In [22]:
```
import numpy as np
import pandas as pd
import scipy.stats as stats
from scipy.stats import skewnorm
import matplotlib.pyplot as plt
%matplotlib inline
```

In [ ]:
```
# we can generate a skewed distribution using skewnorm
```

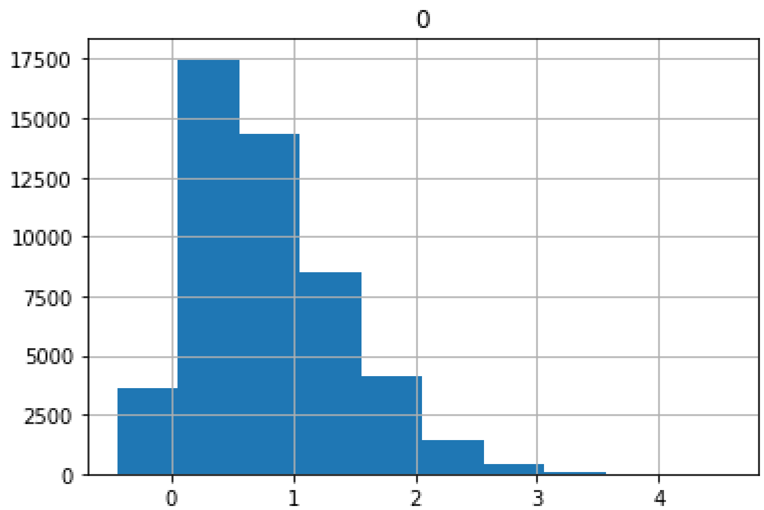
In [23]:
```
import warnings
warnings.filterwarnings('ignore')
```

#Central Limit Theorem

- CLT states that for a large sample drawn from a population with mean μ and standard deviation σ, the sampling distribution of mean, follows an approximate normal distribution with mean, μ and standard error σ / √(n) irrespective of the distribution of the population for large sample size.
- As a general rule, statisticians have found that for any population distribution, when the sample size is at least 30 & above, the sampling distribution of the mean is approximately **normal.**

In [24]:
```
#Let us simulate the population (N=5000) of delivery time of food delivery company with the following specificat
#Mean=60 min ,standard_deviation=20min
pop_skewed=skewnorm.rvs(7,size=50000)
# 7 is the magnitude of the skewness
pop_skewed_df=pd.DataFrame(pop_skewed)
pop_skewed_df.hist()
```

Out[24]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fb2423f0c18>]],
      dtype=object)
```



In [7]:
```
pop_skewed_df.skew()
# this function is to check the level of skewness
```

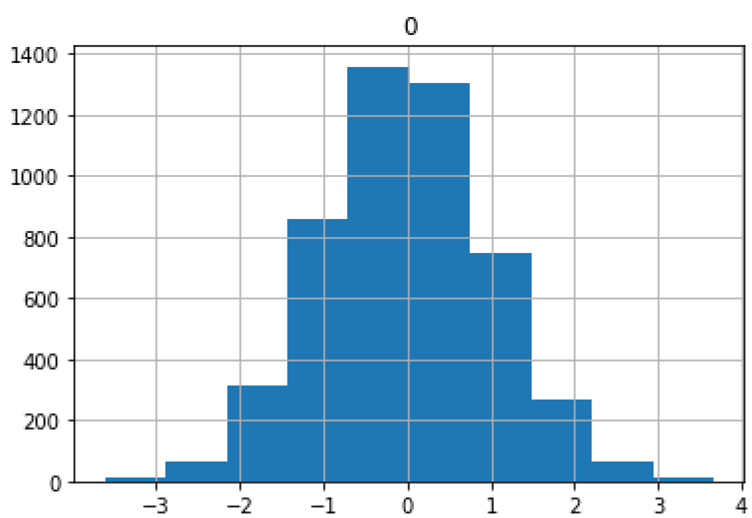
Out[7]:
```
0    0.906077
dtype: float64
```

In [25]:
```
import random
dtime=np.random.randn(5000)
dtime[:50]
```

Out[25]:
```
array([-0.39543272,  0.02856669, -0.49359777, -0.12292297,  0.21653471,
       -0.45869689,  0.49339455, -0.29905773,  1.08431335,  2.04875819,
        0.67991579, -0.88387084, -0.05141271,  0.36357622, -0.43847339,
       -0.06886795, -1.25784609,  0.67384976,  1.58043222, -0.56777726,
       -0.60350349, -1.04470122, -0.27211555,  0.55491037, -1.21991384,
       -0.62979979,  0.82172777,  0.40880364,  0.41838561,  1.61815737,
        1.04441038, -1.21490041, -1.11965455,  0.12574523, -1.39915743,
       -1.25383568,  0.36430638,  0.87107486,  0.97939254, -0.45318494,
       -0.89735164, -0.90836747,  0.46296362, -1.82882981, -0.6014151 ,
        0.12313355, -0.79177815,  0.72756371,  0.01213541,  0.43454622])
```

In [ ]:
```
dtime_df=pd.DataFrame(dtime)
dtime_df.hist()
```

Out[40]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f5869fdf2b0>]],
      dtype=object)
```



In [26]:
```
#convert all 50,000 samples in time scale (pop_mean=709584)
pop=pop_skewed*40000+678000
pop[:100]
```

Out[26]:
```
array([749137.12811536, 691626.59879427, 754723.72781419, 687438.6569944 ,
       731874.16261479, 687776.59951215, 684198.33008517, 678724.89928259,
       696353.87147768, 704619.43019409, 764638.83055503, 689618.99438769,
       697401.74093708, 699677.04609911, 704638.0287711 , 680930.49644295,
       716236.11626228, 694407.51870331, 673476.46695612, 713511.57009729,
       734672.60977538, 757476.28364956, 689366.09765653, 739525.48508047,
       692642.92856149, 687623.76791818, 785742.4013049 , 700214.24072098,
       729075.02460435, 709054.65448348, 700001.33501638, 684501.24818989,
       733226.70637699, 681044.47629105, 701755.65759032, 692200.29224257,
       701945.44888782, 736430.91181564, 710459.45070905, 694784.2630206 ,
       707606.7535224 , 670455.85405403, 729259.04074758, 689400.05837784,
       690428.05323686, 777777.36973378, 694107.65220073, 686268.62227001,
       740536.04644897, 687921.55177946, 706824.40836008, 709495.08167768,
       682165.67822083, 748583.61275232, 773044.72528549, 679524.18296519,
       709650.22523089, 688443.86594368, 701455.88012303, 685167.05446772,
       720868.02581471, 709867.01021752, 687799.53636687, 666765.82671284,
       753062.1039134 , 683601.62121885, 693714.47863187, 753755.217839  ,
       695126.0442992 , 686881.19171522, 730166.19699854, 687151.12024565,
       728197.55829702, 774119.17714239, 711771.35870055, 727104.41764361,
       703719.46221941, 721350.18215787, 680834.64441723, 682479.7637229 ,
       688231.75470134, 710728.66048482, 695601.16353685, 702772.0638699 ,
       700845.17650423, 690246.99278306, 720489.6072847 , 676134.31752801,
       679184.21327045, 688890.24775756, 706473.89825504, 680703.93151359,
       667147.4385214 , 725172.55185038, 672120.1345178 , 705391.09557101,
       701459.99069952, 730333.37757485, 682481.91308063, 724515.48932942])
```

In [27]:
```
#True mean (pop)
np.mean(pop),np.std(pop,ddof=1)
# np.std is the standard error of the mean
```

Out[27]:
```
(709701.666329538, 24515.679325867673)
```

In [28]:
```
from scipy.stats import ttest_1samp
```

In [31]:
```
np.mean(samp)
```

Out[31]:
```
710021.2776104624
```

In [32]:
```
len(samp)
```

Out[32]:
```
500
```

In [34]:
```
SEM
```

Out[34]:
```
1073.369171993358
```

Ho: pop(mean) = 720000 Ha: Pop(mean) != 720000

In [35]:
```
ttest_1samp(samp,720000)
```

Out[35]:
```
Ttest_1sampResult(statistic=-9.27679922704918, pvalue=5.293632917263714e-19)
```

since,p-val<5% (0.05) we reject H0, which implies our sample doesn't represent 720000

In [37]:
```
ttest_1samp(samp,711000)
```

Out[37]:
```
Ttest_1sampResult(statistic=-0.9098771117510696, pvalue=0.36332659503768683)
```

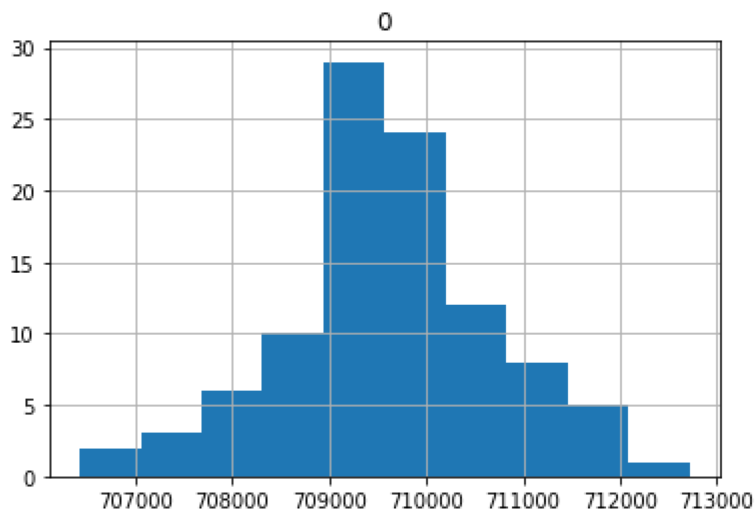
In [ ]:
```

```

- We need to estimate the true mean of the above population as close as possible
- Practically point estimate is impossible, we can do a closer prediction with range estimate with different confidence interval levels

In [10]:
```
#Method-1 (as per the theoretical definition of CLT)
trial=[]
for itr in np.arange(100):
  samp=[]
  for val in np.arange(500):
    samp.append(np.random.choice(pop))
  trial.append(np.mean(samp))
```

In [11]:
```
trial_df=pd.DataFrame(trial)
trial_df.hist()
plt.show()
```



In [12]:
```
trial_df.skew()
```

Out[12]:
```
0   -0.088372
dtype: float64
```

In [13]:
```
np.mean(trial),np.std(trial,ddof=1)
```

Out[13]:
```
(709647.2480975529, 1145.837467928753)
```

In [14]:
```
#95% CI
np.mean(trial)-1.96*np.std(trial,ddof=1)
```

Out[14]:
```
707401.4066604126
```

In [15]:
```
np.mean(trial)+1.96*np.std(trial,ddof=1)
```

Out[15]:
```
711893.0895346933
```

- The above standard deviation represents the STANDARD ERROR OF THE MEAN (SEM)
- 95% Confidence Interval Range [x_bar-1.96xSEM to x_bar+1.96xSEM]
- 99% Confidence Interval Range [x_bar-2.58xSEM to x_bar+2.58xSEM]

In [ ]:
```
print((1/100)/2) # 1% error is symmetrically splitted with 0.5% either side of the normal distribution
print((5/100)/2) # 5% error is symmetrically splitted with 2.5% either side of the normal distribution
```

```
0.005
0.025
```

In [ ]:
```
stats.norm.isf(0.005),stats.norm.isf(0.025)
```

Out[13]:
```
(2.5758293035489, 1.959963984540054)
```

In [ ]:
```
#95% Confidence Interval Range
[np.mean(trial)-1.96*np.std(trial,ddof=1),np.mean(trial)+1.96*np.std(trial,ddof=1)]
```

Out[14]:
```
[57.62658944127126, 61.23190763824089]
```

- From the above range estimate of population mean,we can say that the true mean (59.34) lies in the above 95% confidence interval [57.62658944127126, 61.23190763824089]

In [ ]:
```
#Method-2 (More practical approximated approach)
```

In [29]:
```
samp=[]
for val in np.arange(500):
  samp.append(np.random.choice(pop))
```

In [30]:
```
np.mean(samp)
```

Out[30]:
```
710021.2776104624
```

- To match the theoretical approach of CLT, SEM is calculated as follows: s / √(n)

In [18]:
```
SEM=np.std(samp,ddof=1)/np.sqrt(500)
SEM
```

Out[18]:
```
1073.369171993358
```

In [19]:
```
#95% Confidence Interval Range
[np.mean(samp)-1.96*np.std(samp,ddof=1)/np.sqrt(500),np.mean(samp)+1.96*np.std(samp,ddof=1)/np.sqrt(500)]
```

Out[19]:
```
[708141.0951804518, 712348.7023346658]
```

- From the above range estimate of population mean,we can say that the true mean (59.34) lies in the above 95% confidence interval [56.73968918180259, 60.12895600337146]

In [20]:
```
#90% Confidence Interval Range
[np.mean(samp)-1.64*np.std(samp,ddof=1)/np.sqrt(500),np.mean(samp)+1.64*np.std(samp,ddof=1)/np.sqrt(500)]
```

Out[20]:
```
[708484.5733154897, 712005.2241996279]
```

In [21]:
```
#68% Confidence Interval Range
[np.mean(samp)-1*np.std(samp,ddof=1)/np.sqrt(500),np.mean(samp)+1*np.std(samp,ddof=1)/np.sqrt(500)]
```

Out[21]:
```
[709171.5295855654, 711318.2679295521]
```

ONE SAMPLE t TEST

- Hypothesis is a claim made by a person / organization.

- The claim is usually about the population parameters such as mean or proportion and we seek evidence from a sample for the support of the claim.
- Hypothesis testing is a process used for either rejecting or retaining null hypothesis.

In [ ]:
```
from scipy.stats import ttest_1samp
```

In [ ]:
```
#Ho:mean_del=60min
#Ha:mean_del != 60min
ttest_1samp(samp,60) #Expected mean delivery time is 6omin
```

Out[38]: `Ttest_1sampResult(statistic=28.027535271692038, pvalue=1.5930664416523687e-104)`

In [ ]:
```
x_bar=np.mean(samp)
s=np.std(samp,ddof=1)
x_bar,s
```

Out[24]: `(74.23044363906209, 11.353206415928028)`

In [ ]:
```
sem=s/np.sqrt(500)
sem
```

Out[28]: `0.5077308261720365`

In [ ]:
```
len(samp)
```

Out[27]: `500`

In [ ]:
```
t_stat=(x_bar-60)/sem
t_stat
```

Out[33]: `28.02753527169203`

In [ ]:
```
ttest_1samp(samp,75) #Expected mean delivery time is 75min
```

Out[39]: `Ttest_1sampResult(statistic=-1.5156778380778488, pvalue=0.13023401581188138)`

In [ ]:

```

```

since p-val >5% (0.05) we have enough evidence null hypothesis is TRUE (sample) is the representation of expected mean delivery time of 75min

In [ ]:

```
(32-30)/np.sqrt((15**2/200)+(10**2/500))
```

Out[42]:

```
1.7374889710522776
```