

UNIVERSITY *of* WASHINGTON

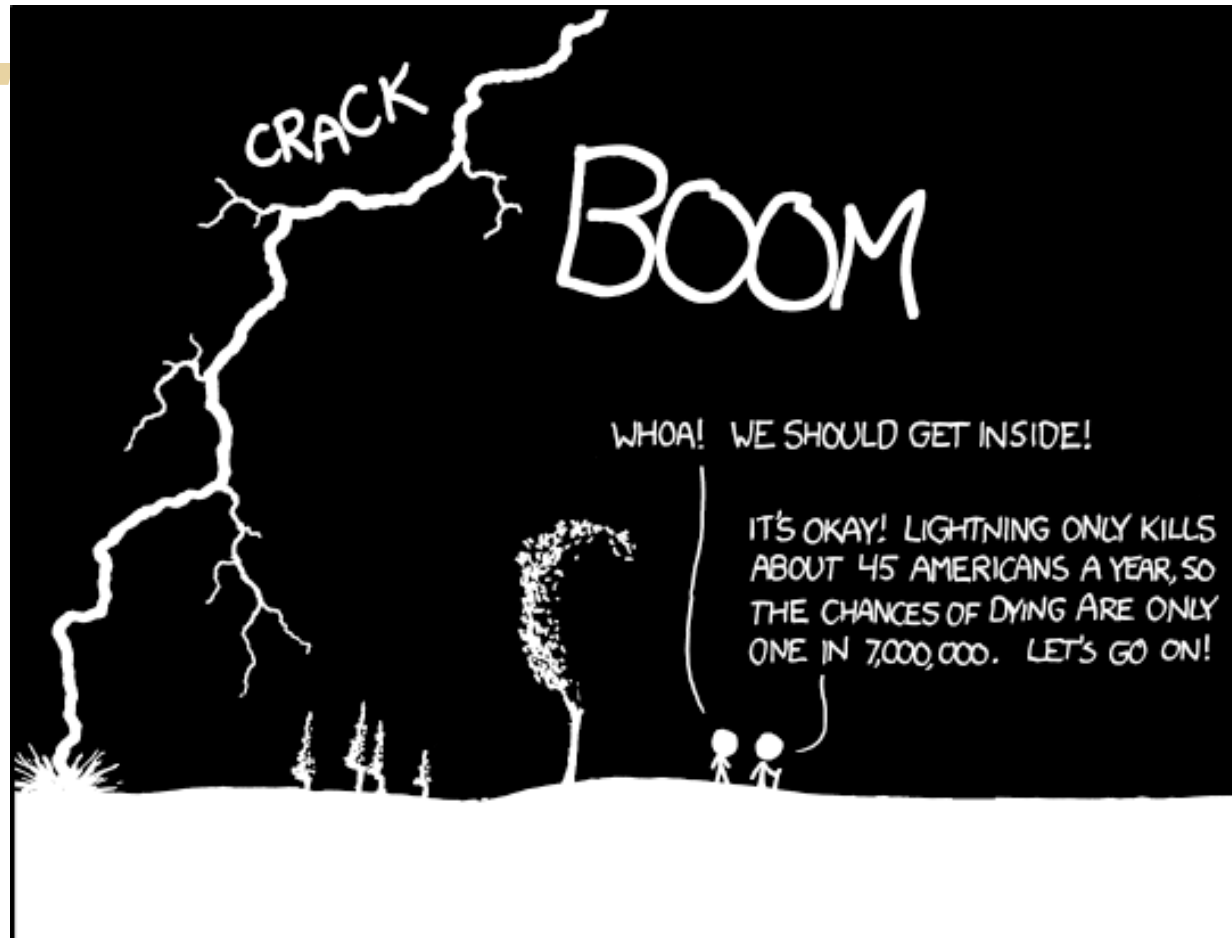
# Data Science UW

## Methods for Data Analysis

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Probability and More on Distributions  
Lecture 2  
Stephen Elston





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

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# Topics



- > Review
- > Counting
- > Axioms of Probability
- > Probability Examples
- > Conditional Probability
- > Simulation



# Review

## Summary statistics

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





# Review



## Data exploration and visualization

- > Develop understanding of relations in data set
- > Use multiple views
- > Iterative process
  - Try lots of things
  - Fail lots and fast
  - Find what works



# 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:

$$\begin{array}{ccccccc} 4 & * & 5 & * & 4 & = & 80 \\ \hline & & & & & & \\ \text{(# of breads)} & & \text{(# of meats)} & & \text{(# of toppings)} & & \end{array}$$

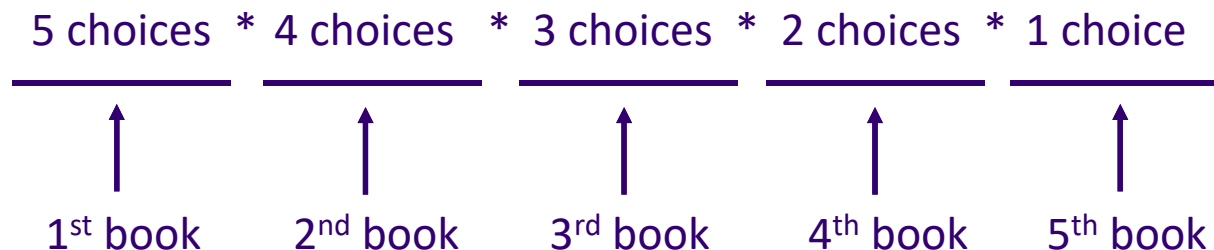
– Beer Problem:

$$\begin{array}{ccccccccccc} 10 & * & 9 & * & 8 & * & 7 & = & 5,040 \\ \hline & & & & & & & & & \\ \text{(# for 1<sup>st</sup> beer)} & & \text{(# for 2<sup>nd</sup> beer)} & & \text{(# for 3<sup>rd</sup> beer)} & & \text{(# for 4<sup>th</sup> beer)} & & & \end{array}$$



# 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.
  - >  $21! = 5.1\text{E}19$
  - > Biggest long int (64 bit) =  $9.2\text{E}18$
- 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):

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

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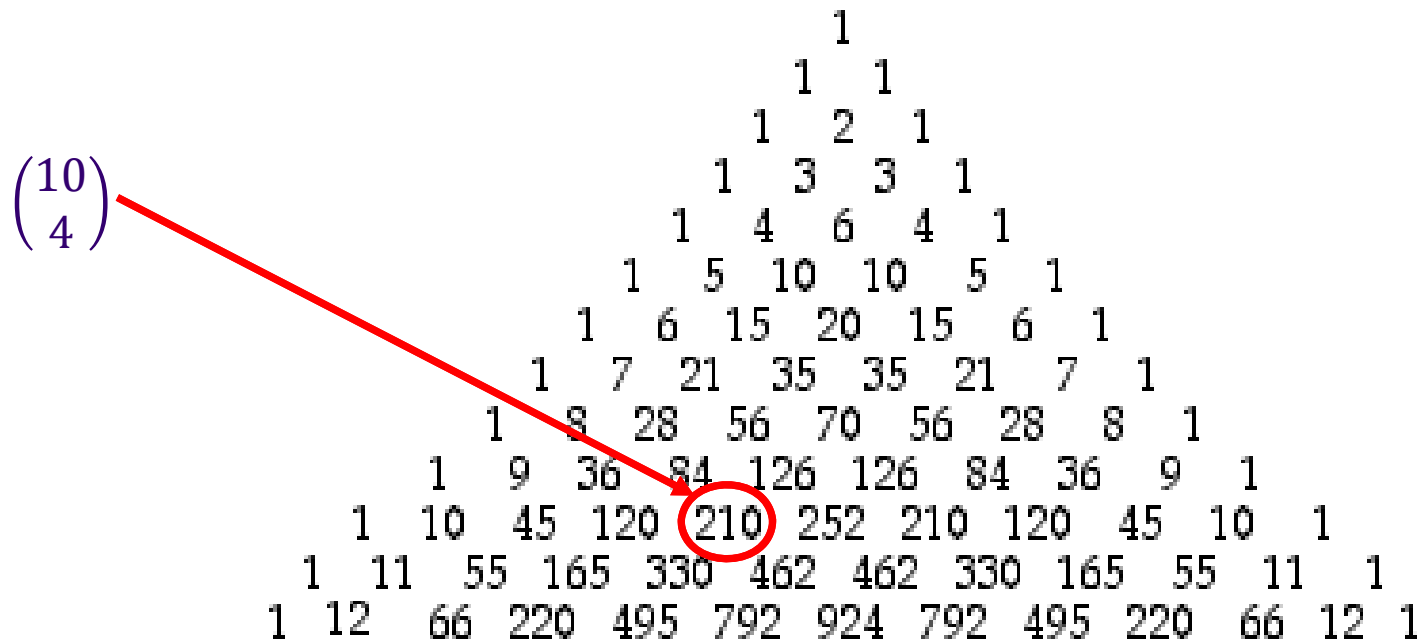
*(# of orderings of 4 beers) = 4!*

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



## More on Combinations

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



## 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)

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

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



## Counting Examples

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

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



## Counting Examples

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

	1	2	3	4	5	6
1	2	3	4	5	6	7
2	3	4	5	6	7	8
3	4	5	6	7	8	9
4	5	6	7	8	9	10
5	6	7	8	9	10	11
6	7	8	9	10	11	12

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## Counting in R

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



# Probability

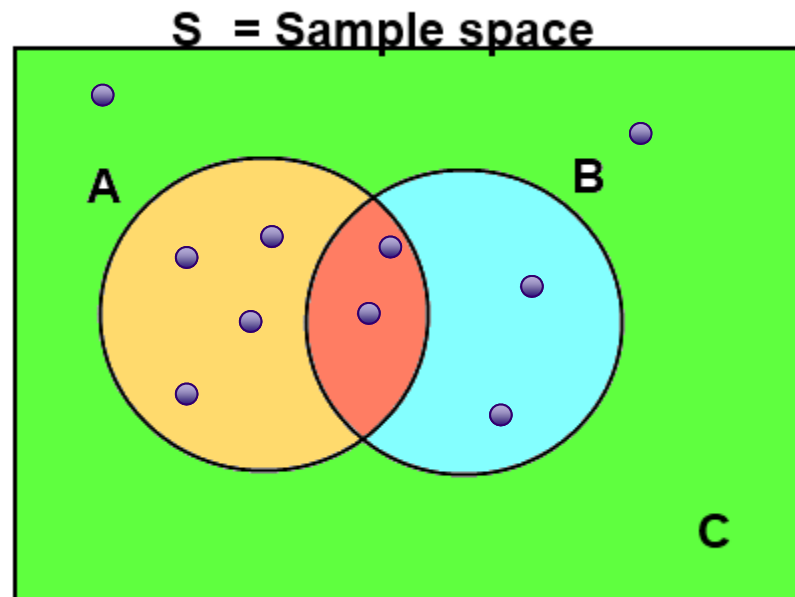
- > The Probability of an event, A, is the number of ways A can occur, divided by the number of total possible outcomes in our Sample Space, S.

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

- > If • is an event, then

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

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



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# Probability

> If  $\bullet$  is an event, then

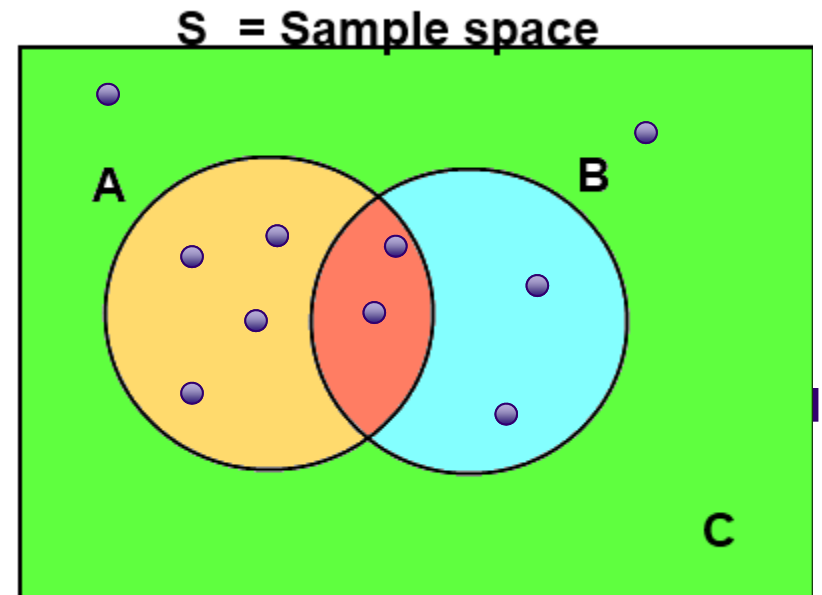
– Intersection:  $P(A \cap B) = \frac{2}{10} = \frac{1}{5}$

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

– Negation:  $P(A') = \frac{4}{10} = \frac{2}{5}$

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

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



# Axioms of Probability

- > Probability is bounded between 0 and 1.

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

Note: “Percent” literally means per one hundred

- > Probability of the Sample Space = 1.

$$P(S) = 1$$

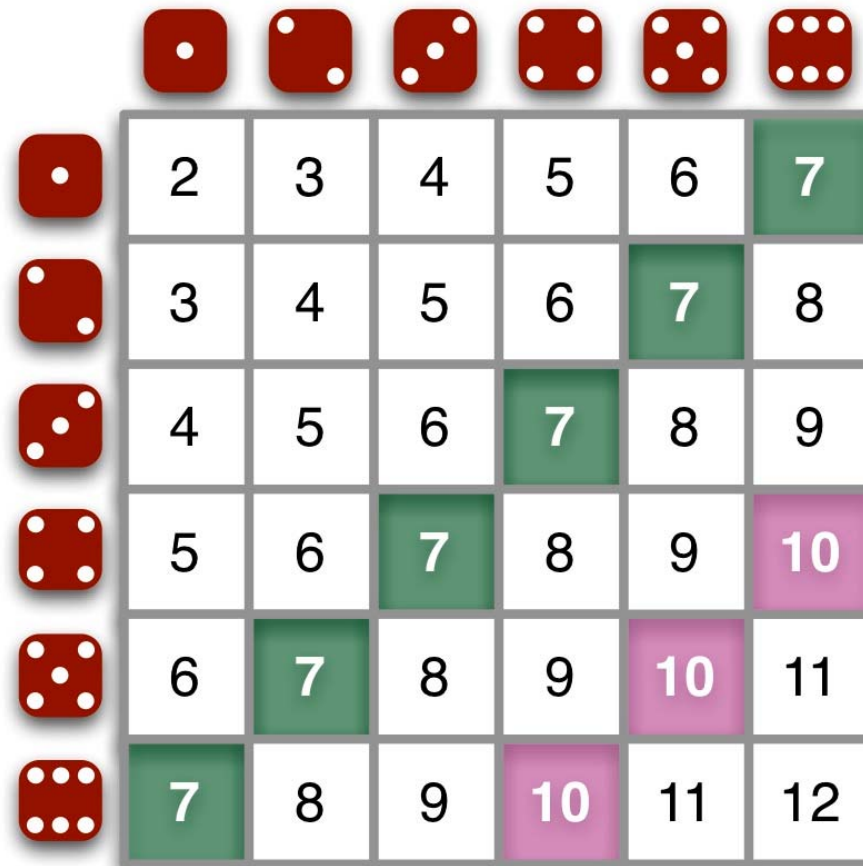
- > The probability of finite *mutually exclusive* unions is the sum of their probabilities.

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



# Probability Examples

> Probability of rolling a sum of 10?



A 6x6 grid of dice rolls. The top and left sides of the grid are labeled with red dice icons showing 1 through 6 dots. The grid contains the following values:

2	3	4	5	6	7
3	4	5	6	7	8
4	5	6	7	8	9
5	6	7	8	9	10
6	7	8	9	10	11
7	8	9	10	11	12

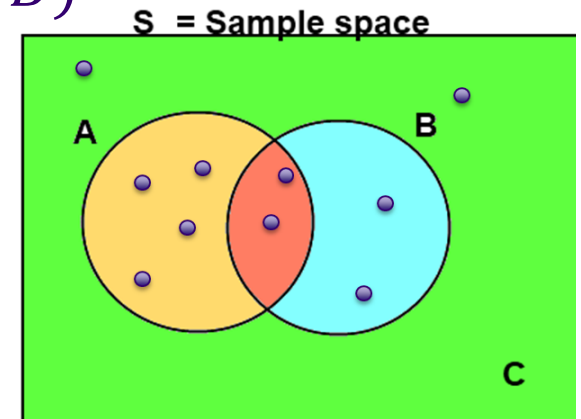
The cells containing the values 7, 7, 7, 7, 10, and 10 are highlighted in green. The cells containing the values 10 and 10 are highlighted in pink.

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# Mutually Exclusive Events

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

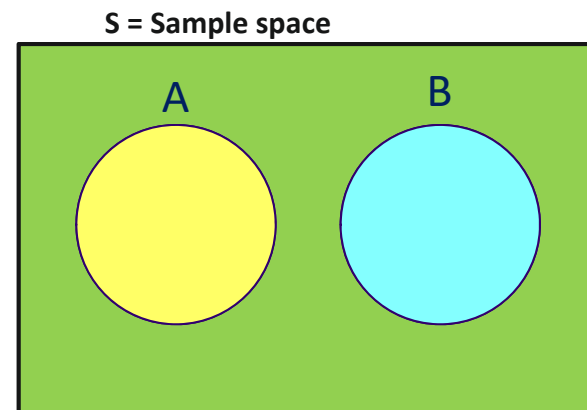
$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$



- > If A and B are mutually exclusive that means that

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

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



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# Conditional Probability

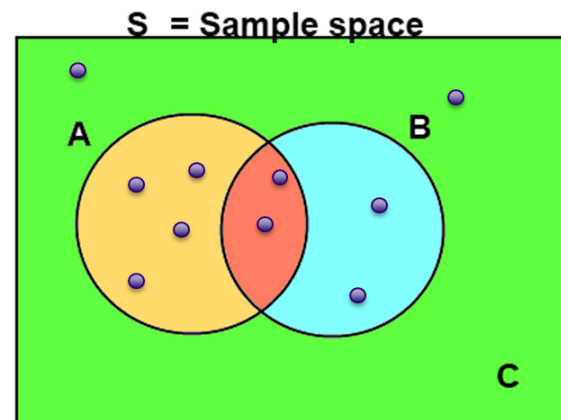
> The probability of *A given B* is written:

$$P(A|B)$$

> And is equal to:

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

$$P(A|B) = \frac{2/10}{4/10} = \frac{2}{4} = \frac{1}{2}$$



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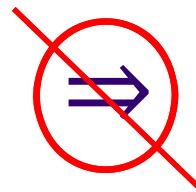
# Independent Events

- > 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.

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



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

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

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:  $P(A|B) = 0$



B 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

$$P(A) = \frac{n}{m} = \frac{n}{\underset{\substack{\uparrow \\ \text{Count in} \\ \text{favor of A}}}{n} + \underset{\substack{\uparrow \\ \text{Count not in} \\ \text{favor of A}}}{(m - n)}}$$

– 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



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# Monty Hall Problem

- > 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?



# Monty Hall Problem

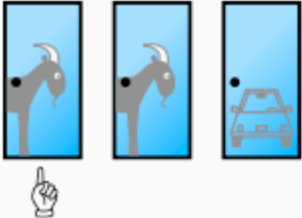
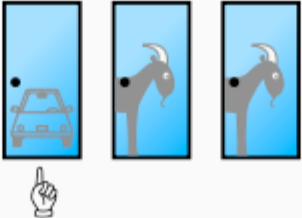
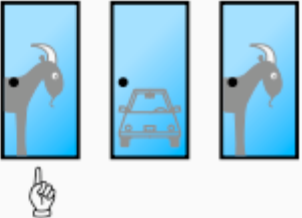
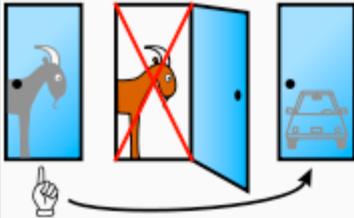
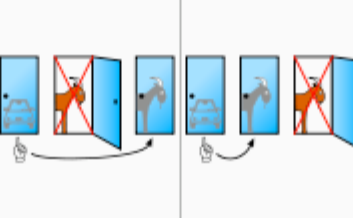
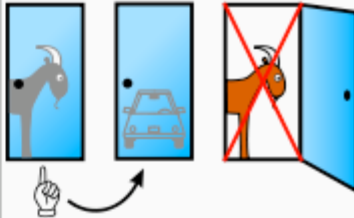
- > Start with 3 doors. One prize behind unknown door. Pick a door. Host reveals a separate door with no prize. Then contestant can switch. Should they?

Car hidden behind Door 3	Car hidden behind Door 1	Car hidden behind Door 2
Player initially picks Door 1		
		
Host must open Door 2	Host randomly opens either goat door	Host must open Door 3



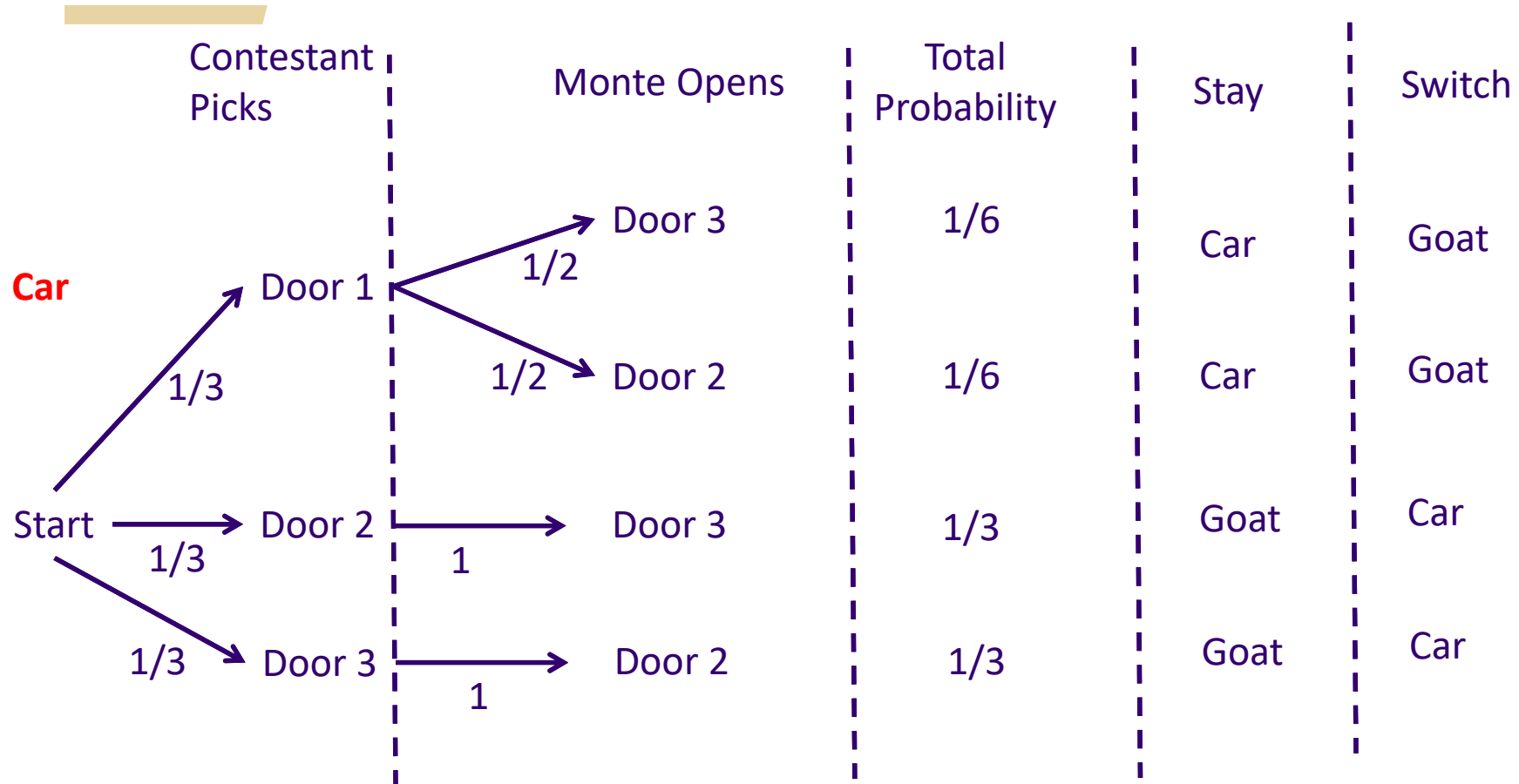
# Monty Hall Problem

- > 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?

Car hidden behind Door 3	Car hidden behind Door 1	Car hidden behind Door 2
Player initially picks Door 1		
		
Host must open Door 2	Host randomly opens either goat door	Host must open Door 3
		
Probability 1/3	Probability 1/6	Probability 1/6
Switching wins	Switching loses	Switching loses
If the host has opened Door 2, switching wins twice as often as staying		If the host has opened Door 3, switching wins twice as often as staying

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# Monty Hall Problem: Conditional Probabilities



$$P(\text{Car} \mid \text{Switch}) = 2/3$$

$$P(\text{Goat} \mid \text{Switch}) = 1/3$$

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# Monty Hall Problem

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- <http://www.stayorswitch.com/>
  - [https://en.wikipedia.org/wiki/Monty\\_Hall\\_problem](https://en.wikipedia.org/wiki/Monty_Hall_problem)



# Statistics Review

- > Familiar Concepts:
  - Discrete vs. Continuous Distributions
  - Probability
  - Statistics
  - $y = mx + b$  vs  $\bar{Y} = \mathbf{M} \cdot \bar{X} + \mathbf{B}$
- > These concepts are the focus of this course.



# Counting Review

## > Factorials

- Count # ways to order N things =  $N!$

## > Permutations

- Count # of ways to **order** R things from N things =  $N!/(N-R)!$
- Ordering matters
- $P(N,R)$

## > Combinations

- Count # of ways to **group** R things from N things =  $N!/(R!(N-R)!)$
- Ordering doesn't matter
- $C(N,R)$  or  $\binom{N}{R}$

## > We will talk about this in depth next class.





# Data Distributions (Discrete)

- > Discrete Distribution Properties
  - Sum of probability of all possible events must equal 1.
  - Probability of event equal to value of distribution at point.
  - All values strictly in range 0-1.



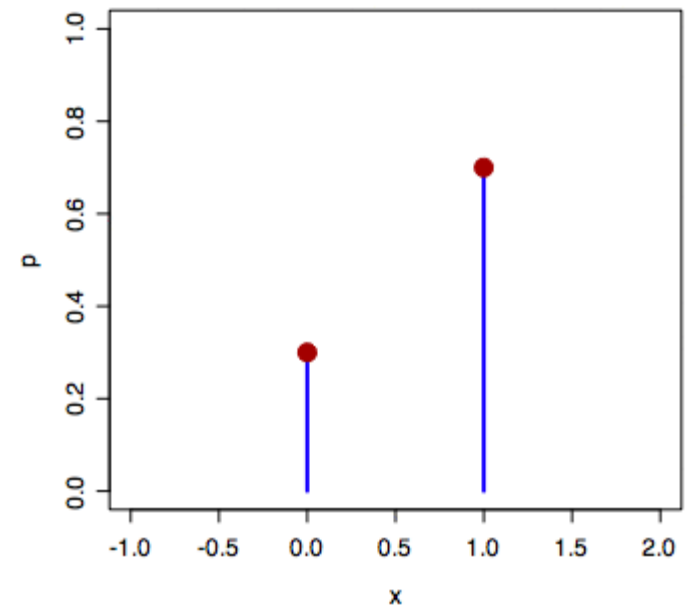
# Data Distributions (Discrete)

> Bernoulli (1 event, e.g.: coin flip)

$$P(x) = \begin{cases} p & \text{if } x = 1 \\ (1 - p) & \text{if } x = 0 \end{cases}$$

$$P(x) = p^x (1 - p)^{(1-x)} \quad x \in \{0,1\}$$

- Mean =  $p$
- Variance =  $p(1-p)$



# Data Distributions (Discrete)

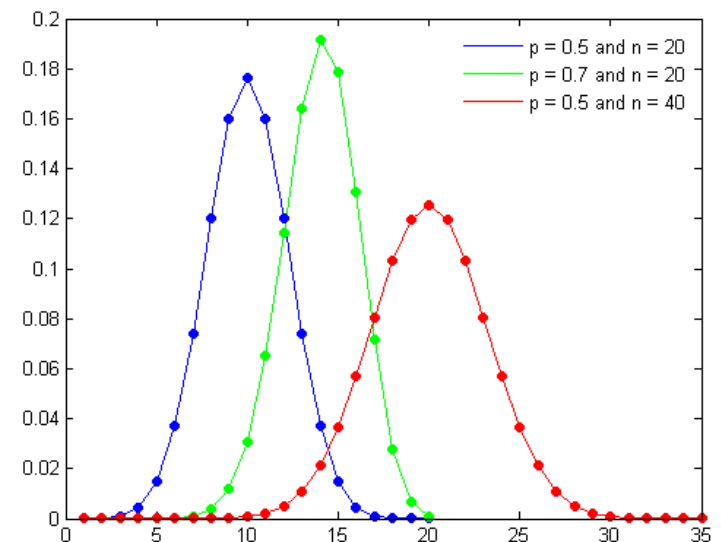
## > Binomial (Multiple Bernoulli's Events)

- Multiple Independent events = Product of Bernoulli Probabilities

$$P(x|N, p) = \binom{N}{x} p^x (1 - p)^{(N-x)}$$

- Mean =  $np$
- Variance =  $np(1-p)$

Note: for larger  $n$ , we approximate this by a normal distribution.



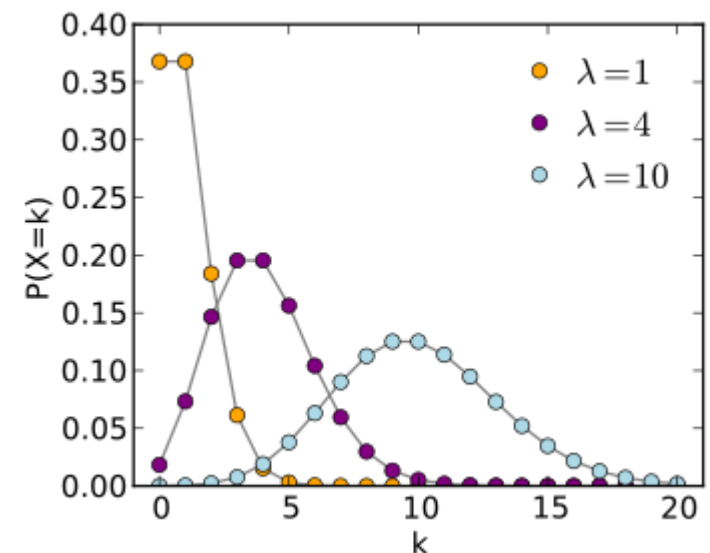
# Data Distributions (Discrete)

- > Poisson (Count of number of events in a time span)

$$P(x|\lambda) = \frac{\lambda^x}{x!} e^{-\lambda}$$

- Mean =  $\lambda$
- Variance =  $\lambda$

Interpret as the rate of occurrence of an event is equal to lambda in a finite period of time.





# R Demo



Discrete distributions



# Data Distributions (Continuous)

## > Continuous Distribution Properties

- Area under the curve must be equal to 1.
- Probability a range of values of an event equal to AREA under curve.
- No negative values.
- Probability of a single, exact value is 0.

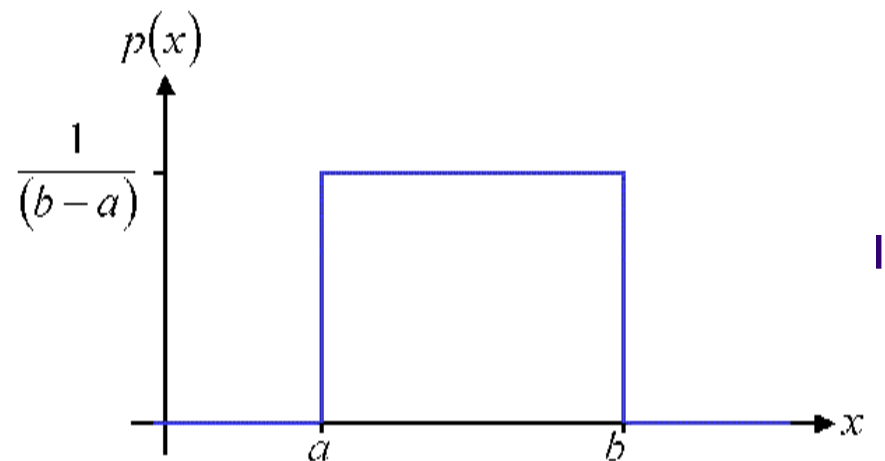


# Data Distributions (Continuous)

- > Uniform (flat, bounded)

$$P(x) = \begin{cases} \frac{1}{(b-a)} & \text{if } a \leq x \leq b \\ 0 & \text{if } x < a \text{ or } x > b \end{cases}$$

- > Used for parameter priors. (future discussion)
  - Mean =  $(a+b)/2$
  - Variance =  $(1/12)(b-a)^2$



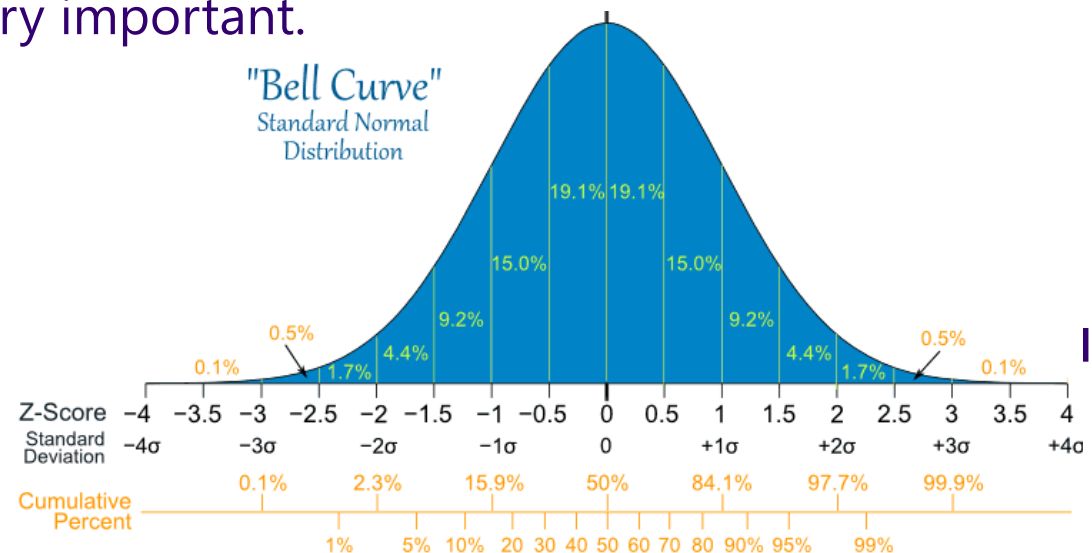
# Data Distributions (Continuous)

## > Normal (Gaussian) distribution

- Most common and occurs naturally.
- Defined by a mean and variance only. (standard =  $N(0,1)$ )

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- Has very nice properties.
- Tests for normality are very important.





# Data Distributions (Continuous)

- > Student's T (normal for small samples)
  - Important for hypothesis testing smaller sample sizes.
  - Used for:
    - > Testing of mean value when st. dev. is unknown.
    - > Testing difference between two distribution means.
  - Looks very similar to the normal distribution.





# R Demo



Continuous distributions





# 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





R DEMO



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## R review and summary statistics



- > Purpose: To gain a clear understanding of your data.
  - How large is it?
  - What columns are of interest?
  - Missing data?
  - Outliers?

