Final

Natalie Schmer

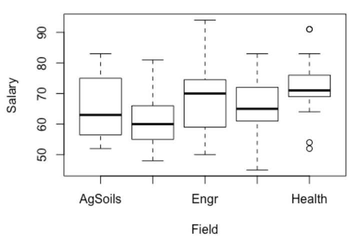
Signature for honor pledge: Natalie Schmer

1. Survey of Graduates

```
library(tidyverse)
graduates <-
read.csv("/Users/natalieschmer/Desktop/GitHub/stats_511/data/career.csv")
```

1A. Summary of plot of Salar by Field

```
boxplot(Salary ~ Field, data= graduates)
```



From this plot, I expect that health, out of all of the fields, health would be the one to be significanly different than the other fields. But, the boxplots all overlap a fair amount so I would not be surprised if there is not a significant difference.

1B. Anova p-value

```
lm_salaries <- lm(Salary ~ Field, data= graduates)
anova(lm_salaries)

## Analysis of Variance Table
##
## Response: Salary
##           Df Sum Sq Mean Sq F value Pr(>F)
## Field      4  788.5  197.14   1.567 0.1943
## Residuals 62 7799.9  125.81
```

Since p > 0.05 at 0.19, we can conclude that variance among salaries are not significantly different between the different fields.

1C. Contrast salary means for two particular fields.

The two fields that seem to have a difference in salaries are health and wildlife ecology.

```r
em_1 <- emmeans::emmeans(lm_salaries, "Field")
emmeans::contrast(em_1, list(
  a = c(0, 1, 0, 0, -1)
))

##  contrast estimate   SE df t.ratio p.value
##  a            -10.7 4.72 62 -2.268  0.0268
```

p < 0.05 at 0.027, and so it is evident that the salaries between health and wildlife ecology are significantly different.

1D. test for salaries by gender

```r
t.test(Salary ~ Gender, data = graduates)

## 
##  Welch Two Sample t-test
## 
## data:  Salary by Gender
## t = 0.57701, df = 47.204, p-value = 0.5667
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -4.281558  7.726003
## sample estimates:
## mean in group F mean in group M 
##        68.22222        66.50000
```

p > 0.05, so we can conclude there is not a significant difference in average salary by gender.

1E Degree by Gender

```r
graduates %>%
          select(Gender, Degree) %>%
          group_by(Gender, Degree) %>%
          summarise(n())

## # A tibble: 4 x 3
## # Groups:   Gender [2]
##   Gender Degree `n()`
##   <fct>  <fct>  <int>
## 1 F      MS         7
## 2 F      PhD       20
## 3 M      MS        30
## 4 M      PhD       10

gender_degree <-matrix(c(7, 30, 20, 10), byrow = TRUE, nrow = 2)
colnames(gender_degree) <-c("Female", "Male")
rownames(gender_degree) <-c("MS", "PhD")

gender_degree
```

```
##     Female Male
## MS       7   30
## PhD     20   10
```

```r
chisq.test(gender_degree)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  gender_degree
## X-squared = 13.777, df = 1, p-value = 0.0002058
```

p is <<< 0.05 at 0.0002, so we can conclude that there is a significant relationship between gender and degree level

1F. Field by Gender

```r
gender_field <- graduates %>%
          select(Gender, Field) %>%
          group_by(Gender, Field) %>%
          summarise(n()) %>%
          pivot_wider(names_from = "Gender",
                      values_from = "n()") %>%
          as.matrix()

gender_field <-matrix(c(4, 3, 3, 7, 6, 13, 5, 13, 9, 4), byrow = TRUE, nrow =
5)
colnames(gender_field) <-c("Female", "Male")
rownames(gender_field) <-c("AgSoil", "Ecol", "Engr", "Envi", "Health")

gender_field
```

```
##        Female Male
## AgSoil      4    3
## Ecol        3    7
## Engr        6   13
## Envi        5   13
## Health      9    4
```

```r
chisq.test(gender_field)
```

```
## Warning in chisq.test(gender_field): Chi-squared approximation may be
incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  gender_field
## X-squared = 7.5628, df = 4, p-value = 0.109
```

```r
chisq.test(gender_field)$expected
```

```
## Warning in chisq.test(gender_field): Chi-squared approximation may be
incorrect

##          Female      Male
## AgSoil 2.820896  4.179104
## Ecol   4.029851  5.970149
## Engr   7.656716 11.343284
## Envi   7.253731 10.746269
## Health 5.238806  7.761194
```

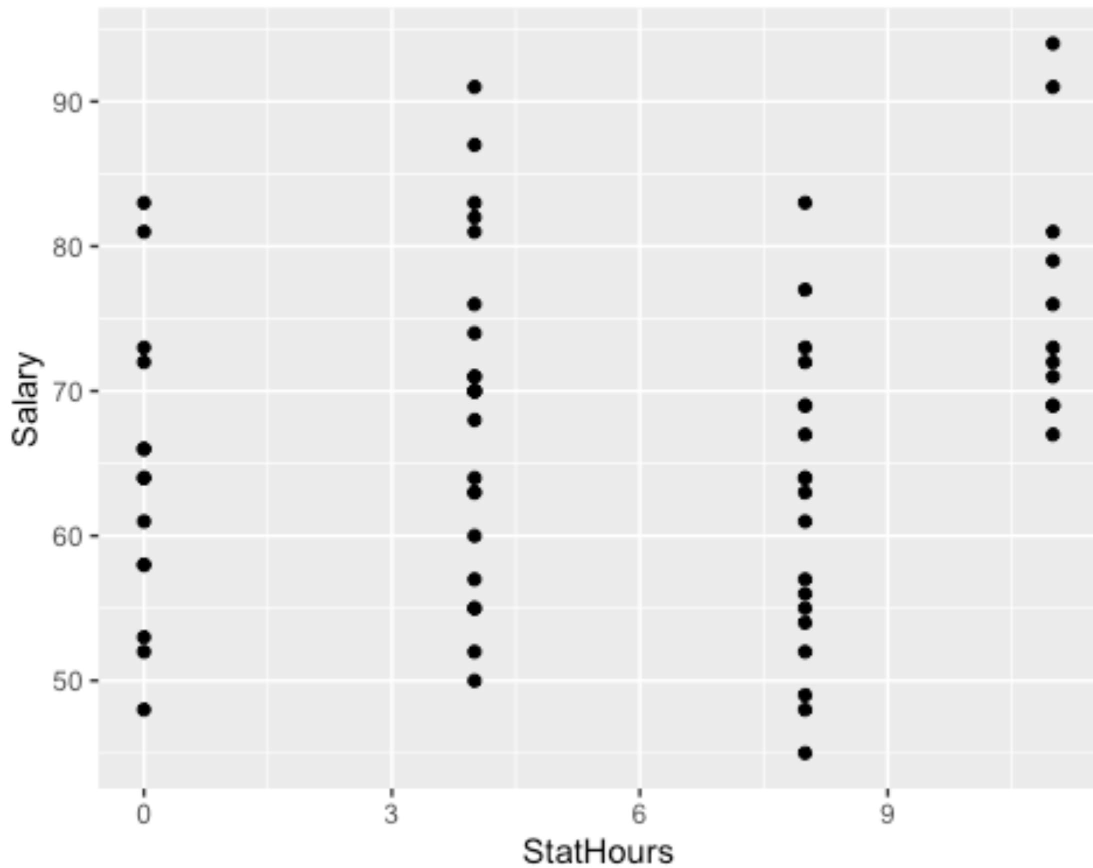
```
fisher.test(gender_field)
```

```
##
##  Fisher's Exact Test for Count Data
##
## data:  gender_field
## p-value = 0.1177
## alternative hypothesis: two.sided
```

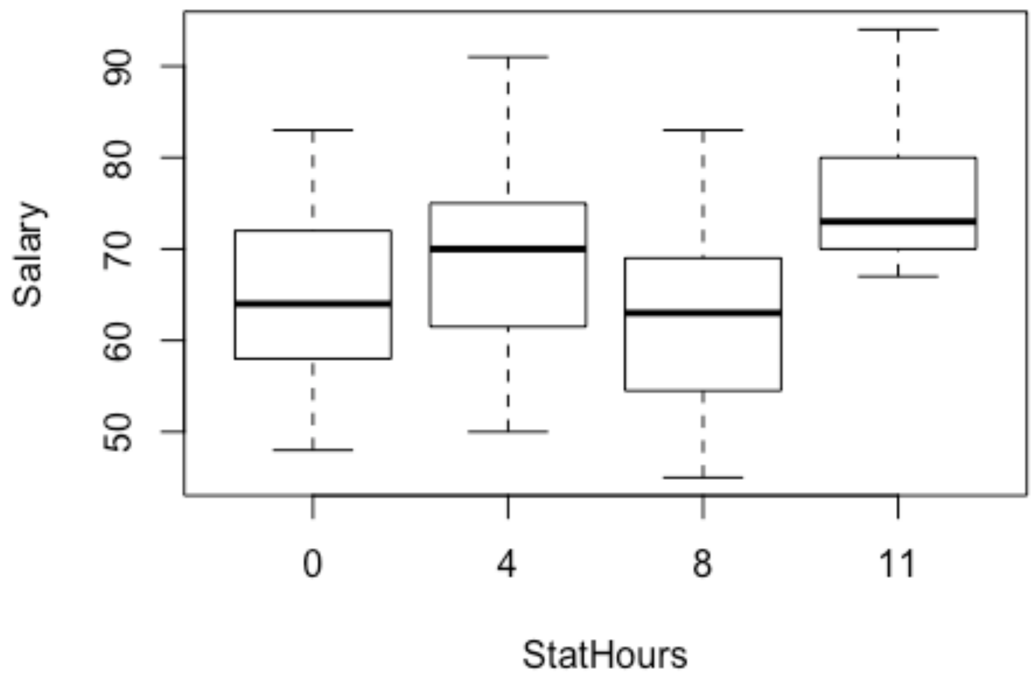
Since the p > 0.05, we conclude that there is not a significant relationship between gender and field.

1G. Statistics coursework with salary…

```
#Visualize
ggplot(data = graduates, aes(x= StatHours, y = Salary))+
  geom_point()
```




```
boxplot(Salary ~ StatHours, data = graduates)
```




```
#anova because categorical
graduates <- graduates %>%
                mutate(StatHours = as_factor(StatHours),
                       StatHours = fct_relevel(StatHours, "0"))

lm_stat_salaries <- lm(Salary ~ StatHours, data = graduates)
summary(lm_stat_salaries)

##
## Call:
## lm(formula = Salary ~ StatHours, data = graduates)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18.8261  -7.2727  -0.2143   7.0000  22.1739
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   64.214      2.803  22.911  < 2e-16 ***
## StatHours4     4.612      3.555   1.297  0.19925
## StatHours8    -2.214      3.694  -0.599  0.55101
## StatHours11   12.331      4.225   2.918  0.00487 **
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.49 on 63 degrees of freedom
## Multiple R-squared:  0.1933, Adjusted R-squared:  0.1549
## F-statistic: 5.032 on 3 and 63 DF,  p-value: 0.003444
```

```r
anova(lm_stat_salaries)
```

```
## Analysis of Variance Table
##
## Response: Salary
##           Df Sum Sq Mean Sq F value   Pr(>F)
## StatHours  3 1660.1  553.36  5.0317 0.003444 **
## Residuals 63 6928.4  109.97
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

I chose to do an anova for this question because upon visualizing the data, the predictor of stat hours seem to be a categoriacal variable rather than continuous, and an anova is more appropriate for categorical predictor data with continuous response, and salary is a continuous response.

1H. What's up with this gender as only predictor for salary from question 1D?

Question D did not take into account the degree, which is important to consider because degree is a major infulence on salary. Additionally, each field pays differently which was not accounted for, and this also matters with degree because the salary for a given dgree in a given field may not be the same for that same degree in another field. This question could have had some sort of interaction or been a multiple regression for predicting salary while taking all variables into account.

2. Jaundice

2A comparing proportions before and after.

```r
{
#2011
totalbirths_2011 <- 1098
jaundice_2011 <- 192

#2013
totalbirths_2013 <- 1303
jaundice_2013 <- 88
}

#2011 proportion
jaundice_2011/totalbirths_2011
```

```
## [1] 0.1748634
```

```r
#2013 proportion
jaundice_2013/totalbirths_2013
```

```
## [1] 0.06753645
```

```r
#2: Test
prop.test(c(192, 88), c(1098, 1303), correct = T)
```

```
##
##  2-sample test for equality of proportions with continuity correction
##
## data:  c(192, 88) out of c(1098, 1303)
## X-squared = 65.59, df = 1, p-value = 5.551e-16
## alternative hypothesis: two.sided
## 95 percent confidence interval:
##  0.08021121 0.13444265
## sample estimates:
##     prop 1     prop 2
## 0.17486339 0.06753645
```

SInce p < 0.05, there is a significant difference in the proportions of cases with jaundice between 2011 and 2013.

2B. 2011 Data only

```r
births2011 <- matrix(c(101, 228,
                       50, 455,
                       41, 223),
                     byrow = T, nrow = 3)
colnames(births2011) <- c("Jaundice", "Not Jaundice")
rownames(births2011) <- c("Exclusive Breast Milk", "Mixed Feeding",
"Exclusive Formula")

births2011
```

```
##                       Jaundice Not Jaundice
## Exclusive Breast Milk      101          228
## Mixed Feeding               50          455
## Exclusive Formula           41          223
```

```r
chisq.test(births2011)
```

```
##
##  Pearson's Chi-squared test
##
## data:  births2011
## X-squared = 60.645, df = 2, p-value = 6.778e-14
```

```r
chisq.test(births2011)$expected
```

```
##                       Jaundice Not Jaundice
## Exclusive Breast Milk 57.53005     271.4699
```

```
## Mixed Feeding          88.30601     416.6940
## Exclusive Formula      46.16393     217.8361
```

####1. *Since p <<< 0.05, there is a significant association between feeding type and jaundice before the program was out in place.*

####2. *Based from the expected vs actual counts, it appears that the exclusive breastmilk feeding deviates the most from all the types of feeding.*

2C. Both before and after BF.

```
before_after <- matrix(c(150, 1104,
                         69, 618,
                         61, 399),
                       byrow = T, nrow = 3)
colnames(before_after) <- c("Jaundice", "Not Jaundice")
rownames(before_after) <- c("Exclusive Breast Milk", "Mixed Feeding",
"Exclusive Formula")

before_after

##                       Jaundice Not Jaundice
## Exclusive Breast Milk      150         1104
## Mixed Feeding               69          618
## Exclusive Formula           61          399

#Odds ratio
{
ebm <- 150/1104
mf <- 69/618
ef <- 61/399
}

epitools::oddsratio(before_after, method = "wald")$p.value

##                          NA
## two-sided                 midp.exact fisher.exact chi.square
##   Exclusive Breast Milk          NA           NA         NA
##   Mixed Feeding           0.2014258    0.2299437  0.2015282
##   Exclusive Formula       0.4669866    0.4567056  0.4682137
```

Since p-values > 0.05, and 1 is included in the confidence intervals, we conclude that there is not a relationship between the bf program and jaundice.

####2. *The results may not be consistant between the A, B, and C with the proportion test, chi-square test, and odds ratio becaue of things like table size and the number of comparisons, in that proportions can only compare 2 proportions but chi square tests and odds ratios can have more than 2 groups. Additionally, differences in sample sizes could play a role. This was seen with the Bird example, where sample sizes made it so the chi square test was not appropriate and gave a different p-value. For this example, two other variables that might help in this explaination include how long the mothers and children were allowed to spend* *together per day since 24 hours per day is ideal, and if pacifiers were used, since it is advised that they are not used.*

3. Bike data

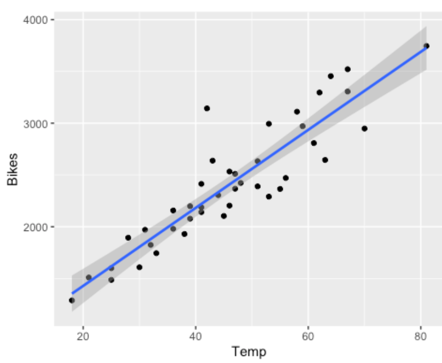
```r
bikedata <-
read.csv("/Users/natalieschmer/Desktop/GitHub/stats_511/data/bikes.csv")
head(bikedata)
```

```
##   Bikes Temp Precip      Time
## 1  2204   46     no   morning
## 2  1971   31     no afternoon
## 3  3521   67     no afternoon
## 4  2188   41    yes   morning
## 5  1600   25    yes afternoon
## 6  2948   70     no afternoon
```

3A. plot orginal data

```r
ggplot(bikedata, aes(x = Temp, y = Bikes))+
  geom_point()+
  geom_smooth(method = "lm")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



3B. Comments on diagnostics for original data

Concerns: There are many points on the residuals vs fitted plot that fall far from 0, and there are some points that are not falling along the 1:1 line (mostly on the extremes, bottom left and upper right) on the Q-Q plot, so this data may not be normal.

3C. Log Transform diagnostics comments (compared to orginal)

Log-transforming the Bikes variable did not help the model in this case. The residuals were even farther from 0 and points were more so off of the 1:1 Q-Q plot line.

3D. Large residual values (raw, standardized, and rstudent values)

```r
#ID outlier, row 31
#temp 42, 3143 bikes
```

```r
#outlier test, Rstudent residual
car::outlierTest(lm_3a)

##    rstudent unadjusted p-value Bonferroni p
## 31 4.244234         0.00013104    0.0055038

rstudent(lm_3a)[31]

##       31
## 4.244234

#Rstudentized residual
rstandard(lm_3a)[31]

##       31
## 3.555007

#Raw residual
resid(lm_3a)[31]

##       31
## 885.1651

lm_3a$residuals[31]

##       31
## 885.1651
```

The outlier here is row 31, with a temperature of 42 f, and 3143 bikes

3E Temp and Bikes relationship observations.

```r
summary(lm_3a)

##
## Call:
## lm(formula = Bikes ~ Temp, data = bikedata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -403.74 -171.76  -30.17  124.98  885.17
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   676.02     132.86   5.088 8.94e-06 ***
## Temp           37.66       2.76  13.645  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 252.3 on 40 degrees of freedom
## Multiple R-squared:  0.8232, Adjusted R-squared:  0.8187
## F-statistic: 186.2 on 1 and 40 DF,  p-value: < 2.2e-16
```

Based on the model, it does appear that there is a clear and significant positive correlation between temperature and number of bikes on campus, in that more students bike to campus when it is warmer outside. The relationship is pretty strong, signified an R-squared of 0.82.