Lab 1, Short Question

Contents


```r
library(tidyverse)
library(ggplot2)
library(stargazer)
if(!"psych"%in%rownames(installed.packages())) {install.packages("psych")}
library("psych")
if(!"car"%in%rownames(installed.packages())) {install.packages("car")}
library(car)
theme_set(theme_bw()) # set the theme (theme_set is built inside ggplot2)
## To do hypothesis testing in ordinal regression model
if(!"ordinal"%in%rownames(installed.packages())) {install.packages("ordinal")}
if(!"stargazer"%in%rownames(installed.packages())) {install.packages("stargazer")}
library(stargazer)
library(ordinal)
## provides  many functions useful for data analysis, high-level graphics, utility operations
library(Hmisc)
## to work with "grid" graphics
library(gridExtra)
## provides function to for Visualization techniques, summary and inference procedures such as
library(vcd)
## for multinomial log-linear models.
library(nnet)
## To use plor()
library(MASS)
## To generate regression results tables and plots
if(!"finalfit"%in%rownames(installed.packages())) {install.packages("finalfit")}
library(finalfit)
theme_set(theme_bw()) # set the theme (theme_set is built inside ggplot2)
```

1 Political ideology (30 points)

These questions are based on Question 14 of Chapter 3 of the textbook "Analysis of Categorical Data with R" by Bilder and Loughin.

> An example from Section 4.2.5 examines data from the 1991 U.S. General Social Survey that cross-classifies people according to
>
> - Political ideology: Very liberal (VL), Slightly liberal (SL),Moderate (M), Slightly conservative (SC), and Very conservative (VC)
> - Political party: Democrat (D) or Republican (R)
> - Gender: Female (F) or Male (M).
>
> Consider political ideology to be a response variable, and political party and gender to be explanatory variables. The data are available in the file pol_ideol_data.csv.

1.1 Recode Data (2 points)

Use the factor() function with the ideology variable to ensure that R places the levels of the ideology variable in the correct order.

```
pol_ideol <- read.csv("~/mids_271/spring_24_central/Labs/w271-labs/pol_ideol_data.csv",
                        header=T,na.strings=c("","NA"))
```

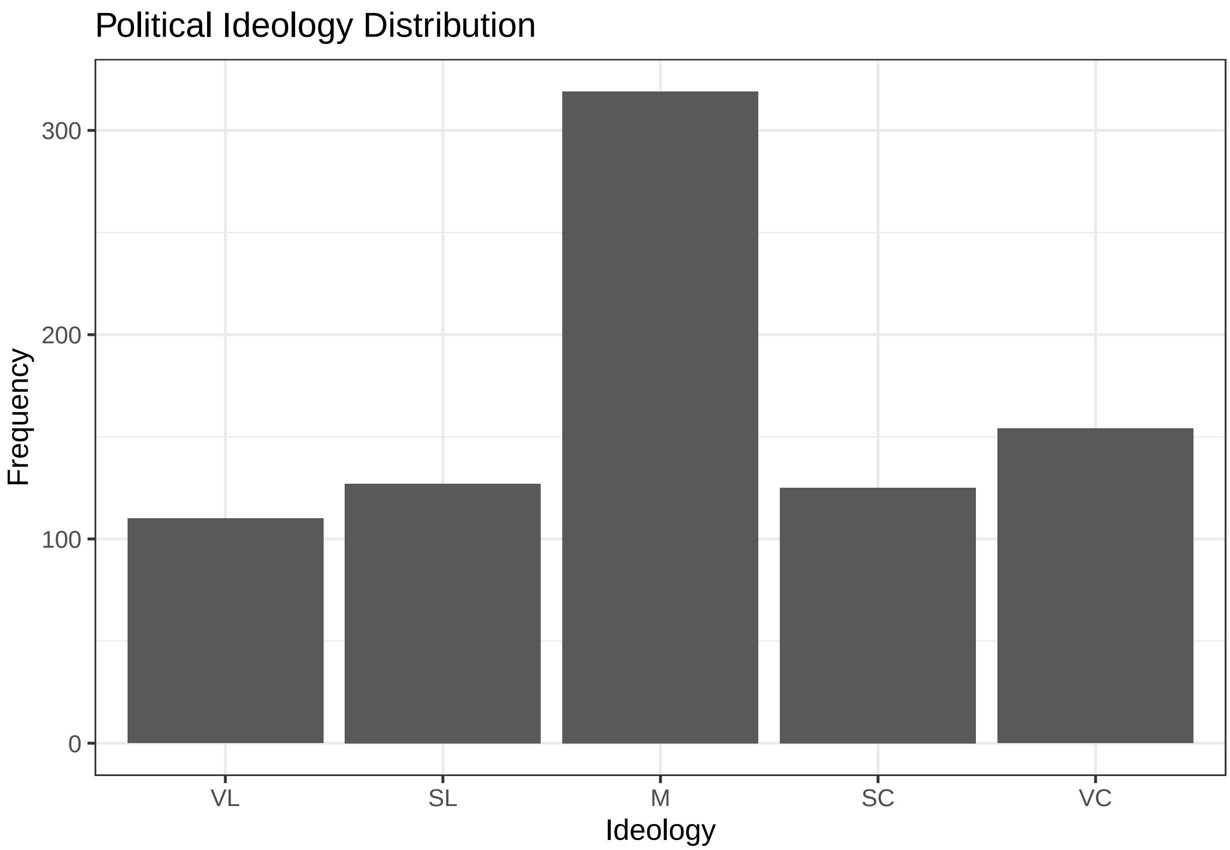
```
pol_ideol$ideol_levels <- factor(pol_ideol$ideol, levels = c("VL", "SL", "M", "SC", "VC"))
pol_ideol$gender <- as.factor(pol_ideol$gender)
pol_ideol$party <- as.factor(pol_ideol$party)

# create new column to identify combos of party and gender
pol_ideol$segment <- ifelse(pol_ideol$gender == 'F' & pol_ideol$party == 'D', "F/D", NA)
pol_ideol$segment <- ifelse(pol_ideol$gender == 'F' & pol_ideol$party == 'R', "F/R", pol_ideol
pol_ideol$segment <- ifelse(pol_ideol$gender == 'M' & pol_ideol$party == 'D', "M/D", pol_ideol
pol_ideol$segment <- ifelse(pol_ideol$gender == 'M' & pol_ideol$party == 'R', "M/R", pol_ideol
# head(pol_ideol)
```

1.2 Test for Independence (5 points)

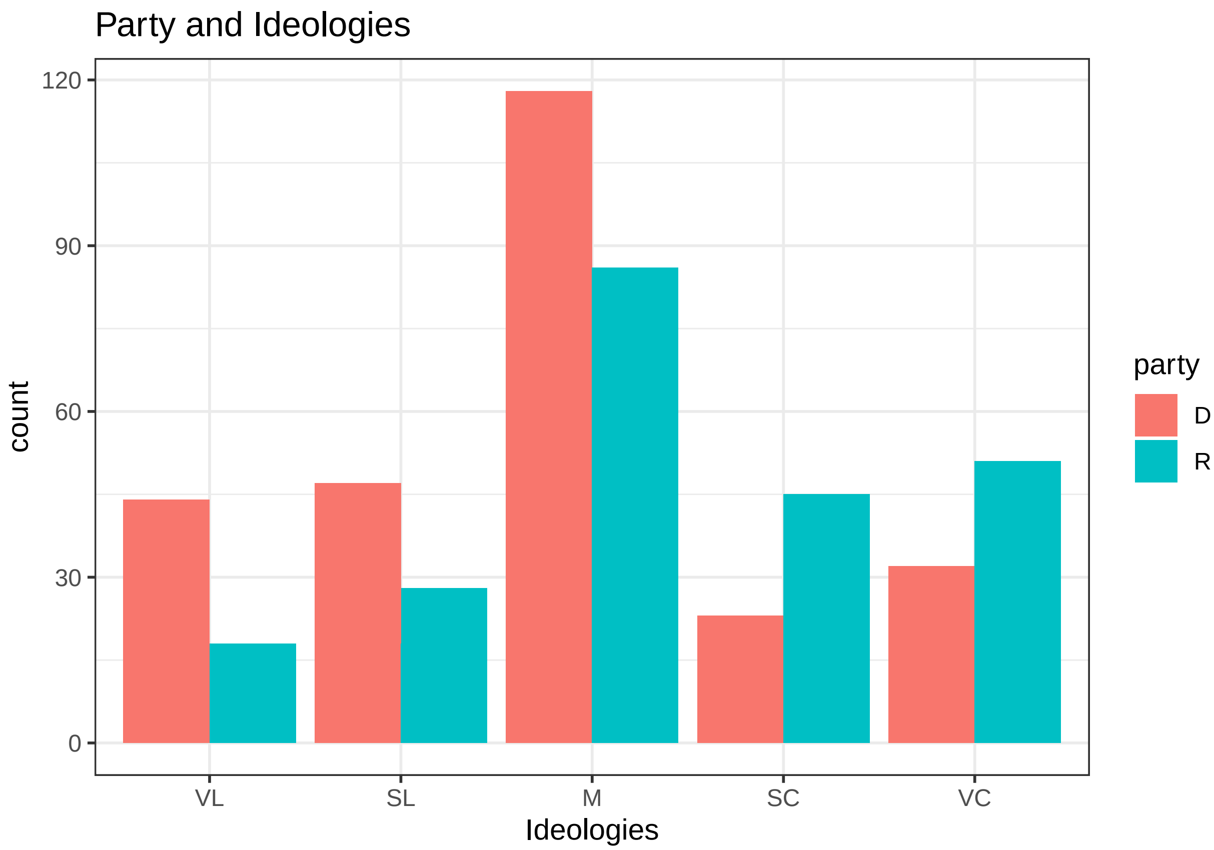
Analyze the relationships between political ideology and political party and gender using basic visualizations. Afterward, generate a contingency table and assess the independence of political ideology from political party and gender.

Comment
The histogram of ideology is presented first by party and then by gender. Both histograms show the largest concentration of voters in the "neutral" political ideology. Democrats are especially likely to be "neutral" as are women. Republicans are more prominent in the "slightly conservative" and "very conservative" categories. Men also are more likely to be in these categories.
The following bar plot suggests the data were collected from an equal number of republicans and democrats, and men and women. Finally, the bar plot "Bar Plot of Ideology Categorically by Gender and Party" also suggests female democrats are more likely to fall in a liberal ideology category while male republicans will be more likely to fall in a conservative ideological category.

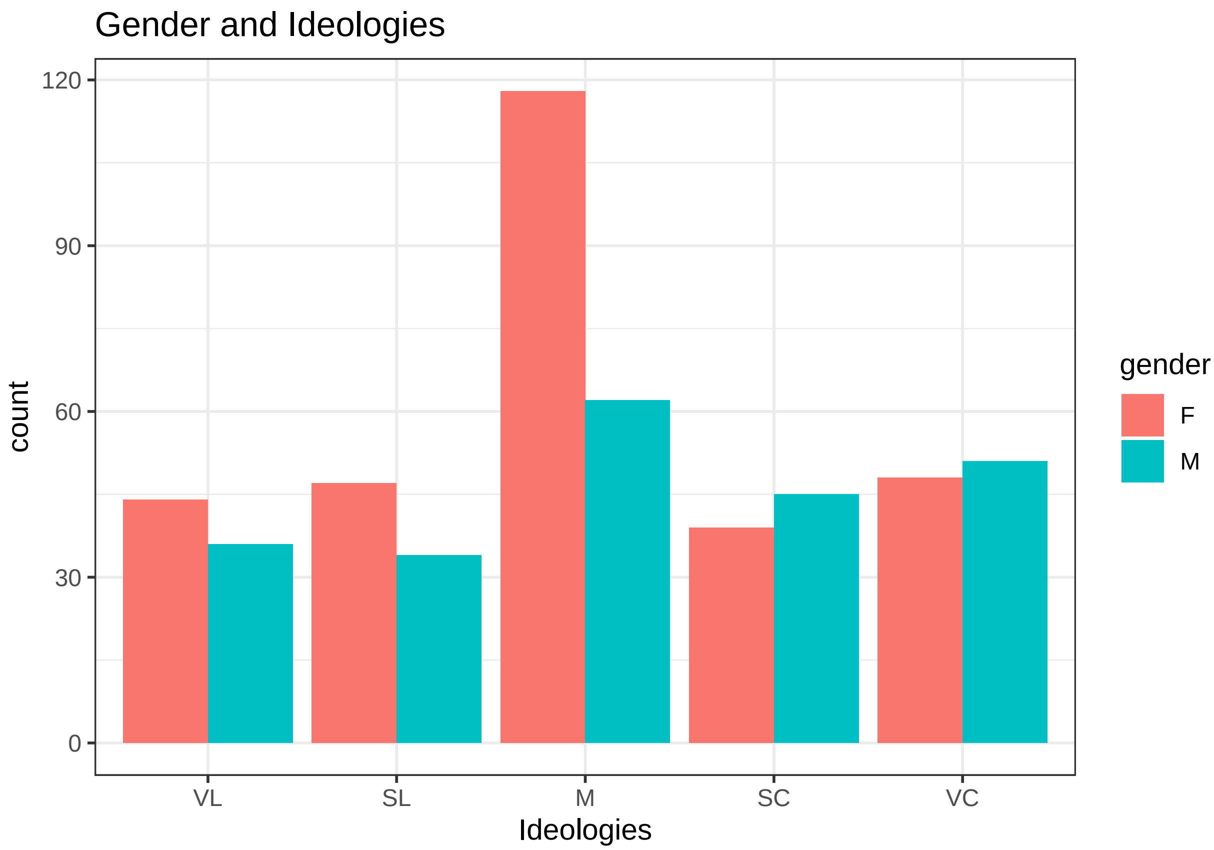
```r
p <- ggplot(data=pol_ideol, aes(x=ideol_levels, y=count))+
  geom_bar(stat='identity') +
  ggtitle("Political Ideology Distribution") +
  xlab("Ideology") + ylab("Frequency")
p
```



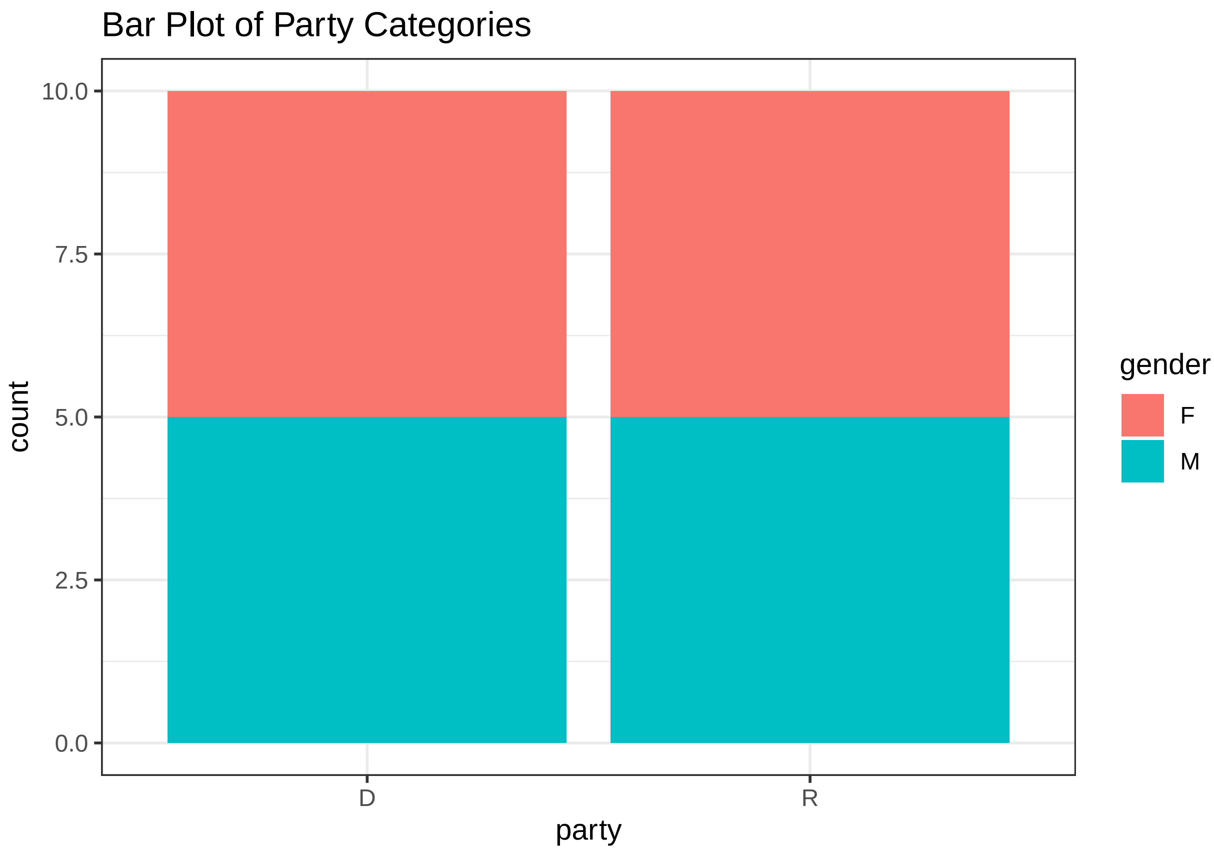

```r
ggplot(pol_ideol, aes(fill=party, y=count, x=ideol_levels)) +
    geom_bar(position="dodge", stat="identity") +
    ggtitle("Party and Ideologies") +
    xlab("Ideologies")
```



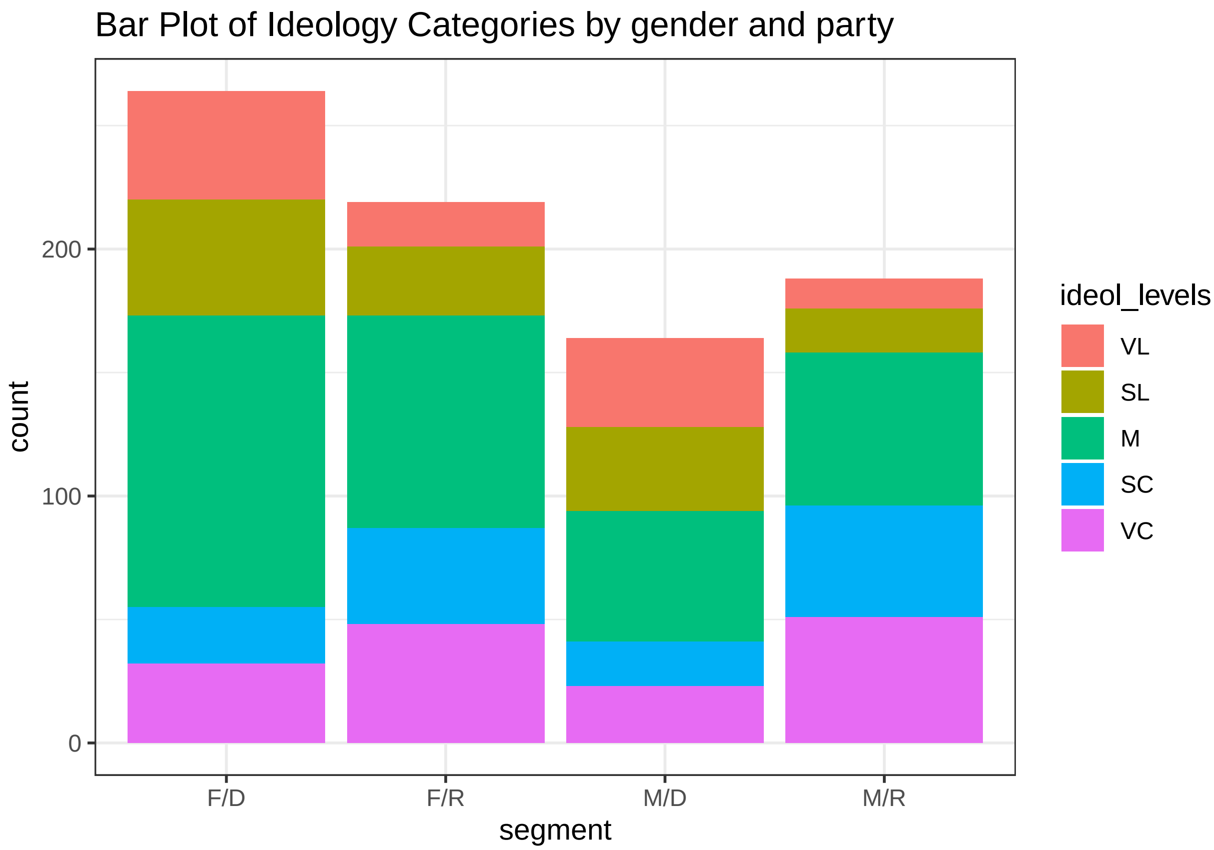

```
ggplot(pol_ideol, aes(fill=gender, y=count, x=ideol_levels)) +
    geom_bar(position="dodge", stat="identity") +
    ggtitle("Gender and Ideologies") +
    xlab("Ideologies")
```




```r
#Plots of party and ideology with gender identified in each bar plot


p2 <- pol_ideol %>%
  ggplot(aes(x=party, fill = gender)) + geom_bar() +  labs(title = "Bar Plot of Party Categori
p2
```




```
# barplot of relative ideology counts for each gender/party category
p1<- pol_ideol %>%
  ggplot(aes(x=segment, y= count, fill = ideol_levels)) + geom_bar(stat = "identity") +  labs(t
p1
```



Comment
The results of the Chi-Square test for independence tests the null hypothesis $H_0 : \pi_{ij} = \pi_i\pi_j$. The alternative hypothesis is $H_a : \pi_{ij} \neq \pi_i\pi_j$. We reject the null hypothesis for the test of independence between gender and ideology ($\chi^2 = 10.73, p < 0.05$). Gender and ideology are not independent according to this test. The chi-square value is 60.905 and p<0.001 for the test of independence between ideology and party. We reject the null. The party and ideology levels are not independent.

```
# independence of political ideology and gender
tab1 <- xtabs(count ~ ideol_levels + gender, data=pol_ideol)
tab1 # contingency table ideol and gender
```

```
##               gender
## ideol_levels    F   M
##           VL   62  48
##           SL   75  52
##           M   204 115
##           SC   62  63
##           VC   80  74
```

```
test1<- chisq.test(tab1, correct=FALSE) ## chi-square test
# test1$stdres
test1
```

```
##
##  Pearson's Chi-squared test
```

```
##
## data:  tab1
## X-squared = 10.732, df = 4, p-value = 0.02975
```

```r
# independence of political ideology and party
tab2 <- xtabs(count ~ ideol_levels + party, data=pol_ideol)
tab2 # contingency table idol an party
```

```
##             party
## ideol_levels   D   R
##           VL  80  30
##           SL  81  46
##           M  171 148
##           SC  41  84
##           VC  55  99
```

```r
test1<- chisq.test(tab2, correct=FALSE) # chi-square test
# test1$stdres
test1
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab2
## X-squared = 60.905, df = 4, p-value = 1.872e-12
```

1.3 Regression analysis (5 points)

Estimate a multinomial regression model and ordinal (proportional odds) regression model that both include party, gender, and their interaction. Perform Likelihood Ratio Tests (LRTs) to test the importance of each explanatory variable.

Also, test whether the proportional odds assumption in the ordinal model is satisfied. Based on this test and other results, which model do you think is more valid?

Comment
We estimate the multinomial logit and ordinal regression models. The AIC for the multinomial logit model is 2491.087. It is 2484.15 for the ordinal model.

Using Anova to test each of the explanatory variables using a χ^2 test. In the multinomial logit model, only one variable, party, is significant–only as an isolated variable and not in the interaction term. In the multinomial logit model, party is positively related to a voter being in any one of the non-neutral categories. Gender does not achieve significance with a p-value of 0.06.

In the ordinal model, both party and gender, and their interaction term is statistically significant ($p<0.001$). For the ordinal model, the p-value for party, gender and its interaction was small, so these variables do have an affect on ideology under this model.

We then use the proportional odds test to determine whether the odds model is appropriate for this task. While the ordinal model performed slightly better than the multinomial by AIC and number of significant coefficients, the hypothesis that the probability of the outcome increases with each level is rejected. The p-value of their significance in explaining the likelihood improvement is does not support the null. The multinomial model is our model of choice for this exercise.

```
# multinomial model
mod.nomial <- multinom(ideol_levels ~ party + gender + party:gender, data=pol_ideol, weights =
```

```
## # weights:  25 (16 variable)
## initial  value 1343.880657
## iter  10 value 1231.244704
## iter  20 value 1229.548447
## final  value 1229.543342
## converged
```

```
summary(mod.nomial)
```

```
## Call:
## multinom(formula = ideol_levels ~ party + gender + party:gender,
##     data = pol_ideol, weights = count, crit = "aicc")
##
## Coefficients:
##    (Intercept)    partyR     genderM partyR:genderM
## SL  0.06598601 0.3758637 -0.12315074      0.0867552
## M   0.98652431 0.5774673 -0.59976058      0.6779778
## SC -0.64869284 1.4219096 -0.04442702      0.5929326
## VC -0.31838463 1.2992041 -0.12968265      0.5957616
##
## Std. Errors:
##    (Intercept)    partyR   genderM partyR:genderM
## SL   0.2097724 0.3677971 0.3181097      0.5756306
## M    0.1766421 0.3136662 0.2790125      0.4944619
## SC   0.2573076 0.3839323 0.3867020      0.5799046
## VC   0.2323285 0.3610630 0.3538841      0.5518725
##
## Residual Deviance: 2459.087
## AIC: 2491.087
```

```
# ordinal model
levels(pol_ideol$ideol_levels)
```

```
## [1] "VL" "SL" "M"  "SC" "VC"
```

```
#mod.ord <- clm(ideol_levels ~ party + gender + party:gender, data=pol_ideol, weights = count,
mod.ord <- polr(ideol_levels ~ party + gender + party:gender, data=pol_ideol, weights = count,
summary(mod.ord)
```

```
##
## Re-fitting to get Hessian
```

```
## Call:
## polr(formula = ideol_levels ~ party + gender + party:gender,
##     data = pol_ideol, weights = count, method = "logistic")
```

```
##
## Coefficients:
##                   Value Std. Error t value
## partyR           0.7562     0.1659  4.5593
## genderM         -0.1431     0.1820 -0.7861
## partyR:genderM  0.5091     0.2550  1.9965
##
## Intercepts:
##       Value    Std. Error t value
## VL|SL  -1.5521   0.1332   -11.6560
## SL|M   -0.5550   0.1157    -4.7965
## M|SC    1.1647   0.1226     9.5009
## SC|VC   2.0012   0.1364    14.6666
##
## Residual Deviance: 2470.15
## AIC: 2484.15
```

```
# anova test on multinomial model
print("Multinomial Logit model chi-sq tests")
```

```
## [1] "Multinomial Logit model chi-sq tests"
```

```
Anova(mod.nomial, test = "LR")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: ideol_levels
##              LR Chisq Df Pr(>Chisq)
## party          60.555  4  2.218e-12 ***
## gender          8.965  4    0.06198 .
## party:gender    3.245  4    0.51763
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# anova test on ordinal model
print("Ordinal model chi-sq tests")
```

```
## [1] "Ordinal model chi-sq tests"
```

```
Anova(mod.ord, test = "Chisq")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: ideol_levels
##              LR Chisq Df Pr(>Chisq)
## party          56.847  1  4.711e-14 ***
## gender          0.843  1    0.35864
## party:gender    3.992  1    0.04571 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# nominal test for proportional odds assumption

mod.ord2 <- clm(ideol_levels ~ party + gender + party:gender, data=pol_ideol, weights = count,

nominal_test(mod.ord2)
```

```
## Tests of nominal effects
##
## formula: ideol_levels ~ party + gender + party:gender
##              Df  logLik    AIC     LRT Pr(>Chi)
## <none>           -1235.1 2484.2
## party          3 -1233.1 2486.3  3.8711   0.2757
## gender         3 -1232.3 2484.6  5.5831   0.1338
## party:gender   9 -1229.5 2491.1 11.0634   0.2714
```

1.4 Estimated probabilities (5 points)

Compute the estimated probabilities for each ideology level given all possible combinations of the party and gender levels.

```
# predict probability of all ideologies for female & democrat
data.f.d <- data.frame(party = 'D', gender = 'F')
pred.f.d <- predict(mod.nomial, newdata = data.f.d, type="probs", se=TRUE)

# predict probability of all ideologies for female & republican
data.f.r <- data.frame(party = 'R', gender = 'F')
pred.f.r <- predict(mod.nomial, newdata = data.f.r, type="probs", se=TRUE)

# predict probability of all ideologies for male & democrat
data.m.d <- data.frame(party = 'D', gender = 'M')
pred.m.d <- predict(mod.nomial, newdata = data.m.d, type="probs", se=TRUE)

# predict probability of all ideologies for male & republican
data.m.r <- data.frame(party = 'R', gender = 'M')
pred.m.r <- predict(mod.nomial, newdata = data.m.r, type="probs", se=TRUE)

# predicted probabilities together into table
tab_dat <- rbind(pred.f.d, pred.f.r, pred.m.d, pred.m.r)
colnames(tab_dat) <- c("VL", "SL", "M", "SC", "VC")
rownames(tab_dat) <- c("Female, Democrat", "Female, Republican", "Male, Democrat", "Male, Repul
tab <- as.table(tab_dat)
tab
```

```
##                            VL         SL          M         SC         VC
## Female, Democrat   0.16666222 0.17803054 0.44697087 0.08711911 0.12121726
## Female, Republican 0.08219087 0.12785463 0.39269600 0.17808499 0.21917351
## Male, Democrat     0.21951379 0.20731727 0.32317009 0.10975989 0.14023895
## Male, Republican   0.06383112 0.09574563 0.32978787 0.23935868 0.27127670
```

1.5 Contingency table of estimated counts (5 points)

Construct a contingency table with estimated counts from the model. These estimated counts are found by taking the estimated probability for each ideology level multiplied by their corresponding number of observations for a party and gender combination.

For example, there are 264 observations for gender = "F" and party = "D". Because the multinomial regression model results in $\hat{\pi}_{VL} = 0.1667$, this model's estimated count is $0.1667 \times 264 = 44$.

- Are the estimated counts the same as the observed? Conduct a goodness of fit test for this and explain the results.

Comment The p-values are large which means that there is not enough evidence to reject the null hypothesis and conclude that the distribution of the expected and actual counts are different from each other. The estimated counts are the same as the observed counts.

```
# get observed total counts for 4 cross-categories
fd.sum <- sum(pol_ideol[which(pol_ideol$gender == "F" & pol_ideol$party == 'D'), ]$count)
fr.sum <- sum(pol_ideol[which(pol_ideol$gender == "F" & pol_ideol$party == 'R'), ]$count)
md.sum <- sum(pol_ideol[which(pol_ideol$gender == "M" & pol_ideol$party == 'D'), ]$count)
mr.sum <- sum(pol_ideol[which(pol_ideol$gender == "M" & pol_ideol$party == 'R'), ]$count)

# VL contingency
vl.prob <- unname(tab[, 1])
vl.dat <- matrix(round(c(vl.prob[1]*fd.sum, vl.prob[2]*fr.sum, vl.prob[3]*md.sum, vl.prob[4]*mr
colnames(vl.dat) <- c("F", "M")
rownames(vl.dat) <- c("D", "R")

# SL contingency
sl.prob <- unname(tab[, 2])
sl.dat <- matrix(round(c(sl.prob[1]*fd.sum, sl.prob[2]*fr.sum, sl.prob[3]*md.sum, sl.prob[4]*mr
colnames(sl.dat) <- c("F", "M")
rownames(sl.dat) <- c("D", "R")

# M contingency
m.prob <- unname(tab[, 3])
m.dat <- matrix(round(c(m.prob[1]*fd.sum, m.prob[2]*fr.sum, m.prob[3]*md.sum, m.prob[4]*mr.sum
colnames(m.dat) <- c("F", "M")
rownames(m.dat) <- c("D", "R")

# SC contingency
sc.prob <- unname(tab[, 4])
sc.dat <- matrix(round(c(sc.prob[1]*fd.sum, sc.prob[2]*fr.sum, sc.prob[3]*md.sum, sc.prob[4]*mr
colnames(sc.dat) <- c("F", "M")
rownames(sc.dat) <- c("D", "R")

# VC contingency
vc.prob <- unname(tab[, 5])
vc.dat <- matrix(round(c(vc.prob[1]*fd.sum, vc.prob[2]*fr.sum, vc.prob[3]*md.sum, vc.prob[4]*mr
```

```r
colnames(vc.dat) <- c("F", "M")
rownames(vc.dat) <- c("D", "R")

# print all contingency tables
print("VL contingency table")
```

```
## [1] "VL contingency table"
```

```r
vl.dat
```

```
##    F  M
## D 44 36
## R 18 12
```

```r
print("SL contingency table")
```

```
## [1] "SL contingency table"
```

```r
sl.dat
```

```
##    F  M
## D 47 34
## R 28 18
```

```r
print("M contingency table")
```

```
## [1] "M contingency table"
```

```r
m.dat
```

```
##     F  M
## D 118 53
## R  86 62
```

```r
print("SC contingency table")
```

```
## [1] "SC contingency table"
```

```r
sc.dat
```

```
##    F  M
## D 23 18
## R 39 45
```

```r
print("VC contingency table")
```

```
## [1] "VC contingency table"
```

```r
vc.dat
```

```
##    F  M
## D 32 23
## R 48 51
```

```r
# GoF test VL observed with expected
vl.actual <- matrix(pol_ideol[which(pol_ideol$ideol_levels == 'VL'), ]$count, nrow=2, ncol=2)
```

```r
chisq.test(vl.dat, vl.actual)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  vl.dat
## X-squared = 0.065069, df = 1, p-value = 0.7987
```

```r
# GoF test SL observed with expected
sl.actual <- matrix(pol_ideol[which(pol_ideol$ideol_levels == 'SL'), ]$count, nrow=2, ncol=2)
chisq.test(sl.dat, sl.actual)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  sl.dat
## X-squared = 0.015786, df = 1, p-value = 0.9
```

```r
# GoF test M observed with expected
m.actual <- matrix(pol_ideol[which(pol_ideol$ideol_levels == 'M'), ]$count, nrow=2, ncol=2)
chisq.test(m.dat, m.actual)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  m.dat
## X-squared = 3.6279, df = 1, p-value = 0.05682
```

```r
# GoF test SC observed with expected
sc.actual <- matrix(pol_ideol[which(pol_ideol$ideol_levels == 'SC'), ]$count, nrow=2, ncol=2)
chisq.test(sc.dat, sc.actual)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  sc.dat
## X-squared = 0.67991, df = 1, p-value = 0.4096
```

```r
# GoF test VC observed with expected
vc.actual <- matrix(pol_ideol[which(pol_ideol$ideol_levels == 'VC'), ]$count, nrow=2, ncol=2)
chisq.test(vc.dat, vc.actual)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  vc.dat
## X-squared = 0.97175, df = 1, p-value = 0.3242
```

1.6 Odds ratios and confidence intervals (8 points)

To better understand relationships between the explanatory variables and the response, compute odds ratios and their confidence intervals from the estimated models and interpret them.

Comment: The odds ratios for a given variable, depend on the category of comparison (e.g., VL, SL, N, SC, or VL). In the multinomial logit model, the left-out gender category was female and the left-out party category was democrat. The comparison level for ideology was 'Neutral.' We compare the odds of the different coefficients for the coefficients from each VL, SL, SC, and VL level. Assuming the model specification $\log(\pi_j/\pi_1) = \beta_{j0} + \beta_{jGender}x_{Gender} + \beta_{jParty} + \beta_{jGender*Party}$ where j = SC, SL, VC, VL.

The Odds Ratio for male versus female for the each jth level is equal to $\frac{exp(\beta_{j0}+\beta_{j1}*(gender+c)+\beta_{j3}*party*(gender+c))}{exp(\beta_{j0}+\beta_{j1}*gender+\beta_{j3}*party*gender)} = exp(\beta_{j1} * c + \beta_{j3} * party * c)$ where c = 1 for a categorical variable. Further, gender will be equal to one as it is also a categorical variable.

The Odds Ratio for republican versus democrat for each jth level is equal to $\frac{exp(\beta_{j0}+\beta_{j2}*(party+c)+\beta_{j3}*gender*(party+c))}{exp(\beta_{j0}+\beta_{j2}*party+\beta_{j3}*gender*party)} = exp(\beta_{j2} * c + \beta_{j3} * gender * c)$ where c = 1.

```
## # weights:  25 (16 variable)
## initial  value 1343.880657
## iter  10 value 1230.618951
## iter  20 value 1229.545101
## final  value 1229.543342
## converged
```

```
## Call:
## multinom(formula = ideol ~ gender + party + party:gender, data = pol_ideol,
##     weights = count)
##
## Coefficients:
##    (Intercept)   genderM     partyR genderM:partyR
## SC  -1.6351796 0.5552530  0.8443896    -0.08493261
## SL  -0.9205509 0.4766365 -0.2015820    -0.59127885
## VC  -1.3049495 0.4701437  0.7218048    -0.08231277
## VL  -0.9864951 0.5997181 -0.5774785    -0.67796167
##
## Std. Errors:
##    (Intercept)   genderM    partyR genderM:partyR
## SC   0.2279304 0.3554943 0.2986994      0.4494401
## SL   0.1724860 0.2793397 0.2776568      0.4439118
## VC   0.1993102 0.3194857 0.2686741      0.4126370
## VL   0.1766403 0.2790119 0.3136642      0.4944618
##
## Residual Deviance: 2459.087
## AIC: 2491.087
```

```
## NULL
```

```
## [1] "model summary"

## Call:
## multinom(formula = ideol ~ gender + party + party:gender, data = pol_ideol,
##     weights = count)
##
## Coefficients:
##    (Intercept)   genderM     partyR genderM:partyR
## SC  -1.6351796 0.5552530  0.8443896    -0.08493261
## SL  -0.9205509 0.4766365 -0.2015820    -0.59127885
## VC  -1.3049495 0.4701437  0.7218048    -0.08231277
## VL  -0.9864951 0.5997181 -0.5774785    -0.67796167
##
## Std. Errors:
##    (Intercept)   genderM    partyR genderM:partyR
## SC   0.2279304 0.3554943 0.2986994      0.4494401
## SL   0.1724860 0.2793397 0.2776568      0.4439118
## VC   0.1993102 0.3194857 0.2686741      0.4126370
## VL   0.1766403 0.2790119 0.3136642      0.4944618
##
## Residual Deviance: 2459.087
## AIC: 2491.087

## [1] "beta_hats"

##    (Intercept)   genderM     partyR genderM:partyR
## SC  -1.6351796 0.5552530  0.8443896    -0.08493261
## SL  -0.9205509 0.4766365 -0.2015820    -0.59127885
## VC  -1.3049495 0.4701437  0.7218048    -0.08231277
## VL  -0.9864951 0.5997181 -0.5774785    -0.67796167
```

Table Odds Ratios for Gender

Generally, there are higher odds men will be rated as either slightly or very conservative rather than neutral compared to women. Men are more likely to fall in the conservative categories instead of the neutral category if they are republicans, rather than democrats. Men were much more likely than women to be in the liberal categories instead of the neutral category conditional if they were classified as democrat. Generally, republican women than democratic women to be in the the conservative categories rather than neutral. Democrats are

```r
ideology_labels <- c('SC', 'SC', 'SC', 'SL', 'SL', 'SL', 'VC', 'VC', 'VC', 'VL', 'VL', 'VL')
gender_labels <- c('Male','Male', 'Female', 'Male','Male', 'Female', 'Male','Male', 'Female',
party_labels <- c('Rep', 'Dem', 'Rep', 'Rep', 'Dem', 'Rep', 'Rep', 'Dem', 'Rep', 'Rep', 'Dem',
odds_ratio_gender <- c(sc.beta.male.rep, sc.beta.male.dem ,sc.beta.fem.rep, sl.beta.male.rep, s

gender_odds <- data.frame(Ideology = ideology_labels, Gender = gender_labels, Party = party_lal
gender_odds
```

```
##    Ideology Gender Party OR.hat
## 1        SC   Male   Rep 1.6005
```

```
## 2        SC   Male   Dem 1.7424
## 3        SC Female   Rep 0.9186
## 4        SL   Male   Rep 0.8917
## 5        SL   Male   Dem 1.6106
## 6        SL Female   Rep 0.5536
## 7        VC   Male   Rep 1.4738
## 8        VC   Male   Dem 1.6002
## 9        VC Female   Rep 0.9210
## 10       VL   Male   Rep 0.9247
## 11       VL   Male   Dem 1.8216
## 12       VL Female   Rep 0.5077
```

Table of Odds Ratio for Party

Adults were more likely to be in conservative categories compared to the neutral category if they were republican. If someone is republican and male, the likelihood of being slightly conservative rather than neutral is 2.13. A woman who is republican is even more likely to be slightly conservative than neutral conditional on republican party membership or her odds ratio is 2.33. Conditional on male gender, democrats are less likely to be in any category compared to Neutral.

```r
odds_ratio_party <- c(sc.beta.rep.male, sc.beta.rep.fem,sc.beta.dem.male, sl.beta.rep.male, sl

party_table_party_labels <- c('Republican', 'Republican', 'Democrat', 'Republican', 'Republican

party_table_gender_labels <- c('Male', 'Female', 'Male', 'Male', 'Female', 'Male','Male', 'Fema

party_odds <- data.frame(Ideology = ideology_labels, Gender = party_table_party_labels, Party =

party_odds
```

```
##    Ideology     Gender  Party OR.hat
## 1        SC Republican   Male 2.1371
## 2        SC Republican Female 2.3266
## 3        SC   Democrat   Male 0.9186
## 4        SL Republican   Male 0.4525
## 5        SL Republican Female 0.8174
## 6        SL   Democrat   Male 0.5536
## 7        VC Republican   Male 1.8955
## 8        VC Republican Female 2.0581
## 9        VC   Democrat   Male 0.9210
## 10       VL Republican   Male 0.2850
## 11       VL Republican Female 0.5613
## 12       VL   Democrat   Male 0.5077
```

##Confidence Intervals for Odds Ratios

The Wald Confidence Interval estimations for each parameter support most betas are not equal to zero. However, the odds a female republican is less likely than a female democrat to be very liberal

are not significantly different from zero. The Wald Confidence interval [-0.1071, 1.1224] includes zero.
When looking at the confidence intervals for party, there are more cases where the odds ratio is not significantly different from zero. The odds a republican male is more or less likely to be slightly liberal than a female democrat are not different from zero (Wald Confidence interval [-0.1535, 1.0586]). The odds a republican male is less likely to be very liberal than a female democrat are also not significantly different from zero as the Wald Confidence Interval ranges from -.3763 to 0.9462. Finally, democratic males odds ratio for very liberal is also not significantly different from zero (Wald Confidence interval [-0.1071, 1.224])

```
conf.beta <- confint(object = mlmodel, level = 0.95)
conf.beta #Results are in 3-D array
```

```
## , , SC
##
##                     2.5 %     97.5 %
## (Intercept)    -2.0819150 -1.1884441
## genderM        -0.1415030  1.2520090
## partyR          0.2589495  1.4298298
## genderM:partyR -0.9658190  0.7959538
##
## , , SL
##
##                      2.5 %     97.5 %
## (Intercept)    -1.25861721 -0.5824845
## genderM        -0.07085921  1.0241321
## partyR         -0.74577933  0.3426154
## genderM:partyR -1.46133007  0.2787724
##
## , , VC
##
##                     2.5 %     97.5 %
## (Intercept)    -1.6955903 -0.9143088
## genderM        -0.1560368  1.0963242
## partyR          0.1952132  1.2483964
## genderM:partyR -0.8910664  0.7264409
##
## , , VL
##
##                      2.5 %      97.5 %
## (Intercept)    -1.33270378 -0.64028647
## genderM         0.05286477  1.14657140
## partyR         -1.19224905  0.03729199
## genderM:partyR -1.64708891  0.29116558
```

```
#Outcomes for Gender
varcov <- vcov(mlmodel)
varcov
```

```
##                   SC:(Intercept)   SC:genderM    SC:partyR SC:genderM:partyR
## SC:(Intercept)       0.051952281 -0.051952281 -0.051952281       0.051952281
## SC:genderM          -0.051952281  0.126376177  0.051952281      -0.126376177
## SC:partyR           -0.051952281  0.051952281  0.089221361      -0.089221361
## SC:genderM:partyR    0.051952281 -0.126376177 -0.089221361       0.201996408
## SL:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## SL:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## SL:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## SL:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## VC:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## VC:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## VC:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## VC:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## VL:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## VL:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## VL:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## VL:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
##                   SL:(Intercept)   SL:genderM    SL:partyR SL:genderM:partyR
## SC:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## SC:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## SC:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## SC:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## SL:(Intercept)       0.029751418 -0.029751418 -0.029751418       0.029751418
## SL:genderM          -0.029751418  0.078030645  0.029751418      -0.078030645
## SL:partyR           -0.029751418  0.029751418  0.077093303      -0.077093303
## SL:genderM:partyR    0.029751418 -0.078030645 -0.077093303       0.197057722
## VC:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## VC:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## VC:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## VC:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## VL:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## VL:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## VL:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## VL:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
##                   VC:(Intercept)   VC:genderM    VC:partyR VC:genderM:partyR
## SC:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## SC:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## SC:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## SC:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## SL:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## SL:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## SL:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## SL:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## VC:(Intercept)       0.039724536 -0.039724536 -0.039724536       0.039724536
## VC:genderM          -0.039724536  0.102071124  0.039724536      -0.102071124
## VC:partyR           -0.039724536  0.039724536  0.072185777      -0.072185777
## VC:genderM:partyR    0.039724536 -0.102071124 -0.072185777       0.170269291
## VL:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
```

```
## VL:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## VL:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## VL:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
##                    VL:(Intercept)   VL:genderM    VL:partyR VL:genderM:partyR
## SC:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## SC:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## SC:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## SC:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## SL:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## SL:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## SL:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## SL:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## VC:(Intercept)       0.008474562 -0.008474562 -0.008474562       0.008474562
## VC:genderM          -0.008474562  0.027342502  0.008474562      -0.027342502
## VC:partyR           -0.008474562  0.008474562  0.020102481      -0.020102481
## VC:genderM:partyR    0.008474562 -0.027342502 -0.020102481       0.055099430
## VL:(Intercept)       0.031201801 -0.031201801 -0.031201801       0.031201801
## VL:genderM          -0.031201801  0.077847652  0.031201801      -0.077847652
## VL:partyR           -0.031201801  0.031201801  0.098385225      -0.098385225
## VL:genderM:partyR    0.031201801 -0.077847652 -0.098385225       0.244492432
```

```
genderlevels1 <- c(1,1,0,1,1,0,1,1,0,1,1,0)
partylevels1 <- c(1,0,1,1,0,1,1,0,1,1,0,1)
interactlevels1 <- c(1,0,0,1,0,0,1,0,0,1,0,0)

sc.beta.male.rep.ci <- sc.beta.male.rep + qnorm(p= c(0.025, 0.975))*sqrt((varcov[1,1]+varcov[3
#sc.beta.male.rep.ci
sc.beta.male.dem.ci <- sc.beta.male.dem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[1,1]))
#sc.beta.male.dem.ci
sc.beta.fem.rep.ci <- sc.beta.fem.rep + qnorm(p= c(0.025, 0.975))*sqrt((varcov[3,3]))
#sc.beta.fem.rep.ci

sl.beta.male.rep.ci <- sl.beta.male.rep + qnorm(p= c(0.025, 0.975))*sqrt((varcov[5,5]+varcov[7
#sl.beta.male.rep.ci
sl.beta.male.dem.ci <- sl.beta.male.dem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[5,5]))
#sl.beta.male.dem.ci
sl.beta.fem.rep.ci <- sl.beta.fem.rep + qnorm(p= c(0.025, 0.975))*sqrt((varcov[7,7]))
#sl.beta.fem.rep.ci

vc.beta.male.rep.ci <- vc.beta.male.rep + qnorm(p= c(0.025, 0.975))*sqrt((varcov[9,9]+varcov[1
#vc.beta.male.rep.ci
vc.beta.male.dem.ci <- vc.beta.male.dem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[9,9]))
#vc.beta.male.dem.ci
vc.beta.fem.rep.ci <- vc.beta.fem.rep + qnorm(p= c(0.025, 0.975))*sqrt((varcov[11,11]))
#vc.beta.fem.rep.ci



vl.beta.male.rep.ci <- vl.beta.male.rep + qnorm(p= c(0.025, 0.975))*sqrt((varcov[13,13]+varcov
```

```r
#vl.beta.male.rep.ci
vl.beta.male.dem.ci <- vl.beta.male.dem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[13,13]))
#vl.beta.male.dem.ci
vl.beta.fem.rep.ci <- vl.beta.fem.rep + qnorm(p= c(0.025, 0.975))*sqrt((varcov[15,15]))
#vl.beta.fem.rep.ci

print("Gender Odds and Confidence Intervals")
```

```
## [1] "Gender Odds and Confidence Intervals"
```

```r
gender_odds_cis <- data.frame(Ideology = ideology_labels, Gender = gender_labels, Party = party

gender_odds_cis
```

```
##    Ideology Gender Party OR.hat Wald.CI.lower Wald.CI.upper
## 1        SC   Male   Rep 2.1371        0.6302        2.5708
## 2        SC   Male   Dem 2.3266        1.2956        2.1891
## 3        SC Female   Rep 0.9186        0.3331        1.5040
## 4        SL   Male   Rep 0.4525        0.0923        1.6911
## 5        SL   Male   Dem 0.8174        1.2726        1.9487
## 6        SL Female   Rep 0.5536        0.0094        1.0978
## 7        VC   Male   Rep 1.8955        0.6164        2.3312
## 8        VC   Male   Dem 2.0581        1.2096        1.9909
## 9        VC Female   Rep 0.9210        0.3944        1.4476
## 10       VL   Male   Rep 0.2850        0.0659        1.7835
## 11       VL   Male   Dem 0.5613        1.4754        2.1678
## 12       VL Female   Rep 0.5077       -0.1071        1.1224
```

```r
#Outcomes for Party

sc.beta.rep.male.ci <- sc.beta.rep.male + qnorm(p= c(0.025, 0.975))*sqrt((varcov[2,2]+varcov[3
sc.beta.rep.fem.ci <- sc.beta.rep.fem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[3,3]))
sc.beta.dem.male.ci <- sc.beta.dem.male + qnorm(p= c(0.025, 0.975))*sqrt((varcov[2,2]))

sl.beta.rep.male.ci <- sl.beta.rep.male + qnorm(p= c(0.025, 0.975))*sqrt((varcov[6,6]+varcov[7
sl.beta.rep.fem.ci <- sl.beta.rep.fem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[6,6]))
sl.beta.dem.male.ci <- sl.beta.dem.male + qnorm(p= c(0.025, 0.975))*sqrt((varcov[7,7]))

vc.beta.rep.male.ci <- vc.beta.rep.male + qnorm(p= c(0.025, 0.975))*sqrt((varcov[10,10]+varcov
vc.beta.rep.fem.ci <- vc.beta.rep.fem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[10,10]))
vc.beta.dem.male.ci <- vc.beta.rep.fem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[11,11]))

vl.beta.rep.male.ci <- vl.beta.rep.male + qnorm(p= c(0.025, 0.975))*sqrt((varcov[14,14]+varcov
vl.beta.rep.fem.ci <- vl.beta.rep.fem + qnorm(p= c(0.025, 0.975))*sqrt((varcov[14,14]))
vl.beta.dem.male.ci <- vl.beta.dem.male + qnorm(p= c(0.025, 0.975))*sqrt((varcov[15,15]))

print("Party Odds and Confidence Intervals")
```

```
## [1] "Party Odds and Confidence Intervals"
```

```r
party_cis <- round(c(sc.beta.rep.male.ci, sc.beta.rep.fem.ci, sc.beta.dem.male.ci, sl.beta.rep

party_odds_cis <- data.frame(Ideology = ideology_labels, Gender = party_table_party_labels, Pa
                             )
party_odds_cis
```

```
##    Ideology     Gender  Party OR.hat Wald.CI.lower Wald.CI.upper
## 1        SC Republican   Male 2.1371        1.4821        2.7921
## 2        SC Republican Female 2.3266        1.7411        2.9120
## 3        SC   Democrat   Male 0.9186        0.2218        1.6153
## 4        SL Republican   Male 0.4525       -0.1535        1.0586
## 5        SL Republican Female 0.8174        0.2699        1.3649
## 6        SL   Democrat   Male 0.5536        0.0094        1.0978
## 7        VC Republican   Male 1.8955        1.2920        2.4990
## 8        VC Republican Female 2.0581        1.4320        2.6843
## 9        VC   Democrat   Male 0.9210        1.5316        2.5847
## 10       VL Republican   Male 0.2850       -0.3763        0.9462
## 11       VL Republican Female 0.5613        0.0145        1.1082
## 12       VL   Democrat   Male 0.5077       -0.1071        1.1224
```