Bank Customer Churn Prediction

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- **EDA.ipynb** - Exploratory Data Analysis
- **Model.ipynb** - Model Building
- **app.py** - Flask App
- **templates** - HTML Templates
- **static** - CSS Stylesheet

Import necessary libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
set_seed = 42
sns.set_style('darkgrid')
```

read in the data

```
data = pd.read_csv('Bank_Customer_Churn_Prediction.csv')
data.head()
```

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_car
0	15634602	619	France	Female	42	2	0.00	1	1

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_car
1	15647311	608	Spain	Female	41	1	83807.86	1	0
2	15619304	502	France	Female	42	8	159660.80	3	1
3	15701354	699	France	Female	39	1	0.00	2	0
4	15737888	850	Spain	Female	43	2	125510.82	1	1

Data Preprocessing

```
#write a function that does data preprocessing for the entire dataset
def data_preprocessing(data):
    #drop the row with missing values
    data.dropna(inplace=True)
    #drop the column with unique values
    data.drop(['RowNumber', 'CustomerId', 'Surname'], axis=1, inplace=True)
    #convert the categorical variables to dummy variables
    data = pd.get_dummies(data, drop_first=True)
    #split the data into features and target
    X = data.drop('Exited', axis=1)
    y = data['Exited']
    return X, y
```

```
# confirm if there are any missing values
data.isnull().sum()
```

```
customer_id         0
credit_score        0
country             0
gender              0
age                 0
tenure              0
balance             0
products_number     0
credit_card         0
active_member       0
estimated_salary    0
churn               0
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customer_id       10000 non-null  int64
 1   credit_score      10000 non-null  int64
 2   country           10000 non-null  object
 3   gender            10000 non-null  object
 4   age               10000 non-null  int64
 5   tenure            10000 non-null  int64
 6   balance           10000 non-null  float64
 7   products_number   10000 non-null  int64
 8   credit_card       10000 non-null  int64
 9   active_member     10000 non-null  int64
 10  estimated_salary  10000 non-null  float64
 11  churn             10000 non-null  int64
dtypes: float64(2), int64(8), object(2)
memory usage: 937.6+ KB
```

Exploration Data Analysis

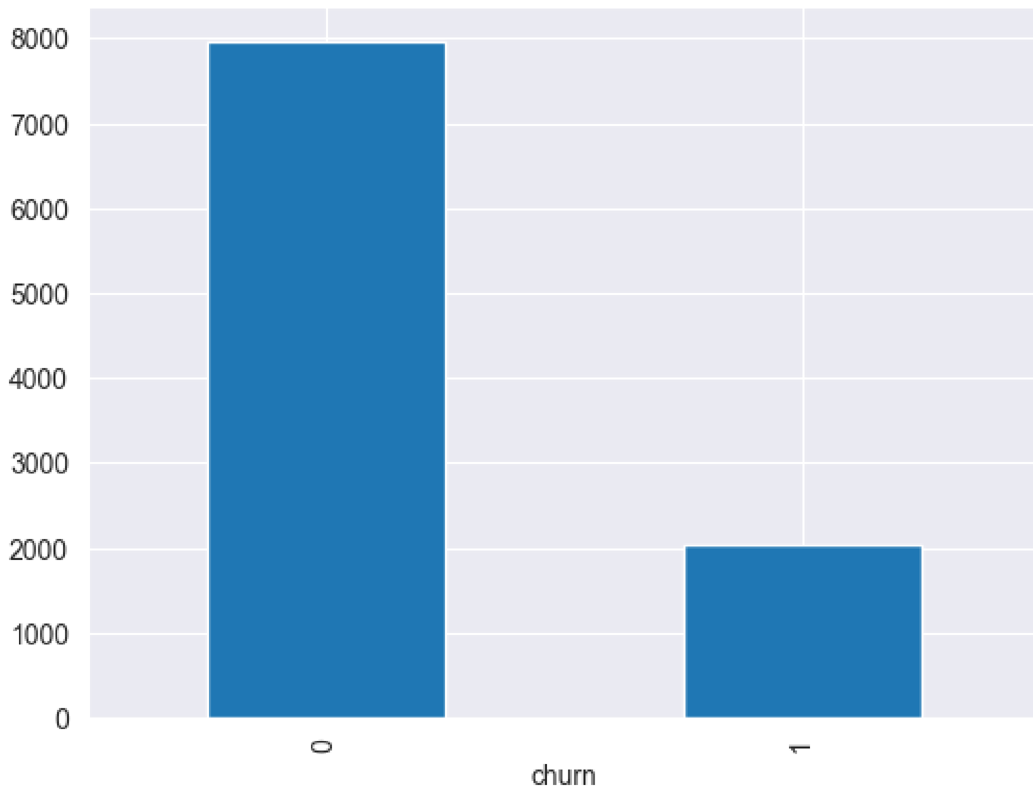
```
#check the distribution of the target variable
data['churn'].value_counts()
```

```
churn
0    7963
1    2037
Name: count, dtype: int64
```

- We observe that about 7963 customers have exited the bank, while 2037 customers have stayed with the bank. This is an imbalanced dataset.

```
color_wheel = {1: "#0392cf",2: "#7bc043"}
colors = data['churn'].map(lambda x: color_wheel.get(x + 1))
print(data.churn.value_counts())
p=data.churn.value_counts().plot(kind="bar")
```

```
churn
0    7963
1    2037
Name: count, dtype: int64
```




```
# check how many unique values are there in each column
data.nunique()
```

```
customer_id         10000
credit_score          460
country                 3
gender                  2
age                    70
tenure                 11
balance              6382
products_number         4
credit_card             2
```

```
active_member          2
estimated_salary    9999
churn                  2
dtype: int64
```

```
# check the distribution of the numerical variables
data.describe()
```

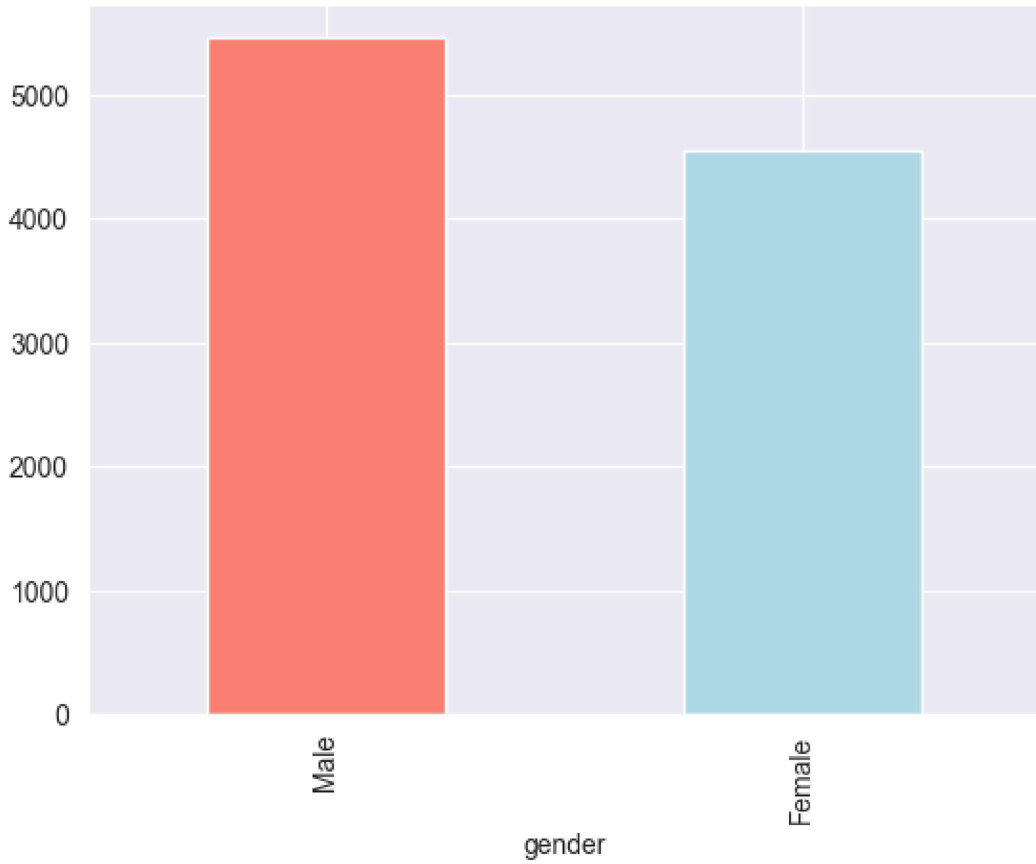
	customer_id	credit_score	age	tenure	balance	products_number	cr
count	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10
mean	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.7
std	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.4
min	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.0
25%	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.0
50%	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.0
75%	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.0
max	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.0

Descriptive of the data is as follows:

- mean age of the customers is 38 years
- mean balance of the customers is 76485
- mean estimated salary of the customers is 100090
- mean credit score of the customers is 650
- mean tenure of the customers is 5 years
- mean number of products used by the customers is 1.5
- mean number of active members is 0.5
- mean number of customers who have credit card is 0.7
- mean number of customers who have exited the bank is 0.2

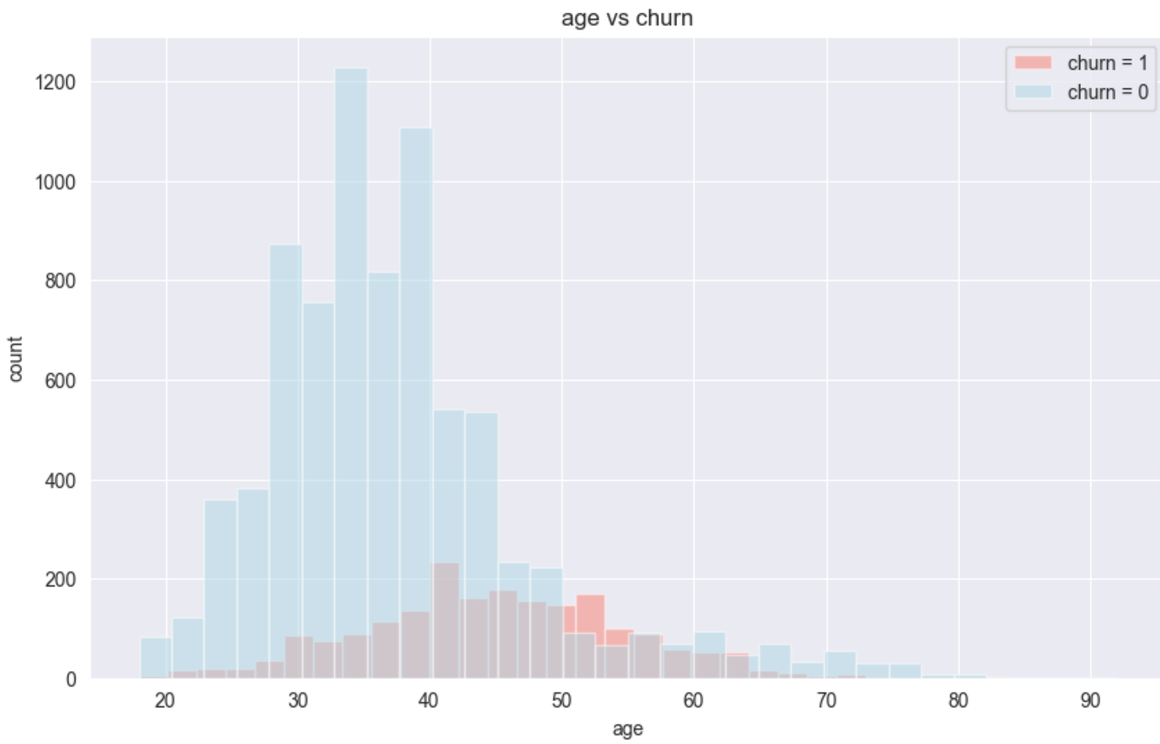
```
#plot how many females and males are there in the dataset
data['gender'].value_counts().plot(kind='bar', color=['salmon', 'lightblue']), data['gende
```

```
(<Axes: xlabel='gender'>,
 gender
 Male      5457
 Female    4543
 Name: count, dtype: int64)
```



- we observe that in our dataset, we have 4543 females and 5457 males.
- which indicates that there are more males than females in our dataset.

```
#plot gender with age
plt.figure(figsize=(10, 6))
data[data['churn'] == 1]['age'].hist(alpha=0.5, color='salmon', bins=30, label='churn = 1'
data[data['churn'] == 0]['age'].hist(alpha=0.5, color='lightblue', bins=30, label='churn =
plt.legend()
plt.xlabel('age')
plt.ylabel('count')
plt.title('age vs churn')
plt.show()
```



- An observation of the distribution of the age of the customers shows that the age of the customers ranges from 18 to 92 years.
- The age of the customers is normally distributed with a mean of 38 years.

```
#plot gender with churn
plt.figure(figsize=(10, 6))
data[data['churn']==1]['gender'].hist(alpha=0.5, color='salmon', bins=30, label='churn = 1
data[data['churn']==0]['gender'].hist(alpha=0.5, color='lightblue', bins=30, label='churn
plt.legend()
plt.xlabel('gender')
plt.ylabel('count')
plt.show()
```


```
data[data['churn']==1]['gender'].value_counts(),data[data['churn']==0]['gender'].value_cou
```

```
(gender
 Female    1139
 Male       898
 Name: count, dtype: int64,
 gender
 Male      4559
 Female    3404
 Name: count, dtype: int64)
```

- an observation based on gender and churn
- 1139 females 898 males churned
- 4559 Males and 3404 females churned

```
#one hotenconding the data for gender and country column
data['gender']=data['gender'].replace(['Female'],'0')
data['gender']=data['gender'].replace(['Male'],'1')
data['country']=data['country'].replace(['France'],'0')
data['country']=data['country'].replace(['Spain'],'1')
```

```python
data['country']=data['country'].replace(['Germany'],'2')
data.head()
```

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_car
0	15634602	619	0	0	42	2	0.00	1	1
1	15647311	608	1	0	41	1	83807.86	1	0
2	15619304	502	0	0	42	8	159660.80	3	1
3	15701354	699	0	0	39	1	0.00	2	0
4	15737888	850	1	0	43	2	125510.82	1	1

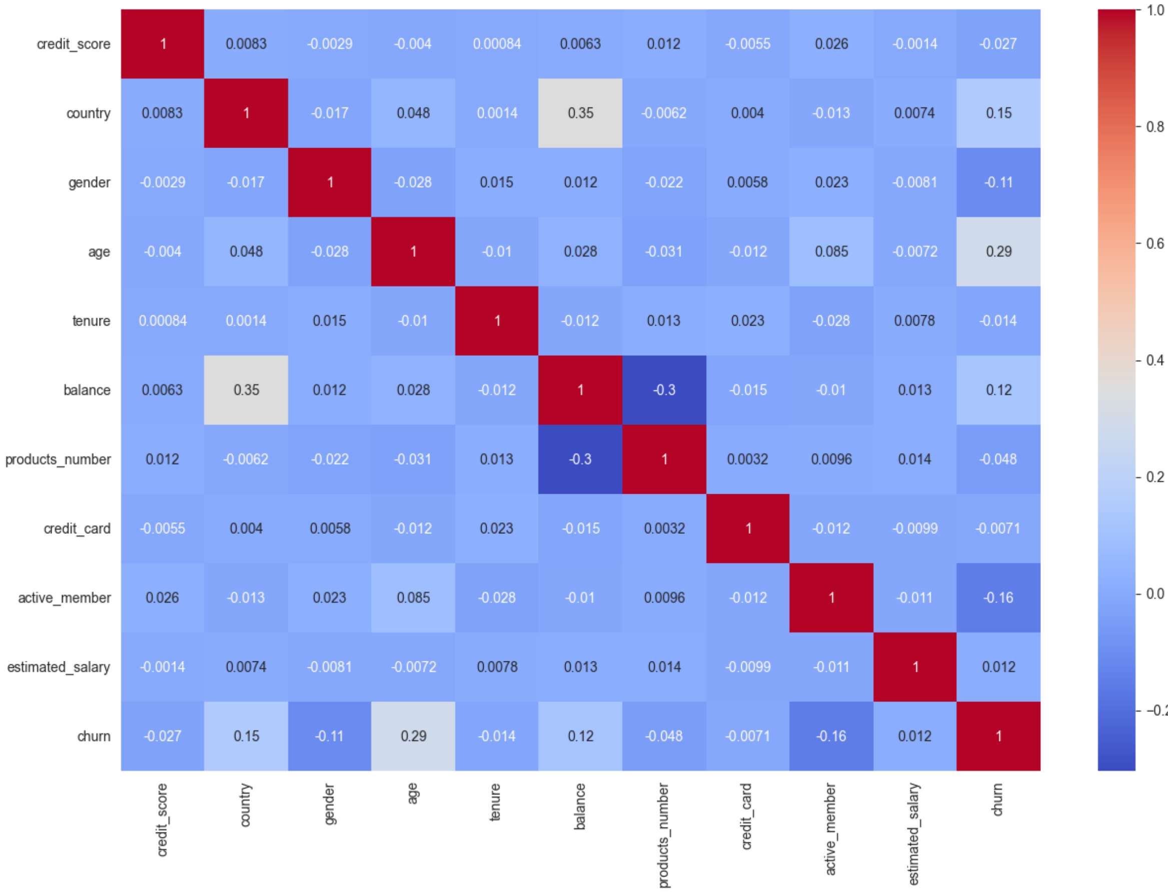
```python
#drop customer id
data.drop(['customer_id'],axis=1,inplace=True)
data.head()
```

	credit_score	country	gender	age	tenure	balance	products_number	credit_card	active_men
0	619	0	0	42	2	0.00	1	1	1
1	608	1	0	41	1	83807.86	1	0	1
2	502	0	0	42	8	159660.80	3	1	0
3	699	0	0	39	1	0.00	2	0	0
4	850	1	0	43	2	125510.82	1	1	1

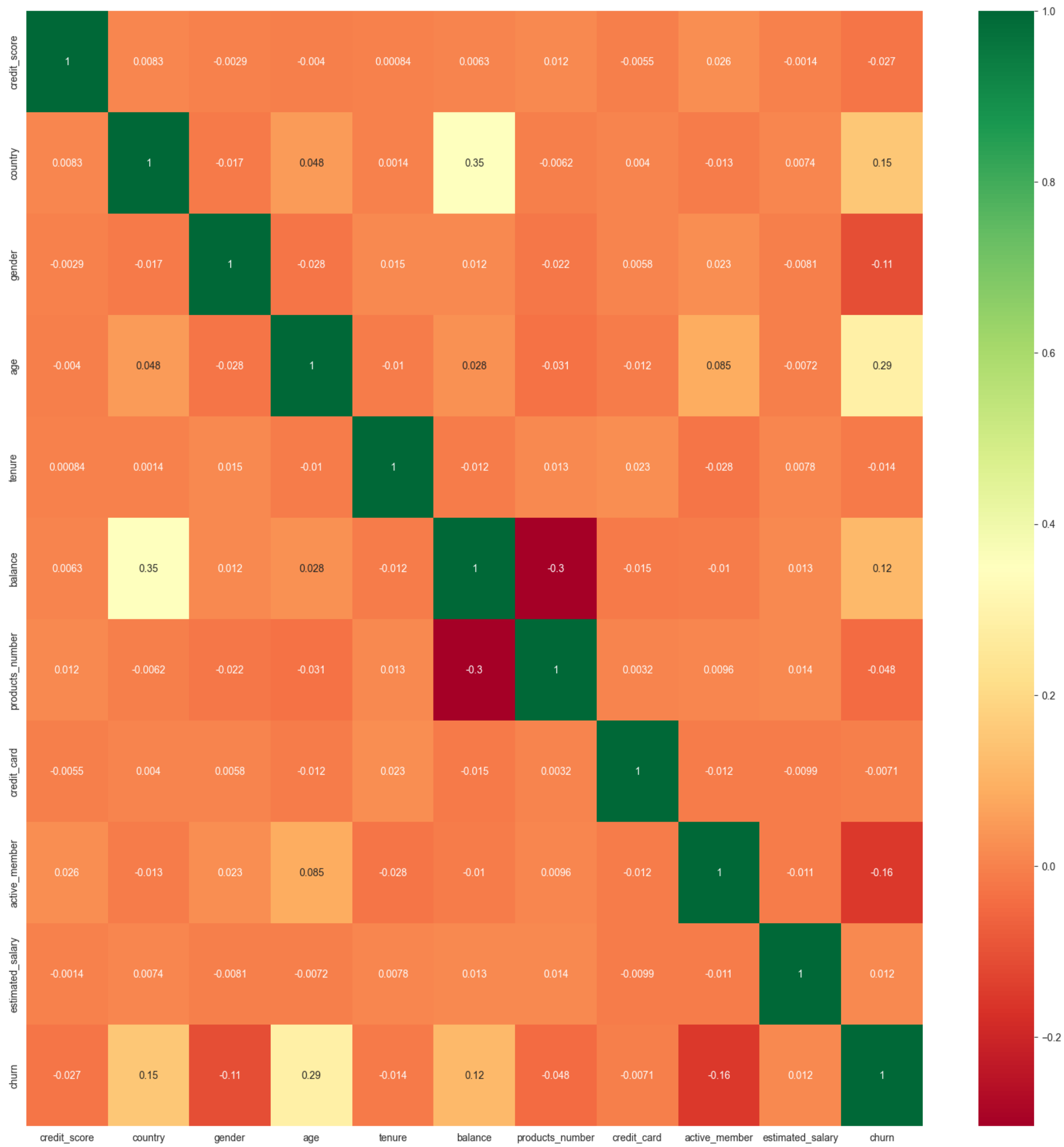
```python
data.corr(method='pearson')
```

	credit_score	country	gender	age	tenure	balance	products_numb
credit_score	1.000000	0.008267	-0.002857	-0.003965	0.000842	0.006268	0.012238
country	0.008267	1.000000	-0.016936	0.048092	0.001418	0.348700	-0.006180
gender	-0.002857	-0.016936	1.000000	-0.027544	0.014733	0.012087	-0.021859
age	-0.003965	0.048092	-0.027544	1.000000	-0.009997	0.028308	-0.030680
tenure	0.000842	0.001418	0.014733	-0.009997	1.000000	-0.012254	0.013444
balance	0.006268	0.348700	0.012087	0.028308	-0.012254	1.000000	-0.304180
products_number	0.012238	-0.006180	-0.021859	-0.030680	0.013444	-0.304180	1.000000
credit_card	-0.005458	0.004036	0.005766	-0.011721	0.022583	-0.014858	0.003183
active_member	0.025651	-0.012692	0.022544	0.085472	-0.028362	-0.010084	0.009612
estimated_salary	-0.001384	0.007382	-0.008112	-0.007201	0.007784	0.012797	0.014204
churn	-0.027094	0.153771	-0.106512	0.285323	-0.014001	0.118533	-0.047820

```
#plot the correlation matrix
plt.figure(figsize=(15, 10))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
plt.show()
```




```
#get the correlation of each feature in the dataset
corrmat = data.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20, 20))
#plot heat map
g = sns.heatmap(data[top_corr_features].corr(), annot=True, cmap='RdYlGn')
```




```
#select the best features
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
X = data.iloc[:,0:11]  #independent columns
y = data.iloc[:,-1]    #target column i.e price range
```

```
#apply SelectKBest class to extract top 10 best features
bestfeatures = SelectKBest(score_func=chi2, k=10)
fit = bestfeatures.fit(X,y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)
#concat two dataframes for better visualization
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['features','score']  #naming the dataframe columns
print(featureScores.nlargest(10,'score'))  #print 10 best features
```

```
            features         score
5            balance  7.151303e+06
9   estimated_salary  4.835088e+04
10             churn  7.963000e+03
3                age  2.300417e+03
1            country  2.175407e+02
8      active_member  1.181994e+02
0       credit_score  1.054035e+02
2             gender  5.153993e+01
6    products_number  5.055394e+00
4             tenure  3.270538e+00
```

Data Modelling

```
#split the data into features and target
from sklearn.model_selection import train_test_split
X = data.drop('churn', axis=1)
y = data['churn']
#split the data into train and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=set_
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((8000, 10), (2000, 10), (8000,), (2000,))
```

```
#scale the data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```python
#build the model
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
y_pred = log_reg.predict(X_test)
print('Accuracy score: {}'.format(accuracy_score(y_test, y_pred)))
print('Confusion matrix: \n{}'.format(confusion_matrix(y_test, y_pred)))
print('Classification report: \n{}'.format(classification_report(y_test, y_pred)))
```

```
Accuracy score: 0.8145
Confusion matrix:
[[1544   63]
 [ 308   85]]
Classification report:
              precision    recall  f1-score   support

           0       0.83      0.96      0.89      1607
           1       0.57      0.22      0.31       393

    accuracy                           0.81      2000
   macro avg       0.70      0.59      0.60      2000
weighted avg       0.78      0.81      0.78      2000
```

```python
# build random forest classifier
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
print('Accuracy score: {}'.format(accuracy_score(y_test, y_pred)))
print('Confusion matrix: \n{}'.format(confusion_matrix(y_test, y_pred)))
print('Classification report: \n{}'.format(classification_report(y_test, y_pred)))
```

```
Accuracy score: 0.862
Confusion matrix:
[[1539   68]
 [ 208  185]]
Classification report:
              precision    recall  f1-score   support
```

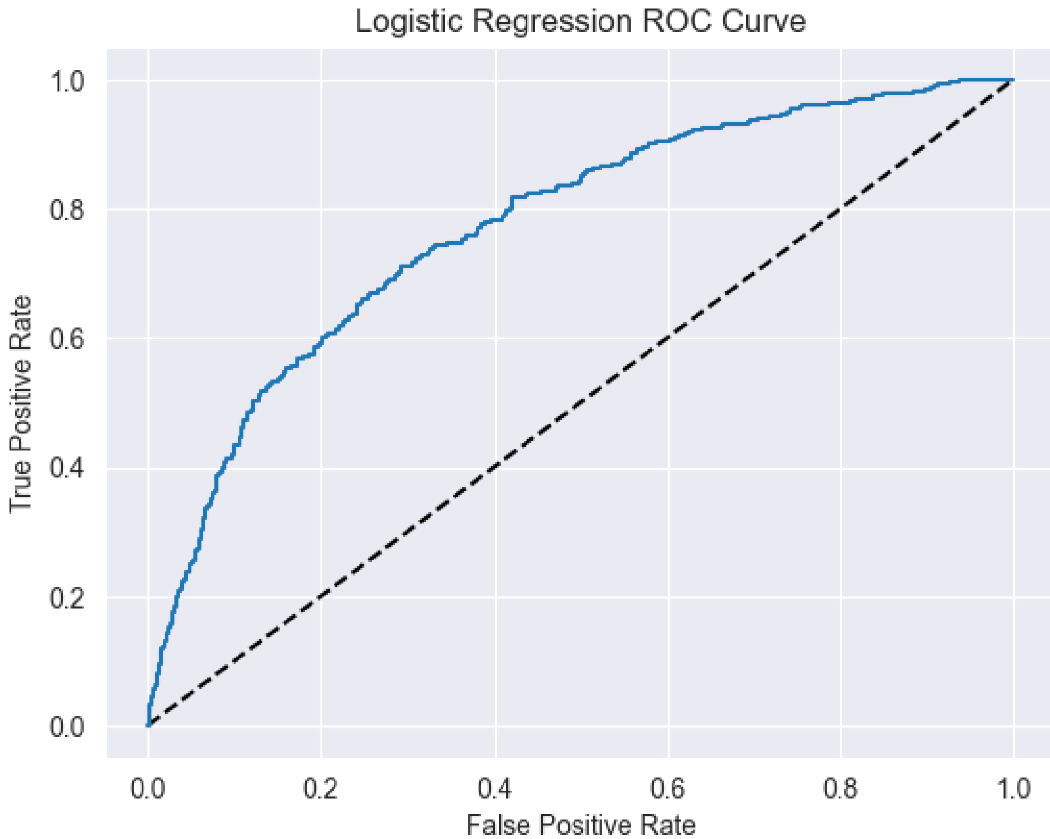
```
           0       0.88      0.96      0.92      1607
           1       0.73      0.47      0.57       393

    accuracy                           0.86      2000
   macro avg       0.81      0.71      0.75      2000
weighted avg       0.85      0.86      0.85      2000
```

```
#build XGBoost classifier
from xgboost import XGBClassifier
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
print('Accuracy score: {}'.format(accuracy_score(y_test, y_pred)))
print('Confusion matrix: \n{}'.format(confusion_matrix(y_test, y_pred)))
print('Classification report: \n{}'.format(classification_report(y_test, y_pred)))
```

```
Accuracy score: 0.861
Confusion matrix:
[[1530   77]
 [ 201  192]]
Classification report:
              precision    recall  f1-score   support

           0       0.88      0.95      0.92      1607
           1       0.71      0.49      0.58       393

    accuracy                           0.86      2000
   macro avg       0.80      0.72      0.75      2000
weighted avg       0.85      0.86      0.85      2000
```

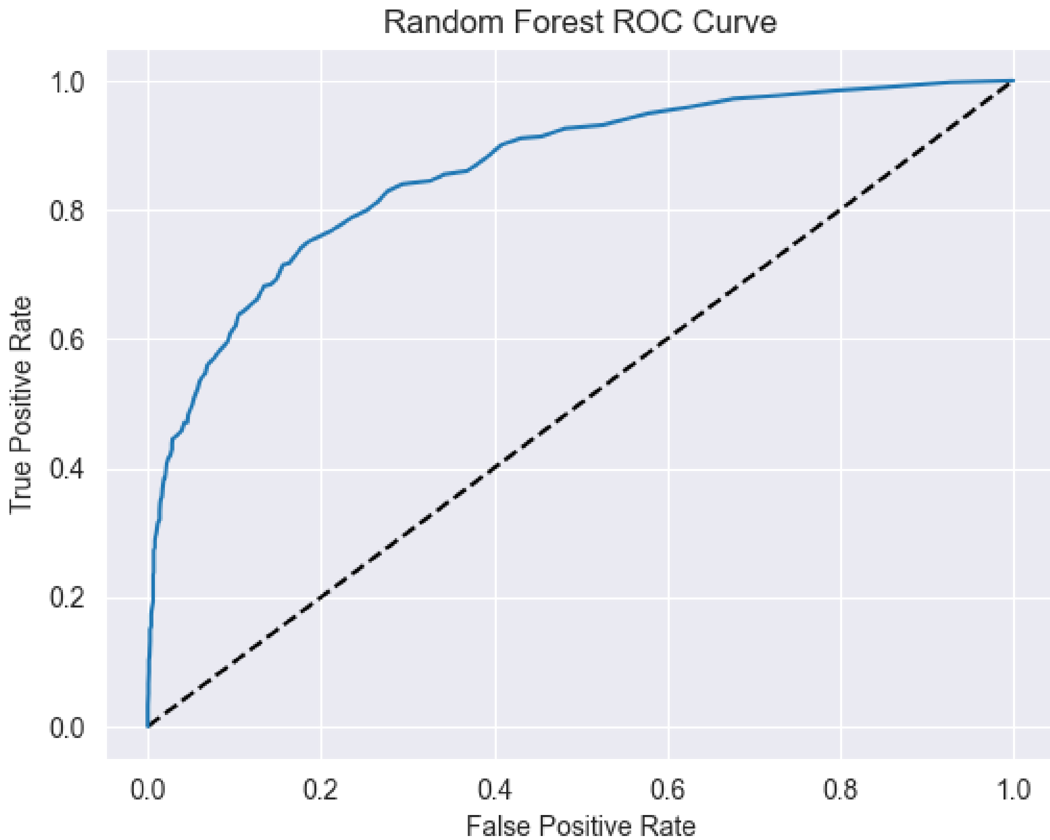
```
#plot roc_curve and roc_auc_score
from sklearn.metrics import roc_curve, roc_auc_score
y_pred_prob = log_reg.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='Logistic Regression')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve')
plt.show()
```

```python
auc_score = roc_auc_score(y_test, y_pred_prob)
print('AUC score: {}'.format(auc_score))
```



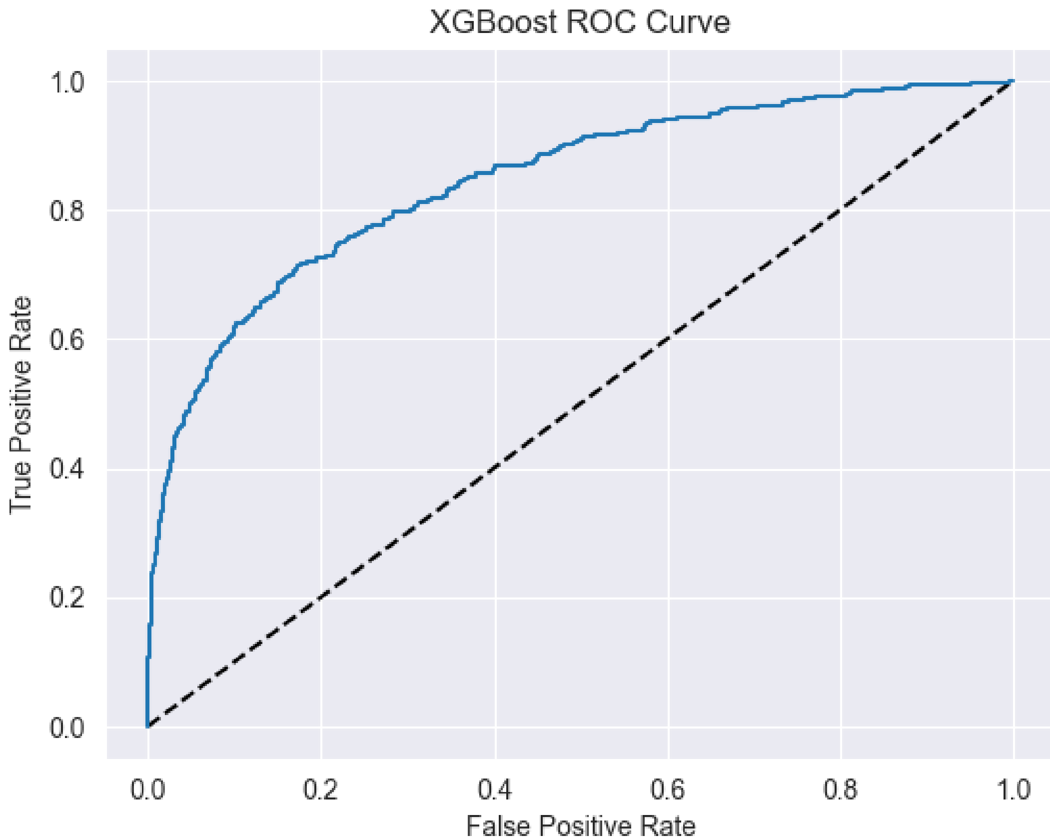

```
AUC score: 0.7726881914524717
```

```python
#plot roc_curve and roc_auc_curve for random forest
y_pred_prob = rf.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='Random Forest')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest ROC Curve')
plt.show()
auc_score = roc_auc_score(y_test, y_pred_prob)
print('AUC score: {}'.format(auc_score))
```



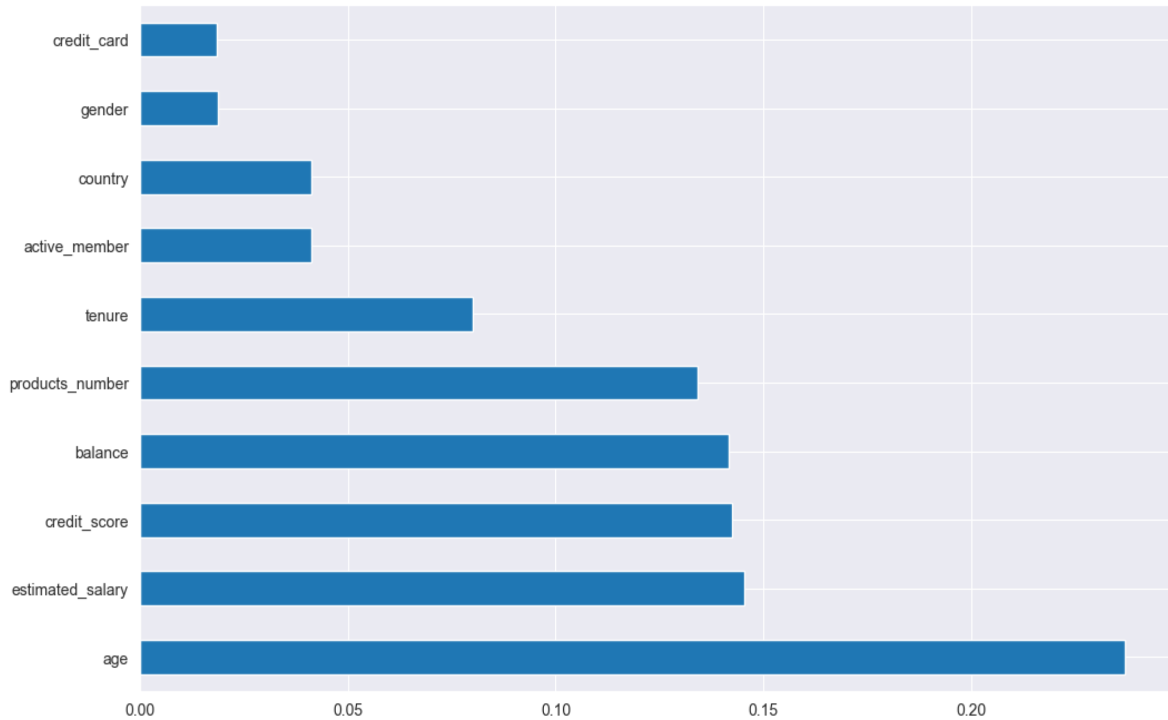

```
AUC score: 0.8613706573182531
```

```
#plot roc_curve and roc_auc_curve for XGBoost
y_pred_prob = xgb.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='XGBoost')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('XGBoost ROC Curve')
plt.show()
auc_score = roc_auc_score(y_test, y_pred_prob)
print('AUC score: {}'.format(auc_score))
```




```
AUC score: 0.8447599639617385
```

```
#plot the feature importance
plt.figure(figsize=(12, 8))
feat_importances = pd.Series(rf.feature_importances_, index=X.columns)
feat_importances.nlargest(10).plot(kind='barh')
plt.show()
```




```
#solve the imbalance problem
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=set_seed)
X_train, y_train = smote.fit_resample(X_train, y_train)
X_train.shape, y_train.shape
```

```
((12712, 10), (12712,))
```

```
#build the model
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
y_pred = log_reg.predict(X_test)
print('Accuracy score: {}'.format(accuracy_score(y_test, y_pred)))
print('Confusion matrix: \n{}'.format(confusion_matrix(y_test, y_pred)))
print('Classification report: \n{}'.format(classification_report(y_test, y_pred)))
```

```
Accuracy score: 0.7225
Confusion matrix:
[[1166  441]
```

```
 [ 114  279]]
Classification report:
              precision    recall  f1-score   support

           0       0.91      0.73      0.81      1607
           1       0.39      0.71      0.50       393

    accuracy                           0.72      2000
   macro avg       0.65      0.72      0.65      2000
weighted avg       0.81      0.72      0.75      2000
```

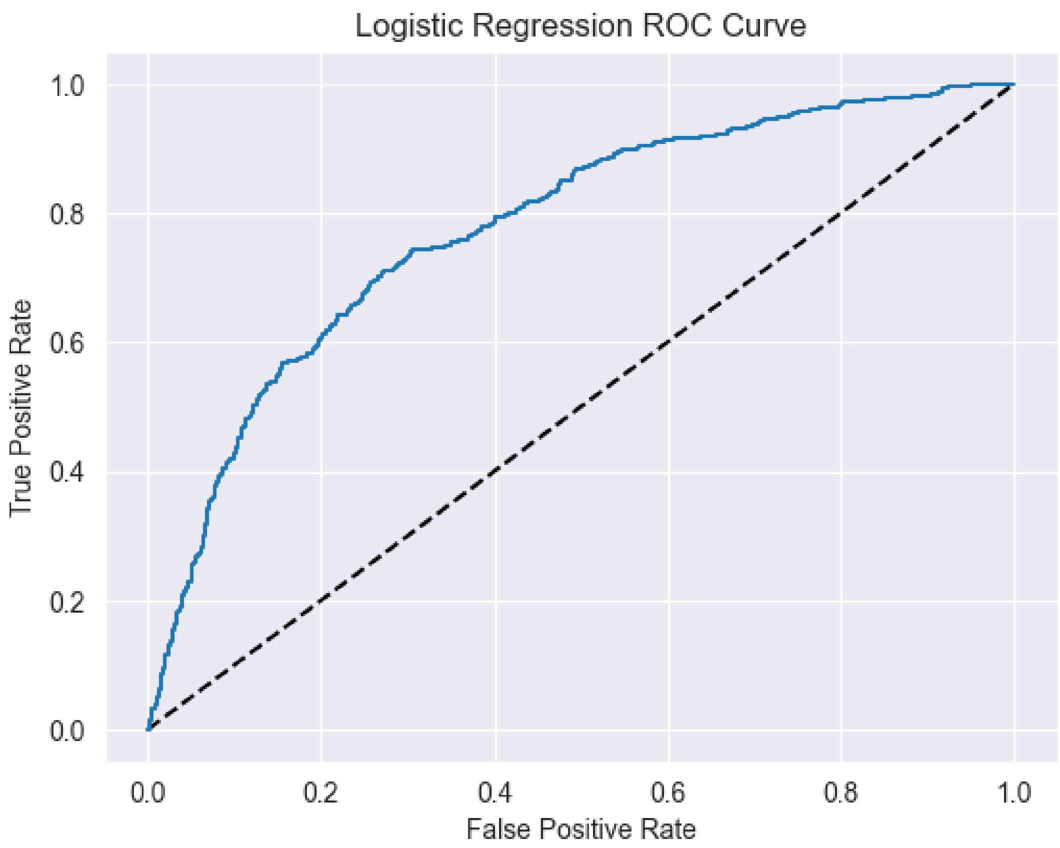
```
#build random forest classifier
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
print('Accuracy score: {}'.format(accuracy_score(y_test, y_pred)))
print('Confusion matrix: \n{}'.format(confusion_matrix(y_test, y_pred)))
print('Classification report: \n{}'.format(classification_report(y_test, y_pred)))
```

```
Accuracy score: 0.8455
Confusion matrix:
[[1456  151]
 [ 158  235]]
Classification report:
              precision    recall  f1-score   support

           0       0.90      0.91      0.90      1607
           1       0.61      0.60      0.60       393

    accuracy                           0.85      2000
   macro avg       0.76      0.75      0.75      2000
weighted avg       0.84      0.85      0.84      2000
```

```
#build XGBoost classifier
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
print('Accuracy score: {}'.format(accuracy_score(y_test, y_pred)))
print('Confusion matrix: \n{}'.format(confusion_matrix(y_test, y_pred)))
```

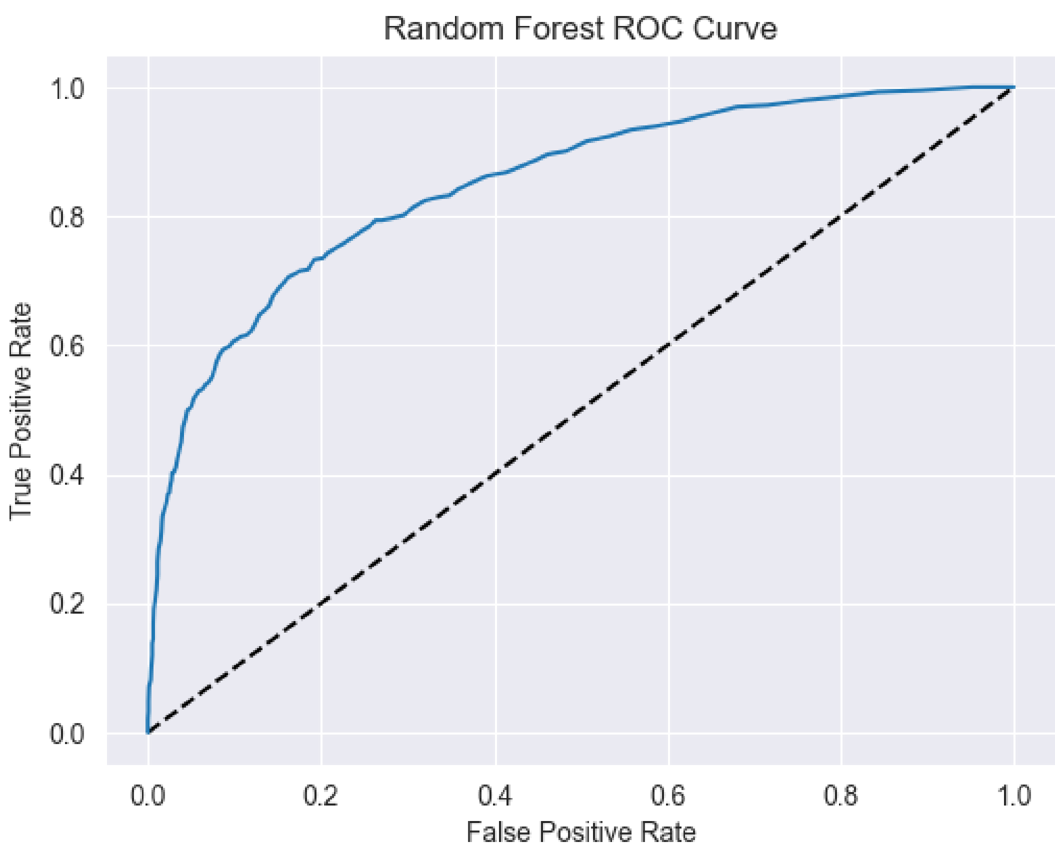
```
Accuracy score: 0.8595
Confusion matrix:
[[1503  104]
 [ 177  216]]
```

```
#plot roc_curve and roc_auc_score
y_pred_prob = log_reg.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='Logistic Regression')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve')
plt.show()
auc_score = roc_auc_score(y_test, y_pred_prob)
print('AUC score: {}'.format(auc_score))
```



```
AUC score: 0.7772594770651935
```

```
#plot roc_curve and roc_auc_curve for random forest
y_pred_prob = rf.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='Random Forest')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest ROC Curve')
plt.show()
auc_score = roc_auc_score(y_test, y_pred_prob)
print('AUC score: {}'.format(auc_score))
```




```
AUC score: 0.8487414318083575
```

```
#plot roc_curve and roc_auc_curve for XGBoost
y_pred_prob = xgb.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='XGBoost')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('XGBoost ROC Curve')
plt.show()
```