal. We can make that assumption because the bars resemble the shape of a normally distributed bell curve. When looking at the Normal Q-Q Plot, we can see that the data fits the line towards the center of the graph, but it does contain some variation towards the ends of the line. Overall, we can conclude that the data fits the normal distribution.

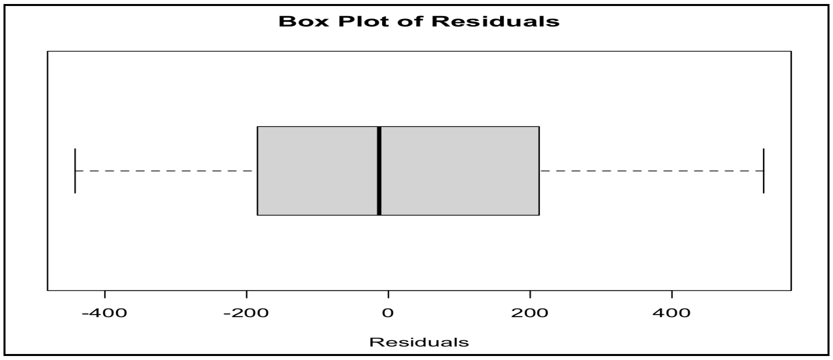
When checking the constant variance assumption, we looked at a Residuals vs. Fitted values plot below. We can say that the constant variance assumption is met because the plot shows an approximately equal distribution of data above and below the abline. When checking for independence, we can also use the Residuals vs Fitted values plot. We can assume that we have independence because the residuals are evenly spaced out.



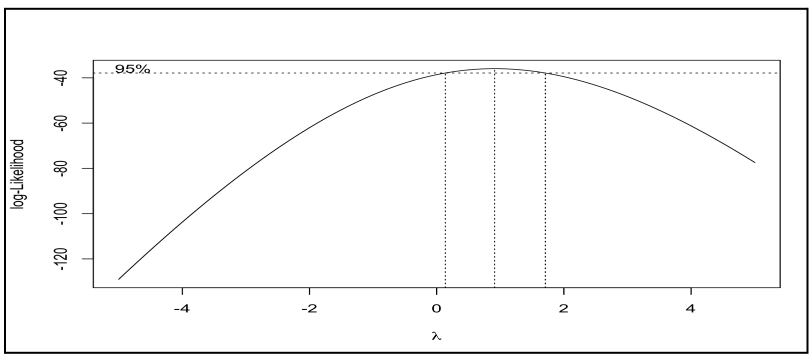

In addition to checking independence using the plot, we decided to run a Durbin Watson test in R. While we did not learn about this test in class, we made sure to familiarize ourselves with the concept in order to portray the correct information. The Durbin Watson statistic is used to detect correlation in the residuals from a regression analysis. The statistic is named after James Durbin and Geoffrey Stuart Watson. James Durbin is a British statistician and Geoffrey Watson is an Australian statistician.The test works by testing a null and alternative hypothesis. The null hypothesis is that the residuals are independent and the alternative hypothesis is that the residuals are not. When plugging in our model to this test we found a p-value of 0.752. Since our p-value is greater than .05, we fail to reject the null hypothesis and can conclude that our values are independent. In addition, a D-W statistic ranges from 0 to 4. 0 being negatively correlated and 4 being positively correlated.Our found D-W statistic of 2.45 is right in the middle, so it further shows we do not have correlation among our residuals.

```
> library("car")
> fit1=aov(time~as.factor(device)*as.factor(light), data=d)
> durbinWatsonTest(fit1)
 lag Autocorrelation D-W Statistic p-value
   1      -0.2358785      2.445208   0.752
 Alternative hypothesis: rho != 0
```

When checking for possible outliers, we decided to use a Box Plot of Residuals. When looking at the Box Plot of Residuals, we can see that there are no outliers in our data. We are assuming this because R software would show the outliers as hollow circles outside of the tails of the box plot.




While the data did pass all of the assumptions checks, we wanted to be absolutely positive it did not need any transformations. In order to completely confirm our assumptions, we checked for lambda using a box cox transformation. Looking at the x-value (lambda) on the box cox plot, we can see that it is close to one. We extracted the actual lambda value and found that it is 0.857208. Since 0.857208 is close enough to 1, we can completely confirm that the data does not require a transformation.




After checking the assumptions and confirming the data does not require a transformation, we were able to move on with our analysis. The first thing we looked at was the way the data was collected and organized. The data contained two independent variables. One of the independent variables was the device and it contained three treatments. The other independent variable was the lighting condition and it contained four treatments. Since there are two factors that are crossed, we determined that the study design was a crossed multifactor study. For our analysis, we decided to run a 3 by 4 factorial design. The research question, null hypothesis, and alternative hypothesis is listed below.

**Does the type of device and lighting conditions affect reading times?**

Null Hypothesis - The type of device and lighting conditions will not affect the reading times from an e-reader.

H0: The sum of all ɒβij = 0

Alternative Hypothesis - The type of device and lighting conditions will affect the reading times from an e-reader.

HA: The sum of all ɒβij ≠ 0

When determining the null and alternative hypothesis, we decided to use the effects model. The effects model is represented as $Y_{ijk} = \mu + \alpha_i + \beta_j + ɒ\beta_{ij} + \varepsilon_{ijk}$. Where $\mu$ is the overall average of the data, $\alpha_i$ is the treatment effects for treatment i, $\beta_j$ is the main effect of factor b at level j, $ɒ\beta_{ij}$ is the interaction effect between a and b for level combination ij, and $\varepsilon_{ijk}$ are iid random errors with mean 0 and variance $\sigma^2$.

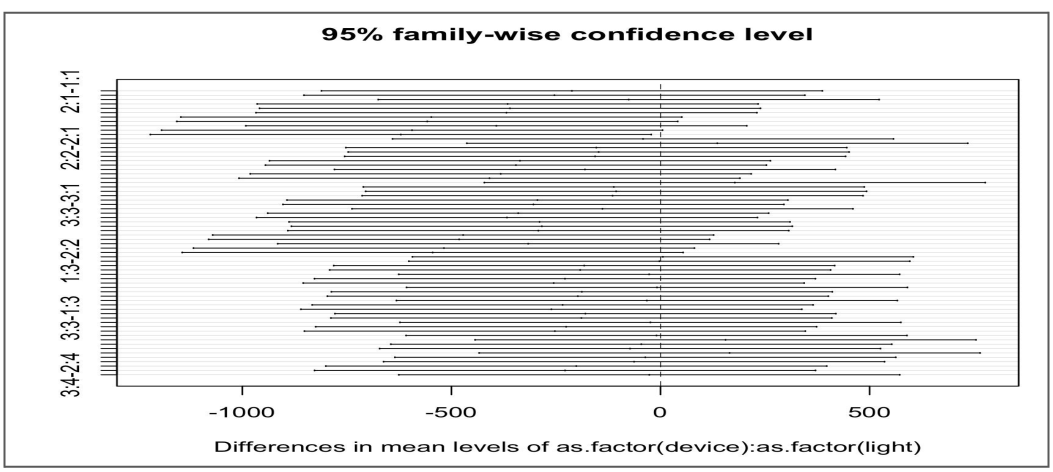
When running anova testing, we looked at the lighting condition and the type of device individually, as well as their interaction. To create an anova table, we set the e reading time as a function of the lighting conditions and the type of device factors.

```
> fit = lm(time ~ as.factor(light)*as.factor(device), data=d)
> anova(fit)
Analysis of Variance Table

Response: time
                                   Df  Sum Sq Mean Sq F value    Pr(>F)
as.factor(light)                    3 1481064  493688  6.4920 0.0008906 ***
as.factor(device)                   2  706968  353484  4.6483 0.0142790 *
as.factor(light):as.factor(device)  6   21543    3591  0.0472 0.9995253
Residuals                          48 3650203   76046
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The first thing we did before starting our anova analysis was checking the table to confirm that all of our degrees of freedom were correct in regards to their respective treatments/conditions. The lighting condition should/does contain 3 degrees of freedom for its 4 conditions and the type of device should/does contain 2 degrees of freedom for its 3 conditions. In addition, the light and device interaction should/does have 3x2=6 degrees of freedom. Once we confirmed that they were correct, we began looking at the observed F-values and p-values to determine any significance.

What we determined was that the interaction between the lighting conditions and the type of device was statistically insignificant. We can see this because the p-value of 0.9995253 is greater than alpha, .05. This is further confirmed by the small $F_{obs}$ value of 0.0472. Even though our interaction was insignificant, we decided to look into the pairwise comparisons and run a Tukey's test. Our Tukey's test determined that every interaction between the two factors was insignificant except for the interaction between lighting conditions 3 + 4 and device 1.



After using Tukey's test we began our final conclusions for the interaction between the type of device and lighting conditions on e reader times. We fail to reject the null hypothesis in favor of the alternative hypothesis. Based on our p-value of 0.99995253 being greater than .05 (alpha), we have enough evidence to conclude that the type of device and lighting conditions do not affect the reader times of an e reader.

After determining that the interaction was insignificant, we looked at the main effects of both treatments individually. This caused us to create two new null and alternative hypotheses to test the main effects.

**Does the type of device affect reading times?**

Null Hypothesis - The type of device will not affect the reading times from an e-reader.

H0: The sum of all ɒi = 0

Alternative Hypothesis - The type of device will affect the reading times from an e-reader.

HA: The sum of all ɒi ≠ 0

**Does the lighting condition affect reading times?**

Null Hypothesis - The lighting conditions will not affect the reading times from an e-reader.

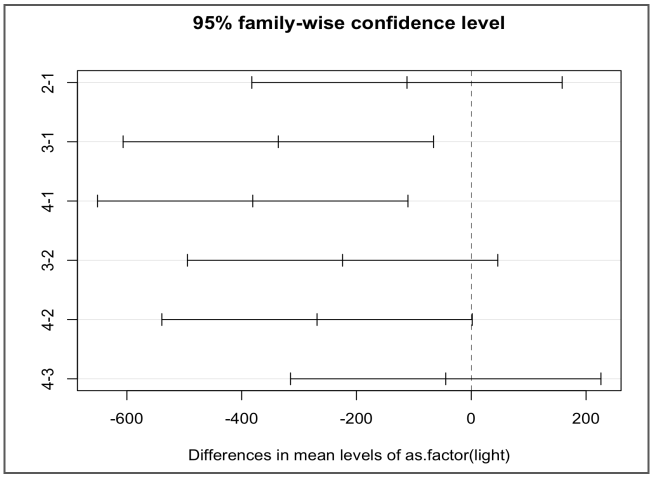
H0: The sum of all βj = 0

Alternative Hypothesis - The lighting conditions will affect the reading times from an e-reader.

HA: The sum of all βj ≠ 0

Our anova table shows us that both factors alone produce statistically significant results. We can see this because the lighting conditions p-value of 0.0008906 is less than .05 (alpha). In addition, the type of device's p-value of 0.0142790 is less than .05 (alpha). Since we received statistically significant results, we looked into the pairwise comparisons of the factors individually by using Tukey's test.

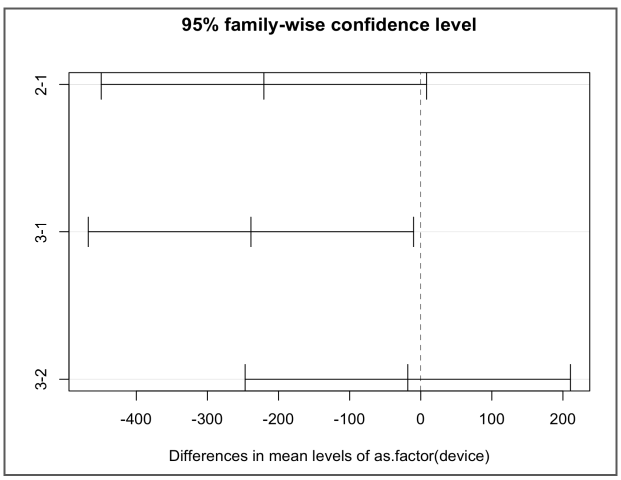
When running Tukey's test for the lighting conditions, we saw that groups 3 + 1 and 4 + 1 produced statistically significant results. Located below, lighting conditions 3 and 1 had a p-value of 0.0090805 and lighting conditions 4 and 1 had a p-value of 0.0024773. In addition, when comparing lighting conditions 4 and 2 there was a marginally significant p-value of 0.0520009.




$`as.factor(light)`

| | diff | lwr | upr | p adj |
|---|---|---|---|---|
| 2-1 | -111.9987 | -382.3622 | 158.364890 | 0.6928843 |
| 3-1 | -336.1987 | -606.5622 | -65.835110 | 0.0090805 |
| 4-1 | -380.6987 | -651.0622 | -110.335110 | 0.0024773 |
| 3-2 | -224.2000 | -494.5636 | 46.163557 | 0.1369553 |
| 4-2 | -268.7000 | -539.0636 | 1.663557 | 0.0520009 |
| 4-3 | -44.5000 | -314.8636 | 225.863557 | 0.9720290 |

When running pairwise comparisons for the type of device, we saw that group 3 + 1 produced statistically significant results. Located below, when comparing devices 3 and 1 we can see that the p-value of 0.0388951 is less than .05 (alpha). In addition, we saw a marginally significant difference between devices 2 and 1. The comparison between devices 2 and 1 received a p-value of 0.0609828.




$`as.factor(device)`

| | diff | lwr | upr | p adj |
|---|---|---|---|---|
| 2-1 | -220.6260 | -449.4258 | 8.173844 | 0.0609828 |
| 3-1 | -238.8265 | -467.6263 | -10.026656 | 0.0388951 |
| 3-2 | -18.2005 | -247.0003 | 210.599344 | 0.9800087 |

After running Tukey’s test for the type of device and lighting conditions individually, we were able to move on to our final conclusions. For the lighting condition alone, we reject the null hypothesis in favor of the alternative hypothesis. Based on our p-value of 0.0008906, we have enough evidence to conclude that the lighting condition affects reading times of an e reader. For the type of device factor alone, we reject the null hypothesis in favor of the alternative hypothesis. Based on our p-value of 0.0142790, we have enough evidence to conclude that the type of device affects reading times of an e reader.

**References**


Chang, Po-Chun, et al. "Reading Performance and Visual Fatigue When Using Electronic Paper Displays in Long-Duration Reading Tasks under Various Lighting Conditions." *Displays*, Elsevier, 12 June 2013, https://www.sciencedirect.com/science/article/pii/S0141938213000425.

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Zach. "The Durbin-Watson Test: Definition & Example." Statology, 2 Apr. 2021, https://www.statology.org/durbin-watson-test/.

# Fully Annotated R Code - Without R Output

```
#############################################################################
# LOADING DATA INTO R

file.choose("d.txt")
[1] "/Users/mikaylathomas/Desktop/d.txt"
d=read.table("/Users/mikaylathomas/Desktop/d.txt", header=TRUE)
device<- d$device
light<- d$light
time<- d$time
light<-as.factor(light)
device<-as.factor(device)

####################################################################################
# CHECKING ASSUMPTIONS IN R

fit=lm(time~as.factor(light)*as.factor(device), data=d)
Yhat=predict(fit)
ei=time-Yhat
qqnorm(ei)
qqline(ei)
boxplot(ei, xlab="Residuals", ylab="", main="Box Plot of Residuals", horizontal=TRUE)
hist(ei, xlab="Residuals", ylab="", main="Histogram of Residuals")
plot(Yhat,ei,ylab="Residuals",xlab="Fitted values",xaxt="n", main="Residuals vs. Fitted values")
abline(0,0)
library("car")
fit1=aov(time~as.factor(device)*as.factor(light), data=d)
durbinWatsonTest(fit1)
install.packages("MASS")
library("MASS")
boxcox(time~device+light, lambda=seq(-5,5,.001))
BoxCox<-function(Y,X,int){
SSE.func<-function(h,Y,X){
n<-length(Y)
a2<-prod(Y^(1/n))
a1<-1/(h*a2^(h-1))
if(h != 0){
W<-a1*(Y^h-1)
}
if(h==0){
W<-a2*log(Y)
}
res<-sum((lm(W~X)$residuals)^2)
return(res)
}
res<-optimize(SSE.func,interval=int, Y=Y, X=X)$minimum
return(res)
}
h<-BoxCox(time,device,c(-10,10))
h
```

```
h<-BoxCox(time,light,c(-10,10))
h

#####################################################################################
#           ANOVA ANALYSIS

fit = lm(time ~ as.factor(light)*as.factor(device), data=d)
anova(fit)
library("multcomp")
fit1=aov(time~as.factor(device)*as.factor(light), data=d)
TukeyHSD(fit1)
plot(TukeyHSD(fit1))
fit2=aov(time~as.factor(device), data=d)
TukeyHSD(fit2)
fit3=aov(time~as.factor(light), data=d)
plot(TukeyHSD(fit3))
TukeyHSD(fit3)
```

## Fully Annotated Code - Including R Output

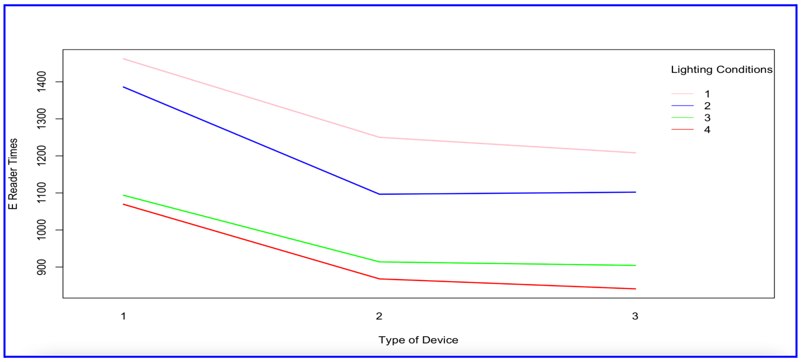
```
#####################################################################################
# LOADING DATA INTO R

file.choose("d.txt")
[1] "/Users/mikaylathomas/Desktop/d.txt"
 d=read.table("/Users/mikaylathomas/Desktop/d.txt", header=TRUE)
d
   device light    time
1       1     1 1656.26
2       1     1 1405.92
3       1     1 1797.21
4       1     1 1155.96
5       1     1 1295.44
6       1     2 1022.32
7       1     2 1538.07
8       1     2 1444.46
9       1     2 1257.76
10      1     2 1667.19
11      1     3 1000.28
12      1     3 1142.75
13      1     3 1494.78
14      1     3 1117.59
15      1     3  713.07
16      1     4 1276.09
17      1     4 1095.61
18      1     4  572.08
```

```
19     1     4 1195.20
20     1     4 1208.47
21     2     1  862.69
22     2     1 1094.63
23     2     1 1203.72
24     2     1 1501.26
25     2     1 1588.64
26     2     2 1290.54
27     2     2 1079.31
28     2     2  741.65
29     2     2 1395.44
30     2     2  976.03
31     2     3 1125.57
32     2     3  634.06
33     2     3  860.09
34     2     3  641.96
35     2     3 1308.35
36     2     4  583.03
37     2     4  894.61
38     2     4  551.34
39     2     4 1092.53
40     2     4 1218.54
41     3     1  947.27
42     3     1 1530.75
43     3     1 1416.07
44     3     1 1022.15
45     3     1 1125.51
46     3     2  797.31
47     3     2 1462.59
48     3     2  911.93
49     3     2 1233.46
50     3     2 1105.44
51     3     3  812.27
52     3     3  991.76
53     3     3  543.75
54     3     3  869.63
55     3     3 1304.59
56     3     4  815.47
57     3     4 1304.63
58     3     4  817.06
59     3     4  670.62
60     3     4  597.72
```

```
device<- d$device
light<- d$light
time<- d$time
```

```
light<-as.factor(light)
device<-as.factor(device)
interaction.plot(x.factor = d$device, #x-axis variable
                 trace.factor = d$light, #variable for lines
                 response = d$time, #y-axis variable
                 ylab = "E Reader Times",
                 xlab = "Type of Device",
                 col = c("pink", "blue", "green", "red"),
                 lty = 1, #line type
                 lwd = 2, #line width
                 trace.label = "Lighting Conditions")
```




```
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Yhat=predict(fit)
ei=time-Yhat
qqnorm(ei)
qqline(ei)
```
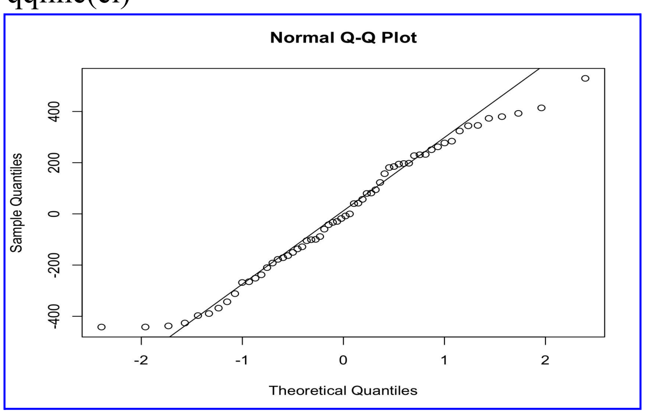
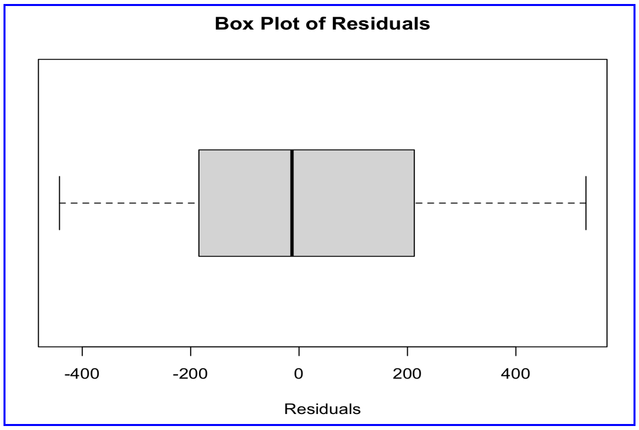
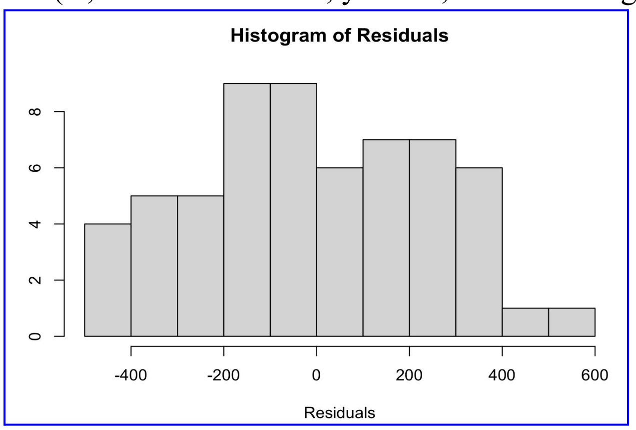



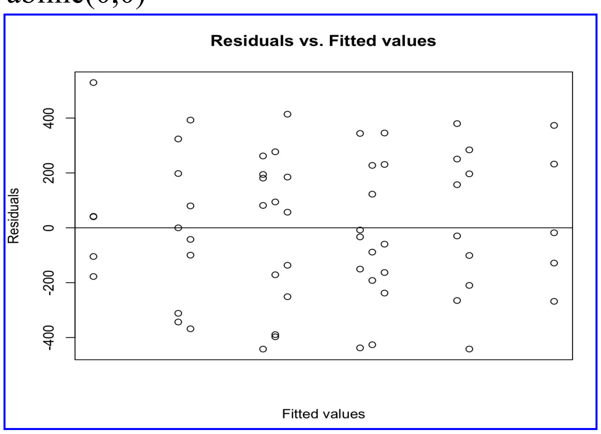

```
boxplot(ei, xlab="Residuals", ylab="", main="Box Plot of Residuals", horizontal=TRUE)
```




hist(ei, xlab="Residuals", ylab="", main="Histogram of Residuals")

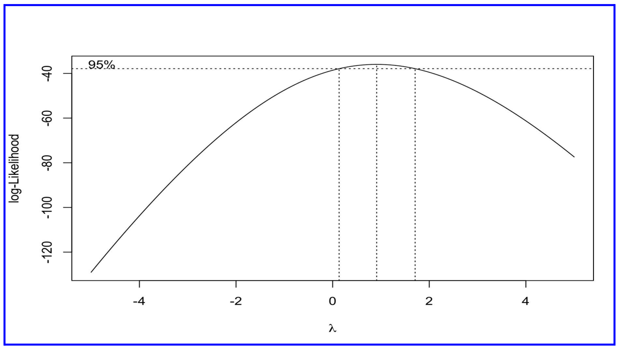



plot(Yhat,ei,ylab="Residuals",xlab="Fitted values",xaxt="n", main="Residuals vs. Fitted values")
abline(0,0)




library("car")
fit1=aov(time~as.factor(device)*as.factor(light), data=d)
durbinWatsonTest(fit1)
lag Autocorrelation D-W Statistic p-value
1 -0.2358785 2.445208 0.752
Alternative hypothesis: rho != 0
install.packages("MASS")

```
library("MASS")
boxcox(time~device+light, lambda=seq(-5,5,.001))
```



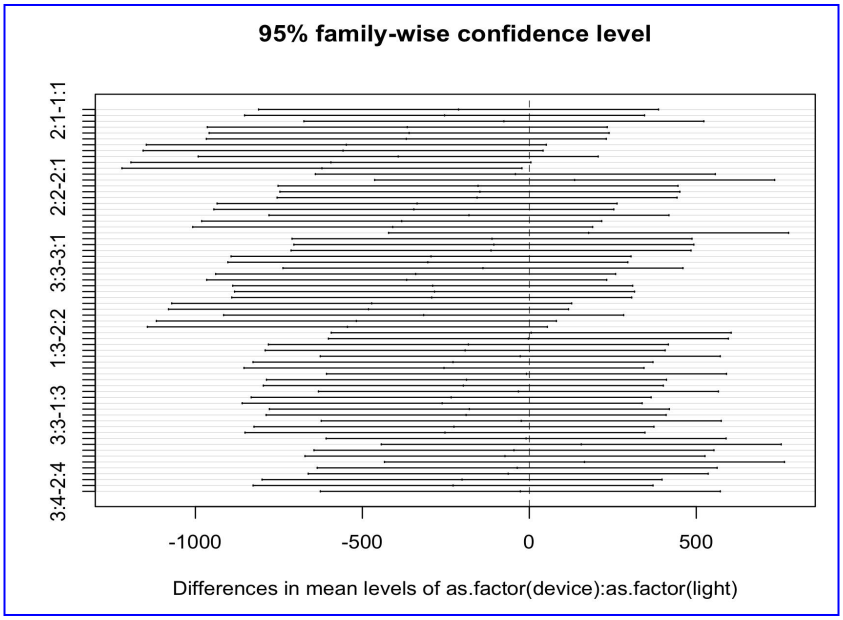

```
 BoxCox<-function(Y,X,int){
SSE.func<-function(h,Y,X){
 n<-length(Y)
 a2<-prod(Y^(1/n))
 a1<-1/(h*a2^(h-1))
 if(h != 0){
 W<-a1*(Y^h-1)
 }
 if(h==0){
 W<-a2*log(Y)
 }
 res<-sum((lm(W~X)$residuals)^2)
return(res)
 }
 res<-optimize(SSE.func,interval=int, Y=Y, X=X)$minimum
 return(res)
 }
h<-BoxCox(time,device,c(-10,10))
h
[1] 0.8889941
 h<-BoxCox(time,light,c(-10,10))
 h
[1] 0.825421

##################################################################################
#         ANOVA ANALYSIS AND TUKEY PROCEDURE

 fit = lm(time ~ as.factor(light)*as.factor(device), data=d)
 anova(fit)
Analysis of Variance Table

Response: time
                            Df  Sum Sq Mean Sq F value    Pr(>F)
as.factor(light)             3 1481064  493688  6.4920 0.0008906 ***
as.factor(device)            2  706968  353484  4.6483 0.0142790 *
```

```
as.factor(light):as.factor(device)  6   21543    3591  0.0472 0.9995253
Residuals                          48 3650203   76046
 library("multcomp")
 fit1=aov(time~as.factor(device)*as.factor(light), data=d)
 TukeyHSD(fit1)
 Tukey multiple comparisons of means
   95% family-wise confidence level

Fit: aov(formula = time ~ as.factor(device) * as.factor(light), data = d)

$`as.factor(device)`
        diff       lwr        upr     p adj
2-1 -220.6260 -431.5285  -9.723488 0.0384849
3-1 -238.8265 -449.7290 -27.923988 0.0230557
3-2  -18.2005 -229.1030 192.702012 0.9762840

$`as.factor(light)`
        diff       lwr          upr     p adj
2-1 -111.9987 -379.9852  155.9878183 0.6838249
3-1 -336.1987 -604.1852  -68.2121817 0.0085849
4-1 -380.6987 -648.6852 -112.7121817 0.0023697
3-2 -224.2000 -492.1865   43.7864849 0.1306514
4-2 -268.7000 -536.6865   -0.7135151 0.0491639
4-3  -44.5000 -312.4865  223.4864849 0.9708523

$`as.factor(device):as.factor(light)`
           diff        lwr       upr     p adj
2:1-1:1 -211.970  -810.8423 386.90225 0.9850663
3:1-1:1 -253.808  -852.6803 345.06425 0.9453317
1:2-1:1  -76.198  -675.0703 522.67425 0.9999991
2:2-1:1 -365.564  -964.4363 233.30825 0.6278106
3:2-1:1 -360.012  -958.8843 238.86025 0.6490458
1:3-1:1 -368.464  -967.3363 230.40825 0.6166464
2:3-1:1 -548.152 -1147.0243  50.72025 0.1017114
3:3-1:1 -557.758 -1156.6303  41.11425 0.0894045
1:4-1:1 -392.668  -991.5403 206.20425 0.5229257
2:4-1:1 -594.148 -1193.0203   4.72425 0.0535747
3:4-1:1 -621.058 -1219.9303 -22.18575 0.0358878
3:1-2:1  -41.838  -640.7103 557.03425 1.0000000
1:2-2:1  135.772  -463.1003 734.64425 0.9996942
2:2-2:1 -153.594  -752.4663 445.27825 0.9990326
3:2-2:1 -148.042  -746.9143 450.83025 0.9993107
1:3-2:1 -156.494  -755.3663 442.37825 0.9988529
2:3-2:1 -336.182  -935.0543 262.69025 0.7366370
3:3-2:1 -345.788  -944.6603 253.08425 0.7021978
1:4-2:1 -180.698  -779.5703 418.17425 0.9959281
```

| | | | | |
|---|---|---|---|---|
| 2:4-2:1 | -382.178 | -981.0503 | 216.69425 | 0.5635108 |
| 3:4-2:1 | -409.088 | -1007.9603 | 189.78425 | 0.4605674 |
| 1:2-3:1 | 177.610 | -421.2623 | 776.48225 | 0.9964864 |
| 2:2-3:1 | -111.756 | -710.6283 | 487.11625 | 0.9999543 |
| 3:2-3:1 | -106.204 | -705.0763 | 492.66825 | 0.9999726 |
| 1:3-3:1 | -114.656 | -713.5283 | 484.21625 | 0.9999410 |
| 2:3-3:1 | -294.344 | -893.2163 | 304.52825 | 0.8649157 |
| 3:3-3:1 | -303.950 | -902.8223 | 294.92225 | 0.8391903 |
| 1:4-3:1 | -138.860 | -737.7323 | 460.01225 | 0.9996215 |
| 2:4-3:1 | -340.340 | -939.2123 | 258.53225 | 0.7219022 |
| 3:4-3:1 | -367.250 | -966.1223 | 231.62225 | 0.6213250 |
| 2:2-1:2 | -289.366 | -888.2383 | 309.50625 | 0.8772624 |
| 3:2-1:2 | -283.814 | -882.6863 | 315.05825 | 0.8902195 |
| 1:3-1:2 | -292.266 | -891.1383 | 306.60625 | 0.8701528 |
| 2:3-1:2 | -471.954 | -1070.8263 | 126.91825 | 0.2545919 |
| 3:3-1:2 | -481.560 | -1080.4323 | 117.31225 | 0.2293346 |
| 1:4-1:2 | -316.470 | -915.3423 | 282.40225 | 0.8021081 |
| 2:4-1:2 | -517.950 | -1116.8223 | 80.92225 | 0.1497849 |
| 3:4-1:2 | -544.860 | -1143.7323 | 54.01225 | 0.1062406 |
| 3:2-2:2 | 5.552 | -593.3203 | 604.42425 | 1.0000000 |
| 1:3-2:2 | -2.900 | -601.7723 | 595.97225 | 1.0000000 |
| 2:3-2:2 | -182.588 | -781.4603 | 416.28425 | 0.9955518 |
| 3:3-2:2 | -192.194 | -791.0663 | 406.67825 | 0.9931727 |
| 1:4-2:2 | -27.104 | -625.9763 | 571.76825 | 1.0000000 |
| 2:4-2:2 | -228.584 | -827.4563 | 370.28825 | 0.9736555 |
| 3:4-2:2 | -255.494 | -854.3663 | 343.37825 | 0.9428860 |
| 1:3-3:2 | -8.452 | -607.3243 | 590.42025 | 1.0000000 |
| 2:3-3:2 | -188.140 | -787.0123 | 410.73225 | 0.9942783 |
| 3:3-3:2 | -197.746 | -796.6183 | 401.12625 | 0.9913848 |
| 1:4-3:2 | -32.656 | -631.5283 | 566.21625 | 1.0000000 |
| 2:4-3:2 | -234.136 | -833.0083 | 364.73625 | 0.9686643 |
| 3:4-3:2 | -261.046 | -859.9183 | 337.82625 | 0.9343013 |
| 2:3-1:3 | -179.688 | -778.5603 | 419.18425 | 0.9961182 |
| 3:3-1:3 | -189.294 | -788.1663 | 409.57825 | 0.9939796 |
| 1:4-1:3 | -24.204 | -623.0763 | 574.66825 | 1.0000000 |
| 2:4-1:3 | -225.684 | -824.5563 | 373.18825 | 0.9760124 |
| 3:4-1:3 | -252.594 | -851.4663 | 346.27825 | 0.9470470 |
| 3:3-2:3 | -9.606 | -608.4783 | 589.26625 | 1.0000000 |
| 1:4-2:3 | 155.484 | -443.3883 | 754.35625 | 0.9989184 |
| 2:4-2:3 | -45.996 | -644.8683 | 552.87625 | 1.0000000 |
| 3:4-2:3 | -72.906 | -671.7783 | 525.96625 | 0.9999994 |
| 1:4-3:3 | 165.090 | -433.7823 | 763.96225 | 0.9981454 |
| 2:4-3:3 | -36.390 | -635.2623 | 562.48225 | 1.0000000 |
| 3:4-3:3 | -63.300 | -662.1723 | 535.57225 | 0.9999999 |
| 2:4-1:4 | -201.480 | -800.3523 | 397.39225 | 0.9899845 |
| 3:4-1:4 | -228.390 | -827.2623 | 370.48225 | 0.9738184 |

3:4-2:4 -26.910 -625.7823 571.96225 1.0000000

plot(TukeyHSD(fit1))

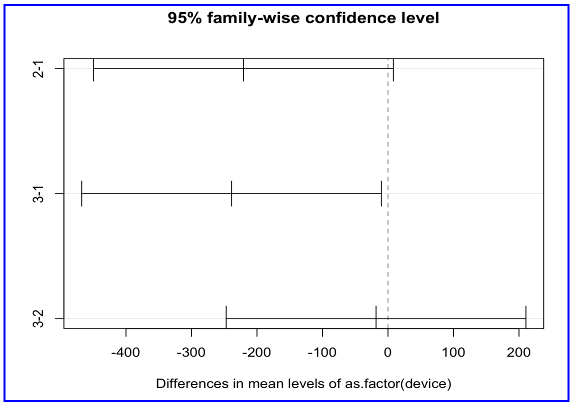



fit2=aov(time~as.factor(device), data=d)
TukeyHSD(fit2)
Tukey multiple comparisons of means
95% family-wise confidence level

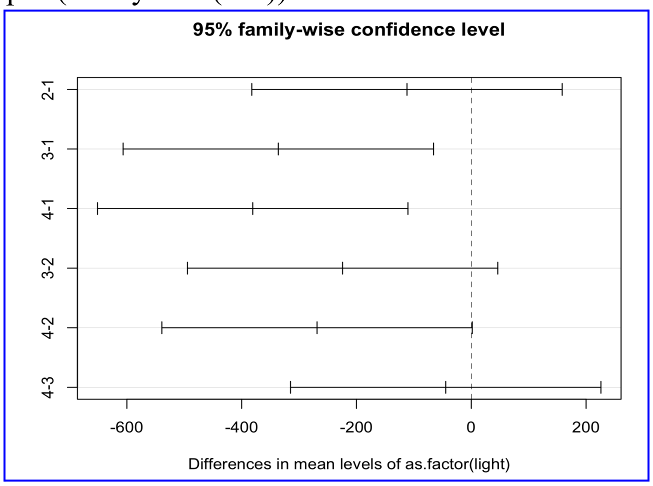
Fit: aov(formula = time ~ as.factor(device), data = d)

```
$`as.factor(device)`
          diff       lwr        upr     p adj
2-1 -220.6260 -449.4258   8.173844 0.0609828
3-1 -238.8265 -467.6263 -10.026656 0.0388951
3-2  -18.2005 -247.0003 210.599344 0.9800087
```

plot(TukeyHSD(fit2))




fit3=aov(time~as.factor(light), data=d)
plot(TukeyHSD(fit3))




TukeyHSD(fit3)

```
Tukey multiple comparisons of means
   95% family-wise confidence level

Fit: aov(formula = time ~ as.factor(light), data = d)

$`as.factor(light)`
        diff       lwr        upr     p adj
2-1 -111.9987 -382.3622  158.364890 0.6928843
3-1 -336.1987 -606.5622  -65.835110 0.0090805
4-1 -380.6987 -651.0622 -110.335110 0.0024773
3-2 -224.2000 -494.5636   46.163557 0.1369553
4-2 -268.7000 -539.0636    1.663557 0.0520009
4-3  -44.5000 -314.8636  225.863557 0.9720290
```