L3_Descriptive_Statistics_filled

January 30, 2019

0.1 Playing with sampling and the Central Limit Theorem

Begin with imports:

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
```

Let's create a population that isn't normally distributed we will concatenate several normal distributions to do so:

```
In [2]: d1 = np.random.normal(loc=-6.4, scale=1.2, size=40000)
        d2 = np.random.normal(loc=4, scale=10, size=16000)
        d3 = np.random.normal(loc=22, scale=8, size=72000)
        population = np.concatenate([d1, d2, d3])
        pop = pd.DataFrame(data=population, columns=['population'])
        pop.head()
```

Out[2]:

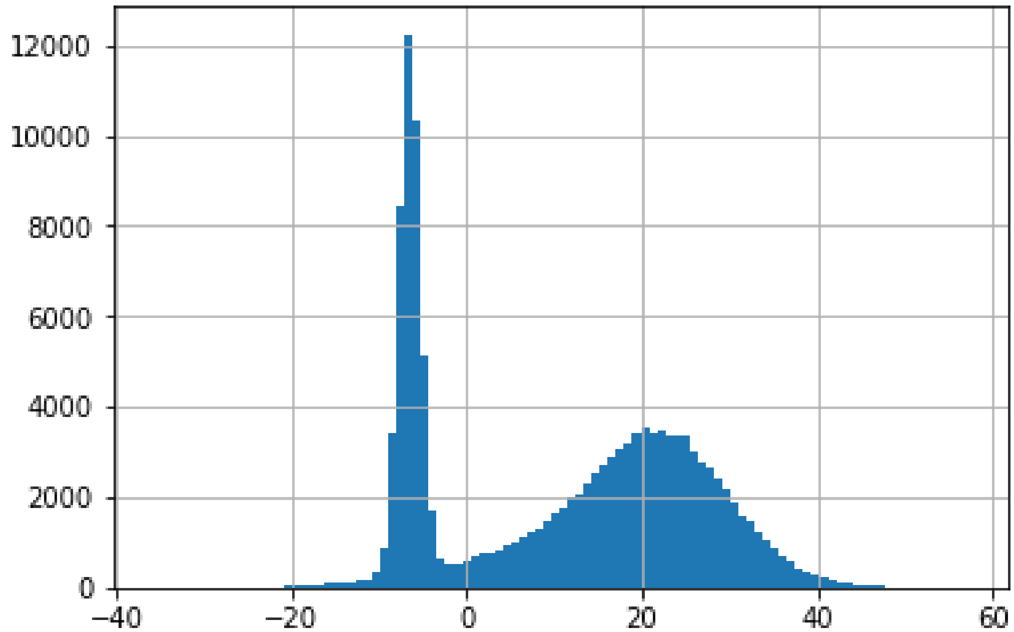
	population
0	-6.150114
1	-6.314954
2	-7.556597
3	-5.396809
4	-5.712484

0.2 Make a histogram. Play around with bin size

Hint: there are multiple ways to do this. Try numpy.histogram or the pandas method hist.

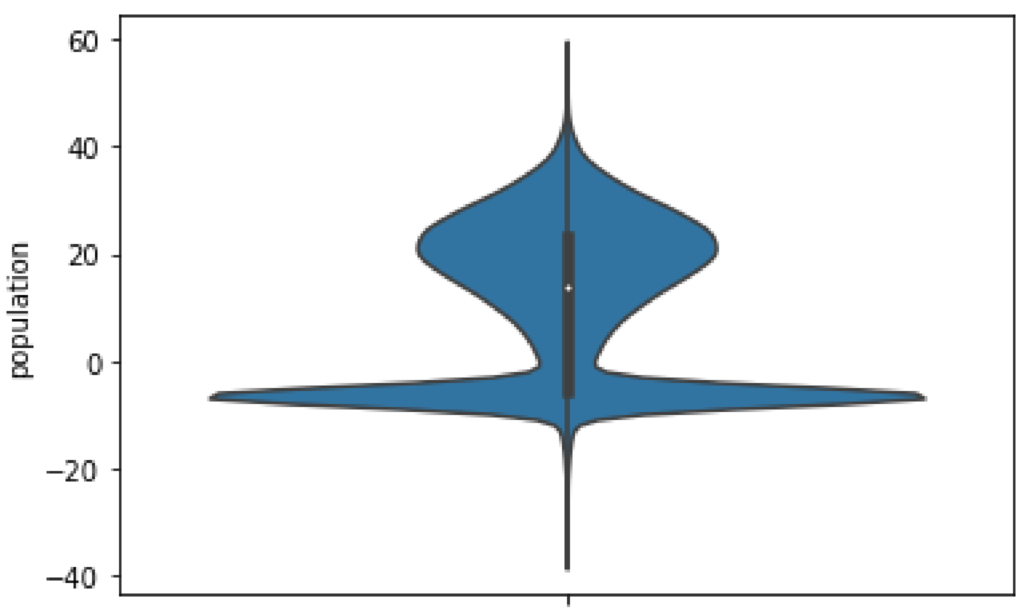
```
In [4]: pop['population'].hist(bins=100)
```

```
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x2466899d1d0>
```



Extra: Try displaying the data using an alternate visualization technique, a violin plot. Seaborn has a built-in method that is useful for this.

```
In [62]: import seaborn as sns
         ax = sns.violinplot(y='population', data=pop)
```

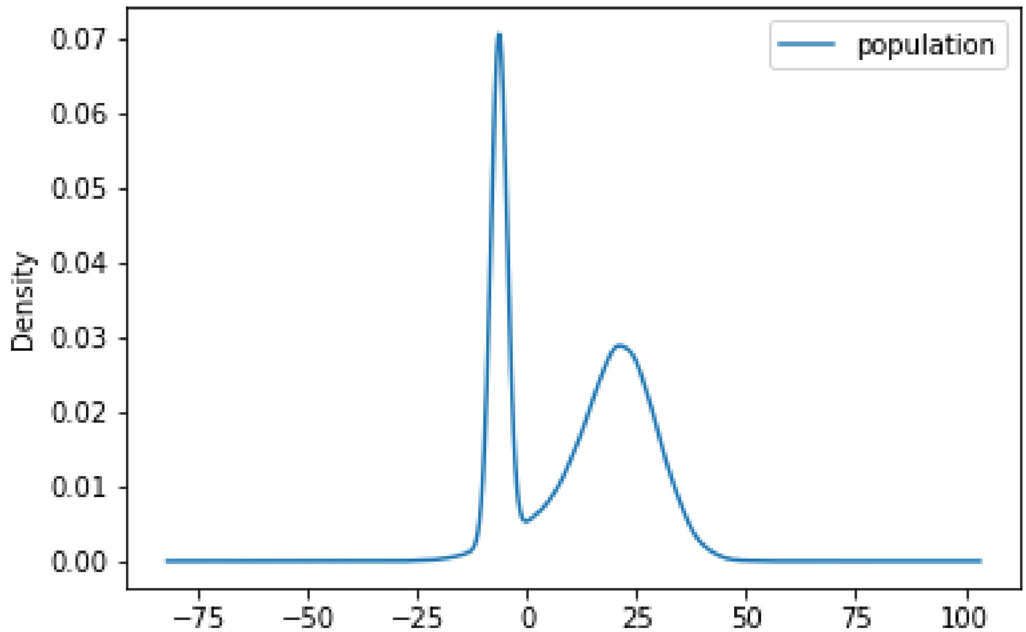


0.3 Make a kernel density estimate of the population distribution

Hint: pandas.DataFrame.plot.kde

```
In [5]: pop.plot.kde()
```

```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x24669a3e828>
```



0.4 Compute the mean of the population

```
In [6]: pop['population'].mean()
```

```
Out[6]: 10.867411157510224
```

0.5 Computer the standard deviation of the population

```
In [7]: pop['population'].std()
```

```
Out[7]: 14.73669533894088
```

0.6 We have described our population. Now let's draw a sample of size n and look at the distrubtion of our sample mean and s.d.

Write a function that samples the pop dataframe with an argument n that is the number of samples to take. Sample without replacement.

In [7]:
```
def draw_sample(pop, n):
    subset = np.random.choice(np.array(list(pop.index)), size=n, replace=False)
    sample = pd.DataFrame(data=pop['population'][subset].values, columns=['sample'])
    return sample
```

In [8]:
```
sample = draw_sample(pop, 20)
```

In [9]:
```
sample
```

Out[9]:

	sample
0	23.707573
1	-5.837157
2	7.805854
3	-5.386720
4	34.429081
5	-4.426331
6	33.312902
7	9.530821
8	22.204563
9	-6.990884
10	2.266210
11	-6.635812
12	20.348430
13	27.600169
14	-5.756415
15	15.770674
16	19.743223
17	15.435585
18	16.755772
19	-4.695216

0.7 Now we want to draw repeated samples of size *n* from the population

Create another function that calls the first `samples` times. Have `samples` be an argument to the function along with n which is the argument to the first function. For each sample, append the mean and the standard deviation of the sample to two separate lists and return them.

Hint: use a loop with range(samples) iterations. To create an empty list at the start of a function, try something like:

```
def repeat_samples(samples, n):
  means = []
  sds = []
  ...
  return (means, sds)
```

then use the append method to append each mean and sd value to the end of each respective list.

```
In [10]: def repeat_samples(pop, samples, n):
             means = []
             sds = []

             for i in range(samples):
                 sample = draw_sample(pop, n)
                 means.append(sample['sample'].mean())
                 sds.append(sample['sample'].std())

             return (means, sds)
```

```
In [11]: means, sds = repeat_samples(pop, 30, 30)
```

0.8 Almost there!

Now make a function with two arguments `samples` and `n` that takes the return values from the last function and * converts the lists to a single dataframe * plots two histograms of the columns (mean, sd) * prints out the mean and sd of the columns

Hint: to get a multi-valued return into new variables, try this:

```
means, sds = repeat_samples(samples, n)
df = pd.DataFrame(data={'means: means, 'sds': sds})
```

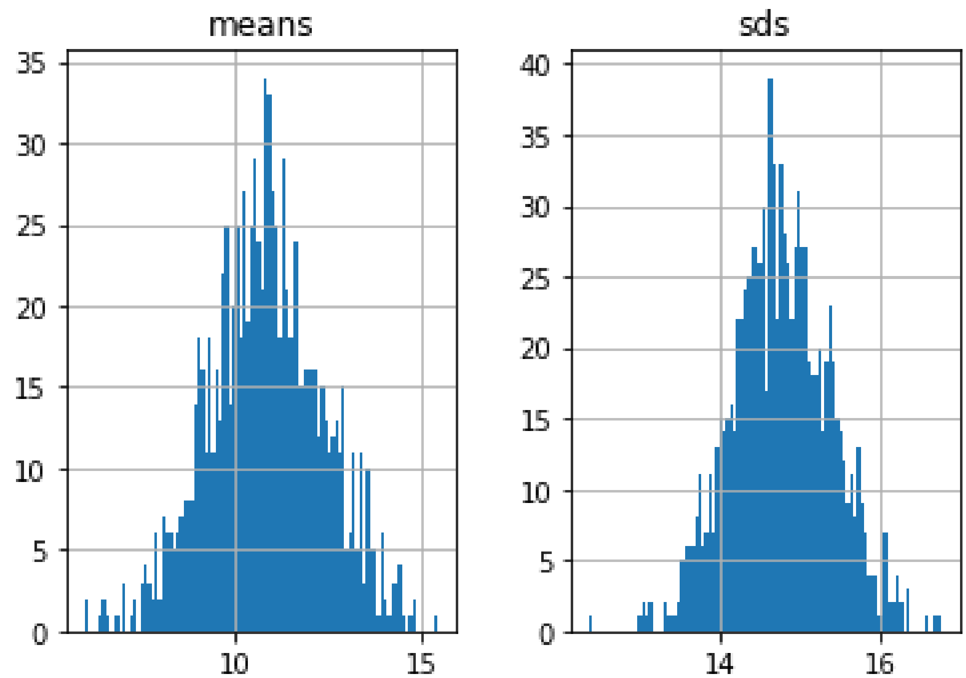
```
In [12]: def describe_sample(pop, samples, n):
             means, sds = repeat_samples(pop, samples, n)
             df = pd.DataFrame(data={'means': means, 'sds': sds})

             df.hist(bins=100)
             print('Mean: {}'.format(np.round(df['means'].mean(), 2)))
             print('Std Dev: {}'.format(np.round(df['sds'].mean(), 2)))

             return df
```

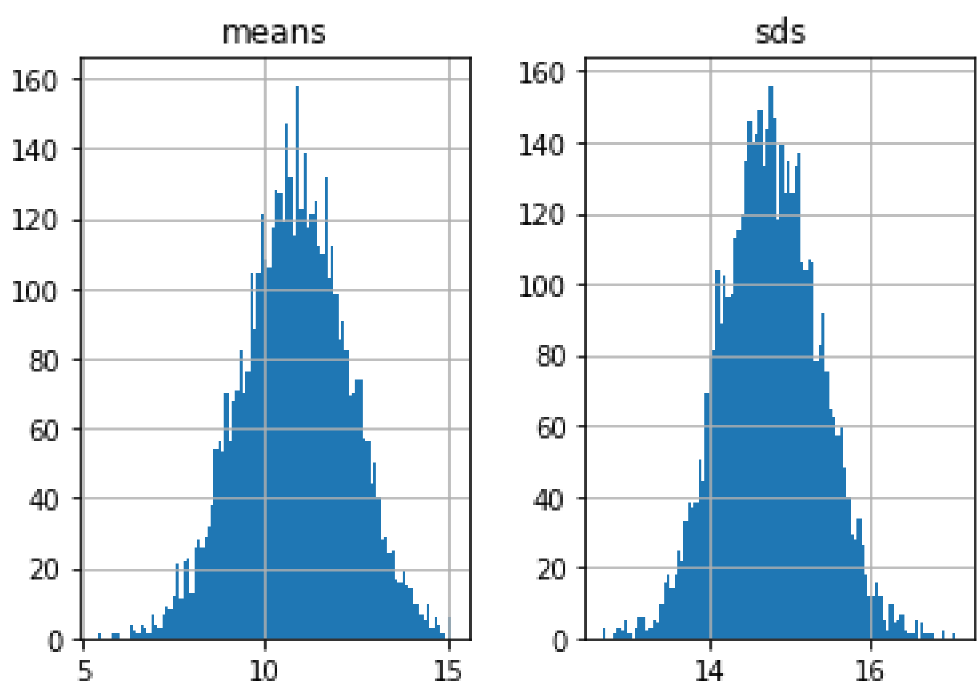
```
In [14]: df = describe_sample(pop, 1000, 100)
```

```
Mean: 10.86
Std Dev: 14.78
```




```
In [15]: df = describe_sample(pop, 5000, 100)
```

```
Mean: 10.81
Std Dev: 14.76
```



0.9 Run your final function several times with varying values of samples and n

How did your result begin to converge on the population mean and sd?

0.10 Bootstrapping your data: Finding confidence intervals

Statisticians take advantage of the central limit theorem as a method of establishing confidence intervals. Create a function that finds the nth and (100-n)th percentiles of the distribution of means found with describe_sample.

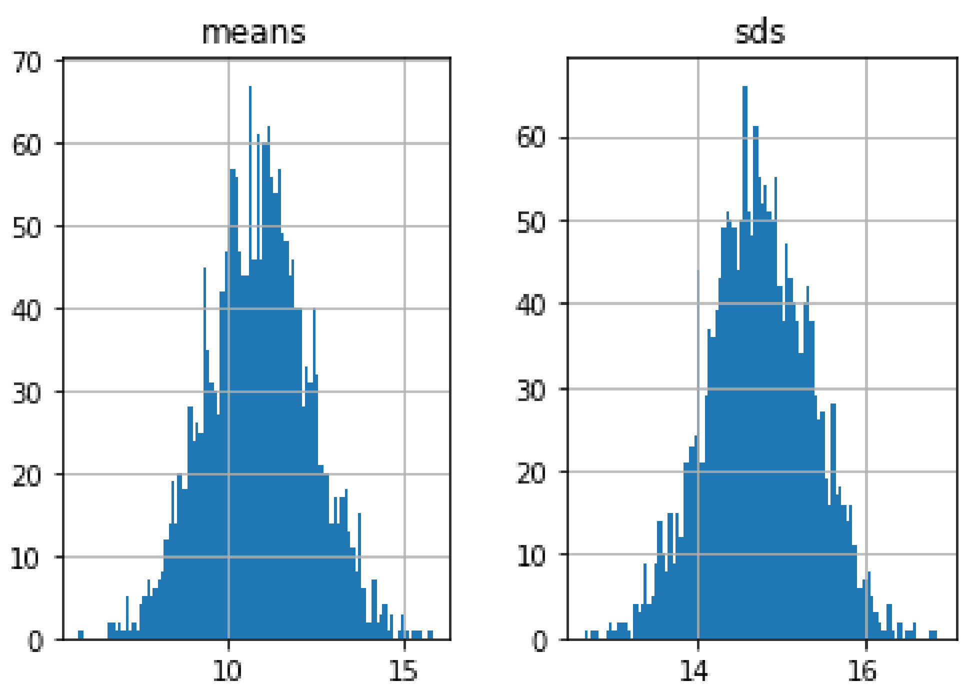
```
In [16]: def bootstrapping(pop, sample, n, percentile):
             df = describe_sample(pop, sample, n)
             li = df['means'].quantile(q=percentile)
             ui = df['means'].quantile(q=1-percentile)
             mean = df['means'].mean()

             print('Mean: {}: and CI: {} - {}'.format(np.round(mean, 2),
                                                      np.round(li, 2), np.round(ui, 2)))

             return df, mean, ui, li
```

```
In [18]: df, mean, ui, li = bootstrapping(pop, 2000, 100, 0.05)
```

```
Mean: 10.86
Std Dev: 14.74
Mean: 10.86: and CI: 8.41 - 13.33
```



```
In [ ]:
```