In [ ]:
```
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
```

In [ ]:
```
dataframe=pd.read_csv("IBM Attrition Data.csv")
```

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

Out[ ]:

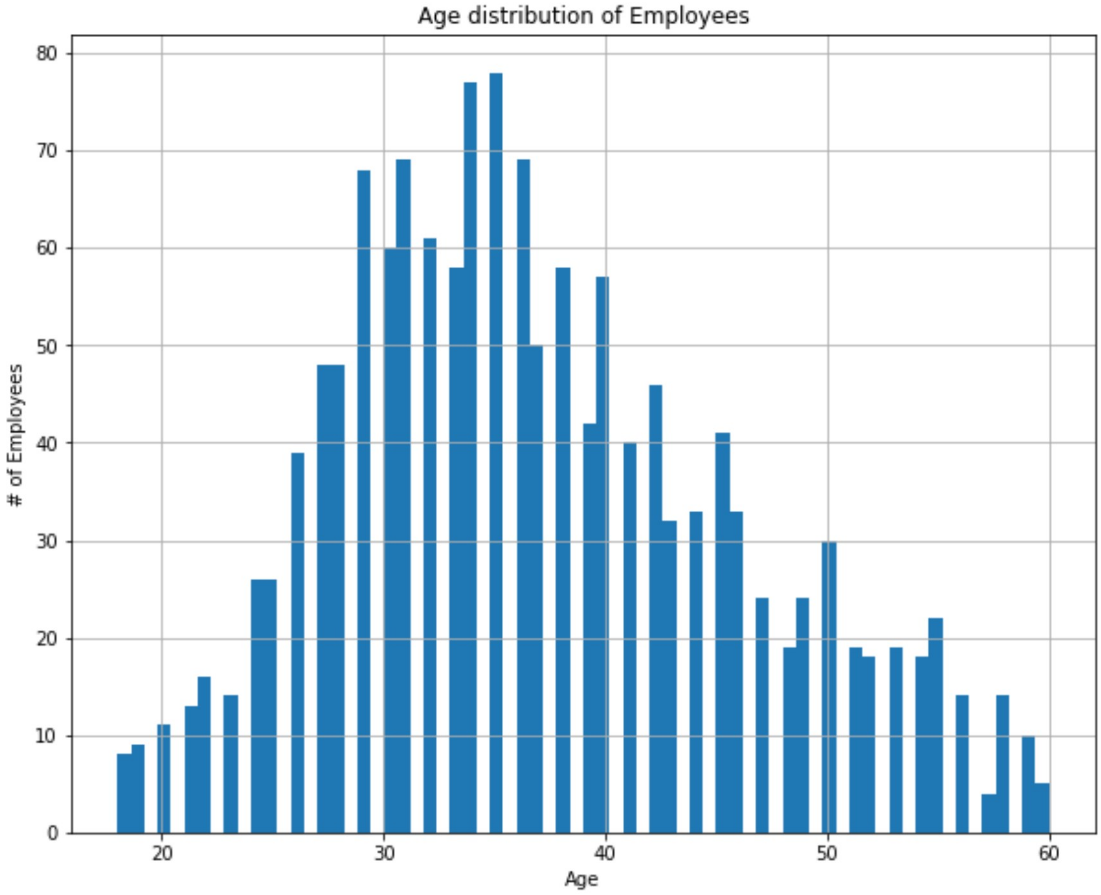
| | Age | Attrition | Department | DistanceFromHome | Education | EducationField | Environmen |
|---|---|---|---|---|---|---|---|
| **0** | 41 | Yes | Sales | 1 | 2 | Life Sciences | |
| **1** | 49 | No | Research & Development | 8 | 1 | Life Sciences | |
| **2** | 37 | Yes | Research & Development | 2 | 2 | Other | |
| **3** | 33 | No | Research & Development | 3 | 4 | Life Sciences | |
| **4** | 27 | No | Research & Development | 2 | 1 | Medical | |

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

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

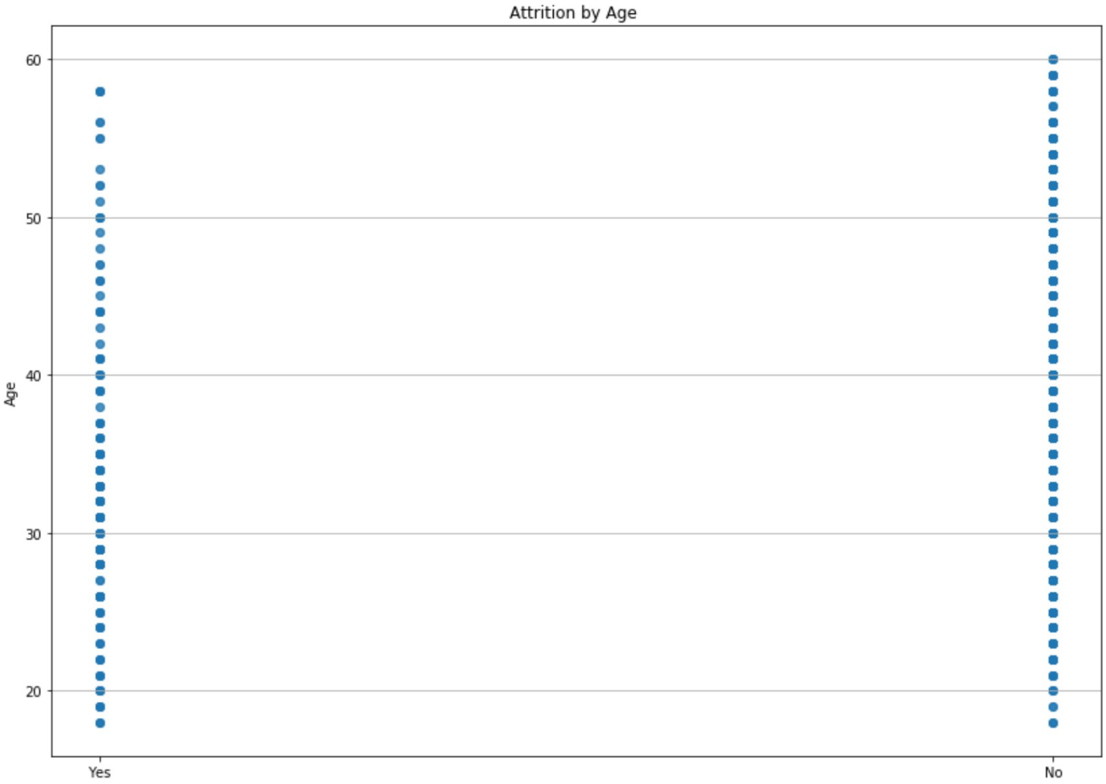
In [ ]:

```
# 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()
```



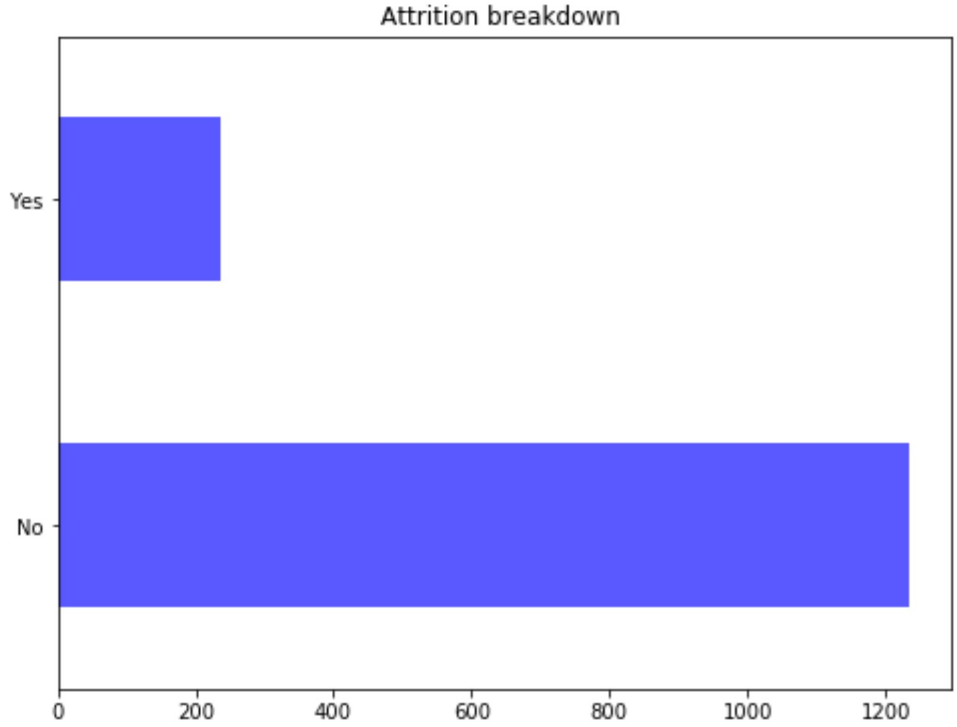
In [ ]:

```
# 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()
```



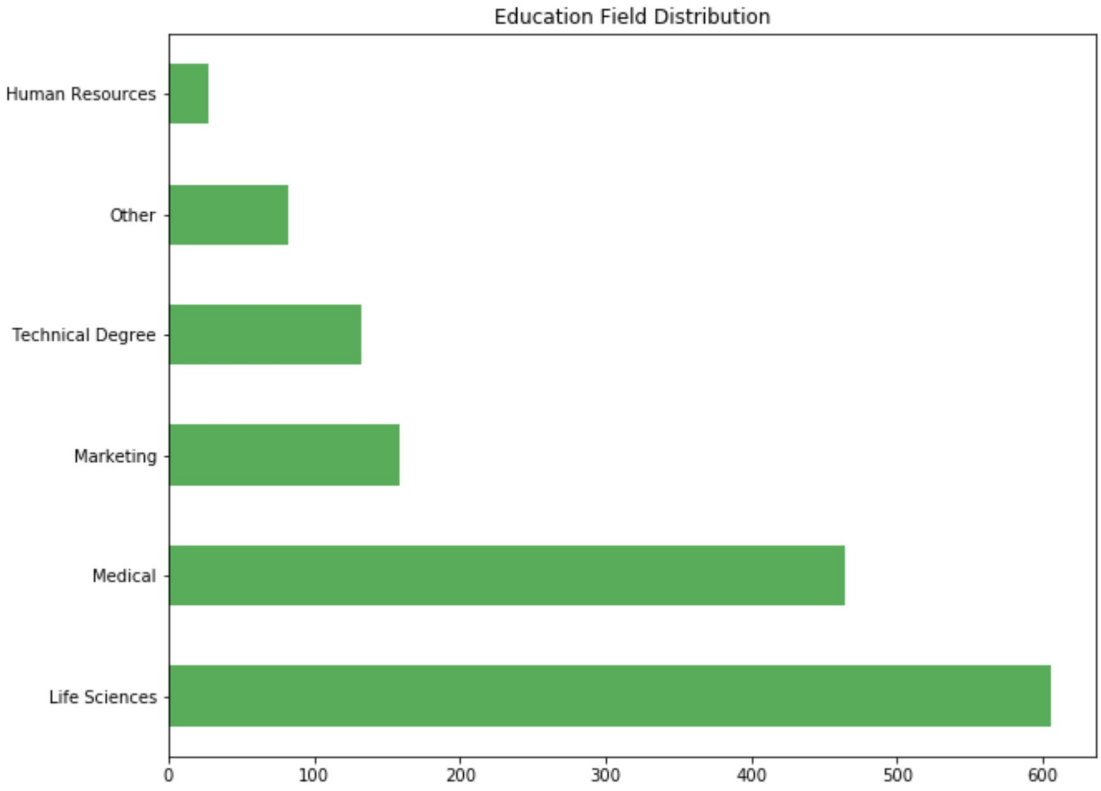
In [ ]:

```
# 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()
```

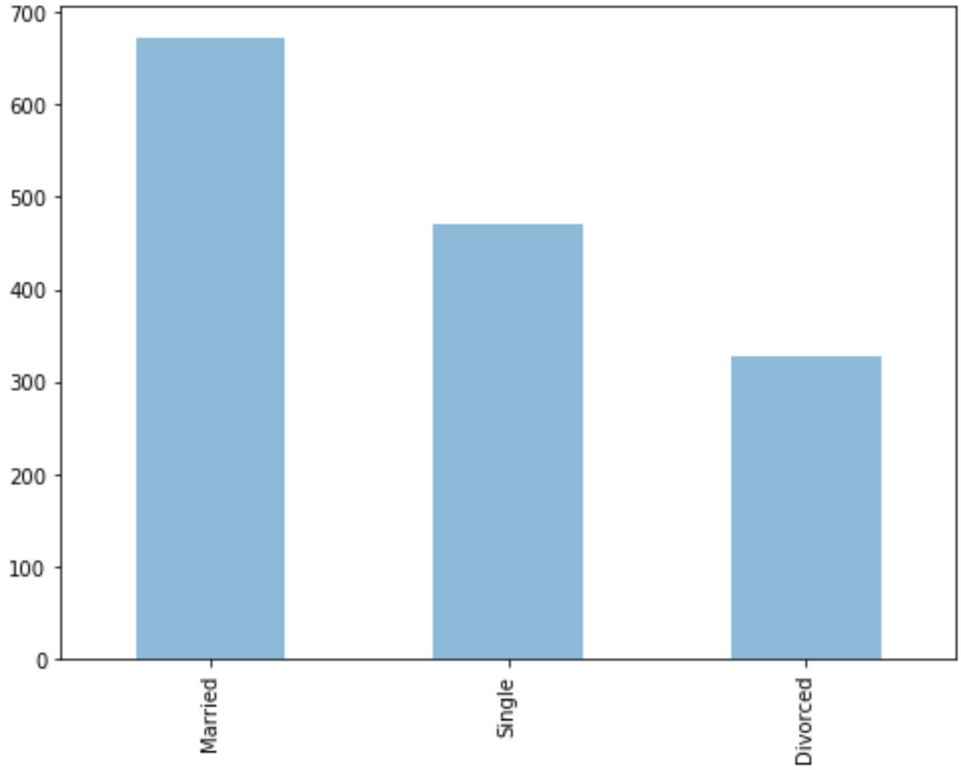


In [ ]:

```
# 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()
```



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



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

Out[ ]:

| | Age | DistanceFromHome | Education | EnvironmentSatisfaction | JobSatisfact |
|---|---|---|---|---|---|
| **count** | 1470.000000 | 1470.000000 | 1470.000000 | 1470.000000 | 1470.000 |
| **mean** | 36.923810 | 9.192517 | 2.912925 | 2.721769 | 2.728 |
| **std** | 9.135373 | 8.106864 | 1.024165 | 1.093082 | 1.102 |
| **min** | 18.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000 |
| **25%** | 30.000000 | 2.000000 | 2.000000 | 2.000000 | 2.000 |
| **50%** | 36.000000 | 7.000000 | 3.000000 | 3.000000 | 3.000 |
| **75%** | 43.000000 | 14.000000 | 4.000000 | 4.000000 | 4.000 |
| **max** | 60.000000 | 29.000000 | 5.000000 | 4.000000 | 4.000 |

```
In [ ]: 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
```

```
In [ ]: dataframe.columns

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

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

Out[ ]: 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
```

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

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

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

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

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

In [ ]:

```
dataframe.head(10)
```

Out[ ]:

| | Age | Attrition | Department | DistanceFromHome | Education | EducationField | Environmen |
|---|---|---|---|---|---|---|---|
| **0** | 41 | 1 | Sales | 1 | 2 | Life Sciences | |
| **1** | 49 | 0 | Research & Development | 8 | 1 | Life Sciences | |
| **2** | 37 | 1 | Research & Development | 2 | 2 | Other | |
| **3** | 33 | 0 | Research & Development | 3 | 4 | Life Sciences | |
| **4** | 27 | 0 | Research & Development | 2 | 1 | Medical | |
| **5** | 32 | 0 | Research & Development | 2 | 2 | Life Sciences | |
| **6** | 59 | 0 | Research & Development | 3 | 3 | Medical | |
| **7** | 30 | 0 | Research & Development | 24 | 1 | Life Sciences | |
| **8** | 38 | 0 | Research & Development | 23 | 3 | Life Sciences | |
| **9** | 36 | 0 | Research & Development | 27 | 3 | Medical | |

In [ ]:

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

Out[ ]:

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

In [ ]:

```
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)
```

In [ ]:

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

Out[ ]:

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

In [ ]:

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

Out[ ]:

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

In [ ]:

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

In [ ]:

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

Out[ ]:

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

In [ ]:

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

Out[ ]:

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

In [ ]:

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

In [ ]:

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

Out[ ]:

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

In [ ]:

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

Out[ ]:

```
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
```

In [ ]:
```
x.columns
```

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

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

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

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

In [ ]:
```
y, x = dmatrices('Attrition ~ Age + Department + \
                  DistanceFromHome + Education + EducationField + YearsAt
Company',
                  dataframe, return_type="dataframe")
print (x.columns)
```

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

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

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

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

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

```
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logisti
c.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.
22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[ ]:
```
0.8408163265306122
```

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

Out[ ]:
```
0.16122448979591836
```

In [ ]:
```
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)
```

```
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logisti
c.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.
22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[ ]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=T
rue,
          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)
```

In [ ]:
```
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.]
```

In [ ]:

```
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]
 [0.82247975 0.17752025]
 [0.82289185 0.17710815]
 [0.89920393 0.10079607]
 [0.78516352 0.21483648]
 [0.89653967 0.10346033]
 [0.91537087 0.08462913]
 [0.92820436 0.07179564]
 [0.96589553 0.03410447]
 [0.94419804 0.05580196]
 [0.93024428 0.06975572]
 [0.66112588 0.33887412]
 [0.84095505 0.15904495]
 [0.82603046 0.17396954]
 [0.80610059 0.19389941]
 [0.96191568 0.03808432]
 [0.93671599 0.06328401]
 [0.94770351 0.05229649]
 [0.97376472 0.02623528]
 [0.79369198 0.20630802]
 [0.87741394 0.12258606]
 [0.85956848 0.14043152]
 [0.95216215 0.04783785]
 [0.93160388 0.06839612]
 [0.75495757 0.24504243]
 [0.74998837 0.25001163]
 [0.95590644 0.04409356]
 [0.86936376 0.13063624]
 [0.81422948 0.18577052]
 [0.76650749 0.23349251]
 [0.80183602 0.19816398]
 [0.92798469 0.07201531]
 [0.91054713 0.08945287]
 [0.94603047 0.05396953]
 [0.93400754 0.06599246]
 [0.69063333 0.30936667]
 [0.93091068 0.06908932]
 [0.74159667 0.25840333]
 [0.78516386 0.21483614]
 [0.93229165 0.06770835]
 [0.80621879 0.19378121]
 [0.85290079 0.14709921]
 [0.66903659 0.33096341]
 [0.9042279  0.0957721 ]
 [0.91210155 0.08789845]
 [0.87547616 0.12452384]
 [0.93020588 0.06979412]
 [0.66879074 0.33120926]
 [0.89374371 0.10625629]
 [0.86196532 0.13803468]
 [0.78749466 0.21250534]
 [0.53185454 0.46814546]
 [0.73337673 0.26662327]
 [0.70603668 0.29396332]
 [0.85434454 0.14565546]
 [0.869108   0.130892  ]
 [0.75104191 0.24895809]
 [0.89891506 0.10108494]
 [0.79281444 0.20718556]
 [0.90787555 0.09212445]
 [0.77348776 0.22651224]
 [0.88287113 0.11712887]
 [0.85302465 0.14697535]
 [0.8195964  0.1804036 ]
 [0.74239392 0.25760608]
 [0.86238441 0.13761559]
 [0.77748616 0.22251384]
 [0.76912758 0.23087242]
 [0.7938589  0.2061411 ]
 [0.92209228 0.07790772]
 [0.74615104 0.25384896]
 [0.87485382 0.12514618]
 [0.85477514 0.14522486]
 [0.77450251 0.22549749]
 [0.87362727 0.12637273]
 [0.67359458 0.32640542]
 [0.93698936 0.06301064]
 [0.82461956 0.17538044]
 [0.95188386 0.04811614]
 [0.83450941 0.16549059]
 [0.81117757 0.18882243]
 [0.80629478 0.19370522]
 [0.87690301 0.12309699]
 [0.6663069  0.3336931 ]
 [0.59350144 0.40649856]
 [0.98983468 0.01016532]
 [0.70381235 0.29618765]
 [0.91693005 0.08306995]
 [0.92230104 0.07769896]
 [0.71009303 0.28990697]
 [0.62307399 0.37692601]
 [0.76273323 0.23726677]
 [0.95379074 0.04620926]
 [0.88139107 0.11860893]
 [0.85805507 0.14194493]
 [0.92153445 0.07846555]
 [0.87986341 0.12013659]
 [0.80455714 0.19544286]
 [0.8045461  0.1954539 ]
 [0.91400939 0.08599061]
 [0.71996681 0.28003319]
 [0.9459133  0.0540867 ]
 [0.90887304 0.09112696]
 [0.73122211 0.26877789]
 [0.98139747 0.01860253]
 [0.85440507 0.14559493]
 [0.89904525 0.10095475]
 [0.82348836 0.17651164]
 [0.83289134 0.16710866]
 [0.88059965 0.11940035]
 [0.87965985 0.12034015]
 [0.87516106 0.12483894]
 [0.8154612  0.1845388 ]
 [0.88085227 0.11914773]
 [0.61440015 0.38559985]
 [0.88813952 0.11186048]
 [0.89579477 0.10420523]
 [0.85493829 0.14506171]
 [0.98316036 0.01683964]
 [0.7717054  0.2282946 ]
 [0.62163203 0.37836797]
 [0.82648597 0.17351403]
 [0.84082886 0.15917114]
 [0.84770539 0.15229461]
 [0.84996276 0.15003724]
 [0.7568283  0.2431717 ]
 [0.86135648 0.13864352]
 [0.90742097 0.09257903]
 [0.84653325 0.15346675]
 [0.81068432 0.18931568]
 [0.74291535 0.25708465]
 [0.87004234 0.12995766]
 [0.83937674 0.16062326]
 [0.86204616 0.13795384]
 [0.66559201 0.33440799]
 [0.90809363 0.09190637]
 [0.87063167 0.12936833]
 [0.92591545 0.07408455]
 [0.84519617 0.15480383]
 [0.89988333 0.10011667]
 [0.91377645 0.08622355]
 [0.79655167 0.20344833]
 [0.63617514 0.36382486]
 [0.8451662  0.1548338 ]
 [0.75229555 0.24770445]
 [0.85439954 0.14560046]
 [0.99258502 0.00741498]
 [0.85979235 0.14020765]
 [0.88042046 0.11957954]
 [0.82752509 0.17247491]
 [0.93110919 0.06889081]
 [0.87320755 0.12679245]
 [0.88685479 0.11314521]
 [0.83757498 0.16242502]
 [0.86470667 0.13529333]
 [0.86456218 0.13543782]
 [0.89956239 0.10043761]
 [0.78624587 0.21375413]
 [0.79354081 0.20645919]
 [0.88436844 0.11563156]
 [0.6517352  0.3482648 ]
 [0.94078665 0.05921335]
 [0.8998614  0.1001386 ]
 [0.72416846 0.27583154]
 [0.68855828 0.31144172]
 [0.87401796 0.12598204]
 [0.86388337 0.13611663]
 [0.97515719 0.02484281]
 [0.86301941 0.13698059]
 [0.54429973 0.45570027]
 [0.91312117 0.08687883]
 [0.74864711 0.25135289]
 [0.86865164 0.13134836]
 [0.88768464 0.11231536]
 [0.87825968 0.12174032]
 [0.85578493 0.14421507]
 [0.77096345 0.22903655]
 [0.80608869 0.19391131]
 [0.85164484 0.14835516]
 [0.7748914  0.2251086 ]
 [0.70330443 0.29669557]
 [0.88920999 0.11079001]
 [0.48805675 0.51194325]
 [0.92443534 0.07556466]
 [0.75730317 0.24269683]
 [0.67532223 0.32467777]
 [0.91267187 0.08732813]
 [0.94004403 0.05995597]
 [0.88105134 0.11894866]
 [0.88500438 0.11499562]
 [0.95620493 0.04379507]
 [0.90018491 0.09981509]
 [0.94913267 0.05086733]
 [0.83164948 0.16835052]
 [0.87828332 0.12171668]
 [0.81856033 0.18143967]
 [0.81510872 0.18489128]
 [0.95165724 0.04834276]
 [0.86885777 0.13114223]
 [0.90404843 0.09595157]
 [0.83568878 0.16431122]
 [0.84565343 0.15434657]
 [0.79355796 0.20644204]
 [0.81574488 0.18425512]
 [0.81449702 0.18550298]
 [0.83624028 0.16375972]
 [0.91389238 0.08610762]
 [0.91564837 0.08435163]
 [0.68306915 0.31693085]
 [0.99086383 0.00913617]
 [0.76974325 0.23025675]
 [0.79740377 0.20259623]
 [0.72822071 0.27177929]
 [0.67182682 0.32817318]
 [0.79710573 0.20289427]
 [0.84931231 0.15068769]
 [0.86433739 0.13566261]
 [0.85920637 0.14079363]
 [0.84420225 0.15579775]
 [0.82853445 0.17146555]
 [0.92215641 0.07784359]
 [0.82960704 0.17039296]
 [0.97700212 0.02299788]
 [0.90454177 0.09545823]
 [0.92773082 0.07226918]
 [0.84754954 0.15245046]
 [0.76612754 0.23387246]
 [0.94894713 0.05105287]
 [0.94800941 0.05199059]
 [0.75328457 0.24671543]
 [0.87742303 0.12257697]
 [0.80519574 0.19480426]
 [0.93916181 0.06083819]
 [0.85990185 0.14009815]
 [0.75971578 0.24028422]
 [0.90848727 0.09151273]
 [0.7529481  0.2470519 ]
 [0.94361137 0.05638863]
 [0.91817801 0.08182199]
 [0.90585801 0.09414199]
 [0.77143638 0.22856362]
 [0.92392657 0.07607343]
 [0.80755229 0.19244771]
 [0.9013237  0.0986763 ]
 [0.87830849 0.12169151]
 [0.8068256  0.1931744 ]
 [0.83483933 0.16516067]
 [0.53939525 0.46060475]
 [0.95106284 0.04893716]
 [0.73235519 0.26764481]
 [0.892211   0.107789  ]
 [0.80131021 0.19868979]
 [0.87926632 0.12073368]
 [0.96835844 0.03164156]
 [0.81435024 0.18564976]
 [0.8595391  0.1404609 ]
 [0.59090241 0.40909759]
 [0.82620318 0.17379682]
 [0.92520542 0.07479458]
 [0.81774745 0.18225255]
 [0.92599818 0.07400182]
 [0.89198781 0.10801219]
 [0.70041077 0.29958923]
 [0.82018762 0.17981238]
 [0.96584774 0.03415226]
 [0.87007757 0.12992243]
 [0.8985835  0.1014165 ]
 [0.89010322 0.10989678]
 [0.81133218 0.18866782]
 [0.85998392 0.14001608]
 [0.83705922 0.16294078]
 [0.83833325 0.16166675]
 [0.82480592 0.17519408]
 [0.94132438 0.05867562]
 [0.83011466 0.16988534]
 [0.77419827 0.22580173]
 [0.69208833 0.30791167]
 [0.86186596 0.13813404]
 [0.82653322 0.17346678]
 [0.84351252 0.15648748]
 [0.87151308 0.12848692]
 [0.89317815 0.10682185]
 [0.82864779 0.17135221]
 [0.7290552  0.2709448 ]
 [0.9473871  0.0526129 ]
 [0.96100837 0.03899163]
 [0.9049959  0.0950041 ]
 [0.88585723 0.11414277]
 [0.84839464 0.15160536]
 [0.78874009 0.21125991]
 [0.67361889 0.32638111]
 [0.93357031 0.06642969]
 [0.65079394 0.34920606]
 [0.74503232 0.25496768]
 [0.9420944  0.0579056 ]
 [0.78550077 0.21449923]
 [0.90782391 0.09217609]
 [0.81479395 0.18520605]
 [0.89162714 0.10837286]
 [0.85619491 0.14380509]
 [0.67747664 0.32252336]
```

In [ ]:

```
from sklearn import metrics

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

```
0.8435374149659864
0.6500577589526376
```

In [ ]:

```
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

   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
```

In [ ]:

```
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]
```

In [ ]:

```
#add random values to KK according to the parameters mentioned above to c
heck 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))
```

```
[[7.14139240e-07 9.99999286e-01]]
```