IBM_Attrition_Assessment

January 18, 2023

[1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from patsy import dmatrices
```

[2]:

```
dataset=pd.read_csv("IBM Attrition Data.csv")
```

[3]:

```
dataset.head()
```

[3]:

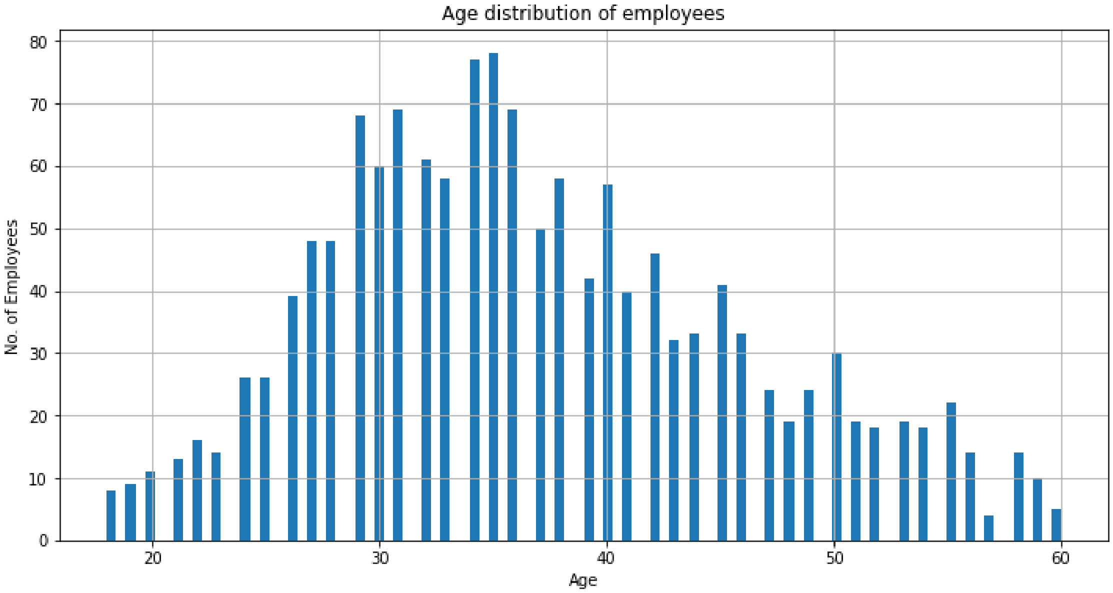
```
   Age Attrition              Department  DistanceFromHome  Education  \
0   41       Yes                   Sales                 1          2
1   49        No  Research & Development                 8          1
2   37       Yes  Research & Development                 2          2
3   33        No  Research & Development                 3          4
4   27        No  Research & Development                 2          1

  EducationField  EnvironmentSatisfaction  JobSatisfaction MaritalStatus  \
0  Life Sciences                        2                4        Single
1  Life Sciences                        3                2       Married
2          Other                        4                3        Single
3  Life Sciences                        4                3       Married
4        Medical                        1                2       Married

   MonthlyIncome  NumCompaniesWorked  WorkLifeBalance  YearsAtCompany
0           5993                   8                1               6
1           5130                   1                3              10
2           2090                   6                3               0
3           2909                   1                3               8
4           3468                   9                3               2
```

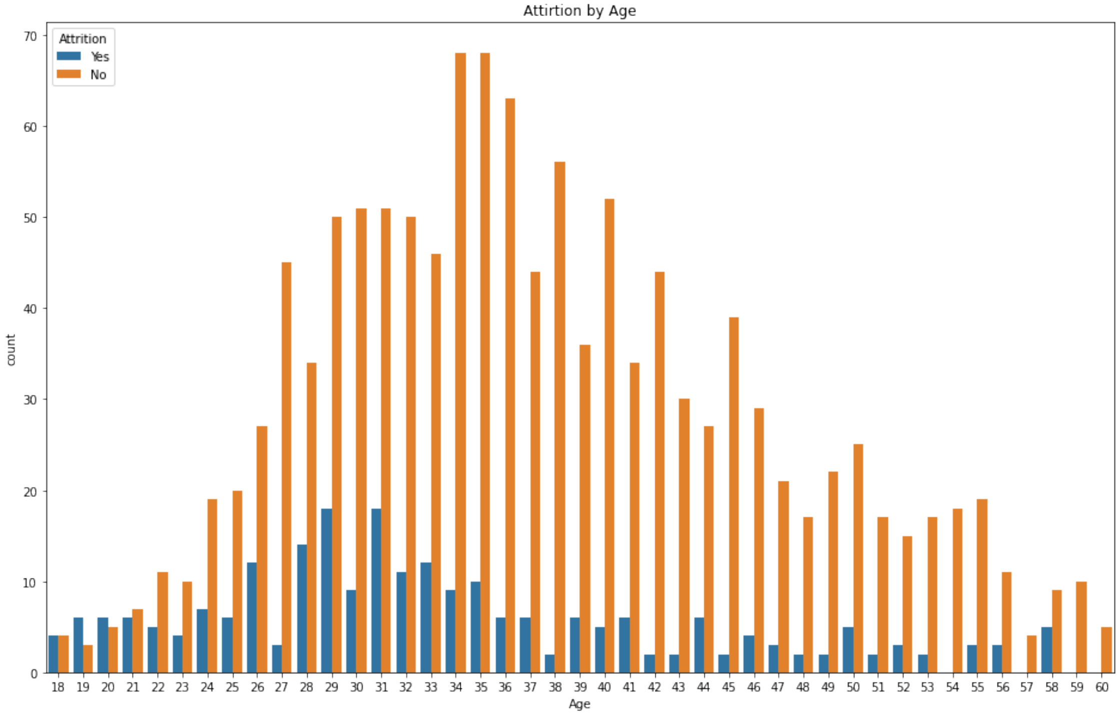
[5]:

```
## Plot the Age distribution
plt.figure(figsize=(12,6))
dataset['Age'].hist(bins=100)
plt.title("Age distribution of employees")
plt.xlabel("Age")
plt.ylabel("No. of Employees")
plt.show()
```



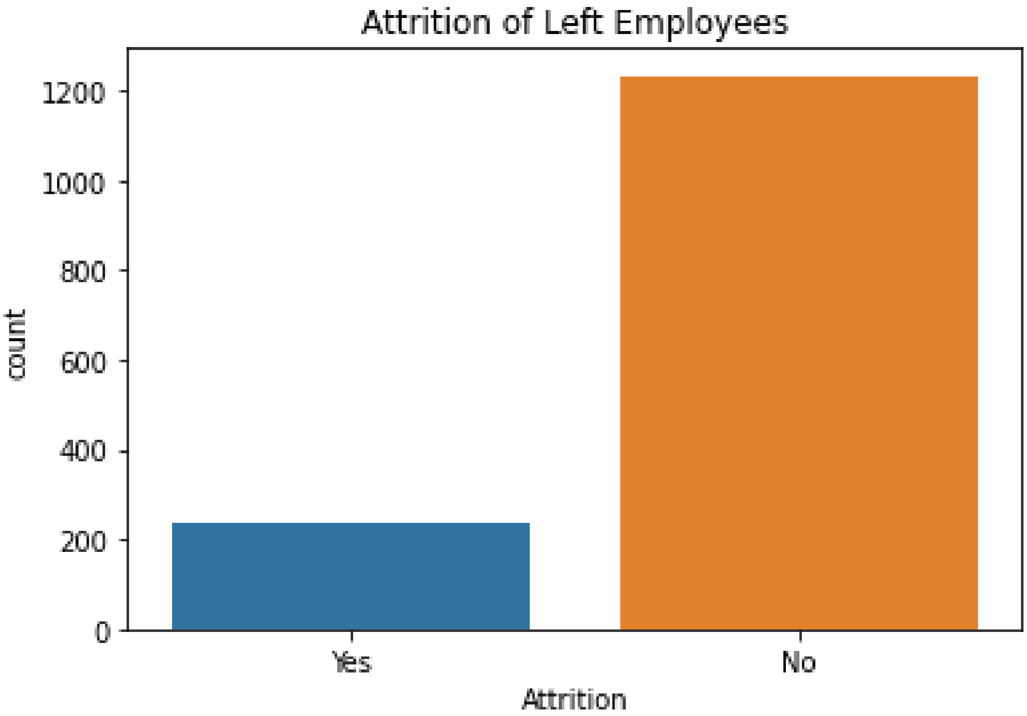
[6]:

```
## Explore Attrition by Age
plt.figure(figsize=(16,10))
sns.countplot(x='Age', hue='Attrition', data=dataset)
plt.title("Attirtion by Age")
plt.show()
```



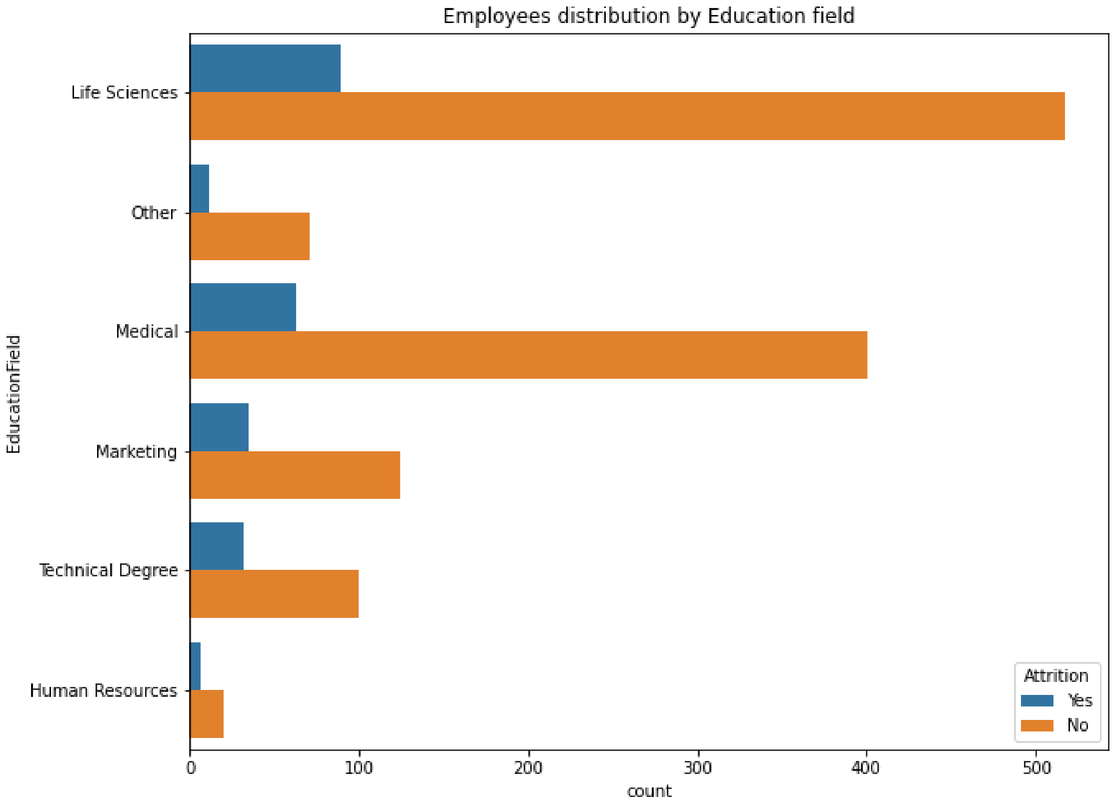
[7]:

```
## Explore data for Left employees
sns.countplot(x='Attrition',data=dataset)
plt.title("Attrition of Left Employees")
plt.show()
```

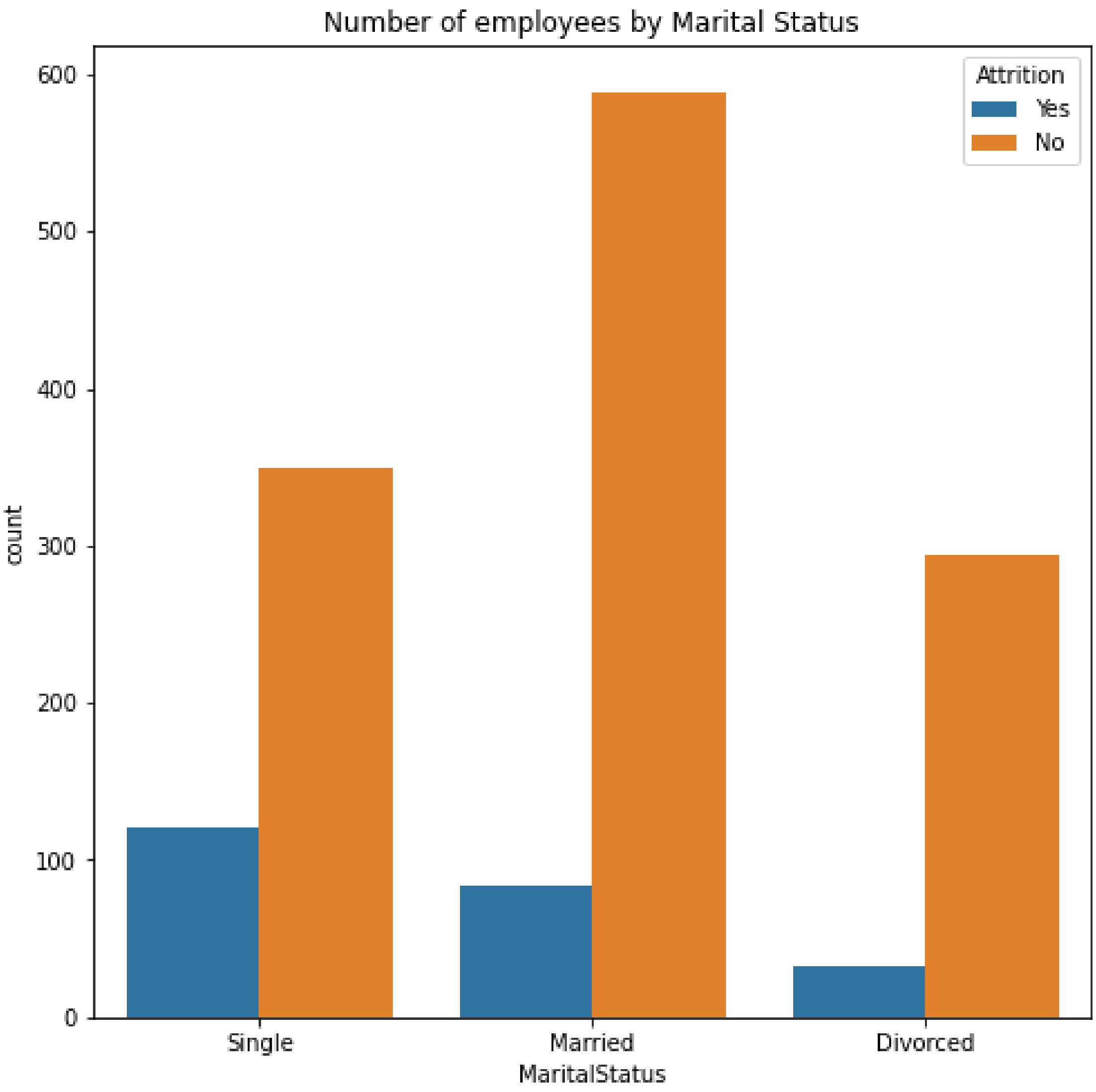


[8]:

```
## Explore the distribution of employees by the education field
plt.figure(figsize=(10,8))
sns.countplot(y='EducationField', hue='Attrition', data=dataset)
plt.title("Employees distribution by Education field")
plt.show()
```



```
[9]: ## Explore number of Married and unmarried employees
     plt.figure(figsize=(8,8))
     sns.countplot(x='MaritalStatus', hue='Attrition', data=dataset)
     plt.title("Number of employees by Marital Status")
     plt.show()
```



[5]:
```
## Build Logistic Regression Model to predict which employees are likely to␣
 ↪attrite
dataset.describe()
```

[5]:
```
                Age  DistanceFromHome    Education  EnvironmentSatisfaction  \
count  1470.000000       1470.000000  1470.000000              1470.000000   
mean     36.923810          9.192517     2.912925                 2.721769   
std       9.135373          8.106864     1.024165                 1.093082   
min      18.000000          1.000000     1.000000                 1.000000   
25%      30.000000          2.000000     2.000000                 2.000000   
50%      36.000000          7.000000     3.000000                 3.000000   
75%      43.000000         14.000000     4.000000                 4.000000   
max      60.000000         29.000000     5.000000                 4.000000   
```

```
       JobSatisfaction  MonthlyIncome  NumCompaniesWorked  WorkLifeBalance  \
count      1470.000000    1470.000000         1470.000000      1470.000000
mean          2.728571    6502.931293            2.693197         2.761224
std           1.102846    4707.956783            2.498009         0.706476
min           1.000000    1009.000000            0.000000         1.000000
25%           2.000000    2911.000000            1.000000         2.000000
50%           3.000000    4919.000000            2.000000         3.000000
75%           4.000000    8379.000000            4.000000         3.000000
max           4.000000   19999.000000            9.000000         4.000000

       YearsAtCompany
count     1470.000000
mean         7.008163
std          6.126525
min          0.000000
25%          3.000000
50%          5.000000
75%          9.000000
max         40.000000
```

[4]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Age                      1470 non-null   int64
 1   Attrition                1470 non-null   object
 2   Department               1470 non-null   object
 3   DistanceFromHome         1470 non-null   int64
 4   Education                1470 non-null   int64
 5   EducationField           1470 non-null   object
 6   EnvironmentSatisfaction  1470 non-null   int64
 7   JobSatisfaction          1470 non-null   int64
 8   MaritalStatus            1470 non-null   object
 9   MonthlyIncome            1470 non-null   int64
 10  NumCompaniesWorked       1470 non-null   int64
 11  WorkLifeBalance          1470 non-null   int64
 12  YearsAtCompany           1470 non-null   int64
dtypes: int64(9), object(4)
memory usage: 149.4+ KB
```

[6]:
```
dataset.columns
```

```
[6]: Index(['Age', 'Attrition', 'Department', 'DistanceFromHome', 'Education',
            'EducationField', 'EnvironmentSatisfaction', 'JobSatisfaction',
            'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked',
            'WorkLifeBalance', 'YearsAtCompany'],
           dtype='object')
```

```
[7]: dataset['Attrition'].value_counts()
```

```
[7]: No     1233
     Yes     237
     Name: Attrition, dtype: int64
```

```
[8]: dataset['Attrition'].dtype
```

```
[8]: dtype('O')
```

```
[6]: dataset['Attrition'].replace('Yes',1, inplace=True)
     dataset['Attrition'].replace('No',0, inplace=True)
```

```
[7]: dataset.head(10)
```

```
[7]:    Age  Attrition              Department  DistanceFromHome  Education  \
     0   41          1                   Sales                 1          2
     1   49          0  Research & Development                 8          1
     2   37          1  Research & Development                 2          2
     3   33          0  Research & Development                 3          4
     4   27          0  Research & Development                 2          1
     5   32          0  Research & Development                 2          2
     6   59          0  Research & Development                 3          3
     7   30          0  Research & Development                24          1
     8   38          0  Research & Development                23          3
     9   36          0  Research & Development                27          3

       EducationField  EnvironmentSatisfaction  JobSatisfaction MaritalStatus  \
     0  Life Sciences                        2                4        Single
     1  Life Sciences                        3                2       Married
     2          Other                        4                3        Single
     3  Life Sciences                        4                3       Married
     4        Medical                        1                2       Married
     5  Life Sciences                        4                4        Single
     6        Medical                        3                1       Married
     7  Life Sciences                        4                3      Divorced
     8  Life Sciences                        4                3        Single
     9        Medical                        3                3       Married

        MonthlyIncome  NumCompaniesWorked  WorkLifeBalance  YearsAtCompany
     0           5993                   8                1               6
```

```
1           5130                   1                3               10
2           2090                   6                3                0
3           2909                   1                3                8
4           3468                   9                3                2
5           3068                   0                2                7
6           2670                   4                2                1
7           2693                   1                3                1
8           9526                   0                3                9
9           5237                   6                2                7
```

[9]:
```
X=dataset.drop(['Attrition'],axis=1)
X.head()
```

[9]:
```
   Age              Department  DistanceFromHome  Education EducationField  \
0   41                   Sales                 1          2  Life Sciences
1   49  Research & Development                 8          1  Life Sciences
2   37  Research & Development                 2          2          Other
3   33  Research & Development                 3          4  Life Sciences
4   27  Research & Development                 2          1        Medical

   EnvironmentSatisfaction  JobSatisfaction MaritalStatus  MonthlyIncome  \
0                        2                4        Single           5993
1                        3                2       Married           5130
2                        4                3        Single           2090
3                        4                3       Married           2909
4                        1                2       Married           3468

   NumCompaniesWorked  WorkLifeBalance  YearsAtCompany
0                   8                1               6
1                   1                3              10
2                   6                3               0
3                   1                3               8
4                   9                3               2
```

[10]:
```
Y=dataset['Attrition']
Y.head()
```

[10]:
```
0    1
1    0
2    1
3    0
4    0
Name: Attrition, dtype: int64
```

[11]:
```
dataset['EducationField'].replace('Life Sciences',1, inplace=True)
dataset['EducationField'].replace('Medical',2, inplace=True)
dataset['EducationField'].replace('Marketing',3, inplace=True)
```

```
dataset['EducationField'].replace('Other',4, inplace=True)
dataset['EducationField'].replace('Technical Degree',5, inplace=True)
dataset['EducationField'].replace('Human Resources',6, inplace=True)
dataset['Department'].replace('Research & Development',1, inplace=True)
dataset['Department'].replace('Sales',2, inplace=True)
dataset['Department'].replace('Human Resources',3, inplace=True)
dataset['MaritalStatus'].replace('Married',1, inplace=True)
dataset['MaritalStatus'].replace('Single',2, inplace=True)
dataset['MaritalStatus'].replace('Divorced',3, inplace=True)
```

[12]:
```
dataset['EducationField'].value_counts()
```

[12]:
```
1    606
2    464
3    159
5    132
4     82
6     27
Name: EducationField, dtype: int64
```

[15]:
```
dataset['Department'].value_counts()
```

[15]:
```
1    961
2    446
3     63
Name: Department, dtype: int64
```

[16]:
```
dataset['MaritalStatus'].value_counts()
```

[16]:
```
1    673
2    470
3    327
Name: MaritalStatus, dtype: int64
```

[17]:
```
x=dataset.select_dtypes(include=['int64'])
x.dtypes
```

[17]:
```
Age                          int64
Attrition                    int64
Department                   int64
DistanceFromHome             int64
Education                    int64
EducationField               int64
EnvironmentSatisfaction      int64
JobSatisfaction              int64
MaritalStatus                int64
MonthlyIncome                int64
```

```
NumCompaniesWorked          int64
WorkLifeBalance             int64
YearsAtCompany              int64
dtype: object
```

[18]:
```
x.columns
```

[18]:
```
Index(['Age', 'Attrition', 'Department', 'DistanceFromHome', 'Education',
       'EducationField', 'EnvironmentSatisfaction', 'JobSatisfaction',
       'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked',
       'WorkLifeBalance', 'YearsAtCompany'],
      dtype='object')
```

[19]:
```
y=dataset['Attrition']
y.head()
```

[19]:
```
0    1
1    0
2    1
3    0
4    0
Name: Attrition, dtype: int64
```

[13]:
```
y, x = dmatrices("Attrition ~ Age + Department + DistanceFromHome + Education +␣
 ↪EducationField + YearsAtCompany",
                 dataset, return_type="dataframe")
print(x.columns)
```

```
Index(['Intercept', 'Age', 'Department', 'DistanceFromHome', 'Education',
       'EducationField', 'YearsAtCompany'],
      dtype='object')
```

[14]:
```
y=np.ravel(y)
```

[15]:
```
import sklearn
import statsmodels.api as sm
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model = model.fit(x, y)

## Check accuracy on the training set

model.score(x, y)
```

[15]:
```
0.8408163265306122
```

[26]:
```
y.mean()
```

[26]:

```
0.16122448979591836
```

[21]:

```
X_train,X_test,y_train,y_test=sklearn.model_selection.train_test_split(x,y,␣
 ↪test_size=0.3, random_state=0)
model2=LogisticRegression()
model2.fit(X_train, y_train)
```

[21]:

```
LogisticRegression()
```

[22]:

```
predicted=model2.predict(X_test)
print(predicted)
```

```
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

[23]:

```
probability=model2.predict_proba(X_test)
print(probability)
```

```
[[0.86179625 0.13820375]
 [0.80754593 0.19245407]
 [0.74123939 0.25876061]
 [0.83441335 0.16558665]
 [0.73499938 0.26500062]
 [0.79097744 0.20902256]
 [0.85615198 0.14384802]
 [0.85699671 0.14300329]
 [0.96699056 0.03300944]
 [0.93685207 0.06314793]
 [0.95099274 0.04900726]
 [0.83101547 0.16898453]
 [0.86296555 0.13703445]
```

```
[0.86581193 0.13418807]
[0.88750601 0.11249399]
[0.88892617 0.11107383]
[0.88569724 0.11430276]
[0.78516585 0.21483415]
[0.7979449  0.2020551 ]
[0.88511301 0.11488699]
[0.70651596 0.29348404]
[0.94676691 0.05323309]
[0.86736255 0.13263745]
[0.84276454 0.15723546]
[0.60336851 0.39663149]
[0.811292   0.188708  ]
[0.91813729 0.08186271]
[0.93285521 0.06714479]
[0.68230761 0.31769239]
[0.87027136 0.12972864]
[0.87266384 0.12733616]
[0.7696874  0.2303126 ]
[0.86435769 0.13564231]
[0.95758879 0.04241121]
[0.84461485 0.15538515]
[0.8671935  0.1328065 ]
[0.90465979 0.09534021]
[0.68936427 0.31063573]
[0.90703616 0.09296384]
[0.80663477 0.19336523]
[0.91515724 0.08484276]
[0.82351275 0.17648725]
[0.93711514 0.06288486]
[0.93411324 0.06588676]
[0.89447653 0.10552347]
[0.85317747 0.14682253]
[0.78922388 0.21077612]
[0.84879887 0.15120113]
[0.66402457 0.33597543]
[0.76252297 0.23747703]
[0.92851109 0.07148891]
[0.78953697 0.21046303]
[0.86166595 0.13833405]
[0.85837887 0.14162113]
[0.87217673 0.12782327]
[0.78950898 0.21049102]
[0.87690792 0.12309208]
[0.84165447 0.15834553]
[0.72847153 0.27152847]
[0.83181407 0.16818593]
[0.90095035 0.09904965]
```

```
[0.71077332 0.28922668]
[0.92823021 0.07176979]
[0.84375681 0.15624319]
[0.79544108 0.20455892]
[0.86826158 0.13173842]
[0.91679451 0.08320549]
[0.84763056 0.15236944]
[0.89253707 0.10746293]
[0.62872122 0.37127878]
[0.9387539  0.0612461 ]
[0.72620335 0.27379665]
[0.85652974 0.14347026]
[0.84226022 0.15773978]
[0.77436391 0.22563609]
[0.71899557 0.28100443]
[0.93587386 0.06412614]
[0.95710069 0.04289931]
[0.79185841 0.20814159]
[0.89370438 0.10629562]
[0.91382038 0.08617962]
[0.7935459  0.2064541 ]
[0.77934023 0.22065977]
[0.79638992 0.20361008]
[0.83800496 0.16199504]
[0.71395671 0.28604329]
[0.97772715 0.02227285]
[0.94645972 0.05354028]
[0.88617624 0.11382376]
[0.79620164 0.20379836]
[0.61863836 0.38136164]
[0.81866469 0.18133531]
[0.74504132 0.25495868]
[0.86779495 0.13220505]
[0.87071139 0.12928861]
[0.81717471 0.18282529]
[0.71840764 0.28159236]
[0.59825899 0.40174101]
[0.83951549 0.16048451]
[0.88351325 0.11648675]
[0.74352581 0.25647419]
[0.76631615 0.23368385]
[0.98033036 0.01966964]
[0.91857466 0.08142534]
[0.77432841 0.22567159]
[0.92514814 0.07485186]
[0.88123383 0.11876617]
[0.74587179 0.25412821]
[0.90478361 0.09521639]
```

```
[0.78685526 0.21314474]
[0.8114777  0.1885223 ]
[0.93472171 0.06527829]
[0.93836501 0.06163499]
[0.79411745 0.20588255]
[0.81372902 0.18627098]
[0.91610918 0.08389082]
[0.90428343 0.09571657]
[0.84669423 0.15330577]
[0.95384551 0.04615449]
[0.91283691 0.08716309]
[0.85919602 0.14080398]
[0.85902499 0.14097501]
[0.87519518 0.12480482]
[0.7611467  0.2388533 ]
[0.92217685 0.07782315]
[0.96859409 0.03140591]
[0.94398218 0.05601782]
[0.81780292 0.18219708]
[0.88058703 0.11941297]
[0.77894283 0.22105717]
[0.97124464 0.02875536]
[0.88807661 0.11192339]
[0.78715261 0.21284739]
[0.82001482 0.17998518]
[0.94934542 0.05065458]
[0.95888932 0.04111068]
[0.73559224 0.26440776]
[0.93416995 0.06583005]
[0.73750637 0.26249363]
[0.8213675  0.1786325 ]
[0.821712   0.178288  ]
[0.89896703 0.10103297]
[0.78745762 0.21254238]
[0.89825348 0.10174652]
[0.91433817 0.08566183]
[0.92724744 0.07275256]
[0.96594965 0.03405035]
[0.94417364 0.05582636]
[0.93073081 0.06926919]
[0.66320586 0.33679414]
[0.84168651 0.15831349]
[0.82636817 0.17363183]
[0.80616639 0.19383361]
[0.96157632 0.03842368]
[0.93515159 0.06484841]
[0.94778623 0.05221377]
[0.97337825 0.02662175]
```

```
[0.79297057 0.20702943]
[0.87770194 0.12229806]
[0.86103662 0.13896338]
[0.95185478 0.04814522]
[0.93131494 0.06868506]
[0.75685359 0.24314641]
[0.74997802 0.25002198]
[0.95527865 0.04472135]
[0.8695072  0.1304928 ]
[0.81376769 0.18623231]
[0.76990617 0.23009383]
[0.80077911 0.19922089]
[0.9280112  0.0719888 ]
[0.90949245 0.09050755]
[0.94557625 0.05442375]
[0.93330465 0.06669535]
[0.69145909 0.30854091]
[0.93056881 0.06943119]
[0.74525426 0.25474574]
[0.78594343 0.21405657]
[0.933086   0.066914  ]
[0.8087829  0.1912171 ]
[0.85096457 0.14903543]
[0.66956281 0.33043719]
[0.90338379 0.09661621]
[0.91158931 0.08841069]
[0.87300498 0.12699502]
[0.92939054 0.07060946]
[0.66661726 0.33338274]
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```

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```

```
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```

```
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```

```
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 [0.93130395 0.06869605]
 [0.89999984 0.10000016]]
```

[25]:

```
model3=sm.OLS(y,x)
result3=model3.fit()
```

```python
print(result3.summary())
from sklearn import metrics

print(metrics.accuracy_score(y_test, predicted))
print(metrics.roc_auc_score(y_test, probability[:, 1]))
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.049
Model:                            OLS   Adj. R-squared:                  0.045
Method:                 Least Squares   F-statistic:                     12.47
Date:                Tue, 17 Jan 2023   Prob (F-statistic):           9.62e-14
Time:                        12:25:24   Log-Likelihood:                -578.62
No. Observations:                1470   AIC:                             1171.
Df Residuals:                    1463   BIC:                             1208.
Df Model:                           6
Covariance Type:            nonrobust
================================================================================
====
                       coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----
Intercept            0.2682      0.051      5.232      0.000       0.168
0.369
Age                 -0.0051      0.001     -4.618      0.000      -0.007
-0.003
Department           0.0424      0.017      2.492      0.013       0.009
0.076
DistanceFromHome     0.0036      0.001      3.068      0.002       0.001
0.006
Education           -0.0008      0.009     -0.090      0.928      -0.019
0.018
EducationField       0.0151      0.007      2.113      0.035       0.001
0.029
YearsAtCompany      -0.0058      0.002     -3.596      0.000      -0.009
-0.003
==============================================================================
Omnibus:                      415.266   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              842.071
Skew:                           1.730   Prob(JB):                    1.40e-183
Kurtosis:                       4.332   Cond. No.                         221.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

```
0.8435374149659864
0.6502502887947632
```

[77]:

```
print(metrics.confusion_matrix(y_test, predicted))
print(metrics.classification_report(y_test, predicted))
```

```
[[371   0]
 [ 69   1]]
              precision    recall  f1-score   support

         0.0       0.84      1.00      0.91       371
         1.0       1.00      0.01      0.03        70

    accuracy                           0.84       441
   macro avg       0.92      0.51      0.47       441
weighted avg       0.87      0.84      0.77       441
```

[79]:

```
print(X_train)
```

```
      Intercept   Age  Department  DistanceFromHome  Education  \
338         1.0  30.0         2.0               5.0        3.0
363         1.0  33.0         2.0               5.0        3.0
759         1.0  45.0         3.0              24.0        4.0
793         1.0  28.0         1.0              15.0        2.0
581         1.0  30.0         1.0               1.0        3.0
…         …   …         …               …        …
763         1.0  34.0         2.0              10.0        4.0
835         1.0  35.0         3.0               8.0        4.0
1216        1.0  43.0         2.0               2.0        3.0
559         1.0  38.0         1.0               2.0        5.0
684         1.0  40.0         2.0              10.0        4.0

      EducationField  YearsAtCompany
338              3.0            10.0
363              3.0             1.0
759              2.0             6.0
793              1.0             4.0
581              1.0             2.0
…               …            …
763              1.0             1.0
835              5.0             5.0
1216             2.0            10.0
559              2.0             1.0
684              3.0             1.0

[1029 rows x 7 columns]
```

[82]:

```
vv=[[1.0, 23.0, 1.0, 500.0, 3.0, 24.0, 100.0]]
print(model.predict_proba(vv))
```

```
[[3.91613733e-04 9.99608386e-01]]
```

```
/usr/local/lib/python3.7/site-packages/sklearn/base.py:451: UserWarning: X does
not have valid feature names, but LogisticRegression was fitted with feature
names
  "X does not have valid feature names, but"
```

[ ]:

```

```