```python
#Generating random samples from the normally distributed interest
rates
import numpy as np
rate=np.random.normal(0.04, 0.01, size=(5000, 20))
print(rate)
```

```
[[0.02820445 0.03219474 0.04353215 ... 0.03275249 0.01464117
0.02777541]
 [0.03672975 0.04480286 0.04939849 ... 0.03129008 0.05564327 0.0526493
]
 [0.04684155 0.03937923 0.02752096 ... 0.03365077 0.03402157
0.04447053]
 ...
 [0.03653047 0.0565073  0.02411989 ... 0.04720342 0.04222862
0.02279175]
 [0.04184615 0.05226512 0.03815559 ... 0.03955166 0.03843141 0.0550812
]
 [0.06002481 0.02643685 0.05049354 ... 0.04302799 0.04831598
0.03381697]]
```

```python
#Method 1
#Building a multiplicative function which will calculate the
compounded return (of 20 years) on a given principal amount
#R is the list of rate of interests over the given period of time
def Compounded(R,p):
    total_compounded=p
    for i in range(len(R)):
        compounded_year_i=(1+R[i])
        total_compounded=total_compounded*compounded_year_i
    return(total_compounded)
```

```python
#Checking the result for one instance of sampling
Compounded([0.02432158, 0.04112696, 0.04631557, 0.04042804, 0.0199667,
0.03202043,
 0.03882695, 0.04043719, 0.06382018, 0.06860884, 0.05975434,
0.02728008,
 0.04171484, 0.05521078, 0.05151336, 0.0554398,  0.02563387,
0.03633402,
 0.0445956,  0.05294341],800000)
```

```
1865094.4241364049
```

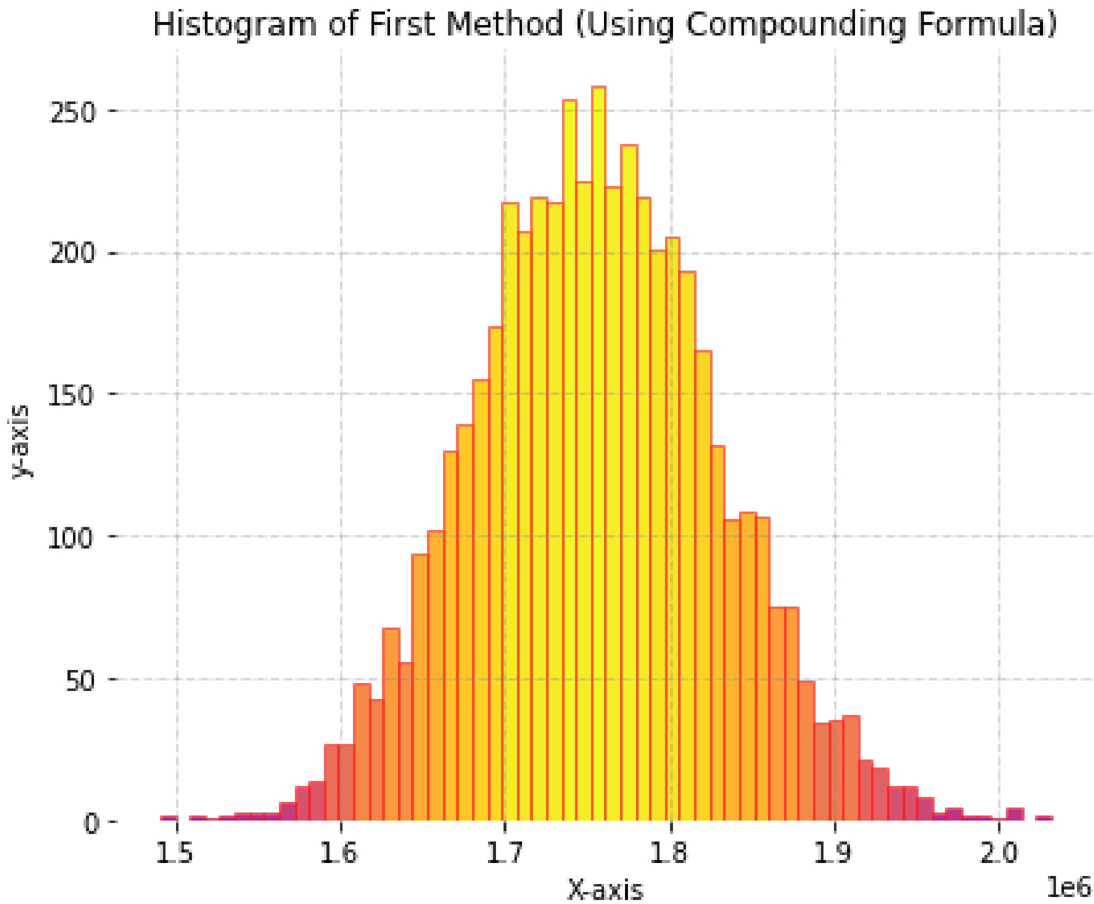
```python
#Generate all possible sample (incremented) outputs
import statistics
p=800000
Sample_ret_1=[]
for r in range(len(rate)):
    amount=Compounded(rate[r],p)
    Sample_ret_1.append(amount)
mean_1=statistics.mean(Sample_ret_1)
var_1=statistics.variance(Sample_ret_1)
```

```
sdev_1=var_1**(1/2)
print('Mean for first method:',mean_1)
print('Variance for first method:',var_1)
print('Standard deviation first method:',sdev_1)
```

```
Mean for first method: 1754674.3926196308
Variance for first method: 5521631765.644559
Standard deviation first method: 74307.6830862365
```

```
#Visualizing the sample in attempt to predict its distribution
from matplotlib import pyplot as plt
from matplotlib import colors
from matplotlib.ticker import PercentFormatter
import seaborn as sns

# Creating histogram frame
fig, axs = plt.subplots(1, 1,
                        figsize =(6, 5),
                        tight_layout = True)

# Remove axes splines
for s in ['top', 'bottom', 'left', 'right']:
    axs.spines[s].set_visible(False)

# Add x, y gridlines
axs.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.5,
        alpha = 0.6)

# Creating histogram
N, bins, patches = axs.hist(Sample_ret_1, edgecolor = "red", linewidth
= 0.5, bins = 60,)

# Setting color
fracs = ((N**(1 / 5)) / N.max())
norm = colors.Normalize(fracs.min(), fracs.max())

for thisfrac, thispatch in zip(fracs, patches):
    color = plt.cm.plasma(norm(thisfrac))
    thispatch.set_facecolor(color)

# Adding extra features
plt.xlabel("X-axis")
plt.ylabel("y-axis")
plt.title('Histogram of First Method (Using Compounding Formula)')
```

```
Text(0.5, 1.0, 'Histogram of First Method (Using Compounding
Formula)')
```




```
#Trying to validate whether this drawn sample follows a normal
distribution or not, by Anderson-Darling Test
from scipy.stats import anderson
anderson(Sample_ret_1)
```

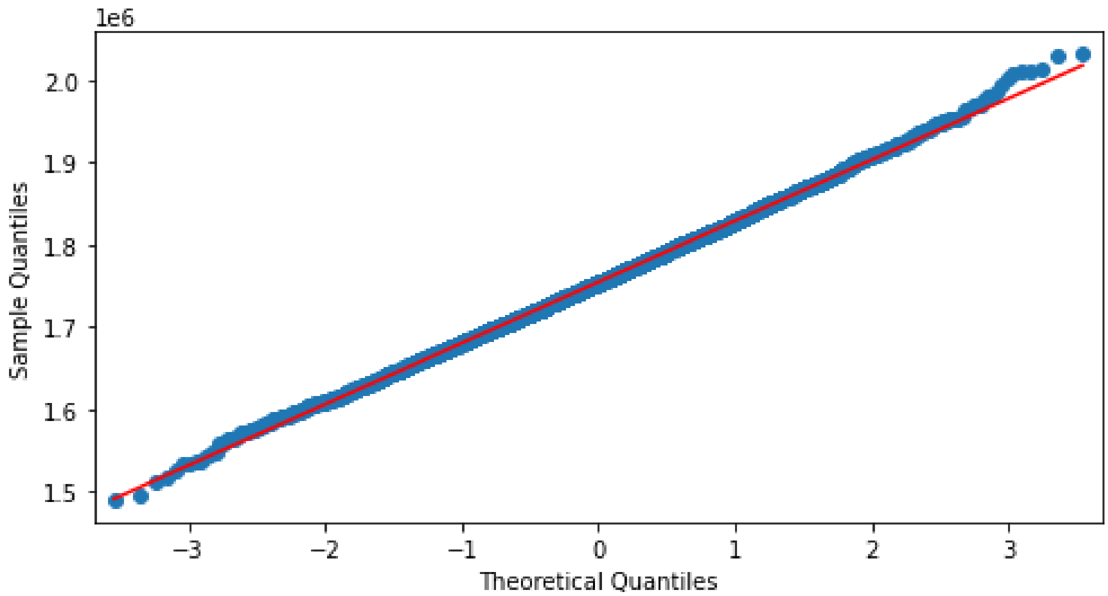
```
AndersonResult(statistic=0.6018516256081057,
critical_values=array([0.576, 0.655, 0.786, 0.917, 1.091]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=1754674.3926196308, scale=74307.6830862365)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
```

```
#Trying to cross-validate with another effective test of normality-
Shapiro-Wilk Test
from scipy import stats
shapiro_test = stats.shapiro(Sample_ret_1)
shapiro_test
```

```
ShapiroResult(statistic=0.9992867708206177,
pvalue=0.04193006455898285)
```

```
#QQplot is there to visualize the tendency of the distribution to be
normal i.e. the proximity to be precise
```

```
import numpy as np
import statsmodels.api as sm
import pylab as py
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(8,4))

sm.qqplot(np.array(Sample_ret_1) , line ='s', ax=ax)
plt.show()
```



Observation 1:

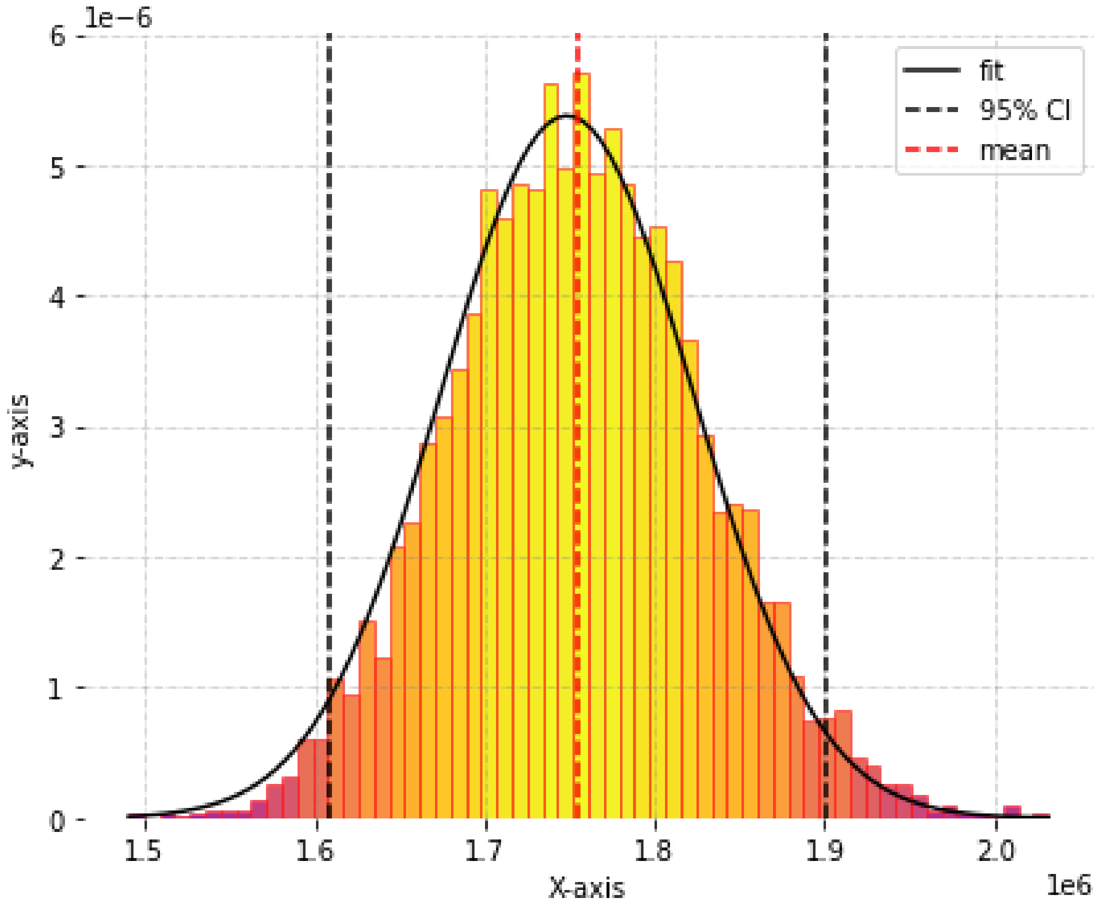
Anderson-Darling's test is declaring the data to be normally distributed, but cross-validating with Shapiro-Wilker's test gives us a completely different scenario. The p-value is less than alpha (0.05) and we reject the null hypothesis. Thus, the sample is not ideally normally distributed which is further affirmed with a Q-Q plot with heavyloaded ends.

```
from scipy.stats import norm
import numpy as np

# Calculating the sample mean and standard deviation
sample_mean = np.mean(Sample_ret_1)
sample_std = np.std(Sample_ret_1, ddof=len(Sample_ret_1)-1)

# Calculating the 95% confidence interval
ci_1 = norm.interval(0.95, loc=sample_mean,
scale=sample_std/np.sqrt(len(Sample_ret_1)))

print(f"95% confidence interval for first method is: {ci_1}")
```

```
95% confidence interval for first method is: (1609048.5747625283,
1900300.2104767333)
```

```python
#Visualixing the data alongwith its mean and confidence interval
import numpy as np
from scipy.stats import norm
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit

# Creating histogram frame
fig, axs = plt.subplots(1, 1,
                        figsize =(6, 5),
                        tight_layout = True)

# Remove axes splines
for s in ['top', 'bottom', 'left', 'right']:
    axs.spines[s].set_visible(False)

# Add x, y gridlines
axs.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.5,
        alpha = 0.6)

# Plot the histogram.
N, bins, patches=plt.hist(Sample_ret_1, edgecolor = "red", linewidth =
0.5, bins = 60, density=True)

# Define the function to fit
def fit_func(x, amp, cen, sigma):
    return amp * np.exp(-(x-cen)**2/(2*sigma**2))

# Initial parameter values for fitting
initial_guess = [1.0, np.mean(Sample_ret_1), np.std(Sample_ret_1)]

# Perform the curve fit
popt, pcov = curve_fit(fit_func, bins[:-1], N, p0=initial_guess)

# Plot the histogram and fitted curve
x = np.linspace(bins[0], bins[-1], 100)
plt.plot(x, fit_func(x, *popt), color='black', linewidth=1.5,
label='fit')

# Setting color
fracs = ((N**(1 / 5)) / N.max())
norm = colors.Normalize(fracs.min(), fracs.max())

for thisfrac, thispatch in zip(fracs, patches):
    color = plt.cm.plasma(norm(thisfrac))
    thispatch.set_facecolor(color)
```

```
l_1=ci_1[0]
u_1=ci_1[1]
axs.axvline(l_1, color='black', linestyle='--', label='95% CI')
axs.axvline(u_1, color='black', linestyle='--')
axs.axvline(mean_1, color='red', linestyle='--', label='mean')
axs.legend()
plt.xlabel("X-axis")
plt.ylabel("y-axis")
plt.show()
```




```
#Method 2
#Building an exponential function which will calculate the compounded
return (of 20 years) on a given principal amount
#R is the list of rate of interests over the given period of time
import math
def Compoundedlog(R,p):
    tot=sum(R)
    e=math.exp(tot)
    changed=p*e
    return(changed)
```

```python
#Checking the result for one instance of sampling
Compoundedlog([0.02432158, 0.04112696, 0.04631557, 0.04042804,
0.0199667,  0.03202043,
 0.03882695, 0.04043719, 0.06382018, 0.06860884, 0.05975434,
0.02728008,
 0.04171484, 0.05521078, 0.05151336, 0.0554398,  0.02563387,
0.03633402,
 0.0445956,  0.05294341],800000)
```

```
1902462.2888895518
```

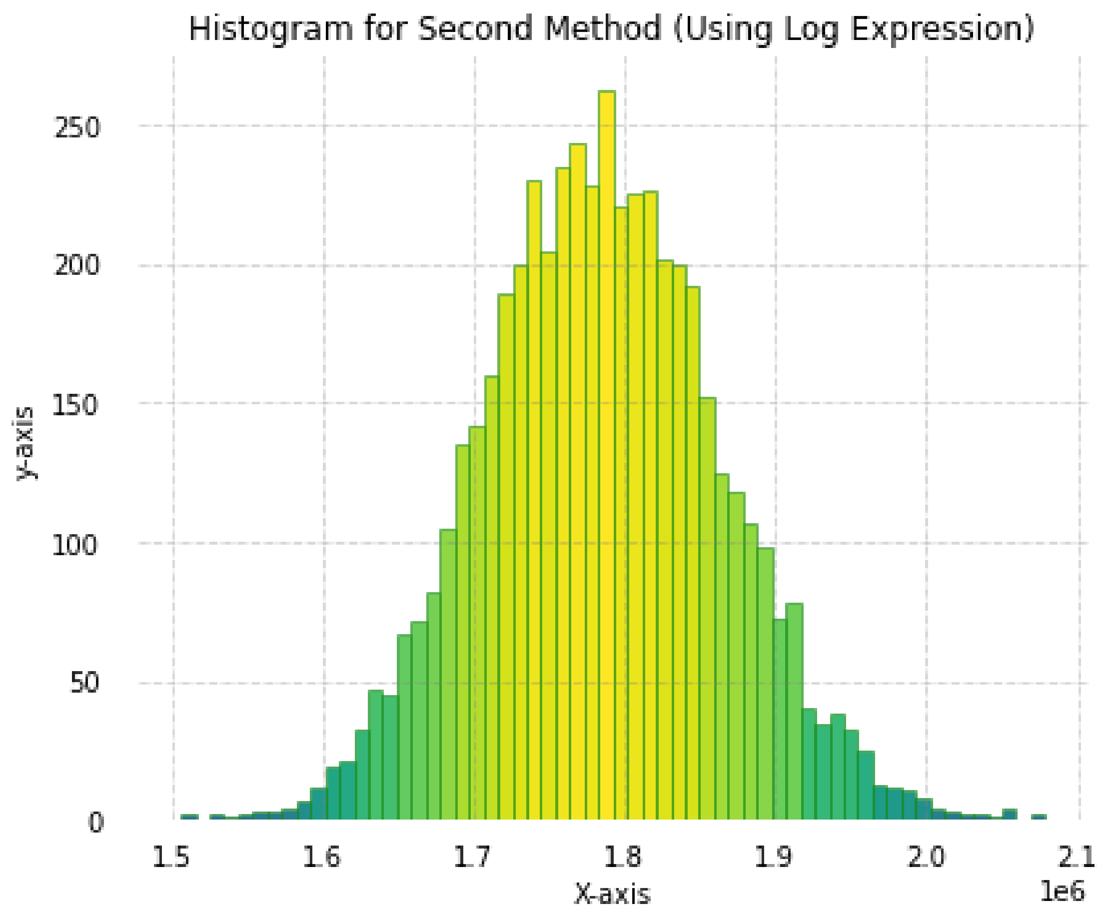
```python
#Generate all possible sample (incremented) outputs
p=800000
Sample_ret_2=[]
for r in range(len(rate)):
    amount=Compoundedlog(rate[r],p)
    Sample_ret_2.append(amount)
mean_2=statistics.mean(Sample_ret_2)
var_2=statistics.variance(Sample_ret_2)
sdev_2=var_2**(1/2)
print('Mean for second method:', mean_2)
print('Variance for second method:',var_2)
print('Standard deviation for second method:',sdev_2)
```

```
Mean for second method: 1784075.4086323252
Variance for second method: 6174815676.927772
Standard deviation for second method: 78579.99539913305
```

```python
#Visualizing the sample in attempt to predict its distribution
from matplotlib import pyplot as plt
from matplotlib import colors
from matplotlib.ticker import PercentFormatter

import seaborn as sns
# Creating histogram
fig, axs = plt.subplots(1, 1,
                        figsize =(6,5),
                        tight_layout = True)

# Remove axes splines
for s in ['top', 'bottom', 'left', 'right']:
    axs.spines[s].set_visible(False)
# Remove x, y ticks
axs.xaxis.set_ticks_position('none')
axs.yaxis.set_ticks_position('none')

# Add padding between axes and labels
axs.xaxis.set_tick_params(pad = 5)
axs.yaxis.set_tick_params(pad = 10)

# Add x, y gridlines
```

```python
axs.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.5,
        alpha = 0.6)

# Creating histogram
N, bins, patches = axs.hist(Sample_ret_2, edgecolor = "green",
linewidth = 0.5, bins = 60)

# Setting color
fracs = ((N**(1 / 5)) / N.max())
norm = colors.Normalize(fracs.min(), fracs.max())

for thisfrac, thispatch in zip(fracs, patches):
    color = plt.cm.viridis(norm(thisfrac))
    thispatch.set_facecolor(color)


# Adding extra features
plt.xlabel("X-axis")
plt.ylabel("y-axis")
plt.title('Histogram for Second Method (Using Log Expression)')
```

```
Text(0.5, 1.0, 'Histogram for Second Method (Using Log Expression)')
```




```
#Trying to validate whether this drawn sample follows a normal
distribution or not, by Anderson-Darling Test
anderson(Sample_ret_2)
```

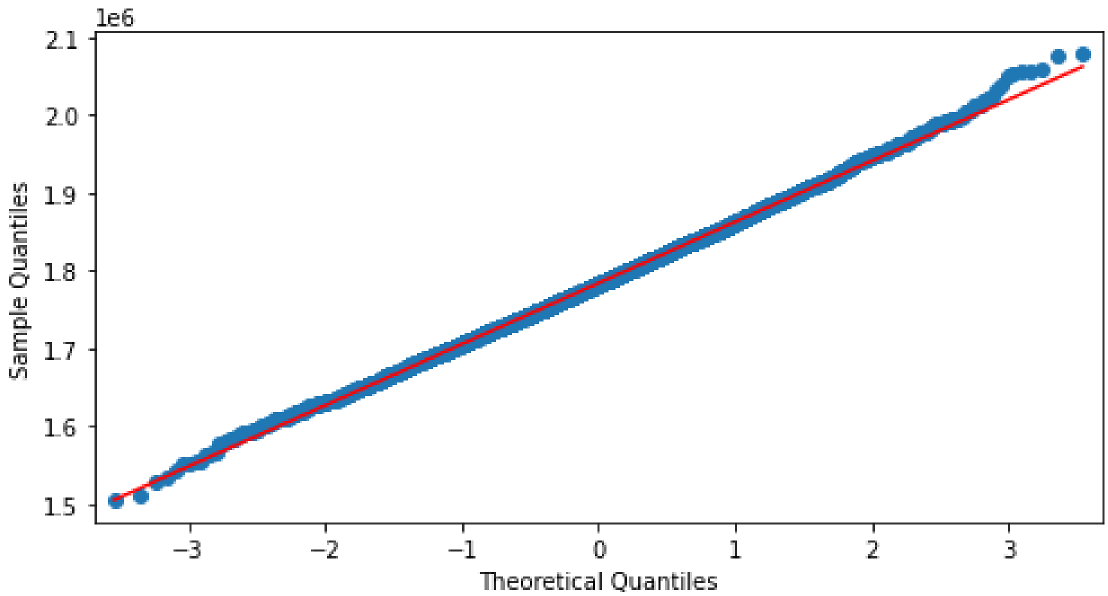
```
AndersonResult(statistic=0.7213879604714748,
critical_values=array([0.576, 0.655, 0.786, 0.917, 1.091]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=1784075.4086323255, scale=78579.99539913305)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
```

```
#Trying to cross-validate with another effective test of normality-
Shapiro-Wilk Test
from scipy import stats
shapiro_test = stats.shapiro(Sample_ret_2)
shapiro_test
```

```
ShapiroResult(statistic=0.9991615414619446,
pvalue=0.01565222442150116)
```

```
#QQplot is there to visualize the tendency of the distribution to be
normal i.e. the proximity to be precise
import numpy as np
```

```
import statsmodels.api as sm
import pylab as py
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(8,4))
# Random data points generated

sm.qqplot(np.array(Sample_ret_2) , line ='s', ax=ax)
plt.show()
```



Observation 2:

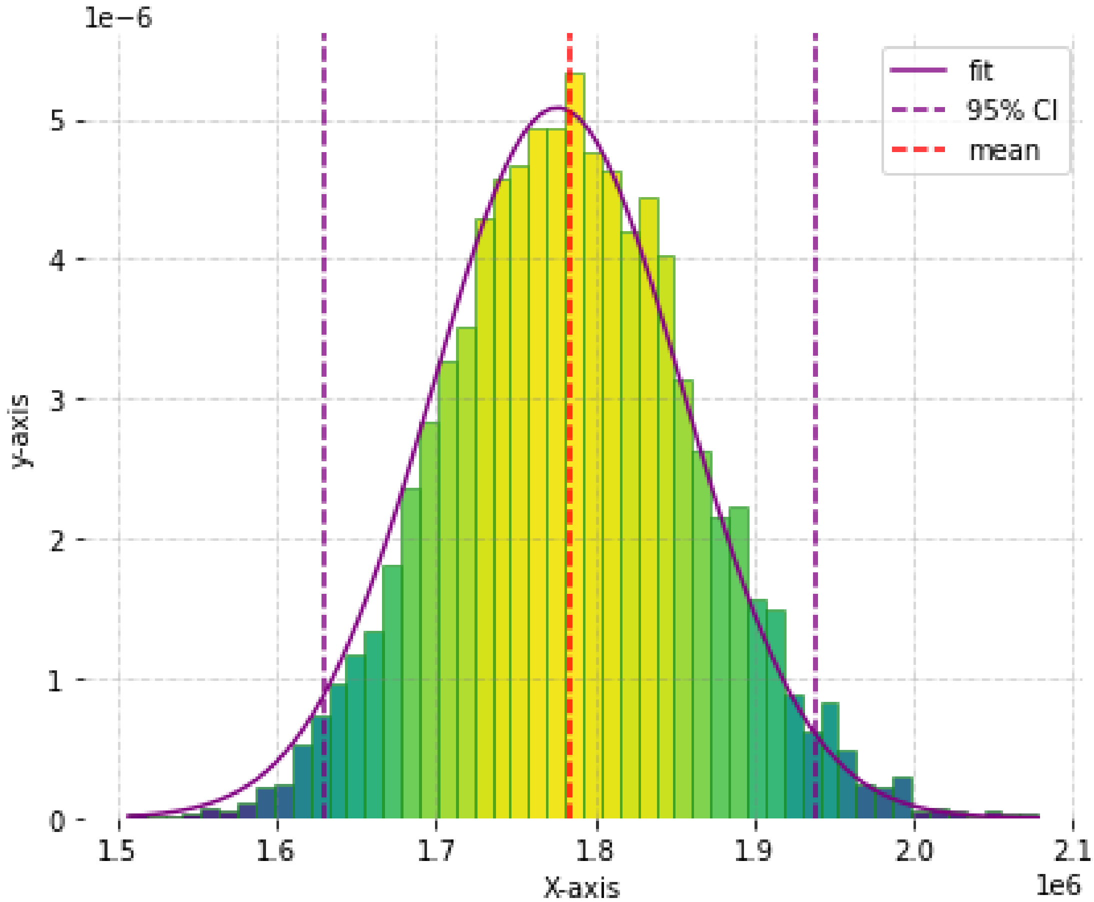
Anderson-Darling's test is declaring the data to be normally distributed, but cross-validating with Shapiro-Wilker's test gives us a completely different scenario. The p-value is less than alpha (0.05) and we reject the null hypothesis. Thus, the sample is not ideally normally distributed which is further affirmed with a Q-Q plot with heavyloaded ends.

```
from scipy.stats import norm
import numpy as np

# Calculate the sample mean and standard deviation
sample_mean = np.mean(Sample_ret_2)
sample_std = np.std(Sample_ret_2, ddof=len(Sample_ret_2)-1)

# Calculate the 95% confidence interval
ci_2 = norm.interval(0.95, loc=sample_mean,
scale=sample_std/np.sqrt(len(Sample_ret_2)))

print(f"95% confidence interval for second method is: {ci_2}")
```

95% confidence interval for second method is: (1630076.8499109372, 1938073.9673537137)

```python
#Visualixing the data alongwith its mean and confidence interval
import numpy as np
from scipy.stats import norm
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit

# Creating histogram frame
fig, axs = plt.subplots(1, 1,
                        figsize =(6, 5),
                        tight_layout = True)

# Remove axes splines
for s in ['top', 'bottom', 'left', 'right']:
    axs.spines[s].set_visible(False)

# Add x, y gridlines
axs.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.5,
        alpha = 0.6)

# Plot the histogram.
N, bins, patches=plt.hist(Sample_ret_2, bins=50, edgecolor = "green",
linewidth = 0.5, density=True)

# Define the function to fit
def fit_func(x, amp, cen, sigma):
    return amp * np.exp(-(x-cen)**2/(2*sigma**2))

# Initial parameter values for fitting
initial_guess = [1.0, np.mean(Sample_ret_2), np.std(Sample_ret_2)]

# Perform the curve fit
popt, pcov = curve_fit(fit_func, bins[:-1], N, p0=initial_guess)

# Plot the histogram and fitted curve
x = np.linspace(bins[0], bins[-1], 100)
plt.plot(x, fit_func(x, *popt), color='purple', linewidth=1.5,
label='fit')

# Setting color
fracs = ((N**(1 / 5)) / N.max())
norm = colors.Normalize(fracs.min(), fracs.max())

for thisfrac, thispatch in zip(fracs, patches):
    color = plt.cm.viridis(norm(thisfrac))
    thispatch.set_facecolor(color)
```

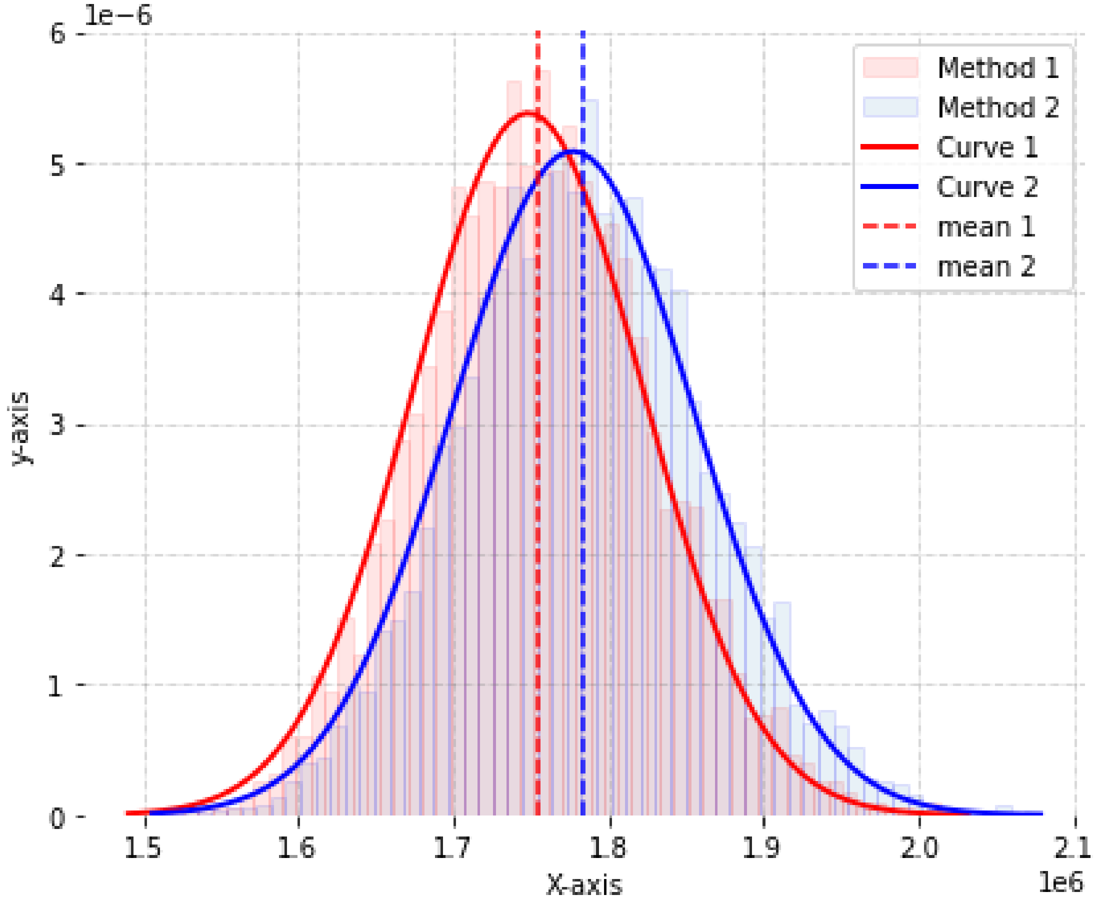
```python
l_2=ci_2[0]
u_2=ci_2[1]
axs.axvline(l_2, color='purple', linestyle='--', label='95% CI')
axs.axvline(u_2, color='purple', linestyle='--')
axs.axvline(mean_2, color='red', linestyle='--', label='mean')
axs.legend()
plt.xlabel("X-axis")
plt.ylabel("y-axis")
plt.show()
```




```python
# Plot histograms of the two data sets on the same plot
# Creating histogram frame
fig, axs = plt.subplots(1, 1,
                        figsize =(6, 5),
                        tight_layout = True)

# Remove axes splines
for s in ['top', 'bottom', 'left', 'right']:
    axs.spines[s].set_visible(False)

# Add x, y gridlines
```

```
axs.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.5,
        alpha = 0.6)


data1=Sample_ret_1
data2=Sample_ret_2

# Plot histograms of the two data sets on the same plot
n1, bins1, patches1 = plt.hist(data1, color='red', bins=60, edgecolor
= "red", alpha=0.1, density=True, label='Method 1')
n2, bins2, patches2 = plt.hist(data2, bins=60, edgecolor = "blue",
alpha=0.1, density=True, label='Method 2')

# Define the function to fit
def fit_func(x, amp, cen, sigma):
    return amp * np.exp(-(x-cen)**2/(2*sigma**2))

# Perform the curve fit on the first data set

popt1, pcov1 = curve_fit(fit_func, bins1[:-1], n1,
p0=[1.0,np.mean(data1), np.std(data1)])
x1 = np.linspace(bins1[0], bins1[-1], 100)
plt.plot(x1, fit_func(x1, *popt1), color='red', linewidth=2,
label='Curve 1')

# Perform the curve fit on the second data set
popt2, pcov2 = curve_fit(fit_func, bins2[:-1], n2, p0=[1.0,
np.mean(data2), np.std(data2)])
x2 = np.linspace(bins2[0], bins2[-1], 100)
plt.plot(x2, fit_func(x2, *popt2), color='blue', linewidth=2,
label='Curve 2')

axs.axvline(mean_1, color='red', linestyle='--', label='mean 1')
axs.axvline(mean_2, color='blue', linestyle='--', label='mean 2')

# Add a legend and labels to the plot
plt.xlabel("X-axis")
plt.ylabel("y-axis")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x1de47a73cd0>
```



Conclusion

Context

To study MSc Data Science, it costs Rs. 8 lakhs today. The underlying assumption is, annual inflation rate follows N(mean = 0.04, sd= 0.01).

Objective:

Predicting the cost of the same course after 20 years from now under the following circumstances.

Brief of our findings:

We have experimented through both the methods (Method 1- Multiplicative & Method 2- Exponential) and have arrived at the following conclusions:

- Method 1 predicts the cost to be Rs. 17,54674.39 on an average, while the 95% confidence interval being (16,09048.58, 19,00300.21)

- Method 2 predicts the cost to be Rs. 17,84075.41 on an average, while the 95% confidence interval being ((16,30076.85, 19,38073.97) (numerical values are rounded off to two decimal places)