In [1]:

```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

import numpy as np
import pandas as pd
pd.set_option('precision', 3)

# Data Visualisation Libraries
import matplotlib.pyplot as plt
%config InlineBackend.figure_format = 'retina'

!pip install seaborn --upgrade
import seaborn as sns
sns.set_style('darkgrid')
import sklearn

# Statistics
from scipy.stats import chi2_contingency
from imblearn.over_sampling import SMOTE

# Machine Learning
from sklearn import model_selection
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import accuracy_score, recall_score, precision_score, auc, roc_auc_score, roc_curve
from sklearn.metrics import confusion_matrix
#import scikitplot as skplt

from sklearn.model_selection import learning_curve
from sklearn.preprocessing import LabelEncoder, StandardScaler

from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, VotingClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier

from sklearn.metrics import accuracy_score, recall_score, precision_score, auc, roc_auc_score, roc_curve
from sklearn.metrics import confusion_matrix
import scikitplot as skplt

print(' Libraries Imported!')
```

```
C:\Users\sarah\Anaconda3\lib\site-packages\pandas\compat\_optional.py:138: UserWarning: Pandas requires version '2.7.0' or
newer of 'numexpr' (version '2.6.9' currently installed).
  warnings.warn(msg, UserWarning)

Requirement already up-to-date: seaborn in c:\users\sarah\anaconda3\lib\site-packages (0.12.2)
Requirement already satisfied, skipping upgrade: matplotlib!=3.6.1,>=3.1 in c:\users\sarah\anaconda3\lib\site-packages (fro
m seaborn) (3.5.1)
Requirement already satisfied, skipping upgrade: pandas>=0.25 in c:\users\sarah\anaconda3\lib\site-packages (from seaborn)
(1.3.5)
Requirement already satisfied, skipping upgrade: typing_extensions; python_version < "3.8" in c:\users\sarah\anaconda3\lib
\site-packages (from seaborn) (4.2.0)
Requirement already satisfied, skipping upgrade: numpy!=1.24.0,>=1.17 in c:\users\sarah\anaconda3\lib\site-packages (from s
eaborn) (1.21.6)
Requirement already satisfied, skipping upgrade: fonttools>=4.22.0 in c:\users\sarah\anaconda3\lib\site-packages (from matp
lotlib!=3.6.1,>=3.1->seaborn) (4.31.2)
Requirement already satisfied, skipping upgrade: cycler>=0.10 in c:\users\sarah\anaconda3\lib\site-packages (from matplotli
b!=3.6.1,>=3.1->seaborn) (0.10.0)
Requirement already satisfied, skipping upgrade: kiwisolver>=1.0.1 in c:\users\sarah\anaconda3\lib\site-packages (from matp
lotlib!=3.6.1,>=3.1->seaborn) (1.1.0)
Requirement already satisfied, skipping upgrade: pyparsing>=2.2.1 in c:\users\sarah\anaconda3\lib\site-packages (from matpl
otlib!=3.6.1,>=3.1->seaborn) (2.4.0)
Requirement already satisfied, skipping upgrade: packaging>=20.0 in c:\users\sarah\anaconda3\lib\site-packages (from matplo
tlib!=3.6.1,>=3.1->seaborn) (21.3)
Requirement already satisfied, skipping upgrade: python-dateutil>=2.7 in c:\users\sarah\anaconda3\lib\site-packages (from m
atplotlib!=3.6.1,>=3.1->seaborn) (2.8.2)
Requirement already satisfied, skipping upgrade: pillow>=6.2.0 in c:\users\sarah\anaconda3\lib\site-packages (from matplotl
ib!=3.6.1,>=3.1->seaborn) (9.1.0)
Requirement already satisfied, skipping upgrade: pytz>=2017.3 in c:\users\sarah\anaconda3\lib\site-packages (from pandas>=
0.25->seaborn) (2019.1)
Requirement already satisfied, skipping upgrade: six in c:\users\sarah\anaconda3\lib\site-packages (from cycler>=0.10->matp
lotlib!=3.6.1,>=3.1->seaborn) (1.12.0)
Requirement already satisfied, skipping upgrade: setuptools in c:\users\sarah\anaconda3\lib\site-packages (from kiwisolver>
=1.0.1->matplotlib!=3.6.1,>=3.1->seaborn) (41.0.1)

---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-1-f0c58783fcdf> in <module>
     39 from sklearn.metrics import accuracy_score, recall_score, precision_score, auc, roc_auc_score, roc_curve
     40 from sklearn.metrics import confusion_matrix
---> 41 import scikitplot as skplt
     42 
     43 print(' Libraries Imported!')

ModuleNotFoundError: No module named 'scikitplot'
```

In [2]:

```
#conda install -c conda-forge scikit-plot
```

In [2]:

```
df = pd.read_csv("C:/BI/CIND 820/Files/Churn_Modelling.csv", encoding = 'utf-8')


print('It contains {} rows and {} columns.'.format(df.shape[0], df.shape[1]))
```

```
It contains 10000 rows and 14 columns.
```

In [3]:

```
df.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estimated!
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101:
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112!
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113!
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93!
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79(

In [4]:

```
#!pip install pandas-profiling
#import sys
#!{sys.executable} -m pip install pandas-profiling
```

In [5]:

```
from pandas_profiling import ProfileReport
ProfileReport(df) #to display the report
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

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Overview

Dataset statistics

Number of variables	14
Number of observations	10000
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	1.1 MiB
Average record size in memory	112.0 B

Variable types

Numeric	7
Categorical	7

Alerts

`Surname` has a high cardinality: 2932 distinct values	High cardinality
`NumOfProducts` is highly overall correlated with `Exited`	High correlation
`Exited` is highly overall correlated with `NumOfProducts`	High correlation
`RowNumber` is uniformly distributed	Uniform
`RowNumber` has unique values	Unique
`CustomerId` has unique values	Unique

Out[5]:

In [ ]:

In [5]:

```
df.drop(['RowNumber', 'CustomerId', 'Surname'], axis=1, inplace=True)
df.columns
```

Out[5]:

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

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CreditScore      10000 non-null  int64  
 1   Geography        10000 non-null  object 
 2   Gender           10000 non-null  object 
 3   Age              10000 non-null  int64  
 4   Tenure           10000 non-null  int64  
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64  
 7   HasCrCard        10000 non-null  int64  
 8   IsActiveMember   10000 non-null  int64  
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64  
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

In [7]:

```
df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
CreditScore	10000.0	650.529	96.653	350.00	584.00	652.000	718.000	850.00
Age	10000.0	38.922	10.488	18.00	32.00	37.000	44.000	92.00
Tenure	10000.0	5.013	2.892	0.00	3.00	5.000	7.000	10.00
Balance	10000.0	76485.889	62397.405	0.00	0.00	97198.540	127644.240	250898.09
NumOfProducts	10000.0	1.530	0.582	1.00	1.00	1.000	2.000	4.00
HasCrCard	10000.0	0.706	0.456	0.00	0.00	1.000	1.000	1.00
IsActiveMember	10000.0	0.515	0.500	0.00	0.00	1.000	1.000	1.00
EstimatedSalary	10000.0	100090.240	57510.493	11.58	51002.11	100193.915	149388.247	199992.48
Exited	10000.0	0.204	0.403	0.00	0.00	0.000	0.000	1.00

In [8]:

```
def plot_continuous(feature):
    '''Plot a histogram and boxplot for the churned and retained distributions for the specified feature.'''
    df_func = df.copy()
    df_func['Exited'] = df_func['Exited'].astype('category')

    fig, (ax1, ax2) = plt.subplots(2,
                                   figsize=(9, 7),
                                   sharex=True,
                                   gridspec_kw={'height_ratios': (.7, .3)})

    for df1, color, label in zip([df_retained, df_churned], colors, ['Retained', 'Churned']):
        sns.histplot(data=df1,
                     x=feature,
                     bins=15,
                     color=color,
                     alpha=0.66,
                     edgecolor='firebrick',
                     label=label,
                     kde=False,
                     ax=ax1)
    ax1.legend()

    sns.boxplot(x=feature, y='Exited', data=df_func, palette=colors, ax=ax2)
    ax2.set_ylabel('')
    ax2.set_yticklabels(['Retained', 'Churned'])

    plt.tight_layout();
```

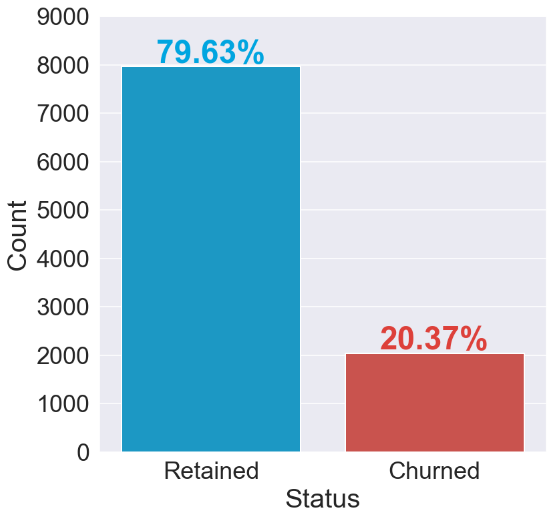
In [9]:

```
def plot_categorical(feature):
    '''For a categorical feature, plot a seaborn.countplot for the total counts of each category next to a barplot for the churn rate.'''
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

    sns.countplot(x=feature,
                  hue='Exited',
                  data=df,
                  palette=colors,
                  ax=ax1)
    ax1.set_ylabel('Count')
    ax1.legend(labels=['Retained', 'Churned'])

    sns.barplot(x=feature,
                y='Exited',
                data=df,
                palette=colors_cat,
                ax=ax2)
    ax2.set_ylabel('Churn rate')

    if (feature == 'HasCrCard' or feature == 'IsActiveMember'):
        ax1.set_xticklabels(['No', 'Yes'])
        ax2.set_xticklabels(['No', 'Yes'])

    plt.tight_layout();
```

In [ ]:

In [28]:

```
#Exploratory Data Analysis


colors = ['#00A5E0', '#DD403A']
colors_cat = ['#E8907E', '#D5CABD', '#7A6F86', '#C34A36', '#B0A8B9', '#845EC2', '#8f9aaa', '#FFB86F', '#63BAAA', '#9D88B3', '#38c4e3']
colors_comp = ['steelblue', 'seagreen', 'black', 'darkorange', 'purple', 'firebrick', 'slategrey']

random_state = 42
scoring_metric = 'recall'
comparison_dict, comparison_test_dict = {}, {}

font_size = 20
plt.rcParams['axes.labelsize'] = font_size
plt.rcParams['axes.titlesize'] = font_size + 2
plt.rcParams['xtick.labelsize'] = font_size - 2
plt.rcParams['ytick.labelsize'] = font_size - 2
plt.rcParams['legend.fontsize'] = font_size - 2


fig, ax = plt.subplots(figsize=(6, 6))

sns.countplot(x='Exited', data=df, palette=colors, ax=ax)

for index, value in enumerate(df['Exited'].value_counts()):
    label = '{}%'.format(round((value / df['Exited'].shape[0]) * 100, 2))
    ax.annotate(label,
                xy=(index, value + 250),
                ha='center',
                va='center',
                color=colors[index],
                fontweight='bold',
                size=font_size + 4)

ax.set_xticklabels(['Retained', 'Churned'])
ax.set_xlabel('Status')
ax.set_ylabel('Count')
ax.set_ylim([0, 9000]);
```



In [ ]:

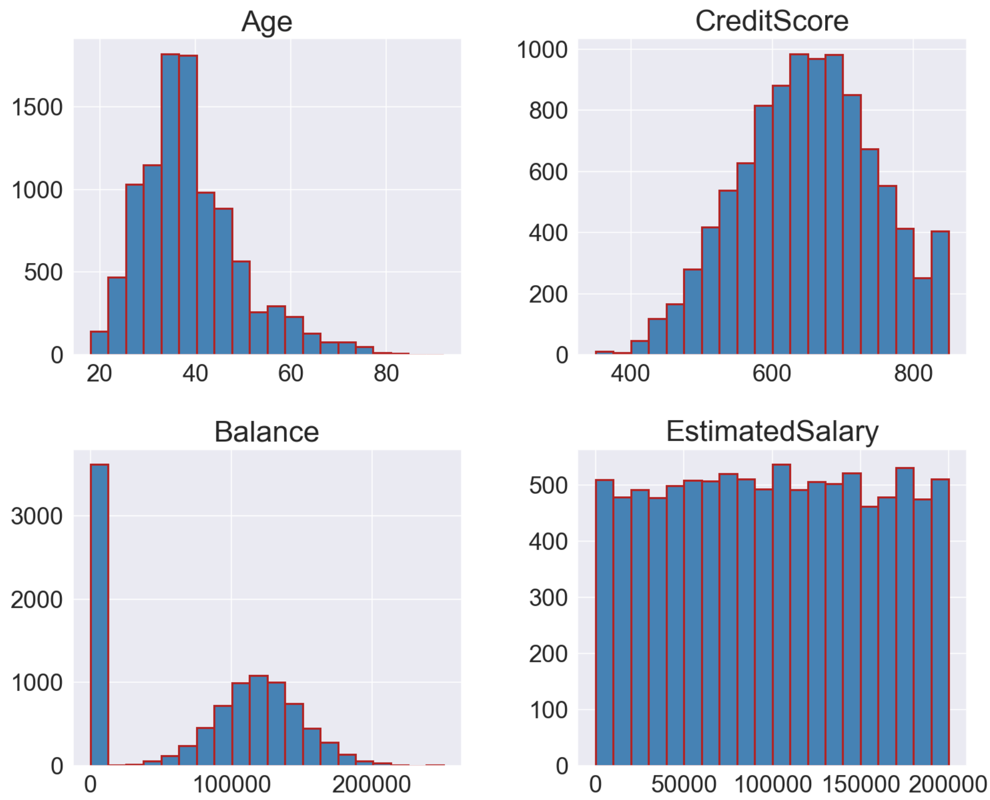
In [10]:

```
continuous = ['Age', 'CreditScore', 'Balance', 'EstimatedSalary']
categorical = ['Geography', 'Gender', 'Tenure', 'NumOfProducts', 'HasCrCard', 'IsActiveMember']

print('Continuous: ', ', '.join(continuous))
print('Categorical: ', ', '.join(categorical))
```

```
Continuous:  Age, CreditScore, Balance, EstimatedSalary
Categorical:  Geography, Gender, Tenure, NumOfProducts, HasCrCard, IsActiveMember
```

In [30]:

```
df[continuous].hist(figsize=(12, 10),
                        bins=20,
                        layout=(2, 2),
                        color='steelblue',
                        edgecolor='firebrick',
                        linewidth=1.5);
```

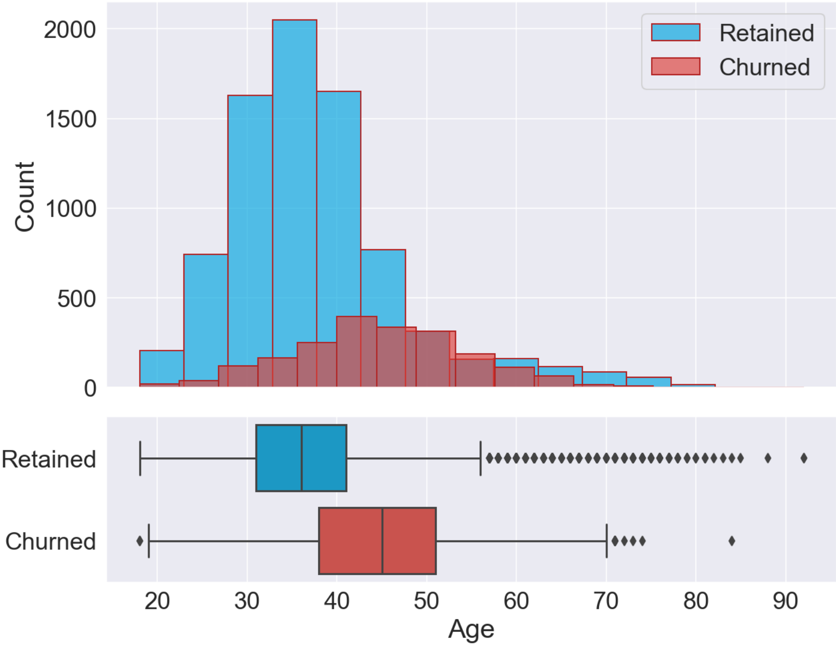


In [31]:

```
fig, ax = plt.subplots(figsize=(7, 6))

sns.heatmap(df[continuous].corr(),
            annot=True,
            annot_kws={'fontsize': 16},
            cmap='Blues',
            ax=ax)

ax.tick_params(axis='x', rotation=45)
ax.tick_params(axis='y', rotation=360);
```

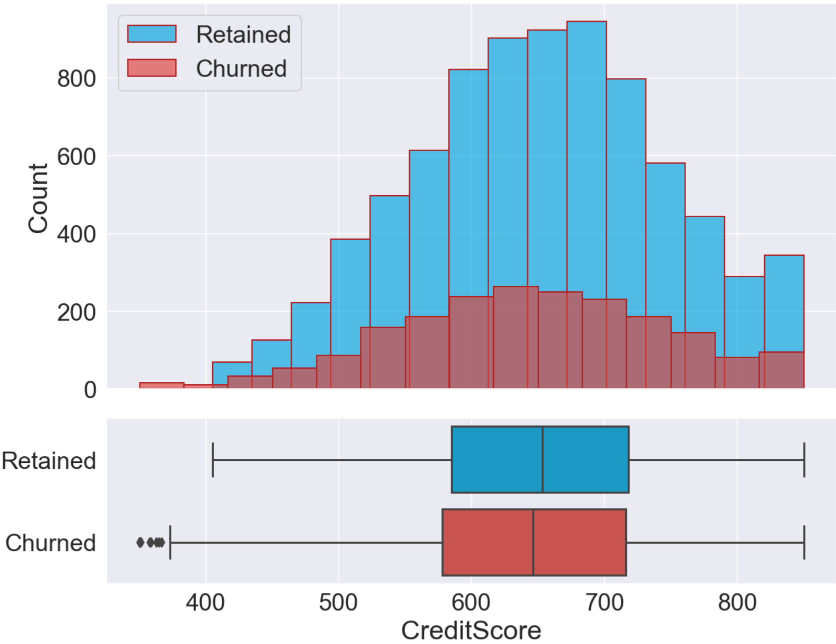
In [37]:

```
df_churned = df[df['Exited'] == 1]
df_retained = df[df['Exited'] == 0]

plot_continuous('Age')
```



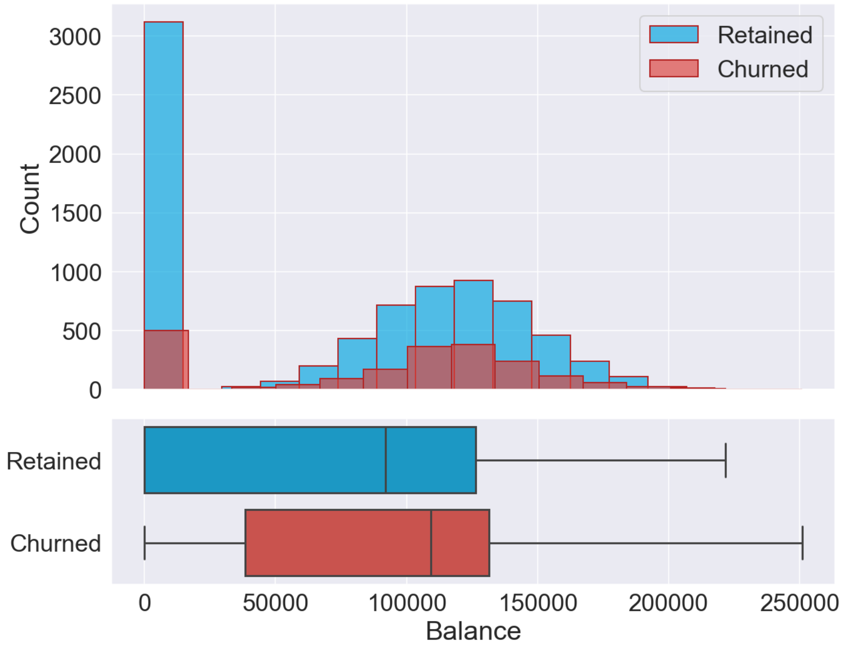
In [38]:

```
plot_continuous('CreditScore')
```



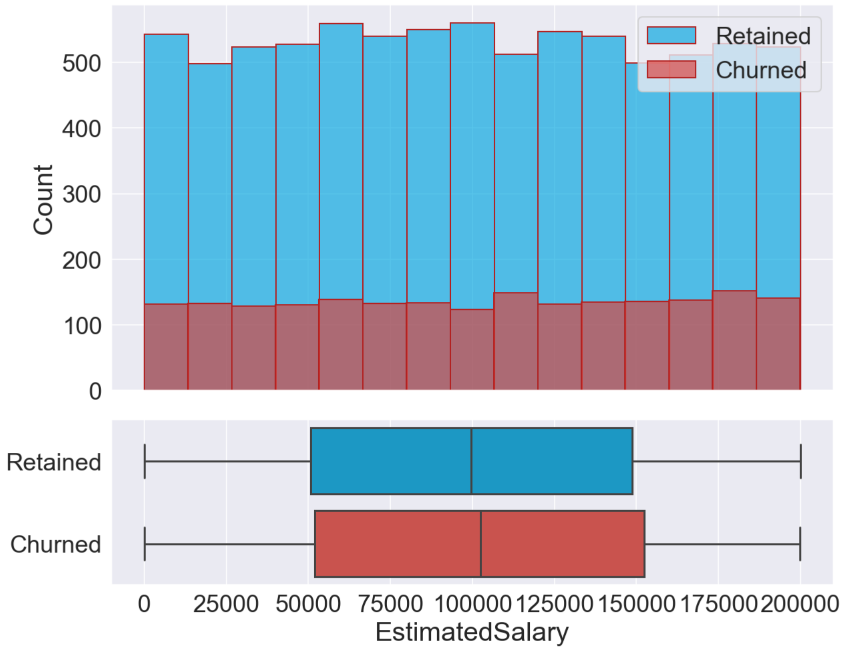
In [39]:

```
plot_continuous('Balance')
```



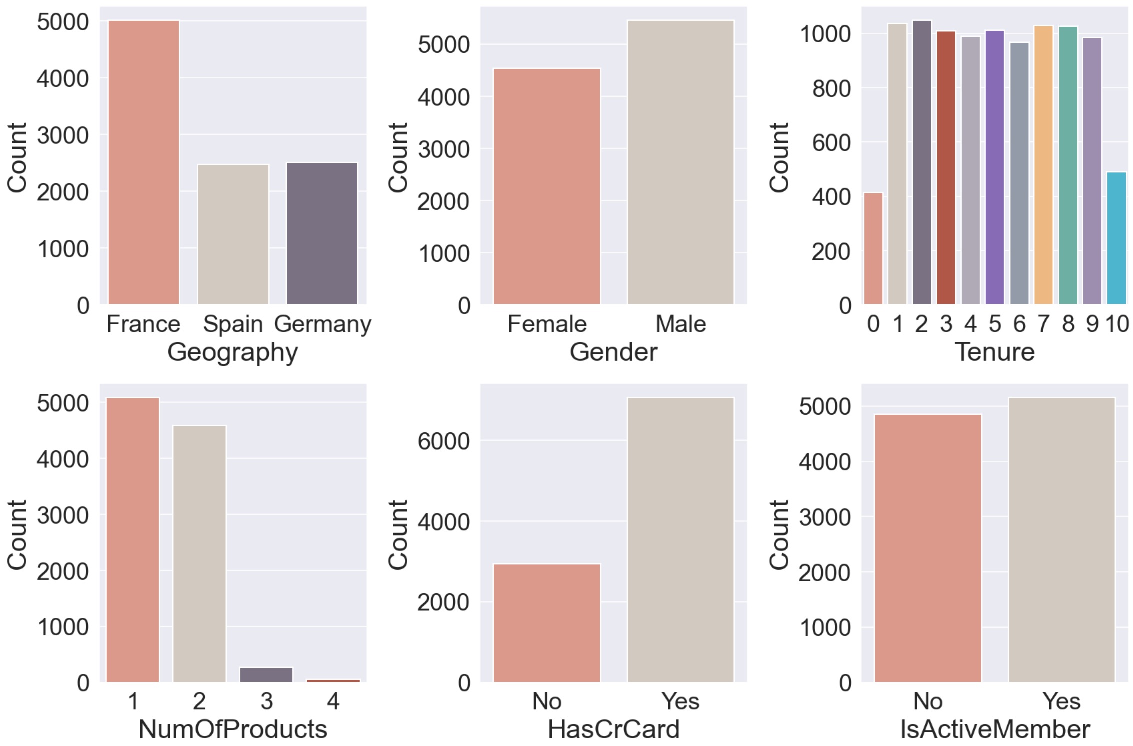
In [40]:

```
plot_continuous('EstimatedSalary')
```



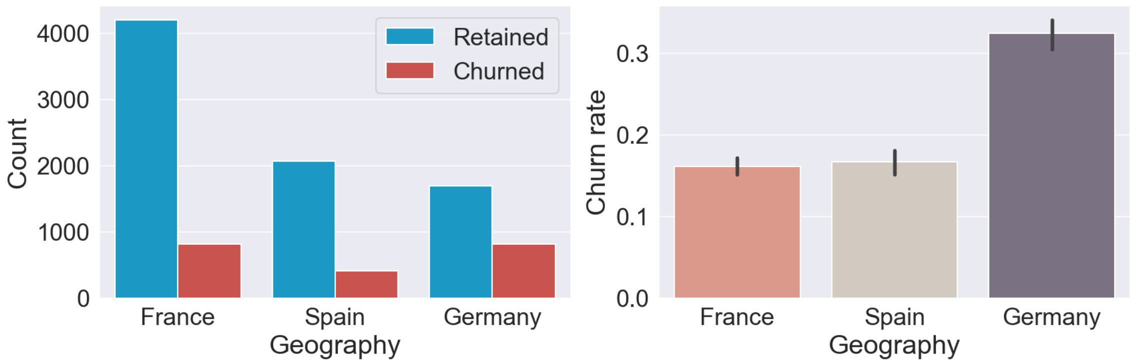
In [41]:

```
df_cat = df[categorical]

fig, ax = plt.subplots(2, 3, figsize=(12, 8))

for index, column in enumerate(df_cat.columns):

    plt.subplot(2, 3, index + 1)
    sns.countplot(x=column, data=df, palette=colors_cat)

    plt.ylabel('Count')
    if (column == 'HasCrCard' or column == 'IsActiveMember'):
        plt.xticks([0, 1], ['No', 'Yes'])

plt.tight_layout();
```



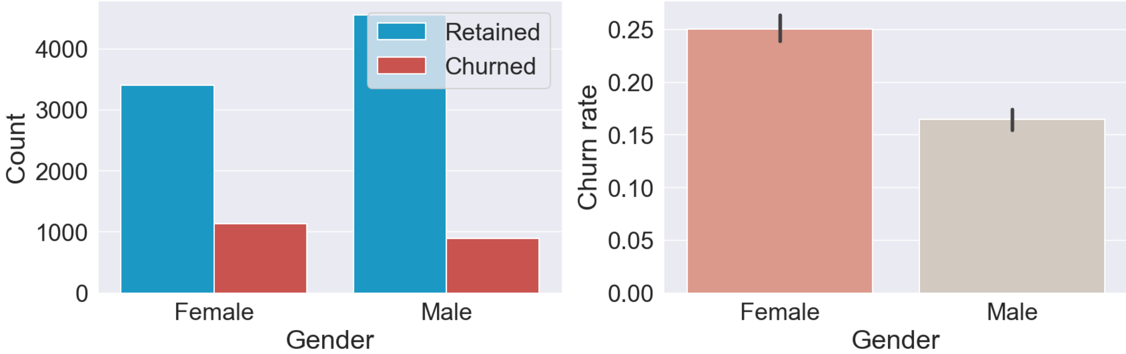
In [42]:

```
plot_categorical('Geography')
```



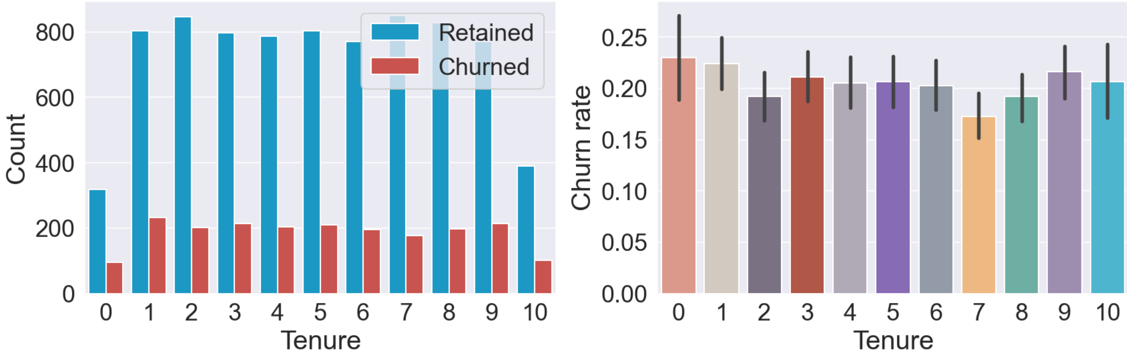
In [43]:

```
plot_categorical('Gender')
```



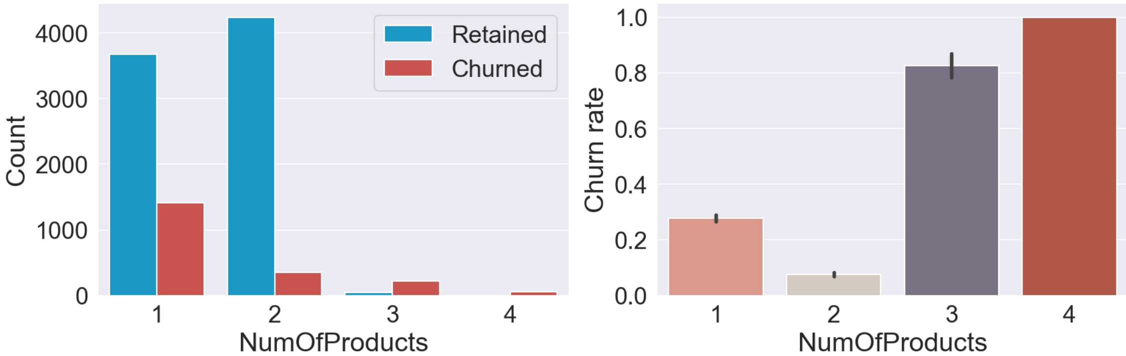
In [44]:

```
plot_categorical('Tenure')
```



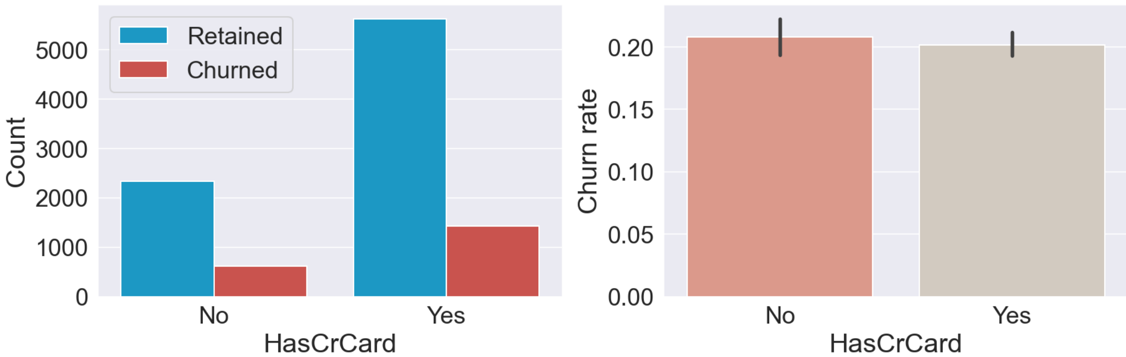
In [45]:

```
plot_categorical('NumOfProducts')
```



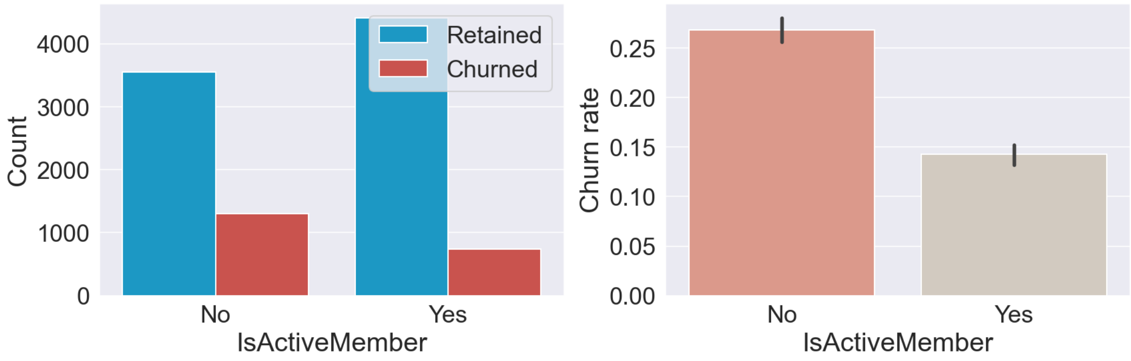
In [46]:

```
plot_categorical('HasCrCard')
```



In [47]:

```
plot_categorical('IsActiveMember')
```



In [48]:

```
#features_drop = ['Tenure', 'HasCrCard', 'EstimatedSalary']
#train_df = train_df.drop(features_drop, axis=1)

#print('✔ Features Dropped!')
```

In [ ]:

```

```

In [11]:

```
 #encoding our categorical attributes

df['Gender'] = LabelEncoder().fit_transform(df['Gender'])

df['Geography'] = df['Geography'].map({
    'Germany': 1,
    'Spain': 2,
    'France': 3
})

print(' Features Encoded!')
```

 Features Encoded!

In [12]:

```
df.head()
```

Out[12]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	3	0	42	2	0.00	1	1	1	101348.88	1
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	502	3	0	42	8	159660.80	3	1	0	113931.57	1
3	699	3	0	39	1	0.00	2	0	0	93826.63	0
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0

In [13]:

```
scaler = StandardScaler()

scl_columns = ['CreditScore', 'Age', 'Balance', 'EstimatedSalary','Tenure']
df[scl_columns] = scaler.fit_transform(df[scl_columns])

print(' Features Scaled!')
df.head()
```

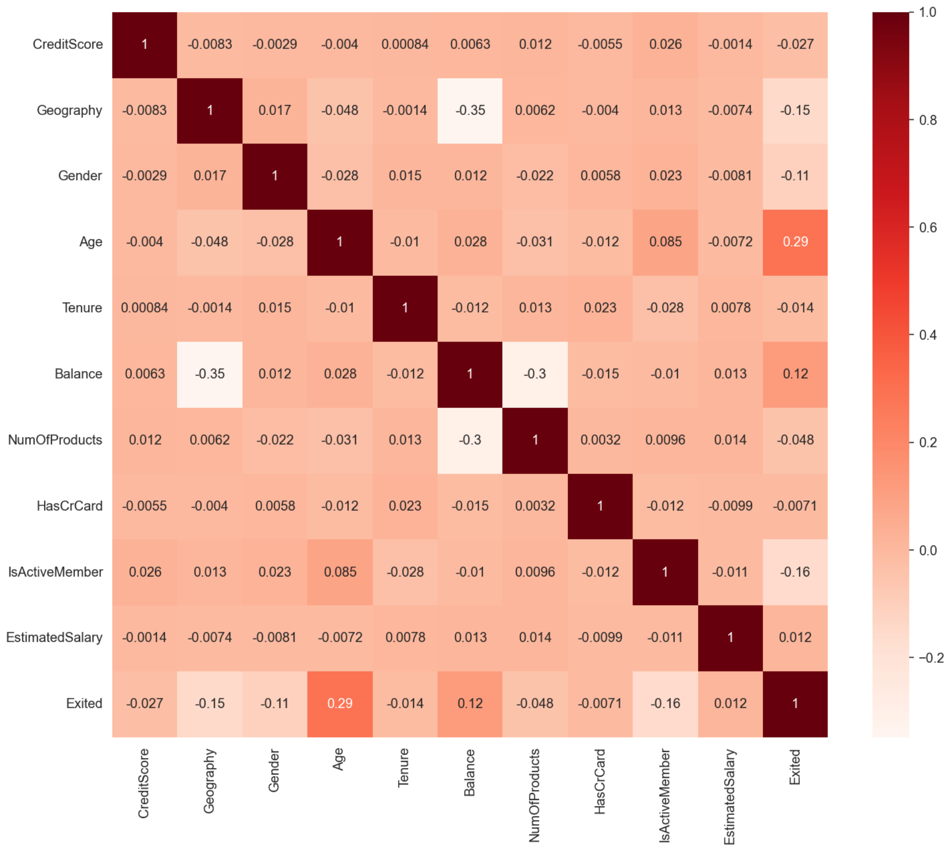
 Features Scaled!

Out[13]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	-0.326	3	0	0.294	-1.042	-1.226	1	1	1	0.022	1
1	-0.440	2	0	0.198	-1.388	0.117	1	0	1	0.217	0
2	-1.537	3	0	0.294	1.033	1.333	3	1	0	0.241	1
3	0.502	3	0	0.007	-1.388	-1.226	2	0	0	-0.109	0
4	2.064	2	0	0.389	-1.042	0.786	1	1	1	-0.365	0

In [73]:

```
#Feature Selection
#filter based

#Using Pearson Correlation
plt.figure(figsize=(12,10))
cor = df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



In [61]:

```
#Correlation with output variable
#Feature Selection
#filter based
cor_target = abs(cor["Exited"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.05]
relevant_features
```

Out[61]:

```
Geography         0.154
Gender            0.107
Age               0.285
Balance           0.119
IsActiveMember    0.156
Exited            1.000
Name: Exited, dtype: float64
```

In [ ]:

```
# pip install pymrmr
```

In [14]:

```
# import pymrmr
# pymrmr.mRMR(df, 'MID',6)
```

In [ ]:

```

```

In [85]:

```
#wrapper feature selection
#forward selection

from mlxtend.feature_selection import SequentialFeatureSelector as SFS
from sklearn.linear_model import LinearRegression
import pandas as pd
import numpy as np




y = df['Exited']
X = df.drop('Exited', 1)


#Define Sequential Forward Selection (sfs)
sfs = SFS(LinearRegression(),
           k_features=6,
           forward=True,
           floating=False,
           scoring = 'r2',
           cv = 5)
#Use SFS to select the top 6 features
sfs.fit(X, y)

#Create a dataframe for the SFS results
df_SFS_results = pd.DataFrame(sfs.subsets_).transpose()
df_SFS_results
```

Out[85]:

	feature_idx	cv_scores	avg_score	feature_names
1	(3,)	[0.08058955522086897, 0.08227376024621502, 0.0...	0.081	(Age,)
2	(3, 8)	[0.13538153836399136, 0.11308643046143596, 0.1...	0.113	(Age, IsActiveMember)
3	(1, 3, 8)	[0.14546484226502177, 0.1280060622036422, 0.13...	0.131	(Geography, Age, IsActiveMember)
4	(1, 2, 3, 8)	[0.15126131453420744, 0.14224830488845808, 0.1...	0.139	(Geography, Gender, Age, IsActiveMember)
5	(1, 2, 3, 5, 8)	[0.15676993786906002, 0.14287816634378248, 0.1...	0.144	(Geography, Gender, Age, Balance, IsActiveMember)
6	(0, 1, 2, 3, 5, 8)	[0.15793905064331581, 0.1430726887227125, 0.14...	0.144	(CreditScore, Geography, Gender, Age, Balance,...

In [27]:

```
#wrapper feature selection
#backward elimination

from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
import pandas as pd
import numpy as np



y = df['Exited']
X = df.drop('Exited', 1)

#Build a logistic regression model
model = LinearRegression()
#Define RFE
#rfe = RFE(model,5)
rfe = RFE(estimator=model, n_features_to_select=8)
#Use RFE to select the top 6 features
rfe.fit(X, y)

#Create a dataframe for the results
df_RFE_results = []
for i in range(X.shape[1]):
    df_RFE_results.append(
        {
            'Feature_names': df.columns[i],
            'Selected':  rfe.support_[i],
            'RFE_ranking':  rfe.ranking_[i],
        }
    )

df_RFE_results = pd.DataFrame(df_RFE_results)
df_RFE_results.index.name='Columns'
df_RFE_results
```

Out[27]:

Columns	Feature_names	Selected	RFE_ranking
0	CreditScore	True	1
1	Geography	True	1
2	Gender	True	1
3	Age	True	1
4	Tenure	True	1
5	Balance	True	1
6	NumOfProducts	True	1
7	HasCrCard	False	3
8	IsActiveMember	True	1
9	EstimatedSalary	False	2

In [67]:

```
#embedded
#pip install mlxtend
from sklearn.linear_model import LassoCV
from sklearn.model_selection import StratifiedKFold

y = df['Exited']
X = df.drop('Exited', 1)
skf = StratifiedKFold(n_splits=10)
lasso = LassoCV(cv=skf, random_state=42).fit(X, y)
print('Selected Features:', list(train_df.columns[np.where(lasso.coef_!=0)[0]]))
```

```
Selected Features: ['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActi
veMember', 'EstimatedSalary']
```

In [72]:

```
#the last test just to compare the result

chi2_array, p_array = [], []
for column in categorical:

    crosstab = pd.crosstab(df[column], df['Exited'])
    chi2, p, dof, expected = chi2_contingency(crosstab)
    chi2_array.append(chi2)
    p_array.append(p)

df_chi = pd.DataFrame({
    'Variable': categorical,
    'Chi-square': chi2_array,
    'p-value': p_array
})
df_chi.sort_values(by='Chi-square', ascending=False)
```

Out[72]:

	Variable	Chi-square	p-value
3	NumOfProducts	1503.629	0.000e+00
0	Geography	301.255	3.830e-66
5	IsActiveMember	242.985	8.786e-55
1	Gender	112.919	2.248e-26
2	Tenure	13.900	1.776e-01
4	HasCrCard	0.471	4.924e-01

In [74]:

```
chi2_array, p_array = [], []
for column in continuous:

    crosstab = pd.crosstab(df[column], df['Exited'])
    chi2, p, dof, expected = chi2_contingency(crosstab)
    chi2_array.append(chi2)
    p_array.append(p)

df_chi = pd.DataFrame({
    'Variable': continuous,
    'Chi-square': chi2_array,
    'p-value': p_array
})
df_chi.sort_values(by='p-value', ascending=True)
```

Out[74]:

	Variable	Chi-square	p-value
0	Age	1607.479	3.779e-290
2	Balance	7340.535	2.579e-16
1	CreditScore	510.216	4.915e-02
3	EstimatedSalary	10000.000	4.925e-01

In [ ]:

```
#the result is compatible with the first test and EDA analysis
```

In [14]:

```
#based on the EDA analysis and feature selection results, one suggestion can be remove the 4 below features but I decided to keep them as

features_drop = ['HasCrCard', 'EstimatedSalary', 'Tenure']
df = df.drop(features_drop, axis=1)

#print(' Features Dropped!')
```

In [ ]:

In [ ]:

In [15]:

```
#spliting our dataset into a train and test
random_state = 42
train_df, test_df = train_test_split(df, test_size=0.2, random_state=random_state)

train_df.reset_index(drop=True, inplace=True)
test_df.reset_index(drop=True, inplace=True)

print('Train set: {} rows x {} columns'.format(train_df.shape[0],
                                               train_df.shape[1]))
print(' Test set: {} rows x {} columns'.format(test_df.shape[0],
                                               test_df.shape[1]))
```

```
Train set: 8000 rows x 8 columns
 Test set: 2000 rows x 8 columns
```

In [16]:

```
y_train = train_df['Exited']
X_train = train_df.drop('Exited', 1)

print(' Sets Created!')
```

```
 Sets Created!
```

In [17]:

```
y_train.value_counts()
```

Out[17]:

```
0    6356
1    1644
Name: Exited, dtype: int64
```

In [18]:

```
train_df.describe()
```

Out[18]:

	CreditScore	Geography	Gender	Age	Balance	NumOfProducts	IsActiveMember	Exited
count	8000.000	8000.000	8000.000	8000.000	8000.000	8000.000	8000.000	8000.000
mean	0.012	2.248	0.545	-0.002	-0.006	1.531	0.513	0.205
std	0.997	0.830	0.498	1.003	1.001	0.580	0.500	0.404
min	-3.110	1.000	0.000	-1.995	-1.226	1.000	0.000	0.000
25%	-0.678	1.000	0.000	-0.660	-1.226	1.000	0.000	0.000
50%	0.026	2.000	1.000	-0.183	0.320	1.000	1.000	0.000
75%	0.708	3.000	1.000	0.484	0.819	2.000	1.000	0.000
max	2.064	3.000	1.000	5.061	2.795	4.000	1.000	1.000

In [19]:

```
X_train.head()
```

Out[19]:

	CreditScore	Geography	Gender	Age	Balance	NumOfProducts	IsActiveMember
0	0.367	3	1	-0.660	-1.226	2	1
1	-0.192	1	1	0.294	0.691	2	1
2	-0.947	2	1	-1.423	0.613	1	0
3	-0.926	3	0	-1.137	0.948	1	0
4	-1.382	3	1	1.628	1.052	1	0

In [20]:

```
#Handling imbalanced data-
#over sampling-SMOTE
over = SMOTE(sampling_strategy='auto', random_state=random_state)
X_train, y_train = over.fit_resample(X_train, y_train)

y_train.value_counts()
```

Out[20]:

```
0    6356
1    6356
Name: Exited, dtype: int64
```

In [21]:

```
y_test = test_df['Exited']
X_test = test_df.drop('Exited', 1)
```

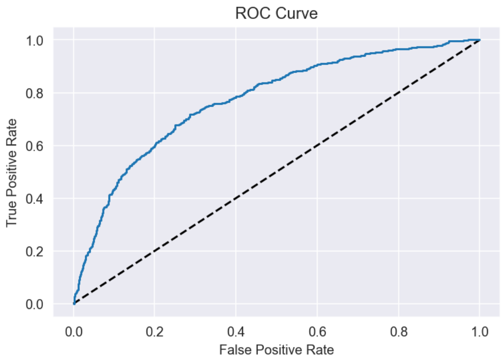
In [22]:

```
####
# Confusion_matrix and other classification model scores Function
####

def classifi_score(model, model_name, y_test, y_pred):

    from sklearn.metrics import confusion_matrix

    confus_mat = confusion_matrix(y_test, y_pred)
    print("Confusion matrix of ", model_name," classifier: ")
    print(confus_mat)
    print("\n")
#     real_positives = sum(y_test==1)
#     real_negatives = sum(y_test==0)
#     print('Real Positives = ', real_positives)
#     print('Real Negatives = ', real_negatives)
#     print('True Positive Rate = ', format(confus_mat[1,1]/real_positives,".2%"))
#     print('True Negative Rate = ', format(confus_mat[0,0]/real_negatives,".2%"))
#     print('False Positive Rate = ', format(confus_mat[0,1]/real_positives,".2%"))
#     print('False Negative Rate = ', format(confus_mat[1,0]/real_negatives,".2%"))
    p = confus_mat[1,1]/(confus_mat[1,1]+confus_mat[0,1])
    print('Precision = ', format(p,".2%"))
    r = confus_mat[1,1]/(confus_mat[1,1]+confus_mat[1,0])
    print('Recall = ', format(r,".2%"))
    print('F1-Score = ', format((2*p*r)/(p+r),".2%"))
    print("\n")

    # classification report
    from sklearn.metrics import classification_report
    print("Classification report of ", model_name," classifier: ")
    print(classification_report(y_test, y_pred))
    print("\n")
```

In [23]:

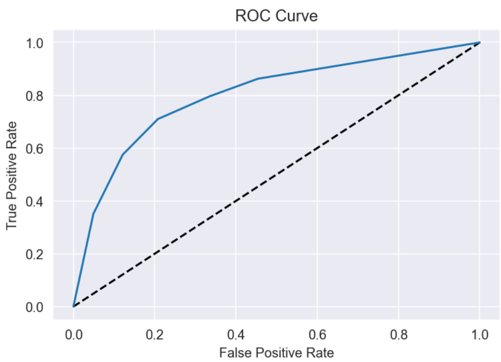
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.ensemble import GradientBoostingClassifier
from catboost import CatBoostClassifier
from sklearn import model_selection
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score


random_state = 42
classifiers = [LogisticRegression(), KNeighborsClassifier(),
               DecisionTreeClassifier(random_state = random_state),RandomForestClassifier(),SVC(gamma='auto', probability=True),
              GradientBoostingClassifier(random_state = random_state),XGBClassifier(random_state = random_state),
               LGBMClassifier(random_state = random_state),
               CatBoostClassifier(random_state = random_state, verbose = False) ]


classifier_name = ['LR','KNN', 'DT', 'RF', 'SVM', 'GBC', 'XGB', 'LightGBM', 'CatBoost']


for i in range(len(classifiers)):
    classifiers[i].fit(X_train, y_train)

    print("Accuracy of ",classifier_name[i]," classifier: ", classifiers[i].score(X_test, y_test))
    print("\n")
    y_pred = classifiers[i].predict(X_test)
    classifi_score(classifiers[i], classifier_name[i], y_test, y_pred)


    # Receiver Operating Characteristic (ROC) Curve
    from sklearn.metrics import roc_curve
    y_pred_prob = classifiers[i].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('ROC Curve')
    plt.show();


    # Area Under Curve (AUC) score
    from sklearn.metrics import roc_auc_score
    print('AUC score over the test set:', roc_auc_score(y_test, y_pred_prob))
    print("\n")
    print("\n")
    print("\n")


#our focus is on Recall score as minimizng the false negatives is critical here in this model.
# false negatives are the customers who are likely to be churned but they are not listed among predicted churned customers)
```

```
Accuracy of  LR  classifier:  0.7195


Confusion matrix of  LR  classifier:
[[1166  441]
 [ 120  273]]


Precision =  38.24%
Recall =  69.47%
F1-Score =  49.32%


Classification report of  LR  classifier:
              precision    recall  f1-score   support

           0       0.91      0.73      0.81      1607
           1       0.38      0.69      0.49       393

    accuracy                           0.72      2000
   macro avg       0.64      0.71      0.65      2000
weighted avg       0.80      0.72      0.74      2000
```

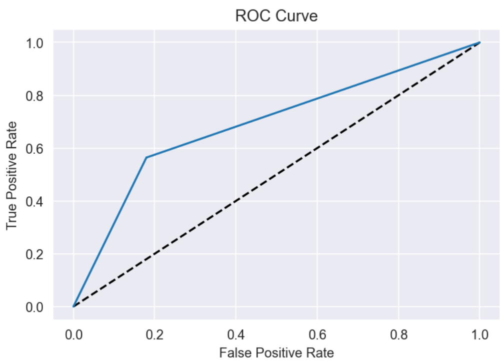



```
AUC score over the test set: 0.7731568788585562
```

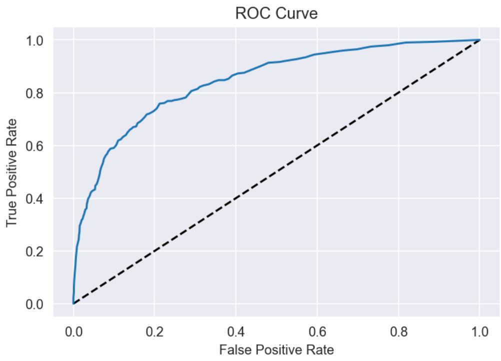
```
Accuracy of  KNN  classifier:  0.776


Confusion matrix of  KNN  classifier:
[[1273  334]
 [ 114  279]]


Precision =  45.51%
Recall =  70.99%
F1-Score =  55.47%


Classification report of  KNN  classifier:
              precision    recall  f1-score   support

           0       0.92      0.79      0.85      1607
           1       0.46      0.71      0.55       393

    accuracy                           0.78      2000
   macro avg       0.69      0.75      0.70      2000
weighted avg       0.83      0.78      0.79      2000
```



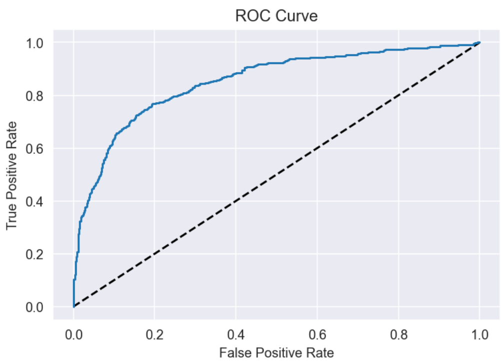
```
AUC score over the test set: 0.8005030472598411




Accuracy of  DT  classifier:  0.77


Confusion matrix of  DT  classifier:
[[1318  289]
 [ 171  222]]


Precision =  43.44%
Recall =  56.49%
F1-Score =  49.12%


Classification report of  DT  classifier:
              precision    recall  f1-score   support

           0       0.89      0.82      0.85      1607
           1       0.43      0.56      0.49       393

    accuracy                           0.77      2000
   macro avg       0.66      0.69      0.67      2000
weighted avg       0.80      0.77      0.78      2000
```



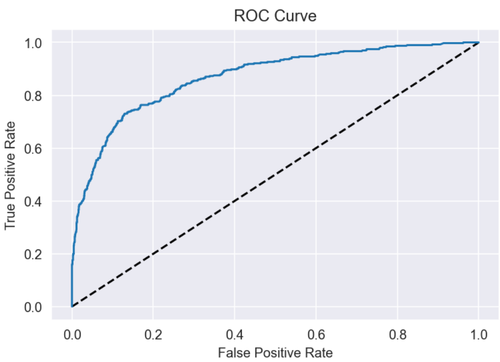

```
AUC score over the test set: 0.6922528821900369




Accuracy of  RF  classifier:  0.8255


Confusion matrix of  RF  classifier:
[[1400  207]
 [ 142  251]]


Precision =  54.80%
Recall =  63.87%
F1-Score =  58.99%


Classification report of  RF  classifier:
              precision    recall  f1-score   support

           0       0.91      0.87      0.89      1607
           1       0.55      0.64      0.59       393

    accuracy                           0.83      2000
   macro avg       0.73      0.75      0.74      2000
weighted avg       0.84      0.83      0.83      2000
```



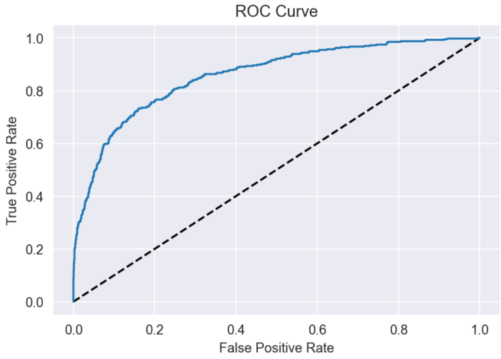

```
AUC score over the test set: 0.8447726311889302




Accuracy of  SVM  classifier:  0.796


Confusion matrix of  SVM  classifier:
[[1290  317]
 [  91  302]]


Precision =  48.79%
Recall =  76.84%
F1-Score =  59.68%


Classification report of  SVM  classifier:
              precision    recall  f1-score   support

           0       0.93      0.80      0.86      1607
           1       0.49      0.77      0.60       393

    accuracy                           0.80      2000
   macro avg       0.71      0.79      0.73      2000
weighted avg       0.85      0.80      0.81      2000
```



```
AUC score over the test set: 0.8533562610145499




Accuracy of  GBC  classifier:  0.8205


Confusion matrix of  GBC  classifier:
[[1348  259]
 [ 100  293]]


Precision =  53.08%
Recall =  74.55%
F1-Score =  62.01%


Classification report of  GBC  classifier:
              precision    recall  f1-score   support

           0       0.93      0.84      0.88      1607
           1       0.53      0.75      0.62       393

    accuracy                           0.82      2000
   macro avg       0.73      0.79      0.75      2000
weighted avg       0.85      0.82      0.83      2000
```




```
AUC score over the test set: 0.86954260226015




Accuracy of  XGB  classifier:  0.86


Confusion matrix of  XGB  classifier:
[[1486  121]
 [ 159  234]]


Precision =  65.92%
Recall =  59.54%
F1-Score =  62.57%


Classification report of  XGB  classifier:
              precision    recall  f1-score   support

           0       0.90      0.92      0.91      1607
           1       0.66      0.60      0.63       393

    accuracy                           0.86      2000
   macro avg       0.78      0.76      0.77      2000
weighted avg       0.86      0.86      0.86      2000
```

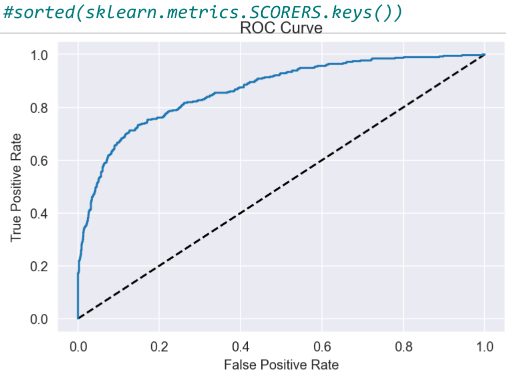



```
AUC score over the test set: 0.858681246645164
```

```
Accuracy of  LightGBM  classifier:  0.8605


Confusion matrix of  LightGBM  classifier:
[[1470  137]
 [ 142  251]]


Precision =  64.69%
Recall =  63.87%
F1-Score =  64.28%


Classification report of  LightGBM  classifier:
              precision    recall  f1-score   support

           0       0.91      0.91      0.91      1607
           1       0.65      0.64      0.64       393

    accuracy                           0.86      2000
   macro avg       0.78      0.78      0.78      2000
weighted avg       0.86      0.86      0.86      2000
```

In [35]:

```
#sorted(sklearn.metrics.SCORERS.keys())
```



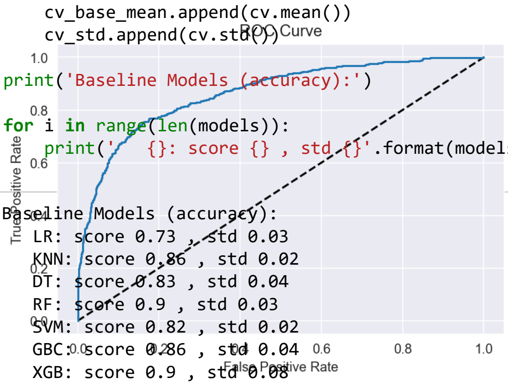
AUC score over the test set: 0.8654748389282894

In [29]:

```
#Evaluate Stability

models = []
models.append(('LR', LogisticRegression()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('DT', DecisionTreeClassifier()))
models.append(('RF', RandomForestClassifier()))
models.append(('SVM', SVC(gamma='auto')))
models.append(('GBC', GradientBoostingClassifier()))
models.append(('XGB', XGBClassifier()))
models.append(("LightGBM", LGBMClassifier()))
models.append(("CatBoost", CatBoostClassifier(verbose = False)))

# evaluate each model in turn
results = []
names = []

scoring_metric = 'accuracy'
#Evaluate Stability

cv_base_mean, cv_std = [], []
for classifier in models:

    cv = cross_val_score(estimator=classifier[1],
                         X=X_train,
                         y=y_train,
                         scoring=scoring_metric,
                         cv=10,
                         n_jobs=-1)

    cv_base_mean.append(cv.mean())
    cv_std.append(cv.std())

print('Baseline Models (accuracy):')

for i in range(len(models)):
    print('   {}: score {} , std {}'.format(models[i][0], np.round(cv_base_mean[i], 2),np.round(cv_std[i], 2)))
```

```
Baseline Models (accuracy):
   LR: score 0.73 , std 0.03
   KNN: score 0.86 , std 0.02
   DT: score 0.83 , std 0.04
   RF: score 0.9 , std 0.03
   SVM: score 0.82 , std 0.02
   GBC: score 0.86 , std 0.04
   XGB: score 0.9 , std 0.08
   LightGBM: score 0.9 , std 0.08
   CatBoost: score 0.9 , std 0.08
```

```
Accuracy of  CatBoost  classifier:  0.8615

Confusion matrix of  CatBoost  classifier:
[[1485  122]
 [ 155  238]]

Precision = 66.11%
Recall = 60.56%
F1 Score =  63.21%

Classification report of  CatBoost  classifier:
              precision    recall  f1-score   support

           0       0.91      0.92      0.91      1607
           1       0.66      0.61      0.63       393

    accuracy                           0.86      2000
   macro avg       0.78      0.76      0.77      2000
weighted avg       0.86      0.86      0.86      2000
```



AUC score over the test set: 0.8665159266630882

In [30]:

```
#Evaluate Stability

# evaluate each model in turn
results = []
names = []

scoring_metric = 'f1'
#Evaluate Stability

cv_base_mean, cv_std = [], []
for classifier in models:

    cv = cross_val_score(estimator=classifier[1],
                         X=X_train,
                         y=y_train,
                         scoring=scoring_metric,
                         cv=10,
                         n_jobs=-1)

    cv_base_mean.append(cv.mean())
    cv_std.append(cv.std())

print('Baseline Models (f1):')

for i in range(len(models)):
    print('   {}: score {} , std {}'.format(models[i][0], np.round(cv_base_mean[i], 2),np.round(cv_std[i], 2)))
```

```
Baseline Models (f1):
   LR: score 0.73 , std 0.03
   KNN: score 0.87 , std 0.02
   DT: score 0.83 , std 0.05
   RF: score 0.9 , std 0.04
   SVM: score 0.82 , std 0.02
   GBC: score 0.85 , std 0.05
   XGB: score 0.88 , std 0.11
   LightGBM: score 0.89 , std 0.1
   CatBoost: score 0.89 , std 0.1
```

In [34]:

```
#Evaluate Stability
# evaluate each model in turn
results = []
names = []

scoring_metric = 'roc_auc'
#Evaluate Stability

cv_base_mean, cv_std = [], []
for classifier in models:

    cv = cross_val_score(estimator=classifier[1],
                         X=X_train,
                         y=y_train,
                         scoring=scoring_metric,
                         cv=10,
                         n_jobs=-1)

    cv_base_mean.append(cv.mean())
    cv_std.append(cv.std())

print('Baseline Models (roc_auc):')

for i in range(len(models)):
    print('   {}: score {} , std {}'.format(models[i][0], np.round(cv_base_mean[i], 2),np.round(cv_std[i], 2)))
```

```
Baseline Models (roc_auc):
   LR: score 0.8 , std 0.03
   KNN: score 0.93 , std 0.02
   DT: score 0.83 , std 0.04
   RF: score 0.96 , std 0.02
   SVM: score 0.9 , std 0.02
   GBC: score 0.93 , std 0.04
   XGB: score 0.96 , std 0.05
   LightGBM: score 0.96 , std 0.04
   CatBoost: score 0.96 , std 0.04
```

In [33]:

```
#Evaluate Stability

# evaluate each model in turn
results = []
names = []

scoring_metric = 'recall'
#Evaluate Stability

cv_base_mean, cv_std = [], []
for classifier in models:

    cv = cross_val_score(estimator=classifier[1],
                         X=X_train,
                         y=y_train,
                         scoring=scoring_metric,
                         cv=10,
                         n_jobs=-1)

    cv_base_mean.append(cv.mean())
    cv_std.append(cv.std())

print('Baseline Models (recall):')

for i in range(len(models)):
    print('   {}: score {} , std {}'.format(models[i][0], np.round(cv_base_mean[i], 2),np.round(cv_std[i], 2)))
```

```
Baseline Models (recall):
   LR: score 0.72 , std 0.05
   KNN: score 0.94 , std 0.03
   DT: score 0.84 , std 0.09
   RF: score 0.91 , std 0.06
   SVM: score 0.81 , std 0.04
   GBC: score 0.85 , std 0.09
   XGB: score 0.87 , std 0.19
   LightGBM: score 0.87 , std 0.17
   CatBoost: score 0.87 , std 0.17
```

In [31]:

```
#Evaluate Efficiency
from sklearn.metrics import  accuracy_score, f1_score, precision_score,confusion_matrix, recall_score, roc_auc_score
random_state = 42

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.ensemble import GradientBoostingClassifier
from catboost import CatBoostClassifier
from sklearn import model_selection
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
models = []
models.append(('LR', LogisticRegression(random_state = random_state)))
models.append(('KNN', KNeighborsClassifier()))
models.append(('DT', DecisionTreeClassifier(random_state = random_state)))
models.append(('RF', RandomForestClassifier(random_state = random_state)))
models.append(('SVM', SVC(gamma='auto', random_state = random_state)))
models.append(('GBC', GradientBoostingClassifier(random_state = random_state)))
models.append(('XGB', XGBClassifier(random_state = random_state)))
models.append(("LightGBM", LGBMClassifier(random_state = random_state)))
models.append(("CatBoost", CatBoostClassifier(random_state = random_state, verbose = False)))

results = []
names = []
```

In [32]:

```
#Evaluate Efficiency
#X=X_train
for name, model in models:
        import time
        start = time.time()
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        f1 = f1_score(y_test, y_pred)
        msg = "%s: (%f)" % (name, f1)
        print(msg)
        end = time.time()
        print('Time', (end - start))
```

```
LR: (0.486537)
Time 0.04487943649291992
KNN: (0.521308)
Time 0.29620838165283203
DT: (0.473214)
Time 0.0768277645111084
RF: (0.604192)
Time 1.788184642791748
SVM: (0.583751)
Time 5.287861108779907
GBC: (0.628763)
Time 1.6934716701507568
XGB: (0.591160)
Time 1.0292460918426514
LightGBM: (0.626703)
Time 0.17852282524108887
CatBoost: (0.611187)
Time 7.462937116622925
```

In [52]:

```
#Evaluate Efficiency
#X=X_train
for name, model in models:
        import time
        start = time.time()
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        recall = recall_score(y_test, y_pred)
        msg = "%s: (%f)" % (name, recall)
        print(msg)
        end = time.time()
        print('Time', (end - start))
```

```
LR: (0.666667)
Time 0.03690052032470703
KNN: (0.669211)
Time 0.2263956069946289
DT: (0.539440)
Time 0.06877851486206055
RF: (0.623410)
Time 1.5598669052124023
SVM: (0.740458)
Time 5.387824058532715
GBC: (0.717557)
Time 1.7682886123657227
XGB: (0.544529)
Time 1.02720046043396
LightGBM: (0.585242)
Time 0.19447922706604004
CatBoost: (0.569975)
Time 7.252615451812744
```

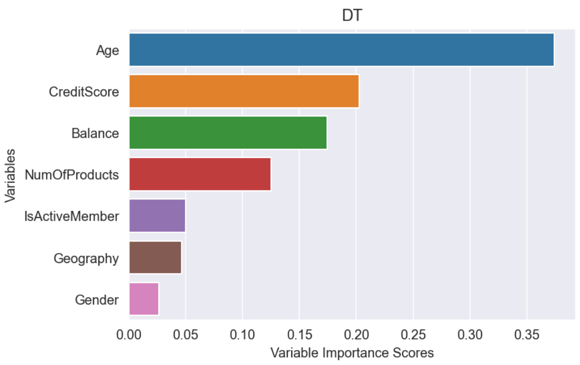
In [24]:

```
#feature imporance charts

rs = 42
models2 = []
models2.append(('DT', DecisionTreeClassifier( random_state = rs)))
models2.append(('RF', RandomForestClassifier( random_state = rs)))
# models2.append(('SVM', SVC( random_state = rs)))
models2.append(('GBC', GradientBoostingClassifier( random_state = rs)))
models2.append(('XGB', XGBClassifier( random_state = rs)))
models2.append(("LightGBM", LGBMClassifier( random_state = rs)))
models2.append(("CatBoost", CatBoostClassifier(random_state = rs, verbose = False)))
```

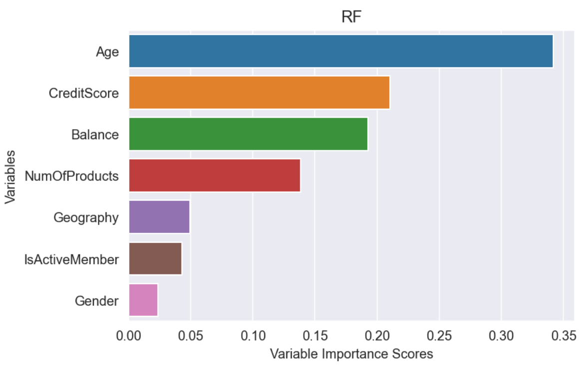
In [25]:

```
for name, model in models2:
        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_train.columns).sort_values(ascending=False)
        print('model Coefficients: {}'.format(sorted(dict(list(zip(X_train.columns,base.feature_importances_))).items(), key=lambda x: x[
        sns.barplot(x=feature_imp, y=feature_imp.index)
        plt.xlabel('Variable Importance Scores')
        plt.ylabel('Variables')
        plt.title(name)
        plt.show()
```

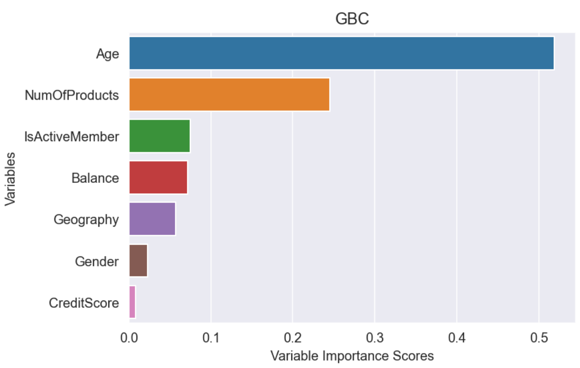
```
model Coefficients: [('Age', 0.37443381807690945), ('CreditScore', 0.20260845148088466), ('Balance', 0.17459726665935177),
('NumOfProducts', 0.1252119164822996), ('IsActiveMember', 0.05009905433618427), ('Geography', 0.04639614077720741), ('Gende
r', 0.02665335218716298)]
```



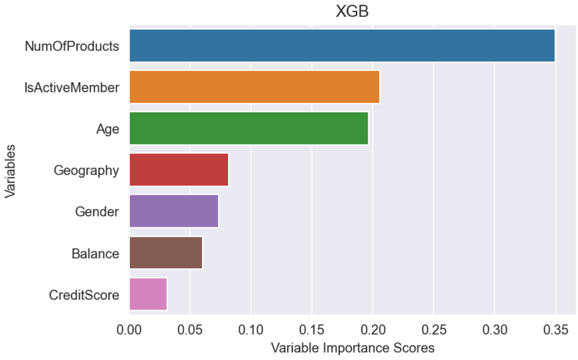

```
model Coefficients: [('Age', 0.3421352989389681), ('CreditScore', 0.21023651534930482), ('Balance', 0.19262918674644344),
('NumOfProducts', 0.13846212300323857), ('Geography', 0.049673528824712695), ('IsActiveMember', 0.04287676286975985), ('Gen
der', 0.023986584267572417)]
```



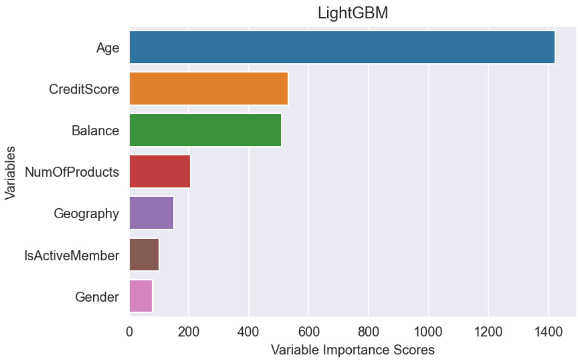

```
model Coefficients: [('Age', 0.519147825525707), ('NumOfProducts', 0.24484293713067057), ('IsActiveMember', 0.0752973141469
9131), ('Balance', 0.07166903408114118), ('Geography', 0.05753280021899225), ('Gender', 0.023353729887070875), ('CreditScor
e', 0.008156359009426777)]
```



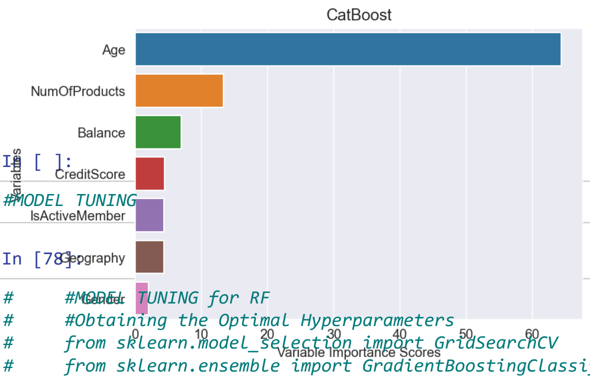

```
model Coefficients: [('NumOfProducts', 0.3499676), ('IsActiveMember', 0.2059714), ('Age', 0.19678941), ('Geography', 0.0817
62165), ('Gender', 0.073562264), ('Balance', 0.06068159), ('CreditScore', 0.031265665)]
```




```
model Coefficients: [('Age', 1424), ('CreditScore', 531), ('Balance', 509), ('NumOfProducts', 206), ('Geography', 150), ('I
sActiveMember', 102), ('Gender', 78)]
```




```
model Coefficients: [('Age', 64.42323227643645), ('NumOfProducts', 13.3501118399526), ('Balance', 6.981514086982471), ('Cre
ditScore', 4.4835824189807125), ('IsActiveMember', 4.3857728119505595), ('Geography', 4.373668463310587), ('Gender', 2.0021
18102386612)]
```



In [ ]:

```
#MODEL TUNING
```

In [78]:

```
#     #MODEL TUNING for RF
#     #Obtaining the Optimal Hyperparameters
#     from sklearn.model_selection import GridSearchCV
#     from sklearn.ensemble import GradientBoostingClassifier
#     RF = RandomForestClassifier()

#     parameters = [{'kernel': ['rbf'],
#                    'gamma': ['scale', 'auto'],
#                    'C': [.1, 1, 2]},
#                   {'kernel': ['linear'],
#                    'C': [.1, 1, 10]}
#                              ]
#     grid_GBC = GridSearchCV(estimator=RF, param_grid = parameters, cv = 5, n_jobs=-1)
#     grid_GBC.fit(X_train, y_train)
#     print(" Results from Grid Search " )
#     print("\n The best estimator across ALL searched params:\n",grid_RF.best_estimator_)
#     print("\n The best score across ALL searched params:\n",grid_RF.best_score_)
#     print("\n The best parameters across ALL searched params:\n",grid_RF.best_params_)
```

In [79]:

```
# RandomForestClassifier.get_params(()).keys()
```

In [ ]:

In [62]:

```
#MODEL TUNING for XGB
#Obtaining the Optimal Hyperparameters

XGB = XGBClassifier()
scoring_metric = 'recall'
parameters = {'n_estimators': [50, 100, 200],
              'learning_rate': [0.001, 0.01, 0.1],
              'max_depth': [3, 4, 6],
              'subsample': [0.5, 0.75],
              'gamma': [0.1, 0.5, 1],
             }
grid_XGB = GridSearchCV(estimator=XGB, param_grid = parameters,scoring= scoring_metric, cv = 5, n_jobs=-1)
grid_XGB.fit(X_train, y_train)
print(" Results from Grid Search " )
print("\n The best estimator across ALL searched params:\n",grid_XGB.best_estimator_)
print("\n The best score across ALL searched params:\n",grid_XGB.best_score_)
print("\n The best parameters across ALL searched params:\n",grid_XGB.best_params_)
```

```
 Results from Grid Search 

 The best estimator across ALL searched params:
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0.5, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=200,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=1, ...)

 The best score across ALL searched params:
0.8635940105597039

 The best parameters across ALL searched params:
{'gamma': 0.5, 'learning_rate': 0.1, 'max_depth': 6, 'n_estimators': 200, 'subsample': 0.5}
```

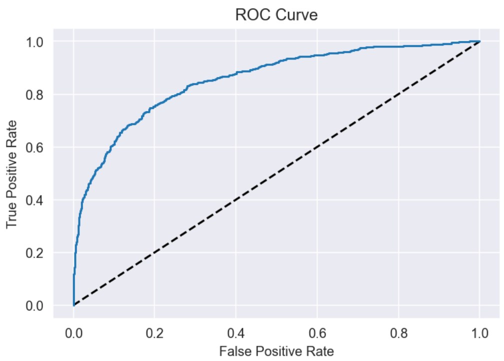
In [ ]:

```
#based on the below result XGB model tuning improved the recall score for about 3%
```

In [63]:

```
print("Accuracy of grid_XGB.best_estimator_ classifier: ", grid_XGB.best_estimator_.score(X_test, y_test))
print("\n")
y_pred = grid_XGB.best_estimator_.predict(X_test)
classifi_score(grid_XGB.best_estimator_, 'grid_XGB.best_estimator__classifier', y_test, y_pred)


# Receiver Operating Characteristic (ROC) Curve
from sklearn.metrics import roc_curve
y_pred_prob = grid_XGB.best_estimator_.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='grid_XGB.best_estimator__classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.show();


# Area Under Curve (AUC) score
from sklearn.metrics import roc_auc_score
print('AUC score over the test set:', roc_auc_score(y_test, y_pred_prob))
print("\n")
print("\n")
print("\n")
```

```
Accuracy of grid_XGB.best_estimator_ classifier:  0.852


Confusion matrix of  grid_XGB.best_estimator__classifier  classifier:
[[1479  128]
 [ 168  225]]


Precision =  63.74%
Recall =  57.25%
F1-Score =  60.32%


Classification report of  grid_XGB.best_estimator__classifier  classifier:
              precision    recall  f1-score   support

           0       0.90      0.92      0.91      1607
           1       0.64      0.57      0.60       393

    accuracy                           0.85      2000
   macro avg       0.77      0.75      0.76      2000
weighted avg       0.85      0.85      0.85      2000
```




```
AUC score over the test set: 0.8570170896728848
```

In [34]:

```
#MODEL TUNING for GBC
#Obtaining the Optimal Hyperparameters for the highest score models
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import GradientBoostingClassifier
GBC = GradientBoostingClassifier()

parameters = {'learning_rate': [0.02, 0.05, 0.1, 0.2],
              'subsample'    : [0.618, 0.65, 0.75, 0.85, 0.95],
              'n_estimators' : [200,350,400, 450],
              'max_depth'    : [5,8,10, 14]
             }
grid_GBC = GridSearchCV(estimator=GBC, param_grid = parameters, cv = 2, n_jobs=-1)
grid_GBC.fit(X_train, y_train)
print(" Results from Grid Search " )
print("\n The best estimator across ALL searched params:\n",grid_GBC.best_estimator_)
print("\n The best score across ALL searched params:\n",grid_GBC.best_score_)
print("\n The best parameters across ALL searched params:\n",grid_GBC.best_params_)
```

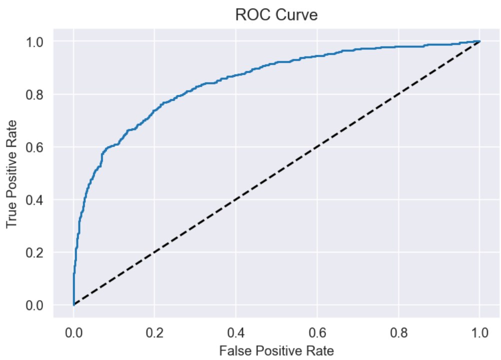
```
 Results from Grid Search

 The best estimator across ALL searched params:
 GradientBoostingClassifier(learning_rate=0.05, max_depth=14, n_estimators=350,
                           subsample=0.85)

 The best score across ALL searched params:
 0.8864065449968533

 The best parameters across ALL searched params:
 {'learning_rate': 0.05, 'max_depth': 14, 'n_estimators': 350, 'subsample': 0.85}
```

In [ ]:

In [36]:

```
print("Accuracy of grid_GBC.best_estimator_ classifier: ", grid_GBC.best_estimator_.score(X_test, y_test))
print("\n")
y_pred = grid_GBC.best_estimator_.predict(X_test)
classifi_score(grid_GBC.best_estimator_, 'grid_GBC.best_estimator__classifier', y_test, y_pred)


# Receiver Operating Characteristic (ROC) Curve
from sklearn.metrics import roc_curve
y_pred_prob = grid_GBC.best_estimator_.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='grid_GBC.best_estimator__classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.show();


# Area Under Curve (AUC) score
from sklearn.metrics import roc_auc_score
print('AUC score over the test set:', roc_auc_score(y_test, y_pred_prob))
print("\n")
print("\n")
print("\n")
```

```
Accuracy of grid_GBC.best_estimator_ classifier:  0.856


Confusion matrix of  grid_GBC.best_estimator__classifier  classifier:
[[1496  111]
 [ 177  216]]


Precision =  66.06%
Recall =  54.96%
F1-Score =  60.00%


Classification report of  grid_GBC.best_estimator__classifier  classifier:
              precision    recall  f1-score   support

           0       0.89      0.93      0.91      1607
           1       0.66      0.55      0.60       393

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




```
AUC score over the test set: 0.8512756689483509
```

In [ ]:

In [ ]:

```
#it couldn't be tunned only based on one specific metric

# #MODEL TUNING for GBC
# #Obtaining the Optimal Hyperparameters for the highest score models

# from sklearn.model_selection import GridSearchCV
# from sklearn.ensemble import GradientBoostingClassifier
# from sklearn.metrics import make_scorer
# GBC = GradientBoostingClassifier()
# scoring_metric = 'recall'

# parameters = {'learning_rate': [0.02, 0.05, 0.1, 0.2],
#               'subsample'    : [0.65, 0.75, 0.85, 0.95],
#               'n_estimators' : [200,300,350],
#               'max_depth'    : [3,4,5,8,10]
#              }
# grid_GBC = GridSearchCV(estimator=GBC, param_grid = parameters,scoring=scoring_metric,refit=False, cv = 5, n_jobs=-1)
# grid_GBC.fit(X_train, y_train)
# print(" Results from Grid Search " )
# print("\n The best estimator across ALL searched params:\n",grid_GBC.best_estimator_)
# print("\n The best score across ALL searched params:\n",grid_GBC.best_score_)
# print("\n The best parameters across ALL searched params:\n",grid_GBC.best_params_)
```

In [116]:

```
#MODEL TUNING for LightGBM
#Obtaining the Optimal Hyperparameters

LightGBM = LGBMClassifier()

parameters = {'max_depth'    : [3,5,7],
              'num_leaves': [5, 10],
              'learning_rate': [0.001, 0.01, 0.1],
              'subsample'    : [0.9,0.8,0.7,0.6],
              'n_estimators' : [100,200,500],
              'reg_alpha': [0.1, 0.5],
              'reg_lambda': [0.1, 0.5]
             }
grid_LightGBM = GridSearchCV(estimator=LightGBM, param_grid = parameters, cv = 5, n_jobs=-1)
grid_LightGBM.fit(X_train, y_train)
print(" Results from Grid Search " )
print("\n The best estimator across ALL searched params:\n",grid_LightGBM.best_estimator_)
print("\n The best score across ALL searched params:\n",grid_LightGBM.best_score_)
print("\n The best parameters across ALL searched params:\n",grid_LightGBM.best_params_)
```

```
 Results from Grid Search 

 The best estimator across ALL searched params:
 LGBMClassifier(max_depth=7, n_estimators=500, num_leaves=10, reg_alpha=0.5,
               reg_lambda=0.5, subsample=0.9)

 The best score across ALL searched params:
 0.8839803994427244

 The best parameters across ALL searched params:
 {'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 500, 'num_leaves': 10, 'reg_alpha': 0.5, 'reg_lambda': 0.5, 'subsam
ple': 0.9}
```

In [39]:

```
#Hyperparameters have previously been obtained with the help of GridSearchCV.

models = []
models.append(('GBC', GradientBoostingClassifier(random_state = 12345, learning_rate = 0.05, max_depth = 10, n_estimators = 350, subsampl
models.append(('XGB', XGBClassifier(random_state = 12345,learning_rate = 0.1, max_depth = 6, min_samples_split = 2, n_estimators = 500, s
models.append(("LightGBM", LGBMClassifier(random_state = 12345,  learning_rate = 0.1, max_depth = 7, n_estimators = 500 , num_leaves =10,
models.append(("CatBoost", CatBoostClassifier(random_state = 12345, verbose = False, depth = 10, iterations = 1000, l2_leaf_reg = 5, lear


# evaluate each model in turn
results = []
names = []

for name, model in models:
        import time
        start = time.time()
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        recall = recall_score(y_test, y_pred)
        msg = "%s: (%f)" % (name, recall)
        end = time.time()
        print(end - start)
        print(msg)
```

```
16.48192548751831
GBC: (0.559796)
[20:43:21] WARNING: C:/Users/administrator/workspace/xgboost-win64_release_1.6.0/src/learner.cc:627:
Parameters: { "min_samples_split" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings but
  then being mistakenly passed down to XGBoost core, or some parameter actually being used
  but getting flagged wrongly here. Please open an issue if you find any such cases.


5.130279302597046
XGB: (0.554707)
0.4330410957336426
LightGBM: (0.587786)
26.597675323486328
CatBoost: (0.631043)
```

In [ ]:

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