

SOC 3811/5811:  
BASIC SOCIAL STATISTICS

Discrete Random Variables

# Probability

## Random Event

An event in which the outcome is determined by chance

## Probability

An expression of how likely it is that a particular event (E) will result from a random event

Probabilities are expressed as a number between 0 (the event will certainly not occur) and 1 (the event certainly will occur)

$P(E)=0.2$  means “the probability that event X will occur is 0.2”

$P(\sim E)=0.8$  means “the probability that event X will not occur is 0.8”

$P(E) + P(\sim E) = 1.0$  ... so ...  $P(\sim E) = 1.0 - P(E)$

# Probability

## Random Event: *Tossing a Fair Coin*

Possible Outcomes:  

Probabilities:  $P(\text{Obverse}) = 0.5$  ;  $P(\text{Reverse}) = 0.5$  ;  $P(\text{Obverse}) + P(\text{Reverse}) = 1.0$

## Random Event: *Roll a Pair of Dice*

Possible Outcomes:      

Probabilities:  $P(1) = 0.167$  ;  $P(2) = 0.167$  ; ... ;  $P(6) = 0.167$

$P(1) + P(2) + \dots + P(6) = 1.0$

## Random Event: *Whether a Person Has Ever Been Arrested*

Possible Outcomes: Has Been Arrested; Has Never Been Arrested

Probabilities:  $P(\text{Ever Arrested}) = 0.3$  ;  $P(\text{Never Arrested}) = 0.7$

$P(\text{Ever Arrested}) + P(\text{Never Arrested}) = 1.0$

# Probability

## Independent Random Events

Events A and B are *independent* if  $P(A)$  is the same regardless of whether Event B happens, and  $P(B)$  is the same regardless of whether Event A happens

*Example:* If you flip two coins,  $P(\text{heads}) = 0.5$  for the second coin regardless of what happened when you flipped the first coin

## Conditional (or non-Independent) Random Events

Event B is conditional on Event A if  $P(B)$  depends on whether or not Event A happened

*Example:* If you draw two cards from a deck of playing cards,  $P(\text{Ace of Spades})$  on your second card depends on what you drew on your first card.

A person's birthday is a random event. If you pick two people at random, are their birthdays **independent** or **dependent** events?

# WORKSHEET

Whether a job applicant gets the job is a random event. If you pick two people from among the applicants for a particular job, and only one of them can get the job, are their application outcomes **independent** or **dependent** events?

# Probability

## Independent Random Events

For two independent random events A and B...

...the probability that both Event A and Event B happen is:

$$P(A \text{ and } B) = P(A) \times P(B)$$

$$\text{Example: } P(\text{🎲} \text{ and } \text{🎲}) = P(\text{🎲}) \times P(\text{🎲}) = 0.167 \times 0.167 = 0.028$$

...the probability that either Event A or Event B happens is:

$$P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$$

$$\text{Example: } P(\text{🎲} \text{ or } \text{🎲}) = P(\text{🎲}) + P(\text{🎲}) - P(\text{🎲} \text{ and } \text{🎲}) \\ 0.167 + 0.167 - 0.028 = 0.361$$

# Probability

## Independent Random Events

For two independent random events A and B...

...the probability that both Event A and Event B happen is:

$$P(A \text{ and } B) = P(A) \times P(B)$$

Example:  $P(\text{🎲} \text{ and } \text{🪙}) = P(\text{🎲}) \times P(\text{🪙}) = 0.167 \times 0.500 = 0.083$

...the probability that either Event A or Event B happens is:

$$P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$$

Example:  $P(\text{🎲} \text{ or } \text{🪙}) = P(\text{🎲}) + P(\text{🪙}) - P(\text{🎲} \text{ and } \text{🪙})$   
 $0.167 + 0.500 - 0.083 = 0.584$



# Probability

## Conditional (or non-Independent) Random Events

If  $P(B)$  for Event B is dependent upon the outcome of Event A, then...

...the probability that both Event A and Event B happen is:

$$P(A \text{ and } B) = P(A) \times P(B|A)$$

Example: What is the probability of drawing two cards (A and B) from a deck and having them both be red? For the first drawn card,  $P(A) = 26/52 = 0.5$ . However, for the second drawn card,  $P(B)$  is not  $26/52$  because there are only 51 cards left in the deck. The probability that the second card is red *given that the first card was red* ...  $P(B|A)$  ... is  $25/51 = 0.4902$ . So  $P(A \text{ and } B) = P(A) \times P(B|A) = 0.5 \times 0.4902 = 0.2451$

		< < < Dealers Up Card > > >									
		2	3	4	5	6	7	8	9	10	A
Y o u r  H a n d	8 or less	H	H	H	H	H	H	H	H	H	H
	9	H	D	D	D	D	H	H	H	H	H
	10	D	D	D	D	D	D	D	D	H	H
	11	D	D	D	D	D	D	D	D	D	H
	12	H	H	S	S	S	H	H	H	H	H
	13	S	S	S	S	S	H	H	H	H	H
	14	S	S	S	S	S	H	H	H	H	H
	15	S	S	S	S	S	H	H	H	H/SU	H
	16	S	S	S	S	S	H	H	H/SU	H/SU	H/SU
	17+	S	S	S	S	S	S	S	S	S	S
	A8-10	S	S	S	S	S	S	S	S	S	S
	A7	S	D	D	D	D	S	S	H	H	H
	A6	H	D	D	D	D	H	H	H	H	H
	A5	H	H	D	D	D	H	H	H	H	H
	A4	H	H	D	D	D	H	H	H	H	H
	A3	H	H	H	D	D	H	H	H	H	H
	A2	H	H	H	D	D	H	H	H	H	H
	A-A,8-8	SP	SP	SP	SP	SP	SP	SP	SP	SP	SP
	10-10	S	S	S	S	S	S	S	S	S	S
	9-9	SP	SP	SP	SP	SP	S	SP	SP	S	S
7-7	SP	SP	SP	SP	SP	SP	H	H	H	H	
6-6	H	SP	SP	SP	SP	H	H	H	H	H	
5-5	D	D	D	D	D	D	D	D	H	H	
4-4	H	H	H	H	H	H	H	H	H	H	
3-3,2-2	H	H	SP	SP	SP	SP	H	H	H	H	
		2	3	4	5	6	7	8	9	10	A
		< < < Dealers Up Card > > >									

**H** = Hit      **S** = Stand      **D** = Double Down      **SP** = Split

**H/SU** = Surrender if able to, otherwise Hit

# Probability Distributions

If we flip a fair coin 3 times, we will observe independent events A, B, and C. What are the possible outcomes? How likely is each outcome?

$$P(\text{H H H}) = 0.5 \times 0.5 \times 0.5 = 0.125$$

$$P(\text{H H T}) = 0.5 \times 0.5 \times 0.5 = 0.125$$

$$P(\text{H T H}) = 0.5 \times 0.5 \times 0.5 = 0.125$$

$$P(\text{H T T}) = 0.5 \times 0.5 \times 0.5 = 0.125$$

$$P(\text{T H H}) = 0.5 \times 0.5 \times 0.5 = 0.125$$

$$P(\text{T H T}) = 0.5 \times 0.5 \times 0.5 = 0.125$$

$$P(\text{T T H}) = 0.5 \times 0.5 \times 0.5 = 0.125$$

$$P(\text{T T T}) = 0.5 \times 0.5 \times 0.5 = 0.125$$

# Probability Distributions

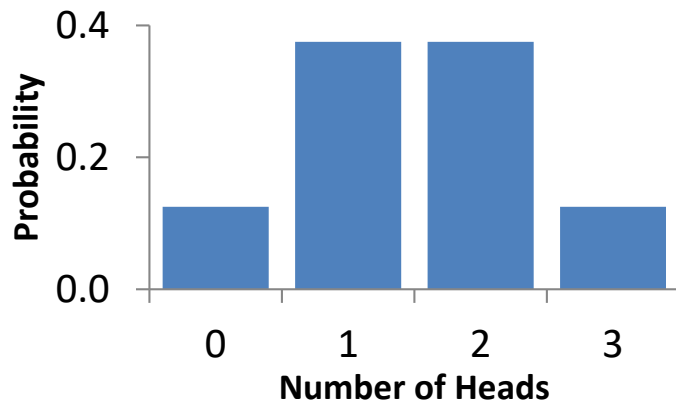
If we flip a fair coin 3 times, how many different numbers of “heads” might come up? How likely is each possible value?

$$P(3 \text{ Heads}) = P(\text{H H H}) = 0.125$$

$$P(2 \text{ Heads}) = P(\text{H H T}) + P(\text{H T H}) + P(\text{T H H}) = 3 \times 0.125 = 0.375$$

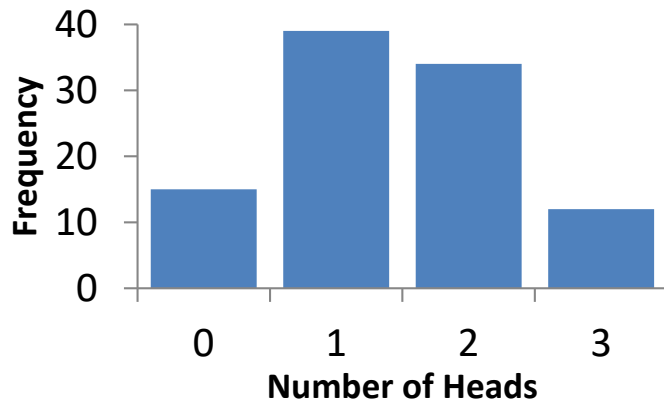
$$P(1 \text{ Head}) = P(\text{T H T}) + P(\text{T T H}) + P(\text{H T T}) = 3 \times 0.125 = 0.375$$

$$P(0 \text{ Heads}) = P(\text{T T T}) = 0.125$$



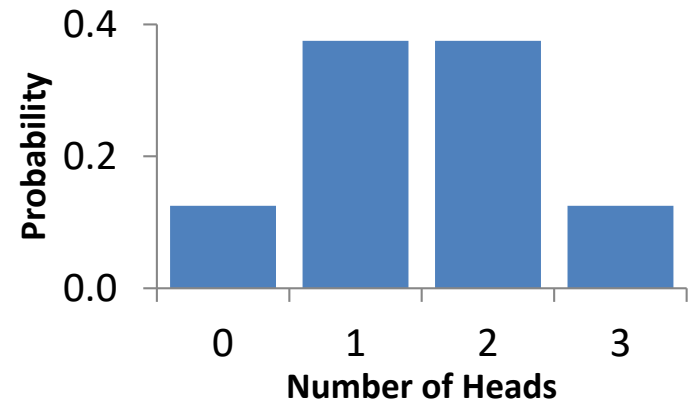
# Probability Distributions

Now imagine I went and *actually* flipped three fair coins, recorded the number of heads, and repeated that game 100 times. On the left is what I observed:



What we saw

This is an observed  
distribution  
(from flipping 3 coins 100 times)

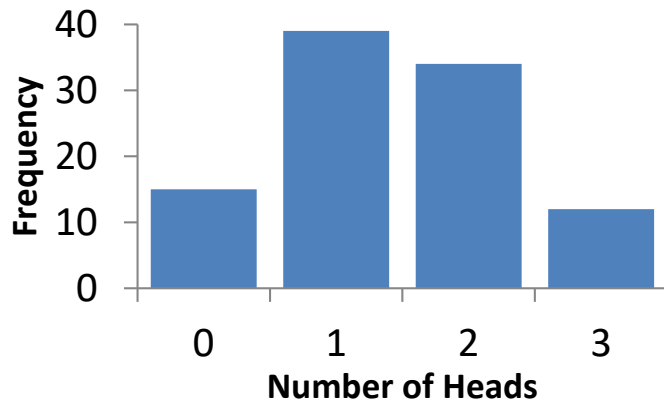


What we expected

This is a theoretical  
distribution  
(if we flipped 3 coins  $\infty$  times)

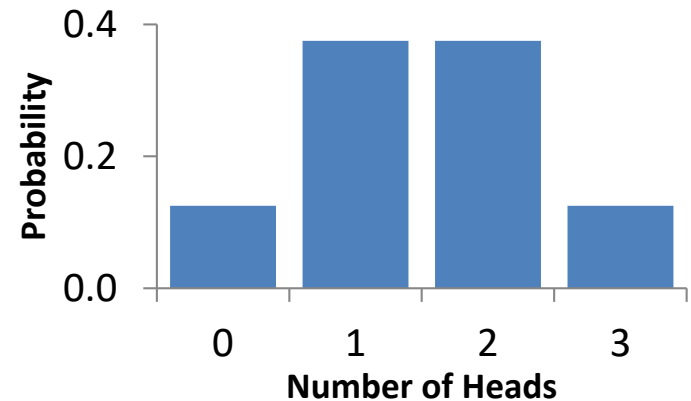
# Probability Distributions

Now imagine I went and *actually* flipped three fair coins, recorded the number of heads, and repeated that game 100 times. On the left is what I observed:



What we saw

This is sample data  
(from flipping 3 coins 100 times)



What we expected

This is population data  
(if we flipped 3 coins  $\infty$  times)

# Random Variables

## Random variable

The numeric outcome of a random event

### Random Event

Flip a fair coin 3 times

Sample a person from the U.S.

Sample water from a lake

### Random Variable

Number of “heads” observed

Whether they have been  
arrested

Bacteria per cubic inch

For each random variable, the outcome values vary across cases as a function of a chance process, and are unknown in advance

# Random Variables

## Random Event

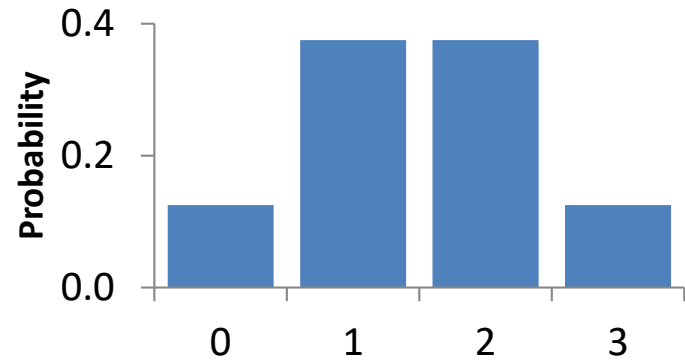
3 Coin Flips

(Repeated Infinitely)



## Theoretical Distribution

for the **Population** of  
All Possible 3 Coin Flips



## Random Event

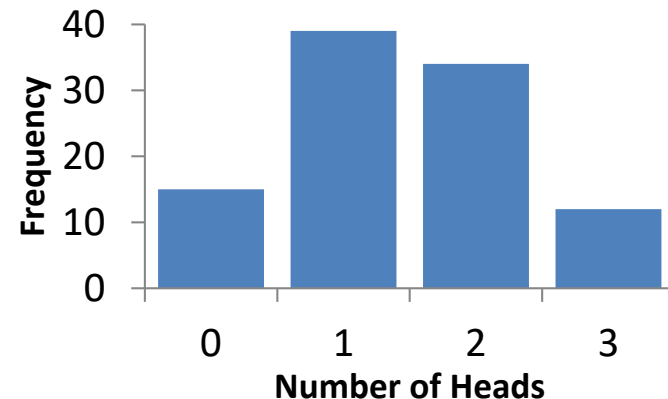
3 Coin Flips

(Repeated 100 Times)



## Observed Distribution

for a **Sample** of  
100 Sets of 3 Coin Flips





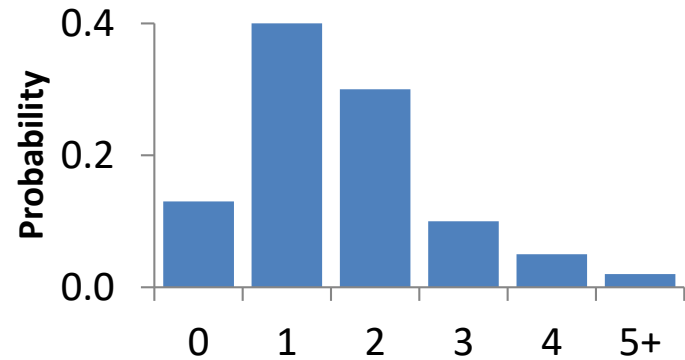
# Random Variables

## Random Event

Survey Question About # of Kids  
(Repeated Infinitely)



**Theoretical Distribution**  
for the **Population** of  
**All Possible Responses**

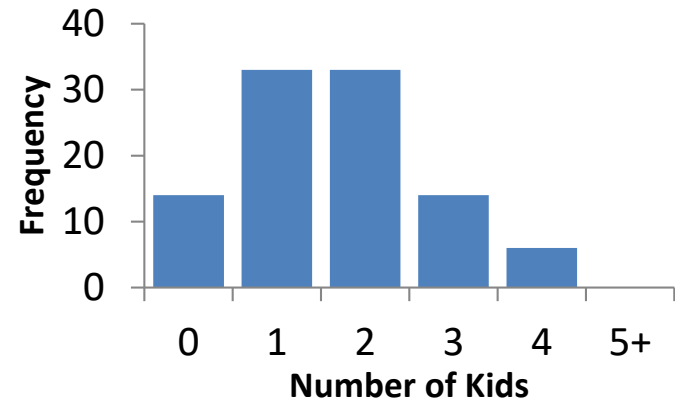


## Random Event

Survey Question About # of Kids  
(Repeated 100 Times)



**Observed Distribution**  
for a **Sample** of  
**100** Sets of Responses



# Reality

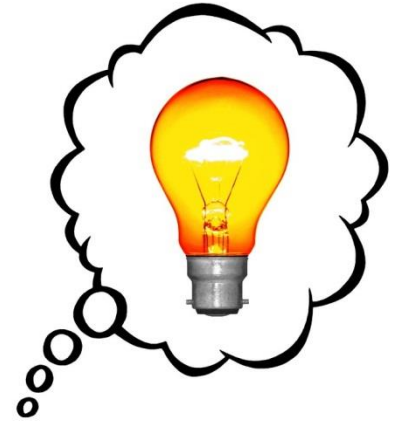


# Data

```
2954462187388221348
8711102682140050851
9291758426493659357
1797402968538728539
4401671369193970834
0165785879715135279
6365488407871392124
2920353540363160907
9546090581563252173
8998220343490929571
8159244365888845385
0229635205640107762
4385245611536981630
9196626803867353805
4956868092019177602
1078342587201850530
2250228297490991053
5575276026995705920
9224813120745604486
```

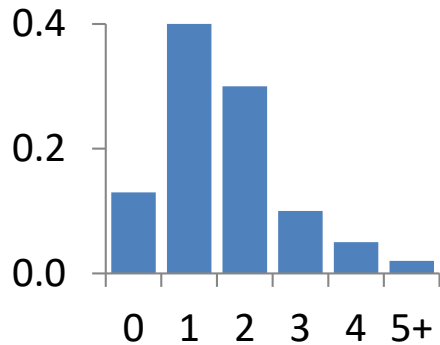


# Knowledge



# Reality

**Theoretical Distribution**  
for the **Population** of  
**All Possible Responses**



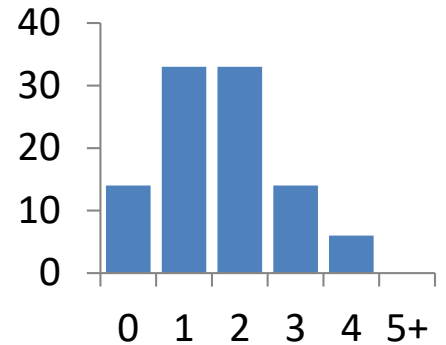
# Data

```
2954462187388221348
8711102682140050851
9291758426493659357
1797402968538728539
4401671369193970834
0165785879715135279
6365488407871392124
2920353540363160907
9546090581563252173
8998220343490929571
8159244365888845385
0229635205640107762
4385245611536981630
9196626803867353805
4956868092019177602
1078342587201850530
2250228297490991053
5575276026995705920
9224813120745604486
```



# Knowledge

**Observed Distribution**  
for a **Sample** of  
**100 Sets of Responses**



# Random Variables

## Today

We know the actual probabilities associated with the random event that generates the theoretical distribution (e.g., coin flips)

We will learn to *describe* and *make practical use* of these theoretical distributions

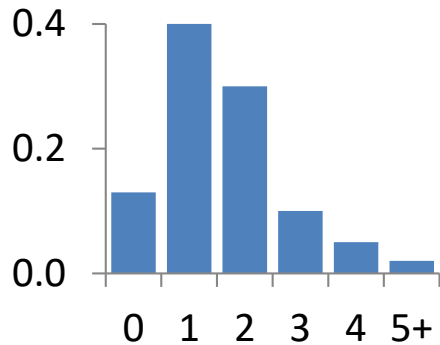
## Later (and in Life)

We do not know the actual probabilities associated with the random event (e.g., number of children per person, which candidate will win)

Our ability to *describe* and *make practical use* of theoretical distributions will allow us to infer those probabilities

# Reality

**Theoretical Distribution**  
for the **Population** of  
**All Possible Responses**



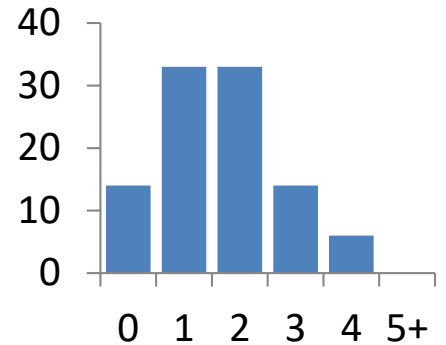
# Data

```
2954462187388221348
8711102682140050851
9291758426493659357
1797402968538728539
4401671369193970834
0165785879715135279
6365488407871392124
2920353540363160907
9546090581563252173
8998220343490929571
8159244365888845385
0229635205640107762
4385245611536981630
9196626803867353805
4956868092019177602
1078342587201850530
2250228297490991053
5575276026995705920
9224813120745604486
```



# Knowledge

**Observed Distribution**  
for a **Sample** of  
**100 Sets of Responses**



# Reality



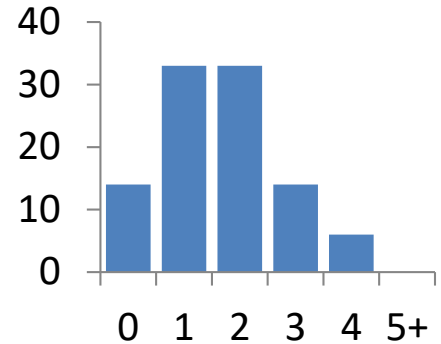
# Data

```
2954462187388221348
8711102682140050851
9291758426493659357
1797402968538728539
4401671369193970834
0165785879715135279
6365488407871392124
2920353540363160907
9546090581563252173
8998220343490929571
8159244365888845385
0229635205640107762
4385245611536981630
9196626803867353805
4956868092019177602
1078342587201850530
2250228297490991053
5575276026995705920
9224813120745604486
```



# Knowledge

**Observed Distribution**  
for a **Sample** of  
**100** Sets of Responses



# Random Variables

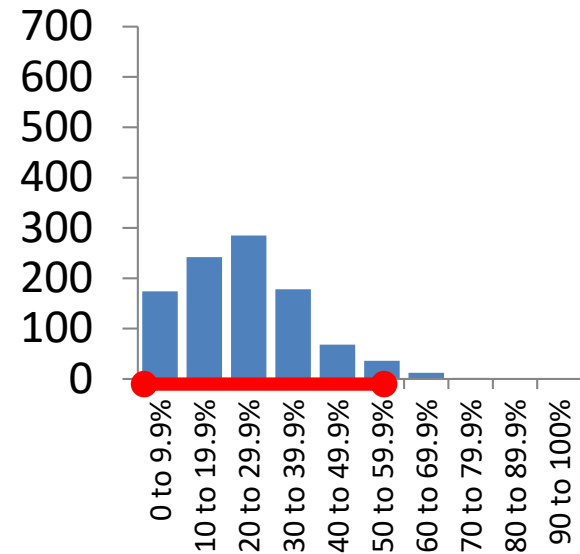
## 1. Confidence Intervals

Based on the distribution of  $Y$  in sample data, we are confident that the distribution of  $Y$  in the population has particular qualities (e.g., that its mean is within a certain range of values)

*“With 95% certainty, I conclude based on my sample data that between 25% and 35% of everyone in the population has been arrested”*

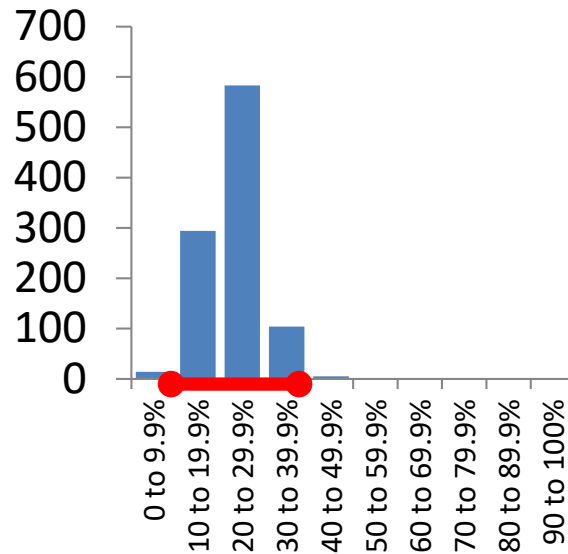
# Random Variables

Question: What percentage of Americans were high school graduates in 1940?



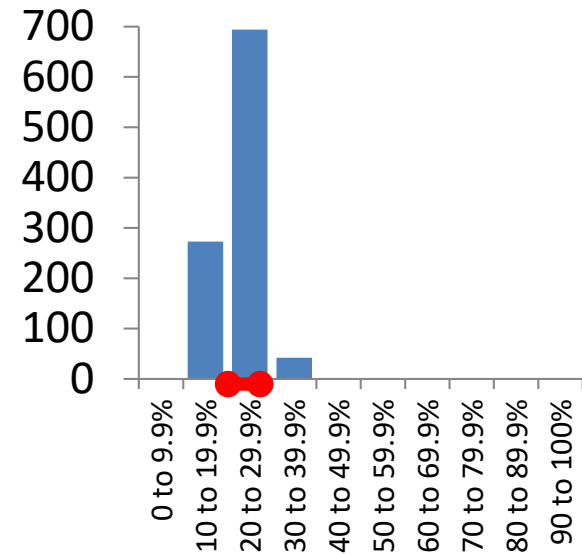
Results from asking **10** randomly selected people; trial repeated 1,000 times

$$\pm \frac{1}{\sqrt{10}} \times 100\% = \pm 32\%$$



Results from asking **50** randomly selected people; trial repeated 1,000 times

$$\pm \frac{1}{\sqrt{50}} \times 100\% = \pm 14\%$$



Results from asking **1,000** randomly selected people; trial repeated 1,000 times

$$\pm \frac{1}{\sqrt{1000}} \times 100\% = \pm 3\%$$



# Random Variables

## 2. Hypothesis Tests

Based on the distribution of  $Y$  in the sample data, we can evaluate the likely truth of theoretically-informed hypotheses about the distribution of  $Y$  in the population (e.g., that the mean of  $X$  is above some value)

*“With 95% certainty, I reject the claim that fewer than 20% of everyone in the population has ever been arrested”*

# Random Variables

Imagine you flip a bottle cap 100 times,  
and count the number of heads

If you got 52 heads out of 100, would you  
reject the idea that  $P(\text{Heads}) = 0.5$ ?

What if you got 75 heads?



# Random Variables

## Discrete Random Variable

Can only equal a finite number of distinct values

*Example:* When you flip a coin 3 times, you can only get four possible values ... the whole numbers 0 through 3

## Continuous Random Variable

Can take any numeric value within a range of values







*Example:* The number of miles from campus students live can take on just about any value (0.12, 1.17, 2.00, etc.)

*Note:* Discrete random variables with lots of values (e.g., number of Facebook friends) are often treated as continuous; continuous variables that are rounded (e.g., age) may seem discrete

# Discrete Random Variables

Random variable  $Y$  has  $k$  possible values


$$P(Y=1) + P(Y=2) + \dots + P(Y=k) = 1.0$$

*Example:* If I roll a single die (the random event) and record the number of pips that come up ( $Y$ ), then there are 6 possible values that might come up:      

$$P(Y= \img alt="die face with 1 pip" data-bbox="125 770 155 810" style="vertical-align: middle; height: 1em;"/>) + P(Y= \img alt="die face with 2 pips" data-bbox="280 770 310 810" style="vertical-align: middle; height: 1em;"/>) + \dots + P(Y= \img alt="die face with 6 pips" data-bbox="490 770 520 810" style="vertical-align: middle; height: 1em;"/>) = 1.0$$

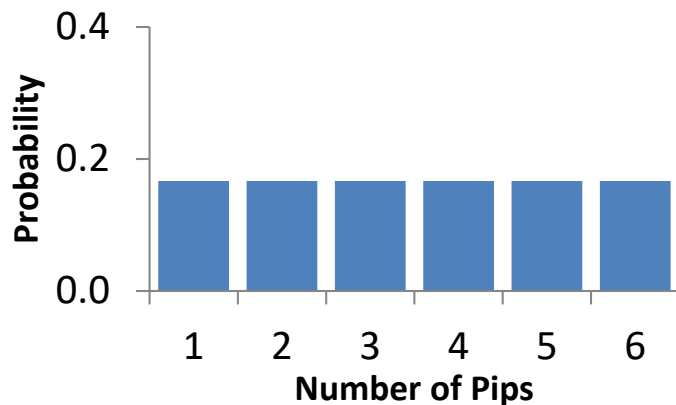
$$0.167 + 0.167 + 0.167 + 0.167 + 0.167 + 0.167 = 1.0$$

# Discrete Random Variables

*Example:* If I roll a single die (the random event) and record the number of pips that come up ( $Y$ ), then there are 6 possible values that might come up: 

The **probability distribution function** for  $Y$  is:

$k$	1	2	3	4	5	6
$p(Y=k)$	0.167	0.167	0.167	0.167	0.167	0.167

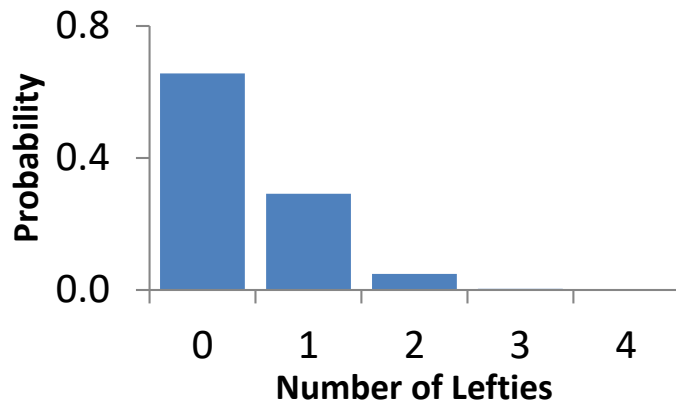


# Discrete Random Variables

*Example:* The probability that a baby is born left-handed is 0.1. For families with 4 babies, the number of left-handed babies ( $Y$ ) can thus be 0, 1, 2, 3, or 4

The **probability distribution function** for  $Y$  is:

$k$	0	1	2	3	4
$p(Y=k)$	0.6561	0.2916	0.0486	0.0036	0.0001



# Discrete Random Variables

Where is the center of the theoretical distribution of discrete random variable  $Y$ ?

The **expected value** of  $Y$  ... called  $E(Y)$  or  $\mu_Y$  ... is the mean of  $Y$  in the population of all possible outcomes

One way to think about it: If you repeated the random event an infinite number of times, the expected value is the mean of  $Y$  that you would observe

# Discrete Random Variables

For discrete random variable  $Y$ :

$Y_1, Y_2, Y_3, \dots, Y_k$  are all of the  $k$  possible values of  $Y$


$p_1, p_2, p_3, \dots, p_k$  are the probabilities of observing each value

The **expected value** of  $Y$  ... the mean of  $Y$  that you would get if you repeated the random trial an infinite number of times ... is:


$$E(Y) = \mu_Y = \sum_{i=1}^k Y_i p(Y_i)$$

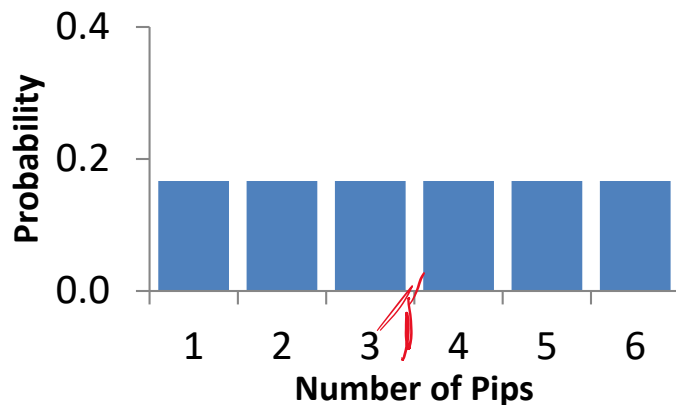


# Discrete Random Variables

*Example:* If I roll a single die (the random event) and record the number of pips that come up ( $Y$ ), then there are 6 possible values that might come up: 

The **probability distribution function** for  $Y$  is:

$k$	1	2	3	4	5	6
						
$p(Y=k)$	0.167	0.167	0.167	0.167	0.167	0.167



$$E(Y) = \mu_Y = \sum_{i=1}^k Y_i p(Y_i)$$

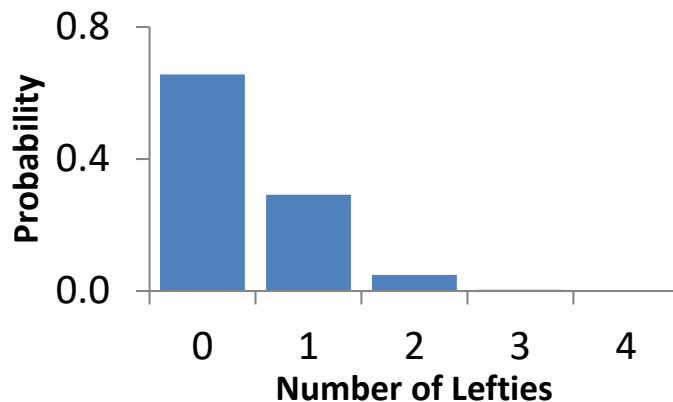
$$E(Y) = (1)(0.167) + (2)(0.167) + (3)(0.167) + (4)(0.167) + (5)(0.167) + (6)(0.167) = 3.5$$

# Discrete Random Variables

*Example:* The probability that a baby is born left-handed is 0.1. For families with 4 babies, the number of left-handed babies ( $Y$ ) can thus be 0, 1, 2, 3, or 4

The **probability distribution function** for  $Y$  is:

$k$	0	1	2	3	4
$p(Y=k)$	0.6561	0.2916	0.0486	0.0036	0.0001



$$E(Y) = \mu_Y = \sum_{i=1}^k Y_i p(Y_i)$$

$$E(Y) = (0)(0.6561) + (1)(0.2916) + (2)(0.0486) + (3)(0.0036) + (4)(0.0001) = 0.4$$

# Discrete Random Variables

$E(Y)$  is a measure of central tendency for the distribution of theoretical discrete variable  $Y$

How much “spread” or variability is there?


For discrete random variable  $Y$ , the variance of  $Y \dots \sigma^2_Y \dots$  is

$$\sigma_Y^2 = \sum_{i=1}^k (Y_i - \mu_Y)^2 p(Y_i)$$

and the standard deviation of  $Y \dots \sigma_Y \dots$  is

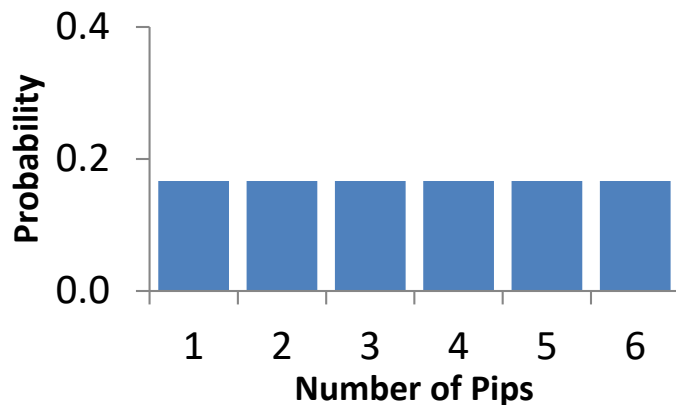
$$\sigma_Y = \sqrt{\sum_{i=1}^k (Y_i - \mu_Y)^2 p(Y_i)}$$

# Discrete Random Variables

*Example:* If I roll a single die (the random event) and record the number of pips that come up ( $Y$ ), then there are 6 possible values that might come up: 

The **probability distribution function** for  $Y$  is:

$k$	1	2	3	4	5	6
$p(Y=k)$	0.167	0.167	0.167	0.167	0.167	0.167



$$\sigma_Y^2 = \sum_{i=1}^k (Y_i - \mu_Y)^2 p(Y_i)$$

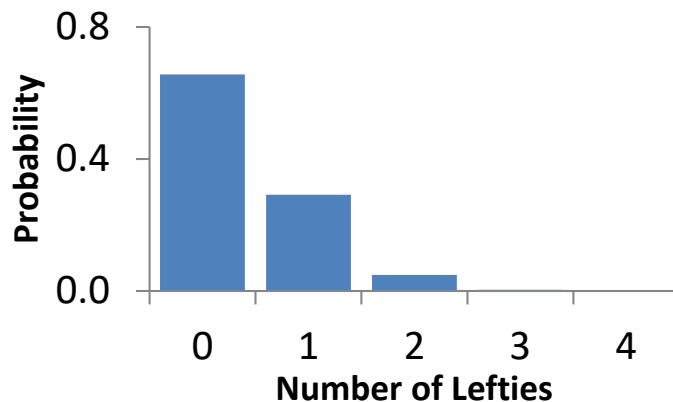
$$\begin{aligned}\sigma_Y^2 &= (1-3.5)^2(0.167) + (2-3.5)^2(0.167) + \\ &\quad (3-3.5)^2(0.167) + (4-3.5)^2(0.167) + \\ &\quad (5-3.5)^2(0.167) + (6-3.5)^2(0.167) \\ &= 2.92\end{aligned}$$

# Discrete Random Variables

*Example:* The probability that a baby is born left-handed is 0.1. For families with 4 babies, the number of left-handed babies ( $Y$ ) can thus be 0, 1, 2, 3, or 4

The **probability distribution function** for  $Y$  is:

$k$	0	1	2	3	4
$p(Y=k)$	0.6561	0.2916	0.0486	0.0036	0.0001



$$\sigma_Y^2 = \sum_{i=1}^k (Y_i - \mu_Y)^2 p(Y_i)$$

$$\begin{aligned} \sigma_Y^2 &= (0-0.4)^2(0.6561) + (1-0.4)^2(0.2916) + \\ &\quad (2-0.4)^2(0.0486) + (3-0.4)^2(0.0036) + \\ &\quad (4-0.4)^2(0.0001) = 0.36 \end{aligned}$$

# Discrete Random Variables

For the discrete random variable  $Y =$  “number of babies out of 4 born left handed” we found that the expected number of left handed babies was  $E(Y)=\mu_Y= 0.4$ , with standard deviation  $\sigma^2_Y=0.36$

If we sampled an infinite number of families with four kids and observed  $Y$  for each, the mean of  $Y$  would be 0.4

We wouldn't always (or ever) see exactly 0.4 left-handed kids;  $\sigma^2_Y$  indicates how much the number of left-handed kids would vary from family to family

# Worksheet

Below is a probability distribution function for discrete variable  $Y$ . Compute the mean and standard deviation of this distribution

$k$	0	1	2	3
$P(Y=k)$	0.8	0.1	0.05	0.05

# Binomial Random Variables


A special kind of discrete random variable ... called a binomial random variable ... is one in which the random event generating it has only two possible outcomes

## Discrete Random Variable

Random event has a finite number of distinct values; the random variable is a count of how often each value occurs.

*Example:* 

## Binomial Random Variable

Random event has exactly two possible values (“success” and “failure”); the random variable is a count of how often “success” occurs over  $n$  repeated trials. *Example:* 



# Binomial Random Variables

Binomial random variable  $Y$  equals the number of “successes” out of  $n$  binomial events when the probability of “success” in any one event is  $p$

The probability that  $Y = k$  (where  $k$  ranges from 0 to  $n$ ) is:

$$P(Y = k) = \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k}$$

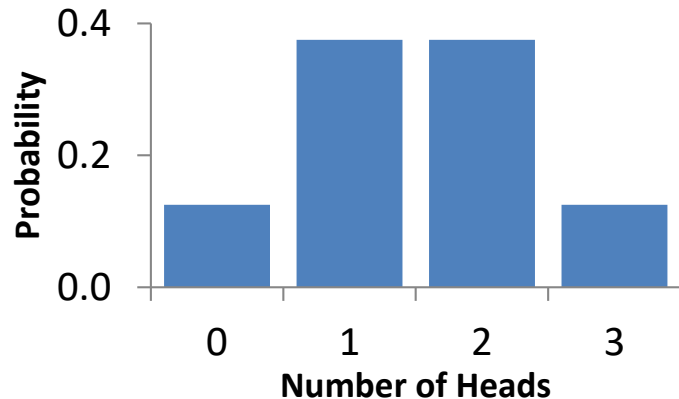
For example, what is the probability of getting  $k=2$  heads out of  $n=3$  flips of a fair coin where  $P(\text{Heads})=0.5$ ?

$$\begin{aligned} P(Y = 2) &= \frac{3!}{2!(3-2)!} 0.5^2 (1-0.5)^{3-2} = \frac{6}{2 \times 1} (0.25)(0.5) \\ &= 0.375 \end{aligned}$$

# Binomial Random Variables

Applying this formula to each possible value of  $Y$  when  $n=3$  and  $p=0.5$ , we get the probability distribution function:

$k$	0	1	2	3
$P(Y=k)$	0.125	0.375	0.375	0.125



# Binomial Random Variables

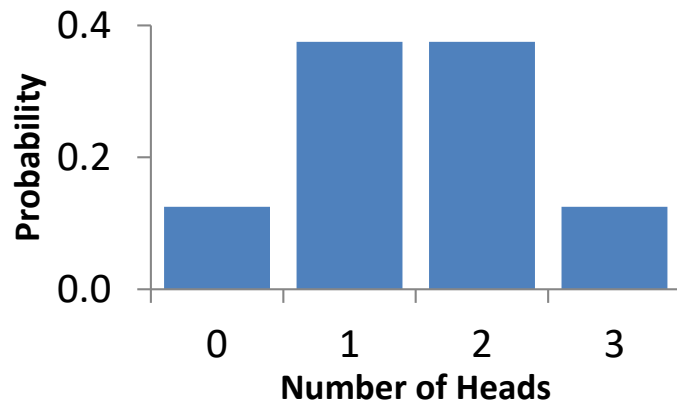
But we already knew this from before...

$$P(3 \text{ Heads}) = P(\text{H H H}) = 0.125$$

$$P(2 \text{ Heads}) = P(\text{H H T}) + P(\text{H T H}) + P(\text{T H H}) = 3 \times 0.125 = 0.375$$

$$P(1 \text{ Heads}) = P(\text{T T H}) + P(\text{T H T}) + P(\text{H T T}) = 3 \times 0.125 = 0.375$$

$$P(0 \text{ Heads}) = P(\text{T T T}) = 0.125$$



# Binomial Random Variables

For binomial random variable  $Y$  based on  $n$  trials with probability of “success” on any given trial equal to  $p$ , the expected value of  $Y$  (or  $\mu_Y$ ) equals

$$E(Y) = \mu_Y = np$$

the variance  $\sigma_Y^2$  equals

$$\sigma_Y^2 = np(1-p)$$

and the standard deviation  $\sigma_Y$  equals

$$\sigma_Y = \sqrt{\sigma_Y^2} = \sqrt{np(1-p)}$$

# Binomial Random Variables

Because a binomial random variable is just a special case of discrete random variables, the formula used to compute the mean and variance of a discrete random variable...

$$E(Y) = \mu_Y = \sum_{i=1}^k Y_i p(Y_i)$$

$$\sigma_Y^2 = \sum_{i=1}^k (Y_i - \mu_Y)^2 p(Y_i)$$

...will also work for binomial random variables (if you are inclined to do extra math)

# Binomial Random Variables

Whether a newborn baby is a boy is a binomial experiment with  $p = 0.512$

For the binomial random variable “number of boys” based on  $n = 100$  randomly selected births:

$$E(Y) = \mu_Y = np = 100 \times 0.512 = 51.2$$

$$\sigma_Y^2 = np(1-p) = 100(0.512)(1-0.512) = 24.99$$

$$\sigma_Y = \sqrt{\sigma_Y^2} = \sqrt{np(1-p)} = \sqrt{24.99} = 4.999$$

If we sampled 100 births and counted the number of boys ... and then repeated that experiment an infinite number of times...we would average 51.2 boys with  $\sigma_Y = 4.999$

# Worksheet

The probability that a new car is a “lemon” is 0.01

A factory produces 8 cars per hour

What is the probability that the factory will produce exactly zero “lemons” in a given hour?

What is the mean and standard deviation of the number of “lemons” the factory produces per hour?

# Want More?

This is a good reading:

<http://www.stat.auckland.ac.nz/~wild/ChanceEnc/Ch05.pdf>

David Lane's Book

<http://onlinestatbook.com/2/probability/probability.html>

Gerard Dallal's Book

<http://www.jerrydallal.com/LHSP/prob.htm>