POLS6382 Quantitative Methods III: Maximum Likelihood Estimation

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Lab 5: Models for Ordinal Data

Objectives

- Learn how to estimate a model suitable for ordinal outcomes.
- Learn how to substantively interprets the statistical results of an ordered logit model.

1 Data Example: Americans' Preferences on Immigrants' Access to Public Health Care

In this section, we will learn how to estimate an ordered logistic regression model, using the example data, `gss2012lab5.dta`. Data are drawn from the 2012 General Social Survey (GSS). In the datafile, we have the following variables. For more details about the dataset, see Zhu, Ling and Kenicia Wright. 2016. "Why Do Americans Dislike Publicly Funded Health Care? Examining the Intersection of Race and Gender in the Ideological Context." *Politics, Groups, and Identities*, 4(4): 618-637.

- `hlthctzen`: Respondents' answers to the question: *Do you agree with the following statement?One should have access to public funded health care if he/she is not a citizen.* This variable is coded as three categories: "1"= disagree, "2"=neigher, and "3"= agree with the statement.
- `female`: respondents' gender, coded as "1" for female respondents, and "0" otherwise.
- `white`: Respondents' race, coded as "1" for whites and "0" otherwise.
- `age`: Respondents' age.
- `educ`: Year of eduction.
- `income`: measured as levels: 1=1-$1,000, 2=$1,00 - 2,999, 3$ =3,000-3,999....12=25,000 or more.
- `partyid`: party identification, measured as levels: 0= strong Democrat, 1=not strong Democrat, 2= independent, near democrat, 3=independent, 4=independent, near Republican, 5=not strong Republican, 6=strong Republican.
- `ideology`: liberal-conservative ideology scale, coded as a 1-to-7 scale, reflecting conservatism.

The variable of interest is `hlthctzen`, respondents' opinions about whether non-citizens should have access to public health care or not. We may just use some descriptive statistics to learn about the sample distribution. A histogram plot could be useful to describe how preferences vary. From Figure 1 we see that the total sample size is about 1,300 cases. About 800 respondents disagree with the statement that a non-citizen should have access to public health care. About 400 respondents agreed with the statement.

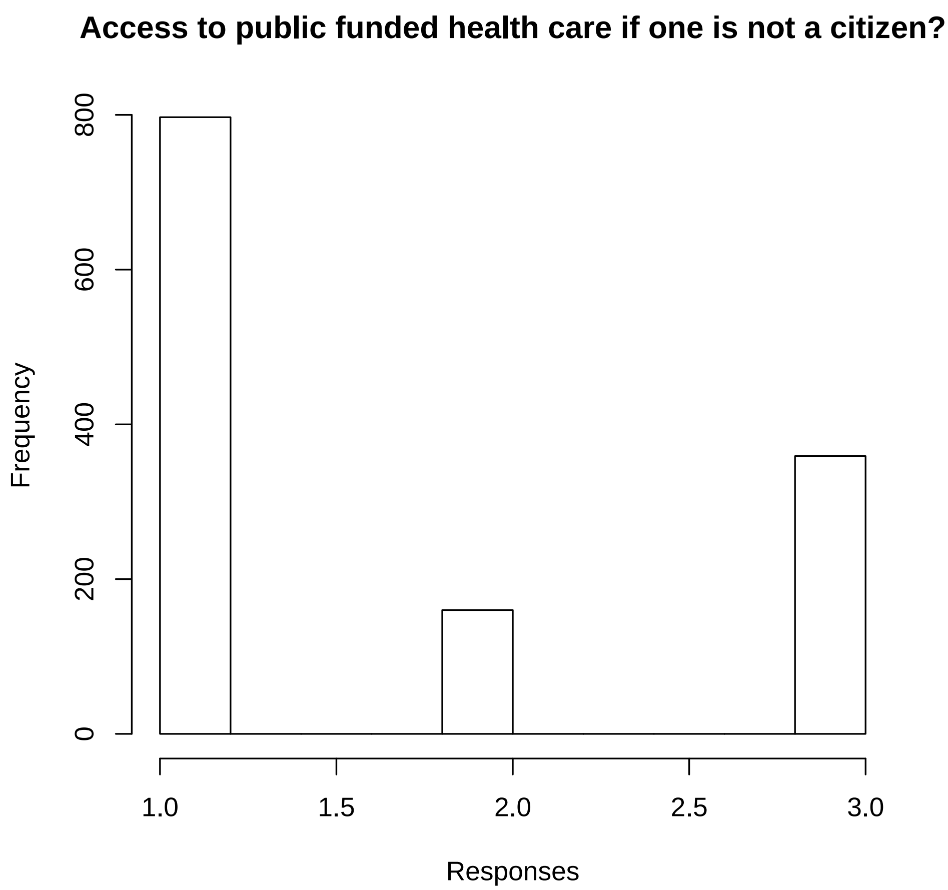
————————————- R Code————————————-

```
pdf(file="response.pdf",height=6, width=6)
hist(hlthctzen,
     main="Access to public funded health care if one is not a citizen?",
```

```
     xlab="Responses"
     )
dev.off()
```

——————————- R Output——————————-

Figure 1: Public Preferences on Non-Citizens' Access to Public Health Care



We can also obtain marginal proportions for each choice category using `R` function, `prob. table()`. Based on the 2012 GSS, 60.6% of the respondents disagreed with the statement. About 12% of the respondents reported neutral attitudes, and only 27.3% of the respondents agreed that non-citizens should have access to public health care. In other words, the majority opinion is that non-citizens should be excluded from accessing public health care.

——————————- R Code/Output——————————-

```
> prop.table(table(hlthctzen))
hlthctzen
        1         2         3
0.6056231 0.1215805 0.2727964
```

2 Estimating an Ordered Logit Model with `polr()`

Various `R` functions can be used to estimate an ordered logit/probit model. One commonly used function is `polr()` from package `MASS`. Estimation with `polr()` is simple. We define a model equation, and the datafile. The default link function is "logit". The statement `Hess=TRUE` returns the Hessian matrix in model object, which will be used in post-estimation simulation later. We specify our ordered-logit model by including `gender, race, age, education, income,` and `ideology` as the explanatory variables.

——————————————- R Code/Output——————————————-

```
> model1<-polr(as.factor(hlthctzen)~female+white+age+educ+income+ideology,
+              data=healthcare,Hess=TRUE)
> summary(model1)
Call:
polr(formula = as.factor(hlthctzen) ~ female + white + age +
    educ + income + ideology, data = healthcare, Hess = TRUE,
    model = TRUE)

Coefficients:
              Value Std. Error t value
female    0.0786593   0.118059  0.6663
white    -1.0827232   0.135465 -7.9926
age      -0.0009609   0.003554 -0.2704
educ      0.0358809   0.020647  1.7378
income   -0.0156195   0.029821 -0.5238
ideology -0.3705436   0.042046 -8.8129

Intercepts:
    Value   Std. Error t value
1|2 -1.5645  0.4641    -3.3707
2|3 -0.9415  0.4631    -2.0332

Residual Deviance: 2232.765
AIC: 2248.765
```

You may notice from the above `R` output that `polr()` does not return p-values. We can just look at the t-value column to evaluate if a variable has a significant effect on respondents' preferences regarding non-citizen's access to health care. You can also get p-values using `pnorm()`. Using `stargazer()`, we can convert the R-output in a well-arranged table in LaTeX .

——————————————- R Code/Output——————————————-

```
> # get p values
> p<-pnorm(abs(ctable[, "t value"]), lower.tail = FALSE) * 2
> #combined table
> (ctable <- cbind(ctable, "p value" = p))
                 Value Std. Error    t value      p value
female    0.0786593115 0.11805945  0.6662687 5.052394e-01
white    -1.0827231790 0.13546543 -7.9926159 1.321053e-15
age      -0.0009608995 0.00355360 -0.2704017 7.868512e-01
educ      0.0358808677 0.02064692  1.7378316 8.224049e-02
income   -0.0156194898 0.02982057 -0.5237824 6.004299e-01
ideology -0.3705435895 0.04204551 -8.8129176 1.219302e-18
```

```
1|2      -1.5644559949 0.46414069 -3.3706504 7.499097e-04
2|3      -0.9415444911 0.46307425 -2.0332474 4.202754e-02
```

Table 1: The Determinants of Preferences on Non-Citizen's Access to Public Health Care

	Value	Std. Error	t value	p value
female	0.079	0.118	0.666	0.505
white	-1.083	0.135	-7.993	0.000
age	-0.001	0.004	-0.270	0.787
education	0.036	0.021	1.738	0.082
income	-0.016	0.030	-0.524	0.600
ideology	-0.371	0.042	-8.813	0.000
τ_1	-1.564	0.464	-3.371	0.001
τ_2	-0.942	0.463	-2.033	0.042

3 Substantive Interpretation

How can we substantively interpret coefficients reported in Table 1? Scott Long discussed various methods in his textbook. Here, we will focus on using odds ratios and predicted probabilities. Because we estimated an ordered logit model, we can convert coefficients into odds ratios, using function `exp()`. Combining `exp()` with `confint()`, we can also obtain confidence intervals for odds ratios. If the confidence intervals of an odds ratio go across 1, it means that odds ratio coefficient is not statistically significant.

——————————- R Code/Output——————————-

```
> exp(coef(model1))
   female     white       age      educ    income  ideology
1.0818357 0.3386720 0.9990396 1.0365324 0.9845019 0.6903590
```

We observe that `white` and `ideology` significantly affect respondents' preferences regarding non-citizens' access to public health care.

1. The odds ratio associated with `white` is 0.34: the odds of reporting "neither" and "agree" versus "disagree" are 66 percent lower for white respondents than that for non-white respondents. In other words, compared with non-white respondents, white respondents are more likely to choose "disagree" than "neither" and "agree".
2. `ideology` has an odds ratio of 0.69: a one-point increase of conservatism decreases the probability of choosing "agree" over "neither" and "disagree" by about 31%. In other words, moving from liberalism to conservatism will decrease the probability of choosing "agree" over the other two lower categories.

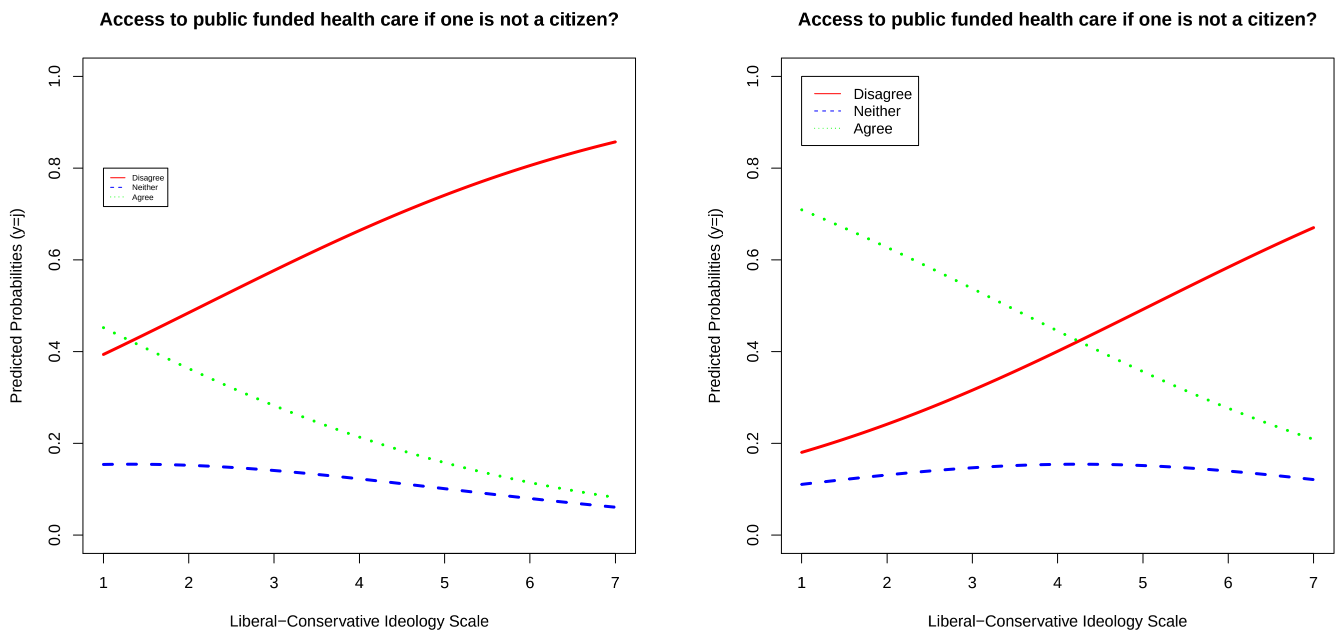
Beyond using odds ratios, another useful way to substantively interpret findings is to calculate predicated probabilities associated with each choice category. First, we will discuss how to present mean predictions. Suppose that we are interested in gauging the substantive effect of `ideology` and `race` (being white) on preferences. What we can do is to predict the probabilities of choosing each choice category across the full range of the ideology scale, but setting the dummy variable `white` to be 1 and 0. This would give us two sets of predictions: one for white respondents, and one for non-white respondents. Note that we hold all the other variables constant. `female=mean(female)` essentially gives variable `female` an artificial value. This is to average the weights between female and male respondents in the sample. Alternatively, you can set `female` to be 0 or 1. That will give you the comparison between white male and non-white male respondents (or white and non-white female respondents) across the full range of `ideology`.

———————————- R Code————————————-

```
# Mean predicted probabilities, white respondents
predictdata<-cbind(ideology=seq(1,7,length=100),
                   age=mean(age),income=mean(income),educ=mean(educ),
                   female=mean(female),white=1)
opinion.hat<-predict(model1,predictdata,type='prob')

# Mean predicted probabilities, non-white respondents
predictdata2<-cbind(ideology=seq(1,7,length=100),
                   age=mean(age),income=mean(income),educ=mean(educ),
                   female=mean(female),white=0)
opinion.hat2<-predict(model1,predictdata2,type='prob')

# Plot pps
ideology<-seq(1,7,length=100)
pdf(file="pp_white.pdf",height=7, width=7)
plot(c(1,7),c(0,1),type='n',
     xlab="Liberal-Conservative Ideology Scale",
     ylab="Predicted Probabilities (y=j)",
     main="Access to public funded health care if one is not a citizen?")
lines(ideology,opinion.hat[1:100,1],lty=1,lwd=3,col="red")
lines(ideology,opinion.hat[1:100,2],lty=2,lwd=3,col="blue")
lines(ideology,opinion.hat[1:100,3],lty=3,lwd=3,col="green")
legend(1,1,cex=0.9,c('Disagree','Neither','Agree'),
       lty=1:3,col=c("red","blue","green"))
dev.off()

pdf(file="pp_nonwhite.pdf",height=7, width=7)
plot(c(1,7),c(0,1),type='n',
     xlab="Liberal-Conservative Ideology Scale",
     ylab="Predicted Probabilities (y=j)",
     main="Access to public funded health care if one is not a citizen?")
lines(ideology,opinion.hat2[1:100,1],lty=1,lwd=3,col="red")
lines(ideology,opinion.hat2[1:100,2],lty=2,lwd=3,col="blue")
lines(ideology,opinion.hat2[1:100,3],lty=3,lwd=3,col="green")
legend(1,1,cex=0.9,c('Disagree','Neither','Agree'),
       lty=1:3,col=c("red","blue","green"))
dev.off()
```

———————————- R Output————————————-

Figure 2: Respondents' Preferences on Non-Citizens' Access to Public Health Care by Ideology and Race



(a) White Respondents

(b) Non-White Respondents

Figure 2 shows `ideology` has a negative impact on supporting non-citizens' access to public health care, which is consistent across the two racial groups. For white respondents, conservatism increases the predicted probabilities of choosing "disagree" with non-citizens having access to public health care, while substantially decreases the predicted probability of choosing "agree" with non-citizens having access to public health care. A similar pattern is observed for non-white respondents that conservatism increases the probability of choosing "disagree" while decreases the probability of choosing "agree".

To show the substantive effect of race, we can graph white and non-white respondents' preferences in one figure. Because an ordered logit/probit model will produce predicted probabilities for at least three categories, plotting all these predicted probabilities in one figure is not a good choice. what we can do is to compare white and non-white respondents' predicted probabilities by choice category. In practice, we normally focus on the bottom and top categories.

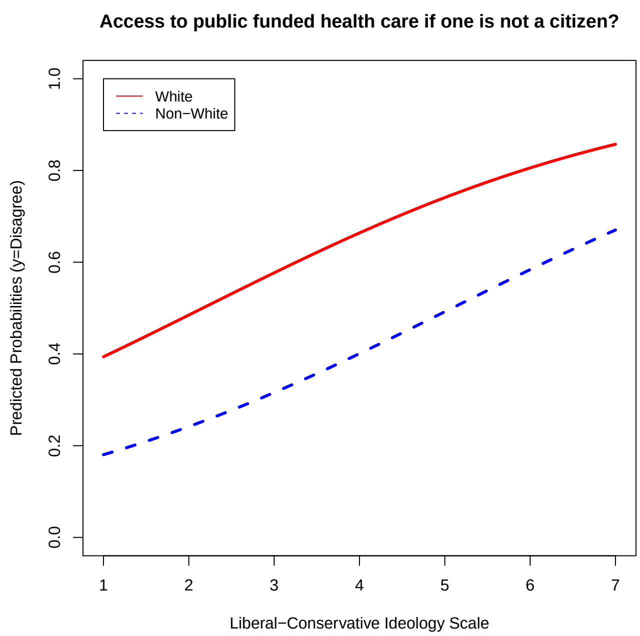
——————————- R Code——————————-

```
# Compare white and non-white respondents' PPs of "disagree"
pdf(file="compare.pdf",height=7, width=7)
plot(c(1,7),c(0,1),type='n',
     xlab="Liberal-Conservative Ideology Scale",
     ylab="Predicted Probabilities (y=Disagree)",
     main="Access to public funded health care if one is not a citizen?")
lines(ideology,opinion.hat[1:100,1],lty=1,lwd=3,col="red")
lines(ideology,opinion.hat2[1:100,1],lty=2,lwd=3,col="blue")
legend(1,1,cex=0.9,c('White','Non-White'),
       lty=1:3,col=c("red","blue"))
dev.off()
```

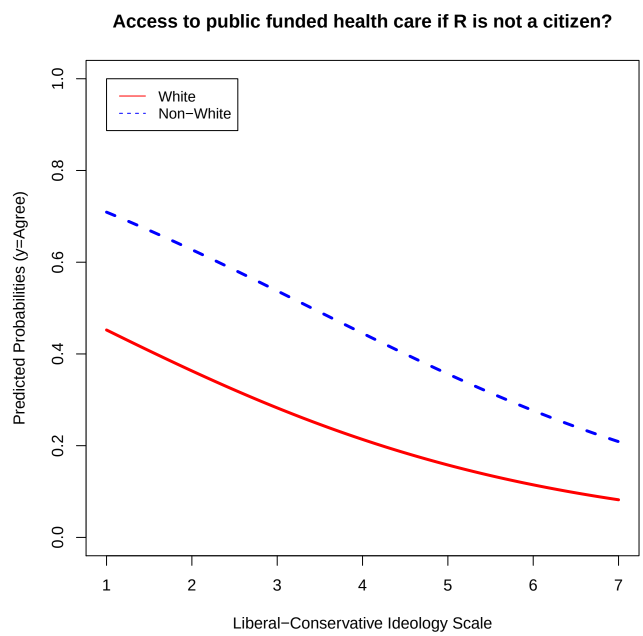
```
# Compare whit and non-white respondents' PPs of "agree"
pdf(file="compare2.pdf",height=7, width=7)
plot(c(1,7),c(0,1),type='n',
     xlab="Liberal-Conservative Ideology Scale",
     ylab="Predicted Probabilities (y=Agree)",
     main="Access to public funded health care if R is not a citizen?")
lines(ideology,opinion.hat[1:100,3],lty=1,lwd=3,col="red")
lines(ideology,opinion.hat2[1:100,3],lty=2,lwd=3,col="blue")
legend(1,1,cex=0.9,c('White','Non-White'),
       lty=1:3,col=c("red","blue"))
dev.off()
```

——————————————- R Output——————————————-

Figure 3: Comparing White and Non-White Respondents' Preferences on Non-Citizens' Access to Public Health Care



(a) White Respondents



(b) Non-White Respondents

Figure 3 shows, across the full range of ideology, white respondents are associated with higher predicted probabilities of choosing "disagree" than non-white respondents; and lower probabilities of choosing "agree" than non-white respondents. Figure 3 shows salient racial differences in attitudes toward non-citizens' access to public health care.