Homework 3, Question 3a

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05 December 2016

#
Data
Descriptives

R

```
"'r
dat
<-
read.csv("data/states_new.csv")
#
datmap
<-
read.csv("data/usmap.csv")
dat
<-
dat[,
c("Q3",
"Q7",
"Q8")]
dat
<-
na.omit(dat)
id <-
seq(1:nrow(dat))
dat
<-
cbind(id,
dat)
"'
```

Multiple Logistic Regression Model

R

```r
library(MASS)
fit <- polr(factor(Q8) ~ Q3 + Q7 + Q3*Q7, data = dat, contrasts = NULL, method = "probit")
library("AER")
print(coeftest(fit))
```

z test of coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
Q3	0.0442	0.0453	0.97	0.3296
Q7	1.4158	0.3637	3.89	0.000099
Q3:Q7	***-0.0436***	***0.0320***	***-1.36***	***0.1742***
0|1	***0.1869***	***0.4902***	***0.38***	***0.7030***
1|2	***1.8536***	***0.5582***	***3.32***	***0.0009***

Signif. codes: 0 ‘’ ***0.001*** ’’ *0.01* ’’ 0.05 ‘.’ 0.1 ‘’ 1

```r
CI.b <- confint(fit, trace = FALSE)

OR <- exp(coef(fit))
CI <- confint(fit)
```

```r
CIb <- cbind(coef(fit), CI.b)
CIb.labs <- c("**$\\beta$**", dimnames(confint(fit))[[2]])
CIb <- rbind(CIb.labs, round(CIb, 4))
dimnames(CIb)[[1]][1] <- " "
dimnames(CIb)[[2]] <- c(" ", "$CI_{\\beta}$", " ")

## odds ratios and 95% CI ##
ORCI <- exp(cbind(coef(fit), CI))
ORCI.labs <- c("**$\\Phi$**", dimnames(confint(fit))[[2]])
ORCI <- rbind(ORCI.labs, round(ORCI, 4))
dimnames(ORCI)[[1]][1] <- " "
dimnames(ORCI)[[2]] <- c(" ", "$CI_{\\Phi}$", " ")


library(lmtest) ## "lrtest()" ##
lrchsq <- lrtest(fit)[2, -3]
lrchsq <- lrchsq[, c(2, 1, 3, 4)]
names(lrchsq) <- c("Log Likelihood", "_df_", "$\\chisq$", "_p_")

library(pscl)
rsq <- pR2(fit)["McFadden"]
rsq[[1]]
```

0.2064

```r
# names(rsq) <- c("McFadden's Pseudo-$R\\sq$")
# rsq.perc <- (rsq[2]*100)
```

Model Fit Indices

Table 2: Likelihood Ratio χ^2, R^2, & G^2

	Log Likelihood	*df*	χ^2	*p*
2	-45.5	2	18.79	0.0003027

```r
kable(CIb, align = rep('r', ncol(CIb)),
      caption = "Logistic Regression Coefficients ($\\beta$) \\&
      Coresponding Confidence Intervals (_CI_)")
```

Table 3: Logistic Regression Coefficients (β) &
Coresponding Confidence Intervals (*CI*)

		CI_β	
	β	2.5 %	97.5 %
Q3	0.0442	-0.0442	0.1334
Q7	1.4158	0.7295	2.1616
Q3:Q7	-0.0436	-0.1066	0.0195

```r
kable(ORCI, align = rep('r', ncol(ORCI)),
      caption = "Logistic Regression Odds Ratios ($\\Phi$) \\&
      Coresponding Confidence Intervals (_CI_) [note]") %>%
    add_footnote("Confidence intervals are based on the logistic regression
                 model's profiled log-likelihood function,
                 rather than the standard errors",
                 threeparttable = TRUE)
```

Table 4: Logistic Regression Odds Ratios (Φ) &
Coresponding Confidence Intervals (*CI*) [1]

		CI_Φ	
	Φ	2.5 %	97.5 %
Q3	1.0451	0.9567	1.1427
Q7	4.1198	2.074	8.6851
Q3:Q7	0.9574	0.8989	1.0197

Note:
[1] Confidence intervals are based on the logistic regression
model's profiled log-likelihood function,
rather than the standard errors

Ordinal Probit Regression Summary. An ordinal probit regression model was tested predicting whether states' batterer intervention program (BIP) standards were gender inclusive (*Q8*) by the size of state standards' committees (*Q3*), whether proccesses were in place for assessing BIPs' feedback about the standards (*Q7*), and the interaction of these two predictors (*Q3-x-Q7*). The predictors collectiely accounted for a significant amount of variance in the outcome, likelihood ratio $\chi^2(2) = 18.79, p < .001$. However, only *Q7* significantly predicted *Q8*, $b = 1.42, SE = .36, p < .001$; such that a one unit increase in *Q7* was associated with approximately 34% increases in *Q8*. Overall, the model accounted for 21% of the variance in reported baseline income adequacy (*McFadden's pseudo*-$R^2 = 0.2064$).

COMPARISON WITH CUMULATIVE LOGISTIC MODEL. The above described ordinal probit regression analysis findings are starkly different from the originally tested logistic regression model, such that the effects of *Q7* are distinquishable in the probit model whereas they were not in the logistic regression model.