# Precept 1: Probability, Simulations, Working with Data

Soc 500: Applied Social Statistics

Shay O'Brien

Princeton University

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### Support Resources

- Office hours
- Piazza
- Email
- Google is your best friend!

#### Office hours

Please raise your hand if you absolutely cannot make any of these office hours:

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- Mondays 10am 12pm (S + Z)
- Mondays 4:30 6:30pm (A + S + Z)
- Wednesdays 10am 12pm (A + S + Z)
- Thursdays 1pm 3pm (A + S)
- Thursdays 5pm 7pm (A + Z)

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Acknowledgements: These slides were most recently edited by Ziyao Tian, and they draw heavily on materials developed by past preceptors Shay O'Brien, Simone Zhang, Elisha Cohen, and Clark Bernier. Thanks!

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### Probability from a Contingency Table

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- Let's find out:
  - What is the probability that a randomly selected person is taking Sociology course for the first time and has never done any R project before?  $P(F, R^c)$ ?
  - Given that a person has done R programming project before, what is the probability that SOC400 is this person's first Sociology course? P(F|R)?

LTP

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# A Card Player's Example

If we randomly draw two cards from a standard 52 card deck and define the events  $A = \{Ace \text{ on Draw } 1\}$  and  $B = \{Ace \text{ on Draw } 2\}$ , then

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$$P(A) = 4/52$$
  
•  $P(B|A) = 3/51$ 

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## Law of Total Probability (LTP)

With 2 Events:

$$P(B) = P(B, A) + P(B, A^c)$$
  
=  $P(B|A) \times P(A) + P(B|A^c) \times P(A^c)$ 

$$P(\textcircled{\bullet}) = P(\textcircled{\bullet}) + P(\textcircled{\bullet})$$
$$= P(\textcircled{\bullet}| \checkmark) \times P(\textcircled{\bullet}) + P(\textcircled{\bullet}| 1) \times P(1)$$

Recall, if we randomly draw two cards from a standard 52 card deck and define the events  $A = \{Ace \text{ on } Draw 1\}$  and  $B = \{Ace \text{ on } Draw 2\}$ , then

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$$P(B) = 3/51 \times 1/13 + 4/51 \times 12/13$$
$$= \frac{3+48}{51 \times 13} = \frac{1}{13} = \frac{4}{52}$$

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A woman has been murdered, and her husband is accused of having committed the murder. It is known that the man abused his wife repeatedly in the past, and the prosecution argues that this is important evidence pointing towards the man's guilt. The defense attorney says that the history of abuse is irrelevant, as only 1 in 1000 women who experience spousal abuse are subsequently murdered.

Assume that the defense attorney's 1 in 1000 figure is correct, and that half of men who murder their wives previously abused them. Also assume that 20% of murdered women were killed by their husbands, and that if a woman is murdered and the husband is not guilty, then there is only a 10% chance that the husband abused her. What is the probability that the man is guilty? Is the prosecution right that the abuse is important evidence in favor of guilt?

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Bayes' Rule R Markdown Simulation Working with Data Fun with Lint!!

Resources

## Prosecutor's Fallacy

• Let's define our events

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  - M = > woman is murdered
  - A => woman has previously experienced abuse
  - G => woman's husband is guilty

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- Let's define our events
  - M = > woman is murdered
  - A => woman has previously experienced abuse
  - $\mathsf{G} =>$  woman's husband is guilty
- What do we know?

Table: What Do We Know?

Statements	We know	We also know
1 in 1000 women who experi-	P(? ?) = 0.001	P(? ?) = 1 - 0.001
ence spousal abuse are subse-		
quently murdered		
half of men who murder their	P(? ?) = 0.5	P(? ?) = 1 - 0.5
wives previously abused them		
20% of murdered women were	P(? ?) = 0.2	P(? ?) = 1 - 0.2
killed by their husbands		
woman is murdered and the	P(? ?) = 0.1	P(? ?) = 1 - 0.1
husband is not guilty, then		
there is only a 10% chance		
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half of men who murder their	P(A M,G)=0.5	$P(A^c M,G) = 1 - 0.5$
wives previously abused them		
20% of murdered women were	P(G M) = 0.2	$P(G^c M) = 1 - 0.2$
killed by their husbands		
woman is murdered and the	$P(A G^c,M)=0.1$	$P(A^{c} G^{c}, M) = 1-0.1$
husband is not guilty, then		
there is only a 10% chance		
that the husband abused her		

#### Prosecutor's Fallacy

• What we know  $P(M|A), P(A|M, G), P(G|M), P(A|G^{c}, M)$ 

- What we know  $P(M|A), P(A|M, G), P(G|M), P(A|G^{c}, M)$
- What do we want to know? P(G|M,A)

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- What we know  $P(M|A), P(A|M, G), P(G|M), P(A|G^c, M)$
- What do we want to know?
   P(G|M, A)
- What can we use to get our quantity of interest? Bayes' Rule

#### Bayes' Rule

- Often we have information about P(B|A), but require P(A|B) instead.
- When this happens, always think Bayes' Rule
- Bayes' rule: if P(B) > 0

$$P(A \mid B) = \frac{P(B|A)P(A)}{P(B)}$$

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• Also recall from the definition of conditional probability:

$$\mathsf{P}(\mathsf{A},\,\mathsf{B})=\mathsf{P}(\mathsf{B}\mid\mathsf{A})\mathsf{P}(\mathsf{A})$$

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P(M|A) = 1/1000P(A|G, M) = 1/2P(G|M) = 1/5 $P(A|G^{c}, M) = 1/10$ 

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$$= \frac{P(M,A,G)}{P(M,A)}$$
$$= \frac{P(A|G,M)P(G|M)P(M)}{P(A|M)P(M)}$$
$$= \frac{P(A|G,M)P(G|M)}{P(A|M)}$$

#### Prosecutor's Fallacy

P(M|A) = 1/1000P(A|G, M) = 1/2P(G|M) = 1/5 $P(A|G^{c}, M) = 1/10$ 

How do we find  $P(A \mid M)$ ?

Recall Law of Total Probability:

$$P(X) = P(X|Y)P(Y) + P(X|Y^{c})P(Y^{c})$$

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#### Prosecutor's Fallacy

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Applying here:

 $P(A|M) = P(A|M, G)P(G|M) + P(A|M, G^{c})P(G^{c}|M)$ 

LTP

## Prosecutor's Fallacy

P(M|A) = 1/1000P(A|G, M) = 1/2P(G|M) = 1/5 $P(A|G^{c}, M) = 1/10$ 

Putting it all together:

$$P(G|M,A) = \frac{P(A|G,M)P(G|M)}{P(A|M,G)P(G|M) + P(A|M,G^c)P(G^c|M)}$$

LTP

## Prosecutor's Fallacy

P(M|A) = 1/1000P(A|G, M) = 1/2P(G|M) = 1/5 $P(A|G^{c}, M) = 1/10$ 

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$$= \frac{(.5)(.2)}{(.5)(.2) + (.1)(1 - 0.2)}$$

LTP

#### Prosecutor's Fallacy

P(M|A) = 1/1000P(A|G, M) = 1/2P(G|M) = 1/5 $P(A|G^{c}, M) = 1/10$ 

Putting it all together:

$$P(G|M,A) = \frac{P(A|G,M)P(G|M)}{P(A|M,G)P(G|M) + P(A|M,G^c)P(G^c|M)}$$
$$= \frac{(.5)(.2)}{(.5)(.2) + (.1)(1 - 0.2)}$$
$$= 0.556$$

Bayes' Rule R Markdown Simulation Working with Data Fun with Lint!!

Resources

## Prosecutor's Fallacy

• What does this mean for our defendant?



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## R Markdown

- install.packages("knitr")
- File New File R Markdown
- Preferences Under Sweave set "Weave Rnw files with" to "knitr"
- See 1\_Sample Markdown Document.Rmd

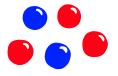
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Simulation Working with Data

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#### ! Resources

## Probability by Simulation

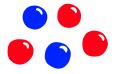


Problem: You have a bag of five marbles. Three are red and two are blue. You draw one marble. Without replacing it, you then draw another marble.

What is the probability that the two marbles are the same color?

• We could do this analytically:

## Probability by Simulation



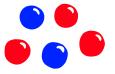
Problem: You have a bag of five marbles. Three are red and two are blue. You draw one marble. Without replacing it, you then draw another marble.

What is the probability that the two marbles are the same color?

• We could do this analytically:  
P(Same color)  
=P(D1 = R)P(D2 = R | D1 = R) + P(D1 = B)P(D2 = B | D1 = B)  
= 
$$(3/5)(2/4) + (2/5)(1/4)$$
  
=  $2/5$ 

Resources

## Probability by Simulation



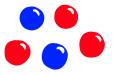
Problem: You have a bag of five marbles. Three are red and two are blue. You draw one marble. Without replacing it, you then draw another marble.

What is the probability that the two marbles are the same color?

- We could do this analytically: P(Same color) =P(D1 = R)P(D2 = R | D1 = R) + P(D1 = B)P(D2 = B | D1 = B)= (3/5)(2/4) + (2/5)(1/4)= 2/5
- Or we can run a simulation! See 2\_Simulation example.R

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# Writing Functions



- We've already used many built in R functions: mean(), head(), etc.
- We can also define our own functions:

Define a function that takes 3 arguments; it will add the first two and divide by the third:

> myfunction <- function(x, y, z){</pre> out <- (x + y) / z + + return(out) + } > ## use the function > myfunction(1, 5, 2) [1] 3

Support Objectives Contingency Table

LTP

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Resources

## Data Manipulation and Tables

#### See 3\_Data Manipulations and Tables.Rmd

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#### Fun with Lint!!



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#### Resources

- R Style Guide: http://adv-r.had.co.nz/Style.html
- R Cookbook: http://www.cookbook-r.com/
- ggplot cheatsheet: https://www.rstudio.com/wp-content/ uploads/2015/08/ggplot2-cheatsheet.pdf
- dplyr cheatsheet: https://www.rstudio.com/wp-content/ uploads/2015/02/data-wrangling-cheatsheet.pdf
- Probability cheatsheet: https://static1.squarespace.com/static/ 54bf3241e4b0f0d81bf7ff36/t/55e9494fe4b011aed10e48e5/ 1441352015658/probability\_cheatsheet.pdf
- Probability and statistics visualizations: http://students.brown.edu/seeing-theory/index.html
- Kosuke Imai's textbook contains lots of sample R code!