## lab 8

### Aisha Lakshman

3/11/2022

## **Packages**

```
library(tidyverse)
## -- Attaching packages ------ tidyverse 1.3.1 --
## v ggplot2 3.3.5
                   v purrr
                              0.3.4
## v tibble 3.1.6 v dplyr 1.0.7
## v tidyr 1.1.4 v stringr 1.4.0
## v readr 2.1.1 v forcats 0.5.1
                                ----- tidyverse_conflicts() --
## -- Conflicts -----
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                   masks stats::lag()
library(nnet)
library(knitr)
library(broom)
library(patchwork)
```

### Data

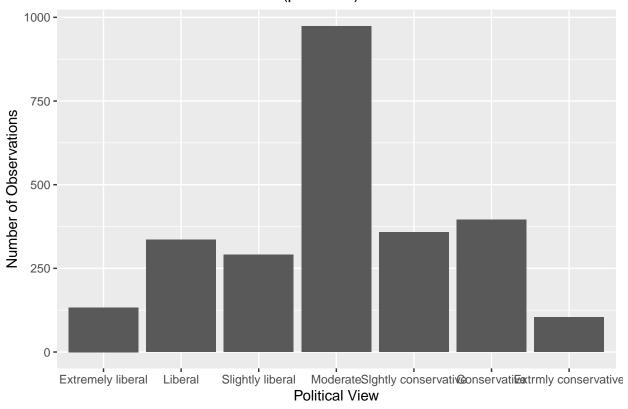
## Part I: Exploratory Data Analysis

#### Exercise 1

```
gss <- gss %>%
  mutate(natmass = fct_relevel(natmass, "About right", "Too little", "Too much"))
```

#### Exercise 2

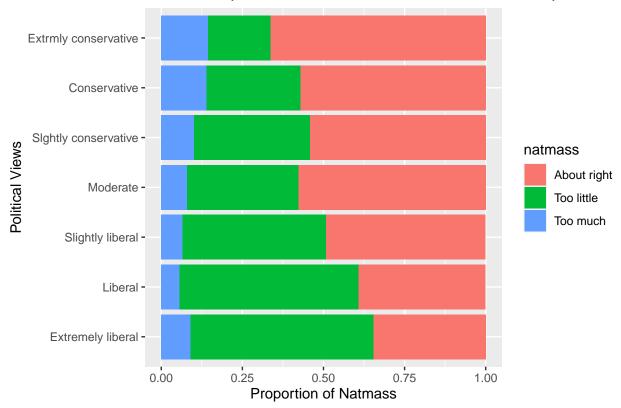
## Distribution of Political Views (polviews)



The political view that occurs most frequently in this data set is "Moderate".

#### Exercise 3

## Relationship between Political Views and Mass Transportation :



This plot demonstrates that liberals believe that government spending on mass transportation is insufficient. The more conservative a person is, the more likely they believe government spending on mass transportation is adequate or excessive.

```
gss <- gss %>%
  mutate(age = if_else(age == "89 or older", 89, as.numeric(age)))

## Warning in replace_with(out, !condition, false, fmt_args(~false), glue("length
## of {fmt_args(~condition)}")): NAs introduced by coercion
```

## Part II: Multinomial Logistic Regression Model

#### Exercise 5

Because our response variable, Natmass, is a categorical variable with more than two categories, a multinomial logistic regression model is the best choice for this problem. Logistic regression is used to solve classification problems, and because our classifier has three categories, we cannot use a binomial model.

```
model <- multinom(natmass ~ ., data = gss)

## # weights: 57 (36 variable)
## initial value 2845.405828
## iter 10 value 2308.054489
## iter 20 value 2277.361046
## iter 30 value 2276.038249
## iter 40 value 2275.922824
## final value 2275.922840
## converged

tidy(model) %>%
    kable(format = "markdown", digits = 4)
```

term	estimate	$\operatorname{std.error}$	statistic	p.value
(Intercept)	-0.4149	0.2584	-1.6058	0.1083
age	0.0062	0.0025	2.4478	0.0144
sexMale	0.2174	0.0870	2.4996	0.0124
sei10	0.0081	0.0018	4.4463	0.0000
regionE. sou. central	0.3339	0.1923	1.7359	0.0826
regionMiddle atlantic	-0.0815	0.1674	-0.4865	0.6266
regionMountain	0.1377	0.1798	0.7658	0.4438
regionNew england	0.4660	0.2053	2.2701	0.0232
regionPacific	0.3637	0.1539	2.3636	0.0181
regionSouth atlantic	0.1319	0.1418	0.9296	0.3526
regionW. nor. central	0.0306	0.1993	0.1535	0.8780
regionW. sou. central	-0.0275	0.1715	-0.1606	0.8724
polviewsLiberal	-0.2016	0.2226	-0.9057	0.3651
polviewsSlightly liberal	-0.5969	0.2267	-2.6330	0.0085
polviewsModerate	-0.9695	0.2026	-4.7847	0.0000
polviewsSlghtly conservative	-0.9400	0.2224	-4.2264	0.0000
polviewsConservative	-1.2207	0.2237	-5.4558	0.0000
polviewsExtrmly conservative	-1.6962	0.3199	-5.3021	0.0000
(Intercept)	-1.8496	0.4356	-4.2463	0.0000
age	0.0143	0.0041	3.4804	0.0005
sexMale	0.5349	0.1462	3.6596	0.0003
sei10	-0.0099	0.0032	-3.0785	0.0021
regionE. sou. central	-0.3234	0.3508	-0.9217	0.3567
regionMiddle atlantic	-0.1435	0.2791	-0.5143	0.6070
	(Intercept) age sexMale sei10 regionE. sou. central regionMiddle atlantic regionMountain regionPacific regionSouth atlantic regionW. nor. central regionW. sou. central polviewsLiberal polviewsLiberal polviewsSlightly liberal polviewsSlightly conservative polviewsConservative polviewsExtrmly conservative (Intercept) age sexMale sei10 regionE. sou. central	(Intercept) age	(Intercept) age	(Intercept) age

y.level	term	estimate	std.error	statistic	p.value
Too much	regionMountain	-0.0255	0.3048	-0.0835	0.9334
Too much	regionNew england	0.8785	0.2922	3.0065	0.0026
Too much	regionPacific	0.3403	0.2438	1.3956	0.1628
Too much	regionSouth atlantic	-0.2740	0.2428	-1.1283	0.2592
Too much	regionW. nor. central	0.1593	0.3038	0.5243	0.6001
Too much	regionW. sou. central	-0.6018	0.3114	-1.9328	0.0533
Too much	polviewsLiberal	-0.6307	0.4113	-1.5333	0.1252
Too much	polviewsSlightly liberal	-0.6699	0.4110	-1.6298	0.1031
Too much	polviewsModerate	-0.6797	0.3510	-1.9362	0.0528
Too much	polviewsSlghtly conservative	-0.4011	0.3768	-1.0645	0.2871
Too much	polviewsConservative	-0.0798	0.3640	-0.2193	0.8264
Too much	polviewsExtrmly conservative	-0.3064	0.4429	-0.6918	0.4891

#### Exercise 7

The fact that the coeficients of the intercepts for "Too Little" and "Too Much" are both negative indicates that the model will favor the more neutral baseline in its predictions.

#### Exercise 8

The age coefficient of "Too little" versus the baseline is slightly positive. This indicates that as people get older, the likelihood that they believe mass transportation spending is insufficient rises.

#### Exercise 9

According to the null hypothesis, political views have no effect on attitudes toward spending on mass transportation. According to the alternative hypothesis, political beliefs influence people's attitudes toward spending on mass transportation. In terms of statistics, I will contrast the above model with one that does not include the polviews variable. The null hypothesis is true if the reduced model has a lower AIC.

```
reduced_model <- multinom(natmass ~ age + sex + sei10 + region, data = gss)

## # weights: 39 (24 variable)
## initial value 2845.405828
## iter 10 value 2345.298055
## iter 20 value 2328.421434
## iter 30 value 2327.225660
## final value 2327.223281
## converged

reduced_model$AIC</pre>
## [1] 4702.447
```

```
## [1] 4623.845
```

model\$AIC

The model with the polviews variable has a lower AIC. As a result, the alternate hypothesis is correct. For the remainder of the lab, we will use the full model.

## Part III: Model Fit

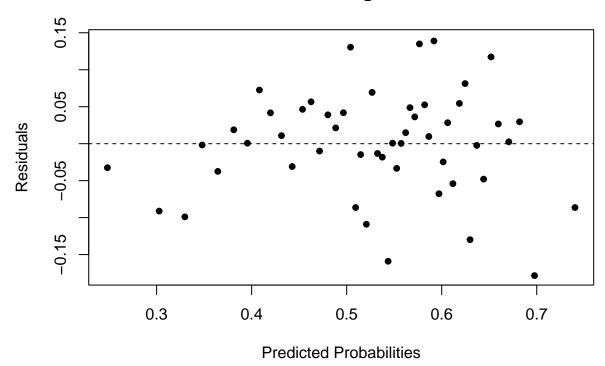
#### Exercise 11

```
fitted <- model$fitted.values
resid <- model$residuals
head(fitted)

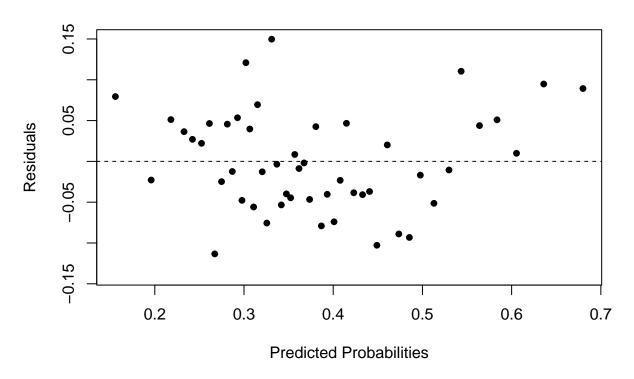
## About right Too little Too much
## 1     0.3824439     0.5151564     0.10239965
## 2     0.2715367     0.5756776     0.15278570
## 3     0.5246593     0.3253687     0.14997198
## 4     0.4155186     0.4653015     0.11917992
## 5     0.4138702     0.4762595     0.10987027
## 6     0.3142385     0.5904887     0.09527281</pre>
```

#### head(resid)

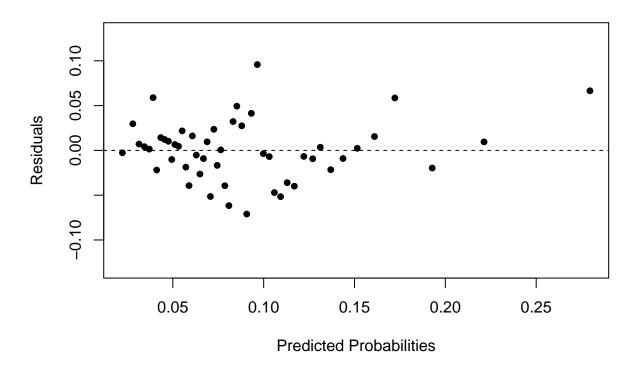
# **About right**



# Too little



# Too much



### Exercise 13

```
aboutright_avg_resid <- mean(resid[,1])
toolittle_avg_resid <- mean(resid[,2])
toomuch_avg_resid <- mean(resid[,3])
aboutright_avg_resid</pre>
```

## [1] -2.238446e-06

toolittle\_avg\_resid

## [1] 1.712403e-06

toomuch\_avg\_resid

## [1] 5.260433e-07

# Part IV: Using The Model

#### Exercise 16

According to the model, the more liberal an individual is, the more liberal their attitude toward spending on mass transportation is "too little". In contrast, the more conservative a person is, the more they believe that spending on mass transportation is "too much".

```
gss <- gss %>%
  mutate(pred_probs = predict(model, type = "class"))
gss %>%
count(natmass, pred_probs)
## # A tibble: 8 x 3
    natmass
                pred_probs
     <fct>
##
                <fct>
                             <int>
## 1 About right About right 1151
## 2 About right Too little
                              219
## 3 About right Too much
                               2
## 4 Too little About right
                               646
## 5 Too little Too little
                               339
## 6 Too much
                About right
                              196
## 7 Too much
                Too little
                              36
## 8 Too much
                Too much
                               1
misclassification rate = (219 + 2 + 646 + 196 + 36) / 2590 = 0.424
```