

Introduction to bootstrapping

SAMPLING IN PYTHON



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With or without

Sampling without replacement:



Sampling with replacement ("resampling"):



Simple random sampling without replacement

Population:



Sample:



Simple random sampling with replacement

Population:



Resample:



Why sample with replacement?

- `coffee_ratings` : a sample of a larger population of all coffees
- Each coffee in our sample represents many different hypothetical population coffees
- Sampling with replacement is a proxy

Coffee data preparation

```
coffee_focus = coffee_ratings[["variety", "country_of_origin", "flavor"]]  
coffee_focus = coffee_focus.reset_index()
```

	index	variety	country_of_origin	flavor
0	0	None	Ethiopia	8.83
1	1	Other	Ethiopia	8.67
2	2	Bourbon	Guatemala	8.50
3	3	None	Ethiopia	8.58
4	4	Other	Ethiopia	8.50
...
1333	1333	None	Ecuador	7.58
1334	1334	None	Ecuador	7.67
1335	1335	None	United States	7.33
1336	1336	None	India	6.83
1337	1337	None	Vietnam	6.67

[1338 rows x 4 columns]

Resampling with .sample()

```
coffee_resamp = coffee_focus.sample(frac=1, replace=True)
```

	index	variety	country_of_origin	flavor
1140	1140	Bourbon	Guatemala	7.25
57	57	Bourbon	Guatemala	8.00
1152	1152	Bourbon	Mexico	7.08
621	621	Caturra	Thailand	7.50
44	44	SL28	Kenya	8.08
...
996	996	Typica	Mexico	7.33
1090	1090	Bourbon	Guatemala	7.33
918	918	Other	Guatemala	7.42
249	249	Caturra	Colombia	7.67
467	467	Caturra	Colombia	7.50

[1338 rows x 4 columns]

Repeated coffees

```
coffee_resamp["index"].value_counts()
```

```
658      5
167      4
363      4
357      4
1047     4
      ..
771      1
770      1
766      1
764      1
0        1
Name: index, Length: 868, dtype: int64
```


Missing coffees

```
num_unique_coffees = len(coffee_resamp.drop_duplicates(subset="index"))
```

```
868
```

```
len(coffee_ratings) - num_unique_coffees
```

```
470
```

Bootstrapping

The opposite of sampling from a population

Sampling: going from a population to a smaller sample

Bootstrapping: building up a theoretical population from the sample

Bootstrapping use case:

- Develop understanding of sampling variability using a single sample

Bootstraps



Bootstrapping process

1. Make a resample of the same size as the original sample
2. Calculate the statistic of interest for this bootstrap sample
3. Repeat steps 1 and 2 many times

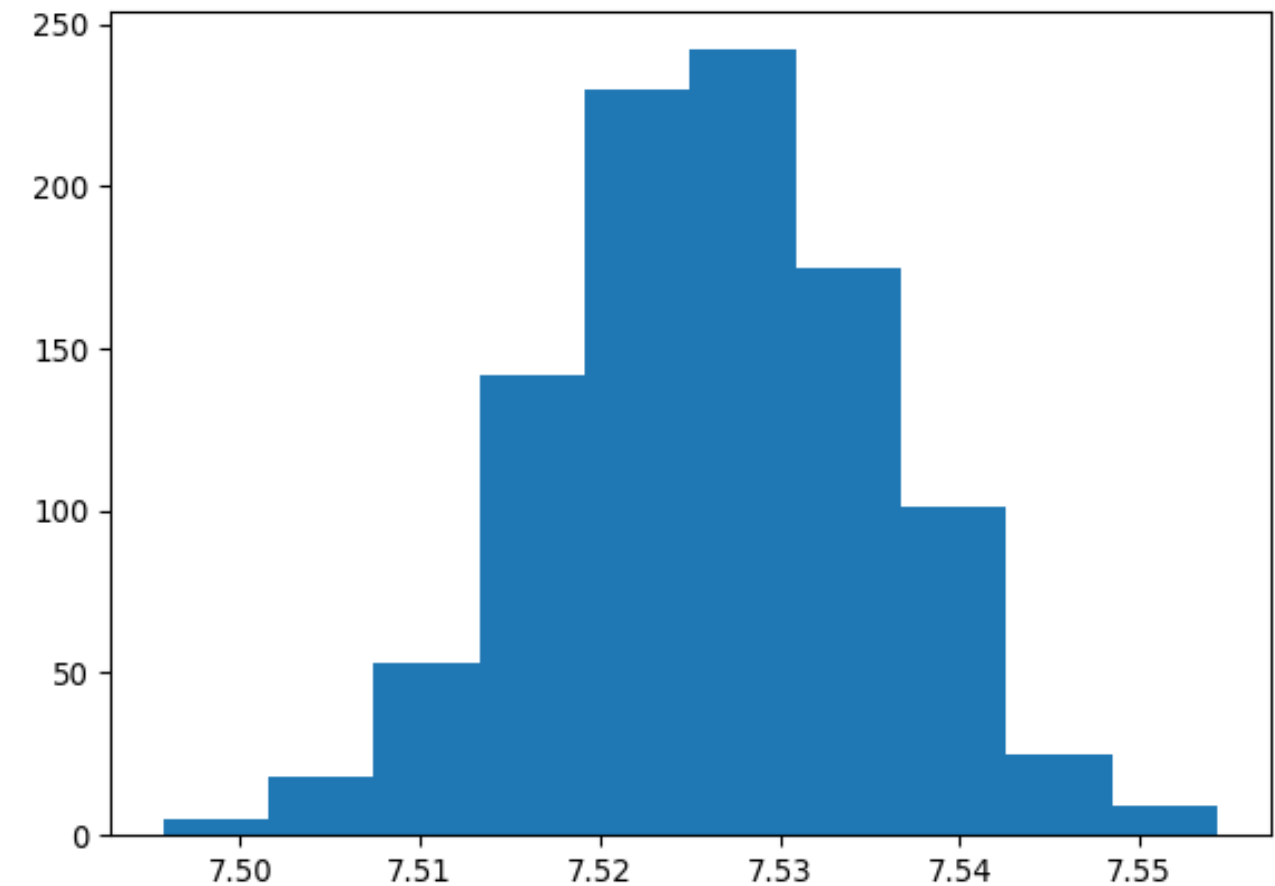
The resulting statistics are *bootstrap statistics*, and they form a *bootstrap distribution*

Bootstrapping coffee mean flavor

```
import numpy as np
mean_flavors_1000 = []
for i in range(1000):
    mean_flavors_1000.append(
        np.mean(coffee_sample.sample(frac=1, replace=True) ['flavor'])
    )
```

Bootstrap distribution histogram

```
import matplotlib.pyplot as plt
plt.hist(mean_flavors_1000)
plt.show()
```

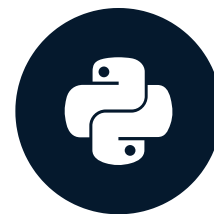


Let's practice!

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Comparing sampling and bootstrap distributions

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Coffee focused subset

```
coffee_sample = coffee_ratings[["variety", "country_of_origin", "flavor"]]\n                        .reset_index().sample(n=500)
```

	index		variety	country_of_origin	flavor
132	132		Other	Costa Rica	7.58
51	51		None	United States (Hawaii)	8.17
42	42	Yellow	Bourbon	Brazil	7.92
569	569		Bourbon	Guatemala	7.67
..
643	643		Catuai	Costa Rica	7.42
356	356		Caturra	Colombia	7.58
494	494		None	Indonesia	7.58
169	169		None	Brazil	7.81

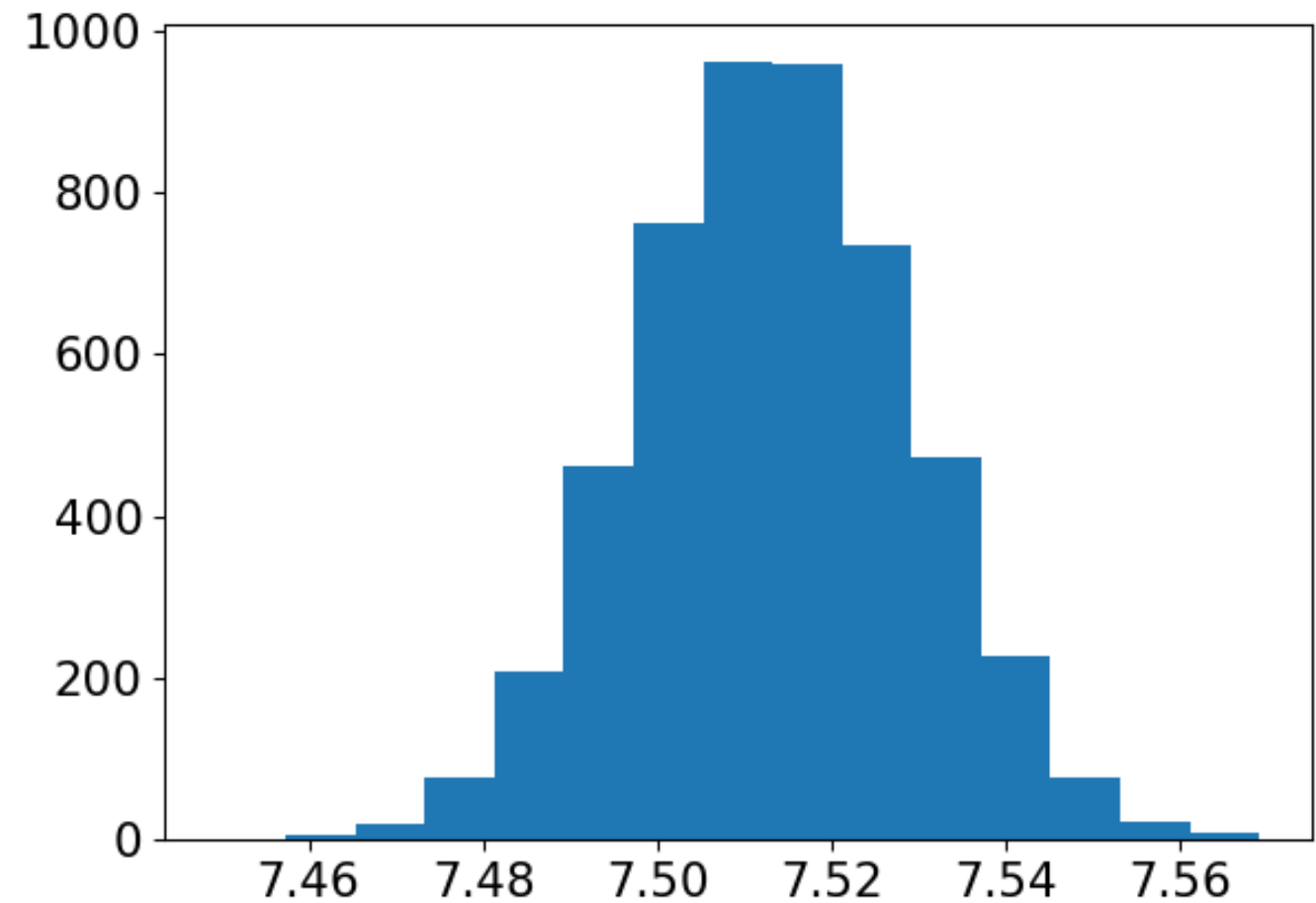
[500 rows x 4 columns]

The bootstrap of mean coffee flavors

```
import numpy as np
mean_flavors_5000 = []
for i in range(5000):
    mean_flavors_5000.append(
        np.mean(coffee_sample.sample(frac=1, replace=True) ['flavor'])
    )
bootstrap_distn = mean_flavors_5000
```

Mean flavor bootstrap distribution

```
import matplotlib.pyplot as plt
plt.hist(bootstrap_distn, bins=15)
plt.show()
```



Sample, bootstrap distribution, population means

Sample mean:

```
coffee_sample['flavor'].mean()
```

```
7.51322000000000005
```

Estimated population mean:

```
np.mean(bootstrap_distn)
```

```
7.513357731999999
```

True population mean:

```
coffee_ratings['flavor'].mean()
```

```
7.526046337817639
```

Interpreting the means

Bootstrap distribution mean:

- Usually close to the sample mean
- May not be a good estimate of the population mean

Bootstrapping cannot correct biases from sampling

Sample sd vs. bootstrap distribution sd

Sample standard deviation:

```
coffee_sample['flavor'].std()
```

```
0.3540883911928703
```

Estimated population standard deviation?

```
np.std(bootstrap_distn, ddof=1)
```

```
0.015768474367958217
```

Sample, bootstrap dist'n, pop'n standard deviations

Sample standard deviation:

```
coffee_sample['flavor'].std()
```

```
0.3540883911928703
```

True standard deviation:

```
coffee_ratings['flavor'].std(ddof=0)
```

```
0.34125481224622645
```

Estimated population standard deviation:

```
standard_error = np.std(bootstrap_distn, ddof=1)
```

Standard error is the standard deviation of the statistic of interest

```
standard_error * np.sqrt(500)
```

```
0.3525938058821761
```

Standard error times square root of sample size estimates the population standard deviation

Interpreting the standard errors

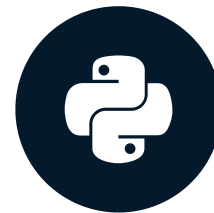
- *Estimated standard error* → standard deviation of the bootstrap distribution for a sample statistic
- Population std. dev \approx Std. Error $\times \sqrt{\text{Sample size}}$

Let's practice!

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Confidence intervals

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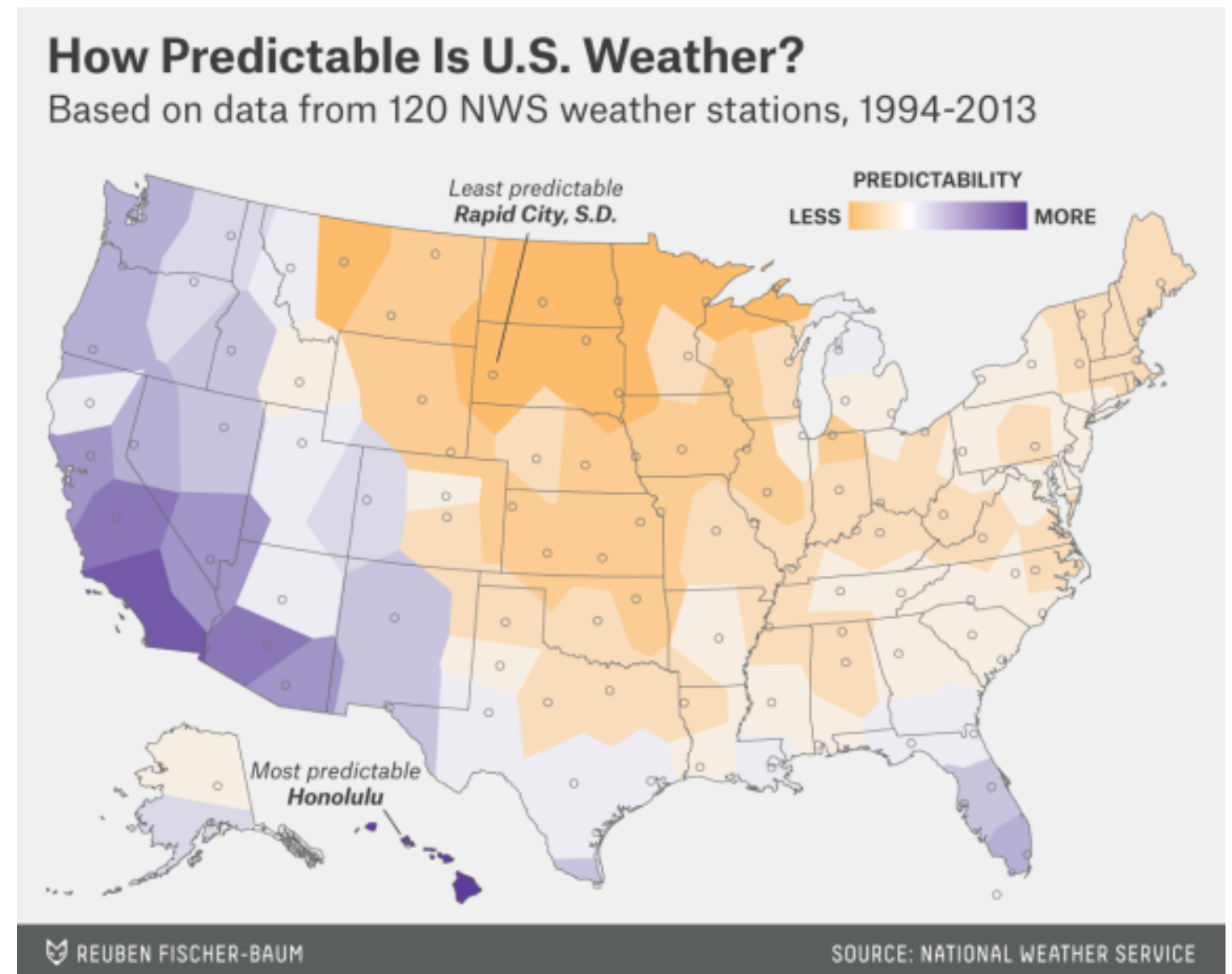
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Confidence intervals

- "Values within one standard deviation of the mean" includes a large number of values from each of these distributions
- We'll define a related concept called a *confidence interval*

Predicting the weather

- Rapid City, South Dakota in the United States has the least predictable weather
- Our job is to predict the high temperature there tomorrow



Our weather prediction

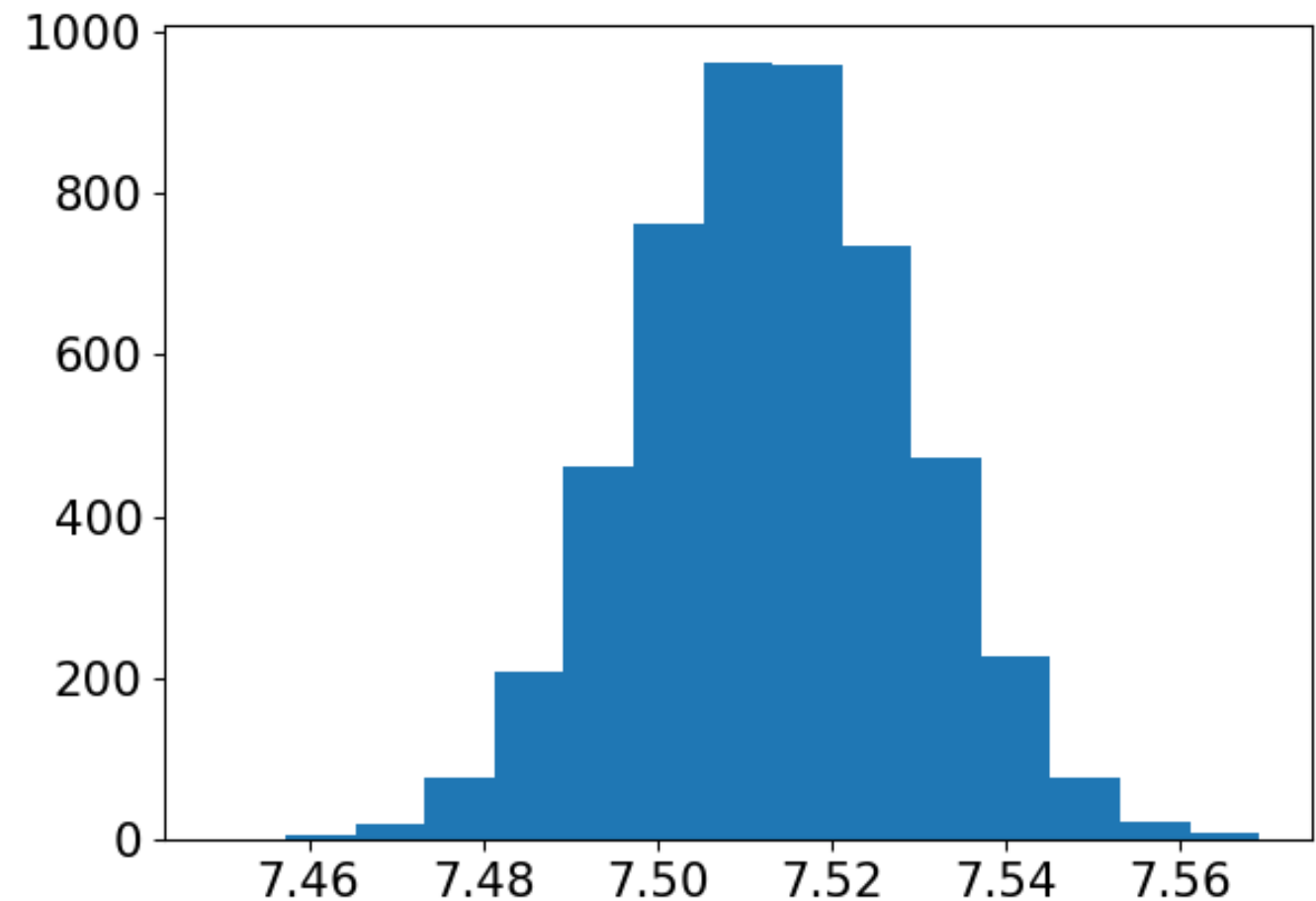
- Point estimate = 47°F (8.3°C)
- Range of plausible high temperature values = 40 to 54°F (4.4 to 12.8°C)

We just reported a confidence interval!

- 40 to 54°F is a *confidence interval*
- Sometimes written as 47 °F (40°F, 54°F) or 47°F [40°F, 54°F]
- ... or, $47 \pm 7^\circ\text{F}$
- 7°F is the *margin of error*

Bootstrap distribution of mean flavor

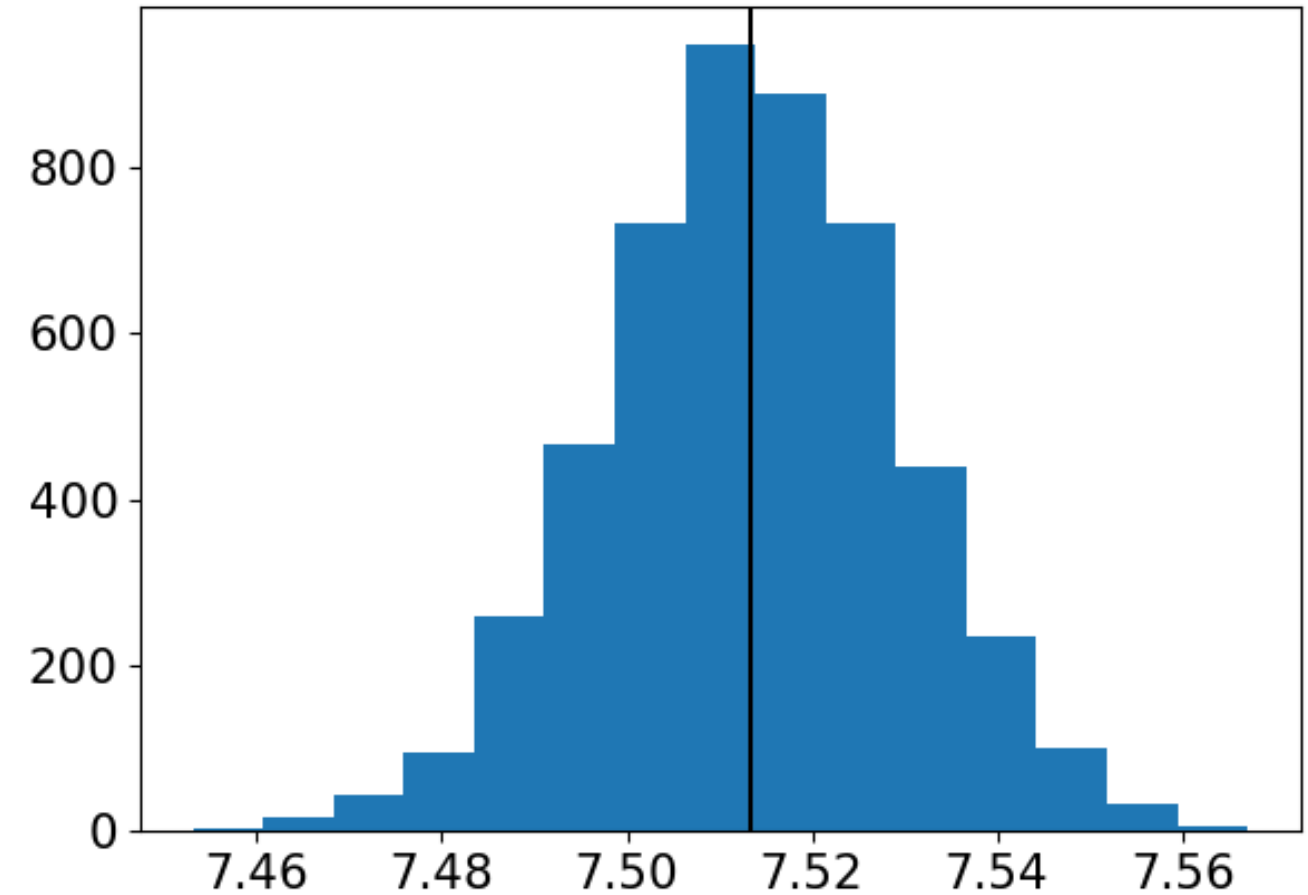
```
import matplotlib.pyplot as plt
plt.hist(coffee_boot_distn, bins=15)
plt.show()
```



Mean of the resamples

```
import numpy as np  
np.mean(coffee_boot_distn)
```

7.513452892



Mean plus or minus one standard deviation

```
np.mean(coffee_boot_distn)
```

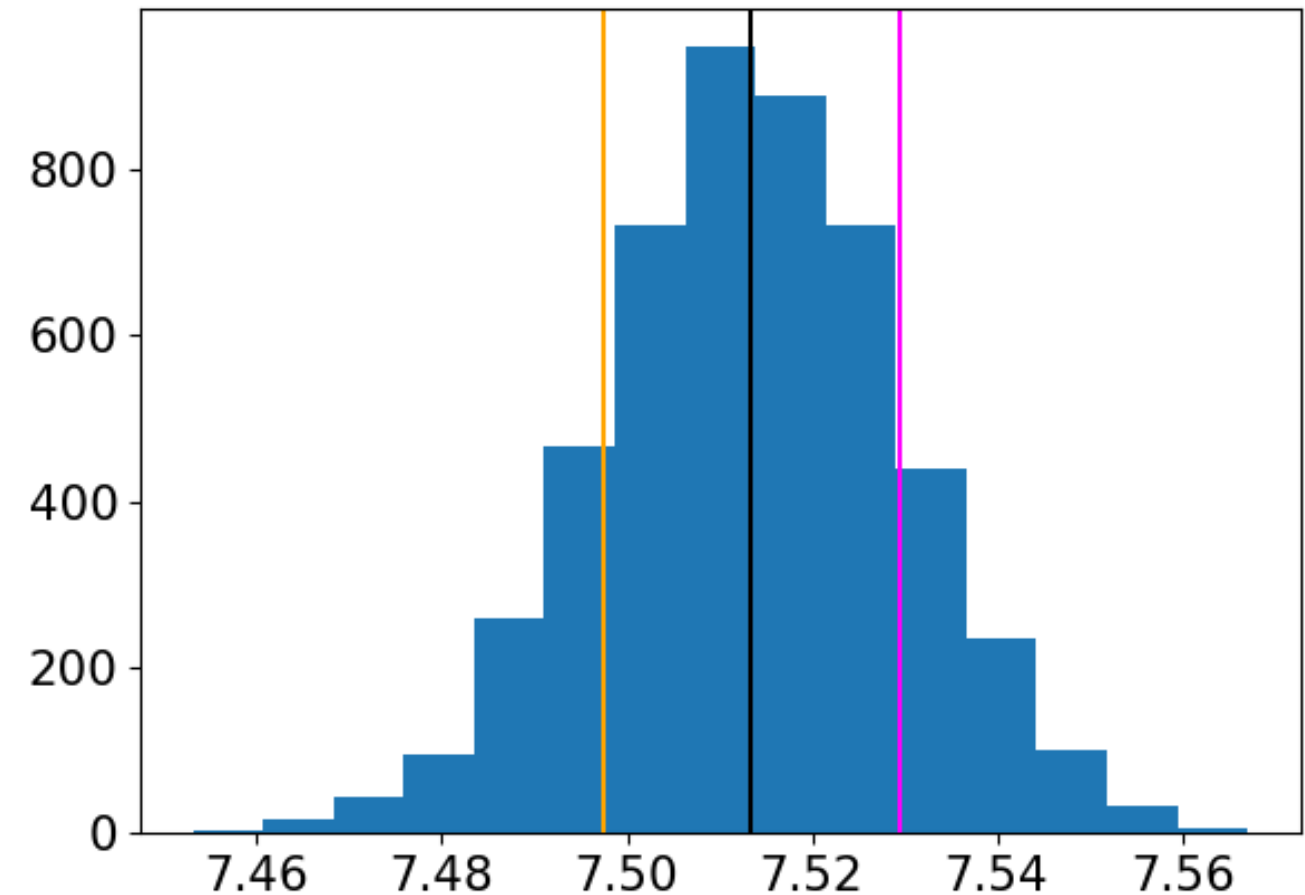
```
7.513452892
```

```
np.mean(coffee_boot_distn) - np.std(coffee_boot_distn, ddof=1)
```

```
7.497385709174466
```

```
np.mean(coffee_boot_distn) + np.std(coffee_boot_distn, ddof=1)
```

```
7.529520074825534
```



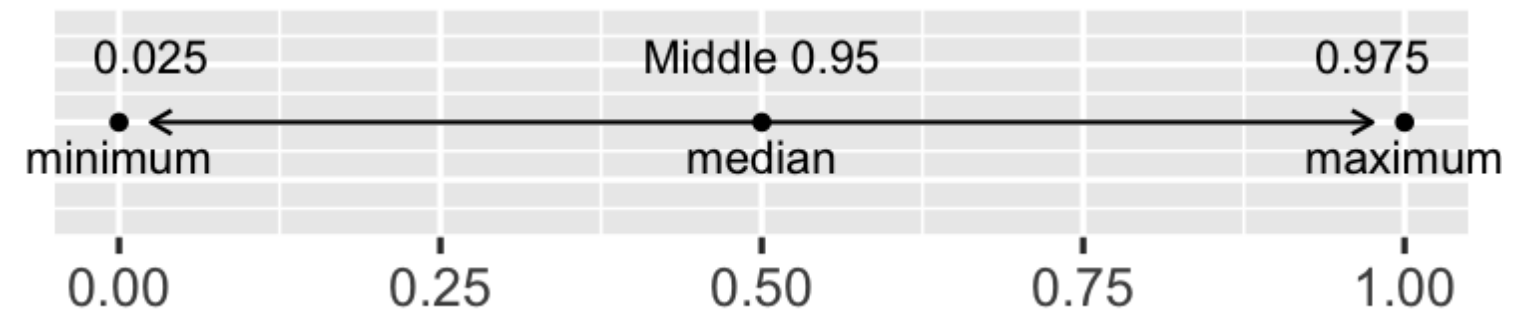
Quantile method for confidence intervals

```
np.quantile(coffee_boot_distn, 0.025)
```

```
7.4817195
```

```
np.quantile(coffee_boot_distn, 0.975)
```

```
7.5448805
```

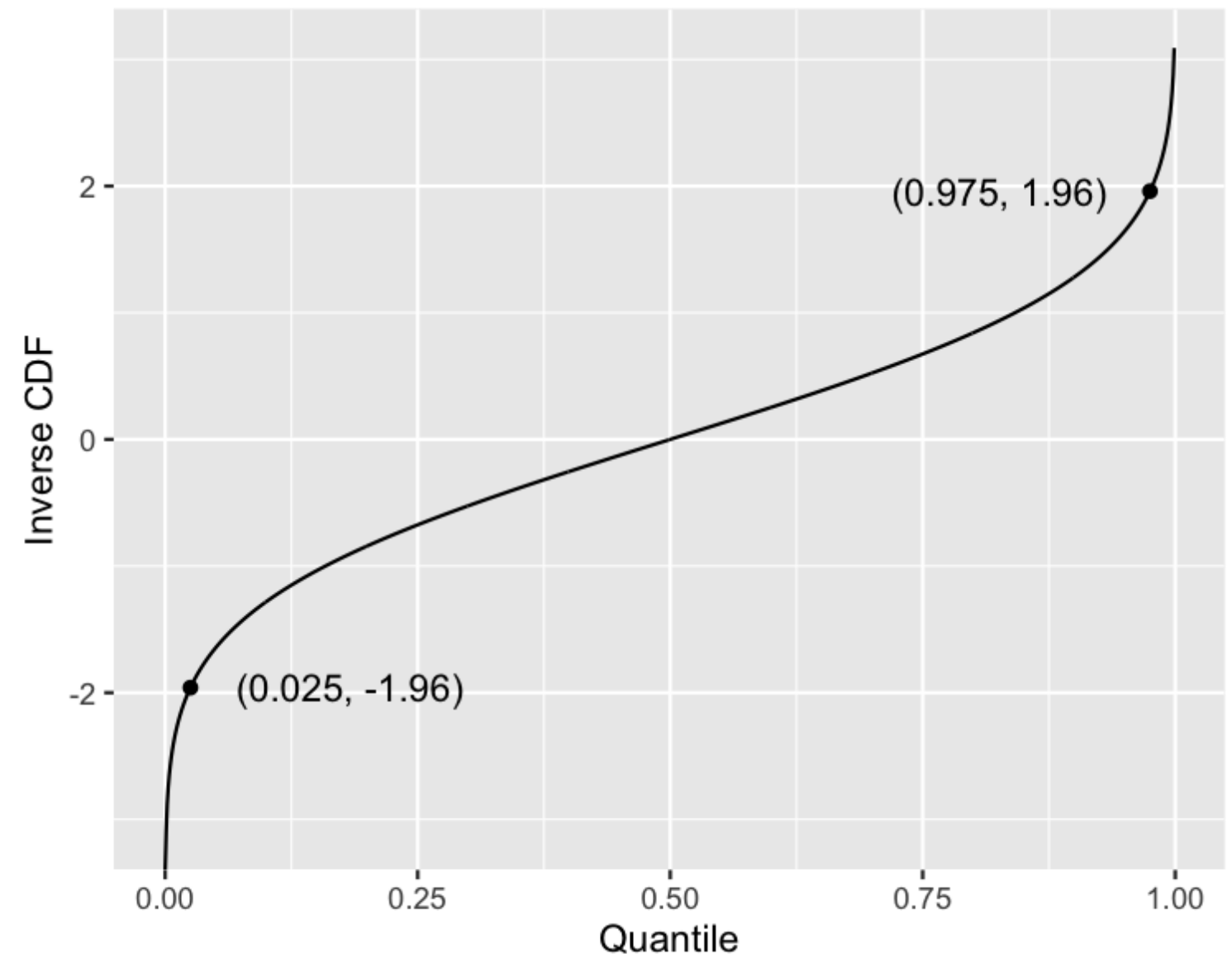


Inverse cumulative distribution function

- PDF: The bell curve
- CDF: integrate to get area under bell curve
- Inv. CDF: flip x and y axes

Implemented in Python with

```
from scipy.stats import norm  
norm.ppf(quantile, loc=0, scale=1)
```



Standard error method for confidence interval

```
point_estimate = np.mean(coffee_boot_distn)
```

```
7.513452892
```

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

```
0.016067182825533724
```

```
from scipy.stats import norm
lower = norm.ppf(0.025, loc=point_estimate, scale=std_error)
upper = norm.ppf(0.975, loc=point_estimate, scale=std_error)
print((lower, upper))
```

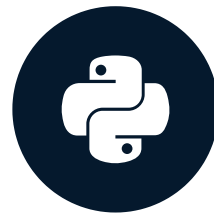
```
(7.481961792328933, 7.544943991671067)
```

Let's practice!

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Congratulations!

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Recap

Chapter 1

- Sampling basics
- Selection bias
- Pseudo-random numbers

Chapter 2

- Simple random sampling
- Systematic sampling
- Stratified sampling
- Cluster sampling

Chapter 3

- Sample size and population parameters
- Creating sampling distributions
- Approximate vs. actual sampling dist'ns
- Central limit theorem

Chapter 4

- Bootstrapping from a single sample
- Standard error
- Confidence intervals

The most important things

- The std. deviation of a bootstrap statistic is a good approximation of the *standard error*
- Can assume bootstrap distributions are normally distributed for confidence intervals

What's next?

- [Experimental Design in Python](#) and [Customer Analytics and A/B Testing in Python](#)
- [Hypothesis Testing in Python](#)
- [Foundations of Probability in Python](#) and [Bayesian Data Analysis in Python](#)

Happy learning!

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