

# Contingency tables I

Timothy Hanson

Department of Statistics, University of South Carolina

Stat 506: Introduction to Experimental Design

## Binary data

- So far we have considered designs that have led to *continuous* outcomes, e.g. hours until bond failure, number of salable flowers, etc.
- Many experimental designs lead to *discrete* outcomes, with the simplest being whether some event has occurred, e.g. cancer going into remission, cure of a rash, etc.
- Without loss of generality, we will consider binary outcomes of “success” and “failure”.
- As with continuous data, the simplest design is to consider one factor with two levels; this is where we start.

## Two-sample binary data

- Consider two populations and will want to compare two population proportions  $p_1$  and  $p_2$ .
- In population 1, we observed  $y_1$  out of  $n_1$  successes; in population 2 we observed  $y_2$  out of  $n_2$  successes.
- This information can be placed in a contingency table

		Group	
		1	2
Outcome	Success	$y_1$	$y_2$
	Failure	$n_1 - y_1$	$n_2 - y_2$
Total		$n_1$	$n_2$

- $\hat{p}_1 = y_1/n_1$  estimates  $p_1$  &  $\hat{p}_2 = y_2/n_2$  estimates  $p_2$ .

## Migraine headache

- Migraine headache patients took part in a double-blind clinical trial to assess experimental surgery.
- 75 patients were randomly assigned to real surgery on migraine trigger sites ( $n_1 = 49$ ) or sham surgery ( $n_2 = 26$ ) in which an incision was made but nothing else.
- The surgeons hoped that patients would experience “a substantial reduction in migraine headaches,” which we will label as success.

# Migraine headache

		Response to migraine surgery	
		Surgery	
		Real	Sham
Substantial reduction in migraine headaches?	Success	41	15
	No success	8	11
	Total	49	26

- $\hat{p}_1 = 41/49 = 83.7\%$  for real surgeries.
- $\hat{p}_2 = 15/26 = 57.7\%$  for sham surgeries.
- Real appears to be better than sham, but is this difference significant?

## HIV testing

A random sample of 120 college students found that 9 of the 61 women in the sample had taken an HIV test, compared to 8 of the 59 men.

HIV testing data		
	Female	Male
HIV test	9	8
No HIV test	52	51
Total	61	59

- $\hat{p}_1 = 9/61 = 14.8\%$  tested among women.
- $\hat{p}_2 = 8/59 = 13.6\%$  tested among men.
- These are pretty close.

## Conditional probabilities

- $p_1$  and  $p_2$  are *conditional probabilities*.
- For the migraine data,  $p_1 = P\{\text{success}|\text{real}\}$  and  $p_2 = P\{\text{success}|\text{sham}\}$ .  $\hat{p}_1 = 0.84$  and  $\hat{p}_2 = 0.58$  estimate these conditional probabilities.
- For the HIV testing data,  $p_1 = P\{\text{tested}|\text{female}\}$  and  $p_2 = P\{\text{tested}|\text{male}\}$ .  $\hat{p}_1 = 0.15$  and  $\hat{p}_2 = 0.14$  estimate these conditional probabilities.

## $\chi^2$ test for independence

- No difference between groups when  $H_0 : p_1 = p_2$  is true.
- That is,  $H_0 : P\{\text{success}|\text{group 1}\} = P\{\text{success}|\text{group 2}\}$ .
- If  $H_0$  is true then the outcome (migraine reduction, being tested for HIV, etc.) is *independent* of the group.
- This is tested using the chi-square statistic

$$\chi^2_S = \sum_{i=1}^4 \frac{(o_i - e_i)^2}{e_i},$$

where  $i = 1, 2, 3, 4$  are the four cells in the middle of the contingency table.

- The  $o_i$  are the observed counts and the  $e_i$  are what's expected if  $p_1 = p_2$ .



## Computing $e_i$

- If  $H_0 : p_1 = p_2$  is true then we can estimate the common probability  $p = p_1 = p_2$  by  $\hat{p} = (y_1 + y_2)/(n_1 + n_2)$ . This is  $\hat{p} = 56/75 = 0.747$  for migraine data.
- In the upper left corner we'd expect to see  $\hat{p}n_1 = 0.747(49) = 36.59$  successes in the real surgery group, and so  $49 - 36.59 = 12.41$  failures in the lower left.
- In the upper right corner we'd expect to see  $\hat{p}n_2 = 0.747(26) = 19.41$  successes in the sham surgery group, and so  $26 - 19.41 = 6.59$  failures in the lower right.

Observed and expected under  $H_0$ 

Observed and expected frequencies for migraine study			
	Surgery		Total
	Real	Sham	
Success	41 (36.59)	15 (19.41)	56
No success	8 (12.41)	11 (6.59)	19
Total	49	26	75

$$\chi^2_S = \frac{(41 - 36.59)^2}{36.59} + \frac{(15 - 19.41)^2}{19.41} + \frac{(8 - 12.41)^2}{12.41} + \frac{(11 - 6.59)^2}{6.59} = 6.06.$$

## The P-value

- When  $H_0 : p_1 = p_2$  is true,  $\chi_S^2$  has a  $\chi_1^2$  distribution, chi-square with 1 degree of freedom.
- The P-value is the tail probability of a chi-square density with 1 *df* greater than what we saw  $\chi_S^2$ . The P-value is the probability of seeing  $\hat{p}_1$  and  $\hat{p}_2$  *even further away from each other* than what we saw.
- We can get the P-value out of R using `chisq.test`, but now we need to put in a contingency table in the form of a matrix to get our P-value.

## Obtaining surgery data P-value in R

- Need to create a 2 × 2 matrix of values first

```
> surgery=matrix(c(41,8,15,11),nrow=2)
> colnames(surgery)=c("Real", "Sham")
> rownames(surgery)=c("Success", "No success")
> surgery
```

	Real	Sham
Success	41	15
No success	8	11

- The default `chisq.test(surgery)` uses

$\chi^2_Y = \sum_{i=1}^4 \frac{(|o_i - e_i| - 0.5)^2}{e_i}$ . Called "Yates continuity correction"  
& gives more accurate P-values in small samples.

```
> chisq.test(surgery)
```

Pearson's Chi-squared test with Yates' continuity correction

```
data: surgery
```

```
X-squared = 4.7661, df = 1, p-value = 0.02902
```

## Obtaining surgery data P-value in R

- To get the usual statistic and P-value, we have to turn the Yates correction “off” using `chisq.test(surgery, correct=FALSE)`.

```
> chisq.test(surgery, correct=FALSE)
```

Pearson's Chi-squared test

```
data: surgery
```

```
X-squared = 6.0619, df = 1, p-value = 0.01381
```

- We reject  $H_0 : p_1 = p_2$  at the 5% level. The surgery significantly reduces migraines.
- Either P-value = 0.029 (using Yate's) or P-value = 0.014 (regular) is fine.

## Two ways to collect data

- There are two ways to collect  $2 \times 2$  contingency table data.
- **Cross-sectional** data is collected by randomly sampling  $n$  individuals and cross-classifying them on two variables.
- Example Ask  $n = 143$  random individuals two questions: salary high/low and education high-school/college.
- The row and column totals are random.
- **Product binomial** data is collected when a fixed number from one group is sampled, and a fixed number from another group is sampled.
- Example: Real vs. sham surgery for migraine.

## Fishers exact test

- For the chi-square test to be valid, we cannot have very small sample sizes, say less than 5 in any cell.
- For small sample sizes there is an exact test, called Fisher's exact test for testing  $H_0 : p_1 = p_2$ .
- Fisher's test computes all possible  $2 \times 2$  tables with the same number of successes and failures (56 successes and 19 failures for the migraine study) that make  $\hat{p}_1$  and  $\hat{p}_2$  even further apart than what we saw, and adds up the probability of seeing each table.
- An alternative, that also works for small sample sizes, is the equivalent of the permutation test discussed at the beginning of the course, only for binary data, given by `chisq.test(surgery, simulate.p.value=TRUE)`.

## Flu shots

A random sample of college students found that 13 of them had gotten a flu shot at the beginning of the winter and 28 had not. Of the 13 who had a flu shot, 3 got the flu during the winter. Of the 28 who did not get a flu shot, 15 got the flu.

		Flu shot data		
		No shot	Flu shot	Total
Flu?	Yes	15	3	18
	No	13	10	<u>23</u>
Total		28	13	41

Want to test  $H_0 : p_1 = p_2$  vs.  $H_0 : p_1 > p_2$  where  $p_1$  is probability of getting flu among those without shots and  $p_2$  is probability of getting flu among those that got shots.



## P-value for flu shot data

Tables where  $p_1$  and  $p_2$  are even further apart in the direction of  $H_A : p_1 > p_2$

<u>Table</u>	<u>Probability</u>				
<table border="1"><tr><td>15</td><td>3</td></tr><tr><td>13</td><td>10</td></tr></table>	15	3	13	10	0.05298
15	3				
13	10				
<table border="1"><tr><td>16</td><td>2</td></tr><tr><td>12</td><td>11</td></tr></table>	16	2	12	11	0.01174
16	2				
12	11				
<table border="1"><tr><td>17</td><td>1</td></tr><tr><td>11</td><td>12</td></tr></table>	17	1	11	12	0.00138
17	1				
11	12				
<table border="1"><tr><td>18</td><td>0</td></tr><tr><td>10</td><td>13</td></tr></table>	18	0	10	13	0.00006
18	0				
10	13				

**Figure 10.4.1**

$$\text{P-value} = 0.05298 + 0.01174 + 0.00138 + 0.00006 = 0.06616.$$

## Fisher's exact test

The probability of each table is given by the *hypergeometric distribution* and is beyond the scope of this course. For the flu shot data to carry out Fisher's test we type

```
> flu=matrix(c(15,13,3,10),nrow=2)
> fisher.test(flu,alternative="greater")
```

Fisher's Exact Test for Count Data

```
data: flu
p-value = 0.06617
alternative hypothesis: true odds ratio is greater than 1
sample estimates:
odds ratio
 3.721944
```

We'll discuss what an odds ratio is next time. For now, we accept  $H_0 : p_1 = p_2$  at the 5% level. There is not statistically significant evidence that getting a flu shot decreases the probability of getting the flu.

## Directional alternatives

- Using `fisher.test` we can test  $H_0 : p_1 = p_2$  versus one of (a)  $H_A : p_1 \neq p_2$ , (b)  $H_A : p_1 < p_2$ , or (c)  $H_A : p_1 > p_2$ .
- Use `alternative="two.sided"` (the default) or `alternative="less"` or `alternative="greater"`.
- Fisher's test is better than the chi-square test; just use the Fisher test in your homework.
- You will use `chisq.test` for tables larger than 2 × 2 instead, our next topic...

## 10.5 $r \times k$ contingency table

- The number of categories is generalized to  $r$  instead of 2.
- The number of groups is generalized to  $k$  instead of 2.
- Still want to test  $H_0$  : the probabilities of being in each of the  $r$  categories do not change across the  $k$  groups.
- In the next example,  $r = 3$  categories (agricultural field, prairie dog habitat, grassland) and  $k = 3$  groups (2004, 2005, 2006).

## Plover Nesting

Wildlife ecologists monitored the breeding habitats of mountain plovers for three years and made note of where the plovers nested.

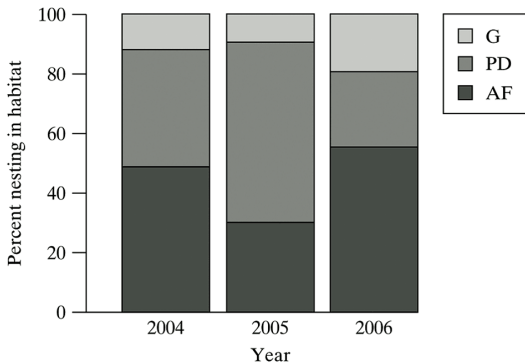
Plover nest locations across three years				
Location	Year			Total
	2004	2005	2006	
<b>Agricultural field (AF)</b>	21	19	26	<b>66</b>
<b>Prairie dog habitat (PD)</b>	17	38	12	<b>67</b>
<b>Grassland (G)</b>	5	6	9	<b>20</b>
<b>Total</b>	<b>43</b>	<b>63</b>	<b>47</b>	<b>153</b>

Question: do nesting choices vary over time?

## Plover nesting percentages over time

Percentage distributions of plover nests by year			
Location	Year		
	2004	2005	2006
<b>Agricultural field (AF)</b>	48.8	30.2	55.3
<b>Prairie dog habitat (PD)</b>	39.5	60.3	25.5
<b>Grassland (G)</b>	11.6	9.5	19.1
<b>Total</b>	<b>99.9*</b>	<b>100.0</b>	<b>99.9*</b>
*The sums of the 2004 and 2006 percentages differ from 100% due to rounding.			

## Stacked bar plot



If the percentages of nesting choice are the same for each year, then the gray areas will be equal.

## Chi-square test

- $H_0$  category percentages do not change across groups.
- The chi-square test statistic is given by

$$\chi_S^2 = \sum_{\text{all cells}} \frac{(e_i - o_i)^2}{e_i}.$$

- Here,  $e_i$  is the total number in the group (column total) times the total row percentage, i.e.

$$e = \frac{\text{row total} \times \text{column total}}{\text{grand total}}.$$

- $\chi_S^2$  has a  $\chi_{df}^2$  where  $df = (r - 1)(k - 1)$ . This is where the P-value comes from.



## Plover data, observed & expected

Observed and expected frequencies of plover nests				
Location	Year			Total
	2004	2005	2006	
<b>Agricultural field (AF)</b>	21 (18.55)	19 (21.18)	26 (20.27)	<b>66</b>
<b>Prairie dog habitat (PD)</b>	17 (18.83)	38 (27.59)	12 (20.58)	<b>67</b>
<b>Grassland (G)</b>	5 (5.62)	6 (8.24)	9 (6.14)	<b>20</b>
<b>Total</b>	<b>43</b>	<b>63</b>	<b>47</b>	<b>153</b>

$$\text{Upper left } 18.55 = \frac{43(66)}{153},$$

$$\chi^2_S = \frac{(21 - 18.55)^2}{18.55} + \dots + \frac{(9 - 6.14)^2}{6.14} = 14.09.$$

## Chi-square test in R

```
> plover=matrix(c(21,17,5,19,38,6,26,12,9),nrow=3)
> plover
      [,1] [,2] [,3]
[1,]   21   19   26
[2,]   17   38   12
[3,]    5    6    9

> chisq.test(plover)
```

Pearson's Chi-squared test

```
data: plover
X-squared = 14.0894, df = 4, p-value = 0.007015
```

We reject  $H_0$  that nesting preference does not change over time at the 5% level.