Empirical_Distribution

December 21, 2021

1 The Empirical Rule and Distribution

In week 2, we discussed the empirical rule or the 68 - 95 - 99.7 rule, which describes how many observations fall within a certain distance from our mean. This distance from the mean is denoted as sigma, or standard deviation (the average distance an observation is from the mean).

The following image may help refresh your memory:

For this tutorial, we will be exploring the number of hours the average college student gets.

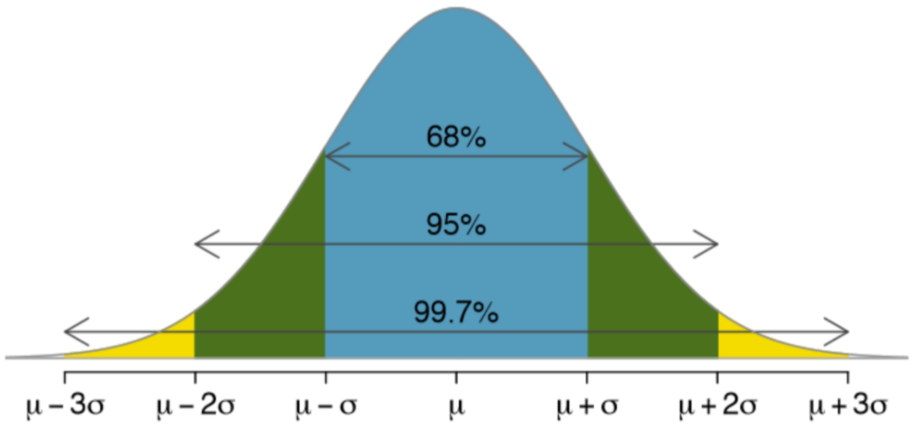
The example used in lecture stated there was a mean of 7 and standard deviation of 1.7 for hours of sleep; we will use these same values.

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
import random
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

random.seed(1738)
```

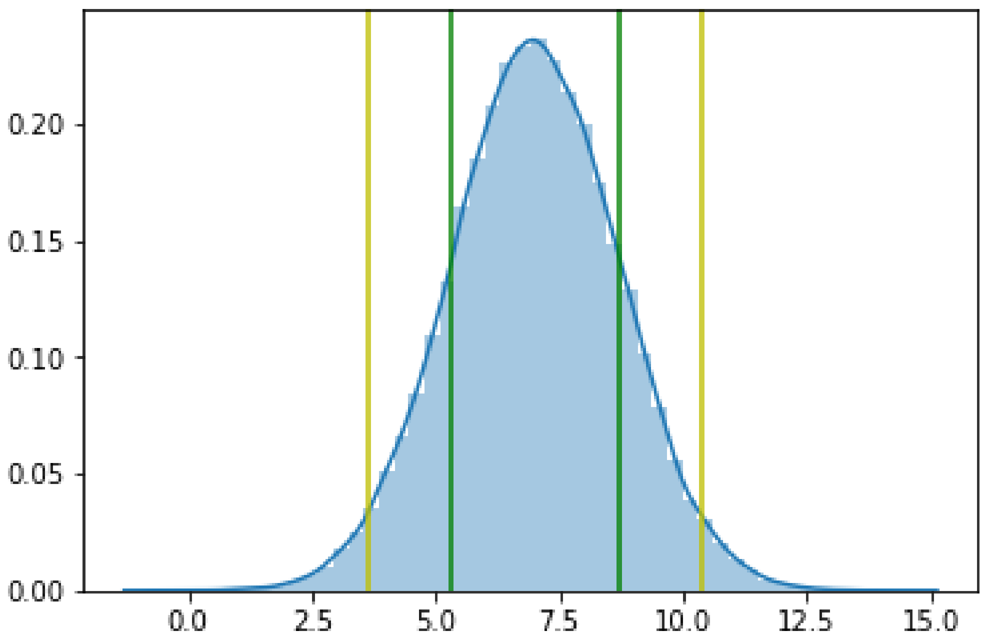
In [2]:
```
mu = 7

sigma = 1.7

Observations = [random.normalvariate(mu, sigma) for _ in range(100000)]
```

In [3]:
```
sns.distplot(Observations)

plt.axvline(np.mean(Observations) + np.std(Observations), color = "g")
plt.axvline(np.mean(Observations) - np.std(Observations), color = "g")

plt.axvline(np.mean(Observations) + (np.std(Observations) * 2), color = "y")
plt.axvline(np.mean(Observations) - (np.std(Observations) * 2), color = "y")
```

Out[3]:
```
<matplotlib.lines.Line2D at 0x7f58ab04a550>
```



Three Sigma Rule




```
In [4]: pd.Series(Observations).describe()
```

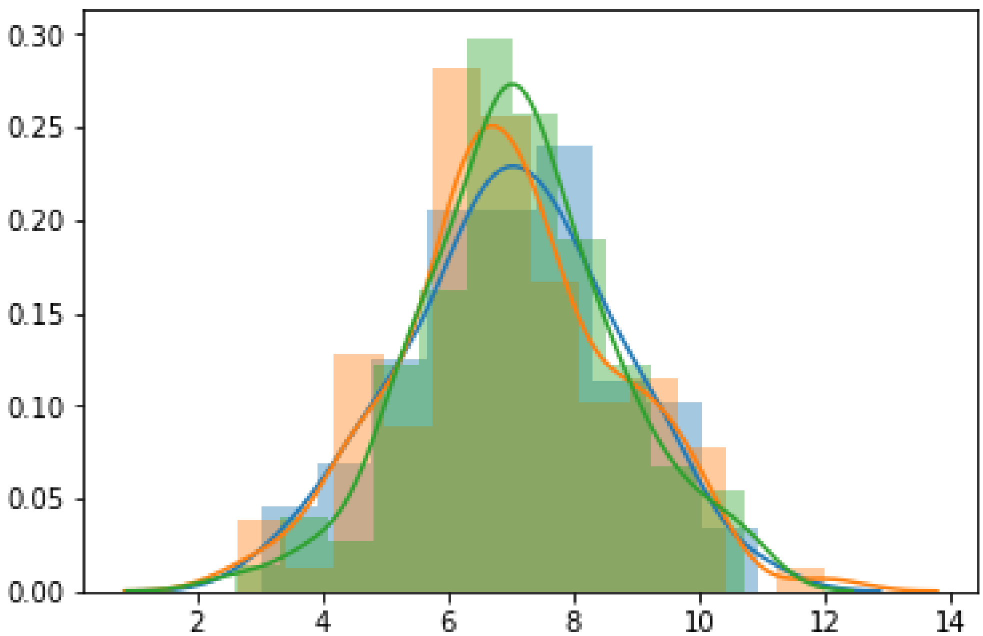
```
Out[4]: count    100000.000000
        mean          7.000626
        std           1.693249
        min          -0.754203
        25%           5.865611
        50%           7.003080
        75%           8.144851
```

```
max          14.595650
dtype: float64
```

In [5]:
```
SampleA = random.sample(Observations, 100)
SampleB = random.sample(Observations, 100)
SampleC = random.sample(Observations, 100)
```

In [6]:
```
fig, ax = plt.subplots()

sns.distplot(SampleA, ax = ax)
sns.distplot(SampleB, ax = ax)
sns.distplot(SampleC, ax = ax)
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f58aaf8e518>



Now that we have covered the 68 - 95 - 99.7 rule, we will take this a step further and discuss the empirical distribution.

The empirical distribution is a cumulative density function that signifies the proportion of observations that are less than or equal to a certain values.

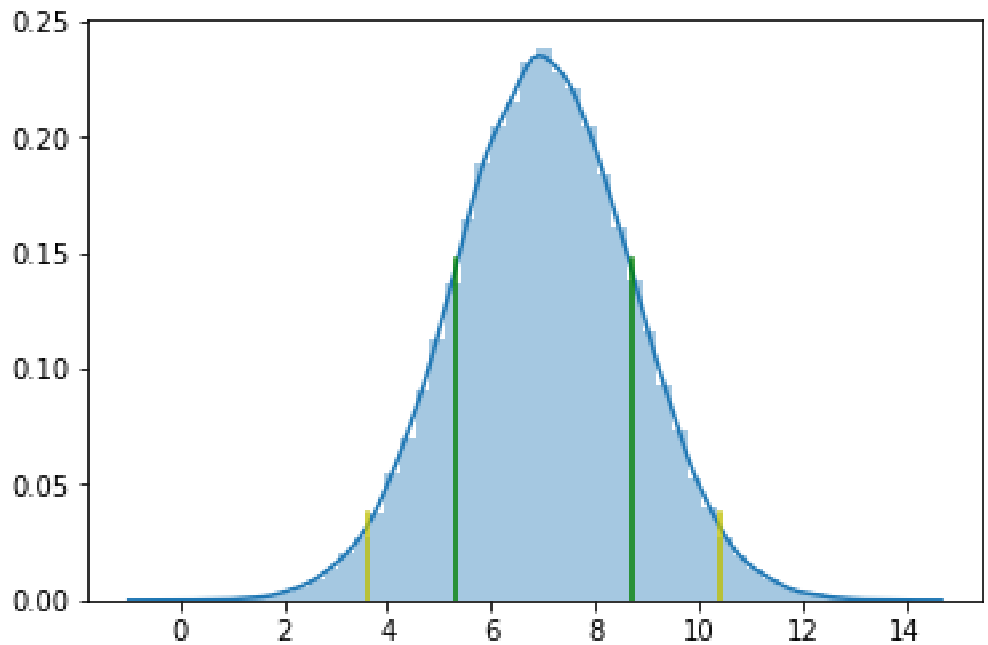
Lets use the initial image above as an example of this concept:

Now, by using our observations for ours of sleep, we can create an empirical distribution in python that signifies the proportion of observations are observed at a specific number for hours of sleep.

In [7]:
```
mu = 7

sigma = 1.7
```

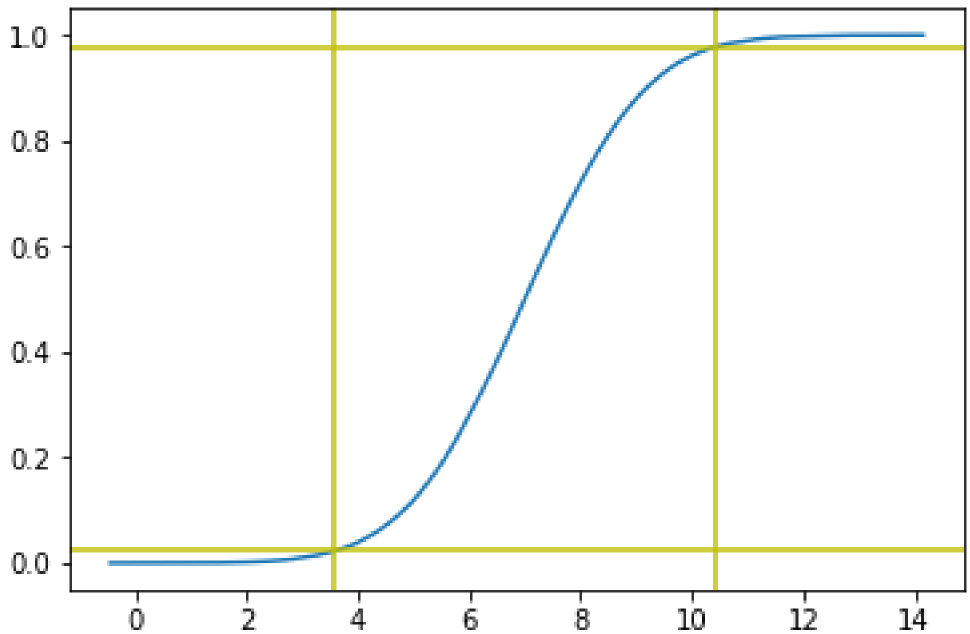
```
Observations = [random.normalvariate(mu, sigma) for _ in range(100000)]

sns.distplot(Observations)
plt.axvline(np.mean(Observations) + np.std(Observations), 0, .59, color = 'g')
plt.axvline(np.mean(Observations) - np.std(Observations), 0, .59, color = 'g')

plt.axvline(np.mean(Observations) + (np.std(Observations) * 2), 0, .15, color = 'y')
plt.axvline(np.mean(Observations) - (np.std(Observations) * 2), 0, .15, color = 'y')
```

Out[7]: <matplotlib.lines.Line2D at 0x7f58ad137eb8>



In [8]:
```
from statsmodels.distributions.empirical_distribution import ECDF
import matplotlib.pyplot as plt

ecdf = ECDF(Observations)

plt.plot(ecdf.x, ecdf.y)

plt.axhline(y = 0.025, color = 'y', linestyle='-')
plt.axvline(x = np.mean(Observations) - (2 * np.std(Observations)), color = 'y', lines

plt.axhline(y = 0.975, color = 'y', linestyle='-')
plt.axvline(x = np.mean(Observations) + (2 * np.std(Observations)), color = 'y', lines
```

Out[8]: <matplotlib.lines.Line2D at 0x7f58ad29cb00>


1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8
10
12
14