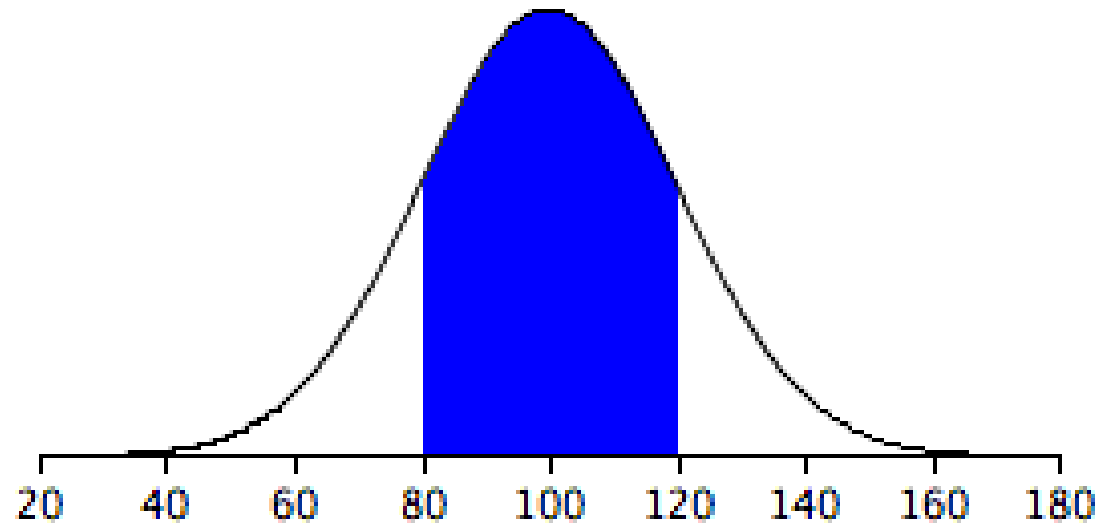


# Sampling distributions



# Overview

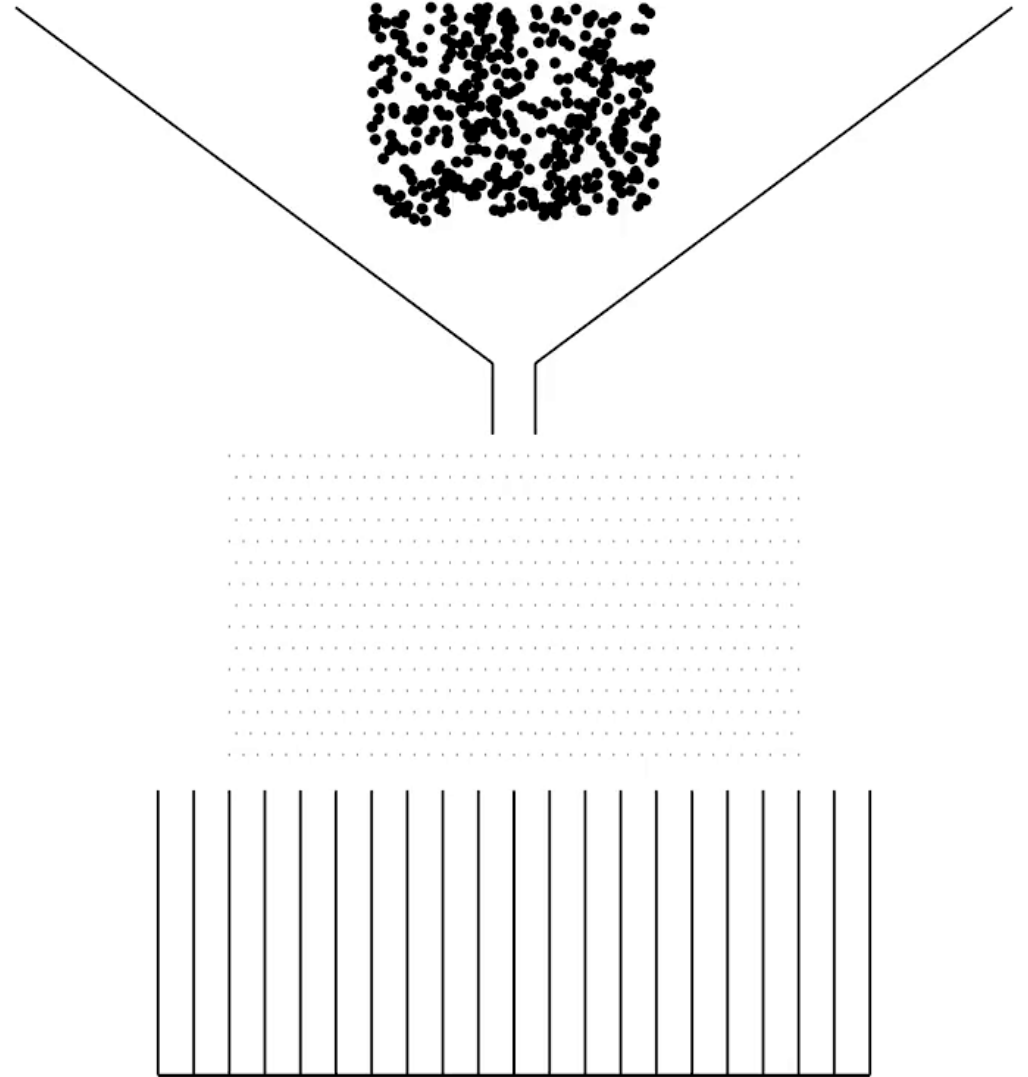
Very quick review

For loops

Generating random numbers and  
selecting random samples

Sampling distributions

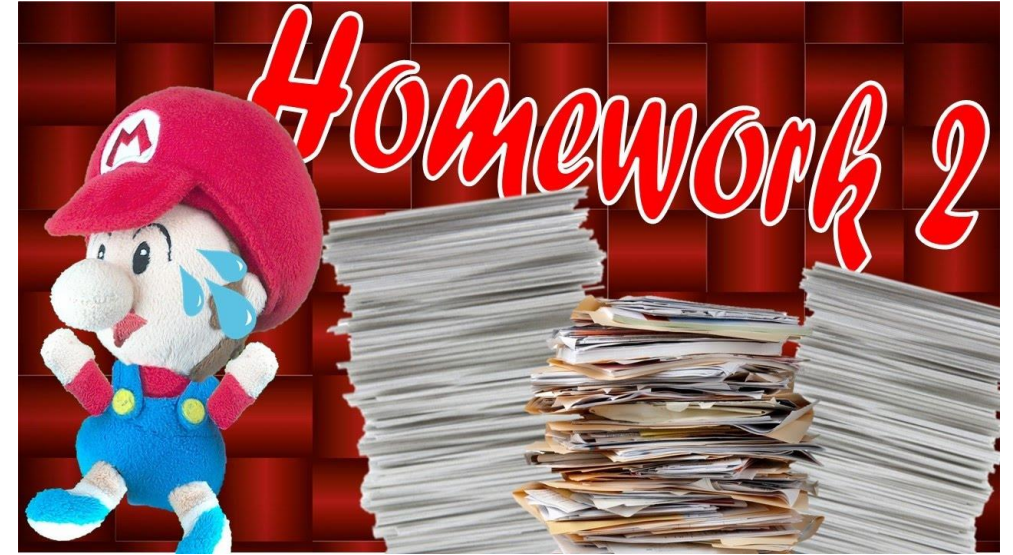
If there is time: confidence intervals



# Announcements

Homework 2 has been posted

- Due Sunday (9/15) at 11pm
- Start early on it!
  - You can do problems 1 and 2 after today's class
- How was homework 1?



Dean's Extension needed for extensions for undergraduates

Extensions for grad students are allowed but need to be requested a week in advance

# Announcement: Office hours cancelled for today

Unfortunately, I need to cancel my office hours today

Feel free to come to my office hours tomorrow (Wednesday) at 2pm in Kline Tower room 1253



# Plan for the semester

- |   |           |   |
|---|-----------|---|
| 1 | Aug 29    | Course overview, introduction to R, descriptive statistics              |
| 2 | Sep 3-6   | Review of central statistical concepts and exploratory analysis using R |
| 3 | Sep 10-12 | Confidence Intervals and the bootstrap                                  |
| 4 | Sep 17-19 | Review of hypothesis tests and permutation tests in R                   |
| 5 | Sep 24-26 | Parametric tests and theories of hypothesis testing                     |

We will be using simulations to justify and validate methods we use throughout the semester

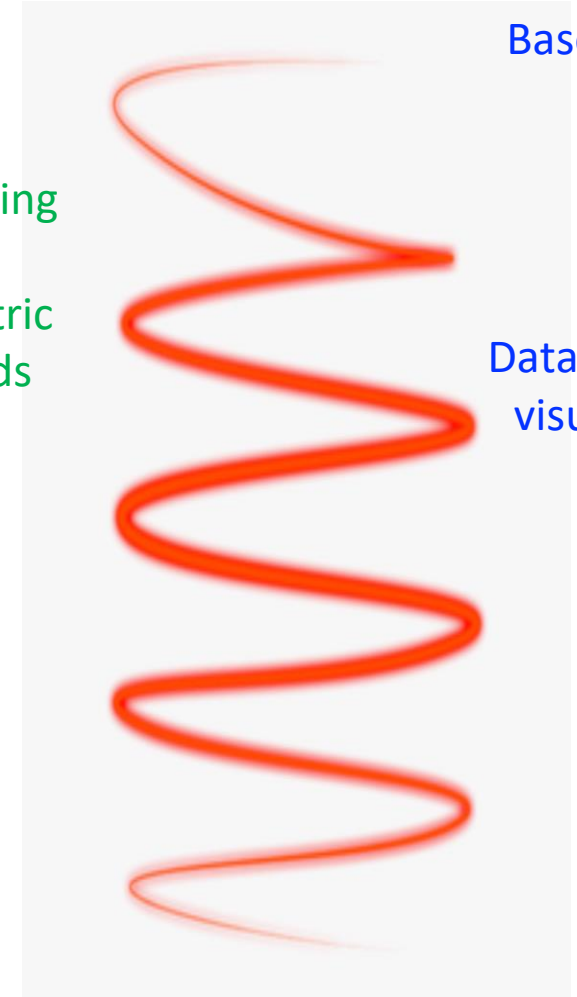
Analysis

R

Resampling  
and  
parametric  
methods

Base R

Data wrangling  
visualization



# Quick review

## Basics of R

```
> my_vec <- c(5, 28, 19)
> my_vec[3]
> my_vec[3] <- 7
```

## How to plot categorical data

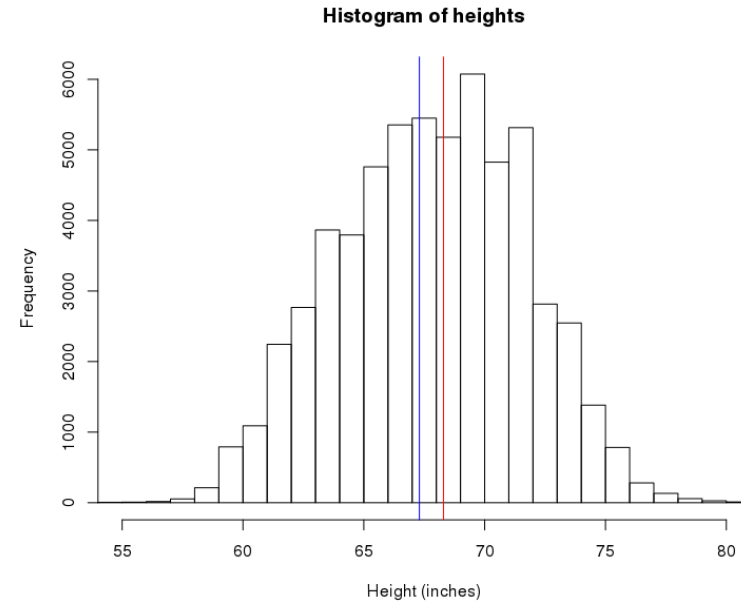
```
> drinks_table <- table(profiles$drinks)
> barplot(drinks_table)
> pie(drinks_table)
```

# Quick review

How to plot quantitative data:

```
> hist(profiles$height)
```

```
> abline(v = 67)
```



# Staying organized

It is useful to create separate folders for different homework and even for the different pieces of class code.

Be sure to **set your working directory** properly so that R can find the relevant files.





A little more R...

For loops

Things that  
begin with

**Rr**



rabbit



rocket



rain



robot



ribbon



rat

# For loops

For loops are useful when you want to repeat a piece of code many times under similar conditions

The syntax for a for loop is:

```
for (i in 1:100) {
```

```
    # do something
```

```
}
```



This is repeated 100 times  
i is incremented by 1 each time

# For loops

For loops are particularly useful in conjunction with vectors...

```
my_results <- NULL    # create an empty vector to store the results
for (i in 1:100) {
  my_results[i] <- i^2
}
```

**Try this at home!:** Use a for loop to create a vector that holds the values at multiples of 3 from 3 to 300

- i.e., 3, 6, 9, ..., 300

Let's try it in R!

Generating random data

# Generating random data

R has built in functions to generate data from different distributions

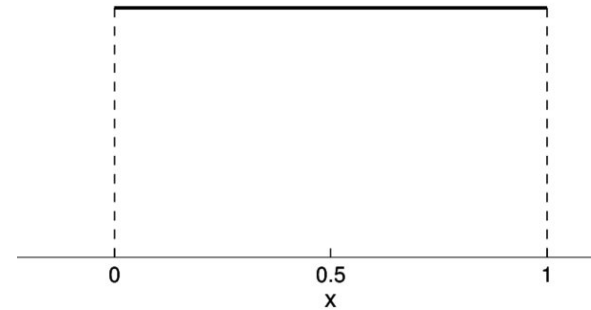
- All these functions start with the letter *r*

## The uniform distribution

# generate  $n = 100$  points from  $U(0, 1)$

```
> rand_data <- runif(100)
```

```
> hist(rand_data)
```

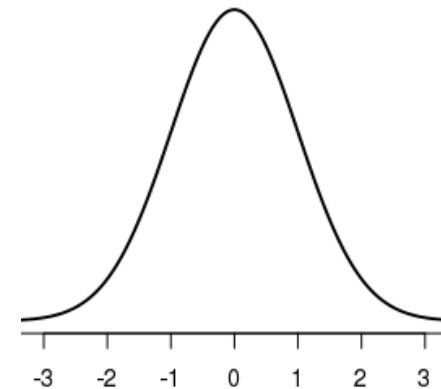


## The normal distribution

# generate  $n = 100$  points from  $N(0, 1)$

```
> rand_data <- rnorm(100)
```

```
> hist(rand_data)
```



# Generating random data

If we want the same sequence of random numbers we can set the random number generating seed

```
> set.seed(123)
```

```
> runif(100)
```

**Q: Why would we want the same sequence of random number?**

# Sampling data

The `sample(v, n)` function samples `n` random points from a vector `v`

For example, suppose we had a vector with the ages of all US citizens in a vector called `pop_ages`

We could sample the ages of 100 random people using:

- `rand_sample <- sample(pop_ages, 100)`

We can sample with replacement using the `replace = TRUE` argument:

- `rand_sample_replace <- sample(pop_ages, 100, replace = TRUE)`

Let's try it in R!

Questions?





Review and extension of statistical concepts

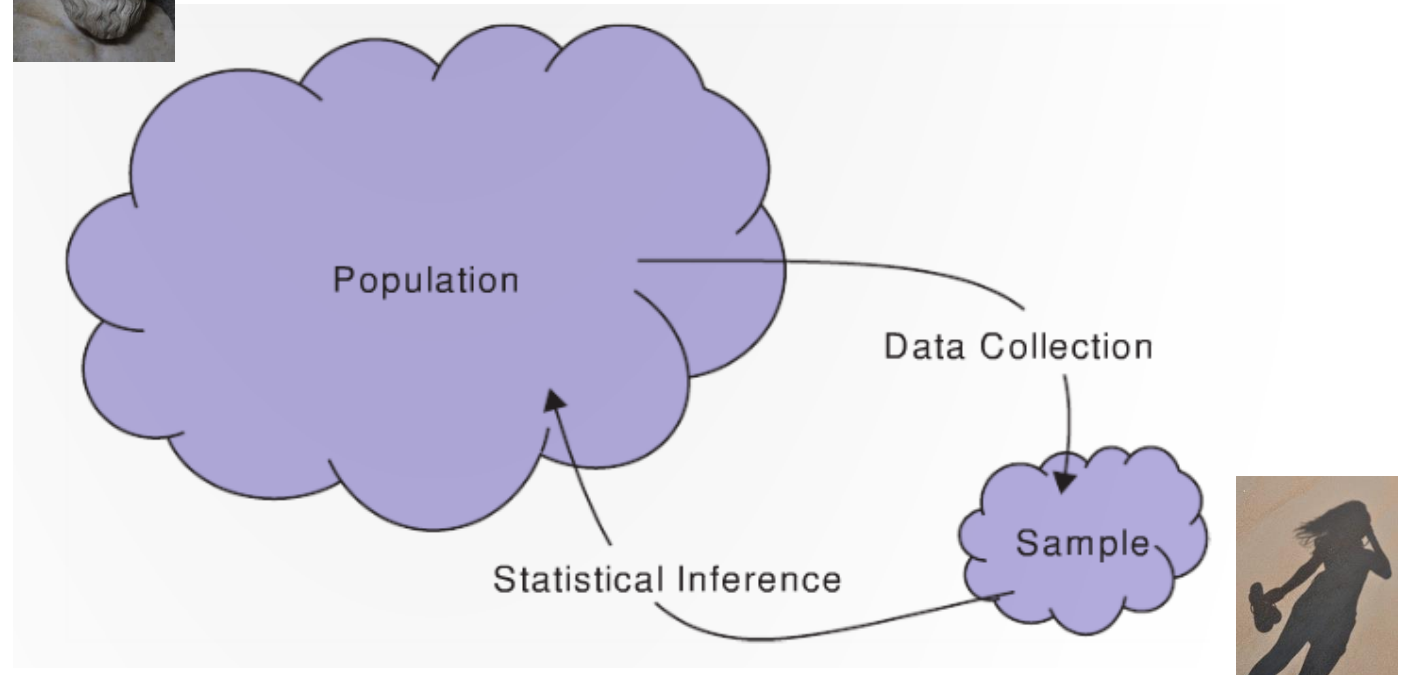
# Where does data come from?



**DATA SCIENCE!!!**



**Population:** all individuals/objects of interest



**Sample:** A subset of the population

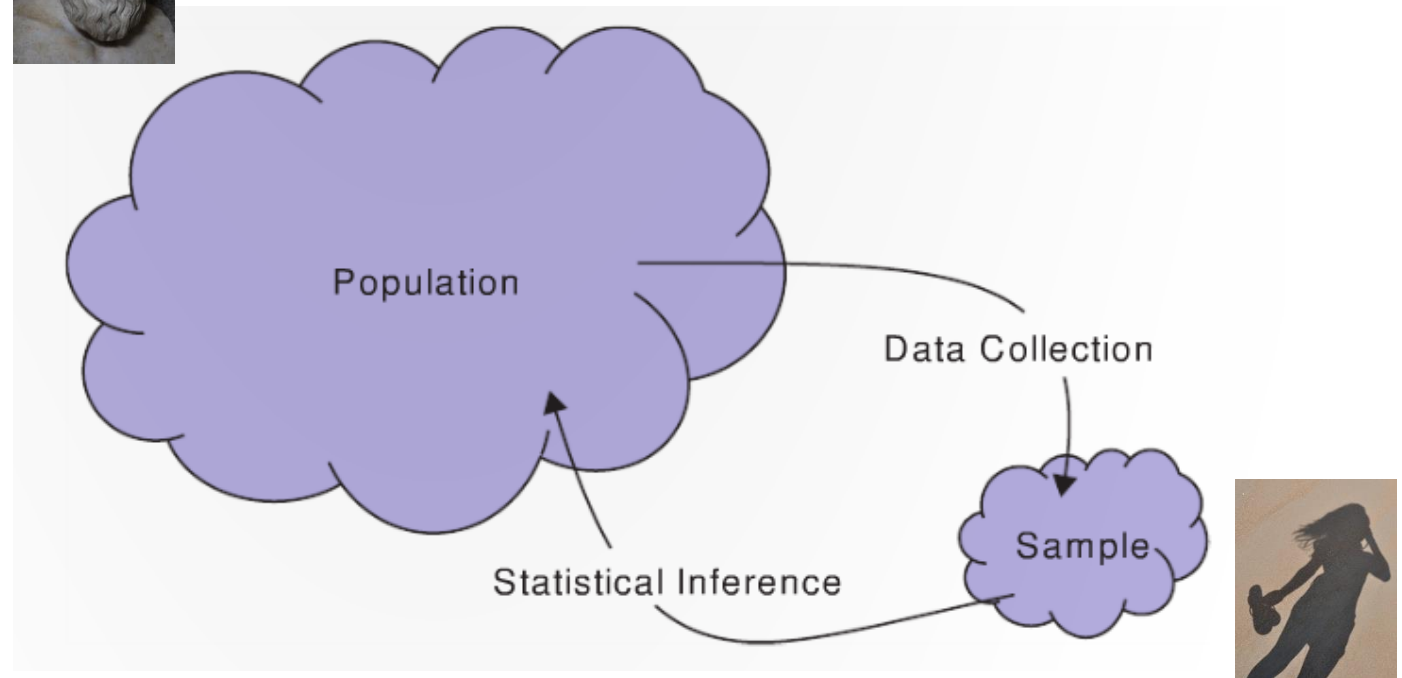
# Where does data come from?

**Question:** Is the okcupid profiles data frame a population or a sample?

**Question:** If the OkCupid profiles data frame is a sample, what is the population?



Parameters:  $\pi, \mu, \sigma, \rho, \beta$



Statistics:  $\hat{p}, \bar{x}, s, r, b$

# How do we get sample of data?

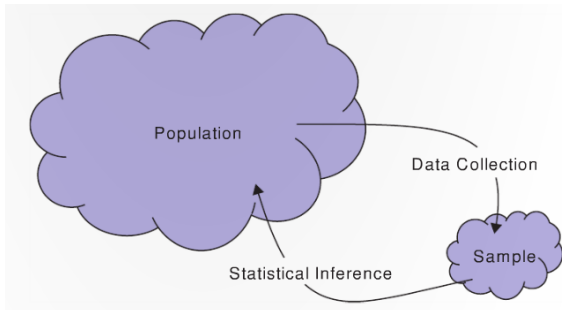
**Simple random sample:** each member in the population is equally likely to be in the sample

**“Random selection”**

**Q:** Why is this good?

**A:** Allows for generalizations to the population!

- No sampling bias
- Statistic (on average) equal parameter
  - E.g.,  $E[\bar{x}] = \mu$



***Soup analogy!***



## Questions:

- Is the OkCupid profiles data a simple random sample?
- Would we expect sampling bias from statistics computed from the OkCupid profiles?

# Big picture for the week

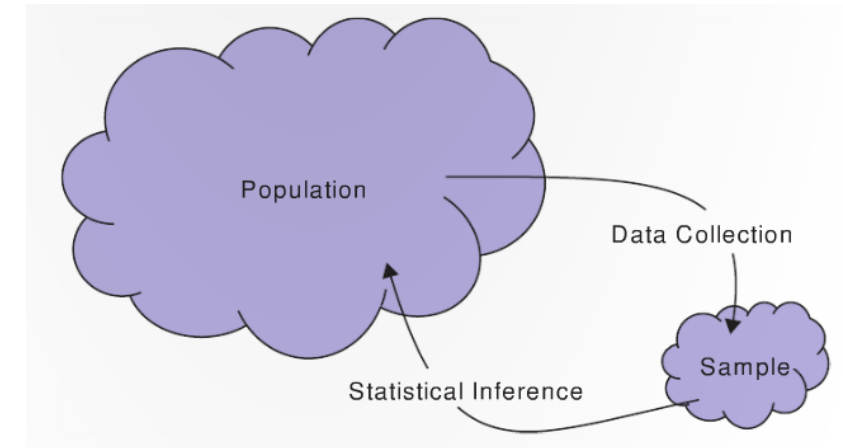
Statistics are point estimates of parameters

We can use sampling distributions (i.e., distributions of statistics) to tell us how much we can trust **any one statistic** to be a good point estimate of a parameter

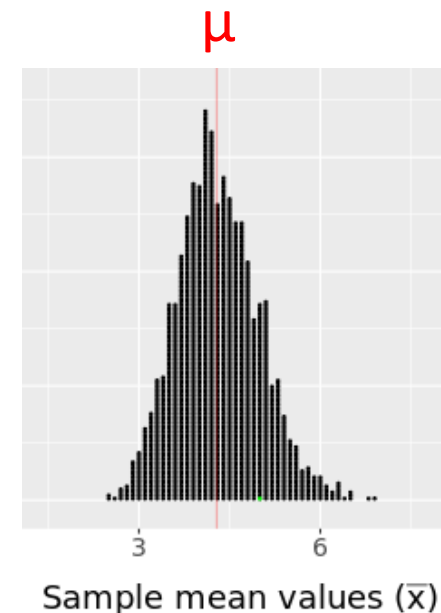
-> confidence interval

Let's start on this now...

parameter:  $\mu$



statistic:  $\bar{x}$



**Sampling  
distribution of  $\bar{x}$**

# Sampling distributions

# Sample statistics

**Q: What is a statistic?**

The sample mean  $\bar{x}$

(shadow of the parameter  $\mu$ )

```
> rand_data <- runif(100) # generate n = 100 points from U(0, 1)  
> mean(rand_data)
```

**Q: If we repeat the code above will we get the same statistic?**

# Sampling distributions

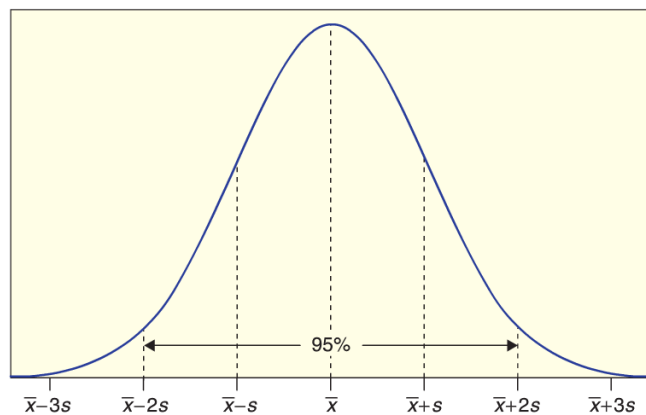
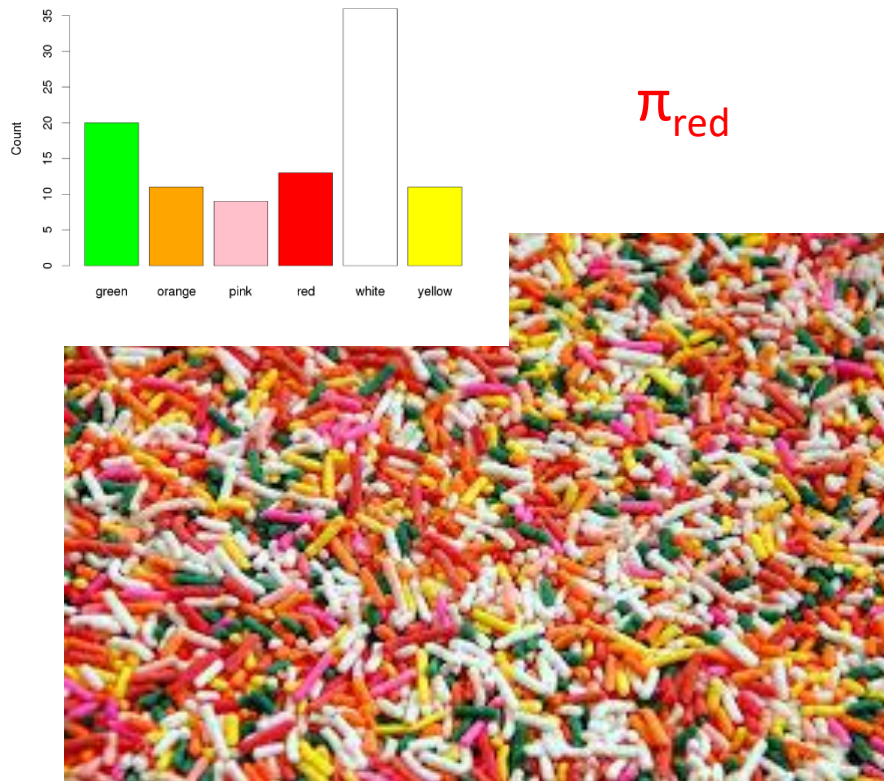
A ***sampling distribution*** is a distribution of ***statistics***

Reminder: For a *single ***categorical variable****, the main statistic of interest is the ***proportion*** ( $\hat{p}$ ) in each category

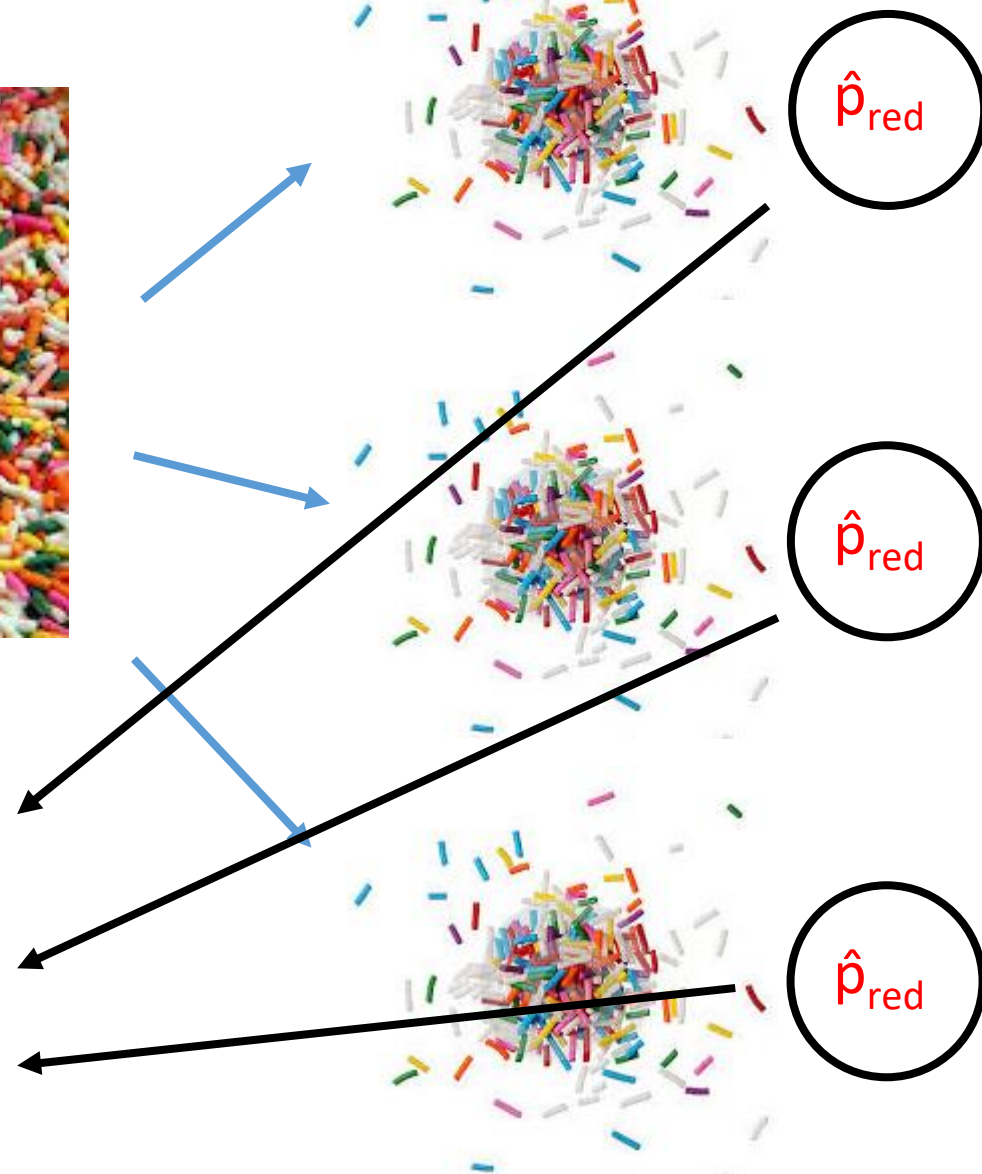
- (shadow of the parameter  $\pi$ )

$$\hat{p} = \text{Proportion in a category} = \frac{\text{number in that category}}{\text{total number}}$$





Sampling distribution!



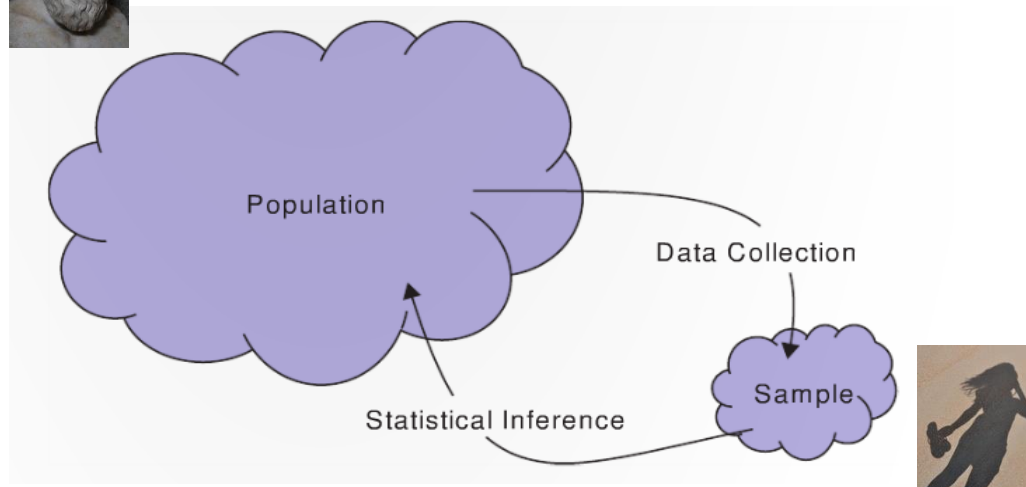
# Sampling distribution

## Why would we be interested in the sampling distribution?

- If we knew what the sampling distribution was, then we could evaluate how much we should trust individual statistics

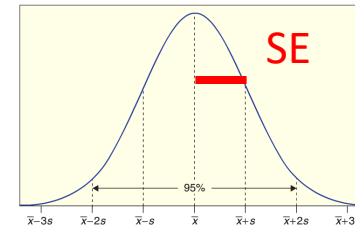


**Parameters:**  $\pi, \mu, \sigma, \rho, \beta$



**Statistics:**  $\hat{p}, \bar{x}, s, r, b$

**Sampling distribution**



The standard error (SE) is the standard deviation of a sampling distribution

It tells us how much statistics vary from sample to sample

# Simulating sampling distributions

```
sampling_dist <- NULL
for (i in 1:1000) {
    rand_data <- runif(100)  # generate n = 100 points from U(0, 1)
    sampling_dist[i] <- mean(rand_data)  # save the mean
}

hist(sampling_dist)
```

# Simulating sampling distributions

Distribution of OkCupid user's heights  $n = 100$

```
heights <- profiles$height
```

```
# get one random sample of heights from 100 people
```

```
height_sample <- sample(heights, 100)
```

```
# get the mean of this sample
```

```
mean(height_sample)
```

# Simulating sampling distributions

Distribution of OkCupid user's heights  $n = 100$

```
sampling_dist <- NULL
for (i in 1:1000) {
  height_sample <- sample(heights, 100)  # sample 100 random heights
  sampling_dist[i] <- mean(height_sample) # save the mean
}

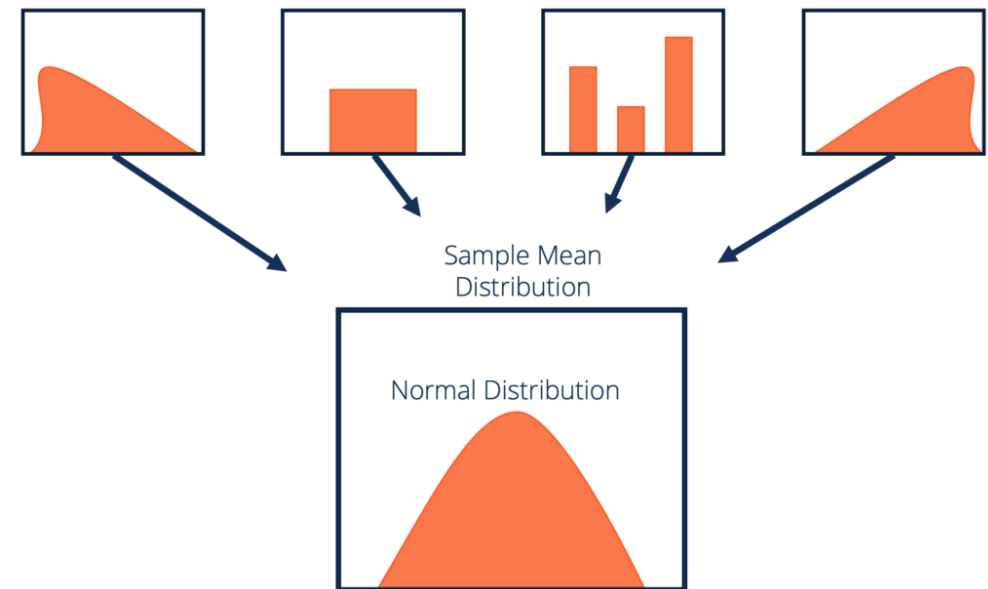
hist(sampling_dist)
```

# The central limit theorem

The **central limit theorem** establishes that, in many situations, when independent random variables are summed up, their properly normalized sum tends toward a normal distribution.

Since many statistics we use are the sum of randomly data, many of our sampling distributions will be approximately normal

- You will explore this more on homework 2



**Statistics:**  $\hat{p}$ ,  $\bar{x}$ ,  $s$ ,  $r$ ,  $b$

**Some would say this sidewalk is broken, but it's actually normal**



# Confidence intervals



# Point Estimate

We use the statistics from a sample as a **point estimate** for a population parameter

- $\bar{x}$  is a point estimate for...?  $\mu$

A recent New York Times/Siena College poll found that Trump's favorability rating was 46%

Symbols:

$\pi$ : Trump's favorability for all voters

$\hat{p}$ : Trump's favorability for those voters in our sample

## *Trump and Harris Neck and Neck After Summer Upheaval, Times/Siena Poll Finds*

The survey finds that Donald J. Trump is retaining his support and that, on the eve of the debate, voters are unsure they know enough about where Kamala Harris stands.



Listen to this article • 10:36 min [Learn more](#)



Share full article



1.9K

THE NEW YORK TIMES/SIENA COLLEGE POLL  
Sept. 3 to 6



# Interval estimate based on a margin of error

An **interval estimate** give a range of plausible values for a population parameter

One common form of an interval estimate is:

*Point estimate  $\pm$  margin of error*

Where the **margin of error** is a number that reflects the precision of the sample statistic as a point estimate for this parameter

# Example: YouGov poll

46% of American have a favorable view of Donal Trump, with a margin of error of 2.8%

- i.e., plus or minus 2.8%

How do we interpret this?

Says that the population parameter ( $\pi$ ) lies somewhere between:

$$46 - 2.8 \text{ to } 46 + 2.8 = 43.2 \text{ to } 48.8$$

i.e., if they sampled all voters the true population proportion ( $\pi$ ) would be likely be in this range

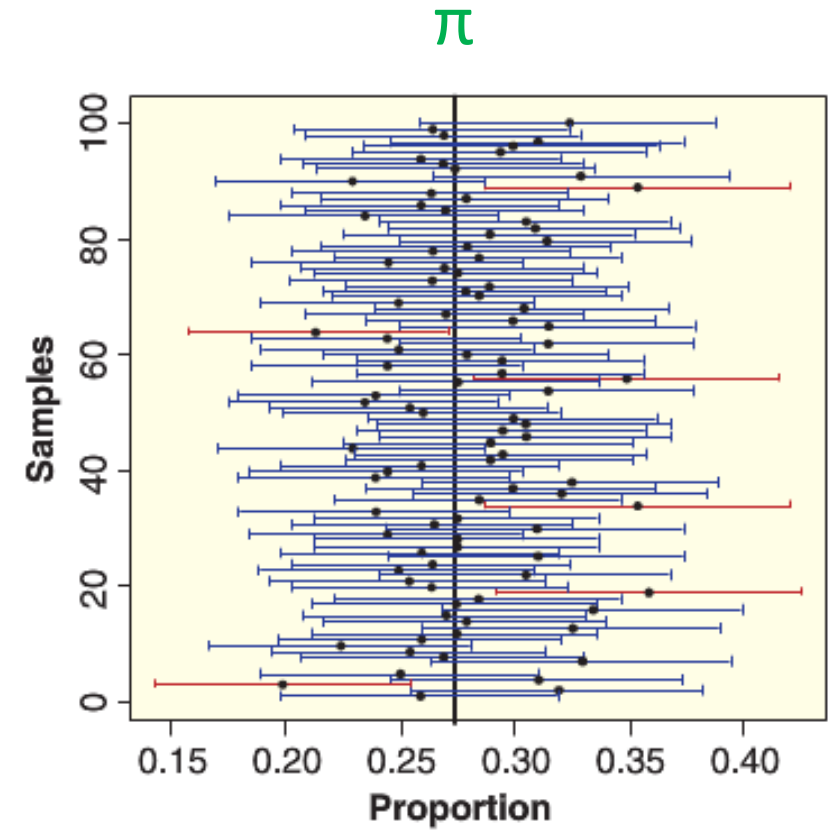


# Confidence Intervals

A **confidence interval** is an interval computed by a method that will contain the ***parameter*** a specified percent of times

- i.e., if the interval was calculated repeatedly from many different random samples, the parameter will be in p% of these intervals

The **confidence level** is the percent of all intervals that contain the parameter



# Think ring toss...

Parameter exists in the ideal world

We toss intervals at it

95% of those intervals capture the parameter

