Churn Prediction

A Machine Learning Model That Can Predict Customers Who Will Leave The Company

The aim is to predict whether a bank's customers leave the bank or not. If the Client has closed his/her bank account, he/she has left.

Dataset

- **RowNumber:** corresponds to the record (row) number and has no effect on the output.
- **CustomerId:** contains random values and has no effect on customer leaving the bank.
- **Surname:** the surname of a customer has no impact on their decision to leave the bank.
- **CreditScore:** can have an effect on customer churn, since a customer with a higher credit score is less likely to leave the bank.
- **Geography:** a customer's location can affect their decision to leave the bank.
- **Gender:** it's interesting to explore whether gender plays a role in a customer leaving the bank.
- **Age:** this is certainly relevant, since older customers are less likely to leave their bank than younger ones.
- **Tenure:** refers to the number of years that the customer has been a client of the bank. Normally, older clients are more loyal and less likely to leave a bank.
- **Balance:** also a very good indicator of customer churn, as people with a higher balance in their accounts are less likely to leave the bank compared to those with lower balances.
- **NumOfProducts:** refers to the number of products that a customer has purchased through the bank.
- **HasCrCard:** denotes whether or not a customer has a credit card. This column is also relevant, since people with a credit card are less likely to leave the bank.
- **IsActiveMember:** active customers are less likely to leave the bank.
- **EstimatedSalary:** as with balance, people with lower salaries are more likely to leave the bank compared to those with higher salaries.
- **Exited:** whether or not the customer left the bank. (0=No,1=Yes)

The model created as a result of LightGBM hyperparameter optimization (0.867300)

```python
# loading necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import pyplot
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix, classification_report,
f1_score, precision_score, recall_score, roc_auc_score, roc_curve
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from catboost import CatBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from lightgbm import LGBMClassifier
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.metrics import accuracy_score,recall_score
from xgboost import XGBClassifier
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score, GridSearchCV

import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore", category=FutureWarning)
warnings.filterwarnings("ignore", category=UserWarning)

%config InlineBackend.figure_format = 'retina'

# to display all columns and rows:
pd.set_option('display.max_columns', None);
pd.set_option('display.max_rows', None);

# reading the data
df = pd.read_csv("../input/churn-for-bank-customers/churn.csv",
index_col=0)
```

1- EDA

```
# The first 5 observation
df.head()
```

```
           CustomerId   Surname  CreditScore Geography  Gender  Age
Tenure  \
RowNumber

1            15634602  Hargrave          619    France  Female   42
2
2            15647311      Hill          608     Spain  Female   41
1
3            15619304      Onio          502    France  Female   42
8
4            15701354      Boni          699    France  Female   39
1
5            15737888  Mitchell          850     Spain  Female   43
2
```

```
               Balance  NumOfProducts  HasCrCard  IsActiveMember  \
RowNumber
1                 0.00              1          1               1
2             83807.86              1          0               1
3            159660.80              3          1               0
4                 0.00              2          0               0
5            125510.82              1          1               1

             EstimatedSalary  Exited
RowNumber
1                  101348.88       1
2                  112542.58       0
3                  113931.57       1
4                   93826.63       0
5                   79084.10       0
```

```
# The size of the data set
df.shape
```

```
(10000, 13)
```

```
# Feature information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 1 to 10000
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CustomerId       10000 non-null  int64
 1   Surname          10000 non-null  object
 2   CreditScore      10000 non-null  int64
 3   Geography        10000 non-null  object
 4   Gender           10000 non-null  object
 5   Age              10000 non-null  int64
 6   Tenure           10000 non-null  int64
 7   Balance          10000 non-null  float64
 8   NumOfProducts    10000 non-null  int64
 9   HasCrCard        10000 non-null  int64
 10  IsActiveMember   10000 non-null  int64
 11  EstimatedSalary  10000 non-null  float64
 12  Exited           10000 non-null  int64
dtypes: float64(2), int64(8), object(3)
memory usage: 1.1+ MB
```

```
# Descriptive statistics of the data set
df.describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99])
```

```
         CustomerId   CreditScore           Age        Tenure
Balance  \
```

```
count  1.000000e+04  10000.000000  10000.000000  10000.000000
10000.000000
mean   1.569094e+07    650.528800     38.921800      5.012800
76485.889288
std    7.193619e+04     96.653299     10.487806      2.892174
62397.405202
min    1.556570e+07    350.000000     18.000000      0.000000
0.000000
5%     1.557882e+07    489.000000     25.000000      1.000000
0.000000
25%    1.562853e+07    584.000000     32.000000      3.000000
0.000000
50%    1.569074e+07    652.000000     37.000000      5.000000
97198.540000
75%    1.575323e+07    718.000000     44.000000      7.000000
127644.240000
90%    1.579083e+07    778.000000     53.000000      9.000000
149244.792000
95%    1.580303e+07    812.000000     60.000000      9.000000
162711.669000
99%    1.581311e+07    850.000000     72.000000     10.000000
185967.985400
max    1.581569e+07    850.000000     92.000000     10.000000
250898.090000

       NumOfProducts    HasCrCard  IsActiveMember  EstimatedSalary  \
count   10000.000000  10000.00000    10000.000000     10000.000000
mean        1.530200      0.70550        0.515100    100090.239881
std         0.581654      0.45584        0.499797     57510.492818
min         1.000000      0.00000        0.000000        11.580000
5%          1.000000      0.00000        0.000000      9851.818500
25%         1.000000      0.00000        0.000000     51002.110000
50%         1.000000      1.00000        1.000000    100193.915000
75%         2.000000      1.00000        1.000000    149388.247500
90%         2.000000      1.00000        1.000000    179674.704000
95%         2.000000      1.00000        1.000000    190155.375500
99%         3.000000      1.00000        1.000000    198069.734500
max         4.000000      1.00000        1.000000    199992.480000

             Exited
count  10000.000000
mean       0.203700
std        0.402769
min        0.000000
5%         0.000000
25%        0.000000
50%        0.000000
75%        0.000000
90%        1.000000
```

```
95%          1.000000
99%          1.000000
max          1.000000
```

```
# categorical Variables
categorical_variables = [col for col in df.columns if col in "O"
                        or df[col].nunique() <=11
                        and col not in "Exited"]

categorical_variables
```

```
['Geography',
 'Gender',
 'Tenure',
 'NumOfProducts',
 'HasCrCard',
 'IsActiveMember']
```

```
# Numeric Variables
numeric_variables = [col for col in df.columns if df[col].dtype !=
"object"
                        and df[col].nunique() >11
                        and col not in "CustomerId"]
numeric_variables
```

```
['CreditScore', 'Age', 'Balance', 'EstimatedSalary']
```

Exited (Dependent Variable)

```
# Frequency of classes of dependent variable
df["Exited"].value_counts()
```

```
0    7963
1    2037
Name: Exited, dtype: int64
```

```
# Customers leaving the bank
churn = df.loc[df["Exited"]==1]

# Customers who did not leave the bank
not_churn = df.loc[df["Exited"]==0]
```

Categorical Variables

Tenure

```
# Frequency of not_churn group according to Tenure
not_churn["Tenure"].value_counts().sort_values()
```

```
0      318
10     389
6      771
9      771
4      786
3      796
5      803
1      803
8      828
2      847
7      851
Name: Tenure, dtype: int64
```

```python
# Frequency of churn group according to Tenure
churn["Tenure"].value_counts().sort_values()
```

```
0      95
10    101
7     177
6     196
8     197
2     201
4     203
5     209
9     213
3     213
1     232
Name: Tenure, dtype: int64
```

NumOfProducts

```python
# Frequency of not_churn group according to NumOfProducts
not_churn["NumOfProducts"].value_counts().sort_values()
```

```
3      46
1    3675
2    4242
Name: NumOfProducts, dtype: int64
```

```python
# Frequency of churn group according to NumOfProducts
churn["NumOfProducts"].value_counts().sort_values()
```

```
4      60
3     220
2     348
1    1409
Name: NumOfProducts, dtype: int64
```

HasCrCard

```python
# examining the HasCrCard of the not_churn group
not_churn["HasCrCard"].value_counts()
```

```
1    5631
0    2332
Name: HasCrCard, dtype: int64
```

```python
# examining the HasCrCard of the churn group
churn["HasCrCard"].value_counts()
```

```
1    1424
0     613
Name: HasCrCard, dtype: int64
```

IsActiveMember

```python
# examining the IsActiveMember of the not_churn group
not_churn["IsActiveMember"].value_counts()
```

```
1    4416
0    3547
Name: IsActiveMember, dtype: int64
```

```python
# examining the IsActiveMember of the churn group
churn["IsActiveMember"].value_counts()
```

```
0    1302
1     735
Name: IsActiveMember, dtype: int64
```

Geography

```python
# Frequency of not_churn group according to Geography
not_churn.Geography.value_counts().sort_values()
```

```
Germany    1695
Spain      2064
France     4204
Name: Geography, dtype: int64
```

```python
# Frequency of churn group according to Geography
churn.Geography.value_counts().sort_values()
```

```
Spain      413
France     810
Germany    814
Name: Geography, dtype: int64
```

Gender

```
# Frequency of not_churn group according to Gender
not_churn.Gender.value_counts()
```

```
Male      4559
Female    3404
Name: Gender, dtype: int64
```

```
# Frequency of churn group according to Gender
churn.Gender.value_counts()
```

```
Female    1139
Male       898
Name: Gender, dtype: int64
```

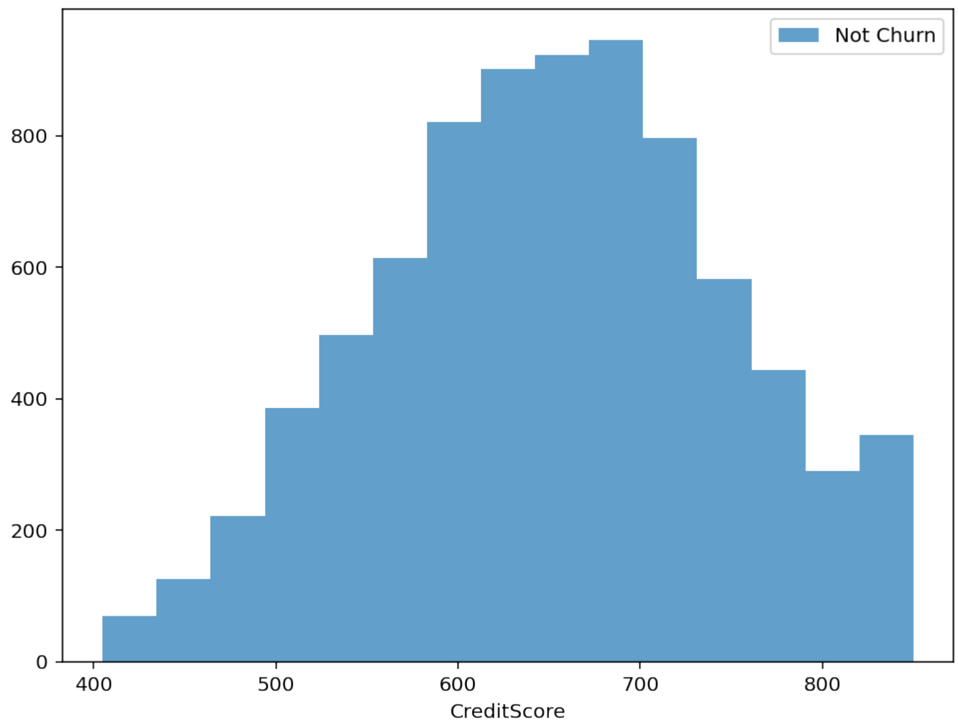
Numerical Variables

CreditScore

```
# Let's examine the credit score of the not_churn group
not_churn["CreditScore"].describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99]
)
```

```
count    7963.000000
mean      651.853196
std        95.653837
min       405.000000
5%        492.000000
25%       585.000000
50%       653.000000
75%       718.000000
90%       778.000000
95%       812.000000
99%       850.000000
max       850.000000
Name: CreditScore, dtype: float64
```

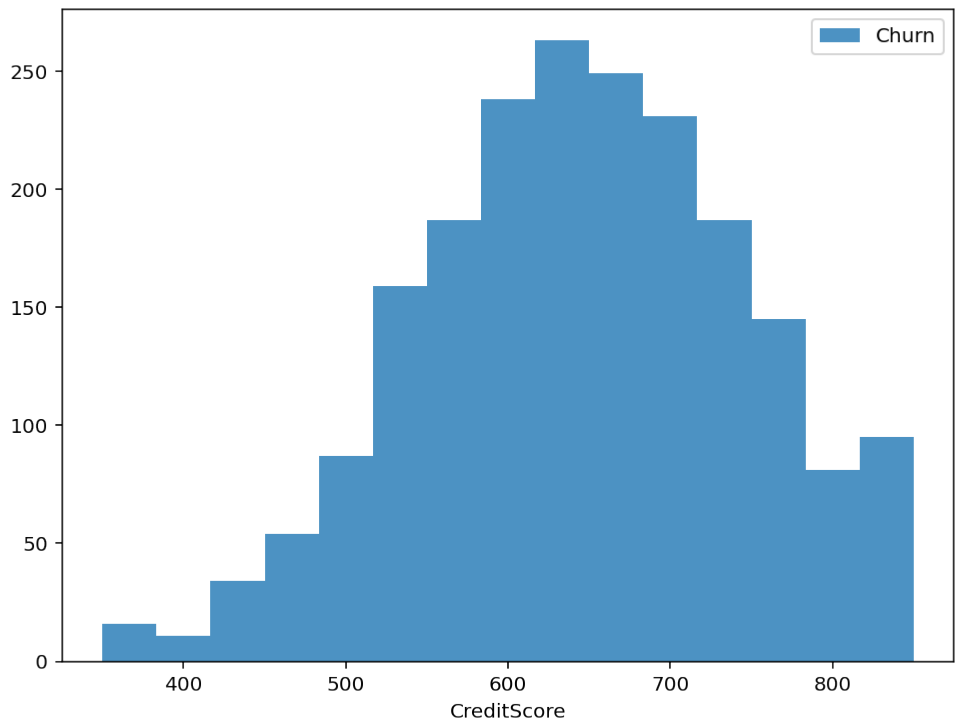
```
# distribution of the Credit Score for not_churn
pyplot.figure(figsize=(8,6))
pyplot.xlabel('CreditScore')
pyplot.hist(not_churn["CreditScore"],bins=15, alpha=0.7, label='Not
Churn')
pyplot.legend(loc='upper right')
pyplot.show()
```




```
# Let's examine the credit score of the churn group
churn["CreditScore"].describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99])
```

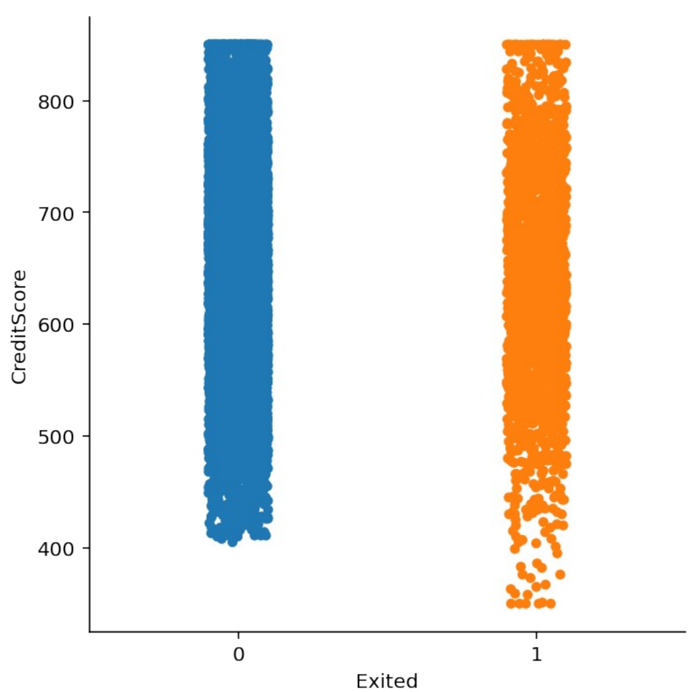
```
count    2037.000000
mean      645.351497
std       100.321503
min       350.000000
5%        479.000000
25%       578.000000
50%       646.000000
75%       716.000000
90%       776.400000
95%       812.200000
99%       850.000000
max       850.000000
Name: CreditScore, dtype: float64
```

```
# distribution of the Credit Score for churn
pyplot.figure(figsize=(8,6))
pyplot.xlabel('CreditScore')
pyplot.hist(churn["CreditScore"],bins=15, alpha=0.8, label='Churn')
pyplot.legend(loc='upper right')
pyplot.show()
```




```
sns.catplot("Exited", "CreditScore", data = df)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f8aecda7f90>
```

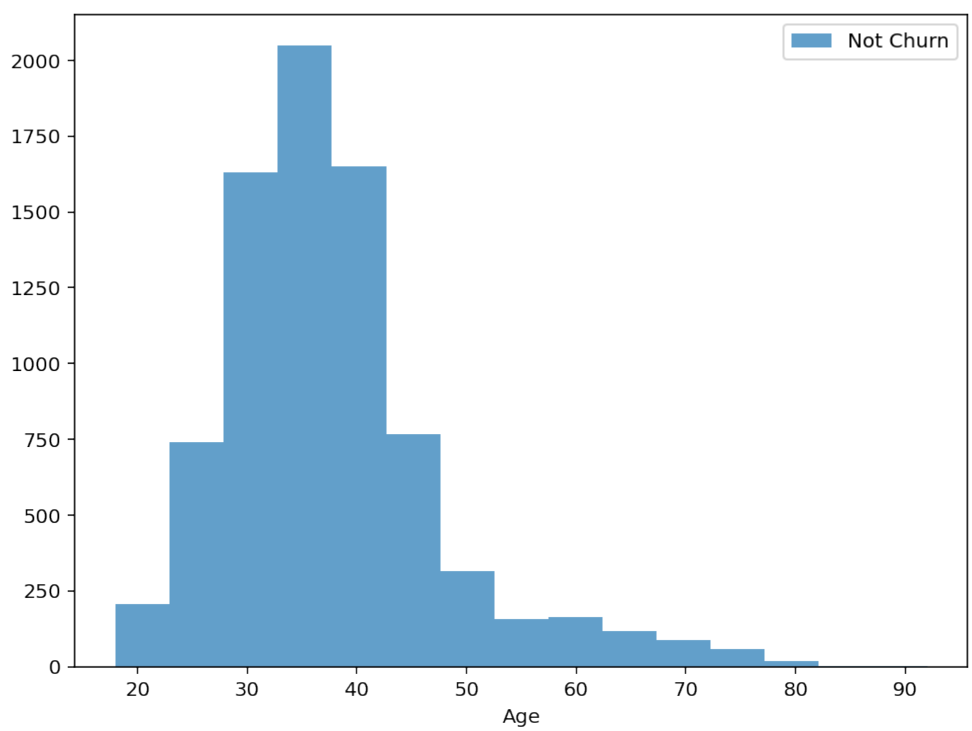


Age

```python
# examining the age of the not_churn group
not_churn["Age"].describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99])
```

```
count    7963.000000
mean       37.408389
std        10.125363
min        18.000000
5%         24.000000
25%        31.000000
50%        36.000000
75%        41.000000
90%        49.000000
95%        59.000000
99%        73.000000
max        92.000000
Name: Age, dtype: float64
```

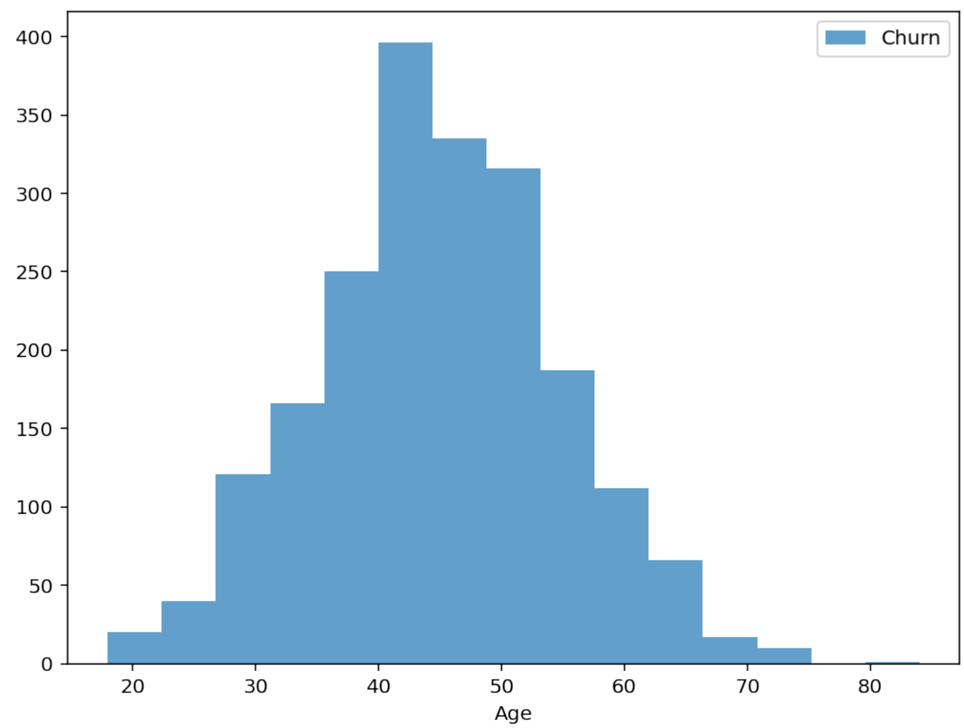
```python
# distribution of the Age for not_churn
pyplot.figure(figsize=(8,6))
pyplot.xlabel('Age')
pyplot.hist(not_churn["Age"],bins=15, alpha=0.7, label='Not Churn')
pyplot.legend(loc='upper right')
pyplot.show()
```



```
# examine the age of the churn group
churn["Age"].describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99])
```

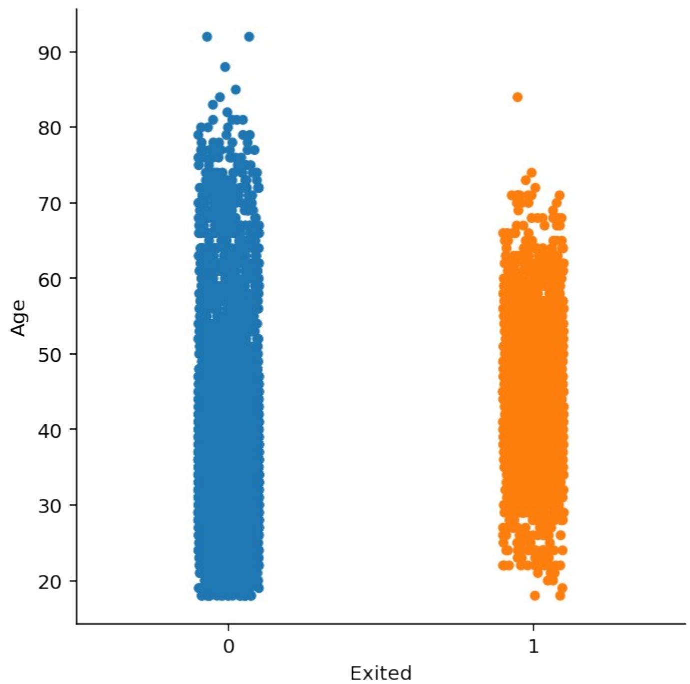
```
count    2037.000000
mean       44.837997
std         9.761562
min        18.000000
5%         29.000000
25%        38.000000
50%        45.000000
75%        51.000000
90%        58.000000
95%        61.000000
99%        68.000000
max        84.000000
Name: Age, dtype: float64
```

```
# distribution of the Age for not_churn
pyplot.figure(figsize=(8,6))
pyplot.xlabel('Age')
pyplot.hist(churn["Age"],bins=15, alpha=0.7, label='Churn')
pyplot.legend(loc='upper right')
pyplot.show()
```




```
sns.catplot("Exited", "Age", data = df)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f8aecb55f50>
```

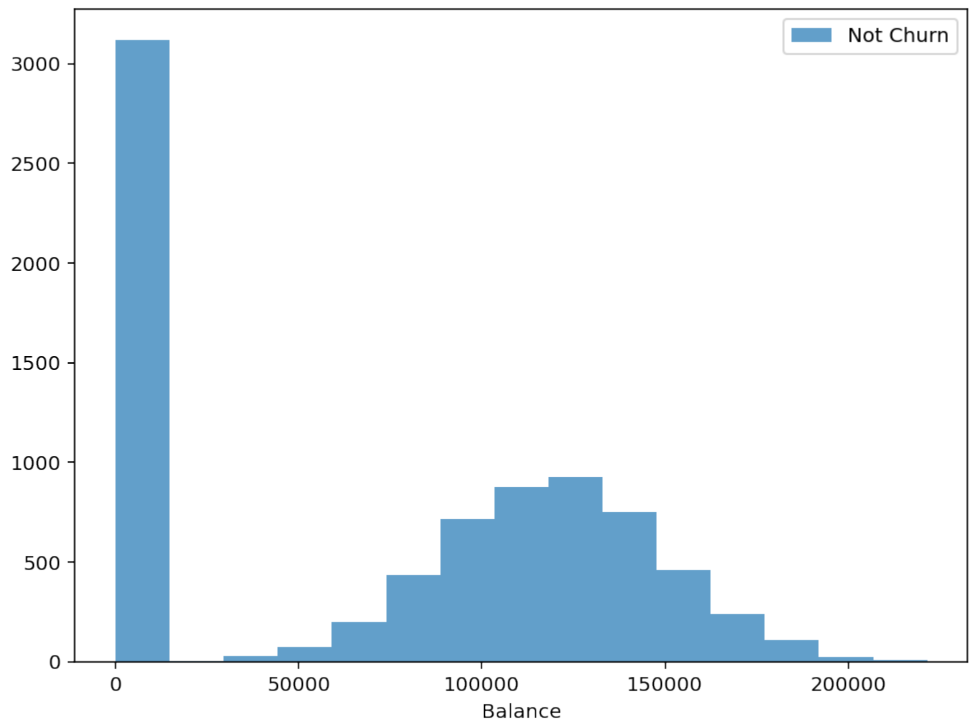


Balance

```
# examining the Balance of the not_churn group
not_churn["Balance"].describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99])
```

```
count      7963.000000
mean      72745.296779
std       62848.040701
min           0.000000
5%            0.000000
25%           0.000000
50%       92072.680000
75%      126410.280000
90%      148730.298000
95%      161592.595000
99%      183753.906200
max      221532.800000
Name: Balance, dtype: float64
```

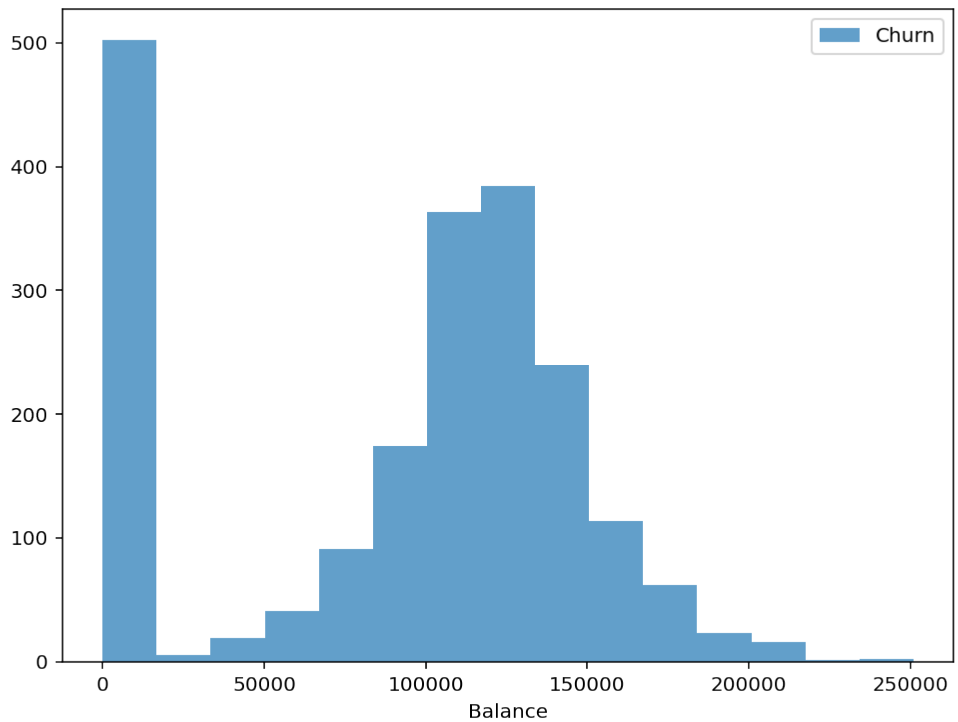
```
# distribution of the Balance for not_churn
pyplot.figure(figsize=(8,6))
pyplot.xlabel('Balance')
pyplot.hist(not_churn["Balance"],bins=15, alpha=0.7, label='Not
Churn')
pyplot.legend(loc='upper right')
pyplot.show()
```




```
# examining the Balance of the churn group
churn["Balance"].describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99])
```

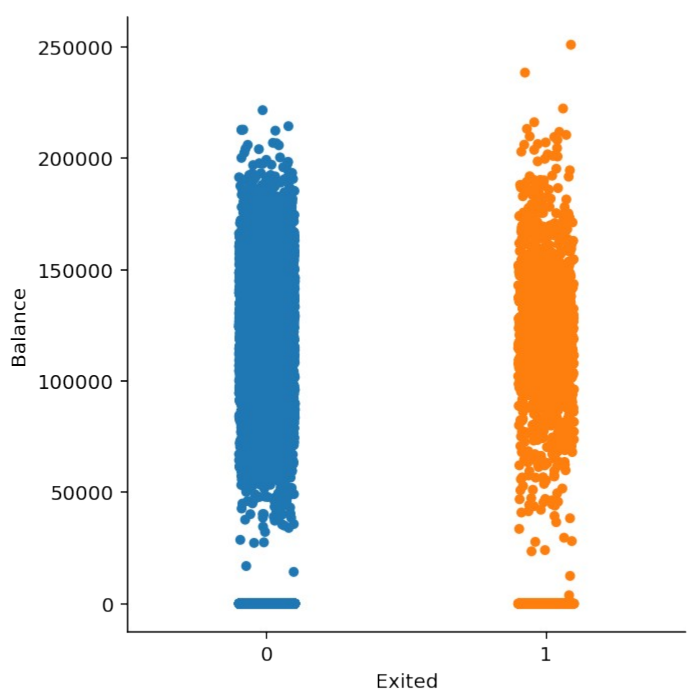
```
count      2037.000000
mean      91108.539337
std       58360.794816
min           0.000000
5%            0.000000
25%       38340.020000
50%      109349.290000
75%      131433.330000
90%      152080.618000
95%      167698.240000
99%      197355.288400
max      250898.090000
Name: Balance, dtype: float64
```

```
# distribution of the Balance for churn
pyplot.figure(figsize=(8,6))
pyplot.xlabel('Balance')
pyplot.hist(churn["Balance"],bins=15, alpha=0.7, label='Churn')
pyplot.legend(loc='upper right')
pyplot.show()
```




```
sns.catplot("Exited", "Balance", data = df)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f8aecace150>
```

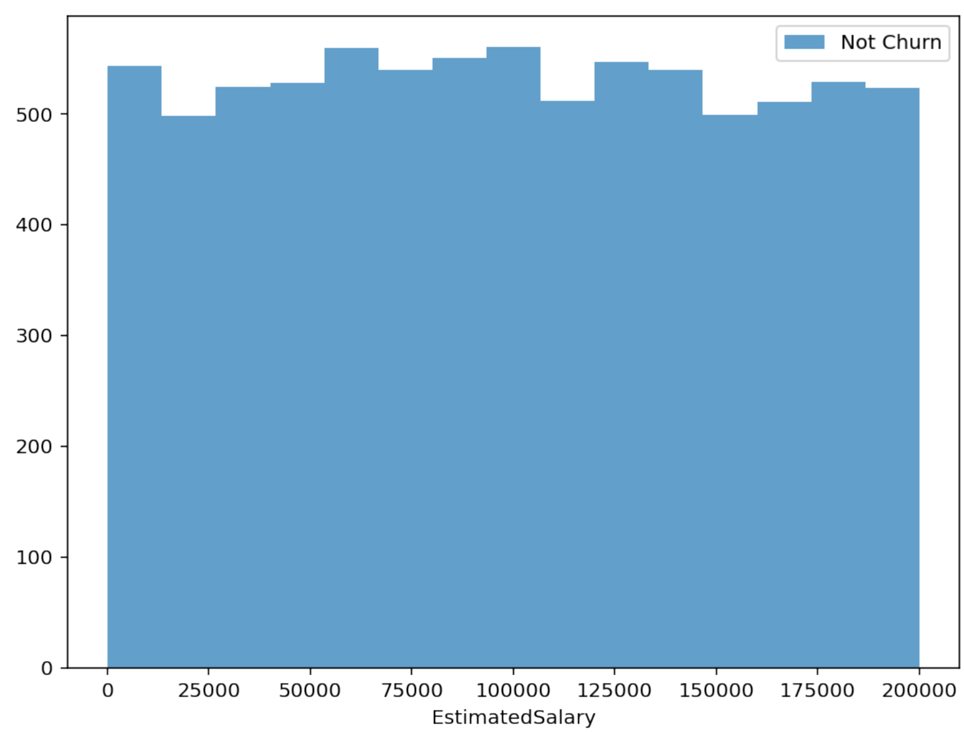


EstimatedSalary

```
# examining the EstimatedSalary of the not_churn group
not_churn["EstimatedSalary"].describe([0.05,0.25,0.50,0.75,0.90,0.95,0
.99])
```

```
count      7963.000000
mean      99738.391772
std       57405.586966
min          90.070000
5%         9773.542000
25%       50783.490000
50%       99645.040000
75%      148609.955000
90%      179453.212000
95%      190107.557000
99%      198131.465200
max      199992.480000
Name: EstimatedSalary, dtype: float64
```

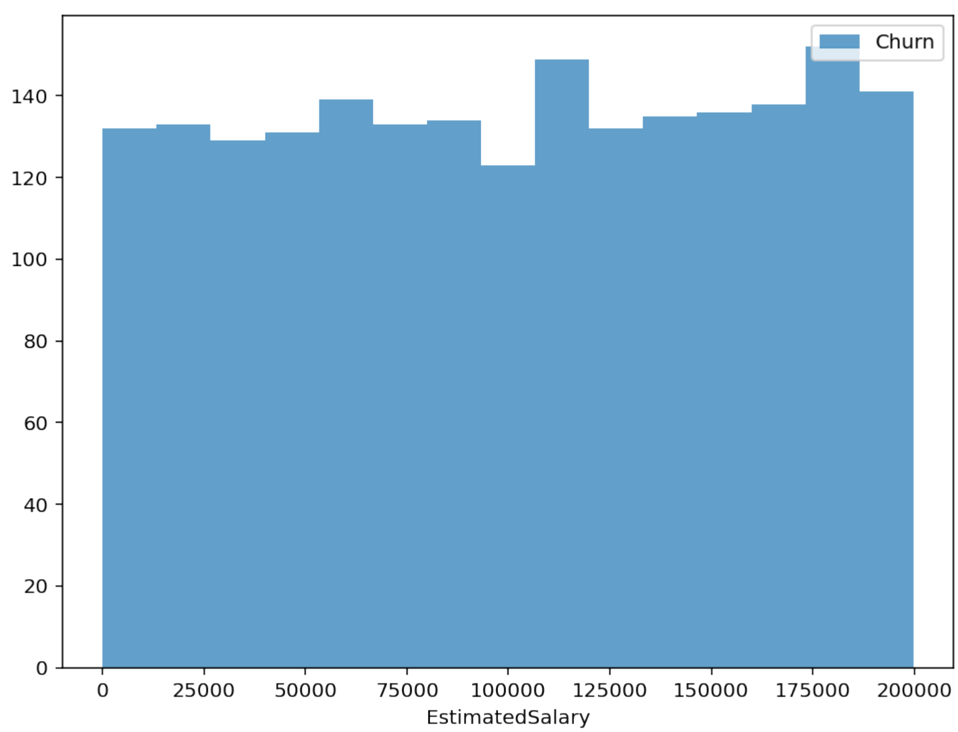
```
# distribution of the Balance for churn
pyplot.figure(figsize=(8,6))
pyplot.xlabel('EstimatedSalary')
pyplot.hist(not_churn["EstimatedSalary"],bins=15, alpha=0.7,
label='Not Churn')
pyplot.legend(loc='upper right')
pyplot.show()
```



```
# examining the EstimatedSalary of the churn group
churn["EstimatedSalary"].describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99]
)
```

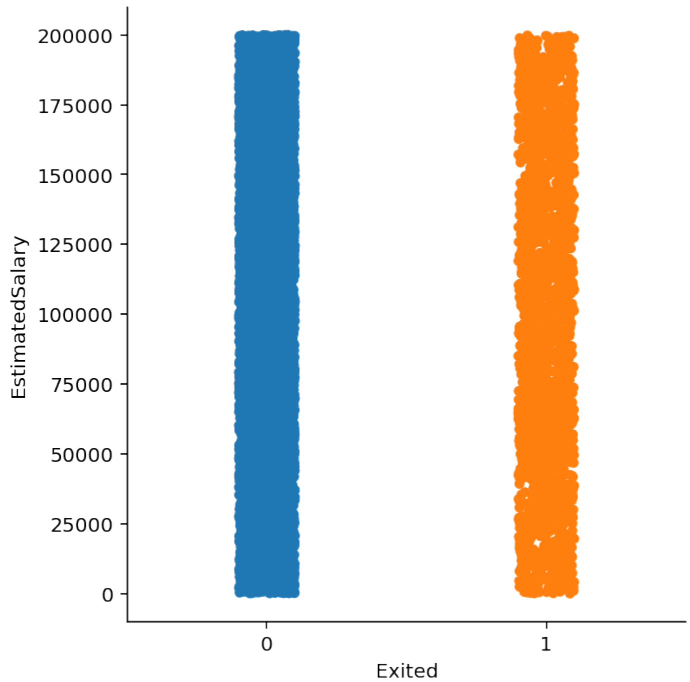
```
count      2037.000000
mean     101465.677531
std       57912.418071
min          11.580000
5%        10030.760000
25%       51907.720000
50%      102460.840000
75%      152422.910000
90%      180169.390000
95%      190328.982000
99%      197717.297600
max      199808.100000
Name: EstimatedSalary, dtype: float64
```

```
# distribution of the EstimatedSalary for churn
pyplot.figure(figsize=(8,6))
pyplot.xlabel('EstimatedSalary')
pyplot.hist(churn["EstimatedSalary"],bins=15, alpha=0.7,
label='Churn')
pyplot.legend(loc='upper right')
pyplot.show()
```




```
sns.catplot("Exited", "EstimatedSalary", data = df)
```

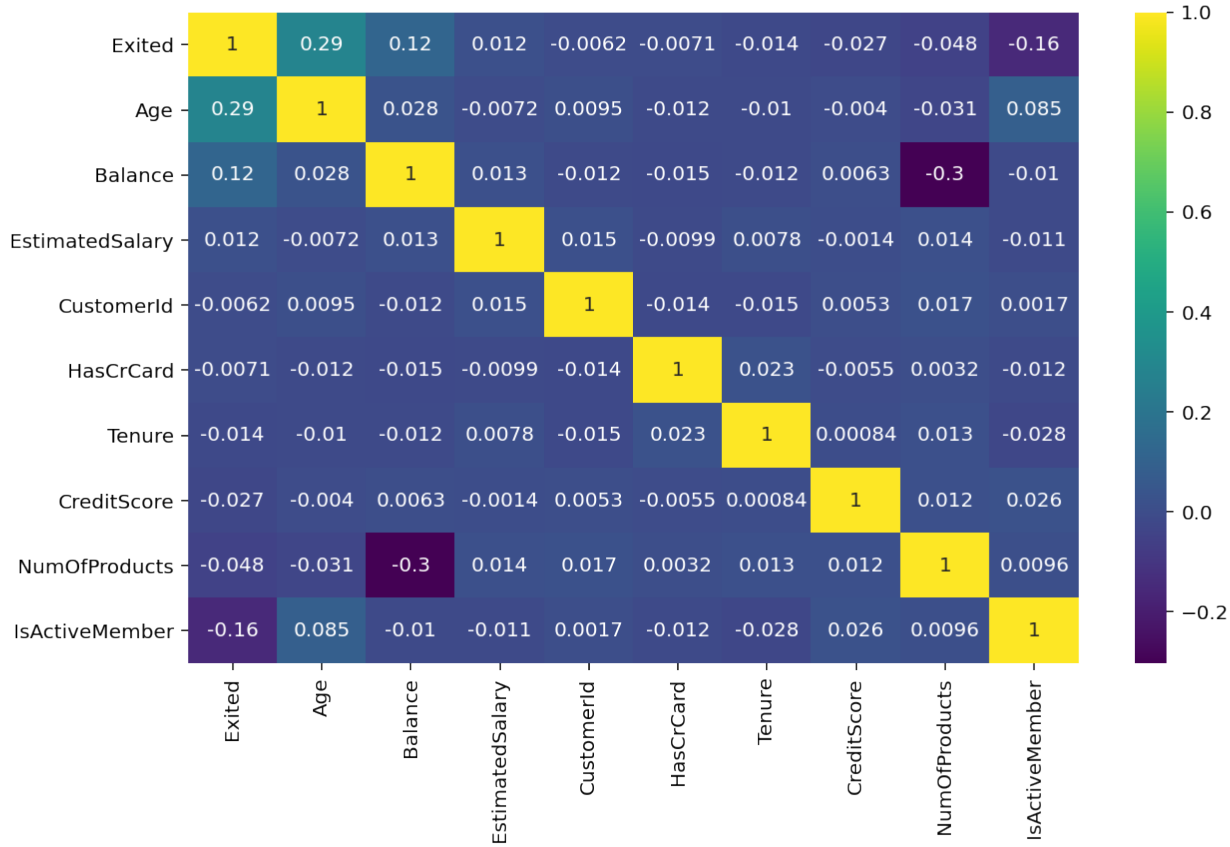
```
<seaborn.axisgrid.FacetGrid at 0x7f8aec586090>
```



Correlation Matrix

```
# Exited correlation matrix
k = 10 #number of variables for heatmap
cols = df.corr().nlargest(k, 'Exited')['Exited'].index
cm = df[cols].corr()
plt.figure(figsize=(10,6))
sns.heatmap(cm, annot=True, cmap = 'viridis')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8aeca8af90>
```



2- Data Preprocessing

Missing Value

```
# # Missing Observation Analysis
df.isnull().sum()
```

```
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
```

Outliers

```
# To determine the threshold value for outliers
def outlier_thresholds(dataframe, variable, low_quantile=0.05,
up_quantile=0.95):
    quantile_one = dataframe[variable].quantile(low_quantile)
    quantile_three = dataframe[variable].quantile(up_quantile)
    interquantile_range = quantile_three - quantile_one
    up_limit = quantile_three + 1.5 * interquantile_range
    low_limit = quantile_one - 1.5 * interquantile_range
    return low_limit, up_limit

# Are there any outliers in the variables
def has_outliers(dataframe, numeric_columns, plot=False):
   # variable_names = []
    for col in numeric_columns:
        low_limit, up_limit = outlier_thresholds(dataframe, col)
        if dataframe[(dataframe[col] > up_limit) | (dataframe[col] <
low_limit)].any(axis=None):
            number_of_outliers = dataframe[(dataframe[col] > up_limit)
| (dataframe[col] < low_limit)].shape[0]
            print(col, " : ", number_of_outliers, "outliers")
            #variable_names.append(col)
            if plot:
                sns.boxplot(x=dataframe[col])
                plt.show()
    #return variable_names

# There is no outlier
for var in numeric_variables:
    print(var, "has " , has_outliers(df, [var]),  "Outliers")
```

```
CreditScore has  None Outliers
Age has  None Outliers
Balance has  None Outliers
EstimatedSalary has  None Outliers
```

Feature Engineering

```
# we standardize tenure with age
df["NewTenure"] = df["Tenure"]/df["Age"]
df["NewCreditsScore"] = pd.qcut(df['CreditScore'], 6, labels = [1, 2,
3, 4, 5, 6])
df["NewAgeScore"] = pd.qcut(df['Age'], 8, labels = [1, 2, 3, 4, 5, 6,
7, 8])
df["NewBalanceScore"] = pd.qcut(df['Balance'].rank(method="first"), 5,
labels = [1, 2, 3, 4, 5])
df["NewEstSalaryScore"] = pd.qcut(df['EstimatedSalary'], 10, labels =
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
```

```
df.head()

           CustomerId   Surname  CreditScore Geography  Gender  Age
Tenure  \
RowNumber

1            15634602  Hargrave          619    France  Female   42
2
2            15647311      Hill          608     Spain  Female   41
1
3            15619304      Onio          502    France  Female   42
8
4            15701354      Boni          699    France  Female   39
1
5            15737888  Mitchell          850     Spain  Female   43
2

             Balance  NumOfProducts  HasCrCard  IsActiveMember  \
RowNumber
1               0.00              1          1               1
2           83807.86              1          0               1
3          159660.80              3          1               0
4               0.00              2          0               0
5          125510.82              1          1               1

           EstimatedSalary  Exited  NewTenure NewCreditsScore
NewAgeScore  \
RowNumber

1                101348.88       1   0.047619               3
6
2                112542.58       0   0.024390               2
6
3                113931.57       1   0.190476               1
6
4                 93826.63       0   0.025641               5
5
5                 79084.10       0   0.046512               6
6

          NewBalanceScore NewEstSalaryScore
RowNumber
1                       1                 6
2                       3                 6
3                       5                 6
4                       1                 5
5                       4                 4
```

One Hot Encoding

```
# Variables to apply one hot encoding
list = ["Gender", "Geography"]
df = pd.get_dummies(df, columns =list, drop_first = True)

df.head()

             CustomerId   Surname  CreditScore  Age  Tenure
Balance  \
RowNumber

1              15634602  Hargrave          619   42       2       0.00

2              15647311      Hill          608   41       1   83807.86

3              15619304      Onio          502   42       8  159660.80

4              15701354      Boni          699   39       1       0.00

5              15737888  Mitchell          850   43       2  125510.82


             NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary
Exited  \
RowNumber

1                        1          1               1        101348.88
1
2                        1          0               1        112542.58
0
3                        3          1               0        113931.57
1
4                        2          0               0         93826.63
0
5                        1          1               1         79084.10
0

             NewTenure NewCreditsScore NewAgeScore NewBalanceScore  \
RowNumber
1             0.047619               3           6               1
2             0.024390               2           6               3
3             0.190476               1           6               5
4             0.025641               5           5               1
5             0.046512               6           6               4

            NewEstSalaryScore  Gender_Male  Geography_Germany
Geography_Spain
RowNumber

1                           6            0                  0
```

```
0
2                            6              0                     0
1
3                            6              0                     0
0
4                            5              0                     0
0
5                            4              0                     0
1
```

Scalling

```python
# Removing variables that will not affect the dependent variable
df = df.drop(["CustomerId","Surname"], axis = 1)

# Scale features using statistics that are robust to outliers.
def robust_scaler(variable):
    var_median = variable.median()
    quartile1 = variable.quantile(0.25)
    quartile3 = variable.quantile(0.75)
    interquantile_range = quartile3 - quartile1
    if int(interquantile_range) == 0:
        quartile1 = variable.quantile(0.05)
        quartile3 = variable.quantile(0.95)
        interquantile_range = quartile3 - quartile1
        if int(interquantile_range) == 0:
            quartile1 = variable.quantile(0.01)
            quartile3 = variable.quantile(0.99)
            interquantile_range = quartile3 - quartile1
            z = (variable - var_median) / interquantile_range
            return round(z, 3)

        z = (variable - var_median) / interquantile_range
        return round(z, 3)
    else:
        z = (variable - var_median) / interquantile_range
    return round(z, 3)

new_cols_ohe = ["Gender_Male","Geography_Germany","Geography_Spain"]
like_num = [col for col in df.columns if df[col].dtypes != 'O' and
len(df[col].value_counts()) <= 10]
cols_need_scale = [col for col in df.columns if col not in
new_cols_ohe
                   and col not in "Exited"
                   and col not in like_num]

for col in cols_need_scale:
    df[col] = robust_scaler(df[col])
```

```
df.head()

           CreditScore    Age  Tenure  Balance  NumOfProducts
HasCrCard  \
RowNumber

1               -0.246  0.417   -0.75   -0.761              1
1
2               -0.328  0.333   -1.00   -0.105              1
0
3               -1.119  0.417    0.75    0.489              3
1
4                0.351  0.167   -1.00   -0.761              2
0
5                1.478  0.500   -0.75    0.222              1
1

           IsActiveMember  EstimatedSalary  Exited  NewTenure
NewCreditsScore  \
RowNumber

1                       1            0.012       1     -0.217
3
2                       1            0.126       0     -0.279
2
3                       0            0.140       1      0.164
1
4                       0           -0.065       0     -0.276
5
5                       1           -0.215       0     -0.220
6

          NewAgeScore NewBalanceScore NewEstSalaryScore
Gender_Male  \
RowNumber

1                   6               1                 6            0

2                   6               3                 6            0

3                   6               5                 6            0

4                   5               1                 5            0

5                   6               4                 4            0


           Geography_Germany  Geography_Spain
RowNumber
1                          0                0
2                          0                1
```

```
3                               0                0
4                               0                0
5                               0                1
```

3- Modeling

```
X = df.drop("Exited",axis=1)
y = df["Exited"]
# Train-Test Separation
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.20, random_state=12345)
# Models for Classification
models = [('LR', LogisticRegression(random_state=123456)),
          ('KNN', KNeighborsClassifier()),
          ('CART', DecisionTreeClassifier(random_state=123456)),
          ('RF', RandomForestClassifier(random_state=123456)),
          ('SVR', SVC(gamma='auto',random_state=123456)),
          ('GB', GradientBoostingClassifier(random_state = 12345)),
          ("LightGBM", LGBMClassifier(random_state=123456))]
results = []
names = []
for name, model in models:
    kfold = KFold(n_splits=10, random_state=123456)
    cv_results = cross_val_score(model, X, y, cv=kfold)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.823800 (0.009304)
KNN: 0.819600 (0.010268)
CART: 0.784700 (0.010460)
RF: 0.861400 (0.008947)
SVR: 0.846900 (0.010114)
GB: 0.864600 (0.009656)
LightGBM: 0.862500 (0.008992)
```

```
# GB Confusion Matrix
model_GB = GradientBoostingClassifier(random_state=12345)
model_GB.fit(X_train, y_train)
y_pred = model_GB.predict(X_test)
conf_mat = confusion_matrix(y_pred,y_test)
conf_mat
```

```
array([[1520,  230],
       [  53,  197]])
```

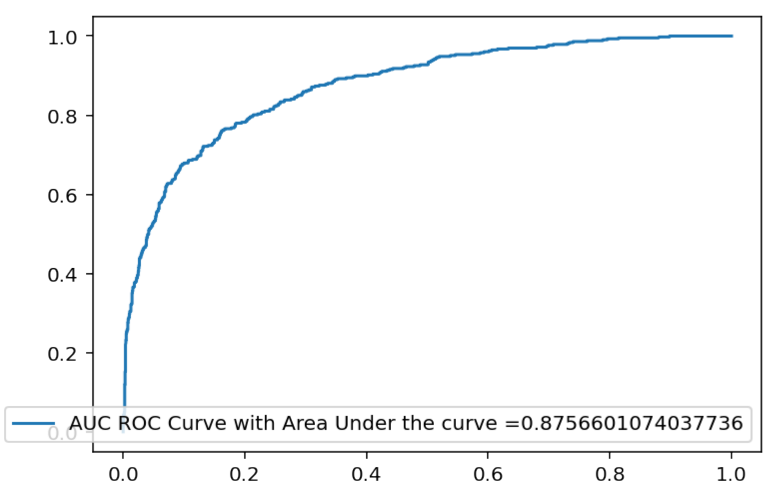
```
print("True Positive : ", conf_mat[1, 1])
print("True Negative : ", conf_mat[0, 0])
print("False Positive: ", conf_mat[0, 1])
print("False Negative: ", conf_mat[1, 0])
```

```
True Positive :  197
True Negative :  1520
False Positive:  230
False Negative:  53
```

```
# Classification Report for XGB Model
print(classification_report(model_GB.predict(X_test),y_test))
```

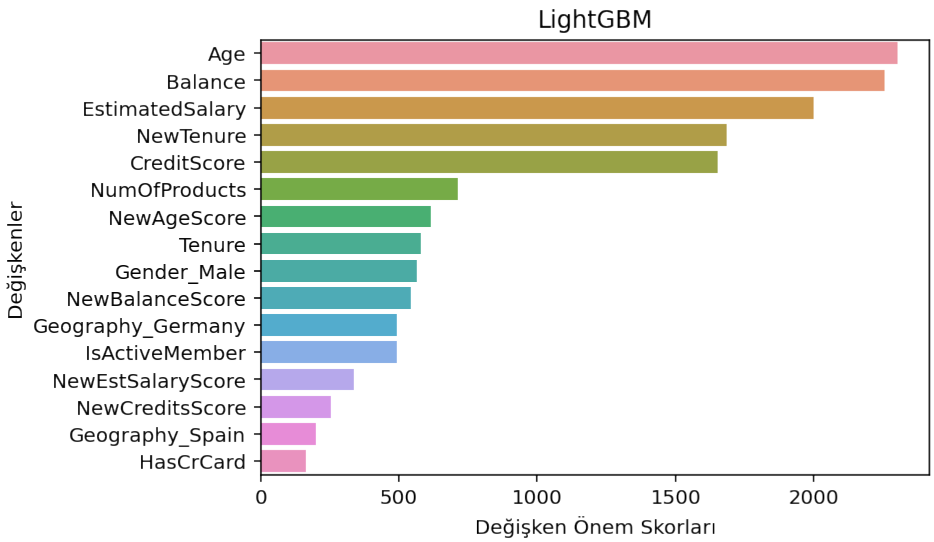
```
              precision    recall  f1-score   support

           0       0.97      0.87      0.91      1750
           1       0.46      0.79      0.58       250

    accuracy                           0.86      2000
   macro avg       0.71      0.83      0.75      2000
weighted avg       0.90      0.86      0.87      2000
```

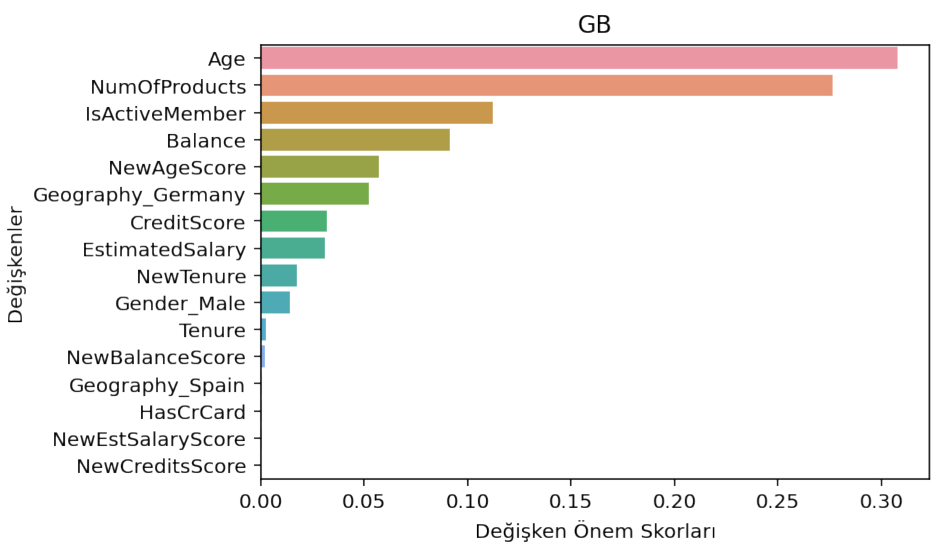
```
# Auc Roc Curve
def generate_auc_roc_curve(clf, X_test):
    y_pred_proba = clf.predict_proba(X_test)[:, 1]
    fpr, tpr, thresholds = roc_curve(y_test,  y_pred_proba)
    auc = roc_auc_score(y_test, y_pred_proba)
    plt.plot(fpr,tpr,label="AUC ROC Curve with Area Under the curve
="+str(auc))
    plt.legend(loc=4)
    plt.show()
    pass

generate_auc_roc_curve(model_GB, X_test)
```



4- Model Tuning

```
# LightGBM:
lgb_model = LGBMClassifier()
# Model Tuning
lgbm_params = {'colsample_bytree': 0.5,
 'learning_rate': 0.01,
 'max_depth': 6,
 'n_estimators': 500}

lgbm_tuned = LGBMClassifier(**lgbm_params).fit(X, y)

#Let's choose the highest 4 models
# GBM
gbm_model = GradientBoostingClassifier()
# Model Tuning
gbm_params = {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators':
200, 'subsample': 1}
gbm_tuned = GradientBoostingClassifier(**gbm_params).fit(X,y)

# evaluate each model in turn
models = [("LightGBM", lgbm_tuned),
          ("GB",gbm_tuned)]
results = []
names = []
for name, model in models:
    kfold = KFold(n_splits=10, random_state=123456)
    cv_results = cross_val_score(model, X, y, cv=10,
scoring="accuracy")
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)

LightGBM: 0.867300 (0.009798)
GB: 0.866900 (0.008514)

for name, model in models:
        base = model.fit(X_train,y_train)
        y_pred = base.predict(X_test)
        acc_score = accuracy_score(y_test, y_pred)
        feature_imp = pd.Series(base.feature_importances_,
                        index=X.columns).sort_values(ascending=False)

        sns.barplot(x=feature_imp, y=feature_imp.index)
        plt.xlabel('Değişken Önem Skorları')
        plt.ylabel('Değişkenler')
        plt.title(name)
        plt.show()
```





Report

1) Churn Data Set read.

2) With Exploratory Data Analysis

4) During Model Buildingost

5) The model created as a result of LightGBM hyperparameter optimization (AUC 0.87)