Multinomial Regression with R

- The ratio of the probability of choosing one outcome category over the probability of choosing the baseline category is often referred as relative risk (and it is also sometimes referred as odds as we have just used to described the regression parameters above).
- The relative risk is the right-hand side linear equation exponentiated, leading to the fact that the exponentiated regression coefficients are relative risk ratios for a unit change in the predictor variable.
- We can exponentiate the coefficients from our model to see these risk ratios.

Multinomial Regression with R

extract the coefficients from the model and exponentiate

```
exp(coef(test))

          (Intercept) sesmiddle seshigh  wri
 general        17.33    0.5867  0.3126 0.94
 vocation      184.61    1.3383  0.3743 0.89
```

Multinomial Regression with R

- The relative risk ratio for a one-unit increase in the variable write is .9437 for being in general program vs. academic program.
- The relative risk ratio switching from ses = 1 to 3 is .3126 for being in general program vs. academic program.

Multinomial Regression with R

- You can also use predicted probabilities to help you understand the model.
- You can calculate predicted probabilities for each of our outcome levels using the fitted function.
- We can start by generating the predicted probabilities for the observations in our dataset and viewing the first few rows

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```
head(pp <- fitted(test))
```

```
  academic general vocation
1   0.1483  0.3382   0.5135
2   0.1202  0.1806   0.6992
3   0.4187  0.2368   0.3445
4   0.1727  0.3508   0.4765
5   0.1001  0.1689   0.7309
6   0.3534  0.2378   0.4088
```

Next, if we want to examine the changes in predicted probability associated with one of our two variables, we can create small datasets varying one

Multinomial Regression with R

```
dses <- data.frame(ses = c("low", "middle", "h
predict(test, newdata = dses, "probs")
```

```
   academic general vocation
 1   0.4397  0.3582   0.2021
 2   0.4777  0.2283   0.2939
 3   0.7009  0.1785   0.1206
```

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Another way to understand the model using the predicted probabilities is to look at the averaged predicted probabilities for different values of the continuous predictor variable write within each level of ses.

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```
dwrite <- data.frame(ses = rep(c("low", "middl
    3))

 store the predicted probabilities for each va
pp.write <- cbind(dwrite, predict(test, newdat
```

Multinomial Regression with R

calculate the mean probabilities within each level of ses

```
by(pp.write[, 3:5], pp.write$ses, colMeans)

 pp.write$ses: high
 academic  general vocation
   0.6164    0.1808    0.2028
 ------------------------------------------------------------
 pp.write$ses: low
 academic  general vocation
   0.3973    0.3278    0.2749
 ------------------------------------------------------------
 pp.write$ses: middle
```

Multinomial Regression with R

- Sometimes, a couple of plots can convey a good deal amount of information.
- Using the predictions we generated for the pp.write object above, we can plot the predicted probabilities against the writing score by the level of ses for different levels of the outcome variable.

Multinomial Regression with R

melt data set to long for ggplot2

```
lpp <- melt(pp.write, id.vars = c("ses", "writ
head(lpp)  # view first few rows

   ses write variable probability
 1 low    30 academic     0.09844
 2 low    31 academic     0.10717
 3 low    32 academic     0.11650
 4 low    33 academic     0.12646
 5 low    34 academic     0.13705
 6 low    35 academic     0.14828
```

Multinomial Regression with R

plot predicted probabilities across write values for each level of ses facetted by program type

```
ggplot(lpp, aes(x = write, y = probability, co
    ., scales = "free")
```

Things to consider

- The Independence of Irrelevant Alternatives (IIA) assumption: Roughly, the IIA assumption means that adding or deleting alternative outcome categories does not affect the odds among the remaining outcomes. There are alternative modeling methods, such as alternative-specific multinomial probit model, or nested logit model to relax the IIA assumption.
- Diagnostics and model fit: Unlike logistic regression where there are many statistics for performing model diagnostics, it is not as straightforward to do diagnostics with

Multinomial Regression with R

Things to consider

- Complete or quasi-complete separation: Complete separation means that the outcome variable separate a predictor variable completely, leading perfect prediction by the predictor variable.
- Perfect prediction means that only one value of a predictor variable is associated with only one value of the response variable. But you can tell from the output of the regression coefficients that something is wrong. You can then do a two-way tabulation of the outcome variable with the problematic variable to confirm this and