# Applied Categorical \& Nonnormal Data Analysis 

## Contingency Tables

A table that cross classifies two variable is called a two-way contingency table. It is also known as a cross tabulation or crosstabs for short. If each of the two variables has two levels then the table is a $2 \times 2$. If there are three levels of one variable and 5 of the other, it would be a $3 \times 5$ table. We will start off by looking at a $2 \times 2$ table.

## Observed Frequencies

The following table gives a representation of the observed frequencies of a $2 \times 2$ contingency table.


Here is what the observed frequencies look like for an example using myocardial infarction and the use of aspirin.


The values in the body of the table represent the joint distribution and the values around the edges represent the marginal distributions.

## Observed Proportions

Here is a representation of the observed proportions which can also be treated as probabilities.


The observed proportions for our example look like this:



## Relative Risk

The relative risk in a $2 \times 2$ table is the ratio of "success" probabilities for the two groups. For the MI example, it would look like this.

$$
\mathrm{RR}=\mathrm{p} 11 / \mathrm{p} 21=.0086 / .0047=1.82
$$

In this example, the sample proportion of myocardial infarction was $82 \%$ higher for the placebo group. If you take the reciprocal of the relative risk the value is .55 . The proportion of myocardial infarction was $45 \%$ lower for the aspirin group.

## Odds Ratio

Before we can talk about odds ratios we need to define odds.

$$
\text { odds }=\mathrm{p} /(1-\mathrm{p})
$$

Theoretically, odds can run from 0 to positive infinity. When the odds equal one, the probability of success is equal to the probability of failure. When the odds are less than one, the probability of success is less than the probability of failure. And, when the odds are greater than one, the probability of success is greater than the probability of failure. An odds ratio is exactly what it seems, the ratio of two odds.

$$
\mathrm{OR}=\frac{\mathrm{ods} s_{1}}{\mathrm{odds}}=\frac{p_{1} /\left(1-p_{1}\right)}{p_{2} /\left(1-p_{2}\right)}=\frac{.0086 / .9914}{.0047 / 9954}=1.632
$$

This is not the only way to compute the odds ratio. It is easier to compute it as a ratio of the cross products of either the frequencies or the proportions.

$$
\begin{aligned}
& \mathrm{OR}=\frac{n_{11} r_{21}}{n_{17} r_{12}}=\frac{189 * 10933}{10845 * 104}=1.832 \\
& \mathrm{OR}=\frac{\mathrm{R}_{1} p_{22}}{\mathrm{R}_{12} r_{12}}=\frac{0086 * .4954}{.4914 * .0047}=1.832
\end{aligned}
$$

When the odds ratio equal 1 , the odds for group 1 are the same as the odds for groups 2 . When the odds ratio is greater than 1 , the odds for group 1 are greater than the odds for groups 2. When the odds ratio is less than 1, the reverse is true. The farther odds ratio goes in either direction, the stronger the association among the variables.

In this example, the odds of a myocardial infarction are $83 \%$ higher for the placebo group. If you take the reciprocal of the odds ratio the value is .546 . Thus, the odds of myocardial infarction was about $45 \%$ lower for the aspirin group than for the placebo group.

Odds ratios are invariant when the orientation of the rows and columns reversed. The odds ratios are relatively invariant to changes in the marginal frequencies. For example, if you were to multiply each of the frequencies in the table by a constant, c , the odds ratio would remain unchanged.

$$
\mathrm{OR}=\frac{\sigma_{14}, n_{22}}{c_{12}, n_{12}}=\frac{n_{1}, r_{22}}{n_{12} r_{21}}
$$

The same is true if you multiply the frequencies for one row by one constant and the frequencies in the other row by a different constant.

$$
O R=\frac{c n_{11} \dot{d n_{22}}}{\omega n_{12} \beta n_{21}}=\frac{n_{11} r_{22}}{r_{12} p_{12}}
$$

## Relation of Relative Risk to Odds Ratio

When p 1 and p 2 are both very small, the value of the odds ratio is close to that of the relative risk, In any case, the odds ratio can be obtained from the relative risk by the following formula.

$$
\mathrm{OR}=\mathrm{FR} * \frac{\left(1-p_{2}\right)}{\left(1-R_{1}\right)}
$$

This is useful because there are times when it isn't possible to estimate relative risk directly.

## Conditional Probabilities

Conditional probabilities are the probabilities of an event given that some other event has occurred. In our MI example, the conditional probabilities for the groups are:


Recall that,


Thus, the conditional probability of a myocardial infarction for the placebo group is .0171 , while for the aspirin group in is .0094 .

Two variables are said to be independent when the conditional distributions of one are identical for each level of the other. In this example, the conditional distributions are not identical.

## Expected Frequencies

Here are the expected frequencies for our example given independence of group and myocardial infarction.


Note that the marginal frequencies are that same as in the table of the observed frequencies. This is the case because the expected frequencies are obtained form the marginal distribution
of the observed frequencies. For example, the expected frequency of 146.480 is obtained as follows:

$$
\mathbf{e}_{\mathbf{i j}}=\left(\mathbf{n}_{\mathrm{i}+}\right)\left(\mathbf{n}_{+\mathbf{j}}\right) / \mathbf{n}_{++}=11034 * 293 / 22071=146.480
$$

where $\mathbf{n}_{\mathbf{i}+}$ is the frequency for the ith row, $\mathbf{n}_{+\mathbf{j}}$ is the frequency for the $j$ th column, and $\mathbf{n}_{++}$is the total frequency for the entire table.

What this means, is that, the joint distribution is determined by the marginal distribution of the variables when the two variables are independent.

This property is just a variation of the rule for the joint probability of independent events $\mathbf{P}(\mathbf{A}$ $\boldsymbol{\&} \mathbf{B})=\mathbf{P}(\mathbf{A}) * \mathbf{P}(\mathbf{B})$.

## Chi-Squared Statistic

In two-way contingency tables chi-squared is used to test the independence of the two marginal variables. The chi-squared test is often called a goodness-of-fit test but is perhaps better thought of as a badness-of-fit test, because a large value of chi-squared is indicative of a bad fit between the observed and expected frequencies.

There are two commonly computed chi-squared statistics; the Pearson chi-squared ( $\chi^{2}$ ) and the likelihood ratio chi-squared ( $\mathbf{G}^{\mathbf{2}}$ )

$$
\begin{aligned}
& \chi^{2}=\sum \frac{\left(x_{i j}-e_{i j}\right)^{2}}{e_{i j}} \\
& G^{2}=2 \sum x_{i j} \ln \left(\frac{x_{i j}}{e_{i j}}\right)
\end{aligned}
$$

with degrees of freedom $=(\mathrm{I}-1)(\mathrm{J}-1)$
Asymptotically, $\chi^{\mathbf{2}}$ and $\mathbf{G}^{\mathbf{2}}$ are equivalent. However, in finite samples there can be a considerable difference the estimates of these two statistics.

## Stata Examples

use http://www.gseis.ucla.edu/courses/data/hsb2

```
tabulate ses prog, all
```



$$
\begin{aligned}
\text { Cramer's } V & =0.2037 \\
\text { gamma } & =0.0109 \text { ASE }=0.097 \\
\text { Kendall's tau-b } & =0.0069 \text { ASE }=0.062
\end{aligned}
$$

## tabulate ses prog, cell nofreq

|  | type of program |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| ses | general | demic | vocation | Total |
| low | 8.00 | 9.50 | 6.00 | 23.50 |
| middle | 10.00 | 22.00 | 15.50 | 47.50 |
| high | 4.50 | 21.00 | 3.50 | 29.00 |
| Total | 22.50 | 52.50 | 25.00 | 100.00 |

tabulate ses prog, row nofreq

|  | type of program |  |  | Total |
| :---: | :---: | :---: | :---: | :---: |
| ses | general | academic | vocation \| |  |
| low | 34.04 | 40.43 | 25.53 | 100.00 |
| middle | 21.05 | 46.32 | 32.63 | 100.00 |
| high | 15.52 | 72.41 | 12.07 \| | 100.00 |
| Total | 22.50 | 52.50 | 25.00 | 100.00 |

tabchi ses prog
observed frequency expected frequency

| ses | general | of progr academic | vocation |
| :---: | :---: | :---: | :---: |
| low | 16 | 19 | 12 |
|  | 10.575 | 24.675 | 11.750 |
|  |  |  |  |
| middle | 20 | 44 | 31 |
|  | 21.375 | 49.875 | 23.750 |
|  |  |  |  |
| high | 9 | 42 | 7 |
|  | 13.050 | 30.450 | 14.500 |

Pearson chi2(4) $=16.6044 \quad \operatorname{Pr}=0.002$
likelihood-ratio chi2(4) $=16.7830 \quad \operatorname{Pr}=0.002$
tabchi ses prog,raw pearson cont adjust noo noe
raw residual
Pearson residual
contribution to chi-square
adjusted residual

$\left.\begin{array}{r|rrr} & 1.668 & -1.142 & 0.073 \\ & 2.783 & 1.305 & 0.005 \\ \text { middle } & -1.375 & -5.875 & 7.250 \\ & & 2.167 & -1.895\end{array}\right) 0.096$

## A note about tetrachoric correlations

Tetrachoric correlations measure the association between two dichotomous variables by estimating the correlation between their associated latent variables.

The tabulate command includes an estimate of phi, a measure of association between dichotomous variables. Stata, in the $2 \times 2$ case, labels phi as "Cramer's V." The same coefficient can be obtained by computing a standard correlation correlation between the two variables.

The tetrac command (findit tetrac) available from ATS uses an approximation of the tetrachoric correlations due to Edwards (1957).

$$
\begin{aligned}
& \text { let } \alpha=\mathbf{a d} / \mathbf{b c} \\
& \text { then } r=\left(\alpha^{\pi / 4}+1\right) /\left(\alpha^{\pi / 4}-1\right)
\end{aligned}
$$

The tetrachoric correlations are often larger than the phi coefficients for the same variables. use http://www.gseis.ucla.edu/courses/data/tetra

```
tabulate hon sci, all
```



```
corr hon sci
```

(obs=200)
| hon
hon | 1.0000
sci | $0.3179 \quad 1.0000$

## tetrac hon sci

(obs=200)
Approximate Tetrachoric Correlations

|  | hon | sci |
| ---: | ---: | ---: |
| hon | 1.0000 |  |
| sci | 0.5204 | 1.0000 |

tetrac female schtyp ses hon sci
(obs=200)
Approximate Tetrachoric Correlations

|  | female | schtyp | ses | hon | sci |
| ---: | ---: | ---: | ---: | ---: | ---: |
| female | 1.0000 |  |  |  |  |
| schtyp | -0.0331 | 1.0000 |  |  |  |
| ses | -0.2844 | -0.5840 | 1.0000 |  |  |
| hon | 0.2504 | 0.0365 | 0.0837 | 1.0000 |  |
| sci | -0.2616 | -0.1434 | 0.2996 | 0.5204 | 1.0000 |

