# GLM/Categorical Data Analysis\_wk1

Yu-Ling Tseng

Depart. of Applied Math, NDHU

Course: Generalized Linear Models/Categorical Data Analysis – Class Notes Instructor: Yu-Ling Tseng (Yes, Heyou) Office: A409 Science Building Office Hours: TBA Phone: 8633518 *Email:* yltseng@mail.ndhu.edu.tw http://faculty.ndhu.edu.tw/yltseng/edu/glm.html

#### Textbook

An Introduction to Categorical Data Analysis, A. Agresti (1996), Wiley and Sons. (Hwa-Tai) 02-23773877.

#### Reference

- ✓ Agresti, A. (1990). Categorical Data Analysis. Wiley.
- ✓ Agresti, A. (2002). Categorical Data Analysis, 2nd Edtion. Wiley.
- ✓ McCullagh, P. and Nelder, J.A. (1989). Generalized Linear Models. 2nd Edition. Chapman and Hall, London.
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- Neter, Kutner, Nachtsheim and Wasserman (1996). Applied Linear Statistical Models. 4th Edtion. McGRAW-HILL International.
- ✓ D. W. Hosmer and S. Lemeshow (1989). Applied Logistic Regression. Wiley.

#### **Course Grade**

In-class Exam (50 % ), Presentation ( 50 % )

 $\sim$  Come to my office if you have any question!  $\sim \stackrel{\cdots}{\smile}$ 

# **Introduction\_1: Statistical problems**

- / Response vs Explanatory variables
  - $y_i, Y_i$ : survival of patients, scores political philosophy, incomes

 $x_i = (x_{i1}, \dots, x_{ik})$ : (medical treatment, age, gender), (training course, major, gender) (income, attained education, religious affiliation, age, gender, race), (attained education, age, gender, years at work)

 $\longrightarrow$  Continuous or Discrete (Categorical) Variables

## **Intro\_1: Scale of measurement**

- Continuous data
  - **\star** interval: arbitrary origin (<sup>o</sup>C)
  - ★ ratio: absolute origin (height)
- / Categorical data
  - nominal: no order involved (religious affiliation, mode of transportation to work)
  - ★ ordinal: order but not necessary can assign distance (poor, fair, good, excellent; low, high, too high; certain, probable, unlikely, definitely not)
  - ★ counts: 0, 1, 2, 3, . . . (ordinal, too)

## **Classification of Stat. methods**

		Response	
		Continuous	Discrete
Explanatory	Continuous	Regression	Logistic
	Discrete	ANOVA	Loglinear model
	Mixed	ANCOVA	Logistic

 $\longrightarrow$  Focus of this course.

Background: stat. estimation, testing and exposure to regression modeling and the analysis of variance.

# **Introduction\_2: Statistical Modeling**

\*\* A model is a simple summary (smoothed version) of the data.

 $\longrightarrow \text{Model}: \quad \text{data}$  = systematic pattern + random component (noise), w/ both parts involving unknown parameters.  $\text{E.G. } Y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad \epsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$   $\longleftrightarrow \text{ matrix form: } Y = X \beta + \epsilon, \quad \epsilon \sim N_n(0, \sigma^2 \cdot I)$   $\longrightarrow \text{est. } \hat{\beta}, \hat{\sigma}^2, \text{ predictors: } \hat{Y} = X \hat{\beta}$ 

# **Statistical Modeling (conti)**

- $\star$  All models are wrong, but some are useful . . .
- Models are only device for data analysis.

\* Simple models provide clear thinking, better prediction, easier interpretation.

 $\rightarrow \star \star$  Parsimony principle  $\star \star$ Should add systematic effects to a model only if substantial evidence for the effect exists

\*\* substantial evidence: sig. F test, small P value, big(add)/small(drop) change in deviance ... \*\*

# **Introduction\_3: Overview**

Topics covered in this course:

- / Discrete distributions (Negative)Binomial, Poisson, Multinomial, ... Exponential family
- Contingency tables
   Study Designs/Sampling Scheme
  - / Generalized linear models (GLM)
    - ★ Logistic models
    - ★ Loglinear models
    - ★ Selected topics for presentation

# Stat. Package: SAS/R

Assumption taken: You can learn SAS/R, basicaly, by yourselves.

Assistance provided: Parts of SAS/R programs for certain GLM analyses will be illustrated in class, once in a while.

## **Recall: 2** $\times$ 2 **Contingency Table**

A real data set, say :

		outcome	
		f	u
Treatment	placebo	16	48
	test	40	20

Of interest: Is "test" sig. better than placebo?

 $\Leftrightarrow$  Hypothesis testing for the indep. between outcome and treatment.

 $\xrightarrow{} \chi^2 \text{ test} \longrightarrow \text{need expected counts} \longrightarrow \text{in SAS/R?}$ Easy!

## A tiny taste on **R**

> x=c(16,40); # placebo, test

```
> n=c(64,60);
```

```
> prop.test(x,n);
```

```
2-sample test for equality of proportions
               with continuity correction
data: x out of n
X-squared = 20.0589, df = 1, p-value = 7.51e-06
alternative hypothesis: two.sided
95 percent confidence interval:
 -0.5924430 -0.2408903
sample estimates:
   prop 1 prop 2
0.2500000 0.6666667
                                               GLM – p. 10/12
```

### SAS code

```
data respire;
   input treat $ outcome $ count ;
   cards;
  placebo f 16
  placebo u 48
  test f 40
   test u 20
proc freq;
weight count;
tables treat*outcome/chisq expected fisher
run;
```

SAS outut in text form:

The FREQ Procedure

Table of treat by outcome

treat Frequency Expected Percent Row Pct Col Pct	outcome       f	u	Total
placebo	+   16	+ 48	-+ 64
-	28.903	35.097	İ
	12.90	38.71	51.61
	25.00	75.00	Ì
	28.57	70.59	
test	+   40	+ 20	-+ 60
	27.097	32.903	
	32.26	16.13	48.39
	66.67	33.33	İ
	71.43	29.41	
Total	+ 56	+68	-+ 124
_ • • • •	45.16	54.84	100.00

Statistics for Table of treat by outcome Statistic DF Value Prob 1 21.7 <.0001 Chi-Square <.0001 Likelihood Ratio Chi-Square 1 22.3 Continuity Adj. Chi-Square 1 20.0 <.0001 Mantel-Haenszel Chi-Square 1 21.5 <.0001 Phi Coefficient -0.41840.3860 Contingency Coefficient 0.4184 Cramer's V

Fisher's Exact Test Cell (1,1) Frequency (F) 16 Left-sided Pr <= F 2.838E-06 Right-sided Pr >= F 1.0000 Table Probability (P) 2.397E-06 Two-sided Pr <= P 4.754E-06</pre>

Sample Size = 124

## Is test "sig. better" than placebo? With R

> prop.test(x,n,alternative=c("less"));

2-sample test for equality of proportions with continuity correction

data: x out of n X-squared = 20.0589, df = 1, p-value = 3.755e-06 alternative hypothesis: less 95 percent confidence interval: -1.0000000 -0.2665547 sample estimates: prop 1 prop 2 0.2500000 0.66666667