# Lab 3: $2 \times 2$ tables and related terms 

January 31 - February 1, 2017

```
Setup
titanic<-read.delim("http://myweb.uiowa.edu/pbreheny/data/titanic.txt")
summary(titanic)
\begin{tabular}{lclccc} 
\#\# & Class & Sex & Age & \multicolumn{2}{c}{ Survived } \\
\#\# & 1st :325 & Female: 470 & Adult:2092 & Died :1490 \\
\#\# & 2nd :285 & Male :1731 & Child: 109 & Survived: 711
\end{tabular}
## 3rd :706
## Crew:885
```


## Making tables and R review

By default, when the summary() function encounters categorical data, it produces a table for that column, as evidenced above, where it created 4 separate tables. We can replicate that using the table() function.

```
table(titanic$Class)
##
## 1st 2nd 3rd Crew
## 325 285 706 885
```

But the table function is more versatile than that. For example, we can create 2 x 2 tables:
(The with() function lets us just use the column names as variables, instead of writing out titanic $\$$ every time.)

```
with(titanic, table(Class,Survived))
```

```
## Survived
## Class Died Survived
## 1st 122 203
## 2nd 167 118
## 3rd 528 178
## Crew 673 212
```

If we give the function more than two variables, it creates multiple tables, 1 for each level:

```
with(titanic, table(Class,Survived,Sex))
## , , Sex = Female
##
## Class Died Survived
## 1st 4 141
## 2nd 13 93
## 3rd 106 90
## Crew 3 20
##
## , , Sex = Male
##
## Survived
## Class Died Survived
## 1st 118 62
## 2nd 154 25
## 3rd 422 88
## Crew 670 192
# with(titanic, table(Class,Survived,Sex,Age))
```

It can be done with 4 and so the code is included, but it is not worth taking up space to print the tables in the lab.
(I'd recommend keeping the number of variables down to 2 or 3 , as 4 is getting a bit cluttered and confusing.)
If we save a table, we can use brackets to access individual numbers [row,column]:

```
tableDemo<-with(titanic, table(Class,Survived))
print(tableDemo)
```

| \#\# | Survived |  |  |
| :--- | ---: | ---: | ---: |
| \#\# | Class | Died | Survived |
| \#\# | 1st | 122 | 203 |
| \#\# | 2nd | 167 | 118 |
| \#\# | 3rd | 528 | 178 |
| \#\# | Crew | 673 | 212 |

tableDemo [3,2] \#This is the number of 3rd class passengers who survived.
\#\# [1] 178

We can also use prop.table() to get the proportions of subjects in each cell of a table:

```
prop.table(tableDemo)
```

| \#\# | Survived |  |  |
| :--- | ---: | ---: | ---: |
| \#\# | Class | Died | Survived |
| \#\# | 1st | 0.05542935 | 0.09223080 |
| \#\# | 2nd | 0.07587460 | 0.05361199 |
| \#\# | 3rd | 0.23989096 | 0.08087233 |
| \#\# | Crew | 0.30577010 | 0.09631985 |

## Vocab Recap

| \#\# | HO False | HO |
| :--- | ---: | ---: |
| \# True |  |  |
| \#\# Reject | A | B |
| \#\# FtR | C | D |

## Type I Error

A Type I error is committed when a true null hypothesis is rejected.
In terms of disease detection (where the null hypothesis is no disease), this is a false positive.
In the table above, this is B.

## Type I Error Rate ( $\alpha$ )

The Type I error rate is the proportion of true hypotheses that were rejected.
In the table above, this is $\mathrm{B} /(\mathrm{B}+\mathrm{D})$.

## Type II Error

A Type II error is committed when a false null hypothesis is not rejected. In the table above, this is C.

## Type II Error Rate ( $\beta$ )

The Type II error rate is the proportion of false null hypotheses that failed to be rejected. In the table above, this is $\mathrm{C} /(\mathrm{C}+\mathrm{A})$.

## False Discovery Rate

The false discovery rate is the fraction of null hypothesis rejections that were incorrect.
In the table above, this is $\mathrm{B} /(\mathrm{B}+\mathrm{A})$.

## Selection bias

Instead of random sampling, certain subgroups of the population were more likely to be included than others.

## Nonresponse bias

Nonresponders can differ from responders in many important ways

## Perception bias

The perception of benefit from a treatment (placebo effect)

## Confirmation bias (touched on, but not named in notes)

The tendency to interpret new evidence as confirmation of one's existing beliefs or theories (If doctors think that the polio vaccine causes polio, a patient with a borderline instance of disease is more likely to be diagnosed with polio if the doctor knows that the vaccine was administered.)

## Confounding

The two things being studied are both highly correlated to a third thing. (Think ice cream sales and murder rates both being related to weather.)

## Weighted Averages

Weighted averages can be tricky, so here's an example:
Let's investigate sexual bias in Titanic survival.
(For the sake of practice, do this by hand.)

| , , Sex $=$ Female |  |  |
| :--- | ---: | ---: |
| Survived |  |  |
| Class | Survived | Total |
| 1st | 141 | 145 |
| 2nd | 93 | 106 |
| 3rd | 90 | 196 |
| Crew | 20 | 23 |

, , Sex = Male

| Survived |  |  |
| :---: | ---: | ---: |
| Class | Survived | Total |
| 1st | 62 | 180 |
| 2nd | 25 | 179 |
| 3rd | 88 | 510 |
| Crew | 192 | 862 |

## Part a

From the tables above, calculate the overall percentages of men and women who survived the Titanic.

## Part b

Create a table listing the percentage of men and women who survived, broken down by class

## Part c

Construct a weighted average of the percentage of male and female passengers who survived, controlling for the effect of class (i.e., report one number for men and one number for women).

```
## Part a
## Women: 0.7319149 , Men: 0.2120162
## Part b
## Women Men
## 1st 0.9724138 0.3444444
## 2nd 0.8773585 0.1396648
## 3rd 0.4591837 0.1725490
## Crew 0.8695652 0.2227378
## Part c
## Women: 0.754
## Men: 0.214
```

