Import Necessary Libraries

In [1]:

```
import pandas as pd
import numpy as np
from collections import Counter

import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns

from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler
from sklearn.metrics import roc_curve, precision_recall_curve, auc, make_scorer,
from sklearn import metrics

from sklearn.model_selection import GridSearchCV
from sklearn import tree

from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier


from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.feature_selection import SelectFromModel

from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline

from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import confusion_matrix, classification_report

from operator import itemgetter, attrgetter

import imblearn
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler

import missingno

import xgboost as xgb
from xgboost import XGBClassifier
from sklearn.compose import ColumnTransformer

pd.set_option('display.max_columns', None)
pd.set_option('display.max_colwidth', None)
```

Import data

In [2]:
```
# import data as csv file form data folder
df_churn = pd.read_csv('../../data/Churn_Modelling.csv')
```

In [3]:
```
# checking the head of dataset
df_churn.head()
```

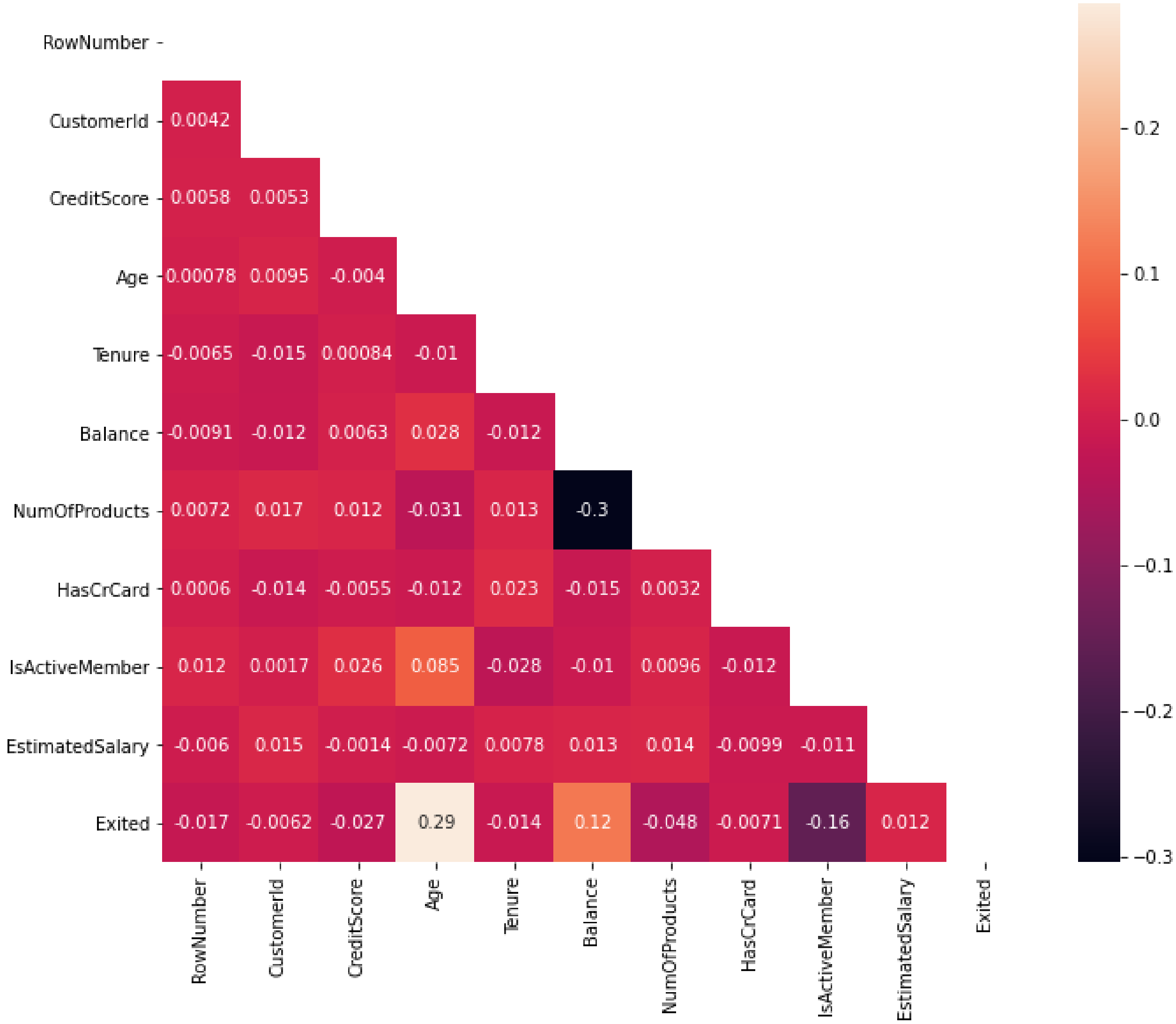
Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance
0	1	15634602	Hargrave	619	France	Female	42	2	0.00
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86
2	3	15619304	Onio	502	France	Female	42	8	159660.80
3	4	15701354	Boni	699	France	Female	39	1	0.00
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82

In [4]:
```
# getting info of dataset
df_churn.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
```

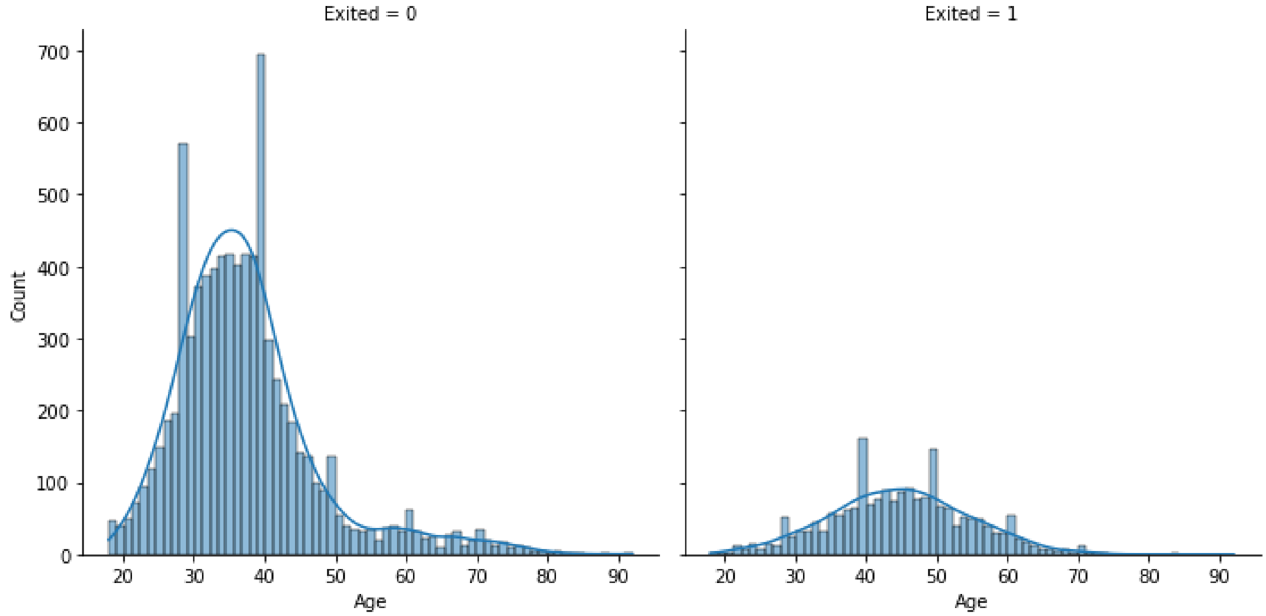
In [5]:
```
# Using hitmap to show the correlation between numerical columns and the target
corr = df_churn.corr()
# The mask is not necessary, but corr() has duplicate values on either side of t
mask = np.triu(np.ones_like(corr, dtype=np.bool))

fig1, ax1 = plt.subplots(figsize=(11, 9))
sns.heatmap(df_churn.corr(), mask=mask, annot = True);
```



There are 3 numerical columns, Age,Balance and Gender whith the most correlation with the target(Exited). I will show some future engineering on these columns.

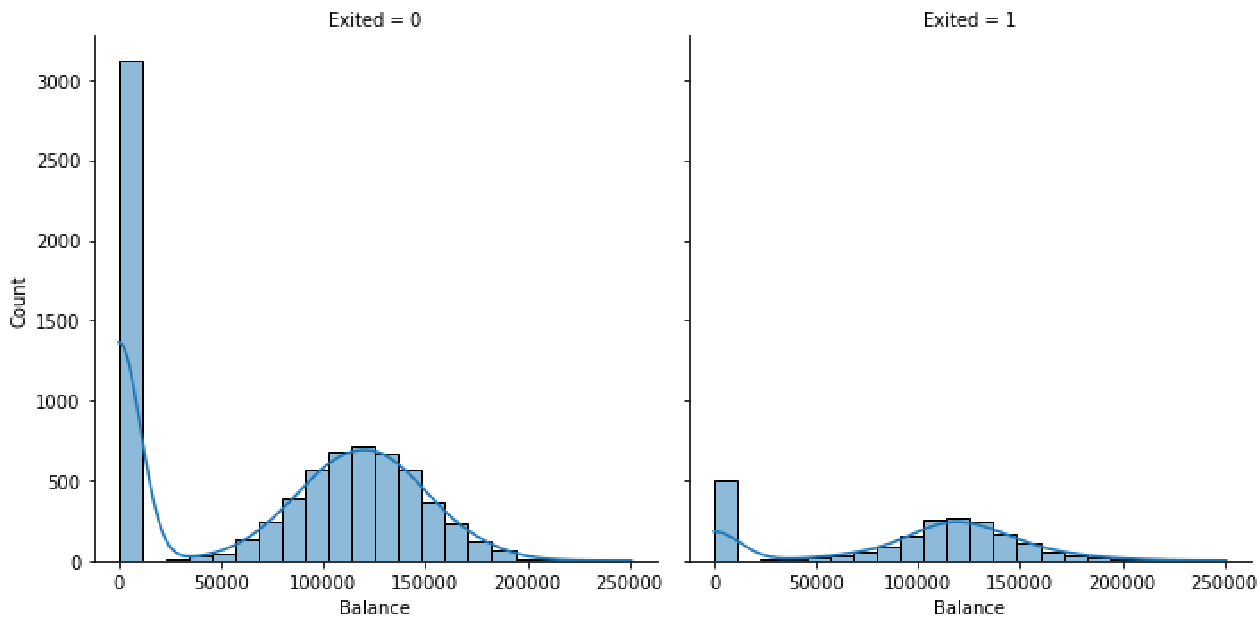
In [6]:

```
# Distribution of Age vs target
sns.displot(data=df_churn, x='Age', col='Exited', kde=True);
#plt.savefig('Age Contribution.png');
```



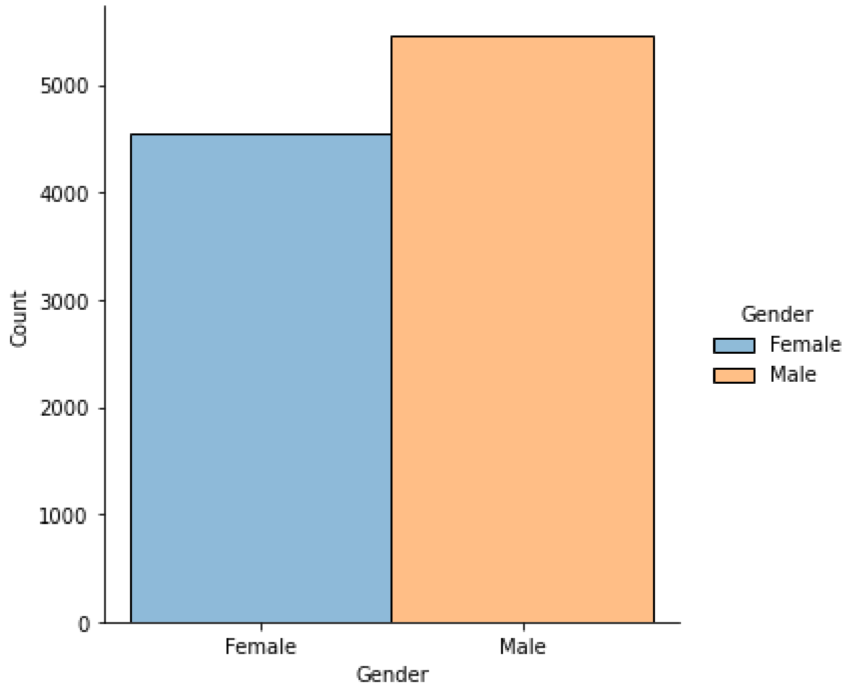
In [7]:

```
# Distribution of Balance vs target
sns.displot(data=df_churn, x='Balance', col='Exited', kde=True);
#plt.savefig('Balance Contribution.png');
```



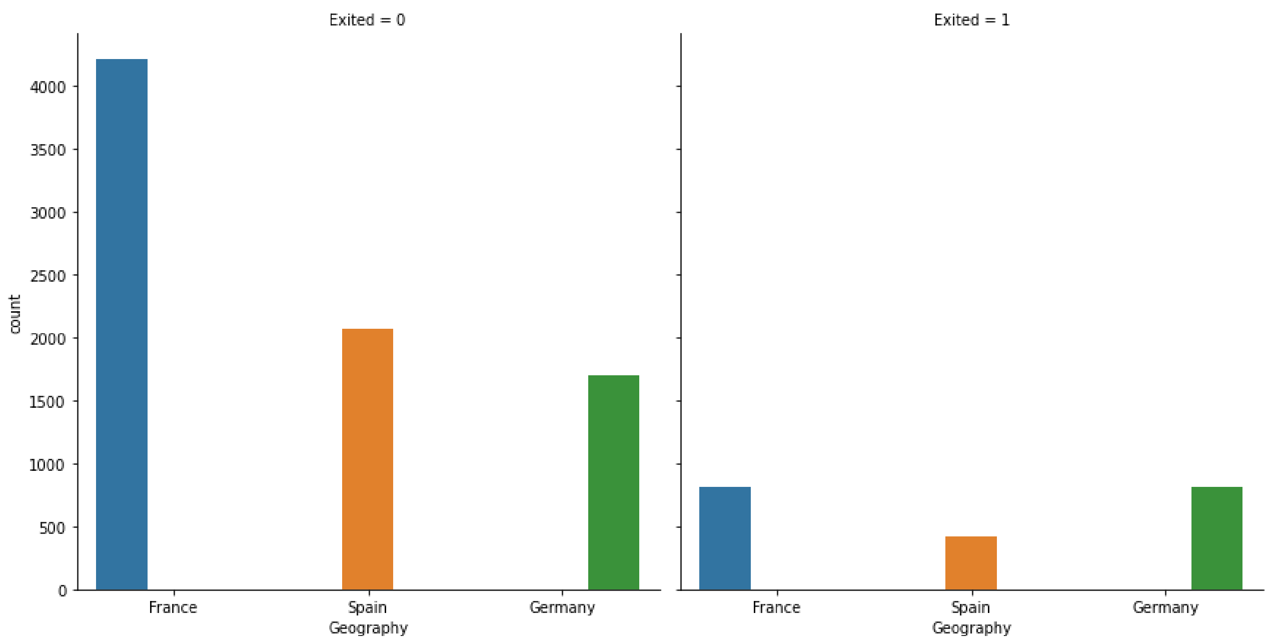
In [8]:

```
sns.displot(df_churn, x='Gender', hue='Gender');
#plt.savefig('Gender count.png')
```



In [132…

```
# distribution of countries vs exited
g = sns.catplot(x='Geography', hue='Geography', col='Exited',
                data=df_churn, kind="count",
                height=6, aspect=1);
#plt.savefig('Geography count.png')
```



In [9]:

```
# Changing  Gender column from categorical to binary(Numerical)
df_churn['Gender'] = df_churn['Gender'].map({'Female': 1, 'Male': 0})
df_churn.head()
```

Out[9]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance
0	1	15634602	Hargrave	619	France	1	42	2	0.00

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance
1	2	15647311	Hill	608	Spain	1	41	1	83807.86
2	3	15619304	Onio	502	France	1	42	8	159660.80
3	4	15701354	Boni	699	France	1	39	1	0.00
4	5	15737888	Mitchell	850	Spain	1	43	2	125510.82

In [10]:

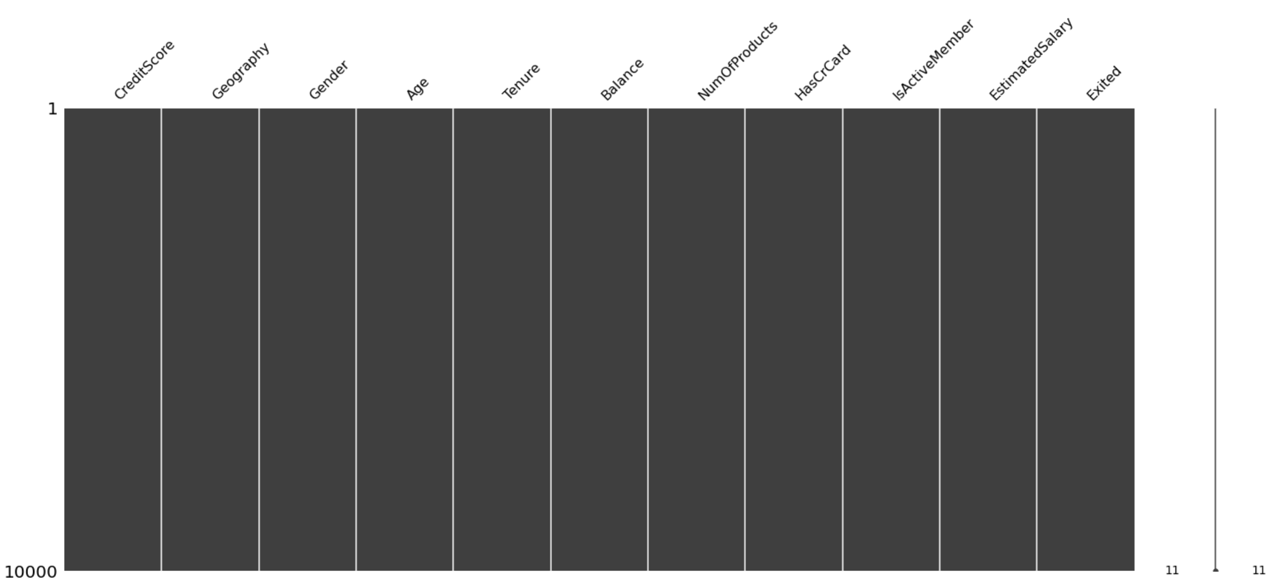
```
# Dropping Useless columns
# These columns are just personal information about customers
df_churn.drop(['RowNumber', 'CustomerId', 'Surname'], axis=1, inplace=True)
df_churn.head()
```

Out[10]:

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

In [11]:

```
# generate preview of entries with null values
if len(df_churn[df_churn.isnull().any(axis=1)] != 0):
    print("\nPreview of data with null values:\nxxxxxxxxxxxxxx")
    print(df_churn[df_churn.isnull().any(axis=1)].head(3))
missingno.matrix(df_churn)
plt.show()
print("\nPreview of data with null values:\nxxxxxxxxxxxxxx")
print(df_churn[df_churn.isnull().any(axis=1)].head(3))
```




```
Preview of data with null values:
xxxxxxxxxxxxx
Empty DataFrame
```

```
Columns: [CreditScore, Geography, Gender, Age, Tenure, Balance, NumOfProducts, H
asCrCard, IsActiveMember, EstimatedSalary, Exited]
Index: []
```

In [12]:

```
# generate count statistics of duplicate entries
if len(df_churn[df_churn.duplicated()]) > 0:
    print("No. of duplicated entries: ", len(df_churn[df_churn.duplicated()]))
    print(df_churn[df_churn.duplicated(keep=False)].sort_values(by=list(df_churn
else:
    print("No duplicated entries found")
```

```
No duplicated entries found
```

It looks like we have Heavy Imbalance target

- I will take care of this imbalance later

In [13]:

```
df_churn.Exited.value_counts(normalize=True)
```

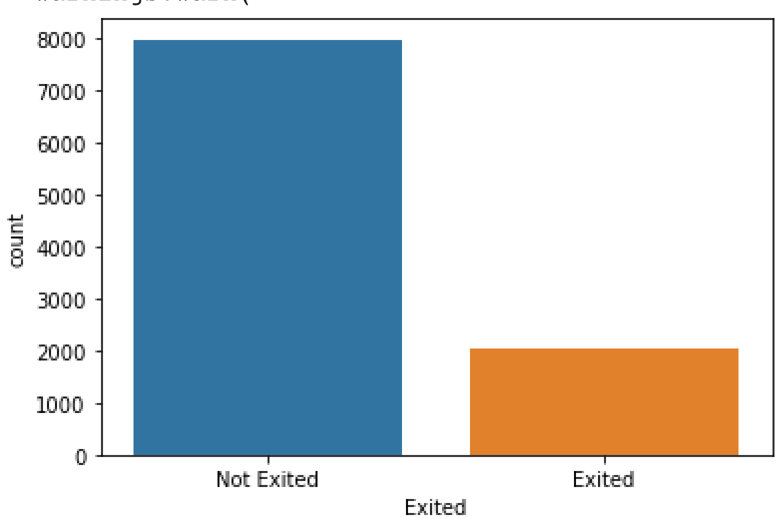
Out[13]:

```
0    0.7963
1    0.2037
Name: Exited, dtype: float64
```

In [14]:

```
imbal = sns.countplot(df_churn['Exited'])
imbal.set_xticklabels(['Not Exited','Exited'])
plt.show();
```

```
/Users/alirezakarimi/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorato
rs.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From v
ersion 0.12, the only valid positional argument will be `data`, and passing othe
r arguments without an explicit keyword will result in an error or misinterpreta
tion.
  warnings.warn(
```



In [15]:

```
df_churn.head()
```

Out[15]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActi
0	619	France	1	42	2	0.00	1	1	

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActi
1	608	Spain	1	41	1	83807.86	1	0	
2	502	France	1	42	8	159660.80	3	1	
3	699	France	1	39	1	0.00	2	0	
4	850	Spain	1	43	2	125510.82	1	1	

In [16]:

```
# making Exited as our target
# Dropping the original Exited column from data frame
X= df_churn.drop('Exited', axis=1)
y = df_churn.Exited
```

In [17]:

```
# type of data in our dataset
X.dtypes.value_counts()
```

Out[17]:

```
int64      7
float64    2
object     1
dtype: int64
```

In [18]:

```
# split our dataset to training and test set.
# I do not touch the test set untill the last part
# which is making the best training model
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42, test_
print(X_train.shape)
print(y_train.shape)
```

```
(8000, 10)
(8000,)
```

In [19]:

```
X_train.columns
```

Out[19]:

```
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary'],
      dtype='object')
```

Dealing with Categorical Columns

In [20]:

```
# dropping the only object column
# making dataset only numerical
X_tr_num = X_train.drop(['Geography'], axis=1)
X_tr_num
```

Out[20]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMembe
9254	686	0	32	6	0.00	2	1	
1561	632	0	42	4	119624.60	2	1	
1670	559	0	24	3	114739.92	1	1	

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMembe
6087	561	1	27	9	135637.00	1	1	
6669	517	0	56	9	142147.32	1	0	
...	...	...	...	...	...	...	...	
5734	768	0	54	8	69712.74	1	1	
5191	682	1	58	1	0.00	1	1	
5390	735	1	38	1	0.00	3	0	
860	667	0	43	8	190227.46	1	1	
7270	697	0	51	1	147910.30	1	1	

8000 rows × 9 columns

In [21]:

```
# using One Hot Encoder to cahnge the only object(categorical) column to binary

ohe = OneHotEncoder(sparse=False, handle_unknown='ignore') # instantiate the fun

X_tr_cat = X_train[['Geography']] # use the numerical dataset

X_tr_oh = pd.DataFrame(ohe.fit_transform(X_tr_cat), columns=ohe.get_feature_name
X_tr_ = X_tr_num.join(X_tr_oh) # join Two dataset
X_tr_
```

Out[21]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMembe
9254	686	0	32	6	0.00	2	1	
1561	632	0	42	4	119624.60	2	1	
1670	559	0	24	3	114739.92	1	1	
6087	561	1	27	9	135637.00	1	1	
6669	517	0	56	9	142147.32	1	0	
...	...	...	...	...	...	...	...	
5734	768	0	54	8	69712.74	1	1	
5191	682	1	58	1	0.00	1	1	
5390	735	1	38	1	0.00	3	0	
860	667	0	43	8	190227.46	1	1	
7270	697	0	51	1	147910.30	1	1	

8000 rows × 12 columns

Scaling data train

In [22]:
```
# we scale our data to avoid the power of bigger numbers.
ss = StandardScaler() # instantiate the function
X_train_sc = pd.DataFrame(ss.fit_transform(X_tr_), index=X_tr_.index, columns=X_
X_train_sc
```

Out[22]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsAc
9254	0.356500	-0.913248	-0.655786	0.345680	-1.218471	0.808436	0.649203	
1561	-0.203898	-0.913248	0.294938	-0.348369	0.696838	0.808436	0.649203	
1670	-0.961472	-0.913248	-1.416365	-0.695393	0.618629	-0.916688	0.649203	
6087	-0.940717	1.094993	-1.131148	1.386753	0.953212	-0.916688	0.649203	
6669	-1.397337	-0.913248	1.625953	1.386753	1.057449	-0.916688	-1.540351	
...	...	...	...	...	...	...	...	
5734	1.207474	-0.913248	1.435808	1.039728	-0.102301	-0.916688	0.649203	
5191	0.314989	1.094993	1.816097	-1.389442	-1.218471	-0.916688	0.649203	
5390	0.865009	1.094993	-0.085351	-1.389442	-1.218471	2.533560	-1.540351	
860	0.159323	-0.913248	0.390011	1.039728	1.827259	-0.916688	0.649203	
7270	0.470655	-0.913248	1.150590	-1.389442	1.149720	-0.916688	0.649203	

8000 rows × 12 columns

Resampling to solve imbalance data

- using over sampling technique(Smote)

In [23]:
```
ros = RandomOverSampler(random_state=42)

# fit predictor and target variable
X_ros, y_ros = ros.fit_resample(X_train_sc, y_train)

print('Original dataset shape', Counter(y_train))
print('Resample dataset shape', Counter(y_ros))
```

```
Original dataset shape Counter({0: 6356, 1: 1644})
Resample dataset shape Counter({0: 6356, 1: 6356})
```

Helper function to get cross_val_score

In [24]:
```
def model_output(model, X_t, X_val, y_t, y_val):
    '''Can be used on final test and train validation''
    input:   model, X_t, X_val, y_t, y_val
    or
    input:   model, X_train, X_test, y_train, y_test
    '''
    model.fit(X_t, y_t)
```

```
    y_hat = model.predict(X_val)
    print(f'''The Cross Val f1 score is: {cross_val_score(estimator = model, X =
    print(f'The test Accuracy is: {accuracy_score(y_val, y_hat)}')
    print(confusion_matrix(y_val, y_hat))
    print(classification_report(y_val, y_hat))
    return
```

Making pipeline

- using pipeline to make our models
- with this pipeline, I can make all models and use this pipeline to predict our test set as well.

Logistic Regression models

- first simple model

In [25]:
```
# use all previous data engineering to make pipeline
pip_line_lg = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder(sparse=False, handle_unknown='ignore'),
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('lg', LogisticRegression(random_state=42))
])
```

In [26]:
```
# fitting model(pipeline) into train set
pip_line_lg.fit(X_train, y_train)
```

Out[26]:
```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('lg', LogisticRegression(random_state=42))])
```

In [27]:
```
# getting the average of f1 score
cross_val_score(pip_line_lg, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[27]:
```
0.4893211212449431
```

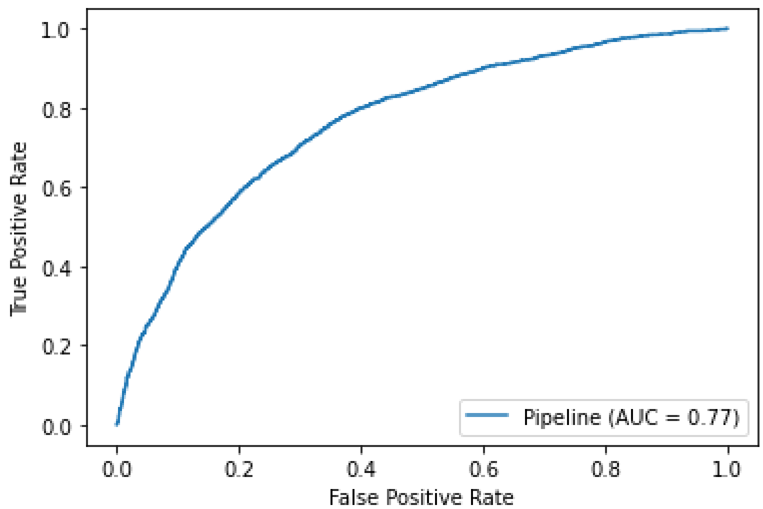
In [28]:
```
# checking the accuracy score
cross_val_score(pip_line_lg, X_train, y_train, cv=3, scoring='accuracy')
```

Out[28]:
```
array([0.69066367, 0.71541057, 0.71267817])
```

In [29]:
```
# using helper function to predict
model_output(pip_line_lg, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.4893211212449431
The test Accuracy is: 0.717
[[1153  454]
 [ 112  281]]
              precision    recall  f1-score   support

           0       0.91      0.72      0.80      1607
           1       0.38      0.72      0.50       393

    accuracy                           0.72      2000
   macro avg       0.65      0.72      0.65      2000
weighted avg       0.81      0.72      0.74      2000
```

In [30]:
```
plot_roc_curve(pip_line_lg, X_train, y_train);
```



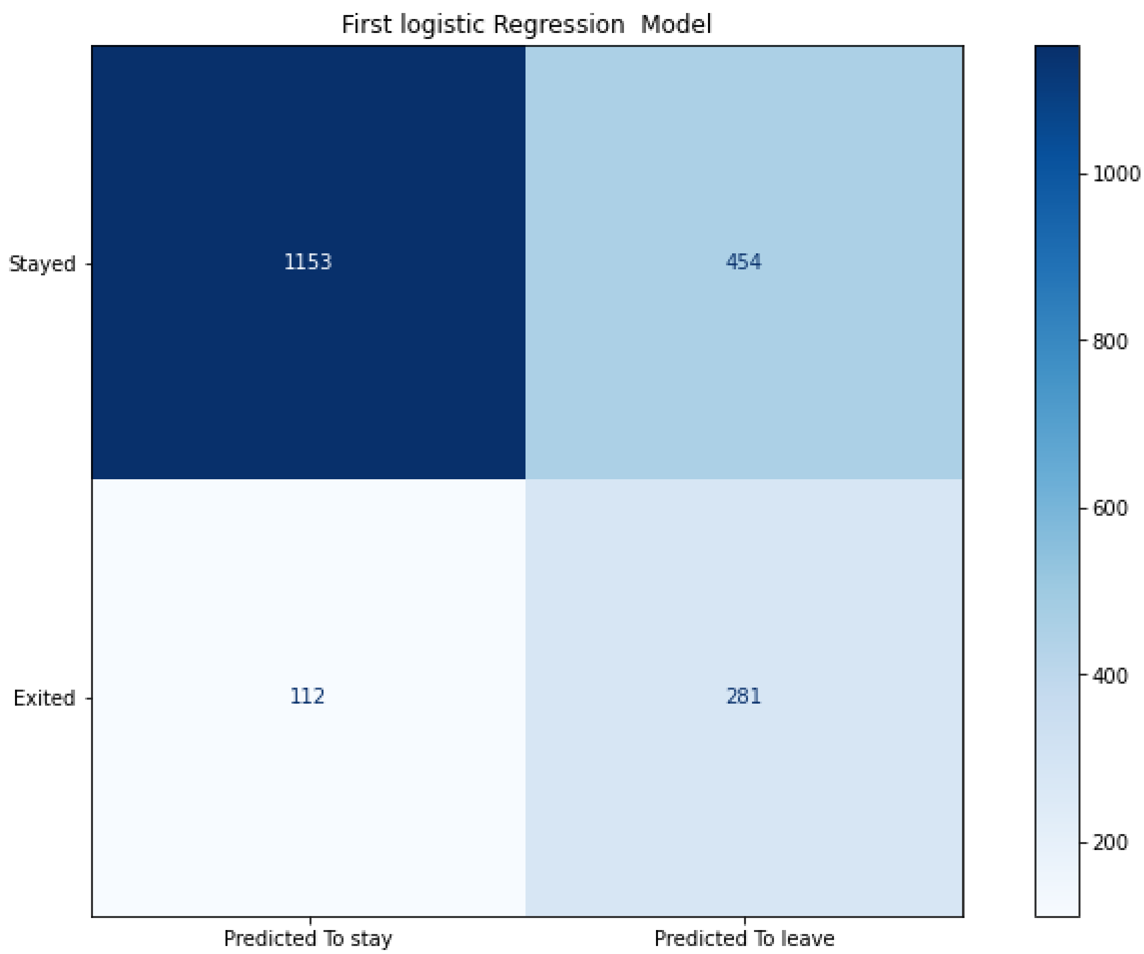
Making helper function to plot confusion matrix

In [31]:
```
def confusion_matrix_info(model, X_train, y_train, save_path=None):
    '''
    Creates a confusion matrix for a given model
    Parameters
    ----------
    model: an estimator
    X_train: training  dataset
    y_train: training dataset
    Returns
    -------
    A confusion matrix of given model
    '''
    fig, axes = plt.subplots(figsize=(13,8))
    #axes.set_title("Model Validation", fontsize=20)
    x_tick_marks = ['Predicted To stay', 'Predicted To leave']
    y_tick_marks = ['Stayed', 'Exited']

    plot_confusion_matrix(model, X_train, y_train, ax=axes, cmap='Blues', displa
    plt.xticks([0,1], x_tick_marks)
```

```
    plt.title('First logistic Regression  Model')

    label_font = {'size':'20'}
    axes.set_xlabel('', fontdict=label_font)
    axes.set_ylabel('', fontdict=label_font)
    SMALL_SIZE = 12
    MEDIUM_SIZE = 14
    BIGGER_SIZE = 16

    confusion_matrix = plt.show()
    if save_path:
        plt.savefig(save_path, transparent=True)
    return confusion_matrix, fig
```

In [32]:

```
confusion_matrix_info(pip_line_lg, X_test, y_test);
```



In [33]:

```
# using pipeloine to make the secong logistic regression
pip_line_lg1 = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder(sparse=False, handle_unknown='ignore'),
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('lg', LogisticRegression(C=.5, class_weight='balanced', random_state=42,   p
])
```

In [34]:
```
# fitting model(pipeline) into train set
pip_line_lg1.fit(X_train, y_train)
```

Out[34]:
```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('lg',
                 LogisticRegression(C=0.5, class_weight='balanced',
                                    penalty='l1', random_state=42,
                                    solver='liblinear'))])
```

In [35]:
```
# getting the average of f1 score
cross_val_score(pip_line_lg1, X_train, y_train, cv=3, scoring='f1')
```

Out[35]:
```
array([0.47558656, 0.51000646, 0.48178138])
```

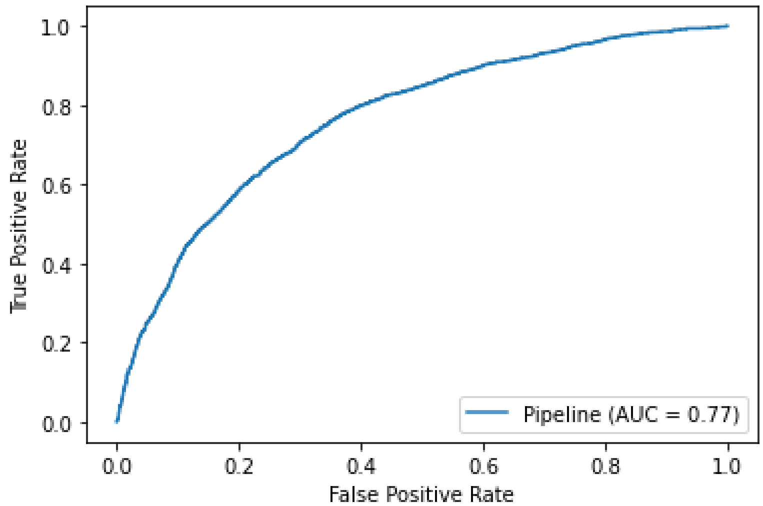
In [36]:
```
# checking the accuracy score
cross_val_score(pip_line_lg1, X_train, y_train, cv=3, scoring='accuracy')
```

Out[36]:
```
array([0.68991376, 0.71541057, 0.71192798])
```

In [37]:
```
# using helper function to predict
model_output(pip_line_lg1, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.4891247963498229
The test Accuracy is: 0.717
[[1153  454]
 [ 112  281]]
              precision    recall  f1-score   support

           0       0.91      0.72      0.80      1607
           1       0.38      0.72      0.50       393

    accuracy                           0.72      2000
   macro avg       0.65      0.72      0.65      2000
weighted avg       0.81      0.72      0.74      2000
```

In [38]:
```
plot_roc_curve(pip_line_lg1, X_train, y_train);
```



Random Forest models

In [39]:
```
# using pipiline to make Random Forest model
pip_line_rf = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder(sparse=False, handle_unknown='ignore'),
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('rf', RandomForestClassifier(random_state=42))
])
```

In [40]:
```
# fitting model(pipeline) into train set
pip_line_rf.fit(X_train, y_train)
```

Out[40]:
```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('rf', RandomForestClassifier(random_state=42))])
```

In [41]:
```
# getting the average of f1 score
cross_val_score(pip_line_rf, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[41]:
```
0.6017686728771269
```

In [42]:
```
# checking the accuracy score
cross_val_score(pip_line_rf, X_train, y_train, cv=3, scoring='accuracy')
```

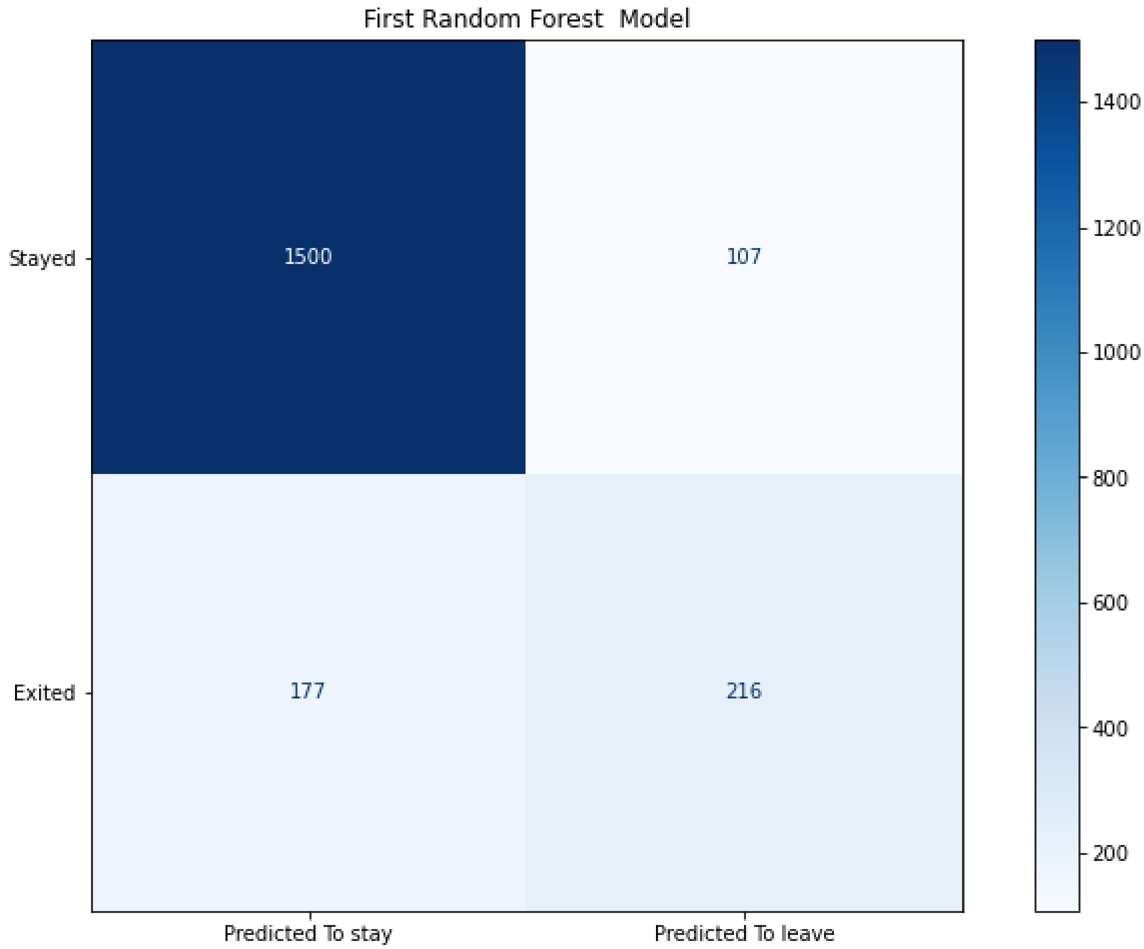
Out[42]:
```
array([0.85564304, 0.85714286, 0.84996249])
```

In [43]:
```
# using helper function to predict
model_output(pip_line_rf, X_train, X_test, y_train, y_test)
```

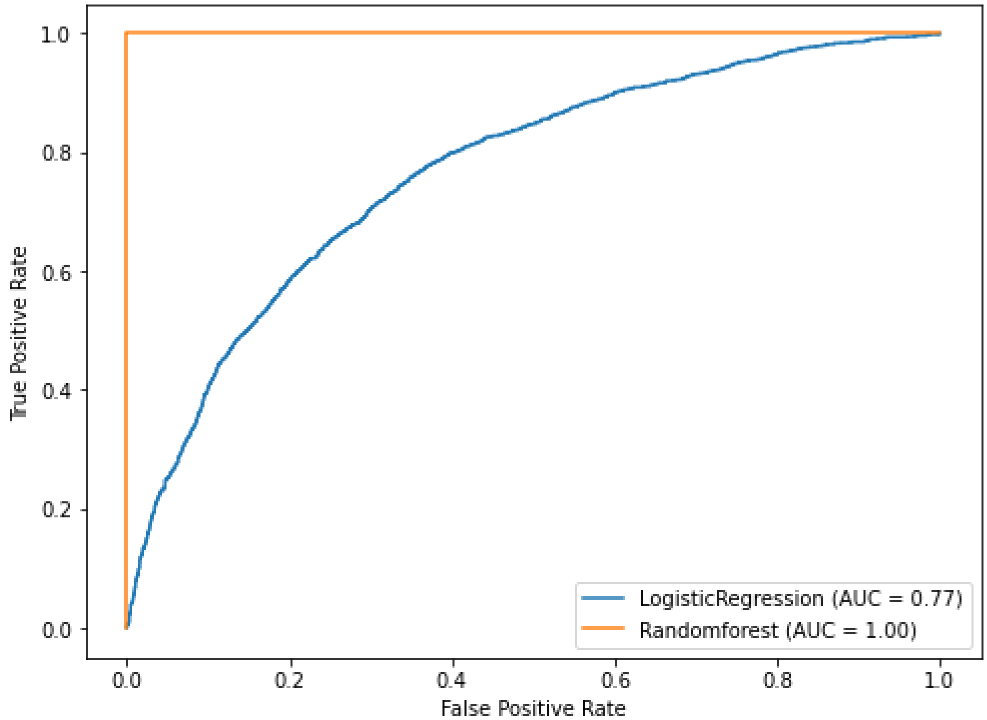
```
The Cross Val f1 score is: 0.6017686728771269
The test Accuracy is: 0.858
[[1500  107]
 [ 177  216]]
              precision    recall  f1-score   support

           0       0.89      0.93      0.91      1607
           1       0.67      0.55      0.60       393

    accuracy                           0.86      2000
   macro avg       0.78      0.74      0.76      2000
weighted avg       0.85      0.86      0.85      2000
```

In [44]:
```
def confusion_matrix_info(model, X_train, y_train, save_path=None):
    '''
    Creates a confusion matrix for a given model
    Parameters
    ----------
    model: an estimator
    X_train: training  dataset
    y_train: training dataset
    Returns
    -------
    A confusion matrix of given model
    '''
    fig, axes = plt.subplots(figsize=(13,8))
    #axes.set_title("Model Validation", fontsize=20)
    x_tick_marks = ['Predicted To stay', 'Predicted To leave']
    y_tick_marks = ['Stayed', 'Exited']

    plot_confusion_matrix(model, X_train, y_train, ax=axes, cmap='Blues', displa
    plt.xticks([0,1], x_tick_marks)
    plt.title('First Random Forest  Model')

    label_font = {'size':'20'}
    axes.set_xlabel('', fontdict=label_font)
    axes.set_ylabel('', fontdict=label_font)
    SMALL_SIZE = 12
    MEDIUM_SIZE = 14
    BIGGER_SIZE = 16

    confusion_matrix = plt.show()
    if save_path:
        plt.savefig(save_path, transparent=True)
    return confusion_matrix, fig
```

In [45]:
```
confusion_matrix_info(pip_line_rf, X_test, y_test);
```



In [46]:
```
fig, ax = plt.subplots(figsize=(8,6))


plot_roc_curve(pip_line_lg, X_train, y_train, ax=ax, name='LogisticRegression' )
plot_roc_curve(pip_line_rf, X_train, y_train, ax=ax, name='Randomforest');
```



In [47]:

```
# using pipiline to make Random Forest model with hyper tuning
pip_line_rf1 = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder
         (sparse=False, handle_unknown='ignore'),
         ['Geography'])
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('rf1', RandomForestClassifier
     (criterion='gini', random_state=42,class_weight='balanced' ))
])
```

In [48]:

```
# fitting model(pipeline) into train set
pip_line_rf1.fit(X_train, y_train)
```

Out[48]:

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('rf1',
                 RandomForestClassifier(class_weight='balanced',
                                        random_state=42))])
```

In [49]:

```
# getting the average of f1 score
cross_val_score(pip_line_rf1, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[49]:

```
0.6017686728771269
```

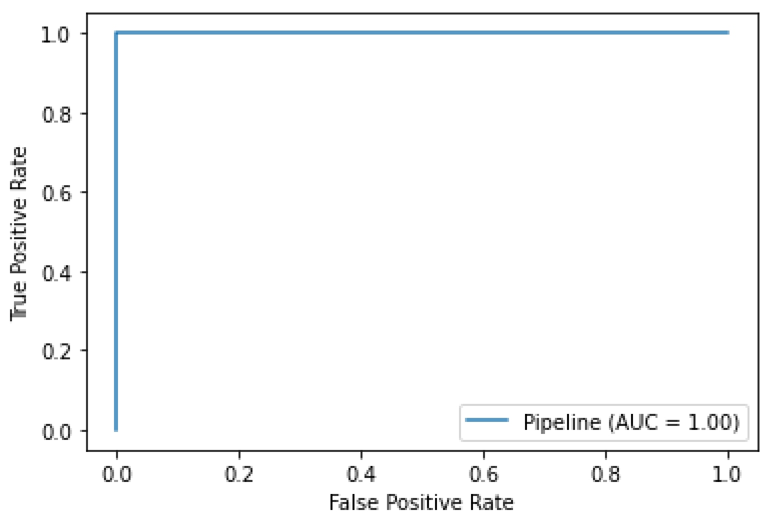
In [50]:
```
# checking the accuracy score
cross_val_score(pip_line_rf1, X_train, y_train, cv=3, scoring='accuracy')
```

Out[50]:
```
array([0.85564304, 0.85714286, 0.84996249])
```

In [51]:
```
# using helper function to predict
model_output(pip_line_rf1, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.6017686728771269
The test Accuracy is: 0.858
[[1500  107]
 [ 177  216]]
              precision    recall  f1-score   support

           0       0.89      0.93      0.91      1607
           1       0.67      0.55      0.60       393

    accuracy                           0.86      2000
   macro avg       0.78      0.74      0.76      2000
weighted avg       0.85      0.86      0.85      2000
```

In [52]:
```
plot_roc_curve(pip_line_rf1, X_train, y_train);
```



GridSearch

In [53]:
```
# using Grid Search function to Hyper-tun Parameters
param_grid = { 'rf1__criterion': ['gini', 'entropy'],'rf1__max_depth': [2,5,10],

grid_search_rf =GridSearchCV(pip_line_rf1,param_grid=param_grid,cv=3, scoring='f
grid_search_rf.fit(X_train,y_train)# fiiting model into training set
```

Out[53]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('Geography_ohe',
                                        ColumnTransformer(remainder='passthroug
h',
                                                          transformers=[('onehot
```

```
encoding',
                                                                                                OneHotE
ncoder(handle_unknown='ignore',

sparse=False),
                                                                                                ['Geogr
aphy'])])),
                                        ('scaler', StandardScaler()),
                                        ('sampling',
                                         RandomOverSampler(random_state=42)),
                                        ('rf1',
                                         RandomForestClassifier(class_weight='bal
anced',
                                                                   random_state=4
2))]),
             n_jobs=-1,
             param_grid={'rf1__criterion': ['gini', 'entropy'],
                         'rf1__max_depth': [2, 5, 10],
                         'rf1__n_estimators': [100, 1000]},
             scoring='f1')
```

In [54]:

```python
# getting the best estimator
grid_search_rf.best_estimator_
```

Out[54]:

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('rf1',
                 RandomForestClassifier(class_weight='balanced', max_depth=10,
                                        n_estimators=1000, random_state=42))])
```

In [55]:

```python
# getting the best score
grid_search_rf.best_score_
```

Out[55]:

```
0.6179687984707218
```

In [56]:

```python
# predicting the f1 score
f1_score(y_train, grid_search_rf.best_estimator_.predict(X_train))
```

Out[56]:

```
0.7843137254901962
```

In [57]:

```python
# using helper function to predict
model_output(grid_search_rf, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.6174563801157579
The test Accuracy is: 0.8355
[[1392  215]
 [ 114  279]]
              precision    recall  f1-score   support

           0       0.92      0.87      0.89      1607
           1       0.56      0.71      0.63       393
```

```
    accuracy                           0.84      2000
   macro avg       0.74      0.79      0.76      2000
weighted avg       0.85      0.84      0.84      2000
```

KNN

In [58]:
```
# using pipiline to make KNN model
pip_line_knn = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder
         (sparse=False, handle_unknown='ignore'),
         ['Geography'])
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('knn', KNeighborsClassifier())
])
```

In [59]:
```
# fitting model(pipeline) into train set
pip_line_knn.fit(X_train, y_train)
```

Out[59]:
```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('knn', KNeighborsClassifier())])
```

In [60]:
```
# getting the average of f1 score
cross_val_score(pip_line_knn, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[60]:
```
0.4960258505949337
```

In [61]:
```
# checking the accuracy score
cross_val_score(pip_line_knn, X_train, y_train, cv=3, scoring='accuracy')
```

Out[61]:
```
array([0.72628421, 0.73078365, 0.73143286])
```

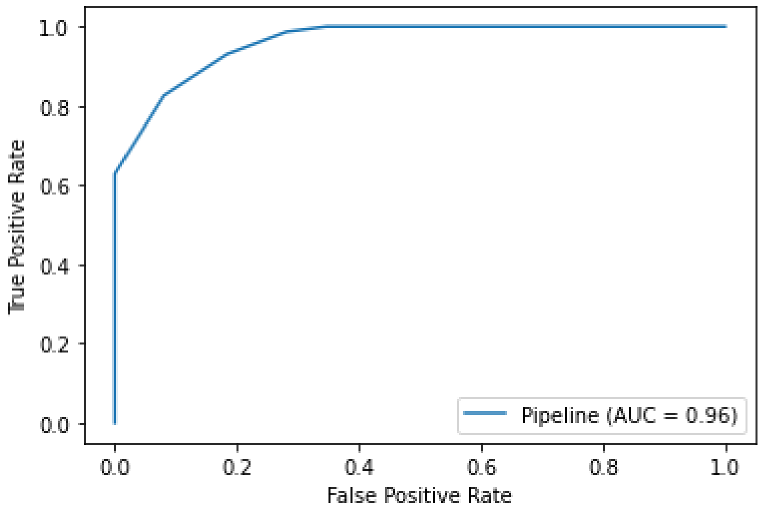
In [62]:
```
# using helper function to predict
model_output(pip_line_knn, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.4960258505949337
The test Accuracy is: 0.731
[[1213  394]
 [ 144  249]]
              precision    recall  f1-score   support
```

```
              0       0.89      0.75      0.82      1607
              1       0.39      0.63      0.48       393

       accuracy                           0.73      2000
      macro avg       0.64      0.69      0.65      2000
   weighted avg       0.79      0.73      0.75      2000
```

In [63]:

```
plot_roc_curve(pip_line_knn, X_train, y_train);
```



In [64]:

```
# using pipiline to make KNN model with hyper-tuning
pip_line_knn1 = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder
         (sparse=False, handle_unknown='ignore'),
         ['Geography'])
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('knn', KNeighborsClassifier(weights='distance', n_neighbors=3, n_jobs=-1))
])
```

In [65]:

```
# fitting model(pipeline) into train set
pip_line_knn1.fit(X_train, y_train)
```

Out[65]:

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('knn',
                 KNeighborsClassifier(n_jobs=-1, n_neighbors=3,
                                      weights='distance'))])
```

In [66]:

```
# getting the average of f1 score
```

```
cross_val_score(pip_line_knn1, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[66]: 0.4880357059430422

In [67]:

```
# checking the accuracy score
cross_val_score(pip_line_knn1, X_train, y_train, cv=3, scoring='accuracy')
```

Out[67]: array([0.75103112, 0.75628046, 0.74456114])

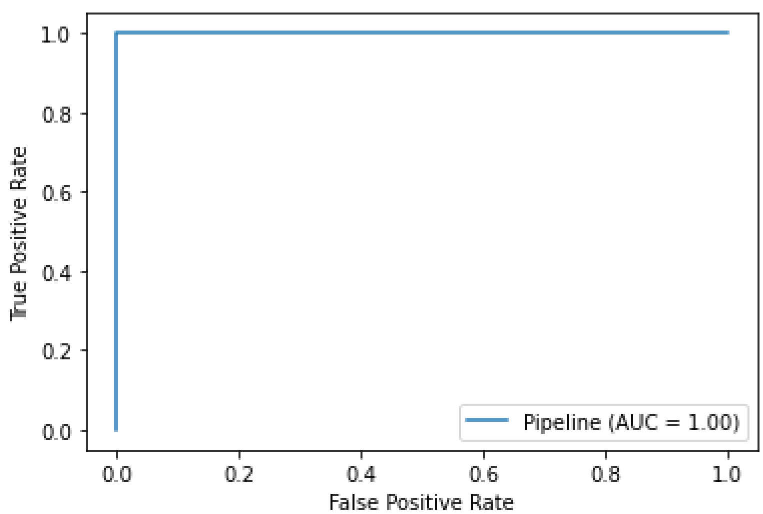
In [68]:

```
# using helper function to predict
model_output(pip_line_knn1, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.4880357059430422
The test Accuracy is: 0.76
[[1292  315]
 [ 165  228]]
              precision    recall  f1-score   support

           0       0.89      0.80      0.84      1607
           1       0.42      0.58      0.49       393

    accuracy                           0.76      2000
   macro avg       0.65      0.69      0.67      2000
weighted avg       0.80      0.76      0.77      2000
```

In [69]:

```
plot_roc_curve(pip_line_knn1, X_train, y_train);
```



Decision Tree

In [70]:

```
# using pipiline to make Decision Tree model
pip_line_dectree = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder
         (sparse=False, handle_unknown='ignore'),
         ['Geography'])
```

```
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('dt', DecisionTreeClassifier())
])
```

In [71]:

```
# fitting model(pipeline) into train set
pip_line_dectree.fit(X_train, y_train)
```

Out[71]:

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('dt', DecisionTreeClassifier())])
```

In [72]:

```
# getting the average of f1 score
cross_val_score(pip_line_dectree, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[72]:

```
0.4863047748678544
```

In [73]:

```
# checking the accuracy score
cross_val_score(pip_line_dectree, X_train, y_train, cv=3, scoring='accuracy')
```

Out[73]:

```
array([0.78177728, 0.78815148, 0.78769692])
```

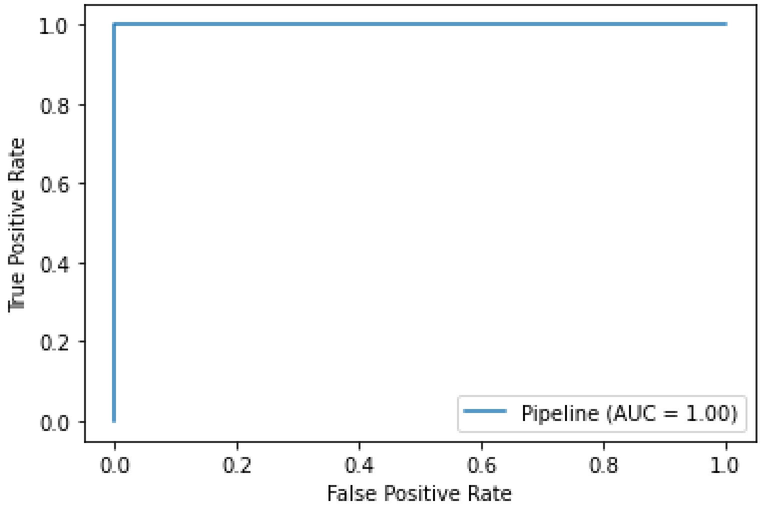
In [74]:

```
# using helper function to predict
model_output(pip_line_dectree, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.48398583775574533
The test Accuracy is: 0.802
[[1406  201]
 [ 195  198]]
              precision    recall  f1-score   support

           0       0.88      0.87      0.88      1607
           1       0.50      0.50      0.50       393

    accuracy                           0.80      2000
   macro avg       0.69      0.69      0.69      2000
weighted avg       0.80      0.80      0.80      2000
```

In [75]:

```
plot_roc_curve(pip_line_dectree, X_train, y_train);
```



In [76]:

```
# using pipiline to make Decision Tree model with hyper-tuning
pip_line_dectree1 = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder
         (sparse=False, handle_unknown='ignore'),
         ['Geography'])
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('dt1', DecisionTreeClassifier
     (criterion='entropy', splitter='random', max_depth=3, class_weight='balance
])
```

In [77]:

```
# fitting model(pipeline) into train set
pip_line_dectree1.fit(X_train, y_train)
```

Out[77]:

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('dt1',
                 DecisionTreeClassifier(class_weight='balanced',
                                        criterion='entropy', max_depth=3,
                                        splitter='random'))])
```

In [78]:

```
# getting the average of f1 score
cross_val_score(pip_line_dectree1, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[78]:

```
0.4993982012050538
```

In [79]:

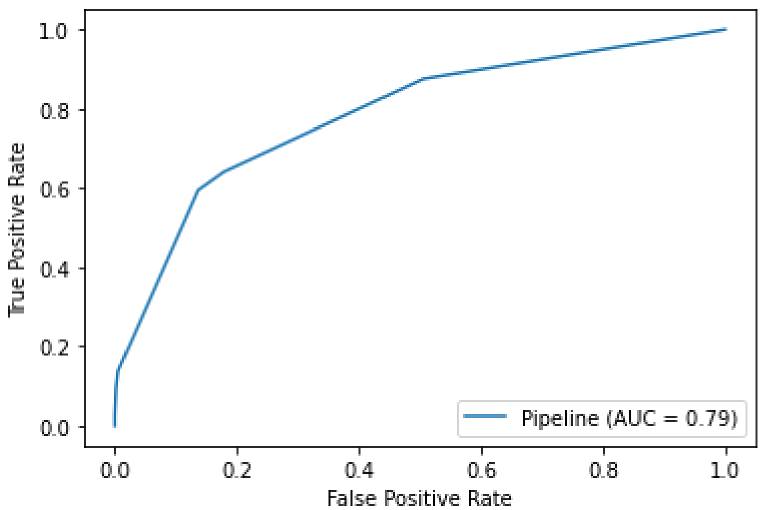
```
# checking the accuracy score
cross_val_score(pip_line_dectree1, X_train, y_train, cv=3, scoring='accuracy')
```

Out[79]:
```
array([0.67566554, 0.59767529, 0.7411853 ])
```

In [80]:
```
# using helper function to predict
model_output(pip_line_dectree1, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.5157861848247117
The test Accuracy is: 0.783
[[1302  305]
 [ 129  264]]
              precision    recall  f1-score   support

           0       0.91      0.81      0.86      1607
           1       0.46      0.67      0.55       393

    accuracy                           0.78      2000
   macro avg       0.69      0.74      0.70      2000
weighted avg       0.82      0.78      0.80      2000
```

In [81]:
```
plot_roc_curve(pip_line_dectree1, X_train, y_train);
```



In [83]:
```
# using Grid Search function to Hyper-tun Parameters
param_grid = {'dt1__class_weight': ['balanced'],
             'dt1__splitter': ['best'],
             'dt1__max_depth': (21, 22, 23, 24, 25),
             'dt1__min_impurity_decrease':[.01, .02, .03, .04]}

grid_search_dectree1 =GridSearchCV(pip_line_dectree1,param_grid=param_grid,cv=3,
```

In [84]:
```
# fitting model(pipeline) into train set
grid_search_dectree1.fit(X_train,y_train)
```

Out[84]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('Geography_ohe',
                                        ColumnTransformer(remainder='passthroug
h',
                                                          transformers=[('onehot
encoding',
                                                                         OneHotE
ncoder(handle_unknown='ignore',
```

```
sparse=False),
                                                                                  ['Geogr
aphy'])])),
                                       ('scaler', StandardScaler()),
                                       ('sampling',
                                        RandomOverSampler(random_state=42)),
                                       ('dt1',
                                        DecisionTreeClassifier(class_weight='bal
anced',
                                                               criterion='entrop
y',
                                                               max_depth=3,
                                                               splitter='rando
m'))]),
             n_jobs=-1,
             param_grid={'dt1__class_weight': ['balanced'],
                         'dt1__max_depth': (21, 22, 23, 24, 25),
                         'dt1__min_impurity_decrease': [0.01, 0.02, 0.03, 0.04],
                         'dt1__splitter': ['best']},
             scoring='f1')
```

In [85]:

```python
# getting the best estimators
grid_search_dectree1.best_estimator_
```

Out[85]:

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('dt1',
                 DecisionTreeClassifier(class_weight='balanced',
                                        criterion='entropy', max_depth=21,
                                        min_impurity_decrease=0.01))])
```

In [86]:

```python
# best f1 score
grid_search_dectree1.best_score_
```

Out[86]:

```
0.5533733050168893
```

In [87]:

```python
# best f1 score predict
f1_score(y_train, grid_search_dectree1.best_estimator_.predict(X_train))
```

Out[87]:

```
0.5464089716058219
```

In [88]:

```python
# using helper function to predict
model_output(grid_search_dectree1, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.5533733050168893
The test Accuracy is: 0.7545
[[1228  379]
 [ 112  281]]
              precision    recall  f1-score   support
```

```
              0       0.92      0.76      0.83      1607
              1       0.43      0.72      0.53       393

       accuracy                           0.75      2000
      macro avg       0.67      0.74      0.68      2000
   weighted avg       0.82      0.75      0.77      2000
```

XGB

In [89]:

```
# using pipiline to make XGBoost model
pip_line_xgb = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder
         (sparse=False, handle_unknown='ignore'),
         ['Geography'])
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('xgb', XGBClassifier() )
])
```

In [90]:

```
# fitting model(pipeline) into train set
pip_line_xgb.fit(X_train, y_train)
```

Out[90]:

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('xgb',
                 XGBClassifier(base_score=0.5, booster='gbtree',
                               colsample_bylevel=1, colsample_bynode=1,
                               colsa..., gpu_id=-1,
                               importance_type='gain',
                               interaction_constraints='',
                               learning_rate=0.300000012, max_delta_step=0,
                               max_depth=6, min_child_weight=1, missing=nan,
                               monotone_constraints='()', n_estimators=100,
                               n_jobs=0, num_parallel_tree=1, random_state=0,
                               reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
                               subsample=1, tree_method='exact',
                               validate_parameters=1, verbosity=None))])
```

In [91]:

```
# getting the average of f1 score
cross_val_score(pip_line_xgb, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[91]:

```
0.5829216775216821
```

In [92]:

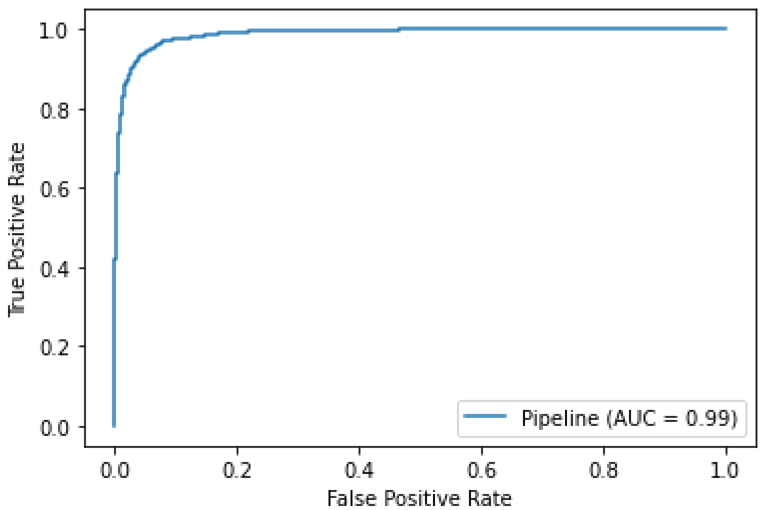
```
# checking the accuracy score
cross_val_score(pip_line_xgb, X_train, y_train, cv=3, scoring='accuracy')
```

Out[92]:
```
array([0.83352081, 0.83352081, 0.81995499])
```

In [93]:
```
# using helper function to predict
model_output(pip_line_xgb, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.5829216775216821
The test Accuracy is: 0.828
[[1399  208]
 [ 136  257]]
              precision    recall  f1-score   support

           0       0.91      0.87      0.89      1607
           1       0.55      0.65      0.60       393

    accuracy                           0.83      2000
   macro avg       0.73      0.76      0.74      2000
weighted avg       0.84      0.83      0.83      2000
```

In [94]:
```
plot_roc_curve(pip_line_xgb, X_train, y_train);
```



In [95]:
```
# using Grid Search function to Hyper-tun Parameters
param_grid = {
    'xgb__max_depth': [2, 10, 1],
    'xgb__n_estimators': [60, 220, 40],
    'xgb__learning_rate': [0.1, 0.01, 0.05]
}

grid_search_xgb =GridSearchCV(pip_line_xgb,param_grid=param_grid,cv=3, scoring='
```

In [96]:
```
# fitting model(pipeline) into train set
grid_search_xgb.fit(X_train,y_train)
```

Out[96]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('Geography_ohe',
                                        ColumnTransformer(remainder='passthroug
h',
                                                          transformers=[('onehot
encoding',
```

```
                                                                              OneHotE
ncoder(handle_unknown='ignore',

sparse=False),
                                                                              ['Geogr
aphy'])])),
                                   ('scaler', StandardScaler()),
                                   ('sampling',
                                    RandomOverSampler(random_state=42)),
                                   ('xgb',
                                    XGBClassifier(base_score=0.5,
                                                  booster='gbtree',
                                                  colsample_byleve...
                                                  min_child_weight=1,
                                                  missing=nan,
                                                  monotone_constraints='()',
                                                  n_estimators=100,
                                                  n_jobs=0,
                                                  num_parallel_tree=1,
                                                  random_state=0,
                                                  reg_alpha=0, reg_lambda=1,
                                                  scale_pos_weight=1,
                                                  subsample=1,
                                                  tree_method='exact',
                                                  validate_parameters=1,
                                                  verbosity=None))]),
             n_jobs=-1,
             param_grid={'xgb__learning_rate': [0.1, 0.01, 0.05],
                         'xgb__max_depth': [2, 10, 1],
                         'xgb__n_estimators': [60, 220, 40]},
             scoring='f1')
```

In [97]:

```
# getting the best estimators
grid_search_xgb.best_estimator_
```

Out[97]:

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('xgb',
                 XGBClassifier(base_score=0.5, booster='gbtree',
                               colsample_bylevel=1, colsample_bynode=1,
                               colsa..., gamma=0, gpu_id=-1,
                               importance_type='gain',
                               interaction_constraints='', learning_rate=0.1,
                               max_delta_step=0, max_depth=2,
                               min_child_weight=1, missing=nan,
                               monotone_constraints='()', n_estimators=220,
                               n_jobs=0, num_parallel_tree=1, random_state=0,
                               reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
                               subsample=1, tree_method='exact',
                               validate_parameters=1, verbosity=None))])
```

In [98]:

```
# best f1 score
grid_search_xgb.best_score_
```

Out[98]:

```
0.6031862264356543
```

In [99]:

```
# best f1 score predict
f1_score(y_train, grid_search_xgb.best_estimator_.predict(X_train))
```

Out[99]: 0.6268878435256251

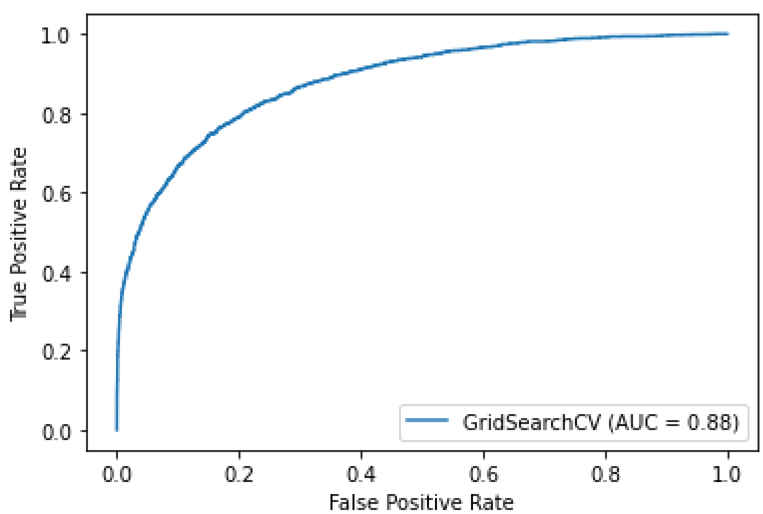
In [100…

```
# using helper function to predict
model_output(grid_search_xgb, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.5989522298770358
The test Accuracy is: 0.8095
[[1305  302]
 [  79  314]]
              precision    recall  f1-score   support

           0       0.94      0.81      0.87      1607
           1       0.51      0.80      0.62       393

    accuracy                           0.81      2000
   macro avg       0.73      0.81      0.75      2000
weighted avg       0.86      0.81      0.82      2000
```

In [101…

```
plot_roc_curve(grid_search_xgb, X_train, y_train);
```



In [102…

```
# using pipiline to make XGBoost model with hyper-tuning
pip_line_xgb1 = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder
         (sparse=False, handle_unknown='ignore'),
         ['Geography'])
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('xgb1', XGBClassifier(scale_pos_weight=1,
                           learning_rate=0.01,
                           colsample_bytree = 0.4,
                           subsample = 0.8,
                           objective='binary:logistic',
```

```
                      n_estimators=1000,
                      reg_alpha = 0.3,
                      max_depth=3,
                      gamma=10))
])
```

In [103…

```
# fitting model(pipeline) into train set
pip_line_xgb1.fit(X_train, y_train)
```

Out[103…

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('xgb1',
                 XGBClassifier(base_score=0.5, booster='gbtree',
                               colsample_bylevel=1, colsample_bynode=1,
                               cols...10, gpu_id=-1,
                               importance_type='gain',
                               interaction_constraints='', learning_rate=0.01,
                               max_delta_step=0, max_depth=3,
                               min_child_weight=1, missing=nan,
                               monotone_constraints='()', n_estimators=1000,
                               n_jobs=0, num_parallel_tree=1, random_state=0,
                               reg_alpha=0.3, reg_lambda=1, scale_pos_weight=1,
                               subsample=0.8, tree_method='exact',
                               validate_parameters=1, verbosity=None))])
```

In [104…

```
# getting the average of f1 score
cross_val_score(pip_line_xgb1, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[104… 0.6014559892337052

In [105…

```
# checking the accuracy score
cross_val_score(pip_line_xgb1, X_train, y_train, cv=3, scoring='accuracy')
```

Out[105… array([0.80089989, 0.7960255 , 0.79144786])

In [106…

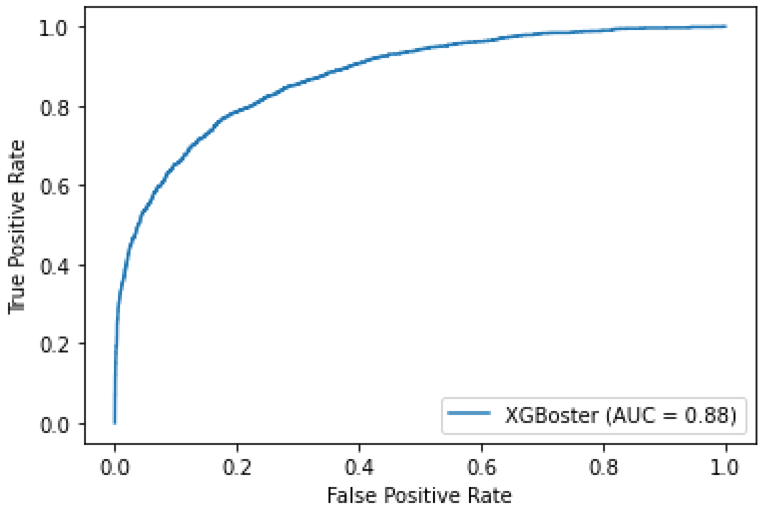
```
# using helper function to predict
model_output(pip_line_xgb1, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.6014559892337052
The test Accuracy is: 0.8045
[[1296  311]
 [  80  313]]
              precision    recall  f1-score   support

           0       0.94      0.81      0.87      1607
           1       0.50      0.80      0.62       393

    accuracy                           0.80      2000
   macro avg       0.72      0.80      0.74      2000
```

```
weighted avg       0.86      0.80      0.82      2000
```

In [107…

```
plot_roc_curve(pip_line_xgb1, X_train, y_train, name='XGBoster');
```



In [108…

```
# using pipiline to make XGBoost model with hyper-tuning
pip_line_xgb2 = Pipeline([
    ('Geography_ohe', ColumnTransformer([
        ('onehotencoding', OneHotEncoder
         (sparse=False, handle_unknown='ignore'),
         ['Geography'])
    ], remainder='passthrough')),
    ('scaler', StandardScaler()),
    ('sampling', RandomOverSampler(random_state=42)),
    ('xgb2', XGBClassifier(scale_pos_weight=1,
                      learning_rate=0.1,
                      colsample_bytree = 0.3,
                      subsample = 0.8,
                      objective='binary:logistic',
                      n_estimators=1000,
                      reg_alpha = 0.3,
                      max_depth=3,
                      gamma=0))
])
```

In [109…

```
# fitting model(pipeline) into train set
pip_line_xgb2.fit(X_train, y_train)
```

Out[109…

```
Pipeline(steps=[('Geography_ohe',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('onehotencoding',
                                                  OneHotEncoder(handle_unknown
='ignore',
                                                                sparse=False),
                                                  ['Geography'])])),
                ('scaler', StandardScaler()),
                ('sampling', RandomOverSampler(random_state=42)),
                ('xgb2',
                 XGBClassifier(base_score=0.5, booster='gbtree',
                               colsample_bylevel=1, colsample_bynode=1,
```

```
cols...a=0, gpu_id=-1,
importance_type='gain',
interaction_constraints='', learning_rate=0.1,
max_delta_step=0, max_depth=3,
min_child_weight=1, missing=nan,
monotone_constraints='()', n_estimators=1000,
n_jobs=0, num_parallel_tree=1, random_state=0,
reg_alpha=0.3, reg_lambda=1, scale_pos_weight=1,
subsample=0.8, tree_method='exact',
validate_parameters=1, verbosity=None))])
```

In [110…

```
# getting the average of f1 score
cross_val_score(pip_line_xgb2, X_train, y_train, cv=3, scoring='f1').mean()
```

Out[110…

```
0.5924046434321384
```

In [111…

```
# checking the accuracy score
cross_val_score(pip_line_xgb2, X_train, y_train, cv=3, scoring='accuracy').mean(
```

Out[111…

```
0.8107493690070436
```

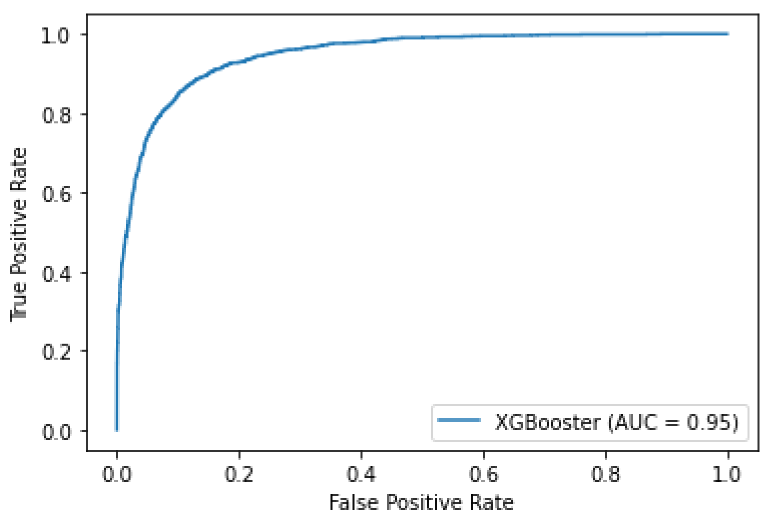
In [112…

```
# using helper function to predict
model_output(pip_line_xgb2, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.5924046434321384
The test Accuracy is: 0.8125
[[1345  262]
 [ 113  280]]
              precision    recall  f1-score   support

           0       0.92      0.84      0.88      1607
           1       0.52      0.71      0.60       393

    accuracy                           0.81      2000
   macro avg       0.72      0.77      0.74      2000
weighted avg       0.84      0.81      0.82      2000
```

In [113…

```
plot_roc_curve(pip_line_xgb2, X_train, y_train, name='XGBooster');
```



test set

In [114…

```
# using the best model to make the final model
# fit the model again
grid_search_rf.fit(X_train, y_train)
```

Out[114…

```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('Geography_ohe',
                                        ColumnTransformer(remainder='passthroug
h',
                                                          transformers=[('onehot
encoding',
                                                                         OneHotE
ncoder(handle_unknown='ignore',

sparse=False),
                                                                         ['Geogr
aphy'])])),
                                       ('scaler', StandardScaler()),
                                       ('sampling',
                                        RandomOverSampler(random_state=42)),
                                       ('rf1',
                                        RandomForestClassifier(class_weight='bal
anced',
                                                               random_state=4
2))]),
             n_jobs=-1,
             param_grid={'rf1__criterion': ['gini', 'entropy'],
                         'rf1__max_depth': [2, 5, 10],
                         'rf1__n_estimators': [100, 1000]},
             scoring='f1')
```

In [115…

```
# make prediction on test set
grid_search_rf.predict(X_test)
```

Out[115…

```
array([0, 0, 0, ..., 1, 0, 1])
```

In [116…

```
# using the predict of test set
y_hat_test = grid_search_rf.predict(X_test)
```

In [117…

```
# getting the f1 score on test set
f1_score(y_test, y_hat_test)
```

Out[117…

```
0.629086809470124
```

In [118…

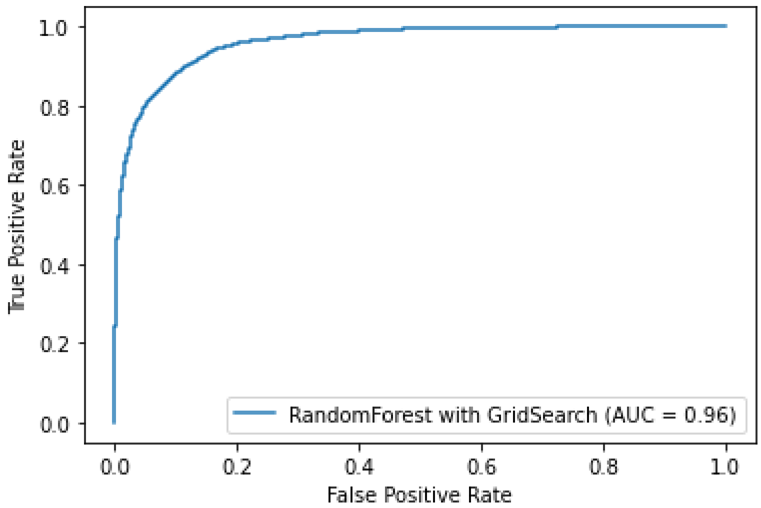
```
# using helper function to predict
model_output(grid_search_rf, X_train, X_test, y_train, y_test)
```

```
The Cross Val f1 score is: 0.6174563801157579
The test Accuracy is: 0.8355
[[1392  215]
 [ 114  279]]
              precision    recall  f1-score   support
```

```
              0       0.92      0.87      0.89      1607
              1       0.56      0.71      0.63       393

       accuracy                           0.84      2000
      macro avg       0.74      0.79      0.76      2000
   weighted avg       0.85      0.84      0.84      2000
```

In [120…

```
plot_roc_curve(grid_search_rf, X_train, y_train, name='RandomForest with GridSea
```



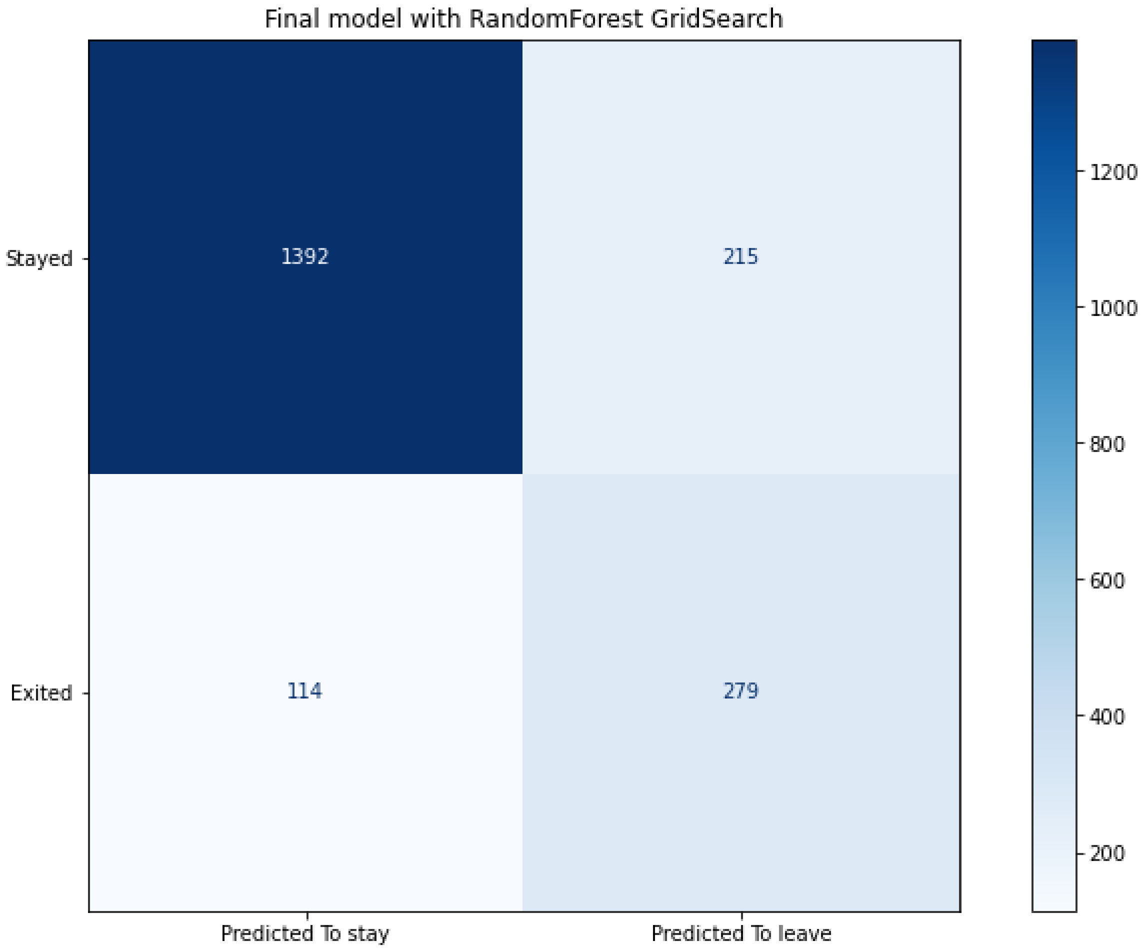
In [121…

```
def confusion_matrix_info(model, X_train, y_train, save_path=None):
    '''
    Creates a confusion matrix for a given model
    Parameters
    ----------
    model: an estimator
    X_train: training  dataset
    y_train: training dataset
    Returns
    -------
    A confusion matrix of given model
    '''
    fig, axes = plt.subplots(figsize=(13,8))
    #axes.set_title("Model Validation", fontsize=20)
    x_tick_marks = ['Predicted To stay', 'Predicted To leave']
    y_tick_marks = ['Stayed', 'Exited']

    plot_confusion_matrix(model, X_train, y_train, ax=axes, cmap='Blues', displa
    plt.xticks([0,1], x_tick_marks)
    plt.title('Final model with RandomForest GridSearch')

    label_font = {'size':'20'}
    axes.set_xlabel('', fontdict=label_font)
    axes.set_ylabel('', fontdict=label_font)
    SMALL_SIZE = 12
    MEDIUM_SIZE = 14
    BIGGER_SIZE = 16

    confusion_matrix = plt.show()
    if save_path:
```

```
        plt.savefig(save_path, transparent=True)
    return confusion_matrix, fig
```

In [122…

```
confusion_matrix_info(grid_search_rf, X_test, y_test);
```



In [ ]: