Assignment2

# Tasks

**Note**:

• Dataset is imbalanced. • Features are categorical (Nominal, Ordinal, Binary) and numerical. • Missing imputation does not seem to be needed in your pipeline. • Use nominal and ordinal polytomous models. • Propose a hierarchical logit approach to predict right, center and left wing voting in the political spectrum.

## Data Preparation

**Univariate Descriptive Analysis (to be included for each variable) [Eliya]:**

• Original numeric variables corresponding to qualitative concepts are present then they have to be converted to factors. • Original numeric variables corresponding to real quantitative concepts are kept as numeric but additional factors should also be created as a discretization of each numeric variable. • Exploratory Data Analysis for each variable (numeric summary and graphic support).

**Data Quality Report [Achraf]:** Per variable, count: • Number of missing values • Number of errors (including inconsistencies) • Number of outliers • Rank variables according the sum of missing values (and errors). Per individuals, count: • number of missing values • number of errors, • number of outliers • Identify individuals considered as multivariant outliers.

Create variable adding the total number missing values, outliers and errors. Describe these variables, to which other variables exist higher associations. • Compute the correlation with all other variables. Rank these variables according the correlation • Compute for every group of individuals (group of age, size of town, singles, married, …) the mean of missing/outliers/errors values. Rank the groups according the computed mean.

**Profiling [Eliya]:** • Polytomous Target: 6 parties • Polytomous Target: right/center/left orientation.

ROSE package for balancing data

## Modeling

* Train and test split
* (use set.seed(your birthday))
* Model reasonable factors as numeric variables also using transformations if needed.
* Grouping levels in factors is allowed.
* Adding factor main effects to the best model containing numeric variables
* Adding factor main effects and interactions (limit your statement to order 2) to the best model containing numeric variables.
* Goodness of fit and Model Interpretation for each proposal (nominal/ordinal).
* Goodness of fit and Model Interpretation for political orientation (right/center/left). Make your own allocation of political parties to the right/center/left wing orientation.

# Clear plots  
if(!is.null(dev.list())) dev.off()

## null device   
## 1

# Clean workspace  
rm(list=ls())

# Load Data

#load libraries  
library("nnet")  
  
#load data  
data("gles", package = "MNLpred")  
df <- gles  
summary(df)

## vote egoposition\_immigration ostwest political\_interest  
## Length:1000 Min. : 0.000 Min. :0.000 Min. :0.000   
## Class :character 1st Qu.: 3.000 1st Qu.:1.000 1st Qu.:2.000   
## Mode :character Median : 4.000 Median :1.000 Median :3.000   
## Mean : 4.361 Mean :0.759 Mean :2.874   
## 3rd Qu.: 6.000 3rd Qu.:1.000 3rd Qu.:4.000   
## Max. :10.000 Max. :1.000 Max. :4.000   
## income gender   
## Min. :0.000 Min. :0.000   
## 1st Qu.:3.000 1st Qu.:0.000   
## Median :3.000 Median :0.000   
## Mean :2.906 Mean :0.462   
## 3rd Qu.:3.000 3rd Qu.:1.000   
## Max. :4.000 Max. :1.000

We can see the summary and nothing too suspicious when look at the data. In addition, no nulls or blanks in the data.

# Preprocessing

## Format and erros

sapply(df, class)

## vote egoposition\_immigration ostwest   
## "character" "numeric" "numeric"   
## political\_interest income gender   
## "numeric" "numeric" "numeric"

We have a lot of categorical variables which have a numerical type. For a better understanding it will be converted to factor taking into account metadata.

# Transform variables to factors  
#df$vote <- factor(df$vote)  
#df$egoposition\_immigration <- factor(df$egoposition\_immigration, ordered = TRUE)  
#df$ostwest <- factor(ifelse(df$ostwest==0,"No","Yes"))  
#df$political\_interest <- factor(df$political\_interest, ordered=TRUE)  
#df$income <- factor(df$income, ordered=TRUE)  
#df$gender <- factor(ifelse(df$gender==0,"Male","Female"))  
  
df$vote <- factor(df$vote)  
df$egoposition\_immigration <- factor(df$egoposition\_immigration)  
df$f.ostwest <- factor(df$ostwest, labels = c("west","east"))  
df$political\_interest <- factor(df$political\_interest)  
df$income <- factor(df$income)  
df$f.gender <- factor(df$gender,labels = c("male","female"))  
summary(df)

## vote egoposition\_immigration ostwest political\_interest  
## AfD : 69 4 :179 Min. :0.000 0: 3   
## CDU/CSU:289 5 :155 1st Qu.:1.000 1: 34   
## FDP :121 3 :134 Median :1.000 2:308   
## Gruene :143 2 :130 Mean :0.759 3:396   
## LINKE :123 6 : 95 3rd Qu.:1.000 4:259   
## SPD :255 7 : 78 Max. :1.000   
## (Other):229   
## income gender f.ostwest f.gender   
## 0: 13 Min. :0.000 west:241 male :538   
## 1: 28 1st Qu.:0.000 east:759 female:462   
## 2:188 Median :0.000   
## 3:582 Mean :0.462   
## 4:189 3rd Qu.:1.000   
## Max. :1.000   
##

#round(prop.table(summary(df$vote)),2)

Now we can understand better the data and we can see that we that we have a balance in gender. Also the majority of people is from Eastern Germany.

Now let’s try to find errors and inconsistencies in format

which(df=="") #no blanks found in the data

## integer(0)

sapply(df, unique) # Check unique values for each attribute

## $vote  
## [1] FDP SPD CDU/CSU Gruene AfD LINKE   
## Levels: AfD CDU/CSU FDP Gruene LINKE SPD  
##   
## $egoposition\_immigration  
## [1] 4 8 3 7 2 1 5 0 6 10 9   
## Levels: 0 1 2 3 4 5 6 7 8 9 10  
##   
## $ostwest  
## [1] 1 0  
##   
## $political\_interest  
## [1] 3 2 1 4 0  
## Levels: 0 1 2 3 4  
##   
## $income  
## [1] 3 2 4 1 0  
## Levels: 0 1 2 3 4  
##   
## $gender  
## [1] 0 1  
##   
## $f.ostwest  
## [1] east west  
## Levels: west east  
##   
## $f.gender  
## [1] male female  
## Levels: male female

df$error = 0  
number\_of\_errors\_per\_attribute = c(rep(0, 6));number\_of\_errors\_per\_attribute

## [1] 0 0 0 0 0 0

summary(df)

## vote egoposition\_immigration ostwest political\_interest  
## AfD : 69 4 :179 Min. :0.000 0: 3   
## CDU/CSU:289 5 :155 1st Qu.:1.000 1: 34   
## FDP :121 3 :134 Median :1.000 2:308   
## Gruene :143 2 :130 Mean :0.759 3:396   
## LINKE :123 6 : 95 3rd Qu.:1.000 4:259   
## SPD :255 7 : 78 Max. :1.000   
## (Other):229   
## income gender f.ostwest f.gender error   
## 0: 13 Min. :0.000 west:241 male :538 Min. :0   
## 1: 28 1st Qu.:0.000 east:759 female:462 1st Qu.:0   
## 2:188 Median :0.000 Median :0   
## 3:582 Mean :0.462 Mean :0   
## 4:189 3rd Qu.:1.000 3rd Qu.:0   
## Max. :1.000 Max. :0   
##

Taking into account metadata, no errors where found in the data since all values are in the specification.

## Outliers

Since data is all categorical there is no way to detect outliers. However, we will label the lest frequent categories as outliers.

### Univariate

Let’s see the frequency of each level in each attribute

number\_of\_outliers\_per\_attribute = c()  
  
df$outlier = 0  
  
# vote  
prop.table(table(df$vote))

##   
## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.069 0.289 0.121 0.143 0.123 0.255

df[which(df$vote == "AfD"),"outlier"] <- 1  
number\_of\_outliers\_per\_attribute <- append(number\_of\_outliers\_per\_attribute, length(which(df$vote == "AfD")))  
  
 # egoposition\_immigration  
prop.table(table(df$egoposition\_immigration))

##   
## 0 1 2 3 4 5 6 7 8 9 10   
## 0.049 0.068 0.130 0.134 0.179 0.155 0.095 0.078 0.031 0.034 0.047

df[which(df$egoposition\_immigration == 8),"outlier"] <- 1  
number\_of\_outliers\_per\_attribute <- append(number\_of\_outliers\_per\_attribute, length(which(df$egoposition\_immigration == 8)))  
  
#ostwest  
prop.table(table(df$f.ostwest))

##   
## west east   
## 0.241 0.759

number\_of\_outliers\_per\_attribute <- append(number\_of\_outliers\_per\_attribute, 0)  
  
# political\_interest  
prop.table(table(df$political\_interest))

##   
## 0 1 2 3 4   
## 0.003 0.034 0.308 0.396 0.259

df[which(df$political\_interest == 0),"outlier"] <- 1  
number\_of\_outliers\_per\_attribute <- append(number\_of\_outliers\_per\_attribute, length(which(df$political\_interest == 0)))  
  
# income  
prop.table(table(df$income))

##   
## 0 1 2 3 4   
## 0.013 0.028 0.188 0.582 0.189

df[which(df$income == 0),"outlier"] <- 1  
number\_of\_outliers\_per\_attribute <- append(number\_of\_outliers\_per\_attribute, length(which(df$income == 0)))  
  
# gender  
prop.table(table(df$f.gender))

##   
## male female   
## 0.538 0.462

#df[which(df$political\_interest == 0),"outlier"] <- 1  
number\_of\_outliers\_per\_attribute <- append(number\_of\_outliers\_per\_attribute,0)  
  
  
str(number\_of\_outliers\_per\_attribute)

## num [1:6] 69 31 0 3 13 0

The levels that are “outliers” won’t be removed. However, it’s important to keep in mind those classes that are a minority in case in further iterations levels are grouped.

### Multivariate

Detecting multivariate outliers it’s not an easy process since all data is factors and we can’t apply methods like mahalanobis or cooks distance. One solution could be using MCA (factorial method) to detect anomalies.

## Missing data

There is no missing data so no imputation is needed.

is.null(df) #no nulls in the data

## [1] FALSE

number\_of\_na\_per\_attribute = c(rep(0, 6));number\_of\_na\_per\_attribute

## [1] 0 0 0 0 0 0

df$na = 0

The results are not great

## Data quality report

Let’s create the report for each attribute and per individual takining into account the results obtained in the different processes.

# per variabe  
attributes\_report <- data.frame(attributes = c(names(df[,c(1:6)])), errors=number\_of\_errors\_per\_attribute, outliers=number\_of\_outliers\_per\_attribute, na=number\_of\_na\_per\_attribute)  
  
print(attributes\_report)

## attributes errors outliers na  
## 1 vote 0 69 0  
## 2 egoposition\_immigration 0 31 0  
## 3 ostwest 0 0 0  
## 4 political\_interest 0 3 0  
## 5 income 0 13 0  
## 6 gender 0 0 0

# per individual  
individuals\_report = df[,c("error","outlier", "na")]  
print(individuals\_report)

## error outlier na  
## 1 0 0 0  
## 2 0 1 0  
## 3 0 0 0  
## 4 0 0 0  
## 5 0 0 0  
## 6 0 0 0  
## 7 0 0 0  
## 8 0 0 0  
## 9 0 0 0  
## 10 0 0 0  
## 11 0 1 0  
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Let’s compute the most problematic atrributes

attributes\_report$total <- attributes\_report$error + attributes\_report$outlier + attributes\_report$na  
attributes\_report = attributes\_report[order(attributes\_report$total,decreasing = TRUE),]  
print(attributes\_report)

## attributes errors outliers na total  
## 1 vote 0 69 0 69  
## 2 egoposition\_immigration 0 31 0 31  
## 5 income 0 13 0 13  
## 4 political\_interest 0 3 0 3  
## 3 ostwest 0 0 0 0  
## 6 gender 0 0 0 0

Finally let’s check the most problematic individuals

individuals\_report$total = individuals\_report$error + individuals\_report$outlier + individuals\_report$na  
individuals\_report = individuals\_report[order(individuals\_report$total,decreasing = TRUE),]  
  
print(individuals\_report)

## error outlier na total  
## 2 0 1 0 1  
## 11 0 1 0 1  
## 23 0 1 0 1  
## 35 0 1 0 1  
## 38 0 1 0 1  
## 39 0 1 0 1  
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As we can see in general, data quality is pretty good. There are no erros, outliers or missing data. The only thing it might need is to group some levels in further iterations. We leveled that categories that are really low in comparison to the others as outliers so we can have in mind which are the least frequent and be able to rank them (they are not really outliers).

summary(df)

## vote egoposition\_immigration ostwest political\_interest  
## AfD : 69 4 :179 Min. :0.000 0: 3   
## CDU/CSU:289 5 :155 1st Qu.:1.000 1: 34   
## FDP :121 3 :134 Median :1.000 2:308   
## Gruene :143 2 :130 Mean :0.759 3:396   
## LINKE :123 6 : 95 3rd Qu.:1.000 4:259   
## SPD :255 7 : 78 Max. :1.000   
## (Other):229   
## income gender f.ostwest f.gender error outlier   
## 0: 13 Min. :0.000 west:241 male :538 Min. :0 Min. :0.0   
## 1: 28 1st Qu.:0.000 east:759 female:462 1st Qu.:0 1st Qu.:0.0   
## 2:188 Median :0.000 Median :0 Median :0.0   
## 3:582 Mean :0.462 Mean :0 Mean :0.1   
## 4:189 3rd Qu.:1.000 3rd Qu.:0 3rd Qu.:0.0   
## Max. :1.000 Max. :0 Max. :1.0   
##   
## na   
## Min. :0   
## 1st Qu.:0   
## Median :0   
## Mean :0   
## 3rd Qu.:0   
## Max. :0   
##

df <- df[,c(1:8)] # Remove attributes that are used for the report

# Univariate Descriptive Analysis

summary(df)

## vote egoposition\_immigration ostwest political\_interest  
## AfD : 69 4 :179 Min. :0.000 0: 3   
## CDU/CSU:289 5 :155 1st Qu.:1.000 1: 34   
## FDP :121 3 :134 Median :1.000 2:308   
## Gruene :143 2 :130 Mean :0.759 3:396   
## LINKE :123 6 : 95 3rd Qu.:1.000 4:259   
## SPD :255 7 : 78 Max. :1.000   
## (Other):229   
## income gender f.ostwest f.gender   
## 0: 13 Min. :0.000 west:241 male :538   
## 1: 28 1st Qu.:0.000 east:759 female:462   
## 2:188 Median :0.000   
## 3:582 Mean :0.462   
## 4:189 3rd Qu.:1.000   
## Max. :1.000   
##

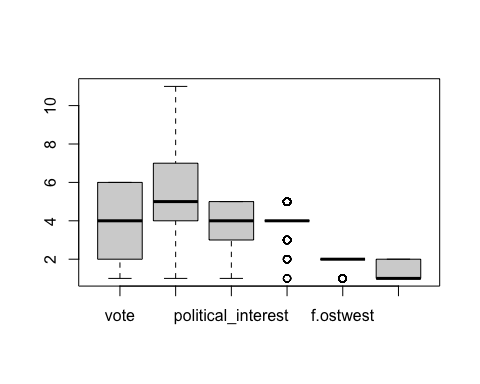
First, we turn qualitative,nominal and ordinal variables into factors. When it’s east/west or gender we trun it into a factor with the actual name.

We can see the summary and nothing too suspicious when look at the data. We can see CDU/CSU party gets most votes on our sample, majority of voters are open for immigration (around 3,4,5), most voters are from the east of Germany, most voters have a plus average intrest in the elections, most voters income is relativity high because we can see that the variable (before being a factor) has a mean and median around 3 and as a factor we see 582 with income 3. In addition, no nulls or blanks in the data. From the boxplot we can see that income and east/west have points outside the box but we know why is it. When ploting the data we don’t see anything suspicious. When define political orientation we see most voters are center, then left and the less is right, we can see that 2/3 of the voters are voting for the center parties.

library(car)

## Loading required package: carData

boxplot(df[,c(1:2,4:5,7:8)])



plot(df[,c(1:2,4:5,7:8)])  
  
round(prop.table(summary(df$vote)),2)

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.07 0.29 0.12 0.14 0.12 0.26

df$f.vote <- ''  
df[which(df$vote=="AfD"),9] <- "right"  
df[which(df$vote=="CDU/CSU"),9] <- "center"  
df[which(df$vote=="FDP"),9] <- "center"  
df[which(df$vote=="Gruene"),9] <- "left"  
df[which(df$vote=="LINKE"),9] <- "left"  
df[which(df$vote=="SPD"),9] <- "center"  
  
df$f.vote <-factor(df$f.vote)  
summary(df)

## vote egoposition\_immigration ostwest political\_interest  
## AfD : 69 4 :179 Min. :0.000 0: 3   
## CDU/CSU:289 5 :155 1st Qu.:1.000 1: 34   
## FDP :121 3 :134 Median :1.000 2:308   
## Gruene :143 2 :130 Mean :0.759 3:396   
## LINKE :123 6 : 95 3rd Qu.:1.000 4:259   
## SPD :255 7 : 78 Max. :1.000   
## (Other):229   
## income gender f.ostwest f.gender f.vote   
## 0: 13 Min. :0.000 west:241 male :538 center:665   
## 1: 28 1st Qu.:0.000 east:759 female:462 left :266   
## 2:188 Median :0.000 right : 69   
## 3:582 Mean :0.462   
## 4:189 3rd Qu.:1.000   
## Max. :1.000   
##

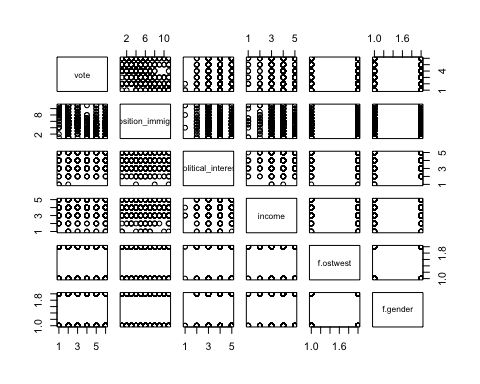
round(prop.table(summary(df$f.vote)),2)

## center left right   
## 0.66 0.27 0.07

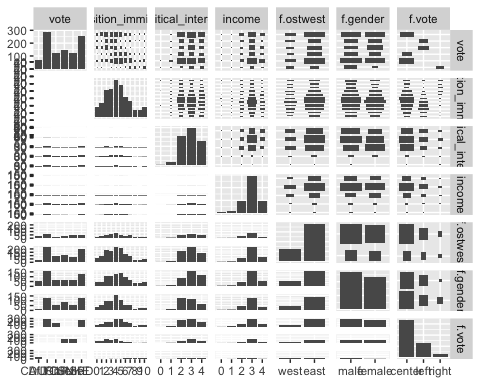
library(GGally)

## Loading required package: ggplot2

## Registered S3 method overwritten by 'GGally':  
## method from   
## +.gg ggplot2



ggpairs(df[,c(1:2,4:5,7:8,9)])



library(FactoMineR)  
res.cat\_f.vote <- catdes(df[,c(2,4,5,7:9)],num.var=6);res.cat\_f.vote

##   
## Link between the cluster variable and the categorical variables (chi-square test)  
## =================================================================================  
## p.value df  
## egoposition\_immigration 1.915697e-45 20  
## f.gender 4.221739e-06 2  
## f.ostwest 2.295310e-04 2  
## political\_interest 3.552831e-03 8  
## income 4.652099e-02 8  
##   
## Description of each cluster by the categories  
## =============================================  
## $center  
## Cla/Mod Mod/Cla Global p.value v.test  
## egoposition\_immigration=5 83.22581 19.398496 15.5 5.513189e-07 5.007534  
## f.ostwest=east 69.43347 79.248120 75.9 5.849772e-04 3.438486  
## egoposition\_immigration=6 81.05263 11.578947 9.5 1.102026e-03 3.263095  
## income=4 74.07407 21.052632 18.9 1.331258e-02 2.475296  
## political\_interest=2 71.75325 33.233083 30.8 1.837781e-02 2.357917  
## egoposition\_immigration=8 48.38710 2.255639 3.1 3.695876e-02 -2.086219  
## egoposition\_immigration=0 48.97959 3.609023 4.9 1.008813e-02 -2.572794  
## egoposition\_immigration=2 54.61538 10.676692 13.0 2.600362e-03 -3.011411  
## f.ostwest=west 57.26141 20.751880 24.1 5.849772e-04 -3.438486  
##   
## $left  
## Cla/Mod Mod/Cla Global p.value v.test  
## egoposition\_immigration=2 45.384615 22.1804511 13.0 7.347278e-07 4.951952  
## egoposition\_immigration=0 48.979592 9.0225564 4.9 6.479798e-04 3.410693  
## egoposition\_immigration=3 38.059701 19.1729323 13.4 1.798442e-03 3.121644  
## f.gender=female 30.086580 52.2556391 46.2 2.119615e-02 2.304472  
## f.gender=male 23.605948 47.7443609 53.8 2.119615e-02 -2.304472  
## income=4 19.576720 13.9097744 18.9 1.362802e-02 -2.466922  
## egoposition\_immigration=10 10.638298 1.8796992 4.7 7.300975e-03 -2.682795  
## egoposition\_immigration=8 6.451613 0.7518797 3.1 5.282681e-03 -2.789271  
## egoposition\_immigration=9 5.882353 0.7518797 3.4 2.382574e-03 -3.037869  
## egoposition\_immigration=5 15.483871 9.0225564 15.5 4.059018e-04 -3.536217  
## egoposition\_immigration=7 10.256410 3.0075188 7.8 2.687651e-04 -3.643682  
## egoposition\_immigration=6 11.578947 4.1353383 9.5 2.154814e-04 -3.700139  
##   
## $right  
## Cla/Mod Mod/Cla Global p.value v.test  
## egoposition\_immigration=8 45.161290 20.289855 3.1 1.675803e-09 6.026469  
## egoposition\_immigration=10 34.042553 23.188406 4.7 1.468400e-08 5.665215  
## f.gender=male 10.408922 81.159420 53.8 1.101835e-06 4.872520  
## egoposition\_immigration=7 17.948718 20.289855 7.8 5.783367e-04 3.441576  
## egoposition\_immigration=9 23.529412 11.594203 3.4 1.731296e-03 3.132830  
## f.ostwest=west 11.618257 40.579710 24.1 1.731634e-03 3.132773  
## political\_interest=0 66.666667 2.898551 0.3 1.377478e-02 2.463084  
## income=1 17.857143 7.246377 2.8 4.793709e-02 1.977926  
## egoposition\_immigration=1 1.470588 1.449275 6.8 4.815760e-02 -1.975975  
## egoposition\_immigration=3 2.985075 5.797101 13.4 4.305493e-02 -2.023177  
## f.ostwest=east 5.401845 59.420290 75.9 1.731634e-03 -3.132773  
## egoposition\_immigration=5 1.290323 2.898551 15.5 6.970986e-04 -3.390718  
## egoposition\_immigration=4 1.117318 2.898551 17.9 1.193747e-04 -3.847407  
## egoposition\_immigration=2 0.000000 0.000000 13.0 4.641675e-05 -4.072973  
## f.gender=female 2.813853 18.840580 46.2 1.101835e-06 -4.872520

res.cat\_vote <- catdes(df[,c(1,2,4,5,7,8)],num.var=1);res.cat\_vote

##   
## Link between the cluster variable and the categorical variables (chi-square test)  
## =================================================================================  
## p.value df  
## egoposition\_immigration 4.487703e-46 50  
## f.gender 1.979157e-05 5  
## f.ostwest 3.803422e-05 5  
## political\_interest 3.931857e-03 20  
## income 2.197016e-02 20  
##   
## Description of each cluster by the categories  
## =============================================  
## $AfD  
## Cla/Mod Mod/Cla Global p.value v.test  
## egoposition\_immigration=8 45.161290 20.289855 3.1 1.675803e-09 6.026469  
## egoposition\_immigration=10 34.042553 23.188406 4.7 1.468400e-08 5.665215  
## f.gender=male 10.408922 81.159420 53.8 1.101835e-06 4.872520  
## egoposition\_immigration=7 17.948718 20.289855 7.8 5.783367e-04 3.441576  
## egoposition\_immigration=9 23.529412 11.594203 3.4 1.731296e-03 3.132830  
## f.ostwest=west 11.618257 40.579710 24.1 1.731634e-03 3.132773  
## political\_interest=0 66.666667 2.898551 0.3 1.377478e-02 2.463084  
## income=1 17.857143 7.246377 2.8 4.793709e-02 1.977926  
## egoposition\_immigration=1 1.470588 1.449275 6.8 4.815760e-02 -1.975975  
## egoposition\_immigration=3 2.985075 5.797101 13.4 4.305493e-02 -2.023177  
## f.ostwest=east 5.401845 59.420290 75.9 1.731634e-03 -3.132773  
## egoposition\_immigration=5 1.290323 2.898551 15.5 6.970986e-04 -3.390718  
## egoposition\_immigration=4 1.117318 2.898551 17.9 1.193747e-04 -3.847407  
## egoposition\_immigration=2 0.000000 0.000000 13.0 4.641675e-05 -4.072973  
## f.gender=female 2.813853 18.840580 46.2 1.101835e-06 -4.872520  
##   
## $`CDU/CSU`  
## Cla/Mod Mod/Cla Global p.value v.test  
## egoposition\_immigration=5 39.35484 21.107266 15.5 2.326304e-03 3.045064  
## egoposition\_immigration=7 43.58974 11.764706 7.8 4.123963e-03 2.868521  
## egoposition\_immigration=6 40.00000 13.148789 9.5 1.484342e-02 2.436177  
## political\_interest=2 33.44156 35.640138 30.8 3.612343e-02 2.095535  
## egoposition\_immigration=1 17.64706 4.152249 6.8 2.975586e-02 -2.173325  
## income=2 22.34043 14.532872 18.8 2.589708e-02 -2.227752  
## egoposition\_immigration=2 14.61538 6.574394 13.0 5.395182e-05 -4.037813  
##   
## $FDP  
## Cla/Mod Mod/Cla Global p.value v.test  
## egoposition\_immigration=6 22.105263 17.3553719 9.5 0.0037845654 2.895582  
## egoposition\_immigration=0 2.040816 0.8264463 4.9 0.0139097453 -2.459586  
## egoposition\_immigration=2 3.076923 3.3057851 13.0 0.0001560324 -3.781267  
##   
## $Gruene  
## Cla/Mod Mod/Cla Global p.value v.test  
## egoposition\_immigration=2 28.461538 25.8741259 13.0 5.773018e-06 4.534536  
## f.gender=female 17.748918 57.3426573 46.2 4.072838e-03 2.872465  
## political\_interest=3 17.676768 48.9510490 39.6 1.459058e-02 2.442385  
## egoposition\_immigration=1 25.000000 11.8881119 6.8 1.540367e-02 2.422746  
## egoposition\_immigration=6 7.368421 4.8951049 9.5 3.395532e-02 -2.120602  
## egoposition\_immigration=8 0.000000 0.0000000 3.1 7.725865e-03 -2.663821  
## egoposition\_immigration=10 2.127660 0.6993007 4.7 6.044056e-03 -2.745382  
## egoposition\_immigration=9 0.000000 0.0000000 3.4 4.782805e-03 -2.821309  
## f.gender=male 11.338290 42.6573427 53.8 4.072838e-03 -2.872465  
## egoposition\_immigration=7 2.564103 1.3986014 7.8 4.551511e-04 -3.505850  
##   
## $LINKE  
## Cla/Mod Mod/Cla Global p.value v.test  
## f.ostwest=west 19.087137 37.398374 24.1 0.0004265885 3.523064  
## egoposition\_immigration=0 28.571429 11.382114 4.9 0.0017370354 3.131859  
## egoposition\_immigration=3 19.402985 21.138211 13.4 0.0109955600 2.542840  
## income=2 17.553191 26.829268 18.8 0.0192505867 2.340643  
## egoposition\_immigration=6 4.210526 3.252033 9.5 0.0061367219 -2.740385  
## egoposition\_immigration=5 5.161290 6.504065 15.5 0.0015851273 -3.158630  
## f.ostwest=east 10.144928 62.601626 75.9 0.0004265885 -3.523064  
## income=4 4.761905 7.317073 18.9 0.0001536281 -3.785130  
##   
## $SPD  
## Cla/Mod Mod/Cla Global p.value v.test  
## egoposition\_immigration=2 36.923077 18.823529 13.0 0.001985233 3.092433  
## egoposition\_immigration=1 38.235294 10.196078 6.8 0.016742431 2.392316  
## political\_interest=1 8.823529 1.176471 3.4 0.016261547 -2.402992

Profile and Feature Selection - we are going to look at two target variables, vote and f.vote *f.vote:* When we analysis the categorical variables we see voters for center parties are most significant when immigration policy is 5 so quite in the middle between open to not. Most of them are from the east part while voters from the west part are least significant. We can also see the income=4 is significant so more stable financially voters are for the center parties. Left parties voters are characterized with open views on immigration, both male and female and high income.

Right parties are mostly against immigration, they don’t have much interest in politics, mostly male voters and quite low income voters. *vote* We can see that for almost all parties the most significant value is immigration views. There is only one right party in the data so the inferring is like the above. CDU/CSU voters immigration openness have a wide spectrum (lowest is 1 and highest is 7). income = 2 so quite in the middle at that aspect. FDP is most significant for immigration while it can be 6, 0 or 2. Gruene is most significant for immigration 2, mostly female voters with quite high political interest. LINKE voters significantly when they from the west part of Germany and open for immigration policy. SPD voters are significant to have openness for immigration and low political interest.

# Modeling

Once data is preprocessed and understanded now we will start modeling and experimenting with the different logistic models. This process will be iterative and we will try mainly the nominal, ordinal and herarchical propousal

The naming we used is mnX for nominal models, moX for ordinal models and mhX for herarchical models.

## Grouping levels

In order to try to ther different models we will grouping of levels.

df$f.pos\_imm <- factor(ifelse(df$egoposition\_immigration %in% c(0,1,2,3),"open",ifelse(df$egoposition\_immigration %in% c(4,5,6,7),"mild","restrictive")))  
  
df$fo.vote <- factor(df$vote,levels = c("AfD","CDU/CSU","FDP","Gruene","LINKE","SPD"),ordered = T)   
  
df$f.vote\_center<-factor(ifelse(df$f.vote=="center", "center","other"))  
summary(df)

## vote egoposition\_immigration ostwest political\_interest  
## AfD : 69 4 :179 Min. :0.000 0: 3   
## CDU/CSU:289 5 :155 1st Qu.:1.000 1: 34   
## FDP :121 3 :134 Median :1.000 2:308   
## Gruene :143 2 :130 Mean :0.759 3:396   
## LINKE :123 6 : 95 3rd Qu.:1.000 4:259   
## SPD :255 7 : 78 Max. :1.000   
## (Other):229   
## income gender f.ostwest f.gender f.vote f.pos\_imm   
## 0: 13 Min. :0.000 west:241 male :538 center:665 mild :507   
## 1: 28 1st Qu.:0.000 east:759 female:462 left :266 open :381   
## 2:188 Median :0.000 right : 69 restrictive:112   
## 3:582 Mean :0.462   
## 4:189 3rd Qu.:1.000   
## Max. :1.000   
##   
## fo.vote f.vote\_center  
## AfD : 69 center:665   
## CDU/CSU:289 other :335   
## FDP :121   
## Gruene :143   
## LINKE :123   
## SPD :255   
##

We created a variable **pos\_imm** that groups the 10 levels of the variable egoposition\_immigration in 3 variables: open, mild, restrictive.

## Nominal proposal

### Train test split

Splitting for train and test before starting any modeling

set.seed(1310)  
  
t <- sample(1:nrow(df),round(0.66\*nrow(df),0)) # rows for training  
train <- df[t,] # working/training set  
test <- df[-t,] # testing set  
col(train)

## [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12]  
## [1,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [2,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [3,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [4,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [5,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [6,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [7,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [8,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [9,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [10,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [11,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [12,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [13,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [14,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [15,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [16,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [17,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [18,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [19,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [20,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [21,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [22,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [23,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [24,] 1 2 3 4 5 6 7 8 9 10 11 12  
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## [27,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [28,] 1 2 3 4 5 6 7 8 9 10 11 12  
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## [30,] 1 2 3 4 5 6 7 8 9 10 11 12  
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## [33,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [34,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [35,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [36,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [37,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [38,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [39,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [40,] 1 2 3 4 5 6 7 8 9 10 11 12  
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## [43,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [44,] 1 2 3 4 5 6 7 8 9 10 11 12  
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## [46,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [47,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [48,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [49,] 1 2 3 4 5 6 7 8 9 10 11 12  
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## [645,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [646,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [647,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [648,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [649,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [650,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [651,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [652,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [653,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [654,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [655,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [656,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [657,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [658,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [659,] 1 2 3 4 5 6 7 8 9 10 11 12  
## [660,] 1 2 3 4 5 6 7 8 9 10 11 12

summary(train)

## vote egoposition\_immigration ostwest political\_interest  
## AfD : 44 4 :109 Min. :0.0000 0: 3   
## CDU/CSU:201 5 :104 1st Qu.:0.0000 1: 25   
## FDP : 76 2 : 93 Median :1.0000 2:199   
## Gruene : 99 3 : 90 Mean :0.7424 3:275   
## LINKE : 73 6 : 62 3rd Qu.:1.0000 4:158   
## SPD :167 7 : 55 Max. :1.0000   
## (Other):147   
## income gender f.ostwest f.gender f.vote   
## 0: 7 Min. :0.0000 west:170 male :352 center:444   
## 1: 19 1st Qu.:0.0000 east:490 female:308 left :172   
## 2:118 Median :0.0000 right : 44   
## 3:391 Mean :0.4667   
## 4:125 3rd Qu.:1.0000   
## Max. :1.0000   
##   
## f.pos\_imm fo.vote f.vote\_center  
## mild :330 AfD : 44 center:444   
## open :260 CDU/CSU:201 other :216   
## restrictive: 70 FDP : 76   
## Gruene : 99   
## LINKE : 73   
## SPD :167   
##

### Baseline model

We are starting with the null model and then looking at a model with numerical variables, since we only have numerical qualitative (and not numerical quantitative variable) we are going to start with them. Then, we run step() to get the best model so far using the AIC (we get deviance of 906.63 and AIC 950.63). We run anova() and we see we cannot reject the null hypothesis and the models are equivalent so it is better for us the small model when we already know it’s significant that they are equivalent

library(nnet)  
mn0 <- multinom(vote ~ 1, data = train) #we start from the null model

## # weights: 12 (5 variable)  
## initial value 1182.561250   
## iter 10 value 1100.448557  
## iter 10 value 1100.448556  
## iter 10 value 1100.448556  
## final value 1100.448556   
## converged

summary(mn0)

## Call:  
## multinom(formula = vote ~ 1, data = train)  
##   
## Coefficients:  
## (Intercept)  
## CDU/CSU 1.5191111  
## FDP 0.5465433  
## Gruene 0.8109241  
## LINKE 0.5062714  
## SPD 1.3337962  
##   
## Std. Errors:  
## (Intercept)  
## CDU/CSU 0.1664401  
## FDP 0.1894334  
## Gruene 0.1811856  
## LINKE 0.1908553  
## SPD 0.1694557  
##   
## Residual Deviance: 2200.897   
## AIC: 2210.897

mn1 <- multinom(vote ~ egoposition\_immigration+political\_interest+income, data = train)

## # weights: 120 (95 variable)  
## initial value 1182.561250   
## iter 10 value 1016.465043  
## iter 20 value 981.826640  
## iter 30 value 974.337101  
## iter 40 value 971.618141  
## iter 50 value 969.399413  
## iter 60 value 968.415151  
## iter 70 value 967.955753  
## iter 80 value 967.832047  
## iter 90 value 967.823834  
## final value 967.823674   
## converged

summary(mn1)

## Warning in sqrt(diag(vc)): Se han producido NaNs

## Call:  
## multinom(formula = vote ~ egoposition\_immigration + political\_interest +   
## income, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 23.88642628 23.74416 24.63179  
## FDP -1.19279656 24.65541 24.89281  
## Gruene 8.51733481 24.36836 25.45159  
## LINKE -0.06838499 22.86734 24.68619  
## SPD -1.25175563 23.92244 25.22893  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU -12.05781 -11.178393  
## FDP -11.12925 -9.985576  
## Gruene -12.01689 -11.610664  
## LINKE -12.05722 -11.895156  
## SPD -11.82766 -11.895634  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU -10.84977 -11.92267  
## FDP -10.18250 -10.55074  
## Gruene -11.92503 -13.49521  
## LINKE -13.57151 -13.92803  
## SPD -11.65607 -12.85135  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU -13.29359 -14.43611  
## FDP -12.55220 -13.59951  
## Gruene -16.13191 -52.89336  
## LINKE -14.76186 -55.24596  
## SPD -14.40459 -15.65376  
## egoposition\_immigration9 egoposition\_immigration10 political\_interest1  
## CDU/CSU -13.69089 -14.28860 2.652758  
## FDP -12.35017 -14.58116 27.238565  
## Gruene -49.13763 -47.38158 19.496821  
## LINKE -15.08960 -15.34929 27.965278  
## SPD -14.60789 -14.62901 27.705532  
## political\_interest2 political\_interest3 political\_interest4 income1  
## CDU/CSU 1.717419 1.075232 1.480053 -12.69920  
## FDP 26.090822 25.173637 26.113876 -13.51474  
## Gruene 18.831472 18.633717 19.188632 -15.65721  
## LINKE 27.009016 26.407272 27.285427 -13.42391  
## SPD 28.113650 27.840059 28.389019 -13.35861  
## income2 income3 income4  
## CDU/CSU -11.64417 -11.01798 -11.28093  
## FDP -12.44573 -12.31734 -12.39050  
## Gruene -14.01281 -13.25524 -13.81278  
## LINKE -12.59278 -12.60377 -13.67993  
## SPD -12.56998 -12.42379 -12.66225  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 1.6090687 0.5047067 0.4822977  
## FDP 1.0128121 0.9240155 0.9460592  
## Gruene 0.7325946 0.5130944 0.4907638  
## LINKE 0.8374575 0.5963552 0.4866259  
## SPD 0.6860927 0.4611791 0.4292430  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU 0.7275925 0.7837726  
## FDP 1.0477539 1.0564755  
## Gruene 0.7775288 0.8354894  
## LINKE 0.7518575 0.8134060  
## SPD 0.7055631 0.7799929  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU 0.7818683 0.7072235  
## FDP 1.0634111 0.9988059  
## Gruene 0.8498136 0.8705807  
## LINKE 0.9595846 0.8909822  
## SPD 0.7764507 0.7190200  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU 0.5716845 0.7485897  
## FDP 0.9455698 1.1517588  
## Gruene 1.1370012 NaN  
## LINKE 0.7007685 NaN  
## SPD 0.6052898 0.9065726  
## egoposition\_immigration9 egoposition\_immigration10 political\_interest1  
## CDU/CSU 0.7062120 6.418397e-01 1.793946  
## FDP 1.0256521 1.317042e+00 1.030999  
## Gruene NaN 6.813618e-14 1.079460  
## LINKE 0.9393739 8.027868e-01 1.036177  
## SPD 0.7719213 6.404239e-01 1.093648  
## political\_interest2 political\_interest3 political\_interest4 income1  
## CDU/CSU 1.3876528 1.3714463 1.4142623 1.186171  
## FDP 0.4911872 0.4702267 0.5213306 1.332294  
## Gruene 0.4842213 0.4380932 0.5088829 1.417601  
## LINKE 0.4736135 0.4452111 0.5064841 1.273951  
## SPD 0.4541323 0.4206888 0.4808438 1.042519  
## income2 income3 income4  
## CDU/CSU 0.9695233 0.9413253 0.9810291  
## FDP 1.0360181 1.0029642 1.0500235  
## Gruene 0.9008534 0.8407436 0.9046876  
## LINKE 1.0205635 0.9908780 1.0785003  
## SPD 0.8143102 0.7816102 0.8327440  
##   
## Residual Deviance: 1935.647   
## AIC: 2125.647

#perform step for the best model so far  
mn2 <- step(mn1)

## Start: AIC=2125.65  
## vote ~ egoposition\_immigration + political\_interest + income  
##   
## trying - egoposition\_immigration   
## # weights: 60 (45 variable)  
## initial value 1182.561250   
## iter 10 value 1088.641763  
## iter 20 value 1081.366345  
## iter 30 value 1079.784519  
## iter 40 value 1076.623616  
## iter 50 value 1076.340277  
## iter 60 value 1076.331090  
## final value 1076.331066   
## converged  
## trying - political\_interest   
## # weights: 96 (75 variable)  
## initial value 1182.561250   
## iter 10 value 1018.199939  
## iter 20 value 990.779395  
## iter 30 value 984.525817  
## iter 40 value 982.445093  
## iter 50 value 981.552772  
## iter 60 value 980.651569  
## iter 70 value 980.514304  
## iter 80 value 980.512245  
## iter 80 value 980.512237  
## iter 80 value 980.512237  
## final value 980.512237   
## converged  
## trying - income   
## # weights: 96 (75 variable)  
## initial value 1182.561250   
## iter 10 value 1019.684488  
## iter 20 value 990.569161  
## iter 30 value 984.299425  
## iter 40 value 981.340135  
## iter 50 value 980.223552  
## iter 60 value 979.406199  
## iter 70 value 979.302915  
## iter 80 value 979.300505  
## iter 80 value 979.300499  
## iter 80 value 979.300499  
## final value 979.300499   
## converged  
## Df AIC  
## - income 75 2108.601  
## - political\_interest 75 2111.024  
## <none> 95 2125.647  
## - egoposition\_immigration 45 2242.662  
## # weights: 96 (75 variable)  
## initial value 1182.561250   
## iter 10 value 1019.684488  
## iter 20 value 990.569161  
## iter 30 value 984.299425  
## iter 40 value 981.340135  
## iter 50 value 980.223552  
## iter 60 value 979.406199  
## iter 70 value 979.302915  
## iter 80 value 979.300505  
## iter 80 value 979.300499  
## iter 80 value 979.300499  
## final value 979.300499   
## converged  
##   
## Step: AIC=2108.6  
## vote ~ egoposition\_immigration + political\_interest  
##   
## trying - egoposition\_immigration   
## # weights: 36 (25 variable)  
## initial value 1182.561250   
## iter 10 value 1093.758181  
## iter 20 value 1090.567430  
## iter 30 value 1086.844712  
## iter 40 value 1086.780802  
## final value 1086.780562   
## converged  
## trying - political\_interest   
## # weights: 72 (55 variable)  
## initial value 1182.561250   
## iter 10 value 1014.850739  
## iter 20 value 996.156887  
## iter 30 value 993.122497  
## iter 40 value 992.400488  
## iter 50 value 991.730191  
## iter 60 value 991.687444  
## final value 991.687363   
## converged  
## Df AIC  
## - political\_interest 55 2093.375  
## <none> 75 2108.601  
## - egoposition\_immigration 25 2223.561  
## # weights: 72 (55 variable)  
## initial value 1182.561250   
## iter 10 value 1014.850739  
## iter 20 value 996.156887  
## iter 30 value 993.122497  
## iter 40 value 992.400488  
## iter 50 value 991.730191  
## iter 60 value 991.687444  
## final value 991.687363   
## converged  
##   
## Step: AIC=2093.37  
## vote ~ egoposition\_immigration  
##   
## trying - egoposition\_immigration   
## # weights: 12 (5 variable)  
## initial value 1182.561250   
## iter 10 value 1100.448557  
## iter 10 value 1100.448556  
## iter 10 value 1100.448556  
## final value 1100.448556   
## converged  
## Df AIC  
## <none> 55 2093.375  
## - egoposition\_immigration 5 2210.897

summary(mn2)

## Warning in sqrt(diag(vc)): Se han producido NaNs

## Call:  
## multinom(formula = vote ~ egoposition\_immigration, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 13.75852 22.46502 23.12141  
## FDP 11.96656 23.24537 23.30388  
## Gruene 13.57600 23.02225 23.85400  
## LINKE 13.75840 21.45354 23.12155  
## SPD 14.04610 22.55214 23.65216  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU -11.86140 -10.896205  
## FDP -11.11927 -9.826382  
## Gruene -11.90201 -11.378654  
## LINKE -12.08442 -11.678852  
## SPD -11.81250 -11.694610  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU -10.62229 -11.63832  
## FDP -10.01990 -10.35719  
## Gruene -11.70345 -13.28841  
## LINKE -13.35219 -13.75852  
## SPD -11.48041 -12.65988  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU -13.06536 -14.09501  
## FDP -12.41855 -13.21933  
## Gruene -15.97399 -50.13675  
## LINKE -14.54686 -51.28199  
## SPD -14.24678 -15.29886  
## egoposition\_immigration9 egoposition\_immigration10  
## CDU/CSU -13.28853 -14.07699  
## FDP -11.96657 -14.36450  
## Gruene -46.41795 -45.19824  
## LINKE -14.67472 -15.05770  
## SPD -14.26926 -14.49809  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 0.4476368 0.4995094 0.4771901  
## FDP 0.8172638 0.9192562 0.9422261  
## Gruene 0.4983661 0.5024783 0.4804243  
## LINKE 0.4566391 0.5873461 0.4772006  
## SPD 0.4207306 0.4554929 0.4246961  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU 0.7070882 0.7782332  
## FDP 1.0275429 1.0497448  
## Gruene 0.7482334 0.8241990  
## LINKE 0.7211129 0.8037791  
## SPD 0.6804557 0.7748553  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU 0.7741962 0.7003156  
## FDP 1.0555496 0.9916394  
## Gruene 0.8365766 0.8591812  
## LINKE 0.9507398 0.8818289  
## SPD 0.7693646 0.7129501  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU 0.5588844 7.159441e-01  
## FDP 0.9341012 1.124934e+00  
## Gruene 1.1262382 NaN  
## LINKE 0.6837388 1.988259e-15  
## SPD 0.5928258 8.800973e-01  
## egoposition\_immigration9 egoposition\_immigration10  
## CDU/CSU 6.930046e-01 6.264599e-01  
## FDP 1.009523e+00 1.300900e+00  
## Gruene 5.361549e-14 4.323579e-13  
## LINKE 9.192968e-01 7.737973e-01  
## SPD 7.588109e-01 6.213479e-01  
##   
## Residual Deviance: 1983.375   
## AIC: 2093.375

anova(mn1,mn2)#we cannot reject the null hypothesis so it's statistically significant to say models are equivalent

## Likelihood ratio tests of Multinomial Models  
##   
## Response: vote  
## Model Resid. df Resid. Dev  
## 1 egoposition\_immigration 3245 1983.375  
## 2 egoposition\_immigration + political\_interest + income 3205 1935.647  
## Test Df LR stat. Pr(Chi)  
## 1   
## 2 1 vs 2 40 47.72738 0.187447

AIC(mn1,mn2)

## df AIC  
## mn1 95 2125.647  
## mn2 55 2093.375

### Improving the model

#### Adding factor and interactions

Once we have the best model at this point we are adding factors to the model whether it’s as interactions or additive to the model. Since we don’t have order between left center right we use multinom() and not polr(). We run step() to get the best model with the factors. We have got better AIC for m4

mn3 <- multinom(vote ~ egoposition\_immigration\*f.ostwest + egoposition\_immigration\*f.gender + egoposition\_immigration+f.gender + f.ostwest + f.gender\*f.ostwest, data = train) #adding factors to the model

## # weights: 210 (170 variable)  
## initial value 1182.561250   
## iter 10 value 986.761026  
## iter 20 value 943.243537  
## iter 30 value 932.465580  
## iter 40 value 926.496030  
## iter 50 value 922.849874  
## iter 60 value 921.228629  
## iter 70 value 920.326399  
## iter 80 value 920.052720  
## iter 90 value 919.977277  
## iter 100 value 919.953461  
## final value 919.953461   
## stopped after 100 iterations

summary(mn3)

## Call:  
## multinom(formula = vote ~ egoposition\_immigration \* f.ostwest +   
## egoposition\_immigration \* f.gender + egoposition\_immigration +   
## f.gender + f.ostwest + f.gender \* f.ostwest, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU -1.035851 19.769458 22.665296  
## FDP 3.132739 15.097966 -2.748651  
## Gruene 10.398893 9.376681 10.590462  
## LINKE 13.362008 4.919963 7.564261  
## SPD 13.940660 4.836495 7.932640  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU 16.539499 1.914865  
## FDP 10.209878 -3.140765  
## Gruene 3.564018 -10.987933  
## LINKE 1.514892 -12.389086  
## SPD 1.807081 -13.985465  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU 2.663997 19.004218  
## FDP -2.505849 13.913803  
## Gruene -20.745519 5.212086  
## LINKE -13.756216 4.263574  
## SPD -13.108260 4.276292  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU 0.9544107 -17.57140  
## FDP -3.6212203 -14.65523  
## Gruene -29.6498740 -21.98542  
## LINKE -15.0970480 -27.07954  
## SPD -14.6437091 -28.04505  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## CDU/CSU -0.8311466 0.1109251 10.434511  
## FDP -5.0003965 -13.1716411 5.581941  
## Gruene -20.3169615 -19.7638521 -1.771040  
## LINKE -13.7692907 -11.8347791 -4.184931  
## SPD -14.9710441 -13.4225090 -3.730153  
## f.genderfemale egoposition\_immigration1:f.ostwesteast  
## CDU/CSU 9.167657 -5.2583871  
## FDP -1.373848 -0.9839354  
## Gruene 10.063200 5.8788251  
## LINKE 7.632504 8.7020161  
## SPD 5.857797 9.0824039  
## egoposition\_immigration2:f.ostwesteast  
## CDU/CSU -9.728754  
## FDP 14.951324  
## Gruene 3.263119  
## LINKE 5.516478  
## SPD 4.433729  
## egoposition\_immigration3:f.ostwesteast  
## CDU/CSU -24.89248  
## FDP -19.11242  
## Gruene -11.89417  
## LINKE -10.50523  
## SPD -10.78409  
## egoposition\_immigration4:f.ostwesteast  
## CDU/CSU 3.103066  
## FDP 7.911430  
## Gruene 16.227166  
## LINKE 16.862789  
## SPD 17.497101  
## egoposition\_immigration5:f.ostwesteast  
## CDU/CSU -8.968881  
## FDP -4.568155  
## Gruene 14.205537  
## LINKE 3.461962  
## SPD 5.522994  
## egoposition\_immigration6:f.ostwesteast  
## CDU/CSU -26.69595  
## FDP -20.99649  
## Gruene -14.73256  
## LINKE -14.68945  
## SPD -13.68970  
## egoposition\_immigration7:f.ostwesteast  
## CDU/CSU -9.448743  
## FDP -5.540596  
## Gruene 9.084654  
## LINKE 4.835490  
## SPD 3.750847  
## egoposition\_immigration8:f.ostwesteast  
## CDU/CSU 8.172188  
## FDP 4.328021  
## Gruene -10.888608  
## LINKE -9.113264  
## SPD 16.916686  
## egoposition\_immigration9:f.ostwesteast  
## CDU/CSU -7.999167  
## FDP -3.977686  
## Gruene -6.672562  
## LINKE -14.096461  
## SPD 3.989437  
## egoposition\_immigration10:f.ostwesteast  
## CDU/CSU -10.498583  
## FDP -23.373745  
## Gruene -8.762297  
## LINKE -25.506710  
## SPD 2.284784  
## egoposition\_immigration1:f.genderfemale  
## CDU/CSU -2.215695  
## FDP 7.807129  
## Gruene -2.674636  
## LINKE -1.369820  
## SPD 0.992890  
## egoposition\_immigration2:f.genderfemale  
## CDU/CSU -4.0991414  
## FDP 6.3669457  
## Gruene -3.3187658  
## LINKE -2.5233710  
## SPD 0.2413348  
## egoposition\_immigration3:f.genderfemale  
## CDU/CSU 2.470592  
## FDP 13.520563  
## Gruene 3.294171  
## LINKE 4.661279  
## SPD 5.799285  
## egoposition\_immigration4:f.genderfemale  
## CDU/CSU 5.485178  
## FDP 15.970916  
## Gruene 5.044801  
## LINKE 5.831162  
## SPD 8.810248  
## egoposition\_immigration5:f.genderfemale  
## CDU/CSU 4.299748  
## FDP 14.818712  
## Gruene 3.835091  
## LINKE 6.368457  
## SPD 7.158491  
## egoposition\_immigration6:f.genderfemale  
## CDU/CSU -11.688704  
## FDP -2.528647  
## Gruene -11.118789  
## LINKE -11.056068  
## SPD -8.961771  
## egoposition\_immigration7:f.genderfemale  
## CDU/CSU -10.0823934  
## FDP -0.2423031  
## Gruene 0.1705946  
## LINKE -8.3305227  
## SPD -6.3041815  
## egoposition\_immigration8:f.genderfemale  
## CDU/CSU -13.485709  
## FDP 12.899453  
## Gruene -9.298014  
## LINKE -8.477075  
## SPD -9.424574  
## egoposition\_immigration9:f.genderfemale  
## CDU/CSU 13.436041  
## FDP 23.979362  
## Gruene -4.728201  
## LINKE -11.002870  
## SPD 16.453585  
## egoposition\_immigration10:f.genderfemale f.ostwesteast:f.genderfemale  
## CDU/CSU -9.402820 3.113586  
## FDP 10.555838 3.601912  
## Gruene -11.151496 2.723986  
## LINKE -29.226233 3.823589  
## SPD -7.330517 3.576934  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 32.70285 5.501084 6.0817967  
## FDP 34.33857 13.146876 0.5172893  
## Gruene 31.14352 4.739939 2.3987149  
## LINKE 31.12606 4.695725 2.2309020  
## SPD 31.12589 4.667901 2.2046900  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU 41.25233 32.71110  
## FDP 40.88155 34.34832  
## Gruene 37.90558 31.15461  
## LINKE 37.89180 31.13471  
## SPD 37.89129 31.13764  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU 32.71393 41.21168  
## FDP 34.35124 40.84467  
## Gruene 104.43047 37.88058  
## LINKE 31.15224 37.85717  
## SPD 31.13961 37.85433  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU 32.70692 38.426597  
## FDP 34.34388 54.766813  
## Gruene 207.15427 114.749375  
## LINKE 31.14252 6.465029  
## SPD 31.13299 38.861420  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## CDU/CSU 32.72320 32.73427 44.55523  
## FDP 34.35793 174.10899 49.39090  
## Gruene 85.75362 133.50884 48.97089  
## LINKE 31.13746 31.14585 48.96431  
## SPD 31.14090 31.14850 48.96354  
## f.genderfemale egoposition\_immigration1:f.ostwesteast  
## CDU/CSU 30.47379 5.509099  
## FDP 83.38970 13.153428  
## Gruene 30.48084 4.699315  
## LINKE 30.47635 4.719861  
## SPD 30.47761 4.679502  
## egoposition\_immigration2:f.ostwesteast  
## CDU/CSU 6.0879449  
## FDP 0.5172924  
## Gruene 2.3067455  
## LINKE 2.2363658  
## SPD 2.2183111  
## egoposition\_immigration3:f.ostwesteast  
## CDU/CSU 36.22815  
## FDP 40.33188  
## Gruene 39.49579  
## LINKE 39.48958  
## SPD 39.48913  
## egoposition\_immigration4:f.ostwesteast  
## CDU/CSU 10.874531  
## FDP 14.651419  
## Gruene 7.448012  
## LINKE 7.410481  
## SPD 7.419863  
## egoposition\_immigration5:f.ostwesteast  
## CDU/CSU 44.57288  
## FDP 49.40867  
## Gruene 111.09620  
## LINKE 48.99356  
## SPD 48.98082  
## egoposition\_immigration6:f.ostwesteast  
## CDU/CSU 36.26752  
## FDP 40.37177  
## Gruene 39.54661  
## LINKE 39.54311  
## SPD 39.53289  
## egoposition\_immigration7:f.ostwesteast  
## CDU/CSU 44.56091  
## FDP 49.39921  
## Gruene 71.91064  
## LINKE 48.98042  
## SPD 48.97238  
## egoposition\_immigration8:f.ostwesteast  
## CDU/CSU 3.842086e+01  
## FDP 5.455108e+01  
## Gruene 1.128638e-03  
## LINKE 8.522896e-05  
## SPD 3.798775e+01  
## egoposition\_immigration9:f.ostwesteast  
## CDU/CSU 44.57589295  
## FDP 49.41049508  
## Gruene 0.11158805  
## LINKE 0.08299103  
## SPD 48.98329466  
## egoposition\_immigration10:f.ostwesteast  
## CDU/CSU 4.457834e+01  
## FDP 1.035588e+00  
## Gruene 1.375834e-01  
## LINKE 2.334203e-05  
## SPD 4.897992e+01  
## egoposition\_immigration1:f.genderfemale  
## CDU/CSU 21.20173  
## FDP 84.71560  
## Gruene 21.20705  
## LINKE 21.21183  
## SPD 21.20697  
## egoposition\_immigration2:f.genderfemale  
## CDU/CSU 21.20093  
## FDP 84.71701  
## Gruene 21.20435  
## LINKE 21.20008  
## SPD 21.20411  
## egoposition\_immigration3:f.genderfemale  
## CDU/CSU 21.15312  
## FDP 84.75945  
## Gruene 21.16027  
## LINKE 21.15371  
## SPD 21.15814  
## egoposition\_immigration4:f.genderfemale  
## CDU/CSU 21.12701  
## FDP 84.78317  
## Gruene 21.13492  
## LINKE 21.12943  
## SPD 21.13470  
## egoposition\_immigration5:f.genderfemale  
## CDU/CSU 21.07318  
## FDP 84.84129  
## Gruene 21.08332  
## LINKE 21.09521  
## SPD 21.08029  
## egoposition\_immigration6:f.genderfemale  
## CDU/CSU 30.49359  
## FDP 83.39681  
## Gruene 30.51501  
## LINKE 30.51830  
## SPD 30.50132  
## egoposition\_immigration7:f.genderfemale  
## CDU/CSU 30.47532  
## FDP 83.39213  
## Gruene 195.90183  
## LINKE 30.48813  
## SPD 30.48383  
## egoposition\_immigration8:f.genderfemale  
## CDU/CSU 2.918773e-04  
## FDP 3.945480e+01  
## Gruene 9.291921e+01  
## LINKE 2.442387e+00  
## SPD 5.766429e-02  
## egoposition\_immigration9:f.genderfemale  
## CDU/CSU 3.530967e+01  
## FDP 7.059702e+01  
## Gruene 1.841280e-05  
## LINKE 4.065602e-05  
## SPD 3.531616e+01  
## egoposition\_immigration10:f.genderfemale f.ostwesteast:f.genderfemale  
## CDU/CSU 30.48743950 1.589755  
## FDP 195.28557182 1.692632  
## Gruene 173.76825042 1.696166  
## LINKE 0.01210097 1.680699  
## SPD 30.48926379 1.586273  
##   
## Residual Deviance: 1839.907   
## AIC: 2179.907

mn4 <- step(mn3)

## Start: AIC=2179.91  
## vote ~ egoposition\_immigration \* f.ostwest + egoposition\_immigration \*   
## f.gender + egoposition\_immigration + f.gender + f.ostwest +   
## f.gender \* f.ostwest  
##   
## trying - egoposition\_immigration:f.ostwest   
## # weights: 150 (120 variable)  
## initial value 1182.561250   
## iter 10 value 1000.863696  
## iter 20 value 965.807679  
## iter 30 value 956.202266  
## iter 40 value 953.474134  
## iter 50 value 952.508741  
## iter 60 value 951.612250  
## iter 70 value 951.189303  
## iter 80 value 951.115232  
## iter 90 value 951.107558  
## iter 100 value 951.106654  
## final value 951.106654   
## stopped after 100 iterations  
## trying - egoposition\_immigration:f.gender   
## # weights: 150 (120 variable)  
## initial value 1182.561250   
## iter 10 value 995.258738  
## iter 20 value 959.918026  
## iter 30 value 950.949076  
## iter 40 value 946.687840  
## iter 50 value 944.054604  
## iter 60 value 942.796861  
## iter 70 value 942.615099  
## iter 80 value 942.590830  
## iter 90 value 942.589851  
## iter 90 value 942.589842  
## iter 90 value 942.589842  
## final value 942.589842   
## converged  
## trying - f.ostwest:f.gender   
## # weights: 204 (165 variable)  
## initial value 1182.561250   
## iter 10 value 988.033325  
## iter 20 value 944.488441  
## iter 30 value 934.681180  
## iter 40 value 928.993020  
## iter 50 value 926.199621  
## iter 60 value 925.361315  
## iter 70 value 924.535078  
## iter 80 value 924.389023  
## iter 90 value 924.365060  
## iter 100 value 924.362490  
## final value 924.362490   
## stopped after 100 iterations  
## Df AIC  
## - egoposition\_immigration:f.gender 120 2125.180  
## - egoposition\_immigration:f.ostwest 120 2142.213  
## - f.ostwest:f.gender 165 2178.725  
## <none> 170 2179.907  
## # weights: 150 (120 variable)  
## initial value 1182.561250   
## iter 10 value 995.258738  
## iter 20 value 959.918026  
## iter 30 value 950.949076  
## iter 40 value 946.687840  
## iter 50 value 944.054604  
## iter 60 value 942.796861  
## iter 70 value 942.615099  
## iter 80 value 942.590830  
## iter 90 value 942.589851  
## iter 90 value 942.589842  
## iter 90 value 942.589842  
## final value 942.589842   
## converged  
##   
## Step: AIC=2125.18  
## vote ~ egoposition\_immigration + f.ostwest + f.gender + egoposition\_immigration:f.ostwest +   
## f.ostwest:f.gender  
##   
## trying - egoposition\_immigration:f.ostwest   
## # weights: 90 (70 variable)  
## initial value 1182.561250   
## iter 10 value 1013.010081  
## iter 20 value 982.363083  
## iter 30 value 977.848693  
## iter 40 value 976.230048  
## iter 50 value 975.629257  
## iter 60 value 975.175406  
## iter 70 value 975.123015  
## final value 975.122149   
## converged  
## trying - f.ostwest:f.gender   
## # weights: 144 (115 variable)  
## initial value 1182.561250   
## iter 10 value 997.861600  
## iter 20 value 965.776163  
## iter 30 value 955.490289  
## iter 40 value 951.222999  
## iter 50 value 947.907610  
## iter 60 value 946.803248  
## iter 70 value 946.598456  
## iter 80 value 946.579926  
## final value 946.579534   
## converged  
## Df AIC  
## - egoposition\_immigration:f.ostwest 70 2090.244  
## - f.ostwest:f.gender 115 2123.159  
## <none> 120 2125.180  
## # weights: 90 (70 variable)  
## initial value 1182.561250   
## iter 10 value 1013.010081  
## iter 20 value 982.363083  
## iter 30 value 977.848693  
## iter 40 value 976.230048  
## iter 50 value 975.629257  
## iter 60 value 975.175406  
## iter 70 value 975.123015  
## final value 975.122149   
## converged  
##   
## Step: AIC=2090.24  
## vote ~ egoposition\_immigration + f.ostwest + f.gender + f.ostwest:f.gender  
##   
## trying - egoposition\_immigration   
## # weights: 30 (20 variable)  
## initial value 1182.561250   
## iter 10 value 1097.706135  
## iter 20 value 1077.832206  
## final value 1077.822072   
## converged  
## trying - f.ostwest:f.gender   
## # weights: 84 (65 variable)  
## initial value 1182.561250   
## iter 10 value 1015.654193  
## iter 20 value 985.372061  
## iter 30 value 981.230513  
## iter 40 value 979.961086  
## iter 50 value 979.309356  
## iter 60 value 979.086244  
## iter 70 value 979.072244  
## final value 979.072226   
## converged  
## Df AIC  
## - f.ostwest:f.gender 65 2088.144  
## <none> 70 2090.244  
## - egoposition\_immigration 20 2195.644  
## # weights: 84 (65 variable)  
## initial value 1182.561250   
## iter 10 value 1015.654193  
## iter 20 value 985.372061  
## iter 30 value 981.230513  
## iter 40 value 979.961086  
## iter 50 value 979.309356  
## iter 60 value 979.086244  
## iter 70 value 979.072244  
## final value 979.072226   
## converged  
##   
## Step: AIC=2088.14  
## vote ~ egoposition\_immigration + f.ostwest + f.gender  
##   
## trying - egoposition\_immigration   
## # weights: 24 (15 variable)  
## initial value 1182.561250   
## iter 10 value 1098.838532  
## iter 20 value 1082.556825  
## final value 1082.554944   
## converged  
## trying - f.ostwest   
## # weights: 78 (60 variable)  
## initial value 1182.561250   
## iter 10 value 1014.431022  
## iter 20 value 989.166405  
## iter 30 value 986.060570  
## iter 40 value 985.017877  
## iter 50 value 984.271843  
## iter 60 value 984.202026  
## final value 984.200970   
## converged  
## trying - f.gender   
## # weights: 78 (60 variable)  
## initial value 1182.561250   
## iter 10 value 1019.333069  
## iter 20 value 991.080746  
## iter 30 value 988.016538  
## iter 40 value 987.241493  
## iter 50 value 986.538843  
## iter 60 value 986.440679  
## final value 986.439482   
## converged  
## Df AIC  
## <none> 65 2088.144  
## - f.ostwest 60 2088.402  
## - f.gender 60 2092.879  
## - egoposition\_immigration 15 2195.110

summary(mn4)

## Warning in sqrt(diag(vc)): Se han producido NaNs

## Call:  
## multinom(formula = vote ~ egoposition\_immigration + f.ostwest +   
## f.gender, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 12.87388 22.69786 23.95421  
## FDP 11.04126 23.46942 24.13506  
## Gruene 12.44048 23.20908 24.67870  
## LINKE 13.42062 21.67882 24.00366  
## SPD 13.21119 22.77007 24.49058  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU -11.92036 -11.017588  
## FDP -11.18180 -9.959415  
## Gruene -11.97919 -11.561083  
## LINKE -12.15894 -11.812496  
## SPD -11.87983 -11.836225  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU -10.67693 -11.71891  
## FDP -10.07080 -10.43605  
## Gruene -11.73672 -13.35886  
## LINKE -13.38159 -13.79394  
## SPD -11.52502 -12.72987  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU -13.06096 -14.03022  
## FDP -12.41817 -13.12650  
## Gruene -15.99003 -50.05268  
## LINKE -14.58748 -51.46609  
## SPD -14.25562 -15.18564  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## CDU/CSU -13.21250 -14.17540 0.82679446  
## FDP -11.89044 -14.46738 0.82560793  
## Gruene -47.59255 -46.48861 0.82484373  
## LINKE -14.66887 -15.18198 0.07834531  
## SPD -14.20410 -14.60946 0.67570739  
## f.genderfemale  
## CDU/CSU 1.212591  
## FDP 1.307153  
## Gruene 1.724084  
## LINKE 1.158749  
## SPD 1.358603  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 0.5122280 0.5003598 0.4778882  
## FDP 0.8739234 0.9196529 0.9424600  
## Gruene 0.5925912 0.5052027 0.4826923  
## LINKE 0.5383720 0.5919499 0.4815835  
## SPD 0.4951240 0.4557195 0.4248370  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU 0.7111779 0.7823976  
## FDP 1.0305406 1.0532228  
## Gruene 0.7551619 0.8309503  
## LINKE 0.7256608 0.8082596  
## SPD 0.6845974 0.7790125  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU 0.7784522 0.7071109  
## FDP 1.0588007 0.9967849  
## Gruene 0.8429810 0.8684546  
## LINKE 0.9549854 0.8873578  
## SPD 0.7735819 0.7197418  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU 0.5671457 7.286095e-01  
## FDP 0.9395561 1.134465e+00  
## Gruene 1.1338526 1.023053e-14  
## LINKE 0.6896313 NaN  
## SPD 0.6006811 8.908181e-01  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## CDU/CSU 7.069300e-01 6.403212e-01 0.3947255  
## FDP 1.020281e+00 1.308350e+00 0.4541452  
## Gruene 5.906620e-15 1.384313e-13 0.4596614  
## LINKE 9.263263e-01 7.845518e-01 0.4426203  
## SPD 7.717977e-01 6.364159e-01 0.4090098  
## f.genderfemale  
## CDU/CSU 0.4486235  
## FDP 0.4875686  
## Gruene 0.4894526  
## LINKE 0.4923775  
## SPD 0.4579042  
##   
## Residual Deviance: 1958.144   
## AIC: 2088.144

AIC(mn4,mn2)

## df AIC  
## mn4 65 2088.144  
## mn2 55 2093.375

#### Try: Model with grouped target

Model with target variable f.vote only

ow, we are taking f.vote which has 3 levels, each party is classified to 3 orientations: left, center or right. When we run the null model we already see a better AIC up to this point. Then we are doing the same process as above where we building a model with numerical qualitative variables, finding the best model so far, adding factors to the model and finding the best model so far with the factors. When we have nested models we are checking anova() to do hypothesis test to whether or not the models are equivalent. lastley, we check AIC for all models to see which one has the lowest. mm4 has Deviance = 890.39 AIC = 942.39. When we compare m4 and mm4 we get a better AIC for mm4 and that is when the parties are classified to 3 orientations.

mn5 <- multinom(f.vote ~ 1, data = train) #we start from the null model

## # weights: 6 (2 variable)  
## initial value 725.084111   
## final value 526.458791   
## converged

summary(mn5)

## Call:  
## multinom(formula = f.vote ~ 1, data = train)  
##   
## Coefficients:  
## (Intercept)  
## left -0.9483304  
## right -2.3116350  
##   
## Std. Errors:  
## (Intercept)  
## left 0.08981206  
## right 0.15804912  
##   
## Residual Deviance: 1052.918   
## AIC: 1056.918

#we do not have numerical quantitative variable and since all of the rest are based on numerical nominal variables we will use all of them  
mn6 <- multinom(f.vote ~ egoposition\_immigration+political\_interest+income, data = train)

## # weights: 60 (38 variable)  
## initial value 725.084111   
## iter 10 value 456.168439  
## iter 20 value 446.057543  
## iter 30 value 444.717209  
## iter 40 value 444.146706  
## iter 50 value 444.131478  
## final value 444.131460   
## converged

summary(mn6)

## Call:  
## multinom(formula = f.vote ~ egoposition\_immigration + political\_interest +   
## income, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## left -11.32642 -0.08588747 0.1167544  
## right -32.42102 -10.30938819 -15.8831716  
## egoposition\_immigration3 egoposition\_immigration4  
## left -0.1975929 -0.4423605  
## right 16.3206555 15.7531927  
## egoposition\_immigration5 egoposition\_immigration6  
## left -1.386498 -1.644621  
## right 15.563881 16.509761  
## egoposition\_immigration7 egoposition\_immigration8  
## left -1.531189 -29.5621  
## right 18.066566 19.2295  
## egoposition\_immigration9 egoposition\_immigration10 political\_interest1  
## left -1.890402 -1.391077 12.242232  
## right 18.278862 18.916510 -3.295561  
## political\_interest2 political\_interest3 political\_interest4 income1  
## left 12.005358 12.176963 12.323467 -1.315327  
## right -2.596897 -2.014394 -2.572874 16.526738  
## income2 income3 income4  
## left -1.11110 -1.080011 -1.586921  
## right 15.59054 15.238101 15.467256  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## left 0.7182638 4.973750e-01 4.554428e-01  
## right 1.0349290 5.875766e-12 3.806327e-14  
## egoposition\_immigration3 egoposition\_immigration4  
## left 0.4648766 0.4562481  
## right 0.5680083 0.6742502  
## egoposition\_immigration5 egoposition\_immigration6  
## left 0.4885262 0.5717643  
## right 0.6756945 0.5744171  
## egoposition\_immigration7 egoposition\_immigration8  
## left 0.5981309 6.497391e-13  
## right 0.3840580 5.340802e-01  
## egoposition\_immigration9 egoposition\_immigration10 political\_interest1  
## left 0.8559670 0.7539513 0.4128703  
## right 0.5165883 0.4292183 1.8222131  
## political\_interest2 political\_interest3 political\_interest4 income1  
## left 0.253046 0.2407271 0.2653714 1.0206290  
## right 1.448797 1.4317272 1.4697677 0.7309116  
## income2 income3 income4  
## left 0.8526212 0.8339727 0.8601191  
## right 0.4099221 0.3911208 0.4742087  
##   
## Residual Deviance: 888.2629   
## AIC: 964.2629

#perform step for the best model so far  
mn7 <- step(mn6)

## Start: AIC=964.26  
## f.vote ~ egoposition\_immigration + political\_interest + income  
##   
## trying - egoposition\_immigration   
## # weights: 30 (18 variable)  
## initial value 725.084111   
## iter 10 value 521.888285  
## iter 20 value 517.181076  
## iter 30 value 516.918542  
## final value 516.912871   
## converged  
## trying - political\_interest   
## # weights: 48 (30 variable)  
## initial value 725.084111   
## iter 10 value 456.988530  
## iter 20 value 450.177382  
## iter 30 value 448.746735  
## iter 40 value 448.688027  
## final value 448.687918   
## converged  
## trying - income   
## # weights: 48 (30 variable)  
## initial value 725.084111   
## iter 10 value 461.481384  
## iter 20 value 450.248582  
## iter 30 value 449.093444  
## iter 40 value 448.962266  
## final value 448.961603   
## converged  
## Df AIC  
## - political\_interest 30 957.3758  
## - income 30 957.9232  
## <none> 38 964.2629  
## - egoposition\_immigration 18 1069.8257  
## # weights: 48 (30 variable)  
## initial value 725.084111   
## iter 10 value 456.988530  
## iter 20 value 450.177382  
## iter 30 value 448.746735  
## iter 40 value 448.688027  
## final value 448.687918   
## converged  
##   
## Step: AIC=957.38  
## f.vote ~ egoposition\_immigration + income  
##   
## trying - egoposition\_immigration   
## # weights: 18 (10 variable)  
## initial value 725.084111   
## iter 10 value 522.541167  
## iter 20 value 522.042457  
## final value 522.038461   
## converged  
## trying - income   
## # weights: 36 (22 variable)  
## initial value 725.084111   
## iter 10 value 461.729548  
## iter 20 value 453.795789  
## iter 30 value 453.317368  
## final value 453.314577   
## converged  
## Df AIC  
## - income 22 950.6292  
## <none> 30 957.3758  
## - egoposition\_immigration 10 1064.0769  
## # weights: 36 (22 variable)  
## initial value 725.084111   
## iter 10 value 461.729548  
## iter 20 value 453.795789  
## iter 30 value 453.317368  
## final value 453.314577   
## converged  
##   
## Step: AIC=950.63  
## f.vote ~ egoposition\_immigration  
##   
## trying - egoposition\_immigration   
## # weights: 6 (2 variable)  
## initial value 725.084111   
## final value 526.458791   
## converged  
## Df AIC  
## <none> 22 950.6292  
## - egoposition\_immigration 2 1056.9176

summary(mn7) #best model so far has D() of 906.63 and AIC 950.63

## Call:  
## multinom(formula = f.vote ~ egoposition\_immigration, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## left -0.3101546 -0.1280989 0.07248564  
## right -15.5255709 -16.0437749 -10.98268115  
## egoposition\_immigration3 egoposition\_immigration4  
## left -0.2314419 -0.4539462  
## right 12.6168574 11.9282743  
## egoposition\_immigration5 egoposition\_immigration6  
## left -1.371602 -1.695178  
## right 11.764392 12.672939  
## egoposition\_immigration7 egoposition\_immigration8  
## left -1.535672 -20.36760  
## right 14.285878 15.27426  
## egoposition\_immigration9 egoposition\_immigration10  
## left -1.82992 -1.363822  
## right 14.30180 15.150879  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## left 0.3969581 4.897283e-01 4.485496e-01  
## right 0.1761316 1.849127e-14 4.682237e-12  
## egoposition\_immigration3 egoposition\_immigration4  
## left 0.4549808 0.4479801  
## right 0.5517438 0.6561703  
## egoposition\_immigration5 egoposition\_immigration6  
## left 0.4813560 0.5653880  
## right 0.6549405 0.5524845  
## egoposition\_immigration7 egoposition\_immigration8  
## left 0.5920795 6.198330e-09  
## right 0.3495674 4.780723e-01  
## egoposition\_immigration9 egoposition\_immigration10  
## left 0.8464060 0.7439148  
## right 0.4820056 0.3877377  
##   
## Residual Deviance: 906.6292   
## AIC: 950.6292

anova(mn6,mn7) #we cannot reject the null hypothesis and the models are equivalent so it is better for us the small model when we already know it's significant that they are equivalent

## Likelihood ratio tests of Multinomial Models  
##   
## Response: f.vote  
## Model Resid. df Resid. Dev  
## 1 egoposition\_immigration 1298 906.6292  
## 2 egoposition\_immigration + political\_interest + income 1282 888.2629  
## Test Df LR stat. Pr(Chi)  
## 1   
## 2 1 vs 2 16 18.36623 0.3028915

mn8 <- multinom(f.vote ~ egoposition\_immigration\*f.ostwest + egoposition\_immigration+f.ostwest + egoposition\_immigration\*f.gender + egoposition\_immigration+f.gender + f.gender\*f.ostwest, data = train) #adding interactions and additive of the factors

## # weights: 105 (68 variable)  
## initial value 725.084111   
## iter 10 value 438.797960  
## iter 20 value 418.826634  
## iter 30 value 414.591115  
## iter 40 value 413.588417  
## iter 50 value 413.492523  
## iter 60 value 413.489420  
## final value 413.489388   
## converged

summary(mn8)

## Warning in sqrt(diag(vc)): Se han producido NaNs

## Call:  
## multinom(formula = f.vote ~ egoposition\_immigration \* f.ostwest +   
## egoposition\_immigration + f.ostwest + egoposition\_immigration \*   
## f.gender + egoposition\_immigration + f.gender + f.gender \*   
## f.ostwest, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## left -0.2856259 0.7047544 -0.3828812  
## right -19.0536105 -7.0410793 -14.8556007  
## egoposition\_immigration3 egoposition\_immigration4  
## left -0.8850325 -0.1402507  
## right -7.5382096 17.5413318  
## egoposition\_immigration5 egoposition\_immigration6  
## left -2.099119 -1.184875  
## right 16.839326 -15.226761  
## egoposition\_immigration7 egoposition\_immigration8  
## left -2.392232 -25.78016  
## right 18.333649 42.73078  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## left 0.2858194 1.061232 -0.9319296  
## right 19.4592953 18.250683 -3.1387583  
## f.genderfemale egoposition\_immigration1:f.ostwesteast  
## left 1.445206 -0.2480027  
## right -9.356520 8.3753943  
## egoposition\_immigration2:f.ostwesteast  
## left 1.383857  
## right 14.652870  
## egoposition\_immigration3:f.ostwesteast  
## left 1.082537  
## right 27.769782  
## egoposition\_immigration4:f.ostwesteast  
## left 0.8217691  
## right -17.1281613  
## egoposition\_immigration5:f.ostwesteast  
## left 1.705784  
## right 1.643096  
## egoposition\_immigration6:f.ostwesteast  
## left -0.3028141  
## right 34.8811567  
## egoposition\_immigration7:f.ostwesteast  
## left 1.368001  
## right 2.579922  
## egoposition\_immigration8:f.ostwesteast  
## left -9.508673  
## right -21.008414  
## egoposition\_immigration9:f.ostwesteast  
## left -27.991519  
## right 1.634357  
## egoposition\_immigration10:f.ostwesteast  
## left -30.049356  
## right 4.214537  
## egoposition\_immigration1:f.genderfemale  
## left -1.33422  
## right 14.83857  
## egoposition\_immigration2:f.genderfemale  
## left -1.202865  
## right 17.875656  
## egoposition\_immigration3:f.genderfemale  
## left -0.3794274  
## right -1.3700620  
## egoposition\_immigration4:f.genderfemale  
## left -1.803952  
## right -13.523145  
## egoposition\_immigration5:f.genderfemale  
## left -1.201668  
## right -13.927514  
## egoposition\_immigration6:f.genderfemale  
## left -0.6452026  
## right 12.3355443  
## egoposition\_immigration7:f.genderfemale  
## left -0.4248866  
## right 10.3460260  
## egoposition\_immigration8:f.genderfemale  
## left -10.82189  
## right -14.32069  
## egoposition\_immigration9:f.genderfemale  
## left -38.20618  
## right -26.06350  
## egoposition\_immigration10:f.genderfemale f.ostwesteast:f.genderfemale  
## left -44.77646 -0.1314716  
## right 10.06435 -3.3142137  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## left 0.8752859 1.073922e+00 1.018067e+00  
## right 0.3846393 4.439104e-07 2.431957e-06  
## egoposition\_immigration3 egoposition\_immigration4  
## left 0.9990708 0.9709799  
## right 0.2977547 0.7643178  
## egoposition\_immigration5 egoposition\_immigration6  
## left 1.1903429 1.1801726  
## right 0.9440034 0.3459024  
## egoposition\_immigration7 egoposition\_immigration8  
## left 1.407314 NaN  
## right 0.572179 0.4816034  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## left 1.3289763 1.329142 0.9859048  
## right 0.8419081 1.111925 0.4807221  
## f.genderfemale egoposition\_immigration1:f.ostwesteast  
## left 0.9295549 1.180111e+00  
## right 0.7960925 4.506639e-07  
## egoposition\_immigration2:f.ostwesteast  
## left 1.105013e+00  
## right 2.432112e-06  
## egoposition\_immigration3:f.ostwesteast  
## left 1.0932910  
## right 0.2977547  
## egoposition\_immigration4:f.ostwesteast  
## left 1.075934e+00  
## right 1.064855e-08  
## egoposition\_immigration5:f.ostwesteast  
## left 1.260064  
## right 1.277593  
## egoposition\_immigration6:f.ostwesteast  
## left 1.2940635  
## right 0.3459024  
## egoposition\_immigration7:f.ostwesteast  
## left 1.5482721  
## right 0.7502783  
## egoposition\_immigration8:f.ostwesteast  
## left 3.961727e-15  
## right 5.617544e-01  
## egoposition\_immigration9:f.ostwesteast  
## left 2.116499e-11  
## right 1.102864e+00  
## egoposition\_immigration10:f.ostwesteast  
## left 5.544838e-12  
## right 1.142630e+00  
## egoposition\_immigration1:f.genderfemale  
## left 1.055651e+00  
## right 4.451431e-07  
## egoposition\_immigration2:f.genderfemale  
## left 9.615969e-01  
## right 2.432509e-06  
## egoposition\_immigration3:f.genderfemale  
## left 9.806000e-01  
## right 7.315275e-06  
## egoposition\_immigration4:f.genderfemale  
## left 9.624480e-01  
## right 9.159327e-10  
## egoposition\_immigration5:f.genderfemale  
## left 1.029048e+00  
## right 4.111612e-10  
## egoposition\_immigration6:f.genderfemale  
## left 1.202503  
## right 1.382038  
## egoposition\_immigration7:f.genderfemale  
## left 1.2951473  
## right 0.8630212  
## egoposition\_immigration8:f.genderfemale  
## left NaN  
## right 0.8850537  
## egoposition\_immigration9:f.genderfemale  
## left 7.628113e-16  
## right 5.714169e-15  
## egoposition\_immigration10:f.genderfemale f.ostwesteast:f.genderfemale  
## left NaN 0.4622766  
## right 0.9851713 1.5237416  
##   
## Residual Deviance: 826.9788   
## AIC: 962.9788

mn9 <- step(mn8)

## Start: AIC=962.98  
## f.vote ~ egoposition\_immigration \* f.ostwest + egoposition\_immigration +   
## f.ostwest + egoposition\_immigration \* f.gender + egoposition\_immigration +   
## f.gender + f.gender \* f.ostwest  
##   
## trying - egoposition\_immigration:f.ostwest   
## # weights: 75 (48 variable)  
## initial value 725.084111   
## iter 10 value 448.575810  
## iter 20 value 434.281433  
## iter 30 value 431.496473  
## iter 40 value 431.251015  
## iter 50 value 431.247801  
## final value 431.247792   
## converged  
## trying - egoposition\_immigration:f.gender   
## # weights: 75 (48 variable)  
## initial value 725.084111   
## iter 10 value 441.618775  
## iter 20 value 429.284741  
## iter 30 value 427.318326  
## iter 40 value 426.955079  
## iter 50 value 426.947763  
## final value 426.947751   
## converged  
## trying - f.ostwest:f.gender   
## # weights: 102 (66 variable)  
## initial value 725.084111   
## iter 10 value 444.344610  
## iter 20 value 421.620687  
## iter 30 value 417.307990  
## iter 40 value 416.535884  
## iter 50 value 416.487048  
## final value 416.486136   
## converged  
## Df AIC  
## - egoposition\_immigration:f.gender 48 949.8955  
## - egoposition\_immigration:f.ostwest 48 958.4956  
## <none> 68 962.9788  
## - f.ostwest:f.gender 66 964.9723  
## # weights: 75 (48 variable)  
## initial value 725.084111   
## iter 10 value 441.618775  
## iter 20 value 429.284741  
## iter 30 value 427.318326  
## iter 40 value 426.955079  
## iter 50 value 426.947763  
## final value 426.947751   
## converged  
##   
## Step: AIC=949.9  
## f.vote ~ egoposition\_immigration + f.ostwest + f.gender + egoposition\_immigration:f.ostwest +   
## f.ostwest:f.gender  
##   
## trying - egoposition\_immigration:f.ostwest   
## # weights: 45 (28 variable)  
## initial value 725.084111   
## iter 10 value 449.783637  
## iter 20 value 444.277160  
## iter 30 value 443.052673  
## iter 40 value 443.018542  
## final value 443.018448   
## converged  
## trying - f.ostwest:f.gender   
## # weights: 72 (46 variable)  
## initial value 725.084111   
## iter 10 value 442.884006  
## iter 20 value 431.127292  
## iter 30 value 429.544698  
## iter 40 value 429.256574  
## iter 50 value 429.252391  
## iter 50 value 429.252388  
## iter 50 value 429.252388  
## final value 429.252388   
## converged  
## Df AIC  
## - egoposition\_immigration:f.ostwest 28 942.0369  
## <none> 48 949.8955  
## - f.ostwest:f.gender 46 950.5048  
## # weights: 45 (28 variable)  
## initial value 725.084111   
## iter 10 value 449.783637  
## iter 20 value 444.277160  
## iter 30 value 443.052673  
## iter 40 value 443.018542  
## final value 443.018448   
## converged  
##   
## Step: AIC=942.04  
## f.vote ~ egoposition\_immigration + f.ostwest + f.gender + f.ostwest:f.gender  
##   
## trying - egoposition\_immigration   
## # weights: 15 (8 variable)  
## initial value 725.084111   
## iter 10 value 510.987881  
## final value 510.730162   
## converged  
## trying - f.ostwest:f.gender   
## # weights: 42 (26 variable)  
## initial value 725.084111   
## iter 10 value 450.771002  
## iter 20 value 445.952057  
## iter 30 value 445.206520  
## iter 40 value 445.193818  
## final value 445.193805   
## converged  
## Df AIC  
## <none> 28 942.0369  
## - f.ostwest:f.gender 26 942.3876  
## - egoposition\_immigration 8 1037.4603

summary(mn9) #best model so far we got f.vote ~ egoposition\_immigration + f.ostwest + f.gender

## Call:  
## multinom(formula = f.vote ~ egoposition\_immigration + f.ostwest +   
## f.gender + f.ostwest:f.gender, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## left -0.1196357 -0.1477489 0.08902546  
## right -14.7291425 -8.4965507 -11.50546378  
## egoposition\_immigration3 egoposition\_immigration4  
## left -0.2444172 -0.4830441  
## right 12.4481845 11.8787667  
## egoposition\_immigration5 egoposition\_immigration6  
## left -1.347746 -1.671159  
## right 11.550250 12.504413  
## egoposition\_immigration7 egoposition\_immigration8  
## left -1.565453 -23.95515  
## right 14.119166 14.76494  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## left -1.862396 -1.377627 -0.3844209  
## right 14.071361 14.962219 -0.3002072  
## f.genderfemale f.ostwesteast:f.genderfemale  
## left 0.06266327 0.1714193  
## right -0.34748631 -1.8830756  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## left 0.4577507 4.918084e-01 4.503731e-01  
## right 0.3347142 3.770825e-11 5.728233e-12  
## egoposition\_immigration3 egoposition\_immigration4  
## left 0.4565982 0.4501811  
## right 0.5571377 0.6611575  
## egoposition\_immigration5 egoposition\_immigration6  
## left 0.4829453 0.5668252  
## right 0.6611408 0.5617162  
## egoposition\_immigration7 egoposition\_immigration8  
## left 0.5941233 1.556453e-10  
## right 0.3635549 4.973523e-01  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## left 0.8484526 0.7455345 0.297174  
## right 0.5013187 0.4114641 0.444625  
## f.genderfemale f.ostwesteast:f.genderfemale  
## left 0.3642132 0.4272778  
## right 0.6077664 0.9884755  
##   
## Residual Deviance: 886.0369   
## AIC: 942.0369

#results are Deviance = 886.0369 AIC = 942.0369  
#since we don't have order between left center right we use multinom() and not polr()  
anova(mn8,mn9)

## Likelihood ratio tests of Multinomial Models  
##   
## Response: f.vote  
## Model  
## 1 egoposition\_immigration + f.ostwest + f.gender + f.ostwest:f.gender  
## 2 egoposition\_immigration \* f.ostwest + egoposition\_immigration + f.ostwest + egoposition\_immigration \* f.gender + egoposition\_immigration + f.gender + f.gender \* f.ostwest  
## Resid. df Resid. Dev Test Df LR stat. Pr(Chi)  
## 1 1292 886.0369   
## 2 1252 826.9788 1 vs 2 40 59.05812 0.02646565

AIC(mn5,mn6,mn7,mn8, mn9)

## df AIC  
## mn5 2 1056.9176  
## mn6 38 964.2629  
## mn7 22 950.6292  
## mn8 68 962.9788  
## mn9 28 942.0369

AIC(mn4,mn9)

## df AIC  
## mn4 65 2088.1445  
## mn9 28 942.0369

#### Try: Model with grouped immigration

Adding 3 levels of immigration policies to see if it will improve the current results we have.

summary(mn4)

## Warning in sqrt(diag(vc)): Se han producido NaNs

## Call:  
## multinom(formula = vote ~ egoposition\_immigration + f.ostwest +   
## f.gender, data = train)  
##   
## Coefficients:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 12.87388 22.69786 23.95421  
## FDP 11.04126 23.46942 24.13506  
## Gruene 12.44048 23.20908 24.67870  
## LINKE 13.42062 21.67882 24.00366  
## SPD 13.21119 22.77007 24.49058  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU -11.92036 -11.017588  
## FDP -11.18180 -9.959415  
## Gruene -11.97919 -11.561083  
## LINKE -12.15894 -11.812496  
## SPD -11.87983 -11.836225  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU -10.67693 -11.71891  
## FDP -10.07080 -10.43605  
## Gruene -11.73672 -13.35886  
## LINKE -13.38159 -13.79394  
## SPD -11.52502 -12.72987  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU -13.06096 -14.03022  
## FDP -12.41817 -13.12650  
## Gruene -15.99003 -50.05268  
## LINKE -14.58748 -51.46609  
## SPD -14.25562 -15.18564  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## CDU/CSU -13.21250 -14.17540 0.82679446  
## FDP -11.89044 -14.46738 0.82560793  
## Gruene -47.59255 -46.48861 0.82484373  
## LINKE -14.66887 -15.18198 0.07834531  
## SPD -14.20410 -14.60946 0.67570739  
## f.genderfemale  
## CDU/CSU 1.212591  
## FDP 1.307153  
## Gruene 1.724084  
## LINKE 1.158749  
## SPD 1.358603  
##   
## Std. Errors:  
## (Intercept) egoposition\_immigration1 egoposition\_immigration2  
## CDU/CSU 0.5122280 0.5003598 0.4778882  
## FDP 0.8739234 0.9196529 0.9424600  
## Gruene 0.5925912 0.5052027 0.4826923  
## LINKE 0.5383720 0.5919499 0.4815835  
## SPD 0.4951240 0.4557195 0.4248370  
## egoposition\_immigration3 egoposition\_immigration4  
## CDU/CSU 0.7111779 0.7823976  
## FDP 1.0305406 1.0532228  
## Gruene 0.7551619 0.8309503  
## LINKE 0.7256608 0.8082596  
## SPD 0.6845974 0.7790125  
## egoposition\_immigration5 egoposition\_immigration6  
## CDU/CSU 0.7784522 0.7071109  
## FDP 1.0588007 0.9967849  
## Gruene 0.8429810 0.8684546  
## LINKE 0.9549854 0.8873578  
## SPD 0.7735819 0.7197418  
## egoposition\_immigration7 egoposition\_immigration8  
## CDU/CSU 0.5671457 7.286095e-01  
## FDP 0.9395561 1.134465e+00  
## Gruene 1.1338526 1.023053e-14  
## LINKE 0.6896313 NaN  
## SPD 0.6006811 8.908181e-01  
## egoposition\_immigration9 egoposition\_immigration10 f.ostwesteast  
## CDU/CSU 7.069300e-01 6.403212e-01 0.3947255  
## FDP 1.020281e+00 1.308350e+00 0.4541452  
## Gruene 5.906620e-15 1.384313e-13 0.4596614  
## LINKE 9.263263e-01 7.845518e-01 0.4426203  
## SPD 7.717977e-01 6.364159e-01 0.4090098  
## f.genderfemale  
## CDU/CSU 0.4486235  
## FDP 0.4875686  
## Gruene 0.4894526  
## LINKE 0.4923775  
## SPD 0.4579042  
##   
## Residual Deviance: 1958.144   
## AIC: 2088.144

mn10 <- multinom(vote ~ f.pos\_imm+ f.ostwest + f.gender, data = train)

## # weights: 36 (25 variable)  
## initial value 1182.561250   
## iter 10 value 1025.447890  
## iter 20 value 1014.424402  
## iter 30 value 1014.010759  
## iter 40 value 1013.989218  
## final value 1013.989184   
## converged

summary(mn10)

## Call:  
## multinom(formula = vote ~ f.pos\_imm + f.ostwest + f.gender, data = train)  
##   
## Coefficients:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.98142339 0.8713091 -2.003682 0.87965638  
## FDP 0.04953250 0.5094032 -2.079536 0.88059188  
## Gruene -0.59457958 2.3292688 -16.060064 0.89632347  
## LINKE -0.03266986 2.1968737 -1.902881 0.09212084  
## SPD 0.37747920 2.0071868 -1.843331 0.74044144  
## f.genderfemale  
## CDU/CSU 1.223919  
## FDP 1.329733  
## Gruene 1.785887  
## LINKE 1.242254  
## SPD 1.388422  
##   
## Std. Errors:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.3615342 0.6479069 4.029835e-01 0.3784585  
## FDP 0.4214786 0.6919057 5.019812e-01 0.4366924  
## Gruene 0.4401078 0.6627350 1.518013e-06 0.4390491  
## LINKE 0.4184671 0.6727932 5.846785e-01 0.4251793  
## SPD 0.3813418 0.6475881 4.467069e-01 0.3915625  
## f.genderfemale  
## CDU/CSU 0.4358619  
## FDP 0.4717393  
## Gruene 0.4729874  
## LINKE 0.4795344  
## SPD 0.4445986  
##   
## Residual Deviance: 2027.978   
## AIC: 2077.978

mn11 <- step(mn10) #the null model is the best in such case

## Start: AIC=2077.98  
## vote ~ f.pos\_imm + f.ostwest + f.gender  
##   
## trying - f.pos\_imm   
## # weights: 24 (15 variable)  
## initial value 1182.561250   
## iter 10 value 1098.838532  
## iter 20 value 1082.556825  
## final value 1082.554944   
## converged  
## trying - f.ostwest   
## # weights: 30 (20 variable)  
## initial value 1182.561250   
## iter 10 value 1030.836516  
## iter 20 value 1020.417047  
## iter 30 value 1020.152831  
## final value 1020.152122   
## converged  
## trying - f.gender   
## # weights: 30 (20 variable)  
## initial value 1182.561250   
## iter 10 value 1034.724193  
## iter 20 value 1022.865731  
## iter 30 value 1022.550634  
## final value 1022.549730   
## converged  
## Df AIC  
## <none> 25 2077.978  
## - f.ostwest 20 2080.304  
## - f.gender 20 2085.099  
## - f.pos\_imm 15 2195.110

summary(mn11)

## Call:  
## multinom(formula = vote ~ f.pos\_imm + f.ostwest + f.gender, data = train)  
##   
## Coefficients:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.98142339 0.8713091 -2.003682 0.87965638  
## FDP 0.04953250 0.5094032 -2.079536 0.88059188  
## Gruene -0.59457958 2.3292688 -16.060064 0.89632347  
## LINKE -0.03266986 2.1968737 -1.902881 0.09212084  
## SPD 0.37747920 2.0071868 -1.843331 0.74044144  
## f.genderfemale  
## CDU/CSU 1.223919  
## FDP 1.329733  
## Gruene 1.785887  
## LINKE 1.242254  
## SPD 1.388422  
##   
## Std. Errors:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.3615342 0.6479069 4.029835e-01 0.3784585  
## FDP 0.4214786 0.6919057 5.019812e-01 0.4366924  
## Gruene 0.4401078 0.6627350 1.518013e-06 0.4390491  
## LINKE 0.4184671 0.6727932 5.846785e-01 0.4251793  
## SPD 0.3813418 0.6475881 4.467069e-01 0.3915625  
## f.genderfemale  
## CDU/CSU 0.4358619  
## FDP 0.4717393  
## Gruene 0.4729874  
## LINKE 0.4795344  
## SPD 0.4445986  
##   
## Residual Deviance: 2027.978   
## AIC: 2077.978

# factors and iunteractions  
mn12 <- multinom(vote ~ f.pos\_imm\*f.gender + f.pos\_imm\*f.ostwest + f.gender\*f.ostwest + f.pos\_imm + f.gender + f.ostwest, data = train)

## # weights: 66 (50 variable)  
## initial value 1182.561250   
## iter 10 value 1028.878277  
## iter 20 value 997.615972  
## iter 30 value 993.963592  
## iter 40 value 992.648866  
## iter 50 value 992.577635  
## final value 992.574782   
## converged

summary(mn12)

## Call:  
## multinom(formula = vote ~ f.pos\_imm \* f.gender + f.pos\_imm \*   
## f.ostwest + f.gender \* f.ostwest + f.pos\_imm + f.gender +   
## f.ostwest, data = train)  
##   
## Coefficients:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.genderfemale  
## CDU/CSU 0.842068810 20.14302 -2.9764183 0.7006387  
## FDP 0.008206608 19.06253 -2.0140379 0.5068699  
## Gruene -1.547900841 22.16873 -17.6872343 1.4002839  
## LINKE 0.063502125 20.71360 -0.0397381 0.3630504  
## SPD 0.242443595 21.24463 -1.1953991 0.4789603  
## f.ostwesteast f.pos\_immopen:f.genderfemale  
## CDU/CSU 1.1704050 10.06332  
## FDP 1.1460906 10.36200  
## Gruene 2.2924395 10.54142  
## LINKE 0.0111558 10.50199  
## SPD 1.0448928 10.34526  
## f.pos\_immrestrictive:f.genderfemale f.pos\_immopen:f.ostwesteast  
## CDU/CSU 0.64875677 -20.11419  
## FDP 1.21318193 -19.39338  
## Gruene -3.18805881 -21.09342  
## LINKE -27.52432998 -19.27786  
## SPD 0.08690619 -20.23095  
## f.pos\_immrestrictive:f.ostwesteast f.genderfemale:f.ostwesteast  
## CDU/CSU 0.7520380 1.0136729  
## FDP -0.9364422 1.1793687  
## Gruene -8.2098669 0.6049963  
## LINKE -28.0914907 1.4755324  
## SPD -0.9283256 1.4553001  
##   
## Std. Errors:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.genderfemale  
## CDU/CSU 0.4359928 0.5080500 1.068288e+00 0.7281806  
## FDP 0.5125814 0.7582589 1.102549e+00 0.8335582  
## Gruene 0.7393181 0.6501022 6.069433e-08 0.9161667  
## LINKE 0.5040206 0.5644682 7.959247e-01 0.8291225  
## SPD 0.4778661 0.5087063 8.756983e-01 0.7684653  
## f.ostwesteast f.pos\_immopen:f.genderfemale  
## CDU/CSU 0.5778084 0.3275690  
## FDP 0.6535921 0.4999632  
## Gruene 0.8298136 0.3917693  
## LINKE 0.6911335 0.4463558  
## SPD 0.6175505 0.3233339  
## f.pos\_immrestrictive:f.genderfemale f.pos\_immopen:f.ostwesteast  
## CDU/CSU 1.078769e+00 0.5198160  
## FDP 1.205001e+00 0.7801821  
## Gruene 4.700456e-09 0.6406191  
## LINKE 1.890442e-11 0.6049102  
## SPD 1.089450e+00 0.5220266  
## f.pos\_immrestrictive:f.ostwesteast f.genderfemale:f.ostwesteast  
## CDU/CSU 1.116927e+00 1.023099  
## FDP 1.153300e+00 1.103223  
## Gruene 1.511062e-10 1.139116  
## LINKE 2.745279e-11 1.122528  
## SPD 9.893533e-01 1.033454  
##   
## Residual Deviance: 1985.15   
## AIC: 2085.15

mn13 <- step(mn12)

## Start: AIC=2085.15  
## vote ~ f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest + f.gender \*   
## f.ostwest + f.pos\_imm + f.gender + f.ostwest  
##   
## trying - f.pos\_imm:f.gender   
## # weights: 54 (40 variable)  
## initial value 1182.561250   
## iter 10 value 1025.543845  
## iter 20 value 1000.676021  
## iter 30 value 998.029288  
## iter 40 value 997.324309  
## iter 50 value 997.313627  
## final value 997.313596   
## converged  
## trying - f.pos\_imm:f.ostwest   
## # weights: 54 (40 variable)  
## initial value 1182.561250   
## iter 10 value 1036.669603  
## iter 20 value 1006.466044  
## iter 30 value 1005.270511  
## iter 40 value 1004.829342  
## iter 50 value 1004.813002  
## iter 50 value 1004.812995  
## iter 50 value 1004.812995  
## final value 1004.812995   
## converged  
## trying - f.gender:f.ostwest   
## # weights: 60 (45 variable)  
## initial value 1182.561250   
## iter 10 value 1021.135931  
## iter 20 value 998.371079  
## iter 30 value 995.805686  
## iter 40 value 994.593594  
## iter 50 value 994.548545  
## final value 994.548232   
## converged  
## Df AIC  
## - f.pos\_imm:f.gender 40 2074.627  
## - f.gender:f.ostwest 45 2079.096  
## <none> 50 2085.150  
## - f.pos\_imm:f.ostwest 40 2089.626  
## # weights: 54 (40 variable)  
## initial value 1182.561250   
## iter 10 value 1025.543845  
## iter 20 value 1000.676021  
## iter 30 value 998.029288  
## iter 40 value 997.324309  
## iter 50 value 997.313627  
## final value 997.313596   
## converged  
##   
## Step: AIC=2074.63  
## vote ~ f.pos\_imm + f.gender + f.ostwest + f.pos\_imm:f.ostwest +   
## f.gender:f.ostwest  
##   
## trying - f.pos\_imm:f.ostwest   
## # weights: 42 (30 variable)  
## initial value 1182.561250   
## iter 10 value 1027.821725  
## iter 20 value 1010.535189  
## iter 30 value 1009.888242  
## iter 40 value 1009.816074  
## final value 1009.814886   
## converged  
## trying - f.gender:f.ostwest   
## # weights: 48 (35 variable)  
## initial value 1182.561250   
## iter 10 value 1025.703570  
## iter 20 value 1005.219931  
## iter 30 value 1001.766558  
## iter 40 value 1001.365284  
## final value 1001.363596   
## converged  
## Df AIC  
## - f.gender:f.ostwest 35 2072.727  
## <none> 40 2074.627  
## - f.pos\_imm:f.ostwest 30 2079.630  
## # weights: 48 (35 variable)  
## initial value 1182.561250   
## iter 10 value 1025.703570  
## iter 20 value 1005.219931  
## iter 30 value 1001.766558  
## iter 40 value 1001.365284  
## final value 1001.363596   
## converged  
##   
## Step: AIC=2072.73  
## vote ~ f.pos\_imm + f.gender + f.ostwest + f.pos\_imm:f.ostwest  
##   
## trying - f.gender   
## # weights: 42 (30 variable)  
## initial value 1182.561250   
## iter 10 value 1022.806301  
## iter 20 value 1011.912273  
## iter 30 value 1009.560751  
## iter 40 value 1009.525971  
## final value 1009.525925   
## converged  
## trying - f.pos\_imm:f.ostwest   
## # weights: 36 (25 variable)  
## initial value 1182.561250   
## iter 10 value 1025.447890  
## iter 20 value 1014.424402  
## iter 30 value 1014.010759  
## iter 40 value 1013.989218  
## final value 1013.989184   
## converged  
## Df AIC  
## <none> 35 2072.727  
## - f.pos\_imm:f.ostwest 25 2077.978  
## - f.gender 30 2079.052

summary(mn13)

## Call:  
## multinom(formula = vote ~ f.pos\_imm + f.gender + f.ostwest +   
## f.pos\_imm:f.ostwest, data = train)  
##   
## Coefficients:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.genderfemale  
## CDU/CSU 0.74607738 13.68937 -2.5627595 1.207207  
## FDP -0.20654951 12.73345 -1.2473539 1.290921  
## Gruene -1.53702238 15.96935 -13.9938317 1.752914  
## LINKE -0.15933075 14.43876 -0.7282273 1.181332  
## SPD -0.01243851 14.90774 -1.1876108 1.355113  
## f.ostwesteast f.pos\_immopen:f.ostwesteast  
## CDU/CSU 1.3642631 -13.63706  
## FDP 1.4056285 -12.90891  
## Gruene 2.2369262 -14.63641  
## LINKE 0.4047132 -12.77170  
## SPD 1.4364846 -13.74643  
## f.pos\_immrestrictive:f.ostwesteast  
## CDU/CSU 0.4081361  
## FDP -1.3610597  
## Gruene -5.2978568  
## LINKE -17.5974410  
## SPD -1.0821078  
##   
## Std. Errors:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.genderfemale  
## CDU/CSU 0.3815785 0.4863802 8.824206e-01 0.4370556  
## FDP 0.4502864 0.7213043 8.155260e-01 0.4716461  
## Gruene 0.6163559 0.5973264 4.820843e-06 0.4741763  
## LINKE 0.4491100 0.5244026 7.262817e-01 0.4782154  
## SPD 0.4270886 0.4873833 7.533086e-01 0.4451183  
## f.ostwesteast f.pos\_immopen:f.ostwesteast  
## CDU/CSU 0.5222971 0.5146901  
## FDP 0.5811688 0.7753481  
## Gruene 0.7185462 0.6328589  
## LINKE 0.6158152 0.5955045  
## SPD 0.5622533 0.5149145  
## f.pos\_immrestrictive:f.ostwesteast  
## CDU/CSU 1.020511e+00  
## FDP 1.044400e+00  
## Gruene 1.770667e-07  
## LINKE 6.417190e-07  
## SPD 9.481562e-01  
##   
## Residual Deviance: 2002.727   
## AIC: 2072.727

anova(mn12,mn13)

## Likelihood ratio tests of Multinomial Models  
##   
## Response: vote  
## Model  
## 1 f.pos\_imm + f.gender + f.ostwest + f.pos\_imm:f.ostwest  
## 2 f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest + f.gender \* f.ostwest + f.pos\_imm + f.gender + f.ostwest  
## Resid. df Resid. Dev Test Df LR stat. Pr(Chi)  
## 1 3265 2002.727   
## 2 3250 1985.150 1 vs 2 15 17.57763 0.2855212

mn14 <- multinom(vote ~ f.pos\_imm\*f.ostwest + f.pos\_imm+f.ostwest + f.pos\_imm\*f.gender + f.pos\_imm+f.gender, data = train)

## # weights: 60 (45 variable)  
## initial value 1182.561250   
## iter 10 value 1021.135931  
## iter 20 value 998.371079  
## iter 30 value 995.805686  
## iter 40 value 994.593594  
## iter 50 value 994.548545  
## final value 994.548232   
## converged

summary(mn14)

## Call:  
## multinom(formula = vote ~ f.pos\_imm \* f.ostwest + f.pos\_imm +   
## f.ostwest + f.pos\_imm \* f.gender + f.pos\_imm + f.gender,   
## data = train)  
##   
## Coefficients:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.76565593 21.82679 -3.12073568 1.361706  
## FDP -0.12274812 20.75086 -2.18501305 1.409739  
## Gruene -1.40250123 23.84432 -18.67417715 2.241614  
## LINKE -0.12634470 22.36512 0.04054433 0.403801  
## SPD 0.01770071 22.93832 -1.31218399 1.434220  
## f.genderfemale f.pos\_immopen:f.ostwesteast  
## CDU/CSU 1.067087 -21.92641  
## FDP 1.001319 -21.21242  
## Gruene 1.391722 -22.95244  
## LINKE 1.009933 -21.08539  
## SPD 1.189739 -22.04872  
## f.pos\_immrestrictive:f.ostwesteast f.pos\_immopen:f.genderfemale  
## CDU/CSU 0.8277184 11.72459  
## FDP -0.8093268 12.02374  
## Gruene -8.0079016 12.28050  
## LINKE -29.8988945 12.22442  
## SPD -0.8733945 11.99327  
## f.pos\_immrestrictive:f.genderfemale  
## CDU/CSU 0.74551032  
## FDP 1.26893616  
## Gruene -2.89565435  
## LINKE -29.92963708  
## SPD 0.08717591  
##   
## Std. Errors:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.3960843 0.5070991 1.035955e+00 0.5218664  
## FDP 0.4625147 0.7592421 1.099541e+00 0.5797765  
## Gruene 0.6343631 0.6363910 2.094639e-08 0.7162220  
## LINKE 0.4740253 0.5666567 7.696027e-01 0.6155962  
## SPD 0.4449089 0.5117873 8.871157e-01 0.5615967  
## f.genderfemale f.pos\_immopen:f.ostwesteast  
## CDU/CSU 0.5996971 0.5208151  
## FDP 0.6362933 0.7803573  
## Gruene 0.6684429 0.6385298  
## LINKE 0.6876548 0.6019060  
## SPD 0.6225991 0.5211162  
## f.pos\_immrestrictive:f.ostwesteast f.pos\_immopen:f.genderfemale  
## CDU/CSU 1.091219e+00 0.3262919  
## FDP 1.131469e+00 0.4971905  
## Gruene 7.768238e-11 0.3860159  
## LINKE 4.378142e-12 0.4373008  
## SPD 9.887854e-01 0.3208952  
## f.pos\_immrestrictive:f.genderfemale  
## CDU/CSU 1.004848e+00  
## FDP 1.170518e+00  
## Gruene 2.246759e-09  
## LINKE 1.728026e-12  
## SPD 1.052021e+00  
##   
## Residual Deviance: 1989.096   
## AIC: 2079.096

mn15 <- step(mn14)

## Start: AIC=2079.1  
## vote ~ f.pos\_imm \* f.ostwest + f.pos\_imm + f.ostwest + f.pos\_imm \*   
## f.gender + f.pos\_imm + f.gender  
##   
## trying - f.pos\_imm:f.ostwest   
## # weights: 48 (35 variable)  
## initial value 1182.561250   
## iter 10 value 1026.393092  
## iter 20 value 1010.011019  
## iter 30 value 1009.035126  
## iter 40 value 1008.766785  
## final value 1008.765509   
## converged  
## trying - f.pos\_imm:f.gender   
## # weights: 48 (35 variable)  
## initial value 1182.561250   
## iter 10 value 1025.703570  
## iter 20 value 1005.219931  
## iter 30 value 1001.766558  
## iter 40 value 1001.365284  
## final value 1001.363596   
## converged  
## Df AIC  
## - f.pos\_imm:f.gender 35 2072.727  
## <none> 45 2079.096  
## - f.pos\_imm:f.ostwest 35 2087.531  
## # weights: 48 (35 variable)  
## initial value 1182.561250   
## iter 10 value 1025.703570  
## iter 20 value 1005.219931  
## iter 30 value 1001.766558  
## iter 40 value 1001.365284  
## final value 1001.363596   
## converged  
##   
## Step: AIC=2072.73  
## vote ~ f.pos\_imm + f.ostwest + f.gender + f.pos\_imm:f.ostwest  
##   
## trying - f.gender   
## # weights: 42 (30 variable)  
## initial value 1182.561250   
## iter 10 value 1022.806301  
## iter 20 value 1011.912273  
## iter 30 value 1009.560751  
## iter 40 value 1009.525971  
## final value 1009.525925   
## converged  
## trying - f.pos\_imm:f.ostwest   
## # weights: 36 (25 variable)  
## initial value 1182.561250   
## iter 10 value 1025.447890  
## iter 20 value 1014.424402  
## iter 30 value 1014.010759  
## iter 40 value 1013.989218  
## final value 1013.989184   
## converged  
## Df AIC  
## <none> 35 2072.727  
## - f.pos\_imm:f.ostwest 25 2077.978  
## - f.gender 30 2079.052

summary(mn15)

## Call:  
## multinom(formula = vote ~ f.pos\_imm + f.ostwest + f.gender +   
## f.pos\_imm:f.ostwest, data = train)  
##   
## Coefficients:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.7460774 13.68937 -2.5627594 1.3642631  
## FDP -0.2065495 12.73345 -1.2473539 1.4056285  
## Gruene -1.5370224 15.96935 -13.9938317 2.2369262  
## LINKE -0.1593308 14.43876 -0.7282273 0.4047132  
## SPD -0.0124385 14.90774 -1.1876108 1.4364846  
## f.genderfemale f.pos\_immopen:f.ostwesteast  
## CDU/CSU 1.207207 -13.63706  
## FDP 1.290921 -12.90891  
## Gruene 1.752914 -14.63641  
## LINKE 1.181332 -12.77170  
## SPD 1.355113 -13.74643  
## f.pos\_immrestrictive:f.ostwesteast  
## CDU/CSU 0.4081361  
## FDP -1.3610597  
## Gruene -5.2978568  
## LINKE -17.5974410  
## SPD -1.0821078  
##   
## Std. Errors:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.3815785 0.4863802 8.824206e-01 0.5222971  
## FDP 0.4502864 0.7213043 8.155260e-01 0.5811688  
## Gruene 0.6163559 0.5973264 4.820843e-06 0.7185462  
## LINKE 0.4491100 0.5244026 7.262817e-01 0.6158152  
## SPD 0.4270886 0.4873833 7.533086e-01 0.5622533  
## f.genderfemale f.pos\_immopen:f.ostwesteast  
## CDU/CSU 0.4370556 0.5146901  
## FDP 0.4716461 0.7753481  
## Gruene 0.4741763 0.6328589  
## LINKE 0.4782154 0.5955045  
## SPD 0.4451183 0.5149145  
## f.pos\_immrestrictive:f.ostwesteast  
## CDU/CSU 1.020511e+00  
## FDP 1.044400e+00  
## Gruene 1.770667e-07  
## LINKE 6.417190e-07  
## SPD 9.481562e-01  
##   
## Residual Deviance: 2002.727   
## AIC: 2072.727

AIC(mn4,mn15)

## df AIC  
## mn4 65 2088.144  
## mn15 35 2072.727

# comparison of all models  
AIC(mn1, mn2, mn3, mn4, mn10,mn11,mn12,mn13, mn14, mn15)

## df AIC  
## mn1 95 2125.647  
## mn2 55 2093.375  
## mn3 170 2179.907  
## mn4 65 2088.144  
## mn10 25 2077.978  
## mn11 25 2077.978  
## mn12 50 2085.150  
## mn13 35 2072.727  
## mn14 45 2079.096  
## mn15 35 2072.727

####maybe we dont have to present them all, because the model after the step necessarily has lower AIC####  
summary(mn10)

## Call:  
## multinom(formula = vote ~ f.pos\_imm + f.ostwest + f.gender, data = train)  
##   
## Coefficients:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.98142339 0.8713091 -2.003682 0.87965638  
## FDP 0.04953250 0.5094032 -2.079536 0.88059188  
## Gruene -0.59457958 2.3292688 -16.060064 0.89632347  
## LINKE -0.03266986 2.1968737 -1.902881 0.09212084  
## SPD 0.37747920 2.0071868 -1.843331 0.74044144  
## f.genderfemale  
## CDU/CSU 1.223919  
## FDP 1.329733  
## Gruene 1.785887  
## LINKE 1.242254  
## SPD 1.388422  
##   
## Std. Errors:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.3615342 0.6479069 4.029835e-01 0.3784585  
## FDP 0.4214786 0.6919057 5.019812e-01 0.4366924  
## Gruene 0.4401078 0.6627350 1.518013e-06 0.4390491  
## LINKE 0.4184671 0.6727932 5.846785e-01 0.4251793  
## SPD 0.3813418 0.6475881 4.467069e-01 0.3915625  
## f.genderfemale  
## CDU/CSU 0.4358619  
## FDP 0.4717393  
## Gruene 0.4729874  
## LINKE 0.4795344  
## SPD 0.4445986  
##   
## Residual Deviance: 2027.978   
## AIC: 2077.978

summary(mn15)

## Call:  
## multinom(formula = vote ~ f.pos\_imm + f.ostwest + f.gender +   
## f.pos\_imm:f.ostwest, data = train)  
##   
## Coefficients:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.7460774 13.68937 -2.5627594 1.3642631  
## FDP -0.2065495 12.73345 -1.2473539 1.4056285  
## Gruene -1.5370224 15.96935 -13.9938317 2.2369262  
## LINKE -0.1593308 14.43876 -0.7282273 0.4047132  
## SPD -0.0124385 14.90774 -1.1876108 1.4364846  
## f.genderfemale f.pos\_immopen:f.ostwesteast  
## CDU/CSU 1.207207 -13.63706  
## FDP 1.290921 -12.90891  
## Gruene 1.752914 -14.63641  
## LINKE 1.181332 -12.77170  
## SPD 1.355113 -13.74643  
## f.pos\_immrestrictive:f.ostwesteast  
## CDU/CSU 0.4081361  
## FDP -1.3610597  
## Gruene -5.2978568  
## LINKE -17.5974410  
## SPD -1.0821078  
##   
## Std. Errors:  
## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.3815785 0.4863802 8.824206e-01 0.5222971  
## FDP 0.4502864 0.7213043 8.155260e-01 0.5811688  
## Gruene 0.6163559 0.5973264 4.820843e-06 0.7185462  
## LINKE 0.4491100 0.5244026 7.262817e-01 0.6158152  
## SPD 0.4270886 0.4873833 7.533086e-01 0.5622533  
## f.genderfemale f.pos\_immopen:f.ostwesteast  
## CDU/CSU 0.4370556 0.5146901  
## FDP 0.4716461 0.7753481  
## Gruene 0.4741763 0.6328589  
## LINKE 0.4782154 0.5955045  
## SPD 0.4451183 0.5149145  
## f.pos\_immrestrictive:f.ostwesteast  
## CDU/CSU 1.020511e+00  
## FDP 1.044400e+00  
## Gruene 1.770667e-07  
## LINKE 6.417190e-07  
## SPD 9.481562e-01  
##   
## Residual Deviance: 2002.727   
## AIC: 2072.727

Aggregating the levels of egoposition\_immigrations improve a little the results of the modeling part.

The model chosen as the best model is the model mn10 which formula is the following: formula = vote ~ f.pos\_imm + f.ostwest + f.gender

This model does not have the lowest Akaike but it’s not much different from the best model (mn15) and it’s more simple and it would be easy to explain.

### Goodness of fit and model interpretation

**Goodness of fit**

mn10$deviance;mn10$edf;2\*nrow(df)-mn10$edf

## [1] 2027.978

## [1] 25

## [1] 1975

1-pchisq(mn10$deviance, 2\*nrow(df)-mn10$edf)

## [1] 0.1987459

For the best model obtained which include f.pos\_imm, f.ostwest and f.gender has a p value of 0.1987459. This means that we fail to reject H0 where the model is consistent to data so we conclude by saying model fit’s well the data.

**Model interpretation**

We will interpret the different we will interpret the effects of the different variables into of f.ostweseast and f.genderfaemale.

coef(mn10)

## (Intercept) f.pos\_immopen f.pos\_immrestrictive f.ostwesteast  
## CDU/CSU 0.98142339 0.8713091 -2.003682 0.87965638  
## FDP 0.04953250 0.5094032 -2.079536 0.88059188  
## Gruene -0.59457958 2.3292688 -16.060064 0.89632347  
## LINKE -0.03266986 2.1968737 -1.902881 0.09212084  
## SPD 0.37747920 2.0071868 -1.843331 0.74044144  
## f.genderfemale  
## CDU/CSU 1.223919  
## FDP 1.329733  
## Gruene 1.785887  
## LINKE 1.242254  
## SPD 1.388422

#f.pos\_immopen  
coef(mn10)[,2]

## CDU/CSU FDP Gruene LINKE SPD   
## 0.8713091 0.5094032 2.3292688 2.1968737 2.0071868

exp(coef(mn10)[,2])

## CDU/CSU FDP Gruene LINKE SPD   
## 2.390038 1.664298 10.270429 8.996843 7.442351

100\*(exp(coef(mn10)[2])-1)

## [1] 5.077974

#f.pos\_immrestrictive  
coef(mn10)[,3]

## CDU/CSU FDP Gruene LINKE SPD   
## -2.003682 -2.079536 -16.060064 -1.902881 -1.843331

exp(coef(mn10)[,3])

## CDU/CSU FDP Gruene LINKE SPD   
## 1.348379e-01 1.249882e-01 1.059749e-07 1.491383e-01 1.582893e-01

100\*(exp(coef(mn10)[3])-1)

## [1] -44.82055

#f.ostwesteast  
coef(mn10)[,4]

## CDU/CSU FDP Gruene LINKE SPD   
## 0.87965638 0.88059188 0.89632347 0.09212084 0.74044144

exp(coef(mn10)[,4])

## CDU/CSU FDP Gruene LINKE SPD   
## 2.410071 2.412327 2.450577 1.096497 2.096861

100\*(exp(coef(mn10)[,4])-1)

## CDU/CSU FDP Gruene LINKE SPD   
## 141.007142 141.232709 145.057692 9.649732 109.686095

#f.genderfemale  
coef(mn10)[5]

## [1] 0.3774792

exp(coef(mn10)[,5])

## CDU/CSU FDP Gruene LINKE SPD   
## 3.400489 3.780032 5.964868 3.463413 4.008520

100\*(exp(coef(mn10)[,5])-1)

## CDU/CSU FDP Gruene LINKE SPD   
## 240.0489 278.0032 496.4868 246.3413 300.8520

With open position in immigration we can see that they have an increasce in the logodds of 2.32 for Gruene, 2.19 for LINKE, 2.007 for SPD, 0.871 FOR CDU/CSU and 0.509 for ADP. The increase is similar for the tree left partys. This makes sense since voters that are from left are more likely to be open about immigration. At the same time we can see that the one with lowest score is ADP that is a party from rights.

People that have a restrictive postition in immigration we get a decreasce in the logodds for all partys. Especially Gruene (-16.06) which is a left party. The other parties have a similar decreasce -2.003 FOR CDU/CSU, -0.079 for FDP, -1.902 for LINKE, -1.84 for SPD.

The log odds of being in from the east of germany will increase by 0.879 fior CDU/CSU, 0.88 for FDP, 0.896 for Gruene, 0.09 for LINKE, 0.74fSPD. The increasce is similar for three of the candidates and then we can see that SPD is following by not that far. Finally LINKE seems the least increasced by people from the east.

Being a female we can see different outcomes where there is also an increase of 1.22 for CDU/CSU, 1.32 for FDP, 1.78for Gruene, 1.24 for LINKE and 1.38 for SPD. In this case, all have a similar incease. However, Gruene is the one being the most benefited of that level.

**Prediction of probabilities**

predict(mn10, type="probs", newdata=data.frame(f.pos\_imm=factor("mild"), f.ostwest = factor("west"), f.gender=factor("male")))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.12991591 0.34664831 0.13651300 0.07168688 0.12574015 0.18949574

predict(mn10, type="probs", newdata=data.frame(f.pos\_imm=factor("mild"), f.ostwest = factor("west"), f.gender=factor("female")))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.03768515 0.34193091 0.14968470 0.12403620 0.12632406 0.22033898

predict(mn10, type="probs", newdata=data.frame(f.pos\_imm=factor("mild"), f.ostwest = factor("east"), f.gender=factor("female")))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.01771463 0.38737371 0.16973660 0.14288237 0.06511118 0.21718151

predict(mn10, type="probs", newdata=data.frame(f.pos\_imm=factor("mild"), f.ostwest = factor("east"), f.gender=factor("male")))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.06477751 0.41656320 0.16419960 0.08759311 0.06874537 0.19812122

predict(mn10, type="probs", newdata=data.frame(f.pos\_imm=factor("open"), f.ostwest = factor("east"), f.gender=factor("male")))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.01497312 0.23013021 0.06316712 0.20794405 0.14296232 0.34082318

predict(mn10, type="probs", newdata=data.frame(f.pos\_imm=factor("restrictive"), f.ostwest = factor("east"), f.gender=factor("male")))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 3.538167e-01 3.067942e-01 1.120973e-01 5.070223e-08 5.599986e-02 1.712918e-01

From this results we obtained that males and females from east and west with a mild pos\_imm are more likely to vote for CDU/CSU and then SPD. So this means that gender and being from the west are not big factors in the predictibility of the model.

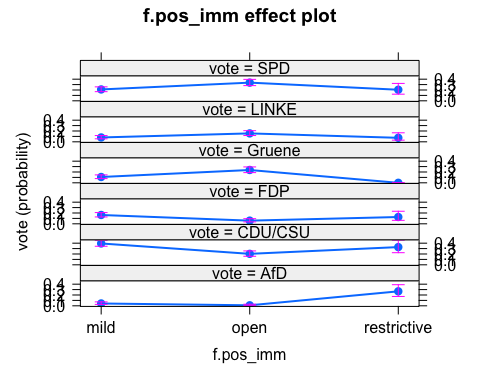
When predicting using pos\_imm we can see that the probabilities actually change a lot. From open we can see that the most probably partys are SPD, GRUENE and CDU/CSU(left-center). And when restrictrive it changes to AfD and CDU/CSU(right-center). So this model depending on if the immigration factor is open or restrictive it will change to be more likekly to vote to the left or right partys.

**Effects**

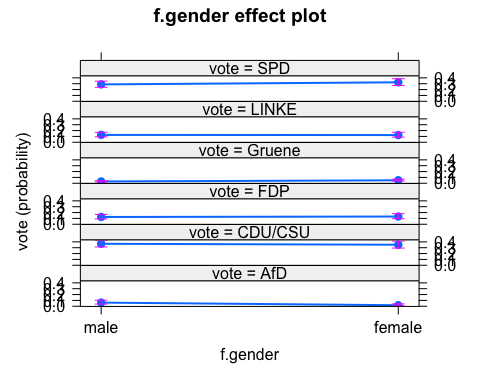
library(effects)

## lattice theme set by effectsTheme()  
## See ?effectsTheme for details.

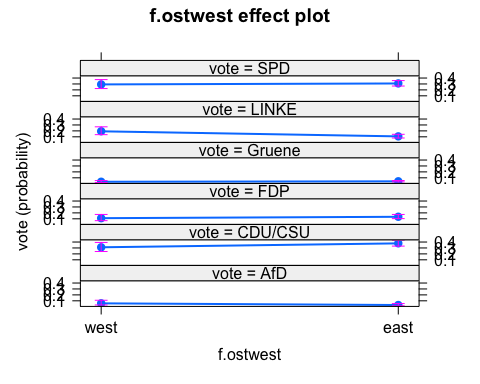
plot(Effect(focal.predictors = c("f.pos\_imm"), mn10))



plot(Effect(focal.predictors = c("f.gender"), mn10))



plot(Effect(focal.predictors = c("f.ostwest"), mn10))



From the effects plot we can see that AfD is getting a big probability when pos\_imm is restrictive and we can see that SPD and Gruene and LINKE are getting better probabilty when pos\_imm is open. From f.gender and f.ost there are no big insights to gather.

**Predictive power**

Let’s check the predictive power of the model using both train and test data and find the performance metrics of the model.

On train

tt<-table(predict(mn10),train$vote);tt #Checks that the model i not predicting part times

##   
## AfD CDU/CSU FDP Gruene LINKE SPD  
## AfD 19 12 3 0 5 8  
## CDU/CSU 22 137 58 36 27 73  
## FDP 0 0 0 0 0 0  
## Gruene 0 0 0 0 0 0  
## LINKE 0 0 0 0 0 0  
## SPD 3 52 15 63 41 86

tt

##   
## AfD CDU/CSU FDP Gruene LINKE SPD  
## AfD 19 12 3 0 5 8  
## CDU/CSU 22 137 58 36 27 73  
## FDP 0 0 0 0 0 0  
## Gruene 0 0 0 0 0 0  
## LINKE 0 0 0 0 0 0  
## SPD 3 52 15 63 41 86

100\*sum(diag(tt))/sum(tt) # ACCURACY of the model

## [1] 36.66667

On test

tt<-table(predict(mn10, newdata = test),test$vote);tt #Checks that the model i not predicting part times

##   
## AfD CDU/CSU FDP Gruene LINKE SPD  
## AfD 11 5 6 0 1 2  
## CDU/CSU 11 64 30 18 21 50  
## FDP 0 0 0 0 0 0  
## Gruene 0 0 0 0 0 0  
## LINKE 0 0 0 0 0 0  
## SPD 3 19 9 26 28 36

100\*sum(diag(tt))/sum(tt) # ACCURACY of the model

## [1] 32.64706

predicted <- predict(mn10, newdata = test)  
actual <- test$vote  
  
library(caret)

## Loading required package: lattice

confusionMatrix(predicted, actual, mode = "everything")

## Confusion Matrix and Statistics  
##   
## Reference  
## Prediction AfD CDU/CSU FDP Gruene LINKE SPD  
## AfD 11 5 6 0 1 2  
## CDU/CSU 11 64 30 18 21 50  
## FDP 0 0 0 0 0 0  
## Gruene 0 0 0 0 0 0  
## LINKE 0 0 0 0 0 0  
## SPD 3 19 9 26 28 36  
##   
## Overall Statistics  
##   
## Accuracy : 0.3265   
## 95% CI : (0.2769, 0.3791)  
## No Information Rate : 0.2588   
## P-Value [Acc > NIR] : 0.003193   
##   
## Kappa : 0.1077   
##   
## Mcnemar's Test P-Value : NA   
##   
## Statistics by Class:  
##   
## Class: AfD Class: CDU/CSU Class: FDP Class: Gruene  
## Sensitivity 0.44000 0.7273 0.0000 0.0000  
## Specificity 0.95556 0.4841 1.0000 1.0000  
## Pos Pred Value 0.44000 0.3299 NaN NaN  
## Neg Pred Value 0.95556 0.8356 0.8676 0.8706  
## Precision 0.44000 0.3299 NA NA  
## Recall 0.44000 0.7273 0.0000 0.0000  
## F1 0.44000 0.4539 NA NA  
## Prevalence 0.07353 0.2588 0.1324 0.1294  
## Detection Rate 0.03235 0.1882 0.0000 0.0000  
## Detection Prevalence 0.07353 0.5706 0.0000 0.0000  
## Balanced Accuracy 0.69778 0.6057 0.5000 0.5000  
## Class: LINKE Class: SPD  
## Sensitivity 0.0000 0.4091  
## Specificity 1.0000 0.6627  
## Pos Pred Value NaN 0.2975  
## Neg Pred Value 0.8529 0.7626  
## Precision NA 0.2975  
## Recall 0.0000 0.4091  
## F1 NA 0.3445  
## Prevalence 0.1471 0.2588  
## Detection Rate 0.0000 0.1059  
## Detection Prevalence 0.0000 0.3559  
## Balanced Accuracy 0.5000 0.5359

We can see that the best model found get’s a 37% of accuracy on train and 32% of accuracy on test. Those are not great results. Maybe there are more important explanatory variables that are missing in the data.

## Ordinal proposal

The target variable does not have a natural order to get so it’s better to use nominal models. However we prupose an order to try also ordinal models. The order we prupose is the following

* AfD<CDU/CSU<FDP<Gruene<LINKE<SPD

### Baseline model

library(MASS)  
mo0 <- polr(fo.vote ~ 1 , data = train)  
summary(mo0)

##   
## Re-fitting to get Hessian

## Call:  
## polr(formula = fo.vote ~ 1, data = train)  
##   
## No coefficients  
##   
## Intercepts:  
## Value Std. Error t value   
## AfD|CDU/CSU -2.6390 0.1560 -16.9118  
## CDU/CSU|FDP -0.5270 0.0806 -6.5410  
## FDP|Gruene -0.0545 0.0779 -0.7003  
## Gruene|LINKE 0.5596 0.0809 6.9161  
## LINKE|SPD 1.0825 0.0895 12.0906  
##   
## Residual Deviance: 2200.897   
## AIC: 2210.897

summary(train)

## vote egoposition\_immigration ostwest political\_interest  
## AfD : 44 4 :109 Min. :0.0000 0: 3   
## CDU/CSU:201 5 :104 1st Qu.:0.0000 1: 25   
## FDP : 76 2 : 93 Median :1.0000 2:199   
## Gruene : 99 3 : 90 Mean :0.7424 3:275   
## LINKE : 73 6 : 62 3rd Qu.:1.0000 4:158   
## SPD :167 7 : 55 Max. :1.0000   
## (Other):147   
## income gender f.ostwest f.gender f.vote   
## 0: 7 Min. :0.0000 west:170 male :352 center:444   
## 1: 19 1st Qu.:0.0000 east:490 female:308 left :172   
## 2:118 Median :0.0000 right : 44   
## 3:391 Mean :0.4667   
## 4:125 3rd Qu.:1.0000   
## Max. :1.0000   
##   
## f.pos\_imm fo.vote f.vote\_center  
## mild :330 AfD : 44 center:444   
## open :260 CDU/CSU:201 other :216   
## restrictive: 70 FDP : 76   
## Gruene : 99   
## LINKE : 73   
## SPD :167   
##

mo1 <- polr(fo.vote ~ political\_interest+income, data = train) #numeric qualitative variables  
summary(mo1)

##   
## Re-fitting to get Hessian

## Call:  
## polr(formula = fo.vote ~ political\_interest + income, data = train)  
##   
## Coefficients:  
## Value Std. Error t value  
## political\_interest1 3.0741 1.2527 2.4539  
## political\_interest2 3.4312 1.2146 2.8249  
## political\_interest3 3.6465 1.2147 3.0021  
## political\_interest4 3.6997 1.2177 3.0383  
## income1 -0.6251 0.7680 -0.8139  
## income2 -0.5193 0.6494 -0.7997  
## income3 -0.7034 0.6350 -1.1078  
## income4 -0.7636 0.6497 -1.1753  
##   
## Intercepts:  
## Value Std. Error t value  
## AfD|CDU/CSU 0.1954 1.3574 0.1440  
## CDU/CSU|FDP 2.3520 1.3638 1.7245  
## FDP|Gruene 2.8323 1.3641 2.0763  
## Gruene|LINKE 3.4550 1.3646 2.5319  
## LINKE|SPD 3.9828 1.3654 2.9170  
##   
## Residual Deviance: 2185.458   
## AIC: 2211.458

mo2 <- step(mo1)

## Start: AIC=2211.46  
## fo.vote ~ political\_interest + income  
##   
## Df AIC  
## - income 4 2205.9  
## <none> 2211.5  
## - political\_interest 4 2217.6  
##   
## Step: AIC=2205.88  
## fo.vote ~ political\_interest  
##   
## Df AIC  
## <none> 2205.9  
## - political\_interest 4 2210.9

summary(mo2)

##   
## Re-fitting to get Hessian

## Call:  
## polr(formula = fo.vote ~ political\_interest, data = train)  
##   
## Coefficients:  
## Value Std. Error t value  
## political\_interest1 3.034 1.254 2.420  
## political\_interest2 3.355 1.215 2.762  
## political\_interest3 3.550 1.214 2.925  
## political\_interest4 3.600 1.217 2.958  
##   
## Intercepts:  
## Value Std. Error t value  
## AfD|CDU/CSU 0.7853 1.2013 0.6537   
## CDU/CSU|FDP 2.9381 1.2096 2.4290   
## FDP|Gruene 3.4165 1.2103 2.8229   
## Gruene|LINKE 4.0364 1.2112 3.3326   
## LINKE|SPD 4.5625 1.2121 3.7641   
##   
## Residual Deviance: 2187.878   
## AIC: 2205.878

### Improving the model

#### Adding factors and interactions

mo3 <- polr(fo.vote ~ f.pos\_imm\*f.gender + f.pos\_imm\*f.ostwest + political\_interest\*f.ostwest + f.gender\*political\_interest + f.pos\_imm + political\_interest + f.ostwest + f.gender + f.pos\_imm\*political\_interest + f.gender\*f.ostwest , data = train,Hess = TRUE) #adding factors #WE GET A WARNING MESSAGE HERE WHICH I THINK IT'S ODD, IT DOESNT LET ME GENERATE SUMMARY UNLESS I ADD Hess = TRUE

## Warning in polr(fo.vote ~ f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest + :  
## design appears to be rank-deficient, so dropping some coefs

###### Missings: f.pos\_imm\*political\_interest + f.gender\*f.ostwest #######  
summary(mo3)

## Call:  
## polr(formula = fo.vote ~ f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest +   
## political\_interest \* f.ostwest + f.gender \* political\_interest +   
## f.pos\_imm + political\_interest + f.ostwest + f.gender + f.pos\_imm \*   
## political\_interest + f.gender \* f.ostwest, data = train,   
## Hess = TRUE)  
##   
## Coefficients:  
## Value Std. Error t value  
## f.pos\_immopen -7.29599 0.3356 -21.7393  
## f.pos\_immrestrictive -1.07968 0.7728 -1.3971  
## f.genderfemale 0.08757 0.4164 0.2103  
## f.ostwesteast -10.40952 0.2695 -38.6236  
## political\_interest1 0.98743 1.8876 0.5231  
## political\_interest2 1.17709 1.7143 0.6866  
## political\_interest3 1.31527 1.7109 0.7687  
## political\_interest4 1.65229 1.7128 0.9647  
## f.pos\_immopen:f.genderfemale -0.07176 0.3115 -0.2303  
## f.pos\_immrestrictive:f.genderfemale 0.63136 0.5924 1.0657  
## f.pos\_immopen:f.ostwesteast -0.29414 0.3582 -0.8212  
## f.pos\_immrestrictive:f.ostwesteast -0.90676 0.6510 -1.3929  
## f.ostwesteast:political\_interest1 10.01834 0.7533 13.2993  
## f.ostwesteast:political\_interest2 10.42995 0.3250 32.0964  
## f.ostwesteast:political\_interest3 10.30939 0.3122 33.0198  
## f.ostwesteast:political\_interest4 10.43031 0.3320 31.4134  
## f.genderfemale:political\_interest1 0.41091 0.9098 0.4516  
## f.genderfemale:political\_interest2 -0.37005 0.4110 -0.9004  
## f.genderfemale:political\_interest3 -0.16754 0.3838 -0.4366  
## f.pos\_immopen:political\_interest1 7.45100 0.7251 10.2763  
## f.pos\_immrestrictive:political\_interest1 1.88603 1.4800 1.2744  
## f.pos\_immopen:political\_interest2 8.77604 0.3024 29.0166  
## f.pos\_immrestrictive:political\_interest2 0.25138 0.7042 0.3570  
## f.pos\_immopen:political\_interest3 8.65011 0.2712 31.8912  
## f.pos\_immrestrictive:political\_interest3 0.74169 0.6990 1.0610  
## f.pos\_immopen:political\_interest4 8.18269 0.3115 26.2724  
## f.genderfemale:f.ostwesteast 0.57685 0.3440 1.6770  
##   
## Intercepts:  
## Value Std. Error t value   
## AfD|CDU/CSU -1.1900 1.6741 -0.7108  
## CDU/CSU|FDP 1.1900 1.6741 0.7109  
## FDP|Gruene 1.7372 1.6750 1.0371  
## Gruene|LINKE 2.4327 1.6760 1.4515  
## LINKE|SPD 2.9873 1.6768 1.7816  
##   
## Residual Deviance: 2089.376   
## AIC: 2153.376

mo4 <- step(mo3)

## Start: AIC=2153.38  
## fo.vote ~ f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest + political\_interest \*   
## f.ostwest + f.gender \* political\_interest + f.pos\_imm + political\_interest +   
## f.ostwest + f.gender + f.pos\_imm \* political\_interest + f.gender \*   
## f.ostwest

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Df AIC  
## - f.pos\_imm:political\_interest 7 2145.2  
## - f.ostwest:political\_interest 3 2147.6  
## - f.gender:political\_interest 3 2148.7  
## - f.pos\_imm:f.gender 2 2150.8  
## - f.pos\_imm:f.ostwest 2 2151.6  
## <none> 2153.4  
## - f.gender:f.ostwest 1 2154.2

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

##   
## Step: AIC=2145.15  
## fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.pos\_imm:f.gender + f.pos\_imm:f.ostwest + f.ostwest:political\_interest +   
## f.gender:political\_interest + f.gender:f.ostwest

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Df AIC  
## - f.gender:political\_interest 3 2139.9  
## - f.pos\_imm:f.gender 2 2141.9  
## - f.ostwest:political\_interest 4 2142.3  
## - f.pos\_imm:f.ostwest 2 2143.9  
## <none> 2145.2  
## - f.gender:f.ostwest 1 2145.8  
##   
## Step: AIC=2139.93  
## fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.pos\_imm:f.gender + f.pos\_imm:f.ostwest + f.ostwest:political\_interest +   
## f.gender:f.ostwest  
##   
## Df AIC  
## - f.pos\_imm:f.gender 2 2136.7  
## - f.ostwest:political\_interest 4 2137.2  
## - f.pos\_imm:f.ostwest 2 2138.8  
## <none> 2139.9  
## - f.gender:f.ostwest 1 2140.5  
##   
## Step: AIC=2136.65  
## fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.pos\_imm:f.ostwest + f.ostwest:political\_interest + f.gender:f.ostwest  
##   
## Df AIC  
## - f.ostwest:political\_interest 4 2133.8  
## - f.pos\_imm:f.ostwest 2 2135.9  
## <none> 2136.7  
## - f.gender:f.ostwest 1 2137.1  
##   
## Step: AIC=2133.82  
## fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.pos\_imm:f.ostwest + f.gender:f.ostwest  
##   
## Df AIC  
## - f.pos\_imm:f.ostwest 2 2132.9  
## <none> 2133.8  
## - f.gender:f.ostwest 1 2134.7  
## - political\_interest 4 2139.4  
##   
## Step: AIC=2132.86  
## fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.gender:f.ostwest  
##   
## Df AIC  
## <none> 2132.9  
## - f.gender:f.ostwest 1 2133.5  
## - political\_interest 4 2138.9  
## - f.pos\_imm 2 2200.5

summary(mo4)

## Call:  
## polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.gender:f.ostwest, data = train, Hess = TRUE)  
##   
## Coefficients:  
## Value Std. Error t value  
## f.pos\_immopen 0.94589 0.1505 6.2837  
## f.pos\_immrestrictive -1.10495 0.2771 -3.9876  
## f.genderfemale -0.06102 0.2855 -0.2137  
## f.ostwesteast -0.27668 0.2270 -1.2187  
## political\_interest1 2.74812 1.3273 2.0705  
## political\_interest2 3.18933 1.2870 2.4781  
## political\_interest3 3.34676 1.2843 2.6059  
## political\_interest4 3.56629 1.2870 2.7711  
## f.genderfemale:f.ostwesteast 0.53377 0.3275 1.6300  
##   
## Intercepts:  
## Value Std. Error t value  
## AfD|CDU/CSU 0.6686 1.2790 0.5228  
## CDU/CSU|FDP 3.0046 1.2871 2.3344  
## FDP|Gruene 3.5426 1.2881 2.7502  
## Gruene|LINKE 4.2275 1.2894 3.2787  
## LINKE|SPD 4.7769 1.2904 3.7019  
##   
## Residual Deviance: 2104.859   
## AIC: 2132.859

anova(mo4,mo3)

## Likelihood ratio tests of ordinal regression models  
##   
## Response: fo.vote  
## Model  
## 1 f.pos\_imm + f.gender + f.ostwest + political\_interest + f.gender:f.ostwest  
## 2 f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest + political\_interest \* f.ostwest + f.gender \* political\_interest + f.pos\_imm + political\_interest + f.ostwest + f.gender + f.pos\_imm \* political\_interest + f.gender \* f.ostwest  
## Resid. df Resid. Dev Test Df LR stat. Pr(Chi)  
## 1 646 2104.859   
## 2 628 2089.376 1 vs 2 18 15.48349 0.6285457

AIC(mo4,mo3)

## df AIC  
## mo4 14 2132.859  
## mo3 32 2153.376

# mo4 Akaike 2131

#### Try: Grouped target

mo5 <- polr(f.vote ~ political\_interest+income, data = train) #numerical qualitative variables  
summary(mo5)

##   
## Re-fitting to get Hessian

## Call:  
## polr(formula = f.vote ~ political\_interest + income, data = train)  
##   
## Coefficients:  
## Value Std. Error t value  
## political\_interest1 -2.90121 1.3801 -2.10214  
## political\_interest2 -2.99554 1.3239 -2.26264  
## political\_interest3 -2.71038 1.3213 -2.05125  
## political\_interest4 -2.72137 1.3256 -2.05298  
## income1 -0.02585 0.8741 -0.02957  
## income2 -0.22890 0.7547 -0.30331  
## income3 -0.31966 0.7379 -0.43322  
## income4 -0.63010 0.7591 -0.83006  
##   
## Intercepts:  
## Value Std. Error t value  
## center|left -2.4213 1.5076 -1.6060  
## left|right -0.4760 1.5021 -0.3169  
##   
## Residual Deviance: 1042.865   
## AIC: 1062.865

mo6 <- step(mo5)

## Start: AIC=1062.87  
## f.vote ~ political\_interest + income  
##   
## Df AIC  
## - income 4 1058.0  
## - political\_interest 4 1061.8  
## <none> 1062.9  
##   
## Step: AIC=1057.98  
## f.vote ~ political\_interest  
##   
## Df AIC  
## - political\_interest 4 1056.9  
## <none> 1058.0  
##   
## Step: AIC=1056.92  
## f.vote ~ 1

summary(mo6)

##   
## Re-fitting to get Hessian

## Call:  
## polr(formula = f.vote ~ 1, data = train)  
##   
## No coefficients  
##   
## Intercepts:  
## Value Std. Error t value  
## center|left 0.7205 0.0830 8.6858  
## left|right 2.6391 0.1560 16.9119  
##   
## Residual Deviance: 1052.918   
## AIC: 1056.918

mo7 <- polr(f.vote ~ f.pos\_imm\*f.gender + f.pos\_imm\*f.ostwest + political\_interest\*f.ostwest + f.gender\*political\_interest + f.pos\_imm + political\_interest + f.ostwest + f.gender + f.pos\_imm\*political\_interest + f.gender\*f.ostwest , data = train,Hess = TRUE) #adding factors

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in polr(f.vote ~ f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest + : design  
## appears to be rank-deficient, so dropping some coefs

summary(mo7)

## Call:  
## polr(formula = f.vote ~ f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest +   
## political\_interest \* f.ostwest + f.gender \* political\_interest +   
## f.pos\_imm + political\_interest + f.ostwest + f.gender + f.pos\_imm \*   
## political\_interest + f.gender \* f.ostwest, data = train,   
## Hess = TRUE)  
##   
## Coefficients:  
## Value Std. Error t value  
## f.pos\_immopen 2.52016 0.4189 6.0155  
## f.pos\_immrestrictive 1.76500 0.8443 2.0906  
## f.genderfemale -0.15993 0.4845 -0.3301  
## f.ostwesteast 34.22685 0.2829 120.9861  
## political\_interest1 -39.25663 0.5248 -74.7969  
## political\_interest2 18.52792 0.3725 49.7441  
## political\_interest3 19.19981 0.3205 59.9031  
## political\_interest4 19.30680 0.3255 59.3129  
## f.pos\_immopen:f.genderfemale 0.57114 0.3791 1.5066  
## f.pos\_immrestrictive:f.genderfemale -2.07895 0.7803 -2.6642  
## f.pos\_immopen:f.ostwesteast 0.76580 0.4117 1.8601  
## f.pos\_immrestrictive:f.ostwesteast -0.79008 0.7455 -1.0598  
## f.ostwesteast:political\_interest1 -4.51207 0.4561 -9.8920  
## f.ostwesteast:political\_interest2 -34.89832 0.3394 -102.8086  
## f.ostwesteast:political\_interest3 -34.88833 0.2920 -119.4734  
## f.ostwesteast:political\_interest4 -35.01638 0.3278 -106.8178  
## f.genderfemale:political\_interest1 30.49430 0.4561 66.8543  
## f.genderfemale:political\_interest2 0.33686 0.5108 0.6595  
## f.genderfemale:political\_interest3 0.08923 0.4575 0.1950  
## f.pos\_immopen:political\_interest1 -6.20820 1.0205 -6.0834  
## f.pos\_immrestrictive:political\_interest1 58.09948 0.7994 72.6793  
## f.pos\_immopen:political\_interest2 -2.51399 0.3931 -6.3947  
## f.pos\_immrestrictive:political\_interest2 0.97995 0.8826 1.1103  
## f.pos\_immopen:political\_interest3 -2.81922 0.3455 -8.1591  
## f.pos\_immrestrictive:political\_interest3 0.19544 0.8113 0.2409  
## f.pos\_immopen:political\_interest4 -2.81058 0.3922 -7.1661  
## f.genderfemale:f.ostwesteast -0.18441 0.4058 -0.4545  
##   
## Intercepts:  
## Value Std. Error t value   
## center|left 19.5514 0.2621 74.5880  
## left|right 21.6650 0.2985 72.5821  
##   
## Residual Deviance: 971.7689   
## AIC: 1029.769

mo8 <- step(mo7)

## Start: AIC=1029.77  
## f.vote ~ f.pos\_imm \* f.gender + f.pos\_imm \* f.ostwest + political\_interest \*   
## f.ostwest + f.gender \* political\_interest + f.pos\_imm + political\_interest +   
## f.ostwest + f.gender + f.pos\_imm \* political\_interest + f.gender \*   
## f.ostwest

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Df AIC  
## - f.gender:f.ostwest 1 1028.0  
## <none> 1029.8  
## - f.gender:political\_interest 3 1030.3  
## - f.pos\_imm:f.ostwest 2 1031.9  
## - f.pos\_imm:political\_interest 7 1033.7  
## - f.ostwest:political\_interest 3 1035.5  
## - f.pos\_imm:f.gender 2 1039.8

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: design appears to be rank-deficient, so dropping some coefs

##   
## Step: AIC=1027.98  
## f.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.pos\_imm:f.gender + f.pos\_imm:f.ostwest + f.ostwest:political\_interest +   
## f.gender:political\_interest + f.pos\_imm:political\_interest

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Warning in polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest +  
## political\_interest + : design appears to be rank-deficient, so dropping some  
## coefs

## Df AIC  
## <none> 1028.0  
## - f.gender:political\_interest 3 1028.4  
## - f.pos\_imm:f.ostwest 2 1029.9  
## - f.pos\_imm:political\_interest 7 1031.9  
## - f.ostwest:political\_interest 3 1033.5  
## - f.pos\_imm:f.gender 2 1037.8

summary(mo8)

## Call:  
## polr(formula = f.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.pos\_imm:f.gender + f.pos\_imm:f.ostwest + f.ostwest:political\_interest +   
## f.gender:political\_interest + f.pos\_imm:political\_interest,   
## data = train, Hess = TRUE)  
##   
## Coefficients:  
## Value Std. Error t value  
## f.pos\_immopen 2.54949 0.4156 6.1348  
## f.pos\_immrestrictive 1.75143 0.8432 2.0772  
## f.genderfemale -0.26922 0.4200 -0.6411  
## f.ostwesteast 34.19781 0.2451 139.5489  
## political\_interest1 -39.14940 0.5234 -74.8026  
## political\_interest2 18.58436 0.3646 50.9657  
## political\_interest3 19.24722 0.3164 60.8405  
## political\_interest4 19.33461 0.3249 59.5017  
## f.pos\_immopen:f.genderfemale 0.56142 0.3783 1.4842  
## f.pos\_immrestrictive:f.genderfemale -2.04753 0.7725 -2.6505  
## f.pos\_immopen:f.ostwesteast 0.74962 0.4099 1.8287  
## f.pos\_immrestrictive:f.ostwesteast -0.76220 0.7430 -1.0259  
## f.ostwesteast:political\_interest1 -4.62716 0.4547 -10.1760  
## f.ostwesteast:political\_interest2 -34.98142 0.3228 -108.3628  
## f.ostwesteast:political\_interest3 -34.93256 0.2912 -119.9716  
## f.ostwesteast:political\_interest4 -35.04489 0.3267 -107.2716  
## f.genderfemale:political\_interest1 30.44788 0.4547 66.9604  
## f.genderfemale:political\_interest2 0.32182 0.5089 0.6324  
## f.genderfemale:political\_interest3 0.06285 0.4525 0.1389  
## f.pos\_immopen:political\_interest1 -6.21223 1.0199 -6.0909  
## f.pos\_immrestrictive:political\_interest1 57.99762 0.7992 72.5695  
## f.pos\_immopen:political\_interest2 -2.51032 0.3915 -6.4118  
## f.pos\_immrestrictive:political\_interest2 0.96506 0.8813 1.0950  
## f.pos\_immopen:political\_interest3 -2.83773 0.3452 -8.2212  
## f.pos\_immrestrictive:political\_interest3 0.18828 0.8102 0.2324  
## f.pos\_immopen:political\_interest4 -2.82382 0.3921 -7.2016  
##   
## Intercepts:  
## Value Std. Error t value   
## center|left 19.5428 0.2494 78.3646  
## left|right 21.6569 0.2875 75.3217  
##   
## Residual Deviance: 971.9755   
## AIC: 1027.975

mo8$zeta

## center|left left|right   
## 19.54275 21.65686

clogodd1 <- mo8$zeta[1];clogodd1 #values of linear predictor

## center|left   
## 19.54275

clogodd2 <- mo8$zeta[2];clogodd2

## left|right   
## 21.65686

gam1 <-exp(clogodd1)/(1+exp(clogodd1));gam1

## center|left   
## 1

gam2 <- exp(clogodd2)/(1+exp(clogodd2));gam2

## left|right   
## 1

pCenter <- gam1;pCenter

## center|left   
## 1

pLeft <- gam2-gam1;pLeft

## left|right   
## 2.862905e-09

pRight <- 1-gam2;pRight

## left|right   
## 3.931373e-10

pCenter+pLeft+pRight==1 #return true

## center|left   
## TRUE

AIC(mo4,mo8) #we get a better AIC when we aggregate the different parties into 3 political ideologies

## df AIC  
## mo4 14 2132.859  
## mo8 28 1027.975

The model with grouped variable gave us a lower Aikaike score but since it’s aggregated target, we decided to keep the target with the 6 ordered levels.

The model chosen as the best model is the model mo4 which formula is the following: formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest + f.gender:f.ostwest.

### Goodness of fit and model interpretation

**Goodness of fit**

mo4$deviance;mo4$edf;2\*nrow(df)-mo4$edf

## [1] 2104.859

## [1] 14

## [1] 1986

1-pchisq(mo4$deviance, 2\*nrow(df)-mo4$edf)

## [1] 0.03143539

For the best model obtained which include egoposition\_immigration, f.gender and political\_interest has a p value of 0.03143539 This means that we reject H0 where the model is consistent to data so we conclude by saying model does not fit well data.

**Model interpretation**

We will interpret the different we will interpret the values of the coefficients obtained.

summary(mo4)

## Call:  
## polr(formula = fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest +   
## f.gender:f.ostwest, data = train, Hess = TRUE)  
##   
## Coefficients:  
## Value Std. Error t value  
## f.pos\_immopen 0.94589 0.1505 6.2837  
## f.pos\_immrestrictive -1.10495 0.2771 -3.9876  
## f.genderfemale -0.06102 0.2855 -0.2137  
## f.ostwesteast -0.27668 0.2270 -1.2187  
## political\_interest1 2.74812 1.3273 2.0705  
## political\_interest2 3.18933 1.2870 2.4781  
## political\_interest3 3.34676 1.2843 2.6059  
## political\_interest4 3.56629 1.2870 2.7711  
## f.genderfemale:f.ostwesteast 0.53377 0.3275 1.6300  
##   
## Intercepts:  
## Value Std. Error t value  
## AfD|CDU/CSU 0.6686 1.2790 0.5228  
## CDU/CSU|FDP 3.0046 1.2871 2.3344  
## FDP|Gruene 3.5426 1.2881 2.7502  
## Gruene|LINKE 4.2275 1.2894 3.2787  
## LINKE|SPD 4.7769 1.2904 3.7019  
##   
## Residual Deviance: 2104.859   
## AIC: 2132.859

coef(mo4)

## f.pos\_immopen f.pos\_immrestrictive   
## 0.94588942 -1.10495291   
## f.genderfemale f.ostwesteast   
## -0.06102228 -0.27668385   
## political\_interest1 political\_interest2   
## 2.74811937 3.18932614   
## political\_interest3 political\_interest4   
## 3.34675645 3.56629241   
## f.genderfemale:f.ostwesteast   
## 0.53377486

mo4$zeta

## AfD|CDU/CSU CDU/CSU|FDP FDP|Gruene Gruene|LINKE LINKE|SPD   
## 0.6686331 3.0046160 3.5426046 4.2275216 4.7769007

summary\_table <- coef(summary(mo4))  
pval <- pnorm(abs(summary\_table[, "t value"]),lower.tail = FALSE)\* 2  
summary\_table <- cbind(summary\_table, "p value" = round(pval,3))  
summary\_table

## Value Std. Error t value p value  
## f.pos\_immopen 0.94588942 0.1505304 6.2837121 0.000  
## f.pos\_immrestrictive -1.10495291 0.2770947 -3.9876368 0.000  
## f.genderfemale -0.06102228 0.2854877 -0.2137475 0.831  
## f.ostwesteast -0.27668385 0.2270300 -1.2187104 0.223  
## political\_interest1 2.74811937 1.3272929 2.0704695 0.038  
## political\_interest2 3.18932614 1.2870108 2.4780881 0.013  
## political\_interest3 3.34675645 1.2842861 2.6059275 0.009  
## political\_interest4 3.56629241 1.2869688 2.7710791 0.006  
## f.genderfemale:f.ostwesteast 0.53377486 0.3274675 1.6300084 0.103  
## AfD|CDU/CSU 0.66863308 1.2789921 0.5227812 0.601  
## CDU/CSU|FDP 3.00461598 1.2870999 2.3344078 0.020  
## FDP|Gruene 3.54260459 1.2881435 2.7501629 0.006  
## Gruene|LINKE 4.22752162 1.2893900 3.2786989 0.001  
## LINKE|SPD 4.77690066 1.2904061 3.7018583 0.000

As we can see the we get a coefieicient of 0.945 for the open level and -1.104 for the restrictive level of pos\_imm. Female h as a coefficient of -0.06 and finally, for each political\_interest variable there are coefficient values around 3. Also there is the interaction of being a female and being from the west which has a coefficient of 0.53377. Finally, if we check the p values, the variable of f.pos\_imm and political\_interest have a p value less than 0.5 which means that they are statistically significant at a 95 CI.

Also from the intercepts, we can see the cumulative logodds and we can see that voting for AfD vs the other parties is 0.668 and voting for AfD or CDU/CSU it goest to 3.000 vs other parties. Then it’s more stable and it does not change that much so CSU/CSU takes into account a lot of the cumulative logodss.

**Prediction of probabilities**

predict(mo4, type="probs", newdata=data.frame(f.pos\_imm=factor("mild"), f.gender=factor("male"), f.ostwest = factor("east"),political\_interest=factor(2)))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.09586747 0.42710975 0.12950369 0.13584758 0.07746403 0.13420748

predict(mo4, type="probs", newdata=data.frame(f.pos\_imm=factor("open"), f.gender=factor("male"),f.ostwest = factor("west"),political\_interest=factor(4)))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.02096837 0.16033144 0.09366496 0.15434686 0.13648429 0.43420407

predict(mo4, type="probs", newdata=data.frame(f.pos\_imm=factor("restrictive"), f.gender=factor("male"),f.ostwest = factor("west"),political\_interest=factor(2)))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.19533026 0.51976130 0.09617045 0.08376476 0.04155748 0.06341574

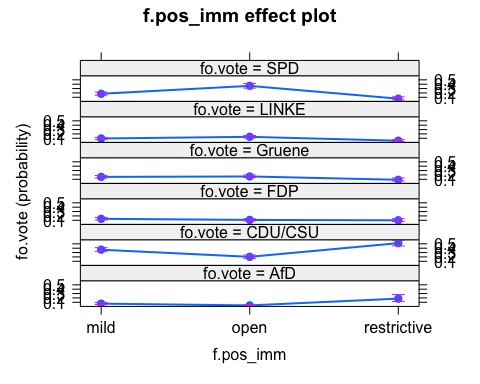
predict(mo4, type="probs", newdata=data.frame(f.pos\_imm=factor("restrictive"), f.gender=factor("male"),f.ostwest = factor("west"),political\_interest=factor(0)))

## AfD CDU/CSU FDP Gruene LINKE SPD   
## 0.854903057 0.128947189 0.006655769 0.004685124 0.002027012 0.002781849

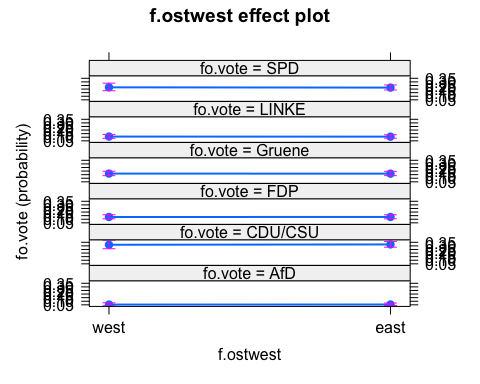
As we can see in the model follows a similar behavior as the nominal model: restrictive about immigration and less political interest are more likely to vote for rights and on the other hand, open and high political\_interest are more likely to vote for left and so on. The other variables (gender and f.ostwest) don’t have to seem to much impact in predictive outcome.

**Effects**

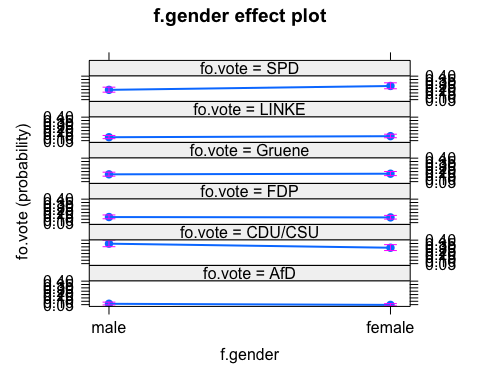
library(effects)  
plot(Effect(focal.predictors = c("f.pos\_imm"), mo4))



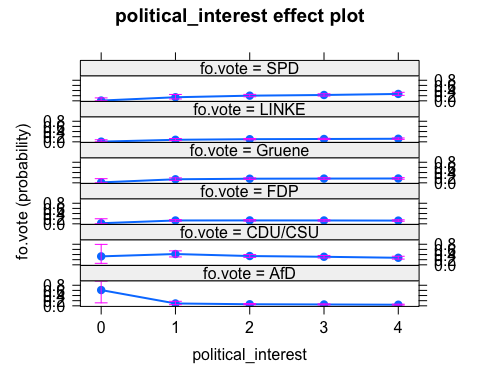
plot(Effect(focal.predictors = c("f.ostwest"), mo4))



plot(Effect(focal.predictors = c("f.gender"), mo4))



plot(Effect(focal.predictors = c("political\_interest"), mo4))



For this model we can see that the effects are similar as the nominal model. The main inights we can gather are that restrictive people in immigration are also more likely to votge for CDU/CSU (right-center). Also for political interest, people with 0 political interest have a 60% of probability to vote for AfD (right).

**Predictive power**

Let’s check the predictive power of the model using both train and test data and find the performance metrics of the model.

On train

tt<-table(predict(mo4),train$fo.vote);tt #Checks that the model i not predicting part times

##   
## AfD CDU/CSU FDP Gruene LINKE SPD  
## AfD 2 1 0 0 0 0  
## CDU/CSU 40 149 61 36 32 81  
## FDP 0 0 0 0 0 0  
## Gruene 0 0 0 0 0 0  
## LINKE 0 0 0 0 0 0  
## SPD 2 51 15 63 41 86

tt

##   
## AfD CDU/CSU FDP Gruene LINKE SPD  
## AfD 2 1 0 0 0 0  
## CDU/CSU 40 149 61 36 32 81  
## FDP 0 0 0 0 0 0  
## Gruene 0 0 0 0 0 0  
## LINKE 0 0 0 0 0 0  
## SPD 2 51 15 63 41 86

100\*sum(diag(tt))/sum(tt) # ACCURACY of the model

## [1] 35.90909

On test

tt<-table(predict(mo4, newdata = test),test$fo.vote);tt #Checks that the model i not predicting part times

##   
## AfD CDU/CSU FDP Gruene LINKE SPD  
## AfD 0 0 0 0 0 0  
## CDU/CSU 22 70 36 18 22 52  
## FDP 0 0 0 0 0 0  
## Gruene 0 0 0 0 0 0  
## LINKE 0 0 0 0 0 0  
## SPD 3 18 9 26 28 36

100\*sum(diag(tt))/sum(tt) # ACCURACY of the model

## [1] 31.17647

predicted <- predict(mo4, newdata = test)  
actual <- test$fo.vote  
  
library(caret)  
  
confusionMatrix(predicted, actual, mode = "everything")

## Confusion Matrix and Statistics  
##   
## Reference  
## Prediction AfD CDU/CSU FDP Gruene LINKE SPD  
## AfD 0 0 0 0 0 0  
## CDU/CSU 22 70 36 18 22 52  
## FDP 0 0 0 0 0 0  
## Gruene 0 0 0 0 0 0  
## LINKE 0 0 0 0 0 0  
## SPD 3 18 9 26 28 36  
##   
## Overall Statistics  
##   
## Accuracy : 0.3118   
## 95% CI : (0.2629, 0.364)  
## No Information Rate : 0.2588   
## P-Value [Acc > NIR] : 0.01642   
##   
## Kappa : 0.0714   
##   
## Mcnemar's Test P-Value : NA   
##   
## Statistics by Class:  
##   
## Class: AfD Class: CDU/CSU Class: FDP Class: Gruene  
## Sensitivity 0.00000 0.7955 0.0000 0.0000  
## Specificity 1.00000 0.4048 1.0000 1.0000  
## Pos Pred Value NaN 0.3182 NaN NaN  
## Neg Pred Value 0.92647 0.8500 0.8676 0.8706  
## Precision NA 0.3182 NA NA  
## Recall 0.00000 0.7955 0.0000 0.0000  
## F1 NA 0.4545 NA NA  
## Prevalence 0.07353 0.2588 0.1324 0.1294  
## Detection Rate 0.00000 0.2059 0.0000 0.0000  
## Detection Prevalence 0.00000 0.6471 0.0000 0.0000  
## Balanced Accuracy 0.50000 0.6001 0.5000 0.5000  
## Class: LINKE Class: SPD  
## Sensitivity 0.0000 0.4091  
## Specificity 1.0000 0.6667  
## Pos Pred Value NaN 0.3000  
## Neg Pred Value 0.8529 0.7636  
## Precision NA 0.3000  
## Recall 0.0000 0.4091  
## F1 NA 0.3462  
## Prevalence 0.1471 0.2588  
## Detection Rate 0.0000 0.1059  
## Detection Prevalence 0.0000 0.3529  
## Balanced Accuracy 0.5000 0.5379

We can see that the best model found get’s a 35% of accuracy on train and 31% of accuracy on test. Those are not better results than the nominal proposal.

## Herarchical proposal

The final propousal is the herarchical which will require to group target variable into 3 levels: left, center, right. We have 665 people hwo are laveled as “center”, 266 as “left” and 69 as “right”. This is a problem since target is clearly unbalanced.

We will try an herarchical model with people who votes for the center (majority) and people who vote for other parties (left or right).

– 1st CENTER OTHER – 2nd LEFT RIGHT

### Baseline model

#we use here the same train and test as above.  
  
mh0 <- glm(f.vote\_center ~ 1, family = "binomial", data = train)  
summary(mh0)

##   
## Call:  
## glm(formula = f.vote\_center ~ 1, family = "binomial", data = train)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -0.8904 -0.8904 -0.8904 1.4946 1.4946   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.72055 0.08296 -8.686 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 834.54 on 659 degrees of freedom  
## Residual deviance: 834.54 on 659 degrees of freedom  
## AIC: 836.54  
##   
## Number of Fisher Scoring iterations: 4

mh1 <- glm(f.vote\_center ~ political\_interest+income, family = "binomial", data = train)  
summary(mh1)

##   
## Call:  
## glm(formula = f.vote\_center ~ political\_interest + income, family = "binomial",   
## data = train)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.4898 -0.9359 -0.8346 1.4342 1.7227   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)  
## (Intercept) 1.1105 1.4517 0.765 0.444  
## political\_interest1 -1.4134 1.3011 -1.086 0.277  
## political\_interest2 -1.5355 1.2387 -1.240 0.215  
## political\_interest3 -1.2586 1.2366 -1.018 0.309  
## political\_interest4 -1.2459 1.2412 -1.004 0.315  
## income1 -0.3154 0.9039 -0.349 0.727  
## income2 -0.4007 0.7919 -0.506 0.613  
## income3 -0.4505 0.7756 -0.581 0.561  
## income4 -0.8016 0.7959 -1.007 0.314  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 834.54 on 659 degrees of freedom  
## Residual deviance: 827.70 on 651 degrees of freedom  
## AIC: 845.7  
##   
## Number of Fisher Scoring iterations: 4

mh2 <- step(mh1)

## Start: AIC=845.7  
## f.vote\_center ~ political\_interest + income  
##   
## Df Deviance AIC  
## - income 4 830.99 840.99  
## - political\_interest 4 831.32 841.32  
## <none> 827.70 845.70  
##   
## Step: AIC=840.99  
## f.vote\_center ~ political\_interest  
##   
## Df Deviance AIC  
## - political\_interest 4 834.54 836.54  
## <none> 830.99 840.99  
##   
## Step: AIC=836.54  
## f.vote\_center ~ 1

summary(mh2)

##   
## Call:  
## glm(formula = f.vote\_center ~ 1, family = "binomial", data = train)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -0.8904 -0.8904 -0.8904 1.4946 1.4946   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.72055 0.08296 -8.686 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 834.54 on 659 degrees of freedom  
## Residual deviance: 834.54 on 659 degrees of freedom  
## AIC: 836.54  
##   
## Number of Fisher Scoring iterations: 4

Grouping variables 2 levels improved drastically the aikaike score.

### Improving the model

#### Adding factors and interactions

# First level  
mh3 <- glm(f.vote\_center ~ f.pos\_imm\*f.ostwest + f.pos\_imm+f.ostwest + f.pos\_imm\*f.gender + f.ostwest\*f.gender + f.pos\_imm+f.gender, family = "binomial", data = train)  
  
summary(mh3)

##   
## Call:  
## glm(formula = f.vote\_center ~ f.pos\_imm \* f.ostwest + f.pos\_imm +   
## f.ostwest + f.pos\_imm \* f.gender + f.ostwest \* f.gender +   
## f.pos\_imm + f.gender, family = "binomial", data = train)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.7274 -0.9474 -0.7302 1.2700 1.7650   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.79171 0.28368 -2.791 0.00526 \*\*  
## f.pos\_immopen 0.26779 0.38424 0.697 0.48584   
## f.pos\_immrestrictive 2.02882 0.64478 3.147 0.00165 \*\*  
## f.ostwesteast -0.39399 0.32828 -1.200 0.23007   
## f.genderfemale 0.01645 0.38050 0.043 0.96551   
## f.pos\_immopen:f.ostwesteast 0.34958 0.40713 0.859 0.39054   
## f.pos\_immrestrictive:f.ostwesteast -1.20901 0.70260 -1.721 0.08529 .   
## f.pos\_immopen:f.genderfemale 0.48864 0.36251 1.348 0.17768   
## f.pos\_immrestrictive:f.genderfemale -1.98486 0.76940 -2.580 0.00989 \*\*  
## f.ostwesteast:f.genderfemale -0.15175 0.39261 -0.387 0.69912   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 834.54 on 659 degrees of freedom  
## Residual deviance: 793.42 on 650 degrees of freedom  
## AIC: 813.42  
##   
## Number of Fisher Scoring iterations: 4

mh4 <- step(mh3)

## Start: AIC=813.42  
## f.vote\_center ~ f.pos\_imm \* f.ostwest + f.pos\_imm + f.ostwest +   
## f.pos\_imm \* f.gender + f.ostwest \* f.gender + f.pos\_imm +   
## f.gender  
##   
## Df Deviance AIC  
## - f.ostwest:f.gender 1 793.57 811.57  
## <none> 793.42 813.42  
## - f.pos\_imm:f.ostwest 2 798.73 814.73  
## - f.pos\_imm:f.gender 2 806.64 822.64  
##   
## Step: AIC=811.57  
## f.vote\_center ~ f.pos\_imm + f.ostwest + f.gender + f.pos\_imm:f.ostwest +   
## f.pos\_imm:f.gender  
##   
## Df Deviance AIC  
## <none> 793.57 811.57  
## - f.pos\_imm:f.ostwest 2 798.74 812.74  
## - f.pos\_imm:f.gender 2 806.64 820.64

summary(mh4)

##   
## Call:  
## glm(formula = f.vote\_center ~ f.pos\_imm + f.ostwest + f.gender +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender, family = "binomial",   
## data = train)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.7421 -0.9397 -0.7237 1.2621 1.7546   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.74782 0.25847 -2.893 0.00381 \*\*  
## f.pos\_immopen 0.27966 0.38157 0.733 0.46361   
## f.pos\_immrestrictive 2.01783 0.64561 3.125 0.00178 \*\*  
## f.ostwesteast -0.45843 0.28244 -1.623 0.10457   
## f.genderfemale -0.09159 0.25870 -0.354 0.72332   
## f.pos\_immopen:f.ostwesteast 0.33787 0.40582 0.833 0.40510   
## f.pos\_immrestrictive:f.ostwesteast -1.18647 0.70030 -1.694 0.09022 .   
## f.pos\_immopen:f.genderfemale 0.48335 0.36232 1.334 0.18220   
## f.pos\_immrestrictive:f.genderfemale -1.94740 0.75735 -2.571 0.01013 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 834.54 on 659 degrees of freedom  
## Residual deviance: 793.57 on 651 degrees of freedom  
## AIC: 811.57  
##   
## Number of Fisher Scoring iterations: 4

#comparision  
anova(mh3, mh4)

## Analysis of Deviance Table  
##   
## Model 1: f.vote\_center ~ f.pos\_imm \* f.ostwest + f.pos\_imm + f.ostwest +   
## f.pos\_imm \* f.gender + f.ostwest \* f.gender + f.pos\_imm +   
## f.gender  
## Model 2: f.vote\_center ~ f.pos\_imm + f.ostwest + f.gender + f.pos\_imm:f.ostwest +   
## f.pos\_imm:f.gender  
## Resid. Df Resid. Dev Df Deviance  
## 1 650 793.42   
## 2 651 793.57 -1 -0.14946

AIC(mh0, mh1,mh2,mh3,mh4)

## df AIC  
## mh0 1 836.5441  
## mh1 9 845.7037  
## mh2 1 836.5441  
## mh3 10 813.4248  
## mh4 9 811.5743

## --- Second level  
mh5 <- glm(f.vote ~ f.pos\_imm+political\_interest+income, family = "binomial", data = train[train$f.vote\_center=="other",])  
summary(mh5)

##   
## Call:  
## glm(formula = f.vote ~ f.pos\_imm + political\_interest + income,   
## family = "binomial", data = train[train$f.vote\_center ==   
## "other", ])  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.68530 -0.50011 -0.18443 -0.09399 2.85748   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 2.9937 2769.4515 0.001 0.999138   
## f.pos\_immopen -2.8617 0.7781 -3.678 0.000235 \*\*\*  
## f.pos\_immrestrictive 3.7019 0.7696 4.810 1.51e-06 \*\*\*  
## political\_interest1 -23.5594 2072.5340 -0.011 0.990930   
## political\_interest2 -20.4054 2072.5335 -0.010 0.992144   
## political\_interest3 -19.0509 2072.5335 -0.009 0.992666   
## political\_interest4 -19.8628 2072.5335 -0.010 0.992353   
## income1 16.1881 1836.9725 0.009 0.992969   
## income2 16.1462 1836.9721 0.009 0.992987   
## income3 14.8533 1836.9721 0.008 0.993549   
## income4 15.8560 1836.9721 0.009 0.993113   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 218.37 on 215 degrees of freedom  
## Residual deviance: 116.12 on 205 degrees of freedom  
## AIC: 138.12  
##   
## Number of Fisher Scoring iterations: 16

mh6 <- step(mh5)

## Start: AIC=138.12  
## f.vote ~ f.pos\_imm + political\_interest + income  
##   
## Df Deviance AIC  
## - income 4 122.55 136.55  
## <none> 116.12 138.12  
## - political\_interest 4 134.64 148.64  
## - f.pos\_imm 2 205.68 223.68  
##   
## Step: AIC=136.55  
## f.vote ~ f.pos\_imm + political\_interest  
##   
## Df Deviance AIC  
## <none> 122.55 136.55  
## - political\_interest 4 139.45 145.45  
## - f.pos\_imm 2 211.48 221.48

summary(mh6)

##   
## Call:  
## glm(formula = f.vote ~ f.pos\_imm + political\_interest, family = "binomial",   
## data = train[train$f.vote\_center == "other", ])  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.8741 -0.5277 -0.2345 -0.1360 2.6862   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 17.9721 1207.7110 0.015 0.988127   
## f.pos\_immopen -2.7772 0.7677 -3.617 0.000298 \*\*\*  
## f.pos\_immrestrictive 3.4679 0.7235 4.793 1.64e-06 \*\*\*  
## political\_interest1 -22.2013 1207.7117 -0.018 0.985333   
## political\_interest2 -19.8734 1207.7111 -0.016 0.986871   
## political\_interest3 -18.7751 1207.7110 -0.016 0.987597   
## political\_interest4 -19.4278 1207.7110 -0.016 0.987165   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 218.37 on 215 degrees of freedom  
## Residual deviance: 122.55 on 209 degrees of freedom  
## AIC: 136.55  
##   
## Number of Fisher Scoring iterations: 15

mh7 <- glm(f.vote ~ f.pos\_imm\*f.ostwest + f.pos\_imm\*f.gender + political\_interest\*f.ostwest + political\_interest\*f.gender + f.pos\_imm + political\_interest + f.ostwest + f.gender + political\_interest\*f.pos\_imm + f.ostwest\*f.gender, family = "binomial", data = train[train$f.vote\_center == "other", ])

## Warning: glm.fit: algorithm did not converge

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

summary(mh7)

##   
## Call:  
## glm(formula = f.vote ~ f.pos\_imm \* f.ostwest + f.pos\_imm \* f.gender +   
## political\_interest \* f.ostwest + political\_interest \* f.gender +   
## f.pos\_imm + political\_interest + f.ostwest + f.gender + political\_interest \*   
## f.pos\_imm + f.ostwest \* f.gender, family = "binomial", data = train[train$f.vote\_center ==   
## "other", ])  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.4517 -0.4477 0.0000 0.0000 2.4131   
##   
## Coefficients: (3 not defined because of singularities)  
## Estimate Std. Error z value Pr(>|z|)  
## (Intercept) 7.926e+14 1.190e+15 0.666 0.505  
## f.pos\_immopen -7.926e+14 1.190e+15 -0.666 0.505  
## f.pos\_immrestrictive -7.926e+14 1.190e+15 -0.666 0.505  
## f.ostwesteast 1.198e+00 1.908e+00 0.628 0.530  
## f.genderfemale 1.588e+00 1.901e+00 0.835 0.403  
## political\_interest1 -2.593e+01 4.745e+07 0.000 1.000  
## political\_interest2 -7.926e+14 1.190e+15 -0.666 0.505  
## political\_interest3 -7.926e+14 1.190e+15 -0.666 0.505  
## political\_interest4 -7.926e+14 1.190e+15 -0.666 0.505  
## f.pos\_immopen:f.ostwesteast 2.893e+06 1.406e+07 0.206 0.837  
## f.pos\_immrestrictive:f.ostwesteast 2.484e+01 5.354e+04 0.000 1.000  
## f.pos\_immopen:f.genderfemale -2.490e+05 9.726e+06 -0.026 0.980  
## f.pos\_immrestrictive:f.genderfemale 2.591e+01 4.170e+04 0.001 1.000  
## f.ostwesteast:political\_interest1 3.021e+01 4.745e+07 0.000 1.000  
## f.ostwesteast:political\_interest2 -1.489e+00 2.122e+00 -0.702 0.483  
## f.ostwesteast:political\_interest3 -3.449e+00 2.156e+00 -1.600 0.110  
## f.ostwesteast:political\_interest4 NA NA NA NA  
## f.genderfemale:political\_interest1 -7.926e+14 1.190e+15 -0.666 0.505  
## f.genderfemale:political\_interest2 -3.005e+00 1.857e+00 -1.618 0.106  
## f.genderfemale:political\_interest3 -2.876e+00 1.990e+00 -1.445 0.148  
## f.genderfemale:political\_interest4 NA NA NA NA  
## f.pos\_immopen:political\_interest1 7.926e+14 1.190e+15 0.666 0.505  
## f.pos\_immrestrictive:political\_interest1 NA NA NA NA  
## f.pos\_immopen:political\_interest2 7.926e+14 1.190e+15 0.666 0.505  
## f.pos\_immrestrictive:political\_interest2 7.926e+14 1.190e+15 0.666 0.505  
## f.pos\_immopen:political\_interest3 7.926e+14 1.190e+15 0.666 0.505  
## f.pos\_immrestrictive:political\_interest3 7.926e+14 1.190e+15 0.666 0.505  
## f.pos\_immopen:political\_interest4 7.926e+14 1.190e+15 0.666 0.505  
## f.pos\_immrestrictive:political\_interest4 7.926e+14 1.190e+15 0.666 0.505  
## f.ostwesteast:f.genderfemale -1.487e+00 1.664e+00 -0.894 0.372  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 218.373 on 215 degrees of freedom  
## Residual deviance: 85.704 on 189 degrees of freedom  
## AIC: 139.7  
##   
## Number of Fisher Scoring iterations: 25

mh8 <- step(mh7)

## Start: AIC=139.7  
## f.vote ~ f.pos\_imm \* f.ostwest + f.pos\_imm \* f.gender + political\_interest \*   
## f.ostwest + political\_interest \* f.gender + f.pos\_imm + political\_interest +   
## f.ostwest + f.gender + political\_interest \* f.pos\_imm + f.ostwest \*   
## f.gender

## Warning: glm.fit: algorithm did not converge  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: algorithm did not converge

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Df Deviance AIC  
## - f.pos\_imm:political\_interest 7 95.1 135.1  
## <none> 85.7 139.7  
## - f.pos\_imm:f.ostwest 2 99.8 149.8  
## - f.ostwest:f.gender 1 340.8 392.8  
## - f.pos\_imm:f.gender 3 1874.3 1922.3  
## - f.ostwest:political\_interest 3 5064.3 5112.3  
## - f.gender:political\_interest 2 6685.3 6735.3

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##   
## Step: AIC=135.08  
## f.vote ~ f.pos\_imm + f.ostwest + f.gender + political\_interest +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender + f.ostwest:political\_interest +   
## f.gender:political\_interest + f.ostwest:f.gender

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Df Deviance AIC  
## - f.ostwest:political\_interest 3 96.904 130.90  
## - f.gender:political\_interest 3 97.974 131.97  
## - f.ostwest:f.gender 1 95.283 133.28  
## - f.pos\_imm:f.gender 2 98.775 134.78  
## <none> 95.079 135.08  
## - f.pos\_imm:f.ostwest 2 101.911 137.91

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##   
## Step: AIC=130.9  
## f.vote ~ f.pos\_imm + f.ostwest + f.gender + political\_interest +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender + f.gender:political\_interest +   
## f.ostwest:f.gender

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Df Deviance AIC  
## - f.gender:political\_interest 3 99.405 127.41  
## - f.ostwest:f.gender 1 96.913 128.91  
## <none> 96.904 130.90  
## - f.pos\_imm:f.gender 2 101.122 131.12  
## - f.pos\_imm:f.ostwest 2 110.333 140.33

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##   
## Step: AIC=127.41  
## f.vote ~ f.pos\_imm + f.ostwest + f.gender + political\_interest +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender + f.ostwest:f.gender

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Df Deviance AIC  
## - f.ostwest:f.gender 1 99.461 125.46  
## <none> 99.405 127.41  
## - f.pos\_imm:f.gender 2 104.898 128.90  
## - political\_interest 4 109.759 129.76  
## - f.pos\_imm:f.ostwest 2 113.087 137.09

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##   
## Step: AIC=125.46  
## f.vote ~ f.pos\_imm + f.ostwest + f.gender + political\_interest +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred  
  
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Df Deviance AIC  
## <none> 99.461 125.46  
## - political\_interest 4 109.875 127.88  
## - f.pos\_imm:f.gender 2 107.079 129.08  
## - f.pos\_imm:f.ostwest 2 114.539 136.54

summary(mh8)

##   
## Call:  
## glm(formula = f.vote ~ f.pos\_imm + f.ostwest + f.gender + political\_interest +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender, family = "binomial",   
## data = train[train$f.vote\_center == "other", ])  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.24602 -0.40469 -0.00007 0.00000 2.34689   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 21.7172 8684.2542 0.003 0.9980   
## f.pos\_immopen -19.1811 2943.5600 -0.007 0.9948   
## f.pos\_immrestrictive 0.7918 0.9458 0.837 0.4025   
## f.ostwesteast -1.1170 0.5764 -1.938 0.0526 .  
## f.genderfemale -0.9392 0.6528 -1.439 0.1502   
## political\_interest1 -40.3936 9236.6876 -0.004 0.9965   
## political\_interest2 -22.3491 8684.2542 -0.003 0.9979   
## political\_interest3 -21.5997 8684.2542 -0.002 0.9980   
## political\_interest4 -22.2524 8684.2542 -0.003 0.9980   
## f.pos\_immopen:f.ostwesteast 17.7194 2943.5601 0.006 0.9952   
## f.pos\_immrestrictive:f.ostwesteast 36.3512 4744.0263 0.008 0.9939   
## f.pos\_immopen:f.genderfemale -16.4491 2147.9323 -0.008 0.9939   
## f.pos\_immrestrictive:f.genderfemale 21.3212 8861.1382 0.002 0.9981   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 218.373 on 215 degrees of freedom  
## Residual deviance: 99.461 on 203 degrees of freedom  
## AIC: 125.46  
##   
## Number of Fisher Scoring iterations: 19

AIC(mh8,mh7)

## df AIC  
## mh8 13 125.4612  
## mh7 27 139.7036

AIC(mh8)+AIC(mh4)

## [1] 937.0355

### Model interpretation

**Model interpretation**

We will interpret the different we will interpret the values of the coefficients obtained.

summary(mh4)

##   
## Call:  
## glm(formula = f.vote\_center ~ f.pos\_imm + f.ostwest + f.gender +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender, family = "binomial",   
## data = train)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.7421 -0.9397 -0.7237 1.2621 1.7546   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.74782 0.25847 -2.893 0.00381 \*\*  
## f.pos\_immopen 0.27966 0.38157 0.733 0.46361   
## f.pos\_immrestrictive 2.01783 0.64561 3.125 0.00178 \*\*  
## f.ostwesteast -0.45843 0.28244 -1.623 0.10457   
## f.genderfemale -0.09159 0.25870 -0.354 0.72332   
## f.pos\_immopen:f.ostwesteast 0.33787 0.40582 0.833 0.40510   
## f.pos\_immrestrictive:f.ostwesteast -1.18647 0.70030 -1.694 0.09022 .   
## f.pos\_immopen:f.genderfemale 0.48335 0.36232 1.334 0.18220   
## f.pos\_immrestrictive:f.genderfemale -1.94740 0.75735 -2.571 0.01013 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 834.54 on 659 degrees of freedom  
## Residual deviance: 793.57 on 651 degrees of freedom  
## AIC: 811.57  
##   
## Number of Fisher Scoring iterations: 4

coef(mh4)

## (Intercept) f.pos\_immopen   
## -0.74781745 0.27966153   
## f.pos\_immrestrictive f.ostwesteast   
## 2.01783396 -0.45842995   
## f.genderfemale f.pos\_immopen:f.ostwesteast   
## -0.09158747 0.33786530   
## f.pos\_immrestrictive:f.ostwesteast f.pos\_immopen:f.genderfemale   
## -1.18646814 0.48334556   
## f.pos\_immrestrictive:f.genderfemale   
## -1.94740421

summary(mh8)

##   
## Call:  
## glm(formula = f.vote ~ f.pos\_imm + f.ostwest + f.gender + political\_interest +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender, family = "binomial",   
## data = train[train$f.vote\_center == "other", ])  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.24602 -0.40469 -0.00007 0.00000 2.34689   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 21.7172 8684.2542 0.003 0.9980   
## f.pos\_immopen -19.1811 2943.5600 -0.007 0.9948   
## f.pos\_immrestrictive 0.7918 0.9458 0.837 0.4025   
## f.ostwesteast -1.1170 0.5764 -1.938 0.0526 .  
## f.genderfemale -0.9392 0.6528 -1.439 0.1502   
## political\_interest1 -40.3936 9236.6876 -0.004 0.9965   
## political\_interest2 -22.3491 8684.2542 -0.003 0.9979   
## political\_interest3 -21.5997 8684.2542 -0.002 0.9980   
## political\_interest4 -22.2524 8684.2542 -0.003 0.9980   
## f.pos\_immopen:f.ostwesteast 17.7194 2943.5601 0.006 0.9952   
## f.pos\_immrestrictive:f.ostwesteast 36.3512 4744.0263 0.008 0.9939   
## f.pos\_immopen:f.genderfemale -16.4491 2147.9323 -0.008 0.9939   
## f.pos\_immrestrictive:f.genderfemale 21.3212 8861.1382 0.002 0.9981   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 218.373 on 215 degrees of freedom  
## Residual deviance: 99.461 on 203 degrees of freedom  
## AIC: 125.46  
##   
## Number of Fisher Scoring iterations: 19

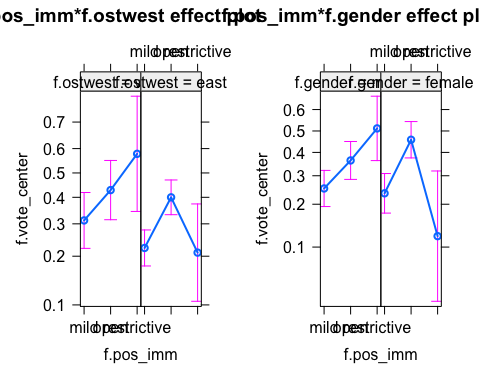
coef(mh8)

## (Intercept) f.pos\_immopen   
## 21.7171524 -19.1810731   
## f.pos\_immrestrictive f.ostwesteast   
## 0.7918290 -1.1169844   
## f.genderfemale political\_interest1   
## -0.9392193 -40.3935506   
## political\_interest2 political\_interest3   
## -22.3490978 -21.5997286   
## political\_interest4 f.pos\_immopen:f.ostwesteast   
## -22.2523647 17.7194385   
## f.pos\_immrestrictive:f.ostwesteast f.pos\_immopen:f.genderfemale   
## 36.3512100 -16.4491236   
## f.pos\_immrestrictive:f.genderfemale   
## 21.3211707

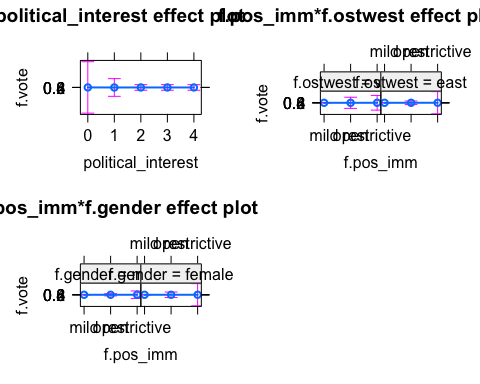
As we can see the we get a coefieicient of 0.279 for the open level and 2.0178 for the restrictive level of pos\_imm. eastern people have a -0.458 of coefficiient and females as a coefficient of -0.09 and finally, for each political\_interest variable there are coefficient vvalues around 3. We can see that restrictive level pos\_imm and the interaction between restrictive and being a female is statsitifically sifnificant for a 95.

**Effects**

library(effects)  
plot(allEffects(mh4))



plot(allEffects(mh8))



summary(mh8)

##   
## Call:  
## glm(formula = f.vote ~ f.pos\_imm + f.ostwest + f.gender + political\_interest +   
## f.pos\_imm:f.ostwest + f.pos\_imm:f.gender, family = "binomial",   
## data = train[train$f.vote\_center == "other", ])  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.24602 -0.40469 -0.00007 0.00000 2.34689   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 21.7172 8684.2542 0.003 0.9980   
## f.pos\_immopen -19.1811 2943.5600 -0.007 0.9948   
## f.pos\_immrestrictive 0.7918 0.9458 0.837 0.4025   
## f.ostwesteast -1.1170 0.5764 -1.938 0.0526 .  
## f.genderfemale -0.9392 0.6528 -1.439 0.1502   
## political\_interest1 -40.3936 9236.6876 -0.004 0.9965   
## political\_interest2 -22.3491 8684.2542 -0.003 0.9979   
## political\_interest3 -21.5997 8684.2542 -0.002 0.9980   
## political\_interest4 -22.2524 8684.2542 -0.003 0.9980   
## f.pos\_immopen:f.ostwesteast 17.7194 2943.5601 0.006 0.9952   
## f.pos\_immrestrictive:f.ostwesteast 36.3512 4744.0263 0.008 0.9939   
## f.pos\_immopen:f.genderfemale -16.4491 2147.9323 -0.008 0.9939   
## f.pos\_immrestrictive:f.genderfemale 21.3212 8861.1382 0.002 0.9981   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 218.373 on 215 degrees of freedom  
## Residual deviance: 99.461 on 203 degrees of freedom  
## AIC: 125.46  
##   
## Number of Fisher Scoring iterations: 19

As we can see from the plot, we can see that people from the east and that they are open about immigration are more likely to vote center. At the same time people that are restrictive and are from the west have a higher probability to vote center as well.

Also we can see that men who are restrictive and females who are open are more likely to vote for center.

However, we can see in the effects plot tthat the confidence interval is very wide.

**Predictive power**

Let’s check the predictive power of the model using both train and test data and find the performance metrics of the model.

#we can see that the HL model gives the lowest AIC.  
  
tt\_first\_level<-table( ifelse(predict(mh4,type="response")>0.5,"other","center"),train$f.vote\_center);tt\_first\_level

##   
## center other  
## center 440 207  
## other 4 9

tt\_second\_level<-table(factor(ifelse(predict(mh8,type="response")<0.5,"left","right"),levels=c("left","right")),train$f.vote[train$f.vote != "center"]);tt\_second\_level

##   
## center left right  
## left 0 165 14  
## right 0 7 30

100\*sum(diag(tt\_first\_level))/sum(tt\_first\_level) + 100\*sum(diag(tt\_second\_level))/sum(tt\_second\_level)

## [1] 71.27104

#hardcoded resutls  
100\*(440+165+30) / 660

## [1] 96.21212

We can see that the best model found get’s a 96% of accuracy. The best metric so far, however it’s important to keep in mind that data is highly unbalanced.

# Comparision of models and conclusions

From each propousal we iterated into the different steps and we obtained the better model for each. All models are trained with the same sample and using the same methodology. Here are the best models obtained:

* Nomina proposal: The best model we found is the mn10 which is described by the folliwng formula: vote ~ f.pos\_imm + f.ostwest + f.gender
* Ordinal proposal: The best model is mo4 which is described by the following formula fo.vote ~ f.pos\_imm + f.gender + f.ostwest + political\_interest + f.gender:f.ostwest.
* Herachical proposal: The best model is mh4 which is described by the following formula: f.vote\_center ~ f.pos\_imm \* f.ostwest + f.pos\_imm + f.ostwest + f.pos\_imm \* f.gender + f.pos\_imm + f.gender

AIC(mn10, mo4)

## df AIC  
## mn10 25 2077.978  
## mo4 14 2132.859

AIC(mh4)+AIC(mh8) # first and second level

## [1] 937.0355

BIC(mn10, mo4)

## df BIC  
## mn10 25 2190.284  
## mo4 14 2195.750

BIC(mh4)+BIC(mh8)

## [1] 1021.344

As we can see the best model obtained based on AIC/BIC scores is clearly the herarchical. Also if we take into account the predictive power metrics for each one, the hierarchical model wins with 96% of accuracy vs 37% (nominal) and 35% (ordinal). Also we think that herarchical modeling is a very natural approach to the kind of data we have (taking into account that each party is labeled as a left, center, right). However, it’s important to keep in mind that the hierarchical model have an aggregated target that is unbalanced so we think that it would perform even better if we manage do get balance data.

Also for nominal and ordinal models we found out that we did not manage to get really good metrics and we think that it’s because it has unbalance targets and we think that maybe there are some exploratory variables that are important factors on deciding between the 6 levels.

In this project we had to iterate for each proposal to try to obtain the best models. The data quality was very good so our main focus was in the modeling part. The main difficulties are that classes are unbalanced and also deciding on whether we should group levels of factors or not. We belive that the results could be improved. However, we iterated and experimented with different steps and methods to try to explain the results.