

# Inference for Two-Way Contingency Tables

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- 2 Two-Way Tables with Ordered Classifications
- 3 Small-Sample Inference for Contingency Tables
- 4 Bayesian Inference for Two-Way Contingency Tables
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- Interval Estimation of Odds Ratio, Difference of Prop., RR
- Testing Independence (Multinomial sampling)
  - ① Pearson  $\chi^2$  test (Under  $H_0$  : independence)

$$\chi^2 = \sum_{i,j} \frac{(n_{ij} - \hat{\mu}_{ij})^2}{\hat{\mu}_{ij}} \xrightarrow{d} \chi_v^2$$

- ② Likelihood-ratio  $\chi^2$  test (Under  $H_0$  : independence)

$$G^2 = -2 \log \Lambda = 2 \sum_{i,j} n_{ij} \log(n_{ij} / \hat{\mu}_{ij}) \xrightarrow{d} \chi_v^2$$

- Testing Independence (Independent binomial sampling)

- ① Homogeneity condition  $\pi_1 = \pi_2$

$$z = \frac{\hat{\pi}_1 - \hat{\pi}_2}{\sqrt{\hat{\pi}(1 - \hat{\pi}) \left( \frac{1}{n_1} + \frac{1}{n_2} \right)}}$$

- Score Confidence Intervals Comparing Proportions  
(Under  $H_0 : \pi_1 - \pi_2 = \delta_0$ )

$$z(\delta_0) = \frac{(\hat{\pi}_1 - \hat{\pi}_2) - \delta_0}{\left( \frac{\hat{\pi}_1(\delta_0)(1 - \hat{\pi}_1(\delta_0))}{n_1} + \frac{\hat{\pi}_2(\delta_0)(1 - \hat{\pi}_2(\delta_0))}{n_2} \right)^{1/2}}$$

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# Two-Way Tables with Ordered Classifications

## Linear Trend Alternative to Independence

Political Ideology	Happiness		
	Not too Happy	Pretty Happy	Very Happy
Liberal	13	29	15
Moderate	23	59	47
Conservative	14	67	54

- $X$  and  $Y$  are ordinal.  $\implies \chi^2$  and  $G^2$  chi-squared tests ignore !!
- How can we examine dependency??  
“Positive or Negative trend”  $\leftarrow$  Correlation
- Assign **scores**  $u_1 \leq u_2 \leq \dots \leq u_I$  and  $v_1 \leq v_2 \leq \dots \leq v_J$

# Two-Way Tables with Ordered Classifications

## Linear Trend Alternative to Independence

Large sample normality of sample correlation coefficient.

$$\begin{aligned}\hat{\rho} &= \frac{\sum_1^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_1^n (X_i - \bar{X})^2 \sum_1^n (Y_i - \bar{Y})^2}} \\&= \left(\frac{1}{n} \sum_1^n X_i^2 - \bar{X}^2\right)^{-1/2} \left(\frac{1}{n} \sum_1^n Y_i^2 - \bar{Y}^2\right)^{-1/2} \left(\frac{1}{n} \sum_1^n X_i Y_i - \bar{X}\bar{Y}\right) \\&= (\bar{X}^2 - \bar{X}^2)^{-1/2} (\bar{Y}^2 - \bar{Y}^2)^{-1/2} (\bar{X}\bar{Y} - \bar{X}\bar{Y})\end{aligned}$$

Define  $W_i = (X_i, Y_i, X_i^2, Y_i^2, X_i Y_i)$ . Then,  $\hat{\rho} = g(\bar{W})$  where

$$g(u_1, u_2, u_3, u_4, u_5) = ((u_3 - u_1^2)(u_4 - u_2^2))^{-1/2}(u_5 - u_1 u_2).$$

W.L.O.G. we may assume  $\mathbb{E}X = \mathbb{E}Y = 0$  and  $\mathbb{E}X^2 = \mathbb{E}Y^2 = 1$

By Central Limit Theorem,  $\sqrt{n}(\bar{W} - (0, 0, 1, 1, \rho)) \xrightarrow{d} \mathcal{N}(0, \text{cov}(W_5))$

# Two-Way Tables with Ordered Classifications

## Linear Trend Alternative to Independence

- $H_0$  : independent vs.  $H_1$  :  $\rho \neq 0$
- $\sqrt{n}\hat{\rho} \xrightarrow{d} \mathcal{N}(0, 1)$  under  $H_0$  (Delta Method)
- $M^2 = (n-1)\hat{\rho}^2$  is approximately  $\chi_1^2$
- Large p-value contradicts independence.
- Small p-value does not imply linear association.



# Two-Way Tables with Ordered Classifications

Example: Is Happiness Associated with Political Ideology? [▶ Code](#)

Political Ideology	Happiness		
	Not too Happy	Pretty Happy	Very Happy
Liberal	13	29	15
Moderate	23	59	47
Conservative	14	67	54

- $\chi^2$  test statistic : 7.07    **p-value : 0.13**
- Pearson Correlation( $\rho$ ) = 0.135
- $M^2$  statistic : 5.82    **p-value : 0.02**

# Two-Way Tables with Ordered Classifications

## Monotone Trend Alternative to Independence

- $H_0$  : Independent vs.  $H_1$  : Monotone Trend
- (Method 1) : Assuming underlying continuous distribution
- (Method 2) : Using ordinal measure of association

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

- $\hat{\gamma}$  has approximately a normal sampling distribution.

$$z = \hat{\gamma} / SE$$

- Agresti (2010) :  $(C - D) / SE_0$

# Two-Way Tables with Ordered Classifications

## Sensitivity to Choice of Scores

- Cochran(1954) “any set of scores gives a valid test, provided that they are constructed **without consulting** the results of the experiment”
- The scale is chosen by a consensus of experts
- (1, 2, 3, 4) and (2, 4, 6, 8) have the same  $\rho$  and hence the same  $M^2$

# Two-Way Tables with Ordered Classifications

Example : Infant Birth Defects by Maternal Alcohol Consumption

► Code

Malformation	Alcohol Consumption (average number of drinks per day)				
	0	<1	1-2	3-5	>5
Absent	17,066	14,464	788	126	37
Present	48	38	5	1	1

- ① Score = (0, 0.5, 1.5, 4.0, 7.0)

$$M^2 = 6.57 \quad \text{p-value : 0.010}$$

- ② Score = (1.0, 2.0, 3.0, 4.0, 5.0)

$$M^2 = 1.83 \quad \text{p-value : 0.176}$$

- ③ *Midrank* = (8557.5, 24365, 32013, 32473, 32555.5)

$$M^2(\text{Spearman's } \rho) = 0.35 \quad \text{p-value : 0.55}$$

# Two-Way Tables with Ordered Classifications

## Trend Tests for $I \times 2$ and $2 \times J$ Tables

- Comparison of two groups in  $2 \times J$  table  
 $\Rightarrow$  *Wilcoxon* or *Mann-Whitney test*
- Linear trend test in  $I \times 2$  table  
 $\Rightarrow$  *Cochran-Armitage trend test* (Section 5.3.5)
- When one is nominal with more than 2 categories..?

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# Small-Sample Inference for Contingency Tables

## Fisher's Exact Test for $2 \times 2$ Tables

- Sampling method : Poisson, Multinomial, Independent binomial
- **Assumption** : Individual observations are independent
- $(\{n_{i+}\}, \{n_{+j}\})$  is a sufficient statistic under  $H_0$  : independent  
 $\Rightarrow P(\{n_{ij}\} | \{n_{i+}\}, \{n_{+j}\})$  does not depend on unknown parameters
- In  $2 \times 2$  table, the conditioning yields *hypergeometric distribution*
- For  $2 \times 2$  table, independence is equivalent to  $\theta = 1$

$$\text{P-value} = P(n_{11} \geq t_o) \cdots H_1 : \theta > 1$$

- The test for  $2 \times 2$  tables is called *Fisher's exact test*.

# Small-Sample Inference for Contingency Tables

Example : Fisher's Tea Drinker

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

- $H_0 : \theta = 1$  vs  $H_1 : \theta > 1$
- $P\text{-value} = P(n_{11} \geq 3) = HG(8, 4, 3) + HG(8, 4, 4) = 0.243$
- As  $n_{11}$  larger,  
odds ratio, RR, and difference of proportions  $\uparrow$   
 $\Rightarrow$  SAME p-value



# Small-Sample Inference for Contingency Tables

## Two-Sided P-values for Fisher's Exact Test

① (Irwin 1935)  $p\text{-value} = \sum_{p(t) \leq p(t_0)} P(n_{11} = t)$

②  $p\text{-value} = \sum_{t \text{ is farther from } H_0 \text{ than } t_0} P(n_{11} = t)$

$$P\text{-value} = P[|n_{11} - \mathbb{E}n_{11}| \geq |t_0 - \mathbb{E}n_{11}|] = P(\chi^2 \geq \chi_o^2)$$

③  $p\text{-value} = 2 \min[P(n_{11} \geq t_o), P(n_{11} \leq t_o)]$

④ (Blaker 2000)  $p\text{-value} = \min[P(n_{11} \geq t_o), P(n_{11} \leq t_o)] + Q_0$

$Q_0$  is the probability in other tail that is close to,

but not greater than  $Q$ .

*The approach of setting type 1 errors for one-sided tests at **half the conventional type 1 error** used in two-sided tests is preferable in regulatory settings. This promotes consistency with two-sided confidence intervals that are generally appropriate for estimating the possible size of the difference between two treatments*

# Small-Sample Inference for Contingency Tables

## Discreteness and Conservatism Issues

- In previous example, possible one-sided p-values were restricted to

0.014, 0.243, 0.757, 0.986, 1.0

- 0.05 is not probable type 1 error  $\Rightarrow$  Conservative
- Achieve any significance level by randomized test
- Tocher(1950) showed that Fisher's test is UMPU
- Or, Mid p-value  $\Rightarrow$  Less Conservative

# Small-Sample Inference for Contingency Tables

## Small-Sample Unconditional Tests for Independence

- Commonly, only  $\{n_{i+}\}$  are fixed.
- Under binomial sampling, consider testing  $H_0 : \pi_1 = \pi_2$

$$T = X^2$$

- Given  $\pi_1 = \pi_2 = \pi$ , the p-value is  $P_\pi(T \geq t_0)$

$$P = \sup_{0 \leq \pi \leq 1} P_\pi(T \geq t_0)$$

- $T = X^2$  table : (3,0/0,3) p-value=?
- **Is it desirable to take supremum over all possible  $\pi$ ?**

# Small-Sample Inference for Contingency Tables

Berger and Boos(1994) P-values Maximized Over a Confidence Set..., JASA

If the data  $X$  have a probability dist.  $P_\nu$  and we wish to test  $H_0 : \nu = \nu_0, \dots$

Test statistic  $T \Rightarrow$  p-value  $= P(T \geq t_0)$

Now consider a model with a *nuisance parameter*  $\theta$ ,  $X \sim P_{\nu, \theta} \dots$

Under  $H_0 : \nu = \nu_0$ , p-value  $= \sup_{\theta} P_{\nu_0, \theta}(T \geq t_0)$

- 1 Choose  $T$  whose distribution under  $H_0$  does not depend on  $\theta$

$$\text{e.g. } \frac{\bar{X} - \mu_0}{\sigma} \implies \frac{\bar{X} - \mu_0}{S}$$

$T$  is ancillary under  $H_0$

- 2 Find a sufficient statistic  $S$  for  $\theta$  under  $H_0$  and condition on  $S$ .

$$p = P_{\nu_0}(T \geq t_0 | S = s) \dots \text{Fisher's exact test}$$

(Increases discreteness)

# Small-Sample Inference for Contingency Tables

Berger and Boos(1994) P-values Maximized Over a Confidence Set..., JASA

- Let  $C_\gamma$  be a  $1 - \gamma$  confidence set for  $\theta$  under  $H_0$ .
- Restrict the maximization to  $C_\gamma$

$$p_\gamma = \sup_{\theta \in C_\gamma} P_{\nu_0, \theta}(T \geq t_0) + \gamma$$

## Definition (Valid p-value)

**Valid p-value** is a statistic  $p$  such that under the null hypothesis,

$$P(p \leq \alpha) \leq \alpha$$

# Small-Sample Inference for Contingency Tables

Berger and Boos(1994) P-values Maximized Over a Confidence Set..., JASA

## Theorem

*Suppose that  $p(\theta)$  is a valid  $p$ -value for any assumed value  $\theta$ . Let  $C_\gamma$  satisfy  $P(\theta \in C_\gamma) \geq 1 - \gamma$ , if the null hypothesis is true. Then,  $p_\gamma$  is a valid  $p$ -value.*

## Proof :

$$\begin{aligned} P(p_\gamma \leq \alpha) &= P(p_\gamma \leq \alpha, \theta_0 \in C_\gamma) + P(p_\gamma \leq \alpha, \theta_0 \in \bar{C}_\gamma) \\ &\leq P(p(\theta_0) + \gamma \leq \alpha, \theta_0 \in C_\gamma) + P(\theta_0 \in \bar{C}_\gamma) \\ &\leq P(p(\theta_0) \leq \alpha - \gamma) + \gamma \\ &\leq \alpha - \gamma + \gamma \\ &= \alpha \end{aligned}$$

# Small-Sample Inference for Contingency Tables

Berger and Boos(1994) P-values Maximized Over a Confidence Set..., JASA

**Example :** Independence Test (Two independent binomial samples)

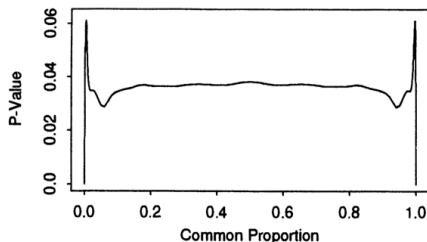
Group	Result		Total
	Success	Fail	
1	14	33	47
2	48	235	283

- $H_0 : \pi_1 = \pi_2$  and  $T = Z^2 = \frac{(\hat{\pi}_1 - \hat{\pi}_2)^2}{\hat{\pi}(1 - \hat{\pi})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}$

- $p_{sup} = \sup_{\pi \in [0,1]} p(\pi) = .061$

# Small-Sample Inference for Contingency Tables

Berger and Boos(1994) P-values Maximized Over a Confidence Set..., JASA



- $\hat{\pi} = .188$  and  $C_{.001} = [.123, .267]$

$$p_{.001} = .036 + .001 = .037$$

- $p(\hat{\pi})$  is typically not a valid p-value
- Maximization on the restricted set is much easier



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# Bayesian Inference for Two-Way Contingency Tables

## Prior Distribution for Computing Proportions in $2 \times 2$ Tables

### Comparison of parameters for two independent binomial samples

$Y_i \sim \text{bin}(n_i, \pi_i)$ ,  $i = 1, 2$ ,  $\pi_i \sim \text{beta}(\alpha_{i1}, \alpha_{i2})$  and  $\pi_1, \pi_2$  independent

$\Rightarrow$  Independent posterior  $\text{beta}(y_i + \alpha_{i1}, n_i - y_i + \alpha_{i2})$

- $H_0 : \pi_1 \leq \pi_2$  vs.  $H_1 : \pi_1 > \pi_2$   
 $\Rightarrow P(\pi_1 \leq \pi_2 | y_1, n_1; y_2, n_2)$  : Bayesian p-value
- Intervals for difference of proportions, RR, Odds ratio

$$P(L < w < U) = F_w(U) - F_w(L)$$

$$F_w(t) = \int_{S_t} f(\pi_1, \pi_2 | y_1, n_1; y_2, n_2) d\pi_1 d\pi_2, \quad S_t = \{w \leq t\}$$

# Bayesian Inference for Two-Way Contingency Tables

Example : Urn Sampling Gives Highly Unbalanced Treatment Allocation

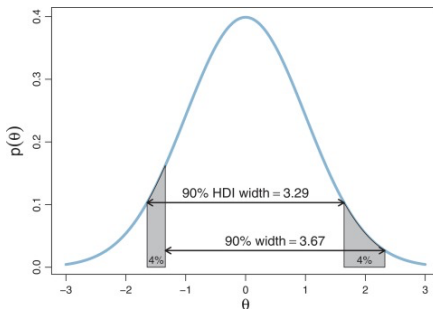
Treatment	Result		Total
	Success	Fail	
A	11	0	11
B	0	1	1

$$H_0 : \pi_1 = \pi_2 \text{ vs } H_1 : \pi_1 > \pi_2$$

- 1 95% *equal-tail* posterior interval for  $\theta$  : (1.2, 218.4)  
(independent beta(2, 2) priors)
- 2 95% *equal-tail* posterior interval for  $\theta$  : (1.7, 4677)  
(independent uniform priors)
- 3 95% *equal-tail* posterior interval for  $\theta$  : (3.3,  $1.4 \times 10^6$ )  
(independent Jeffreys priors)
- 4 **Frequentist** : inverting large-sample score test (4.5,  $\infty$ )

# Bayesian Inference for Two-Way Contingency Tables

## Highest Posterior Density Intervals



- An alternative approach : Highest Posterior Density Interval(**HPDI**)
- Intuitively meaningful!! but, ...

# Bayesian Inference for Two-Way Contingency Tables

## Highest Posterior Density Intervals

Treatment	Result		Total
	Success	Fail	
A	1	9	10
B	5	5	10

- HPDI for  $\theta = (0.0006, 0.82)$
- HPDI for  $1/\theta = (0.17, 38.23) \neq (1/0.82, 1/0.0006)$
- 95% ETI for  $\theta = (0.017, 1.10)$
- 95% ETI for  $1/\theta = (0.91, 57.9) = (1/1.10, 1/0.017)$

# Bayesian Inference for Two-Way Contingency Tables

## Testing Independence

### ① Bayesian Factor

- Alternative to classical hypothesis testing(LRT)
- Bayesian factor  $K$  is given by

$$K = \frac{P(D|H_0)}{P(D|H_1)}$$

### ② Estimate Parameter

- Estimate parameter that describe the association
- correlation( $\rho$ ), Goodman-Kruskal's gamma( $\gamma$ )

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## Exercise 3.3

Political Party	Homosexuals Should Have Right to Marry	
	Strongly Agree	Strongly Disagree
Strong Democrat	60	44
Strong Republican	2	61

- $\log(\hat{\theta}) = ?$
- Standard error of  $\log(\hat{\theta}) = ?$
- The Wald 95% confidence interval for  $\theta$  is ...?

$$\log(\hat{\theta}) = \log(60 * 61 / 2 * 44) = 3.728$$

$$\sigma^2 = \frac{1}{n_1} + \frac{1}{n_2} + \frac{1}{n_3} + \frac{1}{n_4} = 0.5558$$

$$(\exp(3.728 - 1.96 * 0.746), \exp(3.728 + 1.96 * 0.746)) = (9.6, 179.3)$$

$n_{12}$  is too small!  $\rightarrow$  interval estimate is so **imprecise**



## Exercise 3.6

Treatment	Result		Total
	Success	Fail	
A	7	8	15
B	0	15	15
Total	7	23	

**Q : Obtain a 95% confidence interval for the odds ratio**

- The Wald CI :

$$\log(\hat{\theta}) = \infty, \quad \sigma^2 = \infty \Rightarrow \text{Not exists}$$

- Profile Likelihood CI

$$G^2 = 2 \sum_{ij} n_{ij} \log(n_{ij} / \hat{\mu}_{ij}(\theta_0)) < \chi_1^2(.05)$$

- $\hat{\mu}_{ij}(\theta_0)$  is the unique expected frequency estimates that have the same row and column margins as  $\{n_{ij}\}$  and satisfy

$$\frac{\hat{\mu}_{11}(\theta_0)\hat{\mu}_{22}(\theta_0)}{\hat{\mu}_{12}(\theta_0)\hat{\mu}_{21}(\theta_0)} = \theta_0$$

- Put  $\hat{\mu}_{11}(\theta_0) = n_{\theta_0}$ . Then,

$$\frac{n_{\theta_0}(n_{\theta_0} + 8)}{(7 - n_{\theta_0})(n_{\theta_0} + 15)} = \theta_0$$

- We want collect all  $\theta_0$  such that

$$2 \left( 7 \log \frac{7}{n_{\theta_0}} + 8 \log \frac{8}{15 - n_{\theta_0}} + 15 \log \frac{15}{8 + n_{\theta_0}} \right) < 3.841$$

- So we get  $C_{.05} = (2.40, \infty)$