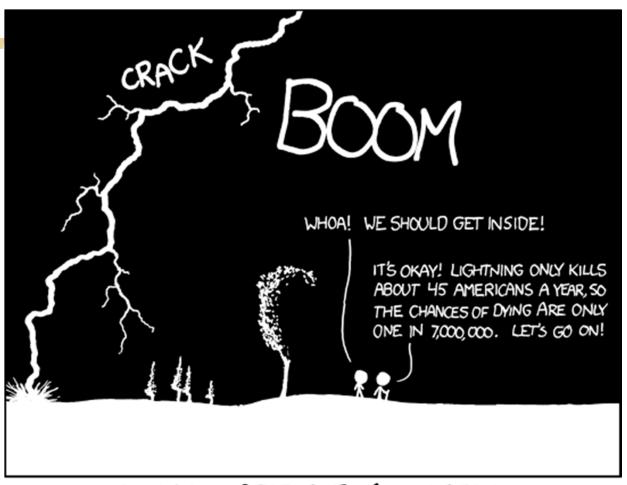
UNIVERSITY of WASHINGTON

# Data Science UW Methods for Data Analysis

Probability and More on Distributions Lecture 2 Stephen Elston





THE ANNUAL DEATH RATE AMONG PEOPLE WHO KNOW THAT STATISTIC IS ONE IN SIX.



## **Topics**

- > Review
- > Counting
- > Axioms of Probability
- > Probability Examples
- > Conditional Probability
- > More on Distributions



#### Review

- > Distributions
  - Discrete: Bernoulli, Binomial, Poisson
  - Continuous: Uniform, Normal, Student's T
- > Numerical and Visual Exploration of Data
- > Transformations
- > Simpson's Paradox



#### Review

#### Summary statistics

- > Sample mean =  $\mu$  = sum( $x_i$ )/n
- > sample var =  $\sigma$  = sum(( $\mu$   $x_i$ )^2) / (n 1)
- > Sample std =  $sqrt(\sigma)$
- > Standard error of the sample mean = se = std/ sqrt(n)



## Counting

- > Combinatorics of the biggest areas of mathematics.
- > Example:
  - Subway has 4 bread choices, 5 meat choices, 4 toppings. How many sandwich combinations?
  - How many different 4-beer tasters can I have in a bar with 10 beers on tap?
- > Solve these using the 'Multiplication Principle'.
  - Subway Problem:

– Beer Problem:

$$\frac{10}{\text{(# for 1st beer)}}$$
 \*  $\frac{9}{\text{(# for 2nd beer)}}$  \*  $\frac{8}{\text{(# for 3rd beer)}}$  \*  $\frac{7}{\text{(# for 4th beer)}}$  = 5,040



## Multiplication Principle

- > If there are A ways of doing task a, and B ways of doing task b, then there are A\*B ways of completing both tasks.
- > Example:
  - If I have 5 books, how many ways can I order them on the bookshelf?

$$= 5 \text{ factorial} = 5! = 120$$



#### **Factorials**

- > Factorials
  - Count # ways to order N things = N!
- > Factorials get VERY LARGE quickly.
  - 21! Is larger than the biggest long-int in 64 bit.
    - > 21! = 5.1E19
    - > Biggest long int (64 bit) = 9.2E18
  - Fun fact, every 52 card shuffle is highly likely to be the only time that shuffle has ever occurred.



## **Counting Subgroups**

- > Revisit: 10 beers on tap, need a sample of 4 different beers.
- > Let's assume order matters, i.e., Amber-Stout-Porter-Red is different from Red-Porter-Stout-Amber.
- > Use 'Permutations' (pick):

$$10 * 9 * 8 * 7 = \frac{10!}{6!} = \frac{10!}{(10-4)!} = 10P4 = P(10,4)$$



## **Counting Subgroups**

- > Now, Let's assume order doesn't matter.
- > Use 'Combinations' (choose):

$$10 * 9 * 8 * 7 = \frac{10!}{6!} = \frac{10!}{(10-4)!} = 10P4 = P(10,4)$$

(# of orderings of 4 beers) = 4!

$$= \frac{10!}{4!(10-4)!} = 10C4 = C(10,4) = {10 \choose 4}$$



#### More on Combinations

- > Combinations appear on the Pascal's Triangle!
- > C(N,x) appears on the Nth row, xth number (starting at 0)

```
 \begin{array}{c} & & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & & 1 \\ & & &
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## **Counting Examples**

> There are 10 Light beers on tap, and 10 Dark beers on tap, how many ways can I get a 4-beer sampler that contains exactly 1 light beer? (ordering doesn't matter)

$$\frac{(\# of \ ways \ for \ light \ beer) \cdot (\# \ of \ ways \ for \ dark \ beer)}{(\# \ of \ ways \ to \ order \ 1L \ and \ 3D)}$$

$$\frac{(10) \cdot \binom{10}{3}}{4} = \frac{10 * 120}{4} = 300$$



## **Counting Examples**

> 6:5 Blackjack is dealt with a 6 shoe deck (52\*6=312 cards). How many ways can someone get dealt two rank 10 cards?

$$\binom{6decks * 4ranks * 4suits}{2} = \binom{96}{2} = \frac{96!}{2! (94!)} = \frac{96 * 95}{2} = 4560$$



## **Counting Examples**

> How many ways can two dice be rolled to get a sum of 10?

	•		$\cdot$			
•	2	3	4	5	6	7
	3	4	5	6	7	8
ldot	4	5	6	7	8	9
	5	6	7	8	9	10
$\Box$	6	7	8	9	10	11
	7	8	9	10	11	12



## Counting in R

- > expand.grid() function that creates a data frame from all combinations of vectors supplied.
- > R-demo



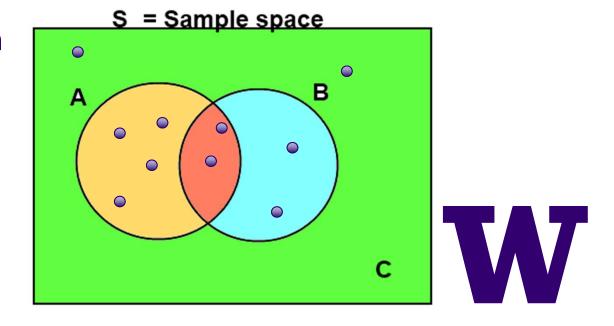
## **Probability**

> The Probability of an event, A, is the number of ways A can occur, divided by the number of total possible outcomes in our Sample Space, S.

$$P(A) = \frac{N(A)}{N(S)}$$

> If • is an event, then

$$P(A) = \frac{6}{10} = \frac{3}{5}$$
$$P(B) = \frac{4}{10} = \frac{2}{5}$$



## **Probability**

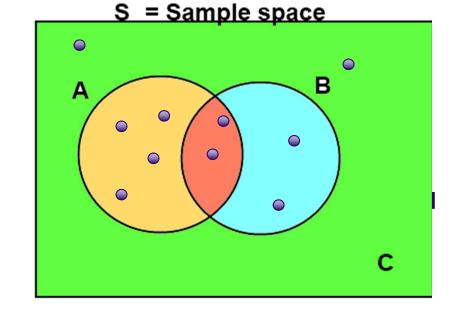
#### > If • is an event, then

- Intersection: 
$$P(A \cap B) = \frac{2}{10} = \frac{1}{5}$$

- Union: 
$$P(A \cup B) = \frac{8}{10} = \frac{4}{5}$$

- Negation: 
$$P(A') = \frac{6}{10} = \frac{3}{5}$$

$$P((A \cup B)') = P(C) = \frac{2}{10} = \frac{1}{5}$$
$$P(A' \cap B') = P(C) = \frac{2}{10} = \frac{1}{5}$$



## **Axioms of Probability**

> Probability is bounded between 0 and 1.

$$0 \le P(A) \le 1$$

Note: "Percent" literally means per one hundred

> Probability of the Sample Space = 1.

$$P(S) = 1$$

> The probability of finite *mutually exclusive* unions is the sum of their probabilities.

$$P(A \cup B) = P(A) + P(B)$$
 If A and B are M.E.



## **Probability Examples**

> Probability of rolling a sum of 10?

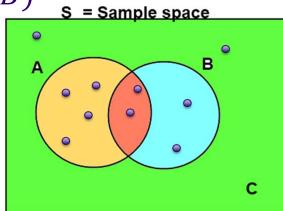
	•		lacksquare			
•	2	3	4	5	6	7
	3	4	5	6	7	8
ldot	4	5	6	7	8	9
	5	6	7	8	9	10
$\Box$	6	7	8	9	10	11
	7	8	9	10	11	12



## Mutually Exclusive Events

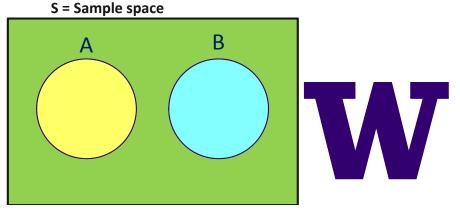
In all cases, the probability of the union of A and B takes the form:

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$



> If A and B are mutually exclusive that means that

$$P(A \cap B) = 0$$
  
 
$$P(A \cup B) = P(A) + P(B)$$

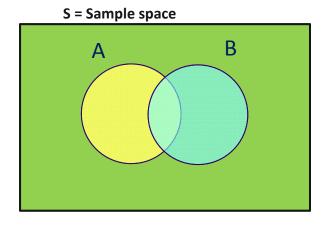


## **Conditional Probability**

> The probability of A *given* B is written:

> And is equal to:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$
 , compare to:  $P(E) = \frac{P(E)}{P(S)}$ 





## Independent Events

> Events A is independent of B if and only if:

$$P(A|B) = P(A)$$

> A being independent of B does NOT imply B is independent of A.

$$P(A|B) = P(A)$$
  $P(B|A) = P(B)$ 

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

E.g. The event that my boss takes vacation has an impact on when I take vacation, but when I take vacation has no impact on when my boss takes vacation. (i.e., his vacation is independent of mine, but not vice versa)



## Independence vs. Mutually Exclusive

- > These are not related AT ALL and in fact, are nearly opposite ideas.
- > If A is M.E. of B then: P(A|B) = 0B occurring has a HUGE impact on P(A)
- > If A is independent of B then: P(A|B) = P(A)

Example: The probability the sidewalk is wet given it is raining is very high, But the probability that it is raining given the sidewalk is wet is lower (if I run my sprinklers often).



#### Odds

- > Odds are expressed as (Count in event favor):(Count not in event favor)
  - Make sure you reduce the fraction first

$$P(A) = \frac{n}{m} = \frac{n}{n + (m - n)}$$

$$\uparrow \qquad \uparrow$$
Count in Count not in favor of A favor of A

– Implies the odds are:

$$n$$
:  $(m-n)$ 

#### Examples:

If P(A)=5/6, then the odds are 5:1. 'Five to one'.

If the odds are 3:20, then P(A)=3/23

A straight up sports bet in Vegas has odds 1:1 (50%), but pays 0.95Xbet.

#### R Demo



- > Famous conditional probability problem that divided statisticians when it came out.
  - Start with 3 doors. One prize behind unknown door. Pick a door. Host reveals a separate door with no prize. Then contestant can switch. Should they?

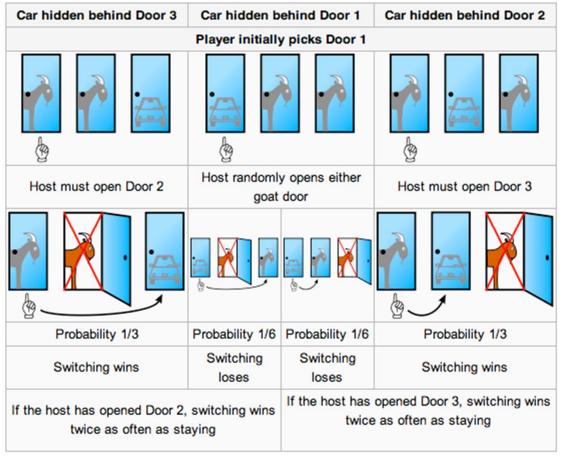


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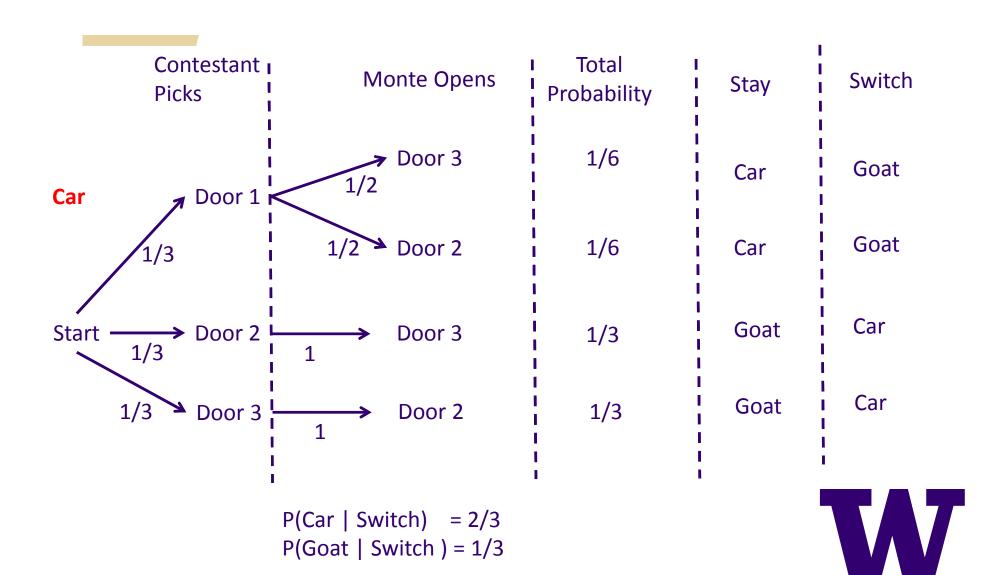


> Start with 3 doors. One prize behind unknown door. Pick a door. Host reveals a separate door with no prize. Then contestant can switch. Should they?





## Monty Hall Problem: Conditional Probabilities



- http://www.stayorswitch.com/
- https://en.wikipedia.org/wiki/Monty\_Hall\_problem



#### **Simulations**

- > Used for complex distributions
- > Can test distributional assumptions
- > Simulate a conditional probability hierarchy
- > Large number of realizations
- > Use system.time() from base or microbenchmark() from microbenchmark package.
- > R Demo



## **Testing Statistical Software**

- > Usual test processes apply: Need to build test cases
- > Test cases must be repeatable (e.g. set.seed())
- > Build test cases as you go: Test driven development



## **Dealing with Missing Data**

- > Reasons for missing data
  - Recording failure (mechanical/software failures)
  - Reporting failure (human decisions)
  - Translation failure (data transferring/parsing errors)
- > Many shapes and types
  - Shapes: block, regular, random, sparse
  - Types:
    - > Missing At Random (MAR): a particular variable has randomly omitted data.
    - > Missing Completely At Random (MCAR): every piece of data has equal chance of being omitted.
    - > Missing Not At Random (MNAR): The value of data is related to chance of being omitted.
- Outliers may also be treated as missing data.

## Dealing with Missing Data

Туре	Benefits	Disadvantages	Notes
Drop Missing	-Speed	-Data Loss	
Substitution	- Speed	- Bias	
Mean/Median/Mode Fill	-No Data Loss	-Variance Reduction	
X~F(independents)	-More Accurate -No Data Loss	-Slower	-Needs most columns to be filled out -Hard on ind. data
knn	-More Accurate -No Data Loss	-Slower -Dependent on distance function - Bias	Forward fill Backward fill
X~F(y,independents)	-Very accurate -No Data Loss	-Slower -Need y	-Only on training set!

## Dealing with Missing Data: Using Outside or New Data Sources

- > Don't forget to explore outside or new data sources to help fill-in missing data.
- > With the advent of free public data and bigger data sources, this is gaining popularity as a tool for imputation.
- > Unstructured text is a major source of data.
- > Ex:
  - Caesar's uses public reviews on websites to mine for customer sentiment about hotel rooms.
  - Zillow uses text descriptions of properties to fill in missing data about # bedrooms, # bathrooms, sq. footage, and various amenities.
  - Subject to human stupidity.

Yelp Rating for Circus-Circus: 2/5

Text Description: "My son and I stayed here. The service was great, the room was great, but it turns out my son is deathly afraid of clowns."



# Dealing with Missing Data: Variance and Multiple Imputation

- Imputation tries and maintain the intrinsic variance in the data set.
- > Multiple different predictions are made for each missing data point. (Using previous methods)
- > Hypothesis testing and predictions are made on all imputed sets to gauge the variance in the outcomes.
- > R package 'Amelia' does this and creates a nested list of data frames.
- > Lots of details at: <a href="https://cran.r-">https://cran.r-</a>
  project.org/web/packages/Amelia/vignettes/amelia.p
  df
- > R demo

## **Getting Data**

#### > Files

- Csv: read.csv
- Txt: read.table

#### > Web/HTML

- readLines
- XML, xpath
- http://gastonsanchez.com/work/webdata/getting\_web\_data\_r4\_p arsing\_xml\_html.pdf

#### > Databases

- Sqlite: sqldf, RSQLite packages
  - > Sqlite example
- MongoDB: rmongodb package
- Postgresql: RPostgreSQL package



## **Storing Data**

- > .csv write.csv()
- > .txt write.txt()
- > .Rdata save()
  - Workspaces are very compressed compared to csv
- > Databases
  - Sqlite: sqldf, RSQLite packages
    - > Sqlite example
  - MongoDB: rmongodb package
  - Postgresql: RPostgreSQL package



#### SQL and R

- > Handle datasets larger than memory
- > Support several common databases.
- > e.g. SQLite: <a href="http://www.r-bloggers.com/r-and-sqlite-part-1/">http://www.r-bloggers.com/r-and-sqlite-part-1/</a>
- > Or with dplyr: <a href="https://cran.r-">https://cran.r-</a>
  project.org/web/packages/dplyr/vignettes/databases.htm
  [
- > And, many other packages and references: search around.
- > R Demo



## Assignment

#### > Homework 2:

- Write an R-script to compute the Monty Hall Probabilities with simulations (get probabilities AND variances for switching and not switching).
- You should submit:
  - > **ONE** R-script that outputs the probabilities and variances.
  - > Submission should include a proof of correct answer: chart and table.
- Read Intro to Data Science Chapter 7 and 10.
- Read Statistical Thinking for Programmers Ch. 4.

