

# Parameters and confidence intervals

FOUNDATIONS OF INFERENCE



**Jo Hardin**  
Instructor

# Research questions

Hypothesis test	Confidence interval
Under which diet plan will participants lose more weight on average?	How much should participants expect to lose on average?
Which of two car manufacturers are users more likely to recommend to their friends?	What percent of users are likely to recommend Subaru to their friends?
Are education level and average income linearly related?	For each additional year of education, what is the predicted average income?

# Parameter

- A parameter is a numerical value from the population
- Examples (continued):
  - The true average amount all dieters will lose on a particular program
  - The proportion of individuals in a population who recommend Subaru cars
  - The average income of all individuals in the population with a particular education level

# Confidence interval

- Range of numbers that (hopefully) captures the true parameter
- "95% confident that between 12% and 34% of the entire population recommends Subaru"

**Let's practice!**  
FOUNDATIONS OF INFERENCE

# Bootstrapping

FOUNDATIONS OF INFERENCE



**Jo Hardin**  
Instructor

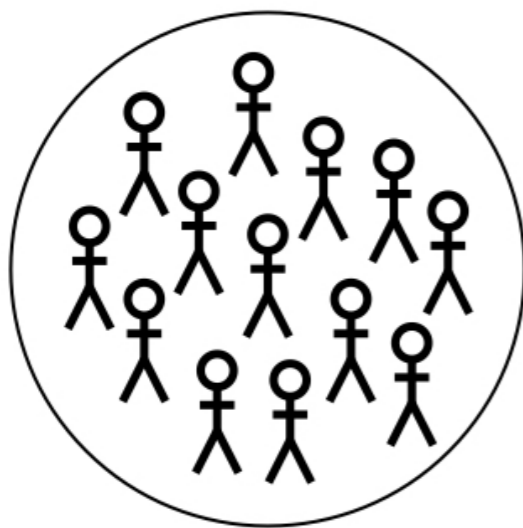
# Hypothesis testing

- How do samples from the null population vary?
- **Statistic**, proportion of successes in *sample*  $\rightarrow \hat{p}$
- **Parameter**, proportion of successes in *population*  $\rightarrow p$

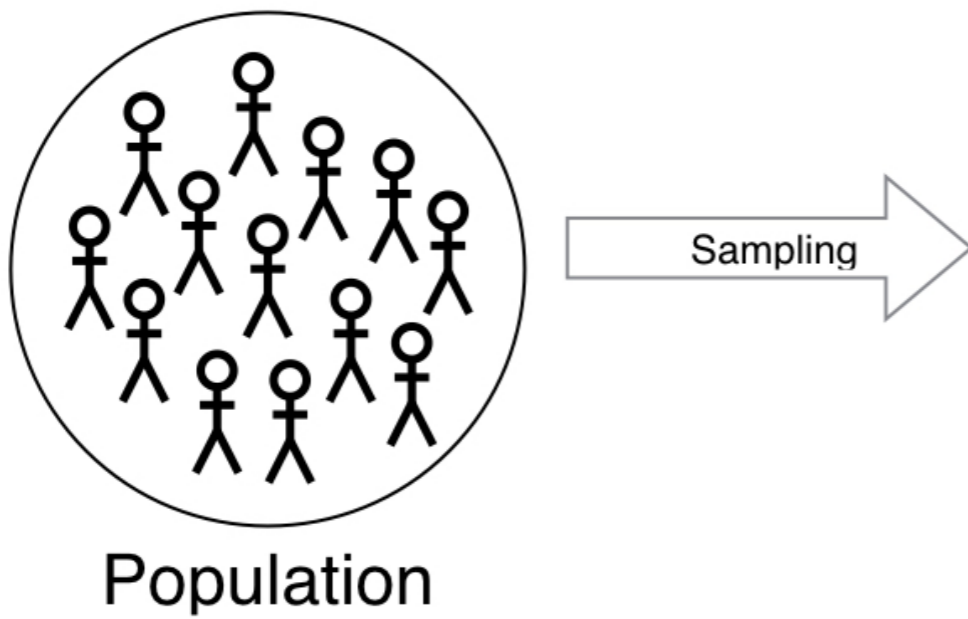
# Confidence intervals

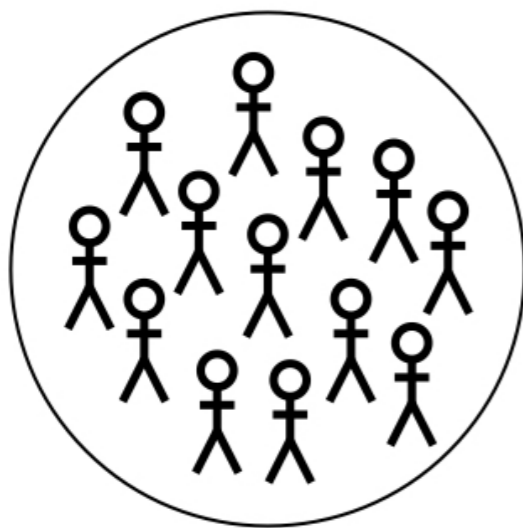
- No null population, unlike in hypothesis testing
- How do  $p$  and  $\hat{p}$  vary?



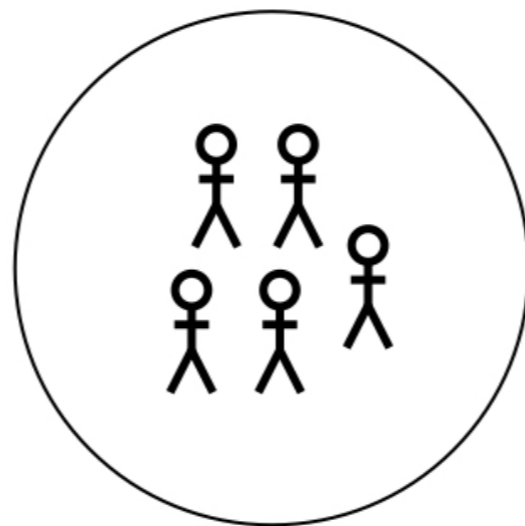


Population

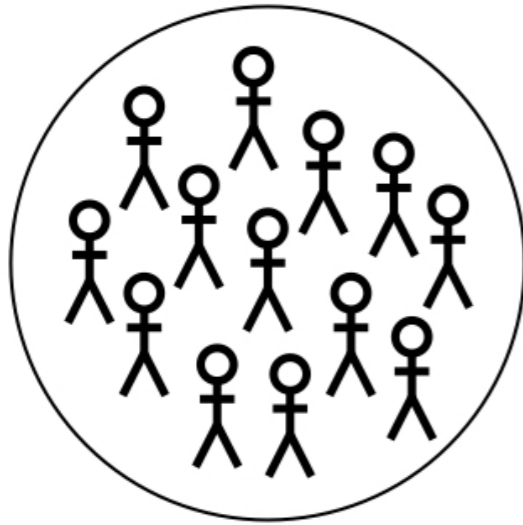




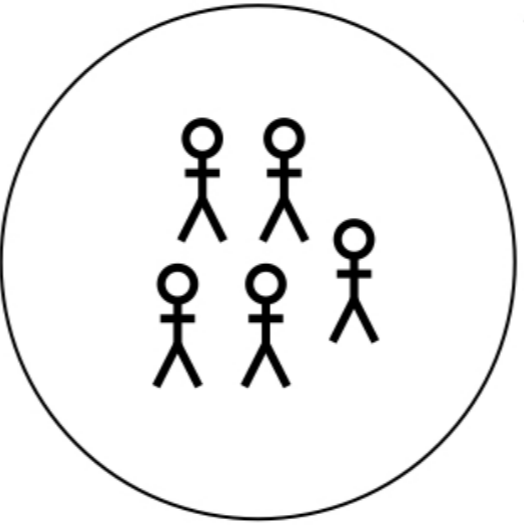
Population



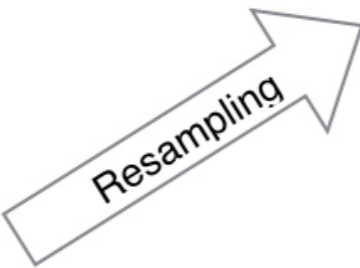
Sample

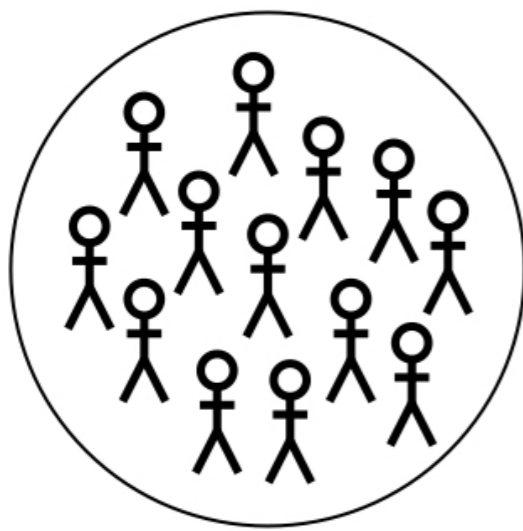


Population

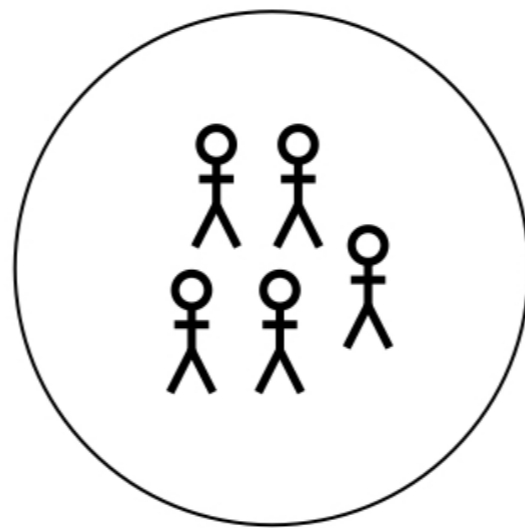


Sample

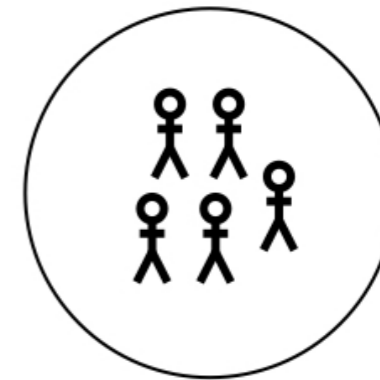
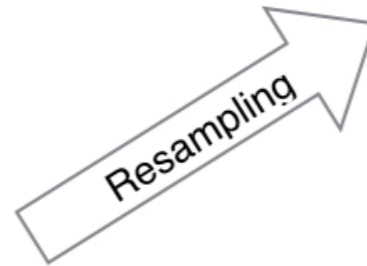




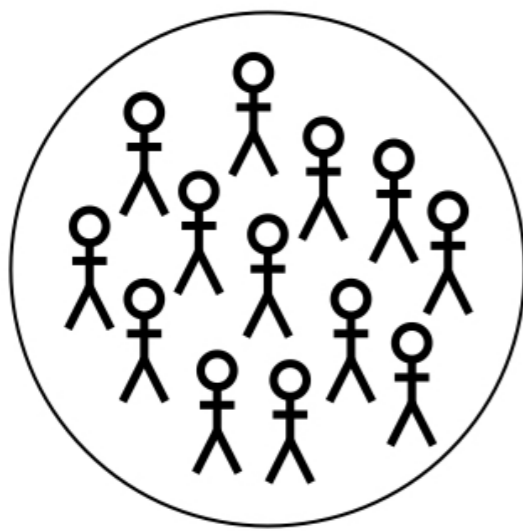
Population



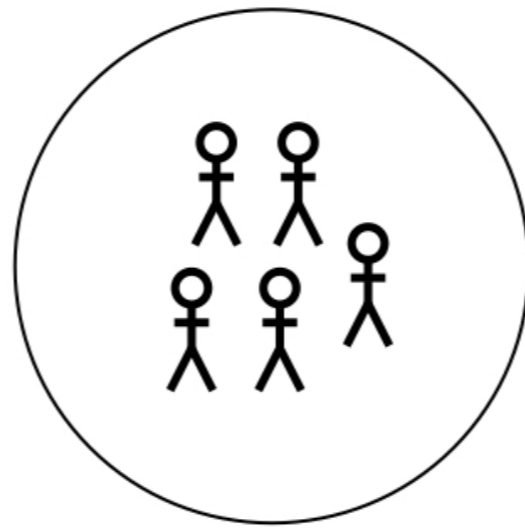
Sample



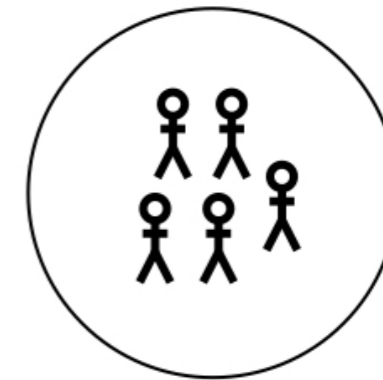
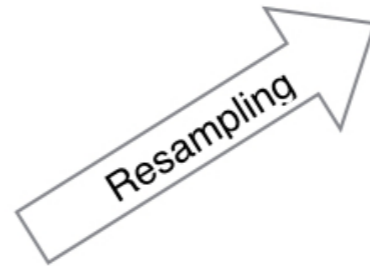
Resample 1



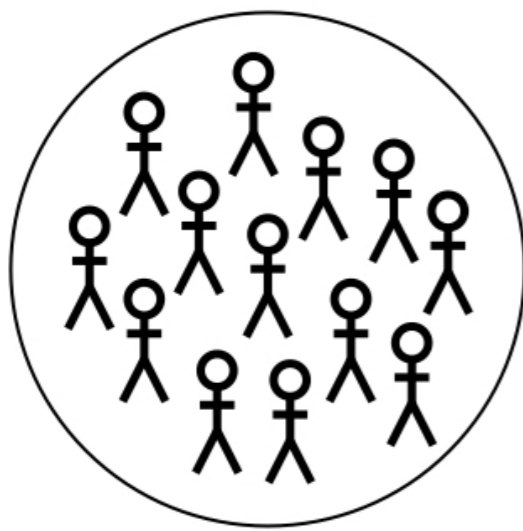
Population



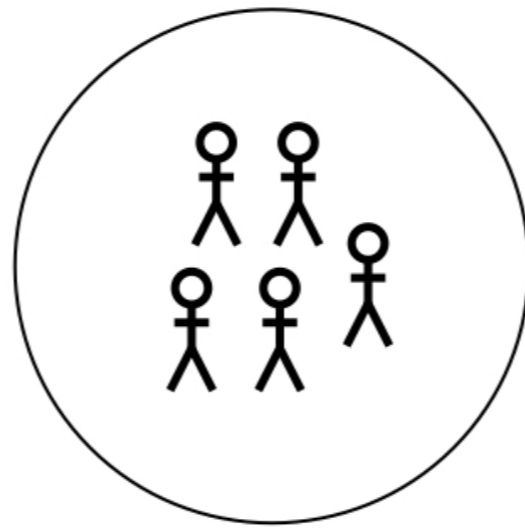
Sample



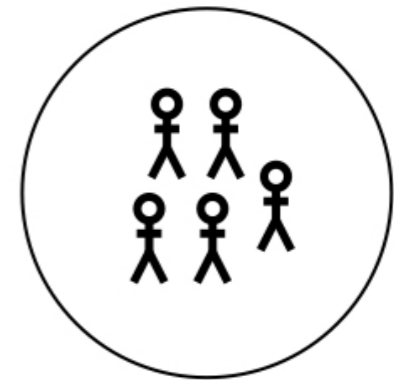
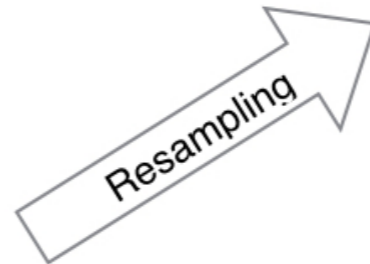
Resample 1



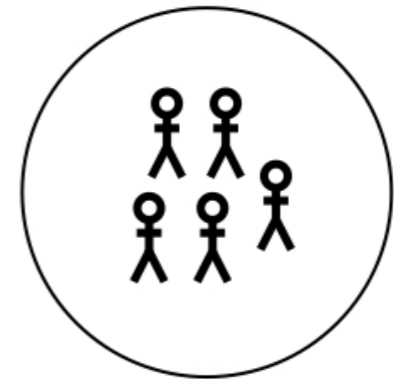
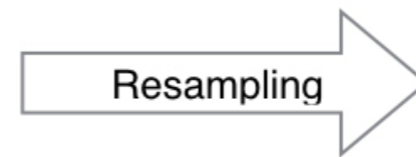
Population



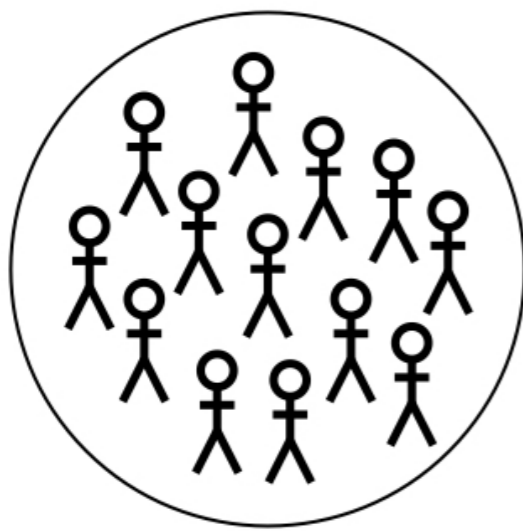
Sample



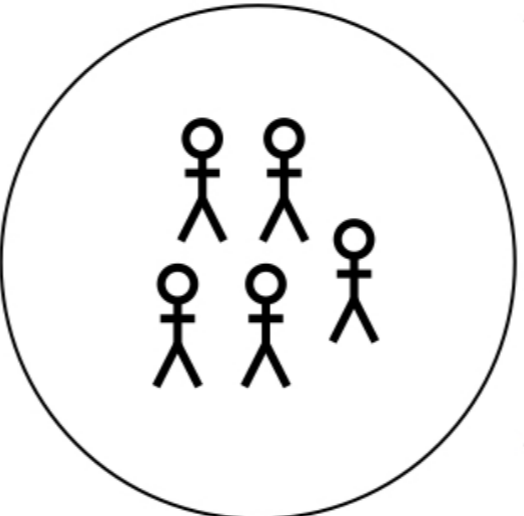
Resample 1



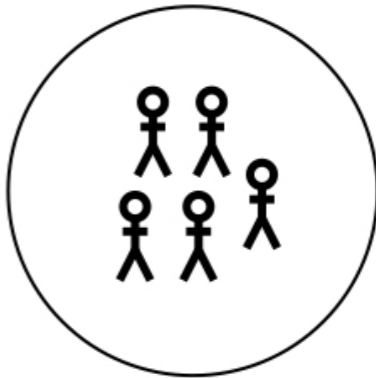
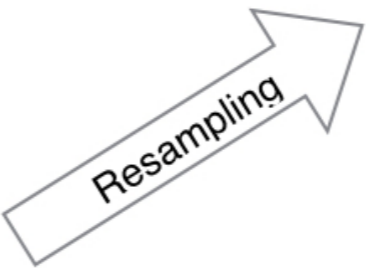
Resample 2



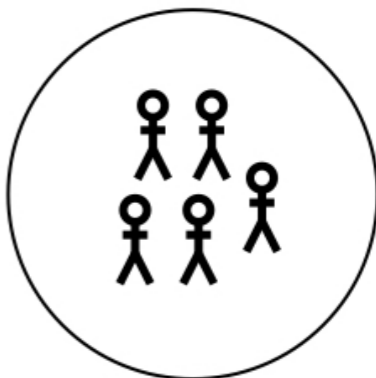
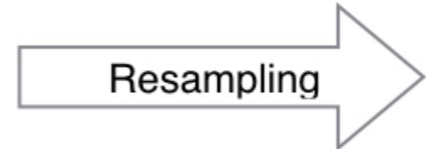
Population



Sample

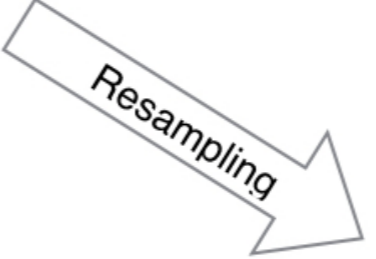


Resample 1

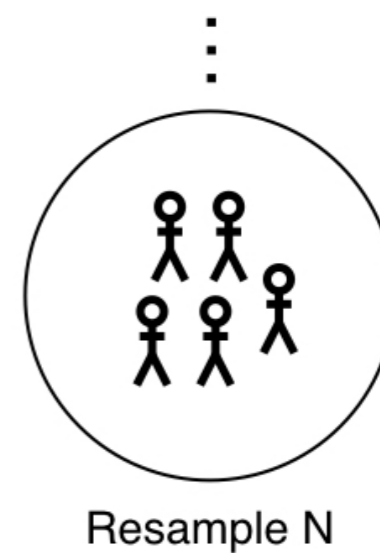
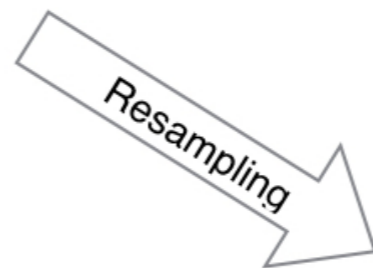
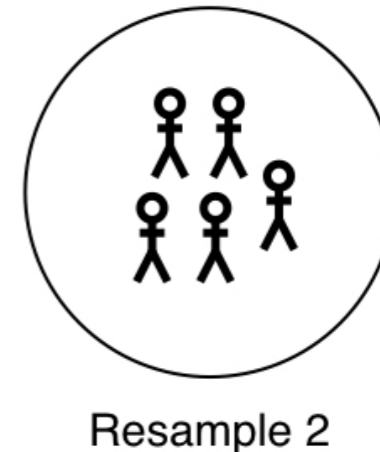
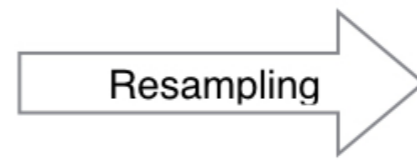
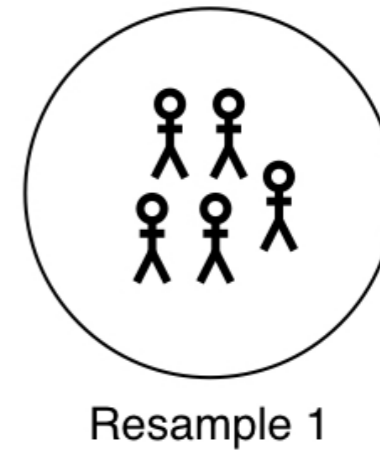
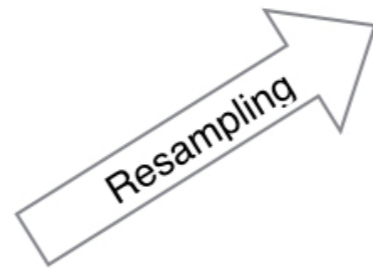
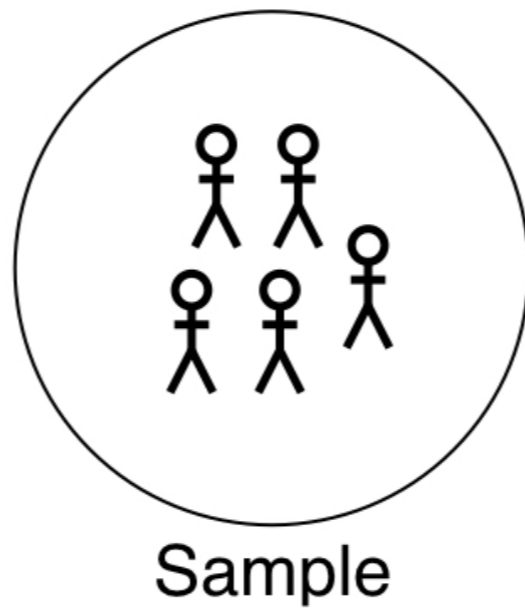
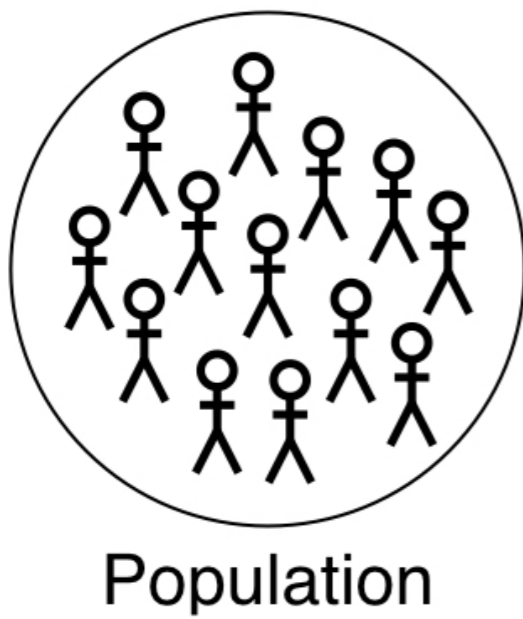


Resample 2

⋮







# Polling

```
# Original data
```

```
Source: local data frame [30 x 3]
```

```
  flip_num flip
  <int> <chr>
1      1    H
2      2    H
3      3    H
4      4    T
5      5    H
6      6    H
# ... with 24 more rows
```

Original data

Candidate X	Total voters	Proportion X
17	30	0.5667

# Polling

```
# First resample
```

```
Source: local data frame [30 x 3]
```

```
  replicate flip_num flip
      <dbl>   <int> <chr>
1         1     7    H
2         1    17    T
3         1    13    H
4         1    14    H
5         1    24    H
6         1    28    T
# ... with 24 more rows
```

First resample

Candidate X	Total voters	Proportion X
17	30	0.5667
14	30	0.4667

# Polling

```
# Second resample
```

```
Source: local data frame [30 x 3]
```

```
  replicate flip_num flip
    <dbl>    <int> <chr>
1         2      21    H
2         2      19    T
3         2      25    H
4         2      24    T
5         2      21    H
6         2      28    T
7         2      13    H
8         2      23    H
9         2      24    T
10        2      24    T
# ... with 20 more rows
```

Second resample

Candidate X	Total voters	Proportion X
17	30	0.5667
14	30	0.4667
18	30	0.6

# Polling

```
# Third resample
```

```
Source: local data frame [30 x 3]
```

```
  replicate flip_num flip
    <dbl>    <int> <chr>
1         3         6    H
2         3        19    H
3         3         1    H
4         3        24    T
5         3        11    H
6         3        28    T
7         3        16    H
8         3        13    H
9         3        21    T
10        3        29    H
# ... with 20 more rows
```

Third resample

Candidate X	Total voters	Proportion X
17	30	0.5667
14	30	0.4667
18	30	0.6
12	30	0.4

# Standard error

- Obtained standard error of 0.09 by resampling many times
- Describes how the statistic varies around parameter
- Bootstrap provides an approximation of the standard error

# Variability of p-hat from the population

```
# Compute p-hat for each poll
ex1_props <- recommend %>%
  group_by(poll) %>%
  summarize(prop_yes =
            mean(vote == "yes"))
```

```
# Variability of p-hat
ex1_props %>%
  summarize(sd(prop_yes))
```

```
# A tibble: 1 × 1
  `sd(prop_yes)`
      <dbl>
1 0.08523512
```

# Variability of p-hat from the sample (bootstrapping)

```
# Select one poll from which to resample
one_poll <- all_polls %>%
  filter(poll == 1) %>%
  select(vote)

# Compute p-hat for each resampled poll
ex2_props <- one_poll %>%
  specify(response = vote,
          success = "yes") %>%
  generate(reps = 1000,
          type = "bootstrap")
```

```
# Variability of p-hat
ex2_props %>%
  summarize(sd(stat))
```

```
# A tibble: 1 × 1
  `sd(stat)`
      <dbl>
1 0.08691885
```



**Let's practice!**  
FOUNDATIONS OF INFERENCE

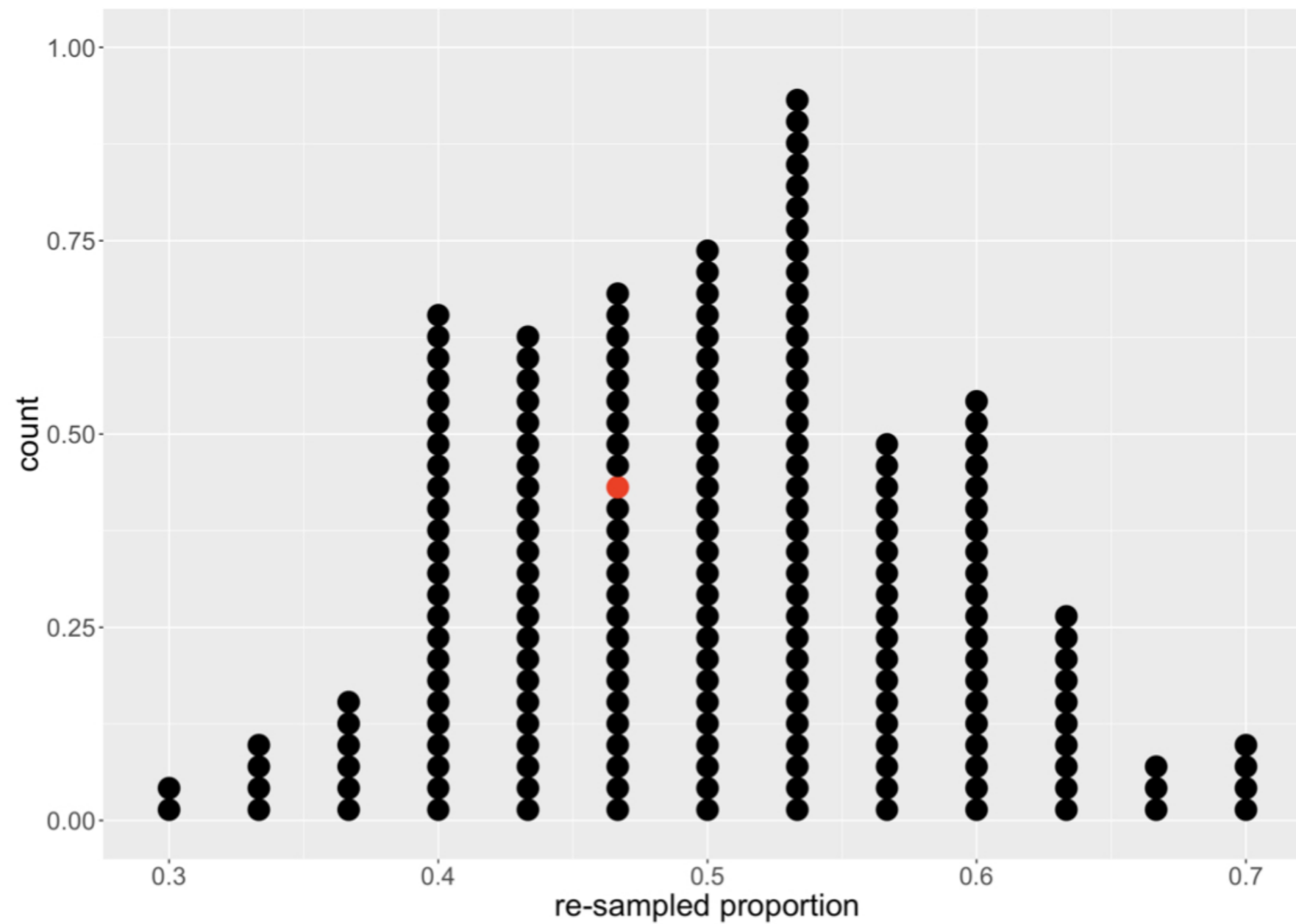
# Variability in $\hat{p}$

FOUNDATIONS OF INFERENCE

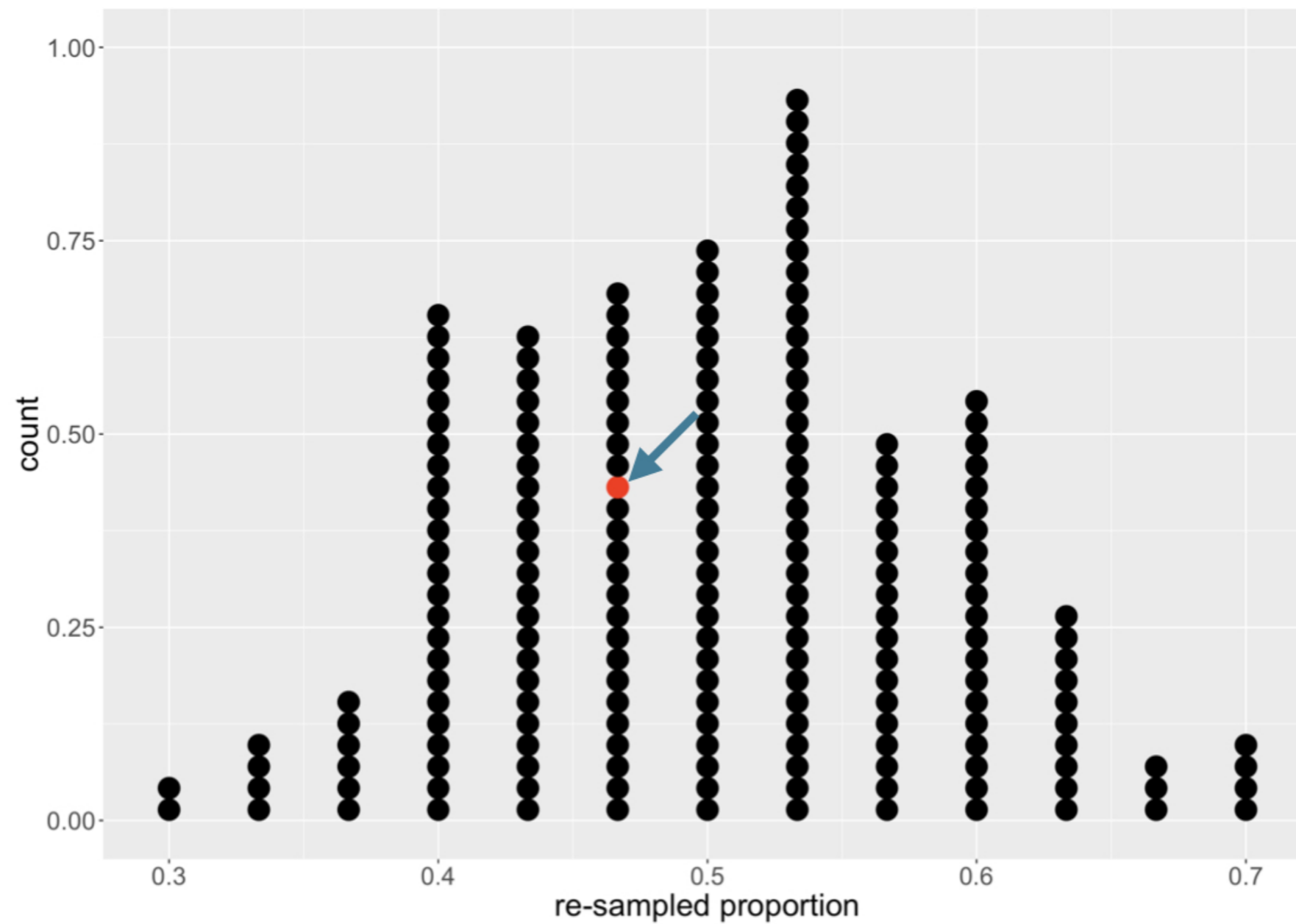


**Jo Hardin**  
Instructor

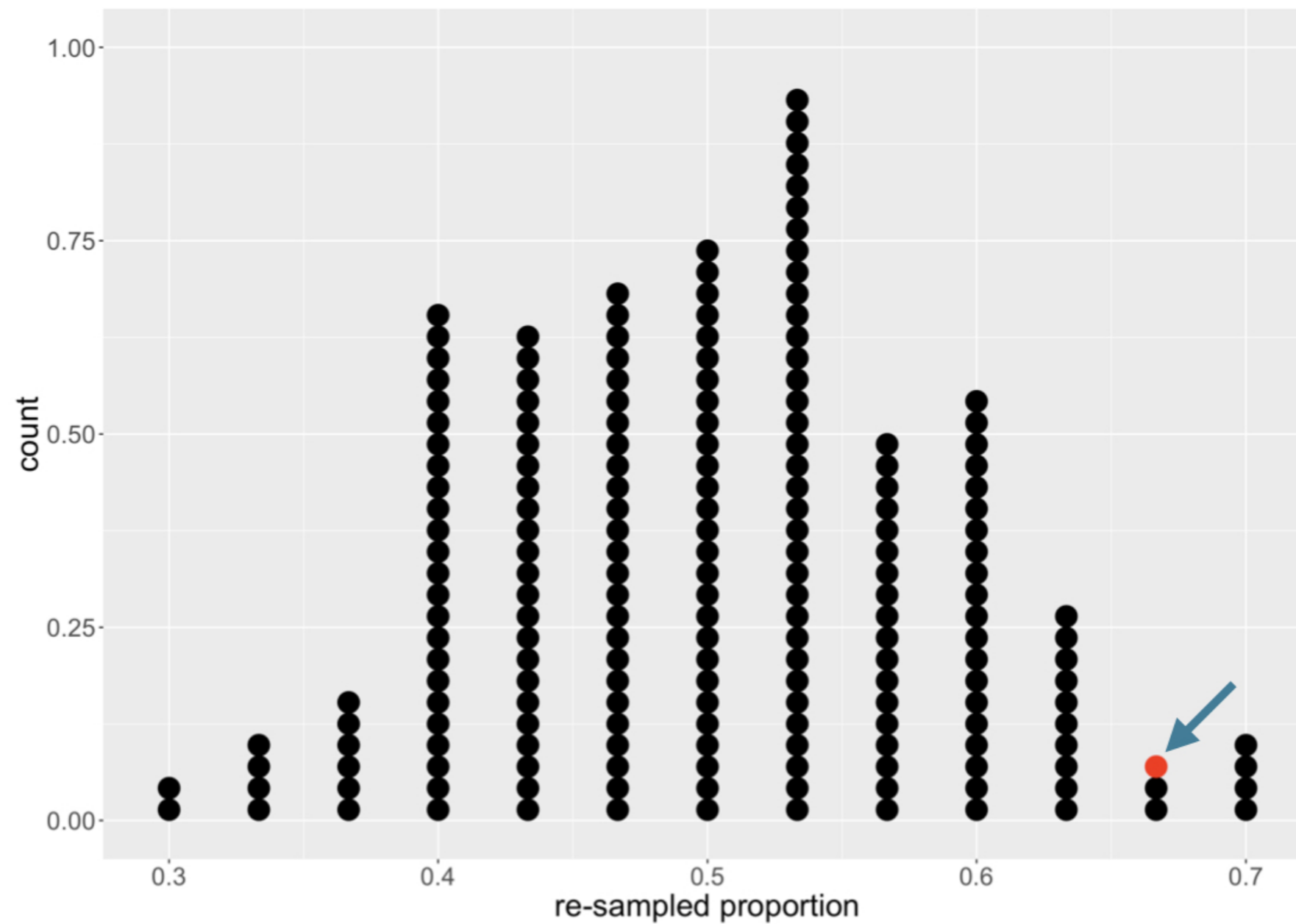
# How far are the data from the parameter?



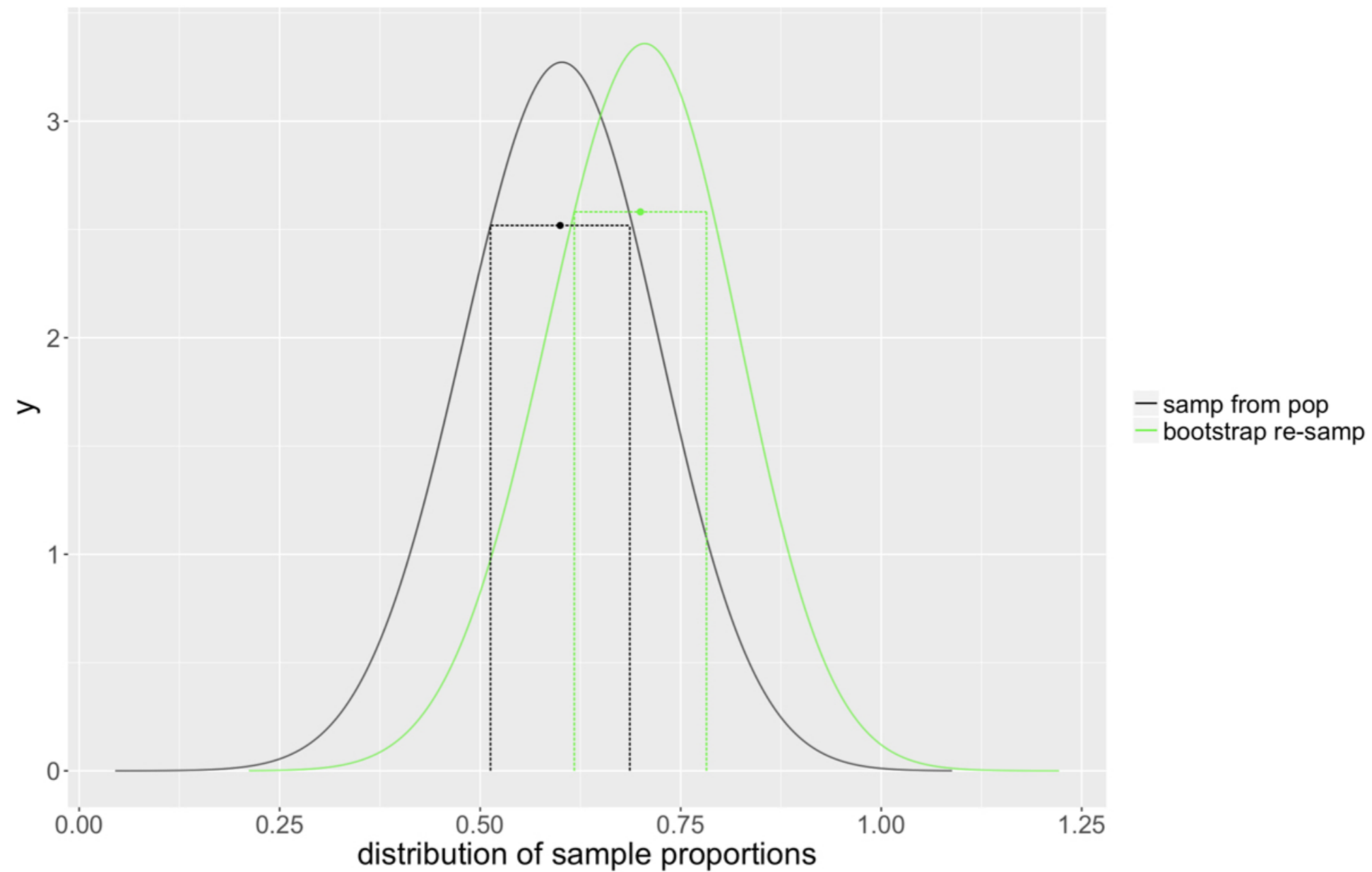
# How far are the data from the parameter?



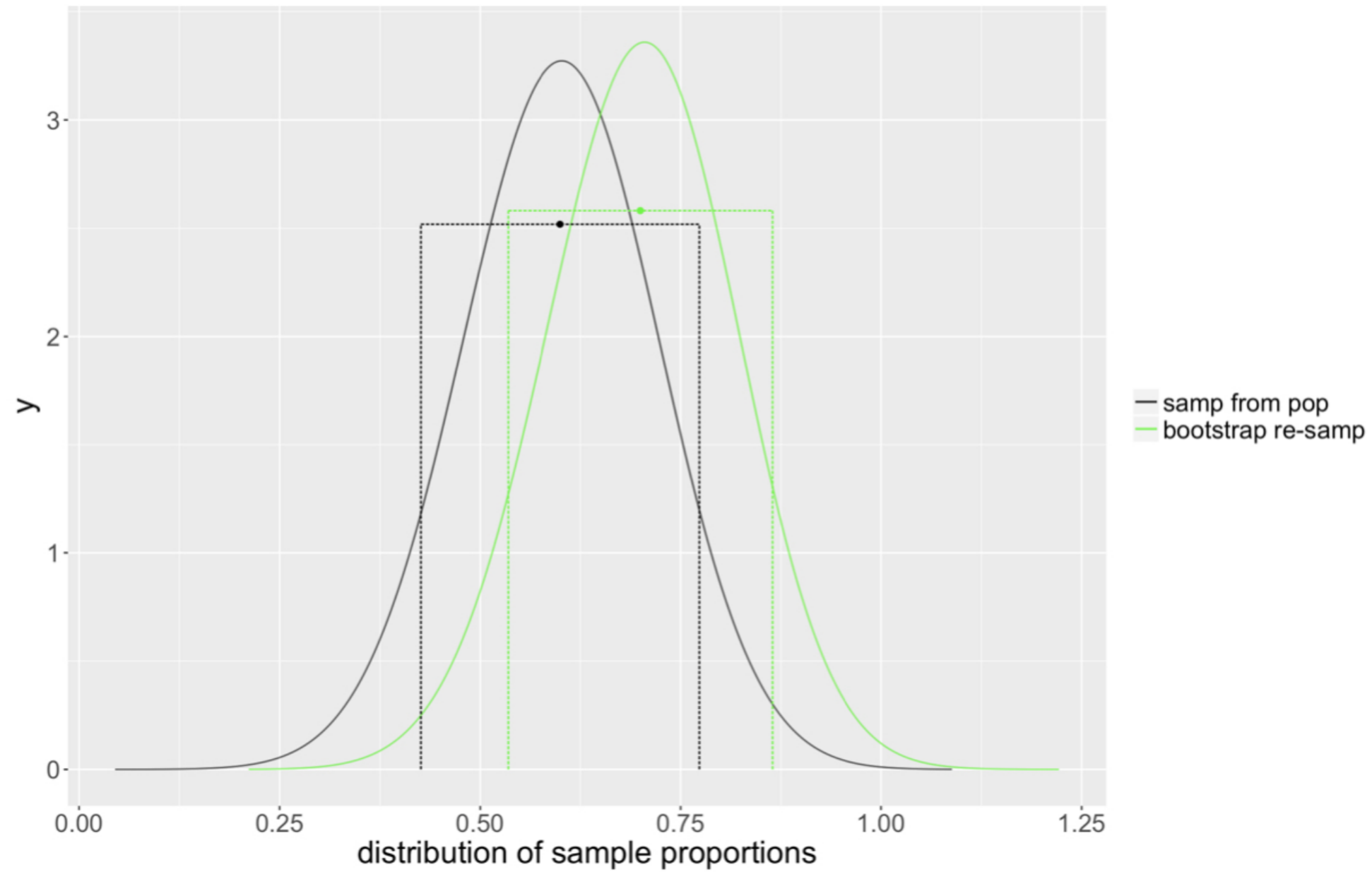
# How far are the data from the parameter?



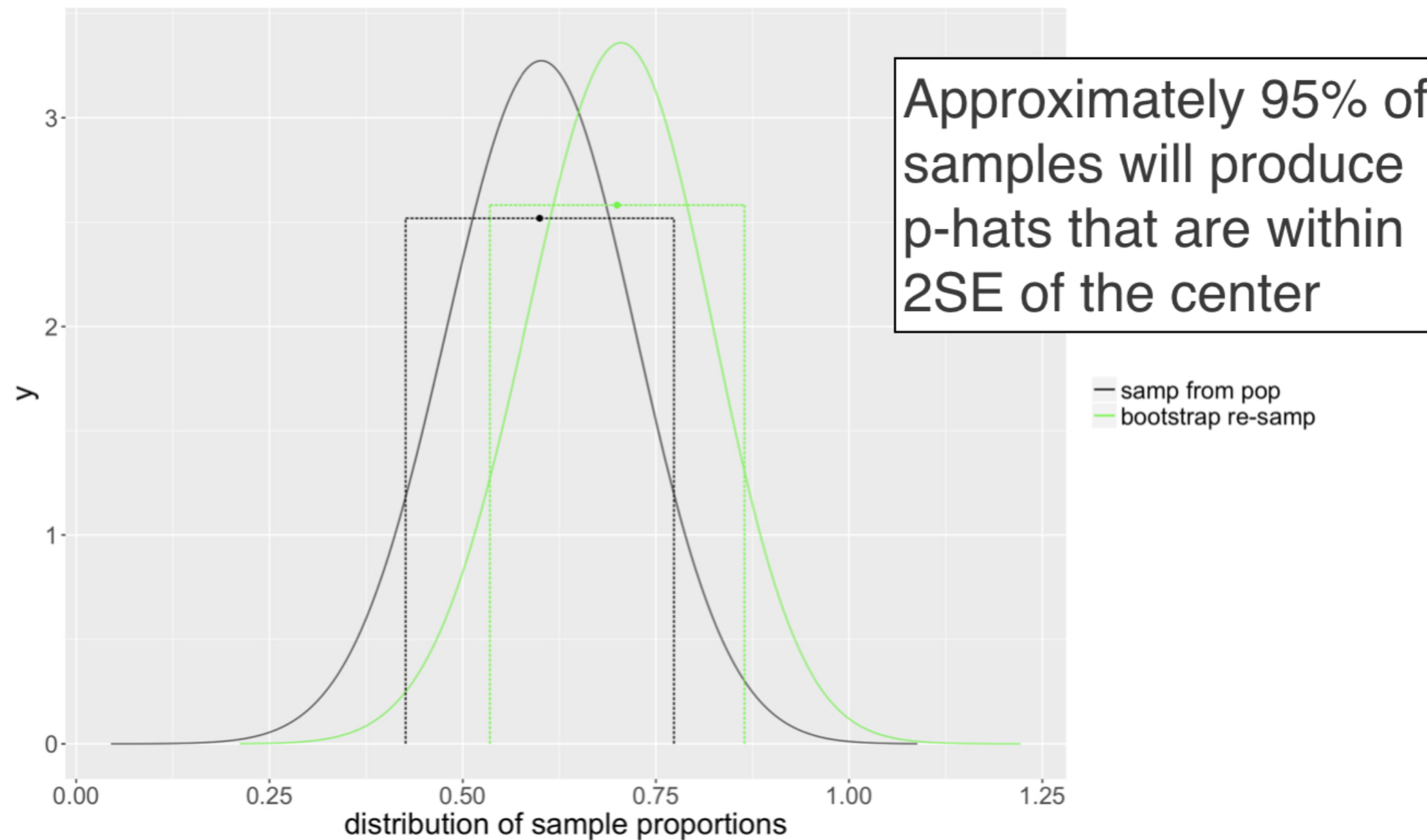
# Standard error of p-hat



# Empirical rule

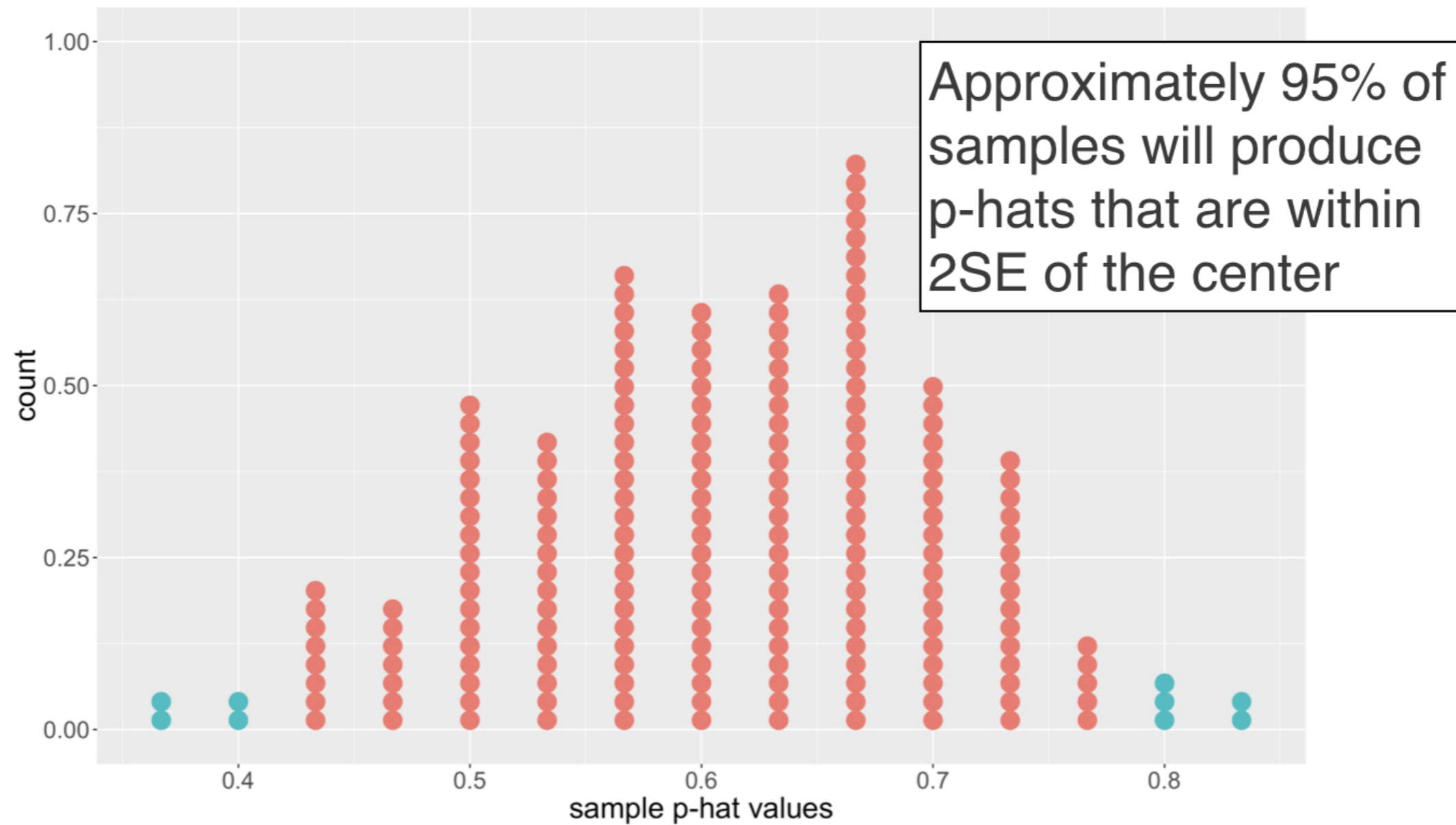


# Empirical rule





# Empirical rule



**Let's practice!**  
FOUNDATIONS OF INFERENCE

# Interpreting CIs and technical conditions

FOUNDATIONS OF INFERENCE



**Jo Hardin**  
Instructor

# Creating CIs

```
# Compare confidence intervals
one_poll_boot %>% summarize(
  lower = p_hat - 2 *
    sd(prop_yes_boot),
  upper = p_hat + 2 *
    sd(prop_yes_boot))
```

```
# A tibble: 1 × 2
  lower    upper
  <dbl>  <dbl>
1 0.536148 0.863852
```

```
# Find 2.5% and 97.5% of p-hat vals
one_poll_boot %>% summarize(
  q025_prop = quantile(prop_yes_boot,
    p = .025),
  q975_prop = quantile(prop_yes_boot,
    p = .975))
```

```
# A tibble: 1 × 2
  q025_prop q975_prop
  <dbl>      <dbl>
1 0.5333333 0.8333333
```

# Motivating CIs

- Goal is to find the parameter when all we know is the statistic
- Never know whether the sample you collected actually contains the true parameter

# Interpreting the CIs

- Bootstrap t-CI: (0.536, 0.864)
- Percentile interval: (0.533, 0.833)

***We are 95% confident that the true proportion of people planning to vote for candidate X is between 0.536 and 0.864 (or 0.533 and 0.833)***

# Technical conditions

- Sampling distribution of the statistic is reasonably symmetric and bell-shaped
- Sample size is reasonably large
- Variability of resampled proportions

**Let's practice!**  
FOUNDATIONS OF INFERENCE



# Summary of statistical inference

FOUNDATIONS OF INFERENCE



**Jo Hardin**  
Instructor

# Inference



# Testing

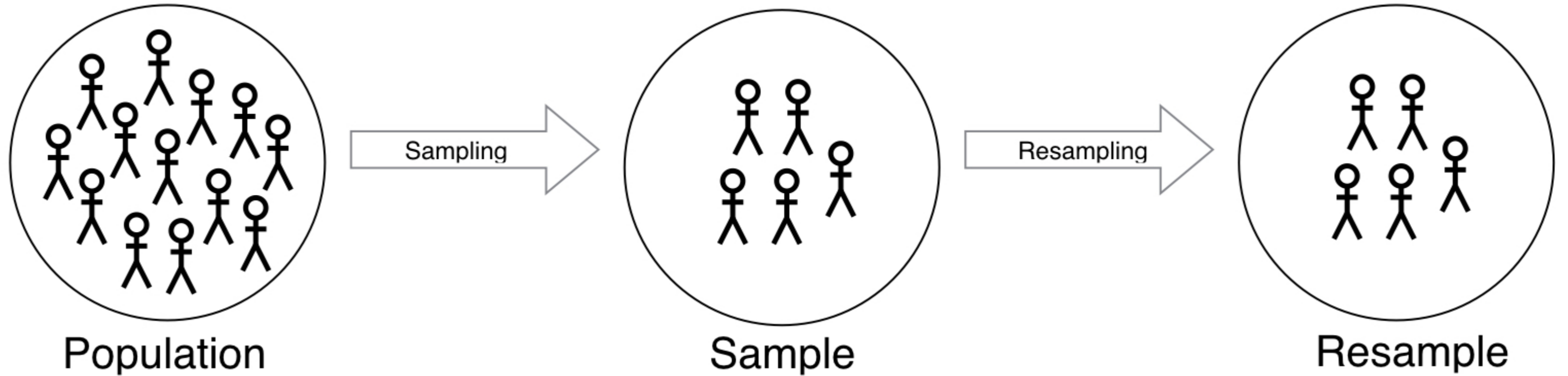
- $H_0$ : There is no gender discrimination in hiring
- $H_A$ : Men are more likely to be promoted than women

		Test	
		Do not reject $H_0$	Reject $H_0$ in favor of $H_A$
Truth	$H_0$ true	✓	Type I error
	$H_A$ true	Type II error	✓

# Estimation

**What proportion of the voters will select candidate X?**

# Bootstrapping



# Congratulations!

FOUNDATIONS OF INFERENCE