

# ScPoEconometrics

## Confidence Intervals and Hypothesis Testing

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# Quick "Quiz" on Last Week's Material

1. From your *computer* ↗ connect to [www.wooclap.com/SCPOSAMP](http://www.wooclap.com/SCPOSAMP)

*OR*

2. From your *phone* ↗ flash QR code below



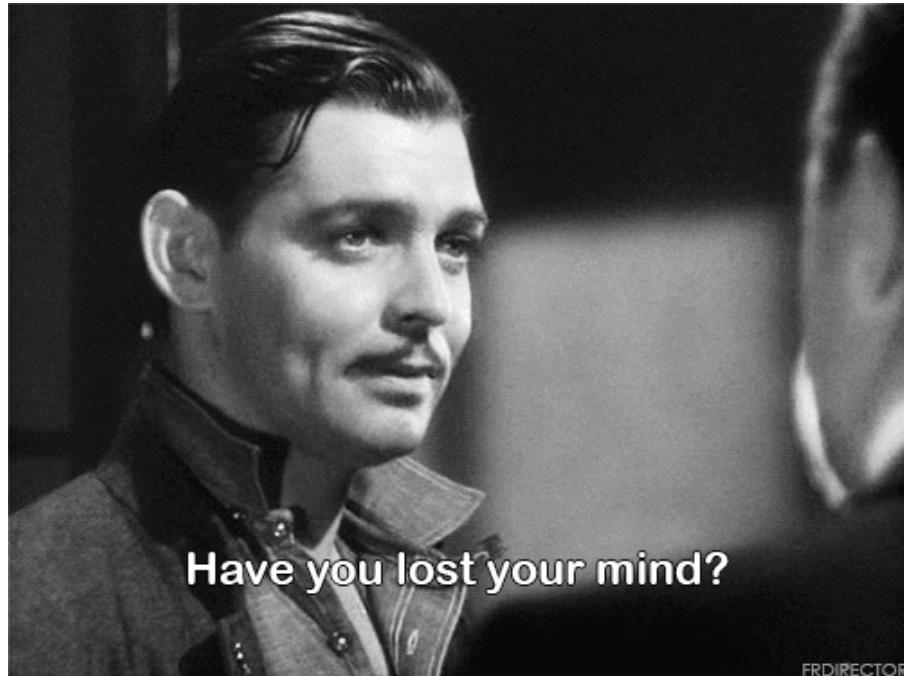
# Today - Deeper dive into *statistical inference*<sup>1</sup>

- *Confidence intervals*: providing plausible *range* of values
- *Hypothesis testing*: comparing statistics between groups



[1]: This lecture is based on the wonderful [confidence interval](#) and [hypothesis testing](#) chapters of [ModernDive](#)

# Back to reality (there goes gravity 😊)



- In real life we only get to take **one** sample from the population (not **1000**!).
- Also, we obviously don't know the true population parameter, that's what we are interested in!
- So what on earth was all of this good for? Fun only?! 😠



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- Even unobserved, we **know** that the sampling distribution does exist, and even better, we know how it behaves!
- Let's see what we can do with this...



# Confidence Intervals

# From Point Estimates to Confidence Intervals

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- We know that this ***sample statistic*** differs from the ***true population parameter*** due to ***sampling variation***.
- Rather than a point estimate, we could give a ***range of plausible values*** for the population parameter.
- This is precisely what a ***confidence interval*** (CI) provides.



# Constructing Confidence Intervals

There are several approaches to constructing confidence intervals:

1. *Theory*: use mathematical formulas (*Central Limit Theorem*) to derive the sampling distribution of our point estimate under certain conditions → *what R does under the hood!*



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We'll focus on simulation to give you the intuition and come back to the maths approach next week.



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In practice, you *don't* need to compute your confidence intervals using *bootstrap*, R uses statistical theory to do it for you.



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- Let's start by drawing one random sample of size  $n = 50$  from our bowl.

```
library(tidyverse)
bowl <- read.csv("https://www.dropbox.com/s/qpjsk0rfgc0gx80/pasta.csv?dl=1")

my_sample = bowl %>%
  mutate(color = ifelse(color == "green", "green", "non-green")) %>%
  rep_sample_n(size = 50) %>%
  ungroup() %>%
  select(pasta_ID, color)

head(my_sample, 3)

## # A tibble: 3 x 2
##   pasta_ID color
##       <int> <fct>
## 1        4 non-green
## 2       41 non-green
## 3       79 non-green
```



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```

```
p_hat = mean(my_sample$color == "green")
p_hat
## [1] 0.46
```

The proportion of green pasta in this sample is:  $\hat{p} = 0.46$ .



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3. Repeat steps 1 and 2 49 times, i.e. *until the new sample is of the same size as the original sample*.



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2. Put this pasta back in the sample.
3. Repeat steps 1 and 2 49 times, i.e. *until the new sample is of the same size as the original sample*.
4. Compute the proportion of green pasta in the bootstrap sample.

This procedure is called *resampling with replacement*:

- *resampling*: drawing repeated samples from a sample.
- *with replacement*: each time the drawn pasta is put back in the sample.



# Resampling our Pasta Sample

Here is one bootstrap sample:

```
one_bootstrap = my_sample %>%
  rep_sample_n(size = 50, replace = TRUE) %>%
  arrange(pasta_ID)

head(one_bootstrap, 8)
```

```
## # A tibble: 8 x 3
## # Groups:   replicate [1]
##   replicate pasta_ID color
##       <int>     <int> <fct>
## 1         1         4 non-green
## 2         1        41 non-green
## 3         1        41 non-green
## 4         1        79 non-green
## 5         1        79 non-green
## 6         1       103 non-green
## 7         1       103 non-green
## 8         1       103 non-green
```

```
nrow(one_bootstrap)
```

```
## [1] 50
```



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## 5         1       79 non-green
## 6         1      103 non-green
## 7         1      103 non-green
## 8         1      103 non-green

nrow(one_bootstrap)

## [1] 50
```

Several pasta have been drawn multiple times. How come?

What's the proportion of green pasta in this bootstrap sample?

```
mean(one_bootstrap$color == "green")

## [1] 0.4
```

The proportion is different than that in our sample! This is due to resampling **with replacement**.

What if we repeated this resampling procedure many times? Would the proportion be the same each time?



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- Let's repeat the resampling procedure 1,000 times: there will be 1,000 bootstrap samples and 1,000 bootstrap estimates!



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We use the `infer` package to ease the bootstrapping procedure.

```
library(infer)

bootstrap_distrib = my_sample %>%
  # specify the variable and level of interest
  specify(response = color, success = "green") %>%
  # generate 1000 bootstrap samples
  generate(reps = 1000, type = "bootstrap") %>%
  # calculate the proportion of green pasta for each
  calculate(stat = "prop")
```



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  calculate(stat = "prop")
```

Here are the first 6 rows:

```
head(bootstrap_distrib)

## # A tibble: 6 x 2
##   replicate stat
##       <int> <dbl>
## 1         1  0.44
## 2         2  0.36
## 3         3  0.46
## 4         4  0.46
## 5         5  0.52
## 6         6  0.52
```

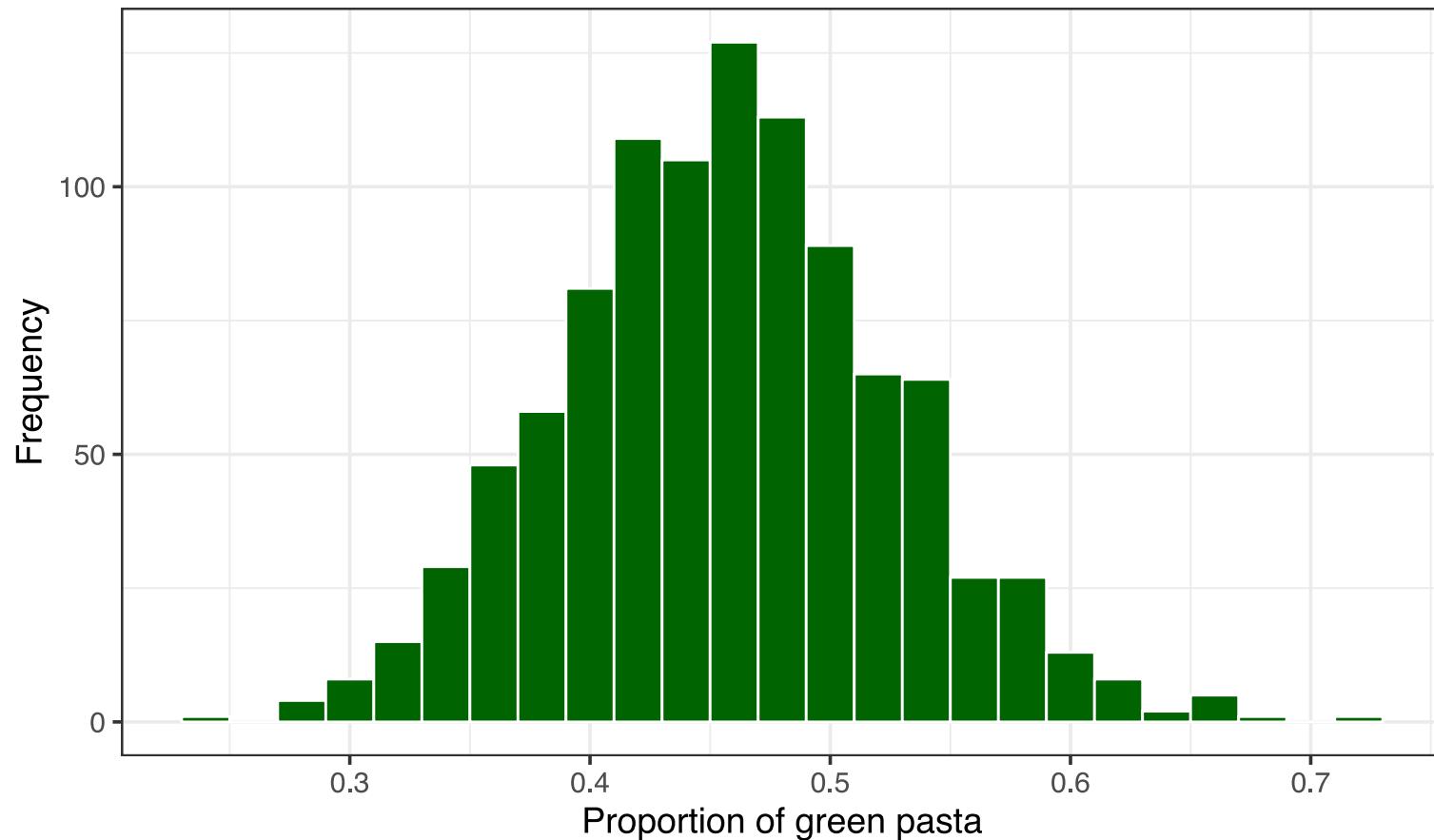
```
nrow(bootstrap_distrib)

## [1] 1000
```

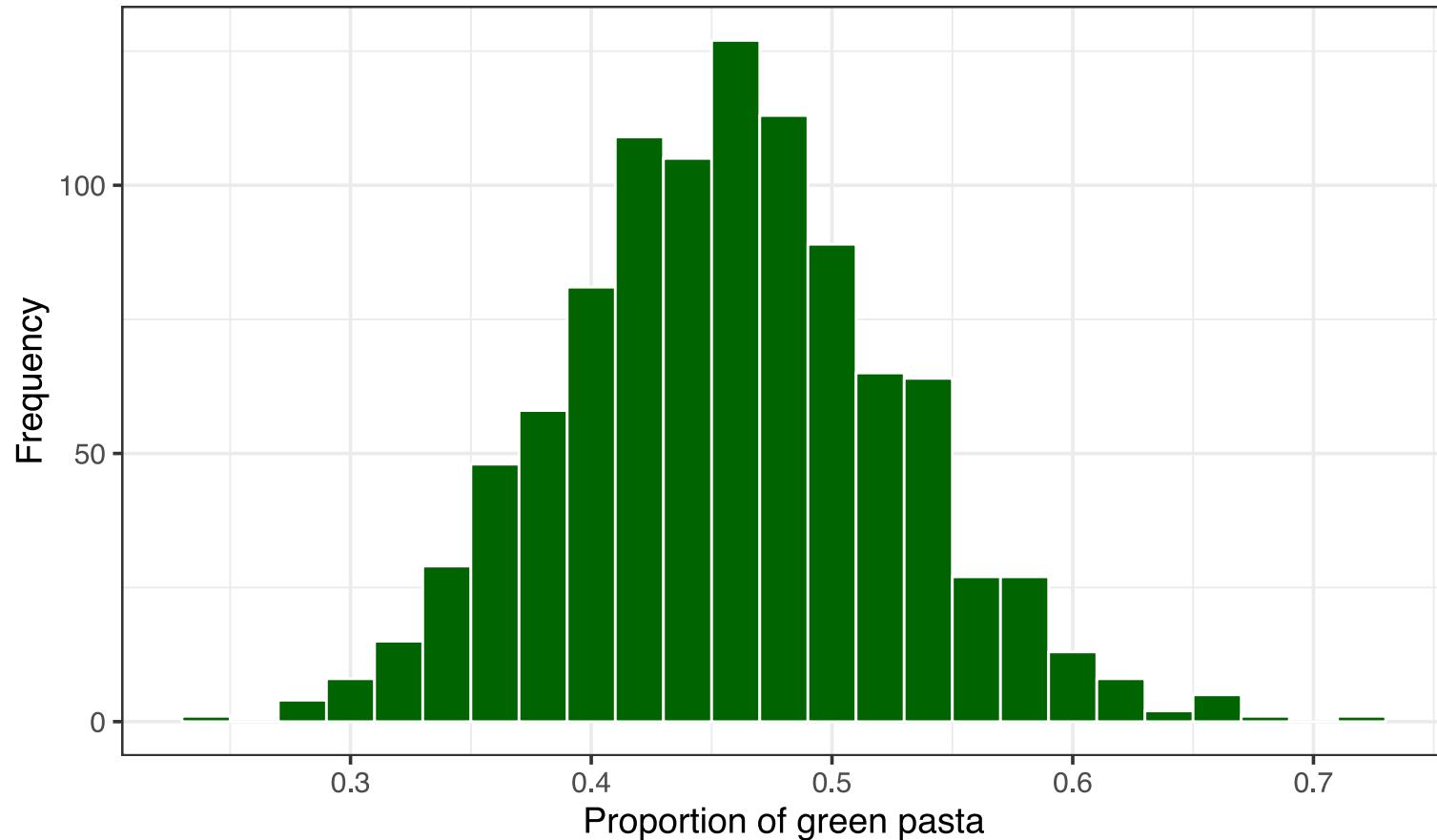
Let's visualize this sampling variation!



# Bootstrap Distribution



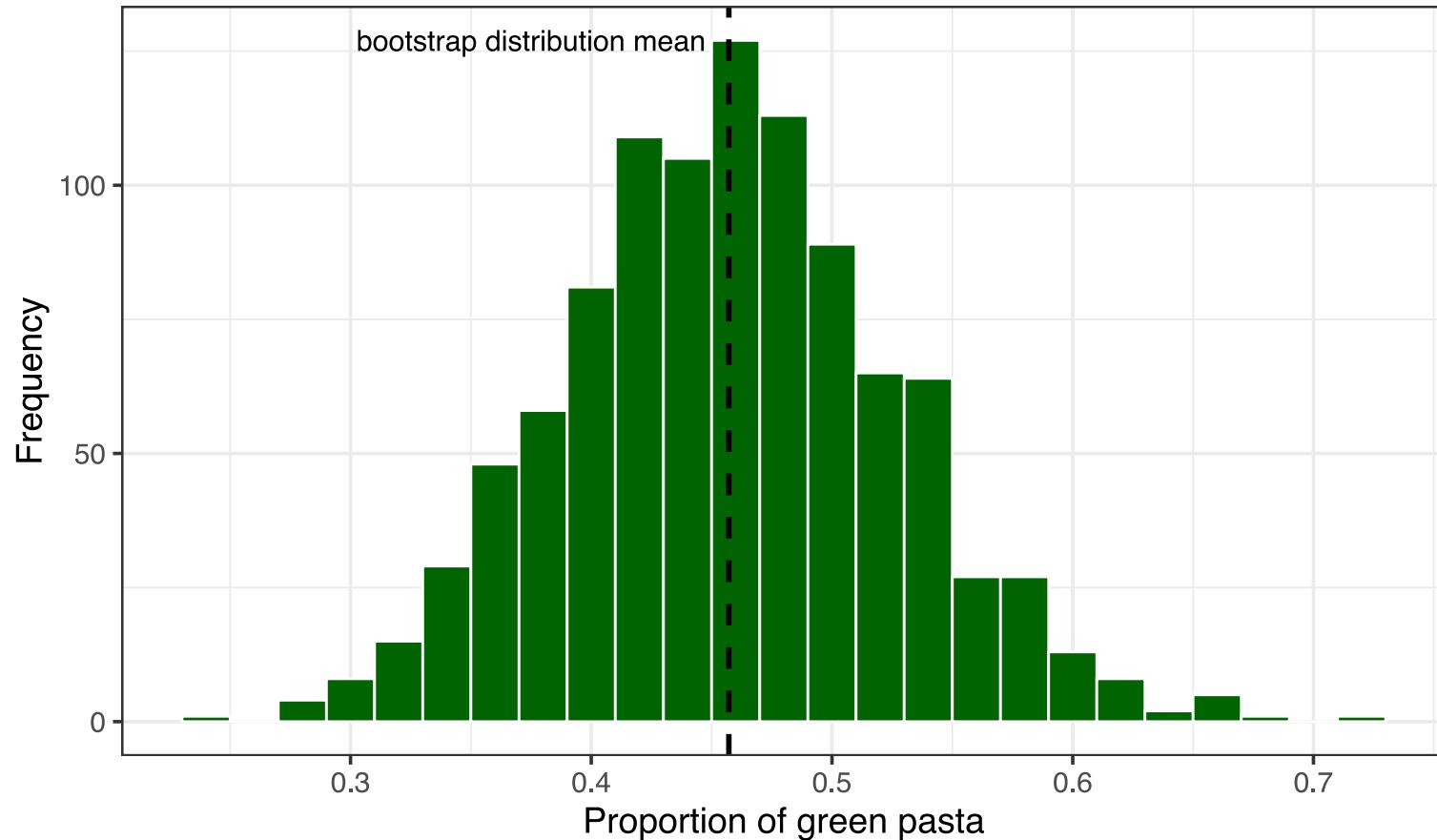
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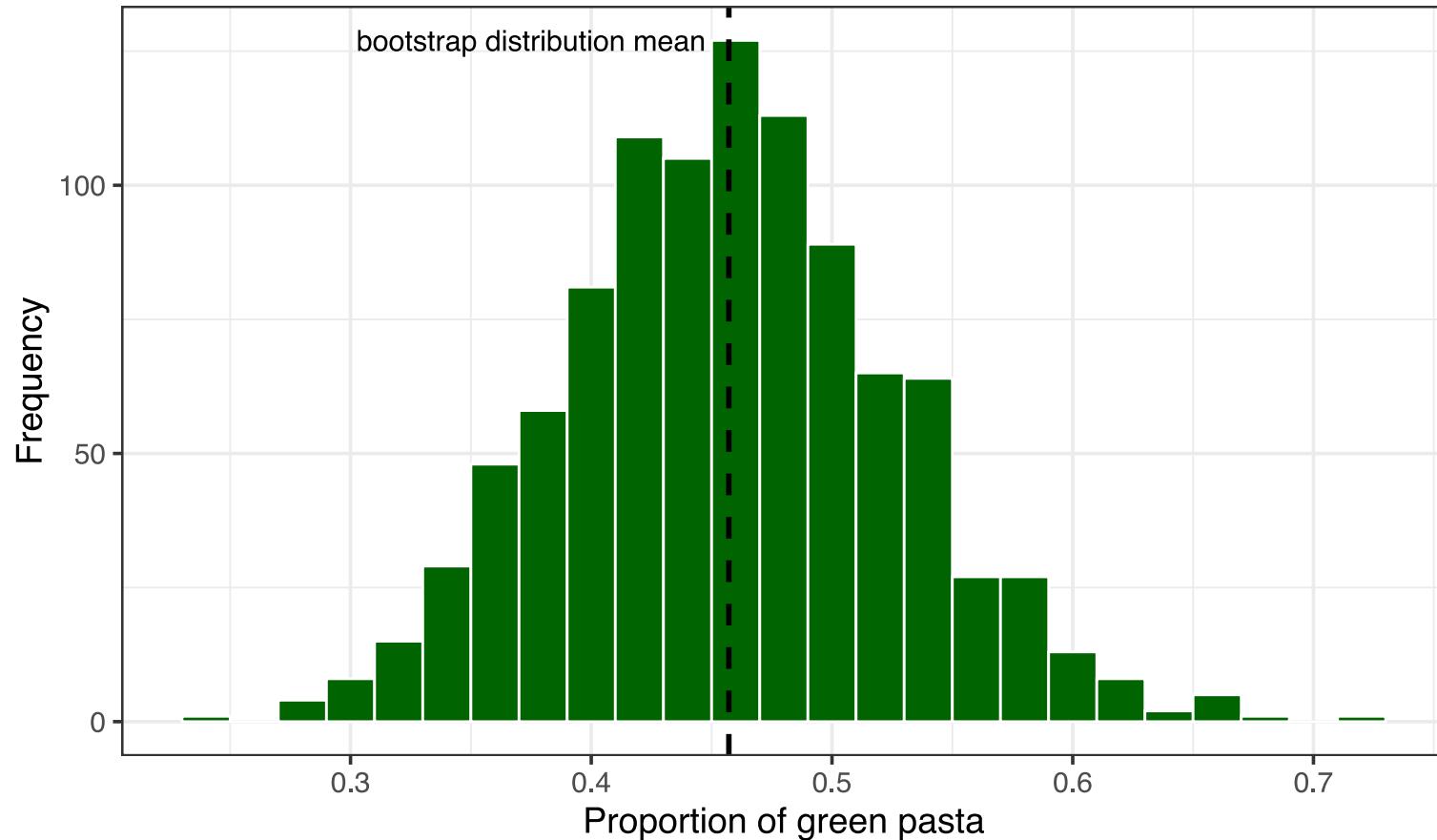
The *bootstrap distribution* is an approximation of the *sampling distribution*.



# Bootstrap Distribution with Mean



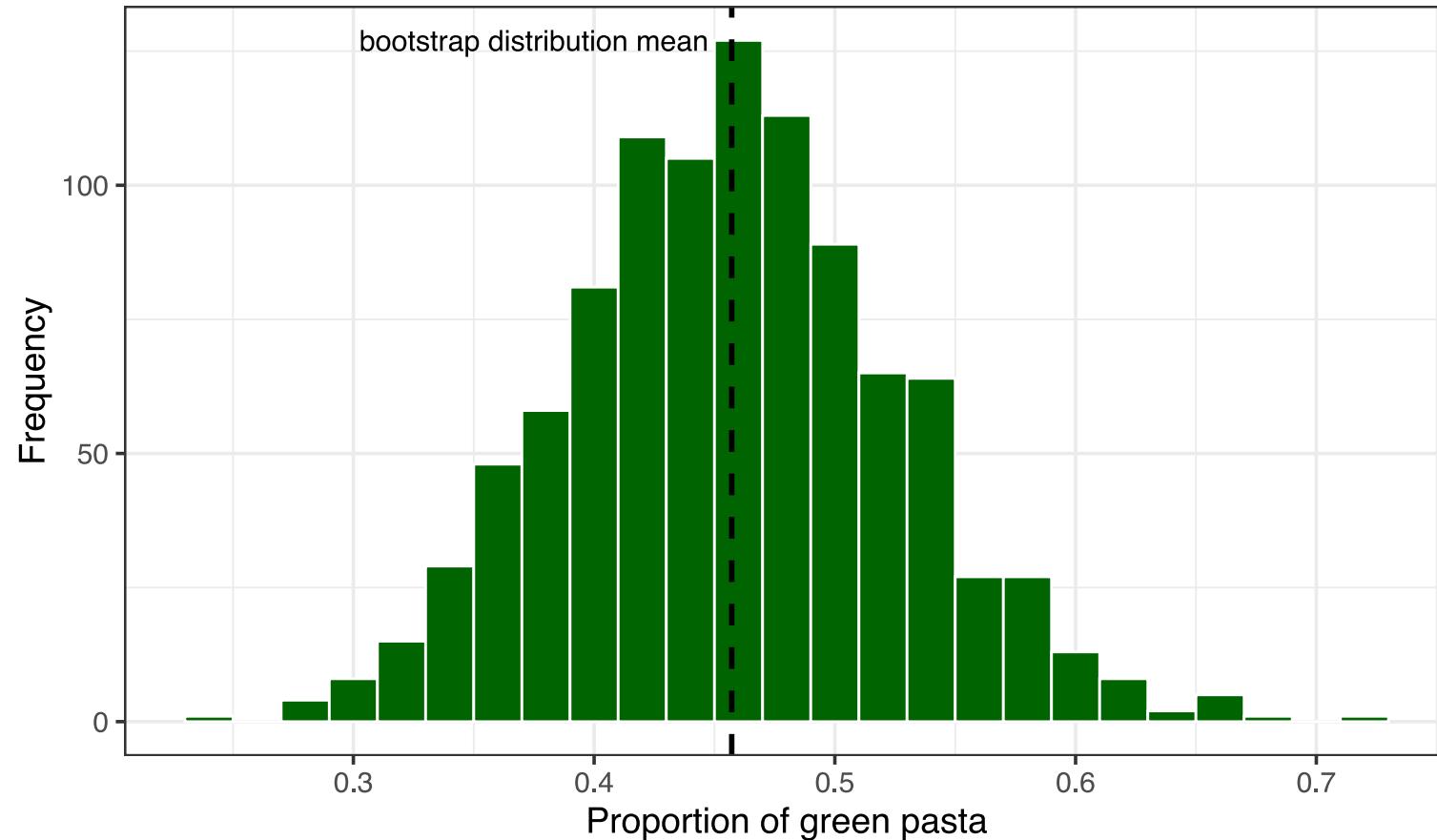
# Bootstrap Distribution with Mean



The *bootstrap distribution* mean is very close to the original sample proportion.



# Bootstrap Distribution with Mean



Let's use this **bootstrap distribution** to construct confidence intervals!



# Understanding Confidence Intervals

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  - *point estimate*: fishing with a spear.



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- The *point estimate* would be the proportion of green pasta obtained from a random sample ( $\hat{p}$ ).



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- Method for confidence interval construction: ***percentile method***.



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- The *confidence interval*: from the previous bootstrap distribution, ***where do most proportions lie?***
- Method for confidence interval construction: ***percentile method***.
- Requires specifying a ***confidence level***: 90%, 95%, and 99% are the most common.



# Percentile Method: 95% Confidence Interval

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- For that, we compute the 2.5% and 97.5% percentile:

```
quantile(bootstrap_distrib$stat, 0.025)
```

```
## 2.5%
## 0.32
```

```
quantile(bootstrap_distrib$stat, 0.975)
```

```
## 97.5%
## 0.6
```

- Therefore the 95% confidence interval is [0.32; 0.6].
- It is a *range* of values.



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```

```
## 2.5%
## 0.32
```

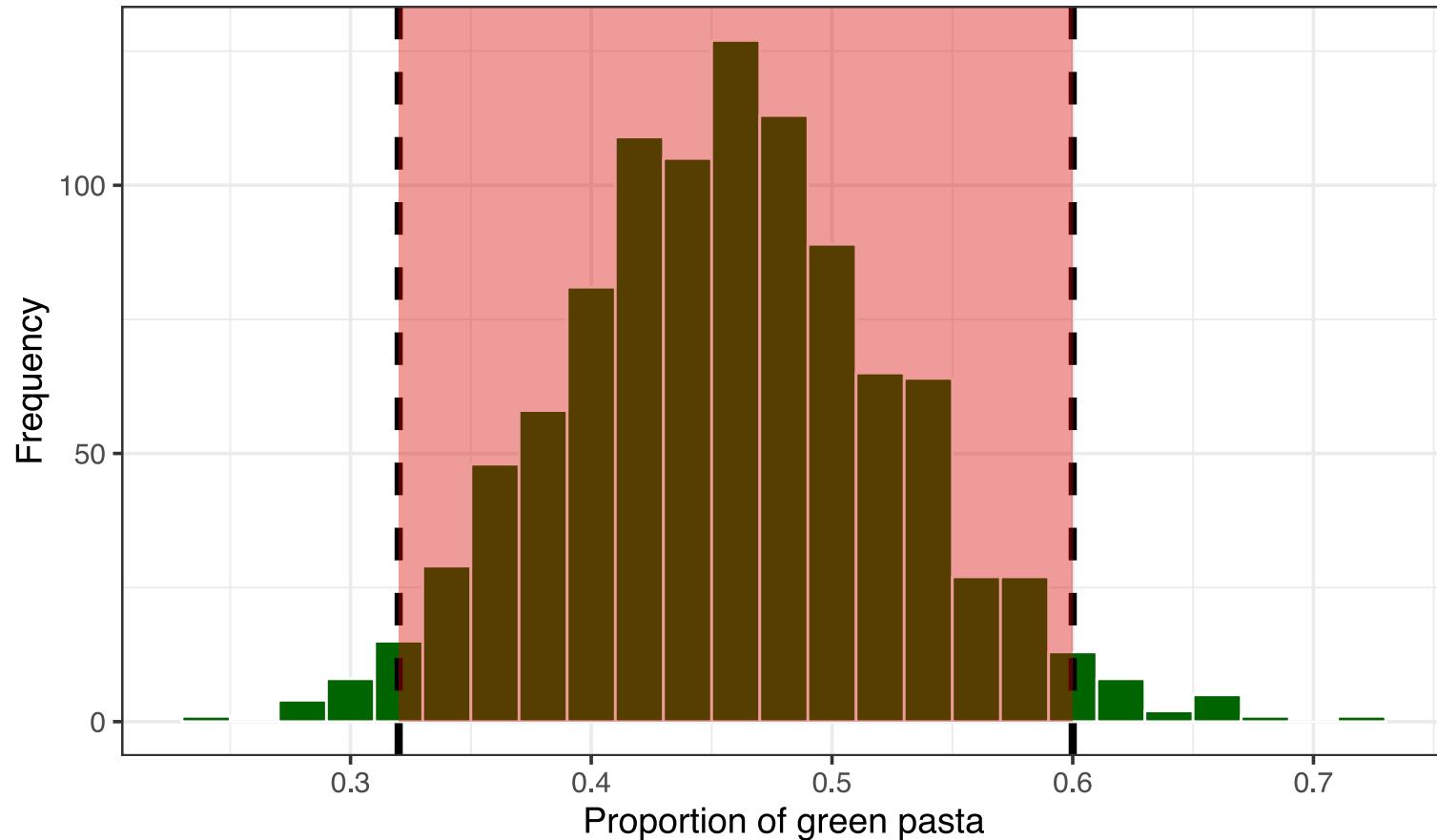
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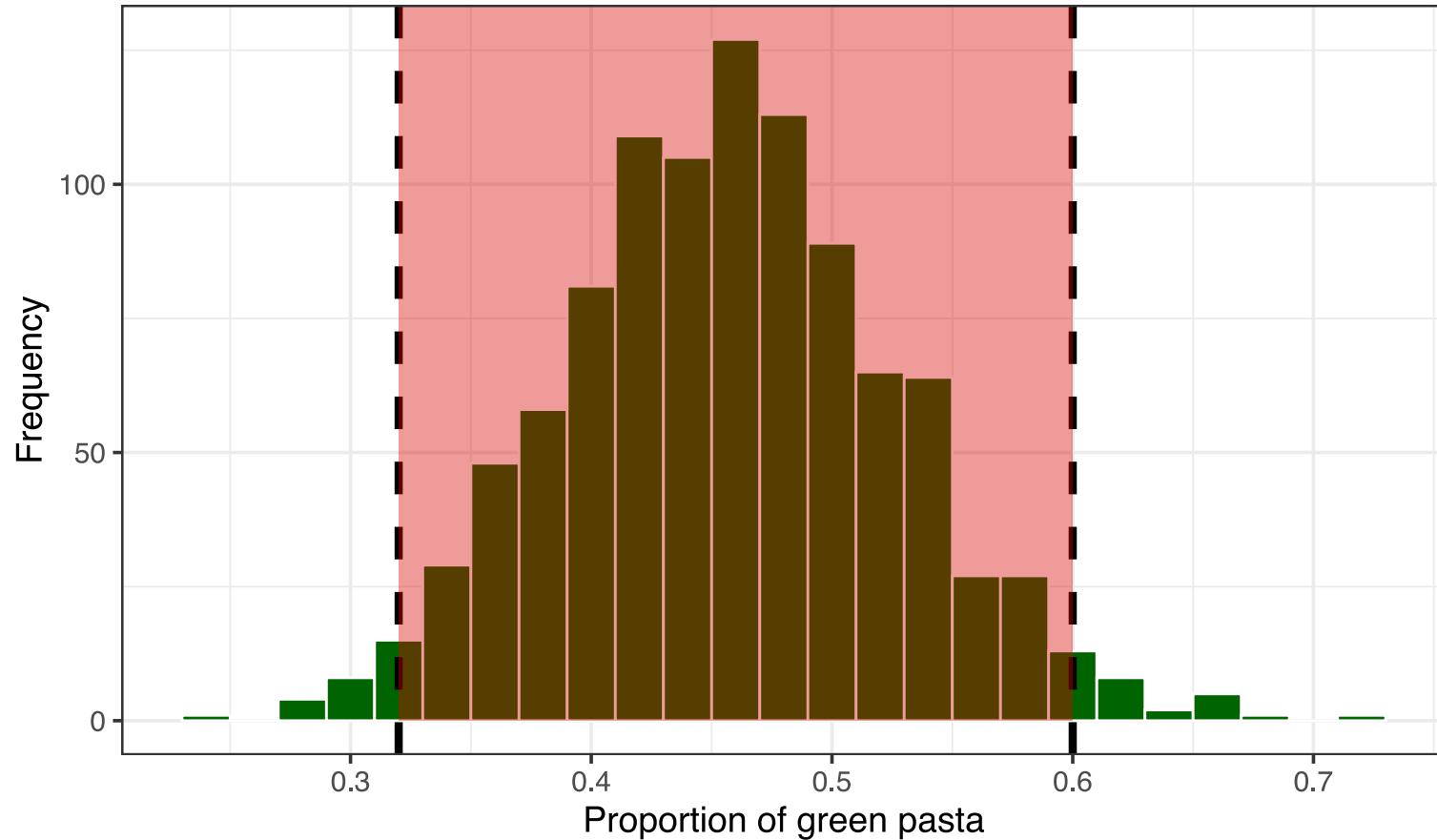
- Therefore the 95% confidence interval is [0.32; 0.6].
- It is a *range* of values.
- Let's see this confidence interval on the sampling distribution.



# Percentile Method: 95% Confidence Interval Visually



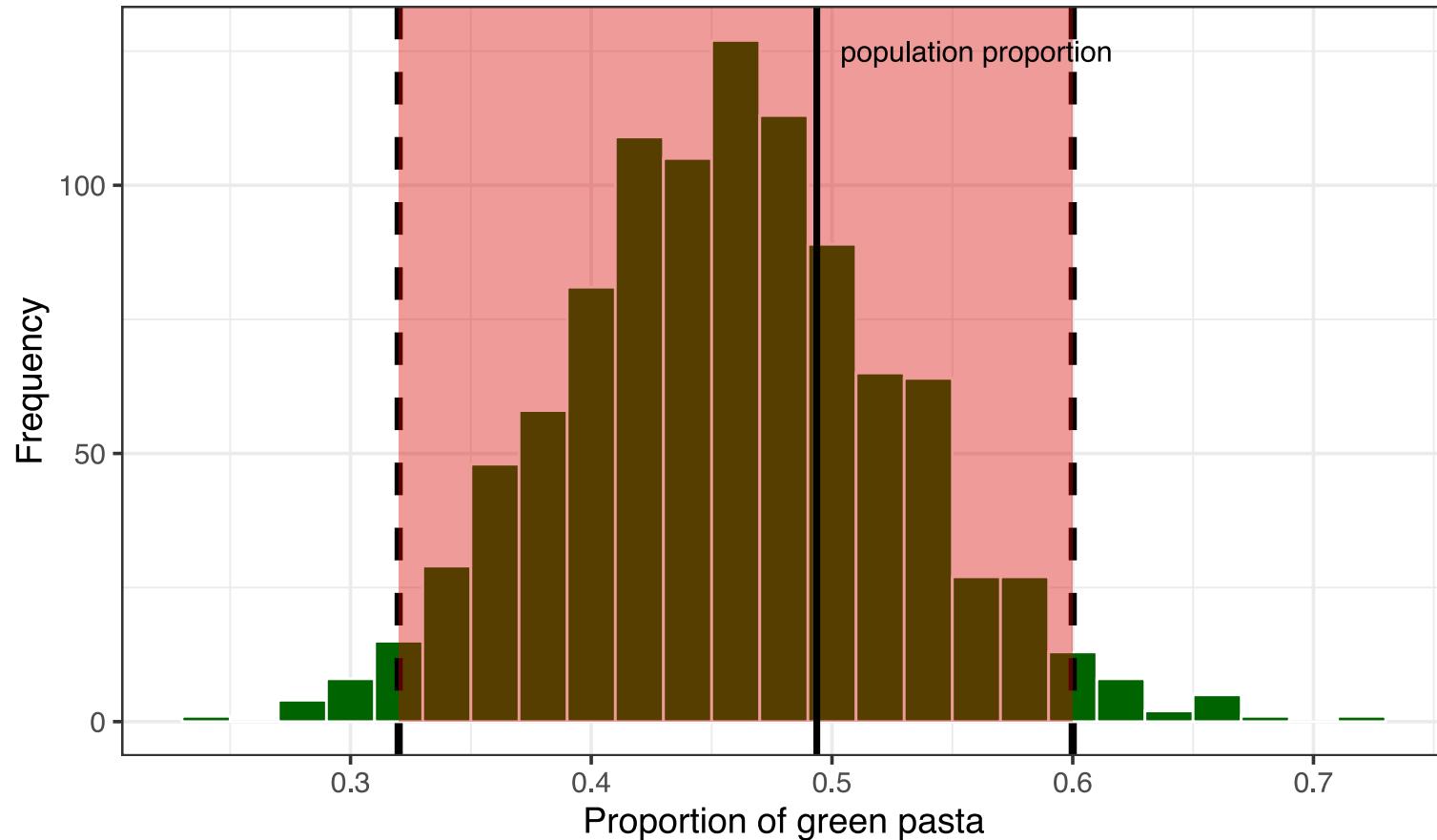
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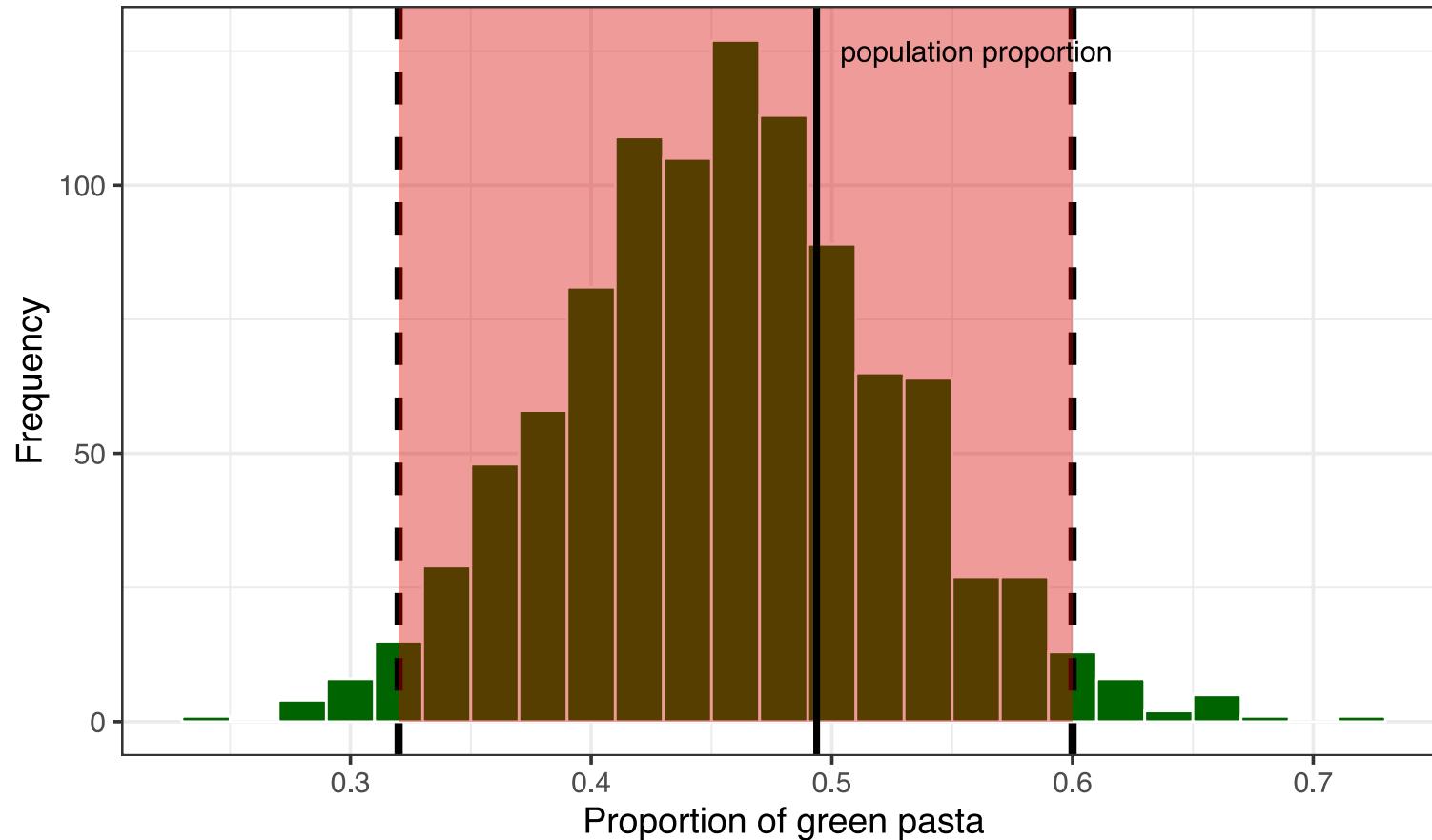
Does the interval contain the true population proportion?



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True population parameter is indeed in our 95% interval! Will it always be?



# Interpreting a 95% Confidence Interval

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How many confidence intervals contain the true parameter? Why?

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*Precise interpretation:* If we repeated our sampling procedure ***a large number of times***, we ***expect about 95%*** of the resulting confidence intervals to capture the value of the population parameter.

In other words, 95% of the time, the 95% confidence interval will contain the true population parameter.



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## ***Questions:***

- How does the width of the confidence interval change as the ***confidence level*** increases?
- How does the width of the confidence interval change as the ***sample size*** increases?



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***Impact of confidence level:*** the greater the confidence level, the wider the confidence intervals.

- *Intuition:* a greater confidence level means the confidence interval needs to contain the true population parameter more often, and thus needs to be wider to ensure this.



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**Impact of confidence level:** the greater the confidence level, the wider the confidence intervals.

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**Impact of sample size:** the greater the confidence level, the wider the confidence intervals.

- *Inuition:* a larger sample size leads to less sampling variation and therefore a narrower bootstrap distribution, which in turn leads to thinner confidence intervals.



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  - *Example:* differences in average wages between men and women. Are the observed differences **significant**?



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  - *Example:* differences in average wages between men and women. Are the observed differences **significant**?
- These comparisons are the realm of ***hypothesis testing***.
- Just like confidence intervals, hypothesis tests are used to make claims about a population based on information from a sample.
- However, we'll see that the framework for making such inferences is slightly different.



# Hypothesis Testing

# Is There Gender Discrimination In Promotions?

- We will use data from an [article](#) published in the *Journal of Applied Psychology* in 1974 which investigated whether female employees at banks were discriminated against.
- 48 (male) supervisors were given *identical* candidate CVs, differing only with respect to the first name, which was male or female.
  - Each CV was "*in the form of a memorandum requesting a decision on the promotion of an employee to the position of branch manager.*"



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- The data from the experiment are provided in the **promotions** dataset from the **moderndive** package.



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- **Hypothesis** we want to test: *Is there gender discrimination?*

- The data from the experiment are provided in the **promotions** dataset from the **moderndive** package.

```
library(moderndive)
head(promotions)

## # A tibble: 6 x 3
##       id decision gender
##   <int> <fct>    <fct>
## 1     1 promoted male
## 2     2 promoted male
## 3     3 promoted male
## 4     4 promoted male
## 5     5 promoted male
## 6     6 promoted male
```



# Evidence of Discrimination?

How many men and women were offered a promotion (and not)?

```
promotions %>%
  group_by(gender, decision) %>%
  tally() %>%
  mutate(percentage = 100 * n / sum(n))

## # A tibble: 4 x 4
## # Groups:   gender [2]
##   gender decision     n percentage
##   <fct>   <fct>   <int>      <dbl>
## 1 male    not         3        12.5
## 2 male    promoted   21       87.5
## 3 female  not        10       41.7
## 4 female  promoted  14       58.3
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There is a **29.2 percentage points difference** in promotions between men and women!



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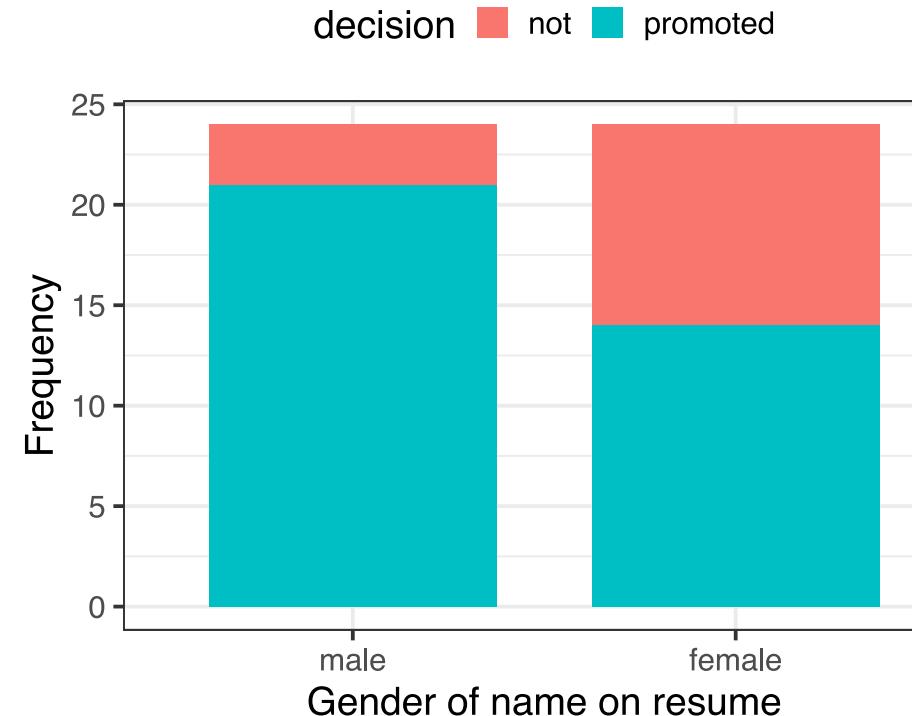
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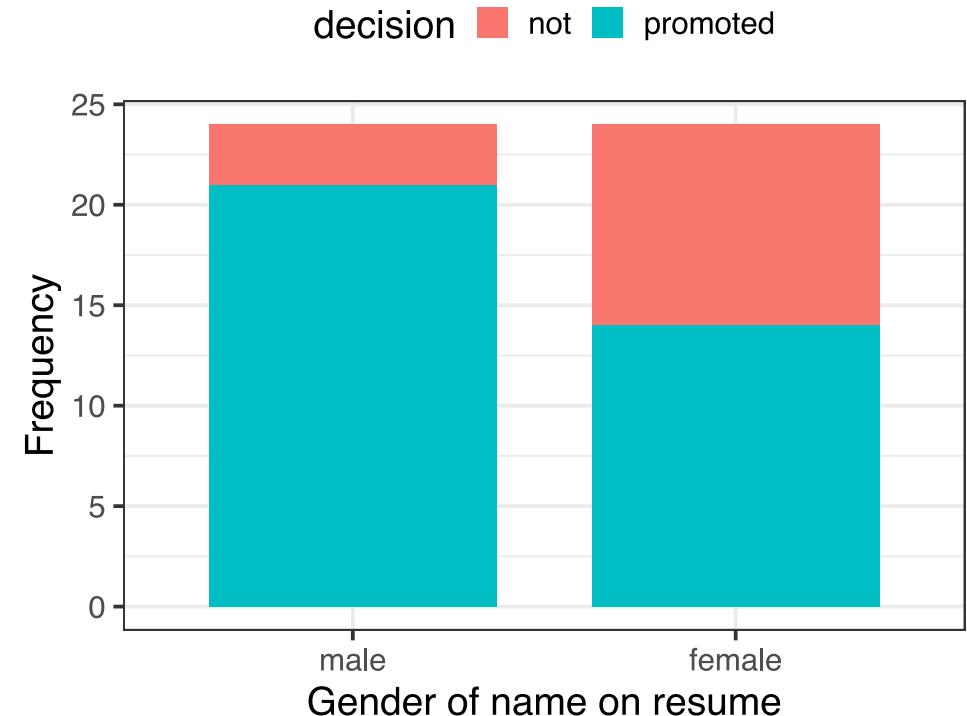
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**Question:** Is this difference **conclusive evidence** of differences in promotion rates between men and women? Could such a difference have been observed **by chance**?



# Imposing A Hypothetical World: No Gender Discrimination

- Suppose we lived in a world without gender discrimination: the promotion decision would be completely *independent* from gender.
- Let's randomly reassign `gender` to each row and see how this affects the result.



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```
promotions %>%
  left_join(promotions_shuffled %>%
             rename(shuffled_gender = gender)) %
  head()

## # A tibble: 6 x 4
##       id decision gender shuffled_gender
##   <int> <fct>    <fct>    <fct>
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How do the promotion rates look like in our reshuffled sample?



# Imposing A Hypothetical World: No Gender Discrimination

- Suppose we lived in a world without gender discrimination: the promotion decision would be completely *independent* from gender.
- Let's randomly reassign `gender` to each row and see how this affects the result.

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```

How do the promotion rates look like in our reshuffled sample?

```
promotions_shuffled %>%
  group_by(gender, decision) %>%
  tally() %>%
  mutate(percentage = 100 * n / sum(n))

## # A tibble: 4 x 4
## # Groups:   gender [2]
##   gender decision      n percentage
##   <fct>   <fct>   <int>      <dbl>
## 1 male    not          6        25
## 2 male    promoted    18       75
## 3 female  not          7       29.2
## 4 female  promoted   17      70.8
```

The difference is much lower: **4.2 percentage points!**



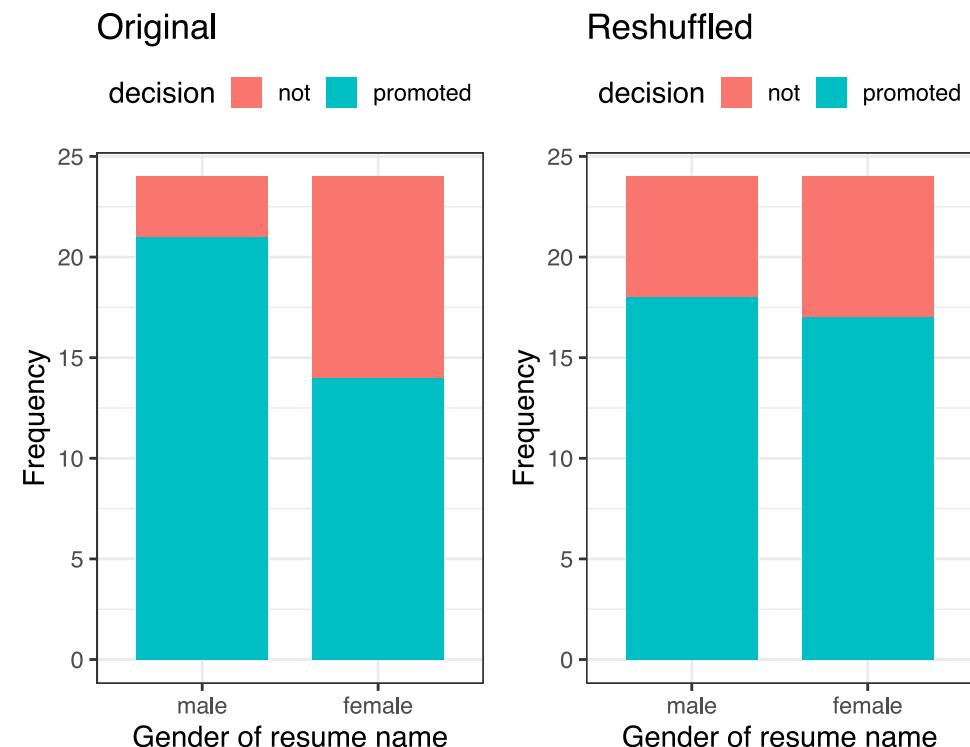
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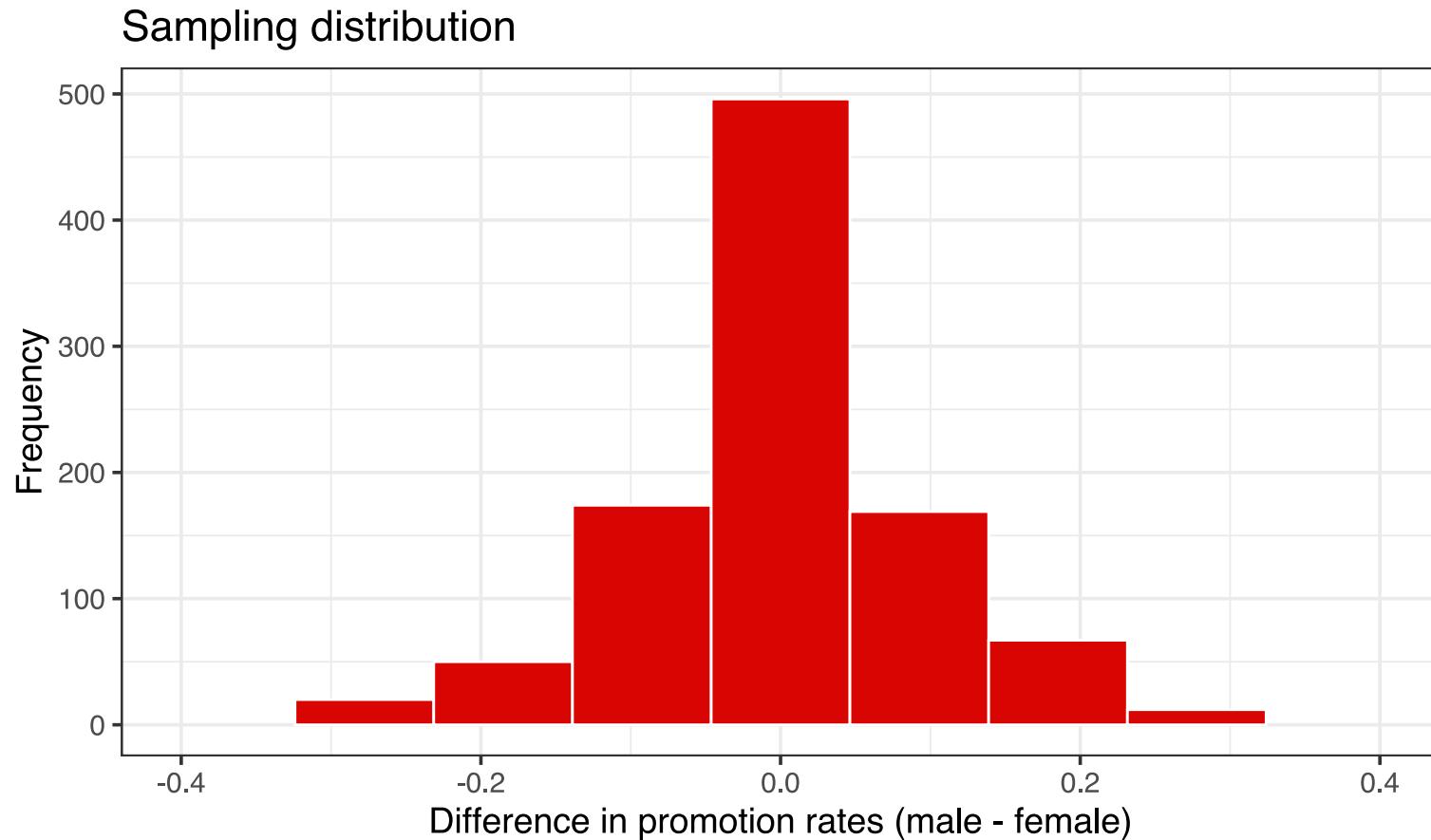


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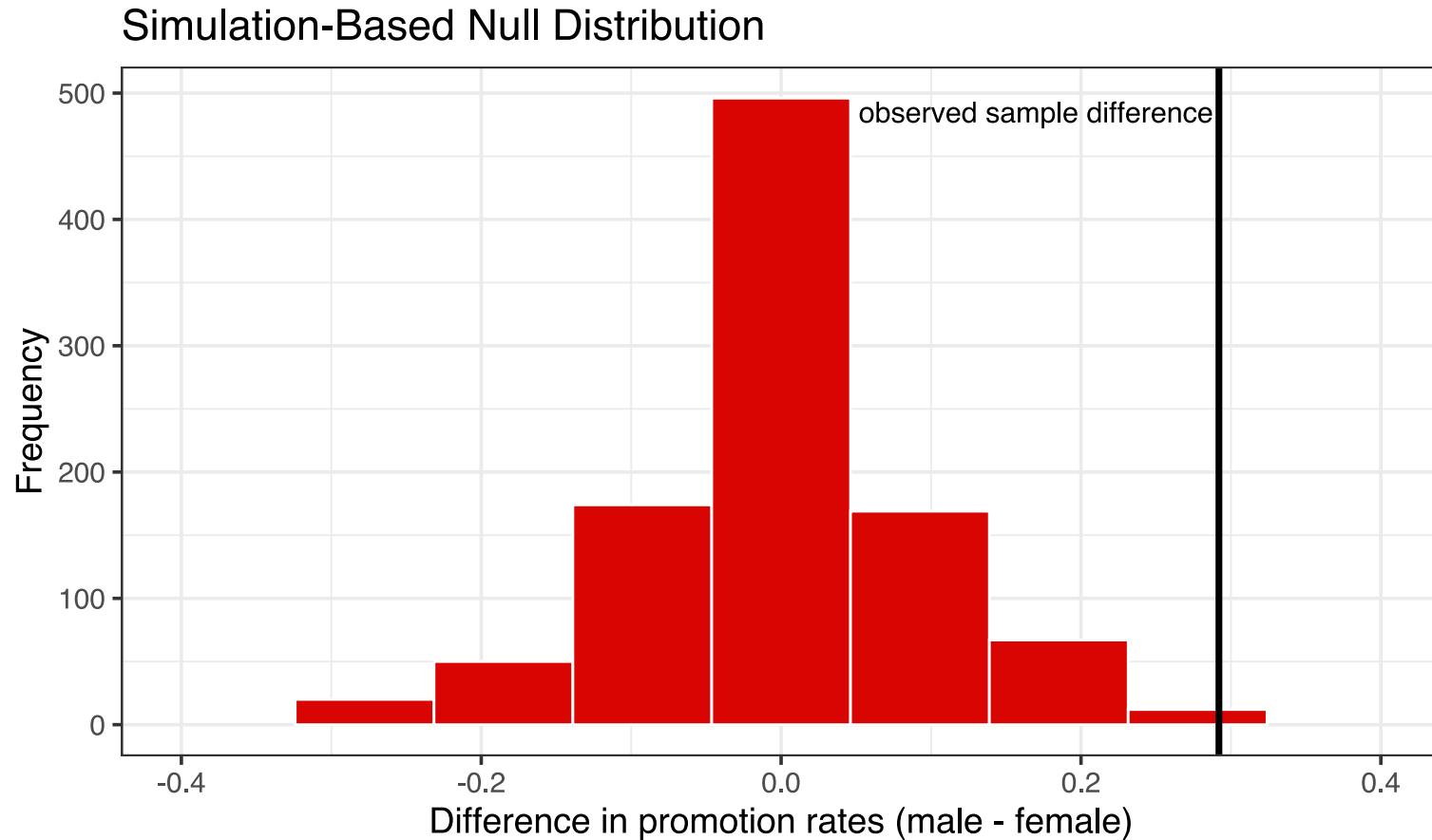
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- How? Just by redoing the reshuffling a large number of times, and computing the difference each time.



# Sampling Distribution with 1000 Reshufflings



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How *likely* is it to observe a 0.292 difference in a world with no discrimination?



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- The question is how likely the observed difference in promotion rates is to occur in a hypothetical universe with no discrimination.
- We concluded *rather not*, i.e. we tended to *reject* the no discrimination hypothesis.
- Let's introduce the formal framework of hypothesis testing now.



# Hypothesis Test Notation and Definitions

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- Here, we considered a ***one-sided*** alternative, stating that  $p_m > p_f$ , i.e. women are discriminated against.
- The ***two-sided*** formulation is just  $H_A : p_m - p_f \neq 0$ .



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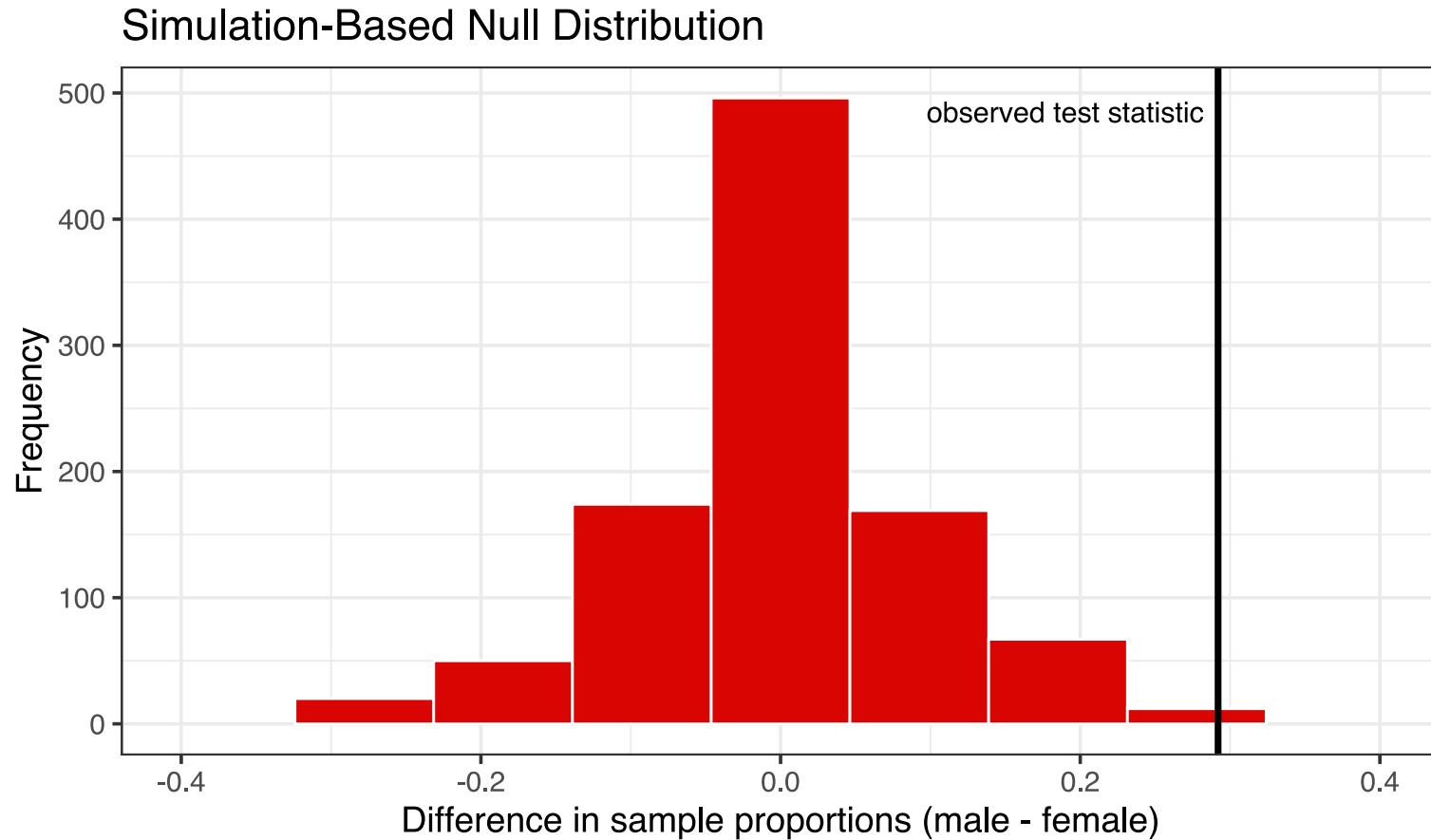


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  - That's the distribution we have seen just before.



# Null Distribution



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- When do we decide to **reject**  $H_0$  or not?



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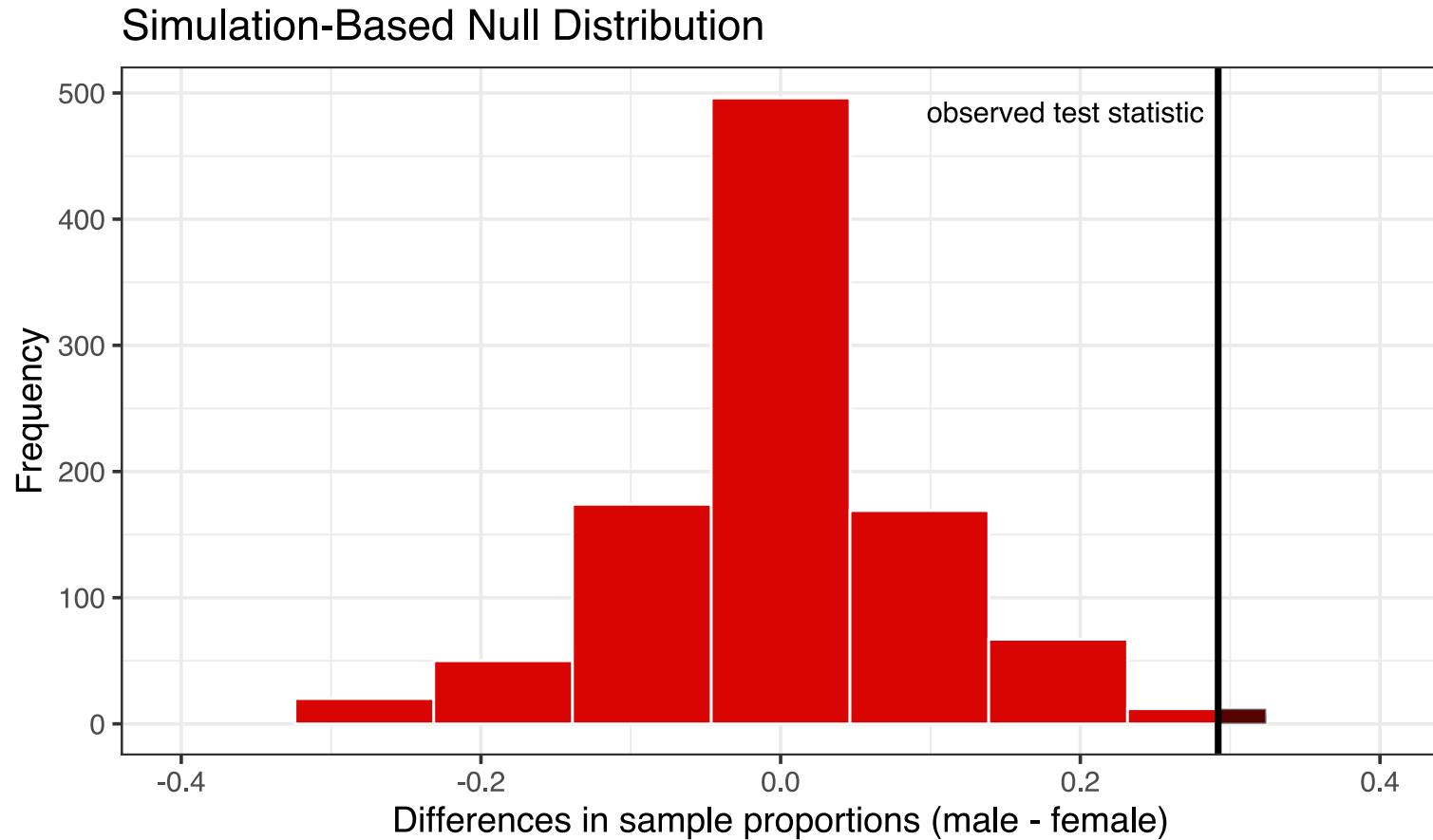


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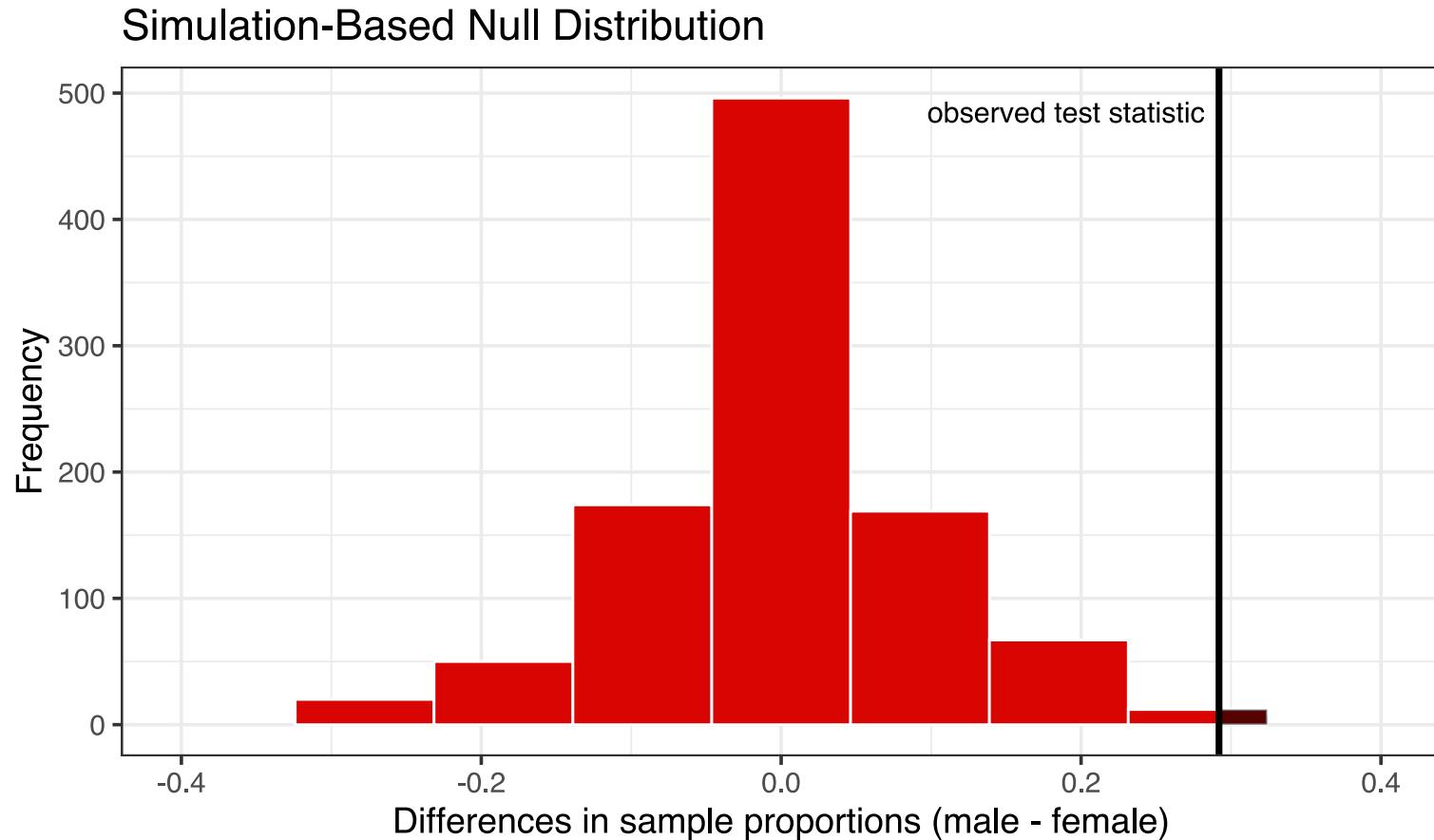
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- Let's illustrate how it works in our example.



# Visualizing the P-value



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The shaded area corresponds to the p-value!



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  - We also say that  $\hat{p}_m - \hat{p}_f = 0.292$  is *statistically significantly different from 0* at the 5% level.
- Question:** Suppose we had set  $\alpha = 0.01 = 1\%$ , would we have rejected the absence of discrimination at this level?



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- A 29% p difference may be *unlikely* under  $H_0$ , but that **doesn't mean it's impossible to occur**.
  - In fact, such a difference (or higher) would occur (approximately) in 0.007% of cases.
- So, it may happen that we sometimes reject  $H_0$ , when in fact it was true.
  - Setting 5% significance level, you make sure it won't happen more than 5% of the time.



# Testing Errors

In hypothesis testing, there are **two types of errors**:

	H0 true	HA true
Verdict		
Fail to reject H0	Correct	Type II error
Reject H0	Type I error	Correct

**Type I error:** reject the null hypothesis when in fact it was true. **false positive**

**Type II error:** don't reject the null hypothesis when in fact it was false. **false negative**

- In practice, we choose the frequency of a Type I error by setting  $\alpha$  and try to minimize the type II error.



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- The answer in the next episode of *Introduction to Econometrics with R!* 🧑



# THANKS

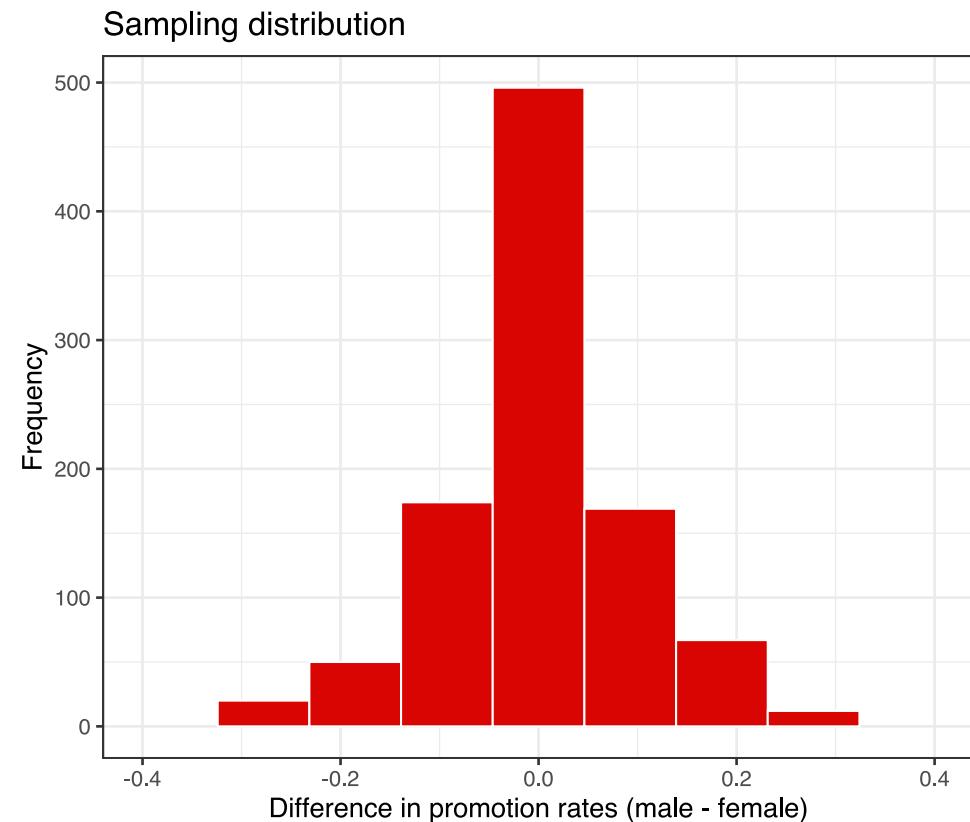
To the amazing **moderndive** team!



# Appendix: code to generate the null distribution

```
null_distribution <- promotions %>%
  # takes formula, defines success
  specify(formula = decision ~ gender,
         success = "promoted") %>%
  # decisions are independent of gender
  hypothesize(null = "independence") %>%
  # generate 1000 reshufflings of data
  generate(reps = 1000, type = "permute") %>%
  # compute p_m - p_f from each reshuffle
  calculate(stat = "diff in props",
            order = c("male", "female"))

visualize(null_distribution,
          bins = 10,
          fill = "#d90502") +
  labs(title = "Sampling distribution",
       x = "Difference in promotion rates (male - female)",
       y = "Frequency") +
  xlim(-0.4, 0.4) +
  theme_bw(base_size = 14)
```



END

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✉ florian.oswald@sciencespo.fr

🔗 Slides

🔗 Book

🐦 @ScPoEcon

�� @ScPoEcon

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