Hypothesis tests and z-scores

HYPOTHESIS TESTING IN PYTHON

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A/B testing

- In 2013, Electronic Arts (EA) released SimCity 5
- They wanted to increase pre-orders of the game
- They used A/B testing to test different advertising scenarios
- This involves splitting users into *control* and *treatment* groups

[1] Image credit: "Electronic Arts" by majaX1 CC BY-NC-SA 2.0

Retail webpage A/B test

Control:

Treatment:

A/B test results

- The treatment group (no ad) got 43.4% more purchases than the control group (with ad)
- Intuition that "showing an ad would increase sales" was false
- Was this result *statistically significant* or just chance?
- Need EA's data to determine this
- Techniques from Sampling in Python + this course to do so

Stack Overflow Developer Survey 2020

```python
import pandas as pd
print(stack_overflow)
```

```
      respondent  age_1st_code  ...   age  hobbyist
0           36.0          30.0  ...  34.0       Yes
1           47.0          10.0  ...  53.0       Yes
2           69.0          12.0  ...  25.0       Yes
3          125.0          30.0  ...  41.0       Yes
4          147.0          15.0  ...  28.0        No
...          ...           ...  ...   ...       ...
2259     62867.0          13.0  ...  33.0       Yes
2260     62882.0          13.0  ...  28.0       Yes

[2261 rows x 8 columns]
```

Hypothesizing about the mean

A hypothesis:

> The mean annual compensation of the population of data scientists is $110,000

The point estimate (sample statistic):

```
mean_comp_samp = stack_overflow['converted_comp'].mean()
```

```
119574.71738168952
```

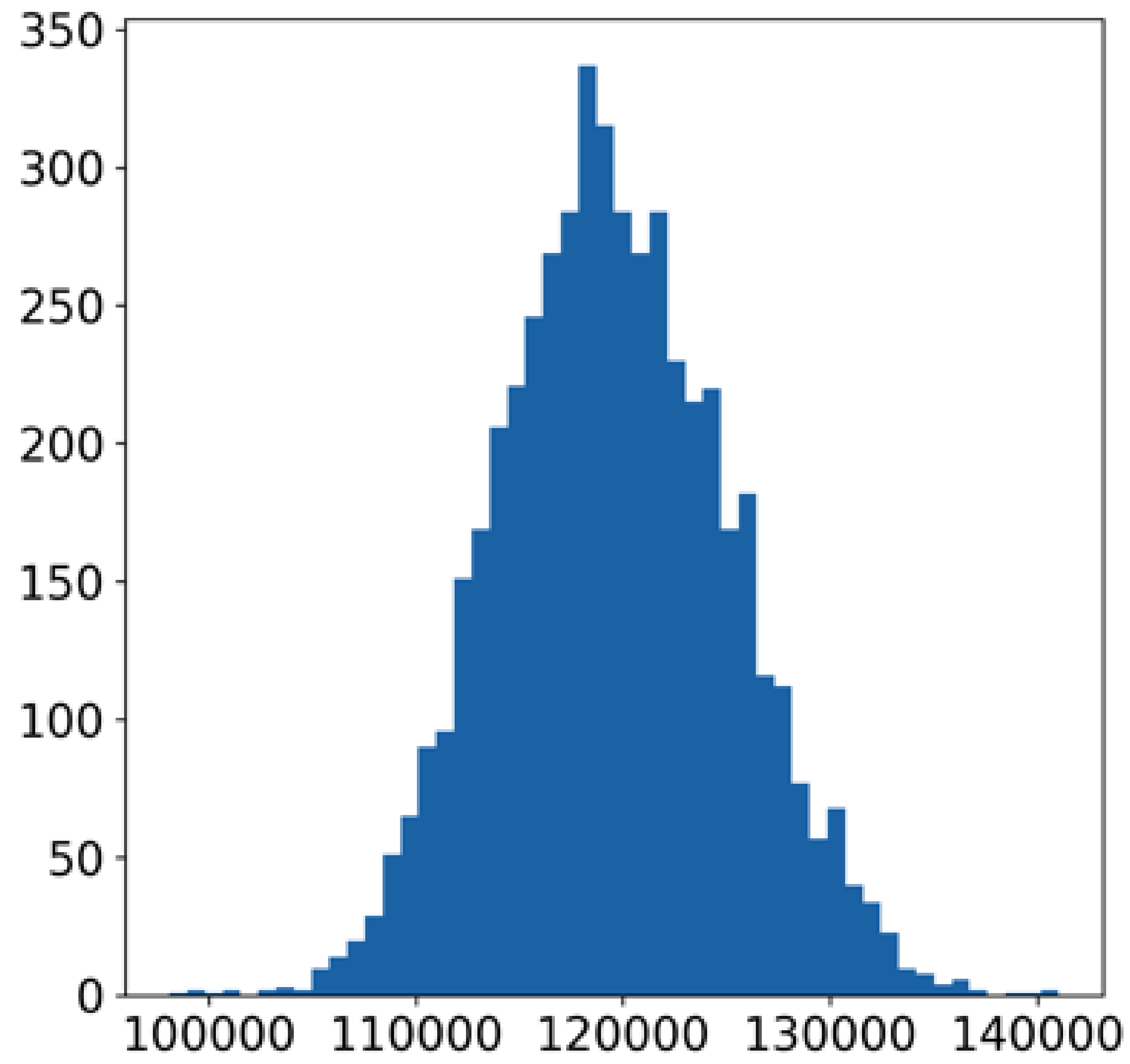
Generating a bootstrap distribution

```
import numpy as np
# Step 3. Repeat steps 1 & 2 many times, appending to a list
so_boot_distn = []
for i in range(5000):
  so_boot_distn.append(
    # Step 2. Calculate point estimate
    np.mean(
        # Step 1. Resample
        stack_overflow.sample(frac=1, replace=True)['converted_comp']
    )
)
```

[1] Bootstrap distributions are taught in Chapter 4 of Sampling in Python

Visualizing the bootstrap distribution

```
import matplotlib.pyplot as plt
plt.hist(so_boot_distn, bins=50)
plt.show()
```



Standard error

```
std_error = np.std(so_boot_distn, ddof=1)
```

```
5607.997577378606
```

z-scores

$$\text{standardized value} = \frac{\text{value} - \text{mean}}{\text{standard deviation}}$$

$$z = \frac{\text{sample stat} - \text{hypoth. param. value}}{\text{standard error}}$$

$$z = \frac{\text{sample stat} - \text{hypoth. param. value}}{\text{standard error}}$$

```
stack_overflow['converted_comp'].mean()
```

```
119574.71738168952
```

```
mean_comp_hyp = 110000
```

```
std_error
```

```
5607.997577378606
```

```
z_score = (mean_comp_samp - mean_comp_hyp) / std_error
```

```
1.7073326529796957
```

Testing the hypothesis

- Is 1.707 a high or low number?
- This is the goal of the course!

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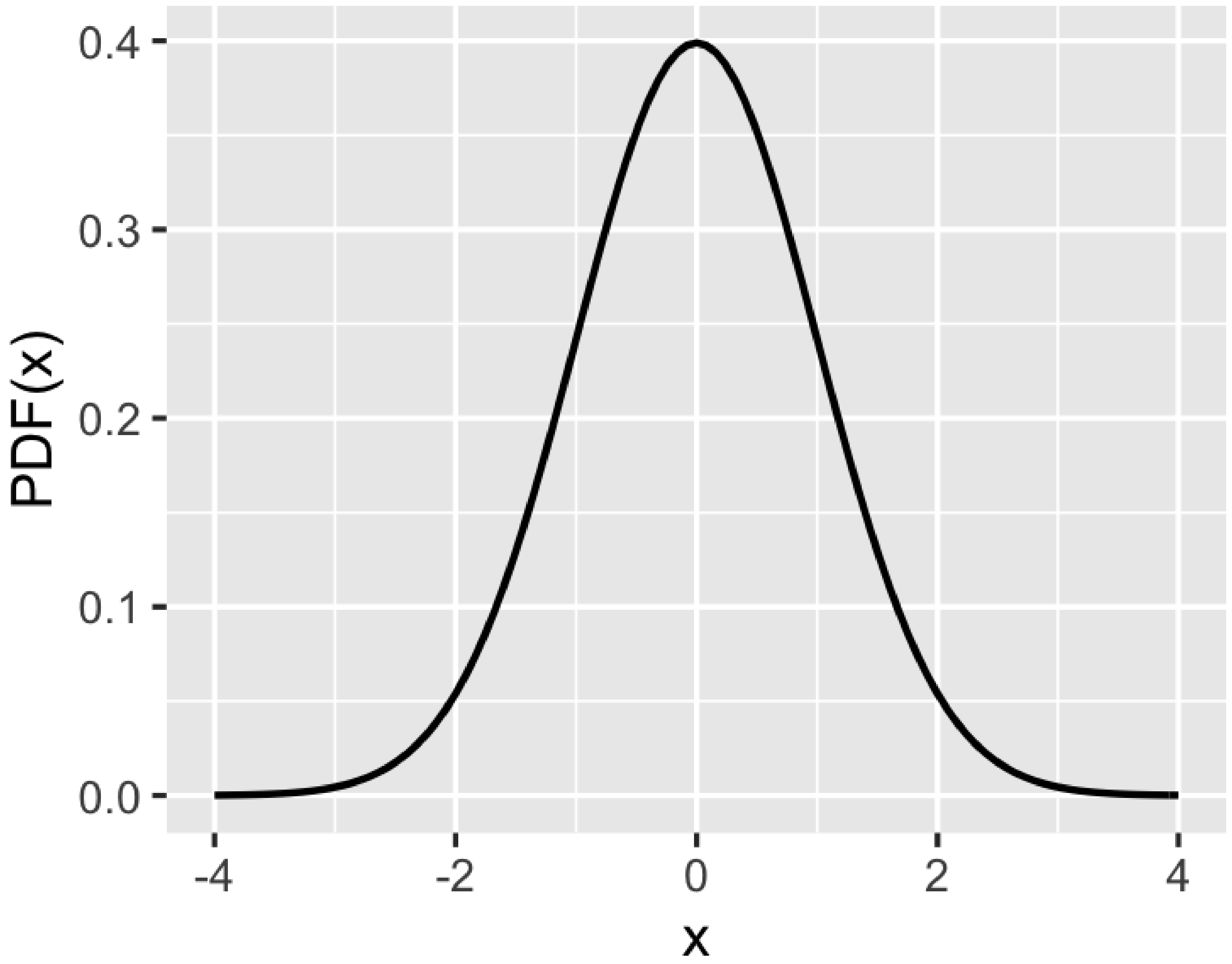
Hypothesis testing use case:

> Determine whether sample statistics are close to or far away from expected (or "hypothesized" values)

Standard normal (z) distribution

Standard normal distribution: normal distribution with **mean = 0 + standard deviation = 1**



Let's practice!

HYPOTHESIS TESTING IN PYTHON

p-values

HYPOTHESIS TESTING IN PYTHON

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Criminal trials

- Two possible true states:
  1. Defendant committed the crime
  2. Defendant did not commit the crime
- Two possible verdicts:
  1. Guilty
  2. Not guilty
- Initially the defendant is assumed to be not guilty
- Prosecution must present evidence "beyond reasonable doubt" for a guilty verdict

Age of first programming experience

- `age_first_code_cut` classifies when Stack Overflow user first started programming
  - `"adult"` means they started at 14 or older
  - `"child"` means they started before 14
- Previous research: 35% of software developers started programming as children
- Evidence that a greater proportion of data scientists starting programming as children?

Definitions

A *hypothesis* is a statement about an unknown population parameter

A *hypothesis test* is a test of two competing hypotheses

- The *null hypothesis* (H_0) is the existing idea
- The *alternative hypothesis* (H_A) is the new "challenger" idea of the researcher

For our problem:

- H_0: The proportion of data scientists starting programming as children is 35%
- H_A: The proportion of data scientists starting programming as children is greater than 35%

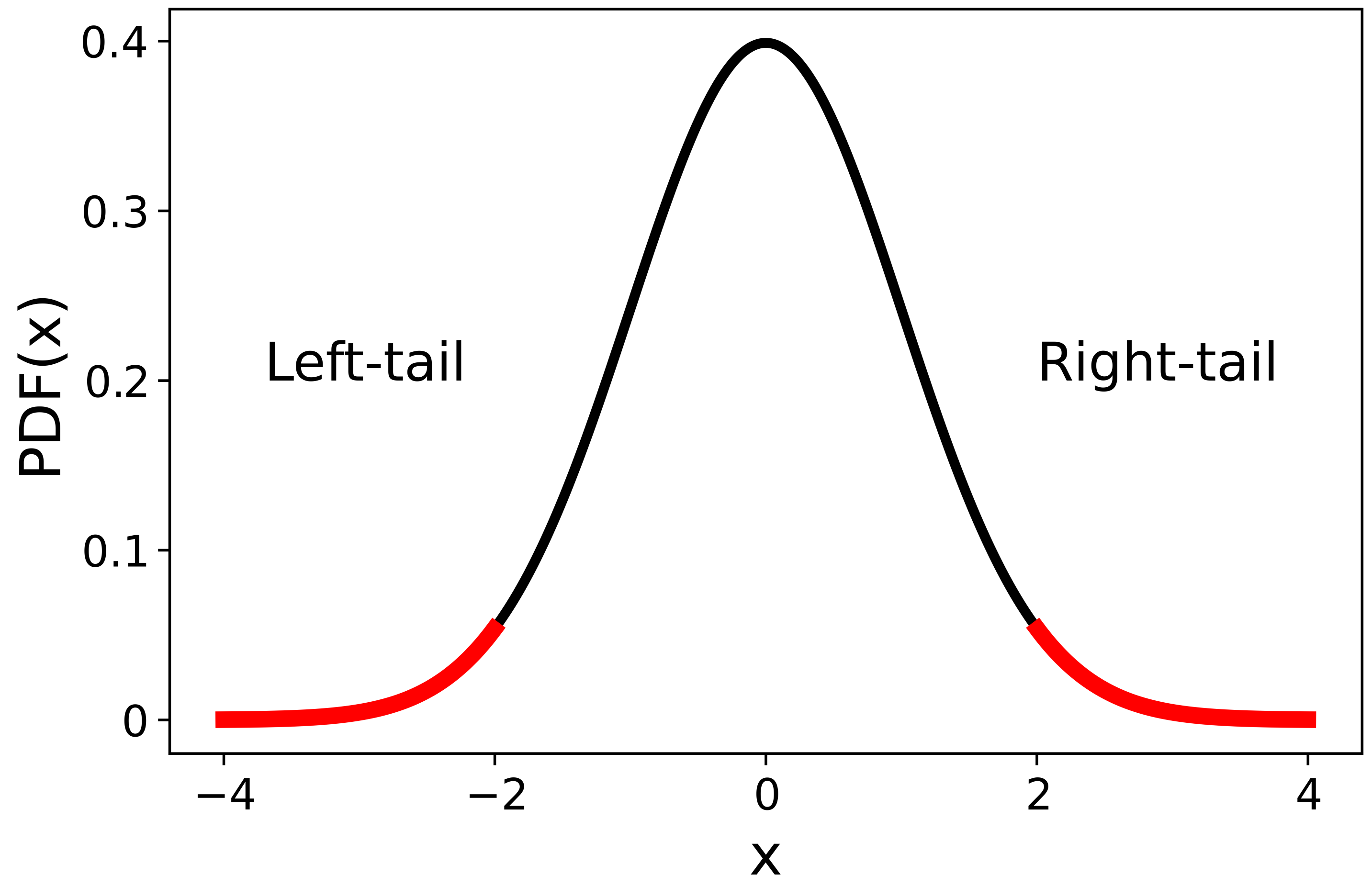
[1] "Naught" is British English for "zero". For historical reasons, "H-naught" is the international convention for pronouncing the null hypothesis.

Criminal trials vs. hypothesis testing

- Either H_A or H_0 is true (not both)
- Initially, H_0 is assumed to be true
- The test ends in either "reject H_0" or "fail to reject H_0"
- If the evidence from the sample is "significant" that H_A is true, reject H_0, else choose H_0

Significance level is "beyond a reasonable doubt" for hypothesis testing

One-tailed and two-tailed tests



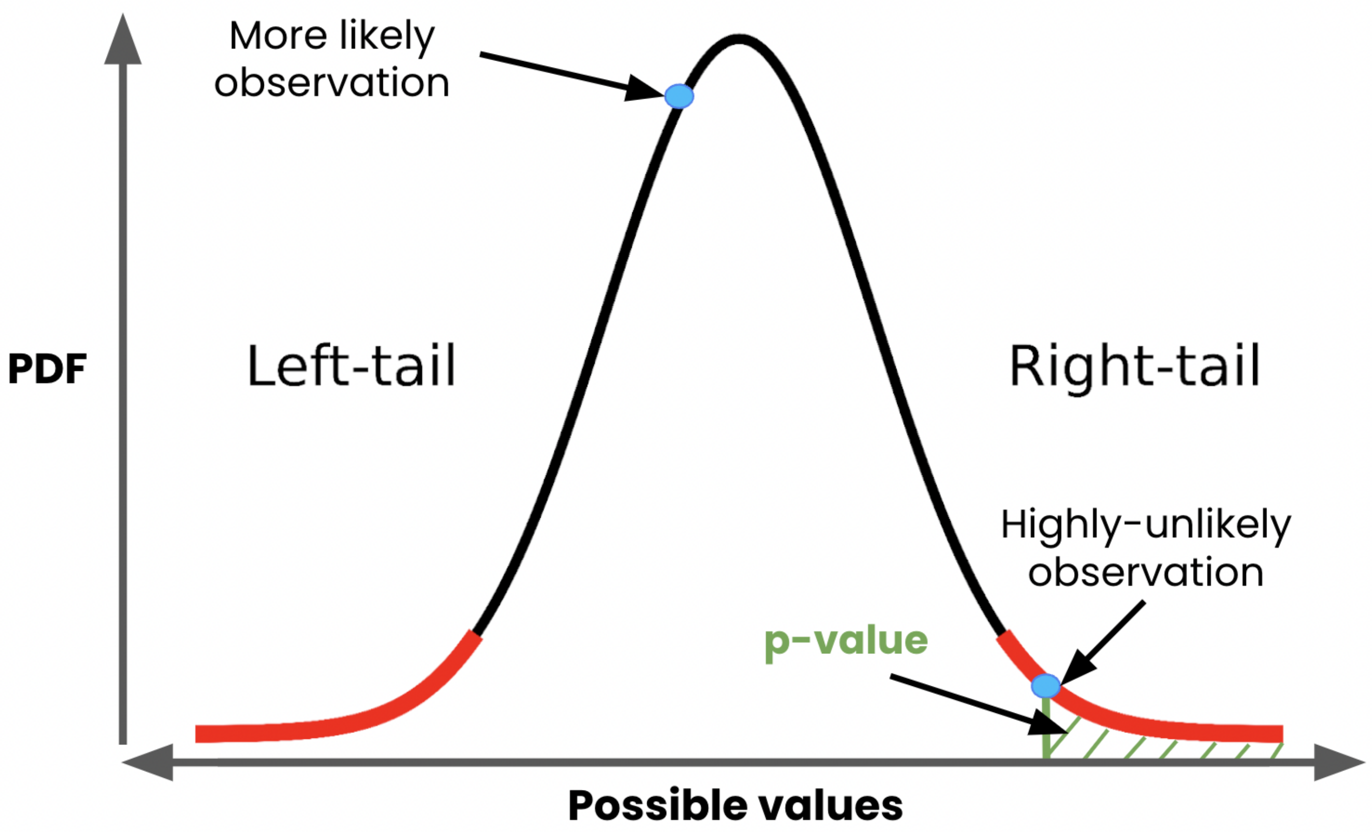
Hypothesis tests check if the sample statistics lie in the tails of the **null distribution**

Test	***Tails***
alternative *different from* null	two-tailed
alternative *greater than* null	right-tailed
alternative *less than* null	left-tailed

H_A: The proportion of data scientists starting programming as children is **greater than** 35%

This is a **right-tailed** test

p-values



p-values: probability of obtaining a result, assuming the null hypothesis is true

- Large p-value, large support for H_0
  - Statistic likely **not in** the tail of the *null distribution*
- Small p-value, strong evidence against H_0
  - Statistic likely **in** the tail of the *null distribution*
- "p" in *p-value* → probability
- "small" means "close to zero"

Calculating the z-score

```
prop_child_samp = (stack_overflow['age_first_code_cut'] == "child").mean()
```

```
0.39141972578505085
```

```
prop_child_hyp = 0.35
```

```
std_error = np.std(first_code_boot_distn, ddof=1)
```

```
0.010351057228878566
```

```
z_score = (prop_child_samp - prop_child_hyp) / std_error
```

```
4.001497129152506
```

Calculating the p-value

- `norm.cdf()` is normal CDF from `scipy.stats`.
- Left-tailed test → use `norm.cdf()`.
- Right-tailed test → use `1 - norm.cdf()`.

```
from scipy.stats import norm
1 - norm.cdf(z_score, loc=0, scale=1)
```

```
3.1471479512323874e-05
```

Let's practice!

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Statistical significance

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p-value recap

- p-values quantify evidence for the null hypothesis
- Large p-value → fail to reject null hypothesis
- Small p-value → reject null hypothesis
- Where is the cutoff point?

Significance level

> The *significance level* of a hypothesis test (α) is the threshold point for "beyond a reasonable doubt"

- Common values of α are `0.2` , `0.1` , `0.05` , and `0.01`
- If $p \leq \alpha$, reject H_0, else fail to reject H_0
- α should be set **prior** to conducting the hypothesis test

Calculating the p-value

```
alpha = 0.05
prop_child_samp = (stack_overflow['age_first_code_cut'] == "child").mean()
prop_child_hyp = 0.35
std_error = np.std(first_code_boot_distn, ddof=1)
```

```
z_score = (prop_child_samp - prop_child_hyp) / std_error
```

```
p_value = 1 - norm.cdf(z_score, loc=0, scale=1)
```

```
3.1471479512323874e-05
```

Making a decision

```
alpha = 0.05
print(p_value)
```

```
3.1471479512323874e-05
```

```
p_value <= alpha
```

```
True
```

Reject H_0 in favor of H_A

Confidence intervals

For a significance level of α, it's common to choose a confidence interval level of 1 - α

- $\alpha = 0.05$ → 95% confidence interval

```
import numpy as np
lower = np.quantile(first_code_boot_distn, 0.025)
upper = np.quantile(first_code_boot_distn, 0.975)
print((lower, upper))
```

```
(0.37063246351172047, 0.41132242370632466)
```

Types of errors

	Truly didn't commit crime	Truly committed crime
Verdict not guilty	correct	they got away with it
Verdict guilty	wrongful conviction	correct

	actual H_0	actual H_A
chosen H_0	correct	false negative
chosen H_A	false positive	correct

False positives are *Type I errors*; false negatives are *Type II errors*.

Possible errors in our example

If $p \leq \alpha$, we reject H_0:

- A false positive (Type I) error: data scientists didn't start coding as children at a higher rate

If $p > \alpha$, we fail to reject H_0:

- A false negative (Type II) error: data scientists started coding as children at a higher rate

Let's practice!

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