

The background of the slide is a photograph of the Barnard College building facade, featuring ornate ironwork and a central crest. The entire image is overlaid with a solid blue color.

COMS BC1016

Introduction to Computational Thinking and Data Science

# Lecture 14: AB Testing



# Reminders and Updates

- Welcome back from fall break! Unfortunately we're back to work...
- HW 5 due today
- HW 6 due date extended to **Monday, Nov 17**
  - The rest of the homeworks have been similarly adjusted to be due the following Monday from their original Wednesday due dates
- Labs start again this week
- Midterms will be passed back in this week's Lab

# Reminders and Updates

- **Don't forget to sign up for final project groups by Friday, Nov 7!!**
- If you want us to match you to a group: [Link](#)
- If you want to be in a specific group: [Link](#)

# Final Project Datasets

- Airbnb - [Link to data](#)

Inside Airbnb (<https://insideairbnb.com/about/>) collects and publishes data on Airbnb listings in major cities across the world. For this dataset, we've downloaded and cleaned the data for 13 of the cities they have listed. You may choose to analyse one (or multiple) of the provided cities. If there is a city you are interested in that we did not clean, you may request permission from the instructors to use that data for that city.

- NYC Restaurant Inspections - [Link to data](#)

The New York Department of Health and Mental Hygiene (DOHMH) provides a database of all violations, both confirmed and still being reviewed, from all restaurant and college cafeteria inspections done in the past three years ([https://data.cityofnewyork.us/Health/DOHMH-New-York-City-Restaurant-Inspection-Results/43nn-pn8j/about\\_data](https://data.cityofnewyork.us/Health/DOHMH-New-York-City-Restaurant-Inspection-Results/43nn-pn8j/about_data)). The Restaurant health data provided was downloaded Oct 2025 and has been separated into three datasets: Grade, Location, and Violation.

- Seattle Pet Licenses- [Link to data](#)

The city of Seattle makes available its database of pet licenses issued from Jan 2017 to Oct 2025 as part of the city's ongoing Open Data Initiative ([https://data.seattle.gov/City-Administration/Seattle-Pet-Licenses/jguy-t9rb/about\\_data](https://data.seattle.gov/City-Administration/Seattle-Pet-Licenses/jguy-t9rb/about_data)). We have also prepared two additional datasets. The first is the Statistics of Income (SOI) dataset for WA from the 2022 tax year (<https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-2022-zip-code-data-soi>), which features the number of tax returns received by the IRS from each zip code broken out by several income brackets. The second is the Seattle Parks and Recreation Park Addresses ([https://data.seattle.gov/Community-and-Culture/Seattle-Parks-And-Recreation-Park-Addresses/v5tj-kqhc/about\\_data](https://data.seattle.gov/Community-and-Culture/Seattle-Parks-And-Recreation-Park-Addresses/v5tj-kqhc/about_data)).

- Spotify- [Link to data](#)

Nidula Elgiryewithana uploaded this dataset onto Kaggle in 2023. A brief summary of the dataset, originally at the conference, is provided below:

"This dataset contains a comprehensive list of the most famous songs of 2023 as listed on Spotify. The dataset offers a wealth of features beyond what is typically available in similar datasets. It provides insights into each song's attributes, popularity, and presence on various music platforms. The dataset includes information such as track name, artist(s) name, release date, Spotify playlists and charts, streaming statistics, Apple Music presence, Deezer presence, Shazam charts, and various audio features."

# Final Project Proposal

- Template is on 1017 Courseworks
- Descriptions of each section are italicized gray and *should be deleted before submitting*
- For the proposal, you need to complete the introduction section *except for the prediction analysis*
- Due next week **Friday, Nov 14**

## Introduction

1. (250-300 words) Introduce the dataset to familiarize your reader with the data/variables involved, including:
  - a. Who collected the dataset and why, when, and where it was collected
  - b. What information is included in the dataset (e.g., what each row represents and what attributes are included)
  - c. The variables most relevant to your analysis (hypothesis test, prediction analysis, plots for data exploration)
2. (150-200 words) Explicitly state your hypothesis test and prediction questions
  - a. Hypothesis test (**groups of three need 2 hypothesis tests**)
    - i. What is the null hypothesis?
    - ii. What is the alternative hypothesis?
  - b. Prediction analysis (**NOT REQUIRED FOR THE PROJECT PROPOSAL**)
    - i. What two attributes will you analyze the relationship between?
    - ii. What is your prediction testing question?
3. What do you expect to learn overall?
  - a. What do your hypothesis test and prediction analysis help you answer about the data?

# Lecture Outline

- Review of last lecture (p-values)
- AB Testing

# P-Value Review

# Probability

- Let's say we have an array

$a = [1, 2, 2, 3, 4, 7, 8, 9, 10, 11]$

- If we randomly sample an element from  $a$ :
  - What is the probability of getting 1?
  - What is the probability of getting less than or equal to 5?



# Probability

- Let's say we have an array

$$a = [1, 2, 2, 3, 4, 7, 8, 9, 10, 11]$$

- If we randomly sample an element from  $a$ :

- What is the probability of getting 1?

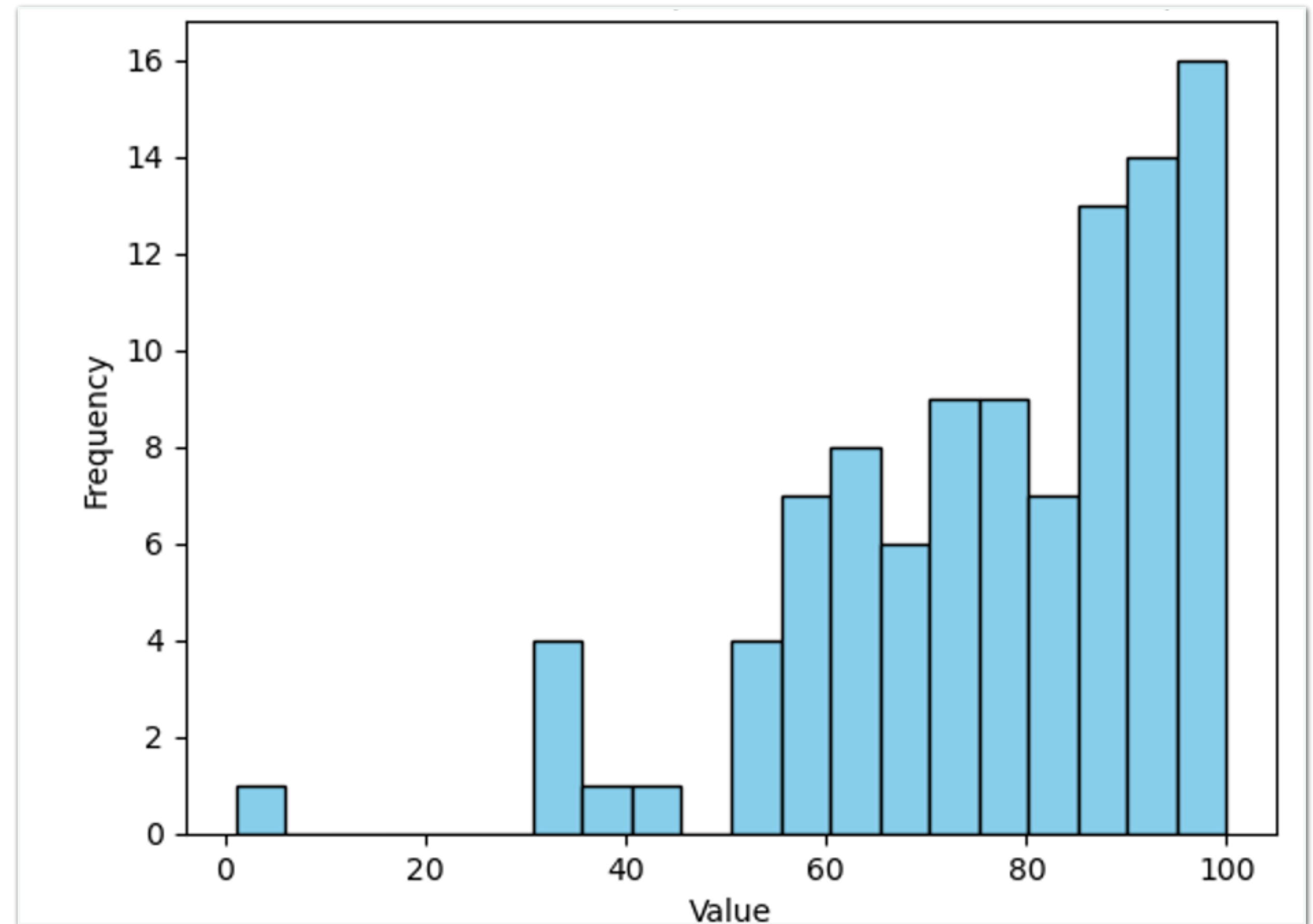
$$\frac{\text{Number of 1s in } a}{\text{Total number of elements in } a} = \frac{1}{10}$$

- What is the probability of getting less than or equal to 5?

$$\frac{\text{Number of elements } \leq 5 \text{ in } a}{\text{Total number of elements in } a} = \frac{5}{10} = \frac{1}{2}$$

# Probability

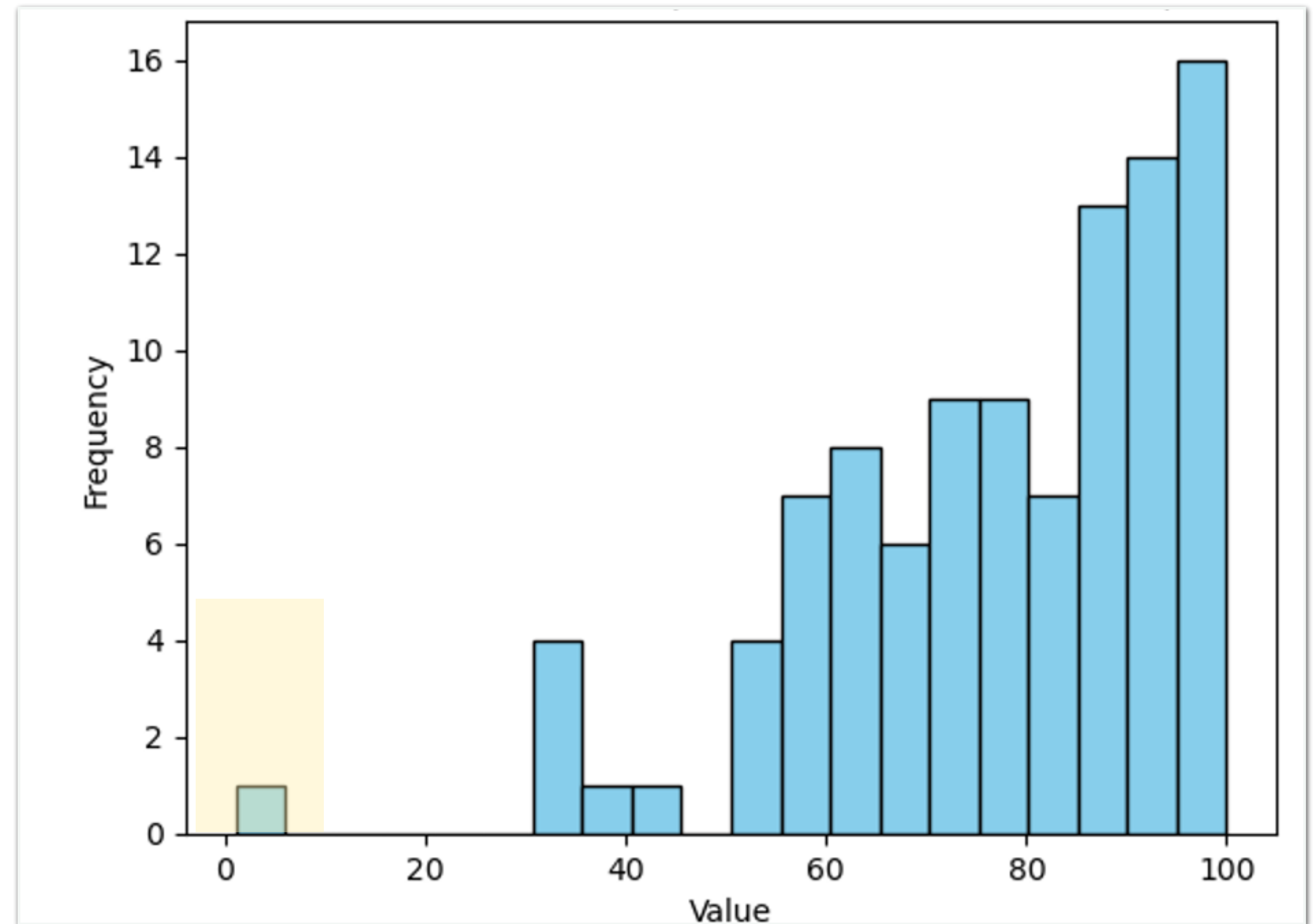
- Let's say we have 100 values
- If we randomly sample an element:
  - What is the probability of getting a value less than 10?
  - What is the probability of getting a value less than 40?





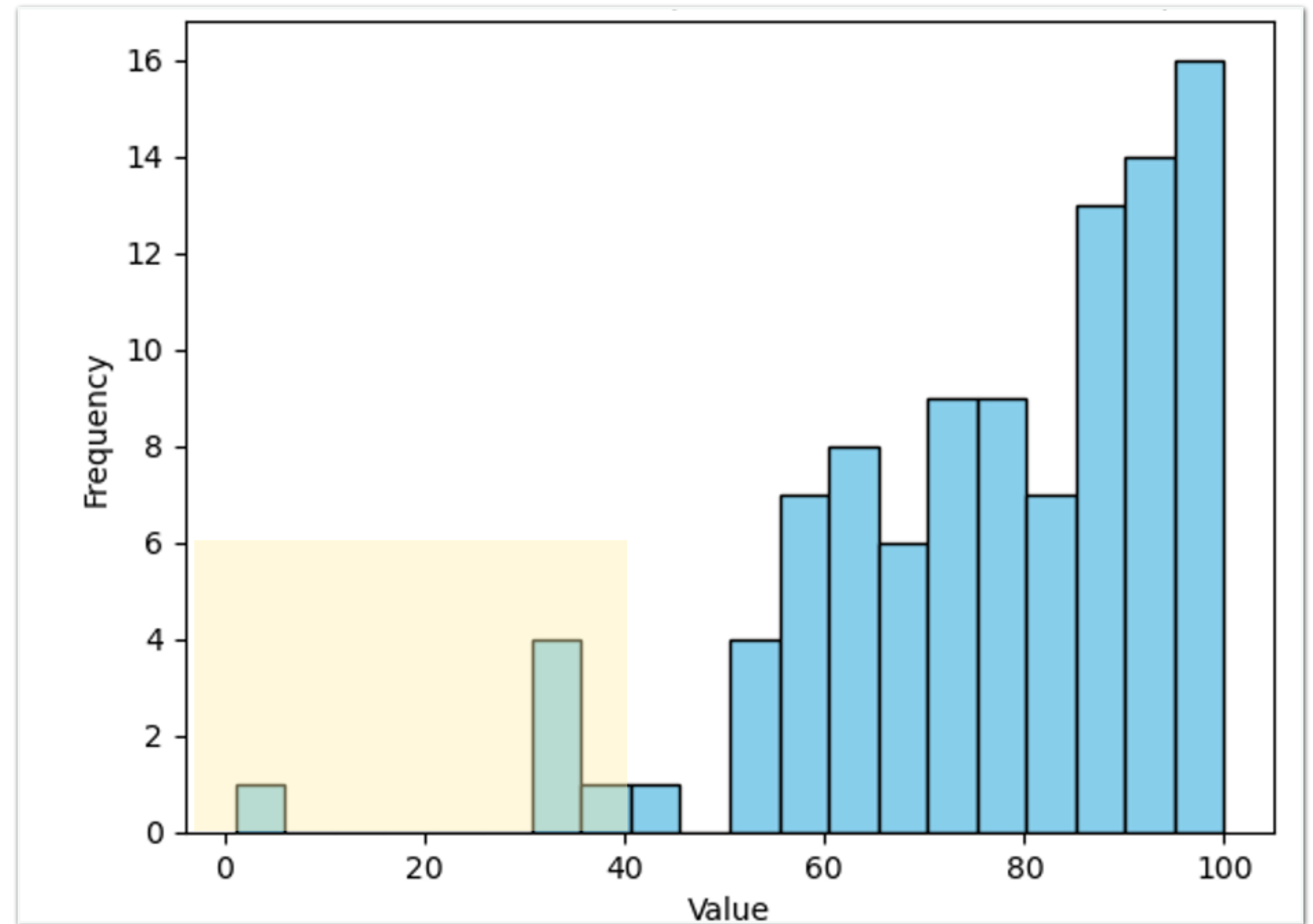
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# Definition of the P-Value

P-value: Observed significance level

5% - statistically significant

1% highly statistically significant

The P-value is the chance under the null hypothesis that the test statistic is equal to the value that was observed in the data or is even further in the direction of the alternative

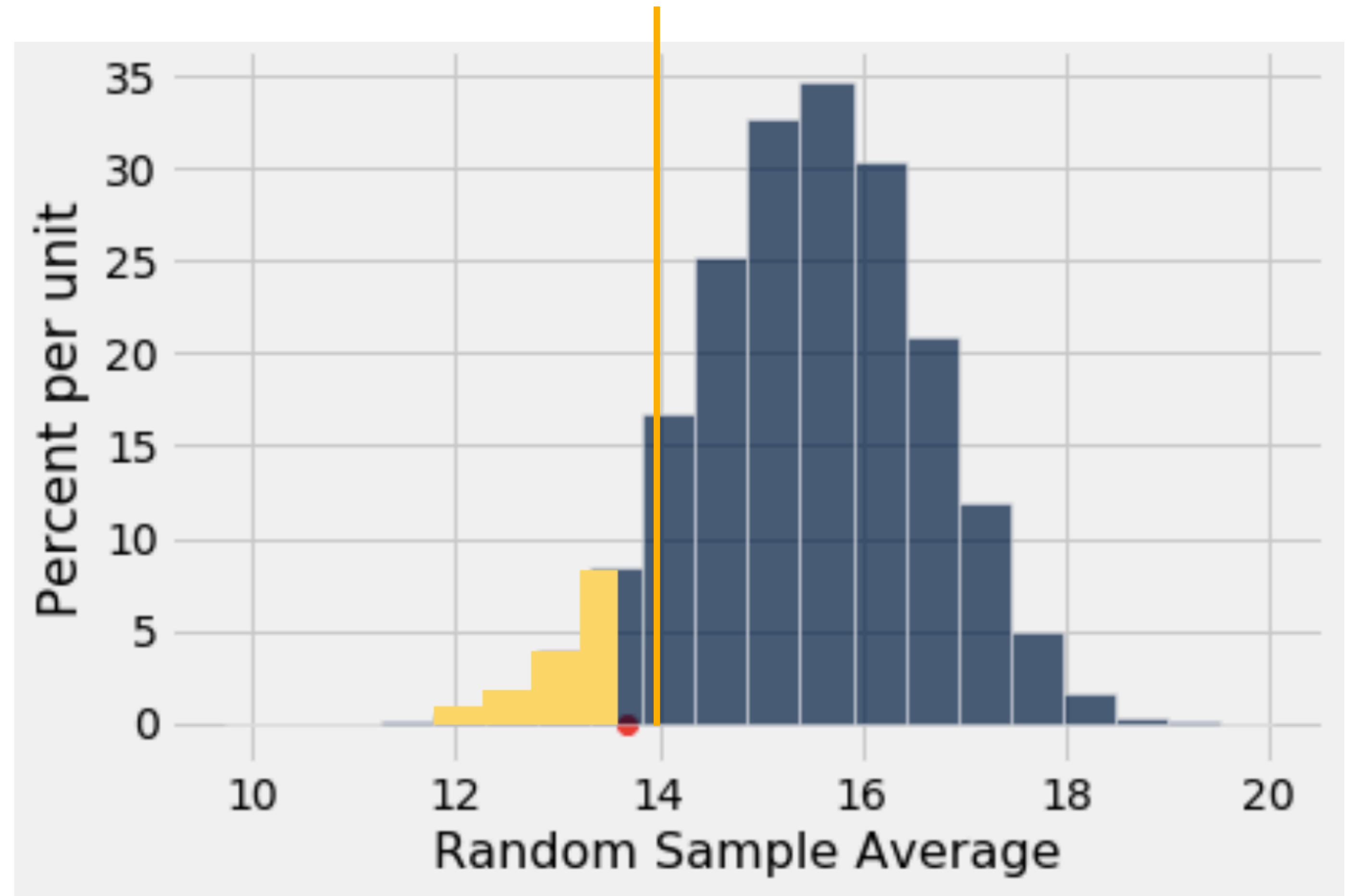
# The P-Value as an Area

P-value is the area of the tail of the empirical distribution

Red dot: observed statistic

Yellow area: tail probability (p-value)

If your threshold (1% / 5%) is beyond the observed value in the direction of the alternative, you can reject the null hypothesis





# Hypothesis Testing Review

**Two Categories** (e.g. percent of flowers that are purple)

- Test Statistic (1): `observed_proportion`
- Test Statistic (2): `abs(observed_proportion - null_proportion)`
- Simulate with: `sample_proportions(n, null_dist)`

**Multiple Categories** (e.g. ethnicity distribution of jury panel)

- Test Statistic: `tv_d(observed_distribution, null_distribution)`
- Simulate with: `sample_proportions(n, null_distribution)`

**Numerical Data** (e.g. scores in a lab section)

- Test Statistic: `observed_mean`
- Simulate with: `population_data.sample(n, with_replacement=False)`

# A/B Testing



# Scenario: Baby weights and Maternal Smoking

Birth Weight	Gestational Days	Maternal Age	Maternal Height	Maternal Pregnancy Weight	Maternal Smoker
120	284	27	62	100	False
113	282	33	64	135	False
128	279	28	64	115	True
108	282	23	67	125	True
136	286	25	62	93	False
138	244	33	62	178	False
132	245	23	65	140	False
120	289	25	62	125	False
143	299	30	66	136	True
140	351	27	68	120	False

# Scenario: Baby weights and Maternal Smoking

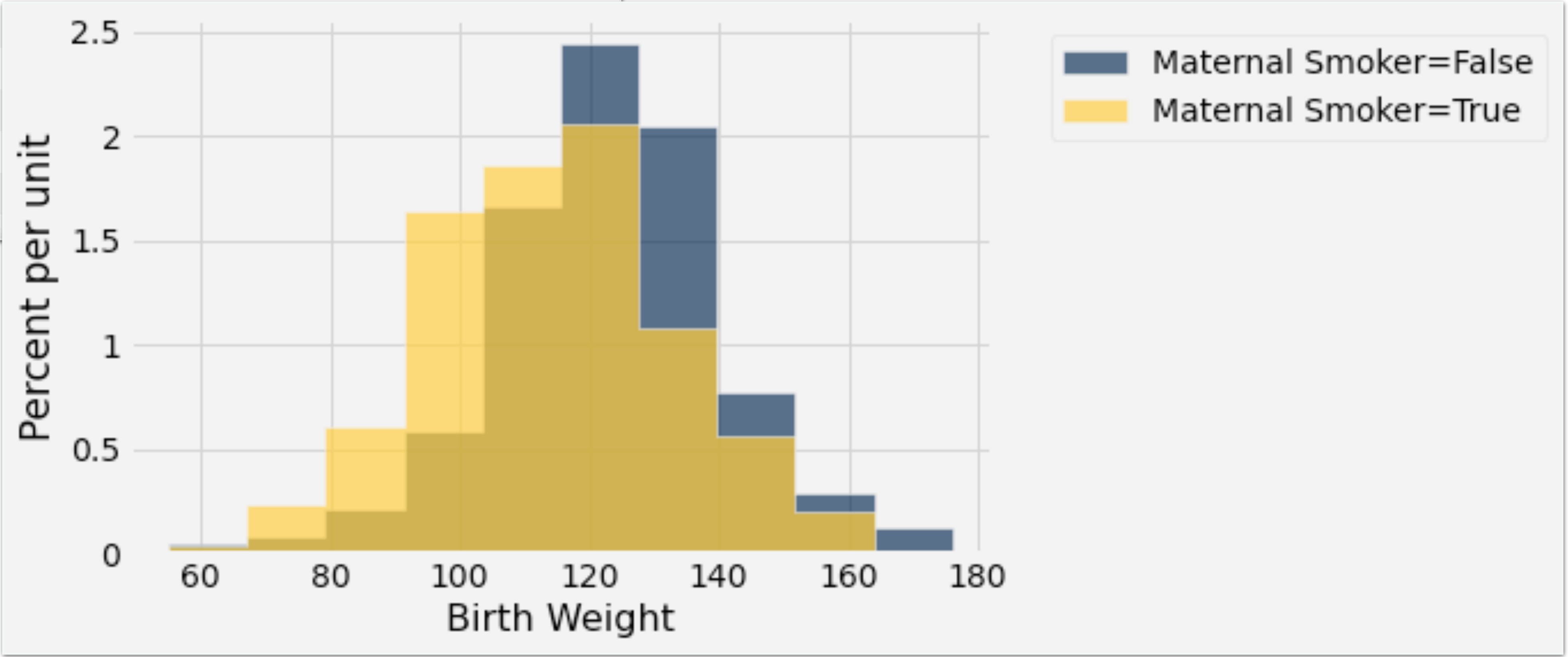
Birth Weight	Gestational Days	Maternal Age	Maternal Height	Maternal Smoking	Is there a relation between maternal smoking and baby weight?
120	284	27	62	100	False
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128	279	28	64	115	True
108	282	23	67	125	True
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# A/B Testing

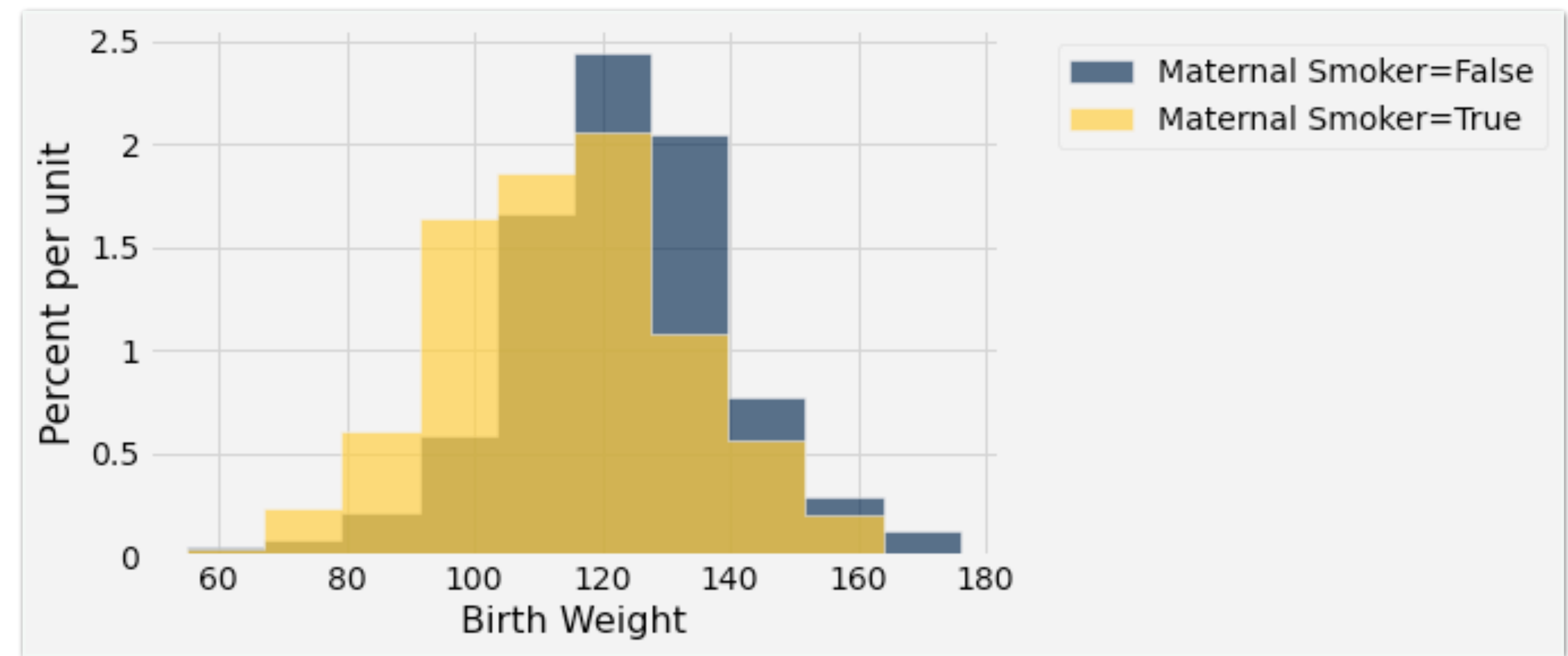
- Used when we want to compare two random samples with one another (from Group A and Group B)
- Examples:
  - Outcomes in a medical trial (treatment / control group)
  - Outcomes of two different versions of a website
- Underlying question:
  - Do the two sets of values come from the same underlying distribution?

# A/B Testing

- Testing whether Group A and Group B have the same underlying distribution or not
  - Null Hypothesis: The distributions of [test statistic] from both groups are the same
    - Any differences we observe are due to chance
  - Alternative Hypothesis: The distributions are different
- If the distributions look different, it supports the alternative hypothesis

# A/B Testing Example: Birth Weight

- Going back to our example:
  - Group A: Mothers who smoked during pregnancy
  - Group B: Mothers who didn't smoke during pregnancy



Question: Can the difference in birth weight be due to chance alone?



# A/B Testing Example: Birth Weight

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- Null Hypothesis:

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  - That is, the difference we observe in the sample is due to chance

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- Test statistic:

# A/B Testing Example: Birth Weight

Question: Can the difference in birth weight be due to chance alone?

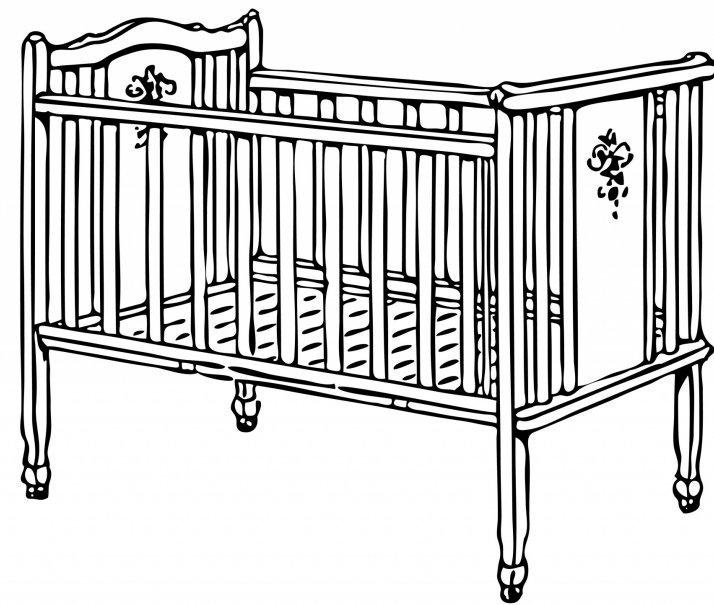
- Null Hypothesis: In the population, the distribution of birth weights of babies from both groups are the same.
  - That is, the difference we observe in the sample is due to chance
- Alternative: Babies of mothers who smoke **weigh less**, on average, than babies of non-smokers
- Test statistic: Difference between average weights
  - Difference in averages = (Group B average) - (Group A average)

# How to simulate differences between 2 groups?



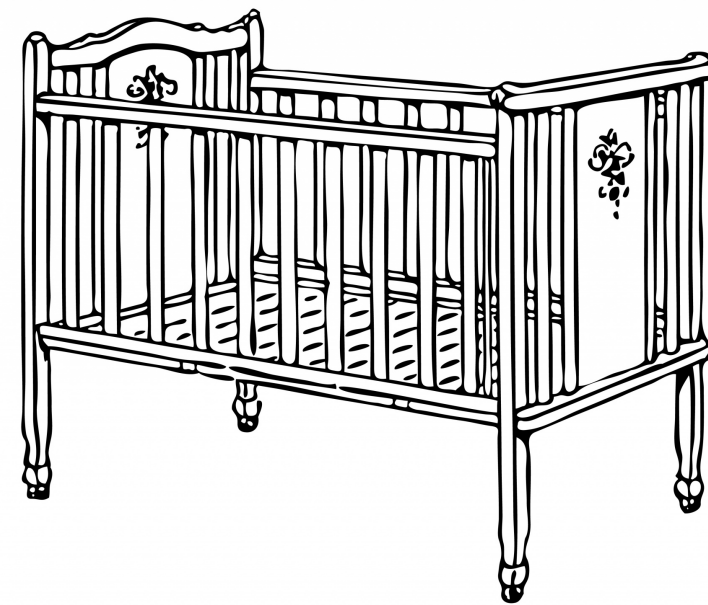
Non-Smoker

120 oz



Non-Smoker

113 oz



Smoker

128 oz

...



Smoker

108 oz

Null Hypothesis: the distribution of birth weights of babies from both groups are the same.

# Shuffling Labels Under the Null



Smoker

120 oz



Non-Smoker

113 oz



Non-Smoker

128 oz

...



Smoker

108 oz

Null Hypothesis: the distribution of birth weights of babies from both groups are the same.



# Simulating Under the Null

- If the null hypothesis is true, all rearrangement of labels are equally likely
- **Permutation Test:**
  - Shuffle all group labels
    - Keep the sizes of Group A and Group B same as before, but mix which weights fall into Group A and Group B
  - Find the difference between the average of two shuffled groups
  - Repeat

# Shuffling with Random Permutation

- `tbl.sample()`
  - Table with same number of rows as original `tbl`, picked randomly with replacement
- `tbl.sample(n)`
  - Table of `n` rows picked randomly with replacement
- `tbl.sample(n, with_replacement = False)`
  - Table of `n` rows picked randomly without replacement
- `tbl.sample(with_replacement = False)`
  - All rows of `tbl`, in random order

# Birth Weight Notebook Demo

# A/B Testing Process

1. Write a function that calculates the test static for one simulation
2. Repeat that process in a for loop many times
3. Plot the distribution and compare to our observed value

```
def one_simulated_difference(table, label, group_label):  
    """Takes: name of table, column label of numerical variable,  
    column label of group-label variable  
    Returns: Difference of means of the two groups after shuffling labels"""  
  
    # array of shuffled labels  
    shuffled_labels = table.sample(with_replacement = False).column(group_label)  
  
    # table of numerical variable and shuffled labels  
    shuffled_table = table.with_column('Shuffled Label', shuffled_labels)  
  
    return difference_of_means(shuffled_table, label, 'Shuffled Label')
```

```
differences = make_array()  
  
for i in np.arange(2500):  
    new_difference = one_simulated_difference(births, 'Birth Weight', 'Maternal Smoker')  
    differences = np.append(differences, new_difference)
```

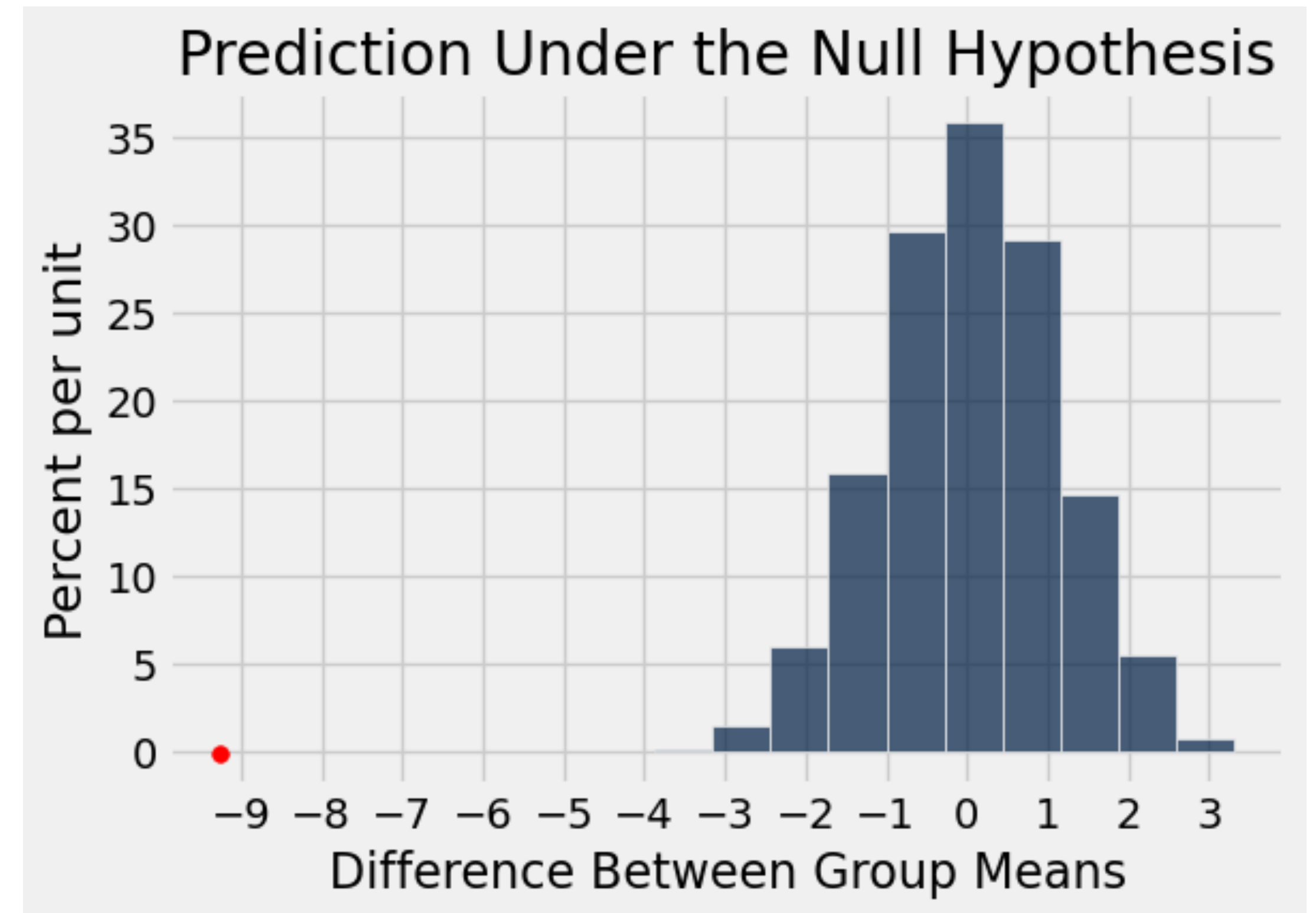
```
diff_tbl = Table().with_column('Difference Between Group Means', differences)  
diff_tbl.hist()
```



# Birth Weight Conclusion

A p-value of 0.0 supports the alternative hypothesis

- Babies from smoking mothers weigh significantly less than babies from non-smoking mothers

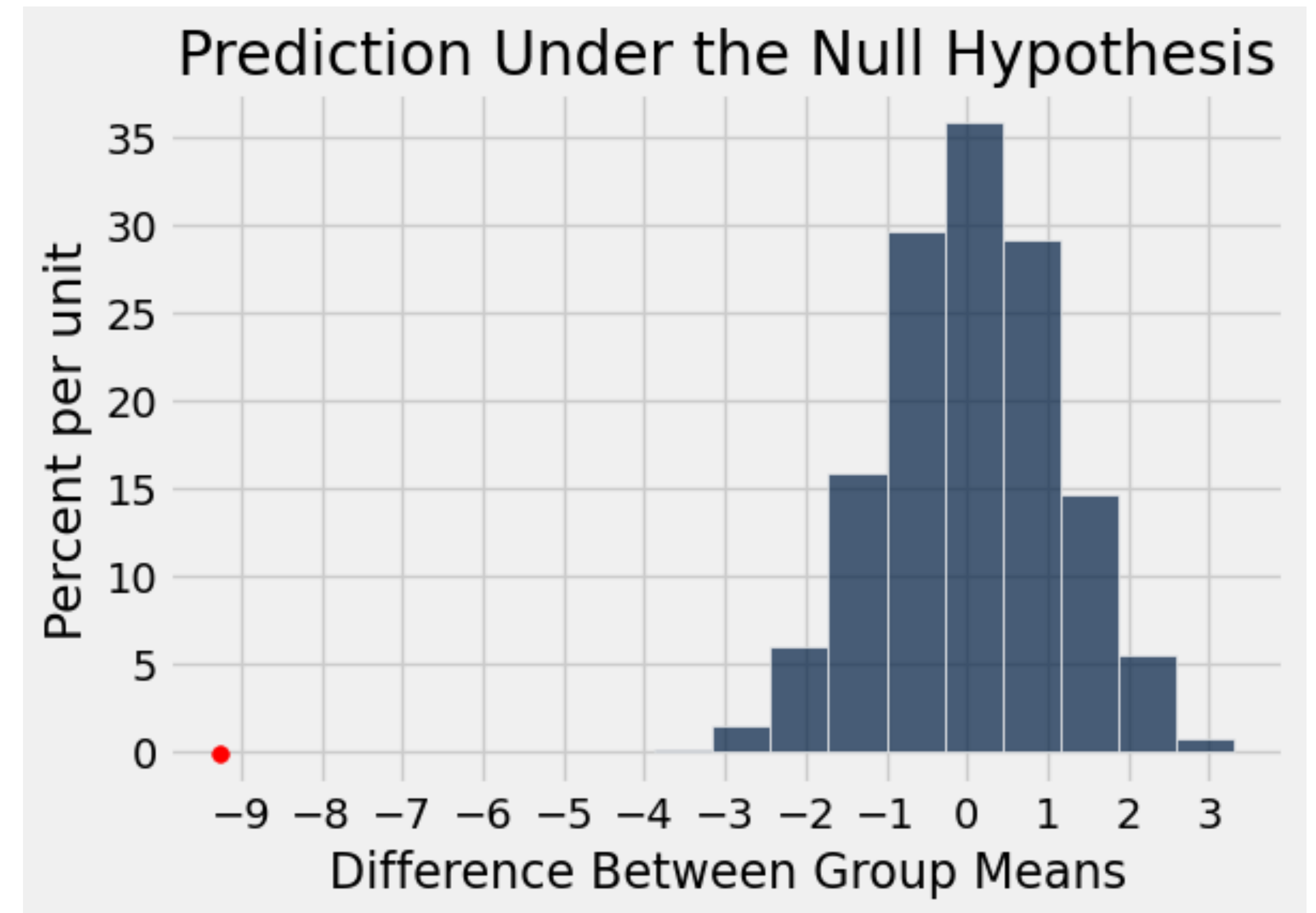


# Birth Weight Conclusion

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Question: Can we say that smoking causes lower birth rates? (Causation)



# Observational Data vs Randomized Control Experiment

- Question: Can we say that smoking causes lower birth rates? (Causation)
- In data science, the gold standard for determining causation is a *randomized control experiment*
  - Group A: control group
  - Group B: treatment group
  - Participants are **randomly assigned to the groups**
- For observational data (e.g., our Maternal Smoking example) we can claim association but not causation

# Estimation

# Estimation

- We computed the mean birth weight in the previous example from “sample” data
  - This is just an estimate since it was based on the sample
- If you have the entire population, you can calculate a parameter directly
- If you don't have the entire population:
  - Take a random sample from the population
  - Use a **statistic** as an **estimate** of the parameter



# Quantifying Uncertainty

- Our estimate depends on the sample we collected. How different would the estimate be if the sample were different?
  - In theory, we could collect a different sample and check how similar the statistic we calculated is
- What if we can't go back and collect more samples?

# The Bootstrap Method

- A technique for simulating repeated random sampling
- Suppose we have a large random sample from the population
  - By the Law of Large Averages, it probably resembles the population from which it's drawn
  - We can replicate sampling from the population by *sampling from the sample*

# The Bootstrap Method

- To generate another sample:
  - Treat the original sample as if it were the populatoion
  - Draw at random with replacement the same number of times as the original sample size
- The distribution we get from the bootstrap is the empirical distribution of the original sample

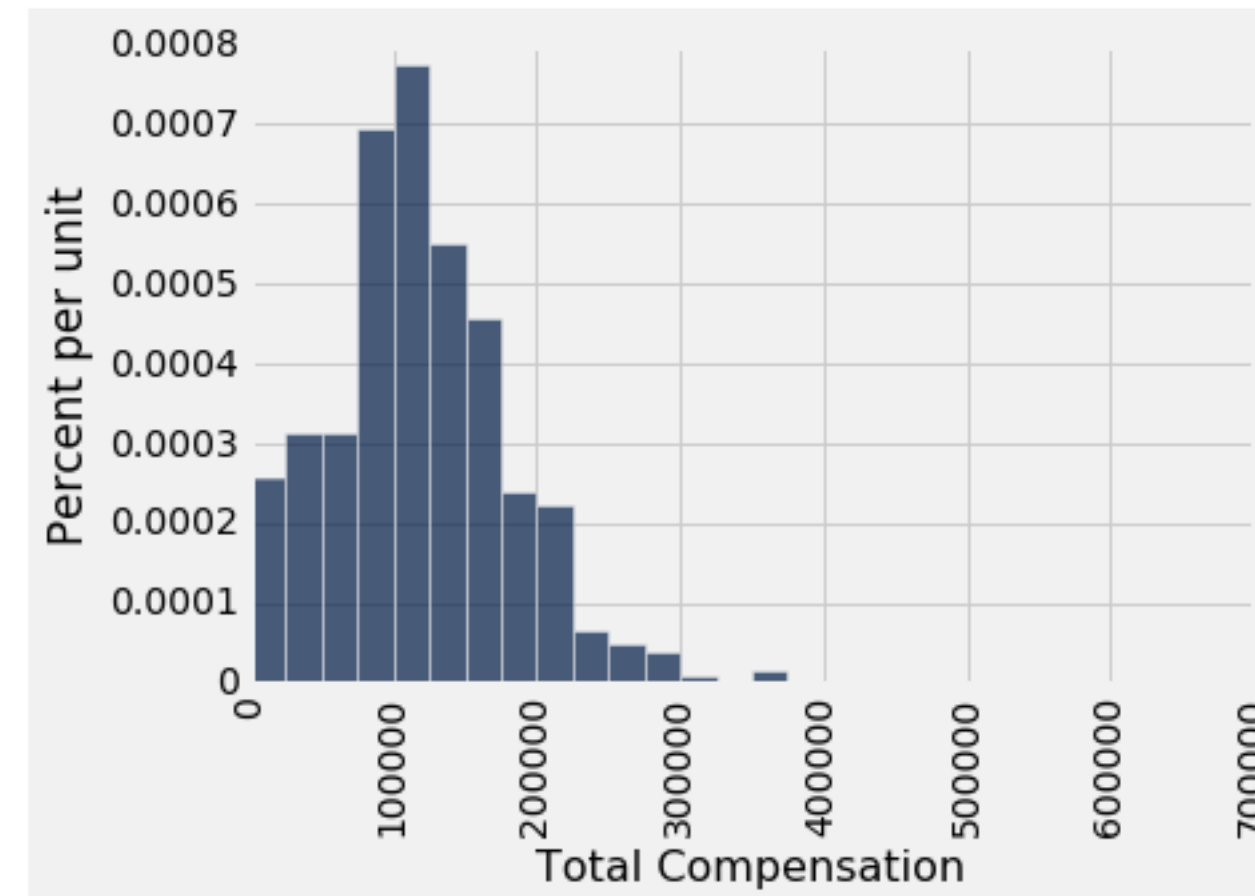
# The Bootstrap

Population

?

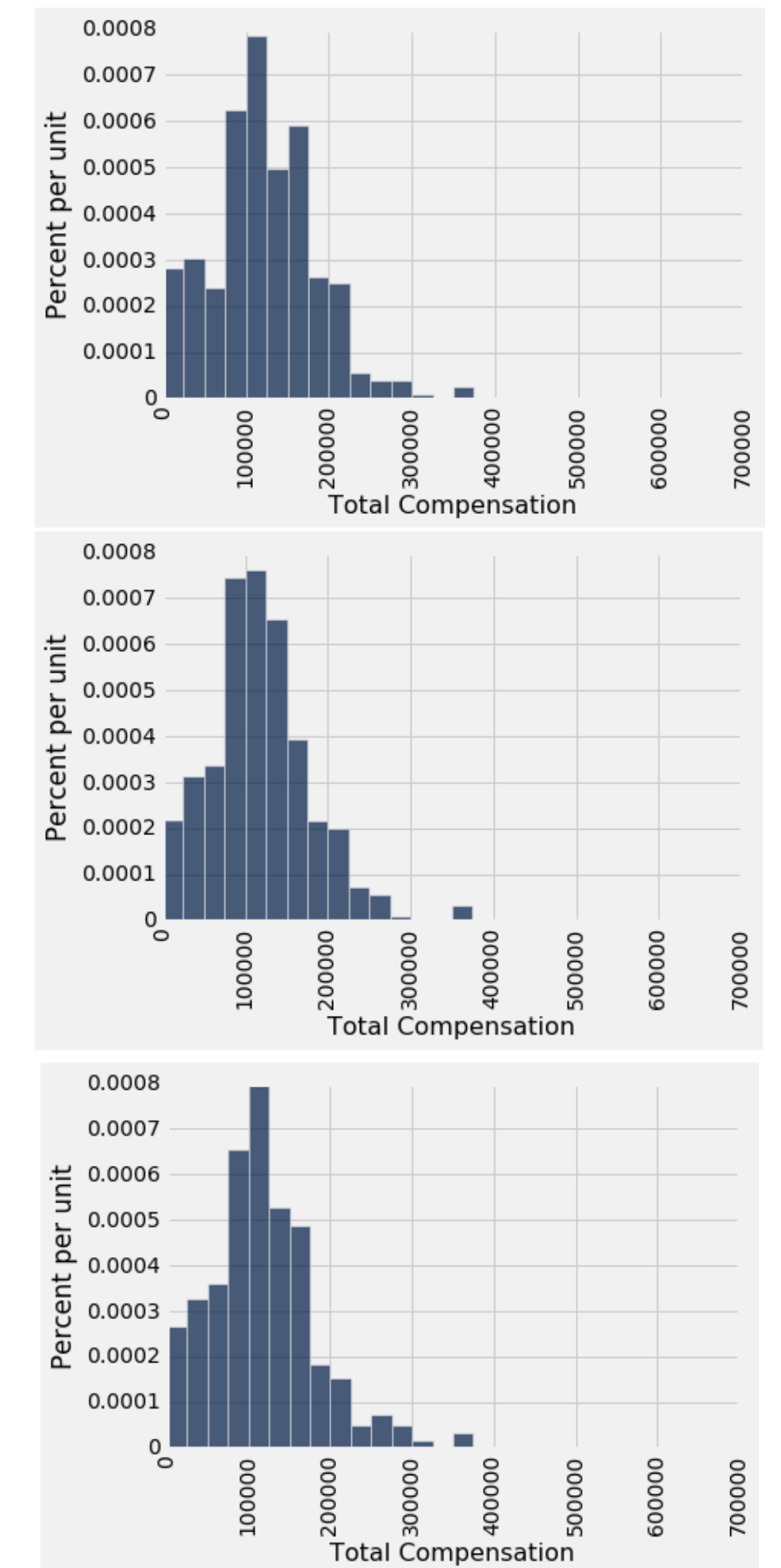
We don't know the entire population and thus can't calculate the **parameter** directly

Sample



However, we can take a single sample...

Resamples



...and generate lots of resamples

# The Bootstrap Method

- Bootstrap principle: Bootstrap sample  $\approx$  real-world sample
- Not always true, but reasonable for large enough samples



# Next time

- Confidence Intervals