Multinomial logistic regression

- We use the multinom function from the nnet package to estimate a multinomial logistic regression model.
- Remark There are other functions in other R packages capable of multinomial regression, such as the **mlogit** package.
- The multinom function does not require the data to be reshaped (as the mlogit package does) and to mirror the example code found in Hilbe's Logistic Regression Models.

Multinomial logistic regression

- We must choose the level of our outcome that we wish to use as our **baseline** and specify this in the relevel function. Let's choose "academic".
- ▶ Then, we run our model using *multinom*.
- The multinom command does not include p-value calculation for the regression coefficients, but we calculate p-values using Wald tests (here z-tests).

```
ml$prog2 <- relevel(ml$prog, ref = "academic")
test <- multinom(prog2 ~ ses + write, data = ml)

# weights: 15 (8 variable)
initial value 219.722458
iter 10 value 179.982880
final value 179.981726
converged</pre>
```

```
summary(test)
Call:
multinom(formula = prog2 ~ ses + write,
  data = m1
Coefficients:
          (Intercept) sesmiddle seshigh write
               2.852 -0.5333 -1.1628 -0.05793
general
               5.218 0.2914 -0.9827 -0.11360
vocation
```

. . . .

```
Std. Errors:
```

```
(Intercept) sesmiddle seshigh write
general 1.166 0.4437 0.5142 0.02141
vocation 1.164 0.4764 0.5956 0.02222
```

Residual Deviance: 360

AIC: 376

```
# 2-tailed z test
# p.values
```

```
(Intercept) sesmiddle seshigh write
general 1.448e-02 0.2294 0.02374 6.819e-03
vocation 7.299e-06 0.5408 0.09895 3.176e-07
```

- Some output is generated by running the model, even though we are assigning the model to a new R object.
- ► This model-running output includes some iteration history and includes the final negative log-likelihood 179.981726.
- This value multiplied by two is then seen in the model summary as the **Residual Deviance** and it can be used in comparisons of nested models.

- As with many summary outputs, the output contains a column of coefficients and a column of standard errors.
- ► Each of these blocks has one row of values corresponding to a model equation.
- Focusing on the block of coefficients, we can look at the first row comparing prog = "general" to our baseline prog = "academic" and the second row comparing prog = "vocation" to our baseline prog = "academic".

▶ If we consider our coefficients from the first row to be b_1 and our coefficients from the second row to be b_2 , we can write our model equations:

$$In\left(\frac{P(prog = gen.)}{P(prog = acad.)}\right) = b_{10} + b_{11}(ses = 2) + b_{12}(ses = 3) + b_{13}write$$

$$In\left(\frac{P(prog = voc.)}{P(prog = acad.)}\right) = b_{20} + b_{21}(ses = 2) + b_{22}(ses = 3) + b_{23}write$$

- A one-unit increase in the variable write is associated with the decrease in the log odds of being in general program vs. academic program in the amount of 0.058 (b₁₃).
- A one-unit increase in the variable write is associated with the decrease in the log odds of being in vocation program vs. academic program in the amount of o.1136 (b₂₃).

- ► The log odds of being in general program vs. in academic program will decrease by 1.163 if moving from ses="low" to ses="high"(b_12).
- The log odds of being in general program vs. in academic program will decrease by 0.533 if moving from ses="low" to ses="middle" (b_−11), although this coefficient is not significant.

- ► The log odds of being in vocation program vs. in academic program will decrease by 0.983 if moving from ses="low" to ses="high" (b_22).
- The log odds of being in vocation program vs. in academic program will increase by 0.291 if moving from ses="low" to ses="middle"(b_21), although this coefficient is not signficant.