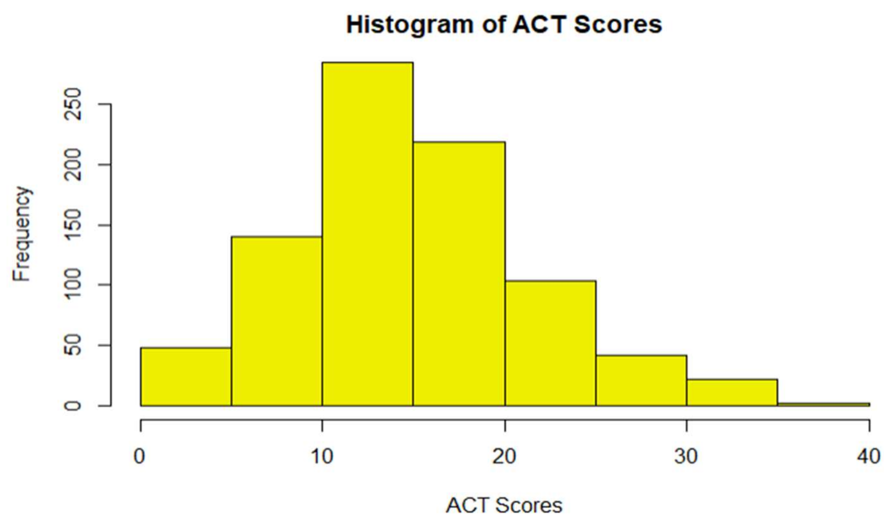
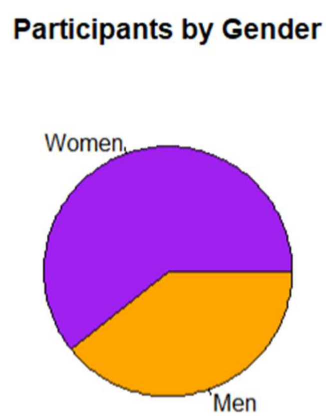
Thomas Gierach
STAT 481
Project 2

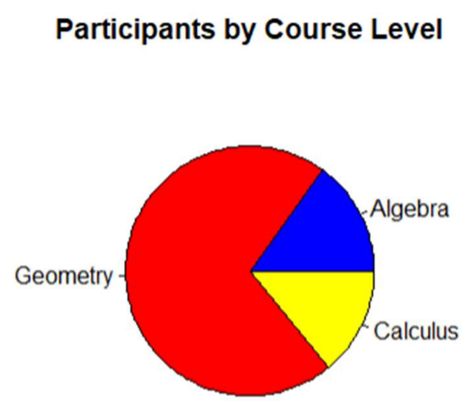
ACT Scores Based on Gender and Math Course Level

Year after year, high school juniors take the ACT test in a competition to get into the best colleges. Does mathematics course level play a significant role in predicting ACT scores? What about gender? Are there any interactions between gender and mathematics course level affecting ACT scores? Data was taken from 2019 ACT scores in Illinois from 861 students. Approximately sixty percent of students were women and forty percent were men. The course levels for mathematics were Algebra (15%), Geometry (70%), and Calculus (15%). Below is the histogram of ACT scores:



One can see the average ACT score is somewhere between 10 and 15 in this group. Indeed, it is 15.33 with a median of 15. The following pie charts and bar plot show the gender make-up and mathematics course level make-up.





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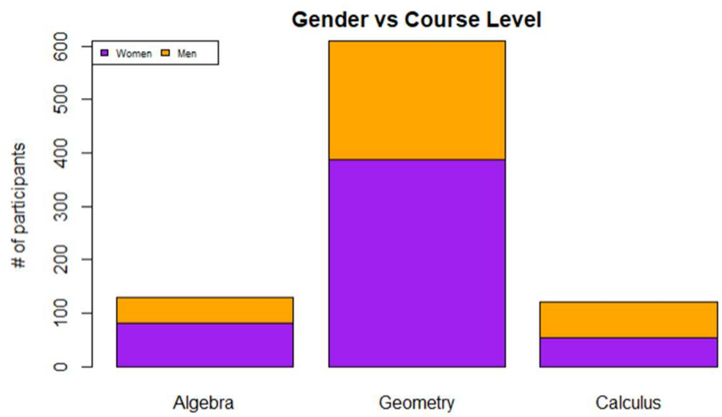
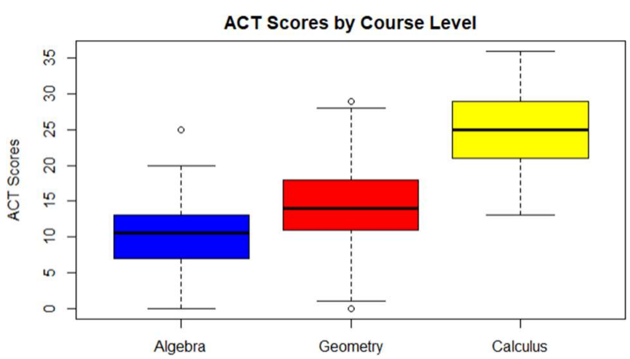
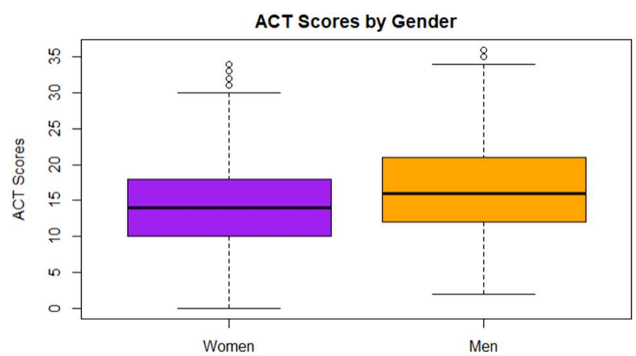


Based on the bar plot, there appears to be more men in Calculus than women, while women outnumber men Geometry and Algebra. So, how do the scores interact by gender and course level taken separately?





It appears there are higher averages and scores as students progress to a higher mathematics level and that men have higher ACT scores than women. Does an ANOVA test confirm this with the model $ACT\ Scores_{ijk} = u_{\blacksquare\blacksquare} + Gender_i + Courses_j + (Gender * Courses)_{ij} + \epsilon_{ijk}$? The model was checked to see if 1) Normality 2) Equal Constancy of Error Variance 3) Homogeneity Test for Equal Variances of Factor Levels.

```
Analysis of Variance Table

Response: score
                Df  Sum Sq Mean Sq  F value    Pr(>F)    
gender           1  1430.5  1430.5  58.5855 5.253e-14 ***
courses          2 14704.7  7352.3 301.1119 < 2.2e-16 ***
gender:courses   2    37.6    18.8   0.7709    0.4629    
Residuals      855 20876.8    24.4                       
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The interaction term does not appear to be significant since the p-value = 0.4629. Therefore, the model is additive. The individual factors of gender and courses both have p-values < 0.05 and are significant. Further evidence that the model is additive is the interaction plot. You can notice how the lines are parallel in the interaction plot showing the model’s additivity.

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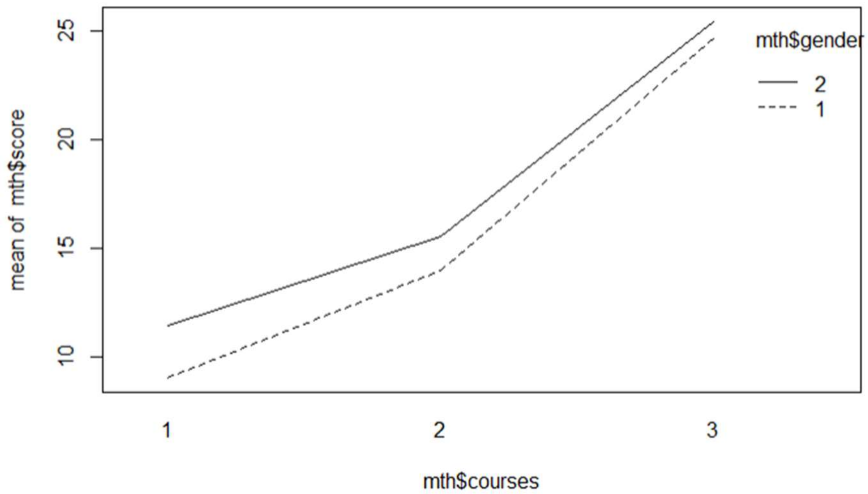

What this all means is that both factors are significant. There are indeed differences in ACT Scores between men and women and students who have completed as their highest mathematics courses Algebra, Geometry, and Calculus.

R-Code

```
library(MASS)
mth <- read.csv("MathTest.csv")
str(mth)
summary(mth)
mth$gender <- as.factor(mth$gender)
mth$courses <- as.factor(mth$courses)

#Histogram of Scores
hist(mth$score, col = "yellow2", main = "Histogram of ACT Scores", xlab = "ACT Scores")

require(graphics)
#Pie Charts
y<- c("blue","red","yellow")
z <- c("purple","orange")
labels1 <- c("Algebra", "Geometry", "Calculus")
labels2 <- c("Women", "Men")
par(mfrow=c(1,2))
pie(table(mth$gender),col=z, main = "Participants by Gender", labels = labels2)
pie(table(mth$courses),col=y, main = "Participants by Course Level", labels = labels1)

#Box Plots
```

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```
plot(mth$score~mth$gender, col = z, main = "ACT Scores by Gender", names = labels2, xlab = "", ylab =
"ACT Scores")
plot(mth$score~mth$courses, col = y, main = "ACT Scores by Course Level", names= labels1, xlab = "",
ylab = "ACT Scores")

#Bar Plots
barplot(table(mth$gender,mth$courses),col= z,main = "Gender vs Course Level",xlab =
"Courses",ylab="# of participants", names.arg= labels1)
legend("topleft", labels2, fill  = z, horiz = T, cex = 0.55,)

lmfit <- lm(score ~ gender * courses, mth)
summary(lmfit)
anova(lmfit)

par(mfrow=c(2,2))
# residual plot
plot(lmfit, 1)    # residual vs fitted value
plot(lmfit, 2)    #  QQ-plot
plot(lmfit, 3)    # sqrt(|standardized residual|) vs FItted value
plot(lmfit, 4)    # cook's distance

## Normality Check
par(mfrow=c(1,1))
qqnorm(lmfit$residual)
qqline(lmfit$residual)
shapiro.test(lmfit$residual)

## Equal Variance Check (top left corner)
par(mfrow=c(2,2))
plot(lmfit)

## Linearity Check
# par(mfrow=c(3,3))
# plot(x = mth$score, y = lmfit$residual, col = "red")
# abline(h=0)
# plot(x = mth$gender, y = lmfit$residual, col = "blue")
# abline(h=0)


## VIF Check
library(car)
vif(lmfit)

## Independence Check (Durbin-Watson): Not required since not time-series data
library(MASS)
dwtest(lmfit, alternative = "two.sided")
```

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```
#now set up a new sequence of interaction

interaction.plot(mth$courses, mth$gender, mth$score)

lmfit2 <- lm(score ~ gender + courses, mth)
summary(lmfit2)
anova(lmfit2)

## Normality Check
par(mfrow=c(1,1))
qqnorm(lmfit2$residual)
qqline(lmfit2$residual)
shapiro.test(lmfit2$residual)

## Equal Variance Check (top left corner)
par(mfrow=c(2,2))
plot(lmfit2)

## Linearity Check
# par(mfrow=c(3,3))
# plot(x = mth$gender, y = lmfit$residual, col = "red")
# abline(h=0)
# plot(x = mth$sodium, y = lmfit$residual, col = "blue")
# abline(h=0)

## VIF Check
library(car)
vif(lmfit2)

## Independence Check (Durbin-Watson): Not required since not time-series data
dwtest(lmfit2, alternative = "two.sided")
#now set up a new sequence of interaction

attach(mth)
row.mean <- tapply(score, gender, mean)
col.mean <- tapply(score, courses, mean)
row.mean
col.mean
```