

# ORDINAL LOGISTIC REGRESSION – EXTRA CONTENT

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# PROPORTIONAL ODDS MODEL

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# What if Assumption Fails?

- The proportional odds assumption may not be met for all variables.
- 2 Approaches:
  1. Partial Proportional Odds Model
  2. Multinomial Logistic Regression

# What if Assumption Fails?

- The proportional odds assumption may not be met for all variables.
  - 2 Approaches:
    1. Partial Proportional Odds Model
    2. Multinomial Logistic Regression
- Diagram illustrating the failure of the proportional odds assumption:
- From "2. Multinomial Logistic Regression", an arrow points to the text: **Some** variables fail assumption
  - From "1. Partial Proportional Odds Model", an arrow points to the text: **All** variables fail assumption

# Partial Proportional Odds – SAS

```
proc logistic data=Logistic.Wallet;  
  class punish(param=ref ref='1');  
  model wallet = male business punish explain /  
               unequalslopes=(business) clodds=pl;  
  title 'Partial Proportional Odds Model';  
run;  
quit;
```

# Partial Proportional Odds – SAS

Analysis of Maximum Likelihood Estimates							
Parameter		wallet	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	1	-2.6695	0.4491	35.3260	<.0001
Intercept		2	1	-0.7730	0.3714	4.3318	0.0374
male			1	1.0707	0.3282	10.6426	0.0011
business		1	1	0.9722	0.4838	4.0389	0.0445
business		2	1	0.6376	0.3810	2.7996	0.0943
punish	2		1	0.6300	0.4048	2.4224	0.1196
punish	3		1	1.3956	0.4829	8.3523	0.0039
explain			1	-1.0532	0.3405	9.5660	0.0020

# Partial Proportional Odds – R

```
plogit.model <- vglm(factor(wallet) ~ male + business + punish +  
  explain,  
  data = train,  
  family = cumulative(parallel = F ~ business))  
  
summary(plogit.model)
```

# Partial Proportional Odds – R

```
## Pearson residuals:
```

```
##           Min       1Q   Median       3Q      Max
## logitlink(P[Y<=1]) -1.241 -0.4759 -0.1765 -0.1099 3.899
## logitlink(P[Y<=2]) -1.850 -0.6623 -0.3859  0.6425 2.730
```

```
##
```

```
## Coefficients:
```

```
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept):1  -2.6695     0.4466  -5.978 2.26e-09 ***
## (Intercept):2  -0.7730     0.3678  -2.102  0.03557 *
## male           1.0707     0.3258   3.287  0.00101 **
## business:1      0.9722     0.4789   2.030  0.04236 *
## business:2      0.6376     0.3810   1.674  0.09423 .
## punish2         0.6300     0.4008   1.572  0.11594
## punish3         1.3956     0.4727   2.952  0.00316 **
## explain        -1.0532     0.3413  -3.086  0.00203 **
```

```
## ---
```

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

```
##
```



# Partial Proportional Odds – R

```
## Names of linear predictors: logitlink(P[Y<=1]), logitlink(P[Y<=2])
##
## Residual deviance: 306.8392 on 382 degrees of freedom
##
## Log-likelihood: -153.4196 on 382 degrees of freedom
##
## Number of Fisher scoring iterations: 5
##
## No Hauck-Donner effect found in any of the estimates
##
##
## Exponentiated coefficients:
##      male business:1 business:2      punish2      punish3      explain
## 2.9174165 2.6438481 1.8918696 1.8776731 4.0373205 0.3488076
```

# INTERPRETATION

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# Model Notation – SAS Option

- With cumulative logits, increasing the right-hand side of the equation leads to an increased log(odds) of **higher** outcome category:

$$\log \left( \frac{p_{i,1}}{p_{i,2} + p_{i,3}} \right) = \beta_{0,1} - \beta_1 \text{male}_i - \beta_2 \text{business}_i \\ - \beta_3 \text{punishM}_i - \beta_4 \text{punishH}_i - \beta_5 \text{explain}_i$$

$$\log \left( \frac{p_{i,1} + p_{i,2}}{p_{i,3}} \right) = \beta_{0,2} - \beta_1 \text{male}_i - \beta_2 \text{business}_i \\ - \beta_3 \text{punishM}_i - \beta_4 \text{punishH}_i - \beta_5 \text{explain}_i$$

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# Model Notation – R Default

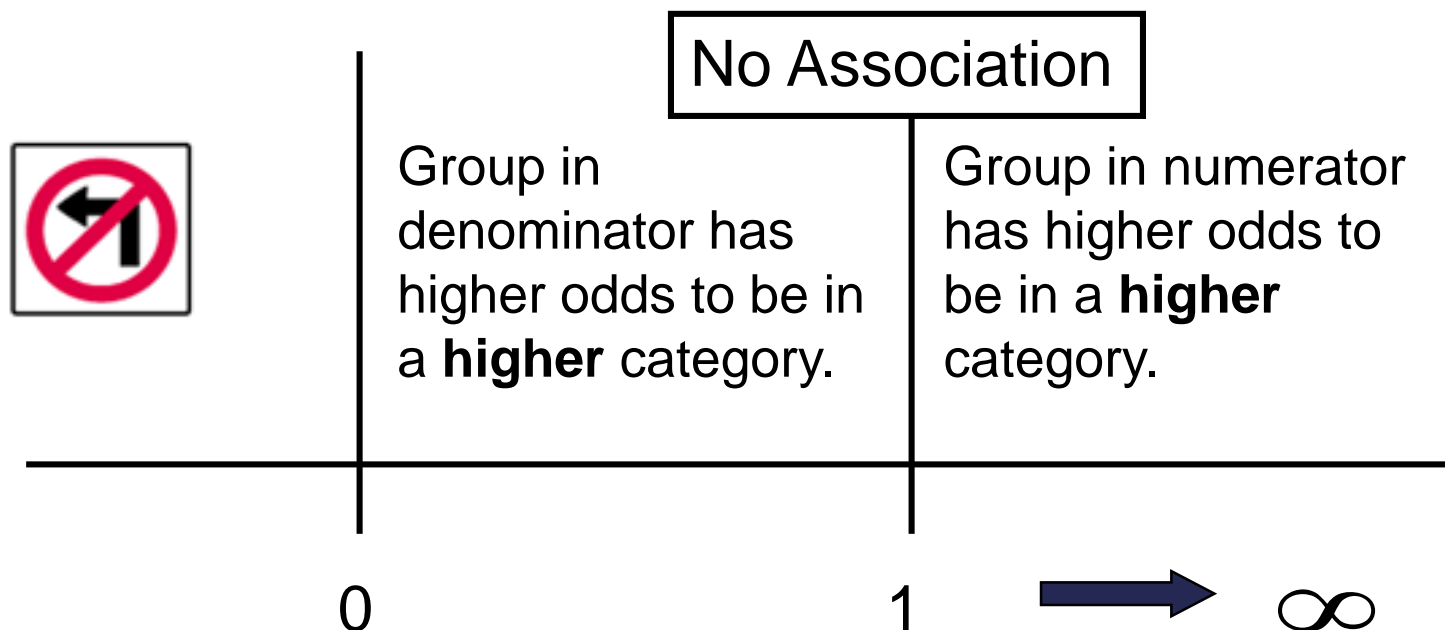
- With cumulative logits, increasing the right-hand side of the equation leads to an increased log(odds) of **higher** outcome category:

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$$\log \left( \frac{p_{i,1} + p_{i,2}}{p_{i,3}} \right) = \beta_{0,2} - \beta_1 \text{male}_i - \beta_2 \text{business}_i - \beta_3 \text{punishM}_i \uparrow \beta_4 \text{punishH}_i - \beta_5 \text{explain}_i$$

# Odds Ratio Interpretation – Descending

- Interpretation is still an odds ratio:  $100 * (e^{\hat{\beta}_j} - 1) \%$   
**higher expected odds** of being in a higher category.



# Odds Ratios Descending – SAS

```
proc logistic data=Logistic.Wallet desc;  
  class punish(param=ref ref='1');  
  model wallet = male business punish explain  
                / clodds=pl;  
run;
```

# Odds Ratios Descending – SAS

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
male	1	10.6047	0.0011
business	1	4.4167	0.0356
punish	2	9.4185	0.0090
explain	1	9.4925	0.0021

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	3	1	0.7890	0.3675	4.6107	0.0318
Intercept	2	1	2.5678	0.4169	37.9321	<.0001
male		1	-1.0598	0.3254	10.6047	0.0011
business		1	-0.7389	0.3516	4.4167	0.0356
punish	2	1	-0.6277	0.4005	2.4564	0.1170
punish	3	1	-1.4031	0.4721	8.8330	0.0030
explain		1	1.0518	0.3414	9.4925	0.0021



# Odds Ratios Descending – SAS

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	69.0	Somers' D	0.465
Percent Discordant	22.5	Gamma	0.508
Percent Tied	8.5	Tau-a	0.249
Pairs	10154	c	0.732

Odds Ratio Estimates and Profile-Likelihood Confidence Intervals				
Effect	Unit	Estimate	95% Confidence Limits	
male	1.0000	0.347	0.180	0.652
business	1.0000	0.478	0.238	0.963
punish 2 vs 1	1.0000	0.534	0.242	1.193
punish 3 vs 1	1.0000	0.246	0.094	0.632
explain	1.0000	2.863	1.469	5.612

# Odds Ratios – R

```
ORtable <- data.frame(OR = exp(coef(clogit.model)),  
                      lower = exp(confint(clogit.model))[,1],  
                      upper = exp(confint(clogit.model))[,2])  
  
print(ORtable)
```

# Odds Ratios – R

##		OR	lower	upper
##	male	0.3465172	0.17995548	0.6522567
##	business	0.4776512	0.23775967	0.9626137
##	punish2	0.5338490	0.24246863	1.1934058
##	punish3	0.2458364	0.09418942	0.6315739
##	explain	2.8630214	1.46945567	5.6121973