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)
```

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_data <- read.csv("~/mids_271/spring_24_central/Labs/Lab_1/data/pol_ideol_data.csv", 
head(pol_ideol_data)
```

```
##   gender party ideol count
## 1      F     D    VL    44
## 2      F     D    SL    47
## 3      F     D     M   118
## 4      F     D    SC    23
## 5      F     D    VC    32
## 6      F     R    VL    18
```

```
describe(pol_ideol_data)
```

```
## pol_ideol_data
##
##  4  Variables      20  Observations
## --------------------------------------------------------------------------------
## gender
##        n  missing distinct
##       20        0        2
##
## Value         F   M
## Frequency    10  10
## Proportion 0.5 0.5
## --------------------------------------------------------------------------------
## party
##        n  missing distinct
##       20        0        2
##
## Value         D   R
```

```
## Frequency   10  10
## Proportion 0.5 0.5
## --------------------------------------------------------------------------------
## ideol
##        n  missing distinct
##       20        0        5
##
## Value        M   SC   SL   VC   VL
## Frequency    4    4    4    4    4
## Proportion 0.2 0.2 0.2 0.2 0.2
## --------------------------------------------------------------------------------
## count
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##       20        0       17    0.996    41.75    26.57    17.70    18.00
##      .25      .50      .75      .90      .95
##    23.00    37.50    48.75    64.40    87.60
##
## Value        12   18   23   28   32   34   36   39   44   45   47   48   51
## Frequency     1    3    2    1    1    1    1    1    1    1    1    1    1
## Proportion 0.05 0.15 0.10 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05
##
## Value        53   62   86  118
## Frequency     1    1    1    1
## Proportion 0.05 0.05 0.05 0.05
##
## For the frequency table, variable is rounded to the nearest 0
## --------------------------------------------------------------------------------
```

```
#Converting the ideology variable to factor
pol_ideol_data$ideol<- factor(pol_ideol_data$ideol)
pol_ideol_data$gender <- factor(pol_ideol_data$gender)
pol_ideol_data$party <- factor(pol_ideol_data$party)

typeof(pol_ideol_data$ideol) #This comes out as an integer. Should it come out as a factor?
```

```
## [1] "integer"
```

```
summary(pol_ideol_data$ideol)
```

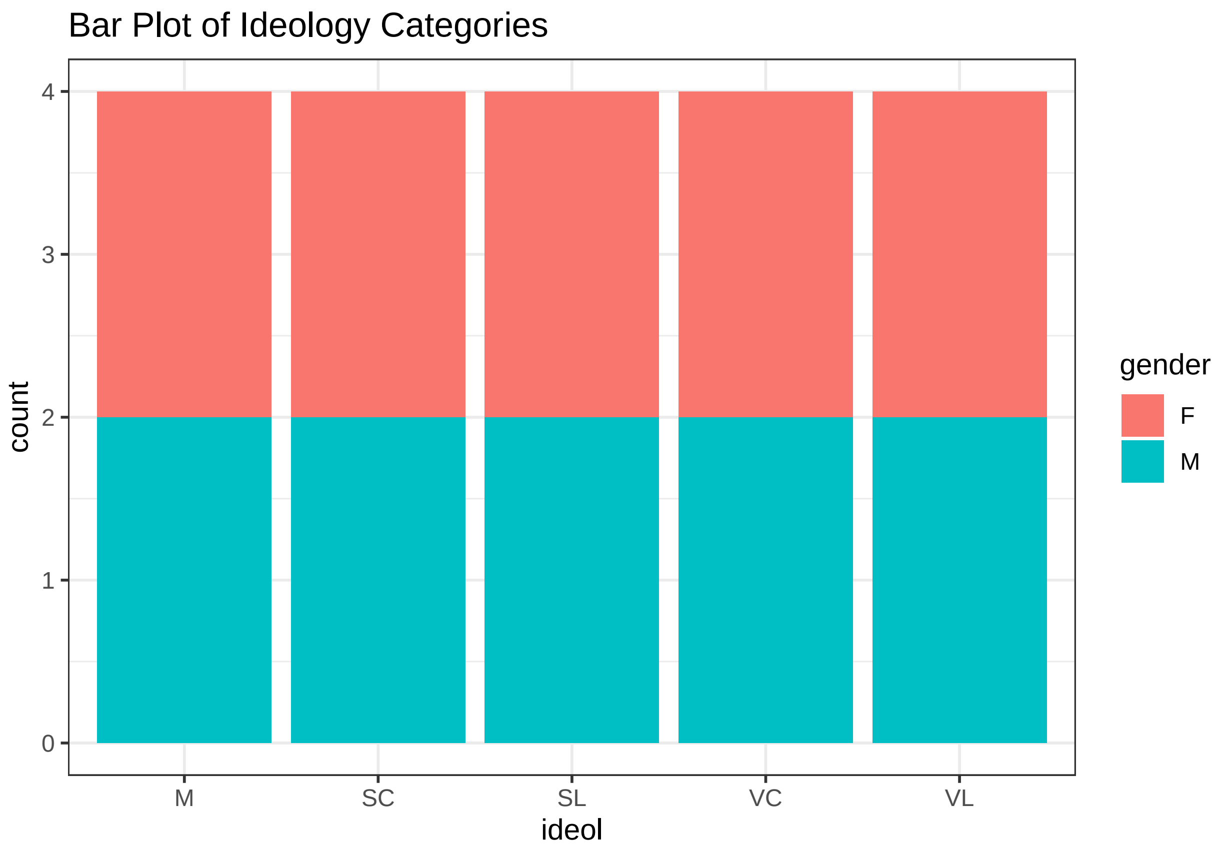
```
##  M SC SL VC VL
##  4  4  4  4  4
```

1.2 Test for Independence (5 points)

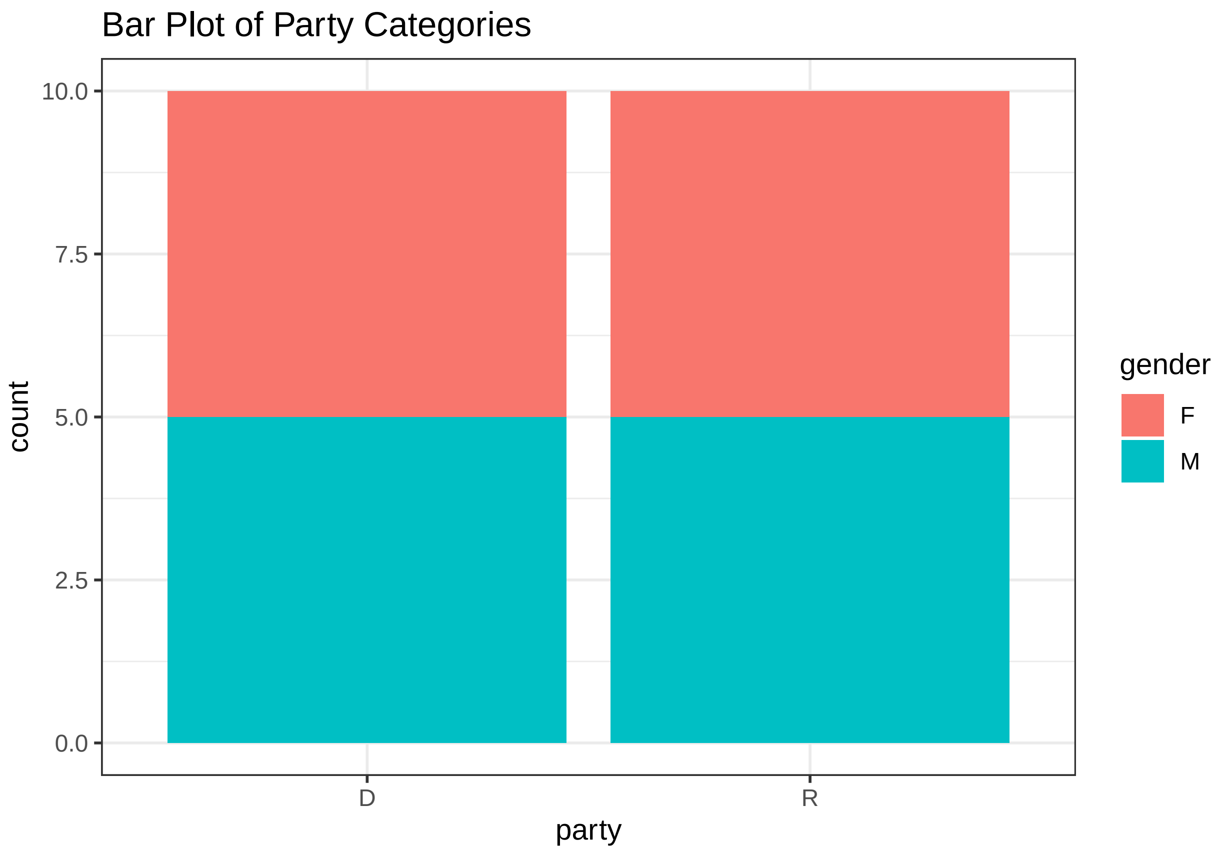
Analyze the relationships between political ideology and political party and gender using basic visualizations. Afterward, generate a contingency table and assess the independence of political ideology from political party and gender.

Comment: The null hypothesis is $H_0 : \pi_{i,j} = \pi_{i+}\pi_{+j}$ for each i, j vs. $H_a : \pi_{i,j} \neq \pi_{i+}\pi_{+j}$. According the chi-square test statistic, the null hypothesis is rejected (p<0.05) for all three relationships. There is independence among the variables.

```
#Plots of party and idology with gender identified in each bar plot
p1<- pol_ideol_data %>%
  ggplot(aes(x=ideol, fill = gender)) + geom_bar() +  labs(title = "Bar Plot of Ideology Catego
p1
```




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




```
print("Contingency table for gender and ideology")
```

```
## [1] "Contingency table for gender and ideology"
```

```
t1 <- xtabs(formula = count ~ gender + ideol, data = pol_ideol_data)
t1
```

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

```
print("Contingency table for party and ideology")
```

```
## [1] "Contingency table for party and ideology"
```

```
t2 <- xtabs(formula = count ~ party + ideol, data = pol_ideol_data) #+ labs(title = "Contingen
t2
```

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

```
print("Contingency table for party and gender")
```

```
## [1] "Contingency table for party and gender"
```

```r
t3 <- xtabs(formula = count ~ party + gender, data = pol_ideol_data)
t3
```

```
##      gender
## party   F   M
##     D 264 164
##     R 219 188
```

```r
#Chi-Square test of independence
ind.test.1 <- chisq.test(x = t1, correct = FALSE)
ind.test.2 <- chisq.test(x = t2, correct = FALSE)
ind.test.3 <- chisq.test(x = t3, correct = FALSE)
ind.test.1
```

```
##
##  Pearson's Chi-squared test
##
## data:  t1
## X-squared = 10.732, df = 4, p-value = 0.02975
```

```r
ind.test.2
```

```
##
##  Pearson's Chi-squared test
##
## data:  t2
## X-squared = 60.905, df = 4, p-value = 1.872e-12
```

```r
ind.test.3
```

```
##
##  Pearson's Chi-squared test
##
## data:  t3
## X-squared = 5.3041, df = 1, p-value = 0.02128
```

```r
#An alternative way to calculate log-likelihood and chi-square
library(package = vcd)
lrt1 <- assocstats(x = t1)
lrt2 <- assocstats(x = t2)
lrt3 <- assocstats(x = t3)
lrt1
```

```
##                     X^2 df P(> X^2)
## Likelihood Ratio 10.743  4 0.029609
## Pearson          10.732  4 0.029751
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.113
## Cramer's V        : 0.113
```

```r
lrt2
```

```
##                       X^2 df   P(> X^2)
## Likelihood Ratio 62.333  4 9.3758e-13
## Pearson          60.905  4 1.8719e-12
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.261
## Cramer's V        : 0.27
```

```r
lrt3
```

```
##                       X^2 df P(> X^2)
## Likelihood Ratio 5.3081  1 0.021227
## Pearson          5.3041  1 0.021275
##
## Phi-Coefficient   : 0.08
## Contingency Coeff.: 0.079
## Cramer's V        : 0.08
```

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: The multinomial regression model is weighted by the count of people in each category. The categorization (in no particular order) of political ideology is regressed against party affiliation, gender, and the interaction of gender and party.

```r
#Multinomial regression
library(package = nnet)
mlmodel <- multinom(formula = ideol ~ gender + party + party:gender, weights = count, data = po
```

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

```r
summary(mlmodel)
```

```
## Call:
## multinom(formula = ideol ~ gender + party + party:gender, data = pol_ideol_data,
##     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
```

```
######################################################

#Ordinal Regression
levels(pol_ideol_data$ideol) #Checking order of dependent variable levels
```

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

```
pol_ideol_data$ideol.order <- factor(pol_ideol_data$ideol, levels = c("VL", "SL", "M", "SC", "V
levels(pol_ideol_data$ideol.order)
```

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

```
library(package = MASS)
ord.model <- polr( formula = ideol.order ~ gender + party + party:gender, data = pol_ideol_data
summary(ord.model)
```

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

## Call:
## polr(formula = ideol.order ~ gender + party + party:gender, data = pol_ideol_data,
##     weights = count, method = "logistic")
##
## Coefficients:
##                   Value Std. Error t value
## genderM        -0.1431     0.1820 -0.7861
## partyR          0.7562     0.1659  4.5593
## genderM:partyR  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
```

```r
print("The likelihood ratio tests for the multinomial parameters")
```

```
## [1] "The likelihood ratio tests for the multinomial parameters"
```

```r
Anova(mlmodel)
```

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

```r
print("The likelihood ratio tests for the ordinal parameters")
```

```
## [1] "The likelihood ratio tests for the ordinal parameters"
```

```r
Anova(ord.model)
```

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

```r
#nominal_test(ord.model)
```

```r
#Is the proportional odds assumption satisfied?

#Can use nominal test

mod.ord2 <- clm(ideol.order ~ gender + party + party:gender, data = pol_ideol_data)

nominal_test(mod.ord2)
```

```
## Tests of nominal effects
##
## formula: ideol.order ~ gender + party + party:gender
##               Df  logLik    AIC LRT Pr(>Chi)
## <none>           -32.189 78.378
```

```
## gender        3 -32.189 84.378   0        1
## party         3 -32.189 84.378   0        1
## gender:party  9 -32.189 96.378   0        1
```

1.4 Estimated probabilities (5 points)

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

```r
#Odds of each ideology given the possible combinations of party and gender levels....
v.table <- xtabs(formula = count ~ ideol.order + gender + party, data = pol_ideol_data)
v.table
```

```
## , , party = D
##
##            gender
## ideol.order   F   M
##          VL  44  36
##          SL  47  34
##          M  118  53
##          SC  23  18
##          VC  32  23
##
## , , party = R
##
##            gender
## ideol.order   F   M
##          VL  18  12
##          SL  28  18
##          M   86  62
##          SC  39  45
##          VC  48  51
```

```r
ideol.prob <- v.table/rowSums(v.table)

ideol.prob
```

```
## , , party = D
##
##            gender
## ideol.order         F         M
##          VL 0.4000000 0.3272727
##          SL 0.3700787 0.2677165
##          M  0.3699060 0.1661442
##          SC 0.1840000 0.1440000
##          VC 0.2077922 0.1493506
##
## , , party = R
##
##            gender
```

```
## ideol.order         F         M
##          VL 0.1636364 0.1090909
##          SL 0.2204724 0.1417323
##          M  0.2695925 0.1943574
##          SC 0.3120000 0.3600000
##          VC 0.3116883 0.3311688
```

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.

```r
#Convert contingency table to data frame
v.flat <- ftable(v.table, row.vars = c("gender", "party"), col.vars = c("ideol.order"))
DF <- as.data.frame(v.flat )
pi.hat <- predict(object = mlmodel, newdata = DF, type = "probs")

pi.hat
```

```
##            M        SC        SL        VC         VL
## 1  0.4469704 0.0871223 0.1780281 0.1212122 0.16666692
## 2  0.3231705 0.1097553 0.2073204 0.1402427 0.21951113
## 3  0.3926937 0.1780812 0.1278550 0.2191782 0.08219185
## 4  0.3297877 0.2393626 0.0957436 0.2712756 0.06383054
## 5  0.4469704 0.0871223 0.1780281 0.1212122 0.16666692
## 6  0.3231705 0.1097553 0.2073204 0.1402427 0.21951113
## 7  0.3926937 0.1780812 0.1278550 0.2191782 0.08219185
## 8  0.3297877 0.2393626 0.0957436 0.2712756 0.06383054
## 9  0.4469704 0.0871223 0.1780281 0.1212122 0.16666692
## 10 0.3231705 0.1097553 0.2073204 0.1402427 0.21951113
## 11 0.3926937 0.1780812 0.1278550 0.2191782 0.08219185
## 12 0.3297877 0.2393626 0.0957436 0.2712756 0.06383054
## 13 0.4469704 0.0871223 0.1780281 0.1212122 0.16666692
## 14 0.3231705 0.1097553 0.2073204 0.1402427 0.21951113
## 15 0.3926937 0.1780812 0.1278550 0.2191782 0.08219185
## 16 0.3297877 0.2393626 0.0957436 0.2712756 0.06383054
## 17 0.4469704 0.0871223 0.1780281 0.1212122 0.16666692
## 18 0.3231705 0.1097553 0.2073204 0.1402427 0.21951113
## 19 0.3926937 0.1780812 0.1278550 0.2191782 0.08219185
## 20 0.3297877 0.2393626 0.0957436 0.2712756 0.06383054
```

```r
estprob <- data.frame(gender = DF[1:4,], party = DF[1:4, 2], round(pi.hat, 4))
```

```
## Warning in data.frame(gender = DF[1:4, ], party = DF[1:4, 2], round(pi.hat, :
```

```
## row names were found from a short variable and have been discarded
```

```r
estprob
```

```
##    gender.gender gender.party gender.ideol.order gender.Freq party      M
## 1              F            D                 VL          44     D 0.4470
## 2              M            D                 VL          36     D 0.3232
## 3              F            R                 VL          18     R 0.3927
## 4              M            R                 VL          12     R 0.3298
## 5              F            D                 VL          44     D 0.4470
## 6              M            D                 VL          36     D 0.3232
## 7              F            R                 VL          18     R 0.3927
## 8              M            R                 VL          12     R 0.3298
## 9              F            D                 VL          44     D 0.4470
## 10             M            D                 VL          36     D 0.3232
## 11             F            R                 VL          18     R 0.3927
## 12             M            R                 VL          12     R 0.3298
## 13             F            D                 VL          44     D 0.4470
## 14             M            D                 VL          36     D 0.3232
## 15             F            R                 VL          18     R 0.3927
## 16             M            R                 VL          12     R 0.3298
## 17             F            D                 VL          44     D 0.4470
## 18             M            D                 VL          36     D 0.3232
## 19             F            R                 VL          18     R 0.3927
## 20             M            R                 VL          12     R 0.3298
##        SC     SL     VC     VL
## 1  0.0871 0.1780 0.1212 0.1667
## 2  0.1098 0.2073 0.1402 0.2195
## 3  0.1781 0.1279 0.2192 0.0822
## 4  0.2394 0.0957 0.2713 0.0638
## 5  0.0871 0.1780 0.1212 0.1667
## 6  0.1098 0.2073 0.1402 0.2195
## 7  0.1781 0.1279 0.2192 0.0822
## 8  0.2394 0.0957 0.2713 0.0638
## 9  0.0871 0.1780 0.1212 0.1667
## 10 0.1098 0.2073 0.1402 0.2195
## 11 0.1781 0.1279 0.2192 0.0822
## 12 0.2394 0.0957 0.2713 0.0638
## 13 0.0871 0.1780 0.1212 0.1667
## 14 0.1098 0.2073 0.1402 0.2195
## 15 0.1781 0.1279 0.2192 0.0822
## 16 0.2394 0.0957 0.2713 0.0638
## 17 0.0871 0.1780 0.1212 0.1667
## 18 0.1098 0.2073 0.1402 0.2195
## 19 0.1781 0.1279 0.2192 0.0822
## 20 0.2394 0.0957 0.2713 0.0638
```

```r
#estimate counts
est.count <- round(estprob[,6:10]*v.flat[,0:5], 1)
```

```r
est.count
```

```
##        M   SC   SL   VC   VL
## 1  19.7  3.8  7.8  5.3  7.3
## 2   5.8  2.0  3.7  2.5  4.0
## 3  14.1  6.4  4.6  7.9  3.0
## 4   4.0  2.9  1.1  3.3  0.8
## 5  21.0  4.1  8.4  5.7  7.8
## 6   9.0  3.1  5.8  3.9  6.1
## 7  13.4  6.1  4.3  7.5  2.8
## 8   5.9  4.3  1.7  4.9  1.1
## 9  52.7 10.3 21.0 14.3 19.7
## 10 27.8  9.4 17.8 12.1 18.9
## 11 20.8  9.4  6.8 11.6  4.4
## 12 20.4 14.8  5.9 16.8  4.0
## 13 10.3  2.0  4.1  2.8  3.8
## 14 12.6  4.3  8.1  5.5  8.6
## 15  7.1  3.2  2.3  3.9  1.5
## 16 14.8 10.8  4.3 12.2  2.9
## 17 14.3  2.8  5.7  3.9  5.3
## 18 15.5  5.3 10.0  6.7 10.5
## 19  9.0  4.1  2.9  5.0  1.9
## 20 16.8 12.2  4.9 13.8  3.3
```

```r
chisq.test(x = est.count, correct = FALSE)
```

```
## Warning in chisq.test(x = est.count, correct = FALSE): Chi-squared
## approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  est.count
## X-squared = 76.543, df = 76, p-value = 0.461
```

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.

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

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

```
## Call:
## multinom(formula = ideol ~ gender + party + party:gender, data = pol_ideol_data,
##     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

```r
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
```

```r
#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
```

```
## [1] 0.6302194 2.5707944
```

```
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
```

```
## [1] 1.295646 2.189117
```

```
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
```

```
## [1] 0.333134 1.504014
```

```
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
```

```
## [1] 0.0922994 1.6910705
```

```
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
```

```
## [1] 1.272581 1.948714
```

```
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
```

```
## [1] 0.009421494 1.097816181
```

```r
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
```

```
## [1] 0.6164013 2.3311599
```

```r
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
```

```
## [1] 1.209583 1.990865
```

```r
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
```

```
## [1] 0.3943923 1.4475754
```

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

```
## [1] 0.06594692 1.78353138
```

```r
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
```

```
## [1] 1.475397 2.167814
```

```r
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
```

```
## [1] -0.1071198  1.1224212
```

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

gender_odds_cis
```

```
##    Ideology Gender Party      Wald.CI
## 1        SC   Male   Rep  0.630219365
## 2        SC   Male   Dem  2.570794363
## 3        SC Female   Rep  1.295646289
## 4        SL   Male   Rep  2.189117158
## 5        SL   Male   Dem  0.333134017
## 6        SL Female   Rep  1.504014344
## 7        VC   Male   Rep  0.092299396
## 8        VC   Male   Dem  1.691070535
## 9        VC Female   Rep  1.272581471
## 10       VL   Male   Rep  1.948714139
## 11       VL   Male   Dem  0.009421494
## 12       VL Female   Rep  1.097816181
## 13       SC   Male   Rep  0.616401324
## 14       SC   Male   Dem  2.331159850
## 15       SC Female   Rep  1.209583409
## 16       SL   Male   Rep  1.990864845
## 17       SL   Male   Dem  0.394392279
```

```
## 18       SL Female   Rep  1.447575434
## 19       VC   Male   Rep  0.065946924
## 20       VC   Male   Dem  1.783531380
## 21       VC Female   Rep  1.475396538
## 22       VL   Male   Rep  2.167813847
## 23       VL   Male   Dem -0.107119819
## 24       VL Female   Rep  1.122421221
```

```
#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]))
```