

exercises_week10

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Question 2

Part a

In the code below, I created both an ordered multinomial logit model (mod_1) and probit model (mod_2). See the stargazer table below for the estimates for both these models. For the dependent variable, partyid3, 1 = Independent, 2 = Democrat, and 3 = Republican. The reference category is Independent.

```
# creating multinomial logit (ordered). Chose to include race so the graphical  
# plot below looks more normal
```

```
mod_1 <- polr(factor(partyid3) ~ age + educ1 + income +  
              ideo7 + race,  
              data = nes_clean)
```

```
# creating probit model
```

```
mod_2 <- polr(factor(partyid3) ~ age + educ1 + income + ideo7 + race,  
              data = nes_clean,  
              method = "probit")
```

```
# summary of both models
```

```
# summary(mod_1)
```

```
# summary(mod_2)
```

```
stargazer(mod_1, mod_2, type = "text")
```

```
##  
## =====  
##               Dependent variable:  
## -----  
##               partyid3  
##               ordered      ordered  
##               logistic      probit  
##               (1)          (2)  
## -----  
## age               -0.007      -0.004  
##               (0.006)      (0.004)  
##
```

```
## educ1          0.343***      0.195***
##               (0.125)       (0.073)
##
## income         0.196**       0.118**
##               (0.094)       (0.056)
##
## ideo7          0.724***      0.429***
##               (0.075)       (0.043)
##
## raceblack      -1.325*       -0.820*
##               (0.725)       (0.431)
##
## racehispanic   -0.061        -0.020
##               (0.711)       (0.427)
##
## racenative_american 0.473      0.281
##               (0.761)       (0.455)
##
## racewhite      0.497         0.286
##               (0.633)       (0.381)
##
## -----
## Observations      559         559
## =====
## Note:              *p<0.1; **p<0.05; ***p<0.01
```

In the code below, I create a graphical representation of the multinomial logit model. The plot is based on figure 6.4 from the text book, where the curves show the expected responses for party identification based off of ideology. The data points do not seem to follow the curve very well, suggesting that the model might not be the best fit.

```
# graphs of both models. Make these like the ones in 6.4 of the textbook. Had to
# create the inverse logit function. Maybe I could have gotten this from the arm
# lib? Not sure

invlogit <- function(Xb) {
  1/(1+exp(-Xb))
}

# taken pretty much directly from the book

expected <- function (x, c1.5, c2.5, sigma){
  p1.5 <- invlogit ((x-c1.5)/sigma)
  p2.5 <- invlogit ((x-c2.5)/sigma)
  return ((1*(1-p1.5) + 2*(p1.5-p2.5) + 3*p2.5))
}

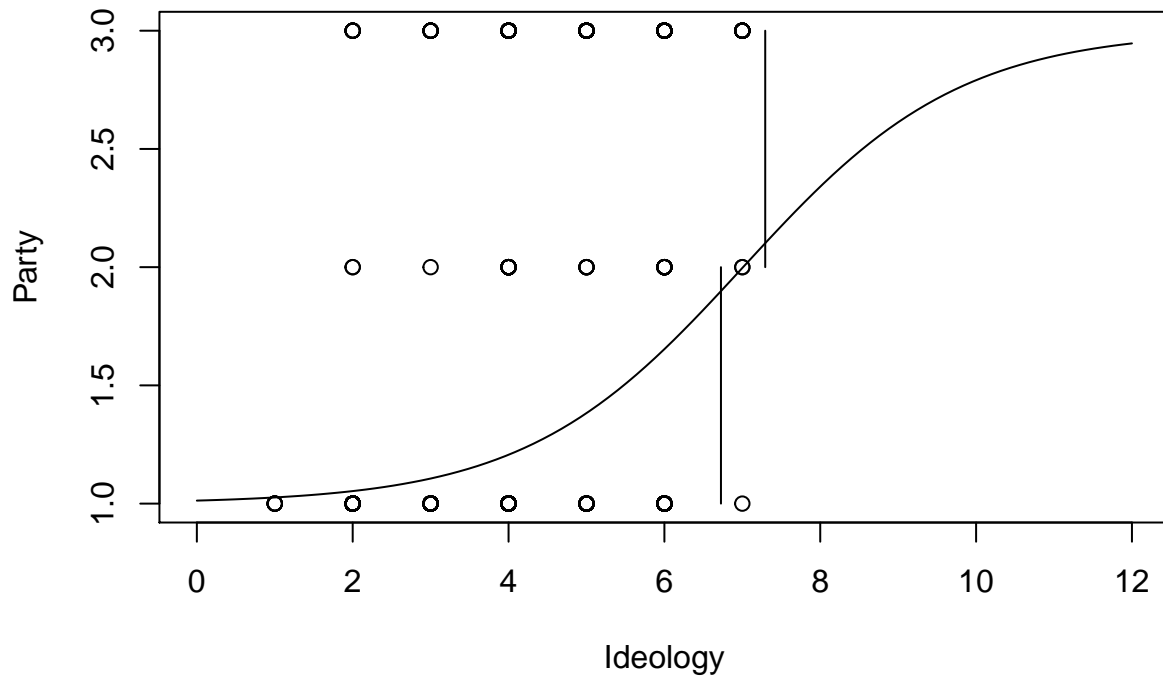
# graph of the mod_1. We don't need to do the probit model for this part. It's a
# bit weird that the cut points are outside of the range of the data.

{
plot (nes_clean$ideo7, nes_clean$partyid3, xlim=c(0,12), ylim=c(1,3),
      xlab="Ideology", ylab="Party")
lines (rep (mod_1$zeta[1]/mod_1$coefficients[4], 2), c(1,2))
}
```

```

lines (rep (mod_1$zeta[2]/mod_1$coefficients[4], 2), c(2,3))
curve (expected (
  x, mod_1$zeta[1]/mod_1$coefficients[4],
  mod_1$zeta[2]/mod_1$coefficients[4],
  1/mod_1$coefficients[4]),
  add=TRUE)
}

```



Part b

Explain the results of the fitted model

Question 3

Data

I am using the rodents data from the week 7 pset.

Part a

In the code below I create a logit (mod_3) and probot (mod_4) model.

```

# logit model
mod_3 <- glm(rodent2 ~ race + dilap + regext , data = rodents,
             family = binomial(link = "logit"))

# probit model
mod_4 <- glm(rodent2 ~ race + dilap + regext , data = rodents,
             family = binomial(link = "probit"))

# displaying the two models
stargazer(mod_3, mod_4, type = "text")

```

```

##
## =====
##                               Dependent variable:
##                               -----
##                               rodent2
##                               logistic      probit
##                               (1)          (2)
## -----
## racePuerto Rican           1.396***      0.789***
##                               (0.226)      (0.131)
##
## raceBlack                    1.545***      0.880***
##                               (0.179)      (0.101)
##
## raceOther Hispanic           1.944***      1.124***
##                               (0.200)      (0.116)
##
## raceAsian/Pacific Islander   0.363         0.196
##                               (0.302)      (0.165)
##
## raceAmer-Indian/Native Alaskan 2.137***      1.249**
##                               (0.829)      (0.517)
##
## raceTwo or More Races        0.801         0.432
##                               (0.803)      (0.458)
##
## dilap                        1.257***      0.750***
##                               (0.294)      (0.177)
##
## regext                       -0.196        -0.099
##                               (0.137)      (0.079)
##
## Constant                     -2.072***      -1.216***
##                               (0.147)      (0.078)
## -----
## Observations                 1,341         1,341
## Log Likelihood                -671.830      -672.341
## Akaike Inf. Crit.            1,361.660      1,362.682

```

```
## =====
## Note:                                *p<0.1; **p<0.05; ***p<0.01
```

The logit and the probit estimates should be more or less the same after scaling by 1.6. We can check this by multiplying the probit coefficients by 1.6. After making this adjustments, we see that the estimates roughly match up with eachother (see table below).

```
# scaling the coefficients by 1.6

new_coefs <- mod_4$coefficients * 1.6

# making table of new coefficients. Using gt for better presentation

coefs_tb <- tibble(mod_3_est = mod_3$coefficients,
  mod_4_est = mod_4$coefficients,
  mod_4_est_scaled_1.6 = new_coefs) %>%
  gt()

# displaying table

coefs_tb
```

mod_3_est	mod_4_est	mod_4_est_scaled_1.6
-2.0718749	-1.21603831	-1.9456613
1.3961628	0.78861560	1.2617850
1.5454828	0.87982092	1.4077135
1.9441400	1.12445689	1.7991310
0.3630638	0.19595209	0.3135233
2.1372837	1.24892146	1.9982743
0.8006222	0.43198668	0.6911787
1.2574108	0.74970148	1.1995224
-0.1963665	-0.09922601	-0.1587616