bank-churn-kaggle-competition

March 10, 2024

1 Binary Classification with a Bank Churn Dataset

1.1 Overview

Welcome to the 2024 Kaggle Playground Series! Happy New Year! This is the 1st episode of Season 4. We plan to continue in the spirit of previous playgrounds, providing interesting an approachable datasets for our community to practice their machine learning skills, and anticipate a competition each month.

1.2 Your Goal:

this task is to predict whether a customer continues with their account or closes it (e.g., churns).

1.2.1 Importing libraries

[1]:
```
# Import required packages

# Data packages
import pandas as pd
import numpy as np

# Machine Learning / Classification packages
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import train_test_split
from sklearn.dummy import DummyClassifier

# Visualization Packages
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
import scipy.stats as stats
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.metrics import recall_score, accuracy_score,␣
 ↪classification_report, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
```

```python
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.feature_selection import SelectKBest
```

1.2.2 Load the datasets

[3]:
```python
url_train = r'/content/drive/MyDrive/train_kaggle_2024.csv'
url_test = r'/content/drive/MyDrive/test_kaggle_2024.csv'
```

[4]:
```python
# loading the train data
train_df = pd.read_csv(url_train)
print('train_df Shape:', train_df.shape)
train_df.head()
```

```
train_df Shape: (165034, 14)
```

[4]:
```
   id  CustomerId         Surname  CreditScore Geography Gender   Age  Tenure  \
0   0    15674932  Okwudilichukwu          668    France   Male  33.0       3
1   1    15749177   Okwudiliolisa          627    France   Male  33.0       1
2   2    15694510           Hsueh          678    France   Male  40.0      10
3   3    15741417             Kao          581    France   Male  34.0       2
4   4    15766172        Chiemenam          716     Spain   Male  33.0       5

     Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  \
0       0.00              2        1.0             0.0        181449.97
1       0.00              2        1.0             1.0         49503.50
2       0.00              2        1.0             0.0        184866.69
3  148882.54              1        1.0             1.0         84560.88
4       0.00              2        1.0             1.0         15068.83

   Exited
0       0
1       0
2       0
3       0
4       0
```

the train dataset have about 165,034 rows and about 14 columns

[5]:
```python
# loading the test datasets
test_df = pd.read_csv(url_test)
print('test_df Shape:', test_df.shape)
test_df.head()
```

```
test_df Shape: (110023, 13)
```

[5]:
```
       id  CustomerId    Surname  CreditScore Geography  Gender   Age  Tenure  \
0  165034    15773898   Lucchese          586    France  Female  23.0       2
1  165035    15782418       Nott          683    France  Female  46.0       2
2  165036    15807120         K?          656    France  Female  34.0       7
3  165037    15808905  O'Donnell          681    France    Male  36.0       8
4  165038    15607314    Higgins          752   Germany    Male  38.0      10

     Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary
0       0.00              2        0.0             1.0        160976.75
1       0.00              1        1.0             0.0         72549.27
2       0.00              2        1.0             0.0        138882.09
3       0.00              1        1.0             0.0        113931.57
4  121263.62              1        1.0             0.0        139431.00
```

the test dataset contain 110023 rows and 13 columns

1.2.3 performing data cleaning on the train_df datasets

[6]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 165034 entries, 0 to 165033
Data columns (total 14 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   id               165034 non-null  int64
 1   CustomerId       165034 non-null  int64
 2   Surname          165034 non-null  object
 3   CreditScore      165034 non-null  int64
 4   Geography        165034 non-null  object
 5   Gender           165034 non-null  object
 6   Age              165034 non-null  float64
 7   Tenure           165034 non-null  int64
 8   Balance          165034 non-null  float64
 9   NumOfProducts    165034 non-null  int64
 10  HasCrCard        165034 non-null  float64
 11  IsActiveMember   165034 non-null  float64
 12  EstimatedSalary  165034 non-null  float64
 13  Exited           165034 non-null  int64
dtypes: float64(5), int64(6), object(3)
memory usage: 17.6+ MB
```

we can see that the columns are in their right format

[7]:
```
# checking for duplicate values
train_df.duplicated().sum()
```

[7]: 0

their are no duplicates in the datasets

[8]:
```
# let check for missing values
train_df.isnull().sum()
```

[8]:
```
id                 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
```

non of the columns contain missing values

it appears that our datasets is free from duplicates, missing values and the columns are formatted correctly

1.3 Exploratory Data Analysis

[9]:
```
train_df.describe().T
```

[9]:
```
                    count          mean           std          min  \
id               165034.0  8.251650e+04  47641.356500         0.00
CustomerId       165034.0  1.569201e+07  71397.816791  15565701.00
CreditScore      165034.0  6.564544e+02     80.103340       350.00
Age              165034.0  3.812589e+01      8.867205        18.00
Tenure           165034.0  5.020353e+00      2.806159         0.00
Balance          165034.0  5.547809e+04  62817.663278         0.00
NumOfProducts    165034.0  1.554455e+00      0.547154         1.00
HasCrCard        165034.0  7.539537e-01      0.430707         0.00
IsActiveMember   165034.0  4.977702e-01      0.499997         0.00
EstimatedSalary  165034.0  1.125748e+05  50292.865585        11.58
Exited           165034.0  2.115988e-01      0.408443         0.00

                      25%         50%           75%          max
id               41258.25     82516.5  1.237748e+05    165033.00
CustomerId    15633141.00  15690169.0  1.575682e+07  15815690.00
CreditScore        597.00       659.0  7.100000e+02       850.00
Age                 32.00        37.0  4.200000e+01        92.00
```

```
Tenure                  3.00        5.0  7.000000e+00       10.00
Balance                 0.00        0.0  1.199395e+05   250898.09
NumOfProducts           1.00        2.0  2.000000e+00        4.00
HasCrCard               1.00        1.0  1.000000e+00        1.00
IsActiveMember          0.00        0.0  1.000000e+00        1.00
EstimatedSalary     74637.57   117948.0  1.551525e+05   199992.48
Exited                  0.00        0.0  0.000000e+00        1.00
```

[10]:

```
# count the occurrences of each unique value in the 'Churn' column
churn_counts = train_df['Exited'].value_counts()

# Calculate the churn rate
total_customers = train_df['Exited'].count()
churn_rate = churn_counts[1] / total_customers

# Print out the descriptive statistics
print("Descriptive Statistics for Exited:")
print(churn_counts)
print(f"churn Rate: {churn_rate:.2%}")
```

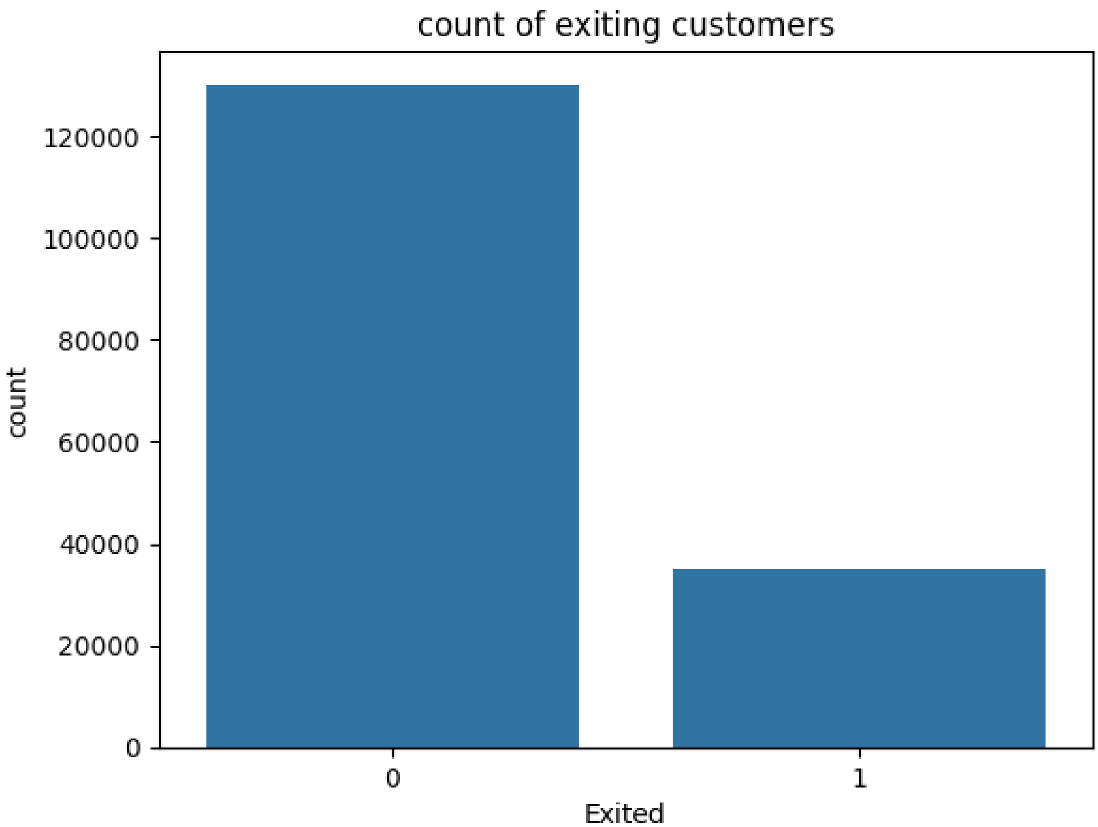
```
Descriptive Statistics for Exited:
0    130113
1     34921
Name: Exited, dtype: int64
churn Rate: 21.16%
```

from the above information we can conclude that the train datasets contain 130113 non_churn customers and 34921 churn customer.

the churn rate i.e the rate at which customers close their bank account is about 21.16%

[11]:

```
# we visualize this using a bar plot
sns.countplot(data= train_df, x='Exited')
plt.title("count of exiting customers")
plt.show()
```



1.3.1 Seperating numerical columns and categorical columns

[12]:
```
train_df.drop(columns=['CustomerId'], inplace=True)
```

[13]:
```
# numerical feature
numerical_feature = {feature for feature in train_df.columns if␣
 ↪train_df[feature].dtypes != 'O'}
print(f'Count of Numerical feature: {len(numerical_feature)}')
print(f'Numerical feature are:\n {numerical_feature}')
```

```
Count of Numerical feature: 10
Numerical feature are:
 {'id', 'HasCrCard', 'CreditScore', 'IsActiveMember', 'Age', 'Tenure',
'Balance', 'EstimatedSalary', 'NumOfProducts', 'Exited'}
```

we have 11 columns that are numerical

[14]:
```
# categorical features
categorical_feature = {feature for feature in train_df.columns if␣
 ↪train_df[feature].dtypes == 'O'}
print(f'Count of Categorical feature: {len(categorical_feature)}')
```

```
print(f'Categorical feature are:\n {categorical_feature}')
```

```
Count of Categorical feature: 3
Categorical feature are:
 {'Surname', 'Gender', 'Geography'}
```

we have 3 columns that are categorical

[15]:
```
from scipy import stats
# Plotting numerical feature with probability distribution and checking outlier
for feature in numerical_feature:
    if feature != 'id':
        plt.figure(figsize=(15,7))

        plt.subplot(1, 3, 1)
        sns.distplot(train_df[feature], bins=30, kde=True)
        plt.title('Histogram')

        plt.subplot(1, 3, 2)
        stats.probplot(train_df[feature], dist="norm", plot=plt)
        plt.ylabel('RM quantiles')

        plt.subplot(1, 3, 3)
        sns.boxplot(x=train_df[feature])
        plt.title('Boxplot')

plt.show()
```

```
<ipython-input-15-f319914515a4>:8: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(train_df[feature], bins=30, kde=True)
<ipython-input-15-f319914515a4>:8: UserWarning:

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```

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```

```
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<ipython-input-15-f319914515a4>:8: UserWarning:

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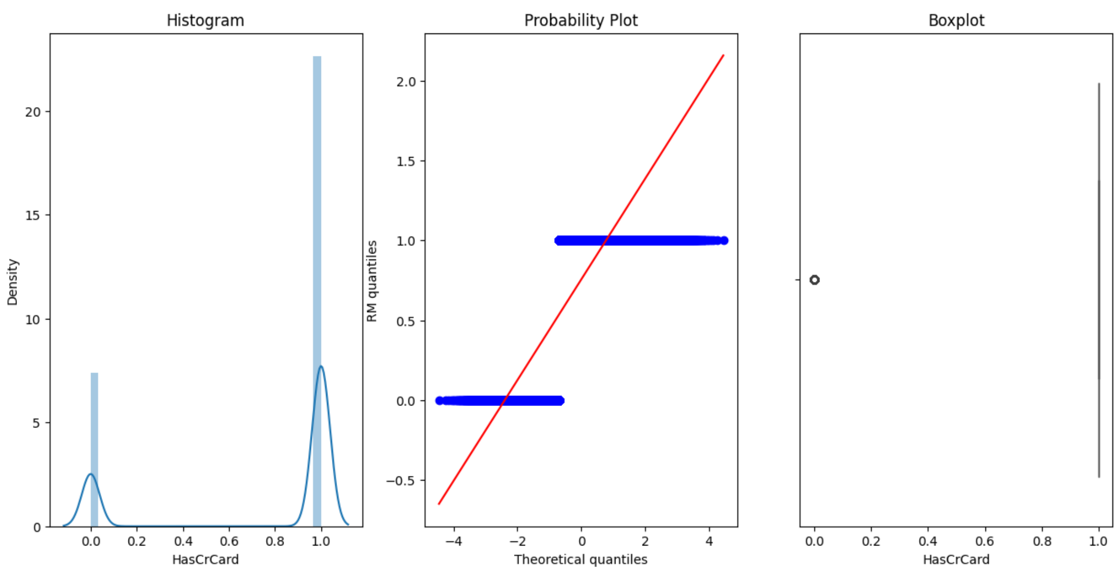
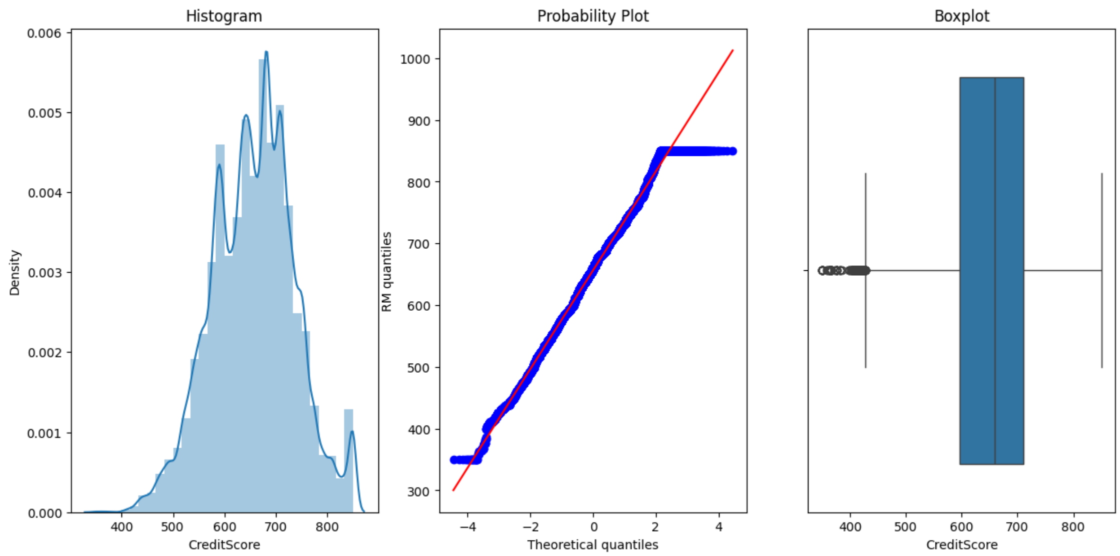
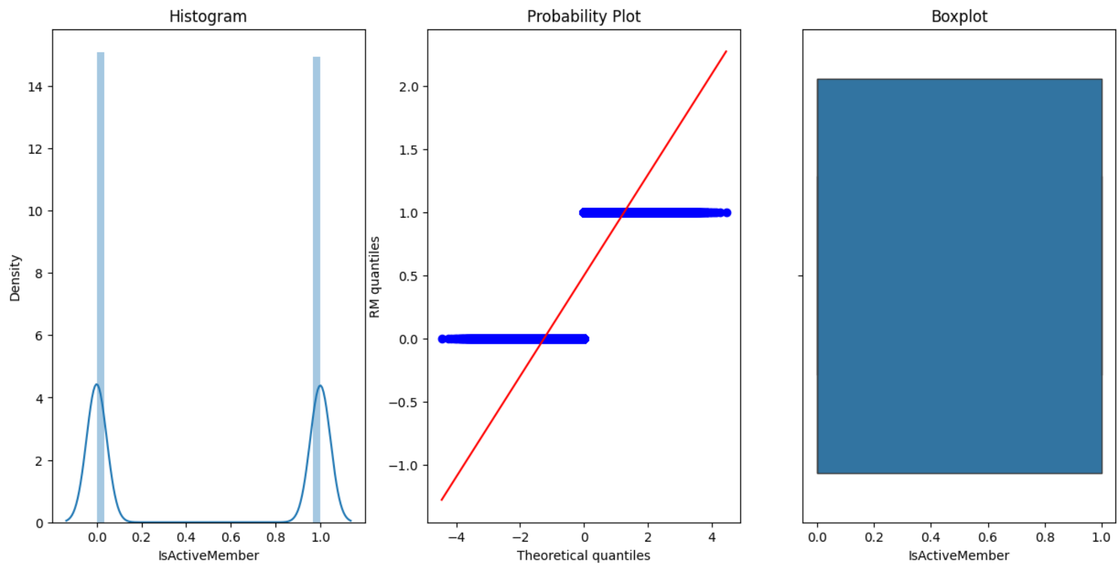
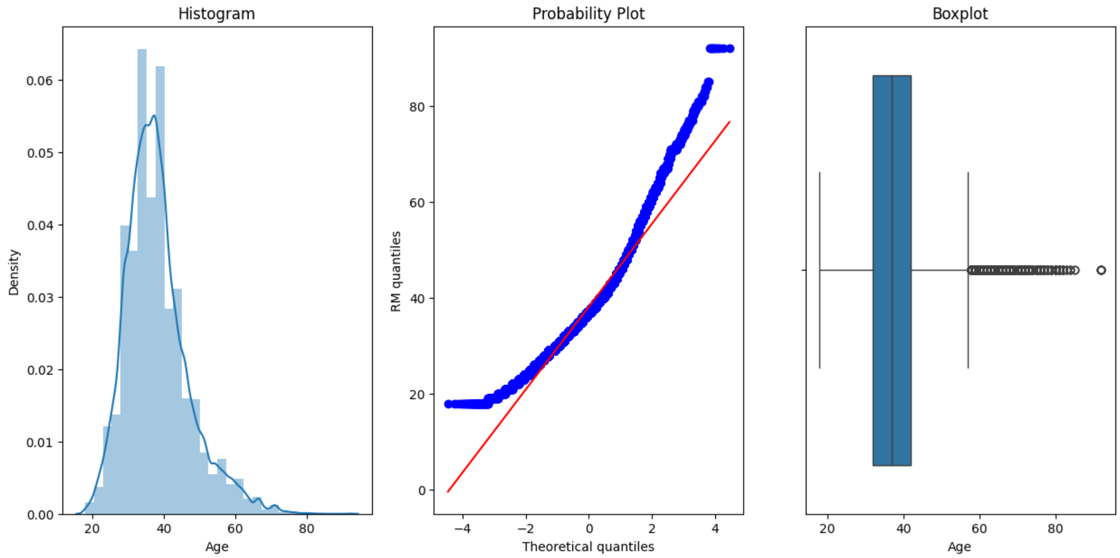
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

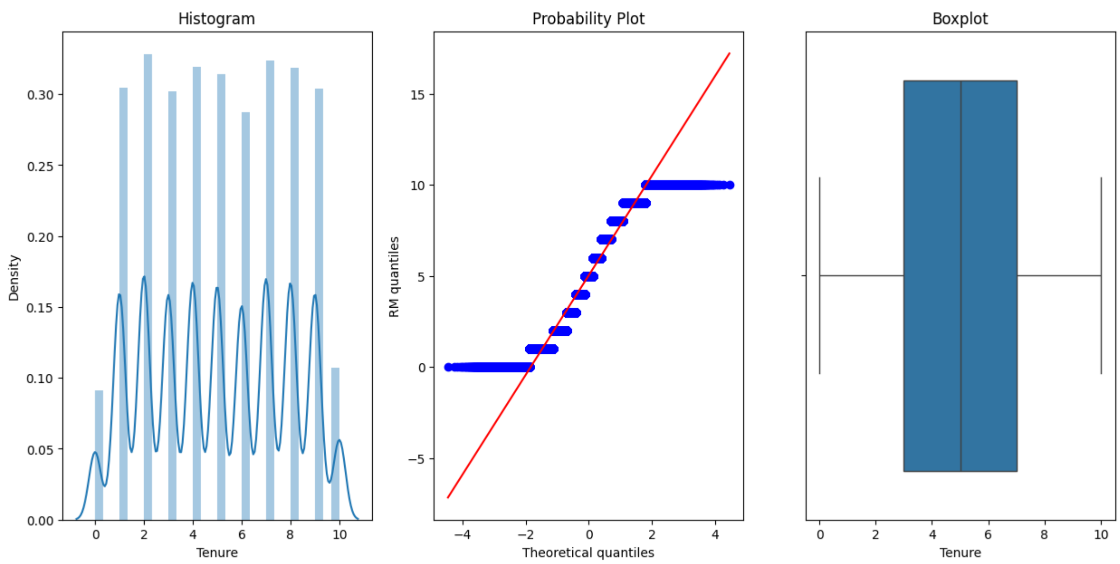
  sns.distplot(train_df[feature], bins=30, kde=True)
```

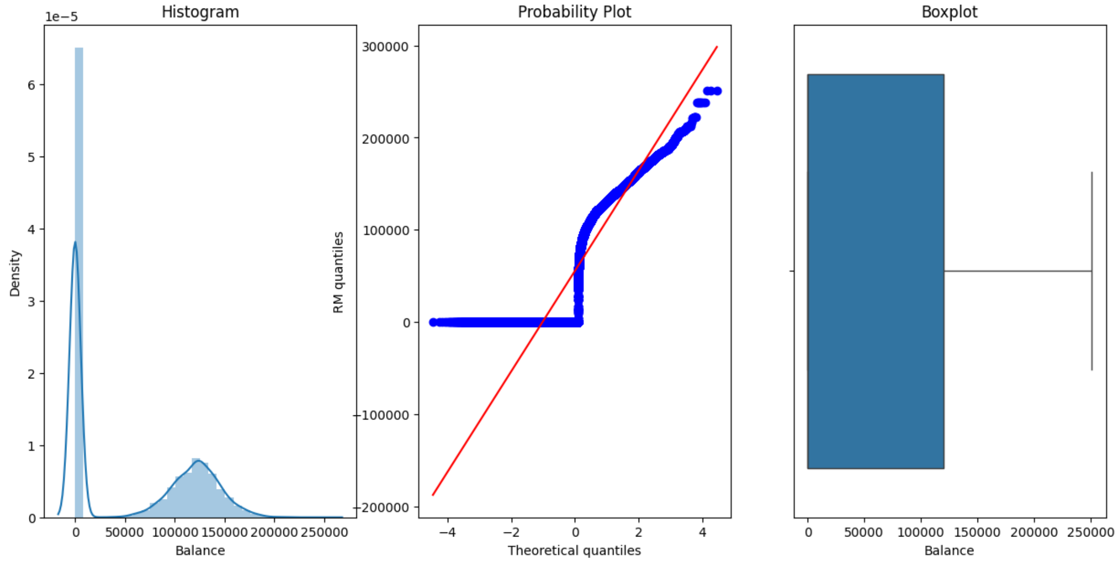



Histogram
Probability Plot
Boxplot
Density
CreditScore
RM quantiles
Theoretical quantiles
CreditScore

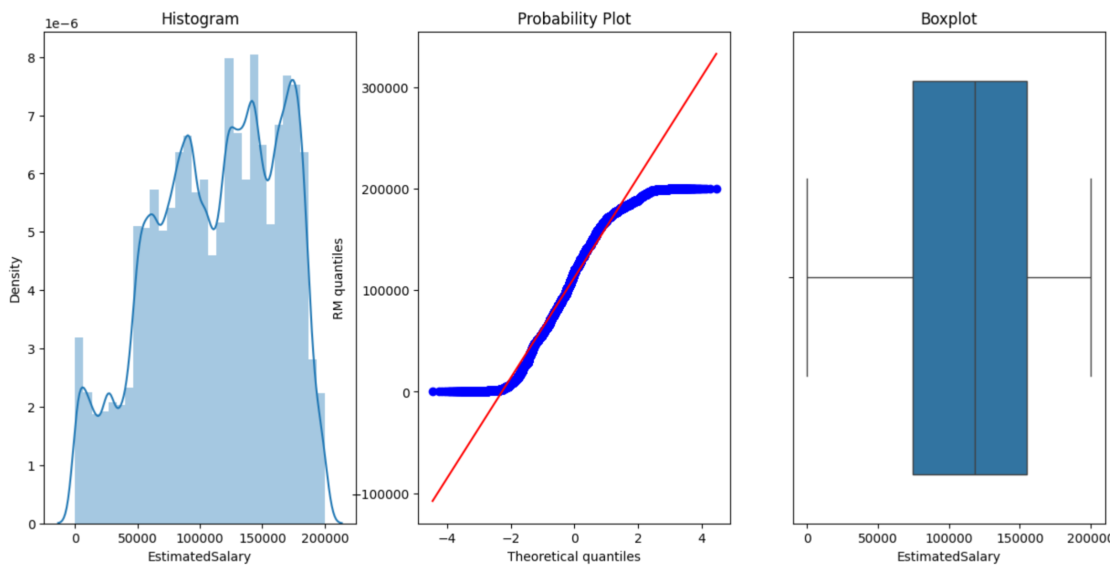

Histogram
Probability Plot
Boxplot
Density
IsActiveMember
RM quantiles
Theoretical quantiles
IsActiveMember


Histogram
Probability Plot
Boxplot
Density
Age
RM quantiles
Theoretical quantiles
Age

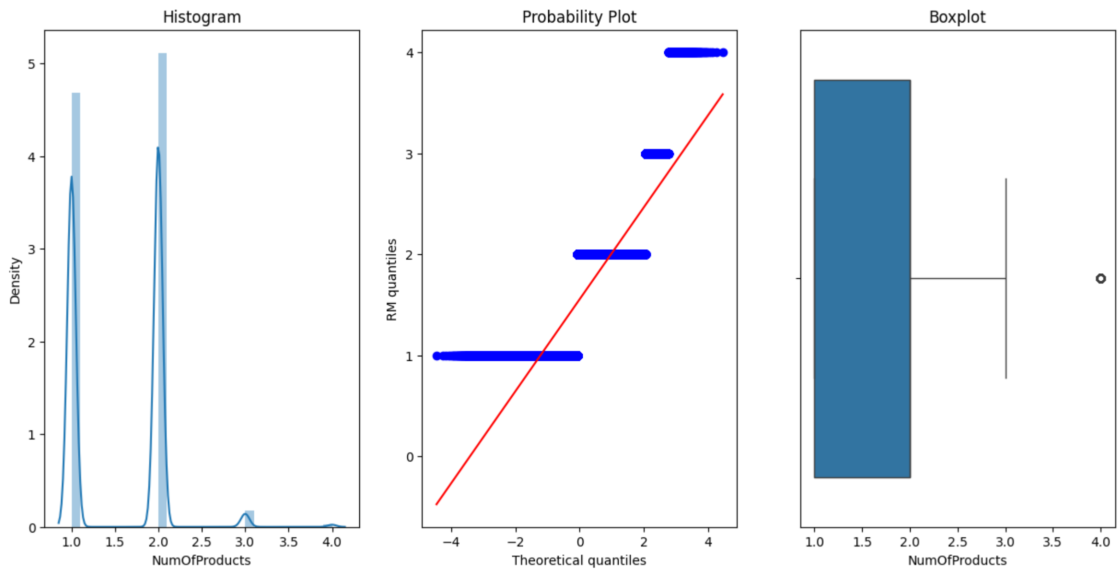

Histogram
Probability Plot
Boxplot
Density
Tenure
RM quantiles
Theoretical quantiles
Tenure

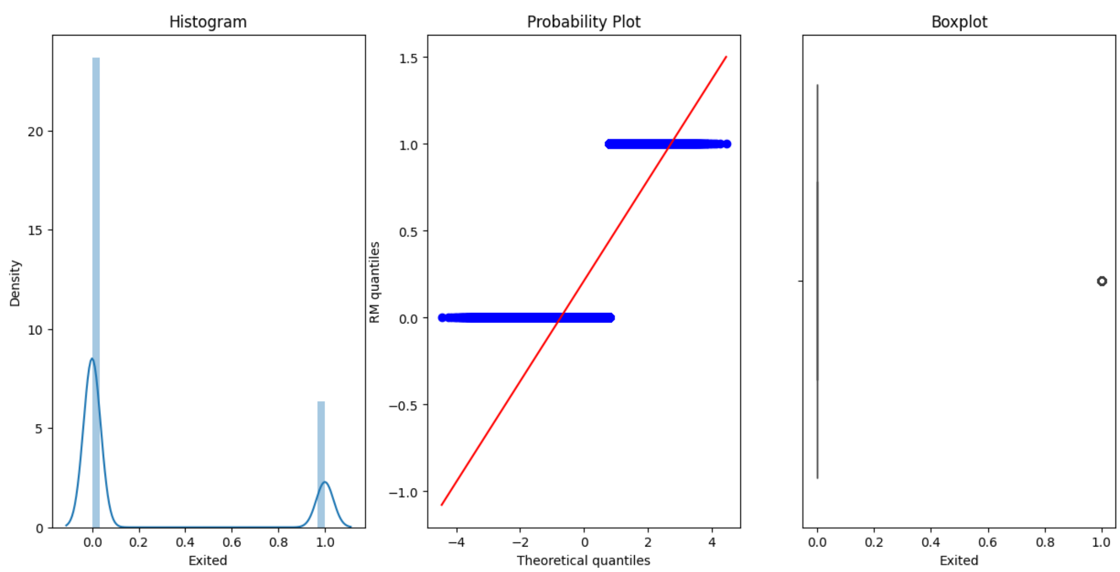


Histogram
1e−5
Density
Balance
Probability Plot
RM quantiles
Theoretical quantiles
Boxplot
Balance



Histogram
1e−6
Density
EstimatedSalary
Probability Plot
RM quantiles
Theoretical quantiles
Boxplot
EstimatedSalary





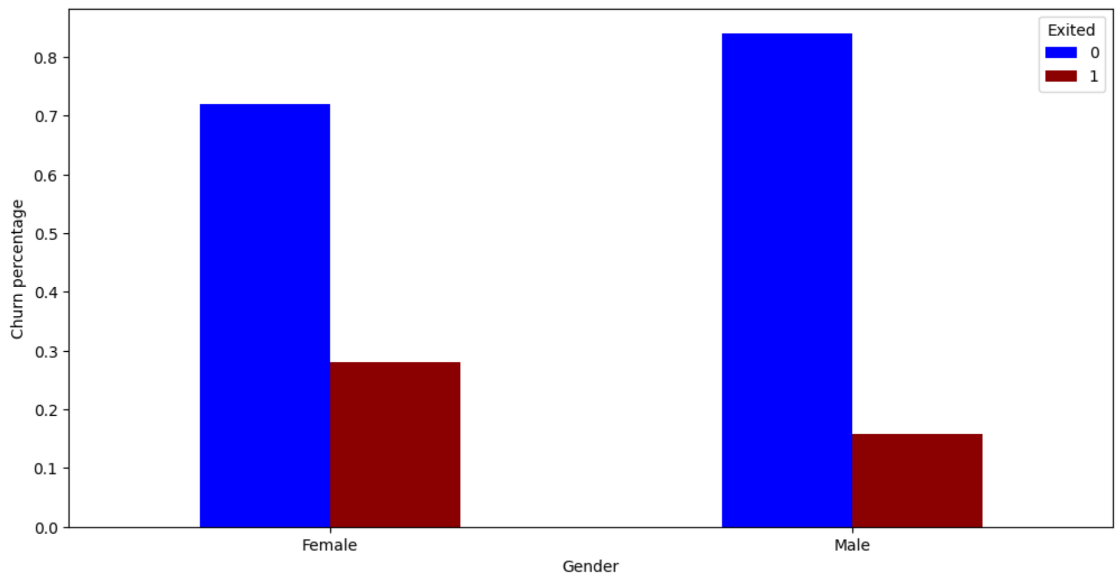
1.4 Univariante Data Visualizations

we will perform some visualisations to help us understand the datasets and the churn behaviour accross the varius variables

[16]:
```
def bar_plot(data, group, target):
    """
    This function returns a bar plot.
    """
    fig, ax = plt.subplots(figsize=(12, 6))
```

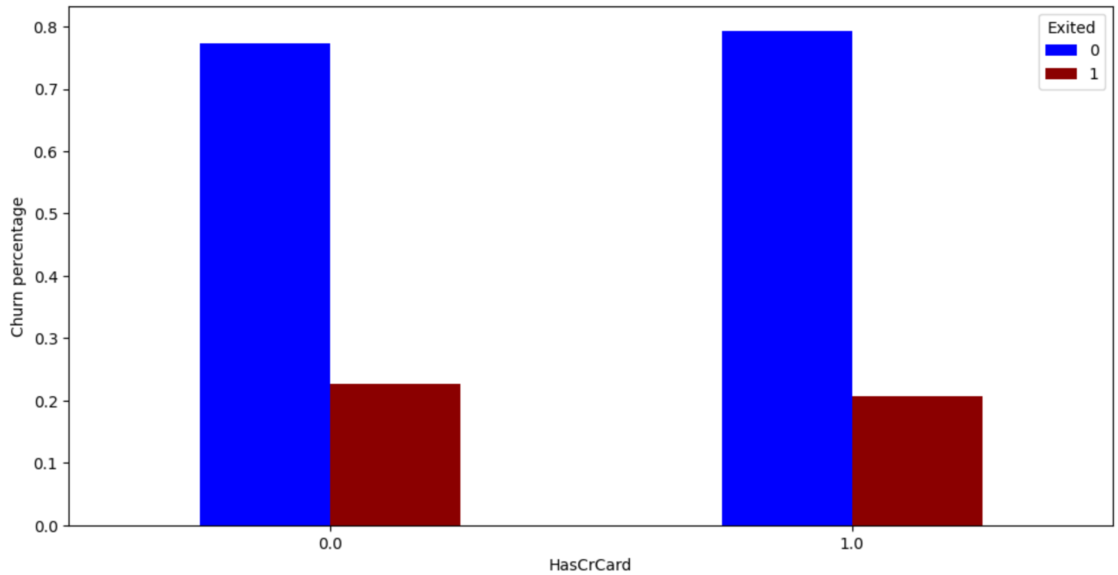
```
    # This will create a pivot table to be plotted
    temp_df = (data.groupby([group, target]).size() / data.
↪groupby(group)[target].count()).reset_index().pivot(index=group,␣
↪columns=target, values=0)
    # We plot the stacked bar
    temp_df.plot(kind='bar', stacked=False, ax=ax, color=["blue", "darkred",␣
↪"green"], legend=True)
    # Set labels and axis
    ax.xaxis.set_tick_params(rotation=0)
    ax.set_xlabel(group)
    ax.set_ylabel('Churn percentage')
```

[17]:
```
bar_plot(train_df, "Gender", "Exited")
```



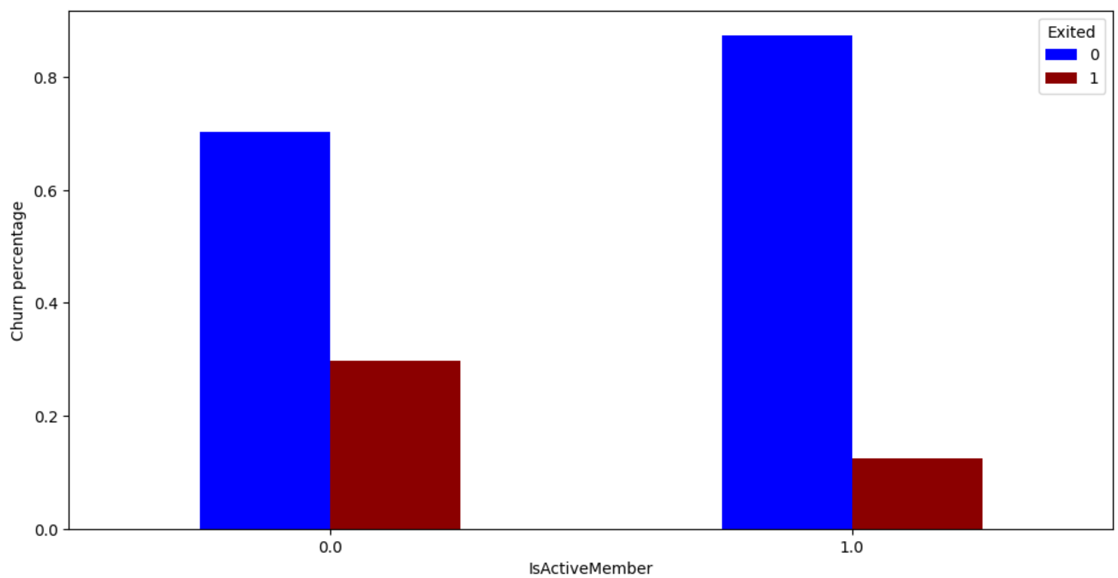
The gender distribution shows that there are more women Exiting/churning that is, closing up there bank accounts than men. although on a general scale the churning rate based on gender is small compared to non-churn

[18]:
```
bar_plot(train_df, "HasCrCard", "Exited")
```



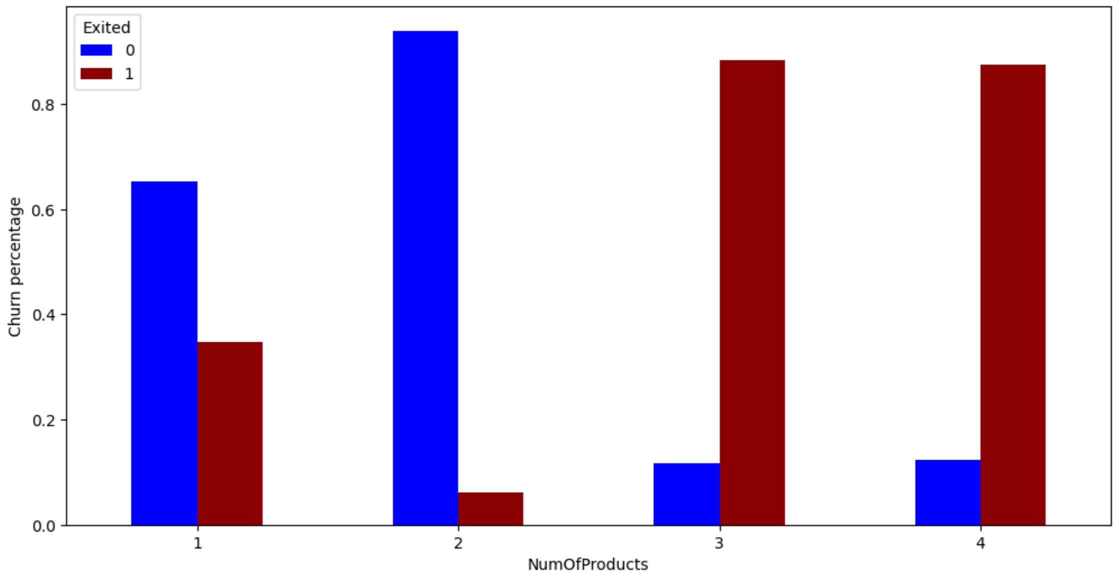
customers without card has the tendency of churning more than customers with cards

[19]:
```
bar_plot(train_df, "IsActiveMember", "Exited")
```



from the above plot, we can conclude that customers that are not active are more likly to churn or close their accounts than active customers

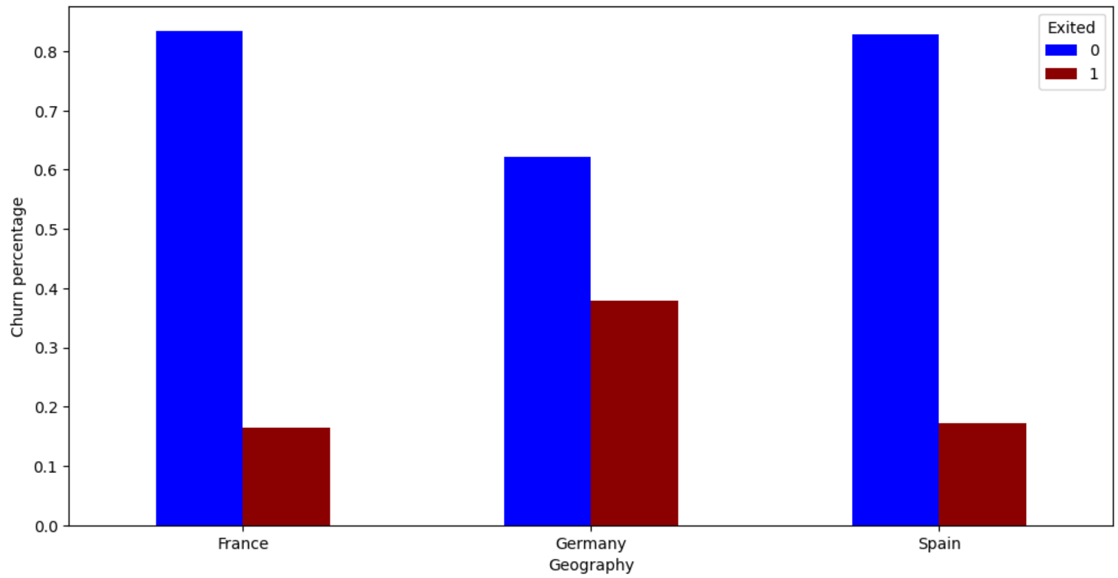
[20]:
```
bar_plot(train_df, "NumOfProducts", "Exited")
```



from the above plots, the following insights can be drawn from number of products based distribution:

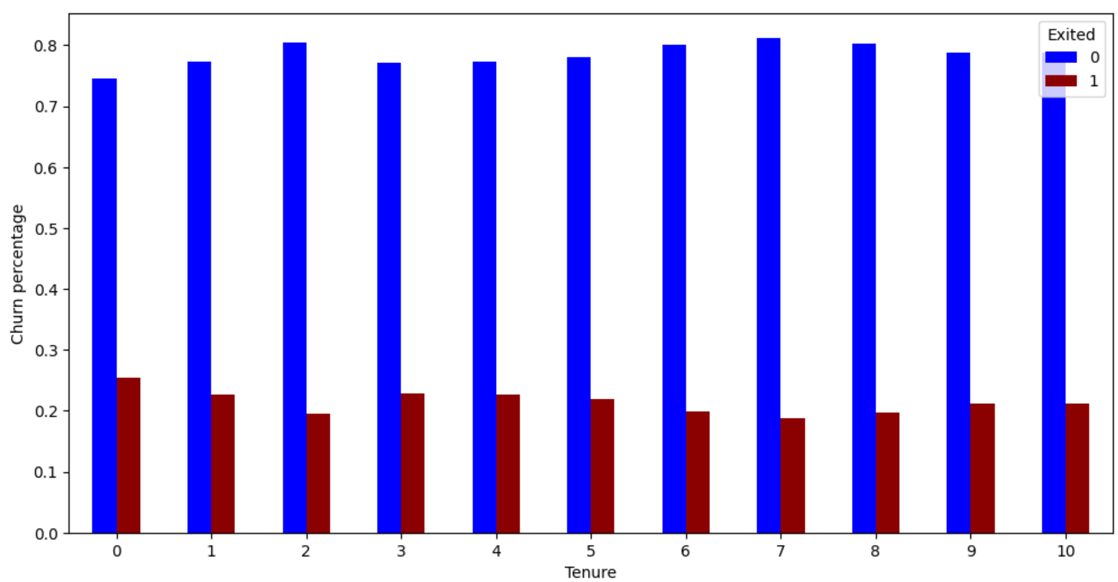
- customers registered to only one product have more than 60% chance of keeping their acoounts and more than 30% churning rate
- customers with 2 registered products tends to have about 96% chance of keeping their account and less than 4% tendency of churning
- for customers with 3 to 4 products, the rate at which customers close up their accounts tends to spike drastically. about 90% have the tendency to churn while only 10% keeps their account

[21]:
```
bar_plot(train_df, "Geography", "Exited")
```



German customers possess the highest tendency to churn with close to 40% churning rate and 60% percent non-churning rate

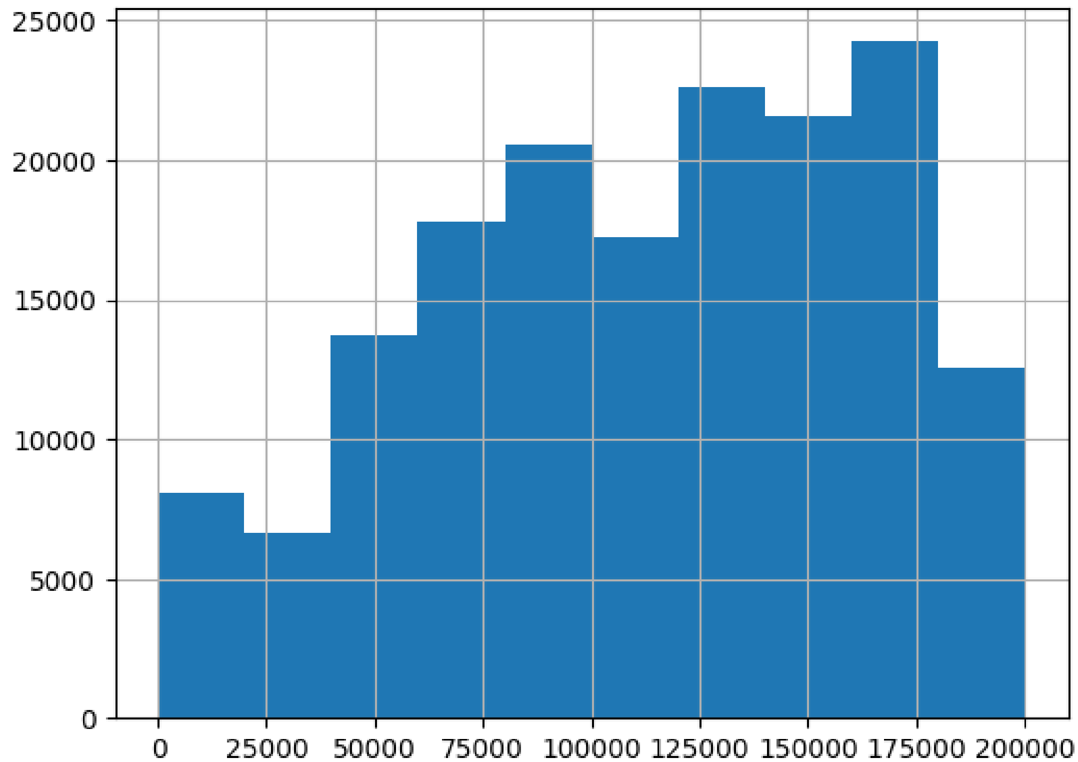
[22]:
```
bar_plot(train_df, "Tenure", "Exited")
```



although the churning rate is approximately same for the various number of tenures, new members tends to possess the highest tendency to churn

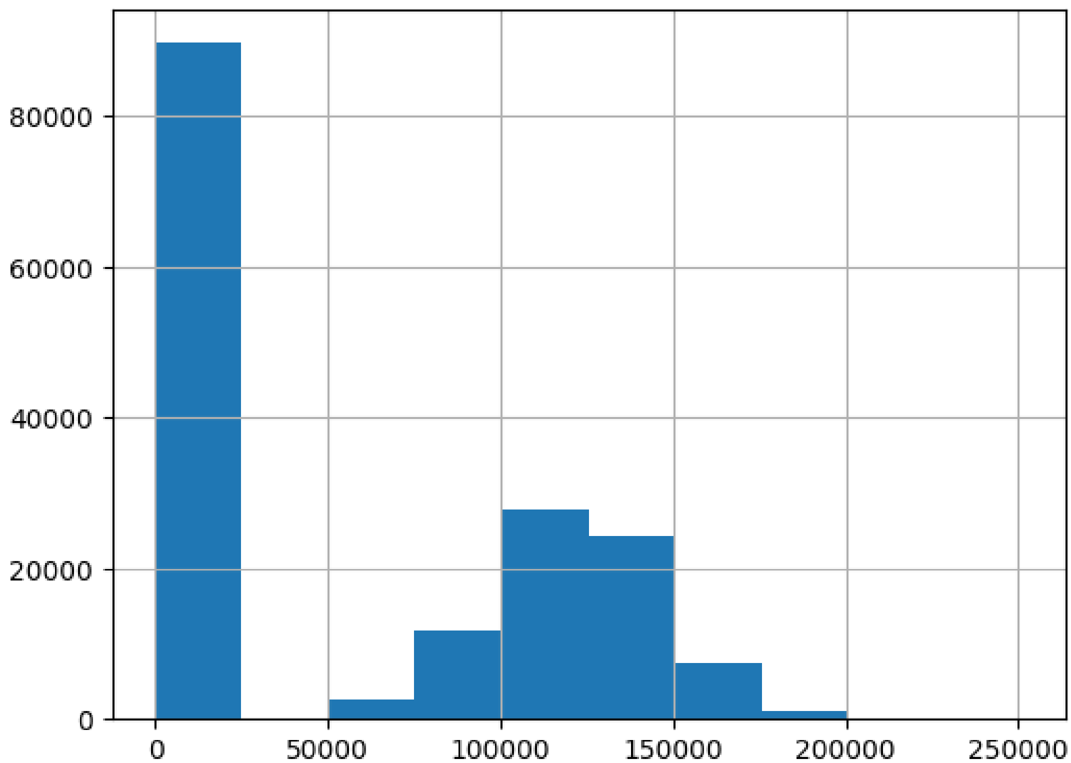
[23]:
```
train_df.EstimatedSalary.hist()
```

[23]: <Axes: >



[24]:
```
train_df.Balance.hist()
```

[24]: <Axes: >

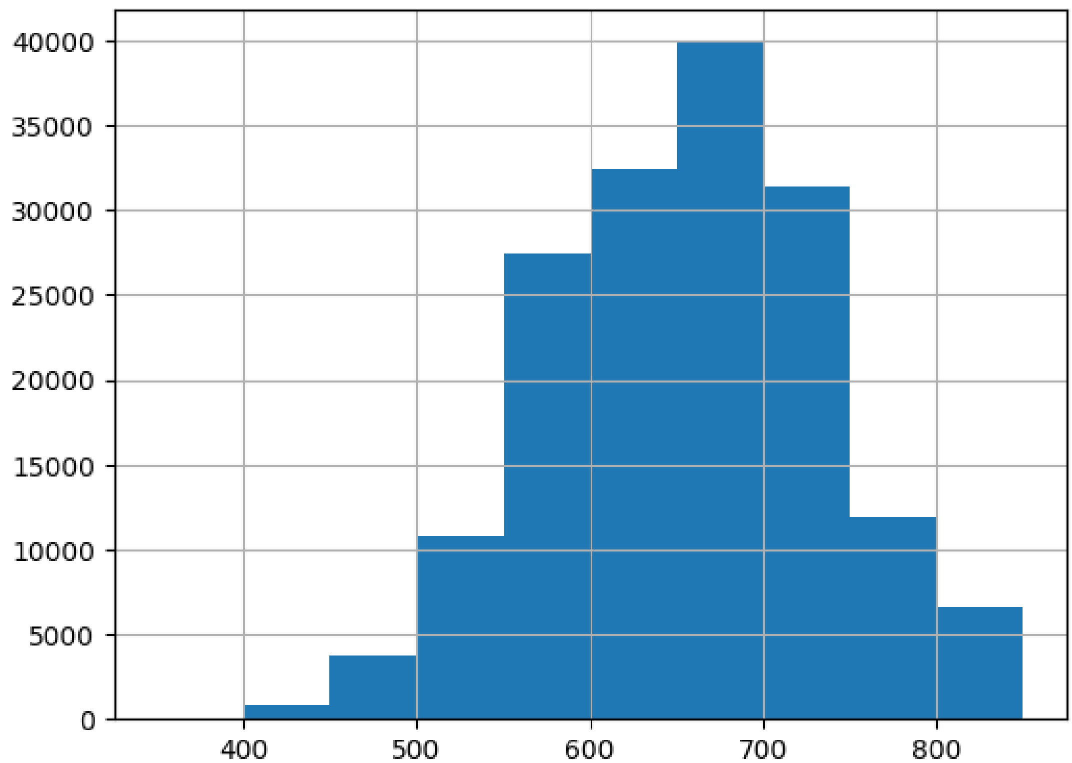


from the histogram of customer account balance, we can draw the following conclusion:

- more than 85000 customers have less than $25000 in their accounts
- About 24000 customers have $100000 to $150000 in their accounts
- Less than 17000 customers have $50000 to $100000 and $150000 to $200000 their accounts

[25]:
```
train_df.CreditScore.hist()
```

[25]: <Axes: >



from the histogram plot of customer credit score, the following conclusion can be made:

- Customers with 400 to 500 credit scores are less than 5000
- about 25000 to 40000 customers have credit scores from 550 to 750
- 40000 Customer have credit score ranging from 650 to 700

1.5 Encoding Categorical Features for Train_df

[26]:
```
print(categorical_feature)
```

```
{'Surname', 'Gender', 'Geography'}
```

[27]:
```
# encoding categorical feature
cat_encoder = LabelEncoder()
for features in categorical_feature:
  train_df[features] = cat_encoder.fit_transform(train_df[features])
```

[28]:
```
# let drop surname from the train_df
train_df.drop(columns=['Surname'], inplace=True )
```

[29]:
```
train_df.head()
```

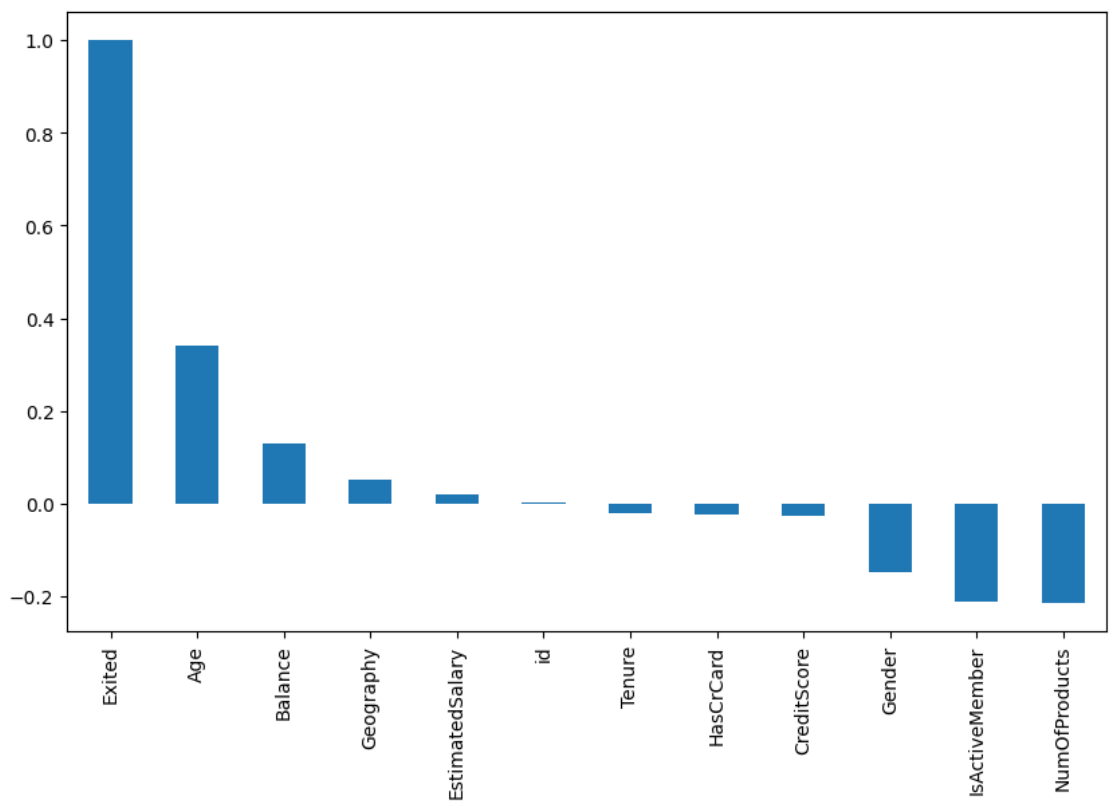
[29]:
```
   id  CreditScore  Geography  Gender   Age  Tenure    Balance  NumOfProducts  \
0   0          668          0       1  33.0       3       0.00              2
1   1          627          0       1  33.0       1       0.00              2
2   2          678          0       1  40.0      10       0.00              2
3   3          581          0       1  34.0       2  148882.54              1
4   4          716          2       1  33.0       5       0.00              2

   HasCrCard  IsActiveMember  EstimatedSalary  Exited
0        1.0             0.0        181449.97       0
1        1.0             1.0         49503.50       0
2        1.0             0.0        184866.69       0
3        1.0             1.0         84560.88       0
4        1.0             1.0         15068.83       0
```

now we will check the correlation of the columns with the target column (Exited)

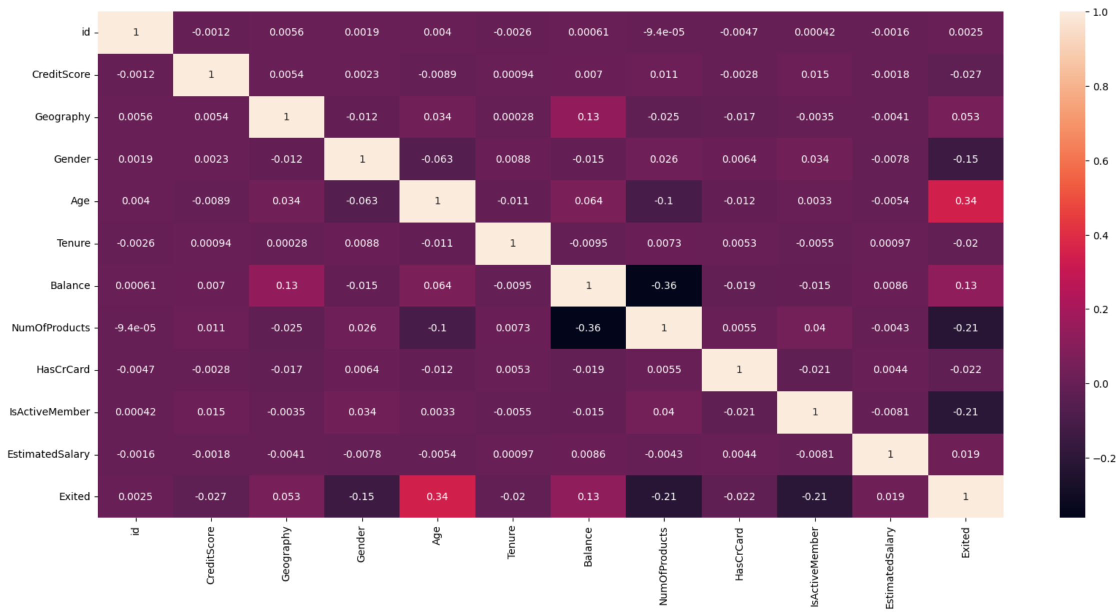
[30]:
```
#Get Correlation of "Churn" with other variables:
plt.figure(figsize=(10,6))
train_df.corr()['Exited'].sort_values(ascending = False).plot(kind='bar')
```

[30]: <Axes: >



[31]:
```python
# Finding the correlation between the independent and dependent feature
plt.figure(figsize=(20, 9))
sns.heatmap(train_df.corr(), annot=True)
```

[31]:
```
<Axes: >
```



1.6 Encoding the test_df

[32]:
```python
test_df.columns
```

[32]:
```
Index(['id', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender',
       'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary'],
      dtype='object')
```

[33]:
```python
# let drop the mer id
test_df.drop(columns=['CustomerId', 'Surname'], inplace=True)
```

now we perform encoding of the categorical features

[34]:
```python
test_cat_encoder = LabelEncoder()
for features in test_df.columns:
  test_df[features] = test_cat_encoder.fit_transform(test_df[features])
```

[35]:
```python
test_df.head()
```

[35]:
```
   id  CreditScore  Geography  Gender  Age  Tenure  Balance  NumOfProducts  \
0   0          189          0       0    5       2        0              1
1   1          286          0       0   31       2        0              0
2   2          259          0       0   17       7        0              1
3   3          284          0       1   19       8        0              0
4   4          355          1       1   22      10    10405              0

   HasCrCard  IsActiveMember  EstimatedSalary
0          0               1            33249
1          1               0             9388
2          1               0            26856
3          1               0            19659
4          1               0            26934
```

1.7 Feature selection

spliting the train_df into dependent (Y) and independent variable(X)

[36]:
```python
X = train_df.drop(columns = 'Exited')
Y = train_df['Exited']
```

we will be selecting the best 7 features with the best correlation with the churn column

[37]:
```python
selection = SelectKBest(k=10)
X = selection.fit_transform(X,Y)
```

now let us display the features with the best correlation, this features will appear as true or false

[38]:
```python
selection.get_support()
```

[38]:
```
array([False,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True])
```

[39]:
```python
train_df.columns
```

[39]:
```
Index(['id', 'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
       'Exited'],
      dtype='object')
```

this are the best features

['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary'],

[40]:
```python
# splitting inot train and test sets randomstate=42
x_train, x_test, y_train, y_test = train_test_split(X,Y, test_size=0.2,␣
 ↪random_state=42)
```

[41]:
```
print("the shape of the X_train data", x_train.shape)
print("the shape of the X_test data", x_test.shape)
print("the shape of the y_train data", y_train.shape)
print("the shape of the y_test data", y_test.shape)
```

```
the shape of the X_train data (132027, 10)
the shape of the X_test data (33007, 10)
the shape of the y_train data (132027,)
the shape of the y_test data (33007,)
```

1.8 Machine Learning

1.8.1 Training and Testing Logistic regression model

[44]:
```
# let fit the model
lr_model = LogisticRegression(C=150, max_iter=150)
lr_model.fit(x_train, y_train)
```

[44]:
```
LogisticRegression(C=150, max_iter=150)
```

[45]:
```
# let predict
lr_pred = lr_model.predict(x_test)

print(f'Accuracy score : {accuracy_score(lr_pred, y_test)}')
print(f'Confusion matrix :\n {confusion_matrix(lr_pred, y_test)}')
print(f'Classification report :\n {classification_report(lr_pred, y_test)}')
```

```
Accuracy score : 0.7879843669524647
Confusion matrix :
 [[25140  6086]
 [  912   869]]
Classification report :
               precision    recall  f1-score   support

           0       0.96      0.81      0.88     31226
           1       0.12      0.49      0.20      1781

    accuracy                           0.79     33007
   macro avg       0.54      0.65      0.54     33007
weighted avg       0.92      0.79      0.84     33007
```

the accuracy score of the logistic regression model is 78.7%, the model was able to predict non churn at 96% but could not predict churn well 12%.

1.9 Training RandomRegression Model

[46]:
```
R_model = RandomForestClassifier(n_estimators=120,criterion='gini',␣
 ↪max_depth=15, min_samples_leaf=100, min_samples_split=5)
R_model.fit(x_train, y_train)
```

[46]:
```
RandomForestClassifier(max_depth=15, min_samples_leaf=100, min_samples_split=5,
                       n_estimators=120)
```

[47]:
```
R_pred = R_model.predict(x_test)

print(f'Accuracy score : {accuracy_score(R_pred, y_test)}')
print(f'Confusion matrix :\n {confusion_matrix(R_pred, y_test)}')
print(f'Classification report :\n {classification_report(R_pred, y_test)}')
```

```
Accuracy score : 0.8613930378404581
Confusion matrix :
 [[24963  3486]
 [ 1089  3469]]
Classification report :
               precision    recall  f1-score   support

           0       0.96      0.88      0.92     28449
           1       0.50      0.76      0.60      4558

    accuracy                           0.86     33007
   macro avg       0.73      0.82      0.76     33007
weighted avg       0.89      0.86      0.87     33007
```

The random forest model performed better than the logistic regression, with an accuracy score of 86%, the precision, recall and f1-score are abit improved but not quite close to what we want

1.10 Training using Decision Tree

[48]:
```
# Training using Decision Tree
tree_model = DecisionTreeClassifier(criterion='gini', splitter='random',␣
 ↪min_samples_leaf=15)
tree_model.fit(x_train, y_train)
```

[48]:
```
DecisionTreeClassifier(min_samples_leaf=15, splitter='random')
```

[49]:
```
tree_pred = tree_model.predict(x_test)

print(f'Accuracy score : {accuracy_score(tree_pred, y_test)}')
print(f'Confusion matrix :\n {confusion_matrix(tree_pred, y_test)}')
print(f'Classification report :\n {classification_report(tree_pred, y_test)}')
```

```
Accuracy score : 0.8579089284091254
Confusion matrix :
 [[24600  3238]
 [ 1452  3717]]
Classification report :
               precision    recall  f1-score   support

           0       0.94      0.88      0.91     27838
           1       0.53      0.72      0.61      5169

    accuracy                           0.86     33007
   macro avg       0.74      0.80      0.76     33007
weighted avg       0.88      0.86      0.87     33007
```

The Decision tree model performed better than the logistic regression too but slightly less than the Randomforest, with an accuracy score of 85%, the precision, recall and f1-score are abit improved but not quite close to what we want

1.11 Training__gradient__boosting

[50]:
```
# GradientBoostingClassifier
gbc = GradientBoostingClassifier()
gbc.fit(x_train, y_train)
```

[50]:
```
GradientBoostingClassifier()
```

[51]:
```
gbc_pred = gbc.predict(x_test)

print(f'Accuracy score : {accuracy_score(gbc_pred, y_test)}')
print(f'Confusion matrix :\n {confusion_matrix(gbc_pred, y_test)}')
print(f'Classification report :\n {classification_report(gbc_pred, y_test)}')
```

```
Accuracy score : 0.865513375950556
Confusion matrix :
 [[24830  3217]
 [ 1222  3738]]
Classification report :
               precision    recall  f1-score   support

           0       0.95      0.89      0.92     28047
           1       0.54      0.75      0.63      4960

    accuracy                           0.87     33007
   macro avg       0.75      0.82      0.77     33007
weighted avg       0.89      0.87      0.87     33007
```

the gradient boosting model still holds semilar results our datasets is very imbalance which might affect the accuracy of our model performance, although our models performance seems ok. we need to do some over sampling on the data to reduce the occurances of TN, FN and and improve FP and TP of the model

1.12 Using SMOTEENN for imbalance dataset:

[52]:
```
# ignore warning
import warnings
warnings.filterwarnings('ignore')
import matplotlib.ticker as mtick # for showing percentage in it
```

[53]:
```
from imblearn.combine import SMOTEENN
from collections import Counter

smot = SMOTEENN()
x_train_2, y_train_2 = smot.fit_resample(x_train, y_train)
print("The number of classes before fit {}".format(Counter(y_train)))
print("The number of classes after fit {}".format(Counter(y_train_2)))
```

```
The number of classes before fit Counter({0: 104061, 1: 27966})
The number of classes after fit Counter({1: 54479, 0: 46005})
```

[54]:
```
# splitting the over sampling dataset
x_train_sap, x_test_sap, y_train_sap, y_test_sap = train_test_split(x_train_2,␣
↪y_train_2, test_size=0.2)
```

1.13 Training Logistic Regression on the sampling set

[55]:
```
# Training Logistic Regression on the sampling
lr_samp = LogisticRegression(C=150, max_iter=150)
lr_samp.fit(x_train, y_train)

# making prediction
lr_samp_pred = lr_samp.predict(x_test_sap)

print(f'Accuracy score : {accuracy_score(lr_samp_pred, y_test_sap)}')
print(f'Confusion matrix :\n {confusion_matrix(lr_samp_pred, y_test_sap)}')
print(f'Classification report :\n {classification_report(lr_samp_pred,␣
↪y_test_sap)}')
```

```
Accuracy score : 0.5018161914713639
Confusion matrix :
 [[9001 9783]
 [ 229 1084]]
Classification report :
               precision    recall  f1-score   support
```

```
           0       0.98      0.48      0.64     18784
           1       0.10      0.83      0.18      1313

    accuracy                           0.50     20097
   macro avg       0.54      0.65      0.41     20097
weighted avg       0.92      0.50      0.61     20097
```

training the Random forest

[56]:
```
# Random forest classifier
Rand_samp = RandomForestClassifier(n_estimators=150,criterion='gini',␣
  ↪max_depth=15, min_samples_leaf=10, min_samples_split=6)
Rand_samp.fit(x_train_sap, y_train_sap)

# making predictions
Rand_samp_pred = Rand_samp.predict(x_test_sap)

print(f'Accuracy score : {accuracy_score(Rand_samp_pred, y_test_sap)}')
print(f'Confusion matrix :\n {confusion_matrix(Rand_samp_pred, y_test_sap)}')
print(f'Classification report :\n {classification_report(Rand_samp_pred,␣
  ↪y_test_sap)}')
```

```
Accuracy score : 0.9320296561675872
Confusion matrix :
 [[ 8654   790]
 [  576 10077]]
Classification report :
               precision    recall  f1-score   support

           0       0.94      0.92      0.93      9444
           1       0.93      0.95      0.94     10653

    accuracy                           0.93     20097
   macro avg       0.93      0.93      0.93     20097
weighted avg       0.93      0.93      0.93     20097
```

2 insights:

- The model achieved an accuracy score of 93.2%. The confusion matrix shows 8654 true negatives (TN), 790 false positives (FP), 576 false negatives (FN), and 10077 true positives (TP).
- Precision for class 0 (non-churn) is 0.94, and for class 1 (churn) is 0.93. Recall for class 0 is 0.92, and for class 1 is 0.95.
- The F1-score for class 0 is 0.93, and for class 1 is 0.94.

In summary, the model exhibits strong performance, with balanced precision, recall, and F1-score across both classes.

training decision tree after sample

[57]:
```
# decisionTree Classifier
tree_samp_model = DecisionTreeClassifier(criterion='gini', splitter='random',␣
↪min_samples_leaf=15)
tree_samp_model.fit(x_train_sap, y_train_sap)
# predicting

tree_samp_pred = tree_samp_model.predict(x_test_sap)

print(f'Accuracy score : {accuracy_score(tree_samp_pred, y_test_sap)}')
print(f'Confusion matrix :\n {confusion_matrix(tree_samp_pred, y_test_sap)}')
print(f'Classification report :\n {classification_report(tree_samp_pred,␣
↪y_test_sap)}')
```

```
Accuracy score : 0.9030701099666617
Confusion matrix :
 [[8515 1233]
 [ 715 9634]]
Classification report :
               precision    recall  f1-score   support

           0       0.92      0.87      0.90      9748
           1       0.89      0.93      0.91     10349

    accuracy                           0.90     20097
   macro avg       0.90      0.90      0.90     20097
weighted avg       0.90      0.90      0.90     20097
```

training the gradient boosting model after sampling

[58]:
```
# GradientBoostingClassifier
gbc_samp = GradientBoostingClassifier()
gbc_samp.fit(x_train_sap, y_train_sap)

# making prediction
gbc_samp_pred = gbc_samp.predict(x_test_sap)

print(f'Accuracy score : {accuracy_score(gbc_samp_pred, y_test_sap)}')
print(f'Confusion matrix :\n {confusion_matrix(gbc_samp_pred, y_test_sap)}')
print(f'Classification report :\n {classification_report(gbc_samp_pred,␣
↪y_test_sap)}')
```

```
Accuracy score : 0.9308354480768274
Confusion matrix :
```

```
[[ 8622   782]
 [  608 10085]]
Classification report :
               precision    recall  f1-score   support

           0       0.93      0.92      0.93      9404
           1       0.93      0.94      0.94     10693

    accuracy                           0.93     20097
   macro avg       0.93      0.93      0.93     20097
weighted avg       0.93      0.93      0.93     20097
```

3 insights:

- The model achieved an accuracy score of 0.93. The confusion matrix shows 8622 true negatives (TN), 782 false positives (FP), 608 false negatives (FN), and 10085 true positives (TP).
- Precision for class 0 (non-churn) is 0.93, and for class 1 (churn) is 0.93. Recall for class 0 is 0.92, and for class 1 is 0.94.
- The F1-score for class 0 is 0.93, and for class 1 is 0.94.

In summary, the model exhibits strong performance, with balanced precision, recall, and F1-score across both classes.

3.1 Saving the Model random forest

[59]:
```
import pickle
```

[60]:
```
filename = 'bank_churn_RFModel.sav'
pickle.dump(Rand_samp, open(filename,'wb'))
```

[61]:
```
load_model = pickle.load(open(filename, 'rb'))
```

[62]:
```
load_model.score(x_test_sap, y_test_sap)
```

[62]:
```
0.9320296561675872
```

3.2 Saving the Model Gradient Boosting

[68]:
```
filename1 = 'bank_churn_GBModel.sav'
pickle.dump(gbc_samp, open(filename1,'wb'))
```

[69]:
```
load_model1 = pickle.load(open(filename1, 'rb'))
```

[70]:
```
load_model1.score(x_test_sap, y_test_sap)
```

[70]: 0.9308354480768274

3.3 making predictions on the test datasets

[71]:
```
test_df.head()
```

[71]:
```
   id  CreditScore  Geography  Gender  Age  Tenure  Balance  NumOfProducts  \
0   0          189          0       0    5       2        0              1
1   1          286          0       0   31       2        0              0
2   2          259          0       0   17       7        0              1
3   3          284          0       1   19       8        0              0
4   4          355          1       1   22      10    10405              0

   HasCrCard  IsActiveMember  EstimatedSalary
0          0               1            33249
1          1               0             9388
2          1               0            26856
3          1               0            19659
4          1               0            26934
```

we need to make the columns in the datasets consistent with what we have in the selected feature

[72]:
```
columns_to_keep = ['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure',␣
↪'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary']
# Create a new DataFrame with only the desired columns
test_df_copy = test_df[columns_to_keep].copy()
```

[73]:
```
# Make predictions on the test data
predicted_probabilities = Rand_samp.predict_proba(test_df_copy)[:, 1]
```

let us load the original test _data

[74]:
```
test_url1 = r'/content/drive/MyDrive/test_kaggle_2024.csv'
df_test = pd.read_csv(test_url1)
df_test.head()
```

[74]:
```
       id  CustomerId    Surname  CreditScore Geography  Gender   Age  Tenure  \
0  165034    15773898   Lucchese          586    France  Female  23.0       2
1  165035    15782418       Nott          683    France  Female  46.0       2
2  165036    15807120         K?          656    France  Female  34.0       7
3  165037    15808905  O'Donnell          681    France    Male  36.0       8
4  165038    15607314    Higgins          752   Germany    Male  38.0      10

     Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary
0       0.00              2        0.0             1.0        160976.75
1       0.00              1        1.0             0.0         72549.27
```

```
2        0.00                2         1.0            0.0         138882.09
3        0.00                1         1.0            0.0         113931.57
4   121263.62                1         1.0            0.0         139431.00
```

[77]:
```python
# Create prediction_df DataFrame
prediction_df = pd.DataFrame({
    'CustomerId': df_test['CustomerId'],
    'predicted_probability': predicted_probabilities
})

# Check the number of entries in prediction_df
print("Number of entries in prediction_df:", len(prediction_df))
```

```
Number of entries in prediction_df: 110023
```

let us calculate the AUCSOC score

[78]:
```python
# Save prediction_df to a CSV file
prediction_df.to_csv('predictions.csv', index=False)
```

[79]:
```python
prediction_df.head()
```

[79]:

	CustomerId	predicted_probability
0	15773898	0.282184
1	15782418	0.326225
2	15807120	0.305148
3	15808905	0.255974
4	15607314	0.426700

[82]:
```python
prediction_df.describe().T
```

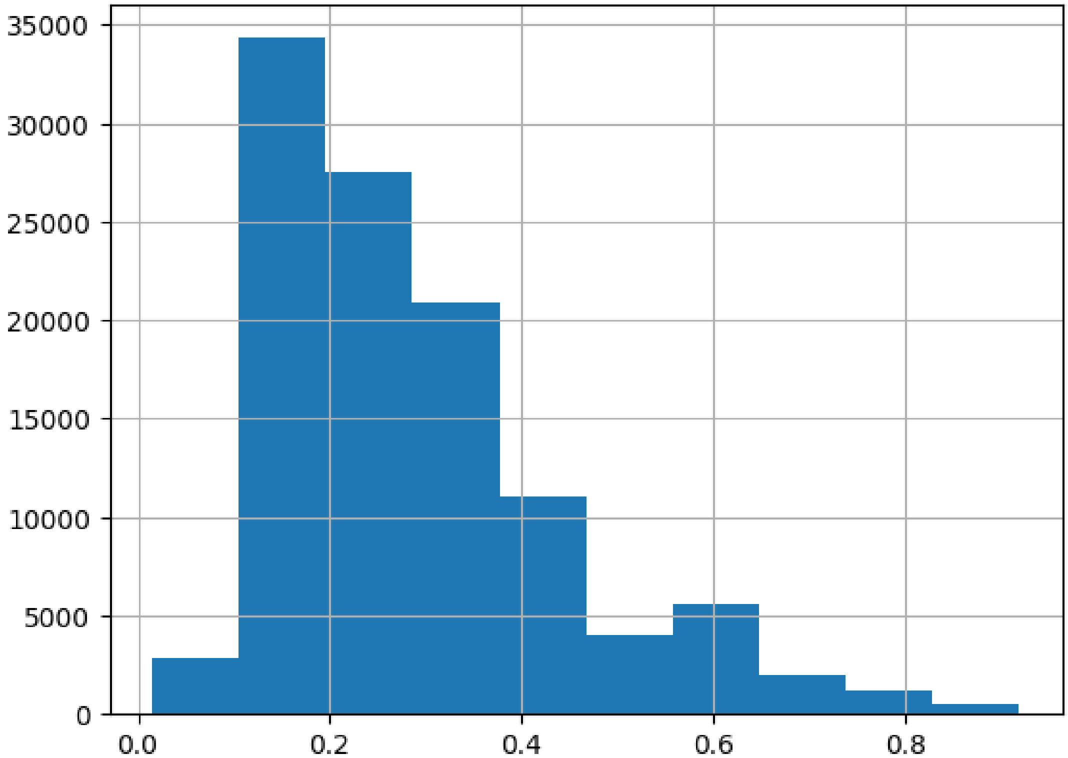
[82]:

	count	mean	std	min	\
CustomerId	110023.0	1.569210e+07	71684.990992	1.556570e+07	
predicted_probability	110023.0	2.862115e-01	0.153742	1.527464e-02	

	25%	50%	75%	max
CustomerId	1.563286e+07	1.569018e+07	1.575693e+07	1.581569e+07
predicted_probability	1.714121e-01	2.550493e-01	3.380290e-01	9.173503e-01

[83]:
```python
prediction_df.predicted_probability.hist()
```

[83]: <Axes: >


35000
30000
25000
20000
15000
10000
5000
0
0.0
0.2
0.4
0.6
0.8