# Categorical Data Analysis

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#### **Outline**

- What are categorical variables?
- When do we need categorical data analysis?
- Some methods for categorical dependent variable
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  - Analysis of a three-way contingency table
  - Three types of logistic regression
    - Logistic regression
    - Ordered Logistic regression
    - Multinomial Logistic regression
- Conclusion



# What Are Categorical Data?

- Four measurement levels
  - Nominal (e.g., gender, race)
  - Ordinal (e.g., attitude toward cohabitation)
  - Interval (e.g., temperature)
  - Ratio (e.g., income)
- Categorical variables are those measured at nominal and ordinal levels
- Interval or ratio variables can be transformed into nominal or ordinal variables, but not the other way around.



## What Is Special about Categorical Variable?

- The distribution of a categorical variable is described by its frequency and proportion rather than by its mean and variance.
- Statistical methods (i.e., t-test, correlation, OLS regression)
  designed for continuous dependent variables are not
  adequate for analyzing categorical dependent variables.
- The decision on how to analyze categorical variables is often based on:
  - The measurement level and number of categories in dependent variables
  - The measurement level and number of categories in independent variables
  - Sample size
  - Number of independent variables



# When Do We Need Categorical Data Analysis?

 You have a categorical variable as the dependent variable.

 You have a continuous variable. However, the distribution of this variable is skewed and cannot be analyzed like regular continuous dependent variables



## Analyzing a Two-way Contingency Table

Analyzing a 2x2 table

Difference of Two Proportions =  $\pi_1 - \pi_2 \approx \rho_1 - \rho_2$ 

$$SE = \sqrt{\frac{\rho_1(1-\rho_1)}{n_1} + \frac{\rho_2(1-\rho_2)}{n_2}}$$

Relative Risk = 
$$\frac{\pi_1}{\pi_2}$$



#### Analyzing a Two-way Contingency Table (Cont.)

#### Odds Ratio

Odds Ratio = 
$$\frac{\text{Odds 1}}{\text{Odds 2}}$$
  
=  $\frac{\pi_1}{\pi_2} = \frac{\pi_{11}}{\pi_{21}} = \frac{\pi_{11} \cdot \pi_{22}}{\pi_{21}} = \frac{\pi_{11} \cdot \pi_{22}}{\pi_{12} \cdot \pi_{21}}$   
 $SE = \sqrt{\frac{1}{n_{11}} + \frac{1}{n_{12}} + \frac{1}{n_{21}} + \frac{1}{n_{22}}}$ 



# Examples

Data

Table. Gender and Employment					
	Employed	Unemployed			
Male	200	200			
Female	200	400			

Difference of two proportions

$$P1 = 200/400 = 0.5$$

$$P2 = 200/600 = 0.33$$

$$P1 - P2 = 0.17$$

Relative risk

$$P1/P2 = 0.66$$

Odds Ratio

$$(200*400)/(200*200) = 2$$

## Analyzing a Three-way Contingency Table

 A three-way contingency table can be viewed as multiple two-way contingency tables created at different levels of a third variable.

#### Example:

Table. Relations among Country, Gender, and Employment							
	Count	ty A	Country B				
	Employed	Unemploye	Employed	Unemployed			
Male	180	120	20	80			
Female	120	80	80	320			

#### Difference of proportion

Country A: (180/300) - (120/200) = 0

Country B: (20/100) -(80/320)=0

#### Relative risk

Country A: (180/300)/(120/200)=0.6/0.6=1

Country B: (20/100) -(80/320)=0.2/0.2=1

#### **Odds Ratio**

Country A: (180\*80)/(120\*120)=1

Country B: (20\*320)\*(80\*80)=1

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## Three Types of Logistic Regression

#### Logistic Regression

$$\log(\frac{\pi_1}{\pi_2}) = \log(\frac{\pi(x)}{1 - \pi(x)}) = \alpha + \beta \chi$$

$$\pi(\chi) = \frac{\exp(\alpha + \beta \chi)}{1 + \exp(\alpha + \beta \chi)} = \frac{e^{\alpha + \beta \chi}}{1 + e^{\alpha + \beta \chi}}$$

#### **Ordered Logistic Regression**

$$p(Y \le j) = \pi_1 + ... + \pi_{j}, j = 1,..., J$$

$$\log it [p(Y \le j)] = \log \left[\frac{p(Y \le j)}{1 - p(Y \le j)}\right] = \log \left[\frac{\pi_1 + \dots + \pi_{j,}}{\pi_{j+1} + \dots + \pi_{J,}}\right], j = 1, \dots, J$$



## Three Types of Logistic Regression (Cont.)

#### **Multinomial Logistic Regression**

$$\log(\frac{\pi_{j}}{\pi_{J}}) = \alpha_{j} + \beta_{j} \chi, j = 1,..., J - 1$$

$$\log(\frac{\pi_{a}}{\pi_{b}}) = \log(\frac{\pi_{a}}{\pi_{J}}) = \log(\frac{\pi_{a}}{\pi_{J}}) - \log(\frac{\pi_{b}}{\pi_{J}})$$

$$= (\alpha_{a} + \beta_{a} \chi) - (\alpha_{b} + \beta_{b} \chi)$$

$$= (\alpha_{a} - \alpha_{b}) + (\beta_{a} - \beta_{b}) \chi$$



## Relations among These Three Models

- Ordered logistic regression and multinomial logistic regression are an extension of logistic regression.
- Both ordered and multinomial logistic regression can be treated as models simultaneously estimating a series of logistic regression.
- Ordered logistic regression assumes different intercepts, but the same slope for different categories, while multinomial logistic regression assumes different intercept and slope parameters for different categories.



#### Example

```
Contains data from http://www.stata-press.com/data/r11/auto.dta
                                           1978 Automobile Data
 obs:
                 74
                12
                                           13 Apr 2009 17:45
 vars:
 size:
             3,478 (99.9% of memory free) (dta has notes)
             storage display value
             type format label variable label
variable name
make
               str18 %-18s
                                           Make and Model
price
               int %8.0qc
                                           Price
mpq
               int %8.0q
                                           Mileage (mpg)
rep78
              int %8.0q
                                           Repair Record 1978
                                           Headroom (in.)
headroom
              float %6.1f
trunk
               int
                                           Trunk space (cu. ft.)
                     %8.0q
weight
               int %8.0qc
                                           Weight (lbs.)
length
               int
                     %8.0q
                                           Length (in.)
                                           Turn Circle (ft.)
turn
              int %8.0q
displacement int %8.0q
                                           Displacement (cu. in.)
             float %6.2f
                                           Gear Ratio
                                                               14
                                 origin
                                           Car type
```

## Generate New Categorical Variables

- A dichotomous variable (repair2)
  - 1 if rep78 > 3 and rep78 ~= . and 0 if rep78 <= 2</li>
  - 1 indicates the car is very likely to break down, and
     0 indicates the car is not.
- A three-category ordinal variable (repair3)
  - 2 if rep78 > 4 and rep78 ~=. 1 if rep78 == 3, and 0 if rep78 <= 2</li>
  - 2 indicates the car is very likely to break down, 1 indicates the car is likely to break down, 0 indicates the car is unlikely to break down



## Logistic Regression Results

logit repair2 price mpg gear\_ratio foreign

```
note: foreign != 0 predicts success perfectly
```

foreign dropped and 21 obs not used

```
Iteration 0: log likelihood = -24.563524
```

.

Iteration 4: log likelihood = -23.786597

•	Logistic regression	Number of obs	=	48
•		LR chi2(3)	=	1.55
•		Prob > chi2	=	0.6699
•	Log likelihood = -23.786597	Pseudo R2	=	0.0316

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	repair2	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
•	price	.0001677	.0001661	1.01	0.313	000158	.0004933
•	mpg	0014679	.099011	-0.01	0.988	1955259	.1925901
•	gear_ratio	1.586402	1.584308	1.00	0.317	-1.518784	4.691588
•	foreign	(omitted)					
2 (6	_cons	-4.019467	4.685599	-0.86	0.391	-13.20307	5.164138



### Ordered Logistic Regression

. ologit repair3 price mpg gear\_ratio foreign Iteration 0: log likelihood = -69.439997Iteration 1: log likelihood = -55.714994 Iteration 2:  $\log likelihood = -55.523055$ Iteration 3: log likelihood = -55.5227 Iteration 4: log likelihood = -55.5227 Number of obs = 69 Ordered logistic regression LR chi2(4) = 27.83Prob > chi2 = 0.0000Pseudo R2 0.2004 Log likelihood = -55.5227Coef. Std. Err. z P>|z| [95% Conf. Interval] repair3

•	+					
• price	.0000722	.0001054	0.68	0.493	0001344	.0002787
• mpg	.0811893	.0689252	1.18	0.239	0539016	.2162802
• gear_ratio	112221	1.035193	-0.11	0.914	-2.141162	1.91672
• foreign	2.748854	.9580416	2.87	0.004	.871127	4.626581
•	-+					
• /cut1	.3380733	3.13436			-5.80516	6.481307
Fami¢yt2	2.980449	3.161144			-3.215279	9.176178
Domogr	caphic					17
	apnic Research	n				

# Multinomial Logistic Regression

mlogit repair3 price mpg gear\_ratio foreign, base(0)

•	• Multinomial logistic regression					of obs = 12(8) = chi2 =	69 31.30 0.0001
•	Log likelihood	d = -53.792211	L		Pseudo	R2 =	0.2253
•	repair3	Coef.	Std. Err.		P>   z	[95% Conf.	Interval]
	not_likely~n						
•	likely_to_~n						
•	price	.0001736	.0001711	1.01	0.310	0001617	.0005089
•	mpg	043372	.1056836	-0.41	0.682	250508	.163764
•	gear_ratio	2.017402	1.635181	1.23	0.217	-1.187493	5.222297
•	foreign	14.14439	2122.177	0.01	0.995	-4145.245	4173.534
•	_cons	-4.795311	4.837551	-0.99	0.322	-14.27674	4.686116
•	very_likel~n						
•	price	.0001394	.0001895	0.74	0.462	0002321	.0005109
•	mpg	.0782156	.1121928	0.70	0.486	1416782	.2981094
•	gear_ratio	.5374572	1.852135	0.29	0.772	-3.09266	4.167575
50	Fafpreign	17.38138	2122.177	0.01	0.993	-4142.008	4176.771
	Demogra	phic 775221 Research	5.406854	-0.70	0.485	-14.37246 	6.82201 <b>78</b>

#### Conclusion

 If you have categorical dependent variables, you need to choose adequate methods to analyze them.

- There are additional models, including Poisson regression, Log-linear model, Negative binomial regression, and Models for matched pairs.
- For additional help with categorical data analysis, feel free to contact me at <u>wuh@bgsu.edu</u> and 372-3119.

