IBM Employee Attrition Prediction

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1 IBM Employee Attrition Prediction

1.1 Description

IBM is an American MNC operating in around 170 countries with major business vertical as computing, software, and hardware. Attrition is a major risk to service-providing organizations where trained and experienced people are the assets of the company. The organization would like to identify the factors which influence the attrition of employees.

1.2 Data Dictionary

- Age: Age of employee
- Attrition: Employee attrition status
- Department: Department of work
- DistanceFromHome
- Education: 1-Below College; 2- College; 3-Bachelor; 4-Master; 5-Doctor;
- EducationField
- EnvironmentSatisfaction: 1-Low; 2-Medium; 3-High; 4-Very High;
- JobSatisfaction: 1-Low; 2-Medium; 3-High; 4-Very High;
- MaritalStatus
- MonthlyIncome
- NumCompaniesWorked: Number of companies worked prior to IBM
- WorkLifeBalance: 1-Bad; 2-Good; 3-Better; 4-Best;
- YearsAtCompany: Current years of service in IBM

2 Import Libraries

[10]:
```
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
%matplotlib inline
from patsy import dmatrices
import sklearn
import seaborn as sns
```

3 Import attrition dataset

[3]:
```
dataframe=pd.read_csv("C:/Users/Anushree/Downloads/1576148666_ibmattritiondata/
↪IBM Attrition Data.csv")
```

4 Exploratory data analysis

[4]:
```
dataframe.head()
```

[4]:

	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

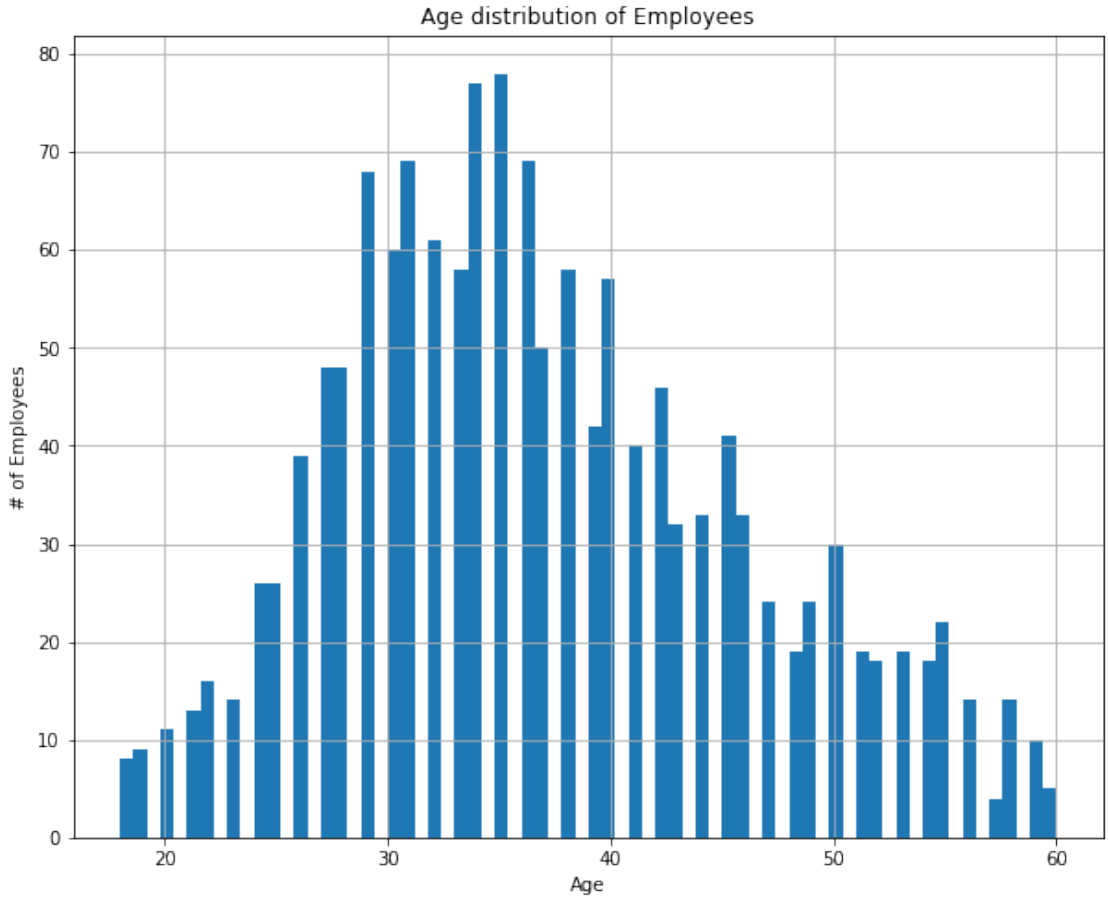
[4]:
```
names = dataframe.columns.values
print(names)
```

```
['Age' 'Attrition' 'Department' 'DistanceFromHome' 'Education'
 'EducationField' 'EnvironmentSatisfaction' 'JobSatisfaction'
 'MaritalStatus' 'MonthlyIncome' 'NumCompaniesWorked' 'WorkLifeBalance'
 'YearsAtCompany']
```

5 Age distribution of Employees

[9]:
```
# histogram for age
plt.figure(figsize=(10,8))
dataframe['Age'].hist(bins=70)
plt.title("Age distribution of Employees")
plt.xlabel("Age")
plt.ylabel("# of Employees")
```

```
plt.show()
```

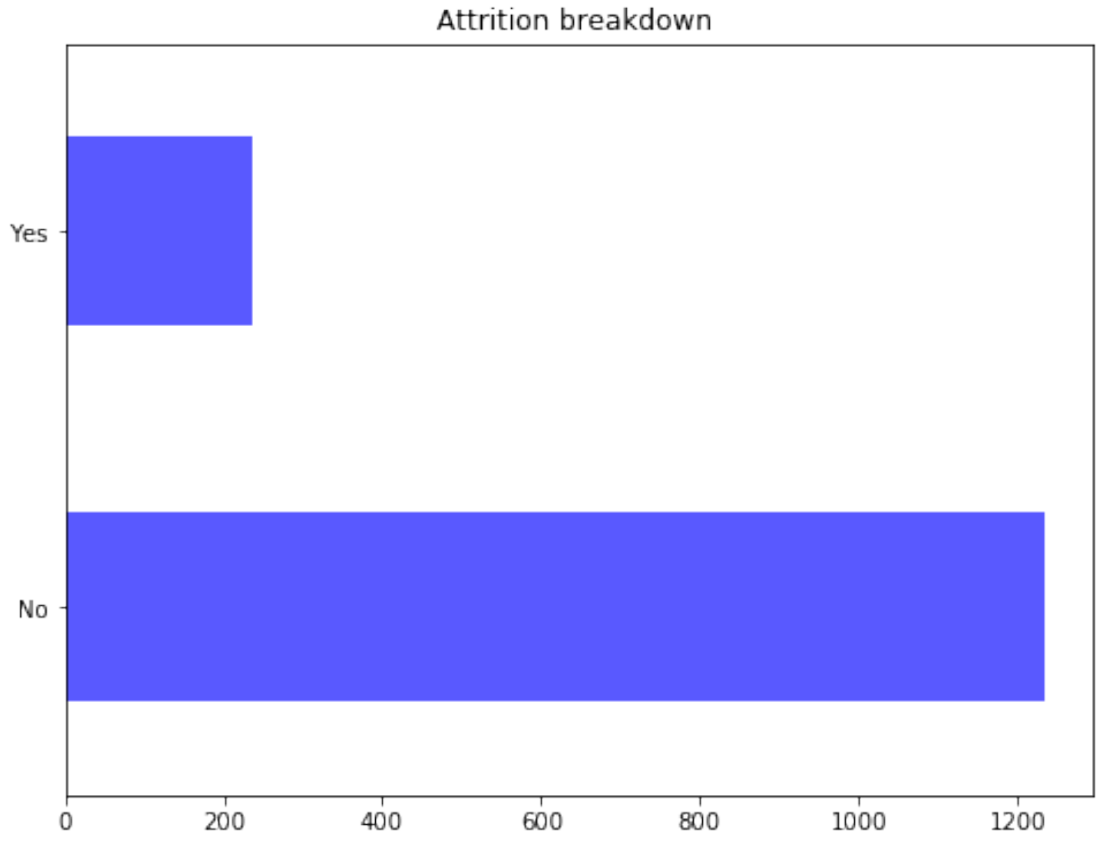


6 Attrition of Employees by Age

[6]:
```
# explore data for Attrition by Age
plt.figure(figsize=(14,10))
plt.scatter(dataframe.Attrition,dataframe.Age, alpha=.55)
plt.title("Attrition by Age ")
plt.ylabel("Age")
plt.grid(b=True, which='major',axis='y')
plt.show()
```

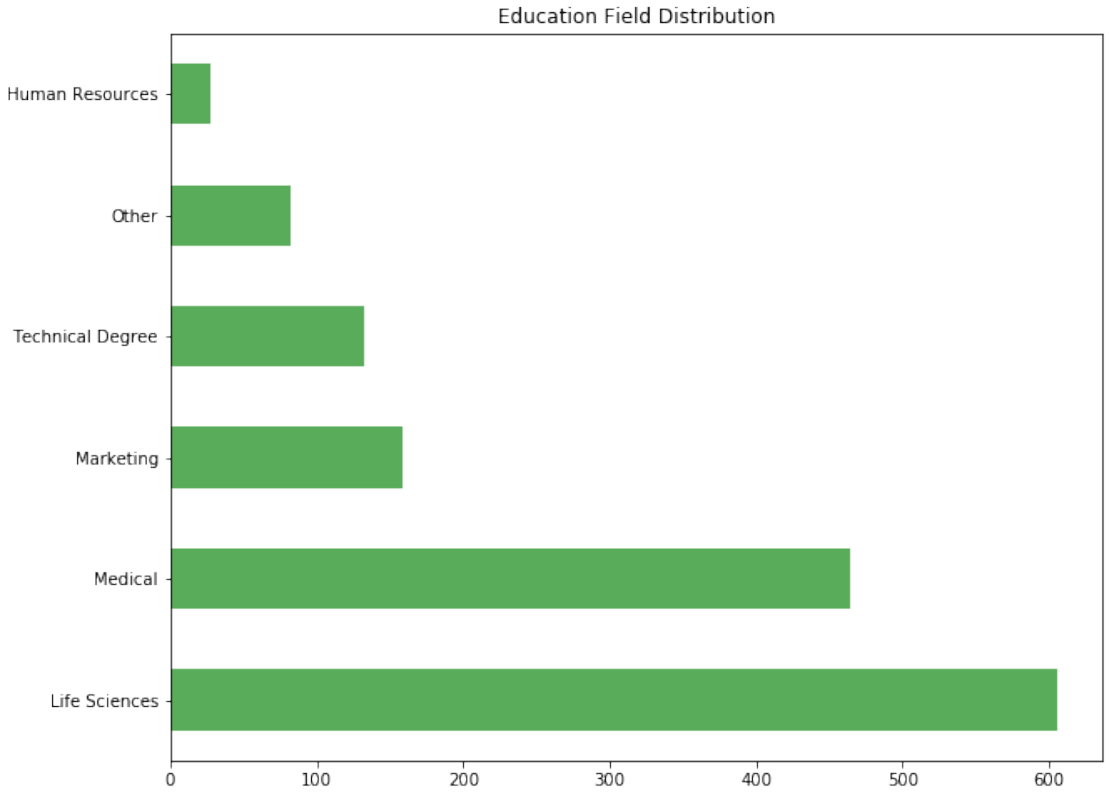
7 Analysis of Left Employees

[7]:
```
# explore data for Left employees breakdown
plt.figure(figsize=(8,6))
dataframe.Attrition.value_counts().plot(kind='barh',color='blue',alpha=.65)
plt.title("Attrition breakdown ")
plt.show()
```



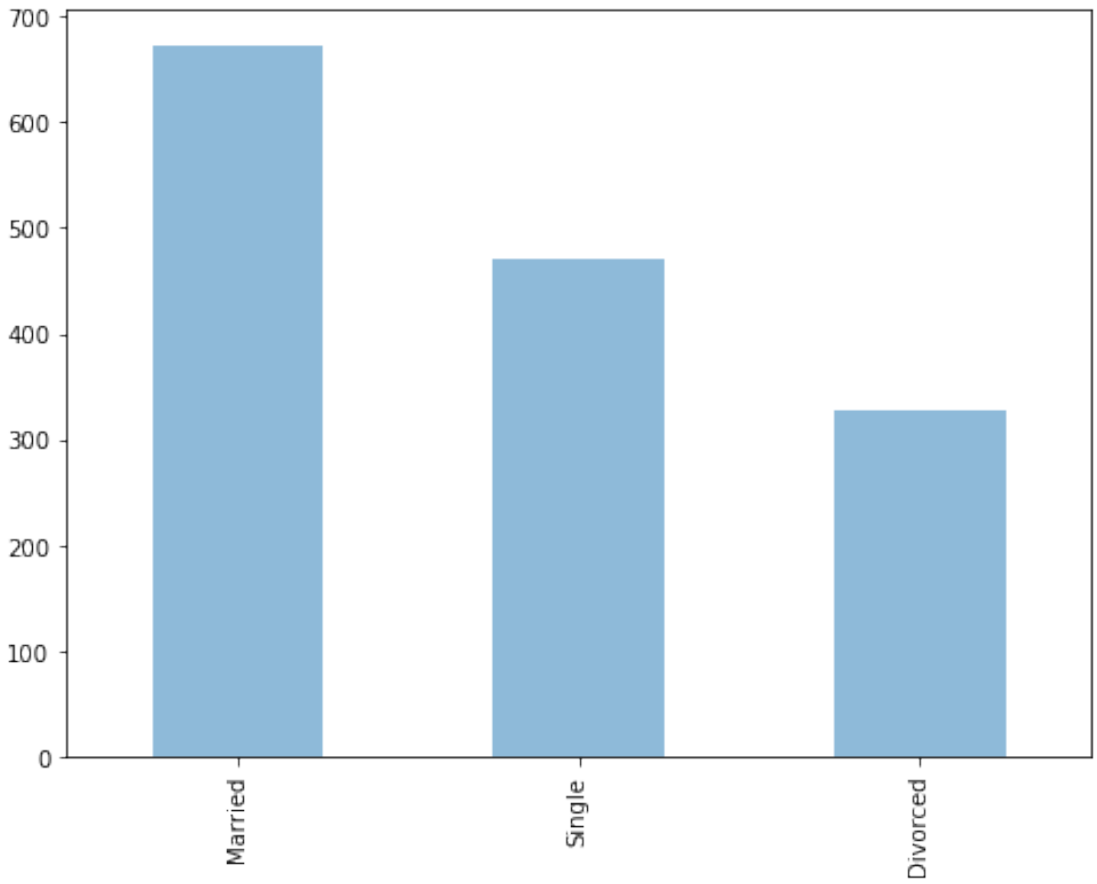
8 Distribution of employees by the education field

[8]:
```
# explore data for Education Field distribution
plt.figure(figsize=(10,8))
dataframe.EducationField.value_counts().plot(kind='barh',color='g',alpha=.65)
plt.title("Education Field Distribution")
plt.show()
```



9 Marital Status of Employees

[9]:
```
# explore data for Marital Status
plt.figure(figsize=(8,6))
dataframe.MaritalStatus.value_counts().plot(kind='bar',alpha=.5)
plt.show()
```



10 Statistical analysis of data

[10]:
```
dataframe.describe()
```

[10]:

	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
```

[11]:
```
dataframe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 13 columns):
Age                         1470 non-null int64
Attrition                   1470 non-null object
Department                  1470 non-null object
DistanceFromHome            1470 non-null int64
Education                   1470 non-null int64
EducationField              1470 non-null object
EnvironmentSatisfaction     1470 non-null int64
JobSatisfaction             1470 non-null int64
MaritalStatus               1470 non-null object
MonthlyIncome               1470 non-null int64
NumCompaniesWorked          1470 non-null int64
WorkLifeBalance             1470 non-null int64
YearsAtCompany              1470 non-null int64
dtypes: int64(9), object(4)
memory usage: 149.4+ KB
```

[11]:
```
dataframe.columns
```

[11]:
```
Index(['Age', 'Attrition', 'Department', 'DistanceFromHome', 'Education',
       'EducationField', 'EnvironmentSatisfaction', 'JobSatisfaction',
       'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked',
       'WorkLifeBalance', 'YearsAtCompany'],
      dtype='object')
```

[13]:
```
dataframe.std()
```

[13]:
```
Age                          9.135373
DistanceFromHome             8.106864
Education                    1.024165
EnvironmentSatisfaction      1.093082
JobSatisfaction              1.102846
MonthlyIncome             4707.956783
NumCompaniesWorked           2.498009
WorkLifeBalance              0.706476
YearsAtCompany               6.126525
dtype: float64
```

[12]:
```
dataframe['Attrition'].value_counts()
```

[12]:
```
No     1233
Yes     237
Name: Attrition, dtype: int64
```

[15]:
```
dataframe['Attrition'].dtypes
```

[15]:
```
dtype('O')
```

11 Encoding of Categorical data

[13]:
```
dataframe['Attrition'].replace('Yes',1, inplace=True)
dataframe['Attrition'].replace('No',0, inplace=True)
```

[14]:
```
dataframe.head(10)
```

[14]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus
0	41	1	Sales	1	2	Life Sciences	2	4	Single
1	49	0	Research & Development	8	1	Life Sciences	3	2	Married
2	37	1	Research & Development	2	2	Other	4	3	Single
3	33	0	Research & Development	3	4	Life Sciences	4	3	Married
4	27	0	Research & Development	2	1	Medical	1	2	Married
5	32	0	Research & Development	2	2	Life Sciences	4	4	Single
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				

```
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
```

12 Data Preprocessing

[15]:
```
# building up a logistic regression model
X = dataframe.drop(['Attrition'],axis=1)
X.head()
Y = dataframe['Attrition']
Y.head()
```

[15]:
```
0    1
1    0
2    1
3    0
4    0
Name: Attrition, dtype: int64
```

[17]:
```
dataframe['EducationField'].replace('Life Sciences',1, inplace=True)
dataframe['EducationField'].replace('Medical',2, inplace=True)
dataframe['EducationField'].replace('Marketing', 3, inplace=True)
dataframe['EducationField'].replace('Other',4, inplace=True)
dataframe['EducationField'].replace('Technical Degree',5, inplace=True)
dataframe['EducationField'].replace('Human Resources', 6, inplace=True)
```

[18]:
```
dataframe['EducationField'].value_counts()
```

[18]:
```
1    606
2    464
3    159
5    132
4     82
```

```
6     27
Name: EducationField, dtype: int64
```

[19]:
```
dataframe['Department'].value_counts()
```

[19]:
```
Research & Development    961
Sales                     446
Human Resources            63
Name: Department, dtype: int64
```

[20]:
```
dataframe['Department'].replace('Research & Development',1, inplace=True)
dataframe['Department'].replace('Sales',2, inplace=True)
dataframe['Department'].replace('Human Resources', 3, inplace=True)
```

[21]:
```
dataframe['Department'].value_counts()
```

[21]:
```
1    961
2    446
3     63
Name: Department, dtype: int64
```

[22]:
```
dataframe['MaritalStatus'].value_counts()
```

[22]:
```
Married     673
Single      470
Divorced    327
Name: MaritalStatus, dtype: int64
```

[23]:
```
dataframe['MaritalStatus'].replace('Married',1, inplace=True)
dataframe['MaritalStatus'].replace('Single',2, inplace=True)
dataframe['MaritalStatus'].replace('Divorced',3, inplace=True)
```

[24]:
```
dataframe['MaritalStatus'].value_counts()
```

[24]:
```
1    673
2    470
3    327
Name: MaritalStatus, dtype: int64
```

[25]:
```
x=dataframe.select_dtypes(include=['int64'])
x.dtypes
```

[25]:
```
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
```

[26]:
```
x.columns
```

[26]:
```
Index(['Age', 'Attrition', 'Department', 'DistanceFromHome', 'Education',
       'EducationField', 'EnvironmentSatisfaction', 'JobSatisfaction',
       'MaritalStatus', 'MonthlyIncome', 'NumCompaniesWorked',
       'WorkLifeBalance', 'YearsAtCompany'],
      dtype='object')
```

[27]:
```
y=dataframe['Attrition']
```

[28]:
```
y.head()
```

[28]:
```
0    1
1    0
2    1
3    0
4    0
Name: Attrition, dtype: int64
```

[29]:
```
y, x = dmatrices('Attrition ~ Age + Department + \
                  DistanceFromHome + Education + EducationField +␣
 ↪YearsAtCompany',
                  dataframe, return_type="dataframe")
print (x.columns)
```

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

[30]:
```
y = np.ravel(y)
```

13 Model Building

[31]:
```
from sklearn.linear_model import LogisticRegression

model = LogisticRegression()
model = model.fit(x, y)
```

```
# check the accuracy on the training set
model.score(x, y)
```

```
C:\Users\Anushree\Anaconda3\envs\tf_training\lib\site-
packages\sklearn\linear_model\logistic.py:433: FutureWarning: Default solver
will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

[31]: 0.8408163265306122

[33]:
```
y.mean()
```

[33]: 0.16122448979591836

[34]:
```
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)
```

```
C:\Users\Anushree\Anaconda3\envs\tf_training\lib\site-
packages\sklearn\linear_model\logistic.py:433: FutureWarning: Default solver
will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

[34]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

14 Prediction on test data

[35]:
```
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.]
```

[36]:
```
probs = model2.predict_proba(X_test)
print (probs)
```

```
[[0.86257761 0.13742239]
 [0.80710189 0.19289811]
 [0.7429987  0.2570013 ]
 [0.83583504 0.16416496]
 [0.73307035 0.26692965]
 [0.78942615 0.21057385]
 [0.85718191 0.14281809]
 [0.85697723 0.14302277]
 [0.96732187 0.03267813]
 [0.93781765 0.06218235]
 [0.95112889 0.04887111]
 [0.83140356 0.16859644]
 [0.86069144 0.13930856]
 [0.863881   0.136119  ]
 [0.88818146 0.11181854]
 [0.88851235 0.11148765]
 [0.88418532 0.11581468]
 [0.78102191 0.21897809]
 [0.79870103 0.20129897]
 [0.88654952 0.11345048]
 [0.70201258 0.29798742]
 [0.94684452 0.05315548]
 [0.86687518 0.13312482]
 [0.84389943 0.15610057]
 [0.60328043 0.39671957]
 [0.8112161  0.1887839 ]
 [0.91914771 0.08085229]
 [0.93333047 0.06666953]
 [0.67850927 0.32149073]
 [0.87080099 0.12919901]
 [0.87277322 0.12722678]
 [0.77054173 0.22945827]
 [0.86434352 0.13565648]
 [0.95829505 0.04170495]
 [0.84589968 0.15410032]
 [0.86642435 0.13357565]
 [0.90489195 0.09510805]
 [0.68640634 0.31359366]
 [0.90762923 0.09237077]
```

```
[0.80686978 0.19313022]
[0.91626105 0.08373895]
[0.82434807 0.17565193]
[0.93702713 0.06297287]
[0.93419719 0.06580281]
[0.89317815 0.10682185]
[0.85163342 0.14836658]
[0.78599372 0.21400628]
[0.84591285 0.15408715]
[0.66035418 0.33964582]
[0.75985595 0.24014405]
[0.92971879 0.07028121]
[0.79073149 0.20926851]
[0.86251514 0.13748486]
[0.86028777 0.13971223]
[0.87176033 0.12823967]
[0.79087814 0.20912186]
[0.87589802 0.12410198]
[0.84351786 0.15648214]
[0.72814826 0.27185174]
[0.83401865 0.16598135]
[0.90193848 0.09806152]
[0.70822548 0.29177452]
[0.92855494 0.07144506]
[0.84184113 0.15815887]
[0.79759143 0.20240857]
[0.86955841 0.13044159]
[0.91690233 0.08309767]
[0.84801457 0.15198543]
[0.89284306 0.10715694]
[0.63214954 0.36785046]
[0.93929587 0.06070413]
[0.72436084 0.27563916]
[0.85581742 0.14418258]
[0.84210919 0.15789081]
[0.77522163 0.22477837]
[0.71561254 0.28438746]
[0.93625216 0.06374784]
[0.95759882 0.04240118]
[0.79115941 0.20884059]
[0.89387487 0.10612513]
[0.9143774  0.0856226 ]
[0.79373481 0.20626519]
[0.78032498 0.21967502]
[0.79647769 0.20352231]
[0.83618218 0.16381782]
[0.71431018 0.28568982]
[0.97808679 0.02191321]
```

```
[0.94675994 0.05324006]
[0.88520539 0.11479461]
[0.79405267 0.20594733]
[0.61481071 0.38518929]
[0.81886235 0.18113765]
[0.74684358 0.25315642]
[0.86722821 0.13277179]
[0.86992409 0.13007591]
[0.81789428 0.18210572]
[0.71822509 0.28177491]
[0.60023923 0.39976077]
[0.83836485 0.16163515]
[0.88216124 0.11783876]
[0.74418148 0.25581852]
[0.76564261 0.23435739]
[0.98067742 0.01932258]
[0.91939455 0.08060545]
[0.77415323 0.22584677]
[0.92564103 0.07435897]
[0.88199097 0.11800903]
[0.74514347 0.25485653]
[0.90673063 0.09326937]
[0.78928203 0.21071797]
[0.80971647 0.19028353]
[0.93515971 0.06484029]
[0.93924676 0.06075324]
[0.79462059 0.20537941]
[0.81215385 0.18784615]
[0.91649218 0.08350782]
[0.90265873 0.09734127]
[0.84731114 0.15268886]
[0.95376317 0.04623683]
[0.91222675 0.08777325]
[0.86028682 0.13971318]
[0.85822982 0.14177018]
[0.87448572 0.12551428]
[0.75985594 0.24014406]
[0.92296733 0.07703267]
[0.96914997 0.03085003]
[0.94407447 0.05592553]
[0.81720383 0.18279617]
[0.88066242 0.11933758]
[0.77639891 0.22360109]
[0.97128842 0.02871158]
[0.88831439 0.11168561]
[0.78631482 0.21368518]
[0.81840678 0.18159322]
[0.94987331 0.05012669]
```

```
[0.95894743 0.04105257]
[0.73447703 0.26552297]
[0.93444274 0.06555726]
[0.73813794 0.26186206]
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```

```
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```

15 Model Evaluation

[40]:
```
from sklearn import metrics

print ("Accuracy=",metrics.accuracy_score(y_test, predicted))
print ("ROC=",metrics.roc_auc_score(y_test, probs[:, 1]))
```

```
Accuracy= 0.8435374149659864
ROC= 0.6500577589526376
```

[41]:
```
print("Confusion Matrix")
print (metrics.confusion_matrix(y_test, predicted))
print("Classification Report")
print (metrics.classification_report(y_test, predicted))
```

```
Confusion Matrix
[[371   0]
 [ 69   1]]
Classification Report
              precision    recall  f1-score   support

         0.0       0.84      1.00      0.91       371
         1.0       1.00      0.01      0.03        70

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

[42]:
```
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
320         1.0  27.0         2.0               2.0        3.0
452         1.0  45.0         2.0               2.0        3.0
195         1.0  37.0         1.0              21.0        3.0
776         1.0  20.0         2.0               9.0        3.0
1295        1.0  41.0         2.0               4.0        1.0
70          1.0  59.0         2.0               1.0        1.0
1135        1.0  46.0         2.0               1.0        4.0
1011        1.0  36.0         2.0               3.0        4.0
10          1.0  35.0         1.0              16.0        3.0
1265        1.0  33.0         1.0               4.0        3.0
1270        1.0  34.0         2.0               3.0        2.0
1257        1.0  31.0         2.0              16.0        4.0
271         1.0  47.0         1.0              29.0        4.0
858         1.0  53.0         1.0               7.0        2.0
790         1.0  33.0         1.0               5.0        3.0
1290        1.0  34.0         1.0               9.0        4.0
915         1.0  21.0         1.0              10.0        2.0
64          1.0  36.0         1.0               8.0        3.0
959         1.0  40.0         1.0               2.0        3.0
1274        1.0  31.0         2.0              29.0        4.0
1394        1.0  32.0         1.0               5.0        4.0
1109        1.0  30.0         2.0              29.0        4.0
416         1.0  38.0         1.0               2.0        2.0
1234        1.0  47.0         2.0               2.0        4.0
687         1.0  36.0         1.0               2.0        4.0
…           …    …            …                 …          …
1445        1.0  41.0         1.0              28.0        4.0
1201        1.0  23.0         1.0               8.0        1.0
99          1.0  44.0         1.0              23.0        3.0
850         1.0  32.0         2.0               2.0        1.0
448         1.0  40.0         1.0               6.0        3.0
755         1.0  45.0         2.0              11.0        2.0
976         1.0  56.0         1.0              23.0        3.0
115         1.0  37.0         2.0               3.0        3.0
777         1.0  21.0         1.0              10.0        3.0
72          1.0  31.0         1.0               1.0        4.0
845         1.0  40.0         1.0              26.0        2.0
537         1.0  27.0         1.0              10.0        2.0
849         1.0  43.0         2.0               9.0        3.0
174         1.0  45.0         2.0               4.0        2.0
```

87	1.0	51.0	1.0	9.0	4.0
551	1.0	39.0	3.0	3.0	3.0
705	1.0	39.0	2.0	2.0	5.0
314	1.0	39.0	1.0	10.0	1.0
1420	1.0	41.0	1.0	1.0	3.0
600	1.0	32.0	1.0	4.0	3.0
1094	1.0	40.0	2.0	9.0	2.0
599	1.0	36.0	3.0	13.0	3.0
277	1.0	38.0	2.0	7.0	2.0
1033	1.0	31.0	1.0	1.0	5.0
1383	1.0	36.0	1.0	9.0	4.0
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
320	1.0	5.0
452	4.0	8.0
195	1.0	8.0
776	3.0	2.0
1295	3.0	22.0
70	1.0	4.0
1135	1.0	26.0
1011	3.0	5.0
10	2.0	5.0
1265	5.0	9.0
1270	1.0	2.0
1257	3.0	1.0
271	1.0	10.0
858	2.0	7.0
790	1.0	3.0
1290	1.0	7.0
915	1.0	2.0
64	5.0	17.0
959	1.0	9.0
1274	3.0	12.0
1394	1.0	1.0
1109	5.0	4.0
416	1.0	1.0
1234	3.0	1.0
687	2.0	11.0

```
...          ...          ...
1445         1.0         20.0
1201         2.0          5.0
99           2.0          3.0
850          1.0          1.0
448          1.0         20.0
755          1.0          9.0
976          1.0         19.0
115          1.0          5.0
777          1.0          1.0
72           2.0          1.0
845          2.0          1.0
537          1.0          9.0
849          3.0          4.0
174          1.0          5.0
87           1.0          4.0
551          6.0          8.0
705          1.0          8.0
314          2.0         21.0
1420         1.0          5.0
600          1.0         14.0
1094         2.0          8.0
599          6.0          5.0
277          2.0          8.0
1033         1.0         10.0
1383         1.0          5.0
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]
```

[43]:
```
#add random values to KK according to the parameters mentioned above to check␣
 ↪the proabily of attrition of the employee
kk=[[1.0, 23.0, 1.0, 500.0, 3.0, 24.0, 1.0]]
print(model.predict_proba(kk))
```

```
[[7.14144701e-07 9.99999286e-01]]
```

16 Conclusion

We have created a Logistic Regression model for the prediction of Employees Attrition. Our model can predict the Attrition of the employee with the accuracy of 84%. We should perform feature engineering on the data and try other classification models such as Random Forest,SVM,KNN and DT to acheive better accuracy.