MA678 homework 05

Multinomial Regression

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Multinomial logit:

Using the individual-level survey data from the 2000 National Election Study (data in folder nes), predict party identification (which is on a 7-point scale) using ideology and demographics with an ordered multinomial logit model.

1. Summarize the parameter estimates numerically and also graphically.

```
# require(VGAM)
# m1 = vglm(partyid7~ideo+age+race+gender,data=nes_data_comp,Hess=TRUE,family=multinomial)
# summary(m1)

m1 = polr(partyid7~ideo+age+race+gender,data=nes_data_comp,Hess=TRUE)
summary(m1)
```

```
## Call:
## polr(formula = partyid7 ~ ideo + age + race + gender, data = nes_data_comp,
##     Hess = TRUE)
##
## Coefficients:
##                          Value Std. Error t value
## ideomoderate         1.00334   0.328139  3.0577
## ideoconservative     1.97643   0.180090 10.9747
## age                 -0.01363   0.004924 -2.7678
## raceblack           -1.73061   0.271850 -6.3660
## raceasian            0.15497   0.546457  0.2836
## racenative american -0.10237   0.367008 -0.2789
## racehispanic        -0.58450   0.294953 -1.9817
## genderfemale        -0.37984   0.155229 -2.4469
##
## Intercepts:
##                                                         Value   Std. Error
## 1. strong democrat|2. weak democrat                     -1.4220  0.3041
## 2. weak democrat|3. independent-democrat                -0.5734  0.2961
## 3. independent-democrat|4. independent-independent       0.2165  0.2956
## 4. independent-independent|5. independent-republican     0.6097  0.2980
## 5. independent-republican|6. weak republican             1.4033  0.3028
## 6. weak republican|7. strong republican                  2.3797  0.3140
##                                                         t value
## 1. strong democrat|2. weak democrat                     -4.6756
## 2. weak democrat|3. independent-democrat                -1.9366
## 3. independent-democrat|4. independent-independent       0.7324
## 4. independent-independent|5. independent-republican     2.0455
## 5. independent-republican|6. weak republican             4.6342
## 6. weak republican|7. strong republican                  7.5787
##
```

```
## Residual Deviance: 1892.422
## AIC: 1920.422
## (8 observations deleted due to missingness)
```

2. Explain the results from the fitted model.

```r
confint(m1)
```

```
## Waiting for profiling to be done...

##                            2.5 %       97.5 %
## ideomoderate          0.35781939  1.648405676
## ideoconservative      1.62688641  2.333204309
## age                  -0.02331781 -0.004001831
## raceblack            -2.27282514 -1.205143777
## raceasian            -0.92251513  1.244407549
## racenative american  -0.82893228  0.616725087
## racehispanic         -1.16729016 -0.008107863
## genderfemale         -0.68466242 -0.075915381
```

The fitted model is: Logit P($\hat{y}$ > j) = (-0.38 female - 0.013 age_10 - 1.73 black + 0.15 asian - 0.102 native - 0.58 hispanic + 1.003 moderate + 1.98 consevative - C_j)

age: holding other factors constant, comparing groups with one unit difference in age (10 year difference), we expect the older group to be on average 0.013 lower in log odds of being republican.

female: holding other factors constant, comparing females with males, we expect that females is on average 0.38 lower in log odds of being republican.

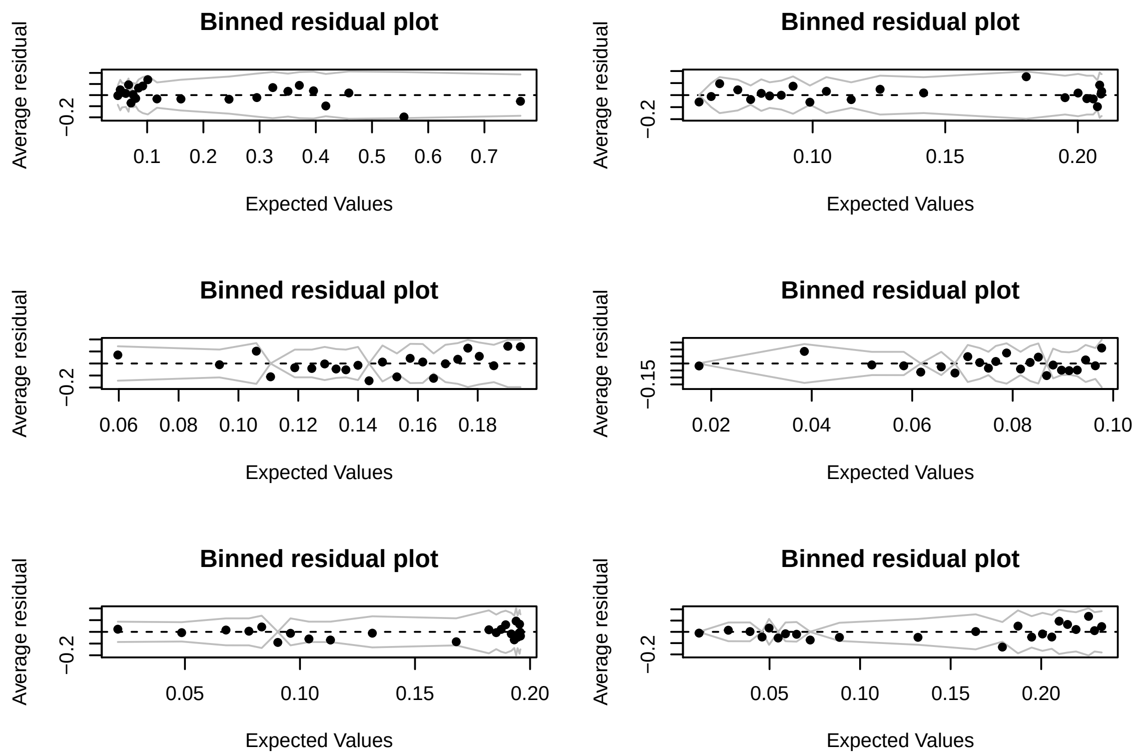
race: holding other factors constant, we expect Asian to be higher in log odds of being republican than whites, while other race groups to be lower in log odds of being republican than whites.

ideo: holding other factors constant, comparing with liberal people, moderate people are expected to be 1.003 higher in log odds of being republican and conservative people are expected to be 1.98 higher in log odds of being republican on average.

3. Use a binned residual plot to assess the fit of the model.

```r
nes <- cbind(partyid7= nes_data_comp$partyid7, ideo = nes_data_comp$ideo, race = nes_data_comp$race ,
nes <- data.frame(na.omit(nes))
resid <- model.matrix(~factor(partyid7)-1, data=nes)-fitted(m1)

par(mfrow= c(3,2))
for (i in 1:6) {
  binnedplot(fitted(m1)[,i], resid[,i], cex.main=1.3, main="Binned residual plot" )
}
```



High School and Beyond

The hsb data was collected as a subset of the High School and Beyond study conducted by the National Education Longitudinal Studies program of the National Center for Education Statistics. The variables are gender; race; socioeconomic status; school type; chosen high school program type; scores on reading, writing, math, science, and social studies. We want to determine which factors are related to the choice of the type of program—academic, vocational, or general—that the students pursue in high school. The response is multinomial with three levels.

```
data(hsb)
?hsb
```

1. Fit a trinomial response model with the other relevant variables as predictors (untransformed).

```
m2 = multinom(prog~read+write+math+science+race,data = hsb,trace=FALSE,HESS=TRUE)
summary(m2)
```

```
## Call:
## multinom(formula = prog ~ read + write + math + science + race,
##     data = hsb, trace = FALSE, HESS = TRUE)
##
## Coefficients:
##          (Intercept)        read       write       math    science
## general     4.924957 -0.05388450 -0.03946933 -0.1071044 0.09229507
## vocation    8.777829 -0.05594167 -0.06281609 -0.1253231 0.05262485
##           raceasian racehispanic   racewhite
## general  1.11489221  -0.60687283 -0.01313942
## vocation 0.08636574   0.07298783  0.42373684
##
```

```
## Std. Errors:
##          (Intercept)       read      write       math    science raceasian
## general     1.528744 0.02853999 0.02864533 0.03391490 0.03053422 0.9950814
## vocation    1.629837 0.03052243 0.02855810 0.03616922 0.03106921 1.3388885
##          racehispanic racewhite
## general     0.8707214 0.6995466
## vocation    0.7864713 0.6836971
##
## Residual Deviance: 332.6696
## AIC: 364.6696
```

2. For the student with id 99, compute the predicted probabilities of the three possible choices.

```r
predict(m2,newdata=hsb[hsb$id==99,],type="probs")
```

```
##  academic   general  vocation
## 0.3756043 0.4338602 0.1905356
```

Happiness

Data were collected from 39 students in a University of Chicago MBA class and may be found in the dataset happy.

```r
library(faraway)
data(happy)
?happy
```

1. Build a model for the level of happiness as a function of the other variables.

```r
m3 = multinom(happy~money+sex+love+work,data=happy,HESS=TRUE,trace=FALSE)
summary(m3)
```

```
## Call:
## multinom(formula = happy ~ money + sex + love + work, data = happy,
##     HESS = TRUE, trace = FALSE)
##
## Coefficients:
##    (Intercept)    money        sex        love      work
## 3     95.34718 8.207436   47.53907 -121.974570 -83.37503
## 4    108.15356 6.448616  126.62067 -144.128459 -19.45492
## 5    103.43665 6.504835   17.26409  -89.127605 -18.72953
## 6    -56.16590 6.632862  -29.02349   -9.832305 -20.71266
## 7     23.22477 6.557004   16.88244  -51.573474 -17.95274
## 8    -94.78326 6.586027  -39.30831    6.352961 -17.99809
## 9   -213.80005 6.596051   16.52875  -14.640589  13.18524
## 10  -149.75016 4.278169 -142.97178   95.281252 -45.18974
##
## Std. Errors:
##    (Intercept)       money          sex        love        work
## 3  0.325485656 27.67909907 3.254857e-01 0.328049326 0.328049314
## 4  0.799797489  4.62411816 7.997975e-01 1.571938267 1.210306606
## 5  0.746595285  4.62366481 1.682088e+00 1.493190570 0.865609268
## 6  2.378685936  4.62378421 4.087284e+00 1.201823879 1.931873302
## 7  1.620528738  4.62359628 1.651471e+00 0.829190888 0.703236473
## 8  1.228910839  4.62360881 1.892117e+00 1.036603126 0.814853390
```

```
## 9  0.103510063  4.62362103 1.035101e-01 0.310530190 0.414040255
## 10 0.001547399  0.06183351 9.923873e-08 0.004642197 0.007414509
##
## Residual Deviance: 53.40729
## AIC: 133.4073
```

2. Interpret the parameters of your chosen model.

```
confint(m3)
```

```
## , , 3
##
##                  2.5 %     97.5 %
## (Intercept)   94.70924   95.98512
## money        -46.04260   62.45747
## sex           46.90113   48.17701
## love        -122.61753 -121.33160
## work         -84.01799  -82.73207
##
## , , 4
##
##                   2.5 %     97.5 %
## (Intercept)  106.585985  109.72113
## money         -2.614489   15.51172
## sex          125.053096  128.18824
## love        -147.209401 -141.04752
## work         -21.827074  -17.08276
##
## , , 5
##
##                  2.5 %    97.5 %
## (Intercept) 101.973346 104.89995
## money        -2.557381  15.56705
## sex          13.967262  20.56093
## love        -92.054205 -86.20101
## work        -20.426092 -17.03297
##
## , , 6
##
##                  2.5 %     97.5 %
## (Intercept) -60.828037 -51.503760
## money        -2.429589  15.695312
## sex         -37.034425 -21.012564
## love        -12.187836  -7.476773
## work        -24.499065 -16.926260
##
## , , 7
##
##                  2.5 %    97.5 %
## (Intercept)  20.048588  26.40094
## money        -2.505078  15.61909
## sex          13.645613  20.11926
## love        -53.198659 -49.94829
## work        -19.331061 -16.57442
##
```

```
## , , 8
##
##                  2.5 %     97.5 %
## (Intercept) -97.191883 -92.374641
## money        -2.476079  15.648134
## sex         -43.016792 -35.599830
## love          4.321256   8.384666
## work        -19.595174 -16.401007
##
## , , 9
##
##                  2.5 %     97.5 %
## (Intercept) -214.00293 -213.59717
## money         -2.46608   15.65818
## sex           16.32588   16.73163
## love         -15.24922  -14.03196
## work          12.37374   13.99675
##
## , , 10
##
##                   2.5 %      97.5 %
## (Intercept) -149.753197 -149.747131
## money          4.156978    4.399361
## sex         -142.971776 -142.971776
## love          95.272153   95.290350
## work         -45.204268  -45.175204
```

Focusing on the block of coefficients, we can look at the first row comparing happiness level of 3 to our baseline-happiness level of 2. Whcih means, the log odds of having happiness level at 3 vs. having happiness level at 2 will decrease by 8.21 if money=0;the log odds will increase by 47.54 if sex moving from 0 to 1.

3. Predict the happiness distribution for subject whose parents earn $30,000 a year, who is lonely, not sexually active and has no job.

```r
predict(m3,newdata=data.frame(love=1,sex=0,work=1,money=30),type="probs")
```

```
##            2            3            4            5            6
## 1.476969e-83 2.134248e-24 1.301533e-23 1.000000e+00 8.507098e-35
##            7            8            9           10
## 3.097618e-18 5.706471e-44 4.207186e-91 4.243541e-71
```

newspaper survey on Vietnam War

A student newspaper conducted a survey of student opinions about the Vietnam War in May 1967. Responses were classified by sex, year in the program and one of four opinions. The survey was voluntary. The data may be found in the dataset `uncviet`. Treat the opinion as the response and the sex and year as predictors. Build a proportional odds model, giving an interpretation to the estimates.

```r
data(uncviet)
?uncviet
m4 = polr(policy~sex+year,data=uncviet,weights=y,Hess = TRUE)
summary(m4)
```

```
## Call:
## polr(formula = policy ~ sex + year, data = uncviet, weights = y,
```

```
##     Hess = TRUE)
##
## Coefficients:
##              Value Std. Error t value
## sexMale    -0.6470    0.08499  -7.613
## yearGrad    1.1770    0.10226  11.510
## yearJunior  0.3964    0.10972   3.613
## yearSenior  0.5444    0.11248   4.840
## yearSoph    0.1315    0.11460   1.148
##
## Intercepts:
##     Value    Std. Error t value
## A|B  -1.1098   0.1107   -10.0210
## B|C  -0.0130   0.1086    -0.1202
## C|D   2.4417   0.1194    20.4455
##
## Residual Deviance: 7757.056
## AIC: 7773.056
```

pneumonoconiosis of coal miners

The pneumo data gives the number of coal miners classified by radiological examination into one of three categories of pneumonoconiosis and by the number of years spent working at the coal face divided into eight categories.

```r
library(faraway)
data(pneumo,package="faraway")
?pneumo
```

```
## Help on topic 'pneumo' was found in the following packages:
##
##   Package               Library
##   VGAM                  /Library/Frameworks/R.framework/Versions/3.5/Resources/library
##   faraway               /Library/Frameworks/R.framework/Versions/3.5/Resources/library
##
##
## Using the first match ...
```

1. Treating the pneumonoconiosis status as response variable as nominal, build a model for predicting the frequency of the three outcomes in terms of length of service and use it to predict the outcome for a miner with 25 years of service.

```r
m5 = vglm(status~year,data=pneumo,Hess=TRUE,family=multinomial)
summary(m5)
```

```
##
## Call:
## vglm(formula = status ~ year, family = multinomial, data = pneumo,
##     Hess = TRUE)
##
##
## Pearson residuals:
##                     Min 1Q Median    3Q   Max
## log(mu[,1]/mu[,3])  -1 -1 -0.366 1.366 1.366
```

```
## log(mu[,2]/mu[,3])  -1 -1 -0.366 1.366 1.366
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept):1 -1.305e-15  1.143e+00       0        1
## (Intercept):2 -1.831e-15  1.143e+00       0        1
## year:1         4.075e-17  3.420e-02       0        1
## year:2         6.835e-17  3.420e-02       0        1
##
## Number of linear predictors:  2
##
## Names of linear predictors: log(mu[,1]/mu[,3]), log(mu[,2]/mu[,3])
##
## Residual deviance: 52.7334 on 44 degrees of freedom
##
## Log-likelihood: -26.3667 on 44 degrees of freedom
##
## Number of iterations: 1
##
## No Hauck-Donner effect found in any of the estimates
##
## Reference group is level  3  of the response
```

```r
predict(m5,newdata=data.frame(year=25))
```

```
##   log(mu[,1]/mu[,3]) log(mu[,2]/mu[,3])
## 1       -2.86551e-16      -1.222499e-16
```

2. Repeat the analysis with the pneumonoconiosis status being treated as ordinal.

```r
m6 = polr(status~year,data=pneumo,Hess = TRUE)
summary(m6)
```

```
## Call:
## polr(formula = status ~ year, data = pneumo, Hess = TRUE)
##
## Coefficients:
##          Value Std. Error   t value
## year 4.341e-11    0.02565 1.692e-09
##
## Intercepts:
##               Value   Std. Error t value
## mild|normal   -0.6931  0.8838    -0.7842
## normal|severe  0.6931  0.8838     0.7842
##
## Residual Deviance: 52.73339
## AIC: 58.73339
```

```r
predict(m6,newdata=data.frame(year=25),type="probs")
```

```
##      mild    normal    severe
## 0.3333333 0.3333333 0.3333333
```

3.Now treat the response variable as hierarchical with top level indicating whether the miner has the disease and the second level indicating, given they have the disease, whether they have a moderate or severe case.

```r
pneumo$status2 <- ifelse(pneumo$status=="normal", "top level",
                  ifelse(pneumo$status=="mild", "second level moderate",
                  ifelse(pneumo$status=="severe", "second level severe",
                                  NA )))
pneumo$status2 <- factor(pneumo$status2, ordered=TRUE)
m7 = polr(status2~year,data=pneumo,Hess = TRUE)
summary(m7)
```

```
## Call:
## polr(formula = status2 ~ year, data = pneumo, Hess = TRUE)
##
## Coefficients:
##          Value Std. Error   t value
## year 4.339e-11    0.02565 1.691e-09
##
## Intercepts:
##                                           Value   Std. Error t value
## second level moderate|second level severe -0.6931  0.8838    -0.7842
## second level severe|top level              0.6931  0.8838     0.7842
##
## Residual Deviance: 52.73339
## AIC: 58.73339
```

```r
predict(m7,newdata=data.frame(year=25),type="probs")
```

```
## second level moderate   second level severe             top level
##             0.3333333             0.3333333             0.3333333
```

4. Compare the three analyses.

```r
AIC(m5)
```

```
## [1] 60.73339
```

```r
AIC(m6)
```

```
## [1] 58.73339
```

```r
AIC(m7)
```

```
## [1] 58.73339
```

It seems ordinal model has lower AIC than unordered.

(optional) Multinomial choice models:

Pardoe and Simonton (2006) fit a discrete choice model to predict winners of the Academy Awards. Their data are in the folder academy.awards.

name	description
No	unique nominee identifier
Year	movie release year (not ceremony year)
Comp	identifier for year/category
Name	short nominee name
PP	best picture indicator
DD	best director indicator

name	description
MM	lead actor indicator
FF	lead actress indicator
Ch	1 if win, 2 if lose
Movie	short movie name
Nom	total oscar nominations
Pic	picture nom
Dir	director nom
Aml	actor male lead nom
Afl	actor female lead nom
Ams	actor male supporting nom
Afs	actor female supporting nom
Scr	screenplay nom
Cin	cinematography nom
Art	art direction nom
Cos	costume nom
Sco	score nom
Son	song nom
Edi	editing nom
Sou	sound mixing nom
For	foreign nom
Anf	animated feature nom
Eff	sound editing/visual effects nom
Mak	makeup nom
Dan	dance nom
AD	assistant director nom
PrNl	previous lead actor nominations
PrWl	previous lead actor wins
PrNs	previous supporting actor nominations
PrWs	previous supporting actor wins
PrN	total previous actor/director nominations
PrW	total previous actor/director wins
Gdr	golden globe drama win
Gmc	golden globe musical/comedy win
Gd	golden globe director win
Gm1	golden globe male lead actor drama win
Gm2	golden globe male lead actor musical/comedy win
Gf1	golden globe female lead actor drama win
Gf2	golden globe female lead actor musical/comedy win
PGA	producer's guild of america win
DGA	director's guild of america win
SAM	screen actor's guild male win
SAF	screen actor's guild female win
PN	PP*Nom
PD	PP*Dir
DN	DD*Nom
DP	DD*Pic
DPrN	DD*PrN
DPrW	DD*PrW
MN	MM*Nom
MP	MM*Pic
MPrN	MM*PrNl
MPrW	MM*PrWl

name	description
FN	FF*Nom
FP	FF*Pic
FPrN	FF*PrNl
FPrW	FF*PrWl

1. Fit your own model to these data.
2. Display the fitted model on a plot that also shows the data.
3. Make a plot displaying the uncertainty in inferences from the fitted model.