Introduction to bootstrapping

SAMPLING IN PYTHON

James Chapman
Content Developer, DataCamp

datacamp

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

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

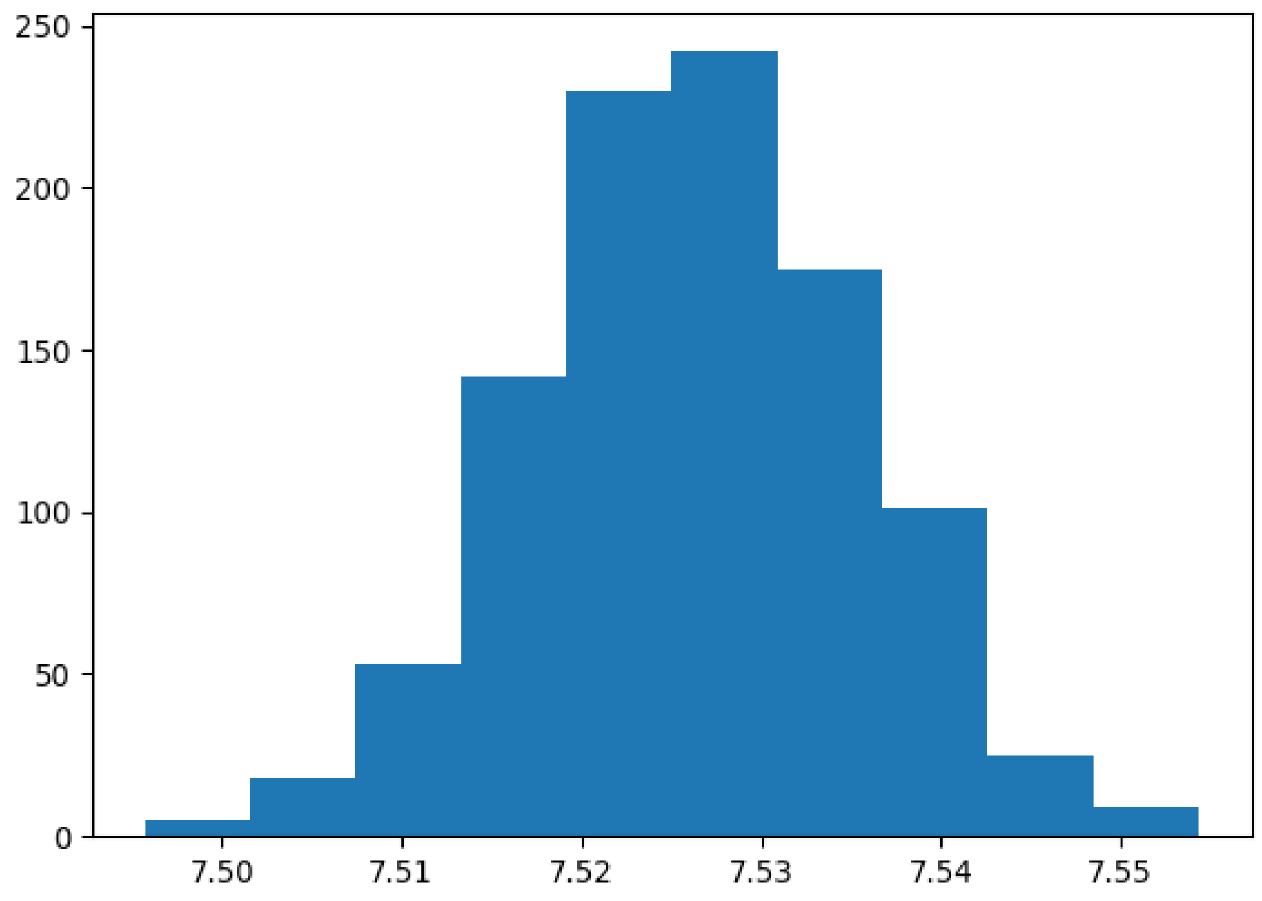
The resulting statistics are *bootstrap statistics*, and they form a *bootstrap distribution*

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

```python
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"]]\
    .reset_index().sample(n=500)
```

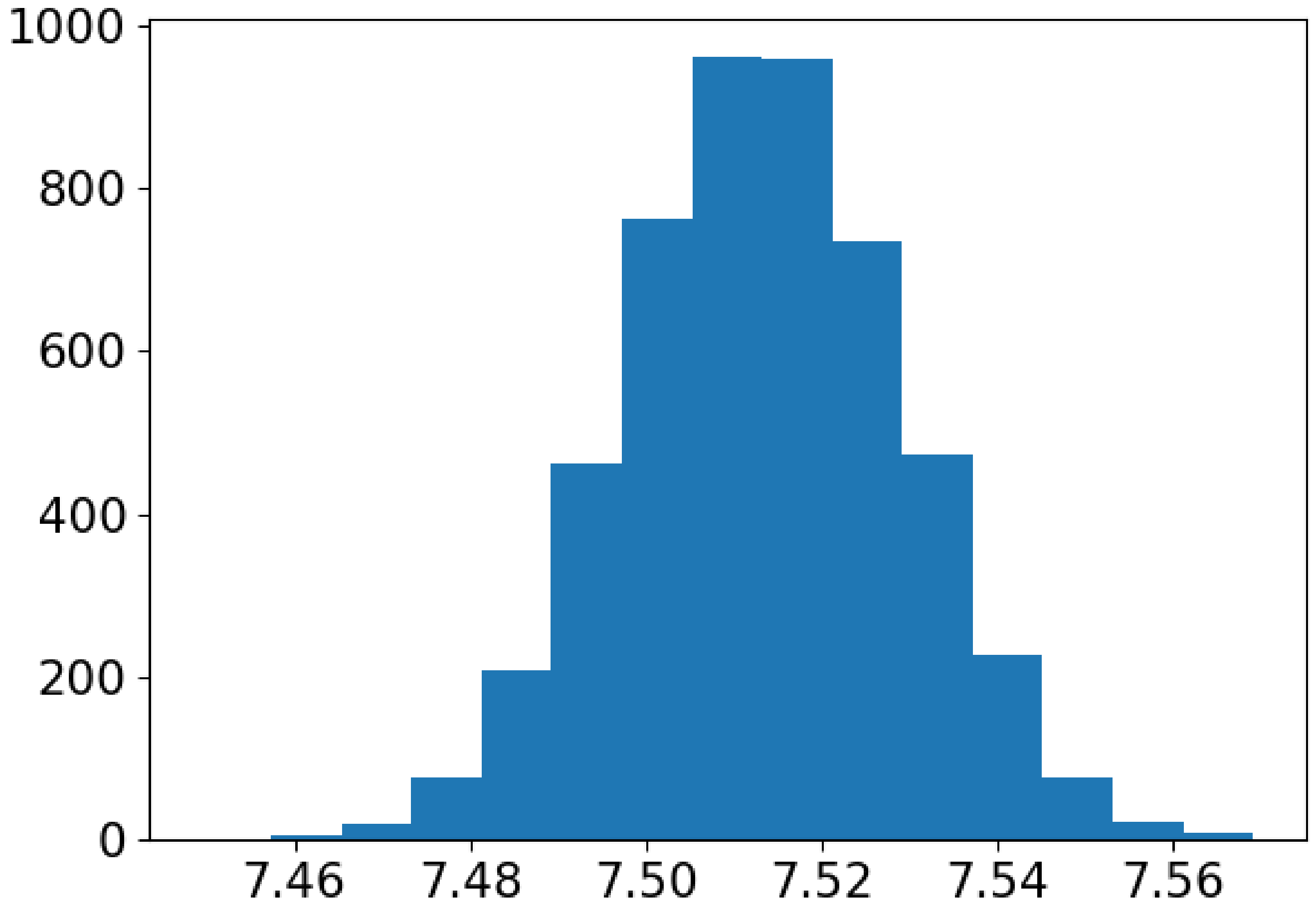
```
     index         variety        country_of_origin  flavor
132    132           Other               Costa Rica    7.58
51      51            None  United States (Hawaii)    8.17
42      42  Yellow Bourbon                   Brazil    7.92
569    569         Bourbon                Guatemala    7.67
..     ...             ...                      ...     ...
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()
```

```
7.5132200000000005
```

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
- $\text{Population std. dev} \approx \text{Std. Error} \times \sqrt{\text{Sample size}}$

Let's practice!

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Confidence intervals

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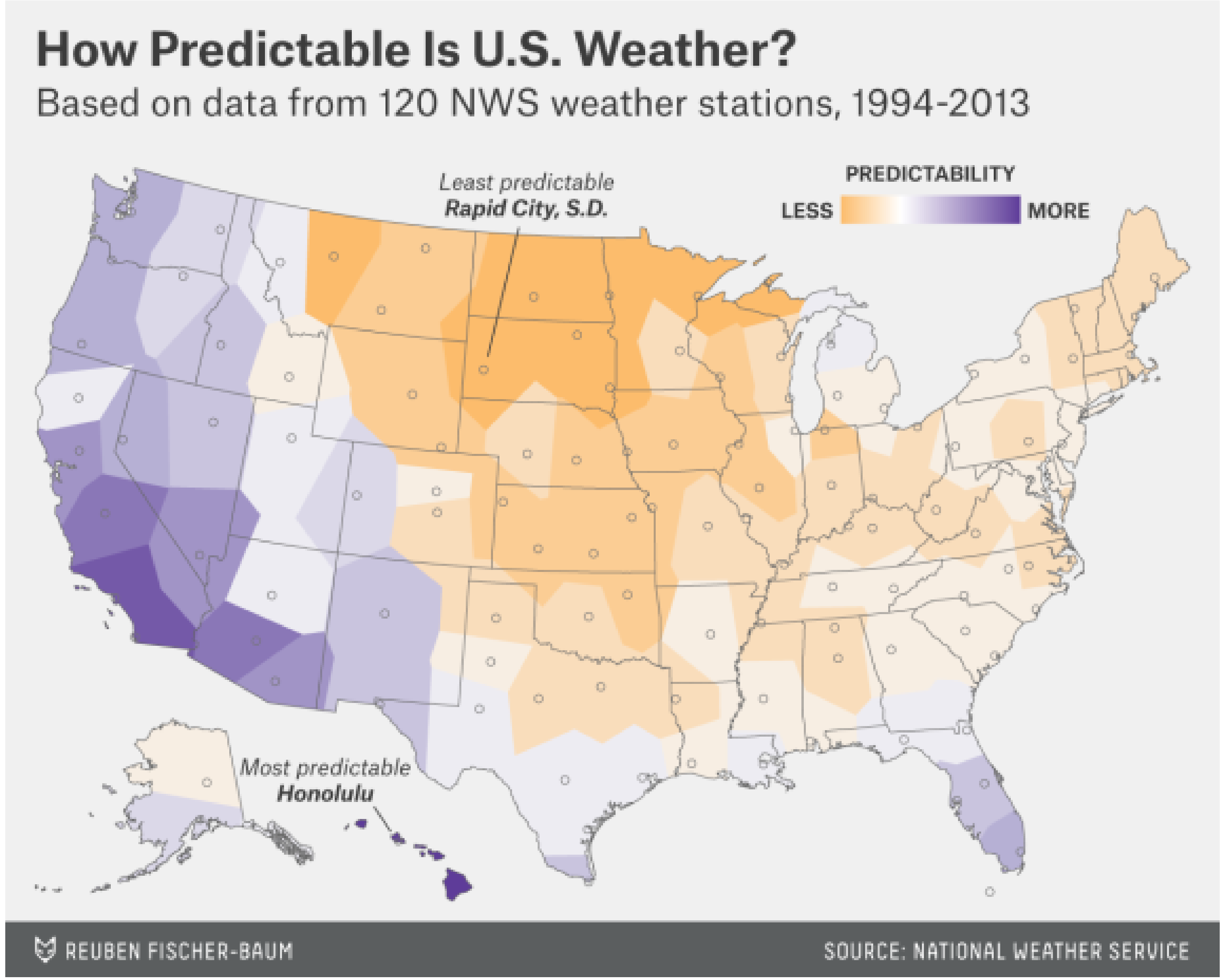
Content Developer, DataCamp

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

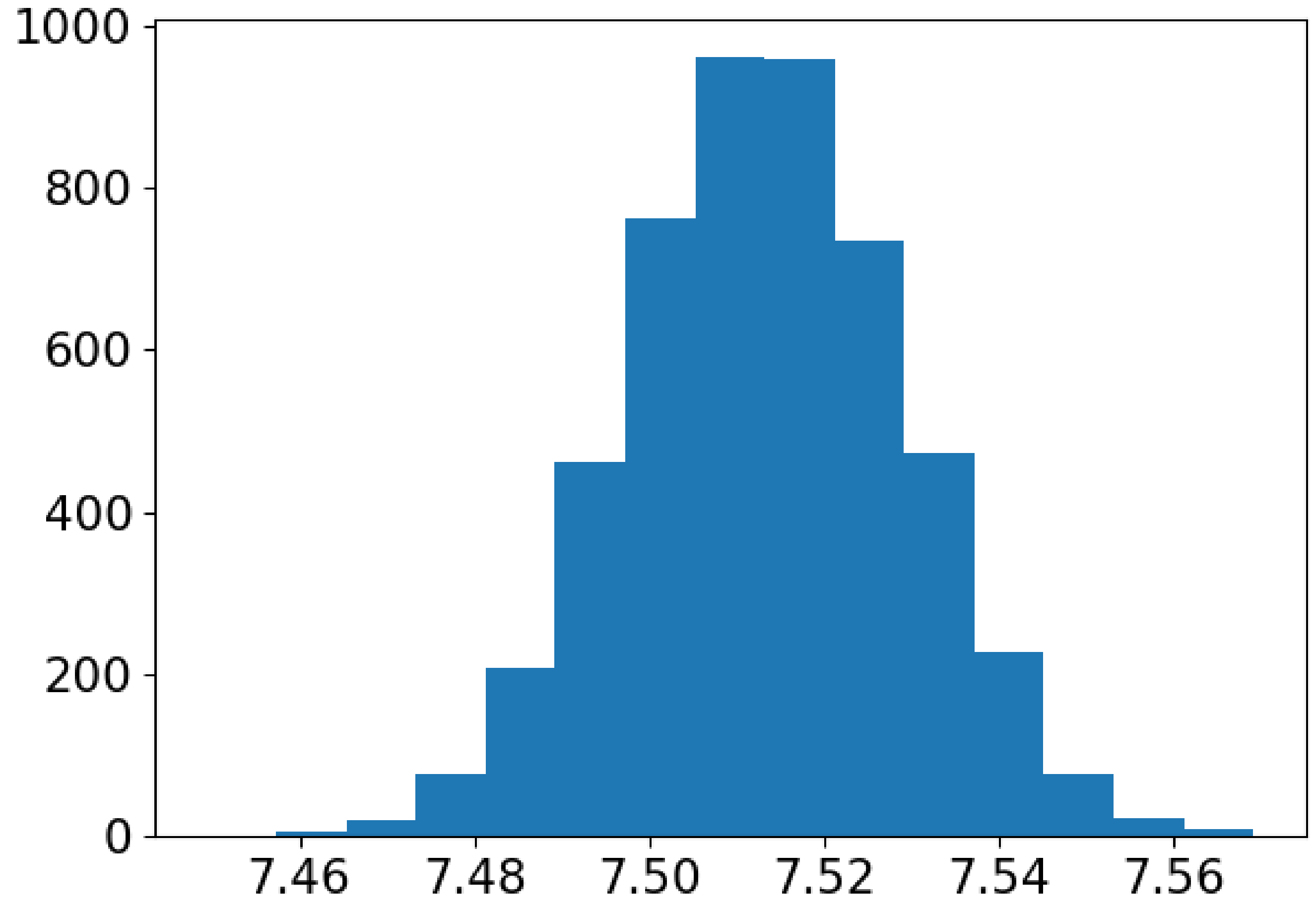
- Point estimate = 47°F (8.3°C)
- Range of plausible high temperature values = 40 to 54°F (4.4 to 12.8°C)

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 ± 7°F
- 7°F is the *margin of error*

Bootstrap distribution of mean flavor

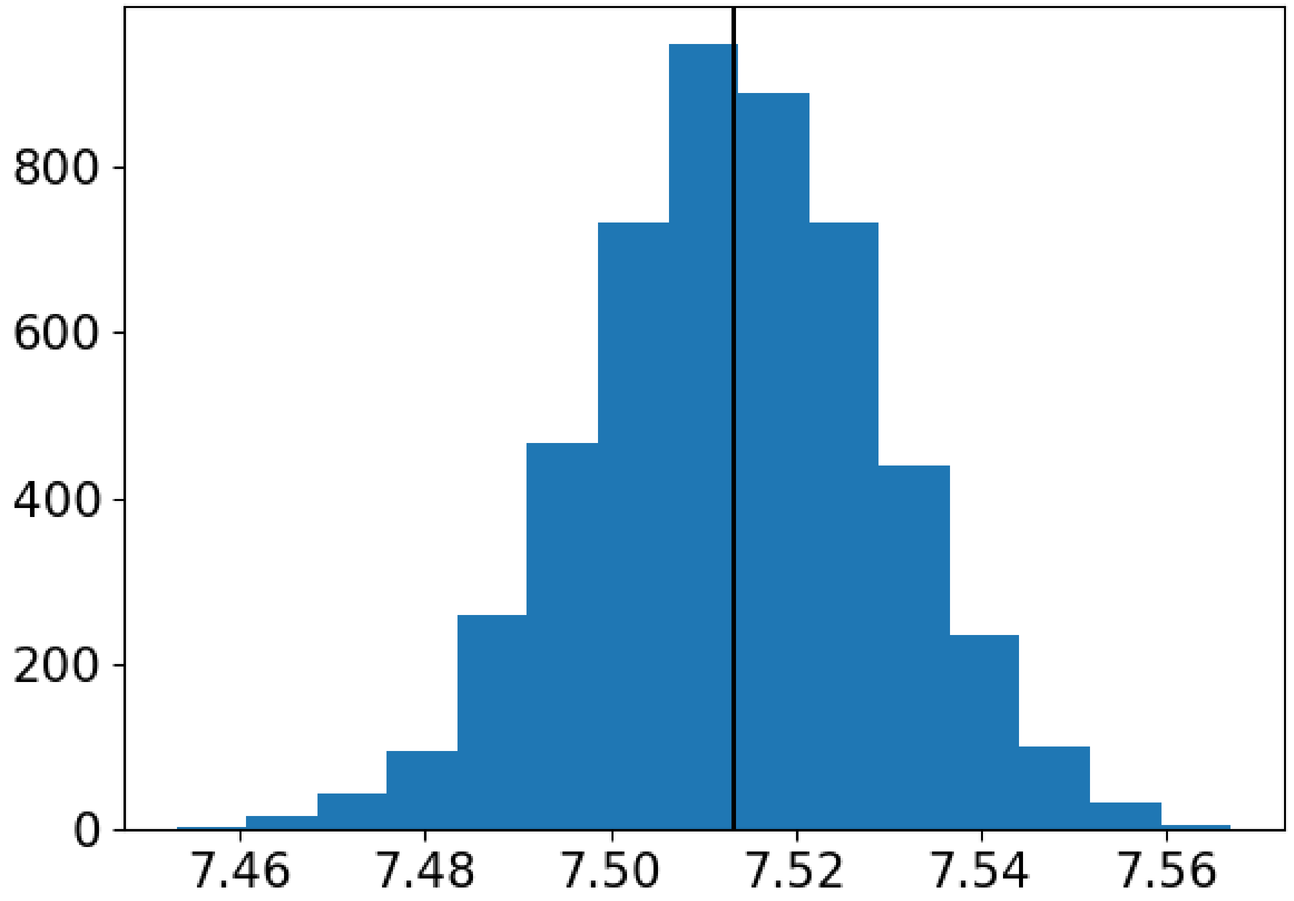
```
import matplotlib.pyplot as plt
plt.hist(coffee_boot_distn, bins=15)
plt.show()
```



Mean of the resamples

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

```
7.513452892
```



Mean plus or minus one standard deviation

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

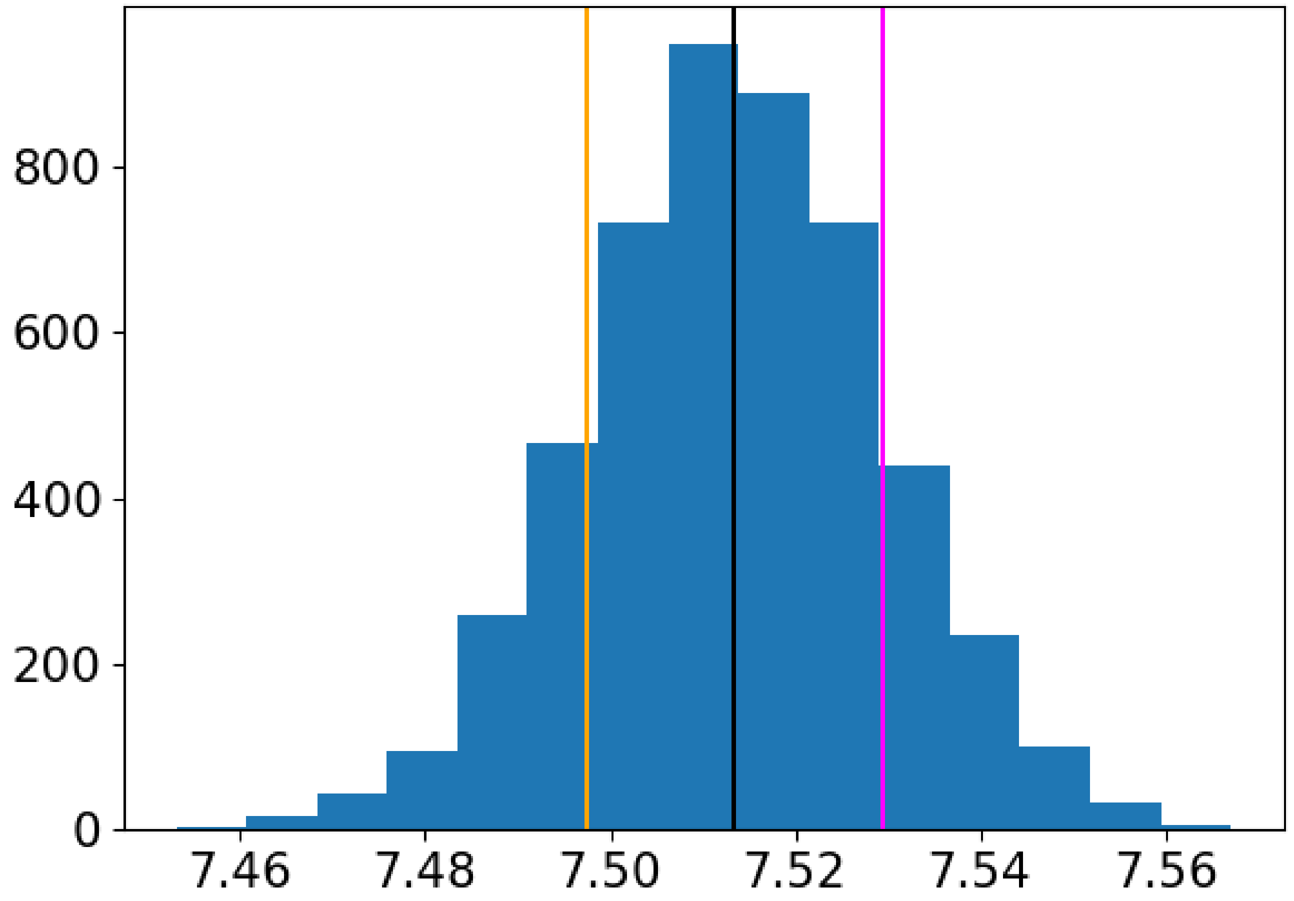
```
7.513452892
```

```
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
```



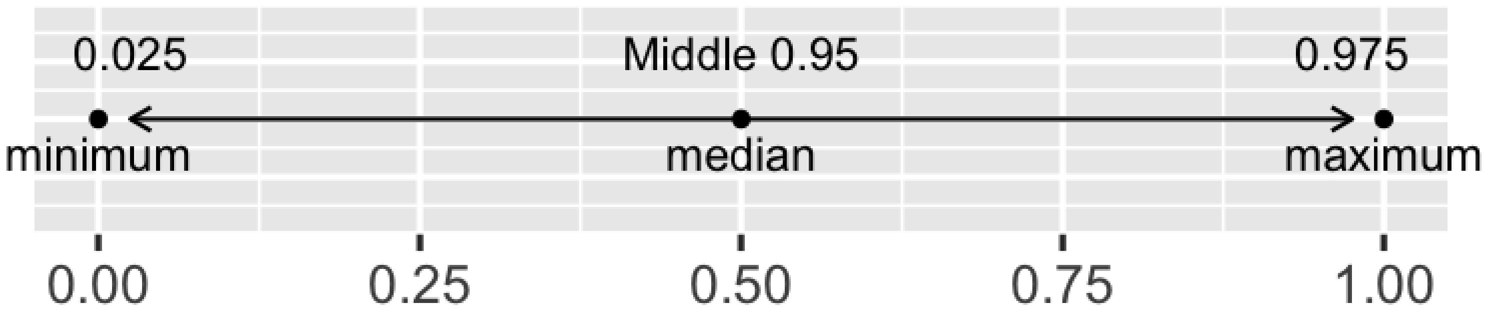
Quantile method for confidence intervals

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

```
7.4817195
```

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

```
7.5448805
```

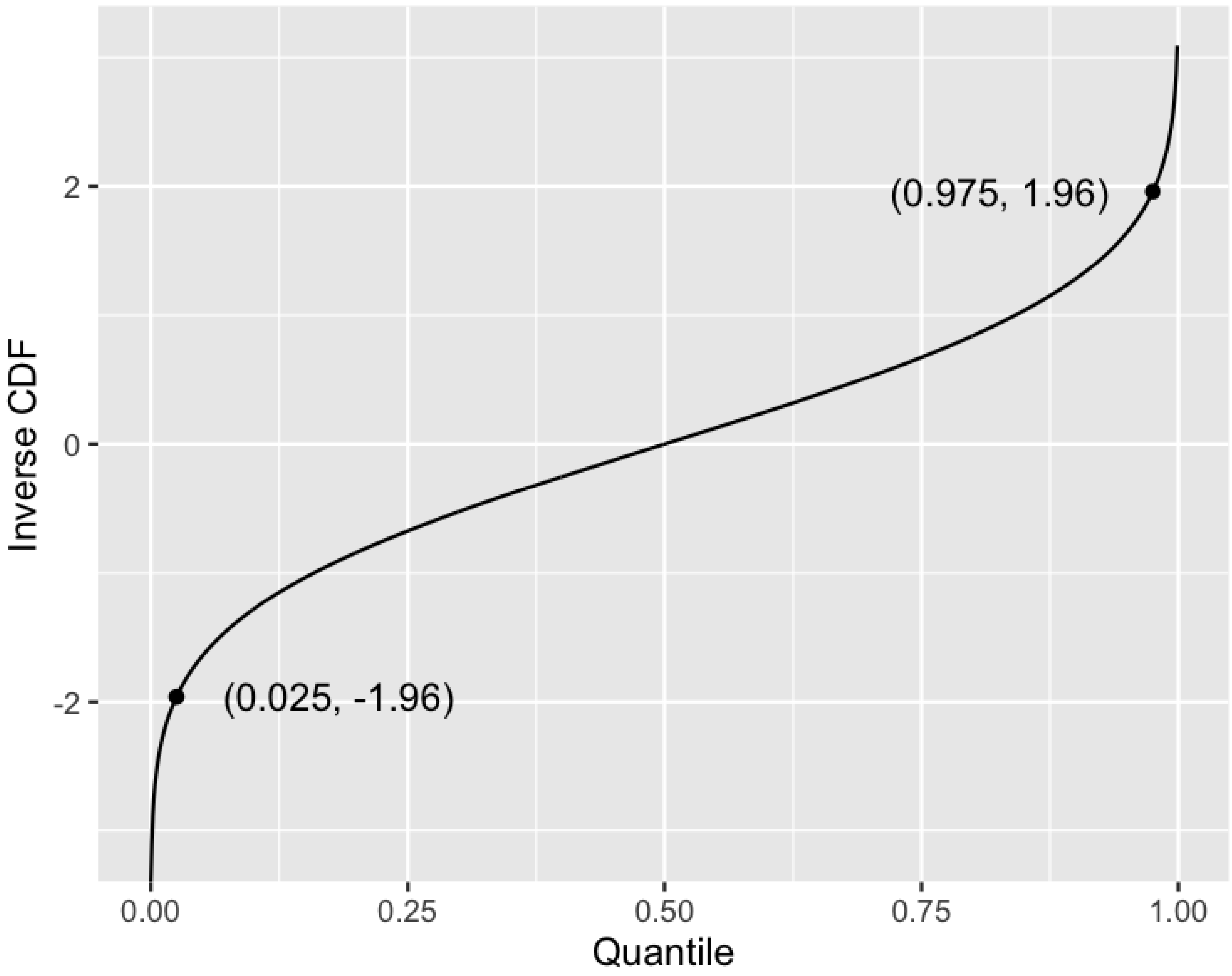


Inverse cumulative distribution function

- 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)
```

```
0.0160671828255 33724
```

```
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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James Chapman
Content Developer, DataCamp

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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