ATTRITION ASSIGNMENT

STEP 1 = LAUNCHING :

import pandas as p

import numpy as n

import matpolib.pyplot as pl

data=pd.read_csv("general_data.csv")

->To find column names .

data.columns

```
In [6]: data.columns
Out[6]:
Index(['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome',
       'Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender',
       'JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome',
       'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager'],
      dtype='object')
```

->To find the data of first 5 rows.

data.head( )

```
In [7]: data.head()
Out[7]:
   Age Attrition  ... YearsSinceLastPromotion YearsWithCurrManager
0   51        No  ...                       0                    0
1   31       Yes  ...                       1                    4
2   32        No  ...                       0                    3
3   38        No  ...                       7                    5
4   32        No  ...                       0                    4

[5 rows x 24 columns]
```

STEP 2 = DATA TREATMENT :

->To find out null values in the table.

data.isnull( )

```
In [8]: data.isnull()
Out[8]:
        Age  Attrition  ...  YearsSinceLastPromotion  YearsWithCurrManager
0     False      False  ...                    False                 False
1     False      False  ...                    False                 False
2     False      False  ...                    False                 False
3     False      False  ...                    False                 False
4     False      False  ...                    False                 False
...     ...        ...  ...                      ...                   ...
4405  False      False  ...                    False                 False
4406  False      False  ...                    False                 False
4407  False      False  ...                    False                 False
4408  False      False  ...                    False                 False
4409  False      False  ...                    False                 False

[4410 rows x 24 columns]
```

->To find out duplicated values of table.

data.duplicated( )

```
In [9]: data.duplicated()
Out[9]:
0       False
1       False
2       False
3       False
4       False
        ...
4405    False
4406    False
4407    False
4408    False
4409    False
Length: 4410, dtype: bool
```

->To drop all duplicated values of the table.

data.drop_duplicates( )

```
In [11]: data.drop_duplicates()
Out[11]:
      Age Attrition  ... YearsSinceLastPromotion YearsWithCurrManager
0      51        No  ...                       0                    0
1      31       Yes  ...                       1                    4
2      32        No  ...                       0                    3
3      38        No  ...                       7                    5
4      32        No  ...                       0                    4
...   ...       ...  ...                     ...                  ...
4405   42        No  ...                       0                    2
4406   29        No  ...                       0                    2
4407   25        No  ...                       1                    2
4408   42        No  ...                       7                    8
4409   40        No  ...                       3                    9

[4410 rows x 24 columns]
```

STEP 3 = UNIVARIATE ANALYSIS :

->To describe the whole table.

data1=data[['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome','Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender','JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours','StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear','YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager']].describe( )

```
In [14]: data1
Out[14]:
              Age  ...  YearsWithCurrManager
count  4410.000000  ...           4410.000000
mean     36.923810  ...              4.123129
std       9.133301  ...              3.567327
min      18.000000  ...              0.000000
25%      30.000000  ...              2.000000
50%      36.000000  ...              3.000000
75%      43.000000  ...              7.000000
max      60.000000  ...             17.000000

[8 rows x 16 columns]
```

->To find out median of each column .

data2=data[['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome','Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender','JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours','StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear','YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager']].median( )

```
In [16]: data2
Out[16]:
Age                           36.0
DistanceFromHome               7.0
Education                      3.0
EmployeeCount                  1.0
EmployeeID                  2205.5
JobLevel                       2.0
MonthlyIncome              49190.0
NumCompaniesWorked             2.0
PercentSalaryHike             14.0
StandardHours                  8.0
StockOptionLevel               1.0
TotalWorkingYears             10.0
TrainingTimesLastYear          3.0
YearsAtCompany                 5.0
YearsSinceLastPromotion        1.0
YearsWithCurrManager           3.0
dtype: float64
```

->To find out mean of each column.

data3=data[['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome','Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender','JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours','StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear','YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager']].mean( )

```
In [18]: data3
Out[18]:
Age                            36.923810
DistanceFromHome                9.192517
Education                       2.912925
EmployeeCount                   1.000000
EmployeeID                   2205.500000
JobLevel                        2.063946
MonthlyIncome               65029.312925
NumCompaniesWorked              2.694830
PercentSalaryHike              15.209524
StandardHours                   8.000000
StockOptionLevel                0.793878
TotalWorkingYears              11.279936
TrainingTimesLastYear           2.799320
YearsAtCompany                  7.008163
YearsSinceLastPromotion         2.187755
YearsWithCurrManager            4.123129
dtype: float64
```

->To find out mode.

data4=data[['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome','Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender','JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours','StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear','YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager']].mode( )

```
In [20]: data4
Out[20]:
       Age Attrition  ... YearsSinceLastPromotion YearsWithCurrManager
0     35.0        No  ...                     0.0                  2.0
1      NaN       NaN  ...                     NaN                  NaN
2      NaN       NaN  ...                     NaN                  NaN
3      NaN       NaN  ...                     NaN                  NaN
4      NaN       NaN  ...                     NaN                  NaN
...    ...       ...  ...                     ...                  ...
4405   NaN       NaN  ...                     NaN                  NaN
4406   NaN       NaN  ...                     NaN                  NaN
4407   NaN       NaN  ...                     NaN                  NaN
4408   NaN       NaN  ...                     NaN                  NaN
4409   NaN       NaN  ...                     NaN                  NaN

[4410 rows x 24 columns]
```

->To find variance of each column.

data5=data[['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome','Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender','JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours','StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear','YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager']].var( )

```
In [22]: data5
Out[22]:
Age                        8.341719e+01
DistanceFromHome           6.569144e+01
Education                  1.048438e+00
EmployeeCount              0.000000e+00
EmployeeID                 1.621042e+06
JobLevel                   1.224760e+00
MonthlyIncome              2.215480e+09
NumCompaniesWorked         6.244436e+00
PercentSalaryHike          1.338907e+01
StandardHours              0.000000e+00
StockOptionLevel           7.257053e-01
TotalWorkingYears          6.056298e+01
TrainingTimesLastYear      1.661465e+00
YearsAtCompany             3.751728e+01
YearsSinceLastPromotion    1.037935e+01
YearsWithCurrManager       1.272582e+01
dtype: float64
```

->To find skewness.

data6=data[['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome','Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender','JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours','StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear','YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager']].skew( )

```
In [24]: data6
Out[24]:
Age                        0.413005
DistanceFromHome           0.957466
Education                 -0.289484
EmployeeCount              0.000000
EmployeeID                 0.000000
JobLevel                   1.024703
MonthlyIncome              1.368884
NumCompaniesWorked         1.026767
PercentSalaryHike          0.820569
StandardHours              0.000000
StockOptionLevel           0.968321
TotalWorkingYears          1.116832
TrainingTimesLastYear      0.552748
YearsAtCompany             1.763328
YearsSinceLastPromotion    1.982939
YearsWithCurrManager       0.832884
dtype: float64
```

->To find out kurtosis.

data7=data[['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome','Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender','JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours','StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear','YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager']].kurt( )

```
In [26]: data7
Out[26]:
Age                         -0.405951
DistanceFromHome            -0.227045
Education                   -0.560569
EmployeeCount                0.000000
EmployeeID                  -1.200000
JobLevel                     0.395525
MonthlyIncome                1.000232
NumCompaniesWorked           0.007287
PercentSalaryHike           -0.302638
StandardHours                0.000000
StockOptionLevel             0.361086
TotalWorkingYears            0.912936
TrainingTimesLastYear        0.491149
YearsAtCompany               3.923864
YearsSinceLastPromotion      3.601761
YearsWithCurrManager         0.167949
dtype: float64
```

->To find standard deviation .

data8=data[['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome','Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender','JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours','StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear','YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager']].std( )

```
In [29]: data8
Out[29]:
Age                             9.133301
DistanceFromHome                8.105026
Education                       1.023933
EmployeeCount                   0.000000
EmployeeID                   1273.201673
JobLevel                        1.106689
MonthlyIncome               47068.888559
NumCompaniesWorked              2.498887
PercentSalaryHike               3.659108
StandardHours                   0.000000
StockOptionLevel                0.851883
TotalWorkingYears               7.782222
TrainingTimesLastYear           1.288978
YearsAtCompany                  6.125135
YearsSinceLastPromotion         3.221699
YearsWithCurrManager            3.567327
dtype: float64
```

INFERENCE :

	MEDIAN	MEAN	STANDARD DEAVIATION	SKEWNESS	KURTOSIS	VARIANCE
Age	36	36.92	9.13	0.41	-0.4	83.41
DistanceFromHome	7	9.19	8.1	0.95	-0.22	65.69
Education	3	2.91	1.02	-0.28	-0.56	1.04
Employee Count	1	1	0	0	0	0
Employee ID	2205	2205.5	1273.2	0	-1.2	1.62E+06
Job Level	2	2.06	1.1	1.02	0.39	1.22
Monthly Income	49190	65029.31	47068.88	1.36	1	2.21E+09
Num Companies Worked	2	2.69	2.49	1.02	0.0072	6.22
Percent Salary Hike	14	15.2	3.65	0.82	-0.3	13.38
Standard Hours	8	8	0	0	0	0
Stock Option Level	1	0.79	0.85	0.96	0.36	72.57
Toatl Working Hours	10	11.27	7.78	1.11	0.91	60.56
Training Times Lasr Year	3	2.79	1.2	0.55	0.49	1.66
Years At Company	5	7	6.125	1.76	3.92	37.51
Years Since Last Promotion	1	2.18	3.22	1.98	3.6	10.37
Years With Current Manager	3	4.12	3.56	0.83	0.16	12.72

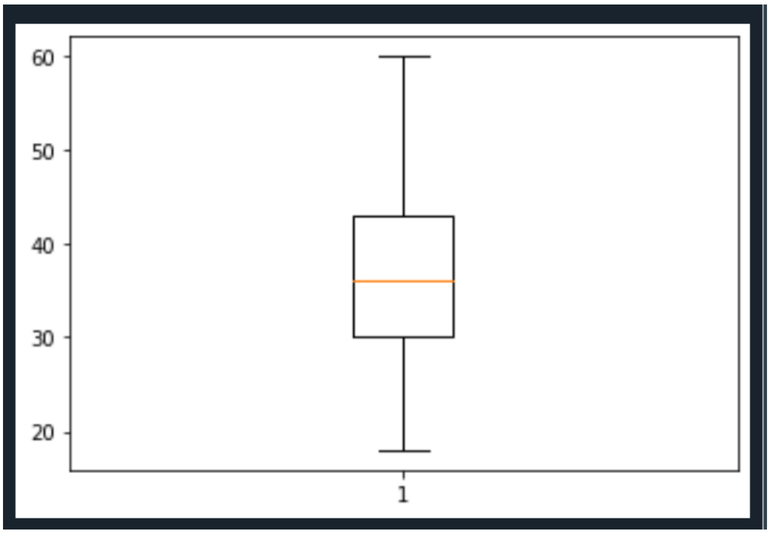
->All the above variables show positive skewness; while Age &Mean_distance_from_home are leptokurtic and all other variables are platykurtic.

OUTLIERS :

There’s no regression found while plotting Age, MonthlyIncome, TotalWorkingYears , YearsAtCompany, etc., on a scatter plot.

box_plot=data.Age

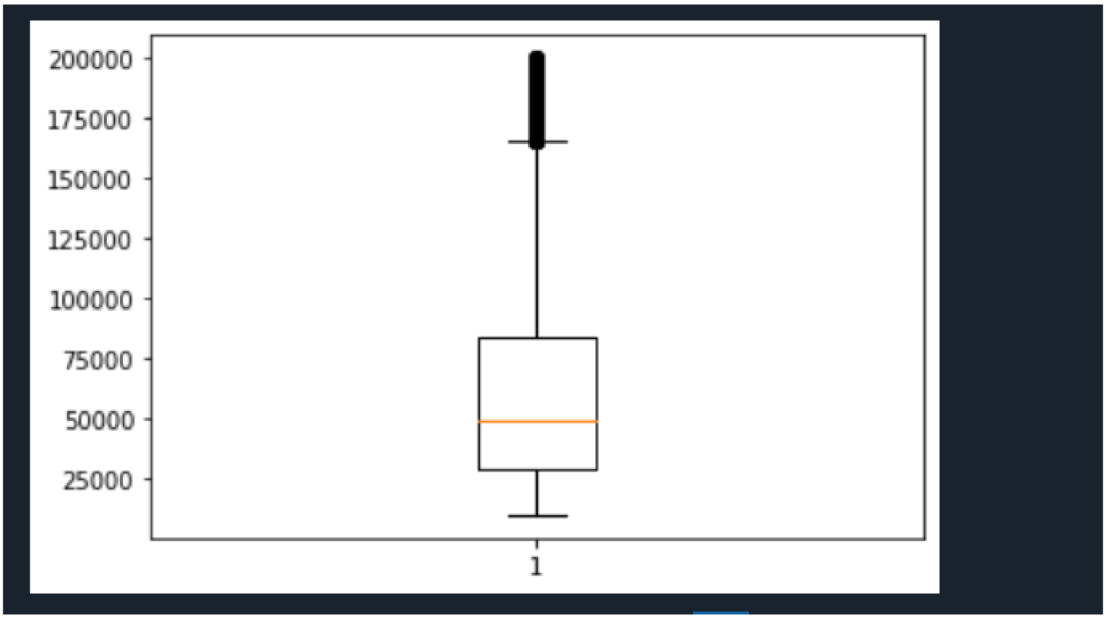
pl.boxplot(box_plot)



Age is normally distributed without any outliers

box_plot=data.MonthlyIncome

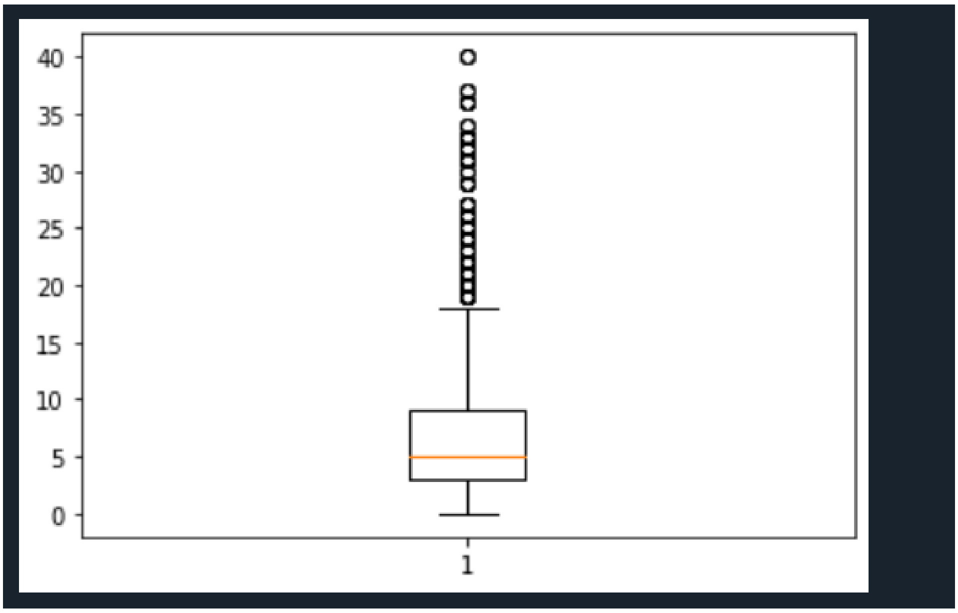
pl.boxplot(box_plot)



Monthly Income is Right skewed with several outliers

box_plot=data.YearsAtCompany

pl.boxplot(box_plot)



Years at company is also Right Skewed with several outliers observed.

4>STATISTICAL TEST (MANN-WHITNEY)

import pandas as pd

data=pd.read_csv("general_data.csv")

data.head()

```
   Age Attrition  ... YearsSinceLastPromotion YearsWithCurrManager
0   51        No  ...                       0                    0
1   31       Yes  ...                       1                    4
2   32        No  ...                       0                    3
3   38        No  ...                       7                    5
4   32        No  ...                       0                    4

[5 rows x 24 columns]
```

data.columns

```
In [5]: data.columns
Out[5]:
Index(['Age', 'Attrition', 'BusinessTravel', 'Department', 'DistanceFromHome',
       'Education', 'EducationField', 'EmployeeCount', 'EmployeeID', 'Gender',
       'JobLevel', 'JobRole', 'MaritalStatus', 'MonthlyIncome',
       'NumCompaniesWorked', 'Over18', 'PercentSalaryHike', 'StandardHours',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'YearsAtCompany', 'YearsSinceLastPromotion', 'YearsWithCurrManager'],
      dtype='object')
```

MANN WHTNEY TEST

import pandas as pd

df=pd.read_csv('general_data.csv')

dummy=pd.get_dummies(df['Attrition'])

df2=pd.concat((df,dummy),axis=1)

df2=df2.drop(['Attrition'],axis=1)

df2=df2.drop(['No'],axis=1)

df2=df2.rename(columns={"Yes":"Attrition"})

df2.head()

```
Out[9]:
   Age      BusinessTravel  ... YearsWithCurrManager  Attrition
0   51       Travel_Rarely  ...                    0          0
1   31   Travel_Frequently  ...                    4          1
2   32   Travel_Frequently  ...                    3          0
3   38          Non-Travel  ...                    5          0
4   32       Travel_Rarely  ...                    4          0
```

ATTRITION VS DISTANCE FROM HOME.

H_0 = There is no significant difference between attrition yes and no for distance from home

H_A= There is significant difference between attrition yes and no for distance from home

from scipy.stats import mannwhitneyu

stats,p=mannwhitneyu(df2.Attrition,df2.DistanceFromHome)

print(stats,p)

```
In [12]: stats,p=mannwhitneyu(df2.Attrition,df2.DistanceFromHome)

In [13]: print(stats,p)
221832.0 0.0
```

As the P value of 0.0 is < 0.05, the H_0 is rejected and H_A is accepted.

So there is difference in attrition and distance from home.

ATTRITION VS TOTAL WORKING YEARS

H_0 = There is no significant difference between attrition yes and no for total working years.

H_A= There is significant difference between attrition yes and no for total working years.

stats,p=mannwhitneyu(df2.Attrition,df2.TotalWorkingYears)

print(stats,p)

```
In [18]: stats,p=mannwhitneyu(df2.Attrition,df2.TotalWorkingYears)

In [19]: print(stats,p)
170527.5 0.0
```

As the P value of 0.0 is < 0.05, the H0 is rejected and Ha is accepted.

So there is difference in attrition and total working years.

ATTRITION VS YEARS AT COMPANY

H_0 = There is no significant difference between attrition yes and no for years at company.

H_A= There is significant difference between attrition yes and no for years at company.

stats,p=mannwhitneyu(df2.Attrition,df2.YearsAtCompany)

print(stats,p)

```
In [20]: stats,p=mannwhitneyu(df2.Attrition,df2.YearsAtCompany)

In [21]: print(stats,p)
520357.5 0.0
```

As the P value of 0.0 is < 0.05, the H0 is rejected and Ha is accepted.

So there is difference in attrition and years at company.

ATTRITION VS YEARS WITH CURRENT MANAGER

H_0 = There is no significant difference between attrition yes and no for years with current manager.

H_A= There is significant difference between attrition yes and no for years with current manager.

stats,p=mannwhitneyu(df2.Attrition,df2.YearsWithCurrManager)

print(stats,p)

```
In [24]: stats,p=mannwhitneyu(df2.Attrition,df2.YearsWithCurrManager)

In [25]: print(stats,p)
2101288.5 0.0
```

As the P value of 0.0 is < 0.05, the H_0 is rejected and H_A is accepted.

So there is difference in attrition and years with current manager.

CORRELATION BETWEEN 2 VARIABLES

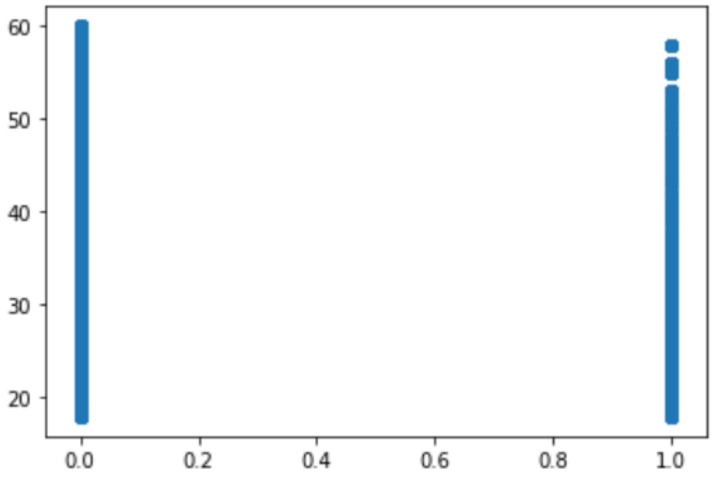
```
import pandas as pd

df=pd.read_csv('general_data.csv')
```

CORRELATION BETWEEN ATTRITION AND AGE

```
from scipy.stats import pearsonr

stats,p=pearsonr(df2.Attrition,df2.Age)

print(stats,p)

if (stats==0):

   print("NO CORRELATION")
```

```
elif(stats<0):
    print("NEGETIVE CORRELATION")
else:
    print("POSITIVE CORRELATION")
import matplotlib.pyplot as plt
plt.scatter(df2.Attrition,df2.Age)
```

```
-0.15920500686577965 1.996801615886744e-26
NEGETIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68b4d388>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and age.

H_A = There is significant difference between attrition and age.

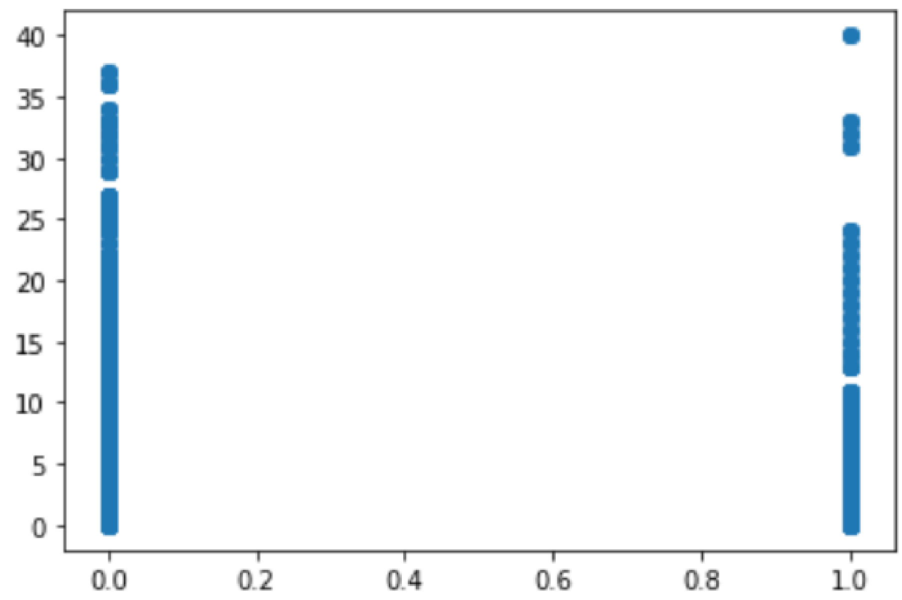
As p value less than .05 so null hypothesis is rejected , so there is significant difference between attrition and age.

CORRELATION BETWEEN ATTRITION AND YEARS AT COMPANY

```
stats,p=pearsonr(df2.Attrition,df2.YearsAtCompany)
print(stats,p)
if (stats==0):
```

```
    print("NO CORRELATION")
elif(stats<0):
    print("NEGETIVE CORRELATION")
else:
    print("POSITIVE CORRELATION")
plt.scatter(df2.Attrition,df2.YearsAtCompany)
```

```
-0.1343922139899772 3.1638831224877484e-19
NEGETIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68bb8688>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and years at company.

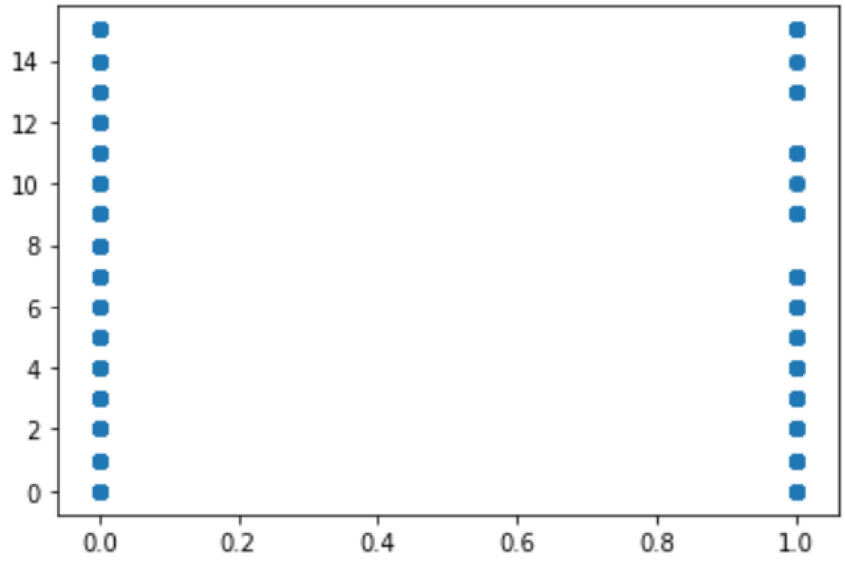
H_A = There is significant difference between attrition and years at company.

As p value less than .05 so null hypothesis is rejected . so there is significant difference between attrition and years at company.

CORRELATION BETWEEN ATTRITION AND YEARS SINCE LAST PROMOTION

```
stats,p=pearsonr(df2.Attrition,df2.YearsSinceLastPromotion)
print(stats,p)
if (stats==0):
   print("NO CORRELATION")
elif(stats<0):
   print("NEGETIVE CORRELATION")
else:
   print("POSITIVE CORRELATION")
plt.scatter(df2.Attrition,df2.YearsSinceLastPromotion)
```

```
-0.03301877514258434 0.028330336189396753
NEGETIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68c27888>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and years since last promotion.

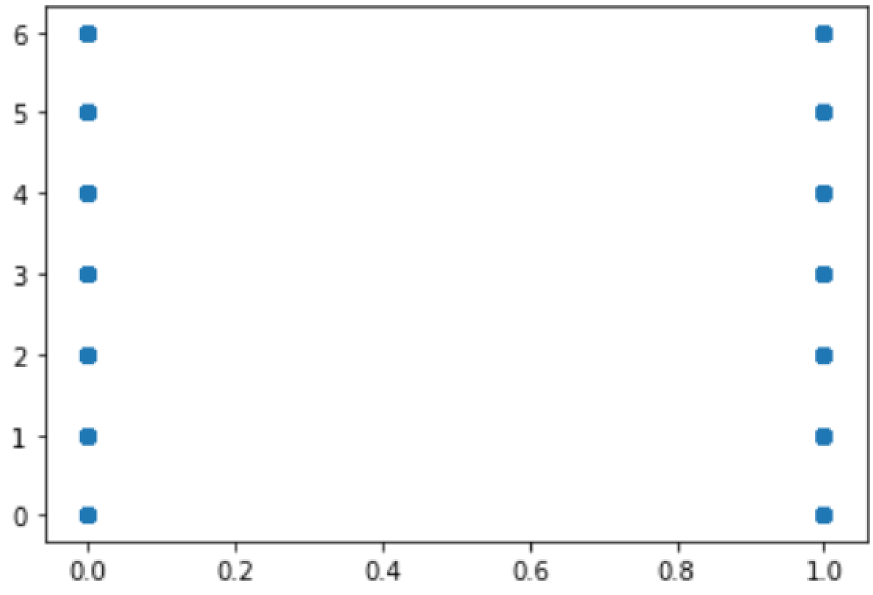
H_A = There is significant difference between attrition and years since last promotion.

As p value less than .05 so null hypothesis is rejected , so there is significant difference between attrition and years since last promotion.

CORRELATION BETWEEN ATTRITION AND TRAINING TIMES LAST YEAR

```
stats,p=pearsonr(df2.Attrition,df2.TrainingTimesLastYear)
print(stats,p)
if (stats==0):
   print("NO CORRELATION")
elif(stats<0):
   print("NEGETIVE CORRELATION")
else:
   print("POSITIVE CORRELATION")
plt.scatter(df2.Attrition,df2.TrainingTimesLastYear)
```

```
-0.04943057624425501 0.0010247061915362814
NEGETIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68c918c8>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and training times last year.

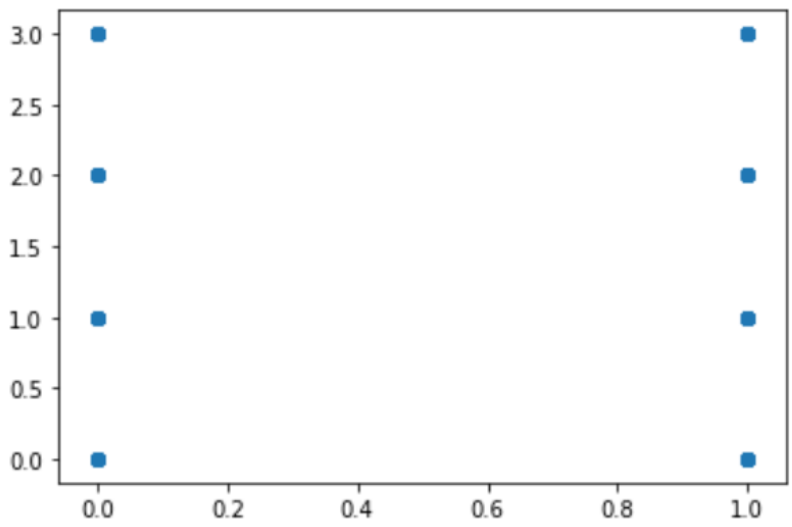
H_A = There is significant difference between attrition and training times last year.

As p value less than .05 so null hypothesis is rejected , so there is significant difference between attrition and training times last year .

CORRELATION BETWEEN ATTRITION AND STOCK OPTION LEVEL

```
stats,p=pearsonr(df2.Attrition,df2.StockOptionLevel)
print(stats,p)
if (stats==0):
    print("NO CORRELATION")
elif(stats<0):
    print("NEGETIVE CORRELATION")
else:
    print("POSITIVE CORRELATION")
plt.scatter(df2.Attrition,df2.StockOptionLevel)
```

```
-0.006838852403261521 0.6498072937475723
NEGETIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68cf9d48>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and stock option level.

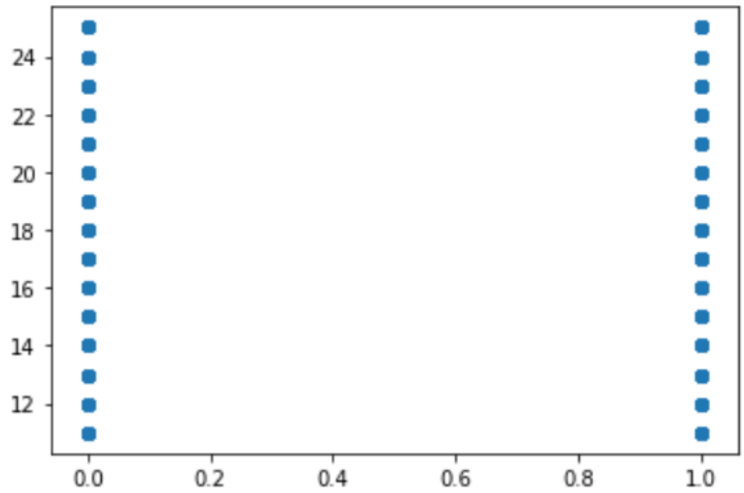
H_A = There is significant difference between attrition and stock option level.

As p value more than .05 so null hypothesis is accepted , so there is no significant difference between attrition and stock option level.

CORRELATION BETWEEN ATTRITION AND PERCENTAGE SALARY HIKE

```
stats,p=pearsonr(df2.Attrition,df2.PercentSalaryHike)
print(stats,p)
if (stats==0):
    print("NO CORRELATION")
elif(stats<0):
    print("NEGETIVE CORRELATION")
else:
    print("POSITIVE CORRELATION")
plt.scatter(df2.Attrition,df2.PercentSalaryHike)
```

```
0.03253259489105351 0.030743386433355353
POSITIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68d64948>
```



It is low positive correlation.

H_0 = There is no significant difference between attrition and percent salary hike.

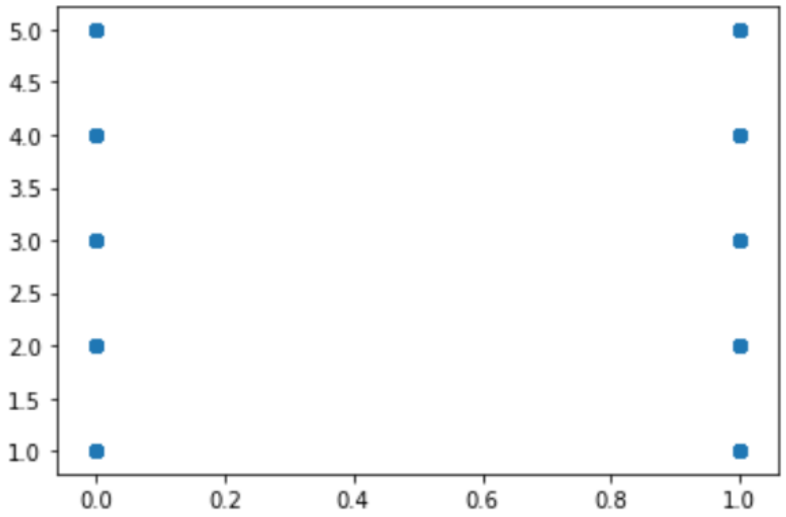
H_A = There is significant difference between attrition and percent salary hike.

As p value less than .05 so null hypothesis is rejected , so there there is significant difference between attrition and percent salary hike.

CORRELATION BETWEEN ATTRITION AND JOB LEVEL

```
stats,p=pearsonr(df2.Attrition,df2.JobLevel)
print(stats,p)
if (stats==0):
    print("NO CORRELATION")
elif(stats<0):
    print("NEGETIVE CORRELATION")
else:
    print("POSITIVE CORRELATION")
plt.scatter(df2.Attrition,df2.JobLevel)
```

```
-0.010289713287495035 0.49451717271828405
NEGETIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68dcd2c8>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and job level.

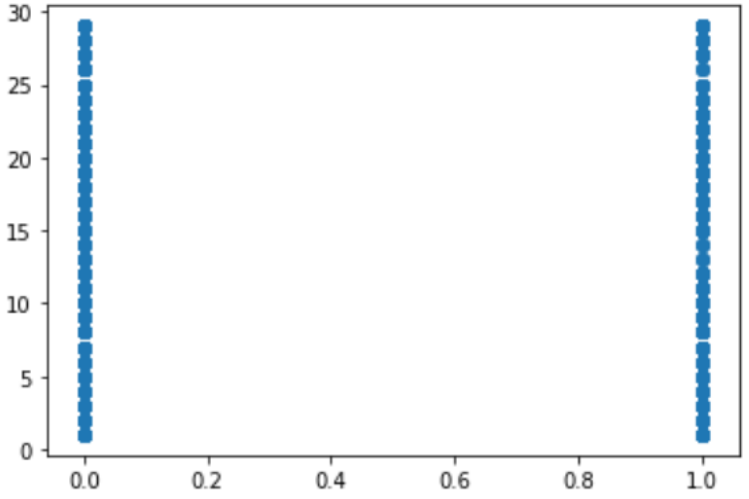
H_A = There is significant difference between attrition and job level.

As p value more than .05 so null hypothesis is accepted , so there there is no significant difference between attrition and job level.

CORRELATION BETWEEN ATTRITIONA ND DISTANCE FROM HOME

```
stats,p=pearsonr(df2.Attrition,df2.DistanceFromHome)
print(stats,p)
if (stats==0):
   print("NO CORRELATION")
elif(stats<0):
   print("NEGETIVE CORRELATION")
else:
   print("POSITIVE CORRELATION")
plt.scatter(df2.Attrition,df2.DistanceFromHome)
```

```
-0.00973014101017966 0.5182860428050771
NEGETIVE CORRELATION
<matplotlib.collections.PathCollection at 0x1cc68e3b5c8>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and distance from home.

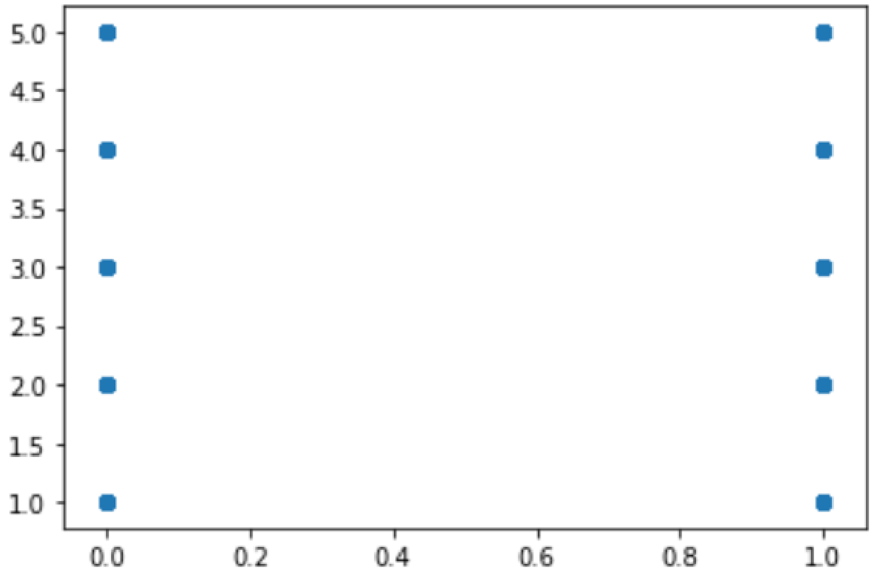
H_A = There is significant difference between attrition and distance from home.

As p value more than .05 so null hypothesis is accepted , so there is no significant difference between attrition and distance from home.

CORRELATION BETWEEN ATTRITION AND EDUCATION

```
stats,p=pearsonr(df2.Attrition,df2.Education)

print(stats,p)

if (stats==0):

   print("NO CORRELATION")

elif(stats<0):

   print("NEGETIVE CORRELATION")

else:

   print("POSITIVE CORRELATION")

plt.scatter(df2.Attrition,df2.Education)
```

```
-0.015111167710968711 0.3157293177118575
NEGETIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68f0ce08>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and education.

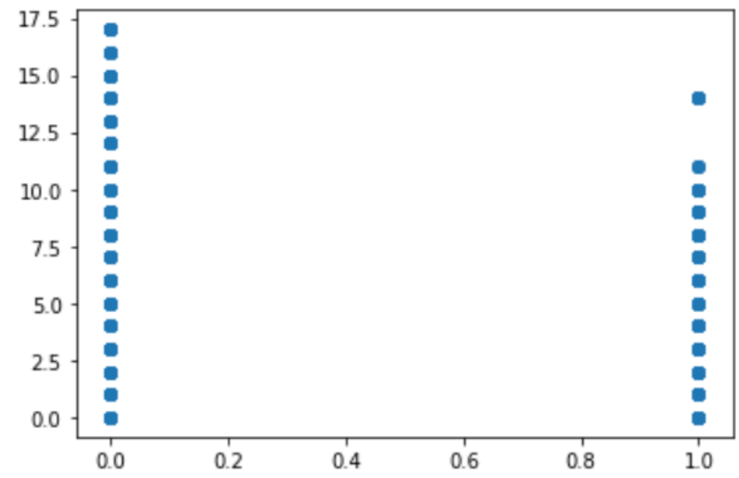
H_A = There is significant difference between attrition and education.

As p value more than .05 so null hypothesis is accepted , so there is no significant difference between attrition and education.

CORRELATION BETWEEN ATTRTION AND YEARS WITH CURRENT MANAGER

```
stats,p=pearsonr(df2.Attrition,df2.YearsWithCurrManager)
print(stats,p)
if (stats==0):
   print("NO CORRELATION")
elif(stats<0):
   print("NEGETIVE CORRELATION")
else:
   print("POSITIVE CORRELATION")
plt.scatter(df2.Attrition,df2.YearsWithCurrManager)
```

```
-0.15619931590162842 1.7339322652900218e-25
NEGETIVE CORRELATION

<matplotlib.collections.PathCollection at 0x1cc68e95888>
```



It is low negative correlation.

H_0 = There is no significant difference between attrition and years with current manager.

H_A = There is significant difference between attrition and years with current manager.

As p value less than .05 so null hypothesis is rejected , so there is significant difference between attrition and years with current manager.