## Multinomial Regression for Student Program Choice Prediction

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Students entering high school can make program choices among general program, vocational program and academic program.

So, to predict the program type,

Lets try to fit multinomial logistic regression for their choice of program with respective to other categorical and ordinal variables

Data: https://stats.idre.ucla.edu/stat/data/hsbdemo.dta

#### **Data Import**

Lets import the data and have a look at summary of it.

```
# library(rio)
hsb_data = read.dta("hsbdemo.dta")
# Required predictors and dependent variable
head(hsb_data[, c(3, 7, 5)])
##
       ses write
                     prog
## 1
              35 vocation
       low
## 2 middle
              33 general
## 3
      high
              39 vocation
## 4
       low
              37 vocation
## 5 middle
            31 vocation
              36 general
## 6
      high
summary(hsb_data[, c(3, 7, 5)])
##
       ses
                   write
                                     prog
##
  low
        :47
              Min. :31.00
                               general: 45
  middle:95
              1st Qu.:45.75
                               academic:105
##
  high :58
               Median :54.00
                               vocation: 50
##
               Mean
                      :52.77
##
               3rd Qu.:60.00
##
               Max.
                      :67.00
# baseline level of 'prog' dependent variable
hsb_data$prog_l <- relevel(hsb_data$prog, ref = "academic")
```

#### Exploring bivariate relation counts

```
# ses ~ prog_l
with(hsb_data, table(ses, prog_l))
```

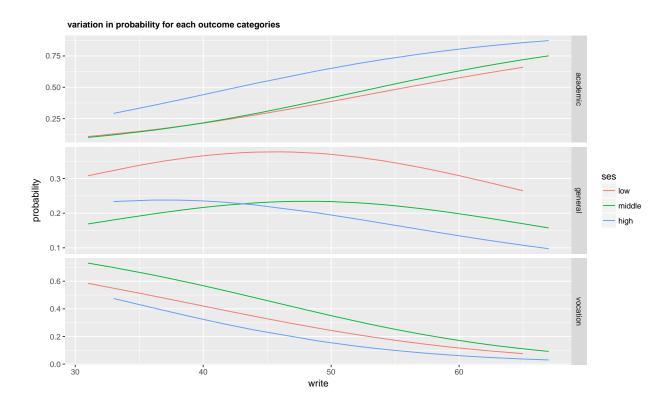
```
##
           prog_l
## ses
            academic general vocation
##
     low
                  19
                          16
                                    31
##
     middle
                  44
                          20
##
    high
                  42
                           9
                                     7
# write ~ prog_l
with(hsb_data, do.call(rbind, tapply(write, prog_l, function(x) c(M = mean(x),
    SD = sd(x))))
##
## academic 56.25714 7.943343
## general 51.33333 9.397775
## vocation 46.76000 9.318754
```

#### Applying Multinomial Logistic Regression Model

```
# Multinomial Regression
model <- multinom(prog_l ~ ses + write, data = hsb_data)</pre>
## # weights: 15 (8 variable)
## initial value 219.722458
## iter 10 value 179.982880
## final value 179.981726
## converged
## Call:
## multinom(formula = prog_l ~ ses + write, data = hsb_data)
## Coefficients:
             (Intercept) sesmiddle
                                           seshigh
                                                          write
                 2.852198 -0.5332810 -1.1628226 -0.0579287
## general
## vocation
                 5.218260 0.2913859 -0.9826649 -0.1136037
##
## Std. Errors:
             (Intercept) sesmiddle
                                         seshigh
## general
                 1.166441 0.4437323 0.5142196 0.02141097
## vocation
                 1.163552 0.4763739 0.5955665 0.02221996
## Residual Deviance: 359.9635
## AIC: 375.9635
              (Intercept) sesmiddle
                                         seshigh
                                                        write
                 1632.582 -41.33231 -68.73974 -5.628277
## general
                18361.262 33.82809 -62.56877 -10.738840
## vocation
First row compares prog = "general" to baseline prog = "academic". Second row compares prog = "vocation"
to baseline prog = "academic".
Interpretations for the General vs. Academic model:
\ln(\frac{P(prog="general")}{P(prog="academic")}) = b_{10} + b_{1}1 * (ses = 2) + b_{12} * (ses = 3) + b_{13} * write
Interpretations for the Vocational vs. Academic model:
\ln(\frac{P(prog="vocation")}{P(prog="academic")}) = b_{20} + b211 * (ses = 2) + b_{12} * (ses = 3) + b_{23} * write
```

#### Plot the fitted values against writing score and social economic status

```
model.df <- data.frame(ses = hsb_data$ses, write = hsb_data$write)
model.df.prob <- cbind(model.df, fitted.values(model))
# dataframe for ggplot
pred_prob.ggplot <- melt(model.df.prob, id.vars = c("ses", "write"), value.name = "probability")
## plot of fitted probabilities facet over program type
ggplot(pred_prob.ggplot, aes(x = write, y = probability, colour = ses)) + geom_line() +
    facet_grid(variable ~ ., scales = "free") + ggtitle(" variation in probability for each outcome cat
    theme(plot.title = element_text(size = 10, face = "bold"))</pre>
```



# Based on the models defined, for "ses=middle and write=54", making a prediction for prog

```
data <- data.frame(ses = "middle", write = 54)
cat("\nFor ses=middle and write=54, the predicted probabilities for prog_type are:\n",
    predict(model, newdata = data, "probs"))

##

## For ses=middle and write=54, the predicted probabilities for prog_type are:
## 0.504927 0.2247932 0.2702798

probs <- predict(model, newdata = data, "probs")
# Calculating required ratios

vocation_over_academic = probs[3]/probs[1]</pre>
```

```
general_over_academic = probs[2]/probs[1]

cat("\n\nProbability of choosing each outcome category over the baseline category are \n")

##

##

## Probability of choosing each outcome category over the baseline category are

vocation_over_academic

## vocation

## 0.535285

general_over_academic

## general

## 0.4451995
```

#### Proportional odds logistic regression

Lets treat prog as an ordered categorical variable and fit a proportional odds logistic regression with the same predictors ses and write.

```
# Model
hsb_data.polr = polr(factor(prog) ~ ses + write, data = hsb_data)
display(hsb_data.polr)
## polr(formula = factor(prog) ~ ses + write, data = hsb_data)
##
                     coef.est coef.se
## sesmiddle
                      0.68
                               0.36
                      0.40
                               0.38
## seshigh
## write
                     -0.04
                               0.02
## general|academic -3.15
                               0.87
## academic|vocation -0.71
                               0.83
## ---
## n = 200, k = 5 (including 2 intercepts)
## residual deviance = 397.0, null deviance is not computed by polr
probs <- predict(hsb_data.polr, data.frame(ses = "middle", write = 54), type = "probs")</pre>
cat("\nProbability for each outcome category.\n")
## Probability for each outcome category.
probs
     general academic vocation
## 0.1780447 0.5357214 0.2862339
```

Therefore, prediction for prog given ses=middle and write=54 is "academic".

We also have their reading, math, science and standardized test score for social studies in the data set ("read", "math", "science" and "socst").

### PCA for above variables and "write" to explore first two principal components

```
pca_cols <- c("read", "math", "science", "socst", "write")</pre>
pca_data <- hsb_data[pca_cols]</pre>
data.pca = prcomp(pca_data, scale. = TRUE)
data.pca
## Standard deviations (1, .., p=5):
## [1] 1.8387006 0.7465777 0.6378031 0.5967980 0.5466638
## Rotation (n x k) = (5 \times 5):
##
                 PC1
                             PC2
                                           PC3
                                                       PC4
           0.4664184 \ -0.02727868 \quad 0.5312736731 \ -0.02057541 \ -0.7064239
## read
           0.4587755 \ -0.26090184 \quad 0.0005952692 \ -0.78003732 \quad 0.3361498
## math
## science 0.4355824 -0.61089329 0.0069539237 0.58947561 0.2992449
           ## write
           0.4483893 \quad 0.20754742 \ -0.8064237887 \quad 0.05575345 \ -0.3200677
ggbiplot(data.pca, obs.scale = 1, groups = hsb_data$prog) + ggtitle("Biplot for first two principal com
    theme(plot.title = element_text(size = 10, face = "bold"))
```

