

# **Chapter 10. Discrete Data Analysis**

**10.1 Inferences on a Population Proportion**

**10.2 Comparing Two Population Proportions**

**10.3 Goodness of Fit Tests for One-Way Contingency Tables**

**10.4 Testing for Independence in Two-Way Contingency Tables**

## 10.1 Inferences on a Population Proportion

Sample proportion  $\hat{p}$

- $X \sim B(n, p)$ .
- $\hat{p} = \frac{x}{n}$ .
- $E(\hat{p}) = p$  and  $\text{Var}(\hat{p}) = \frac{p(1-p)}{n}$ .

For large  $n$ ,

- $\hat{p} \sim N\left(p, \frac{p(1-p)}{n}\right) \approx N\left(p, \frac{\hat{p}(1-\hat{p})}{n}\right)$

## 10.1.1 Confidence Intervals for Population Proportions

- Two-sided conf. intervals for a population proportion

$$\left( \hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}, \hat{p} + z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \right)$$

- One-sided conf. intervals for a population proportion with a lower bound

$$\left( \hat{p} - z_{\alpha} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}, 1 \right)$$

- One-sided conf. intervals for a population proportion with an upper bound

$$\left( 0, \hat{p} + z_{\alpha} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \right)$$

- These approximate results are safe as long as both  $x$  and  $n - x$  are larger than 5.

- Example 57 : Building Tile Cracks

Random sample  $n = 1250$  of tiles in a certain group of downtown building for cracking.  $x = 98$  are found to be cracked.

$$\hat{p} = \frac{98}{1250} = 0.0784. z_{0.005} = 2.576.$$

99% two-sided conf. interval

$$(\hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}, \hat{p} + z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}) = (0.0588, 0.0980)$$

## 10.1.2 Hypothesis Tests on a Population Proportion

- Two-sided hypothesis tests

$$H_0: p = p_0 \text{ vs } H_A: p \neq p_0$$

$$\text{p-value} = 2 \times \min\{P(X \geq x), P(X \leq x)\}$$

where  $X \sim B(n, p_0)$ .

- When  $np_0$  and  $n(1 - p_0)$  are both larger than 5, a normal approximation may be used to compute the p-value.

$$\text{p-value} = 2 \times \Phi(-|z|) \text{ where}$$

$$z = \frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}}$$

- Continuity correction can be used for a better approximation to the p-value.
- A size  $\alpha$  hypothesis test rejects  $H_0$  when

$$|z| > z_{\alpha/2} \text{ or p-value} < \alpha.$$

Otherwise, accept  $H_0$ .

# One-sided hypothesis tests for a population proportion

- For testing

$$H_0: p \geq p_0 \text{ vs } H_A: p < p_0$$

$$\text{P-value} = P(X \leq x) \text{ where } X \sim B(n, p_0)$$

The p-value by the normal approximation:

$$\text{P-value} = \Phi(z) \text{ where } z = \frac{x+0.5-np_0}{\sqrt{np_0(1-p_0)}}.$$

- For testing

$$H_0: p \leq p_0 \text{ vs } H_A: p > p_0$$

$$\text{P-value} = P(X \geq x) \text{ where } X \sim B(n, p_0)$$

The p-value by the normal approximation:

$$\text{P-value} = 1 - \Phi(z) \text{ where } z = \frac{x-0.5-np_0}{\sqrt{np_0(1-p_0)}}.$$

- Example 57 : Building Tile Cracks

10% or more of the building tiles are cracked ?

$$H_0: p \geq 0.1 \text{ vs } H_A: p < 0.1$$

From data:  $n = 1250, x = 98$ .

$$z = \frac{x + 0.5 - np_0}{\sqrt{np_0(1 - p_0)}} = -2.50$$

$$\text{P-value} = \Phi(-2.50) = 0.0062$$



# Python codes

```
import numpy as np
from statsmodels.stats.proportion import proportions_ztest
from scipy.stats import binom_test
zstat, pvalue = proportions_ztest(45,100,0.5)
print("Two-sided 1 sample proportions test \n Z = %.4f, p-value
= %.4f" %(zstat, pvalue))
    Two-sided 1 sample proportions test
    Z = -1.0050, p-value = 0.3149
```

```
pvalue = binom_test(8,20,0.5)
print("Two-sided exact binomial test \n p-value = %.4f" %pvalue)
    Two-sided exact binomial test
    p-value = 0.5034
```

## 10.1.3 Sample Size Calculations

- Consider a two-sided  $1 - \alpha$  level CI for  $p$  which is obtained by normal approximation

The interval length  $L$  is given by

$$L = 2 z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}$$

In case  $\hat{p}$  is not available,

$$L = 2 z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \leq z_{\alpha/2} \sqrt{\frac{1}{n}}$$

- Example 61 : Political Polling

To determine the proportion  $p$  of people who agree with the statement “The city mayor is doing a good job.” within 3% accuracy, how many people do they need to poll?

A 99% CI for  $p$  with length no larger than  $L_0 = 6\%$

$$L = 2 z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \leq 0.06$$

Since  $\hat{p}$  is not available,

$$L \leq z_{0.005} \sqrt{\frac{1}{n}} \leq 0.06.$$

The smallest sample size  $n$  satisfying the above inequality is desired.

$$n \geq \frac{z_{0.005}^2}{0.06^2} = \frac{2.576^2}{0.06^2} = 1843.3.$$

## 10.2 Comparing Two Population Proportions

### 10.2.1 Confidence Intervals for the Difference Between Two Population Proportions

- Assume  $X \sim B(n, p_A)$  and  $Y \sim B(m, p_B)$  and  $X$  and  $Y$  are independent.
- Approximate two-sided  $1 - \alpha$  level CI for  $p_A - p_B$  with end-points:

$$\hat{p}_A - \hat{p}_B \pm z_{\alpha/2} \sqrt{\frac{\hat{p}_A(1-\hat{p}_A)}{n} + \frac{\hat{p}_B(1-\hat{p}_B)}{m}}$$

- Approximate one-sided  $1 - \alpha$  level CI for  $p_A - p_B$  with a lower bound:

$$(\hat{p}_A - \hat{p}_B - z_{\alpha} \sqrt{\frac{\hat{p}_A(1-\hat{p}_A)}{n} + \frac{\hat{p}_B(1-\hat{p}_B)}{m}}, \quad 1)$$

- Approximate two-sided  $1 - \alpha$  level CI for  $p_A - p_B$  with an upper bound:

$$(-1, \hat{p}_A - \hat{p}_B + z_{\alpha} \sqrt{\frac{\hat{p}_A(1-\hat{p}_A)}{n} + \frac{\hat{p}_B(1-\hat{p}_B)}{m}})$$

- These approximations are reasonable as long as  $x$ ,  $n - x$ ,  $y$ , and  $n - y$  are all larger than 5.

- Example 57 : Building Tile Cracks

Building A : 406 cracked tiles out of  $n = 6000$ .

Building B : 83 cracked tiles out of  $m = 2000$ .

$$\hat{p}_A = \frac{406}{6000} = 0.0677. \hat{p}_B = \frac{83}{2000} = 0.0415.$$

A  $1 - \alpha$  level CI for  $p_A - p_B$ :

$$\hat{p}_A - \hat{p}_B \pm z_{\alpha/2} \sqrt{\frac{\hat{p}_A(1 - \hat{p}_A)}{n} + \frac{\hat{p}_B(1 - \hat{p}_B)}{m}}$$

$$\Rightarrow (0.0120, 0.0404) \text{ when } \alpha = 0.01.$$

## 10.2.2 Hypothesis Tests on the Difference Between Two Population Proportions

- For testing  $H_0: p_A = p_B$  vs  $H_A: p_A \neq p_B$

p-value =  $2 \times \Phi(-|z|)$  where

$$z = \frac{\hat{p}_A - \hat{p}_B}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n} + \frac{1}{m}\right)}} \text{ and } \hat{p} = \frac{x+y}{n+m}$$

- For testing  $H_0: p_A \geq p_B$  vs  $H_A: p_A < p_B$

p-value =  $\Phi(z)$

- For testing  $H_0: p_A \leq p_B$  vs  $H_A: p_A > p_B$

p-value =  $1 - \Phi(z)$

- Conclusion:

Reject  $H_0$  if p-value is smaller than the sig. level  $\alpha$ .

Otherwise, accept  $H_0$ .

- Example 57 : Building Tile Cracks

Test  $H_0: p_A = p_B$  vs  $H_A: p_A \neq p_B$

$$\hat{p}_A = \frac{406}{6000} = 0.0677. \hat{p}_B = \frac{83}{2000} = 0.0415.$$

p-value =  $2 \times \Phi(-|z|) \approx 0$  where

$$z = \frac{\hat{p}_A - \hat{p}_B}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n} + \frac{1}{m}\right)}} = 4.3755 \quad \text{and}$$

$$\hat{p} = \frac{x+y}{n+m} = \frac{489}{8000} = 0.0611.$$

## Python codes for two-sample test of proportions

```
from statsmodels.stats.proportion import proportions_ztest
stat, pvalue = proportions_ztest([12, 8], [34, 24])
#([x1,x2],[n1,n2])
print("2 sample test for equality of proportions \n z = %.4f, p-
value = %.4f" %(stat, pvalue))
2 sample test for equality of proportions
z = 0.1547, p-value = 0.8770
```



## 10.3 Goodness of Fit Tests for One-Way Contingency Tables

### 10.3.1 One-Way Classifications

Each of  $n$  observations is classified into one of  $k$  categories or cells.

Cell frequencies:  $x_1, \dots, x_k$ .  $\sum_{i=1}^k x_i = n$

Cell probabilities:  $p_1, \dots, p_k$ .  $\sum_{i=1}^k p_i = 1$ .

- Test  $H_0: p_i = p_i^*, i = 1, \dots, k$  vs  $H_A: \text{not } H_0$ .

Under  $H_0$ , the expected cell frequency at cell  $i$ ,  $e_i$ , is given by

$$e_i = np_i^*$$

Two test statistics:

(1) Pearson's Chi-square statistic:

$$X^2 = \sum_{i=1}^k \frac{(x_i - e_i)^2}{e_i}.$$

(2) Likelihood ratio Chi-square statistic:

$$G^2 = 2 \sum_{i=1}^k x_i \ln\left(\frac{x_i}{e_i}\right).$$

Both of the statistics,  $X^2$  and  $G^2$ , follow asymptotically Chi-square distribution with  $df = k - 1$ .

This asymptotic result is reasonable as long as all the  $e_i$ 's are larger than 5.

P-value =  $P(X^2 \geq \text{obs}(X^2))$

Conclusion: Reject  $H_0$  if the p-value is smaller than the sig. level  $\alpha$ .  
Otherwise, accept  $H_0$ .

# Mathematics for goodness-of-fit test

- Likelihood function  $L(p_1, \dots, p_k) = f(x^1, x^2, \dots, x^n; p_1, \dots, p_k) = \prod_{i=1}^k p_i^{x_i}$   
where  $x^l$  is the  $l$ -th observation of data.

- $\log L = \sum_{i=1}^k x_i \log p_i.$

- For  $i \neq k$ ,  $\frac{\partial \log L}{\partial p_i} = x_i \frac{\partial \log p_i}{\partial p_i} + x_k \frac{\partial \log p_k}{\partial p_i} = \frac{x_i}{p_i} - \frac{x_k}{p_k}.$

$$\frac{\partial \log L}{\partial p_i} = 0. \implies \hat{p}_i = \hat{p}_k \frac{x_i}{x_k}.$$

$$\text{Therefore, } \hat{p}_i = \frac{x_i}{n}, \quad i = 1, 2, \dots, k.$$

- $\gamma = \log \frac{\prod_{i=1}^k \hat{p}_i^{x_i}}{\prod_{i=1}^k p_i^{x_i}} = \log \prod_{i=1}^k \left( \frac{\hat{p}_i}{p_i} \right)^{x_i} = \sum_i x_i \log \frac{\hat{p}_i}{p_i}$

$$G^2 = 2 \gamma \text{ when } p_i \text{'s are the cell probabilities under } H_0.$$

- Example 1 : Machine Breakdowns

$n = 46$  machine breakdowns.

$x_1 = 9$  : electrical problems

$x_2 = 24$  : mechanical problems

$x_3 = 13$  : operator misuse

It is suggested that the cell probabilities are

$$p^*_1 = 0.2, p^*_2 = 0.5, p^*_3 = 0.3.$$

For testing  $H_0 : p_1 = 0.2, p_2 = 0.5, p_3 = 0.3$  vs  $H_A: \text{not } H_0$ .

	Electrical	Mechanical	Operator misuse	
Observed cell freq.	$x_1 = 9$	$x_2 = 24$	$x_3 = 13$	$n = 46$
Expected cell freq.	$e_1 = 46 \cdot 0.2 = 9.2$	$e_2 = 46 \cdot 0.5 = 23.0$	$e_3 = 46 \cdot 0.3 = 13.8$	$n = 46$

$$X^2 = 0.0942. \quad G^2 = 0.0945. \quad df=3-1=2.$$

$$P\text{-value} \approx P(X^2 \geq 0.0942) = 0.95.$$

- Check for homogeneity

$$H_0: p_1 = p_2 = p_3 = \frac{1}{3} \quad \text{vs } H_A: \text{not } H_0$$

$$\text{P-value} = P(X^2 \geq 7.87) \approx 0.02.$$

## 10.3.2 Testing Distributional Assumptions

Number of errors found in a software product	0	1	2	3	4	5	6	7	8	
Frequency	3	14	20	25	14	6	2	0	1	$n = 85$

$H_0$  : number of errors,  $X$ , has a Poisson distribution with mean  $\lambda = 3.0$

Cell	Expected cell frequency	
$X = 0$	$e_1 = 85 \times P(X = 0) = 85 \times \frac{e^{-3} \times 3^0}{0!} = 4.23$	} Group
$X = 1$	$e_2 = 85 \times P(X = 1) = 85 \times \frac{e^{-3} \times 3^1}{1!} = 12.70$	
$X = 2$	$e_3 = 85 \times P(X = 2) = 85 \times \frac{e^{-3} \times 3^2}{2!} = 19.04$	
$X = 3$	$e_4 = 85 \times P(X = 3) = 85 \times \frac{e^{-3} \times 3^3}{3!} = 19.04$	
$X = 4$	$e_4 = 85 \times P(X = 4) = 85 \times \frac{e^{-3} \times 3^4}{4!} = 14.28$	} Group
$X = 5$	$e_5 = 85 \times P(X = 5) = 85 \times \frac{e^{-3} \times 3^5}{5!} = 8.57$	
$X = 6$	$e_6 = 85 \times P(X = 6) = 85 \times \frac{e^{-3} \times 3^6}{6!} = 4.28$	
$X = 7$	$e_7 = 85 \times P(X = 7) = 85 \times \frac{e^{-3} \times 3^7}{7!} = 1.84$	
$X = 8$	$e_8 = 85 \times P(X = 8) = 85 \times \frac{e^{-3} \times 3^8}{8!} = 0.69$	
$X \geq 9$	$e_9 = 85 \times P(X \geq 9) = 0.33$	
	$n = 85.0$	

- Example 3 : Software Errors

For some of expected values are smaller than 5, it is appropriate to group the cells.

- Test if ( $H_0$ ) the data are from a Poisson distribution with mean=3.

Number of errors	After grouping						
	0-1	2	3	4	5	$\geq 6$	
Observed cell frequency	$x_1 = 17$	$x_2 = 20$	$x_3 = 25$	$x_4 = 14$	$x_5 = 6$	$x_6 = 3$	$n = 85$
Expected cell frequency	$e_1 = 16.93$	$e_2 = 19.04$	$e_3 = 19.04$	$e_4 = 14.28$	$e_5 = 8.57$	$e_6 = 7.14$	$n = 85$

$$\begin{aligned}
 X^2 &= \frac{(17.00 - 16.93)^2}{16.93} + \frac{(20.0 - 19.04)^2}{19.04} + \frac{(25.00 - 19.04)^2}{19.04} \\
 &\quad + \frac{(14.00 - 14.28)^2}{14.28} + \frac{(6.00 - 8.57)^2}{8.57} + \frac{(3.00 - 7.14)^2}{7.14} \\
 &= 5.12
 \end{aligned}$$

P-value =  $P(X^2 \geq 5.12) = 0.40$  where  $X^2$  follows a Chi-square distribution with df=5.



## 10.4 Testing for Independence in Two-Way Contingency Tables

### 10.4.1 Two-Way Classifications

- A two-way ( $r \times c$ ) contingency table.

		Second Categorization						
		Level 1	Level 2	.....	Level j	.....	Level c	
First Categorization	Level 1	$x_{11}$	$x_{12}$	.....		.....	$x_{1c}$	$x_{1\cdot}$
	Level 2	$x_{21}$	$x_{22}$	.....		.....	$x_{2c}$	$x_{2\cdot}$
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Level i				$x_{ij}$			$x_{i\cdot}$
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Level r	$x_{r1}$	$x_{r2}$	.....		.....	$x_{rc}$	$x_{r\cdot}$
		$x_{\cdot 1}$	$x_{\cdot 2}$	.....	$x_{\cdot j}$	.....	$x_{\cdot c}$	$n = x_{\cdot \cdot}$
		Column marginal frequencies						Row marginal frequencies

### Example 57 : Building Tile Cracks

	Location			
Tile Condition		Building A	Building B	
	Undamaged	$x_{11} = 5594$	$x_{12} = 1917$	$x_{1\cdot} = 7511$
	Cracked	$x_{21} = 406$	$x_{22} = 83$	$x_{2\cdot} = 489$
		$x_{\cdot 1} = 6000$	$x_{\cdot 2} = 2000$	$n = x_{\cdot\cdot} = 8000$

Notice that the column marginal frequencies are fixed.  
 (  $x_{\cdot 1} = 6000$ ,  $x_{\cdot 2} = 2000$  )

## 10.4.2 Testing for Independence

- Testing for independence in a Two-way contingency table

$H_0$ : Two factors are independent vs  $H_A$ : not  $H_0$

$$X^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(x_{ij} - e_{ij})^2}{e_{ij}}. \quad G^2 = 2 \sum_{i=1}^r \sum_{j=1}^c x_{ij} \ln\left(\frac{x_{ij}}{e_{ij}}\right).$$

Here  $e_{ij} = \frac{x_{i.}x_{.j}}{n}$ .

The two test statistics follow asymptotically Chi-square distribution with  $df = rc - 1 - (r - 1) - (c - 1) = (r - 1)(c - 1)$ .

This result is valid as long as all the  $e_{ij}$ 's are larger than 5.

$$\text{P-value} = P(X^2 \geq \text{obs}(X^2))$$

- Example 57 : Building Tile Cracks

	Building A	Building B	
Undamaged	$x_{11} = 5594$ $e_{11} = 5633.25$	$x_{12} = 1917$ $e_{12} = 1877.75$	$x_{1.} = 7511$
Cracked	$x_{21} = 406$ $e_{21} = 366.75$	$x_{22} = 83$ $e_{22} = 122.25$	$x_{2.} = 489$
	$x_{.1} = 6000$	$x_{.2} = 2000$	$n = x_{..} = 8000$

$$obs(X^2) = 17.896$$

$$P - value = 0.000023 \approx 0$$

# Python codes for Independence test

```
import numpy as np
import pandas as pd
from scipy.stats import chi2_contingency
chi, pvalue, dof, expctd = chi2_contingency(np.array([[24,12],[8,10]]))
print("Pearson's Chi-squared test \nX-squared = %.4f, p-value = %.4f,
df = %d," %(chi, pvalue, dof))
print("Expected cell frequencies:\n", pd.DataFrame(expctd,
index=[1,2], columns=[1,2]))
```

Pearson's Chi-squared test

X-squared = 1.6204, p-value = 0.2030, df = 1,

Expected cell frequencies:

	1	2
1	21.333333	14.666667
2	10.666667	7.333333

# Mathematics for Independence Test (1)

- Likelihood function  $L(p_{11}, \dots, p_{rc}) = f(x^1, x^2, \dots, x^n; p_{11}, \dots, p_{rc}) = \prod_{i=1}^r \prod_{j=1}^c p_{ij}^{x_{ij}}$

where  $x^l$  is the  $l$ -th observation of data.

- $\log L = \sum_i^r \sum_j^c x_{ij} \log p_{ij}$ .

- Under  $H_0$ :

$$\begin{aligned} \log L &= \sum_i^r \sum_j^c x_{ij} \log p_{i \cdot} p_{\cdot j} = \sum_i^r \sum_j^c x_{ij} \log p_{i \cdot} + \sum_i^r \sum_j^c x_{ij} \log p_{\cdot j} \\ &= \sum_{i=1}^r x_{i \cdot} \log p_{i \cdot} + \sum_{j=1}^c x_{\cdot j} \log p_{\cdot j} \end{aligned}$$

$$\text{For } i \neq r, \quad \frac{\partial \log L}{\partial p_{i \cdot}} = x_{i \cdot} \frac{\partial \log p_{i \cdot}}{\partial p_{i \cdot}} + x_{r \cdot} \frac{\partial \log p_{r \cdot}}{\partial p_{i \cdot}} = \frac{x_{i \cdot}}{p_{i \cdot}} - \frac{x_{r \cdot}}{p_{r \cdot}}.$$

$$\frac{\partial \log L}{\partial p_{i \cdot}} = 0. \quad \Rightarrow \quad \hat{p}_{i \cdot} = \hat{p}_{r \cdot} \frac{x_{i \cdot}}{x_{r \cdot}}.$$

$$\text{Therefore, } \hat{p}_{i \cdot} = \frac{x_{i \cdot}}{n}, \quad i = 1, 2, \dots, r.$$

$$\text{In the same way, we obtain } \hat{p}_{\cdot j} = \frac{x_{\cdot j}}{n}, \quad j = 1, 2, \dots, c.$$

# Mathematics for Independence Test (2)

- Under  $H_0$ :

$$e_{ij} = n\hat{p}_{ij} = n\hat{p}_{i.}\hat{p}_{.j} = \frac{x_{i.}x_{.j}}{n}$$

## Example 10.4.a SAT score and occupation

- The following data is a two-dimensional contingency table data of 4353 individuals. They are cross-classified into 4 occupational groups (O) and 5 aptitude levels (A) as measured by a SAT test (Beaton, 1975) The aptitude levels are from low (A1) to high (A5) and the occupational levels are:

O1 = self-employed, business

O2 = self-employed, professional

O3 = teacher

O4 = salaried, employed

- Test if the SAT score and the occupation are independent with the sig. level 0.05.

✓ Beaton, A.E. (1975). The influence of educational and ability on alary and attitudes. In F.T. Juster (ed.), *Education, Income, and Human Behavior*, pp. 365-396. New York, McGraw-Hill.



```
import numpy as np
import pandas as pd
from scipy.stats import chi2_contingency

aptocc =
np.array([[122,30,20,472],[226,51,66,704],[306,115,96,1
072], [130,59,38,501],[50,31,15,249]])

aptocc = pd.DataFrame(data=aptocc,
index=['A1','A2','A3','A4','A5'],
columns=['O1','O2','O3','O4'])

print("Observed cell frequencies:\n", aptocc)
```

Observed cell frequencies:

	O1	O2	O3	O4
A1	122	30	20	472
A2	226	51	66	704
A3	306	115	96	1072
A4	130	59	38	501
A5	50	31	15	249

```
chi, pvalue, dof, expctd = chi2_contingency(aptocc)
print("Pearson's Chi-squared test \nX-squared = %.4f, p-value = %.4f, df = %d," %(chi, pvalue, dof))
print("Expected cell frequencies:\n", pd.DataFrame(expctd, index=['A1','A2','A3','A4','A5'],
columns=['O1','O2','O3','O4']))
```

Pearson's Chi-squared test

X-squared = 35.7989, p-value = 0.0003, df = 12,

Expected cell frequencies:

	O1	O2	O3	O4
A1	123.385252	42.311969	34.766827	443.535952
A2	200.596830	68.789800	56.523088	721.090283
A3	304.439697	104.400184	85.783368	1094.376752
A4	139.478980	47.830921	39.301631	501.388468
A5	66.099242	22.667126	18.625086	237.608546

- Conclusion:

This result strongly suggests that the SAT level and the occupation are not independent at the sig. level 0.05.

# Simpson's paradox

Suppose  $P(A|B' \cap C_i) < P(A'|B' \cap C_i)$  for  $i = 1, 2, \dots, k$ ,  
with  $\sum_{i=1}^k P(C_i) = 1$ .

It is possible that  $P(A|B') > P(A'|B')$

This phenomenon is called a Simpson's paradox.

# Example 41 (Internet commerce).

**FIGURE 10.34**

Simpson's paradox

		Internet sales	Telephone sales
<b>Product A Sales</b>	New customers	199 (11.10%)	63 (6.71%)
	Repeat customers	1594 (88.90%) <u>1793</u>	876 (93.29%) <u>939</u>
<b>Product B Sales</b>	New customers	243 (11.10%)	138 (9.98%)
	Repeat customers	1946 (88.90%) <u>2189</u>	1245 (90.02%) <u>1383</u>
<b>Product C Sales</b>	New customers	864 (16.15%)	1107 (15.90%)
	Repeat customers	4486 (83.85%) <u>5350</u>	5855 (84.10%) <u>6962</u>
<b>Product D Sales</b>	New customers	128 (38.32%)	180 (36.59%)
	Repeat customers	206 (61.68%) <u>334</u>	312 (63.41%) <u>492</u>
<b>Total Sales</b>	New customers	1434 (14.84%)	1488 (15.22%)
	Repeat customers	8232 (85.16%) <u>9666</u>	8288 (84.78%) <u>9776</u>

# **Chapter summary**

**10.1 Inferences on a Population Proportion**

**10.2 Comparing Two Population Proportions**

**10.3 Goodness of Fit Tests for One-Way Contingency Tables**

**Two test statistics. Asymptotic distributions of them.**

**Conditions for asymptotic distributions.**

**10.4 Testing for Independence in Two-Way Contingency Tables**