Lab 11

November 18, 2021

1 Lab 11

In this lab we discuss confidence intervals and bootstrap method.

1.1 Quantifying Uncertainty

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

np.random.randint: https://numpy.org/doc/stable/reference/random/generated/numpy.random.randint.html

[2]:
```
# We generate 1000 random integer numbers from 100 to 250 to simulate body␣
↪weights of 1000 people.
np.random.seed(0)
weight = np.random.randint(100, 250, size = 1000)
df = pd.DataFrame({"Weight":weight})
df
```

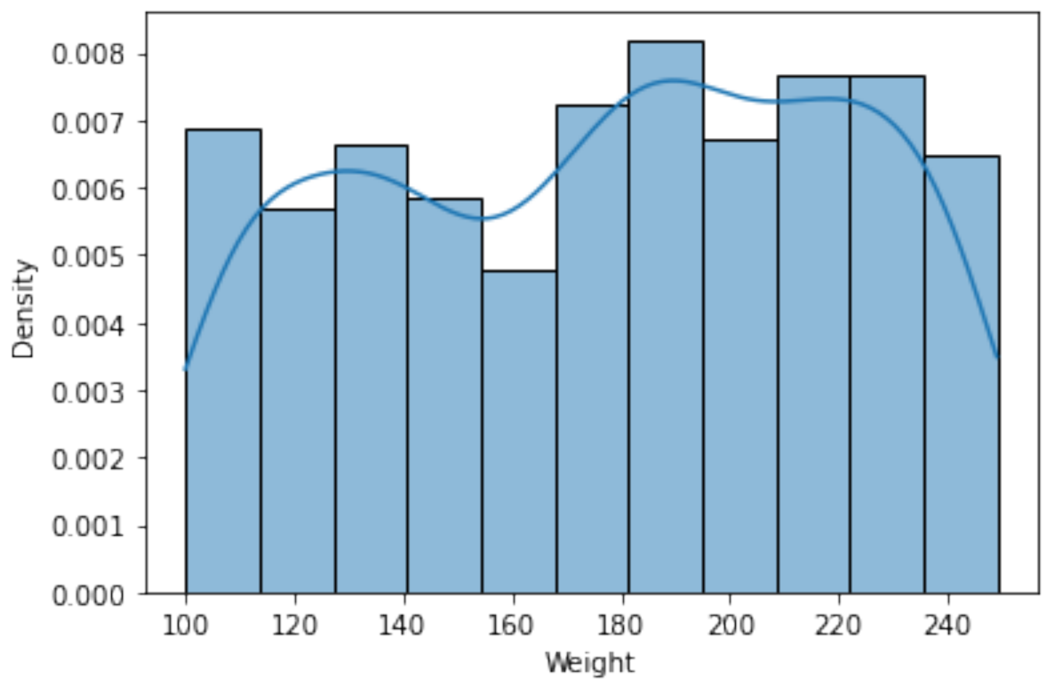
[2]:
```
     Weight
0       147
1       217
2       167
3       203
4       109
..      …
995     219
996     127
997     151
998     178
999     186

[1000 rows x 1 columns]
```

[3]:
```
# Calculating summary statistics for the variable "Weight"
df.describe()
```

[3]:

	Weight
count	1000.000000
mean	177.241000
std	43.189423
min	100.000000
25%	139.000000
50%	181.000000
75%	215.000000
max	249.000000

[4]:
```
# We can see the distribution of the values in the column "Weight".
# This is not a normal distribution!
sns.histplot(df['Weight'], stat = 'density', kde = True)
plt.show()
```



1.1.1 Constructing Confidence Interval via Central Limit Theorem

A confidence interval is the interval which has a prespecified probability of containing the parameter of interest.

[5]:
```
# We can obtain confidence interval using the central limit theorem.
# First we need to calculate the standard error.
std_err = np.std(df.Weight, ddof = 1) / np.sqrt(len(df))
print("standard error:", std_err)
```

standard error: 1.3657694700223935

[6]:
```
# 95% of the area under a normal curve lies within roughly 1.96 standard␣
↪deviations of the mean.
# Due to the CLT, 1.96 is therefore used in the construction of approximate 95%␣
↪confidence intervals.
crit_val = 1.96
norm_ci = [df.Weight.mean() - crit_val * std_err, df.Weight.mean() + crit_val *␣
↪std_err]
print("confidence interval via CLT:", norm_ci)
```

```
confidence interval via CLT: [174.56409183875613, 179.9179081612439]
```

1.1.2 Constructing Confidence Interval via Bootstrap

The bootstrap method is a resampling technique used to estimate statistics on a population by sampling a dataset with replacement. It can be used to estimate summary statistics such as mean or standard deviation.

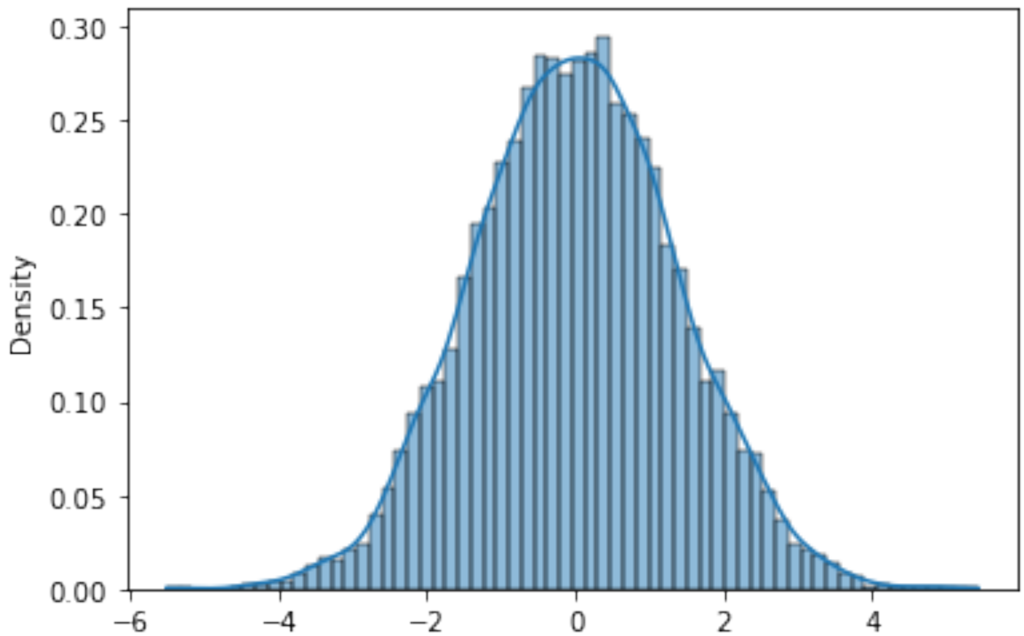
np.zeros: https://numpy.org/doc/stable/reference/generated/numpy.zeros.html

[7]:
```
# We define a function to create 10000 bootstrap datasets and compute mean for␣
↪each.
def CreateBootstrapMeans(data):
    num_boot = 10000
    n = len(data)
    boot_means = np.zeros(num_boot)
    np.random.seed(0)
    for i in range(num_boot):
        d = data.sample(n, replace = True)
        boot_means[i] = d.mean()
    return boot_means
```

[8]:
```
# Let's find the mean values for bootstrap samples!
boot_means = CreateBootstrapMeans(df)
boot_means
```

[8]:
```
array([178.29 , 175.828, 177.224, …, 177.354, 176.787, 176.975])
```

[9]:
```
# We can see the distribution of the differences between the bootstrap means␣
↪and mean of the original dataset.
diff = boot_means - df.Weight.mean()
sns.histplot(diff, stat = 'density', kde = True)
plt.show()
```



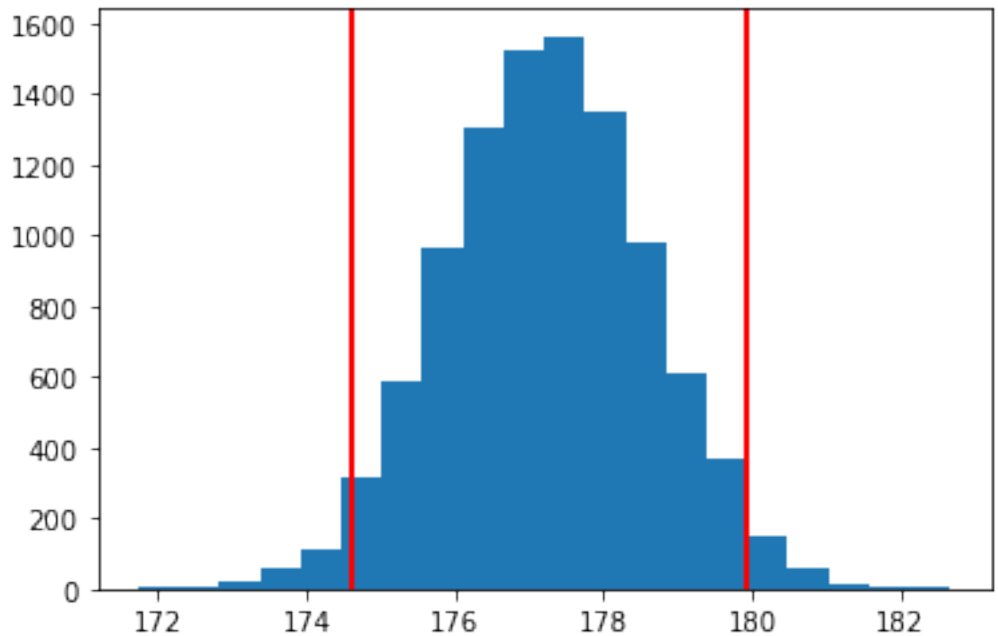
np.quantile: https://numpy.org/doc/stable/reference/generated/numpy.quantile.html

[11]:
```
# Computing the necessary quantiles for 95% confidence interval
boot_ci = np.quantile(boot_means, [0.025, 0.975])
print(boot_ci)
```

```
[174.612975 179.916075]
```

plt.hist: https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.hist.html

[12]:
```
# Visualizing the confidence interval
plt.hist(boot_means, bins = 20)
plt.axvline(boot_ci[0], color = 'red', linewidth = 2)
plt.axvline(boot_ci[1], color = 'red', linewidth = 2)
plt.show()
```



1600
1400
1200
1000
800
600
400
200
0
172
174
176
178
180
182


```
[ ]:
```