

Ordered and Multinomial Logit

Implementation and interpretation

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Introduction

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Introduction Logistic Regression

- Limited outcomes in the dependent variable
- Use logarithmic transformation on the outcome variable
 - model a nonlinear association in a linear way

Ordered Logit

Motivation Ordered

- Finite and discrete values with more than two outcomes

Motivation Ordered

- Finite and discrete values with more than two outcomes
- Data with meaningful sequential values
 - income levels
 $(0, 10000], (10000, 30000], (30000, \infty]$
 - Likert-type scale

Motivation Ordered

- Finite and discrete values with more than two outcomes
- Data with meaningful sequential values
 - income levels
 $(0, 10000], (10000, 30000], (30000, \infty]$
 - Likert-type scale
 - Gender
 - Party affiliation
 - Education

Mechanics Ordered

Proportional Odds Assumption[2]

The assumption that the explanatory variables have the same effect on the odds regardless of the threshold.

$$\text{poor, } \log \frac{p_1}{p_2+p_3+p_4+p_5}, 0$$

$$\text{poor or fair, } \log \frac{p_1+p_2}{p_3+p_4+p_5}, 1$$

$$\text{poor, fair, or good,, } \log \frac{p_1+p_2+p_3}{p_4+p_5}, 2$$

$$\text{poor, fair, good, or very good, } \log \frac{p_1+p_2+p_3+p_4}{p_5}, 3$$

Math Ordered

Formula

$$y_i^* = \alpha + \mathbf{x}_i' \beta + \epsilon_i = \alpha + Z_i + \epsilon_i$$

y_i^* = latent utility
where $\epsilon_i \sim \text{Logistic}(0, \sigma^2)$

Distribution

$$F(Z_i) = \exp(Z_i) / (1 + \exp(Z_i))$$

$$y_i = 1, \quad \text{if } Z_i \leq \eta_1 \quad (\text{Region 1})$$

$$y_i = j, \quad \text{if } \eta_{j-1} < Z_i \leq \eta_j \quad (\text{Region } j)$$

$$y_i = J, \quad \text{if } \eta_{J-1} < Z_i \quad (\text{Region } J)$$

where $\eta_1 < \eta_2 < \eta_3, \dots, \eta_n$ & $\eta_1 \geq 0$,
parameters known as *thresholds* or *cutpoints*

Math Ordered

Marginal Effects:

Obtained by evaluating the appropriate density functions at the relevant points and multiplying by the associated coefficient [1]

Continuous:

$$\begin{aligned} & \frac{d}{dx} \left[\frac{\exp x}{1+\exp x} \right] \\ &= \frac{[1+\exp(x)] \exp(x) - [\exp(x)]^2}{[1+\exp(x)]^2} \end{aligned}$$

Math Intuition Ordered

$$\text{logit}[P(Y \leq j)] = \alpha + \mathbf{x}_i' \beta, j = 1, \dots, J - 1$$

Prob. answering specific level consv. given party

	Democrat[1]	Republican[0]
Very Liberal[1]	0.1832505	0.07806044
Slightly Liberal[2]	0.1942837	0.10819225
Moderate[3]	0.3930552	0.37275214
Slightly Conservative[4]	0.1147559	0.18550357
Very Conservative[5]	0.1146547	0.25549160

Call:

```
polr(formula=pol.ideology party, data = dat
```

Coefficients:

	Value	Std. Error	t-value
partyDem	-0.9745	0.1292	-7.545
VeryLiberal Slightly Liberal	-2.4690	0.1318	-18.7363
Slightly Liberal Moderate	-1.4745	0.1090	-13.5314
Moderate Slightly Conservative	0.2371	0.0942	2.5165
Slightly Conservative Very Conservative	1.0695	0.1039	10.2923

If we wanted to find the odds a Democrat identifies as 'Slightly Liberal' or less:

$$\text{logit}[P(Y \leq 2)] = -1.4745 - 0.9745(1) = -0.5$$

$$P(Y \leq j) = \frac{\exp(\alpha + \mathbf{x}_i' \beta)}{1 + \exp(\alpha + \mathbf{x}_i' \beta)} \Rightarrow \frac{\exp(-0.5)}{1 + \exp(-0.5)} = .378$$

Math Intuition Ordered

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Benefits Ordered

- Non-linear

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Benefits Ordered

- Non-linear
- Overcomes OLS i.i.d. assumption
- Applicable to discrete or continuous independent variables

Shortcomings Ordered

- Vague
 - Move toward larger values of dv

Shortcomings Ordered

- Vague
 - Move toward larger values of dv
- Trivial differences
 - Quasi-normal data w/ 3-4 scale dv

Multinomial Logit

Motivation Multinomial

- Discrete, mutually exclusive, unordered dependent variables
 - Party ID
 - 0=Republican, 1=Independent, 2=Democrat

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Motivation Multinomial

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 - Region
- Choice Model

Mechanics Multinomial

- M outcomes
 - $M-1$ binary logistic regression models
- Extension of binomial logistic regression
- Probability of success in a given category M

Mechanics Multinomial

Independence of Irrelevant Alternatives (IIA):

The **assumption** that the introduction or improvement of any alternative will have the same proportional impact on the original alternatives

Example

1= Train ; 2= Bus ; 3 = Car

IIA assumes that adding a 4th option, a bike, will not have any impact on the probability of choosing your original 1-3 choices

Math Multinomial

Formula

$$Z_{ij} = \sum_{r=1}^R \beta_{jr} X_{ir}$$

Normalization

$$Pr(Y = 1) = \frac{1}{1 + \sum_{j=2}^M \exp(Z_{ij})}$$

$$Pr(Y_i = K) = \frac{\exp(Z_{iK})}{1 + \sum_{j=2}^M \exp(Z_{ij})}$$

Math Multinomial

Risk Ratio[3]:

The logarithm of the ratio of
the probability of outcome m
to that of outcome k
k = excluded observation

$$\left(\frac{Pr(Y_i=m)}{Pr(Y_i=1)} \right) = \exp(Z_{im})$$

Benefits Multinomial

- Does not assume
 - normality
 - linearity
 - homoscedasticity

Benefits Multinomial

- Does not assume
 - normality
 - linearity
 - homoscedasticity
- Independent variables
 - can be unbounded
 - needn't be interval

Shortcomings Multinomial

- IIA assumption

Examples

TAPS Data Multinomial

- pid
 - Generally speaking, do you usually think of yourself as [Republican/a Democrat] and independent?
 - 1-Democrat; 2-Independent; 3-Republican
- abort
 - Do you generally support or oppose a woman's right to abortion
 - 1-support; 2-oppose;
- taxes
 - Please tell me if you would favor or oppose a federal tax policy that increases income taxes for people with the highest incomes .
 - 1-support; 2-oppose;
- $n = 1164$

Example Multinomial

```
#library(nnet)
> m2 <- multinom(pid ~ abort + taxes, data = dat2)
> summary(m2)
```

Coefficients:

	(Intercept)	abort	taxes
2	-3.636725	0.8829103	2.034146
3	-6.683510	1.7884000	3.316103

Example Multinomial

```
>Anova(m2)
```

Analysis of Deviance Table (Type II tests)

Response: pid

	LR	Chisq	Df	Pr(>Chisq)
abort	75.68	2	< 2.2e-16	***
taxes	231.17	2	< 2.2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>
Residual Deviance: 2086.295

AIC: 2098.295

Example Multinomial

Risk Ratio:

```
> exp(coef(m1))
```

	(Intercept)	abort	taxes
2	0.026338453	2.417926	7.645719
3	0.001251378	5.979877	27.552755

TAPS Data Ordered

- y
 - Do you agree or disagree that an American-born child of illegal immigrants should not be considered a U.S. citizen.
 - 1-strongly oppose; 2-oppose; 3-neutral; 4-support; 5-strongly support
- dt_strong
 - In your opinion, how well does the phrase 'is a strong leader' describe Donald Trump?
 - 1-not well at all; 2-slightly well; 3-moderately well; 4-very well; 5-extremely well
- party_id
 - Generally speaking, do you usually think of yourself as [Republican/a Democrat] and independent?
 - 1-Democrat; 2-Independent; 3-Republican
- n = 1332

Example Ordered

```
> m1 <- polr(y ~ dt_strong + party_id, data = dat)
> summary(m1)
```

Coefficients:

	Value	Std. Error	t value
dt_strong	0.2924	0.03800	7.693
party_id	0.6589	0.06776	9.723

Example Ordered

Intercepts :

	Value	Std. Error	t value
s. oppose oppose	0.4459	0.1329	3.3550
oppose nuetral	1.7214	0.1388	12.4035
nuetral support	2.3707	0.1466	16.1738
support s. support	3.5660	0.1640	21.7435

Residual Deviance: 3983.457

AIC: 3995.457

Residual Deviance: 717.0249 AIC: 727.0249

Example Ordered

```
> pval <- Anova(m1)
> pval
```

Response: y

	LR	Chisq	Df	Pr(>Chisq)	
dt_strong	59.977		1	9.595e-15	***
party_id	96.387		1	< 2.2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
>
```

Example Ordered

Log Odds:

```
> exp(coef(m1))
```

dt_strong	party_id
1.397655	1.566525

Example Ordered

Predicted Probabilities:

```
> > (Effect(focal.predictors = ('party_id'), m1, given.values = c(dt_strong = mean(dt_strong))))
```

```
party_id effect (probability) for s. oppose
      1      1.5      2      2.5      3
0.27964294 0.21828910 0.16727061 0.12625036 0.09415224
```

```
party_id effect (probability) for oppose
      1      1.5      2      2.5      3
0.3019306 0.2816622 0.2510610 0.2147011 0.1770585
```

```
party_id effect (probability) for neutral
      1      1.5      2      2.5      3
0.1452534 0.1568680 0.1609246 0.1566210 0.1448073
```

```
party_id effect (probability) for support
      1      1.5      2      2.5      3
0.1710500 0.2066518 0.2405438 0.2683739 0.2858336
```

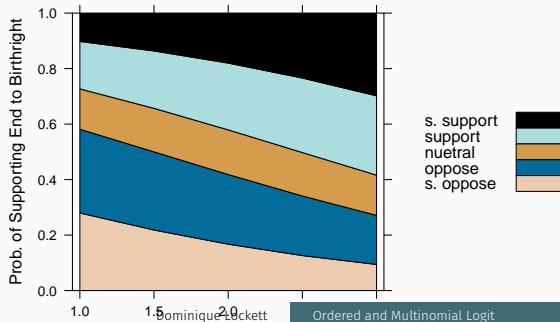
```
party_id effect (probability) for s. support
      1      1.5      2      2.5      3
0.1021230 0.1365289 0.1802000 0.2340536 0.2981484
```

Example Ordered

Predicted Probability:

```
#require(wesanderson)
> e.out <- (Effect(focal.predictors = ('party_id'), m1, given.values = c(dt_strong = mean(dt_strong))))
> mean(dt_strong) = 2.508258
> plot(e.out, rug = F, style = 'stacked', main = 'PTitle', key.args = list(space = 'right'), ylab = 'Title',
xlab = 'Title', colors = palette(wes_palette("Darjeeling2")))
```

Predicted Prob of y by Party ID and Mean Perception of Trump

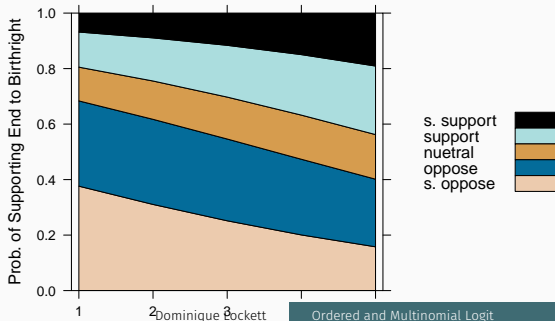


Example Ordered

Predicted Probability:

```
#require(wesanderson)
> e.out2 <- (Effect(focal.predictors = ('dt_strong'), m1, given.values = c(party_id = mean(party_id))))
> mean(party_id) = 2.916667
>>plot(e.out2, rug = F, style = 'stacked', main = 'Title', key.args = list(space = 'right'),
xlab = 'Title', ylab = 'Title', colors = palette(wes_palette("Darjeeling2")))
```

Pred Prob of y by Perception of Trump & Mean Party ID

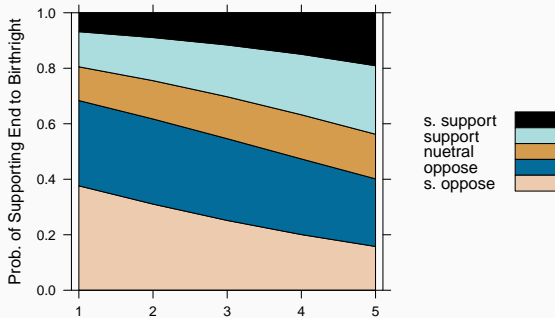


Example Ordered

Predicted Probability:

```
#require(wesanderson)
>e.out3 <- (Effect(focal.predictors = ('dt_strong'), m1, given.values = c(party_id = 1)))
>plot(e.out3, rug = F, style = 'stacked', main = 'title', key.args = list(space = 'right'),
xlab = 'title', colors = palette(wes_palette("Darjeeling2")))
```

Pred Prob y by Perception of DT among Democrats

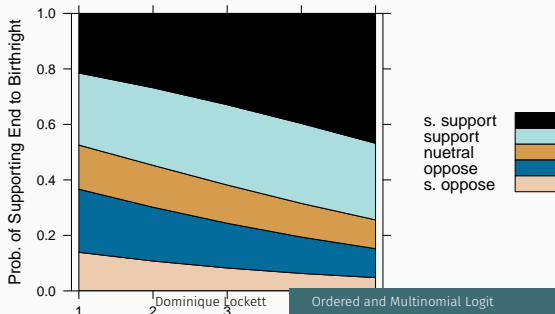


Example Ordered

Predicted Probability:

```
#require(wesanderson)
> e.out4 <- (Effect(focal.predictors = ('dt_strong'), m1, given.values = c(party_id = 3)))
> plot(e.out4, rug = F, style = 'stacked', main = 'Title', key.args = list(space = 'right'),
      xlab = 'Title', ylab = 'Title',
      colors = palette(wes_palette("Darjeeling2")))
xlab = 'title', colors = palette(wes_palette("Darjeeling2"))
```

Pred Prob of y by Perception of DT among Republicans



Example Ordered

```
# library(brant)
> brant(model)
```

```
Test for  $\chi^2$  IdF probability
```

```
Omnibus  $\chi^2$  12.11  $df$  6  $p$  0.06  
dt_strong  $\chi^2$  17.36  $df$  3  $p$  0.06  
party_id  $\chi^2$  16.03  $df$  3  $p$  0.11
```

A significant test statistic provides evidence that the parallel regression assumption has been violated.

Conclusion

Summary

- Feasible alternatives to linear regression
- Interpreted in log odds
- Useful and basic

Questions?

References i



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Modern Applied Statistics with S.

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