STAT 522 —— Assignment 4

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1 Exercise 5.1

(a)

```
## Given
df_tot = 17
df_err = 12
df_a = 1
ss_a = 0.322
ss_b = 80.554
ss_{err} = 105.327
ss_{tot} = 231.551
ms_b = 40.2771
ms_err = 9.773
F_b = 4.59
ms_a = ss_a/df_a
df_b = round(ss_b/ms_b, 0)
df_ab = df_tot - df_err - df_b - df_a
ss_ab = ss_tot - ss_err - ss_a - ss_b
ms_ab = ss_ab/df_ab
F_a = ms_a/ms_err
F_ab = ms_ab/ms_err
p_a = 1 - pf(F_a, df_a, df_err)
p_b = 1 - pf(F_b, df_b, df_err)
p_ab = 1 - pf(F_ab, df_ab, df_err)
rbind(df_b, df_ab)
## [,1]
## df_b
## df_ab
rbind(ms_a, ms_ab)
##
          [,1]
## ms_a 0.322
## ms_ab 22.674
rbind(F_a, F_ab)
##
           [,1]
## F_a 0.03295
## F_ab 2.32007
rbind(p_a, p_b, p_ab)
##
           [,1]
## p_a 0.85899
## p_b 0.03308
## p_ab 0.14065
```

The ANOVA Table:

	DF	SS	MS	F	P
Α	1	0.322	0.322	0.0367	0.859
В	2	80.554	40.2771	4.59	0.033
Interaction	2	45.348	22.674	2.5832	0.14
Error	12	105.327	8.7773		
Total	17	231.551			

- (b) 3
- (c) 3
- (d) From the p-values, it's found that only B is significant.

2 Exercise 5.3

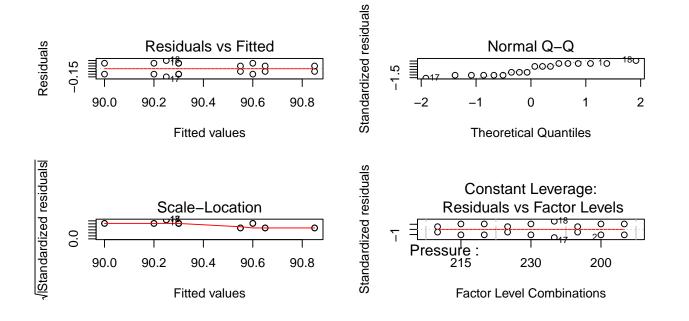
(a) Analyze the data and draw conclusions. Use $\alpha = 0.05$

```
setwd("C:/Users/Subasish/Dropbox/A Spring 2014/Dr Novelo/HW")
yield <- read.csv("5.3.csv")</pre>
yield$Pressure <- as.factor(yield$Pressure)</pre>
yield$Temperature <- as.factor(yield$Temperature)</pre>
yield.aov <- aov(Yield ~ Pressure * Temperature, data = yield)</pre>
summary(yield.aov)
##
                          Df Sum Sq Mean Sq F value
                              0.768
                                       0.384
                                               21.59 0.00037 ***
## Pressure
                           2
                              0.301
                                       0.151
                                                 8.47 0.00854 **
## Temperature
                              0.069
                                       0.017
## Pressure: Temperature
                                                 0.97 0.47001
                           4
                                       0.018
## Residuals
                              0.160
## Signif. codes:
                    0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

From the R code values, the F-value for pressure is 21.594 with a corresponding p-value of 0.00037 and the F-value for temperature is 8.469 with a corresponding p-value of 0.0085. From these values, we understand that both pressure and temperature are significant. The interaction of pressure and temperature is not significant (because of its higher p-value.)

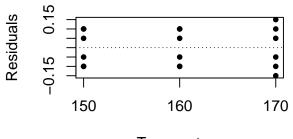
(b) Prepare appropriate residual plots and comment on the model's adequacy.

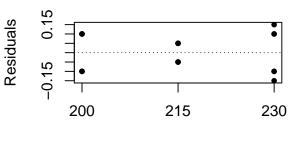
```
par(mfrow = c(2, 2))
plot(yield.aov)
```



Residuals vs. Temperature

Residuals vs. Pressure



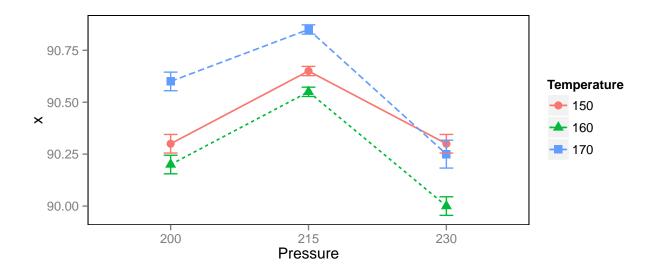


Temperature

Pressure

By observing the residual plots, no significant deviations from the observations are noticed.

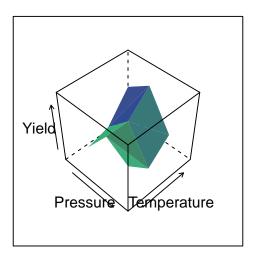
(c) Under what conditions would you operate this process?



```
theme_set(opar)

#### Response Surface Plot
library(lattice)
```

```
wireframe(Yield \tilde{} Pressure * Temperature, data = yield, screen = list(z = -45, x = -45), colorkey = FALSE, shade = TRUE, light.source = c(0, 10, 10), zlim = range(seq(90, 91, by = 0.05)))
```

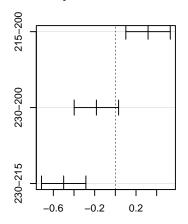


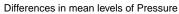
From the interaction plot, it's visible that temperature at 170 and pressure at 215 gives the highest yield.

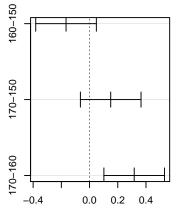
3 Exercise 5.12

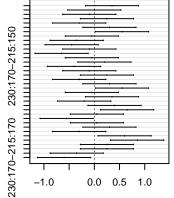
```
TukeyHSD(yield.aov, which = "Pressure", conf.level = 0.95)
##
     Tukey multiple comparisons of means
##
       95% family-wise confidence level
##
## Fit: aov(formula = Yield ~ Pressure * Temperature, data = yield)
##
## $Pressure
##
              diff
                       lwr
                               upr p adj
## 215-200 0.3167 0.1017
                            0.5316 0.0067
## 230-200 -0.1833 -0.3983 0.0316 0.0945
## 230-215 -0.5000 -0.7149 -0.2851 0.0003
par(mfrow = c(1, 3))
plot(TukeyHSD(yield.aov), cex = 0.8)
```

95% family-wise confidence leve 95% family-wise confidence leve 95% family-wise confidence leve









Differences in mean levels of Temperature Differences in mean levels of Pressure:Temperature Differences in mean levels of Differences in mean levels of Differences in mean levels of Differences in mean levels

Three different ranges of pressure are compared. Pressure range of 230 to 200 is insignificant because of its higher p-value (greater than 0.05). The difference in pressure range (230-215) seems more than the other two pressure range.

4 Exercise 5.15

```
setwd("C:/Users/Subasish/Dropbox/A Spring 2014/Dr Novelo/HW")
exp <- read.csv("5.15.csv")</pre>
exp$Row <- as.factor(exp$Row)</pre>
exp$Column <- as.factor(exp$Column)</pre>
exp.aov <- aov(Data ~ Row * Column, data = exp)
anova(exp.aov)
## Warning: ANOVA F-tests on an essentially perfect fit are unreliable
## Analysis of Variance Table
##
## Response: Data
             Df Sum Sq Mean Sq F value Pr(>F)
##
## Row
              2
                 581
                         290.3
## Column
              3
                    29
                          9.6
## Row:Column 6
                    29
                           4.8
## Residuals 0
                    0
## As F-values can't be determined in this test, we condider anova without
## any interaction.
exp.aov_noint <- aov(Data ~ Row + Column, data = exp)</pre>
anova(exp.aov_noint)
## Analysis of Variance Table
##
## Response: Data
##
            Df Sum Sq Mean Sq F value Pr(>F)
            2 581 290.3 60.40 0.00011 ***
## Row
## Column
            3
                  29
                         9.6
                                 2.01 0.21472
## Residuals 6
                   29
                          4.8
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

By considering interaction, the F-value and p-values are not generated. When we consider there's no interaction, the p-values for row is very low (less than 0.05) which indicates significance.

```
library(asbio)

## Warning: package 'asbio' was built under R version 3.0.3

## Loading required package: tcltk

setwd("C:/Users/Subasish/Dropbox/A Spring 2014/Dr Novelo/HW")
exp <- read.csv("5.15.csv")
tukey.add.test(exp$Data, exp$Row, exp$Column)

##

## Tukey's one df test for additivity
## F = 0.6999 Denom df = 5 p-value = 0.441

### From the test
F_nonadd = 0.6999
df_nonadd = 1
ss_nonadd = 3.54</pre>
```

```
ms_nonadd = ss_nonadd/df_nonadd
ss_err = 28.83 - ss_nonadd
df_err = 6 - df_nonadd
ms_err = ss_err/df_err
F_{row} = 580.5
F_{col} = 28.92
df_row = 2
df_col = 3
p_nonadd = 1 - pf(F_nonadd, df_nonadd, df_err)
p_row = 1 - pf(F_row, df_col, df_err)
p_col = 1 - pf(F_col, df_col, df_err)
rbind(p_row, p_col, p_nonadd)
                 [,1]
##
## p_row
         8.925e-07
## p_col 1.384e-03
## p_nonadd 4.410e-01
```

The ANOVA Table (including Nonadditivity row):

	SS	DF	MS	F	P
Row	580.25	2	290.125	57.360	8.92E-07
Column	28.92	3	9.64	1.906	1.38E-03
Nonadd	3.54	1	3.54	0.700	4.41E-01
Error	25.29	5	5.058		3
Total	638.25	11			

From Tukey's one df test for additivity, the p-value is high enough (greater than 0.05). So, we can't reject the null hypothesis.

5 Exercise 5.21

```
setwd("C:/Users/Subasish/Dropbox/A Spring 2014/Dr Novelo/HW")
yield2 <- read.csv("5.21a.csv")</pre>
head(yield2, n = 2)
## Pressure Temperature Day Yield
## 1
         250
                    Low 1 86.3
## 2
         250
                    Low 2 86.1
library(easyanova) ## 'easyanova' package is utilized for convenience.
## Loading required package:
## Loading required package: MASS
## Loading required package: nnet
## Loading required package:
                            nlme
r1 = ea2(yield2, design = 2)
```

Standardized residuals

Standardized residuals vs Sequence data

Sequence data

```
r1[[1]]
##
                     df type III SS mean square F value
## factor_1
                      2
                              5.508
                                          2.7539 5.1838 0.036
                      2
## factor_2
                             99.854
                                         49.9272 93.9807 < 0.001
## blocks
                      1
                             13.005
                                         13.0050
                                                   24.48 0.0011
                     4
                              4.452
                                          1.1131
                                                  2.0952 0.1733
## factor_1:factor_2
## Residuals
                              4.250
                                          0.5312
```

From the ANOVA table values, it is easily interpreted that both temperature and pressure have significant effects. The usage of blocks is also significant. The interaction of temperature and pressure is not significant (greater than 0.05) in this experiment.

6 Exercise 5.24

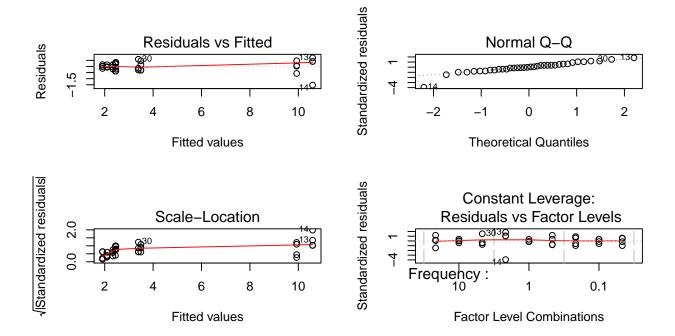
(a) Analyze the data from this experiment. Use $\alpha = 0.05$

```
setwd("C:/Users/Subasish/Dropbox/A Spring 2014/Dr Novelo/HW")
environ <- read.csv("5.24.csv")</pre>
environ$Frequency <- as.factor(environ$Frequency)</pre>
environ.aov <- aov(Crack.Growth ~ Frequency * Environment, data = environ)
summary(environ.aov)
##
                         Df Sum Sq Mean Sq F value Pr(>F)
                          2 209.9 104.9
## Frequency
                                               522 < 2e-16 ***
                          2
## Environment
                              64.3
                                     32.1
                                               160 1.1e-15 ***
## Frequency: Environment 4
                            102.0
                                      25.5
                                               127 < 2e-16 ***
## Residuals
                         27
                               5.4
                                       0.2
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

Both frequency and environment as well as the interaction between them are significant because of their low p-values (less than 0.05).

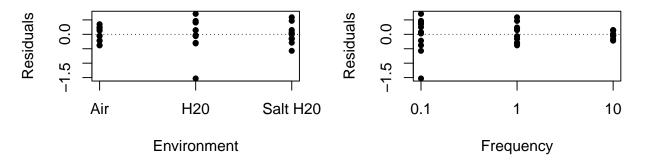
(b) Analyze the residuals.

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



Residuals vs. Environment

Residuals vs. Frequency

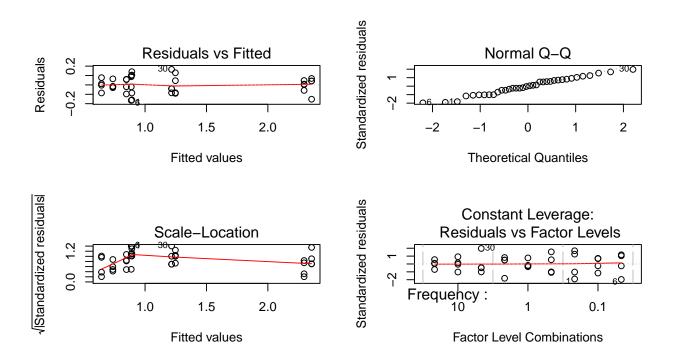


The inequality of variance seems problematic from the observation of the residuals plots. This is visible on the plots of residuals versus predicted response and the plots of residuals versus frequency.

(c) Repeat the analyses from parts (a) and (b) using ln(y) as the response. Comment on the results.

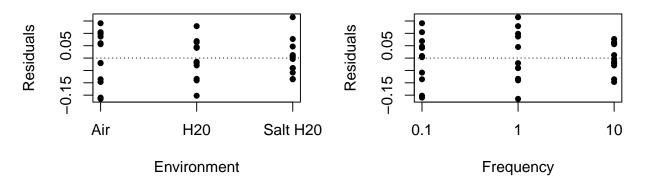
```
environ1.aov <- aov(log(Crack.Growth) ~ Frequency * Environment, data = environ)</pre>
summary(environ1.aov)
##
                          Df Sum Sq Mean Sq F value Pr(>F)
                                               404.1 < 2e-16 ***
## Frequency
                           2
                               7.57
                                        3.79
## Environment
                           2
                               2.36
                                        1.18
                                               125.8 2.1e-14 ***
## Frequency: Environment
                           4
                               3.53
                                        0.88
                                                 94.2 1.9e-15 ***
## Residuals
                               0.25
                          27
                                        0.01
##
## Signif. codes:
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
par(mfrow = c(2, 2))
plot(environ1.aov)
```



Residuals vs. Environment

Residuals vs. Frequency



From the transformed data, both frequency and environment as well as their interaction are significant. The residual plots on the transformed data seems better than the original data.

7 Exercise 5.26

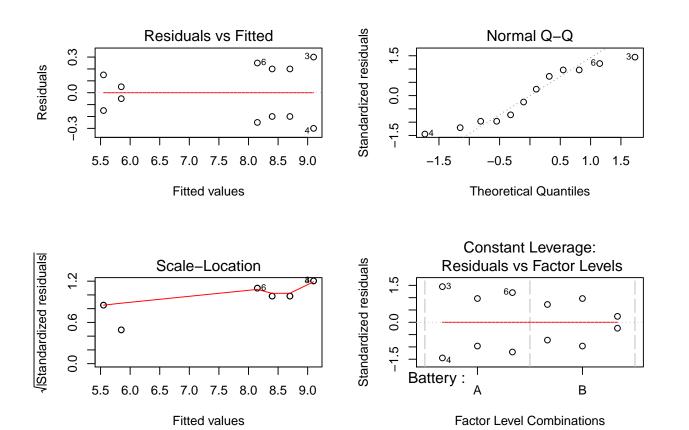
(a) Analyze the data and draw conclusions. Use $\alpha = 0.05$

```
setwd("C:/Users/Subasish/Dropbox/A Spring 2014/Dr Novelo/HW")
battaries <- read.csv("5.26.csv")</pre>
battaries.aov <- aov(Life.Hours ~ Battery * Device, data = battaries)</pre>
summary(battaries.aov)
##
                   Df Sum Sq Mean Sq F value
                                               Pr(>F)
## Battery
                        0.80
                                 0.80
                                         9.33
                                                 0.022 *
## Device
                    2
                       22.45
                                11.22
                                       130.75 1.1e-05 ***
## Battery:Device
                    2
                        0.08
                                 0.04
                                         0.48
                                                 0.643
                                 0.09
## Residuals
                        0.52
## ---
                    0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
```

From the p-values, we can say that both the battery and device are significant (p-values are less than 0.05), but the interaction between them is not significant (p value is greater than 0.05).

(b) Investigate model adequacy by plotting the residuals.

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

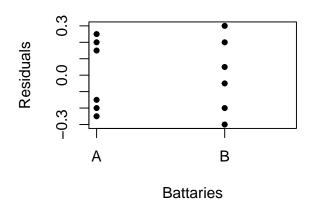


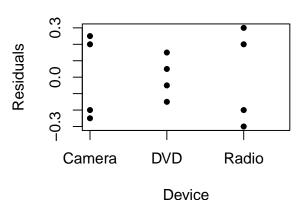
```
par(mfrow = c(1, 2))
stripchart(residuals(battaries.aov) ~ battaries$Battery, method = "stack", vertical = TRUE,
    jitter = 0, xlab = "Battaries", ylab = "Residuals", cex = 1.1, pch = 20,
    main = "Residuals vs. Battaries")

stripchart(residuals(battaries.aov) ~ battaries$Device, method = "stack", vertical = TRUE,
    jitter = 0, xlab = "Device", ylab = "Residuals", cex = 1.1, pch = 20, main = "Residuals vs. Device"
```

Residuals vs. Battaries

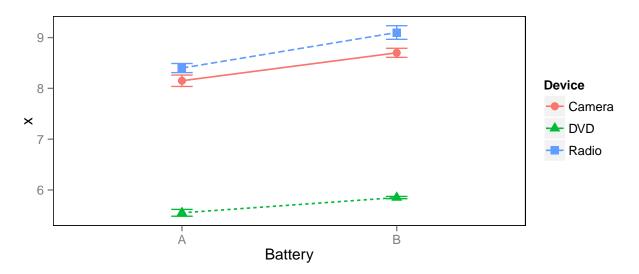
Residuals vs. Device





By observing the residual plots, no significant variation from the assumption is visible.

(c) Which brand of batteries would you recommend?



From the interaction, we can recommend battery brand B.

8 Exercise 5.43

```
## Given
ss_tot = 1000
ss_err = 150
ss_a = 350
ss_b = 300
```

```
ss_ab = 200
df_a = 2
df_err = 18
ms_b = 150
ms_ab = 50
ms_a = ss_a/df_a
df_b = ss_b/ms_b
df_ab = ss_ab/ms_ab
df_tot = df_a + df_b + df_ab + df_err
ms_err = ss_err/df_err
F_a = ms_a/ms_err
F_b = ms_b/ms_err
F_ab = ms_ab/ms_err
p_a = 1 - pf(F_a, df_a, df_err)
p_b = 1 - pf(F_b, df_b, df_err)
p_ab = 1 - pf(F_ab, df_ab, df_err)
rbind(df_b, df_ab, df_tot)
##
         [,1]
## df_b
          2
## df_ab
           4
## df_tot
          26
rbind(ms_a, ms_err)
##
             [,1]
## ms_a 175.000
## ms_err 8.333
rbind(F_a, F_b, F_ab)
## [,1]
## F_a 21
## F_b
       18
        6
## F_ab
rbind(p_a, p_b, p_ab)
##
             [,1]
## p_a 1.968e-05
## p_b 5.081e-05
## p_ab 2.996e-03
## standard deviation of response variable
sd = sqrt(ms_err)
sd
## [1] 2.887
```

The ANOVA Table:

	SS	DF	MS	F	Р
Α	350	2	175	21	1.97E-05
В	300	2	150	18	5.08E-05
AB	200	4	50	6	0.00299
Error	150	18	8.333		
Total	1000	26			

(a) 3

```
(b) 4
(c) 8.333
(d) 175
(e) 3
(f) The p-values for A, B and the interaction are very low (less than 0.05). So, the effect of A, B and interaction are significant.
(g) 2.886
(h) 2
```

9 Exercise 5.44

```
## Given
ss\_tot = 1000
ss_block = 60
ss_a = 350
ss_b = 300
ss_ab = 200
n = 3
ss_err = ss_tot - ss_block - ss_a - ss_b - ss_ab
df_block = n - 1
ms_block = ss_block/df_block
## From 5.43
df_a = 2
ms_a = 175
df_b = 2
ms_b = 150
df_ab = 4
ms_ab = 50
df_tot = 26
df_err = df_tot - df_a - df_b - df_ab - df_block
ms_err = ss_err/df_err
F_a = ms_a/ms_err
F_b = ms_b/ms_err
F_ab = ms_ab/ms_err
F_block = ms_block/ms_err
p_a = 1 - pf(F_a, df_a, df_err)
p_b = 1 - pf(F_b, df_b, df_err)
p_block = 1 - pf(F_block, df_block, df_err)
ss_err
## [1] 90
rbind(df_block, df_err, df_tot)
##
            [,1]
## df_block
              2
## df_err
              16
## df_tot
              26
rbind(ms_block, ms_err)
## ms_block 30.000
## ms_err
            5.625
F_block
```

The ANOVA Table:

	SS	DF	MS	F	P
Blocks	60	2	30	5.333	1.68E-02
Α	350	2	175	31.111	3.06E-06
В	300	2	150	26.667	8.04E-06
AB	200	4	50	8.889	
Error	90	16	5.625		
Total	1000	26	() = = = = = = = = = = = = = = = = = =		