

Exemplar_Explore sampling

July 17, 2024

1 Exemplar: Explore sampling

1.1 Introduction

In this activity, you will engage in effective sampling of a dataset in order to make it easier to analyze. As a data professional you will often work with extremely large datasets, and utilizing proper sampling techniques helps you improve your efficiency in this work.

For this activity, you are a member of an analytics team for the Environmental Protection Agency. You are assigned to analyze data on air quality with respect to carbon monoxide—a major air pollutant—and report your findings. The data utilized in this activity includes information from over 200 sites, identified by their state name, county name, city name, and local site name. You will use effective sampling within this dataset.

1.2 Step 1: Imports

1.2.1 Import packages

Import pandas, numpy, matplotlib, statsmodels, and scipy.

```
[1]: # Import libraries and packages

### YOUR CODE HERE ###

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
from scipy import stats
```

1.2.2 Load the dataset

Load the dataset provided. The dataset is in the form of a csv file.

```
[2]: # Load data
```

```
### YOUR CODE HERE ###
```

```
epa_data = pd.read_csv("c4_epa_air_quality.csv", index_col = 0)
```

Hint 1

Use the function in the **pandas** library that allows you to read in data from a csv file and load it into a DataFrame.

Hint 2

Use the **read_csv** function from the pandas library. Set the **index_col** parameter to 0 to read in the first column as an index (and to avoid "Unnamed: 0" appearing as a column in the resulting Dataframe).

1.3 Step 2: Data exploration

1.3.1 Examine the data

To understand how the dataset is structured, examine the first 10 rows of the data.

```
[3]: # First 10 rows of the data
```

```
### YOUR CODE HERE ###
```

```
epa_data.head(10)
```

```
[3]:
```

	date_local	state_name	county_name	city_name \
0	2018-01-01	Arizona	Maricopa	Buckeye
1	2018-01-01	Ohio	Belmont	Shadyside
2	2018-01-01	Wyoming	Teton	Not in a city
3	2018-01-01	Pennsylvania	Philadelphia	Philadelphia
4	2018-01-01	Iowa	Polk	Des Moines
5	2018-01-01	Hawaii	Honolulu	Not in a city
6	2018-01-01	Hawaii	Honolulu	Not in a city
7	2018-01-01	Pennsylvania	Erie	Erie
8	2018-01-01	Hawaii	Honolulu	Honolulu
9	2018-01-01	Colorado	Larimer	Fort Collins

	local_site_name	parameter_name \
0	BUCKEYE	Carbon monoxide
1	Shadyside	Carbon monoxide
2	Yellowstone National Park - Old Faithful Snow ...	Carbon monoxide
3	North East Waste (NEW)	Carbon monoxide
4	CARPENTER	Carbon monoxide
5	Kapolei	Carbon monoxide
6	Kapolei	Carbon monoxide
7	NaN	Carbon monoxide

```

8                                     Honolulu Carbon monoxide
9                                Fort Collins - CSU - S. Mason Carbon monoxide

```

```

      units_of_measure  arithmetic_mean  aqi
0  Parts per million      0.473684      7
1  Parts per million      0.263158      5
2  Parts per million      0.111111      2
3  Parts per million      0.300000      3
4  Parts per million      0.215789      3
5  Parts per million      0.994737     14
6  Parts per million      0.200000      2
7  Parts per million      0.200000      2
8  Parts per million      0.400000      5
9  Parts per million      0.300000      6

```

Hint 1

Use the function in the `pandas` library that allows you to get a specific number of rows from the top of a `DataFrame`.

Hint 2

Use the `head` function from the `pandas` library. Set the `n` parameter to 10 to print out the first 10 rows.

Question: What does the `aqi` column represent?

- The `aqi` column represents the Air Quality Index.

1.3.2 Generate a table of descriptive statistics

Generate a table of some descriptive statistics about the data. Specify that all columns of the input be included in the output.

```
[4]: ### YOUR CODE HERE ###
```

```
epa_data.describe(include='all')
```

```

[4]:      date_local  state_name  county_name  city_name  local_site_name  \
count          260          260          260          260          257
unique           1           52          149          190          253
top    2018-01-01  California  Los Angeles  Not in a city      Kapolei
freq          260           66           14           21           2
mean           NaN           NaN           NaN           NaN           NaN
std            NaN           NaN           NaN           NaN           NaN
min            NaN           NaN           NaN           NaN           NaN
25%            NaN           NaN           NaN           NaN           NaN
50%            NaN           NaN           NaN           NaN           NaN
75%            NaN           NaN           NaN           NaN           NaN

```

max	NaN	NaN	NaN	NaN	NaN
	parameter_name	units_of_measure	arithmetic_mean		aqi
count	260	260	260.000000	260.000000	
unique	1	1	NaN	NaN	
top	Carbon monoxide	Parts per million	NaN	NaN	
freq	260	260	NaN	NaN	
mean	NaN	NaN	0.403169	6.757692	
std	NaN	NaN	0.317902	7.061707	
min	NaN	NaN	0.000000	0.000000	
25%	NaN	NaN	0.200000	2.000000	
50%	NaN	NaN	0.276315	5.000000	
75%	NaN	NaN	0.516009	9.000000	
max	NaN	NaN	1.921053	50.000000	

Hint 1

Use function in the **pandas** library that allows you to generate a table of basic descriptive statistics in a DataFrame.

Hint 2

Use the **describe** function from the **pandas** library. Set the **include** parameter passed in to this function to 'all' to specify that all columns of the input be included in the output.

Question: Based on the preceding table of descriptive statistics, what is the mean value of the **aqi** column?

- The value is **6.757692**. This value will be compared to the mean value after sampling with replacement later in the notebook.

Question: Based on the preceding table of descriptive statistics, what do you notice about the count value for the **aqi** column?

- The count value for the **aqi** column is 260. This means there are 260 AQI measurements represented in this dataset.

1.3.3 Use the **mean()** function on the **aqi** column

Now, use the **mean()** function on the **aqi** column and assign the value to a variable **population_mean**. The value should be the same as the one generated by the **describe()** method in the above table.

```
[5]: ### YOUR CODE HERE ###
```

```
population_mean = epa_data['aqi'].mean()
population_mean
```

```
[5]: 6.757692307692308
```

Hint 1

Use the function in the `pandas` library that allows you to generate a mean value for a column in a `DataFrame`.

Hint 2

Use the `mean()` method.

1.4 Step 3: Statistical tests

1.4.1 Sample with replacement

First, name a new variable `sampled_data`. Then, use the `sample()` dataframe method to draw 50 samples from `epa_data`. Set `replace` equal to `'True'` to specify sampling with replacement. For `random_state`, choose an arbitrary number for random seed. Make that arbitrary number 42.

```
[6]: ### YOUR CODE HERE ###

sampled_data = epa_data.sample(n=50, replace=True, random_state=42)
```

1.4.2 Output the first 10 rows

Output the first 10 rows of the `DataFrame`.

```
[7]: ### YOUR CODE HERE ###

sampled_data.head(10)
```

```
[7]:
```

	date_local	state_name	county_name	city_name \
102	2018-01-01	Texas	Harris	Houston
106	2018-01-01	California	Imperial	Calexico
71	2018-01-01	Alabama	Jefferson	Birmingham
188	2018-01-01	Arizona	Maricopa	Tempe
20	2018-01-01	Virginia	Roanoke	Vinton
102	2018-01-01	Texas	Harris	Houston
121	2018-01-01	North Carolina	Mecklenburg	Charlotte
214	2018-01-01	Florida	Broward	Davie
87	2018-01-01	California	Humboldt	Eureka
99	2018-01-01	California	Santa Barbara	Goleta

		local_site_name	parameter_name	units_of_measure \
102		Clinton	Carbon monoxide	Parts per million
106		Calexico-Ethel Street	Carbon monoxide	Parts per million
71		Arkadelphia/Near Road	Carbon monoxide	Parts per million
188		Diablo	Carbon monoxide	Parts per million
20	East Vinton Elementary School		Carbon monoxide	Parts per million
102		Clinton	Carbon monoxide	Parts per million
121		Garinger High School	Carbon monoxide	Parts per million

214	Daniela Banu	NCORE	Carbon monoxide	Parts per million
87		Jacobs	Carbon monoxide	Parts per million
99		Goleta	Carbon monoxide	Parts per million

	arithmetic_mean	aqi
102	0.157895	2
106	1.183333	26
71	0.200000	2
188	0.542105	10
20	0.100000	1
102	0.157895	2
121	0.200000	2
214	0.273684	5
87	0.393750	5
99	0.222222	3

Hint 1

Use the function in the `pandas` library that allows you to get a specific number of rows from the top of a `DataFrame`.

Hint 2

Use the `head` function from the `pandas` library. Set the `n` parameter to 10 to print out the first 10 rows.

Question: In the `DataFrame` output, why is the row index 102 repeated twice?

- Sampling with replacement is random, allowing sampling units to occur more than once. Row index 102 just happened to be sampled more than once.

Question: What does `random_state` do?

- The parameter allows for the reproduction of the same exact sample (i.e., the same set of numbers). This means that the same rows in the dataset will be sampled with replacement each time the command is run.

1.4.3 Compute the mean value from the `aqi` column

Compute the mean value from the `aqi` column in `sampled_data` and assign the value to the variable `sample_mean`.

```
[8]: ### YOUR CODE HERE ###

sample_mean = sampled_data['aqi'].mean()
sample_mean
```

```
[8]: 5.54
```

Question: Why is `sample_mean` different from `population_mean`?

- Due to sampling variability, the sample mean (`sample_mean`) is usually not the same as the population mean (`population_mean`). In this case, the sample mean is a point estimate of the population mean based on a random sample of 50 AQI values rather than the 260 AQI values from the original population in `epa_data`.

1.4.4 Apply the central limit theorem

Imagine repeating the the earlier sample with replacement 10,000 times and obtaining 10,000 point estimates of the mean. In other words, imagine taking 10,000 random samples of 50 AQI values and computing the mean for each sample. According to the **central limit theorem**, the mean of a sampling distribution should be roughly equal to the population mean. Complete the following steps to compute the mean of the sampling distribution with 10,000 samples.

- Create an empty list and assign it to a variable called `estimate_list`.
- Iterate through a `for` loop 10,000 times. To do this, make sure to utilize the `range()` function to generate a sequence of numbers from 0 to 9,999.
- In each iteration of the loop, use the `sample()` function to take a random sample (with replacement) of 50 AQI values from the population. Do not set `random_state` to a value.
- Use the list `append()` function to add the value of the sample mean to each item in the list.

```
[9]: ### YOUR CODE HERE ###

estimate_list = []
for i in range(10000):
    estimate_list.append(epa_data['aqi'].sample(n=50,replace=True).mean())
```

Hint 1

Review [the content about sampling in Python](#).

1.4.5 Create a new DataFrame

Next, create a new DataFrame from the list of 10,000 estimates. Name the new variable `estimate_df`.

```
[10]: ### YOUR CODE HERE ###

estimate_df = pd.DataFrame(data={'estimate': estimate_list})
estimate_df
```

```
[10]:      estimate
0      6.60
1      7.42
2      8.20
3      6.68
4      6.60
...      ...
9995    7.14
```

```
9996      8.12
9997      7.88
9998      5.78
9999      5.48
```

```
[10000 rows x 1 columns]
```

Hint 1

Review [the content about sampling in Python](#).

Hint 2

Use the `mean()` function.

1.4.6 Compute the `mean()` of the sampling distribution

Next, compute the `mean()` of the sampling distribution of 10,000 random samples and store the result in a new variable `mean_sample_means`.

```
[11]: ### YOUR CODE HERE ###

mean_sample_means = estimate_df['estimate'].mean()
mean_sample_means
```

```
[11]: 6.7639979999999989
```

Hint 1

Use the function in the `pandas` library that allows you to generate a mean value for a column in a `DataFrame`.

Hint 2

Use the `mean()` function.

Question: What is the mean for the sampling distribution of 10,000 random samples?

This number will vary as `random_state` was not set to a value.

Hint 3

This value is contained in `mean_sample_means`.

Hint 4

According to the central limit theorem, the mean of the preceding sampling distribution should be roughly equal to the population mean.

Question: How are the central limit theorem and random sampling (with replacement) related?

Random sampling with replacement is related to the central limit theorem because it means you are drawing observations independently from a population. The central limit theorem states that if a

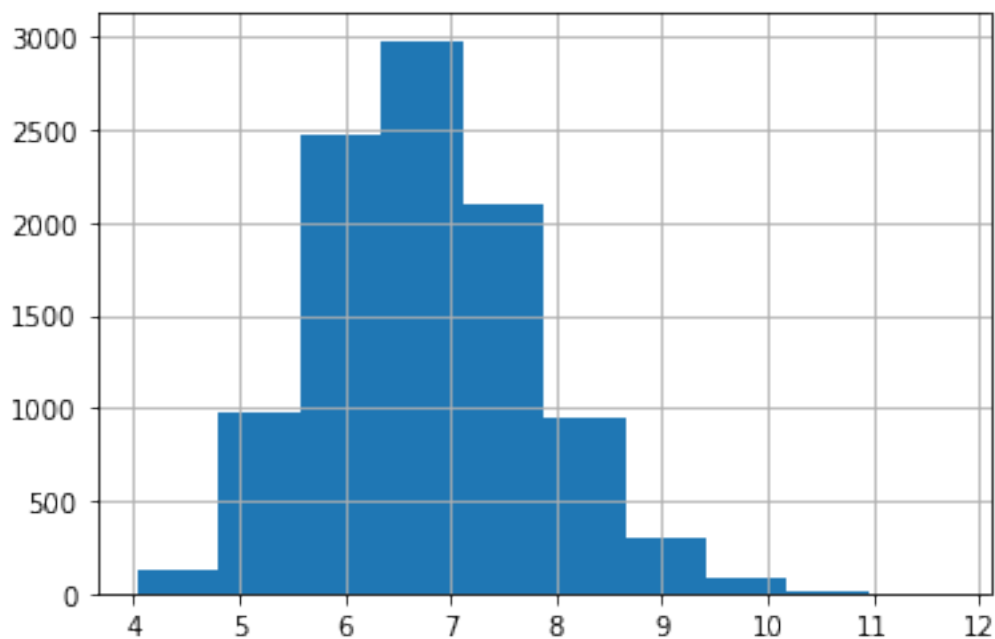
sample size is large enough and the observations are drawn independently—or with replacement—the sampling distribution of the sample mean is approximately the normal distribution. Furthermore, the mean parameter is the population mean and the variance parameter is the standard error.

1.4.7 Output the distribution using a histogram

Output the distribution of these estimates using a histogram. This provides an idea of the sampling distribution.

```
[12]: ### YOUR CODE HERE ###  
  
estimate_df['estimate'].hist()
```

```
[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8bd6872c10>
```



Hint 1

Use the `hist()` function.

1.4.8 Calculate the standard error

Calculate the standard error of the mean AQI using the initial sample of 50. The **standard error** of a statistic measures the sample-to-sample variability of the sample statistic. It provides a numerical measure of sampling variability and answers the question: How far is a statistic based on one particular sample from the actual value of the statistic?

```
[13]: ### YOUR CODE HERE ###

standard_error = sampled_data['aqi'].std() / np.sqrt(len(sampled_data))
standard_error
```

```
[13]: 0.7413225908290327
```

Hint 1

Use the `std()` function and the `np.sqrt()` function.

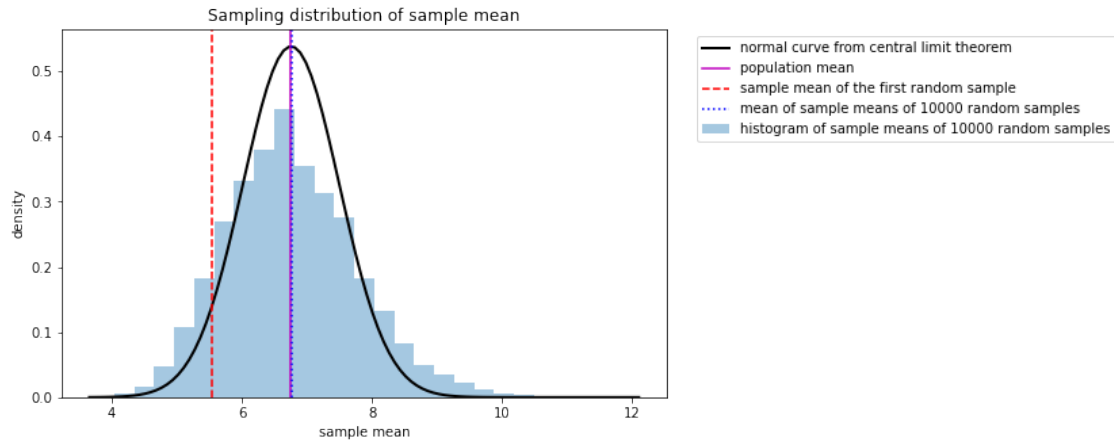
1.5 Step 4: Results and evaluation

1.5.1 Visualize the relationship between the sampling and normal distributions

Visualize the relationship between your sampling distribution of 10,000 estimates and the normal distribution. The following code overlays the density curve of the normal distribution described in the theorem on top of the histogram of the sampling distribution obtained by repeated sampling. The solid magenta line in the graph is the population mean, the blue dotted line is the mean of the 10,000 sample means, and the red dashed line is the mean of the first random sample of 50.

```
[14]: # Generate a grid of 100 values from xmin to xmax.

### YOU CODE HERE ###
plt.figure(figsize=(8,5))
plt.hist(estimate_df['estimate'], bins=25, density=True, alpha=0.4, label = 
    ↳ "histogram of sample means of 10000 random samples")
xmin, xmax = plt.xlim()
x = np.linspace(xmin, xmax, 100) # generate a grid of 100 values from xmin to
    ↳ xmax.
p = stats.norm.pdf(x, population_mean, standard_error)
plt.plot(x, p, 'k', linewidth=2, label = 'normal curve from central limit
    ↳ theorem')
plt.axvline(x=population_mean, color='m', linestyle = 'solid', label = 
    ↳ 'population mean')
plt.axvline(x=sample_mean, color='r', linestyle = '--', label = 'sample mean of
    ↳ the first random sample')
plt.axvline(x=mean_sample_means, color='b', linestyle = ':', label = 'mean of
    ↳ sample means of 10000 random samples')
plt.title("Sampling distribution of sample mean")
plt.xlabel('sample mean')
plt.ylabel('density')
plt.legend(bbox_to_anchor=(1.04,1));
```



Question: What insights did you gain from the preceding sampling distribution?

1. The histogram of the sampling distribution is well-approximated by the normal distribution described by the central limit theorem.
2. The estimate based on one particular sample (red dashed line) is off-center. This is expected due to sampling variability. The red dashed line would be in a different location if `epa_data.sample(n=50, replace=True, random_state=42)` had a different value for `random_state`.
3. The population mean (green solid line) and the mean of the sample means (blue dotted line) overlap, meaning that they are essentially equal to each other.

2 Considerations

What are some key takeaways that you learned from this lab? - Sampling with replacement on a dataset leads to duplicate rows. - Sample means are different from population means due to sampling variability. - The central limit theorem helps describe the sampling distribution of the sample mean for many different types of datasets.

What findings would you share with others? - The mean AQI in a sample of 50 observations was below 100 in a statistically significant sense (at least 2–3 standard errors away). For reference, AQI values at or below 100 are generally thought of as satisfactory. - This notebook didn't examine values outside the "satisfactory" range so analysis should be done to investigate unhealthy AQI values.

What would you convey to external stakeholders? - Carbon monoxide levels are satisfactory in general.
- Funding should be allocated to further investigate regions with unhealthy levels of carbon monoxide and improve the conditions in those regions.

Congratulations! You've completed this lab. However, you may not notice a green check mark next to this item on Coursera's platform. Please continue your progress regardless of the check mark. Just click on the "save" icon at the top of this notebook to ensure your work has been logged.