## Modeling categorical relationships

Stats 60/Psych 10
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## Last time

- Null Hypothesis Statistical Testing (NHST)
- Confidence Intervals (CI)
- The connection between NHST and CI


## This time

- Modeling categorical relationships
- contingency tables
- chi-squared test for goodness of fit
- Odds ratio


## What is a "categorical relationship"?

- A relationship between categorical variables
- Variables on a nominal or (sometimes) ordinal scale
- Usually expressed in terms of counts
- How many observations fall into each level of the variable?
- or each combination of levels across variables?


## Are births more common on certain days than others?


data from http://chmullig.com/2012/06/births-by-day-of-year/

# What kind of variable is the day of the year (recorded as a number, 1-365)? 

Nominal<br>Ordinal<br>Interval<br>Rational

## Pearson's chi-squared test for goodness of fit

$$
\chi^{2}=\sum_{i, j} \frac{\left(\text { observed }_{i j}-\text { expected }_{i j}\right)^{2}}{\text { expected }_{i j}}
$$

- Compare the observed data to the expected data
- Ho: birth rates on all days are equal
- HA: birth rates differ between days
- If births are equally likely on all days, then the expected value for each day is just the mean number of births per day across the entire year

$$
\chi^{2}=\sum_{i, j} \frac{\left(\text { observed }_{i j}-\text { expected }_{i j}\right)^{2}}{\text { expected }_{i j}}=132764.2
$$



## The chi-squared distribution

- Chi-squared distribution describes the distribution of the sum of squares of a set of standard normal random variables
- with degrees of freedom (df) equal to the number of variables being summed


FIgure 13.2 The $\chi 2$ distribution changes shape with the degrees of freedom
from Field, An Adventure in Statistics

## d=replicate(10000,rnorm(8)**2) dMean=apply(d,2,sum)



```
d=replicate(10000,rnorm(8)**2)
dMean=apply(d,2,sum)
```



## Chi-squared test in R

## chisq.test(bdata\$smoothbirths)

Chi-squared test for given probabilities
data: bdata\$smoothbirths
X-squared $=132760$, $\mathrm{df}=365$, p -value $<2.2 \mathrm{e}-16$
degrees of freedom $=N-1$
length(bdata\$smoothbirths)
[1] 366

## Comparing two variables: The contingency table

Counts
Diabetes

| TVOver3Hrs | No <br> <int> | Yes <br> <int> |
| :--- | ---: | ---: |
| FALSE | 3509 | 225 |
| TRUE | 974 | 148 |

Proportions of total N
Diabetes

|  | No | Yes <br> TVOver3Hrs |
| :--- | ---: | ---: |
| <int> |  |  | int>

## A societally relevant example: Racial disparities in policing

- Are black individuals more likely to be searched when they are stopped by the police, compared to white individuals?

https://openpolicing.stanford.edu/


## Representing the data as a contingency table

- State of Connecticut, 318,669 total stops, 2013-2015

Raw counts

|  | Not <br> searched | Searched |
| :---: | :---: | :---: |
| White | 239,241 | 3,108 |
| Black | 36,244 | 1,219 |

Proportions of total N

|  | Not <br> searched | Searched |
| :---: | :---: | :---: |
| White | 0.855 | 0.011 |
| Black | 0.129 | 0.004 |

What would we expect if there was no relationship?

## Expected probabilities under independence

- Remember that if X and Y are independent, then:

$$
P(X \cap Y)=P(X) * P(Y)
$$

- So we expect:
"marginal probabilities"

|  | Not searched | Searched |
| :---: | :---: | :---: |
| White | $p(N S)^{*} P(W)$ | $p(S)^{*} P(W)$ |
| Black | $p(W))^{*} P(B)$ | $p(S)^{*} P(B)$ |

## Computing expected probabilities

Observed proportions

|  | Not <br> searched | Searched |
| :---: | :---: | :---: |
| White | 0.855 | 0.011 |
| Black | 0.129 | 0.004 |

Expected under independence $\left(\mathrm{H}_{0}\right)$

|  | Not searched | Searched |
| :---: | :---: | :---: |
| White | 0.853 | 0.013 |
| Black | 0.132 | 0.002 |

.985 .015

How can we tell if these are different?

## Pearson's chi-squared statistic for goodness of fit

$$
\chi^{2}=\sum_{i, j} \frac{\left(\text { observed }_{i j}-\text { expected }_{i j}\right)^{2}}{\text { expected }_{i j}}
$$

standardized squared

Observed

|  | Not <br> searched | Searched |
| :---: | :---: | :---: |
| White | 239241 | 3108 |
| Black | 36244 | 1219 |

Expected

|  | Not <br> searched | Searched |
| :---: | :---: | :---: |
| White | 238601 | 3748 |
| Black | 36884 | 579 |

difference

|  | Not <br> searched | Searched |
| :---: | :---: | :---: |
| White | 1.71 | 109 |
| Black | 11.1 | 706 |

$$
\chi^{2}=828.3
$$

Degrees of freedom for chi-square on contingency tables

$$
d f=(r-1)(c-1) \quad \begin{aligned}
& \text { where: } \\
& r=\text { number of rows } \\
& c=\text { number of columns }
\end{aligned}
$$

for a $2 \times 2$ contingency table:
r=2 rows
$\mathrm{c}=2$ columns
$\mathrm{df}=(2-1)^{\star}(2-1)=1$
Intuition: once we know the marginal sums, then only one number is free to vary

|  | Not <br> searched | Searched | sum |
| :---: | :---: | :---: | :---: |
| White | 239,241 | 3,108 | 242,349 |
| Black | 36,244 | 1,219 | 37,463 |
| sum | 275,485 | 4327 |  |

## Police search example: A parametric test in $R$

summaryDf2wayTable=summaryDf2way \%>\%
spread (searched,n) \%>\%
select(-driver_race)

| driver_race <br> <fctr> | FALSE <br> <int> | TRUE <br> <int> |
| :--- | ---: | ---: |
| Black | 36244 | 1219 |
| White | 239241 | 3108 |

## Police search example: A parametric test in $R$

```
chisqTestResult = chisq.test(summaryDf2wayTable,1,
    correct=FALSE)
chisqTestResult
```

Pearson's Chi-squared test
data: summaryDf2wayTable
X-squared $=828.3, \mathrm{df}=1, \mathrm{p}$-value $<2.2 e-16$

This is a non-directional hypothesis test H0: searches and race are unrelated HA: searches and race are related

Another example: diabetes vs. TV watching

- Example from Week 5 PSet:

Counts
Diabetes

| TVOver3Hrs | No <br> <int> | Yes <br> <int> |
| :--- | ---: | ---: |
| FALSE | 3509 | 225 |
| TRUE | 974 | 148 |

Proportions of total N
Diabetes
No Yes
TVOver3Hrs <int> <int>
$\begin{array}{lll}\text { FALSE } & 0.7220 .046\end{array}$

TRUE
$0.200 \quad 0.030$

## Chi-squared test on NHANES diabetes/TV data

chisq.test(summaryTable[,2:3], correct=FALSE)

Pearson's Chi-squared test
data: summaryTable[, 2:3]
X-squared $=60$, df $=1, p$-value $=3 e-15$

## Standardized residuals

$$
\text { standardized residual }=\frac{\text { observed }_{i j}-\text { expected }_{i j}}{\sqrt{\text { expected }_{i j}}}
$$

can be interpreted as a Z-score

Observed

|  | Not <br> searched | Searched |
| :---: | :---: | :---: |
| White | 239241 | 3108 |
| Black | 36244 | 1219 |

Expected

|  | Not <br> searched | Searched |
| :--- | :---: | :---: |
| White | 238601 | 3748 |
| Black | 36884 | 579 |

standardized residual

|  | Not <br> searched | Searched |
| :---: | :---: | :---: |
| White | 1.3 | -10.4 |
| Black | -3.3 | 26.5 |

## Odds ratio

- Expresses the relative likelihood of different outcomes
- Odds are the relative likelihood of some event happening versus not happening


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- Expresses the relative likelihood of different outcomes
- Odds are the relative likelihood of some event happening versus not happening

The odds ratio is simply the ratio of two odds

$$
\text { odds of } \mathrm{A}=\mathrm{P}(\mathrm{~A}) / \mathrm{P}(\neg \mathrm{~A})
$$

## Odds ratio

- Expresses the relative likelihood of different outcomes

$$
\begin{gathered}
o d d s_{\text {searched } \mid \text { black }}=\frac{N_{\text {searched,black }}}{N_{\text {not searched,black }}}=0.034 \\
\text { odds } s_{\text {searched } \mid w h i t e}=\frac{N_{\text {searched }, w h i t e}}{N_{\text {not searched,white }}}=0.013
\end{gathered}
$$

$$
\text { odds ratio }=\frac{o d d s_{\text {searched } \mid \text { black }}}{\text { odds } s_{\text {searched } \mid \text { white }}}=2.59
$$

## ODDS RATIO EXAMPLE: SMOKING AND LUNG CANCER

"What is the relationship between smoking and lung cancer?

$$
\begin{gathered}
o d d s(\text { cancer in smokers })=\frac{P(\text { cancer in smokers })}{P(\text { no cancer in smokers })} \\
\text { odds }(\text { cancer in nonsmokers })=\frac{P(\text { cancer in nonsmokers })}{P(\text { no cancer in nonsmokers })} \\
\text { oddsratio }=\frac{o d d s(\text { cancer in smokers })}{o d d s(\text { cancer in nonsmokers })}
\end{gathered}
$$

## ODDS RATIO EXAMPLE: SMOKING AND LUNG CANCER

Using the data from a published study (Pesch et al., 2012) we can compute these values:
" The odds of someone having lung cancer who has never smoked is 0.08
" the odds of a current smoker having lung cancer is 1.77
" The odds ratio of 23.22 tells us that the odds of cancer in smokers are roughly 23 times higher than never-smokers.

## Categorical analysis beyond the $2 \times 2$ table

- Survey data example: is programming experience related to year?


```
\begin{tabular}{|c|c|c|c|c|c|}
\hline \#\# & programmedBefore & 1 & 2 & 3 & 4 \\
\hline \#\# & <lgl> & <int> & <int> & <int> & <int> \\
\hline \#\# 1 & F & 23 & 18 & 16 & 17 \\
\hline & T & 9 & 27 & 18 & 21 \\
\hline
\end{tabular}
```

programmedBefore
FALSE TRUE

## Chi-squared test: year vs. programming experience

HO: Year is unrelated to programming experience HA: Year and programming experience are related

```
csResult = chisq.test(tableData$year,tableData$programmedBefore)
```

csResult
Pearson's Chi-squared test
data: tableData\$year and tableData\$programmedBefore X-squared $=8, \mathrm{df}=3, \mathrm{p}$-value $=0.04$

## Group discussion

Seasonal batting averages for Derek Jeter and David Justice, 1995-7

|  | 1995 |  | 1996 |  | 1997 |  | Combined |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Derek Jeter | $12 / 48$ | 0.250 | $183 / 582$ | 0.314 | $190 / 654$ | 0.291 | $385 / 1284$ | 0.300 |
| David Justice | $104 / 411$ | 0.253 | $45 / 140$ | 0.321 | $163 / 495$ | 0.329 | $312 / 1046$ | 0.298 |

How could this happen? Which one of them is a better batter?

## Sometimes summaries can be misleading: Simpson's paradox

- A pattern that is present in the overall data may be reversed in different subsets of the data
- Due to a "lurking variable"
- Different frequencies of at-bats across years
- Often reflects different frequencies and proportions in subsets of the data

|  | 1995 |  | 1996 |  | 1997 |  | Combined |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Derek Jeter | $12 / 48$ | 0.250 | $183 / 582$ | 0.314 | $190 / 654$ | 0.291 | $385 / 1284$ | 0.300 |
| David Justice | $104 / 411$ | 0.253 | $45 / 140$ | 0.321 | $163 / 495$ | 0.329 | $312 / 1046$ | 0.298 |

## Berkeley graduate admissions example

|  | Applicants | Admitted |
| :---: | ---: | ---: |
| Men | 8442 | $44 \%$ |
| Women | 4321 | $35 \%$ |


| Dept | $\|c\|$ |  | Men |  |
| ---: | ---: | ---: | ---: | ---: |
|  | Admitted | Apps |  | Admitted |
| A | 825 | $62 \%$ | 108 | $82 \%$ |
| B | 560 | $63 \%$ | 25 | $68 \%$ |
| C | 325 | $37 \%$ | 593 | $34 \%$ |
| D | 417 | $33 \%$ | 375 | $35 \%$ |
| E | 191 | $28 \%$ | 393 | $24 \%$ |
| F | 373 | $6 \%$ | 341 | $7 \%$ |

## Recap

- We can summarize categorical variables in terms of contingency tables
- We can test for relations between categorical variables using a chi-squared test
- Sometimes combined data can be misleading
- Always important to think about potentially lurking variables

