Categorical Data Analysis Using SAS and Stata

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Outline

- Why do we need to learn categorical data analyses?
- A summary of different categorical data analyses
  - Analyses of contingency tables
  - Regression models
    - Logistic regression
    - Ordered logistic regression
    - Multinomial logistic regression
- Stata commands
- SAS commands
- Interpreting the results
- Predicted probability
- Conclusions

Why Do We Need to Learn Categorical Data Analysis?

- 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

Different Models for Categorical Dependent Variables

Categorical models address three types of questions:

- Examination of contingency tables
  - Proportions
  - Relative risks
  - Odds ratio
- How the characteristics of individuals affect the choice
  - Binary logistic regression
  - Ordered logistic regression
  - Multinomial logistic regression

Analyzing a Two-way Contingency Table

- Analyzing a 2x2 table

Table. Gender and Employment

	Employed	Unemployed
Male	200	200
Female	200	400

Table. Gender and Employment

	Employed	Unemployed
Male	ρ_1	$1-\rho_1$
Female	ρ_2	$1-\rho_2$

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

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

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Analyzing a Two-way Contingency Table (Cont.)

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

Odds Ratio

$$\text{Odds Ratio} = \frac{\text{Odds1}}{\text{Odds2}}$$

$$= \frac{\pi 1 / (1 - \pi 1)}{\pi 2 / (1 - \pi 2)} = \frac{\pi 11 / \lambda 12}{\pi 21 / \pi 22} = \frac{\pi 11 \cdot \pi 22}{\pi 12 \cdot \pi 21}$$

$$SE = \sqrt{\frac{1}{n11} + \frac{1}{n12} + \frac{1}{n21} + \frac{1}{n22}}$$

Example

- Data

  P1 = 200/400 = 0.5

  P2 = 200/600 = 0.33

  - Difference of two proportions

    P1 - P2 = 0.17

  - Relative risk

    P1/P2 = 1.51

  - Odds Ratio

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

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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

	County A		Country B	
	Employed	Unemploye	Employed	Unemployed
Male	180	120	20	80
Female	120	80	80	320

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Example

– 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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Models for Examining How Characteristics of Individuals Affect Choices

Logistic Regression

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

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

Ordered Logistic Regression

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

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

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Models for Examining How Characteristics of Individuals Affect Choices (Cont.)

Multinomial Logistic Regression

$$\log\left(\frac{\pi_j}{\pi_J}\right) = \alpha_j + \beta_j \chi,\ j = 1,\ldots,J-1$$

$$\log\left(\frac{\pi_a}{\pi_b}\right) = \log\left(\frac{\pi_a / \pi_J}{\pi_b / \pi_J}\right) = \log\left(\frac{\pi_a}{\pi_J}\right) - \log\left(\frac{\pi_b}{\pi_J}\right)$$

$$= (\alpha_{\mathrm{a}} + \beta_a \chi) - (\alpha_{\mathrm{b}} + \beta_b \chi)$$

$$= (\alpha_\alpha - \alpha_b) + (\beta_a - \beta_b)\chi$$

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.

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A List of Variables in the Data

variable name	variable label	Label Value	Label Label
aid	ID	57101310 - 99719978	
married	Marital Status	0	Not married
		1	Married
educ	Education	1	Less than High School
		2	High School
		3	Some college
		4	colleges or more
union	Union Status	0	single
		1	cohabiting
		2	married
female	Female	0	Male
		1	Female
age	Age		24-33
agesq	Age squared		576-1089
femaleage	Interaction term of female and age		0-33

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Data for Logistic Regression, Ordered Logistic Regression, and Multinomial Logistic Regression

	aid	married	educ	union	female	age	agesq	femaleage
1	57101310	1	2	2	1	31	961	31
2	57103869	0	1	0	0	32	1024	0
3	57109625	0	1	0	0	27	729	0
4	57111071	0	3	0	0	27	729	0
5	57113943	0	3	1	0	29	841	0
6	57117542	0	1	0	0	28	784	0
7	57118381	1	3	2	1	25	625	25
8	57118943	1	4	2	1	29	841	29
9	57120005	0	4	0	0	26	676	0
10	57120046	1	3	2	0	31	961	0
11	57120371	1	2	2	1	31	961	31
12	57121404	1	4	2	1	28	784	28
13	57121476	0	2	0	1	27	729	27
14	57127241	0	3	1	1	26	676	26
15	57129567	0	3	1	0	27	729	0
16	57131432	1	3	2	0	29	841	0
17	57131909	0	3	1	0	26	676	0
18	57133772	0	3	0	1	26	676	26
19	57134457	0	3	0	1	28	784	28
20	57134967	0	1	1	1	26	676	26

Stata Commands

Logistic Regression

```
logit married female age femaleage
logit married female age femaleage, or
```

Ordered Logistic Regression

```
ologit educ female age femaleage
ologit educ female age femaleage, or
```

Multinomial Logistic Regression

```
mlogit union female age femaleage, base(0)
```

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SAS Commands

Logistic Regression

```
Proc Logistic data = in.annotated_3_2;
Format married marriedf. educ educf.;
Model married = educ female age femaleage;
run;
```

SAS and Stata Commands

Ordered Logistic Regression

```
Proc Logistic data = in.annotated descending;
Format educ educf. female femalef.;
Model educ = female age femaleage;
run;

PROC QLIM data = in.annotated;
MODEL educ = female age
femaleage/DISCRETE (DIST=LOGISTIC);
RUN;
```

Multinomial Logistic Regression

```
mlogit union educ female age femaleage, base(0)
```

SAS and Stata Commands

Multinomial Logistic Regression

```
proc logistic data = in.annotated_3_2;
class union (ref = "0");
model union = educ female age femaleage/
link = glogit;
run;
```

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Interpreting the Results

- The sample size
- The reference category
- The regression coefficients
- The odds ratio

Predicted Probability

- Predicted probability is useful to describe the results
- Odds = Exp(the sum of coefficients)
- Predicted Probability = Odds/(1+Odds)
- You can present predicted probability with graphs

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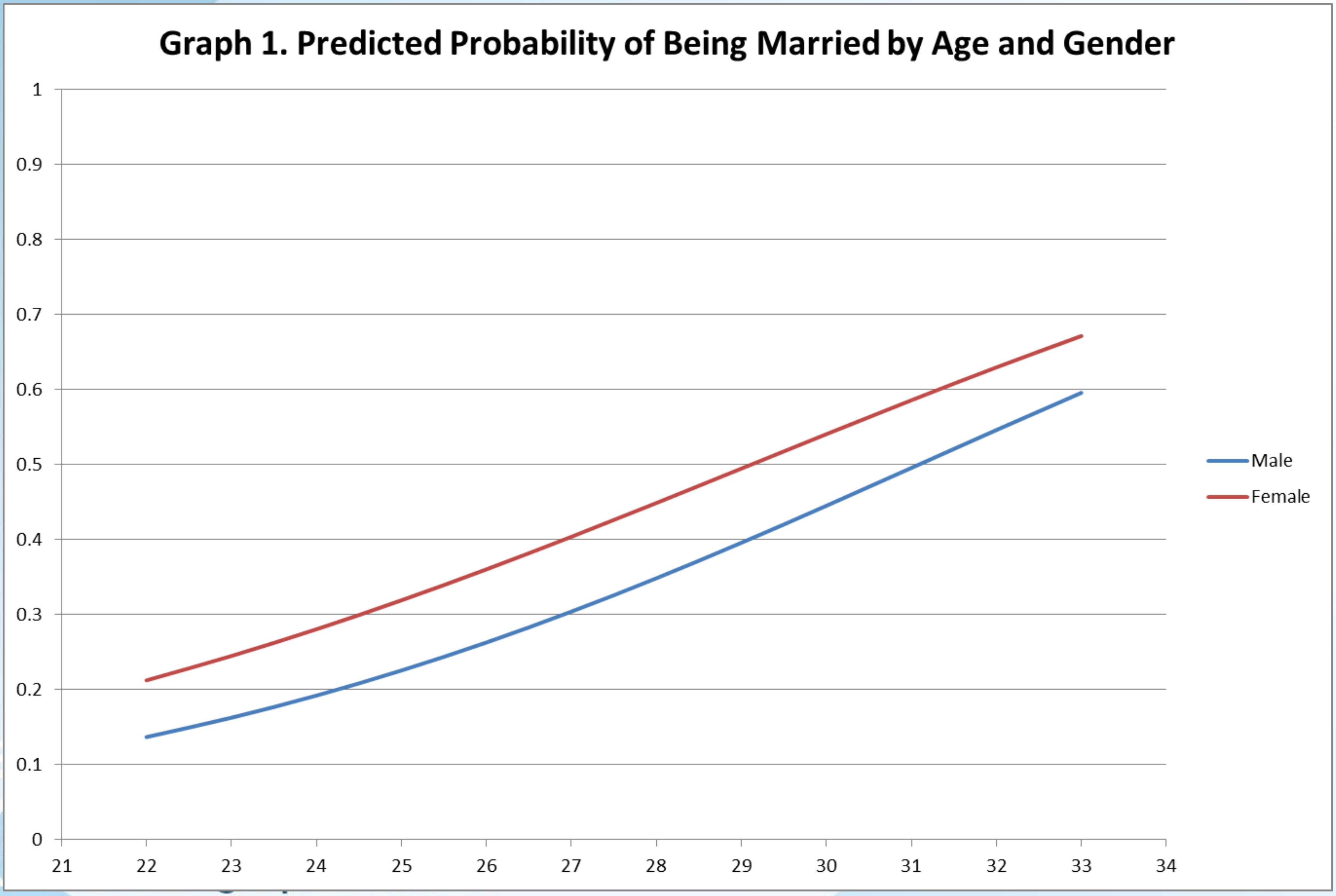
Predicted Probability (continued)

Table 3. Predicated Probability for Male and Female Respondents

Intercept	Female		Age		Age*Female		Sum of coefficents	Odds Ratio	Predicted Probability
coefficent	value	coefficent	value	coefficent	value	coefficent			
-6.295917	0	0.9380865	22	0.2025471	0	-0.0185092	-1.8398808	0.158836358	0.137065391
-6.295917	0	0.9380865	23	0.2025471	0	-0.0185092	-1.6373337	0.194497941	0.162828193
-6.295917	0	0.9380865	24	0.2025471	0	-0.0185092	-1.4347866	0.238166183	0.192353972
-6.295917	0	0.9380865	25	0.2025471	0	-0.0185092	-1.2322395	0.291638721	0.225789701
-6.295917	0	0.9380865	26	0.2025471	0	-0.0185092	-1.0296924	0.357116793	0.263143743
-6.295917	0	0.9380865	27	0.2025471	0	-0.0185092	-0.8271453	0.437295855	0.30424902
-6.295917	0	0.9380865	28	0.2025471	0	-0.0185092	-0.6245982	0.53547654	0.348736386
-6.295917	0	0.9380865	29	0.2025471	0	-0.0185092	-0.4220511	0.655700532	0.396026044
-6.295917	0	0.9380865	30	0.2025471	0	-0.0185092	-0.219504	0.802916946	0.44534328
-6.295917	0	0.9380865	31	0.2025471	0	-0.0185092	-0.0169569	0.983186059	0.495760877
-6.295917	0	0.9380865	32	0.2025471	0	-0.0185092	0.1855902	1.203928789	0.546264832
-6.295917	0	0.9380865	33	0.2025471	0	-0.0185092	0.3881373	1.474232182	0.595834212
-6.295917	1	0.9380865	22	0.2025471	22	-0.0185092	-1.3089967	0.270090903	0.212654781
-6.295917	1	0.9380865	23	0.2025471	23	-0.0185092	-1.1249588	0.324665843	0.245092636
-6.295917	1	0.9380865	24	0.2025471	24	-0.0185092	-0.9409209	0.390268272	0.280714363
-6.295917	1	0.9380865	25	0.2025471	25	-0.0185092	-0.756883	0.469126417	0.319323383
-6.295917	1	0.9380865	26	0.2025471	26	-0.0185092	-0.5728451	0.563918749	0.360580592
-6.295917	1	0.9380865	27	0.2025471	27	-0.0185092	-0.3888072	0.67786495	0.404004476
-6.295917	1	0.9380865	28	0.2025471	28	-0.0185092	-0.2047693	0.814835277	0.448985805
-6.295917	1	0.9380865	29	0.2025471	29	-0.0185092	-0.0207314	0.979482018	0.494817336
-6.295917	1	0.9380865	30	0.2025471	30	-0.0185092	0.1633065	1.177397507	0.540736133
-6.295917	1	0.9380865	31	0.2025471	31	-0.0185092	0.3473444	1.415304072	0.585973455
-6.295917	1	0.9380865	32	0.2025471	32	-0.0185092	0.5313823	1.701282367	0.629805454
-6.295917	1	0.9380865	33	0.2025471	33	-0.0185092	0.7154202	2.04504583	0.671597718

Predicted Probability (continued)



Conclusions

- If you have categorical dependent variables, you need to choose adequate methods to analyze them.
- You need to choose the regression models that fit your data and research questions.
- If you have event counts (e.g., the number of accidents), you need to use other models such as Poisson regression, Log-linear model, or Negative binomial regression for analyses.
- For additional help with categorical data analysis, feel free to contact me at wuh@bgsu.edu and 372-3119.

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