Customer Churn Prediction

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Name of the Intern : Tejas Vidyadhar Kudalkar

Internship Project Name - Customer Churn Prediction Using Machine Learning

Company Name - CodSoft

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
dataset = pd.read_csv('C:\\Users\\Dell\\Downloads\\Churn_Modelling.csv')
```

[3]:
```
dataset
```

[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	\
0	1	15634602	Hargrave	619	France	Female	42	
1	2	15647311	Hill	608	Spain	Female	41	
2	3	15619304	Onio	502	France	Female	42	
3	4	15701354	Boni	699	France	Female	39	
4	5	15737888	Mitchell	850	Spain	Female	43	
…	…	…	…	…	…	…	…	
9995	9996	15606229	Obijiaku	771	France	Male	39	
9996	9997	15569892	Johnstone	516	France	Male	35	
9997	9998	15584532	Liu	709	France	Female	36	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	
9999	10000	15628319	Walker	792	France	Female	28	

	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	\
0	2	0.00	1	1	1	
1	1	83807.86	1	0	1	
2	8	159660.80	3	1	0	
3	1	0.00	2	0	0	
4	2	125510.82	1	1	1	
…	…	…	…	…	…	
9995	5	0.00	2	1	0	
9996	10	57369.61	1	1	1	
9997	7	0.00	1	0	1	
9998	3	75075.31	2	1	0	

```
9999       4  130142.79              1          1               0

      EstimatedSalary  Exited
0           101348.88       1
1           112542.58       0
2           113931.57       1
3            93826.63       0
4            79084.10       0
…                 …     …
9995         96270.64       0
9996        101699.77       0
9997         42085.58       1
9998         92888.52       1
9999         38190.78       0

[10000 rows x 14 columns]
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

[5]:
```
dataset = dataset.drop(columns = ['RowNumber','CustomerId','Surname'])
```

[6]:
```
dataset
```

[6]:
```
      CreditScore Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
0             619    France  Female   42       2       0.00              1
1             608     Spain  Female   41       1   83807.86              1
```

```
2             502    France  Female   42       8  159660.80              3
3             699    France  Female   39       1       0.00              2
4             850     Spain  Female   43       2  125510.82              1
…             …       …      …        …        …          …              …
9995          771    France    Male   39       5       0.00              2
9996          516    France    Male   35      10   57369.61              1
9997          709    France  Female   36       7       0.00              1
9998          772   Germany    Male   42       3   75075.31              2
9999          792    France  Female   28       4  130142.79              1

      HasCrCard  IsActiveMember  EstimatedSalary  Exited
0             1               1        101348.88       1
1             0               1        112542.58       0
2             1               0        113931.57       1
3             0               0         93826.63       0
4             1               1         79084.10       0
…         …              …               …      …
9995          1               0         96270.64       0
9996          1               1        101699.77       0
9997          0               1         42085.58       1
9998          1               0         92888.52       1
9999          1               0         38190.78       0

[10000 rows x 11 columns]
```

[7]:
```
dataset['Geography'].unique()
```

[7]:
```
array(['France', 'Spain', 'Germany'], dtype=object)
```

[8]:
```
dataset['Gender'].unique()
```

[8]:
```
array(['Female', 'Male'], dtype=object)
```

[9]:
```
# One hot encoding
```

[10]:
```
dataset = pd.get_dummies(data = dataset,drop_first = True)
```

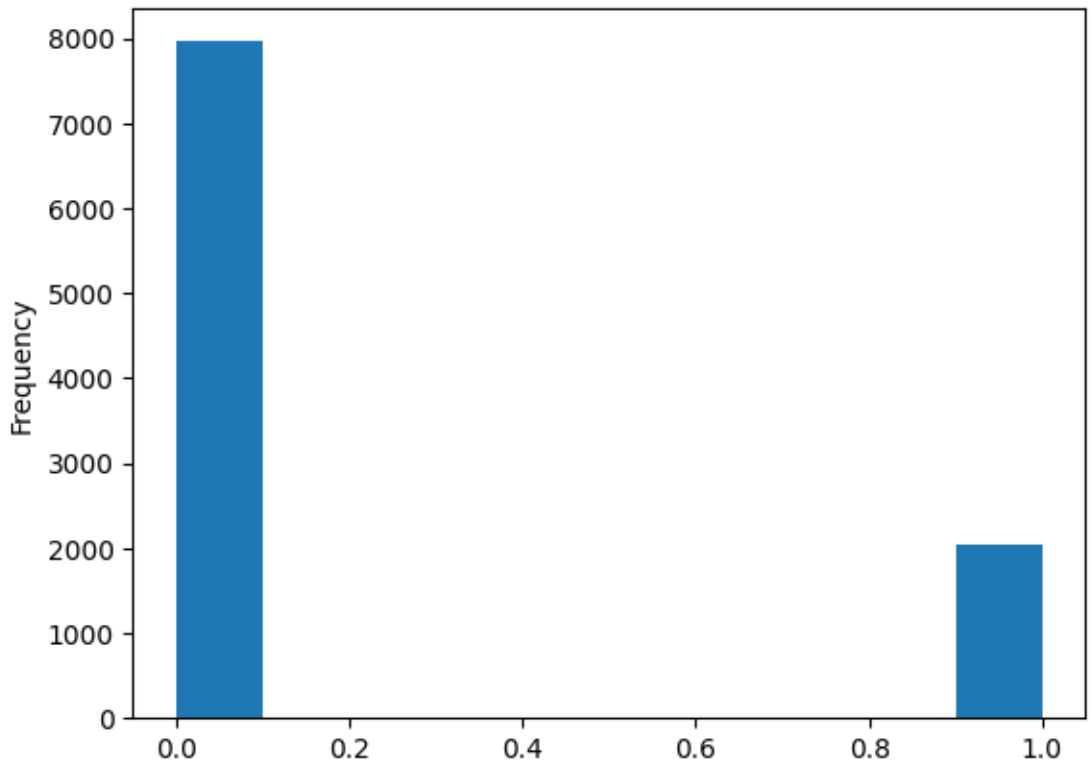
[11]:
```
dataset
```

[11]:
```
      CreditScore  Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0             619   42       2       0.00              1          1
1             608   41       1   83807.86              1          0
2             502   42       8  159660.80              3          1
3             699   39       1       0.00              2          0
4             850   43       2  125510.82              1          1
…             …     …        …          …              …          …
9995          771   39       5       0.00              2          1
9996          516   35      10   57369.61              1          1
```

```
9997          709   36       7       0.00              1          0
9998          772   42       3   75075.31              2          1
9999          792   28       4  130142.79              1          1

      IsActiveMember  EstimatedSalary  Exited  Geography_Germany  \
0                  1        101348.88       1                  0
1                  1        112542.58       0                  0
2                  0        113931.57       1                  0
3                  0         93826.63       0                  0
4                  1         79084.10       0                  0
…                …                …     …                  …
9995               0         96270.64       0                  0
9996               1        101699.77       0                  0
9997               1         42085.58       1                  0
9998               0         92888.52       1                  1
9999               0         38190.78       0                  0

      Geography_Spain  Gender_Male
0                   0            0
1                   1            0
2                   0            0
3                   0            0
4                   1            0
…                 …          …
9995                0            1
9996                0            1
9997                0            0
9998                0            1
9999                0            0

[10000 rows x 12 columns]
```

[12]:
```
dataset.Exited.plot.hist()
```

[12]:
```
<AxesSubplot: ylabel='Frequency'>
```



[13]:
```
(dataset.Exited==0).sum()
```

[13]: 7963

[14]:
```
(dataset.Exited==1).sum()
```

[14]: 2037

[15]:
```
x = dataset.drop(columns =['Exited'])
y = dataset['Exited']
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.
 ↪2,random_state = 0)
```

[16]:
```
x
```

[16]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	\
0	619	42	2	0.00	1	1	
1	608	41	1	83807.86	1	0	
2	502	42	8	159660.80	3	1	
3	699	39	1	0.00	2	0	
4	850	43	2	125510.82	1	1	

```
…            …  …     …        …             …         …
9995          771   39       5       0.00              2          1
9996          516   35      10   57369.61              1          1
9997          709   36       7       0.00              1          0
9998          772   42       3   75075.31              2          1
9999          792   28       4  130142.79              1          1

      IsActiveMember  EstimatedSalary  Geography_Germany  Geography_Spain  \
0                  1        101348.88                  0                0
1                  1        112542.58                  0                1
2                  0        113931.57                  0                0
3                  0         93826.63                  0                0
4                  1         79084.10                  0                1
…                …                …                  …              …
9995               0         96270.64                  0                0
9996               1        101699.77                  0                0
9997               1         42085.58                  0                0
9998               0         92888.52                  1                0
9999               0         38190.78                  0                0

      Gender_Male
0               0
1               0
2               0
3               0
4               0
…             …
9995            1
9996            1
9997            0
9998            1
9999            0

[10000 rows x 11 columns]
```

[17]:
```
y
```

[17]:
```
0       1
1       0
2       1
3       0
4       0
       ..
9995    0
9996    0
9997    1
9998    1
```

```
9999    0
Name: Exited, Length: 10000, dtype: int64
```

[18]:
```
x_train.shape
```

[18]:
```
(8000, 11)
```

[19]:
```
y_train.shape
```

[19]:
```
(8000,)
```

[20]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.transform(x_test)
```

[21]:
```
x_train_scaled
```

[21]:
```
array([[ 0.16958176, -0.46460796,  0.00666099, …, -0.5698444 ,
         1.74309049, -1.09168714],
       [-2.30455945,  0.30102557, -1.37744033, …,  1.75486502,
        -0.57369368,  0.91601335],
       [-1.19119591, -0.94312892, -1.031415  , …, -0.5698444 ,
        -0.57369368, -1.09168714],
       …,
       [ 0.9015152 , -0.36890377,  0.00666099, …, -0.5698444 ,
        -0.57369368,  0.91601335],
       [-0.62420521, -0.08179119,  1.39076231, …, -0.5698444 ,
         1.74309049, -1.09168714],
       [-0.28401079,  0.87525072, -1.37744033, …,  1.75486502,
        -0.57369368, -1.09168714]])
```

[22]:
```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state=0).fit(x_train_scaled,y_train)
```

[23]:
```
y_pred = clf.predict(x_test_scaled)
```

[24]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score,␣
↪precision_score, recall_score
```

[25]:
```
acc = accuracy_score(y_test, y_pred)
conf = confusion_matrix(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
```

[26]:
```
result = pd.DataFrame([['Logistic Regression',acc,conf,f1,prec,recall]],columns␣
↪= ['Model','acc','conf','f1','prec','recall'])
```

[27]:
```
result
```

[27]:
```
                 Model    acc                     conf        f1      prec  \
0  Logistic Regression  0.811  [[1526, 69], [309, 96]]  0.336842  0.581818

     recall
0  0.237037
```

[28]:
```
from sklearn.ensemble import GradientBoostingClassifier

# Create and train the GradientBoostingClassifier
clf_gb = GradientBoostingClassifier(random_state=0)
clf_gb.fit(x_train_scaled, y_train)

# Make predictions using the trained model
y_pred_gb = clf_gb.predict(x_test_scaled)

# Calculate the metrics for the GradientBoostingClassifier
acc_gb = accuracy_score(y_test, y_pred_gb)
conf_gb = confusion_matrix(y_test, y_pred_gb)
f1_gb = f1_score(y_test, y_pred_gb)
prec_gb = precision_score(y_test, y_pred_gb)
recall_gb = recall_score(y_test, y_pred_gb)

# Create a DataFrame to store the results of the GradientBoostingClassifier
gb_result = pd.DataFrame([['GradientBoostingClassifier', acc_gb, conf_gb,␣
 ↪f1_gb, prec_gb, recall_gb]],
                         columns=['Model', 'acc', 'conf', 'f1', 'prec',␣
 ↪'recall'])

# Append the results to the existing DataFrame
result = result.append(gb_result, ignore_index=True)
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_17024\1530228444.py:22:
FutureWarning: The frame.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  result = result.append(gb_result, ignore_index=True)
```

[29]:
```
result
```

[29]:
```
                       Model    acc                       conf        f1  \
0        Logistic Regression  0.811    [[1526, 69], [309, 96]]  0.336842
1  GradientBoostingClassifier  0.867  [[1523, 72], [194, 211]]  0.613372

       prec    recall
0  0.581818  0.237037
1  0.745583  0.520988
```

[30]:
```
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score,␣
 ↪precision_score, recall_score

# Create and train the Random Forest Classifier
clf_rf = RandomForestClassifier(random_state=1)
clf_rf.fit(x_train_scaled, y_train)

# Make predictions using the trained model
y_pred_rf = clf_rf.predict(x_test_scaled)

# Calculate the metrics for the Random Forest Classifier
acc_rf = accuracy_score(y_test, y_pred_rf)
conf_rf = confusion_matrix(y_test, y_pred_rf)
f1_rf = f1_score(y_test, y_pred_rf)
prec_rf = precision_score(y_test, y_pred_rf)
recall_rf = recall_score(y_test, y_pred_rf)

# Create a DataFrame to store the results of the Random Forest Classifier
rf_result = pd.DataFrame([['RandomForestClassifier', acc_rf, conf_rf, f1_rf,␣
 ↪prec_rf, recall_rf]],
                         columns=['Model', 'acc', 'conf', 'f1', 'prec',␣
 ↪'recall'])

# Check if 'result' DataFrame already exists, if not, create it
try:
    result  # Try accessing 'result'
except NameError:
    result = pd.DataFrame(columns=['Model', 'acc', 'conf', 'f1', 'prec',␣
 ↪'recall'])

# Append the results to the existing DataFrame
result = result.append(rf_result, ignore_index=True)

# Now 'result' contains the results from the Random Forest Classifier and␣
 ↪potentially any other models you add
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_17024\3283121621.py:30:
FutureWarning: The frame.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  result = result.append(rf_result, ignore_index=True)
```

[31]:
```
result
```

[31]:

	Model	acc	conf	f1	\
0	Logistic Regression	0.811	[[1526, 69], [309, 96]]	0.336842	

```
1  GradientBoostingClassifier  0.867  [[1523, 72], [194, 211]]  0.613372
2      RandomForestClassifier  0.869  [[1525, 70], [192, 213]]  0.619186

       prec    recall
0  0.581818  0.237037
1  0.745583  0.520988
2  0.752650  0.525926
```

The Random Forest Classifier has the highest accuracy score of 0.869. Therefore, if accuracy is your primary concern, the Random Forest model might seem like the best choice.