Week 4 Imbalanced Classification Independent Project

1. Defining the Question

a) Specifying the Data Analysis Question

We are needed to predict whether a customer in Beta Bank will leave the bank soon or not.

b) Understanding the Context

Beta Bank customers are leaving: little by little, chipping away every month. The bankers figured out it's cheaper to save the existing customers rather than to attract new ones. We need to predict whether a customer will leave the bank soon. You have the data on clients' past behavior and termination of contracts with the bank. Build a model with the maximum possible F1 score. To pass the project, you need an F1 score of at least 0.59. Check the F1 for the test set. Additionally, measure the AUC-ROC metric and compare it with the F1.

1. Download and prepare the data. Explain the procedure.
2. Examine the balance of classes. Train the model without taking into account the imbalance. Briefly describe your findings.
3. Improve the quality of the model. Make sure you use at least two approaches to fixing class imbalance. Use the training set to pick the best parameters. Train different models on training and validation sets. Find the best one. Briefly describe your findings.
4. Perform the final testing.

c) Recording the Experimental Design in this analysis

- Data Importation
- Data Exploration
- Data Preparation
- Data Modeling (Using Decision Trees, Random Forest and Logistic Regression)
- Model Evaluation
- Hyparameter Tuning
- Findings and Recommendations

d) Metric of success

Designing a model that will predict whether a customer will leave bank with an F1 score of at least 0.59

Data Importation

Loading the necessary libraries

```
#Importing the required libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score
from joblib import dump
from sklearn.metrics import mean_absolute_error
from sklearn.linear_model import LinearRegression
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.utils import resample
from sklearn.metrics import roc_auc_score
from sklearn.metrics import make_scorer
from sklearn.utils import shuffle
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_curve
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import classification_report
%matplotlib inline
```

Loading data from the dataset

```
# Loading the dataset using pd.read_csv() function
betabank_df = pd.read_csv('https://bit.ly/2XZK7Bo')
betabank_df.head()
```

RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProduct

Observation: Three columns have boolean values, HasCrCard, IsActiveMember and Exited columns. Others have either text or numeric values

```
#Checking additional data information using .info() fucntion
betabank_df.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           9091 non-null   float64
 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(3), int64(8), object(3)
memory usage: 1.1+ MB
```

Observation:- We have a mixture of integer, object and float data types

Data Exploration: Exploratory Data Analysis (EDA)

```
#Checking for nulls
betabank_df.isnull().sum()
```

```
RowNumber            0
CustomerId           0
Surname              0
CreditScore          0
Geography            0
Gender               0
Age                  0
Tenure             909
Balance              0
NumOfProducts        0
HasCrCard            0
IsActiveMember       0
EstimatedSalary      0
Exited               0
dtype: int64
```

We will use Exited column as our target. For this analysis some of the columns i.e RowNumber, CustomerId and Surname will be remove as they aren't useful features. For the nulls in Tenure, will replace them with the mean.

Data cleaning

```
#Replace nulls in tenure with mean
betabank_df['Tenure']= df['Tenure'].fillna(df['Tenure'].mean())
#Convert float datatype in tenure to int
betabank_df['Tenure'] = df['Tenure'].astype(int)
```

```
#Check the data again using .info() function
betabank_df.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
```

Observation: Float datatype in Tenure column converted successfully to integer

```
#Confirm if we have nulls again
betabank_df.isnull().sum()
```

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
```

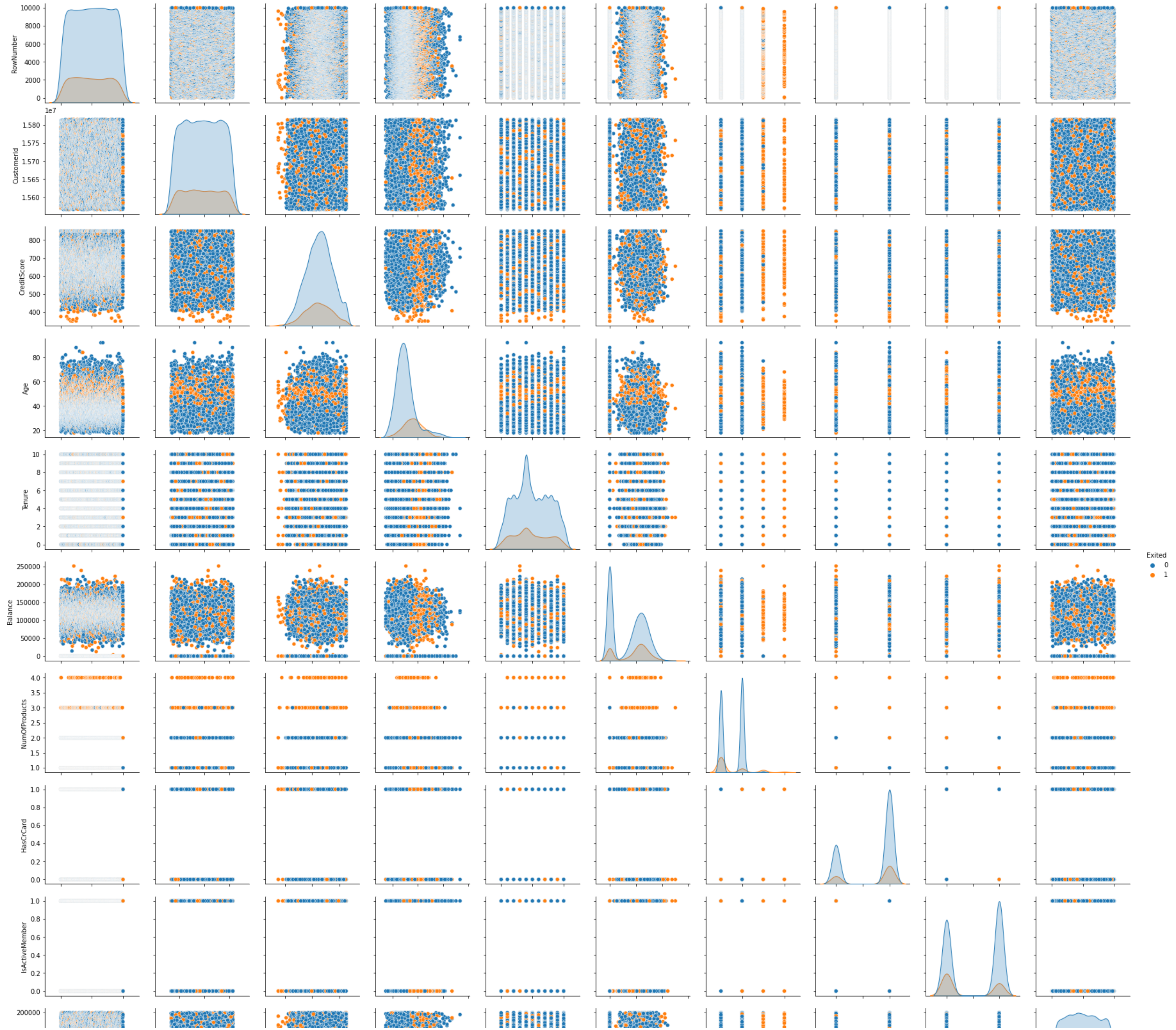
```
Exited            0
dtype: int64
```

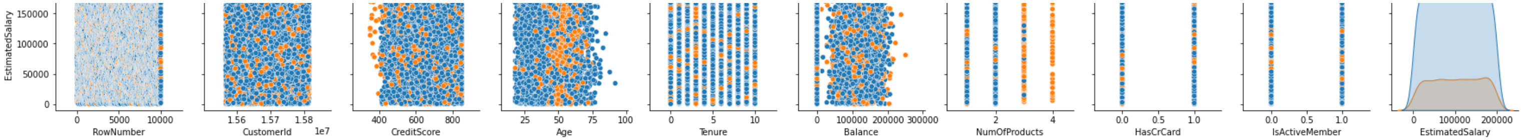
Observation: - We don't nulls anymore in any of the column

Data visualization

```
#Checking the distribution of the target column
sns.pairplot(betabank_df, hue = 'Exited')
```

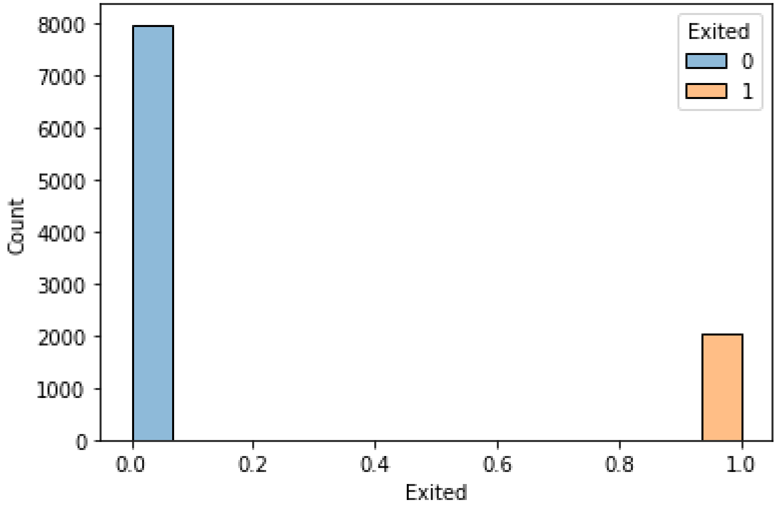
```
<seaborn.axisgrid.PairGrid at 0x7f3435c43490>
```






```
sns.histplot(x=betabank_df['Exited'], hue= df['Exited'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f343354e510>
```



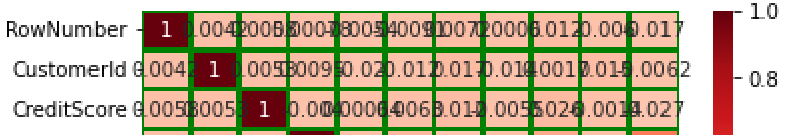
There are more customers who haven't left. This might affect model biasness

```
#Getting the co-relation
betabank_df.corr()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCr
RowNumber	1.000000	0.004202	0.005840	0.000783	-0.005420	-0.009067	0.007246	0.00
CustomerId	0.004202	1.000000	0.005308	0.009497	-0.019709	-0.012419	0.016972	-0.01
CreditScore	0.005840	0.005308	1.000000	-0.003965	0.000644	0.006268	0.012238	-0.00
Age	0.000783	0.009497	-0.003965	1.000000	-0.011683	0.028308	-0.030680	-0.0
Tenure	-0.005420	-0.019709	0.000644	-0.011683	1.000000	-0.007301	0.011345	0.02
Balance	-0.009067	-0.012419	0.006268	0.028308	-0.007301	1.000000	-0.304180	-0.01
NumOfProducts	0.007246	0.016972	0.012238	-0.030680	0.011345	-0.304180	1.000000	0.00
HasCrCard	0.000599	-0.014025	-0.005458	-0.011721	0.025468	-0.014858	0.003183	1.00
IsActiveMember	0.012044	0.001665	0.025651	0.085472	-0.030212	-0.010084	0.009612	-0.0
EstimatedSalary	-0.005988	0.015271	-0.001384	-0.007201	0.010514	0.012797	0.014204	-0.00
Exited	-0.016571	-0.006248	-0.027094	0.285323	-0.015710	0.118533	-0.047820	-0.00

```
#Plotting the heat map of the correlations
sns.heatmap(betabank_df.corr(),annot=True, cmap='Reds', linecolor='Green', linewidths=1.5)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f34335434d0>
```



Data preparation

Setting the targets and features ready for the models

```
#One hot encoding
df = pd.get_dummies(betabank_df, drop_first=True)
```

```
#Creating dataframes: Features and target dataframes
features = betabank_df.drop(columns=['Exited', 'RowNumber','Gender', 'CustomerId','Surname', 'Geography'])
target =  betabank_df['Exited']
```

```
# Splitting the data inot four variables
features_train, features_test, target_train, target_test = train_test_split(features, target, test_size=0.20, random_state=12345)
features_train, features_valid, target_train, target_valid = train_test_split(features_train, target_train, test_size=0.2, random_sta
```

```
# Let us try normalizing the data now
to_normalize = ['CreditScore', 'Age', 'Balance', 'EstimatedSalary', 'Tenure', 'NumOfProducts']
scaler = StandardScaler()
scaler.fit(features_train[to_normalize])
features_train.loc[:,to_normalize] = scaler.transform(features_train[to_normalize])
features_valid.loc[:,to_normalize] = scaler.transform(features_valid[to_normalize])
features_test.loc[:,to_normalize] = scaler.transform(features_test[to_normalize])
```

Note that, one hot encoding was required to convert the categorical variable to numeric. Allowing the 'inverse' of each data type will damage our outcomes since there will be high correlation between them. It makes sense to 'drop first' and only let one of them remain. Similarly, we don't need France, Germany and Spain coulmns since a row not being 1 for Germany and Spain implies that it is France. After splitting, I checked to see if the splits make sense, and they do. The sample size is also good.

Data Modelling : Machine Learning Modelling, Evaluation and Hyparameter Tuning

Without taking into account the imbalance

```
#  Looking at the class imbalance:
print(betabank_df[betabank_df['Exited'] == 1]['Exited'].count())
print(betabank_df[betabank_df['Exited'] == 0]['Exited'].count())
```

```
2037
7963
```

There is an evident mbalance, approximately a ration of 1:4.

Logistic Regression

```
#Assuming theclass imbalance:
LogRegModImb = LogisticRegression(solver='liblinear', random_state=12345)
LogRegModImb.fit(features_train,target_train)
print('Accuracy', LogRegModImb.score(features_valid, target_valid))
print('f1 score:' ,f1_score(target_valid, LogRegModImb.predict(features_valid)))
print('AUC:', roc_auc_score(target_valid, LogRegModImb.predict_proba(features_valid)[:,1]))
```

```
Accuracy 0.815
```

```
f1 score: 0.2371134020618557
AUC: 0.7422892636218132
```

```
features_train.head()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSa
6007	1.082953	-1.034700	-0.693040	-0.022281	-0.896464	1	1	1.74
3936	0.567340	-0.653628	-0.333253	0.900456	-0.896464	0	0	0.64
7142	-0.412324	2.299682	-1.052827	0.881081	0.821312	1	0	0.38
5572	-0.897000	-0.463092	0.386321	-1.232928	-0.896464	1	1	-0.63
332	0.113601	0.489589	-1.052827	0.646591	0.821312	0	1	0.78

We have a accuracy of 0.81, f1 score of 0.31, and AUC of 0.76 when we do not account for imbalance and use logistic regression. We don't need to check Random Forest and Decision Tree because if the imbalance affects the results of Logistic Regression, it will naturally affect the results of Random Forest and Decision Tree since they do not perform well on imbalanced data sets.

Taking into account the imbalance

Logistic Regression

```
#Upsampling function
def upsample(features, target, repeat):
    features_zeros = features[target == 0]
    features_ones = features[target == 1]
    target_zeros = target[target == 0]
    target_ones = target[target == 1]

    features_upsampled = pd.concat([features_zeros] + [features_ones] * repeat)
```

```
    target_upsampled = pd.concat([target_zeros] + [target_ones] * repeat)

    features_upsampled, target_upsampled = shuffle(
        features_upsampled, target_upsampled, random_state=12345)

    return features_upsampled, target_upsampled

features_upsampled, target_upsampled = upsample(features_train, target_train, 10)

upsampled_LogReg_model =LogisticRegression(random_state=12345,solver='liblinear')
upsampled_LogReg_model.fit(features_upsampled, target_upsampled)
upsampled_LogReg_predicted_valid = upsampled_LogReg_model.predict(features_valid)

print('Accuracy', upsampled_LogReg_model.score(features_valid, target_valid))
print('f1 score:' ,f1_score(target_valid, upsampled_LogReg_predicted_valid))
print('AUC:',roc_auc_score(target_valid, upsampled_LogReg_model.predict_proba(features_valid)[:,1]))
```

```
Accuracy 0.41875
f1 score: 0.37999999999999995
AUC: 0.7492003633671
```

Upsampling makes our f1 score 0.393. This isn't as good as the in built balanced feature of the Logisitic regression model.

```
#Downsampling function
def downsample(features, target, fraction):
    features_zeros = features[target == 0]
    features_ones = features[target == 1]
    target_zeros = target[target == 0]
    target_ones = target[target == 1]

    features_downsampled = pd.concat(
        [features_zeros.sample(frac=fraction, random_state=12345)] + [features_ones])
    target_downsampled = pd.concat(
        [target_zeros.sample(frac=fraction, random_state=12345)] + [target_ones])

    features_downsampled, target_downsampled = shuffle(
```

```
        features_downsampled, target_downsampled, random_state=12345)

    return features_downsampled, target_downsampled

features_downsampled, target_downsampled = downsample(features_train, target_train, 0.1)

down_LogReg_model =LogisticRegression(random_state=12345,solver='liblinear')
down_LogReg_model.fit(features_downsampled, target_downsampled)
down_LogReg_predicted_valid = down_LogReg_model.predict(features_valid)

print("F1:", f1_score(target_valid, down_LogReg_predicted_valid))
print('Accuracy:', down_LogReg_model.score(features_valid, target_valid))
print("AUC-ROC:", roc_auc_score(target_valid, down_LogReg_model.predict_proba(features_valid)[:,1]))
```

```
F1: 0.3819028609447771
Accuracy: 0.419375
AUC-ROC: 0.7462995335771048
```

Downsampling makes our f1 score 0.391. This isn't as good as the in built balanced feature of the Logisitic regression model and is almost the same as upsampling.

Decision Tree

```
depth_param = {'max_depth':range(1,25)}
DecTreeMod = DecisionTreeClassifier(random_state=12345)
DecTreeModOpt = GridSearchCV(DecTreeMod,depth_param)
DecTreeModOpt.fit(features_train, target_train)
print(DecTreeModOpt.best_estimator_)
DecTreeModOpt_predicted_valid = DecTreeModOpt.predict(features_valid)
print("F1:", f1_score(target_valid, DecTreeModOpt_predicted_valid))
print('Accuracy:', DecTreeModOpt.score(features_valid, target_valid))
print("AUC-ROC:", roc_auc_score(target_valid, DecTreeModOpt.predict_proba(features_valid)[:,1]))
```

```
DecisionTreeClassifier(max_depth=6, random_state=12345)
```

```
F1: 0.5224839400428266
Accuracy: 0.860625
AUC-ROC: 0.8154245262614157
```

Just from using decision trees with optimized hyper parameters, our f1 score 0.51. This is better than the in built balanced feature of the Logisitic regression model, but not by much.

```
# Using the optimal max depth
decision_classifier = DecisionTreeClassifier(max_depth = 7, random_state = 12345)
decision_classifier.fit(features_train, target_train)
score = decision_classifier.score(features_test, target_test)
print('Score: {}'.format(score))
```

```
Score: 0.841
```

- Random Forest Classifier had the best accuracy score of 80.87%
- Decision Tree Classifier had the second best accuracy score of 79.78%
- Logic Regression had the least accuracy score of 76.51%

Random Forest

```
depth_param = {'max_depth':range(1,10), 'n_estimators':range(1,50)}
RandForestMod = RandomForestClassifier(random_state=12345)
RandForestOpt = GridSearchCV(RandForestMod,depth_param)
RandForestOpt.fit(features_train, target_train)
print(RandForestOpt.best_estimator_)
RandForestOpt_predicted_valid = RandForestOpt.predict(features_valid)
print("F1:", f1_score(target_valid, RandForestOpt_predicted_valid))
print('Accuracy', RandForestOpt.score(features_valid, target_valid))
print("AUC-ROC:", roc_auc_score(target_valid, RandForestOpt.predict_proba(features_valid)[:,1]))
```

```
RandomForestClassifier(max_depth=9, n_estimators=46, random_state=12345)
F1: 0.5304347826086956
Accuracy 0.865
AUC-ROC: 0.844156736413811
```

Random forests gives us a f1 score of 0.54, although it took a very long time to run this chunk of code. If run time is a priority, the parameter space needs to be greatly reduced. However, we have come across an issue. We need an f1 score of at least 0.59, and we have already done an exhaustive search over a huge parameter space. Let us try to keep one parameter constant and increase the range of the other parameter to see if that can help us improve our score. For the above model, max_depth of 8 gave us the best result. Let's keep that constant and increase the range of n_estimators and try again. Most importantly, let us add the argument: 'class weight = balanced' since simply increasing the parameter space alone is most likely not going to increase our f1 score by so much.

```
depth_param = {'n_estimators':range(1,200)}
RandForestMod = RandomForestClassifier(random_state=12345, max_depth = 8,class_weight='balanced')
RandForestOpt = GridSearchCV(RandForestMod, depth_param)
RandForestOpt.fit(features_train, target_train)
print(RandForestOpt.best_estimator_)
RandForestOpt_predicted_valid = RandForestOpt.predict(features_valid)
print("F1:", f1_score(target_valid, RandForestOpt_predicted_valid))
print('Accuracy:', RandForestOpt.score(features_valid, target_valid))
print("AUC-ROC:", roc_auc_score(target_valid, RandForestOpt.predict_proba(features_valid)[:,1]))
```

```
RandomForestClassifier(class_weight='balanced', max_depth=8, n_estimators=27,
                       random_state=12345)
F1: 0.5475841874084919
Accuracy: 0.806875
AUC-ROC: 0.8346654249079496
```

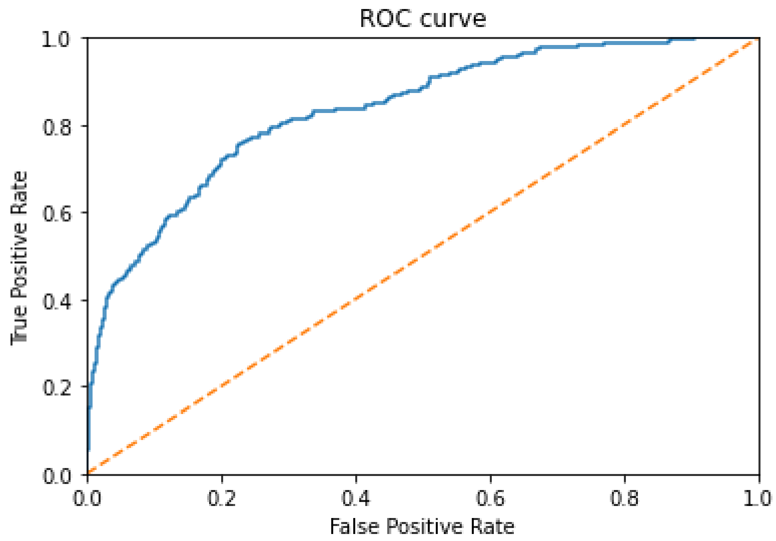
We get a f1 score of 0.604 and the n_estimators we need is 190. Finally, we have achieved an acceptable number gives us enough confidence to take our model to the testing data. Max depth is 8 since we specified that.

Evaluate the best model: random forest

```
RandForestOpt_predicted_test = RandForestOpt.predict(features_test)
print("F1:", f1_score(target_test, RandForestOpt_predicted_test))
print("AUC-ROC:", roc_auc_score(target_test, RandForestOpt.predict_proba(features_test)[:,1]))
print('Accuracy:', RandForestOpt.score(features_valid, target_valid))

print(classification_report(target_test, RandForestOpt_predicted_test))
```

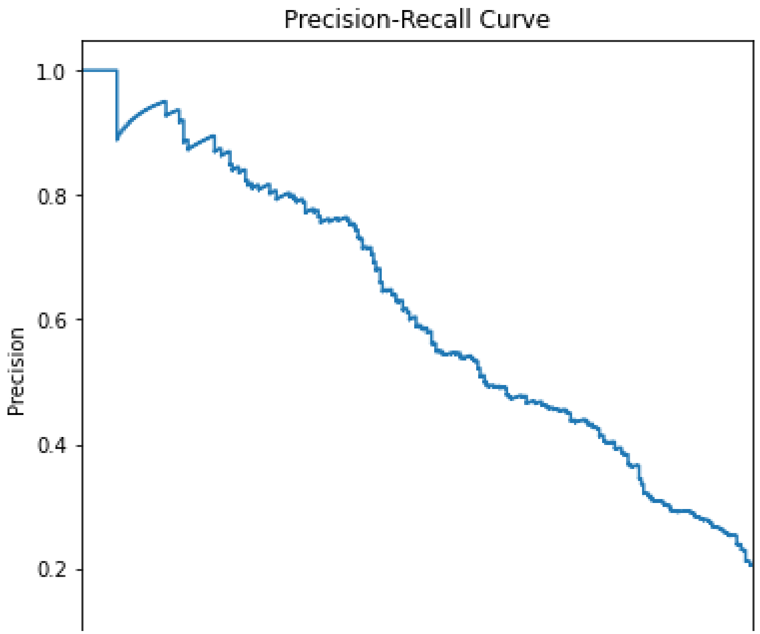
```
F1: 0.6074380165289255
AUC-ROC: 0.8426536205969888
Accuracy: 0.806875
              precision    recall  f1-score   support

           0       0.91      0.84      0.87      1573
           1       0.54      0.69      0.61       427

    accuracy                           0.81      2000
   macro avg       0.73      0.77      0.74      2000
weighted avg       0.83      0.81      0.82      2000
```

```
# Let's plot the AUC-ROC curve.
probabilities_valid = RandForestOpt.predict_proba(features_valid)
probabilities_one_valid = probabilities_valid[:, 1]

fpr, tpr, thresholds = roc_curve(target_valid, probabilities_one_valid)

plt.figure()
plt.plot(fpr, tpr)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC curve')
plt.show()
```



We see a deviation from the random model (orange line) that signifies that our model performs that much better than someone just working by chance. This is validated by the AUC we calculated.

```
# Let's plot the precision-recall curve
precision, recall, thresholds = precision_recall_curve(target_valid, probabilities_valid[:, 1])

plt.figure(figsize=(6, 6))
plt.step(recall, precision, where='post')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Precision-Recall Curve')
plt.show()
```



Findings and Recommendations

Findings

- The best model is a Random Forest Classifier. Bootstrap is set to true and the class_weight parameter is set to ' balanced '. Setting it to balanced is very important otherwise the performance expectations are not met.
- The hyperparameters max_depth is set to 8 and n_estimators is set to 190. A random_state = 12345 will give you the exact results I produced above.
- For the test dataset, the F1 score is 0.64 and the AUC-ROC score is 0.86. Both these metrics signify good quality and meet the expectations of the assignment.

Recommendations

- Use of Random Forest model is recommended
- More training data with less bias will increase the accuracy of the model
- Hyper paramter tuning is required in order to improve model accuracy.

0s completed at 10:41 PM