

# Analysis of Categorical Data

## Chapter 3: Inference for Contingency Table

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# Intended Learning Outcome

Through this chapter, you should be able to

- ① test independence in contingency table,
- ② test monotone trend.

# Odds Ratio

Suppose that we have observed a  $2 \times 2$  table

$X$	$Y$	
	1	2
1	$n_{11}$	$n_{12}$
2	$n_{21}$	$n_{22}$

The sample odds ratio is

$$\hat{\theta} = \frac{n_{11}n_{22}}{n_{12}n_{21}} \geq 0.$$

If  $\hat{\theta} > 0$ , then we can consider

$$\log \hat{\theta} = \log n_{11} + \log n_{22} - \log n_{12} - \log n_{21}.$$

## Wald Confidence Interval

An estimated standard error of  $\log \hat{\theta}$  is

$$\sqrt{\frac{1}{n_{11}} + \frac{1}{n_{12}} + \frac{1}{n_{21}} + \frac{1}{n_{22}}}.$$

Hence, a **Wald confidence interval** for  $\log \theta$  is

$$\log \hat{\theta} \pm z_{\alpha/2} \sqrt{\frac{1}{n_{11}} + \frac{1}{n_{12}} + \frac{1}{n_{21}} + \frac{1}{n_{22}}}.$$

However,

$$\hat{\theta} = \frac{n_{11}n_{22}}{n_{12}n_{21}}$$

can be 0 (if  $n_{11}n_{22} = 0$ ),  $\infty$  ( $n_{12}n_{21} = 0$ ), or undefined (if  $n_{11}n_{22} = n_{12}n_{21} = 0$ ). Consequently, the Wald interval may not exist.

- An ad-hoc approach is to add 0.5 to  $n_{ij}$ .
- Use other approaches such as the **score interval** or the **likelihood ratio confidence interval**.

## Example: Aspirin Use and Myocardial Infraction

Compute  $\hat{\theta}$  and find a 95% confidence interval for  $\theta$

	Myocardial Infraction	
	Yes	No
Placebo	28	656
Aspirin	18	658

# Independence

We have an  $I \times J$  contingency table from [multinomial sampling](#) with probabilities  $\{\pi_{ij}\}$ . We want to test

$H_0$  : independence as  $\pi_{ij} = \pi_{i+}\pi_{+j}$  for all  $i, j$ ,

$H_1$  :  $H_0$  is not true.

The log-likelihood under  $H_0$  is

$$\ell_0(\pi_{i+}, \pi_{+j}) = \log \left( \frac{n!}{n_{11}! \cdots n_{IJ}!} \right) + \sum_i \sum_j n_{ij} \log(\pi_{i+} \pi_{+j}).$$

The log-likelihood under  $H_1$  is

$$\ell_1(\pi_{ij}) = \log \left( \frac{n!}{n_{11}! \cdots n_{IJ}!} \right) + \sum_i \sum_j n_{ij} \log(\pi_{ij}).$$

# Likelihood Ratio Test

The MLE under  $H_0$  is

$$\hat{\pi}_{i+} = \frac{n_{i+}}{n}, \quad \hat{\pi}_{+j} = \frac{n_{+j}}{n}.$$

The MLE under  $H_1$  is

$$\hat{\pi}_{ij} = \frac{n_{ij}}{n}.$$

The likelihood ratio test statistic is

$$G^2 = -2 [\ell_0(\hat{\pi}_{i+}, \hat{\pi}_{+j}) - \ell_1(\hat{\pi}_{ij})] = -2 \sum_{i=1}^I \sum_{j=1}^J n_{ij} \log \left( \frac{n_{i+} n_{+j} / n}{n_{ij}} \right).$$

If  $H_0$  holds,  $G^2$  also converges in distribution to chi-square with  $(IJ - 1) - (I - 1) - (J - 1) = (I - 1)(J - 1)$  degrees of freedom. A **rule-of-thumb** is that no more than 20% of  $\hat{\mu}_{ij} < 5$ .

# Pearson Chi-Square

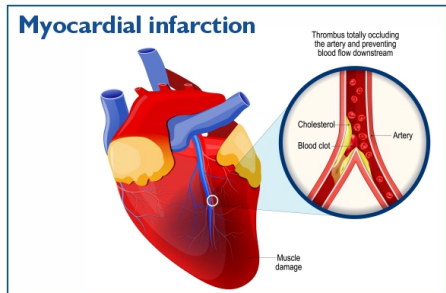
The **Pearson chi-square** that tests  $H_0$  : independence is

$$\begin{aligned} X^2 &= \sum_{i=1}^I \sum_{j=1}^J \frac{(\text{observed frequency}_{ij} - \text{expected frequency}_{ij})^2}{\text{expected frequency}_{ij}} \\ &= \sum_{i=1}^I \sum_{j=1}^J \frac{(n_{ij} - n\hat{\pi}_{i+}\hat{\pi}_{+j})^2}{n\hat{\pi}_{i+}\hat{\pi}_{+j}}. \end{aligned}$$

If  $H_0$  holds,  $X^2$  converges in distribution to to chi-square with  $(I - 1)(J - 1)$  degrees of freedom. A **rule-of-thumb** is still that no more than 20% of  $\hat{\mu}_{ij} < 5$ .



# Aspirin Use and Myocardial Infarction



## Test independence

	Myocardial Infarction	
	Yes	No
Placebo	28	656
Aspirin	18	658

# Fisher's Exact Test

For  $2 \times 2$  tables, regardless of sampling, under the independence assumption, conditioning on both sets of marginal totals, the only free cell is  $n_{11}$ . It follows the hypergeometric distribution

$$P(n_{11} = t) = \frac{\binom{n_{1+}}{t} \binom{n_{2+}}{n_{+1} - t}}{\binom{n}{n_{+1}}}.$$

- For  $H_0 : \theta = 1$  (independence) versus  $H_1 : \theta > 1$ , the [Fisher's exact test](#) uses the p-value  $P(n_{11} \geq t_o)$  where  $t_o$  is the observed value of  $n_{11}$ .
- For  $H_0 : \theta = 1$  versus  $H_1 : \theta \neq 1$ , there are different ways of computing the p-value. They lead to different p-values.

# Example

## Fisher's Tea Tasting Experiment

Poured First	Guess Poured First		Total
	Milk	Tea	
Milk	3	1	4
Tea	1	3	4
Total	4	4	8

# Ordinality and Scoring

If our data are ordinal, using the above  $X^2$  and  $G^2$  are less ideal since they ignore ordinality of data.

To keep ordinality, many people choose to assign scores to the ordinal variables:  $u_1 \leq u_2 \leq \cdots \leq u_I$  be the scores for the rows, and  $v_1 \leq v_2 \leq \cdots \leq v_J$  be the scores for the columns. The scores are then treated as the values of the variables. However, this approach has several serious issues:

- ① How shall we assign scores?
- ② Are the distance between the assigned score actually reflect the “distance” between categories?

# Ordinal Variables

Suppose that both  $X$  and  $Y$  are ordinal.

- 1 A pair of subjects is **concordant** if the subject ranked higher on  $X$  also ranks higher on  $Y$ .
- 2 A pair of subject is **discordant** if the subject ranking higher on  $X$  ranks lower on  $Y$ .

Age	Job satisfaction		
	1: Not satisfied	2: Satisfied	3: Very satisfied
1: < 30	34	53	88
2: 30 – 50	80	174	304
3: > 50	29	75	172

# Concordant/Discordant Pairs

Age	Job satisfaction		
	1: Not satisfied	2: Satisfied	3: Very satisfied
1: < 30	34	53	88
2: 30 – 50	80	174	304
3: > 50	29	75	172

- Subject  $A$  belongs to (1, 1) and subject  $B$  belongs to (2, 2). The pair  $(A, B)$  is concordant.
- Subject  $A$  belongs to (2, 2) and subject  $B$  belongs to (1, 1). Also concordant.
- Subject  $A$  belongs to (1, 2) and subject  $B$  belongs to (2, 1). The pair  $(A, B)$  is discordant.
- Subject  $A$  belongs to (2, 1) and subject  $B$  belongs to (1, 2). Also discordant.

# Probability of Concordant/Discordant

Suppose that we have two independent subjects  $A$  and  $B$  from a joint distribution  $\{\pi_{ij}\}$ .

- ① The probability of a **concordant** pair is

$$\begin{aligned}\Pi_c &= \sum_{i,j} \{P[A = (i,j)] P[B = (h,k), h > i, k > j \mid A = (i,j)]\} \\ &\quad + \sum_{i,j} \{P[A = (i,j)] P[B = (h,k), h < i, k < j \mid A = (i,j)]\} \\ &= 2 \sum_{i,j} \left\{ \pi_{ij} \sum_{h>i} \sum_{k>j} \pi_{hk} \right\}.\end{aligned}$$

- ② The probability of a **discordant** pair is

$$\Pi_d = 2 \sum_{i,j} \left\{ \pi_{ij} \sum_{h>i} \sum_{k<j} \pi_{hk} \right\}.$$

# Gamma Coefficient

We define the Goodman-Kruskal's gamma as

$$\gamma = \frac{\Pi_c - \Pi_d}{\Pi_c + \Pi_d}.$$

- ①  $\gamma$  has the range  $-1 \leq r \leq 1$ . It work in a similar way as the Pearson correlation coefficient.
- ② If  $\gamma > 0$  ( $\Pi_c > \Pi_d$ ), then it is more likely to have concordant pairs than discordant pairs (positive trend).
- ③ If  $\gamma < 0$  ( $\Pi_c < \Pi_d$ ), then it is less likely to have concordant pairs than discordant pairs (negative trend).
- ④ If  $\gamma = 0$ , then no trend.
- ⑤ If  $X$  and  $Y$  are independent, then  $\gamma = 0$ . But  $\gamma = 0$  does not mean independence.



## Alternative Method

For ordinal data, we use the sample [Goodman-Kruskal's gamma](#) is

$$\hat{\gamma} = \frac{C - D}{C + D}$$

to check whether they have a monotone trend, where  $C$  is the total number of concordant pairs of observations, and  $D$  is the total number of discordant pairs of observations.

- If  $\gamma = 0$ , there is no trend between  $X$  and  $Y$ .
- For a large sample size,  $\hat{\gamma}$  is approximately normal.

## Example Sample Gamma Coefficient

The sample version of  $\gamma$  is

$$\hat{\gamma} = \frac{C - D}{C + D},$$

where  $C$  is the total number of concordant pairs and  $D$  is the total number of discordant pairs.

Compute  $\hat{\gamma}$

Age	Job satisfaction		
	1: Not satisfied	2: Satisfied	3: Very satisfied
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# Wilcoxon Test or Mann-Whitney Test

Suppose that we have two random variables  $Y_0$  and  $Y_1$ . The [Wilcoxon test](#) or the [Mann-Whitney test](#) tests whether

$$P(Y_0 > Y_1) = P(Y_0 < Y_1).$$

In the special case where we have a  $2 \times J$  table ( $I = 2$ ) and the scores for  $X$  are  $\{0, 1\}$ . We have two groups, one group with  $X = 0$  and another group with  $X = 1$ . Then the general idea is that

- ① Assign ranks to the whole sample of size  $n_{0+} + n_{1+}$ .
- ② Compute the sum of ranks assigned to the group  $X = 0$ .
- ③ If  $H_0$  is not true, the sum of ranks tends to be either small or large.

The [Kruskal-Wallis test](#) generalizes the Mann-Whitney test to more than 2 groups. The Kruskal-Wallis test can be viewed as a non-parametric version of one-way ANOVA.

# Be Careful With Their Hypotheses

$X$	$Y$			
	1	2	3	4
0	0.05	0.5	0.35302019	0.09697981
1	0.1666553	0.2833447	0.5000000	0.0500000

