

Nominal Dependent Variables

Week 19

Winnie Xia

Nominal Data in Political Science

- If outcome or dependent variable is binary, then use **logit or probit models**.
- If outcome or dependent variable is categorical but ordered (i.e low to high), then use **ordered logit or ordered probit models**
 - Agree; Neutral; Disagree
 - Low; Middle; High
- If outcome or dependent variable is categorical without any particular order, then use **multinomial logit/probit models**.

Models for Nominal DVs

- Multinomial logit model: Series of binary logit models; similar to ordered logit. **Easiest to interpret.**
- Multinomial probit model: Series of binary probit models; similar to ordered probit. **Drops the IIA assumption.**
- Conditional logit model
- Joint multinomial and conditional logit model
- Mixed multinomial logit model
- Nested multinomial logit model

R packages for Nominal families

	nnet	mlogit	mnlogit	MNP	mclogit
Multinomial logit model	yes	yes	yes	no	yes
Multinomial probit model	no	yes	no	yes	no
Conditional logit model	no	yes	yes	no	yes
Joint multinomial and conditional logit model	no	yes	no	no	yes
Mixed multinomial logit model	no	yes	yes	no	no
Mixed multinomial logit model	no	no	yes	no	no

Multinomial Logit Model in R

```
library(foreign)
library(texreg)
dat <- read.dta("https://stats.idre.ucla.edu/stat/data/hsbdemo.dta")
head(dat)
```

##	id	female	ses	schtyp	prog	read	write	math	science	socst	hon
## 1	45	female	low	public	vocation	34	35	41	29	26	not enrol
## 2	108	male	middle	public	general	34	33	41	36	36	not enrol
## 3	15	male	high	public	vocation	39	39	44	26	42	not enrol
## 4	67	male	low	public	vocation	37	37	42	33	32	not enrol
## 5	153	male	middle	public	vocation	39	31	40	39	51	not enrol
## 6	51	female	high	public	general	42	36	42	31	39	not enrol

Multinomial Logit Model in R

```
library(nnet)
dat$prog2 <- relevel(dat$prog, ref = "academic")
m1 <- multinom(prog2 ~ ses + write, data = dat)
```

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

```
# prog, program type: general academic, and vocation
# ses, social economic status, categorical
# write, continuous,
```

Multinomial Logit Model in R

Coefficients are log odds-ratios of the respective category over the reference category.

```
screenreg(m1, single.row = TRUE, beside = TRUE)
```

```
##
## =====
##               general               vocation
## -----
## (Intercept)      2.85 (1.17) *      5.22 (1.16) ***
## sesmiddle        -0.53 (0.44)      0.29 (0.48)
## seshigh          -1.16 (0.51) *    -0.98 (0.60)
## write            -0.06 (0.02) **   -0.11 (0.02) ***
## -----
## AIC              375.96            375.96
## BIC              402.35            402.35
## Log Likelihood   -179.98           -179.98
## Deviance         359.96            359.96
## Num. obs.       200                200
## K                3                  3
## =====
## *** p < 0.001; ** p < 0.01; * p < 0.05
```

Multinomial Logit Interpretation

```
z <- summary(m1)$coefficients/summary(m1)$standard.errors  
p <- (1 - pnorm(abs(z), 0, 1))*2  
data.frame(p)
```

```
##           X.Intercept. sesmiddle    seshigh      write  
## general  0.0144766100 0.2294379 0.02373856 6.818902e-03  
## vocation 0.0000072993 0.5407530 0.09894976 3.176045e-07
```


Interpretation

```
data.frame(exp(coef(m1)))
```

```
##           X.Intercept. sesmiddle  seshigh    write
## general      17.32582 0.5866769 0.3126026 0.9437172
## vocation     184.61262 1.3382809 0.3743123 0.8926116
```

- All else being equal, a one unit increase in **writing** decreases the relative odds of being in **general program** over **academic program** by approximately 0.94 %, and decreases the relative odds of **vocational program** over **academic program** by 0.89 %.

Interpretation

- Again, we recommend, to use **predicted probabilities**.

```
head(fitted(m1))
```

```
##      academic   general  vocation
## 1 0.1482764 0.3382454 0.5134781
## 2 0.1202017 0.1806283 0.6991700
## 3 0.4186747 0.2368082 0.3445171
## 4 0.1726885 0.3508384 0.4764731
## 5 0.1001231 0.1689374 0.7309395
## 6 0.3533566 0.2377976 0.4088458
```

Interpretation

- Then, we create a scenario to plot the predicted probabilities.

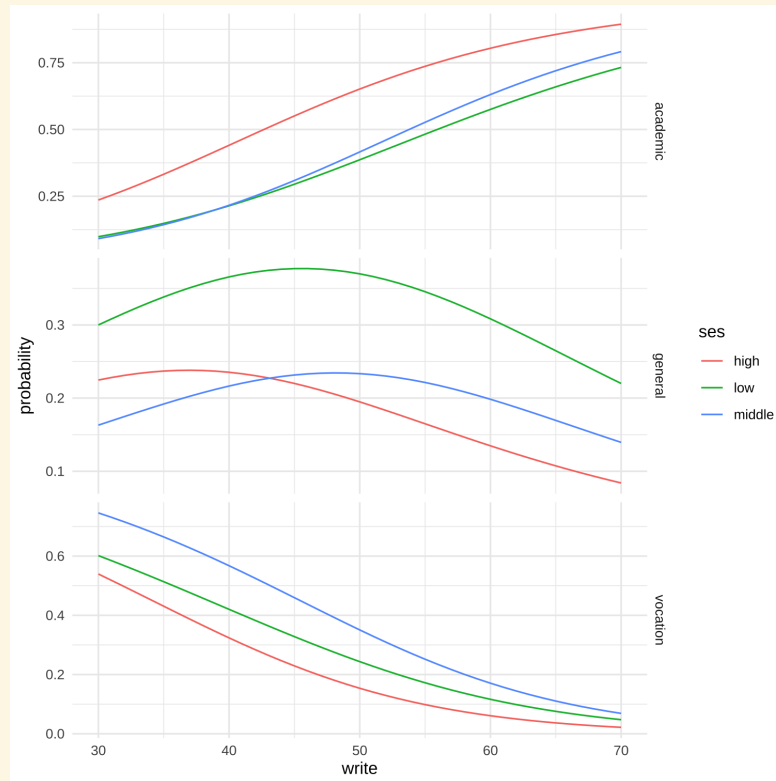
```
library(reshape2)
newdat <- data.frame(ses = rep(c("low", "middle", "high"),
                              each = 41),
                    write = rep(c(30:70), 3))

## store the predicted probabilities for each value of ses and write
pre <- cbind(newdat, predict(m1, newdata = newdat, type = "probs", se =
## melt data set to long for ggplot2
lpp <- melt(pre, id.vars = c("ses", "write"), value.name = "probability")
```

- Here, we are looking at the averaged predicted probabilities is to look at the averaged predicted probabilities for different values of the continuous predictor variable **write** within each level of **ses**.

Plot

```
library(ggplot2)
ggplot(lpp, aes(x = write, y = probability, colour = ses)) +
  geom_line() + facet_grid(variable ~ ., scales = "free") +
  theme_minimal()
```



Independence of Irrelevant Alternatives (IIA)

- IIA assumption states that the addition of a new category does not change the odds-ratios of the existing alternatives.
- In other words, the alternatives need to be **"distinct and weighed independently in the eyes of each decision maker"**.

Test IIA assumption

- The Hausman-McFadden Test

```
library(mlogit)  
#mlogit::hmfptest(prog2 ~ 0 | ses + write, data = dat,  
                  #alt.subset = c("general",  
                                  #"vocation"))
```